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A geospatial model of global ambient sound levels[a)]

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ABSTRACT:
This paper presents AMBIENT | GLOBAL, an ambient soundscape model developed to predict global ambient sound levels from all anthropogenic, biological, and geophysical sources. The soundscape model adopts a geospatial approach by modeling the ambient sound level as a function of geospatial features at a location. The soundscape model consists of an ensemble of four machine learning regression models fitted at acoustic measurement sites where both the geospatial features and ambient sound levels are known. The fitted model is then applied to predict ambient sound levels at any location where the geospatial features are known. The results quantify the spatial, temporal, and spectral patterns of ambient sound levels across the world under various scenarios. This paper presents maps of the existing ambient sound levels across the world in terms of the daytime overall A-weighted L_{50}, or median sound level, and partitions the existing sound levels into their natural and anthropogenic constituents. Ultimately, the soundscape model will enable research into the impacts of humans and nature on the ambient soundscape and the impacts of ambient sound levels on humans and nature across the world.
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I. INTRODUCTION

"How loud is it?" or more precisely, "What is the outdoor ambient sound level?" This question is asked by land use planners, environmental analysts, military mission planners, public health researchers, municipal governments, homebuyers, and others affected by outdoor ambient sounds. In fact, all people are affected by outdoor ambient sounds. The World Health Organization reports that anthropogenic noise is the second leading environmental cause of disease in Western Europe after air pollution,[1] and the impact of ambient noise on human health is receiving increasing attention among researchers and the general public.[2] However, most parts of the world lack the ambient sound level data required to assess the effects of environmental noise. For public health studies and the other applications listed above, research is needed to model ambient sound levels in various environments across the world.

Modeling ambient sound levels in various environments fits within the field of soundscape ecology. Soundscape ecology is the study of the spatial, temporal, and spectral patterns of sound in relation to geographic context within landscapes.[3] In soundscape ecology, the term *soundscape* describes the relationship between a landscape and the composition of its sounds.[3] The ambient soundscape, or acoustic environment, is composed of anthropogenic, biological, and geophysical sounds of the built and natural environments. These sounds are categorized as *anthrophony* (sounds produced by humans), *biophony* (sounds produced by other organisms), and *geophony* (nonbiological natural sounds). Research in soundscape ecology studies the interactions between human activities, natural processes, and the soundscape.[3] Humans, animals, and natural processes produce the sounds that make up the soundscape, and, in turn, the soundscape affects the behavior and well-being of humans and animals.[4,5] Assessing the impact of the soundscape on humans and animals requires knowledge of the spatial, temporal, and spectral patterns of ambient sound levels.

Soundscape modeling is a useful tool to understand the spatial, temporal, and spectral patterns of soundscapes in relation to landscapes.[6] Mullet *et al.*[7] and Mennitt *et al.*[8] were among the first to develop geospatial regression models to identify spatial relationships between the ambient soundscape and environmental variables using machine learning. Mullet *et al.*[7] extrapolated those spatial relationships to predict anthrophony, biophony, and geophony across a large landscape in the Kenai National Wildlife Refuge in Alaska. Mennitt *et al.*[8] and Mennitt and Fristrup[9] trained machine learning models to predict long-term average ambient sound levels across the contiguous United States for different times of day, seasons, and frequencies. Mennitt *et al.*[8] also estimated the natural sound levels that would exist in the absence of anthropogenic noise by attempting to remove the influence of humans from the

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environmental variables used as inputs to the machine learning models. Buxton *et al.*[10] calculated the anthropogenic impact level as the difference between the modeled existing and natural sound levels and demonstrated that anthropogenic noise is pervasive in protected areas in the United States.

The National Park Service[11,12] distributes the maps of ambient sound levels in the United States produced by Mennitt *et al.*[8] and Mennitt and Fristrup.[9] The publicly available maps include predictions of the existing sound level, natural sound level, and anthropogenic impact level in terms of the summer daytime overall A-weighted L_{50}. The L_{50} metric, which describes the median sound level exceeded 50% of the time, is a measure of the typical sound level at a location. The anthropogenic impact level is defined as the difference between the existing and natural sound levels.[12] Prior to the research described in this paper, the maps distributed by the National Park Service were the only publicly available maps of ambient sound levels at nationwide scales.

As described in this paper, we developed an ambient soundscape model named AMBIENT | GLOBAL to predict the first maps of ambient sound levels across the entire world. AMBIENT | GLOBAL can predict ambient sound levels for different times of day (daytime, nighttime, and hourly), frequencies (overall A-weighted and one-third octave bands), and acoustic metrics (L_{eq}, L_{10}, L_{50}, and L_{90}). This paper focuses on the daytime overall A-weighted L_{50} as a demonstration of the soundscape model. Section II outlines the geospatial modeling approach to predict ambient sound levels using machine learning. Section III describes the database of geospatial features used as inputs to the model. Section IV describes the database of ambient acoustic measurements used to train the model. Section V describes the ambient soundscape model and its associated error and uncertainty. Section VI presents maps of the predicted existing, natural, and anthropogenic sound levels across the world. Finally, Section VII summarizes the research and identifies opportunities for future work.

II. MODELING APPROACH

AMBIENT | GLOBAL builds upon the geospatial modeling approach developed by Mennitt *et al.*[8] and Mennitt and Fristrup[9] and extended by Pedersen *et al.*,[13] who applied machine learning regression algorithms to model the nonlinear statistical relationship between ambient sound levels and geospatial variables. Rather than modeling individual sound sources and propagation physics, these geospatial models employ a statistical approach to predict ambient sound levels. In the geospatial approach, the ambient sound level at a location is modeled as a function of the geospatial features at that location,

$$\text{ambient sound level} = f(\text{geospatial features}), \tag{1}$$

where the function, f, is unknown. The unknown function f is determined by fitting a regression model to a training dataset at locations where both the geospatial features and ambient sound levels are known. Once the regression model is fitted, the fitted model is applied to predict ambient sound levels at any location where the geospatial features are known.

Equation (1) is a purely empirical model that relates geospatial features as explanatory variables to the ambient sound level as the response variable. Empirical modeling is appropriate for sound sources that cannot be modeled individually. For example, the average ambient sound levels produced by chirping birds, falling rain, and rolling thunder must be modeled statistically because the exact time and place of each birdsong, raindrop, and thunderclap are unknowable. Machine learning is useful for identifying nonlinear relationships between the geospatial features and ambient sound level. AMBIENT | GLOBAL applies an ensemble of machine learning algorithms as the empirical regression model.[13]

However, empirical modeling has several drawbacks. Machine learning requires a large training dataset to learn the nonlinear relationships between the geospatial features and ambient sound level, but the number of acoustic measurement locations across the world is limited because of the time and expense of acquiring measurements. Empirical models are most robust when interpolating within a dataset, but the acoustic measurement locations do not span all possible acoustic environments across the world. Finally, machine learning models do not produce easily interpretable physical relationships between the geospatial features and ambient sound levels. Nevertheless, empirical modeling provides the only currently viable approach to model ambient sound levels from all anthropogenic, biological, and geophysical sound sources across the world.

III. GEOSPATIAL DATABASE

Geospatial features are the explanatory variables in AMBIENT | GLOBAL. The soundscape model requires a database of global geospatial features to fit the machine learning models at locations where the ambient sound levels are known and to predict ambient sound levels worldwide. Section III A describes the geospatial properties of the global database, and Section III B presents the geospatial features in the database. Section III C presents a modified set of geospatial features that represent the natural environment without human influence for predicting natural sound levels.

A. Geospatial properties

The spatial extent and resolution of the geospatial database determines the extent and resolution of the predicted ambient sound levels. Table I summarizes the geospatial properties of the database. The geospatial features are stored as rectilinear latitude and longitude grids with 15 arcsecond (arcsec) resolution. At 15 arcsec resolution across the world, each geospatial feature contains over 3.7×10^9 raster cells,

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TABLE I. Geospatial properties of the global geospatial database.

Property	Value
Datum	World Geodetic System 1984
Reference system	Latitude and longitude
Spatial resolution	15 arcsec (approximately 463 m at the equator)
Longitude extents	–180° to 180°
Latitude extents	–90° to 90°
Number of pixels	86 400 × 43 200

of which almost 1.3×10^9 are on land where the soundscape model predicts ambient sound levels.

Although the geospatial features are stored as rectilinear latitude and longitude grids, the global maps presented in this paper are displayed using the Robinson projection. The Robinson projection is a compromise projection intended to produce visually appealing maps of the world.

B. Geospatial features

Because geospatial features are the explanatory variables in the ambient soundscape model, the geospatial features must be appropriate predictors of ambient sound levels. Table II lists the 53 geospatial features selected for the global geospatial database and provides references to the original data sources from government agencies, peer-reviewed research, and open-source datasets. The geospatial features include population, transportation, land cover, biology, topography, climate, and hydrology variables. These

TABLE II. Global geospatial features in the ambient soundscape model.

Feature name	Area	Units	Reference	Description
Population				
Nighttime Lights	15″, 5′	$nW/(cm^2 \cdot sr)$	14	Mean upward radiance at night
Population Density	15″, 5′	$People/km^2$	15	Population density
Transportation				
Distance to Highways	Point	m	16, 17	Distance to nearest highway
Distance to Primary Roads	Point	m	16, 17	Distance to nearest primary road
Distance to Minor Roads	Point	m	16, 17	Distance to nearest minor road (secondary or tertiary road)
Density of Local Roads	15″, 5′	m/m^2	16, 17	Length of local roads per unit area
Distance to Large Airports	Point	m	18	Distance to nearest large airport
Distance to Medium Airports	Point	m	18	Distance to nearest medium airport
Land cover				
Barren	15″, 5′	Fraction	19	Barren land cover
Cropland	15″, 5′	Fraction	19	Cropland land cover
Deciduous Broadleaf Forest	15″, 5′	Fraction	19	Deciduous broadleaf forest land cover
Developed	15″, 5′	Fraction	19	Developed land cover
Evergreen Broadleaf Forest	15″, 5′	Fraction	19	Evergreen broadleaf forest land cover
Grassland	15″, 5′	Fraction	19	Grassland land cover
Mixed Forest	15″, 5′	Fraction	19	Mixed forest land cover
Needleleaf Forest	15″, 5′	Fraction	19	Needleleaf forest land cover
Savanna	15″, 5′	Fraction	19	Savanna land cover
Shrubland	15″, 5′	Fraction	19	Shrubland land cover
Snow and Ice	15″, 5′	Fraction	19	Snow and ice land cover
Water	15″, 5′	Fraction	19	Water land cover
Wetlands	15″, 5′	Fraction	19	Wetlands land cover
Woody Savanna	15″, 5′	Fraction	19	Woody savanna land cover
Biology				
Vegetation Height	15″, 5′	m	20, 21	Mean vegetation height
Topography				
Mean Elevation	15″, 5′	m	22	Mean elevation
Elevation Range	15″, 5′	m	22	Difference in max and min elevation
Climate				
Annual Temperature Range	Point	°C	23, 24	Annual temperature range
Diurnal Temperature Range	Point	°C	23, 24	Diurnal temperature range
Mean Temperature	Point	°C	23, 24	Mean temperature
Mean Vapor Pressure	Point	hPa	23, 24	Mean vapor pressure
Precipitation	Point	mm	23, 24	Average monthly precipitation
Hydrology				
Distance to Lakes	Point	m	25, 26	Distance to nearest lake
Distance to Major Rivers	Point	m	27, 28	Distance to nearest major river
Distance to Oceans	Point	m	29	Distance to nearest ocean

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features directly or indirectly account for anthropogenic, biological, and geophysical sound sources. For example, population features describe areas with significant human influence, and transportation features account for specific sources of anthropogenic noise. Land cover features, as shown in Fig. 1, categorize multiple types of anthropogenic and natural areas that are expected to have different ambient sound levels. Biology, topography, climate, and hydrology variables indirectly describe biological and geophysical sources of sound that vary across different environments and landscapes.

Ambient soundscapes are influenced by variables outside a single 15 by 15 arcsec raster cell in the geospatial database. For example, transportation noise can propagate for kilometers, and animals may roam over large areas. To account for these physical phenomena, the geospatial database includes distance features and area-averaged features. Distance features, such as the distance to the nearest road or river, aim to account for acoustic propagation from sound sources with well-defined locations. Area-averaged features, such as population density and land cover, represent average values over a defined area of analysis. The features at 15 arcsec and 5 arcminute (arcmin) areas of analysis (listed as 15″ and 5′ in Table II) account for smaller- and larger-scale effects on the ambient soundscape. Although the ambient soundscape model does not directly model acoustic propagation or moving sound sources, the selected geospatial features aim to account for these physical phenomena.

Ambient soundscapes are also influenced by variables other than the 53 geospatial features listed in Table II. For anthrophony, local zoning maps would help quantify sound levels in different types of residential, commercial, and industrial land use better than developed land cover alone. Similarly, transportation noise features would help quantify road traffic, aviation, and rail noise more precisely than distances to roads and airports. For biophony, species range and distribution maps would help quantify sound levels produced by different types of animals. For geophony, features that describe the flow rate and slope of streams and rivers would help quantify sound levels produced by flowing water. However, we are unaware of any publicly available datasets with global coverage that describe these explanatory variables. Future research should incorporate these global datasets into the geospatial database as they become available.

C. Natural geospatial features

To estimate the natural sound levels that would exist in the absence of anthropogenic noise, Mennitt *et al.*[8] modified existing geospatial features to remove human influences. The population, transportation, and selected land cover features listed in Table II represent human influences. Like Mennitt *et al.*,[8] we modified the population and transportation features by setting the population density, nighttime lights, and density of local roads to zero everywhere, and by setting the distances to transportation sound sources to a maximum value everywhere. Whereas Mennitt *et al.*[8] removed developed land cover and did not replace it with a presumed natural land cover, we reclassified developed and cropland land cover to the closest natural land cover categories without human influence. Figure 2 shows a map of the reclassified natural land cover categories. Each contiguous region of developed land cover is reclassified as the

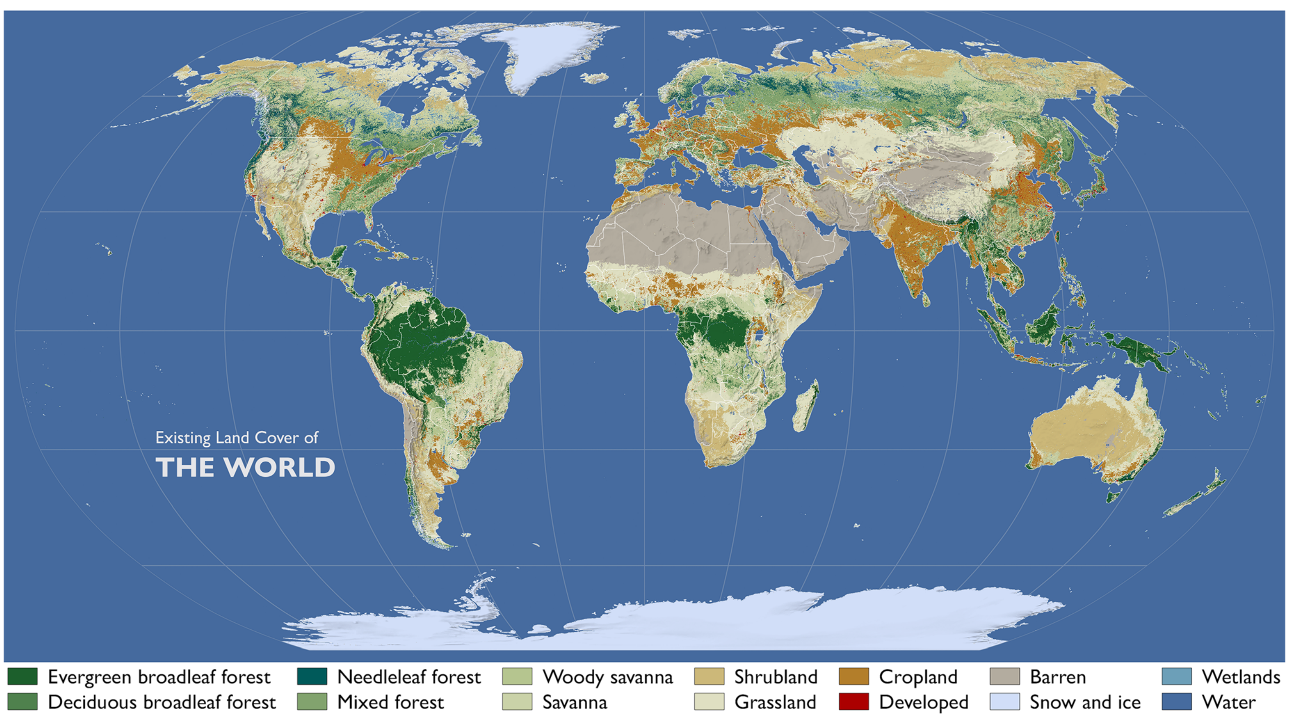

FIG. 1. Map of the existing land cover categories across the world.

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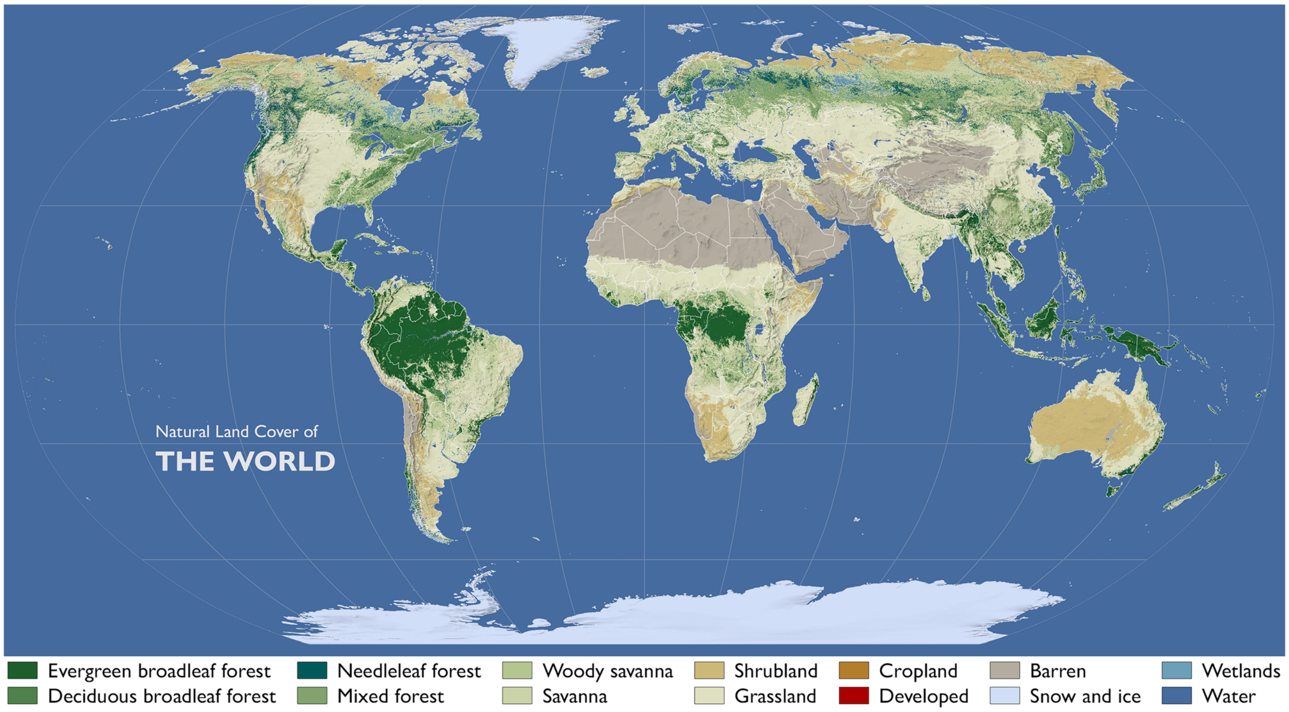

FIG. 2. Map of the reclassified natural land cover categories without human influences across the world.

dominant surrounding natural land cover. Cropland with a low proportion of natural vegetation is reclassified as grassland, and cropland with a high proportion of natural vegetation is reclassified as savanna. The other land cover, biology, topography, climate, and hydrology features listed in Table II remain unchanged for estimating natural sound levels.

IV. ACOUSTIC DATABASE

The ambient sound level is the response variable in AMBIENT | GLOBAL. The soundscape model requires a database of ambient acoustic measurements to fit the machine learning models at measurement locations. The quality and geospatial diversity of the acoustic measurements determine the quality and generalizability of the soundscape model. Section IV A summarizes the acoustic measurements in the database. Section IV B presents the geographic distribution of measurement sites, and Sec. IV C presents the geospatial distribution of measurement sites.

A. Acoustic measurement sites

The acoustic database contains almost 900 000 h of acoustic measurements at 962 unique measurement sites across North America. The database combines acoustic measurements performed by Blue Ridge Research and Consulting, LLC (BRRC), the National Park Service,[30] the Environmental Protection Agency,[31] Brigham Young University, and trusted third parties. The acoustic metrics in the database include the overall A-weighted and one-third octave equivalent continuous sound level (L_{eq}) and statistical exceedance levels (L_n) for each hour. L_n describes the sound level exceeded n% of the time. L_{10}, the sound level exceeded only 10% of the time, describes the loudest typical events. L_{50}, the sound level exceeded 50% of the time, describes the median sound level. L_{90}, the sound level exceeded 90% of the time, describes the typical background sound level. The following subsections describe the measurement setup and duration at each site to acquire these metrics.

1. Acoustic measurement setup

Each acoustic measurement requires the measuring organization to travel to a measurement site, deploy long-term acoustic measurement equipment, and collect the equipment at the end of the measurement. BRRC's soundscape measurement setup, shown in Fig. 3, consists of a Class 1 sound level meter, a 1/2 in. condenser microphone, an ultrasonic anemometer, a solar panel, cables, and environmental enclosures. The ultrasonic anemometer is mounted on a tripod 5 ft above the ground, and the microphone is inverted over a ground plate and protected by a 9-in. diameter custom windscreen. The sound level meter, which is enclosed within a weatherproof case underneath the solar panel, logs acoustic metrics from the microphone simultaneously with the wind speed and direction from the ultrasonic anemometer in 1 s time steps. This setup supports long-term measurements of ambient soundscapes. The National Park Service[30] deploys a similar measurement setup but mounts the microphone on a tripod 5 ft above the ground.

BRRC's soundscape measurement setup is designed to minimize wind noise contamination. Part 2 of the

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FIG. 3. Photograph of BRRC's soundscape measurement setup.

Acoustical Society of America (ASA)/American National Standards Institute (ANSI) S12.9 standard[32] for measuring long-term, wide-area sound allows the microphone to be located at a height of 5 ft or at the ground. Placing the microphone at the ground where the wind speed is lowest reduces wind noise contamination. BRRC's measurement setup uses a custom windscreen with a larger diameter than commercial windscreens to further reduce wind noise contamination. The ultrasonic anemometer identifies periods that may be contaminated by high wind noise. The National Park Service[30] excludes acoustic measurements when the wind speed exceeds 5 m/s, but wind noise contamination may still occur at wind speeds below 5 m/s. Remaining wind noise contamination can be identified using the measured one-third octave spectra and mitigated using automated methods.[33] Despite these mitigation strategies, the acoustic database still contains wind noise contamination at some measurement sites, especially in quiet acoustic environments.

2. Acoustic measurement duration

Existing recommendations for the minimum deployment duration to characterize the dynamic ambient soundscape vary from hours to weeks based on the goals of the measurement. National Park Service guidelines require up to 25 days of data collection at each measurement site.[30] Federal Aviation Administration recommendations for documenting low-level ambient noise include a minimum of two visits of 3 to 9 h each depending on the acoustic variability.[34] Part 2 of the ASA/ANSI S12.9 standard[32] specifies typical measurement durations varying from 1 day for highways, industrial areas, and residential areas, and up to 30 days for military installations.

To characterize the ambient soundscape at each measurement site, BRRC deploys the soundscape measurement setup for a minimum of 24 h, with a median of 7 days per deployment. The deployment duration balances the desire for longer-term measurements with the need for many geospatially diverse measurement sites for the ambient soundscape model. Although long-term acoustic monitoring increases confidence in the measurements at a few locations, long deployment durations reduce the number of locations that can be measured with finite resources. The minimum deployment duration prioritizes measurements at many geospatially diverse sites.

B. Geographic distribution of acoustic measurement sites

Figure 4 shows a map of the 962 unique measurement sites across North America, where the color of each marker represents the land cover category at the measurement site. The measurement sites are spread across the United States and Nova Scotia, Canada. The measurement sites provide widespread geographic coverage of the United States and into Canada, but sites are not uniformly distributed because of the practicalities of conducting acoustic measurements. For example, the National Park Service conducts acoustic measurements in National Parks, most of which are located in the Western United States and Alaska. The densest clusters of BRRC's measurement sites are in Washington, DC, and near our office in Asheville, North Carolina. BRRC also conducted acoustic measurements that added geographic diversity across the United States and conducted the only measurements outside the United States in the acoustic database.

Figure 4 shows that most measurement sites in the acoustic database are in the United States, and all

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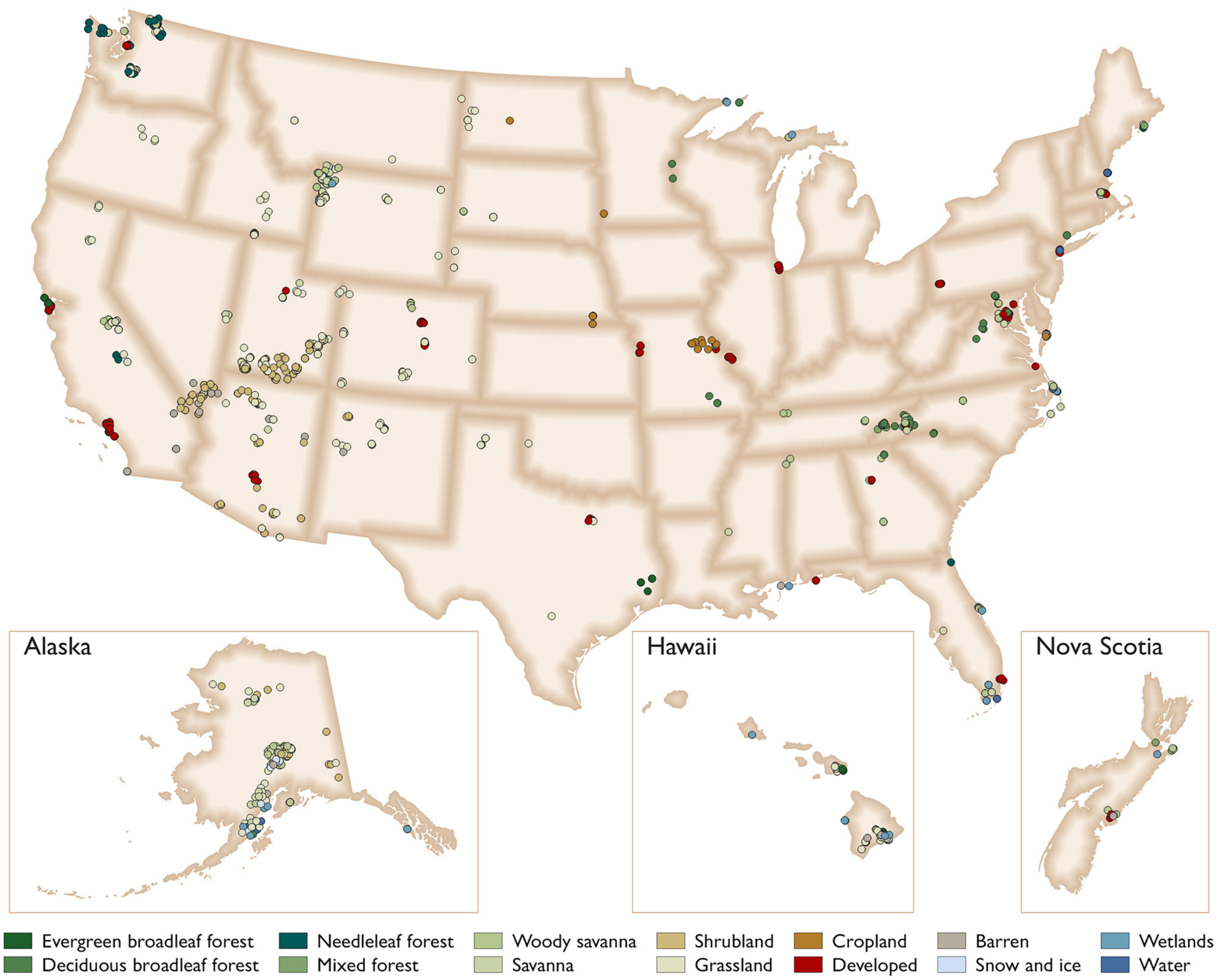

FIG. 4. Map of the measurement sites in the acoustic database by land cover category.

measurement sites are in North America. Future acoustic measurements in unique acoustic environments across the world would add geographic diversity to the training dataset for the ambient soundscape model.

C. Geospatial distribution of acoustic measurement sites

Because the soundscape model uses geospatial features as predictors of the ambient soundscape, geospatial diversity in the training data is critical to predict ambient sound levels in different acoustic environments. Whereas geographic diversity accounts for the locations of the measurement sites, geospatial diversity considers the geospatial features at the measurement sites. Although geographic diversity of acoustic measurements is desirable, geospatial diversity is more important for the ambient soundscape model. For example, acoustic measurements in an urban area are typically more predictive of ambient sound levels in distant urban areas than in nearby suburban and rural areas.

Geospatial diversity requires the acoustic measurements to span a wide range of geospatial feature values representative of the unique acoustic environments across the world. As an example of the geospatial diversity in the acoustic database, Fig. 5 shows a swarm chart of the acoustic measurements categorized by land cover at each measurement site. Each marker represents a single measurement site. The vertical axis indicates the median measured daytime A-weighted L_{50} at the measurement site, and the horizontal spread between markers represents the statistical distribution of measured sound levels in each land cover category. Although each land cover category contains a wide range of measured sound levels, the typical sound levels vary between different types of land cover. For example, typical sound levels in developed land cover are significantly higher than typical sound levels in barren, grassland, and shrubland land cover. The differences in measured sound levels between land cover categories illustrate the importance of geospatial diversity in the training data.

The number of measurement sites shown in Fig. 5 demonstrates that certain land cover categories, such as developed, woody savanna, shrubland, and grassland, are well-represented in the acoustic database. However, other land cover categories, such as mixed forest, snow and ice,

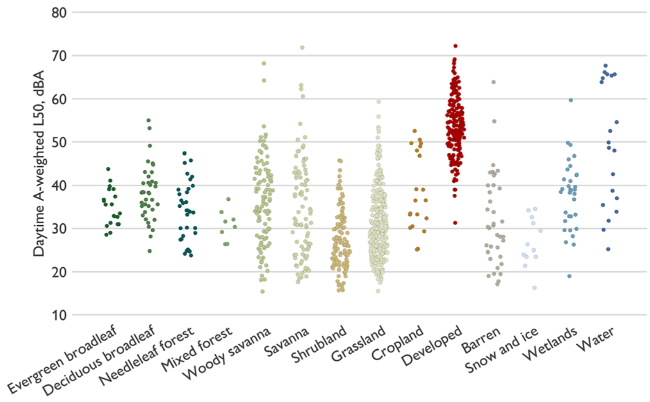

FIG. 5. Swarm chart showing the median measured daytime A-weighted L_{50} at the acoustic measurement sites grouped by land cover category.

and water, have fewer measurement sites. Similar analyses can reveal the representativeness of the acoustic database for each of the geospatial features listed in Table II. K-means clustering has been applied to group geospatial features into unique acoustic environments in the contiguous United States and to identify poorly sampled regions for targeted acoustic measurements.[35] Future acoustic measurements in poorly represented acoustic environments across the world would add geospatial diversity to the training dataset for the ambient soundscape model.

V. AMBIENT SOUNDSCAPE MODEL

The purpose of AMBIENT | GLOBAL is to predict ambient sound levels from all anthropogenic, biological, and geophysical sources in various environments. The soundscape model consists of an ensemble of machine learning regression models that relate the ambient acoustic measurements to the geospatial features. Section V A describes the machine learning models in the ensemble. Section V B describes geospatial feature scaling for fitting the models, and Sec. V C describes the model tuning process. Section V D quantifies the leave-one-out cross-validation error in the soundscape model at acoustic measurement sites, and Sec. V E estimates uncertainty in acoustic environments across the world. Finally, Sec. V F summarizes current limitations of the soundscape model and proposes future improvements.

A. Machine learning models

AMBIENT | GLOBAL consists of an ensemble of four machine learning regression models based on the ensemble approach developed by Pedersen *et al.*[13] Each model is trained independently, and the predicted ambient sound level is given by the median of the outputs from the four individual models. As the individual models have unique functional forms that extrapolate differently, the ensemble median increases the likelihood of robust predictions at locations away from training sites. Furthermore, the standard deviation between the individual models in the ensemble provides a measure of the uncertainty in the predicted sound levels, as discussed in Sec. V E.

The ensemble model consists of the following four machine learning regression models from the PYTHON SCIKIT-LEARN library:

- Gradient boosting regression implements an ensemble of decision trees to form a forest.[36] This model generalizes the random forest approach to arbitrary differentiable loss functions. Gradient boosting regression typically does not require extensive tuning and tends to be robust to outliers.
- Kernel ridge regression combines ridge regression with the kernel trick.[37] Ridge regression is linear regression with a regularization term to prevent overfitting. The kernel trick transforms data into a higher-dimensional space to better model nonlinear relationships. Kernel ridge regression first performs the kernel trick followed by ridge regression on the transformed data.
- Multi-layer perceptron regression is a type of neural network model.[38] Neural networks have gained popularity in recent years and have found widespread applications in deep learning. However, the training dataset contains too few acoustic measurement sites to justify deep learning with multiple hidden layers. The soundscape model uses a multi-layer perceptron regression model with no hidden layers to avoid overfitting.
- Support vector regression uses the kernel trick to transform data into a higher-dimensional space like kernel ridge regression, but it uses a different loss function than kernel ridge regression.[39] Support vector regression partitions data using hyperplanes in higher-dimensional space.

B. Feature scaling

The machine learning models are sensitive to the selected geospatial features and to the scales of those features. Features with larger magnitudes can dominate features with smaller magnitudes in certain regression models. Because the geospatial features listed in Table II have different scales that span multiple orders of magnitude, the features must be scaled before fitting the machine learning models. Common feature scalers include the MinMaxScaler,[40] which normalizes the data range from zero to one, and the StandardScaler,[41] which subtracts the mean value and normalizes the data to unit variance.

The soundscape model applies a custom feature scaler to each geospatial feature based on its physical characteristics and its expected contribution to the ambient sound level, as described in Table III. The custom scaler applies no scaling to land cover features, which are already constrained between zero and one. To scale features that span multiple orders of magnitude, including the population density and nighttime lights features, the custom scaler first computes the logarithm of the feature and then applies a MinMaxScaler. The ambient sound level is better correlated with the logarithms of these features than with the features themselves.[42] For features describing the distance to a sound

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TABLE III. Custom scaling applied to the geospatial features in the soundscape model.

Geospatial features	Scaler	Rationale
Land cover	None	Land cover is reported as a fraction between zero and one
Population	MinMaxScaler of logarithm	Logarithm normalizes features that span many orders of magnitude
Distance to source	MinMaxScaler of negative logarithm	Negative logarithm accounts for qualitative acoustic propagation
Other features	StandardScaler	Normalization for features without minimum and maximum bounds

source, the custom scaler first ensures the distance is at least 250 m, which is roughly half the 15 arcsec raster cell resolution, and then applies a MinMaxScaler to the negative logarithm of the feature. The negative logarithm ensures the scaled feature values decay with increasing distance from the source to approximate acoustic propagation effects. Finally, the custom scaler applies a StandardScaler to all other geospatial features.

C. Hyperparameter tuning

The machine learning models are also sensitive to their hyperparameters, which are configurable model parameters that control the fitting process. Tuning the hyperparameters of a machine learning model can significantly affect the predicted ambient sound levels. Hyperparameters are often tuned to minimize validation error within the training dataset.[13,43] Because of the limited number of acoustic measurement sites in the training dataset, minimizing the validation error would likely result in overfitting. Overfitting occurs when a model fits the training data well but generalizes poorly to other locations. To mitigate the risk of overfitting, we tuned the hyperparameters of each machine learning model to not only achieve low validation error at measurement sites but also to predict physically realistic ambient sound level maps. Although judging physical realism is somewhat subjective, it helps produce tuned models that are more likely to generalize to locations beyond the limited measurement sites.

D. Leave-one-out cross-validation

Leave-one-out cross-validation is a common method used to estimate the performance of machine learning models with small training datasets. For the soundscape model, the leave-one-out error at a single acoustic measurement site is computed by removing that site from the training dataset and fitting the machine learning regression models to the remaining sites. This process is repeated for all measurement sites. The leave-one-out error quantifies how well the soundscape model generalizes to the acoustic environments represented by the measurement sites. Although the acoustic database contains 962 unique measurement sites, the number of sites is small compared with the number of unique acoustic environments across the world. Thus, the leave-one-out cross-validation error at measurement sites is a useful but incomplete error metric.[43]

The leave-one-out cross-validation error across measurement sites is quantified in terms of three error metrics: mean error, median absolute error, and root mean square (RMS) error. The mean error quantifies bias between the predicted and measured sound levels. The median absolute error quantifies the typical error between the predicted and measured sound levels in a manner that is less sensitive to outliers, and the RMS error quantifies the typical error in a manner that is more sensitive to outliers.

Table IV lists the leave-one-out cross-validation error metrics for the ambient soundscape model. The soundscape model has negligible bias error. The gradient boosting regression and kernel ridge regression models have lower typical errors than the multi-layer perceptron regression and support vector regression models. Further hyperparameter tuning could likely improve the machine learning models with greater error metrics. The error metrics for the ensemble median fall within the range of error metrics for the individual machine learning models. The error metrics demonstrate that the soundscape model is sufficiently accurate for many practical applications within the acoustic environments represented by the acoustic measurement sites.

E. Uncertainty quantification

The leave-one-out cross-validation results quantify soundscape model errors at the acoustic measurement sites, which are the only locations where the "true" sound levels are known. However, the number of measurement sites is small compared with the number of unique acoustic environments across the world. Error metrics at the measurement sites alone cannot account for soundscape model errors in acoustic environments that are not represented in the acoustic database.

As discussed in Sec. V A, the soundscape model consists of an ensemble of four machine learning regression models. As the individual models have unique functional forms that extrapolate differently, the standard deviation between the sound levels predicted by the individual models in the ensemble provides a measure of the prediction uncertainty.[13] Although the ensemble standard deviation does not quantify all sources of error between the predictions and true sound levels, it is the best available measure of uncertainty at locations beyond the acoustic measurement sites. At acoustic measurement sites, the average leave-one-out cross-validation error is approximately 2.5 times greater than the ensemble standard deviation.

Figure 6 shows the ensemble standard deviation of the daytime A-weighted L_{50} predicted by the four machine learning models in the soundscape model. The uncertainty is reasonably low across many acoustic environments

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TABLE IV. Leave-one-out cross-validation error metrics for the daytime A-weighted L_{50} in the ambient soundscape model.

Model	Mean error (dBA)	Median absolute error (dBA)	RMS error (dBA)
Gradient boosting regression	−0.1	3.2	5.8
Kernel ridge regression	−0.0	3.5	5.7
Multi-layer perceptron regression	0.0	4.2	6.6
Support vector regression	−0.7	4.0	6.5
Ensemble median	−0.3	3.6	5.9

worldwide, which corresponds to the reasonably low leave-one-out cross-validation error at measurement sites. The uncertainty increases in acoustic environments that are poorly represented in the acoustic database. Regions with the greatest uncertainty include Antarctica, the Himalayas, the Sahara Desert, the Atacama Desert, tropical rainforests, the Mongolian-Manchurian grassland, and the Australian Outback. These landscapes are not commonly found in the United States, and their acoustic environments are not currently represented in the acoustic database. Acoustic environments with high ensemble standard deviation are potential targets for future acoustic measurements to reduce uncertainty in the ambient soundscape model.

F. Future improvements

The uncertainty in the ambient soundscape model is primarily driven by limitations of the acoustic and geospatial databases. Although the acoustic database contains 962 unique measurement sites in diverse acoustic environments across the United States and Nova Scotia, Canada, the number of sites is small compared with the number of unique acoustic environments across the world. Future research should incorporate measurements in acoustic environments outside North America into the soundscape model as additional data for training and validation across the world. Similarly, because ambient soundscapes are influenced by variables other than the 53 features currently in the geospatial database, future research should incorporate impactful global geospatial features into the soundscape model as they become available.

Another driver of uncertainty is the finite spatial resolution of the soundscape model. The predicted ambient sound level in each raster cell represents an average over a 15 by 15 arcsec area (approximately 463 by 463 m at the equator), but ambient sound levels may vary significantly over that area. For example, if a road runs along one side of a raster cell, sound levels are significantly higher near the road than on the other side of the raster cell. Because the soundscape model predicts a single average sound level for the entire raster cell, the predicted sound level is unlikely to match acoustic measurements at specific points within the raster cell. Currently, the soundscape model is most useful for assessing ambient sound levels across community-scale and larger geographic areas. Future research should increase the spatial resolution of the soundscape model to improve its accuracy at specific points.

The soundscape model provides a framework for incorporating new acoustic and geospatial datasets to continuously improve the accuracy and resolution of predicted ambient sound levels across the world. Even with these opportunities for improvement, the soundscape model is sufficiently accurate for many practical applications now. Leave-one-out cross-validation demonstrates that the soundscape model has reasonably low error within the acoustic environments represented by the acoustic measurement

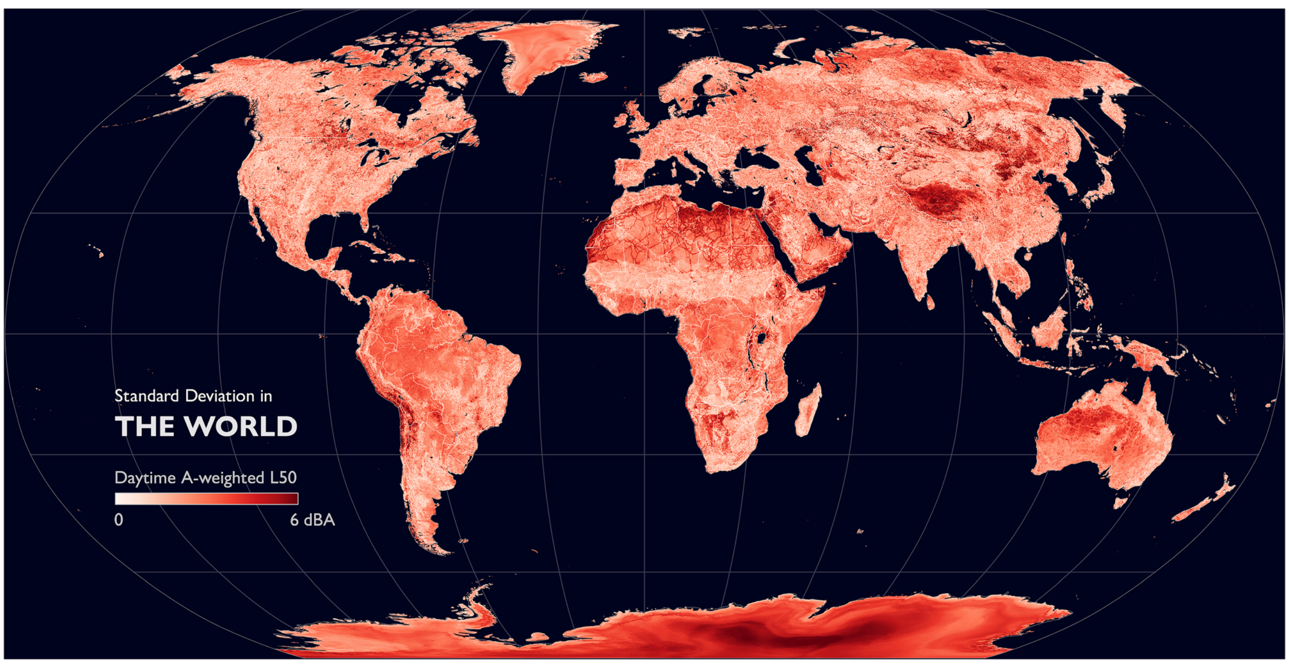

FIG. 6. Ensemble standard deviation of the daytime A-weighted L_{50} across the world.

sites, and the ensemble standard deviation demonstrates that the uncertainty remains reasonably low in most acoustic environments across the world. Thus, the soundscape model can support applications that require knowledge of ambient sound levels across the world.

VI. MAPS OF GLOBAL AMBIENT SOUND LEVELS

AMBIENT | GLOBAL produces maps of ambient sound levels from all anthropogenic, biological, and geophysical sources across the world. Section VI A presents maps of the existing ambient sound levels, Sec. VI B presents maps of the natural sound levels, and Sec. VI C presents maps of anthropogenic noise across the world. Sec. VI D discusses potential applications of the soundscape model.

A. Ambient sound level maps

Figure 7 shows a global map of the daytime A-weighted L_{50} predicted by AMBIENT | GLOBAL. The spatial resolution is 15 arcsec, which is approximately 463 m at the equator. The global soundscape map demonstrates that the highest ambient sound levels on earth occur in densely populated areas such as the East Coast of the United States, Western Europe, the Indian Subcontinent, and East China. As expected, anthropogenic activity creates the highest typical sound levels. The lowest ambient sound levels occur in remote polar, desert, and mountainous regions such as Antarctica, Greenland, the Sahara Desert, and the Himalayas. These regions have few anthropogenic, biological, or geophysical sound sources.

Figure 8 shows maps of the daytime A-weighted L_{50} in the Northeastern United States and along the Nile River in Egypt. These regions highlight spatial contrasts in the ambient sound levels in diverse regions of the world. The Northeastern United States region highlights the gradual decrease in sound levels from louder urban areas to quieter surrounding suburban and rural areas. The Nile River region highlights the stark contrast between the higher sound levels in the densely populated fertile lands of the Nile Valley and Nile Delta and the lower sound levels in the sparsely populated Sahara Desert and Arabian Desert.

These maps demonstrate the capability of the soundscape model to predict the spatial variability of ambient sound levels in various acoustic environments across the world. However, the maps do not reveal the physical mechanisms that drive the ambient sound levels, which is a drawback of many machine learning models. Mennitt *et al.*[8] and Martinez *et al.*[44] analyzed the relative importance of each geospatial feature in random forest models of ambient sound levels, but similar feature importance rankings are not available for all four machine learning algorithms in the ensemble model. As an alternative, the correlation coefficients between the scaled geospatial features and the measured daytime A-weighted L_{50} at the acoustic measurement sites provide a measure of relative feature importance. The most correlated geospatial features are nighttime lights (0.77), population density (0.77), density of local roads (0.72), distance to highways (0.69), and developed land cover (0.67), with correlation coefficients listed in parentheses. These features are all anthropogenic variables, which confirms that anthropogenic activity creates the highest typical sound levels.

B. Natural sound level maps

AMBIENT | GLOBAL provides the capability not only to predict existing ambient sound levels across the world but also to estimate changes to ambient sound levels under various scenarios. One such scenario is the natural sound level that would exist in the absence of anthropogenic noise. To

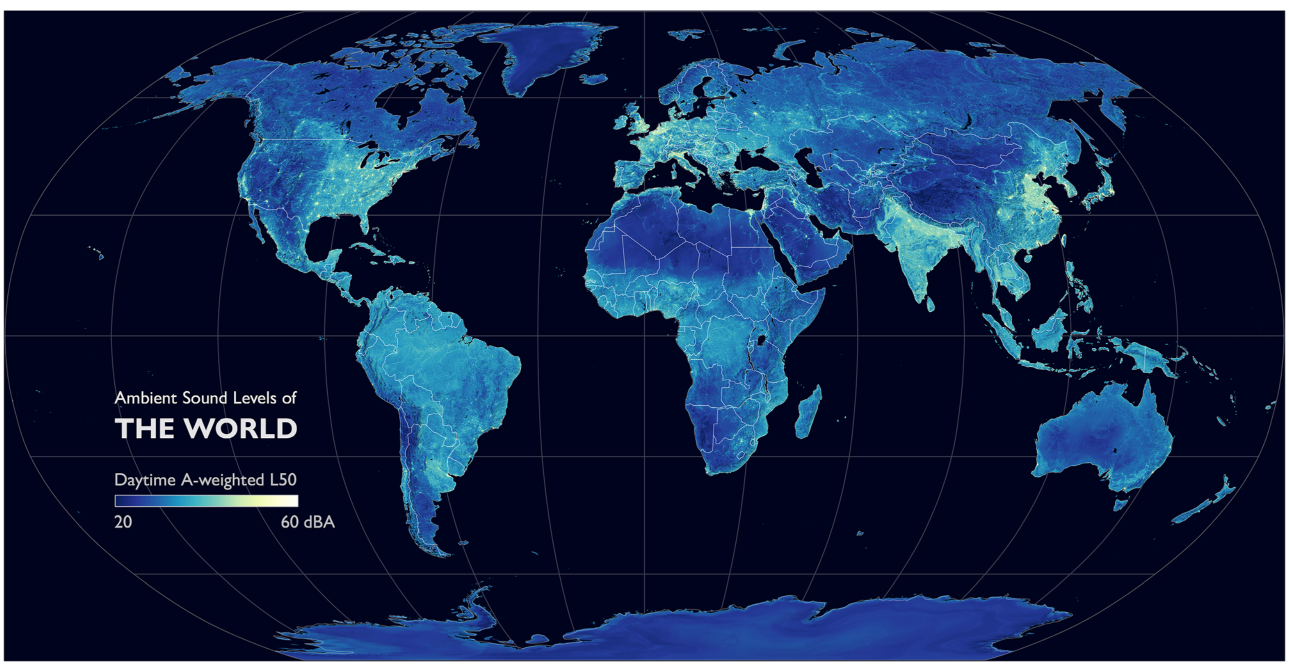

FIG. 7. Daytime A-weighted L_{50} across the world predicted by the soundscape model.

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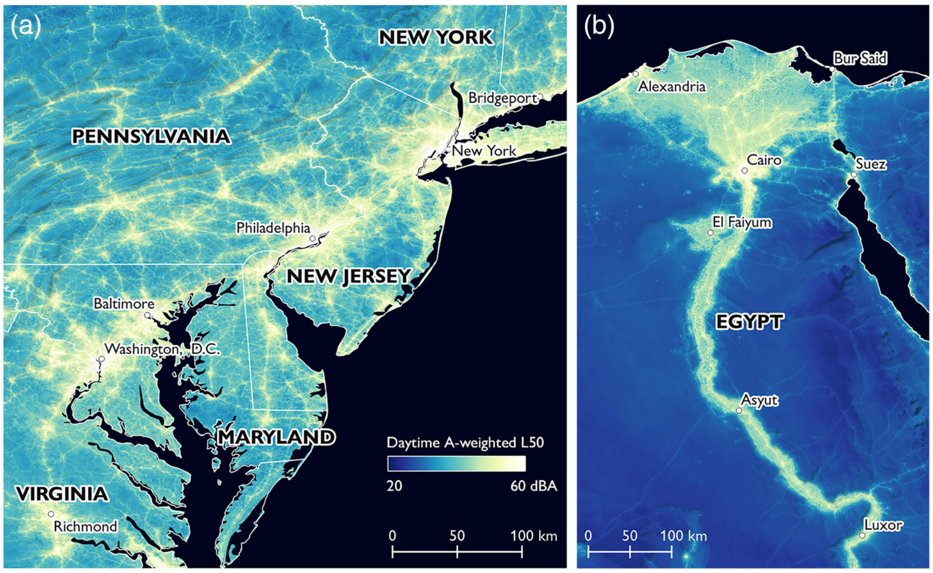

FIG. 8. Daytime A-weighted L_{50} in selected regions of the world predicted by the soundscape model.

estimate the natural sound level, the soundscape model was first trained using the unmodified geospatial features to fit the relationship between measured ambient sound levels and existing geospatial features. The trained soundscape model was then applied to geospatial features that were modified to remove human influences from the population, transportation, and selected land cover features, as discussed in Sec. III C.

Mennitt *et al.*[8] applied a similar approach to estimate natural sound levels in the United States. This approach estimates natural sound levels in the absence of existing anthropogenic noise, not the sound levels that would exist if humans had never modified the natural environment. For example, declining bird populations have contributed to a decrease in natural sound levels,[45] but this approach does not attempt to project the bird populations that would exist without humans. The accuracy of the estimated natural sound levels is limited by the training dataset of acoustic measurements, which record all sources of existing anthropogenic and natural sounds. Furthermore, this approach requires the soundscape model to accurately learn the drivers of anthropogenic noise in the geospatial variables. Nevertheless, scenario modeling is a reasonable approach to estimate natural sound levels across large spatial scales.

Figure 9 shows the natural daytime A-weighted L_{50} estimated by the soundscape model applied to the geospatial features modified to remove human influence. In populated areas, the natural sound levels that would exist in the absence of anthropogenic noise are significantly lower than the existing sound levels shown in Fig. 7. The highest natural sound levels occur in tropical rainforests such as the Amazon Rainforest in South America and the Congo Basin in Africa, which are some of the most biodiverse regions on earth containing many biological sources of sound. Prior studies have shown that natural sound levels are related to biodiversity.[46,47] The lowest natural sound levels occur in remote polar, desert, and mountainous regions with few biological or geophysical sound sources.

C. Anthropogenic noise maps

The differences between the existing ambient sound levels shown in Fig. 7 and the natural sound levels shown in Fig. 9 demonstrate the significant influence of anthropogenic activity on the ambient sound levels in populated areas. Buxton *et al.*[10] quantified the decibel difference between the modeled existing and natural sound levels in the United States but did not calculate anthropogenic sound levels directly. The anthropogenic sound level is calculated from the existing and natural sound levels by

$$L_{anthropogenic} = 10\log_{10}\left[10^{(L_{existing}/10)} - 10^{(L_{natural}/10)}\right]. \quad (2)$$

Figure 10 shows the anthropogenic daytime A-weighted L_{50} calculated by applying Eq. (2) to the existing and natural sound levels predicted by the soundscape model. The map of global anthropogenic noise quantifies the impact of humans on ambient sound levels across the world. Figure 11 shows maps of the anthropogenic daytime A-weighted L_{50} in the Northeastern United States and along the Nile River in Egypt. The Northeastern United States region demonstrates that anthropogenic sound levels are highest in major urban areas and gradually decrease in surrounding suburban and rural areas, but anthropogenic noise is present throughout most of the region. The Nile River region highlights the stark contrast between the highest anthropogenic sound levels in major cities such as Cairo and Alexandria, the presence of anthropogenic noise throughout the populated fertile lands of the Nile Valley and Nile Delta, and the lack of anthropogenic noise in the sparsely populated Sahara Desert and Arabian Desert.

D. Applications

The ambient sound level maps presented above demonstrate some of the capabilities of AMBIENT | GLOBAL, which has numerous applications in fields such as land use planning, environmental science, and public health. Researchers

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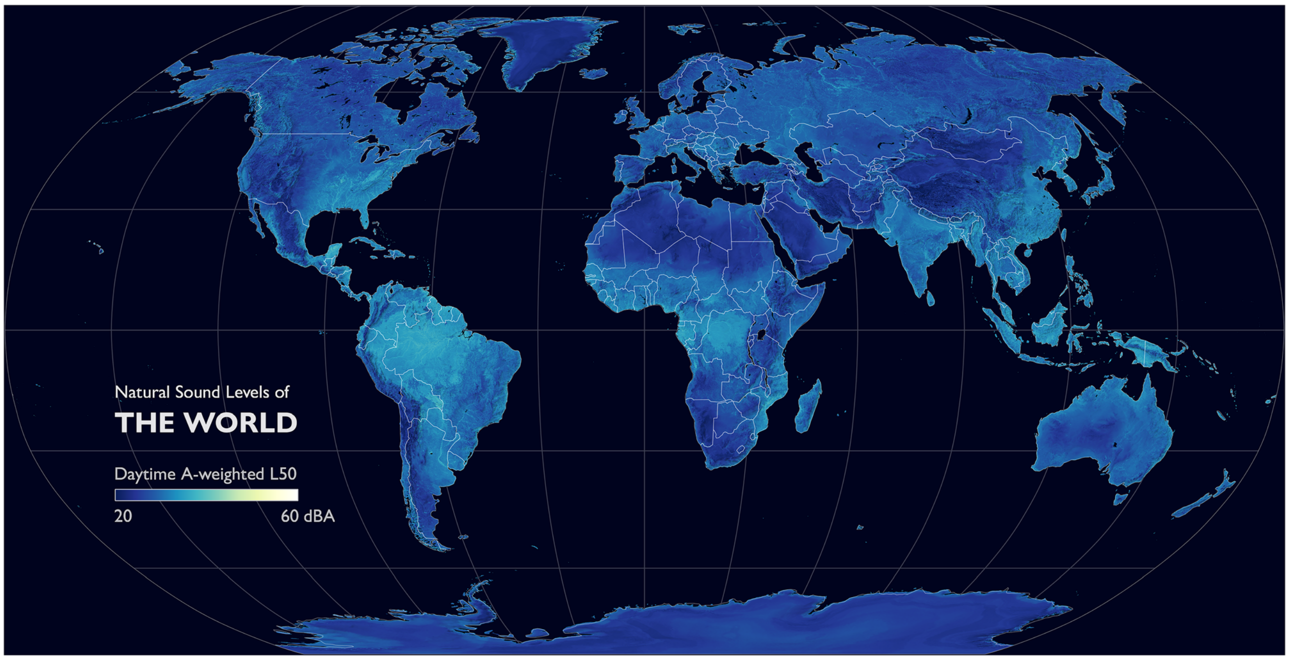

FIG. 9. Natural daytime A-weighted L_{50} across the world estimated by the soundscape model.

in these fields will benefit from predictions of ambient sound levels to study relationships among humans, nature, and the ambient soundscape across community- to global-scale geographic areas. For example, the maps of natural and anthropogenic sound levels demonstrate the capability of the soundscape model to estimate changes in ambient sound levels under scenarios with and without human influence. Scenario modeling is subject to several potential limitations: the scenario must be definable by modifying the geospatial features, the soundscape model must accurately learn the relationship between the acoustic measurements and the relevant geospatial features, and opportunities for validation are limited. Despite these limitations, scenario modeling is a powerful tool that enables researchers to predict changes to ambient sound levels across the world under historical or future scenarios.

VII. CONCLUSION

This paper presents AMBIENT | GLOBAL, the first global ambient soundscape model developed to predict maps of ambient sound levels from all anthropogenic, biological, and geophysical sources across the world. The soundscape model adopts a geospatial approach by modeling the ambient sound level at a location as an unknown function of geospatial features at that location. The soundscape model fits an ensemble of four machine learning regression models to a training dataset at locations where both the geospatial features and ambient sound levels are known. The fitted model is then applied to predict ambient sound levels at any location where the geospatial features are known. The explanatory variables in the soundscape model consist of 53 geospatial features that describe population, transportation, land cover, biology, topography, climate, and hydrology variables. The response variable in the training dataset for fitting the soundscape model is an acoustic database that contains almost 900 000 h of acoustic measurements at 962 unique measurement sites in various acoustic environments across North America.

Leave-one-out cross-validation reveals that the soundscape model has a median absolute error of 3.6 dBA for the daytime overall A-weighted L_{50} at the acoustic measurement sites. However, the number of measurement sites is small compared with the number of unique acoustic environments across the world. The best available measure of prediction uncertainty across the world is the standard deviation between the sound levels predicted by the four individual machine learning models in the ensemble. The prediction uncertainty is reasonably low across most acoustic environments worldwide, but the uncertainty increases in acoustic environments that are poorly represented in the acoustic database. These acoustic environments are targets for future acoustic measurements to reduce uncertainty in the soundscape model. Despite some regions of higher uncertainty, the soundscape model is sufficiently accurate for many practical applications in most acoustic environments across the world. Furthermore, the soundscape model provides a framework for incorporating new acoustic and geospatial datasets to continuously improve the accuracy and resolution of predicted ambient sound levels across the world.

This paper presents maps of the existing, natural, and anthropogenic ambient sound levels across the world to demonstrate the capabilities of the soundscape model. The existing ambient sound level is predicted by the trained soundscape model. The natural sound level is estimated by applying the soundscape model to geospatial features that are modified to remove human influences. The

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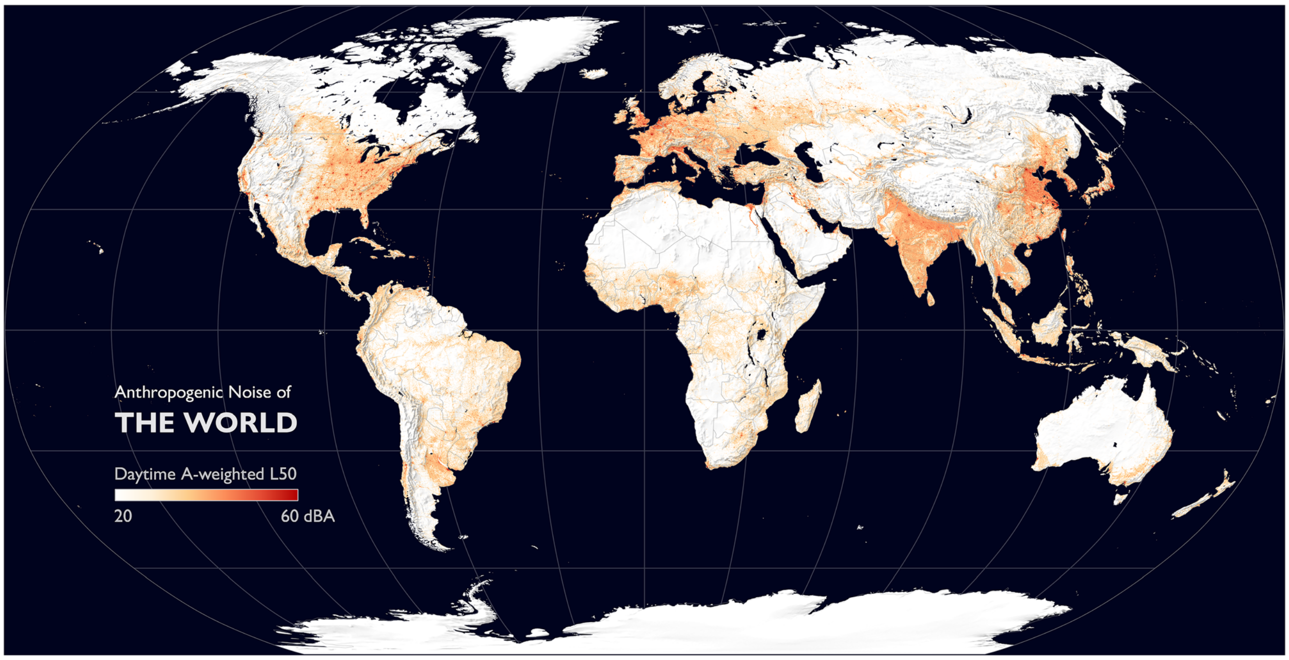

FIG. 10. Anthropogenic daytime A-weighted L_{50} across the world calculated from the existing and natural sound levels predicted by the soundscape model.

anthropogenic sound level is calculated as the energy difference between the existing and natural sound levels. These maps reveal the spatial variability of ambient sound levels in various acoustic environments across the world: the highest ambient sound levels occur in densely populated urban areas, the highest natural sound levels occur in areas with the greatest biodiversity, and the lowest ambient sound levels occur in remote polar, desert, and mountainous areas. Furthermore, these maps demonstrate the capability of the soundscape model to estimate large-scale changes in ambient sound levels under various scenarios defined by modified sets of geospatial features. These capabilities have numerous applications in fields such as land use planning, environmental science, and public health.

Although this paper presents ambient sound levels in terms of the daytime overall A-weighted L_{50} metric, AMBIENT | GLOBAL can also predict ambient sound levels for different times of day (daytime, nighttime, and hourly), frequencies (overall A-weighted and one-third octave bands), and acoustic metrics (L_{eq}, L_{10}, L_{50}, and L_{90}). Thus, the soundscape model quantifies the spatial, temporal, and spectral patterns of ambient sound levels across the world. The soundscape model addresses three of the key research themes identified by Pijanowski *et al.*[3] to advance the field of soundscape ecology: improving the understanding of spatial and temporal dynamics of soundscapes across different scales, improving the understanding of how environmental variables impact soundscapes, and assessing the impacts of

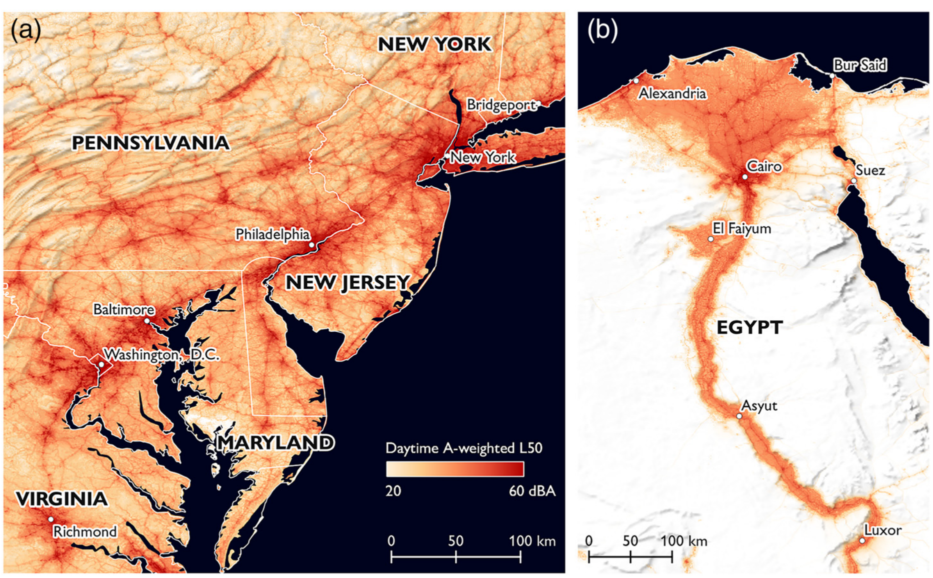

FIG. 11. Anthropogenic daytime A-weighted L_{50} in selected regions of the world calculated from the existing and natural sound levels predicted by the soundscape model.

humans on soundscapes. Ultimately, the soundscape model will enable researchers to investigate the impacts of humans and nature on the ambient soundscape and the impacts of ambient sound levels on humans and nature across the world.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

DATA AVAILABILITY

Downsampled global maps of the existing, natural, and anthropogenic ambient sound levels are available at https://www.blueridgeresearch.com/ambient. Other requests for ambient sound level data should be addressed to the corresponding author.

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