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Sound anomalies of Cornell Swift recorders affect ecoacoustic studies, and a workaround solution

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Abstract

The Swift Terrestrial Passive Acoustic Recording Unit from The Cornell Lab of Ornithology, running firmware v. STM32 0.18.6.3, produced an initial 4-sec sound anomaly in each sound (wave file) recording, created by the power-saving features of the unit as it switches from standby to record mode. The sound anomaly had a statistically significant impact on several soundscape indices calculated from the recordings. Here, as a case study of identifying and solving this problem, I dissected the nature of the anomaly and analyzed the variable effects it has on calculated ecoacoustic soundscape indices. I used a sample of 150, 10-min sound files, recorded during my ecoacoustics study in central boreal Alaska during 2019 (June-August) and 2020 (April-September), stratified by several landscape conditions and by types of sounds representing anthrophony, biophony, and geophony conditions. The sound anomaly statistically significantly biased the calculations of 7 of 13 ecoacoustic indices analyzed from all of these landscape and soundscape conditions. There is no simple correction factor that can be applied to the calculated index values to account for the effects of the anomaly. I suggest several workarounds, notably to automate a procedure to delete a specified segment of each sound file to eliminate the anomaly prior to soundscape analysis, and in general to watch and correct for such anomalies when using Autonomous Recording Units recordings in ecoacoustic analyses.

KEYWORDS
ARU, automated recording unit, Cornell Swift, ecoacoustics, sound anomaly

The study of sounds in the environment has become a major field of ecological research (Pijanowski et al. 2011, Farina and Gage 2017) and conservation (Dumyahn and Pijanowski 2011). In general, the study of environmental sound can be divided into bioacoustics, which is the study of individual organisms, species, or other singular sources, and ecoacoustics, which is the study of overall soundscapes or the combination of various sound sources. Ecoacoustics, in turn, can be divided into studies of natural sounds, termed biophony for sounds produced by organisms, and geophony for abiotic natural sounds; and anthropogenic or human-created sounds, termed anthrophony for sounds of people, and technophony for sounds of technological sources. Some authors include ecoacoustic components under the term bioacoustics (Kvsn et al. 2020), but for purposes here they are separated.

Environmental sound studies are commonly conducted by use of autonomous recording units (ARU) that are placed in the field to monitor specific locations or environmental conditions and that are programmed to record at specified times and intervals (Duchac et al. 2020). The sounds gathered from ARU are then transferred to a computer and analyzed with a variety of programs depending on the type of sound and study objective. For such analyses, it is important that the sound files are free of interference and extraneous (non-environmental) noise. A wide array of indices, which, by one count, number more than 60 different indices (Bradfer-Lawrence et al. 2019), are used in ecoacoustic studies. More specifically, Wildlife Acoustic's Kaleidoscope Pro© (www.wildlifeacoustics.com/products/kaleidoscope-pro, accessed September 2020) can generate 13 ecoacoustic indices, which were analyzed in the current study and often by others (Pieretti et al. 2011, Kasten et al. 2012, Fairbrass et al. 2017, Mahoney et al. 2018, Ng et al. 2018, Cifuentes et al. 2021).

In my ongoing study of the ecoacoustics of boreal ecosystems in the U.S. Army's Fort Wainwright, central Alaska (Figure 1), I discovered that a particular ARU make and model—the Swift Terrestrial Passive Acoustic Recording Unit from The Cornell Lab of Ornithology (www.birds.cornell.edu/ccb/swift/), hereafter Swift, running firmware v. STM32 0.18.6.3 (Koch 2016)—created sound files containing an auditory anomaly occurring in the first few seconds of each recording. The anomaly is created by the power-saving features of the Swift unit, particularly in duty-cycle mode for programming and executing a repeated schedule of date and time recording events. When the unit switches from standby to record mode, the microphone circuitry is powered on and creates the anomaly sound internally (R. Koch, Cornell Lab of Ornithology, personal communication).

For those using the Swift ARU for continuous and not duty-cycle scheduled recording, the anomaly would not occur and thus would not be a concern for acoustic analyses. In continuous-recording mode, the Swift will segment the recordings into individual wave sound files which would not contain the anomaly, which occurs instead only with the duty-cycle recording scheduling using the firmware version noted above. Also, the anomaly would have no influence on species-specific bioacoustic analyses, which separate and cluster similar sound events pulled from within individual sound files (e.g., bird songs and calls). Consequently, the anomaly, as put into its own sound cluster, could be ignored in bioacoustic analyses. However, the anomaly potentially can severely affect calculations of ecoacoustic index values that treat entire sound files as a whole. In this paper, I explain the nature of the anomaly, demonstrate its influence on ecoacoustic analyses, suggest a workaround, and provide cautions on first examining and dealing with any ARU recordings for such sound recording anomalies.

I discovered the sound anomaly during inspection of my field ARU recordings graphically displaying sound amplitude as a function of time. The initial anomaly also can be heard aurally as a brief scratch sound at the beginning of the file. I then investigated the specific audio characteristics of the anomaly by producing sound spectrogram (frequency-time) and power (amplitude-frequency) plots to determine the anomaly's frequencies, amplitudes, and durations. It became apparent from this inspection that the anomaly could greatly influence values of ecoacoustic indices calculated from the ARU's sound files. Should the anomaly introduce irregular results, the

FIGURE 1 Example of placement of a Cornell Swift automated recording unit in a lowland landscape at an early successional thermokarst (thawed permafrost) site dominated by dwarf scrub bog, central boreal Alaska, USA, August 2019.

implications would not be trivial for an ecoacoustic study. Further, I draw some general conclusions and suggestions for being aware of, and how to detect and correct for, such potential effects.

METHODS

To test the potential effects of the ARU recorder sound anomaly on index calculations, I drew from my soundscape study in central boreal Alaska as a representation of an ecoacoustic research project. This project consisted of collecting sound files from 24 remote locations over spring through fall 2019 and 2020, totalling 2.80TB of 82,023, 10-minute sound (wave,.wav) files recorded by the ARU. The sound anomaly occurred in all of these sound files. I selected a sample of 150 sound files from this set for analysis, consisting of 80 files representing 4 landscape types and 70 files representing 3 ecoacoustic types. I stratified the sound files into the 4 landscape and 3 ecoacoustic types because each type could have unique acoustic properties and might be differentially affected by the sound anomaly. The 80 files of landscape types included 20 wave files for each of 4 landscape categories of lacustrine, lowland, riverine, and upland conditions, and samples of each landscape category were in turn divided among early-, mid-, and late-successional conditions. The 70 files representing ecoacoustic types consisted of 22 files representing anthrophony conditions (road vehicles, helicopters, jets, propeller aircraft, radio noise, and people talking and walking), 25 files representing biophony conditions (woodpecker hammers, raptor calls, squirrels, insect buzz, and bird songs and calls in high-, mid-, low-, and mixed-frequency ranges), and 23 files representing geophony conditions (rainfall, thunder, wind, and silence).

I created and saved trimmed versions of each of the 150 sound files in which I deleted the initial 4 seconds in each file to eliminate the sound anomaly. I then calculated a suite of 13 ecoacoustic index values using the acoustic options in Kaleidoscope Pro© v. 5.3.9, for each of the 150 untrimmed and the 150 trimmed sound files. I used the program's default settings which were fully suitable for my ecoacoustic research explorations. The 13 ecoacoustic indices (Table 1) variously emphasize different portions or combinations of the sound frequency spectrum. The emphasis on different frequencies serves to represent the dimensions of natural and anthropogenic sounds, or to express the overall diversity of frequency bands as indicators of the variety of sound sources in an environment. The 13 ecoacoustic indices and their default values are described in the Kaleidoscope Pro 5 program's users guide (Wildlife Acoustics, http://condor.wildlifeacoustics.com/Kaleidoscope.pdf, accessed Sep 2020).

To determine the potential effect of the anomaly on ecoacoustic analysis, I statistically compared values of each of the 13 ecoacoustic indices between the untrimmed and trimmed sound files by using paired t-tests with the null hypothesis of no difference between mean index values, stratifying the sound files by the 4 landscape types and the 3 ecoacoustic categories as mentioned above. Statistically significant deviations from zero differences of mean values denoted potential biases in ecoacoustic analyses caused by the anomaly. I compared ecoacoustic index values in scatter diagrams and graphed the dispersion of index values in box plots, comparing untrimmed and

TABLE 1 Results of paired, 2-sample t-tests for determining the difference in sample mean values of acoustic indices comparing native wave (.wav) sound files from the Cornell Swift automated recording unit containing the initial sound anomaly, with the same sound files having the first 4 sec deleted to eliminate the anomaly. The test null hypotheses were that the mean index values did not differ between raw and truncated sound files (i.e., the difference of mean values = 0). All recordings were taken in 4 main landscape conditions in central boreal Alaska, USA, August 2019 to September 2020 (n = 20 recordings per landscape, n = 80 total; each analysis df = 18).

	Lacustrine landscape		Lowland landscape		Riverine landscape		Upland landscape	
Acoustic index[a]	*P* value	*t* value	*P* value	*t* value	*P* value	*t* value	*P* value	*t* value
NDSI	**0.000	6.717	**0.000	11.569	*0.001	4.031	**0.000	20.13
ACI	**0.000	6.553	**0.000	14.401	**0.000	8.212	**0.000	8.751
ADI	**0.000	−9.79	*0.009	−2.932	*0.014	−2.702	*0.003	−3.38
AEI	**0.000	4.558	0.488	0.706	0.603	0.528	0.15	1.499
BI	**0.000	5.297	**0.000	10.422	**0.000	7.341	**0.000	7.067
BGN	**0.000	18.102	**0.000	7.596	**0.000	7.414	0.159	1.466
SNR	*0.028	−2.371	0.624	0.498	0.757	0.314	**0.000	9.346
ACT	0.172	−1.418	0.788	0.273	0.482	0.717	**0.000	7.58
EVN	0.083	−1.831	0.074	−1.89	0.868	−0.169	0.318	−1.026
LFC	0.115	−1.653	0.676	0.424	0.248	1.191	0.917	−0.106
MFC	0.833	−0.214	*0.004	3.326	0.132	1.573	0.432	0.802
HFC	0.788	−0.273	0.128	1.591	0.067	1.944	0.613	0.514
CENT	**0.000	−6.449	**0.000	−6.827	**0.000	−9.128	**0.000	−11.069

[a]NDSI = Normalized Difference Soundscape Index; ACI = Acoustic Complexity Index; ADI = Acoustic Diversity Index; AEI = Acoustic Evenness Index; BI = Bioacoustic Index; BGN = Background Noise Index; SNR = Signal to Noise Ratio Index; ACT = Activity Index; EVN = Events Index; LFC = Low-frequency Cover Index; MFC = Mid-frequency Cover Index; HFC = High-frequency Cover Index; CENT = Concentration Index.

*$0.05 \leq P \leq 0.001$.

**$P < 0.001$.

trimmed conditions, by landscape type and ecoacoustic category. I also calculated Pearson correlations (r) with Bonferroni significance levels (*P*) comparing the untrimmed and trimmed values of each acoustic index, by landscape type and ecoacoustic category. I examined the untrimmed and trimmed ecoacoustic index values to determine if some sort of correction factor could be applied to compensate for the anomaly.

In this paper I have presented the comparisons of all ecoacoustic indices, but I also selected and presented more detailed results of 2 specific ecoacoustic indices: the normalized difference soundscape index (NDSI) and the acoustic diversity index (ADI). I selected these 2 example indices because they are calculated quite differently from one another, their values are uncorrelated, and they represent diverse and complementary insights into soundscape structure. The NDSI assigns values based on dominant frequencies of the soundscape that correspond with the sound's source. Values of NDSI range from −1 to +1, where −1 generally represents low-frequency, anthrophonic sources and +1 generally represents high-frequency, biophonic sources, although some phonic sources can range into each other's values. The formula for calculating NDSI (Kasten et al. 2012) is $(\beta - \alpha)/(\beta + \alpha)$, where α = the power spectral density for frequency ranges generally pertaining to anthrophonic sources (ranging 1 kHz to 2 kHz), and β = the power spectral density for frequency ranges generally pertaining to biophonic sources (ranging 2 kHz and 8+ kHz). Differently, ADI measures the overall frequency diversity of sounds. Acoustic diversity index values theoretically span $(0, \infty)$, although in practice values tend to range from 0 to 5, where low values denote that most sound is constrained to a narrow frequency band, and high values denote sounds spread across multiple frequency bands. The index is calculated as the Shannon diversity of power spectra exceeding a specified threshold (−50 dB fs, in this analysis) among 10 frequency bands each of 1 kHz width (as implemented in Pianowski et al. 2011). In a sense, ADI is the soundscape equivalent of the Shannon-Weiner H' species diversity index (Shannon and Weaver 1949).

I summarized results of the potential effect of the Swift recorder's sound anomaly on the ecoacoustic indices as stratified by landscape and soundscape types, and if the effects seem linearly consistent a simple correction could be made to ecoacoustic index values derived from the unedited sound files to account for effects of the sound anomaly. Overall conclusions are presented as to how the Swift unit's sound anomaly could impact ecoacoustic index studies, if the analyses can correct for such outcomes, and, as needed, how the anomaly can be eliminated. I also provide general suggestions for evaluating and correcting for potential sound anomalies in ecoacoustic ARU-based studies and offer this example as a case study.

RESULTS

Anatomy of a sound anomaly

The specific sound anomaly created by this particular Cornell Swift ARU occurs at the beginning of each recorded sound file, fading to inconsequential amplitude after 4 sec. The acoustic structure of the anomaly is shown as amplitude-time and frequency-time plots (Figure 2) and in amplitude-frequency power plots (Figure 3). There are 4 brief but distinct phases of (1) maximum amplitude at low frequency, (2) maximum amplitude across all frequencies, (3) a pulse increasing in amplitude across all frequencies, and (4) a slower gradient of declining amplitude across all frequencies.

Ecoacoustic effects of a sound anomaly

The anomaly profile presented above demonstrates how this sound anomaly includes elements encompassing all recordable frequencies and maximum recordable amplitudes. The ecoacoustic indices explored here rely variously on amplitude and frequency sound characteristics, so they are each potentially influenced by the sound anomaly. The analysis results among all index values are summarized next, and calculations of each index value by landscape and soundscape type are more fully presented in Supporting Information.

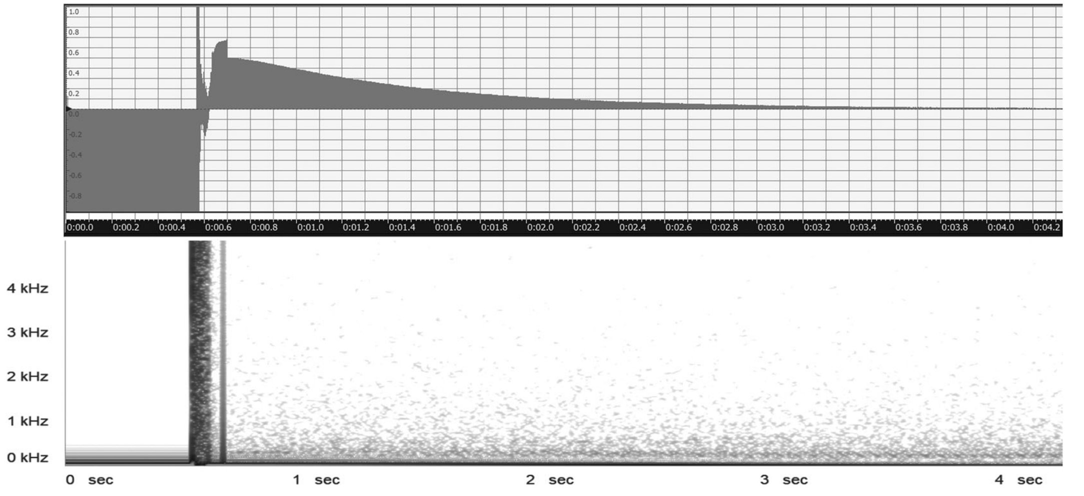

FIGURE 2 Audio characteristics of the anomalous start-up sound during the initial 4 sec of recordings made by the Cornell Swift automated recording unit (top = power [amplitude, dBA]; bottom = sound spectrogram [kHz]). In the spectrogram plot, the sound at 0.6 sec extends to the highest frequency recorded by the unit (16 kHz) but is shown truncated here to 5 kHz to also display the low frequency (<0.5 kHz) anomalies. The Swift ARU unit records wave (.wav) files in monaural, encoded as a 16-bit signal with a sampling rate of 3200 Hz.

Among all 4 landscape types, NDSI values calculated from the untrimmed sound files that contain the anomaly clustered mostly in index values >0.6, whereas values in the same sound files with the anomaly trimmed out are more evenly spread (Figure 4). The same generally holds true with ADI, where index values in the untrimmed sound files clustered <0.25 but are more widely dispersed among values in the trimmed sound files (Figure 5). Median and quartile NDSI values were reduced in the trimmed files, particularly in lacustrine environments (Figure S1, available in Supporting Information), better signifying a greater dominance of the lower anthrophony or geophony sound frequencies than would be signified by the influence of the sound anomaly that included the full frequency spectrum. Median and quartile ADI values were substantially greater in the trimmed files among all 4 landscape types (Figure S2), suggesting a greater diversity of frequencies by amplitude when the anomaly was eliminated. Comparing mean values of each of the 13 ecoacoustic indices tested among the 4 landscape types showed a statistically significant effect of the anomaly on all but 4 of the indices (Table 1), and nearly all indices showed no significant correlation between untrimmed and trimmed values among the 4 landscape types (Supplemental Table S1).

Comparing results among the 3 soundscape phonic categories yielded similar findings, with NDSI and ADI having variably different values as calculated from the untrimmed and trimmed sound files (Figures 6 and 7). Trimming out the sound anomaly resulted in significantly lower NDSI median and quartile values in sound files representing anthrophony conditions and somewhat lower values for biophony and geophony conditions (Figure S3). For NDSI values, the effect on anthrophony was with aircraft, vehicle, and people sounds, the greatest effect on biophony was with insect sounds, and the effect on geophony was on all sounds of rain, thunder, wind, and silence (Figure S4). That is, the effect of the anomaly was to generally introduce more higher-frequency sound, thus biasing the interpretation of NDSI values to suggest greater biophony conditions over anthrophony conditions than actually present.

Trimming out the anomaly resulted in substantially greater ADI median and quartile values for anthrophony and biophony conditions and increased only the upper quartile for geophony conditions (Figure S5). For ADI values, the effect on anthrophony was mostly on aircraft and people sounds, the effect on biophony was mostly on bird songs and mammal (squirrel) sounds, and the effect on geophony was largely on rain sounds (Figure S6). The effect of the anomaly was to generally reduce ADI values, suggesting lower overall sound diversity than actually present.

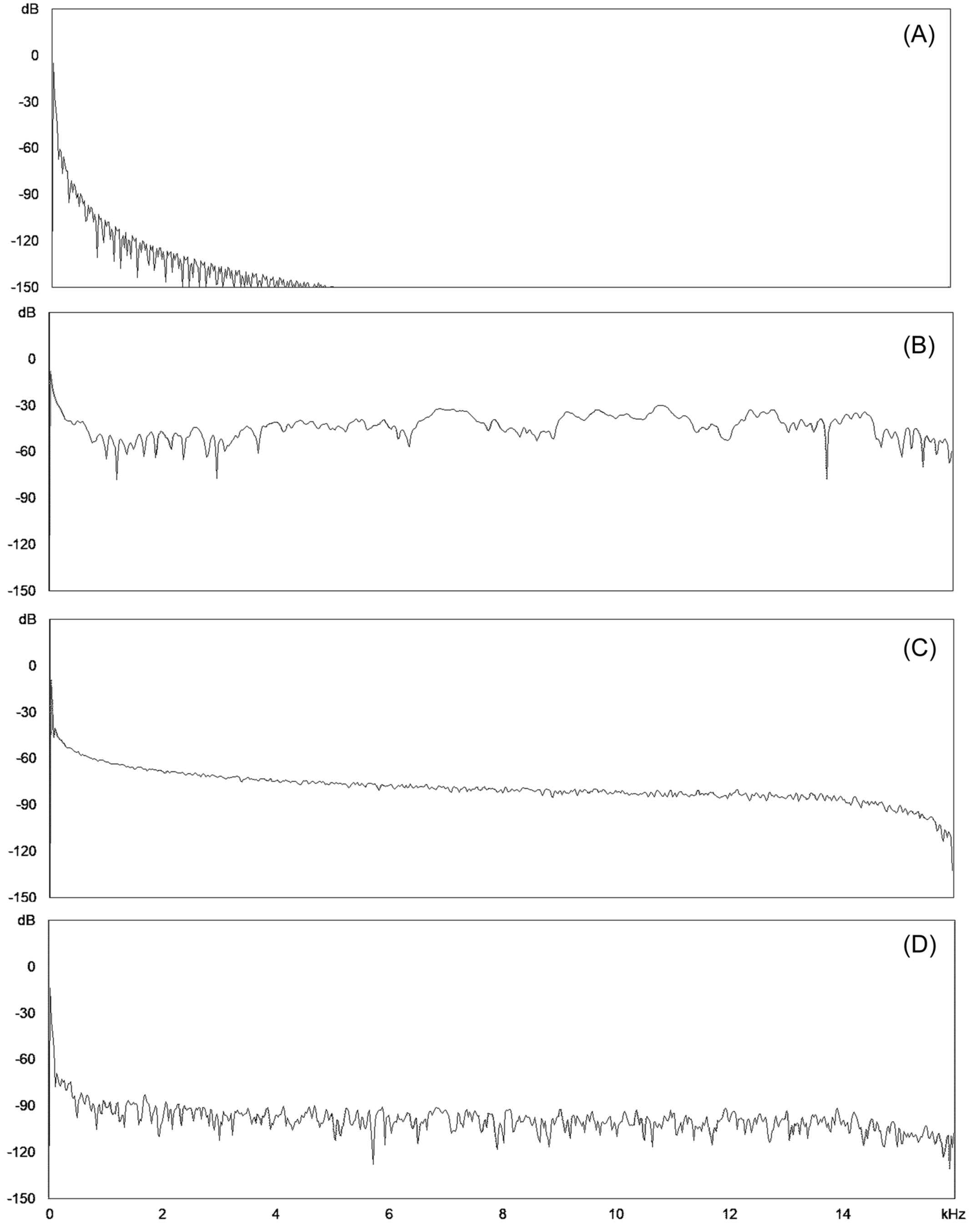

FIGURE 3 Power (dBA)-frequency (kHz) profile plots taken at 4 time points in the sound spectrogram shown in Figure 2: (A) at 0.25 sec, showing low-frequency dominance; (B) at 0.54 sec, at the first and strongest sound anomaly covering all frequencies; (C) at 0.67 sec, at the second and lesser sound anomaly; (D) at 1 sec, with a noisy coverage of all frequencies but less amplitude than in (C). The pattern in (D) decreases in amplitude monotonically to cease at 4 sec.

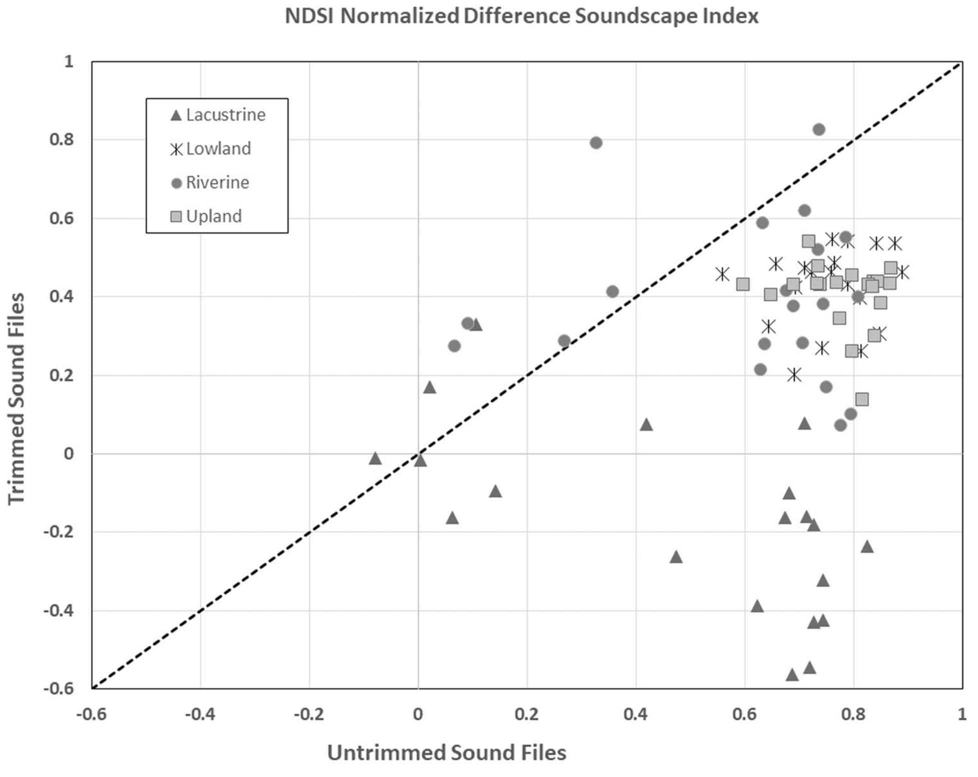

FIGURE 4 Comparison of native wave (.wav) sound files from the Cornell Swift automated recording unit containing the initial sound anomaly (untrimmed sound files, x-axis) and with the first 4 sec deleted (trimmed sound files, y-axis), in recordings taken in 4 main landscape conditions in central boreal Alaska, USA, August 2019, for the normalized difference soundscape index (NDSI). The dotted line denotes where trimmed and untrimmed files would produce the same NDSI values.

Among all 13 ecoacoustic indices tested, mean values were statistically significantly different to varying degrees in all 3 soundscape phonic conditions for 6 indices, including NDSI and ADI (Table 2). The 7 ecoacoustic indices without significant differences in mean index values calculated from untrimmed and trimmed sound files showed significant correlation of values between the untrimmed and trimmed files for one or more of the phonic conditions of anthrophony, biophony, and geophony (Table S2). Specifically, the NDSI and ADI trimmed values were themselves uncorrelated within the landscape type trimmed sound samples ($r = -0.024$, $P = 0.835$, $n = 80$) and within the soundscape type trimmed sound samples ($r = -0.128$, $P = 0.293$, $n = 70$; see also the diagonal lines in Figures 4–7). Comparisons of values of untrimmed and trimmed sound files for all 13 ecoacoustic indices are presented in Supporting Information (Figures S7–19 for the 4 landscape types and Figures S20–32 for the 3 soundscape types).

DISCUSSION

This study by no means analyzed effects of the Swift sound anomaly on all possible ecoacoustic indices. Nor can this, or any, study quantify potential effects of the sound anomaly in all possible landscape and soundscape recording conditions in all types of ARUs. Results, however, still clearly indicated a sound anomaly of the type that was introduced into recordings from the Swift ARU can adversely affect values of at least some ecoacoustic indices

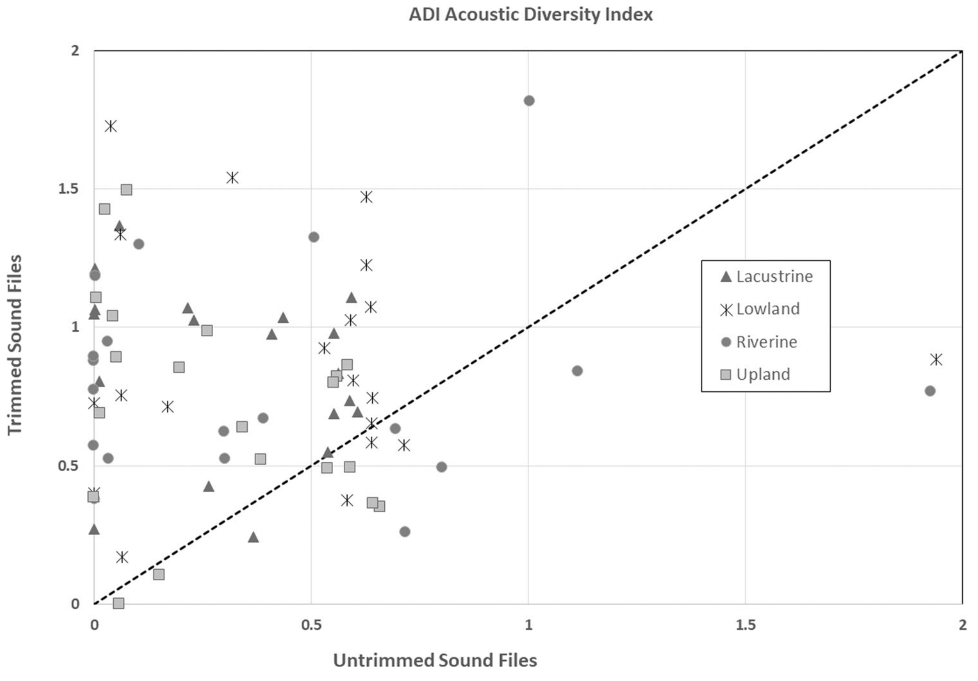

FIGURE 5 Comparison of native wave (.wav) sound files from the Cornell Swift automated recording unit containing the initial sound anomaly (untrimmed sound files, x-axis) and with the first 4 sec deleted (trimmed sound files, y-axis), in recordings taken in 4 main landscape conditions in central boreal Alaska, USA, August 2019, for the acoustic diversity index (ADI). The dotted line denotes where trimmed and untrimmed files would produce the same ADI values.

in some landscape and soundscape conditions. Determining the degree of variability of sounds, and the degree to which anomalous or extraneous sounds can influence ecoacoustic indices, are significant research concerns in soundscape analysis (Fairbrass et al. 2017, Bradfer-Lawrence et al. 2019).

No simple analytic solution

The anomaly clearly resulted in biased calculations and interpretations of most of the ecoacoustic indices tested. Unfortunately, no simple analytic solution seemed to emerge for a single correction factor or adjustment coefficient to apply to index values calculated from the untrimmed sound files recorded by the Cornell Swift ARU. The relationships of ecoacoustic index values with and without the sound anomaly varied greatly among the individual indices, landscape types, and soundscape contexts.

Should the presence of consistent sound anomalies be a recurring concern not just with the ARU tested here but in other recording situations, I suggest that sound editing and analysis programs such as Kaleidoscope Pro© and The Cornell Lab's Raven Pro© include a rudimentary file-editing feature by which a user-specified portion of each sound file would be either ignored during analysis or discarded (trimmed and resaved) prior to analysis of the remaining portion of the file. Failing to account for any such anomalies could greatly bias results, including conclusions drawn on soundscape characteristics of interest to managers, such as determining the degree to which anthrophonic sound sources may dominate biophonic sources. Further, I suggest that others conduct similar tests with their ARU makes and models, and that a further study could compare results controlling for recording conditions, recording length, ecoacoustic indices selected, software used to calculate the indices, and other factors.

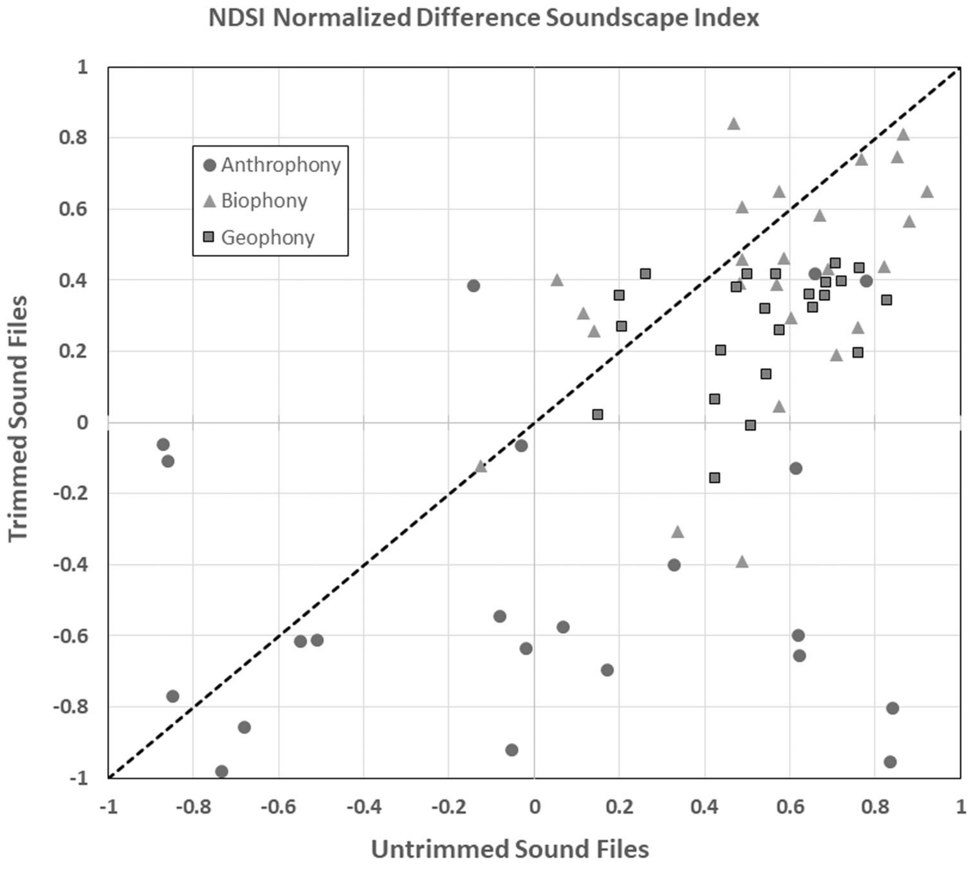

FIGURE 6 Comparison of native wave (.wav) sound files from the Cornell Swift automated recording unit containing the initial sound anomaly (untrimmed sound files, x-axis) and with the first 4 sec deleted (trimmed sound files, y-axis), in recordings representing 3 soundscape phonic conditions (see text for details) in central boreal Alaska, USA, August 2019, for the normalized difference soundscape index (NDSI). The dotted line denotes where trimmed and untrimmed files would produce the same NDSI values.

Workaround solutions

Conceptually, several potential solutions might help solve the problem of how the calculated values of ecoacoustic indices are affected by the sound anomaly introduced by the Cornell Swift ARU. First is to consider if the specific index of interest is significantly affected by the anomaly; as noted above, for my sample of sound files, 7 of the indices did not significantly differ in mean value among the 4 landscape and 3 phonic conditions I tested, but this could vary with other studies and soundscape conditions, and the implications of any effect a recording anomaly would depend on which ecoacoustic indices are of central interest.

Another solution to consider is whether it is feasible to derive and use a correction factor as a coefficient to adjust affected ecoacoustic index values calculated from untrimmed sound files containing the sound anomaly. However, from my sound samples, the deviations in each index value, indicated by the statistical tests and graphical comparisons, varied substantially within and among categories of landscape and soundscape types with no consistent pattern. This deviation suggested no simple adjustment factor can correct for the sound anomaly for those affected ecoacoustic indices.

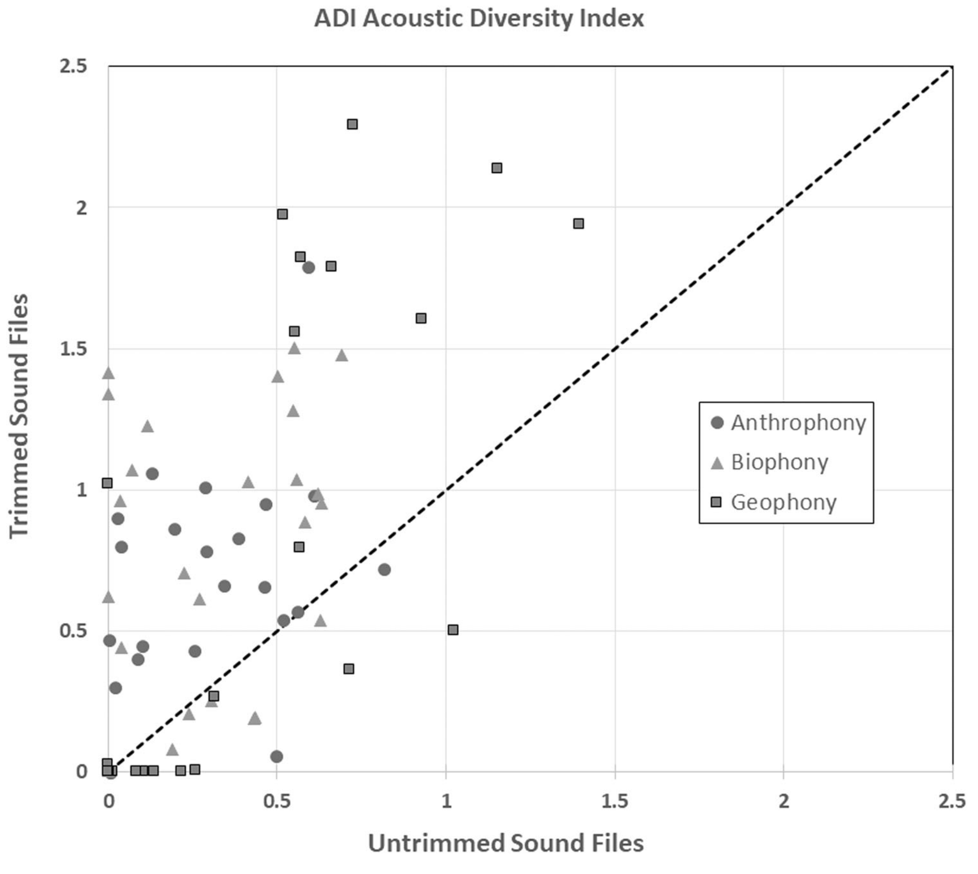

FIGURE 7 Comparison of native wave (.wav) sound files from the Cornell Swift automated recording unit containing the initial sound anomaly (untrimmed sound files, x-axis) and with the first 4 sec deleted (trimmed sound files, y-axis), in recordings representing 3 soundscape phonic conditions (see text for details) in central boreal Alaska, USA, August 2019, for the acoustic diversity index (ADI). The dotted line denotes where trimmed and untrimmed files would produce the same ADI values.

A further possible solution is to use specific features, if available, within sound analysis programs to essentially ignore the first segment of the sound file, thus effectively skipping over the sound anomaly. To a limited extent, for example, the program Kaleidoscope Pro can be used to partition each sound file into shorter segments and discard the first segment, but this feature does not reintegrate the segments after one is discarded and would then treat each segment as a separate sound sample.

Another general solution is to edit each individual wave file to delete the initial 4 sec of sound, thereby eliminating the sound anomaly. Sound editing programs, such as Audacity© (https://sourceforge.net/projects/audacity/; accessed Aug 2022) and GoldWave© (www.goldwave.com; accessed Aug 2022), can be used to clip and resave each sound file. However, such an approach quickly becomes infeasible with the hundreds or thousands of individual sound files that are typically generated from acoustic studies, such as from this study.

A final workaround is to automate the file-clipping procedure, which was the tactic used here. I applied a small stand-alone program coded in Python (provided by Z. Ruff, U.S. Forest Service, personal communication; https://www.python.org/, accessed Dec 2020) to strip the first 4 sec of each sound file and then to save each file under an alternative file name. The program code can be modified to specify the duration to be clipped, whether to save or

TABLE 2 Results of paired 2-sample t-tests for determining the difference in sample mean values of acoustic indices comparing native wave (.wav) sound files from the Cornell Swift automated recording unit containing the initial sound anomaly, with the same sound files having the first 4 sec deleted to eliminate the anomaly. The test null hypotheses were that the mean acoustic index values did not differ between raw and truncated sound files (i.e., the difference of mean values = 0). All recordings were taken in central boreal Alaska, USA, August 2019 to September 2020, representing 3 ecoacoustic sound types of anthrophony, biophony, and geophony.

	Anthrophony		Biophony		Geophony	
Acoustic Index[a]	*P* value	*t* value	*P* value	*t* value	*P* value	*t* value
NDSI	*0.006	3.063	*0.013	2.691	**0.000	6.175
ACI	**0.000	8.387	**0.000	7.891	*0.002	3.615
ADI	**0.000	−4.821	**0.000	−5.079	*0.014	−2.663
AEI	*0.010	2.852	*0.001	3.697	*0.028	2.35
BI	*0.001	3.851	**0.000	6.25	**0.000	6.119
BGN	*0.004	3.187	*0.013	2.67	*0.012	2.745
SNR	0.669	0.434	0.06	1.977	0.334	−0.988
ACT	0.727	0.353	0.653	0.455	0.604	−0.526
EVN	0.895	0.134	0.115	−1.637	0.562	−0.588
LFC	0.954	0.059	0.926	−0.094	0.918	−0.104
MFC	0.924	0.096	0.877	0.157	0.941	0.075
HFC	0.744	0.331	0.771	0.294	0.998	−0.003
CENT	0.69	−0.405	0.197	−1.327	0.208	−1.296
DF:		21		24		22

[a]See Table 1 for acoustic index codes and names.

*$0.05 \le P \le 0.001$.

**$P < 0.001$.

delete the original sound file, and the naming convention for the saved, altered file. I found this workaround to be the most efficient of those explored here. (Also in Supporting Information is the same code in an R format file).

Any work-around solution is, at best, a post hoc fix. The best approach, especially when dealing with an untried ARU unit with unknown acoustic attributes, is to initially conduct a small trial run of recordings and then do a small sampling—even just 10 or fewer recordings—and analysis of those to determine their acoustic properties and if a sound anomaly of any type is present. Anomalies may include a brief start-up glitch noise, as in this study, or some unintended incursion of a background frequency, or an unintentional lowpass or highpass filtering of desired frequencies, or other conditions. A quick check at the onset could save much trouble and consternation later. Such an initial check can be added to Bradfer-Lawrence et al.'s (2019) recommended workflow for ecoacoustic studies. Ameliorations might include editing the final sound files, adjusting the recording settings, updating the ARU firmware, switching microphones, or other tactics.

In some cases, a sound anomaly produced by an ARU model might not have an adverse impact on ecoacoustic analyses, particularly if the sound recording is lengthy (e.g., >1 hr). In my study, however, with 10-min recordings, the brief initial sound glitch did bias the ecoacoustic index values I used. Thus, sound recording length should also be considered when determining potential bias from a recording anomaly. Further, one might argue that, if all recordings have the same anomaly, then that bias is essentially held constant so that comparisons among recordings can still be made reliably. However, this argument is fallacious when the absolute values of the ecoacoustic indices are of interest, such as with the values of the NDSI index that suggest the degree of biophony vs. technophony sounds.

In closing, it is important to emphasize that this study in no way was intended to denigrate the Cornell Swift ARUs, which performed admirably under the harshest weather conditions in central Alaska including local flooding and even bear attacks. The intent here is to provide cautions against blindly using ARU sound recordings without at least spot-checking, reviewing, and inspecting their characteristics, and, as necessary, to correct for such anomalies when using ARU recordings in ecoacoustic analyses. The best advice is to know your sounds before conducting a major acoustic analysis.

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CONFLICTS OF INTEREST

The author declares no conflicts of interest.

ETHICS STATEMENT

The use of trade or firm names in this publication is for reader information and does not imply endorsement by the U.S. Department of Agriculture of any product or service. No potential conflict of interest is reported by the author. This study followed the institutional and national ethical guidelines for scientific research in the United States under the U.S. Forest Service. Permits were not required for this research as no direct handling or treatment of animals was conducted.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher’s website.

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