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JASA ARTICLE

Toward a dynamic national transportation noise map: Modeling temporal variability of traffic volume

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ABSTRACT:
The National Transportation Noise Map (NTNM) gives time-averaged traffic noise across the continental United States (CONUS) using annual average daily traffic. However, traffic noise varies significantly with time. This paper outlines the development and utility of a traffic volume model which is part of VROOM, the Vehicular Reduced-Order Observation-based model, which, using hourly traffic volume data from thousands of traffic monitoring stations across CONUS, predicts nationwide hourly varying traffic source noise. Fourier analysis finds daily, weekly, and yearly temporal traffic volume cycles at individual traffic monitoring stations. Then, principal component analysis uses denoised Fourier spectra to find the most widespread cyclic traffic patterns. VROOM uses nine principal components to represent hourly traffic characteristics for any location, encapsulating daily, weekly, and yearly variation. The principal component coefficients are predicted across CONUS using location-specific features. Expected traffic volume model sound level errors—obtained by comparing predicted traffic counts to measured traffic counts—and expected NTNM-like errors, are presented. VROOM errors are typically within a couple of decibels, whereas NTNM-like errors are often inaccurate, even exceeding 10 decibels. This work details the first steps towards creation of a temporally and spectrally variable national transportation noise map.
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I. INTRODUCTION

Road 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] Not only humans are adversely affected by loud road noise,[2,3] but many other species are as well.[4,5] While studies typically look at 24-h averaged levels,[6] road noise exhibits significant temporal variability, as will be shown further on in this paper. Most significantly, diurnal variability in road traffic does not show equal variation in all locations, and so even when areas have similar 24-h equivalent levels, actual hourly levels can differ. Road noise cannot be effectively measured along every roadside in the country, and long-time-averaged levels are seldom accurate for particular times of day, so accurate modeling of road noise is necessary for improving road 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 characterization of traffic volume itself, along with other parameters such as vehicle class mix, vehicle speed, pavement type, and road inclination.[7,8] The National Transportation Noise Map 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).[9] While 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.

Traffic volume can show large variation, not only diurnally, but also from weekday to weekend and from summer to winter. Characterizing the dynamic nature of traffic volume is not only useful for determining the changes in sound levels at locations where traffic counts are known but can also lead to a model for predicting variable traffic volume at other locations, and therefore to predicting sound levels across CONUS for particular time periods.

Traffic volume can be modeled in various ways, though a simplified model can be made using vehicle count data at various locations across CONUS.[10,11] The Federal Highway Administration tabulates hourly traffic counts recorded at thousands of traffic monitoring stations across the United States. While hourly counts give a detailed representation of hourly traffic volume for individual stations, this representation requires thousands of individual hourly counts for each location, and using vehicle counts to predict traffic volume at other times or at other locations is not straightforward. Other methods such as wavelet decomposition[12,13] can be used to model temporal variability. In this paper, the first

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part of an original model is introduced. This model is called VROOM, which stands for the Vehicular Reduced-Order Observation-based Model. VROOM predicts hourly traffic noise for roads across CONUS. The first part of VROOM, which is the focus of this paper, predicts vehicle numbers—used synonymously with traffic volume—across CONUS.

Treating traffic volume as a time-dependent signal enables application of signal processing techniques. VROOM was developed using Fourier analysis[14] and principal component analysis, PCA, to characterize traffic patterns common across CONUS. VROOM requires only nine values—which are predictable from geospatial and road-specific feature values—at a location to fully represent hourly traffic volume for any time period.

VROOM was developed using hourly resolution vehicle counts, and does not consider shorter-term traffic volume behavior, though it may be possible to adapt this approach for shorter time scales.[15–17] VROOM predicts hourly traffic volume at any location using geospatial or location-specific features. While predicting traffic counts is itself a useful result, VROOM is also able to predict traffic noise across the continent on hourly, rather than time-averaged, time scales.[18]

To create a temporally and spectrally varying national transportation noise map, the following steps are needed:

- Predict traffic volume along roads.
- Predict time-varying traffic class mix along roads, e.g., heavy trucks vs smaller vehicles.
- Calculating traffic noise emissions along roads based on vehicle class numbers.
- Propagate source vehicle noise to other locations to create noise maps.

Figure 1 shows a schematic of these steps. The user inputs include road data and geospatial data. Road data includes values such as the number of through lanes, the speed limit along road segments, the f-system—or type of road, such as interstate, principal arterial, or local road—and whether the location is urban or rural. Geospatial data[19] can include features such as nighttime light brightness, land cover, urban population, etc.

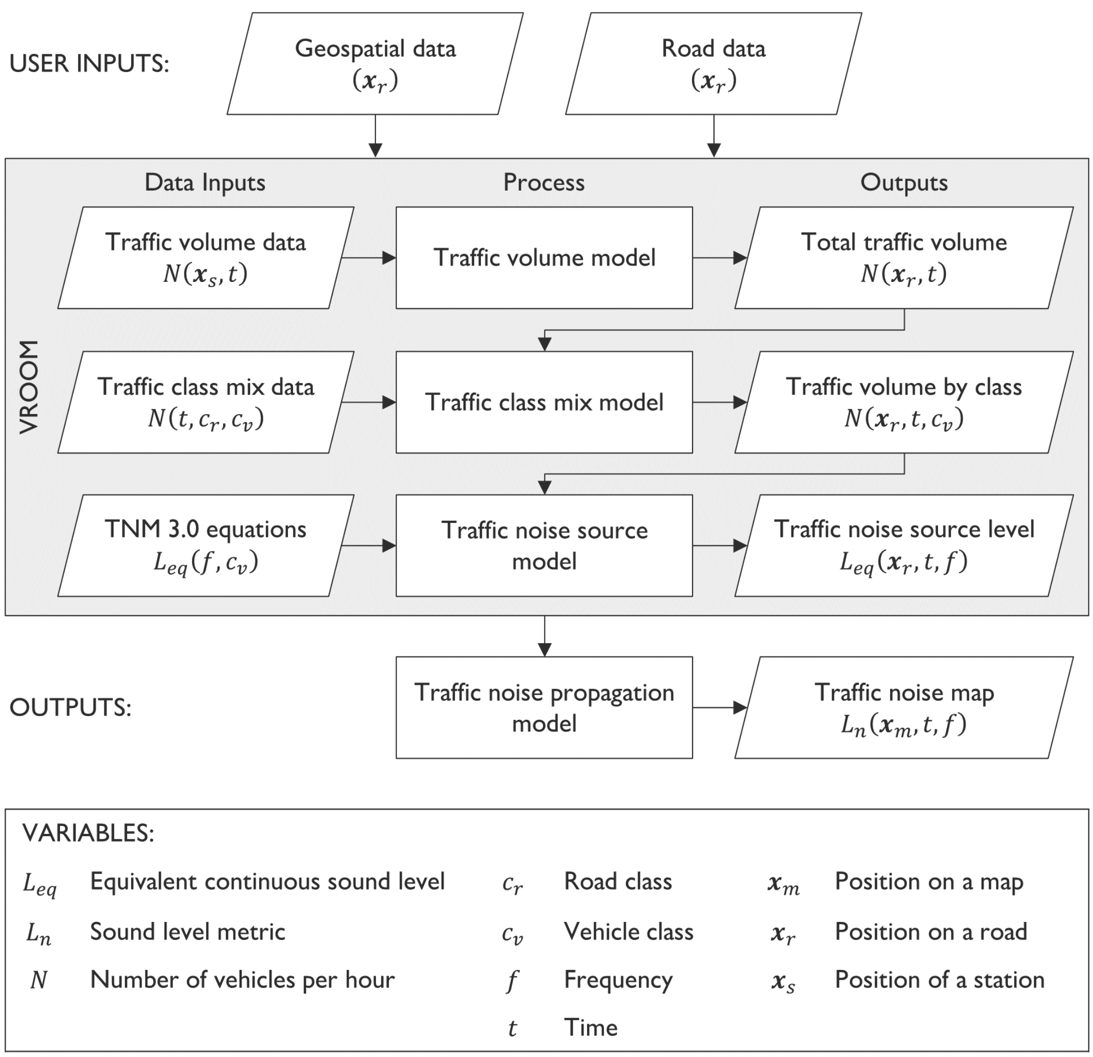

FIG. 1. Flowchart outlining the steps towards creating a dynamic national road traffic noise map.

This paper considers only the traffic volume model part of VROOM—the first line of VROOM as shown in Fig. 1—and does not consider the traffic class mix model or the traffic noise source model parts of VROOM. Instead of considering the full model, a simplified error metric for the traffic volume model is presented, which gives predicted decibel errors for VROOM-predicted traffic volume. Predicted errors when using yearly averaged vehicle numbers are also presented, which would be similar to expected errors in the Bureau of Transportation Statistics' National Transportation Noise Map near roads. Errors are calculated by comparing predicted vehicle numbers to reported vehicle numbers.

II. FOURIER ANALYSIS AND PRINCIPAL COMPONENT ANALYSIS OF TRAFFIC VOLUME

Fourier analysis can be used to find repeating temporal cycles or patterns in data. Reported hourly vehicle counts from 2015 to 2018 from by thousands of traffic monitoring stations located across CONUS[20] were used; by investigating the Fourier spectra produced, strong temporal patterns were found that represent daily, weekly, and yearly variation in traffic volume at individual stations. Repeatable temporal cycles were found in the Fourier spectra with periods corresponding to daily, weekly, and yearly patterns. For further details, see Ref. 21.

While using a denoised Fourier spectrum does create a simplified model for temporal variability of traffic volume at a particular location, PCA was also used to create a generalized model that can predict traffic volume at other locations. Fourier spectra were split into separate weekly and yearly cycles, and principal components were found to represent the most common combinations of cyclic weekly and yearly traffic patterns found across stations. Because data from all stations were not equally reliable, a weighted PCA was used. See Cook *et al.* for further details.[21] Each resulting principal component represents a linear combination of several Fourier amplitudes or, by using an inverse Fourier transform, a specific traffic volume pattern. The principal component coefficients, which are simply numeric values, give the combination of these traffic volume patterns.

The first principal component vectors, one for the weekly data and another for the yearly data, are shown in temporal space in Fig. 2 and give the weighted average traffic volume pattern seen across all stations. The yearly pattern shows little variation across the course of a year. The weekly pattern shows the weighted average hourly traffic pattern found across CONUS during the course of a week; weekends show a smooth hourly variation during daytime hours, while weekdays show an increase in morning and evening hours higher than that during the middle of the day (during rush hours), with less traffic activity during the nighttime hours. This type of traffic pattern is common for urban locations and is similar to data shown in Fu *et al*.[22] A complete description of these principal component vectors and how they were obtained would necessitate several additional pages of explanation, and so is not included in this paper. The additional principal component vectors are shown in the supplementary material[23] and additional details are available upon request.

By using a normalized approach, VROOM was created to model hourly traffic volume, and requires just nine total coefficients to represent hourly traffic volume for any location. Eight of the values are the principal component coefficients and are used to calculate the variation of traffic volume from the average traffic pattern. The other coefficient is the AADT, which scales the total traffic pattern to give the correct average number of vehicles and is often known for any particular road. The methods for predicting VROOM coefficients are considered in Sec. III.

III. PREDICTION OF VROOM COEFFICIENTS

VROOM predicts dynamic traffic volume by predicting nine coefficients—or eight coefficients when the AADT is known. These coefficients can be predicted along any road by using location-dependent features. Pedersen and coworkers[19,24,25] showed that several features (slope, distance to railroads, land cover, etc.) for a location can be represented using a non-linear basis, called diffusion coordinates (DCs). Because these DCs characterize locations, they can also be used to predict traffic volume for that location by predicting VROOM coefficients. For the current analysis, these 12 DCs are used, along with road data, including features such as speed limit and the number of through lanes. Together these comprise the VROOM predictors. All the predictive features are shown spatially across CONUS in the supplementary material.[23]

Using the VROOM predictors and the known VROOM coefficients at traffic monitoring stations, a weighted least

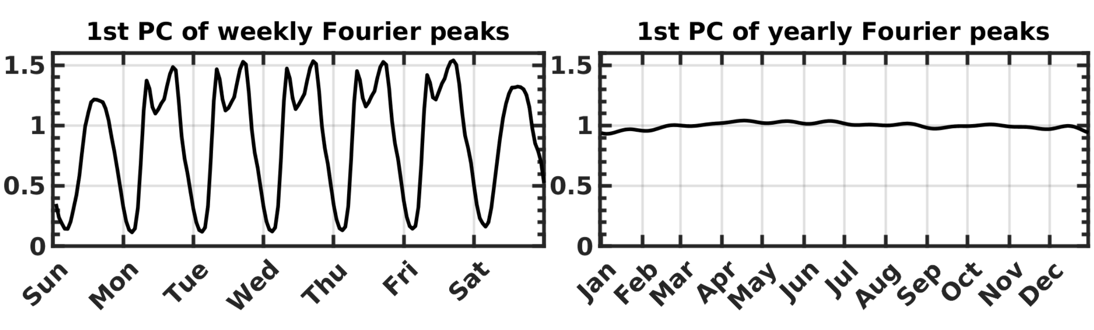

FIG. 2. Normalized principal components which represent the most common normalized traffic patterns found across CONUS.

squares method is used to find a best-fit linear transformation from predictors to coefficients. This yields a best-fit multiplying matrix X_0 so that VROOM predictors at arbitrary locations can be used to predict VROOM coefficients and therefore traffic volume at arbitrary locations. Using P as a matrix containing the VROOM predictors at each traffic monitoring station, W as a diagonal matrix for the station weightings, and C as a matrix containing the coefficients at each station, the matrix X_0 can then be obtained and used to predict coefficients for arbitrary locations. The coefficient matrix for arbitrary locations $\tilde{C}_{loc}$ is given by multiplying the matrix P_{loc}, which contains the VROOM predictors for those locations, by X_0,

$$X_0 = \min_X ||PWX - C|| = \left(P^T WP\right)^{-1}\left(P^T WC\right),$$
$$\tilde{C}_{loc} = P_{loc} X_0. \quad (1)$$

Spatial maps of the VROOM coefficients are given in the supplementary material.[23] The predicted coefficients $\tilde{C}_{loc}$ can then be used to obtain predicted traffic volume for any hour desired using the VROOM traffic volume model.

Figure 3 shows the normalized weekly and yearly VROOM predictions for stations in Idaho, Wyoming, and Oklahoma, known as sites A, B, and C, respectively. Also, shown are the average normalized traffic counts and the AADT representation, which uses the average value for all time periods. The average normalized traffic counts across a year are obtained by using the mean number of traffic counts for each week of the year, rather than each hour or day of the year. This is necessary because with only four years of data (2015–2018), average daily or hourly counts across a year would be heavily impacted by the days of the week for which data were available (at most four different days of the week). This approach removes this bias; unfortunately, it can also mask some of the benefit of predicting hourly values when looking at yearly predictions but is necessary for accurate comparison. Thus, comparisons show 168 hourly values for weekly results, and 52 weekly values for yearly results.

Figure 3(a) shows the weekly patterns for site A, located in southern Idaho, with the corresponding yearly patterns shown in Fig. 3(d). There is high agreement between the averaged data and the VROOM prediction. This site is typical of several locations across CONUS where the VROOM prediction faithfully approximates reported vehicle counts.

Site B, which is located in northwest Wyoming and is shown in Figs. 3(b) and 3(e), has a very different traffic pattern than site A. The average reported traffic counts increase dramatically in the summer and are higher on weekends than on weekdays, without any sort of rush hour. This behavior, while not uncommon for seasonal roads like those near ski resorts or some national parks, as this site is, is found in only a few locations across CONUS. While the VROOM prediction is unable to fully capture the variability of the reported traffic counts, differing by up to 25%, it is still an improvement over the AADT approach, which can differ up to 57%.

Site C, located in Oklahoma and shown in Figs. 3(c) and 3(f), reported only counts for April through December for a single year. As such, yearly errors cannot be calculated from January through March. Though errors cannot be calculated for this time period, VROOM can still predict the traffic volume despite the missing traffic counts. This shows an example of how VROOM predictions can be made not just where and when counts are reported, but at roads across all of CONUS for any time period.

While looking at results for a few individual locations is insightful, it is infeasible to show an adequate number of locations individually, since there are millions of road segments across the country. Mm. 1 shows the relative VROOM predicted weekly traffic volume and Mm. 2 shows the relative VROOM predicted yearly traffic volume at roads across the country, alongside average traffic counts at traffic monitoring stations. Normalized traffic volumes are shown, and so do not indicate total number of vehicles, but rather whether each location has more or less traffic than it does on average. Differences between interstates and other roads can be seen, as well as behaviors such as rush hours in cities. The AADT approach is not shown here, as it would give a value of 100% for all time periods and locations.

Mm. 1. Relative VROOM-predicted weekly traffic volume for locations across CONUS. Each location is shown relative to its average weekly value of 100%.

Mm. 2. Relative VROOM-predicted yearly traffic volume for locations across CONUS. Each location is shown relative to its average yearly value of 100%.

A. Sound level error metric

Model prediction accuracies of both the VROOM and the AADT approaches can be calculated by comparing average reported normalized traffic counts $N_{reported}$ to the predicted normalized traffic volume $N_{predicted}$ at traffic monitoring stations. The "prediction" for the AADT approach is simply the average number of vehicles. A normalized approach is taken so that errors are a result of the model prediction, and not caused by differences between the reported AADT and reported hourly counts. From an acoustics viewpoint, a useful error metric is a sort of expected sound level error in decibels. Because different vehicles can be considered to be uncorrelated sound sources, the expected sound level error, E_{dB}, at a site can be determined at a particular time by

$$E_{dB} = 10 \log_{10}\left(\frac{N_{predicted}}{N_{reported}}\right). \quad (2)$$

With this metric, an error of $+3$ dB means that the number of vehicles predicted is double the average reported

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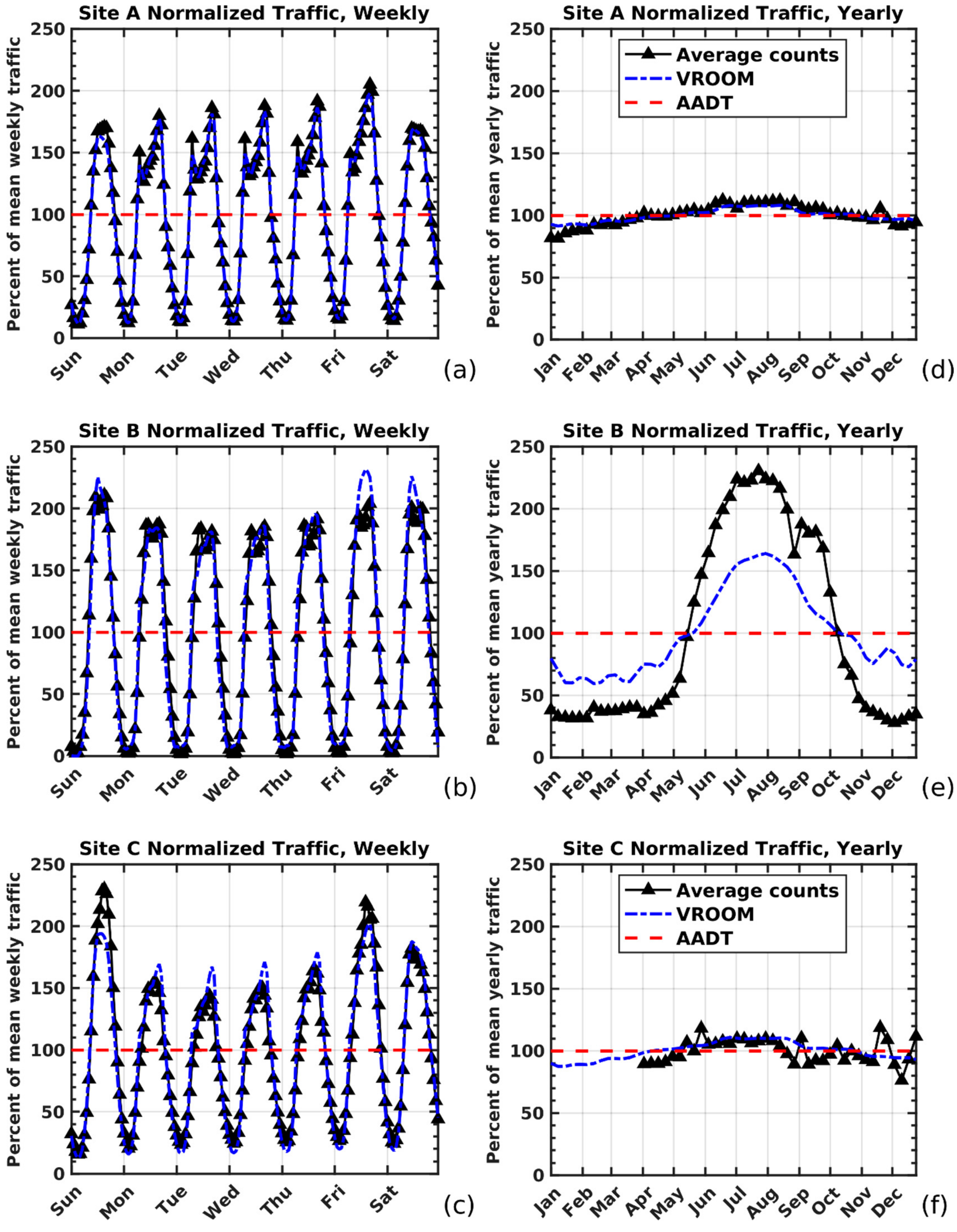

FIG. 3. (Color online) For three sites, the weekly traffic patterns (left) and the yearly traffic patterns (right) are shown. The average traffic counts can be compared with the VROOM prediction.

number of vehicles, and an error of –3 dB means that the prediction is half the average reported value.[7] This error metric gives expected model sound level errors based solely on the total hourly traffic volume representation and reported hourly vehicle numbers, without considering things such as vehicles types or vehicle speed, and as such assumes no temporal change in vehicle class mix or road conditions. While incomplete, with more viable metrics being a topic for future publications on VROOM, this error metric is still viable to show relative errors between VROOM and the AADT approach because everything except total traffic volume is assumed to be the same for both methods. The AADT errors are at least partially indicative of possible expected errors of the National Transportation Noise Map at the locations and times considered.

B. Prediction accuracy

While the prediction accuracy cannot be obtained for all locations, the weekly and yearly errors for predictions of

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both methods can be calculated at traffic monitoring stations. Errors for sites A, B, and C are shown in Fig. 4. VROOM prediction errors are much smaller than AADT prediction errors for most time periods, more noticeably for hours across a week and most drastically during nighttime hours. The largest consistent VROOM prediction errors occur near midnight on weekdays at sites with low traffic volume and are a result of either the predicted normalized traffic volume or the normalized reported traffic counts being close to zero. Errors for each station are shown geographically and temporally in Mm. 3, which shows the weekly errors, and in Mm. 4 which shows the yearly errors.

Mm. 3. VROOM weekly errors are shown alongside AADT weekly errors, shown geographically and temporally. VROOM gives much smaller errors than the AADT method for weekly errors.

Mm. 4. VROOM yearly errors are shown alongside AADT yearly errors, shown geographically and temporally.

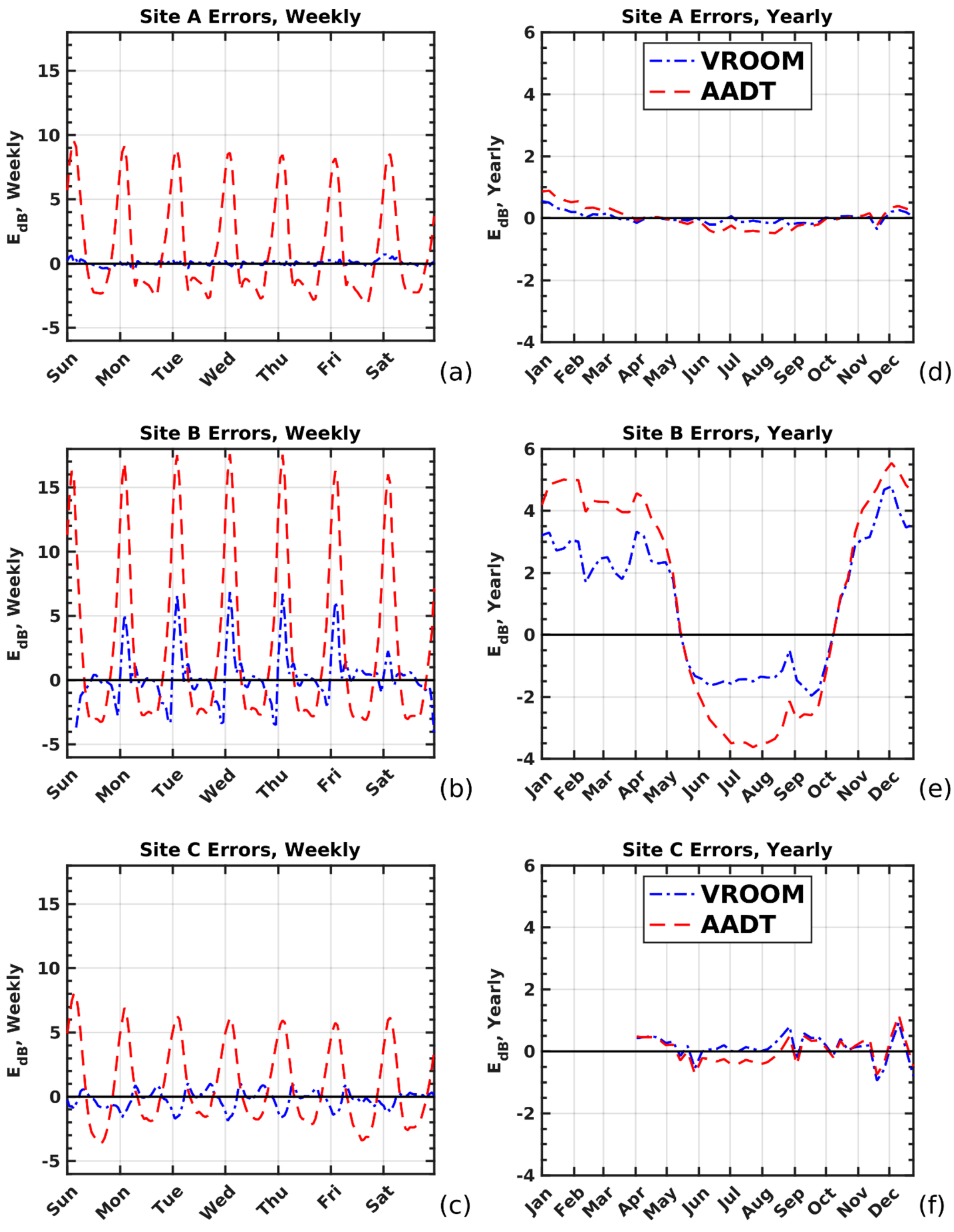

FIG. 4. (Color online) Predicted model errors, both weekly (left) and yearly (right), for three sites.

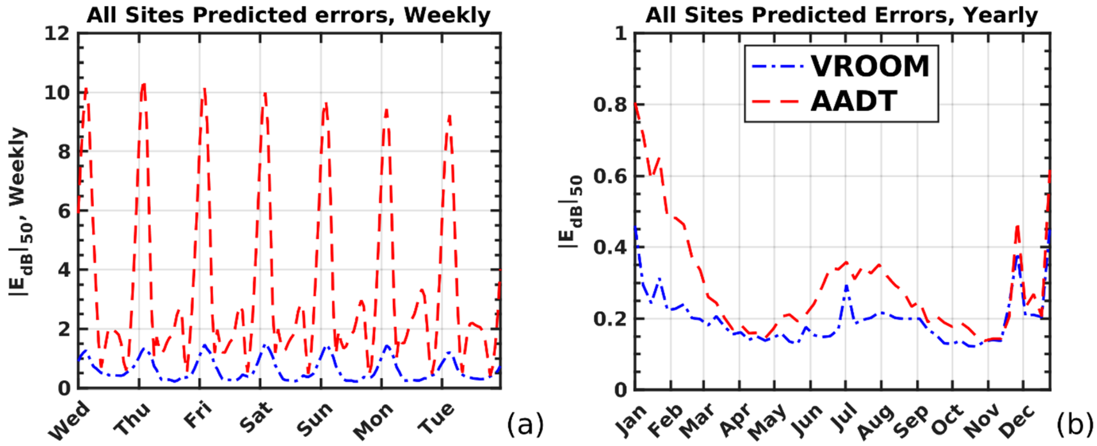

FIG. 5. (Color online) Median location-averaged absolute VROOM and AADT errors, shown both weekly and yearly. The VROOM prediction errors are clearly smaller than AADT prediction errors, most especially for weekly errors. Median nighttime AADT prediction errors can exceed 10 dB, and median daytime errors can exceed 3 dB.

VROOM gives slightly smaller errors than the AADT method for yearly errors, though differences are not as extreme as the weekly errors.

While errors vary across both time and space, and so are shown in video format, median absolute decibel errors, $|E_{dB}|_{50}$, averaged across either time or space, can be shown in static figures. The absolute value is needed so that positive and negative errors do not unjustly cancel one another out. The median errors across all locations can be calculated for each time period and are shown in Fig. 5. The VROOM prediction errors are much smaller errors than the AADT prediction errors, again most noticeably across the hours of a week. While the absolute error does not show the sign, AADT errors are generally positive during nighttime hours and during the winter months, and negative during daytime hours and the summer months. VROOM errors may be either positive or negative. The largest errors occur during

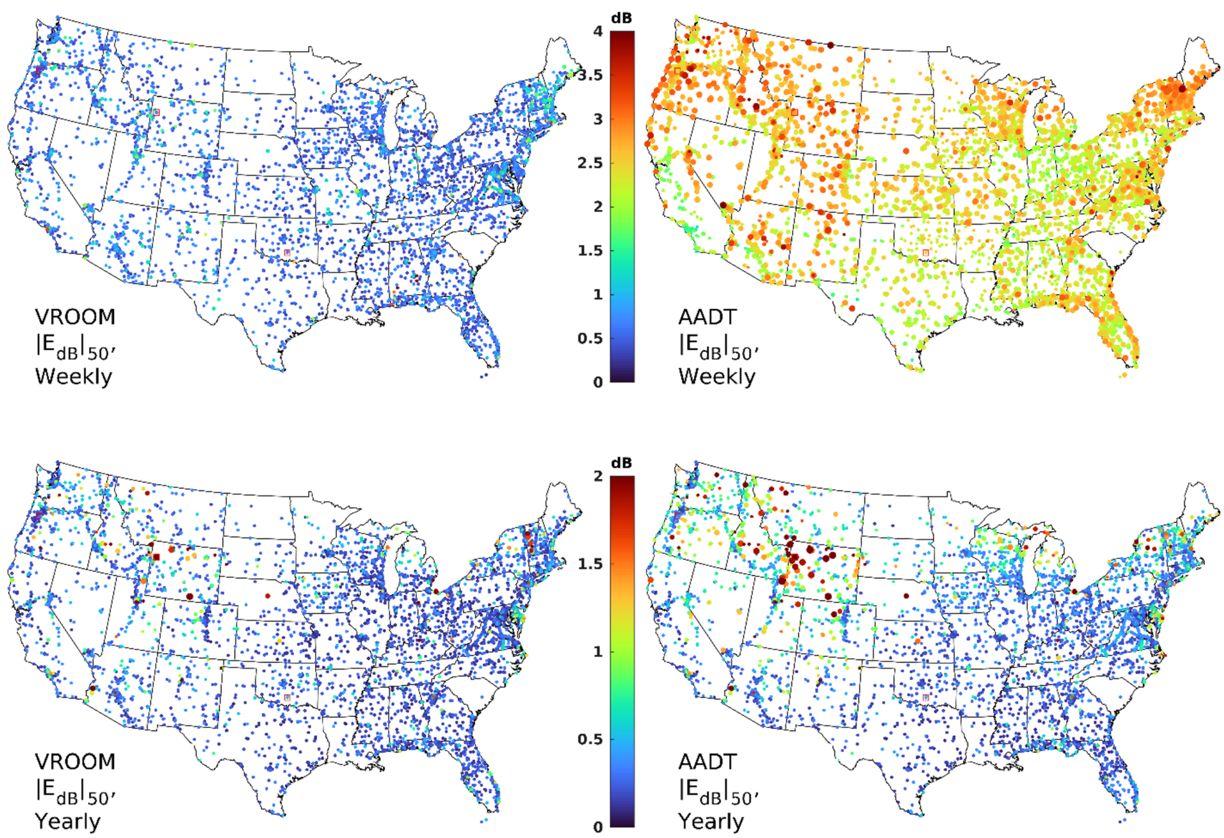

FIG. 6. (Color online) Median time-averaged absolute VROOM and AADT errors, shown both weekly and yearly. The VROOM prediction errors are clearly smaller than AADT predictions, most especially for weekly errors. Notably, AADT weekly errors exceed 1.5 dB for 98.4% of locations VROOM weekly errors are less than 1.5 dB for 98.4% of locations.

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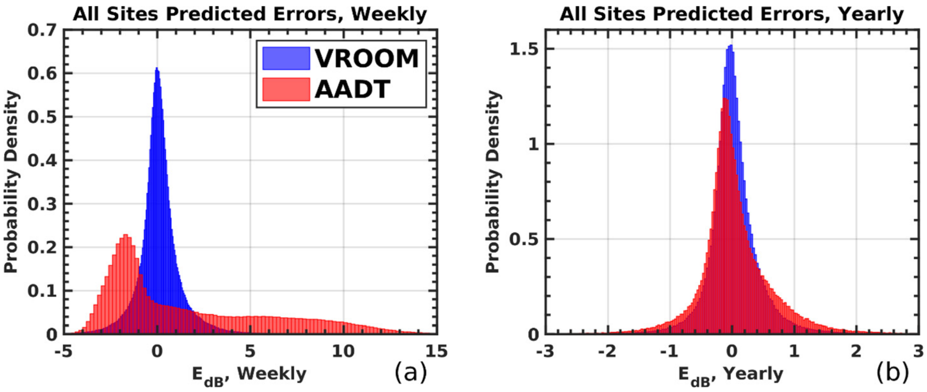

FIG. 7. (Color online) Histogram of expected errors in decibels for the AADT approach and for VROOM. Weekly errors in particular are significantly reduced using VROOM.

nighttime hours for both methods, and median AADT errors can exceed 10 decibels.

Figure 6 shows the median absolute errors when, instead of averaging across location, the absolute errors are averaged across time. The yearly expected errors for both methods are typically within 1 dB. This is because traffic volume does not change drastically by week of the year for most locations, with some notable exceptions, primarily in the northwest. While the VROOM prediction errors are generally slightly smaller, the AADT approach is a valid representation for most locations. The largest yearly errors for both methods can occur at sites near seasonal roads, like site B, which is in Jackson, Wyoming. While the VROOM prediction does not always reproduce that amount of variation faithfully, VROOM is still more accurate than the AADT method for nearly all locations.

A large difference between the methods is seen when considering the temporally averaged weekly errors. The AADT prediction errors exceed 1.5 dB for 98.4% of locations and exceed 3 dB for 4.3% of locations. In contrast, the VROOM prediction errors exceed 1.5 dB for only 1.6% of locations and exceed 3 dB for only 0.2% of locations. By predicting traffic volume for each hour with VROOM, errors are dramatically reduced across CONUS, with few significant errors.

Further insight can be gained by viewing the full distribution of errors, without using absolute median errors. Figure 7 shows histograms for both methods' errors, both for weekly and yearly time periods. The yearly errors for both methods, seen in Fig. 7(b), are typically within ± 1 dB, as was seen previously, with the AADT errors forming a slightly wider distribution with larger tails.

The weekly errors tell a more interesting story. The weekly VROOM errors form a tight distribution, as do the yearly errors. However, the AADT error distribution is much different, peaking around -2 dB with a long, flat tail of positive errors. This indicates that hourly averaged traffic volumes very poorly represent reported hourly traffic volumes. Expected errors evidence that average sound levels are seldom indicative of actual sound levels across the hours of a week. Modeling hourly traffic volume with VROOM can vastly improve expected hourly sound level predictions.

IV. CONCLUSION

The hourly dynamic nature of traffic volume in its variety across CONUS can be represented in a concise manner using VROOM, which also enables prediction of traffic volume. Requiring just nine values—predictable from geospatial and road data—vehicle counts can be accurately represented and predicted with full temporal variability. By improving representation of traffic volume, road traffic sound levels can be better represented and predicted.

While using annual average daily traffic counts can give a decently accurate representation of traffic volume for most days of the year, daily and yearly averaged traffic counts do not accurately represent particular hourly traffic volumes. This means that annual average daily sound levels do not accurately portray what the actual sound level would be for most hours—not just during nighttime hours, where errors can often exceed 10 dB—but also for many daytime hours. By instead modeling traffic volume using reported hourly traffic counts with VROOM, sound levels can be more accurately predicted.

The approach outlined in this paper is the first step towards a dynamic national transportation noise map. In future, advancements towards predicting hourly road traffic noise can be made by accounting for dynamic differences in different vehicle classes, such as medium or heavy trucks, as different vehicle classes have different characteristic sound emission spectra. By accounting for differences in vehicle classes, both spectral and temporal variability of traffic noise can be better modeled and is a topic of ongoing analysis.

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