An app for nationwide dynamic traffic noise prediction

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ABSTRACT

Despite being so pervasive, road traffic noise can be difficult to model and predict on a national scale. Detailed road traffic noise predictions can be made on small geographic scales using the US Federal Highway Administration's Traffic Noise Model (TNM), but TNM becomes infeasible for the typical user on a nationwide scale because of the complexity and computational cost. Incorporating temporal and spectral variability also greatly increases complexity. To address this challenge, physics-based models are made using reported hourly traffic counts at locations across the country together with published traffic trends. Using these models together with TNM equations for spectral source emissions, a streamlined app has been created to efficiently predict traffic noise at roads across the nation with temporal and spectral variability. This app, which presently requires less than 700 MB of stored geospatial data and models, incorporates user inputs such as location, time period, and frequency, and gives predicted spectral levels within seconds.

1. INTRODUCTION

Noise from road traffic contributes heavily to ambient noise levels in urban and even rural areas. Increased noise levels are correlated with anything from mild annoyance to an increase in violent crime.[1] Noise can also negatively impact other species.[2-5] Characterizing road traffic noise levels is therefore important for anything from urban planning to species conservation and human wellbeing.

Despite being so pervasive, even when they are known or predicted, road traffic noise levels on a national scale are reported only for large-period average time scales, such as a yearly averaged 24-hr LAeq (A-weighted equivalent overall sound pressure level), like in the National Transportation Noise Map.[8] Noise levels and spectra vary with traffic volume and traffic class composition, as well as with other factors such as vehicle speed, pavement type, road inclination, and land cover.[6,7] Temporal changes can be drastic, particularly from daytime to nighttime, though also by day of week and time of year.

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Using hourly traffic counts across the continental United States (CONUS) together with reported temporal variation of traffic classes, the Vehicular Reduced-Order Observation-based Model, or VROOM, has been developed to predict hourly-varying spectral source road traffic noise.[9-Error! Reference source not found.] VROOM uses a concise set of location-specific features and developed models to allow for fast and efficient prediction of source noise levels for roads across CONUS. The VROOM app enables user inputs such as specific location, time period, and frequency, and can calculate and geographically plot source noise emissions within seconds.

2. PREDICTING TRAFFIC WITH VROOM

To predict temporally varying traffic noise, temporally varying traffic volume must be predicted. Additionally, the traffic class mix must also be predicted, as different types of vehicles can produce very different spectral sounds. VROOM predicts total hourly traffic volume using reported hourly vehicle counts from thousands of traffic monitoring stations across CONUS, and hourly traffic class mix is predicted using published traffic class mix characteristics. Traffic noise emissions are then calculated using TNM source noise emission equations for each vehicle class.

2.1. Predicting hourly traffic volume

The Federal Highway Administration tabulates reported hourly vehicle counts from thousands of traffic monitoring stations across CONUS. Using data from 2015-2018, Fourier analysis was used to find weekly and yearly patterns.[11] Principal component analysis was then used on the denoised Fourier spectra. This resulted in a simplified representation for traffic volume dynamics at traffic monitoring stations, which includes a set of traffic volume representative coefficients and principal component vectors. For further details, see “Toward improving road traffic noise characterization: A reduced-order model for representing hourly traffic volume dynamics” by Cook et. al.[Error! Reference source not found.]

To enable prediction of traffic volume at other locations, regression was used to find a transformation from location-specific values to coefficients. The location-specific features include 12 diffusion coordinates[Error! Reference source not found.], urban or rural designation, and road features such as road classification (interstate, principal arterial, etc.), through lanes, speed limit, and the annual average daily traffic (AADT). The resulting predictive traffic volume model, which is the first part of VROOM, uses location-specific features to predict coefficients, and therefore traffic volume, anywhere across CONUS.

2.2. Predicting hourly traffic volume of each traffic class

Like average annual sound levels, average annual traffic class mix is known for many locations across CONUS. However, where the class mix is unknown, it must be predicted. This is done using regression with the same location-specific features as are used to predict traffic volume representative coefficients. Due to physical constraints, there is some additional nuance. Each traffic class mix percentage must be between 0% and 100%, and the sum of each class mix percentage must equal 100%. One way to ensure this is by using angular coordinates. This approach is generalizable to any number of traffic classes, though most often three traffic classes—vehicles, medium trucks, and heavy trucks—are used.

Regression on the angular coordinates where traffic class mix is known yields a transformation from location-specific features to angular traffic class mix. This enables VROOM to predict traffic class anywhere using location-specific features, much the same as VROOM predicts traffic volume dynamics by predicting traffic volume representative coefficients.

Average annual class mix is necessary to determine traffic noise characteristics, but, as with traffic volume, traffic class mix varies temporally. Traffic class mix is not reported with temporal variation at thousands of traffic monitoring stations, and so published trends of national temporal variability of traffic classes from a Federal Highway Administration report by Hallenbeck, et al. are used.[14]

Average temporal variability of individual traffic classes is reported for different types of road designations (such as freeways or local roads) in either urban or rural locations across hours of the day, days of the week, and months of the year. By combining and normalizing the temporal variation, temporal multipliers for the traffic class mix are obtained.

VROOM predicts the total number of vehicles of a particular traffic class for any particular hour by multiplying the following values:

- The annual average total hourly traffic volume (AADT/24)
- The predicted normalized hourly traffic volume
- The average traffic class mix percentage
- The predicted hourly traffic class mix percentage

The product is calculated for each traffic class individually and gives the predicted number of vehicles of that class type. With the number of vehicles of each class type, the noise emissions for each class can be calculated.

2.3. Calculating noise emissions

For a known number of vehicles of a particular vehicle class type, the spectral noise emissions are calculated using equations from the Traffic Noise Model (TNM). These equations give the noise emissions at 50 feet from the road at a height of 5 feet based on traffic class numbers, pavement type, and vehicle speed. These equations can be found in Appendix A of the TNM Technical Manual.[15]

For any time period greater than one hour, average hourly noise emissions are calculated by averaging the relevant hourly VROOM-predicted vehicle numbers. The TNM equations are then used on the average numbers of vehicles of each class type, which results in the predicted spectral levels for the desired time period. Figure 1 shows the predicted 1-hr LAeq for a fully averaged time period, without regard for the time of day, day of week, or time of the year. This can be compared to TNM-predicted average sound levels and the National Transportation Noise Map's sound levels 50 feet from each road.

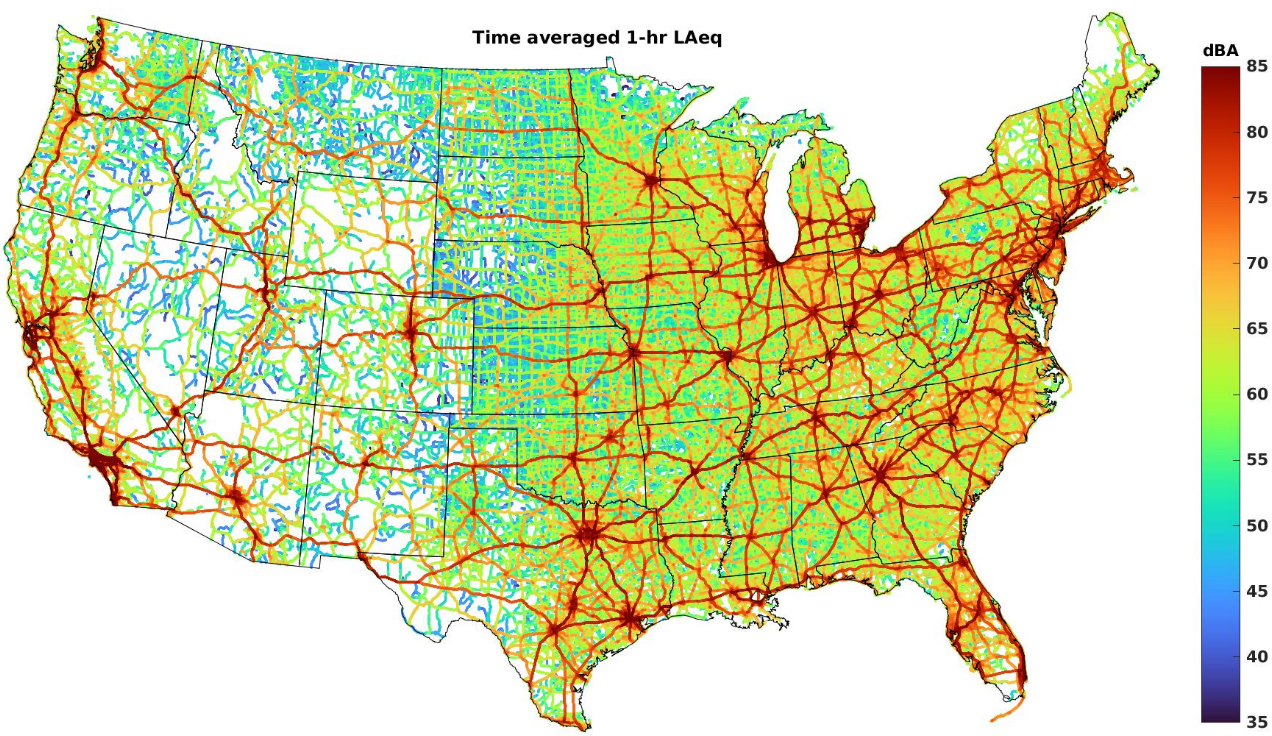

Figure 1. Temporally averaged VROOM-predicted A-weighted 1-hr LAeq.

The average sound levels, while important to know, are given in the National Transportation Noise Map. The utility of VROOM is that it can predict not just time-averaged levels, but levels for any time period and frequency of interest, down to hourly time scales. This is important because sound levels can change drastically across the course of a single day. Predictions for two different time periods are shown in Figure 2 and in Figure 3. Differences of a few decibels are hard to see with a large range, like the 70 dBA range used in Figure 1, and so the figures show not overall levels, but differences from the average sound levels shown in Figure 1. Across the country, sound levels are much lower than average during nighttime hours on weekdays in December, and for many locations sound levels are higher on weekend afternoons in July.

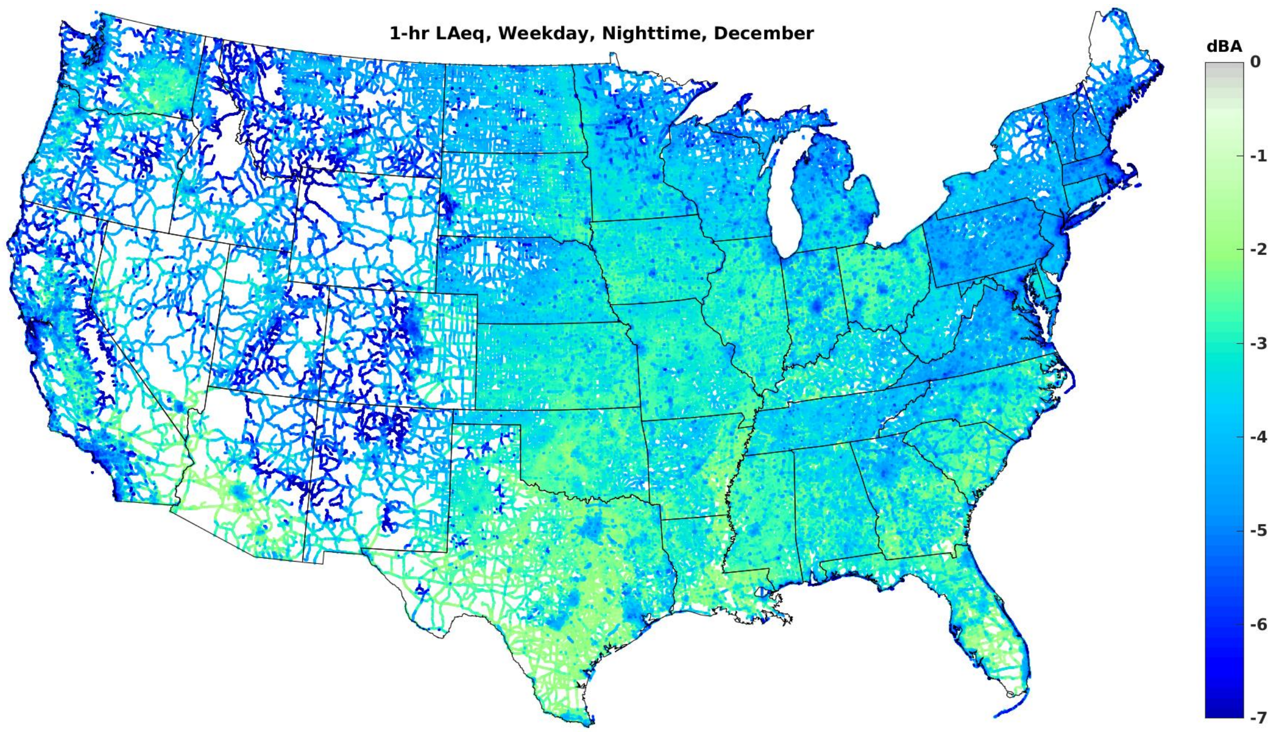

Figure 2. 1-hr LAeq for an average weekday nighttime in December, relative to the average sound level.

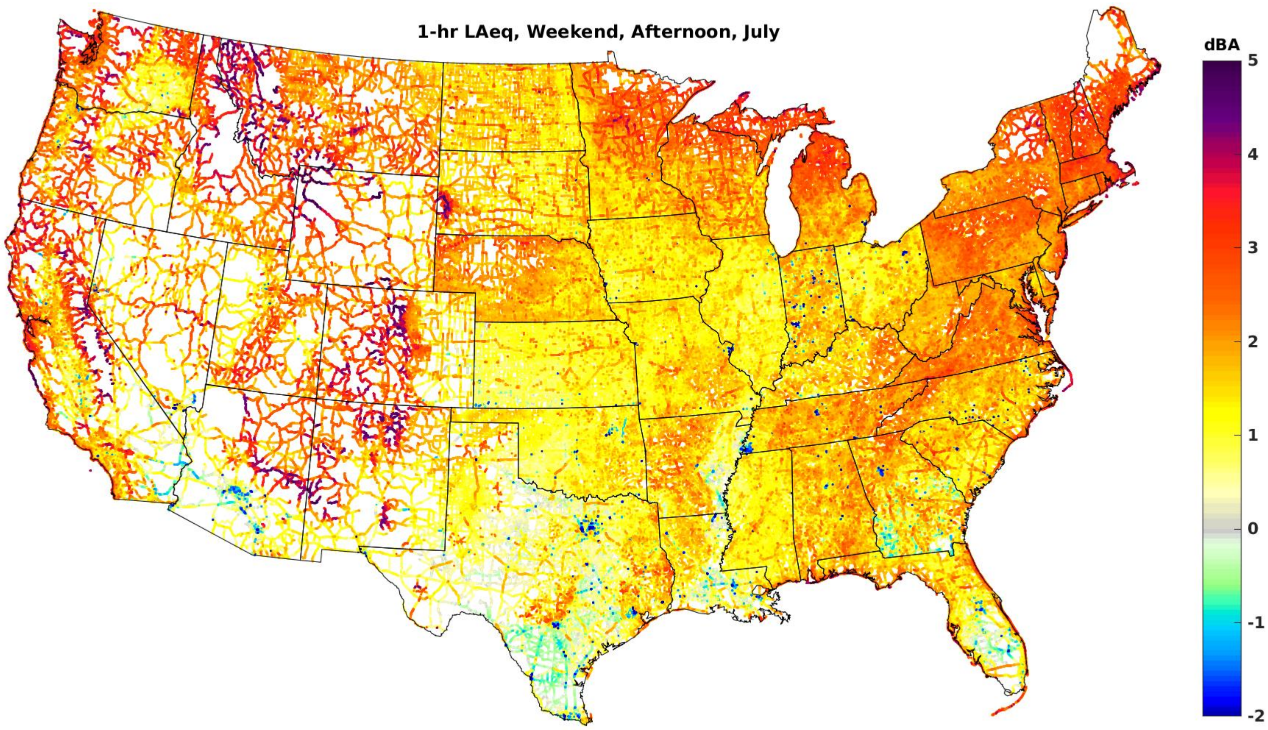

Figure 3. 1-hr LAeq for an average weekend afternoon in July, relative to the average sound level.

3. THE VROOM APP

VROOM can predict hourly sound emissions for roads across the country in a computationally simple manner. By using about 18 features for each location of interest, a few matrix and linear multiplications and additions yield the predicted hourly source noise emissions. While computer RAM and memory can limit the number of parallel computations for millions of road locations—and especially the number of locations for which results can be plotted—using VROOM to calculate and plot results for even state-wide scales can be done in a relatively short amount of time for even a simple laptop computer.

The VROOM app was developed using the methods described in this paper to allow calculation and plotting of source road traffic noise using user inputs. The models consist of a few streamlined codes, and the ~18 location-specific features for millions of locations across CONUS can be stored using less than 700 MB of memory. Thus, predicted sound characteristics for geographic areas as large as individual states can be shown using a simple computer.

The VROOM app performs calculations and plots results in real time. Because of the speed of calculation, user inputs can be utilized. Figure 4 shows a snapshot of the user interface for the VROOM app, together with the predicted sound levels in Grand Rapids, Michigan at 5:00 pm on a spring weekday. Users can input the location by state, county, and city, or by latitude and longitude. When a state is selected, the county options are updated automatically. Likewise, the cities options are updated when the county is selected. Alternatively, the user can select latitude and longitude limits, which are automatically updated when states, counties, or cities are selected.

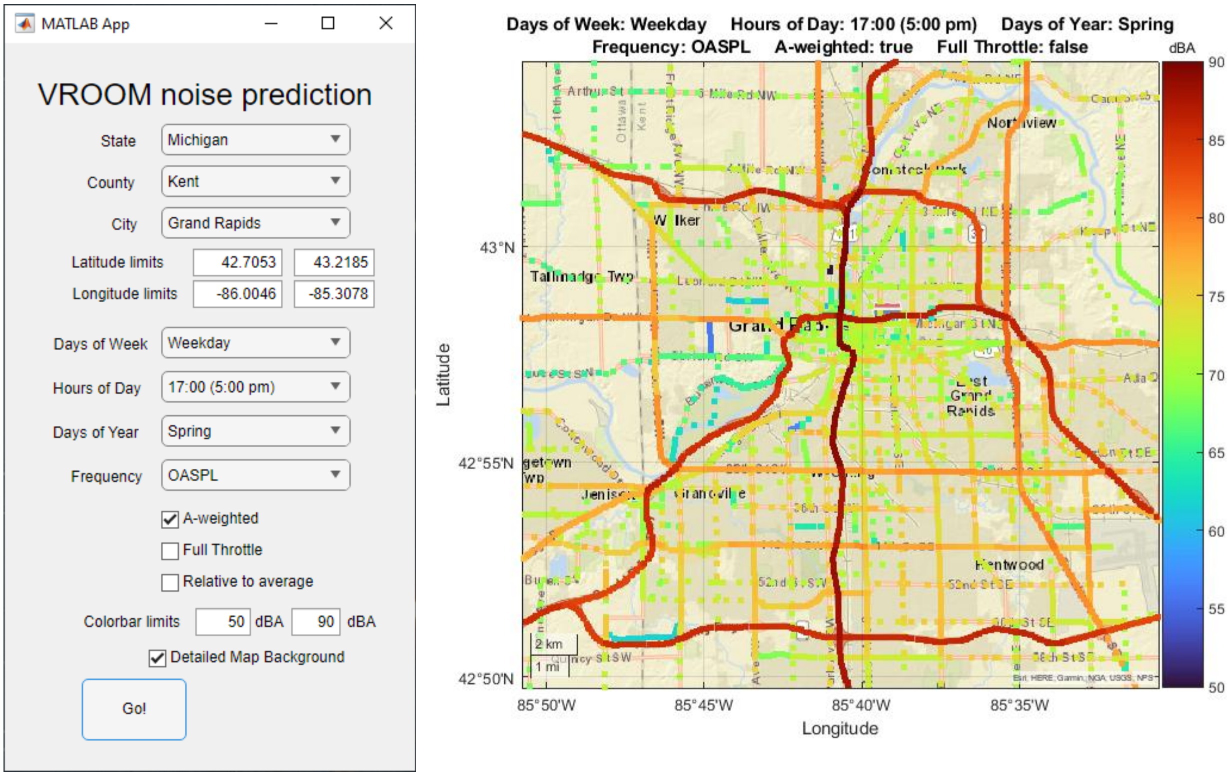

Figure 4. The user interface for the VROOM app, alongside the predicted overall sound pressure level for roads near Grand Rapids, Michigan on a spring weekday at 5:00 pm.

Users can also input the desired time period, which can be as specific as a particular hour of the day, day of the week, and month or season of the year. Individual one-third octave band frequencies or overall sound pressure levels can likewise be selected, along with flat or A-weighted levels. Additional inputs, such as vehicle throttle—which indicates whether or not vehicles are accelerating—and additional mapping preferences are also incorporated.

The VROOM app is a powerful tool that allows users to predict source traffic noise emissions quickly and efficiently for roads across CONUS. The versatility and simplicity for the user make this app useful for a variety of applications.

4. CONCLUSIONS

The VROOM app allows users to input parameters such as location, time period, and frequency, and predicts and plots predicted traffic noise along roads throughout the country. The app uses a concise set of location-specific features and physics-guided, observation-based models totaling less than 700 MB to efficiently predict traffic noise for the user-defined inputs.

While predicted average sound levels agree with national average levels, and the models used were made with reported vehicle numbers and traffic class mix, noise emission error validations have yet to be performed. Improvements to the VROOM app, such as incorporating minor roads and reducing overhead computation and memory storage, are being made. Work is also being done to propagate source noise levels to surrounding areas, as well as to predict noise characteristics such as median or percentile-based noise emissions in addition to equivalent sound levels.

While standard national traffic noise levels are only given for average time scales, the VROOM app can predict noise levels with hourly resolution, and can do so in real time. With a simple user interface, desired temporal and spectral characteristics can be highlighted. VROOM is a powerful tool for predicting traffic noise across the country.

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