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Quantifying the Soundscape: How filters change acoustic indices

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ABSTRACT

Monitoring biodiversity can be time consuming and costly. Automated recording units (ARUs) have rapidly emerged as an efficient and cost-effective tool for measuring biodiversity. Acoustic indices are one output from recordings from ARUs that can be quantified to serve as an ecological indicator for biodiversity. However, there is a lack of guidance on what acoustic filters to apply to these indices and when. To address this gap, we collected acoustic data from study locations spanning temperate and tropical forests, agricultural grasslands and croplands, and peri-urban development. We applied filters of 80, 500, 1000, and 2000 Hz to these data when calculating the different indices. In addition, we considered the effect landscape context, road noise, season, and elevation have on seven of the most commonly used acoustic indices with different frequency filters. We found that two indices, Acoustic Diversity Index (ADI) and Acoustic Evenness Index (AEI), were most sensitive to filtering, changing significantly between an 80 and 1000 Hz filter across the different covariates. Acoustic Complexity Index (ACI), however, remained consistent with the different filters. These results suggest that when using acoustic indices, one should be cognizant of the context of the study location and the season of the study period when using ADI and AEI. ACI can be used more generously since it is not as sensitive to filtering. ARUs and acoustic indices are an effective tool for measuring biodiversity, but to ensure proper reporting and ability to compare results across studies, more guidelines on appropriate filtering of acoustic indices should be developed.

1. Introduction:

Assessing and monitoring biodiversity can be time consuming and costly. Thus, decisions need to be made to optimize these data (Field et al. 2005). To address this challenge, novel tools for collecting and analyzing biodiversity data have been developed to understand humans' impact on the environment as well as indicators of natural characteristics of ecosystems (Ceballos et al. 2017; Pieretti et al 2011). Automated recording units (ARUs) and other passive sampling tools are an increasingly common method to measure biodiversity and calculate indicators in real time and across dispersed landscapes (Sugai et al. 2019). The ability to be deployed in remote locations and collect large quantities of spatially and temporarily replicated data makes them useful tools in biodiversity monitoring (Acevado and Villanueva-Rivera 2006; Roe et al., 2018). Programmable by design, ARUs require little time for the researcher to be in the field; by one estimate about 12.5 % of time required for field point count surveying (Jorge et al., 2018). However, they do require more time dedicated towards analysis after data collection (Acevado and Villanueva-Rivera 2006, Jorge et al., 2018). While there have been many advances in using machine learning to identify individual species in these recordings, this still remains a time intensive process. Acoustic indices are another, and more rapid, way to summarize recordings and describe the ecosystem.

Acoustic indices that describe a soundscape, or the human (anthrophony), biological (biophony), and geological (geophony) sounds that make up a landscape, are a post-processing output from acoustic recordings that have been used with increasing frequency as indicators of biodiversity (Bradfer-Lawrence et al., 2019). Much like other ecological indicators (e.g., species richness or landscape heterogeneity), these indices illustrate environmental differences across space and time by aggregating multiple pieces of information. Acoustic indices have been shown to correlate with species assemblage diversity (Benocci et al 2020), vegetation structure ((Do Nascimento et al., 2020)), quality of the habitat (Stowell & Sueur, 2020; Quinn et al., 2018), used as a benchmark for measuring restoration success and prioritizing effective conservation efforts (Znidersic et al., 2022), and to describe phenology based on decreases in indices values during winter seasons (Mullet et al., 2015). Acoustic indices have also successfully captured circadian

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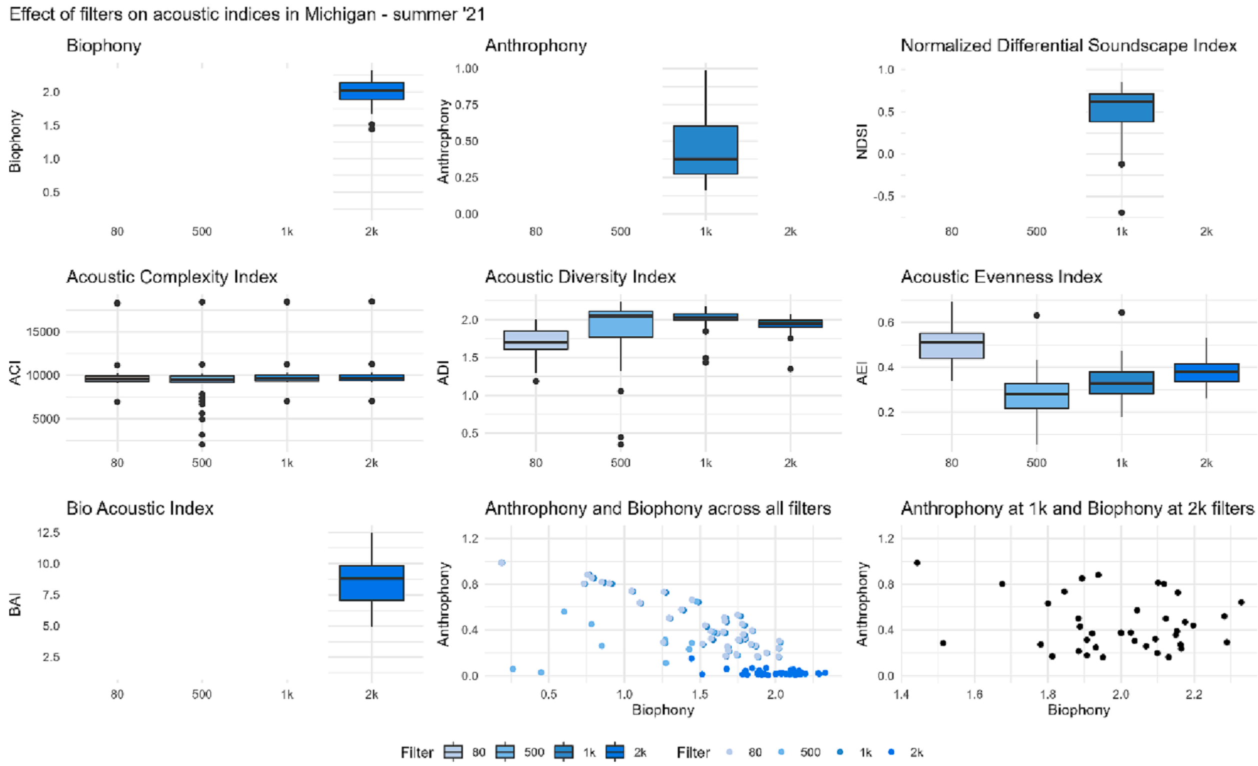

Fig. 1. Effect of three filters, 80, 1000, and 2000 Hz, on seven acoustic indices, correlation between Anthrophony and Biophony across all filters, and the correlation only at 1000 and 2000 respectively in agricultural landscapes of Michigan, USA in summer of 2021. Note that the × axis in panel 9 does not start at zero.

rhythms (e.g., songbird vocalizations as they correlate to the sunrise and sunset) at different temporal extents (Pijanowski et al., 2011), including novel ecological events like changes to the circadian rhythms during a solar eclipse (Buckley et al. 2018; Gerber et al. 2020).

Like other data collection techniques and biodiversity indices, audio files and acoustic indices can be influenced by confounding factors. For example, landscape structure determines sound propagation due to the fact that sound may be absorbed by air, ground, or vegetation, or redirected by reflection or diffraction (Morton 1975, Zwerts et al., 2022). Similarly, ambient sounds, noise, and microphone feedback may alter the data in the recordings. Filters are one tool available to address these factors. But choice of filters should reflect the nature of the index, the goals of the analysis, and, perhaps as importantly, be consistent across efforts to make data more comparable.

However, despite calls for standardization (Sugai et al. 2019) and the growth in both the use of ARUs and acoustic indices, there is a lack of consensus or clear recommendations about what filters should be used. In a brief review of the literature (Appendix Table A1), there is a clear haphazardness to choosing if and how to filter the audio data, which makes it difficult to compare results across studies. Some researchers manually remove audio that they cannot use (e.g., Brown et al., 2018; Zhao et al., 2022). Many do not mention the use of filters (e.g., Jorge et al., 2018, Fuller et al., 2015) or they allude to the need to apply a filter without further guidance or specifics for what was used in the study (e.g., Gasc et al., 2015). Of the articles that do mention filtering audio data, they do not report the effects of different filters (Buckley et al., 2018; Khanaposhtani et al., 2019; Bradfer-Lawrence et al., 2019; Metcalf et al. 2021, Borker et al., 2020), thus minimizing the ability for future comparison. Ultimately, the inconsistency in methodology for processing and assessing acoustic indices makes it difficult to form a consensus or best analysis processes. To fill this gap in the literature, we compare the effects that four filters (80, 500, 1000, and 2000 Hz) have on acoustic indices in different ecoregions.

2. Methods:

2.1. Study areas:

We collected data in multiple ecoregions, landscapes, and seasons. The diverse sites within each represent different land use and land cover types within distinct biomes including, mixed use landscapes in a tropical forest, agricultural fields in a temperate grassland, mixed use landscape in a temperate forest, and a peri-urban landscape in a temperate forest. In Costa Rica data was collected in the Bellbird Biological Corridor, a multifunctional space that stretches from the Monteverde Cloud Forest at 1800 m to the Gulf of Nicoya. The corridor is separated into several distinct life zones based on environmental factors like precipitation, temperature, and elevation (Oduber et al., 2011). In the Midwest USA, audio data was collected from agricultural landscapes in Kansas and Michigan USA. Recorders were placed on farms in Kansas and Michigan across a diversity of land use practices but the main land use type in both study regions is cultivated crops and other agricultural land (NLCD 2019). In the Upstate of South Carolina, USA audio data was collected from areas classified as either having low, medium, or high traffic noise. The main land cover type in this region is deciduous, evergreen, and mixed forest accounting for 58 % of land cover (NLCD 2013).

2.2. Data collection:

Audio data was collected using automated recordings units (ARUs) (Table A2). In the Bellbird Biological Corridor of Costa Rica, we collected data from December 2011 to September 2013 using SM2 from Wildlife Acoustics Inc. programmed with 48 dB gain (left and right) and to record a half hour each hour both day and night. Daytime recordings began at 5:30 a.m. and night recordings began at 6:00 p.m. The recorders were left for a 1, 1.5, or 2 days at each site. Recorders were deployed 4 times a year within this period. In Kansas and Michigan,

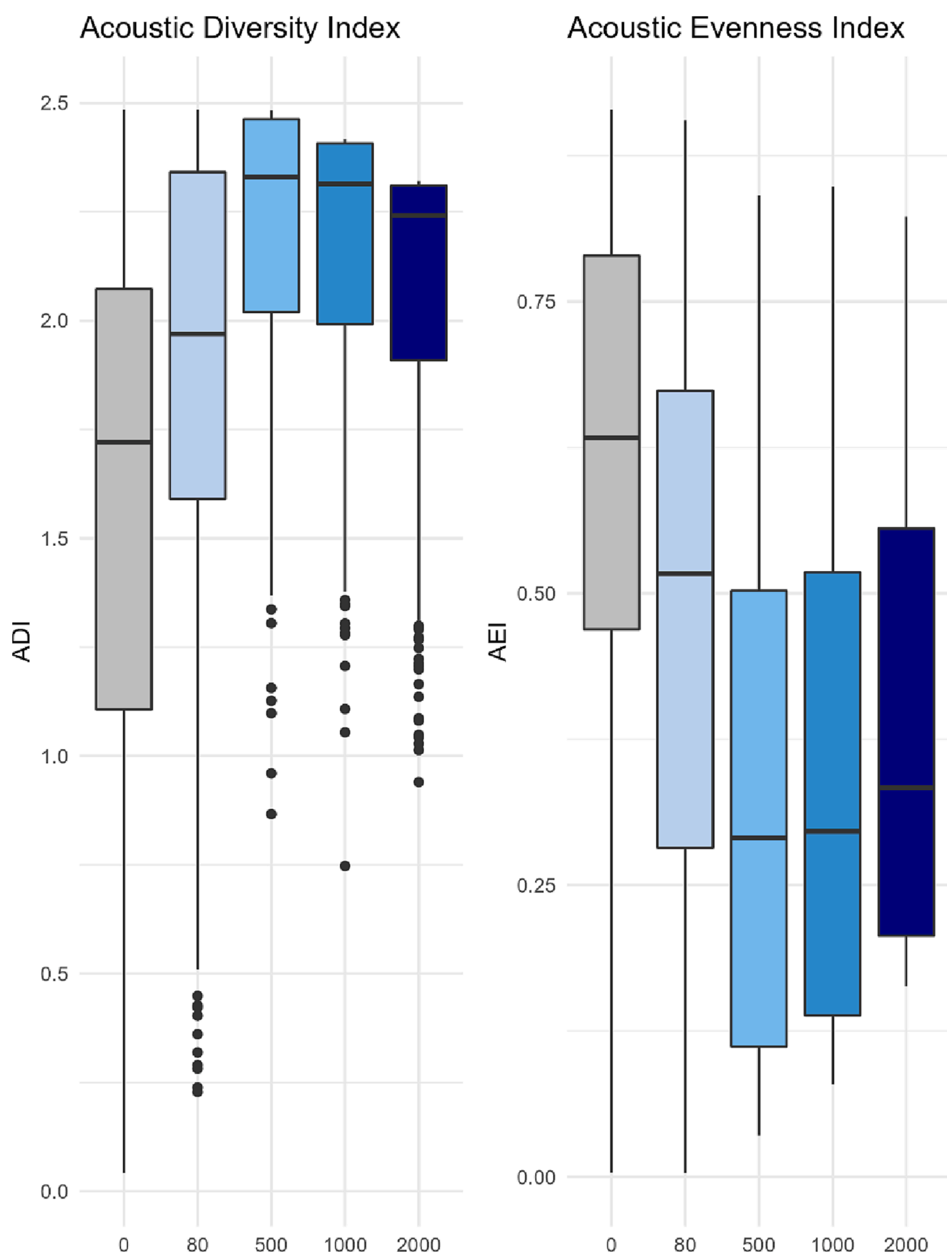

Fig. 2. Variation of Acoustic Diversity Index and Acoustic Evenness Index over 0, 80, 500, 1000, and 2000 Hz filters in the Bellbird Biological Corridor, Costa Rica.

Table 1
Dunn test for Acoustic Diversity Index (ADI) and Acoustic Evenness Index (AEI), with the filter variables in Michigan, USA in the summer of 2021.

ADI	Comparison	Z	P.unadj	P.adj
	1 k – 2 k	2.935	0.003	0.010
	1 k – 500	1.055	0.291	0.291
	2 k – 500	−1.880	0.060	0.120
	1 k – 80	6.642	0.000	0.000
	2 k – 80	3.707	0.000	0.001
	500–80	5.587	0.000	0.000
AEI	Comparison	Z	P.unadj	P.adj
	1 k – 2 k	−2.406	0.016	0.032
	1 k – 500	2.023	0.043	0.043
	2 k – 500	4.429	0.000	0.000
	1 k – 80	−6.399	0.000	0.000
	2 k – 80	−3.993	0.000	0.000
	500–80	−8.421	0.000	0.000

USA, we collected audio data using Song Meter Mini by Wildlife Acoustics Inc. programmed to record, with 18 dB gain on a single microphone, for 5 minutes on the hour, 24 h a day between the months of March and November in 2020 in Kansas and in 2021 in Michigan. In the Upstate of South Carolina, USA, we collected recordings using SM2 from Wildlife Acoustics Inc during May-June in 2013. We programmed each ARU in the Upstate to record for 10 minutes at the start of each hour from 6:00 A.M. to 10:00 A.M daily. Each unit was left at the study site for a minimum of four days. Recorders were kept on consistent settings throughout the study, with a sampling rate of 16000 Hz, 48 dB gain (left and right).

2.3. Data processing and analysis:

We processed the audio data using R packages seewave (Sueur et al., 2008), tuneR (Ligges et al. 2018), and soundecology (Villanueva-Rivera and Pijanowski 2018). We applied filters of 80, 500, 1000, and 2000 Hz to each audio file by limiting the minimum frequency read when

Table 2
Dunn test for Acoustic Diversity Index (ADI) and Acoustic Evenness Index (AEI), with the filter variables in BBC of Costa Rica.

ADI	Comparison	Z	P.unadj	P.adj
	0–1000	−2.82	0.005	0.044
	0–2000	−2.09	0.037	0.258
	1000–2000	0.73	0.465	0.930
	0–500	−3.49	0.000	0.005
	1000–500	−0.68	0.498	0.498
	2000–500	−1.41	0.159	0.795
	0–80	−0.99	0.322	0.965
	1000–80	1.83	0.068	0.407
	2000–80	1.10	0.273	1.000
	500–80	2.50	0.012	0.098
AEI	Comparison	Z	P.unadj	P.adj
	0–1000	2.87	0.004	0.037
	0–2000	2.01	0.045	0.312
	1000–2000	−0.86	0.389	0.779
	0–500	3.31	0.001	0.009
	1000–500	0.44	0.657	0.657
	2000–500	1.30	0.192	0.961
	0–80	0.94	0.348	1.000
	1000–80	−1.93	0.054	0.322
	2000–80	−1.07	0.285	1.000
	500–80	−2.37	0.018	0.141

processing the data through the aforementioned R packages. The acoustic indices used include Acoustic Complexity Index (*ACI*), Acoustic Diversity Index (ADI), Acoustic Evenness Index (AEI), Normalized Difference Soundscape Index (NDSI), Bioacoustic Index (BAI), Biophony, and Anthrophony. *ACI* measures the variation of sound intensity (Pieretti et al. 2011). ADI and AEI measure the distribution of sound power across frequency ranges (Villanueva-Rivera et al. 2011). ADI specifically measures sound diversity similarly to species diversity using the Shannon diversity index to quantify sound power distributions. AEI, however, measures sound evenness similarly to species evenness by utilizing the Gini index of evenness. NDSI measures the proportion of biophony to anthrophony and therefore acts as an index of anthropogenic noise disturbance (Kasten et al. 2012). BAI is a function of both power and frequency range of sound between 2000 and 11,000 Hz (Boelman et al. 2007). Biophony measures biological sounds above 2000 Hz and anthrophony measures human noises between 1000 and 2000 Hz. These indices were chosen because they are the most commonly used in the literature (Bradfer-Lawrence et al., 2019; Quinn et al. 2021; Metcalf et al., 2021; Khanaposhtani et al. 2019; Gasc et al. 2015).

We calculated the means of the acoustic indices across the sites for each sampling location in each of the regions and their respective seasons as described in above sections on study area and data collection as well as in Table A2. We then compared the index averages across the filters, seasons, and land use within each location. We conducted statistical analyses to determine significance and explanations of variations in the data using a Kruskal-Wallis or Spearman rank correlation test in R v 4.2.1 (R Core Team 2022).

3. Results:

The seven acoustic indices responded differently to the various filters applied to them depending on location, season, land treatment type, and traffic levels. However, there were some similarities across the different landscape types. Of the seven acoustic indices we measured, we mainly focus here on the effects filters have on ACI, ADI, and AEI because the frequencies used to make their calculations span our chosen filter levels.

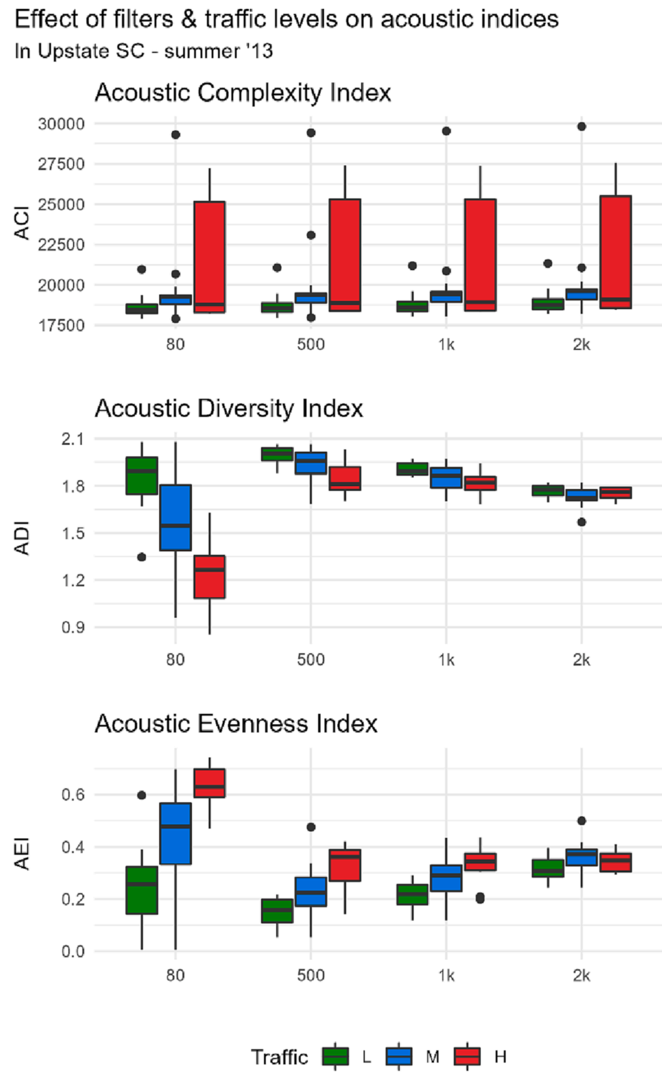

Fig. 3. Effect of the three filters, 80, 1000, 2000 Hz, across three acoustic indices, ACI, ADI, and AEI with varying traffic levels (low, medium, high) in the Upstate South Carolina, USA in the summer of 2013.

3.1. *Effect of filters on acoustic indices:*

Starting with the simplest comparison with the data we see that ADI ($\chi2 = 15.706\ _{df=4}$, p value = 0.003) and AEI ($\chi2 = 14.903\ _{df=4}$, p value = 0.004) in Costa Rica and ADI ($\chi2 = 51.16\ _{df=3}$, p value < 0.001) and AEI ($\chi2 = 78.65\ _{df=3}$, p value < 0.001) in Michigan changed in magnitude and variance when the filters were applied (Figs. 1, 2). For both ADI and AEI, there was significant difference between filters except with 500 Hz (Tables 1 and 2) and was greatest between an 80 and 1000 Hz filter (Figs. 1, 2). ADI was highest with a filter 1000 Hz, whereas AEI was highest with an 80 Hz filter. However, *ACI* showed no variation with the different filters (p value greater than 0.10). This pattern held across subsequent analysis in other locations (Figs. 3-5, Table 3a, Table 4a). Although variation between the filters was not relevant for biophony or anthrophony due to their underlying parameter assumption, it is interesting to note the correlation between them before and after filtering. Without applying filters, the correlation between anthrophony and biophony is strongly negative (rho = -0.78 and a p-value < 0.001). After

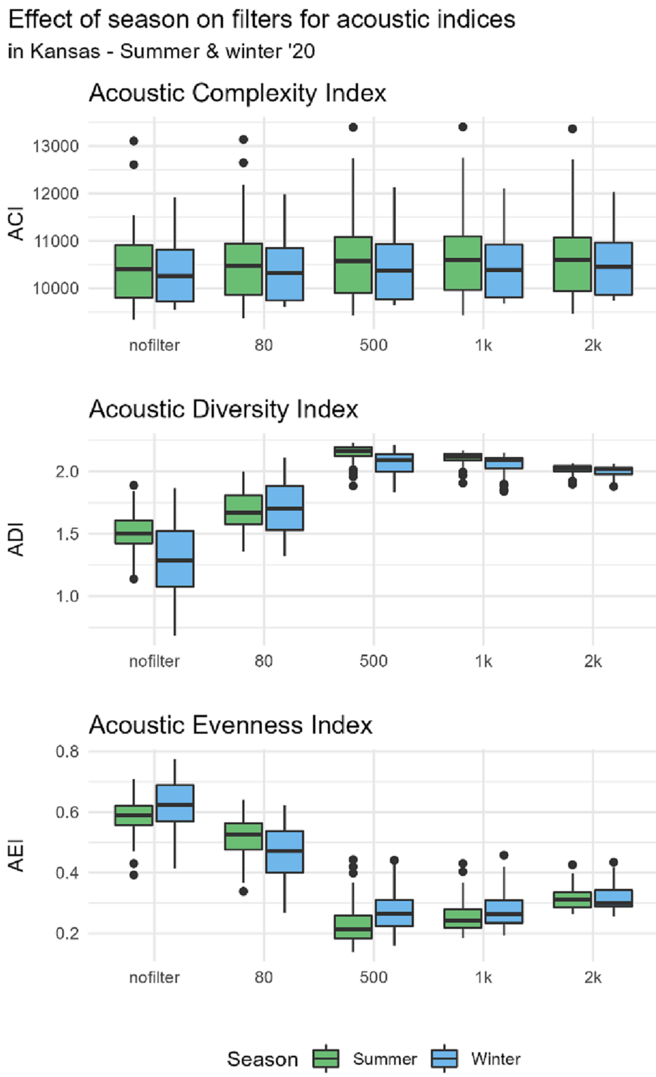

Fig. 4. Effect of season on the four filters on acoustic indices Acoustic Complexity Index, Acoustic Diversity Index, and Acoustic Evenness Index in Kansas, USA in the summer and winter of 2020.

adding a 1000 Hz filter to anthrophony and a 2000 Hz filter to biophony, that correlation is weaker (Fig. 1, rho value = -0.028, p-value = to 0.86) (Table 5).

3.2. Acoustic indices with other covariates:

In Upstate South Carolina, acoustic indices (except ACI) changed in response to traffic levels measured and as a function of the filter applied (Fig. 3, table 3a). ADI and AEI maintained a similar pattern across the three traffic levels, low, medium, high, for 80 and 1000 Hz filters, except when the 2000 Hz filter was applied (Fig. 3, table 3b). ADI in high traffic sites increased slightly above medium traffic sites when a 2000 Hz filter was applied, whereas AEI in high traffic sites decreased slightly below medium traffic sites. The magnitude of change for both ADI and AEI were highest between 80 and 1000 Hz. The relative difference between traffic levels decreased greatly between the 1000 and 2000 Hz filters.

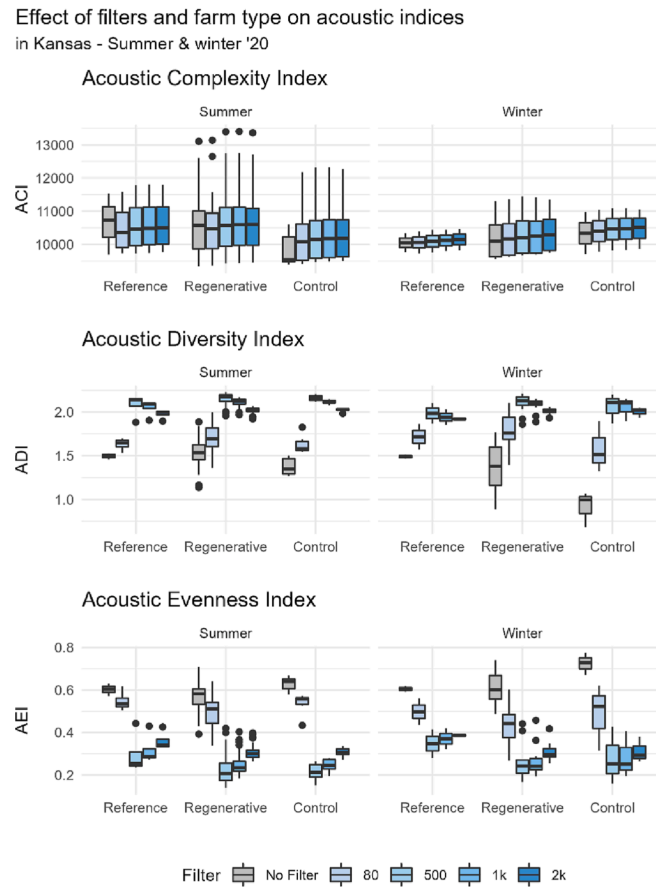

Fig. 5. Effect of four filters, 80, 500, 1000, and 2000 Hz, and land treatment type, reference, regenerative, and control, on acoustic indices ACI, ADI, and AEI in the agricultural landscape of Kansas, USA in the summer and winter of 2020. Reference land type refers to grasslands and control represents conventional agricultural methods.

In Kansas, ADI and AEI were different across seasons (Fig. 4, Table 4a). The differences are lost between seasons when filters greater than 2000 Hz or 1000 Hz respectively are applied. Patterns for ADI and AEI varied across filters and the different agricultural treatments (Fig. 5, Table 4a, b), but significant differences varied by filter (Table 4b).

In Costa Rica, acoustic indices at various filters are correlated to elevation, with only one relationship significant (Fig. 6, Table 5). Specifically, biophony at 2000 Hz varied negatively as a function of elevation ($p < 0.01$). However, there were interesting patterns or changes in the coefficients across filters. Anthrophony and elevation have a negative correlation −0.36 at 1000 Hz. NDSI and BAI have weaker positive correlations of 0.14 and 0.07, respectively. Correlations between ADI and AEI with elevation were more varied. The strength of ADI and elevation's correlation decreased from −0.18 to -0.07 from 0 to 80 Hz, then increased to −0.11 from 80 to 500 Hz, and further increased to −0.32 at 2000 Hz. Finally, AEI maintains a positive correlation with elevation but flips to a negative one only at 500 Hz.

Table 3

A) Kruskal-Wallis rank sum test and B) Dunn test for all acoustic indices (Acoustic Complexity Index (ACI), Acoustic Diversity Index (ADI), Acoustic Evenness Index (AEI), Normalized Differential Soundscape Index (NDSI), Anthrophony (ANT), Biophony (BIO), Bioacoustic Index (BAI)) with the interaction between traffic and filter variables in Upstate South Carolina, USA in the summer of 2013. Bold numbers are statistically significant.

A.

Indices	Traffic	Filter	Chi-squared	DF	p-value
ACI	H	ALL	2.13	3	0.547
	M	ALL	4.75	3	0.191
	L	ALL	2.24	3	0.523
	ALL	80	5.03	2	0.081
	ALL	500	5.42	2	0.066
	ALL	1 k	4.29	2	0.117
	ALL	2 k	4.39	2	0.111
ADI	H	ALL	25.27	3	0.000
	M	ALL	38.67	3	0.000
	L	ALL	21.24	3	0.000
	ALL	80	16.87	2	0.000
	ALL	500	0.74	2	0.008
	ALL	1 k	7.54	2	0.023
	ALL	2 k	3.53	2	0.171
AEI	H	ALL	21.96	3	0.000
	M	ALL	29.41	3	0.000
	L	ALL	18.53	3	0.000
	ALL	80	18.40	2	0.000
	ALL	500	12.00	2	0.002
	ALL	1 k	10.98	2	0.004
	ALL	2 k	4.56	2	0.103
NDSI	ALL	1 k	21.327	2	0.000
ANT	ALL	1 k	19.673	2	0.000
BIO	ALL	2 k	5.0552	2	0.080
BAI	ALL	2 k	9.5491	2	0.008

B.

ADI H	Comparison	Z	P.unadj	P.adj	**ADI M**	Comparison	Z	P.unadj	P.adj
	1k – 2k	1.568	0.117	0.234		1k – 2k	2.960	0.003	0.009
	1k – 500	−0.019	0.985	0.985		1k – 500	−1.898	0.058	0.115
	2k – 500	−1.588	0.112	0.337		2k – 500	−4.858	0.000	0.000
	1k – 80	4.342	0.000	0.000		1k – 80	3.484	0.000	0.002
	2k – 80	2.773	0.006	0.022		2k – 80	0.524	0.600	0.600
	500–80	4.361	0.000	0.000		500–80	5.382	0.000	0.000
ADI L	Comparison	Z	P.unadj	P.adj	**AEI H**	Comparison	Z	P.unadj	P.adj
	1k – 2k	2.722	0.006	0.032		1k – 2k	−0.077	0.939	1.000
	1k – 500	−1.859	0.063	0.126		1k – 500	−0.038	0.969	1.000
	2k – 500	−4.581	0.000	0.000		2k – 500	0.038	0.969	0.969
	1k – 80	0.365	0.715	0.715		1k – 80	−3.864	0.000	0.001
	2k – 80	−2.357	0.018	0.074		2k – 80	−3.787	0.000	0.001
	500–80	2.224	0.026	0.078		500–80	−3.825	0.000	0.001
AEI M	Comparison	Z	P.unadj	P.adj	**AEI L**	Comparison	Z	P.unadj	P.adj
	1k – 2k	−2.388	0.017	0.051		1k – 2k	−2.689	0.007	0.036
	1k – 500	1.524	0.127	0.255		1k – 500	1.560	0.119	0.237
	2k – 500	3.912	0.000	0.000		2k – 500	4.249	0.000	0.000
	1k – 80	−3.327	0.001	0.004		1k – 80	−0.564	0.573	0.573
	2k – 80	−0.939	0.348	0.348		2k – 80	2.124	0.034	0.101
	500–80	−4.851	0.000	0.000		500–80	−2.124	0.034	0.135
ADI 80	Comparison	Z	P.unadj	P.adj	**ADI 500**	Comparison	Z	P.unadj	P.adj
	H - L	−4.106	0.000	0.000		H - L	−3.109	0.002	0.006
	H - M	−2.489	0.013	0.026		H - M	−2.048	0.041	0.081
	L - M	2.211	0.027	0.027		L - M	1.506	0.132	0.132
ADI 1k	Comparison	Z	P.unadj	P.adj	**AEI 80**	Comparison	Z	P.unadj	P.adj
	H - L	−2.701	0.007	0.021		H - L	4.288	0.000	0.000
	H - M	−1.196	0.232	0.232		H - M	2.597	0.009	0.019
	L - M	1.909	0.056	0.112		L - M	−2.312	0.021	0.021
AEI 500	Comparison	Z	P.unadj	P.adj	**AEI 1k**	Comparison	Z	P.unadj	P.adj
	H - L	3.458	0.001	0.002		H - L	3.264	0.001	0.003
	H - M	1.875	0.061	0.061		H - M	1.466	0.143	0.143
	L - M	−2.090	0.037	0.073		L - M	−2.287	0.022	0.044
ANT	Comparison	Z	P.unadj	P.adj	**NDSI**	Comparison	Z	P.unadj	P.adj
	H - L	4.054	0.000	0.000		H - L	−4.438	0.000	0.000
	H - M	3.847	0.000	0.000		H - M	−3.653	0.000	0.001
	L - M	−0.749	0.454	0.454		L - M	1.396	0.163	0.163
BAI	Comparison	Z	P.unadj	P.adj					
	H - L	−3.074	0.002	0.006					
	H - M	−2.069	0.039	0.077					
	L - M	1.443	0.149	0.149					

Table 4
A) Kruskal-Wallis rank sum test and B) Dunn testacoustic indices (Acoustic Complexity Index (ACI), Acoustic Diversity Index (ADI), Acoustic Evenness Index (AEI), Normalized Differential Soundscape Index (NDSI), Anthrophony (ANT), Biophony (BIO), Bioacoustic Index (BAI)) with the interaction between filter and Farming practice and Season respectively in Kansas, USA in the summer and winter of 2020.

A.

Indices	Filter	Farming Practices Chi-squared	DF	p-value	Season Chi-squared	DF	p-value
ACI	ALL	2.22	4	0.695	0.04	1	0.833
	No Filter	1.96	2	0.376	0.04	1	0.846
	80	0.24	2	0.888	0.06	1	0.809
	500	0.30	2	0.860	0.13	1	0.717
	1 k	0.35	2	0.840	0.04	1	0.846
	2 k	0.43	2	0.805			
ADI	ALL	256.30	4	0.000	7.71	1	0.005
	No Filter	7.07	2	0.029	0.07	1	0.790
	80	4.16	2	0.125	11.08	1	0.001
	500	2.73	2	0.256	8.91	1	0.003
	1 k	6.44	2	0.040	2.13	1	0.144
	2 k	8.47	2	0.014			
AEI	ALL	250.67	4	0.000			
	No Filter	7.58	2	0.023	3.97	1	0.046
	80	3.90	2	0.143	4.61	1	0.032
	500	5.49	2	0.064	8.43	1	0.004
	1 k	8.36	2	0.015	2.84	1	0.092
	2 k	9.04	2	0.011	0.11	1	0.736
NDSI	1 k	2.60	2	0.272	3.21	1	0.073
ANT	1 k	3.45	2	0.178	2.00	1	0.158
BIO	2 k	0.68	2	0.711	7.05	1	0.008
BAI	2 k	7.10	2	0.029	51.09	1	0.000

B.

ADI	Comparison	Z	P.unadj	P.adj
	1k – 2k	3.589	0.000	0.001
	1k – 500	−1.078	0.281	0.281
	2k – 500	−4.667	0.000	0.000
	1k – 80	9.313	0.000	0.000
	2k – 80	5.724	0.000	0.000
	500–80	10.391	0.000	0.000
	1k - nofilter	11.842	0.000	0.000
	2k - nofilter	8.348	0.000	0.000
	500 - nofilter	12.891	0.000	0.000
	80 - nofilter	2.777	0.005	0.011
ADI No Filter	Comparison	Z	P.unadj	P.adj
	Control - Reference	−1.814	0.070	0.139
	Control - Regenerative	−2.629	0.009	0.026
	Reference - Regenerative	0.034	0.973	0.973
ADI 1k	Comparison	Z	P.unadj	P.adj
	Control - Reference	2.040	0.041	0.083
	Control - Regenerative	−0.056	0.956	0.956
	Reference - Regenerative	−2.521	0.012	0.035
ADI 2k	Comparison	Z	P.unadj	P.adj
	Control - Reference	2.457	0.014	0.028
	Control - Regenerative	0.143	0.886	0.886
	Reference - Regenerative	−2.859	0.004	0.013
BAI 2k	Comparison	Z	P.unadj	P.adj
1	Control - Reference	2.656	0.008	0.024
2	Control - Regenerative	1.359	0.174	0.174
3	Reference - Regenerative	−2.079	0.038	0.075
AEI	Comparison	Z	P.unadj	P.adj
	1k – 2k	−3.369	0.001	0.002
	1k – 500	0.775	0.438	0.438
	2k – 500	4.144	0.000	0.000
	1k – 80	−9.145	0.000	0.000
	2k – 80	−5.776	0.000	0.000
	500–80	−9.920	0.000	0.000
	1k - nofilter	−11.955	0.000	0.000
	2k - nofilter	−8.676	0.000	0.000
	500 - nofilter	−12.709	0.000	0.000
	80 - nofilter	−3.054	0.002	0.005

Table 4 (*continued*)

B.

AEI No Filter	Comparison	Z	P.unadj	P.adj
	Control - Reference	1.352	0.176	0.353
	Control - Regenerative	2.742	0.006	0.018
	Reference - Regenerative	0.614	0.539	0.539
AEI 1k	Comparison	Z	P.unadj	P.adj
	Control - Reference	−2.221	0.026	0.053
	Control - Regenerative	0.230	0.818	0.818
	Reference - Regenerative	2.887	0.004	0.012
AEI 2k	Comparison	Z	P.unadj	P.adj
	Control - Reference	−2.432	0.015	0.030
	Control - Regenerative	0.038	0.969	0.969
	Reference - Regenerative	2.982	0.003	0.009

4. Discussion:

Acoustic indices respond differently to filters and this difference is confounded by variation in the landscape, season, and ecoregion. These conditions are important to consider when utilizing acoustic indices to provide accurate representation of the soundscape. Of the seven acoustic indices, ADI and AEI show the most variation with the filters and covariates. The greatest magnitude of change occurs between 80 and 1000 Hz filters. This variation is expected for these indices because they are calculated across the different filter frequencies, whereas indices like biophony are only calculated above 2000 Hz. ACI is resilient to change with the application of filters. This effect was also observed in the winter soundscape of agriculture landscapes in Nebraska (Quinn et al., 2021) and may reflect the fact that ACI is not sensitive to consistent sounds of constant intensity but is sensitive to sounds of irregular intensity (Bradfer-Lawrence et al., 2019). Seasonality does influence the values of ACI, where it is higher in the summer reflecting a seasonal change with more birds and insects vocalizing and producing irregular sounds involved in ACI calculations.

The differences in the acoustic indices across the filters demonstrates the need to look closely at the study site and time to ensure the appropriate filters are applied to have accurate results. Moreover, to closely contemplate the goals of your study to correctly select the appropriate index and subsequent filter level. If using AEI and ADI, you need to consider the effect of the different filters because the results differ across seasons and ecoregions. However, ACI is less sensitive to filtering and different ecoregions and therefore can be used more generously. The change in the correlation between biophony and anthrophony with and without their respective filters for the frequencies at which these indices are measured, illustrates the need for filter application and understanding. For natural and unperturbed settings like protected areas, soundscape analyses should utilize an 80 Hz filter but also report the other filters mentioned in this paper for comparing results across studies. We argue that future manuscripts prepared by researchers should report acoustic indices results with various filters to avoid the siloing of datasets from different research and monitoring efforts. Future acoustic indices not included in this paper should be tested with these filters. Overall, ARUs are an effective ecological indicator for biodiversity monitoring and with the vast amount of data that stems from their use, filtering is something to consider to ensure proper analysis of acoustic indices.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 5
Correlation coefficients between filters of acoustic indices and elevation in Bellbird Biological Corridor, Costa Rica with the four filters, 80, 500, 1000, and 2000. P-values above 0.05 except for biophony.

Filter	Biophony	Anthrophony	NDSI	BAI	ADI	AEI	ACI
0					−0.18	0.36	0.00
80					0.07	0.07	0.00
500					−0.11	−0.07	0.00
1 k		−0.36	0.14		−0.11	−0.07	0.00
2 k	**−0.89**			0.07	−0.32	0.21	0.00

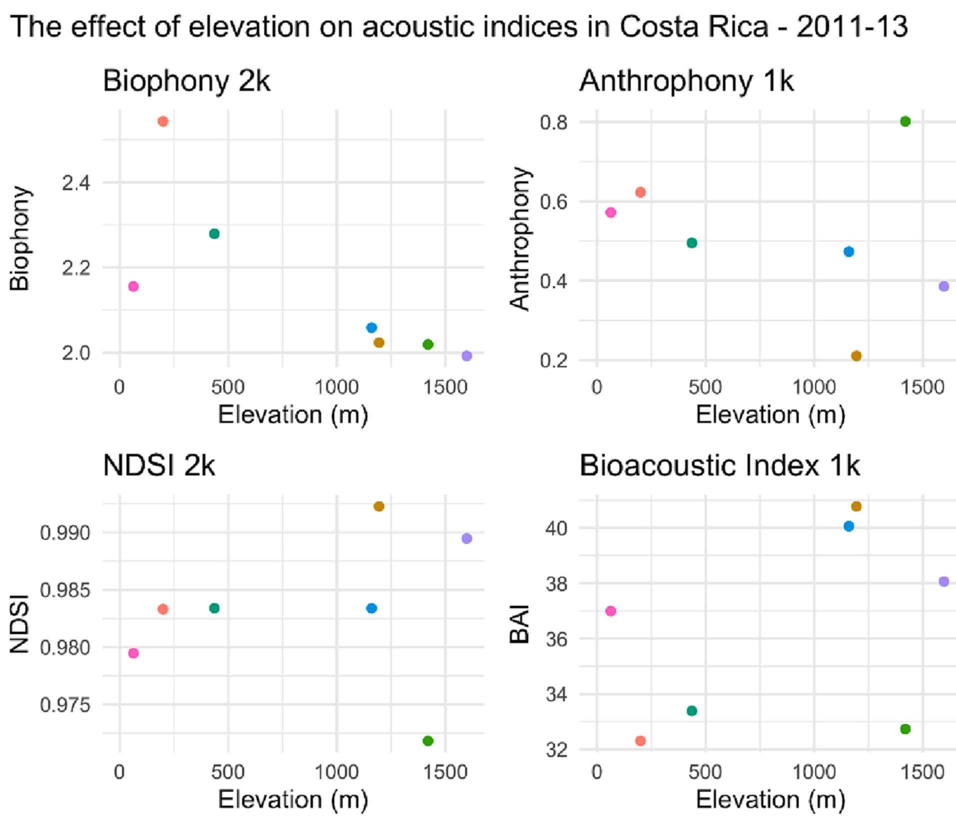

Fig. 6. Biophony at 2000 Hz, Anthrophony at 1000 Hz, Normalized Differential Soundscape Index at 2000 Hz, and Bioacoustic Index at 1000 Hz as a function of elevation for the seven study locations in the Bellbird Biological Corridor, Costa Rica.

Data availability

Data will be made available on request.

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Author contributions

Emilia B. Hyland and John E. Quinn conceived the ideas and designed methodology; no new data was collected for this paper; Emilia B. Hyland, John E. Quinn, and Annie Schulz analyzed the data; Emilia B. Hyland and John E. Quinn led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Appendix

Table A1..
Table A2..

Table A1
Literature that uses and or mentions filters.

Paper	Filter Used	Filters values	Filters compared	Biome/Anthrome	Season	Noise pollution considered
Borker et al., 2020	Yes	0–200 Hz	No	Tundra (Alaska)	Summer	No
Bradfer-Lawrence et al., 2019	Yes	500 Hz	No	Tropical (Panama)	Multiple seasons	No
Brown et al., 2018	Machine learning	Specific to rain & cicadas	Yes	N/A (theoretical study)	N/A	Yes (rain & cicadas)
Buckley et al. 2018	Yes	2 kHz	No	Temperate cropland (Nebraska)	Summer	No
Flowers et al., 2021	No	Specifically mention not using filters for a more holistic soundscape	N/A	Sonoran desert	Monsoon & dry seasons	No
Fuller et al., 2015	No	N/A	Compared different acoustic indices and landscape conditions	Subtropics (Australia)	Spring	No
Gasc et al., 2015	Mention use of filters but no specifics provided	Selecting specific indices that aren't sensitive to background noise	N/A	N/A (Simulated bird assemblages)	N/A	No
Gerber et al. 2020	No	N/A	N/A	Temperate forest (South Carolina)	Summer	Yes
Jorge et al., 2018	No	N/A	Compared different acoustic indices	Savanna (Brazil)	N/A	N/A
Khanaposhtani et al. 2019	Yes	2 kHz	No	Temperate grasslands (Wisconsin)	Summer	Yes (traffic)
Metcalf et al. 2021	Yes	300 Hz, and 4 kHz	No	Tropical forest (Brazilian Amazon)	Summer	No
Quinn et al. 2021	Yes	80 Hz, 1 kHz, & 2 kHz	Yes	Temperate croplands (Nebraska)	Winter	Yes (traffic)
Roe et al., 2018	Yes	Sensor & cloud analysis removal	N/A	Tropical savanna (North Australia)	N/A	N/A
Schindler et al., 2020	No	N/A	N/A	Temperate forest (South Carolina)	N/A	Yes
Zhao et al., 2022	No	N/A	N/A	Temperate forest (Beijing urban parks)	Spring	Yes (traffic)
Zwerts et al., 2021	No	N/A	N/A	Tropical forest	N/A	N/A
Zwerts et al., 2022	Yes	Rain removal & 22,050 Hz	No	Tropical forest	Multiple seasons	Yes (logging & traffic)

Table A2
Table of data locations, season and filters applied to audio.

Location	Season	Year	80	500	1 k	2 k
Kansas	Summer	2020	x	x	x	x
	Winter	2020	x	x	x	x
Michigan	Summer	2021	x	x	x	x
SC Upstate	Summer	2013	x	x	x	x
Costa Rica	Summer	2011–2013	x	x	x	x

References:

Acevado, M.A., Villanueva-Rivera, L.J., 2006. Using automated digital recording systems as effective tools for the monitoring of birds and amphibians. Wildlife Society Bulletin 34 (1), 211–214. https://doi.org/10.2193/0091-7648(2006)34[211:UADRSA]2.0.CO;2.

Benocci, R., Brambilla, G., Bisceglie, A., Zambon, G., 2020. Eco-Acoustic Indices to Evaluate Soundscape Degradation Due to Human Intrusion. Sustainability 12 (10455), 10455. https://doi.org/10.3390/su122410455.

Boelman, N.T., Asner, G.P., Hart, P.J., Martin, R.E., 2007. Multitrophic invasion resistance in Hawaii: Bioacoustics, field surveys, and airborne remote sensing. Ecol Appl 17 (8), 2137–2144.

Borker, A.L., Buxton, R.T., Jones, I.L., Major, H.L., Williams, J.C., Tershy, B.R., Croll, D. A., 2020. Do soundscape indices predict landscape-scale restoration outcomes? A comparative study of restored seabird island soundscapes. Restoration Ecology 28 (1), 252–260. https://doi.org/10.1111/rec.13038.

Bradfer-Lawrence, T., Gardner, N., Bunnefeld, L., Bunnefeld, N., Willis, S.G., Dent, D.H., Zamora-Gutierrez, V., 2019. Guidelines for the use of acoustic indices in environmental research. Methods in Ecology and Evolution 10 (10), 1796–1807.

Brown, A., Garg, S., Montgomery, J., 2018. Automatic Rain and Cicada Chorus Filtering of Bird Acoustic Data. Applied Soft Computing 81, 1–18. https://doi.org/10.1016/j.asoc.2019.105501.

Buckley, E.M.B., Caven, A.J., Gottesman, B.L., Harner, M.J., Pijanowski, B.C., Forsberg, M.L., 2018. Assessing biological and environmental effects of a total solar eclipse with passive multimodal technologies. Ecological Indicators 95, 353–369. https://doi.org/10.1016/j.ecolind.2018.07.017.

Ceballos, G., Ehrlich, P. R., & Dirzo, R. (2017). Biological annihilation via the ongoing sixth mass extinction signaled by vertebrate population losses and declines. *PNAS, 114*(30), E6089-E6096. doi:10.1073/pnas.1704949114.

Field, S.A., Tyre, A.J., Possingham, H.P., Lubow, 2005. Optimizing allocation of monitoring effort under economic and observational constraints. The Journal of Wildlife Management 69 (2), 473–482.

Flowers, C., Tourneau, F.L., Merchant, N., Heidorn, B., Ferriere, R., Harwood, J., 2021. Looking for the -scape in the sound: Discriminating soundscapes categories in the Sonoran Desert using indices and clustering. Ecological Indicators 127, 1–13. https://doi.org/10.1016/j.ecolind.2021.107805.

Fuller, S., Axel, A.C., Tucker, D., Gage, S.H., 2015. Connecting soundscape to landscape: Which acoustic index best describes landscape configuration? Ecological indicators 58, 207–215. https://doi.org/10.1016/j.ecolind.2015.05.057.

Gasc, A., Pavione, S., Lellouch, L., Grandcolas, P., Sueur, J., 2015. Acoustic indices for biodiversity assessments: Analyses of bias based on simulated bird assemblages and recommendations for field surveys. Biological Conservation 191, 306–312. https://doi.org/10.1016/j.biocon.2015.06.018.

Gerber, J.E., Howard, D., Quinn, J.E., 2020. Soundscape shifts during the 2017 total solar eclipse: an application of dispersed automated recording units to study ephemeral acoustic events. Biodiversity 21 (1), 41–47.

Jorge, F.C., Machado, C.G., da Cunha Nogueira, S.S., Nogueira-Filho, S.L.G., 2018. The effectiveness of acoustic indices for forest monitoring in Atlantic rainforest fragments. Ecological Indicators 91, 71–76. https://doi.org/10.1016/j.ecolind.2018.04.001.

Kasten, E.P., Gage, S.H., Fox, J., Joo, W., 2012. The remote environmental assessment laboratory's acoustic library: an archive for studying soundscape ecology. Ecol Inform 12, 50–67.

Khanaposhtani, M.G., Gasc, A., Francomano, D., Villanueva-Rivera, L.J., Jung, J., Mossman, M.J., Pijanowski, B.C., 2019. Effects of highways on bird distribution and soundscape diversity around Aldo Leopold's shack in Baraboo, Wisconsin, USA. Landscape and Urban Planning 192, 1–13. https://doi.org/10.1016/j.landurbplan.2019.103666.

Ligges, U., Krey, S., Mersmann, O., & Schnackenberg, S., (2018). tuneR: Analysis of Music and Speech. URL: https://CRAN.R-project.org/package=tuneR.

Metcalf, O.C., Barlow, J., Devenish, C., Marsden, S., Berenguer, E., Lees, A.C., Freckleton, R., 2021. Acoustic indices perform better when applied at ecologically meaningful time and frequency scales. Methods in Ecology and Evolution 12 (3), 421–431.

Morton, E.S., 1975. Ecological Sources of Selection on Avian Sound. The American Naturalist 109 (965), 17–34.

Mullet, T.C., Gage, S.H., Morton, J.M., Huettmann, F., 2015. Temporal and spatial variation of a winter soundscape in south-central Alaska. Landscape Ecology 31 (5), 1117–1137. https://doi.org/10.1007/s10980-015-0323-0.

Nascimento, L. A., Campos-Cerqueira, M., & Beard, K. H. (2020). Acoustic metrics predict habitat type and vegetation structure in the Amazon. *Ecological Indicators, 117*. doi:106679. 10.1016/j.ecolind.2020.106679.

Oduber, J., J. Welch, A. Chavarria, R. Crespo, J. Bolanos B., W. Brenes M., S. Feoli B., A. Gomez, V. Cerdas, S. Carvajal B., A. Vargas, F. Camacho C., A. Guevara V., E. Villegas V., G. Alguilar, M. E. Mora, O. Valverde A., D. Hamilton, Y. Méndez, M. Días F., W. Bello V., R. Segura M., S. Arce F., A. Castillo M., K. Molina A., E. Mata, N. Vargas, Q. Newcomer, K. Irwin, N. Nibbelink, J. Shelton, S. Connelly, and R. Malloy. (2011). Corredor Biológico Pájaro Campana: Plan estratégico 2011-2016. Costa Rica: Concejo Local del Corredor Biologico Pajaro Campana (Online PDF).

Pieretti, N., Farina, A., Morri, D., 2011. A new methodology to infer the singing activity of an avian community: The Acoustic Complexity Index (ACI). Ecological Indicators 11 (3), 868–873. https://doi.org/10.1016/j.ecolind.2010.11.005.

Pijanowski, B.C., Villanueva-Rivera, L.J., Dumyahn, S.L., Farina, A., Krause, B.L., Napoletano, B.M., Pieretti, N., 2011. Soundscape Ecology: The Science of Sound in a Landscape. Bioscience 60 (3), 244. https://doi.org/10.1525/bio.2010.60.3.14.

Quinn, J.E., Markey, A.J., Howard, D., Crummett, S., Schindler, A., 2018. Intersections of soundscapes and conservation: Ecologies of sound in naturecultures. MUSICultures 45 (1). https://journals.lib.unb.ca/index.php/MC/issue/view/2073.

Quinn, J.E., Schindler, A.E., Blake, L., Schaffer, S.K., Hyland, E., 2021. Loss of winter wonderland: Proximity to different road types has variable effects on winter soundscapes. Landscape Ecology 37, 381–391. https://doi.org/10.1007/s10980-021-01364-x.

R Core Team (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Roe, P., Ferroudj, M., Towsey, M., & Schwarzkopf, L. (2018, Oct 29 - Nov 1). Catching Toad Calls in the Cloud: Commodity Edge Computing for Flexible Analysis of Big Sound Data. 2018 IEEE 14th International Conference on e-Science (pp. 67-74). Amsterdam, Netherlands. doi: 10.1109/eScience.2018.00022.

Schindler, A.R., Gerber, J.E., Quinn, J.E., 2020. An ecoacoustic approach to understand the effects of human sound on soundscapes and avian communication. Biodiversity 21 (1), 15–27.

Stowell, D., Sueur, J., 2020. Ecoacoustics: Acoustic sensing for biodiversity monitoring at scale. Remote Sensing in Ecology and Conservation 6, 1–3. https://doi.org/10.1002/rse2.174.

Sueur, JEROME, Aubin, THIERRY, Simonis, CAROLINE, 2008. seewave: a free modular tool for sound analysis and synthesis. Bioacoustics 18 (2), 213–226.

Sugai, L.S.M., Silva, T.S.F., Ribeiro Jr, J.W., Llusia, D., 2019. Terrestrial passive acoustic monitoring: review and perspectives. BioScience 69 (1), 15–25.

Villanueva-Rivera LJ, Pijanowski BC, (2018). soundecology: Soundscape Ecology. R package version 1.3.3. https://CRAN.R-project.org/package=soundecology.

Villanueva-Rivera, L.J., Pijanowski, B.C., Doucette, J., Pekin, B., 2011. A primer of acoustic analysis for landscape ecologists. Landscape Ecol 26 (9), 1233–1246.

Zhao, Y., Sheppard, S., Sun, Z., Hao, Z., Jin, J., Bai, Z., Bian, Q., Wang, C., 2022. Soundscape of urban parks: An innovative approach for ecosystem monitoring and adaptive management. Urban Forestry & Urban Greening 71 (127555). https://doi.org/10.1016/j.ufug.2022.127555.

Znidersic, E., Watson, D.M., Lawler, J., 2022. Acoustic restoration: Using soundscapes to benchmark and fast-track recovery of ecological communities. Ecology Letters 25 (7), 1597–1603.

Zwerts, J., Stephenson, P.J., Maisels, F., Rowcliffe, M., Astaras, C., van der Jansen, P., Waarde, J., Sterck, L., Verweij, P.A., Bruce, T., Brittain, S., Kuijk, M., 2021. Methods for wildlife monitoring in tropical forests: Comparing human observations, camera traps, and passive acoustic sensors. Conservation Science and Practice 3, 1–19. https://doi.org/10.1111/csp2.568.

Zwerts, J.A., Wiegers, J.N., Sterck, E.H.M., van Kuijk, M., 2022. Exploring spatio-temporal variation in soundscape saturation of an African tropical forest landscape. Ecological Indicators 137, 1–10. https://doi.org/10.1016/j.ecolind.2022.108712.