Characterizing functional relationships between technophony and biophony: A western New York soundscape case study

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Abstract

We develop a modeling framework to characterize the functional relationship between anthropogenic (technophony) and biological (biophony) sounds in western New York. The proposed framework also facilitates statistical attribution of sound sources to observed technophony and/or biophony, a capability we use to assess technophony variance explained by a road sound variable. Roads are a widespread feature of most landscapes worldwide, and the sound from road traffic potentially makes nearby habitat unsuitable for acoustically communicating organisms. Thus, it is important to understand the influence of roads at the soundscape level to mitigate negative impacts of road sound on individual species as well as subsequent effects on the surrounding landscape. Recordings were obtained in the spring of 2016 at 18 different sites throughout western New York. Model parameter estimates and resulting map predictions illustrate the intuitive result that technophony and biophony have an inverse relationship, and technophony is greatest in close proximity to high traffic volume roads. The predictions have large uncertainty, resulting from the temporal coarseness of public road data used as a proxy for traffic sound. Results suggest that finer temporal resolution traffic sound data, such as crowdsourced time-indexed traffic data from geographic positioning systems, might better account for observed temporal changes in the soundscape. Given the widespread breadth of road networks, an increased understanding of the distribution of road sound on soundscapes over space and
time is essential to mitigate the negative effects that technophony has on the soundscape and it’s underlying biodiversity.

**Keywords**: ecoacoustics, soundscape ecology, bioacoustics, technophony, Bayesian, road effect
Introduction

Roads are a widespread feature of most landscapes worldwide, with road networks growing dramatically in the past 100 years. In the United States alone, there are over 6.3 million kilometers of public roads, most of those (80%) found in rural areas (Forman et al., 2003). Nowhere in the United States is very far from a road, with the farthest straight line distance from a road in the lower 48 states being a spot in Wyoming 21 miles from the nearest road (Project Remote, 2019). Since 1970, the traffic on US roads has at least tripled to almost 5 trillion vehicle kilometers traveled per year (Barber et al., 2010). This means wildlife in almost every landscape and habitat is impacted by roads and traffic. Habitat fragmentation caused by roads is detrimental to wildlife due to direct mortality via wildlife-vehicle collisions, exposure to pollutants, and perhaps most importantly, exposure to sound from road traffic (Barber et al., 2011; Parris and Schneider, 2008; McClure et al., 2013; Snow et al., 2018). Thus, while roads alter habitats and landscapes structurally, impacts of roads on animal diversity and abundance can also be impacted by altered acoustic environments (Katti and Warren, 2004; McClure et al., 2013).

Acoustic space, or the soundscape, is an essential resource for both terrestrial and marine animals (Pijanowski et al., 2011a; Farina, 2018). Animals utilize the auditory spectrum for a variety of functions, including reproduction (McGregor, 2005), predation and to warn of danger (Templeton, 2006; Marler and Slabbekoorn, 2003; Sloan and Hare, 2008; Ridley et al., 2007), and to find food (Rice, 1982; Knudsen and Konishi, 1979; Neuweiler, 1989). The sounds organisms produce are collectively called biophony, which combine together with sounds from the earth, like wind and rushing water (geophony), and sounds produced from human technology (anthropogenic noise, anthropophony, or technophony, henceforth referred to as technophony) to form the soundscape (Pijanowski et al., 2011a). While all habitats are noisy in some measure, the addition of technophony to a soundscape introduces evolutionarily novel and measurably different sounds to a natural soundscape (Slabbekoorn and Ripmeester, 2008). Road sound may be the most pervasive form of technophony impacting natural habitats and contributes sound with
particular characteristics to the soundscapes of those habitats. Sound from a road is a linear rather than a point source (Katti and Warren, 2004), the sound from traffic tends to be low frequency (typically below 2 kHz) and high amplitude, and the timing of road sound in some places can vary greatly over time (e.g., rush hour peaks) and depend on traffic load (Slabbekoorn and Ripmeester, 2008).

Traffic sound and other sources of technophony have created soundscapes with novel acoustic characteristics in which acoustically communicating animals send and receive signals. High amounts of technophony reduce the perception of biologically important sound (Barber et al., 2010) and are thought to have negative effects on both cognitive processes (Potvin, 2017) as well as behavior (Brumm and Slabbekoorn, 2005). Traffic sound often masks auditory signals, limiting or preventing senders and receivers from communicating effectively, a phenomenon that is well-documented (Brumm and Slabbekoorn, 2005; Patricelli and Blickley, 2006), particularly for birds and frogs. Traffic sound was shown to cause physiological stress and impair breeding behavior in multiple frog populations throughout the world (Tennessen et al., 2014), and similar effects have been demonstrated in birds (Ortega, 2012; Warren et al., 2006). Some bird species are able to respond to technophony by adapting characteristics of their song to overcome masking. A study on Song Sparrows (Melospiza melodia), found a positive correlation between the minimum frequency of a male’s song and the loudness of technophony (Wood and Yezerinac, 2006), suggesting the organisms are attempting to adapt to increased low frequency sound by changing the pitch of their songs to overcome masking. However, not all species are able to change signal frequency or amplitude in a short term response to increased sound in the environment (Patricelli and Blickley, 2006; Oberweger and Goller, 2001; Brackenbury, 1978). Further, even organisms that are able to adapt their signals may suffer from reduced fitness (Phillips and Derryberry, 2018), suggesting technophony can have negative effects even on the species that change their signals in response to increasing sound (Patricelli and Blickley, 2006). An alternative response to technophony is for species to avoid habitats where it impacts the soundscapes, a conclusion drawn from tests of the “phantom road” effect (McClure et al., 2013) and observations of changes in
species abundances near roads (Fahrig and Rytwinski, 2009).

Without proper management of technophony, the negative impacts could cause changes in species composition with potentially far reaching effects on the ecosystem. Thus, it is necessary to analyze the relationship between biophony and technophony and understand how it changes across temporal and spatial gradients in order to accurately predict how technophony will influence the species comprising the biophony. More specifically, the identification of technophony “hot spots” in space and time will allow natural resource managers and others to pinpoint the times and locations in which human sound should be mitigated to maintain the integrity of local ecosystems (Ortega, 2012). To do this requires understanding the relationship between biophony and prominent sources of technophony, such as road sound.

Ecoacoustics researchers (Farina and Gage, 2017; Sueur et al., 2008) have developed a number of acoustic indices, such as the Acoustic Complexity Index (ACI) (Pieretti et al., 2011), Acoustic Diversity Index (ADI) (Villanueva-Rivera et al., 2011), Bioacoustic Index (BI) (Boelman et al., 2007), and Normalized Difference Soundscape Index (NDSI) (Kasten et al., 2012) to quantify soundscapes and understand how biophony relates to technophony. NDSI was developed to compare the relative amounts of technophony and biophony within an environment (Kasten et al., 2012) and has been shown to correlate well with landscape characteristics despite it’s relative simplicity (Fuller et al., 2015), and thus seems like a suitable measure to further characterize the relationship between technophony and biophony across different spatio-temporal gradients. The NDSI is built using the power spectral density (PSD) (Welch, 1967) for 1 kHz frequency bins within the recording.

The NDSI and PSD are useful tools for tracking spatio-temporal changes in soundscapes (Mullet et al., 2016; Pijanowski et al., 2011a). However, soundscape data present some unique challenges that cannot be addressed using these indices and simple statistical models. The data are multivariate (partitioned into frequencies associated with anthropogenic and natural sounds), compositional (frequency ranges sum to total sound at a given location and time), non-Gaussian, non-stationary, and are correlated across
space and time. Data are also typically sparsely sampled in space, and often comprise high-dimensional continuous time series for short time intervals with large intervening time gaps. While contemporary statistical literature offers modeling theory for such data complexities (Clark, 2007; Hobbs and Hooten, 2015), applied methodology and software are not yet available in the field of ecoacoustics.

In this study, we propose a hierarchical Bayesian modeling approach to assess the spatial distribution of biophony and technophony in western New York soundscapes in relation to roads and traffic density. Hierarchical Bayesian models (HBMs) offer an intuitive framework to decompose complex ecological problems into logical parts (data, process, and parameters) (Berliner, 1996; Cressie et al., 2009). The framework is ideal for drawing inference about soundscapes as it can accommodate high-dimensional, multivariate, compositional data with time and space dependence. Specifically, our objectives are to: 1) characterize the functional relationship between technophony and biophony; 2) assess the extent to which available traffic data explains variability in technophony; 3) develop a methodology to deliver statistically valid maps of technophony and biophony that reflect the relationship identified in Objective 1 with accompanying uncertainty quantification.

Materials and Methods

Study Location and Data Collection

Recording sites were located in nine forest patches in western New York. This region provides habitat for hundreds of breeding bird species throughout the spring and summer months, and thus the soundscape is an important resource that should be monitored to ensure the habitat remains viable breeding area for these species.

We obtained recordings at two locations (interior and exterior) at each of the nine forest plots, resulting in 18 recording sites. From May-June 2016 we obtained three 30 minute recordings at each recording site in the morning (between 6-8am), afternoon (between 12-2pm), and evening (between 6-9pm), resulting in a total of 54 30 minute record-
ings. We recorded in stereo at a sampling rate of 44.1 kHz using a Song Meter SM4 from Wildlife Acoustics (Wildlife Acoustics, 2012) mounted on a tripod one meter above the ground. We discarded the last minute of each 30 minute recording as a result of extraneous sound. Each 29 minute recording was broken up into 29 consecutive one-minute sound bites, resulting in a total of $n = 18 \text{ sites} \times 3 \text{ times per day} \times 29 \text{ sound bites} = 1566$ observations. We recorded on days with similar weather conditions during which birds are known to communicate (i.e., no rain, minimal wind) to minimize any influence of weather on the observed soundscape patterns.

**Soundscape Metrics**

Each one minute soundscape recording was summarized using the PSD as computed by Welch (Welch, 1967). The PSD represents the amount of soundscape power within each frequency band in units of watts / kHz (Figure 1). We computed the PSD for each 1 kHz frequency band between 1-8 kHz, where each value ranged from 0 (no sound) to 1 (filled with sound). We used the PSD from the 1-2 kHz band to represent the amount of technophony in each recording following the technique of Kasten et al. (2012) and the sum of the PSD values from 2 - 8 kHz to represent the amount of biophony in each recording. 8 kHz was used as a cutoff frequency to minimize computational time and because of the range of sounds known to occur in the recording locations at the given times of day. The biophony values were scaled to the range of 0-1 watts/kHz to have the same range as the technophony (0-1). We used the soundecology (Villanueva-Rivera and Pijanowski, 2018), tuneR (Ligges et al., 2018), and seewave (Sueur et al., 2008) packages within the R Statistical Software (R Core Team, 2019) environment to compute these measures. PSD values were averaged over the left and right channels to obtain a single value of technophony and biophony for each recording.

**Road Influence**

To assess the influence of roads and traffic sound on the soundscapes we used public data from the New York State GIS Clearinghouse (NYS ITS GIS Program Office, 2019)
Figure 1: Computation of biophony ($y_{ijk}$) and technophony ($\alpha_{ijk}$) values using the power spectral density for a single recording minute ($i$) at a single location ($j$) at a single time of day ($k$).

containing road locations and average speeds. A second data set was acquired from the New York State Department of Transportation (NYS Department of Transportation, 2018) containing the average annual daily traffic (AADT) on Federal and State highways, and on county and town roads. The roads from these data sets are plotted in Figure 2, clearly showing the ubiquitousness of roads throughout western New York. We created a road covariate to quantify the road influence on the soundscape at any given location. This road covariate (RC) took into account 4 factors: 1) average speed; 2) distance of recording site to road; 3) AADT; 4) shape of the road. To quantify the shape of the road, we broke each road into $10 \times 10$ m pixels, obtained the corresponding AADT and speed values with each road pixel, and computed the distance of each road pixel within 600 m of a given recording site. The 600m boundary was used as it is a rough estimate of how far technophony will travel through a forested landscape (Forman and Deblinger, 2000; MacLaren et al., 2018).

We predicted average speed and AADT to have a positive relationship with technophony and distance to have a negative relationship with technophony. Thus, the road covariate
Figure 2: Distribution of roads in New York State. (a) Public road data is displayed across all of NYS. (b) The road covariate is computed at a $30 \times 30$ m resolution for the boxed area.

is computed as follows for a given $10 \times 10$ m pixel $i$:

$$RC_i = \frac{\log(AADT_{100}) + \log(speed) - \log(distance)}{100}$$

The AADT is divided by 100 to provide approximately equal weight to all three variables. The complete road covariate for a given recording site is then computed by summing the $RC_i$ for all locations $i$ within 600m of the given recording site. This road covariate is visualized in the study region in Figure 2, indicating the covariate is only high near roads, and highest near intersections in the Rochester area.

Quantification of roads was limited to the roads assessed by the New York State Department of Transportation. These data come primarily from 12,000 short traffic counts of 2-7 days of duration that are taken annually on Federal and State highways, as well as county and town roads. However, it is not feasible to obtain measurements of every road, and more counts took place in urban areas than in rural and agricultural areas (NYS Department of Transportation, 2018), which could potentially lead to the road covariate being an underestimate in rural and agricultural regions.
Model

We seek a model that: 1) provides parameter estimates and associated uncertainty regarding the relationship between biophony and technophony; 2) assesses the amount of technophony variance explained by the road covariate; 3) enables biophony and technophony prediction with associated uncertainty. Importantly, we take the view that biophony is conditional on technophony, and both variables are observed with error. We considered three hierarchical Bayesian models of increasing complexity, henceforth referred to as Model 1, Model 2, and Model 3. Each model consisted of two stages. Stage 1 models technophony as a function of the road covariate. Stage 2 models biophony conditional on Stage 1 such that uncertainty in observed technophony is appropriately propagated through the two stages for inferences and subsequent prediction (Lunn et al., 2013).

Consider the PSD value for technophony $\alpha_{i,j,k}$ and the road covariate $x_j$, where $i = 1, 2, \ldots, 29$ is the minute of the continuous 29-minute recording, $j = 1, 2, \ldots, 18$ indexes recording site, and $k = 1, 2, 3$ indexes time of day. All first stage models use a beta regression to account for the bounded support of $\alpha_{i,j,k}$ on $[0, 1]$ and follow the mean and precision parameterization detailed in Ferrari and Cribari-Neto (2004).

Exploratory data analysis revealed the relationship between technophony and the road covariate was non-linear and residuals (i.e., after accounting for the road covariate) were serially correlated with non-constant variance. These features were accommodated using cubic b-splines to obtain a smooth curve over the technophony and road covariate functional relationship, and a temporally structured random effect to acknowledge the correlation among the one-minute technophony sound bites over each 29 minute recording. More specifically, the random effect followed a multivariate normal distribution with mean 0 and an AR(1) covariance matrix.

Inferences proceeded by assigning model parameters non-informative prior distributions then a Markov Chain Monte Carlo (MCMC) algorithm sampled from posteriors distributions. The full hierarchical model for Model 1, including prior specifications, is detailed below ($[a \mid b]$ is the probability distribution of $a$ conditional on $b$) :

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**Stage 1:**

\[
\begin{align*}
[\beta_\alpha, \sigma^2_\alpha, \rho_\alpha, \phi_\alpha, w_{i,j,k} \mid x_j, \alpha_{i,j,k}] & \propto \\
\prod_{i=1}^{29} \prod_{j=1}^{18} \prod_{k=1}^{3} \text{beta}(\alpha_{i,j,k} \mid g(\beta_\alpha, x_j, w_{i,j,k})\phi_\alpha, (1 - g(\beta_\alpha, x_j, w_{i,j,k}))\phi_\alpha) \times \\
\text{multivariate normal}(w_{i,j,k} \mid 0, \sigma^2_\alpha \Sigma(\rho_\alpha)) \times \\
\text{inverse gamma}(\phi_\alpha \mid 2, 20000) \times \\
\text{inverse gamma}(\sigma^2_\alpha \mid 2, 5) \times \\
\prod_{l=1}^{5} \text{normal}(\beta_{\alpha,l} \mid 0, 10000) \times \\
\text{uniform}(\rho_\alpha \mid 0, 1)
\end{align*}
\]

where \( g(\beta_\alpha, x_j, w_{i,j,k}) = \text{inverse logit}(Z_{x_j} \beta_\alpha + w_{i,j,k}) \), \( Z_{x_j} \) is the row in the b-spline design matrix for the specific value of the road covariate \( x_j \), \( w_{i,j,k} \) is the random effect with mean 0 and an AR(1) covariance structure with variance \( \sigma^2_\alpha \), correlation \( \rho_\alpha \), and \( n \times n \) matrix \( \Sigma \) (with block diagonal structure where each block is the covariance among 29 consecutive sound bites), \( \beta_\alpha \) are spline regression coefficients, and \( \phi_\alpha \) is the precision.

Point and interval estimates for parameters and fitted values were obtained from the joint posterior distribution (Gelman et al., 2004). Recall, the central role of the Stage 1 model is to explore the relationship between the road covariate and \( \alpha \), and propagate the uncertainty in \( \alpha \) to the Stage 2 model for the biophony. This was accomplished by obtaining \( M \) post burn-in samples of the fitted values from Stage 1, i.e. \( M n \times 1 \) vectors of \( \hat{\alpha}^{(m)} = (\hat{\alpha}_1^{(m)}, \hat{\alpha}_2^{(m)}, \hat{\alpha}_3^{(m)}, \ldots, \hat{\alpha}_n^{(m)})^\top \) where \( m = 1, \ldots, M \), and use them as the covariate in a similar mixed effect beta regression model for the biophony, \( y_{i,j,k} \). The overall structure of Stage 2 is exactly the same as Stage 1, with the exception that each MCMC iteration \( m \) fits the biophony to a different sample \( \hat{\alpha}^{(m)} \). Stage 2 takes the following form, where all parameters are analogous to Stage 1:
Stage 2:

\[
[\beta_y, \sigma_y^2, \rho_y, \phi_y, v_{i,j,k} | \hat{\alpha}_{i,j,k}^{(m)}, y_{i,j,k}] \propto \\
\prod_{i=1}^{29} \prod_{j=1}^{18} \prod_{k=1}^{3} \beta(y_{i,j,k} | g(\beta_y, \hat{\alpha}_{i,j,k}^{(m)}, v_{i,j,k}) \phi_y, (1 - g(\beta_y, \hat{\alpha}_{i,j,k}^{(m)}, v_{i,j,k})) \phi) \times \\
\text{multivariate normal}(v_{i,j,k} | 0, \sigma_y^2 \Sigma(\rho_y)) \times \\
\text{inverse gamma}(\phi_y | 2, 2000) \times \\
\text{inverse gamma}(\sigma_y^2 | 2, 2) \times \\
\prod_{l=1}^{8} \text{normal}(\beta_{y,l} | 0, 10000) \times \\
\text{uniform}(\rho_y | 0.1, 1). 
\]

While Model 1 does accommodate the serial correlation among the one-minute sound bites, it does not acknowledge within day (i.e., morning, afternoon, and evening) repeated measures aspect of the sampling design. This within day covariance is explicitly taken into account in Model 2 by replacing the scalar variance parameters, \(\sigma_\alpha^2\) and \(\sigma_y^2\), with a 3 \times 3 covariance matrix, \(\lambda_\alpha\) and \(\lambda_y\), whose diagonal elements represent the random effect variance for the respective time period (morning, afternoon, evening) and whose off-diagonal elements represent the covariance between recordings in different time periods. Unlike in Model 1, this structure allows us to make inferences about similarities or differences between the soundscape recordings across the three time periods. The \(\lambda\)'s are modeled with a non-informative inverse wishart prior with degrees of freedom 3 and a diagonal scale matrix with all diagonal elements equal to 0.1. We use Kronecker products to obtain the desired structure of the covariance matrix, and apply this structure in both Stage 1 and Stage 2.

After examining output from Model 1 and Model 2, diagnostic plots showed observed versus fitted values exhibited heteroskedasticity and associate credible intervals were not appropriately capturing the variability. This non-constant variance was directly addressed in Model 3. For Stage 1, the heteroskedasticity resulted from the relationship between technophony and the road covariate. This was remedied by fitting two separate precision
parameters $\phi_{a,l}$ and $\phi_{a,u}$, the expression of which was controlled by an indicator function such that $\phi_{a,l}$ is the precision at values of the road covariate less than 2, while $\phi_{a,u}$ is the precision at values of the road covariate greater than 2. While we could have formally estimated the indicator function break point parameter, it was clear from diagnostic plots that a road covariate value of 2 was adequate, see, e.g., Figure 3. Both $\phi_{a,l}$ and $\phi_{a,u}$ are modeled with non-informative inverse gamma priors. In Stage 2, we model the precision parameter $\phi_y$ as a function of technophony, specifically taking the form $\phi_y = \phi_2 \exp(\hat{\alpha}_{i,j,k})$. We modeled $\phi_{y,1}$ and $\phi_{y,2}$ using vague uniform priors from 0 to 10000.

**Prediction**

We seek to develop statistically valid maps of technophony and biophony that reflect the relationships obtained from the three models with associated uncertainty quantification. We computed the road covariate as described previously across a square region in western New York (Figure 2). The posterior predictive distribution for technophony is

$$[\alpha^* | \alpha, x] = \int_{-\infty}^{\infty} [\alpha^* | \theta_\alpha] [\theta_\alpha | \alpha] d\theta_\alpha$$

(1)

where $\alpha^*$ is a vector of technophony values at new locations, $x$ is a vector of road covariate values at new locations, and $\theta_\alpha$ is a vector of Stage 1 parameters. Similarly, the posterior predictive distribution for biophony is

$$[y^* | y, \hat{A}] = \int_{-\infty}^{\infty} [y^* | \theta_y] [\theta_y | y] d\theta_y$$

(2)

where $y$ is a vector of biophony values at new locations, $\hat{A}$ is an $n^* \times M$ matrix, where $n^*$ is the number of new locations to predict, and $M$ is the number of post-burn MCMC iterations of the fitted values of Stage 1, and $\theta_y$ is a vector of Stage 2 parameters.

The integrals in (1) and (2) are approximated using MCMC based composition sampling (see, e.g., Banerjee et al., 2014). Posterior predictive samples from $\alpha^*$ and $y^*$ were used to compute technophony and biophony medians and associated credible intervals.
Convergence Diagnostics and Model Validation

Diagnostics were performed to ensure convergence of the MCMC chains. We used a combination of visual assessment of trace plots and an alternative version of the Gelman-Rubin diagnostic that does not assume normality of the correction factor (Brooks and Gelman, 1998).

True assessment of the predictive ability of a model requires some form of hold out data that are not used for fitting the model. To accomplish this, we performed a k-fold cross validation technique with $k = 6$ (Vehtari and Lampinen, 2002). This technique requires fitting the model $k$ times, where each time the model is fit on $n/k$ data points, where $n$ is the length of the data set. Each run of the model fits on a different portion of the data, and predicts the remaining $n - n/k$ hold out values. Since these data are not used in the model fitting process, they represent true draws from the posterior predictive distribution that can be compared with the actual values of the data to assess the predictive capabilities of the model. We used the Continuous Rank Probability Score (Gneiting and Raftery, 2007) and the Expected Log Pointwise Predictive Density (Vehtari et al., 2017) to compare the predictive capabilities of the model. Further, we computed the 95% coverage interval for each of the models, which gives us the percentage of the actual data values that fall within the 95% credible interval of the model.

Software Implementation

MCMC samplers were written in C++ using an Adaptive-Metropolis-within-Gibbs algorithm (Roberts and Rosenthal, 2009). Computationally expensive matrix operations were coded using the Intel Math Kernel Library (MKL) BLAS and LAPACK routines. Prediction and model validation were performed in both C++ and R utilizing the scoringRules package to compute the CRPS (Jordan et al., 2018). All subsequent analysis was performed in R (R Core Team, 2019) (data and code will be published on a public repository upon acceptance or upon the request of a reviewer).
Results

Candidate model parameter estimates are given in Table 1. Convergence diagnostics suggested rapid convergence for all model parameters with the exception of a few spline coefficients, $\beta$’s, in Stage 1. Such lack of convergence is common in spline-based regression components, especially in the presence of an additive structured random effect (Wood and Yezerinac, 2006; Hanks et al., 2015). This lack of convergence is of no concern because we are not interested in interpreting the individual spline basis function coefficients—we simply look to Stage 1 to adequately capture the uncertainty in observed technophony, and characterize the relationship between technophony and the road covariate. Figure 3 shows that both of these objectives are met.

Table 1: Stage 1 posterior parameter medians and 95% credible intervals, 50% (2.5%, 97.5%). Subscript in parentheses on $\lambda$ indicate the row and column element in $\lambda$.

| Parameter      | Model 1         | Model 2         | Model 3         |
|----------------|-----------------|-----------------|-----------------|
| $\beta_{\alpha,0}$ | 0.40 (0.37, 0.42) | 0.74 (0.69, 0.78) | 0.41 (0.37, 0.51) |
| $\beta_{\alpha,1}$ | 3.27 (3.22, 3.50)  | 1.68 (1.62, 1.72) | 3.15 (3.08, 3.27) |
| $\beta_{\alpha,2}$ | 2.93 (2.24, 3.12) | 3.97 (3.68, 4.22) | 6.82 (5.92, 7.35) |
| $\beta_{\alpha,3}$ | 4.56 (4.05, 5.06) | 4.40 (3.65, 5.33) | 4.59 (4.00, 5.21) |
| $\beta_{\alpha,4}$ | 3.96 (3.59, 4.24) | 4.52 (3.88, 5.06) | 5.63 (5.14, 6.09) |
| $\phi_{\alpha}$  | 103947 (21897, 293241) | 70913 (24985, 255927) | - |
| $\phi_{\alpha,l}$ | - | - | 33404 (7347, 162582) |
| $\phi_{\alpha,u}$ | - | - | 42272 (13075, 226625) |
| $\lambda_{\alpha,1}$ | - | 2.22 (2.02, 2.45) | 1.93 (1.77, 2.12) |
| $\lambda_{\alpha,2}$ | - | 0.06 (-0.15, 0.25) | 0.02 (-0.15, 0.19) |
| $\lambda_{\alpha,3}$ | - | 0.36 (0.13, 0.59) | 0.30 (0.10, 0.49) |
| $\lambda_{\alpha,4}$ | - | 2.34 (2.12, 2.61) | 2.03 (1.84, 2.34) |
| $\lambda_{\alpha,5}$ | - | -0.082 (-0.32, 0.15) | -0.09 (-0.30, 0.11) |
| $\lambda_{\alpha,6}$ | - | 2.65 (2.39, 2.97) | 2.30 (2.08, 2.53) |
| $\sigma_{\alpha}^2$ | 5.59 (4.73, 6.90) | - | - |
| $\rho_{\alpha}$ | 0.89 (0.87, 0.91) | 0.89 (0.87, 0.91) | 0.86 (0.83, 0.88) |

Candidate model parameter estimates are given in Table 2. All Stage 2 model parameters showed strong convergence. Model fits are shown in Figure 4 along with the estimated relationship between biophony and technophony. Model 3 provided the best (i.e., closest to the nominal 95% coverage) credible interval coverage of the observed data Figure 4(e); however, all models performed very well in this regard.
Figure 3: Stage 1 model fits. 95% credible intervals are displayed as gray lines in (a), (c), and (e). Posterior medians of model fitted values are displayed in black and 95% credible intervals are displayed as the blue shaded regions in (b), (d), and (f).
Figure 4: Stage 2 model fits. 95% credible intervals are displayed as gray lines in (a), (c), and (e). Posterior medians of model fitted values are displayed in black and 95% credible intervals are displayed as the blue shaded regions in (b), (d), and (f).
Table 2: Stage 2 posterior parameter medians and 95% credible intervals, 50% (2.5%, 97.5%). Subscript in parentheses on $\lambda_y$ indicate the row and column element in $\lambda_y$.

| Parameter | Model 1         | Model 2         | Model 3         |
|-----------|-----------------|-----------------|-----------------|
| $\beta_{y,0}$ | -1.04 (-1.10, -0.99) | -0.98 (-1.04, -0.94) | -1.00 (-1.05, -0.95) |
| $\beta_{y,1}$ | -1.00 (-1.09, -0.92) | -0.87 (-0.96, -0.80) | -0.94 (-1.02, -0.81) |
| $\beta_{y,2}$ | -0.83 (-0.89, -0.74) | -0.79 (-0.84, -0.73) | -0.78 (-0.84, -0.72) |
| $\beta_{y,3}$ | -1.58 (-1.62, -1.55) | -1.52 (-1.55, -1.46) | -1.54 (-1.58, -1.49) |
| $\beta_{y,4}$ | -1.73 (-1.79, -1.68) | -1.70 (-1.75, -1.65) | -1.70 (-1.77, -1.65) |
| $\beta_{y,5}$ | -2.89 (-2.92, -2.85) | -2.85 (-2.90, -2.82) | -2.84 (-2.89, -2.77) |
| $\beta_{y,6}$ | -3.56 (-3.61, -3.51) | -3.58 (-3.66, -3.53) | -3.52 (-3.56, -3.47) |
| $\beta_{y,7}$ | -4.53 (-4.64, -4.43) | -4.53 (-4.64, -4.45) | -4.41 (-4.48, -4.35) |
| $\phi_y$ | 2495.88 (2058.78, 3182.64) | 2365.00 (1877.63, 2914.21) | - |
| $\phi_{y,1}$ | - | - | 12.33 (1.27, 120.65) |
| $\phi_{y,2}$ | - | - | 542.76 (450.31, 791.90) |
| $\lambda_{y,(1,1)}$ | - | 0.17 (0.15, 0.19) | 0.18 (0.15, 0.20) |
| $\lambda_{y,(2,1)}$ | - | 0.006 (-0.02, 0.03) | 0.01 (-0.01, 0.04) |
| $\lambda_{y,(3,1)}$ | - | 0.06 (0.03, 0.09) | 0.09 (0.06, 0.13) |
| $\lambda_{y,(2,2)}$ | - | 0.18 (0.16, 0.21) | 0.18 (0.16, 0.21) |
| $\lambda_{y,(3,2)}$ | - | 0.006 (-0.02, 0.03) | 0.03 (-0.02, 0.07) |
| $\lambda_{y,(3,3)}$ | - | 0.21 (0.18, 0.23) | 0.20 (0.17, 0.25) |
| $\sigma_{y}^2$ | 0.06 (0.05, 0.08) | - | - |
| $\rho_y$ | 0.89 (0.87, 0.92) | 0.81 (0.77, 0.86) | 0.92 (0.90, 0.96) |

To ease interpretation, covariance matrix estimates are often best expressed as correlations. Converting each MCMC sample from the $\lambda$’s posterior to a correlation provides access to the corresponding correlation matrix posterior which are summarized in Tables 3 and 4 for Stage 1 and 2, respectively.

Table 3: Model 3 Stage 1 random effect correlation matrix posterior medians and 95% credible intervals, 50% (2.5%, 97.5%). Boldface indicates parameter values not containing 0 in the associated 95% credible interval.

|           | Morning | Afternoon | Evening  |
|-----------|---------|-----------|----------|
| Morning   | -       | -         | -        |
| Afternoon | 0.01 (-0.08, 0.10) | - | - |
| Evening   | **0.14(0.05, 0.23)** | -0.04 (-0.14, 0.05) | - |

Because inference is primarily focused on estimating biophony given technophony in the soundscapes, we perform model comparison only for Stage 2 models. A 6-fold-cross validation was used to compare candidate models’ out-of-sample prediction using the
Table 4: Model 3 Stage 2 random effect correlation matrix posterior medians and 95% credible intervals, 50% (2.5%, 97.5%). Boldface indicates parameter values not containing 0 in the associated 95% credible interval.

|            | Morning | Afternoon | Evening |
|------------|---------|-----------|---------|
| Morning    | -       | -         | -       |
| Afternoon  | 0.08 (-0.08, 0.25) | -   | -       |
| Evening    | 0.50 (0.29, 0.71) | 0.14 (-0.13, 0.34) | -       |

CRPS and ELPD. High values of the ELPD and low values of the CRPS suggest a better model fit. We also report the percentage of points covered by the 95% credible intervals of the predicted biophony versus technophony relationship, which should ideally cover 95% of the data points (Table 5).

The models yield technophony and biophony prediction at the 29 minute observation resolution for three times of the day. Such fine temporal resolution is likely not that useful from an assessment or management perspective. Hence, we summed each 29 minute biophony and technophony posterior predictive sample, resulting in a posterior predictive distribution for the total technophony and biophony at each pixel across the study area for morning, afternoon, and evening. The median and range between the upper and lower 95% credible interval bounds for each pixel-level predictive distribution were mapped. Very little differences were detected among the models and between predictions at the morning, afternoon, and evening, and thus we only present posterior predictive maps for the afternoon soundscapes in Figure 5.

Table 5: Comparison of ELPD, CRPS, and 95% Coverage Intervals

|          | Model 1 | Model 2 | Model 3 |
|----------|---------|---------|---------|
| ELPD     | 574.83  | 584.50  | 566.83  |
| CRPS     | 0.016   | 0.014   | 0.015   |
| 95% Coverage | 97.19  | 93.74   | 96.10   |
Figure 5: Model 3 afternoon predictions of technophony and biophony over a sample region in western New York. Posterior medians are shown in (a) and (c), while posterior 95% credible interval widths are shown in (b) and (d).


Discussion

We proposed three two-stage mixed effects beta regression models to assess the degree to which public traffic data explains variability in technophony and to characterize the relationship between biophony and technophony in western New York soundscapes. The models were compared using inference delivered and out-of-sampled prediction. Models were then applied to provided technophony and biophony predictive maps over a sample region in western New York using public road data.

Figure 3 shows the relationship between the road covariate and technophony, and the fitted relationships for the models. Here, we see that the relationship between the road covariate and technophony depends upon the value of the road covariate. When the road covariate is high, there are large amounts of technophony, aligning with intuition and previous research suggesting that technophony is higher in more urban areas (Pijanowski et al., 2011b,a). However, at low values of the road covariate we obtain essentially no information about human sound in the soundscape (Figure 3). This is evident in the predictions of technophony given new values of the road covariate, as the credible interval widths are extremely large at areas where the road covariate is low (Figures 5). The large variation in the technophony values at low levels of the road covariate is probably a result of individual effects that are not accounted for by the road covariate, which is a site level-covariate. These individual effects are likely a result of large variations in the number/type of automobiles on the road at any given minute of time, which is not captured by the single measure of Average Annual Daily traffic for each road. We listened to all recordings, and confirmed road sound was the most prominent source of technophony, further suggesting the high variation of the relationship between the road covariate and the human sound is a result of high temporal variation in the number of cars on a given road, a phenomenon that is well-described in literature on traffic sound modeling (Can et al., 2008; Conesel et al., 2005). The use of models that incorporate the dynamic temporal changes of road sound across time could help account for the temporal changes in traffic and subsequent traffic sound if traffic data are limited as in this study (Can et al., 2008). Utilizing crowd-sourced traffic data from traffic and navigation apps
(i.e., Google Maps, Waze) is an intriguing alternative that would enable more time-specific measures of traffic and subsequently the sound it produces. These data comprise almost real-time estimates of traffic speed and congestion. Such space-time data, in combination with the modeling frameworks proposed here, could result in near real-time maps of technophony that could have important implications for the development of soundscape and sound management policies.

Because we did not have such time-specific information, we utilized the flexibility of random effects to account for the unknown variability among individual sound recordings, which allowed us to obtain extremely accurate model fits. Utilizing random effects in soundscape models can potentially be a source of improving model accuracy when the data are limited and the researcher suspects there are individual effects causing variation not explained by the data (Clark, 2007). In this study, the use of random effects allowed us to incorporate temporal dependence between recordings, obtain accurate model fits, and make predictions of technophony and biophony despite using a predictor (the road covariate) that does not explain large amounts of variation of technophony.

Figure 4 shows the relationship between biophony and technophony and the fitted values for each model. Generally, as technophony increases, biophony decreases, aligning with previous research (Pijanowski et al., 2011b). Table 5 shows that Model 2 has the highest ELPD and lowest CRPS values, while Model 3 has the most accurate 95% coverage. This suggests that accounting for the repeated measures across time of day in the soundscape recordings provides a slight improvement in the model. We expected Model 3 to perform the best according to all measures, but the additional variability in predicting high values of biophony resulted in more inaccurate predictions at these high levels, explaining the lower ELPD value and higher CRPS value for Model 3 as compared to Model 2. However, the more accurate 95% credible intervals in both Stage 1 and Stage 2 for Model 3 suggest that Model 3 more properly represents our uncertainty, which is a desirable quality when making predictions.

The additional complexities in Models 2 and 3 did not lead to as large of improvements in the model validation criteria (ELPD, CRPS, 95% coverage) as we had expected over the
more simple Model 1. Specifically, the additional complexity in Model 3 brought about by
the variance model more properly represented the uncertainty in the relationship between
technophony and the road covariate when compared to Models 1 and 2, but it did not
provide large improvements over the 95% coverage in Stage 2.

However, the additional time of day covariance estimates (after converted to a cor-
relation matrix) in Models 2 and 3 provide inference on the relationship between the
soundsapes over the morning, afternoon, and evening recordings. For Model 3, Stage 1
(Table 3), we see the correlation between the random effects of the afternoon recordings
with both the random effects of the morning and evening recordings are not different
from 0 (i.e., 0 is contained within the 95% credible interval), whereas the correlation be-
tween morning and evening random effects are small but different from 0, with a posterior
median of 0.14. This suggests that variations in technophony that are not explained by
the road covariate are similar in the morning and evening recordings, although the cor-
relation coefficient of 0.14 suggests this is not a strong relationship. For Model 3, Stage
2 (Table 4), we see similar results in that the correlation between morning and evening
recordings is different from 0, with a posterior median of 0.50, suggesting that varia-
tions in biophony not explained by technophony are more similar in the morning and the
evening recordings than they are between the afternoon recordings and either the morn-
ing or evening recordings. This is likely a result of the dawn and dusk choruses, which
are captured by the morning and evening recording time periods, respectively. Thus, we
see that even though Models 2 and 3 only provide slight improvements in terms of the
model validation criteria, they provide additional insights into the temporal relationships
between biophony and technophony that are not available from the more simple Model 1.
Given the time-series nature of soundscape data collection and the abundance of longi-
tudinal data sets in the field of ecoacoustics, data where such correlations are large could
lead to important inferences regarding the relationship between variables across different
time periods.

We provide soundscape maps of a sample region in western New York at a 250 × 250
m resolution where we predict technophony and biophony from public road data. Because
model 3 has the best 95% coverage, we only show maps of posterior predictions for Model 3 (Figure 5). Previous studies have identified road effects on animals at distances under 100 m to roads (McClure et al., 2013; Herrera-Montes and Aide, 2011), but we found a resolution at a finer level did not show any additional trends that are not evident in the current resolution, and thus, the increase in computational time for a finer resolution was not necessary. Visualization of the posterior median suggests that biophony is highest in areas farther away from roads, while technophony is high in regions of more concentrated and highly used roads. This aligns with previous research and intuition, as the probability of detection of avian species vocalizations is lower closer to roads (Parris and Schneider, 2008) and technophony increases with the degree of urbanization (Pijanowski et al., 2011a). However, a visualization of the 95% credible interval widths shows that there are large amounts of uncertainty associated with these estimates at areas with low technophony, largely a result of the inability of technophony to be accurately predicted at low levels of the road covariate. Thus, any inference drawn from these maps should be limited due to our lack of certainty. To have more certainty in predictions of technophony and biophony from road data, we propose using space-time indexed crowdsourcing data from navigation software as opposed to the public traffic data used in this study, or utilizing similar models of road sound from the literature on traffic sound modeling that can potentially account for the high variability in traffic sound across small time periods (Can et al., 2008; Conesel et al., 2005).

In addition, despite the fact that there is a clear negative relationship between biophony and technophony, we see that past a given distance from the road the predictions of biophony are all very similar. Thus, if more accurate predictions of biophony are desired, it will be important to include covariates in the model that quantify the landscape structure that will likely determine the types of organisms communicating in the soundscape (Pijanowski et al., 2011b; Farina and Gage, 2017). One example of successful soundscape maps of biophony, technophony, and geophony were obtained in a study of south-central Alaska from numerous landscape measurements (Mullet et al., 2016). In the landscape we have mapped, the habitat ranges from small patches of forest, to agricultural fields,
small towns and villages, and suburban development. This range of habitats would be expected to support many different assemblages of acoustically communicating species resulting in different biophony.

The PSD and acoustic indices derived from it (NDSI) have previously been shown to correlate positively with anthropogenic activity (Fairbrass et al., 2017) and change with landscape structure (Fuller et al., 2015). Our soundscape maps support these findings as the PSD of the 1-2 kHz range that represents technophony is highest in areas of high road concentration. However, the use of the PSD to represent technophony and biophony as we did in this study is limited in application to long-term soundscape monitoring studies, as numerous organisms communicate within the 1-2 kHz region that is designated as technophony, and geophony also occurs in numerous recordings when not controlled for. In our study, we only recorded on days with no rain and minimal wind, thus minimizing geophony, and listening to the recordings in their entirety revealed few organisms communicating within the range of the 1-2 kHz region that we assumed to be representative of technophony, supporting the use of the PSD values as representative of biophony and technophony in this setting. However, for long-term monitoring of soundscapes where such assumptions are not valid, we require more accurate methods to distinguish between biophony, technophony, and geophony. Convolutional neural networks have recently been utilized in a deep learning system called CityNet to predict the presence or absence of biophony and technophony in urban soundscapes (Fairbrass et al., 2019). Recent work on utilizing the spectral properties of sound as is done in Music Information Retrieval also shows promise for distinguishing between the three soundscape components (Bellisario and Pijanowski, 2019; Bellisario et al., 2019). Ecoacoustics researchers should focus on how such methods, in conjunction with current acoustic indices and landscape measurements, could provide reasonable estimations of the relative amounts of biophony, technophony, and geophony in a soundscape to allow for long-term monitoring of soundscapes and landscape health.

The proposed models were used to assess the extent to which available traffic data explains variability in technophony and to quantify the functional relationship between
technophony and biophony. Roads represent the dominant source of technophony across the landscape in our study area, and have a large and growing impact around the world (Buxton et al., 2017; Barber et al., 2011). Understanding and predicting the sound impacts of roads on biological communities is an important focus of ecoacoustics researchers in many locations (Forman and Deblinger, 2000; Herrera-Montes and Aide, 2011; Mullet et al., 2016). The Bayesian hierarchical framework allows us to obtain parameter estimates, fitted values, and predicted values at new locations all within the same modeling framework. This framework can incorporate a range of soundscape data to answer the wide variety of topics in ecoacoustics and bioacoustics, such as the relationship between biological sounds and anthropogenic impacts like road sound or habitat fragmentation, the monitoring of species density and population estimates using acoustic recordings, the recovery of environments to natural/anthropogenic disturbances, and the general monitoring of soundscapes over time to ensure they maintain desirable natural qualities. Road ecologists, conservation biologists, urban planners, and road engineers all have an interest in these questions. Utilization of such a broadly applicable modeling framework will greatly improve our ability to make inference regarding the ways technophony contributes to the soundscape and influences biophony and the biodiversity that it represents.

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