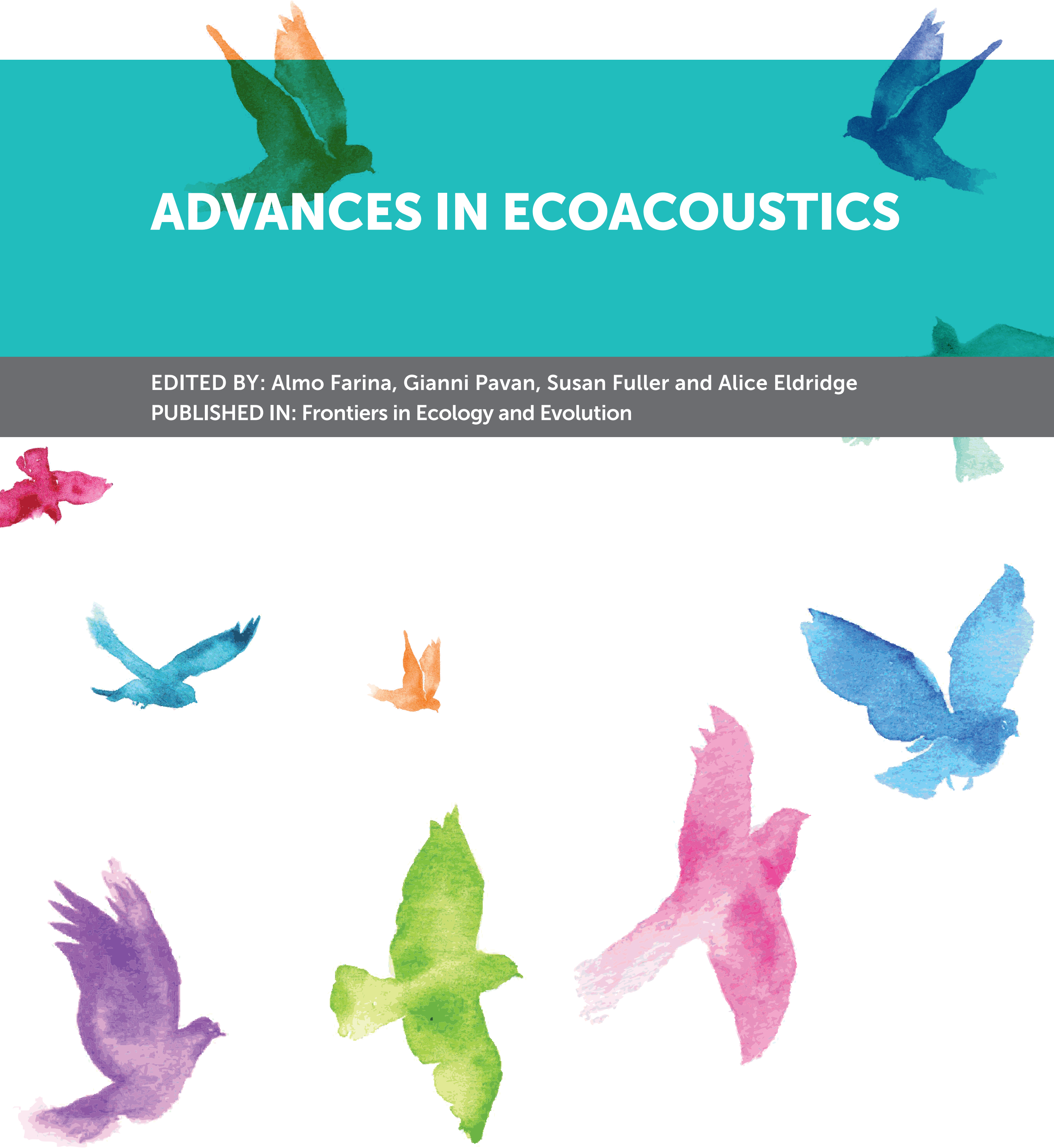

ADVANCES IN ECOACOUSTICS

EDITED BY: Almo Farina, Gianni Pavan, Susan Fuller and Alice Eldridge
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ADVANCES IN ECOACOUSTICS

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Editorial: Advances in ecoacoustics

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ecoacoustics epistemology, ecoacoustic methods, ecoacoustic monitoring, biotremology, machine learning

Editorial on the Research Topic
Advances in ecoacoustics

The global decline of biodiversity in the wake of expanding human development (United Nations, 2019a), resource depletion (United Nations, 2019b), and climate change (IPCC, 2021) motivates research in basic and applied ecological science. The new scientific discipline of ecoacoustics (Sueur and Farina, 2015) creates an epistemological bridge between ecology, acoustics, animal behavior, biotremology, and semiotics, providing fresh perspectives to study ecosystem function and new tools for ecological monitoring in terrestrial and aquatic ecosystems. Advances in affordable hardware (Pavan et al., 2022) mean that we can now passively, remotely and continuously record acoustic environments; advances in machine learning provide potential methods to digest the big data generated, but many theoretical and practical issues remain. We are pleased to introduce this special issue on Advances in Ecoacoustics that makes important contributions to the development of the semantic, conceptual and theoretical foundations, analysis methods and infrastructures necessary for ecoacoustics to advance as a scientific discipline that is equipped to tackle the urgent environmental issues we face today.

Four articles address core definitions, concepts, and theoretical principles in ecoacoustics. A primary focus of the field is the investigation of the ecological role of soundscape. However, the term "soundscape" encompasses diverse concepts, including objective physical phenomena and subjective perceptions (ISO 12913-1, 2014). With the aim of operationalising the concept of soundscape in conservation, Grinfeder et al. propose three new functional categories to clarify soundscape definitions: distal, proximal, and perceptual.

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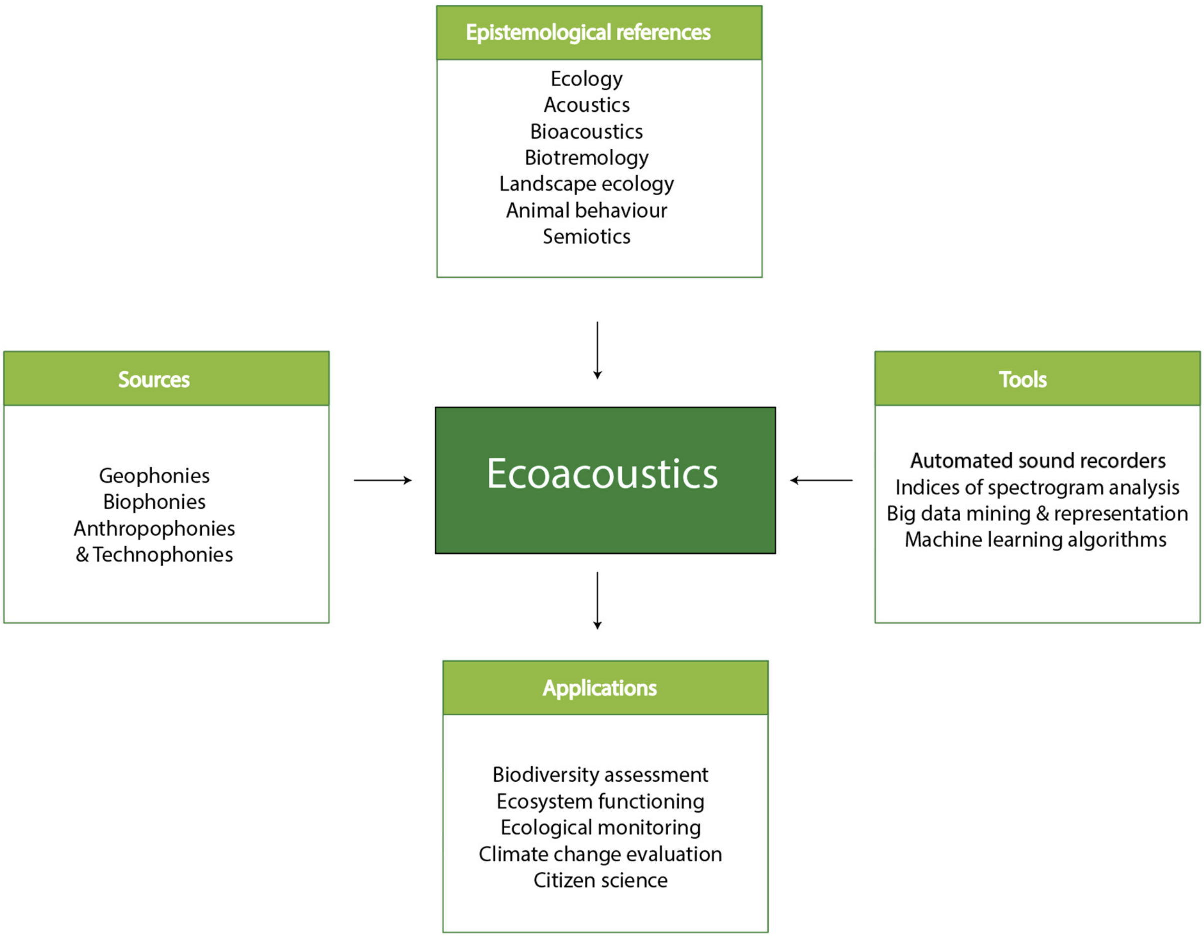

FIGURE 1
Ecoacoustics epistemological domain and competencies.

Ecoacoustics has traditionally focused on air-borne sounds in the range of human hearing [soundscape definition given by (ISO 12913-1, 2014)]; but now includes infrasounds and ultrasounds used by animals for communication and echolocation. In addition, recent research suggests that substrate-born vibrations are important sources of environmental information (Hill et al., 2019), as studied by the new discipline of Biotremology. Šturm et al. introduce the concept of *vibroscape* as the substrate-borne analogy of the soundscape and *ecotremology* as the study of its ecological significance. Ecotremology expands the paradigm of ecocoustics to new registers and opens fresh possibilities for non-invasive monitoring of arthropod species that are essential for ecosystem functioning.

The conceptual framework of ecoacoustics describes the components of the soundscape according to their sources: biological (biophony), geophysical (geophony), and human-produced (anthropophony and technophony) sounds. However, it is common in applied ecoacoustics to focus on biophony, disregarding anthropophony and geophony as noise (Figure 1). Farina et al. emphasize the importance of geophonies as key drivers of adaptation and habitat selection and highlight the value of including geophonies in ecocoustic analyses, especially when monitoring climatic changes and their ecological consequences. Following classical niche theory (Hutchinson, 1957), the acoustic niche hypothesis (ANH) (Krause, 1987), posits that species' acoustic repertoires tend to be partitioned in acoustic space to avoid interference and signal masking. In contrast, the clustering hypothesis (Tobias et al., 2014) predicts that convergent acoustic features may be beneficial to reinforce acoustic communities. By observing signal overlap between montane tropical wet forest bird communities in Costa Rica and Hawai‘I, Hart et al. tested these hypotheses and found evidence of temporal partitioning but not of clustering, lending support to the ANH.

Two articles address the theory and application of ecoacoustics in land-management. Human impact on natural systems is typically considered in terms of physical aspects of habitat degradation. Sánchez et al. investigated the impact of vegetation structure versus industrial anthropophony on the Lincoln sparrow (*Melospiza lincolnii*) occupancy at three sites in Northern Alberta, Canada. Their results demonstrate the importance of species-specific *acoustic habitat* and promote further research on the ecological consequences of human impact on soundscapes as well as physical habitats. The need for cost-effective tools to guide decision-making in sustainable forest management has never been more pressing and there is growing evidence that forest diversity is related to acoustic diversity. Using simple soundscape features to analyse the acoustic environment of Panamian forests, Müller et al. report that relative to monoculture forests, polycultures increased orthopteran acoustic activity at night in tropical forests. These results bolster growing evidence for the value of ecoacoustics as a cost-effective monitoring tool in land-management.

Three articles focus on new computational methods for ecoacoustic monitoring using both global soundscape indices and automated species identification. Acoustic indices provide simple statistical summaries of the spectral and/or temporal distribution of energy in an acoustic recording. Single indices may capture intensity or spectral distribution but are insufficient to capture the complex patterns emerging from soundscapes. Scarpelli et al. integrate compound indices with time series classification and machine learning to provide a semi-automated classification method for terrestrial soundscapes.

Fully automated species detection remains a challenge. Traditional methods require an extensive, manually labeled call library for training data, which is often obviated by time, funding or data availability. Eichinski et al. describe the successful application of active learning methods (a semi-supervised machine learning approach using unlabelled data) to predict multiple avian species in a novel habitat. Brodie et al. similarly address the inherent challenges of working with vast data sets. False-color spectrograms (Towsey et al., 2018a), generated from an open-source analysis tool (Towsey et al., 2018b), are used to visualize and detect chorusing of multiple species of frogs in large acoustic data sets, creating an efficient manual ecoacoustic analysis workflow that complements automated approaches.

The final two articles address the critical issues of ensuring ecoacoustics is founded on open-access principles to ensure sustainable, scalable and open practices. Parsons et al. sound the call for a global library of underwater biological sounds and stress the value of an open-access reference library, data repository, training platform, and citizen science application to support aquatic ecoacoustics. Vella et al. report the results of an Australia-wide workshop to identify key issues in realizing open ecoacoustic monitoring in Australia. This is an important exercise that would be valuable to carry out globally.

At a time of unprecedented biodiversity decline, ecoacoustics has the potential to become a key ecological discipline to support cost-effective, long-term monitoring of ecosystems and provide a scalable paradigm for ecological research. The articles in this special issue contribute to the important tasks of developing the language, concepts, theoretical foundations, research tools, methods, and open infrastructures necessary to advance the field in order to address some of the pressing environmental issues of our time through open and equitable science.

Author contributions

AF, SF, and GP: concepts. AE: concepts and revision. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Timing Is Everything: Acoustic Niche Partitioning in Two Tropical Wet Forest Bird Communities

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When acoustic signals sent from individuals overlap in frequency and time, acoustic interference and signal masking may occur. Under the acoustic niche hypothesis (ANH), signaling behavior has evolved to partition acoustic space and minimize overlap with other calling individuals through selection on signal structure and/or the sender's ability to adjust the timing of signals. Alternately, under the acoustic clustering hypothesis, there is potential benefit to convergence and synchronization of the structural or temporal characteristics of signals in the avian community, and organisms produce signals that overlap more than would be expected by chance. Interactive communication networks may also occur, where species living together are more likely to have songs with convergent spectral and or temporal characteristics. In this study, we examine the fine-scale use of acoustic space in montane tropical wet forest bird communities in Costa Rica and Hawai'i. At multiple recording stations in each community, we identified the species associated with each recorded signal, measured observed signal overlap, and used null models to generate random distributions of expected signal overlap. We then compared observed vs. expected signal overlap to test predictions of the acoustic niche and acoustic clustering hypotheses. We found a high degree of overlap in the signal characteristics (frequency range) of species in both Costa Rica and Hawai'i, however, as predicted under ANH, species significantly reduced observed overlap relative to the random distribution through temporal partitioning. There was little support for acoustic clustering or the prediction of the network hypothesis that species segregate across the landscape based on the frequency range of their vocalizations. These findings constitute strong support that there is competition for acoustic space in these signaling communities, and this has resulted primarily in temporal partitioning of the soundscape.

Keywords: acoustic niche hypothesis, birdsong, spectral and temporal overlap, acoustic signaling, temporal partitioning, acoustic clustering hypothesis

INTRODUCTION

Acoustic signaling is a major form of social behavior in many terrestrial and aquatic organisms. When acoustic signals sent from individuals overlap in frequency and time, acoustic interference and signal masking occurs, which may reduce the receiver's ability to discriminate information from the signal (Klump, 1996; Brumm and Slabbekoorn, 2005). Under the acoustic niche hypothesis

(ANH; Krause, 1987, 1993), signaling behavior has evolved to minimize overlap with heterospecific calling individuals through selection on signal structure and the sender's ability to adjust the timing of signals. This hypothesis may be viewed as an extension of the niche theory of Hutchinson (1957) whereby acoustic space is a resource that organisms may compete for and that can be partitioned both spectrally (frequency range of the signal) and temporally.

The ANH is central to describing how animal signals in diverse calling communities are dispersed in space and time and is a major organizing hypothesis in the field of soundscape ecology (Pijanowski et al., 2011). While the ANH makes intuitive sense and is based on both anecdotal and empirical evidence from a broad range of studies and signaling taxa (Farina and James, 2016), the degree to which organisms partition acoustic space in order to reduce interference remains the subject of recent debate (Tobias et al., 2014). Studies in biodiverse calling communities such as cicadas (Sueur, 2002), crickets (Schmidt et al., 2013), anurans (Chek et al., 2003; Sinsch et al., 2012; Villanueva-Rivera, 2014), and birds (Planqué and Slabbekoorn, 2008; Kirschel et al., 2009; Luther, 2009) have found evidence for niche partitioning through the apparent evolution of signal character displacement among species (e.g., by adjusting the frequency range of a signal to minimize overlap with those of other calling species in the community). However, acoustic signaling across a calling community typically occurs within a relatively narrow frequency range that reflects transmissibility of the signal in a particular habitat (Acoustic Adaptation Hypothesis; Morton, 1975; Ey and Fischer, 2009), body size and morphology of the sound producing organs (Ryan and Brenowitz, 1985; Suthers and Zollinger, 2008; Friis et al., 2021), the receiver's ability to detect and interpret signals (Wiley and Richards, 1982), and sexual selection (Mikula et al., 2021). Thus, acoustic signals are relatively constrained in the way their spectral characteristics can vary to reduce interference with other biotic and abiotic sounds.

Time is a second major dimension along which acoustic niche partitioning may occur. Studies have demonstrated that birds can adjust the fine-scale timing of their signals (as opposed to adjusting the signals themselves) to take advantage of temporal gaps in acoustic space and thus minimize temporal acoustic overlap with other birds (Ficken et al., 1974; Popp et al., 1985; Suzuki et al., 2012; Yang et al., 2014) and even insects (Hart et al., 2015). However, those studies that have reported temporal adjustments in signals generally did so for select species or species groups and not the signaling community as a whole. Because the time axis of the acoustic niche is less constrained and thus may be more finely partitioned than the spectral axis, there is great potential for the evolution of behaviors that allow individuals within diverse calling assemblages to adjust the timing of their signals to avoid other signals at the community level. Thus, ANH may operate more through the temporal dimension than the spectral one.

Alternately, signals produced in diverse calling communities may converge in their spectral characteristics, timing, or both. Cody (1969, 1973) and Grether et al. (2009) described convergence in song and other behaviors in sympatric species that may function to reduce interspecific competition. Song characteristics may also converge on spectra that maximize the propagation of vocalizations under the characteristics of the habitat (Cardoso and Price, 2010), or they may converge in time due to intentional song overlapping (Todt and Naguib, 2000; Malavasi and Farina, 2013). Song within diverse signaling communities may also function as an extended communication network that selects for the clustering of species with similar signaling characteristics (Tobias et al., 2014). Under the acoustic clustering hypothesis, instead of partitioning acoustic space, organisms in diverse signaling communities produce signals that converge structurally and/or temporally and that overlap more than would be expected by chance. This hypothesis also predicts that species living together are more likely to have songs with convergent spectral and or temporal characteristics than those not living together (Tobias et al., 2014).

Tropical wet forests have the most species-rich assemblages of organisms that signal acoustically, and thus competition for acoustic niche-space is expected to be strongest there (Slabbekoorn, 2004; Planqué and Slabbekoorn, 2008). In this study, we examine the fine-scale timing of signals in acoustic space and the relevance of the acoustic niche and acoustic clustering hypotheses in montane tropical wet forest bird communities in both Hawaiʻi and Costa Rica. We first assessed the potential for acoustic interference by characterizing the frequency range of signals produced by bird species we recorded during the dawn chorus in each community. We then identified the species associated with each recorded signal at multiple recording stations in each community and measured observed signal overlap within and among species. Null models (Gotelli and Graves, 1996; Masco et al., 2015) were used to generate random distributions of expected signal overlap, and observed vs. expected signal overlap was compared to test predictions of the acoustic niche and acoustic clustering hypotheses for the two bird communities. We also used null models to test a prediction of the acoustic clustering hypothesis that species living together are more likely to have songs with convergent characteristics.

MATERIALS AND METHODS

Study Sites

The Costa Rica study site was within an approximately 360 ha forest fragment at the Organization for Tropical Studies (OTS) Las Cruces Biological Field Station in southern Costa Rica at elevations between 1,025 and 1,200 m. This site is dominated by a mix of primary and secondary wet forest with a canopy up to 30 m tall and a midcanopy layer comprised of broadleaf trees, palms, and tree-ferns. Mean annual precipitation ranges from 3,500 to 4,000 mm and mean annual temperature at Las Cruces Biological Station is ∼21°C (Zahawi et al., 2015). The bird checklist maintained by OTS for the station is comprised of over 400 species, including many migrants (Martìnez, 2010). The Hawaiʻi study site was within the Maulua tract of Hakalau Forest National Wildlife Refuge on the island of Hawaiʻi. The canopy at this site is dominated by *Metrosideros polymorpha-Acacia koa* trees up to 25 m tall with a mid-canopy of at least six native tree and tree-fern species. Mean annual precipitation is approximately 2,250 mm and mean annual daily temperature is ∼15°C at the study site (Juvik and Juvik, 1998). Hakalau contains the most intact forest bird community remaining in the state with nine native species, plus an additional four non-native species that are common in the forest. Within each of the two study sites, we recorded bird songs using autonomous acoustic recorders (SM2 Wildlife Acoustics Inc.) placed ∼1 meter above the ground at six different locations separated by at least 200 m. Recordings were made for 3–5 days at each location, depending on weather conditions. We programmed the acoustic recorders to record at 5-min intervals (5-min on and 5-min off) from first light until 11:30 during the breeding season months of June through July 2012 in Costa Rica and March through April 2015 in Hawai'i. Recordings were made in WAV file format at a sampling rate of 44.1 kHz using a single omnidirectional microphone (SMX-II Wildlife Acoustics) with a sensitivity of −35 dBV/pa and frequency response of 20–20,000 Hz. This study relied solely on the use of passive acoustic monitors placed in the forest to collect acoustic data. No animals were captured, handled, housed, monitored, or followed. No University IACUC permits were required for this study. Permission to conduct fieldwork was given by landowners in both Costa Rica (Organization for Tropical Studies) and Hawai'i (Hakalau Forest National Wildlife Refuge).

Acoustic and Statistical Analysis

Within each study site, we randomly selected 1 day at each of the six sensor locations. We then selected three consecutive 5-min recordings per day during the dawn chorus (when birds are most acoustically active) that did not contain rain for acoustic analysis. Cicada choruses, particularly those of the large-bodied cicada (*Zammara smaragdina*), generally occur near the end of the dawn chorus and can alter signal production for birds in Costa Rica [22]. We excluded recordings with cicada choruses from the analyses, resulting in two recording locations in Costa Rica with only two 5-min recordings available. All selected recordings were then visualized on a spectrogram using Raven Pro 1.5 software (K. Lisa Yang Center for Conservation Bioacoustics, 2014).

We identified the bird species associated with each vocalization, then used the selection tool in RavenPro 1.5 to determine the minimum and maximum frequency and signal start and end time for all bird vocalizations within each 5-min recording period. Only selected vocalizations > 5 dB of the background noise of each recording were included in the analysis. All signals were measured using a Hann window type and a window size of 23.2 ms, window overlap of 50%, and DFT (discreet Fourier transform) size of 1024 samples. For each of the six recording locations in Costa Rica and Hawai'i, we calculated total species richness across the 10–15 min recording periods, and vocalization rate as the total number of vocalizations within a 5-min time period. We examined differences in frequency range (Hz), signal length (s), vocalization rate (per 5-min period), and species richness between Hawai'i and Costa Rica using Wilcoxon Rank Sum tests in R (R Core Development Team, 2018, version 3.5.1).

We used a novel null model approach to test the ANH. For each of the six recording locations in Costa Rica and Hawai'i (10–15-min recording period), we computed the observed number of overlapping pairs of vocalizations as the number of times any two vocalizations overlapped simultaneously on the temporal and spectral axes by at least 1-Hz. We then generated an expected level of overlap by randomizing the beginning of each vocalization (within each 10–15-min recording period) but keeping the duration and frequency range unchanged. This was repeated 500 times to generate an expected distribution of vocalization overlaps. We then used the *pnorm* R function to calculate *P*-values as the probabilities of getting the observed numbers of overlapping pairs of vocalizations, or more extreme numbers, if the null hypothesis is true. Significantly fewer (*P*-value < 0.025) observed overlaps than expected based on the null distribution supports the ANH, while significantly more observed overlaps than expected (*P*-value > 0.975) supports the acoustic clustering hypothesis.

To test an additional prediction of the acoustic clustering hypothesis that species with similar vocalization characteristics are more likely to co-occur across the landscape, we calculated the observed number of species pairs with vocalizations that overlapped in mean frequency range at each recording location (six in Costa Rica and six in Hawai'i). We then calculated an expected number of species pairs with overlapping vocalizations by randomizing the occurrence of species at each recording location (from the pool of all species recorded in either Costa Rica or Hawai'i) while keeping species richness at that location unchanged. This was repeated 500 times to generate an expected distribution of number of species pairs that overlap in frequency and used the *pnorm* function in R to calculate *P*-values as described above. This allowed us to examine if the species detected at a recording location converge in their song characteristics more than those collected randomly from the pool of species that were detected from the study site.

RESULTS

Vocalizations Pool

We detected 39 vocalizing species from Costa Rica and 10 from Hawai'i in the recordings selected for analysis. Three of the 10 species from Hawai'i were non-native (*Cardinalis cardinalis*, *Leiothrix lutea*, *Zosterops japonicus*) and accounted for < 10% of total vocalizations. There was a total of 2,880 vocalizations with a duration of 1,614 s from Costa Rica and 4,489 vocalizations detected with a duration of 6,097 s from Hawai'i. According to species accumulation curves the recording length (10–15 min) was long enough to capture species diversity at a location (**Figure 1**). In all recording locations except one in Costa Rica (CR1), the number of recorded species reached a plateau by the end of the recording period.

Potential for Overlap Between Species Vocalizations

We found a high degree of overlap in the frequency range used by species in both Costa Rica and Hawai'i (**Figure 2**). In

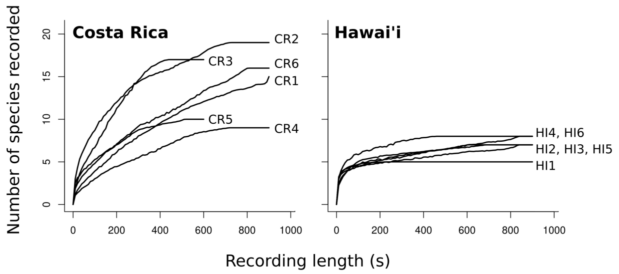

FIGURE 1 | Species accumulation curves (mean of 500 iterations) for each of six recording locations in Costa Rica and Hawai‘i.

Hawai‘i, 44 of the 45 pairs of species (i.e., 98%) had potentially overlapping vocalizations (i.e., the mean frequency range of their signals overlapped by at least 1-Hz). Indeed, only the native *Loxops coccineus* and the non-native *Cardinalis cardinalis* vocalized using totally different frequencies (**Figure 2**). In Costa Rica, 570 of the 741 pairs of species (i.e., 77%) had potentially overlapping vocalizations. The mean frequency range used by species was significantly higher in Hawai‘i than in Costa Rica (**Figure 3A**, $P = 0.0014$) while species' vocalization lengths were similar (**Figure 3B**, $P = 0.1320$). Vocalization rates (i.e., the number of recorded vocalizations per 5-min. period) tended to be lower in Costa Rica (median = 135) than Hawai‘i (median = 258) (**Figure 3C**, $P = 0.1320$), but the number of species per location was significantly higher in Costa Rica (median = 16) than in Hawai‘i (median = 7) (**Figure 3D**, $P = 0.0047$).

Temporal Overlap

Observed signal overlap was far less than expected if the beginning time of each vocalization was random. Despite the high degree of overlap in frequency range used by species as described above for Costa Rica and Hawaii, the temporal distribution of vocalizations was arranged in a way to reduce vocalization overlaps (**Figure 4**). In most recording locations the observed number of pairs of overlapping vocalizations (in both time and frequency) was significantly lower than expected under random temporal distribution of vocalizations.

Species Co-occurrence

There was little relationship between species distribution (recording locations the species was detected at) and the vocalization frequencies of species across recording locations in Costa Rica and Hawai‘i (**Figure 5**). In most locations the observed number of species pairs vocalizing in overlapping frequencies (by at least 1-Hz) did not differ significantly from expectations under random distribution of species between locations. However, in two locations in Costa Rica the observed number of species pairs vocalizing in overlapping frequencies was significantly higher than expected, indicating that species with overlapping frequencies were more likely to occur in these locations than species with non-overlapping frequencies.

DISCUSSION

There was a high degree of overlap in the spectral characteristics of the signals (vocalization frequency range) of species in both Costa Rica and Hawai‘i, and thus great potential for interference between the different signals. However, we found significantly fewer observed overlaps of acoustic signals than expected if the beginning of signals were dispersed randomly at five out of six locations in Costa Rica and 4 out of six in Hawai‘i (**Figure 4**). We found only weak evidence for the prediction of the acoustic clustering hypothesis that species living together (at the level of recording location within a study site) are more likely to have songs with convergent spectral and or temporal characteristics than those not living together (**Figure 5**). There was also no support for the hypothesis that signals would be temporally clustered in acoustic space as there were no cases from our recording locations in either Costa Rica or Hawai‘i where the observed number of overlaps between signals was greater than expected (based on randomization of signal timing). Together, these findings indicate that birds adjust the timing of their signals to minimize spectral overlap at the community level and constitute strong support for ANH.

Adaptive timing of signal production has been demonstrated for select pairs or groups of species, but has not yet been shown to operate across entire bird communities within the short temporal scales as described here. Cody and Brown (1969) were the first to demonstrate that birds can reduce competition for acoustic space by adjusting the fine-scale timing of their signals. In this case wren-tits (*Chamaea fasciata*) and Bewick's wrens (*Thryomanes bewickii*) were shown to sing asynchronously, based on when the other species was vocalizing. Similarly, Ficken et al. (1974) showed that two species of forest birds, the least flycatcher (*Empidonax minimus*) and red-eyed vireo (*Vireo olivaceous*), adjust the temporal pattern of their singing to reduce overlap among their songs. Popp et al. (1985) showed that four species that commonly sang in a Wisconsin broad-leaf forest, wood thrush (*Hylocichla mustelina*), eastern wood pewee (*Contopus virens*), great crested flycatcher (*Myiarchus crinitus*), and ovenbird (*Seiurus aurocapilla*), significantly avoided singing during the song of the other species. Yang et al. (2014) experimentally demonstrated that Eurasian wrens (*Troglodytes troglodytes*) avoid song overlaps by timing their songs to start right after the end of a stimulus song. Planqué and Slabbekoorn (2008) examined signal dispersion in a diverse Peruvian bird assemblage and found significantly less temporal overlap among select species pairs that vocalize in overlapping frequencies. Similarly, Luther (2009) created principal components from the acoustic characteristics of signals of 82 species in a Brazilian wet forest and found evidence of acoustic partitioning for those species that sing at similar locations and time. In particular, species that sang at a recording location during a 30-min period beginning at sunrise had songs that were more greatly dispersed in acoustic space than those that sang at different times throughout the morning. We should note that analysis of principal components of signal characteristics is a helpful way to examine how the signals of different

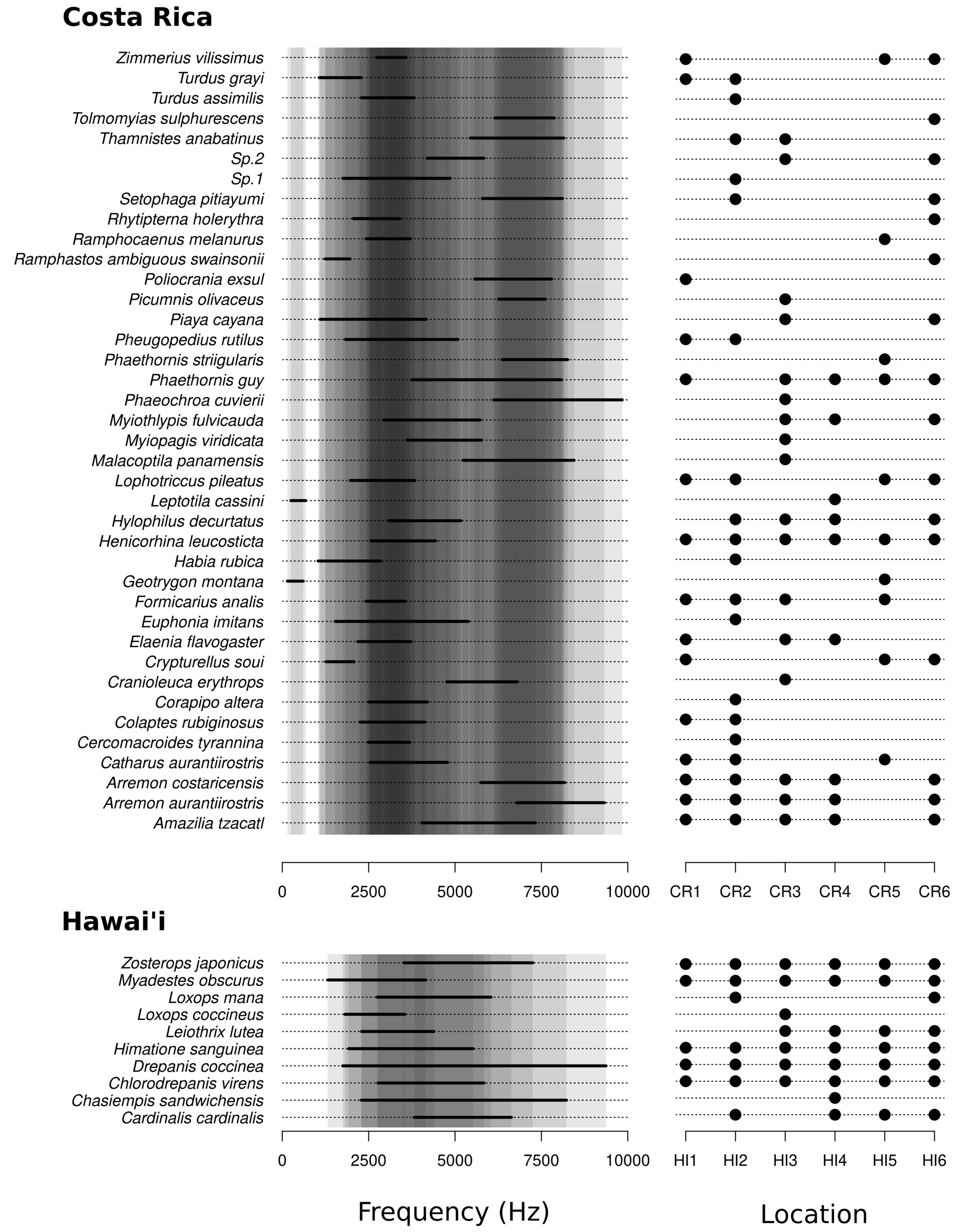

FIGURE 2 | List of detected species with their vocalization ranges (**left** figures) and their locations of occurrence (**right** figures) in Costa Rica and Hawai'i. On the left figures, gray background represents potential overlapping in a given frequency, the darker the background, the higher the number of species using this frequency.

species are dispersed relative to each other but cannot clarify differences in observed vs. expected (random) overlap of those characteristics in real time.

Can birds process incoming auditory signals quickly enough to avoid overlap between their own signals and those of others in a species rich calling community? The mechanisms by

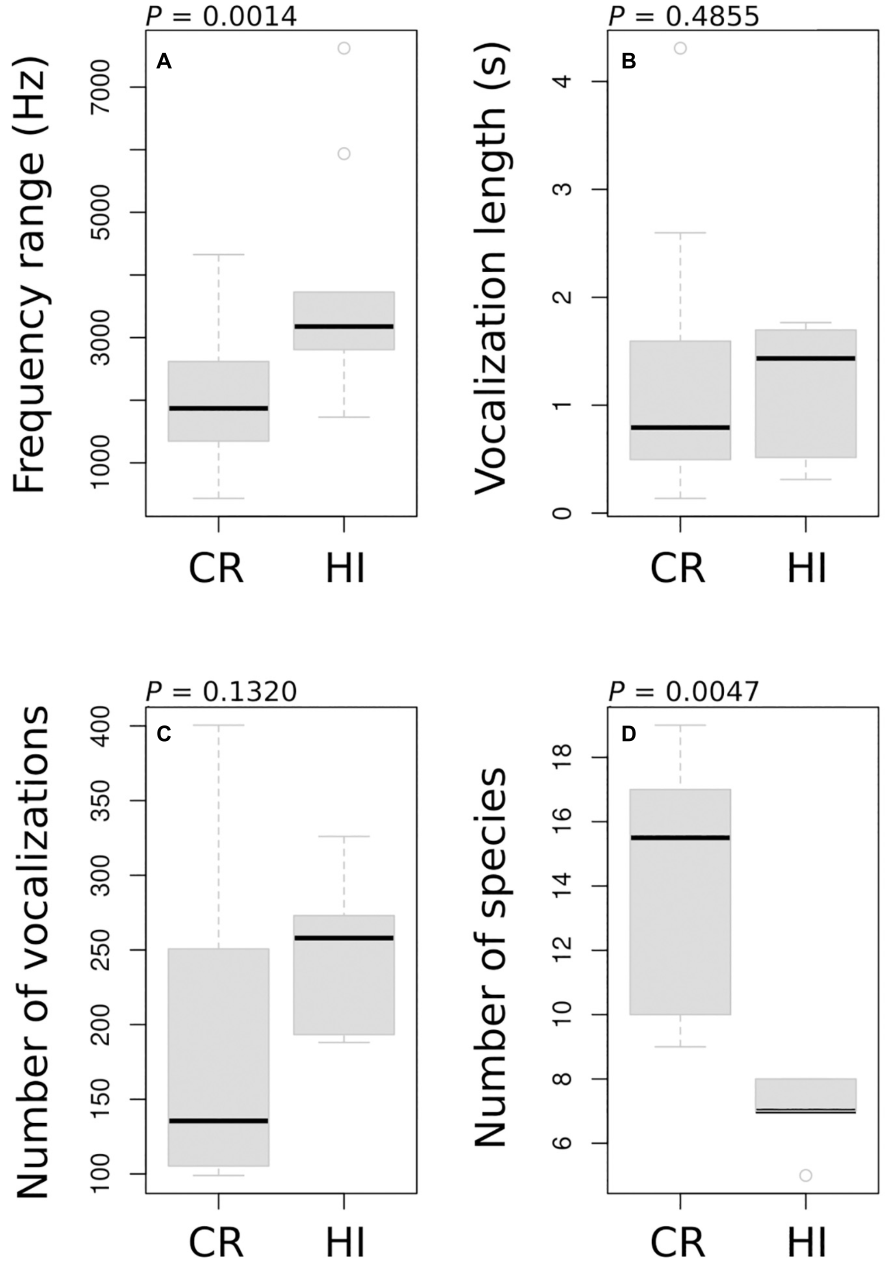

FIGURE 3 | Comparison of species vocalization characteristics **(A,B)**, the number of vocalizations per 5-min record **(C)**, and number of species recorded per location **(D)** between Costa Rica (CR) and Hawai'i (HI) (*P*-value indicates the significance of Wilcoxon's rank sum test).

which birds are able to temporally partition acoustic space have received little attention, but center on how long it takes for a signal to travel from sender to receiver, and how long it takes the receiver to process it and make a decision to not sing. Sound travels approximately 1 m in 2.9 ms (0.0029 s) so it would take a signal at most about 90 ms to reach a receiver within its approximate 30 m radius signal envelope. Reaction times to auditory signals have been described for a range of species and environmental conditions, particularly for those that engage in elaborate duets that involve precise timing of signals among mates. Thorpe (1963) measured a mean reaction time of 144 ± 12.6 ms between first and second note in antiphonal duetting black-headed gonolek (*Laniarius erythrogaster*) pairs, and Power (1966) reported mean reaction times ranging from 100 to 164 ms in duetting orange-chinned parakeets (*Brotogeris jugularis*). Mean reaction time to sound stimuli for starlings (*Sturnus vulgaris*) in a laboratory setting was 80 ms ± 14.4 ms (Pomeroy and Heppner, 1977) while

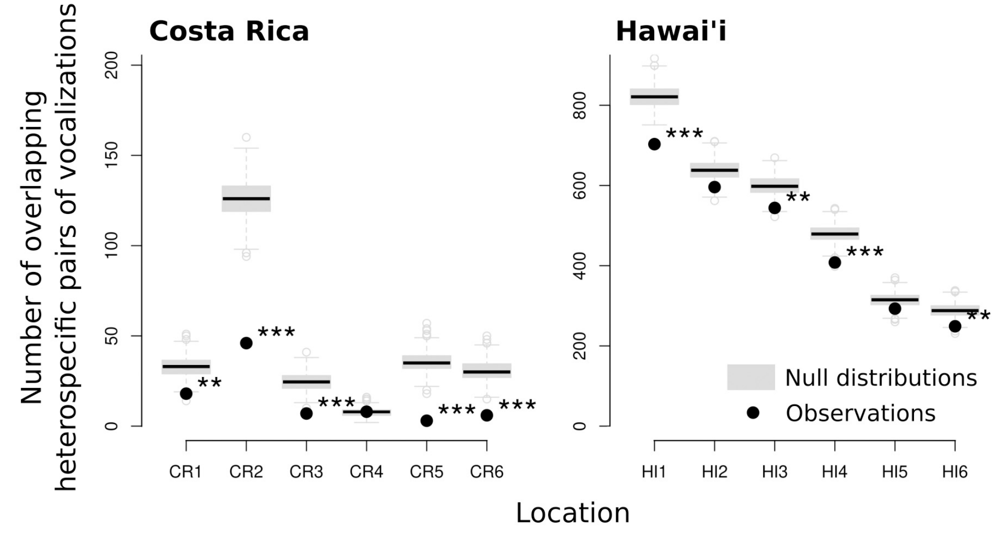

FIGURE 4 | Comparison of observed and expected number of heterospecific pairs of vocalizations with overlapping vocalization times and frequencies in each location (significance "***"α = 0.001, "**"α = 0.01). The null distributions were generated using 500 randomizations of the beginning of vocalizations (keeping number, length and spectral characteristics unchanged).

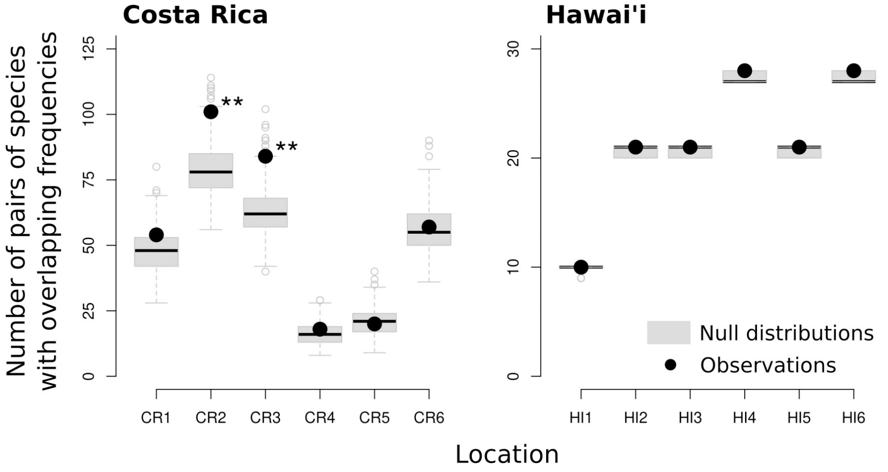

FIGURE 5 | Comparison of observed and expected number of pairs of species with overlapping vocalization frequencies in each location (significance "**"α = 0.01). The null distributions were generated using 500 randomizations of species distribution across locations (keeping species richness per location unchanged).

Cuthbert and Mennill (2007) described mean gaps between M and F phrases in Plain wren (*Thryothorus modestus modestus*) duets to be as little as 50 ms. Thus, birds may make a decision in as little as 50 ms or less to hold off on vocalizing if they detect another vocalization in very close proximity, with the lag time in the decision to not produce a vocal signal due to the presence of another signal increasing by 2.9 ms for each meter further away a signaler is located. The ability to avoid signal overlap would therefore increase with decreasing distance from signaler to receiver. This may be one reason (along with amplitude differences) why signals that are produced at greater distances overlap more than those produced nearby.

Birds may also make use of temporal patterns in song among acoustically active species, allowing them to better predict when empty "niches" will occur in acoustic space and to quickly fill them. Of course, timing songs based on the temporal patterns of other species can become complicated in a diverse calling community, and most studies of song timing based on the calls of other individuals have primarily been demonstrated for intraspecific song (Todt and Naguib, 2000). For example, both blackbirds (Wolffgramm and Todt, 1982) and nightingales (Hultsch and Todt, 1982) have been shown to base the timing of their song on the patterns of other calling individuals. In a diverse neotropical wet forest in Brazil, Luther (2008) demonstrated that four co-occurring species of birds coordinated both the timing and response of signals in order to reduce acoustic interference during the dawn chorus. Malavasi and Farina (2013) found evidence of coordinated choruses among different bird species in an Italian bird community whereby deliberate temporal overlaps occurred while at the same time avoiding spectral overlap and thus signal jamming. Some bird species may also be specialized for calling at different periods during the dawn chorus, possibly to take advantage of favorable environmental conditions for sound propagation. There may be a range of strategies among species in each community for avoiding overlap, and none are mutually exclusive. In fact, some of the acoustic overlaps we detected may be intentional forms of song-overlap within and among species (Todt and Naguib, 2000).

In weak support of the network hypothesis, we did observe significantly more species pairs with overlapping frequencies co-occurring than expected under the null at two out of six recording locations in Costa Rica, though there were none in Hawai'i. This indicates that bird species in these forests may segregate to some degree across the landscape based on the frequency range of their vocalizations. It would be worthwhile to expand the number of sites and recording locations in Costa Rica to further explore the possibility that there is synchronization in the use of acoustic space through interactive communication networks. In contrast to our findings, and in support of the network hypothesis, Tobias et al. (2014) and Kleyn et al. (2021) reported significant clustering of acoustic signals in a species-rich wet forest bird community in southeast Peru and southeastern Brazil, respectively. However, the temporal scale at which clustering occurred was within 10-min time blocks, much larger than the finer scale of individual songs that we report here. The more subtle form of partitioning that we describe provides evidence that birds have evolved and/or learned behaviors to significantly reduce interference and masking by other birds signals primarily through fine-scale temporal partitioning. This reduces the selection pressure for the evolution of structurally dissimilar signals, and allows birds to produce signals that are better adapted for information transmission (e.g., mate attraction, territoriality, contact) in their particular habitat. This form of acoustic niche partitioning can occur even where signal synchrony and communication networks are common in the community. Thus, temporal acoustic niche partitioning and acoustic clustering (that results from communication networks) are not necessarily mutually exclusive, at least at the level at which they have been examined to date.

While we found evidence for acoustic niche partitioning in both communities, and despite similarities in signaling rate and in the range of spectral bandwidths used, we found that overlap between different vocalizations was more common in Hawai'i than in Costa Rica (**Figure 4**), possibly because greater species richness in Costa Rica has led to stronger selection for reducing interspecific signal overlap there. In addition, the island of Hawai'i is geologically younger than much of Costa Rica (∼0.5 vs. 2.5–15 my) (Alvarado and Cárdenes, 2016) so there are likely differences in length of time available for the evolution of signal character displacement between locations. There may be a phylogenetic effect as well—the Costa Rican bird community represents a far greater diversity of avian lineages than Hawai'i, where most of the current species have evolved through adaptive radiation from just a handful of colonizations from distant continents (Freed et al., 1987; Lerner et al., 2011). Differences in signal function may also partially explain the different levels of signal overlap between the two communities. Most of the Costa Rica species sampled here maintain year-round territories (Stiles and Skutch, 1989), whereas most of the Hawaiian species are generally non-territorial outside the breeding season. The function of song may be more associated with promoting social cohesion, with less selection against reducing interspecific signal overlap, in communities with higher densities of individual species that are non-territorial.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://datadryad.org/stash/dataset/doi:10.5061/dryad.w6m905qkp.

ETHICS STATEMENT

Ethical review and approval was not required for the animal study because the study relied solely on the use of passive acoustic monitors placed in the forest to collect acoustic data. No animals were captured, handled, housed, monitored, or followed.

AUTHOR CONTRIBUTIONS

PH and ES-G conceived the idea. PH acquired the data. TI, KP, ES-G, GT, and AT-J analyzed the data. PH, KP, and TI wrote the first draft. All authors contributed to interpreting the results and writing the final draft.

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Multi-Index Ecoacoustics Analysis for Terrestrial Soundscapes: A New Semi-Automated Approach Using Time-Series Motif Discovery and Random Forest Classification

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High rates of biodiversity loss caused by human-induced changes in the environment require new methods for large scale fauna monitoring and data analysis. While ecoacoustic monitoring is increasingly being used and shows promise, analysis and interpretation of the big data produced remains a challenge. Computer-generated acoustic indices potentially provide a biologically meaningful summary of sound, however, temporal autocorrelation, difficulties in statistical analysis of multi-index data and lack of consistency or transferability in different terrestrial environments have hindered the application of those indices in different contexts. To address these issues we investigate the use of time-series motif discovery and random forest classification of multi-indices through two case studies. We use a semi-automated workflow combining time-series motif discovery and random forest classification of multi-index (acoustic complexity, temporal entropy, and events per second) data to categorize sounds in unfiltered recordings according to the main source of sound present (birds, insects, geophony). Our approach showed more than 70% accuracy in label assignment in both datasets. The categories assigned were broad, but we believe this is a great improvement on traditional single index analysis of environmental recordings as we can now give ecological meaning to recordings in a semi-automated way that does not require expert knowledge and manual validation is only necessary for a small subset of the data. Furthermore, temporal autocorrelation, which is largely ignored by researchers, has been effectively eliminated through the time-series motif discovery technique applied here for the first time to ecoacoustic data. We expect that our approach will greatly assist researchers in the future as it will allow large datasets to be rapidly processed and labeled, enabling the screening of recordings for undesired sounds, such as wind, or target biophony (insects and birds) for biodiversity monitoring or bioacoustics research.

Keywords: acoustic complexity index, acoustic ecology, acoustic indices, ecoacoustics, terrestrial soundscapes

INTRODUCTION

Biodiversity loss is a global environmental issue (Cardinale et al., 2012), and it is now imperative to develop methods to efficiently monitor wildlife, accounting for spatial and temporal coverage (Joppa et al., 2016). Remote sensing techniques are being used to fill this gap, as they can be applied over large geographic areas where access may be difficult, allowing for some degree of unattended monitoring (Kerr and Ostrovsky, 2003). Remote sensing techniques include a range of technologies, like satellite imaging (Bonthoux et al., 2018), camera traps (Fontúrbel et al., 2021), Unmanned Aerial Vehicles (UAVs) (Nowak et al., 2019), and passive acoustic monitoring (PAM) (Froidevaux et al., 2014; Wrege et al., 2017).

Passive acoustic monitoring is now routinely used in terrestrial environments to monitor biodiversity (Gibb et al., 2019) with several purposes, such as understanding acoustic community composition of frog choruses (Ulloa et al., 2019), investigating acoustic species diversity of different taxonomic groups (Aide et al., 2017), and bird species recognition based on syllable recognition (Petrusková et al., 2016). Long-term recording can enable detection of species responses to important environmental impacts like climate change (Krause and Farina, 2016), and species recovery following extreme weather events (Duarte et al., 2021). However, recordings comprise large datasets which can be challenging to store, access and analyze (Ulloa et al., 2018). Subsampling is one way of dealing with these constraints, but it can limit the temporal and/or spatial scale of monitoring, therefore methods to analyze and filter recordings are necessary.

Currently, analysis of acoustic recordings still heavily relies on manual listening and inspection of recordings: this greatly limits the applicability of PAM. One alternative to that is to summarize acoustic information using acoustic indices, which mathematically represent different aspects of sound (e.g., frequency, intensity, etc.) (Sueur et al., 2014). Acoustic indices have, in some cases, been inspired by ecological indices. For example, the acoustic diversity index (Villanueva-Rivera et al., 2011) is based on the Shannon diversity index (Shannon and Weaver, 1964). NDSI (Gage and Axel, 2014) measures the ratio between biophony (biological sounds) and anthrophony (human and technological sounds) and is derived from NDVI, an index used in the remote sensing analysis of vegetation (Pettorelli, 2013). Acoustic indices have been used in different contexts such as to evaluate the differences in faunal beta-diversity between forests and plantations (Hayashi et al., 2020), to detect rainfall in acoustic recordings (Sánchez-Giraldo et al., 2020), to examine differences among indices representing taxonomic groups (e.g., birds, anurans, mammals and insects) (Ferreira et al., 2018), to relate indices with bird diversity (Tucker et al., 2014), and to identify frog species (Brodie et al., 2020).

Although there are numerous acoustic indices to choose from, different indices represent different acoustic phenomena in terrestrial environments, and the translation of acoustic into ecological information may vary depending on the context (Machado et al., 2017; Jorge et al., 2018; Bradfer-Lawrence et al., 2020). While there is no consensus on linking one index to one taxa, research has shown that combining indices can provide a good representation of different soundscapes (i.e., sounds in the landscape), especially across varying environments (Towsey et al., 2018), and can even be used to recognize different species (Brodie et al., 2020). Visualization tools such as false-color spectrograms (FCS) successfully combine three acoustic indices [Acoustic Complexity Index (Pieretti et al., 2011), Temporal Entropy (Sueur et al., 2008) and Events per Second (Towsey, 2018)] allowing different sound sources to be identified. The FCS and its combination of indices have been shown to provide a good representation of soundscapes in different contexts (e.g., Brodie et al., 2020; Znidersic et al., 2020). While visual representations of soundscapes are useful for scanning recordings for different phenomena (like rain, wind, or a frog chorus, for example), there is currently no available tool to statistically analyze these images. The underlying index data used to create the FCS can be retrieved and analyzed, but the mathematical interpretation of multiple indices remains a challenge, and therefore the statistical analysis of single indices is currently the favored approach. If mass deployments are required, [e.g., Australian Acoustic Observatory—(Roe et al., 2021)], we need to develop reliable, reproducible analysis methods with some degree of automation.

Furthermore, most statistical methods used for continuous recordings require an approach that accounts for temporal autocorrelation of the data (i.e., most statistical tests applied in ecology require independence of data). This means that each minute is not independent of the previous one in a recording, and this is often ignored in ecoacoustic studies. While spatial autocorrelation can be dealt with through experimental design, temporal correlation exists even when data are non-continuous (e.g., subsampled for example 1 min every 15 min) or arbitrarily split into time periods (e.g., day/night). Standard statistical approaches which assume independence of data cannot be applied for autocorrelated data.

Aiming to address the different challenges faced by researchers when analyzing recordings, we present a novel workflow for analyzing multi-index acoustic data. Our goal was to provide a tool that can be used by ecologists in a rapid assessment of terrestrial acoustic recordings. By having such a tool, ecologists can forward recordings of interest (i.e., for species identification) to specialists more efficiently, but also have quick metrics to compare ecosystems and/or recordings from different points in time. To deal with autocorrelated data capturing repeated patterns in acoustic indices is an alternative. Using the Hierarchical Based Motif Enumeration (HIME) (Gao and Lin, 2017) of acoustic indices, repetitive patterns of the data were detected (here referred to as motifs) in continuous recordings. As the algorithm searches for repetition of patterns in the time-series (Zolhavarieh et al., 2014) it was expected that noisy minutes (i.e., non-signal) would be excluded from the results as they tend to be random and not have a structure that repeats across time. Here we outline a semi-supervised method to classify the motifs according to dominant sounds. We demonstrate the transferability of the analysis in different environments and timescales with two case studies using data from two distinct ecosystems and recorded with different sampling schemes and devices.

MATERIALS AND METHODS

Acoustic Analysis

The recordings were analyzed using AnalysisPrograms.exe (Towsey et al., 2020) three indices were used to create FCS (Towsey et al., 2014). These indices are: (1) Acoustic Complexity – quantification of relative changes in amplitude (Pieretti et al., 2011); (2) Temporal Entropy – concentration of energy overall the amplitude envelope (Sueur et al., 2008); (3) Events Per Second – number of acoustic events that exceeds 3dB per second (Towsey, 2018). FCS have been used successfully to represent a range of different soundscapes (Brodie et al., 2020; Gan et al., 2020; Indraswari et al., 2020; Znidersic et al., 2020), and provide a visual tool to aid in the identification of sounds, reducing the time required for verification of data.

The analysis was done directly on the unprocessed recordings, meaning that no noise (unwanted sounds) was removed beforehand. Acoustic data will have different sound sources and the presence of noise is common. Moreover, pre-processing can be time consuming, and so we tested the method without any type of pre-processing (i.e., cleaning up) of the data.

All analyses were performed using R and scripts are available at http://doi.org/10.5281/zenodo.4784758 (Scarpelli, 2021).

The HIME algorithm was applied to find significant motifs in variable length time-series. This algorithm was used because it accounts for temporal structure in data. It is widely used in other fields, including medical research (Liu et al., 2015), weather prediction (McGovern et al., 2011), and animal behavior (Stafford and Walker, 2009). The algorithm works by applying a moving window along the time-series and searching for repetitive sequences. The user sets the minimum window length, which will be the starting point and the length will progressively increase. There is a compromise between the window length and the motifs' identification: small windows are more likely to have a pair, but not with necessarily meaningful patterns while big windows are less likely to have a matching sequence.

The analysis process can be seen in **Figure 1** and detailed steps are presented in the text below.

Subsequence Time-Series Search

The step-by-step process of the sub-sequence search is described in **Table 1**.

Feature Extraction and Random Forest Model

Wavelet transform (Lau and Weng, 1995) and feature extraction were then performed on individual motifs (which are also time-series). Wavelets was used so both frequency and time information were preserved when extracting features. Each time-series was treated as an individual sample for feature extraction, training, and testing. Based on the extracted features, a Random Forest (RF) classification model was trained using manually labeled data and then the classification model was used to discriminate between sound categories within motifs, attributing ecological meaning to the motifs. RF classification is a supervised machine learning technique (Breiman, 2001), and has been used in numerous research fields such as genomics (Díaz-Uriarte and Alvarez de Andrés, 2006), satellite image classification (Pal, 2005), and soundscape analysis (Buxton et al., 2018). The algorithm classifies the data into groups using different combinations of features. It has been reported to perform well because it uses an ensemble learn strategy by combining different methods during the learning process, providing more accurate and generalized results (Cutler et al., 2012). In this study all the motifs were labeled. It was necessary to first test the testing sample size that maximized accuracy, while avoiding overfitting. This was done by progressively increasing training samples and measuring accuracy at each round. Accuracy was not greatly improved using more than 30% labeled data, and so this threshold was established. It was important that motifs were labeled using their corresponding spectrogram to show exactly what sound the index was capturing. In cases where the signal was unclear, these recordings were sound-truthed. This allowed maximizing label information, while keeping some generalization (i.e., not identifying species, for example). More categories of labels can increase training difficulty because categories become similar, making it difficult for the algorithm to discriminate between them. Additionally, biophony is now classified according to their soundtope (Farina, 2014). Soundtopes are the collective sounds produced by biophony at the same time.

Table 2 describes each step of the process and the expected output.

Case Study

One of the limitations of using acoustic indices as a measure of biodiversity is that recent studies have shown variable success, that is largely context-dependent. In this case study, we demonstrate how our novel method overcomes this issue by testing and validating our approach in two very different ecosystems, including varying background noise and different acoustic recorders.

Dataset 1: Bowra

Data were collected at Bowra Wildlife Sanctuary in semi-arid western Queensland, Australia (**Figures 2A,B**). The sanctuary is owned by the Australian Wildlife Conservancy, and it is known for its abundant birdlife. The property covers more than 14,000 hectares in the Mulga Lands Bioregion of Australia (**Figure 2B**). The topography is mostly flat, and the vegetation is dominated by *Acacia* woodlands, Mitchell tussock grasslands, and Coolabah (*Eucalyptus coolabah*) woodlands along ephemeral creek lines. The region has very low annual precipitation rates, with an annual mean of 373.3 mm (Australian Government Bureau of Meteorology, 2020).

Audio Sampling

Data were acquired using 12 SongMeter four recorders (Wildlife Acoustics), with a sampling rate of 44.1 kHz and 16 bits in stereo. Recorders were placed 200 m apart, (**Figures 2B,C**), operating continuously for approximately 40 h/sampling point. Sampling points were selected across a gradient of different vegetation communities and proximity to creek lines. To demonstrate the

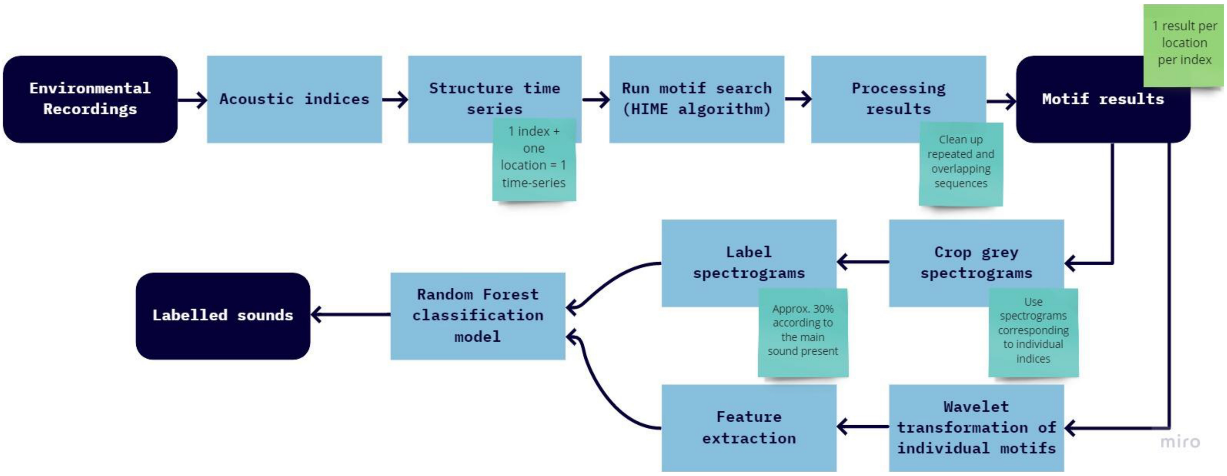

FIGURE 1 | Flowchart with the analysis steps and expected results.

TABLE 1 | Description of the steps to be followed to perform subsequence motif search, actions that should be done by the user and expected output.

Step	Action	Output
1.1 Structure acoustic indices values as time-series	Order acoustic indices as a time series (i.e., date, time, and minute).	One time-series per index/location, resulting in three files (one per index) per location.
1.2 Motif search algorithm	Set start window length.	Motifs start, end, length and distance metric.
1.3 Process motif results	Using the output from the motif search and provided parameters, overlapping sequences were identified and removed, retaining only non-overlapping patterns. This is conducted for each index and location because different indices measure different aspects of sound, and therefore overlaps in time were permitted across different indices.	Unique sequences, i.e., non-overlapping patterns
1.4 Crop spectrograms using motif parameters	Cut spectrograms corresponding to each index (provided by AnalysisPrograms.exe) according to each motif to provide images for each sequence.	One image per motif

methods in a graphical way, one sampling point was chosen (white square in **Figure 2C**) for data visualization.

The data collection period coincided with a dust storm with high wind speeds, so recordings were very noisy and biophony was masked for large recording segments (pink/purple across all frequency bands in **Figure 4A**). While noise presents a challenge for data analysis, environmental conditions vary and are beyond researcher control, thus it is important that the method presented here is tested under varied and real circumstances.

Dataset 2: Samford Ecological Research Facility

The second dataset used was 1 month of data (March 2015) from the Samford Ecological Research Facility (SERF), a SuperSite in the Terrestrial Ecosystem Research Network (TERN). The TERN initiative established in 2009 monitors terrestrial ecosystem attributes over time at a continental scale. The data collected through this initiative are freely available through the TERN data portal[1].

Samford Ecological Research Facility is situated approximately 20 km from Brisbane in the South-East Queensland Bioregion, Australia (**Figure 3**). The region experiences a sub-tropical climate and high levels of forest fragmentation and urbanization (**Figure 3**). The topography is gently undulating, and the vegetation consists of Eucalypt open forest (dominated by *Eucalyptus tereticornis*, *Eucalyptus crebra* and *Corymbia* species) and notophyll vine forest.

Audio Sampling

The audio was collected continuously for 1 month using one SongMeter2 (Wildlife Acoustics) at 22,050 Hz, in WAV format. The sampling point was located on the edge of the property as demonstrated in **Figure 3**.

RESULTS

Different lengths and minimum window sizes were tested for the two datasets and the minimum length selected was 30 min for both datasets. From an ecological perspective, 30 min of recording provides good resolution of fine-scale phenomena (e.g., a single species calling). Moreover, it can reveal soundscape changes throughout a day as the HIME progressively increases the window size. Having the same window length for both datasets is an advantage as it allows future comparisons to be made between results. All the selected motifs were labeled for

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[1] https://portal.tern.org.au

TABLE 2 | Description of the steps to be followed to random forest classification, actions that should be done by the user and expected output.

Step	Action	Output
2.1 Feature extraction	Wavelet transform was used to extract the discriminant features of the motifs (*dwt* function in *wavelets* package in R (Aldrich, 2020), with *haar* filter applied and *periodic* boundary)	Individual time-series transformed
2.2 Labeling the data	Data was labeled using two categories of sounds: *Class*, representing the dominant sound present (i.e., bird, insect, wind, silence), and *Component*, representing the category the Class belongs to in the soundscape context (i.e., geophony, biophony or silence). A set of labeling rules was followed to standardize the process, minimize biases and simplify data input into the RF algorithm. The motifs were labeled according to the predominant sound visualized on the corresponding spectrogram. For motifs with more than one sound source, the dominant sound in terms of duration and/or intensity was chosen as its corresponding label. Motifs that were predominantly quiet but with a minimum presence of any sound type, were labeled accordingly. New label categories were only created if the label was persistent throughout the dataset, providing enough samples for training and testing.	30% of dataset labeled
2.3 RF—component	Classification was first run based on Component, splitting the data into bigger groups, and then categorized into constituent Classes. Preference was given to maintaining a similar number of labels per category, index, and location, so that the training set contains most of the expected variation. However, depending on the amount of variation within each Class, it may be necessary to have more labels in one Class than another. To maintain balance between Classes and the need to prioritize labels in a certain Class, labeling and training was undertaken iteratively. That is, a small subset of labels were created (approximately 10%), the RF model run, accuracy checked (count of correctly assigned labels), and the process repeated. In each round, the new labels were taken from the random sample pool but because balance plays a significant role, if a category needed more labels (i.e., accuracy was much lower than other categories), they were "arbitrarily" selected from the pool. The "out-of-bag" method of selecting predictors used in the RF algorithm usually results in overfitting avoidance (Genuer et al., 2010), nevertheless, overfitting can still occur if run without splitting the data into training and testing. Therefore, training was kept between 60–70%, and testing between 40–30%.	Best number of features to be used, mean decrease in accuracy (based on Gini coefficient) and overall accuracy of the classification model (n labels correctly assigned/n labels incorrectly assigned)
2.4 RF—optimizing Component	The first run of the complete model was undertaken with default parameters and then optimized by finding the hyperparameters, i.e., the number and type of wavelet features that contribute the most to improving accuracy. The number of decision trees was 500. The parameters were optimized by using the function *tuneRF* in package *randomForest* in R (Liaw and Wiener, 2003) and by selecting the variables with mean decrease accuracy > 0. If accuracy was improved with optimized parameters, this version was retained. Lastly, the model was run for the entire dataset to classify unlabeled data.	All motifs with component labels
2.5 RF—class	Repeat steps from the Component model using only data that had been labeled by the algorithm as biophony (unwanted Classes from the previous labeling—wind, rain, and silence—were now filtered). In addition, the accuracy across Classes was iteratively checked, and if unbalanced, more motifs were labeled.	Best number of features to be used, mean decrease in accuracy (based on Gini coefficient) and overall accuracy of the classification model (n labels correctly assigned/n labels incorrectly assigned)
2.6 RF—optimizing classes	The first run of the complete model was undertaken as described above in 2.4.	All motifs with Classes labeled

both datasets so that the model accuracy could be measured, and sample size could be correctly estimated. The Bowra dataset had 549 selected motifs with a mean distance of 3.88 ± 1.24 and a mean length (in minutes) of 35.14 ± 3.88. The SERF dataset had 789 selected motifs with a mean distance of 4.28 ± 0.81 and a mean length (in minutes) of 36.02 ± 2.83. SERF dataset had 10% more hours than Bowra (542 and 494, respectively) and 43% more selected motifs.

Dataset 1: Bowra

Figures 4C,E,G show the motifs found (in color) for each index in relation to the whole time-series for one sampling point at Bowra. These figures reveal that for all three indices, the hours of the day that correspond to dawn (5:15–5:16 h) and dusk (6:49–6:50 h) most motifs were identified, while almost none in the middle of the day. It can also be seen on the gray-scale spectrograms how each index is capturing slightly different soundscape components, although all of them recorded wind in the middle of the day (blurred sections) (**Figures 4B,D,F**). It is also evident different motifs identified across indices (**Figures 4C,E,G**).

Component Classification

The Component classification had an overall accuracy of 75%. The accuracy per category and overall misclassifications can be seen in **Figure 5**. The model correctly identified most biophony (94%) motifs while geophony motifs were less accurately identified (45%).

Class Classification

The overall accuracy of the Class labels was 70%. The model performed better for birds (80%) than insects (59%) for this dataset (**Figure 6**).

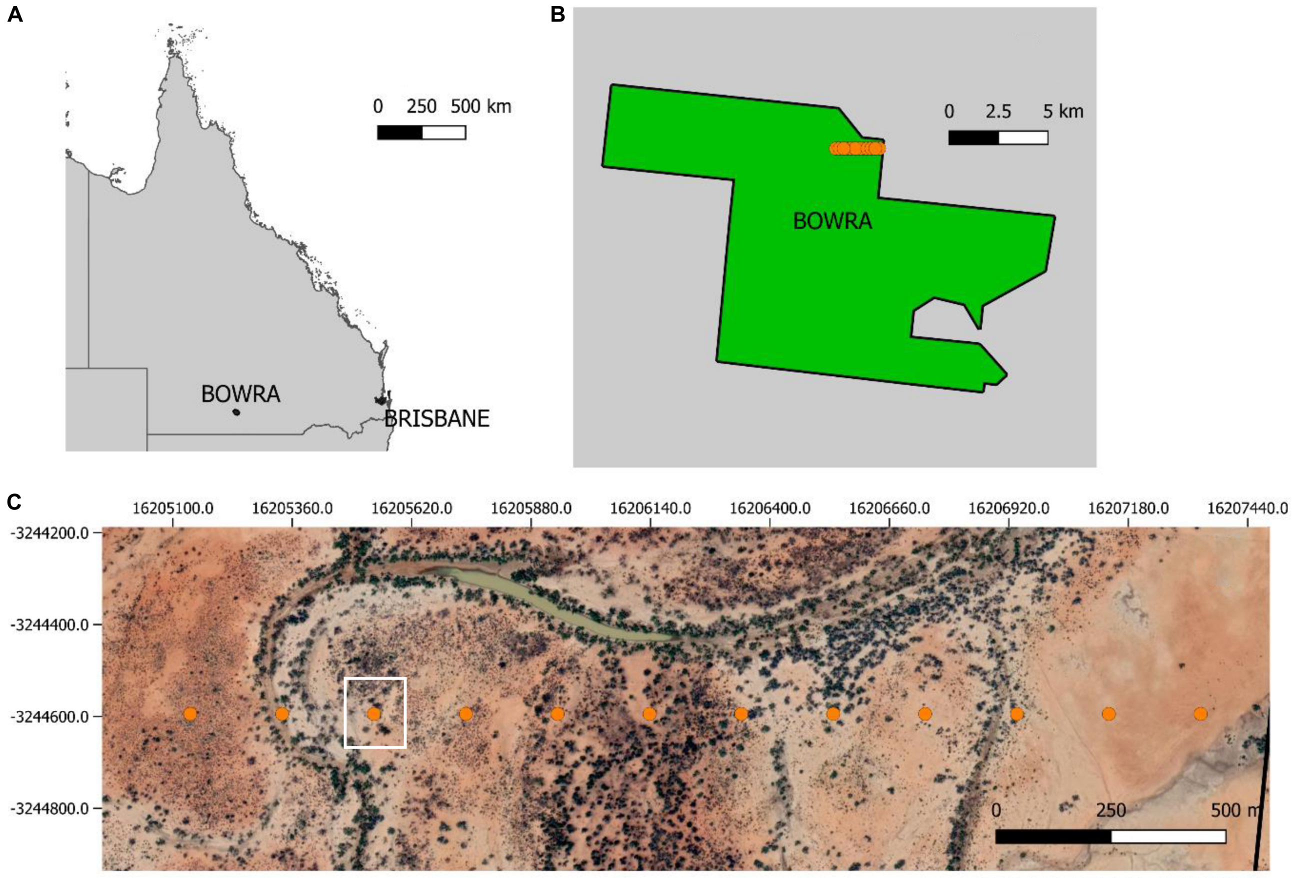

Image: Google Satellite

FIGURE 2 | (A) Queensland map indicating Brisbane and Bowra. **(B)** shows in orange the transect inside the property and **(C)** show the transects and a Google satellite layer with the different vegetation communities across the transect. The white square highlights the point that will be used here as an example for figures.

Dataset 2: Samford Ecological Research Facility

Figures 7C,E,G shows 1 day of the complete time-series with the motifs identified in color. The false-color spectrogram can be seen in **Figure 7A** and the corresponding gray-scale spectrograms can be seen in **Figures 7B,D,F**. As seen for Bowra, some segments were interpreted as significant by the motif search algorithm, whereas others were not.

Component Classification

The overall accuracy of the model classification was 73% and the performance per Component can be seen in **Figure 8**. The model misclassified motifs primarily due to the presence of geophony alongside "dominant sounds" in the recordings. In these cases, the algorithm has identified segments as geophony, whereas the researcher has not.

Class Classification

The overall accuracy for the Classes was 81%. The individual accuracies for the Classes can be seen in **Figure 9**. There were three classes for this dataset: birds, insects and "both," as there were motifs with both insects and birds, especially during the dawn and dusk choruses.

DISCUSSION

The approach proposed here using time-series motif discovery and random forest classification represents a significant improvement in how acoustic indices are currently analyzed for terrestrial soundscapes. It resolves some major challenges and constraints associated with acoustic data analysis including: (1) accounts for temporal autocorrelation of acoustic data, which violates most statistical test assumptions; (2) combines more than one index to assign soundscape components; and (3) performs in different contexts, as demonstrated by the finding that the same set of indices identified the same soundscape components in different ecosystems surveyed at different times, using varying recording schemes.

Acoustic recording and indices are now routinely used to monitor biodiversity (Doohan et al., 2019; Moreno-Gómez et al., 2019), but statistical analysis of recordings is problematic due to temporal autocorrelation. By using sub-sequence time-series

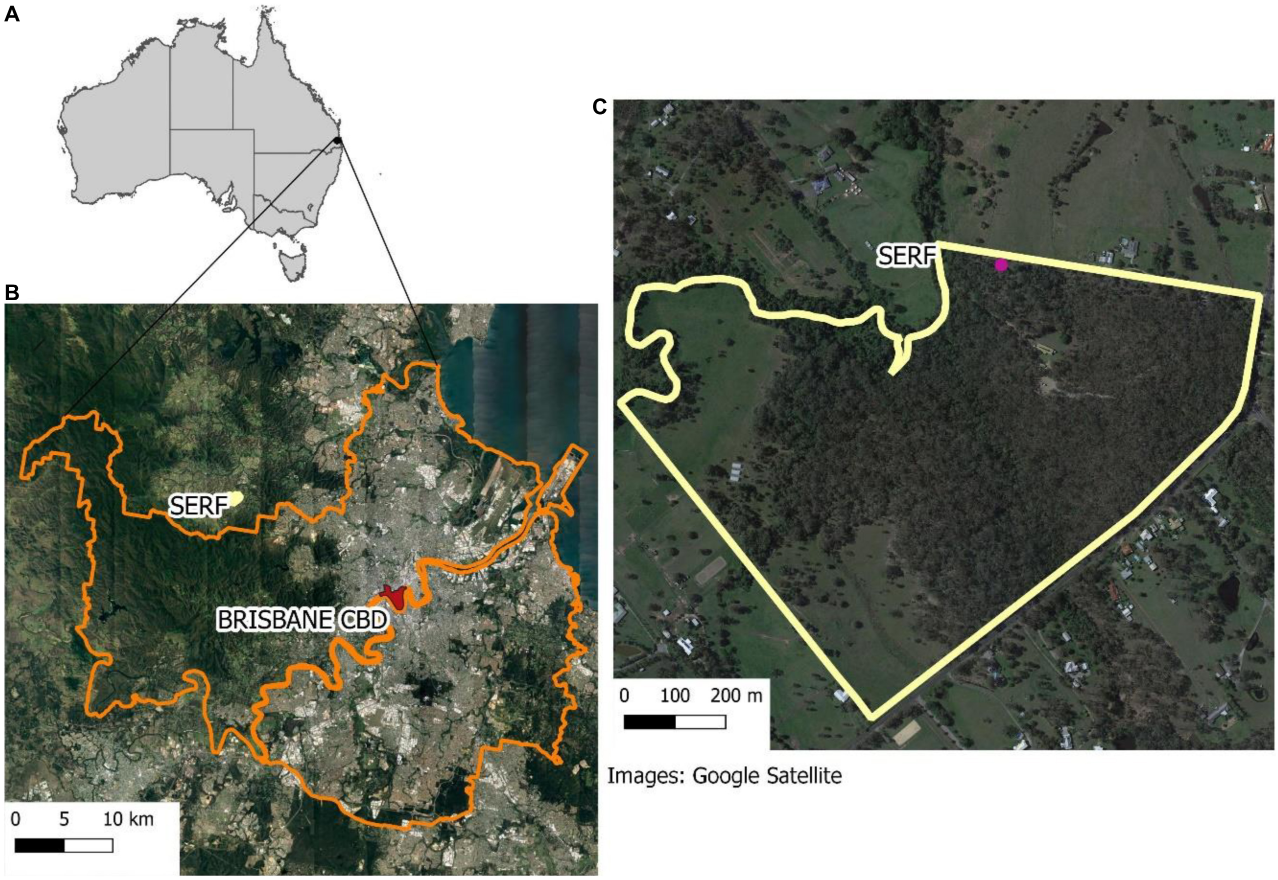

FIGURE 3 | (A) Location map of Samford Ecological Research Facility (SERF) in Australia. **(B)** SERF in relation to Brisbane CBD and great Brisbane. **(C)** Shows the property and the pink dot corresponding to the sampling point.

search, we were able to group sequences of minutes with repetitive patterns across the recordings, reducing the number of consecutive minutes analyzed as independent samples.

Acoustic data analysis approaches are varied and include linear mixed models (Francomano et al., 2020), mean differences (Carruthers-Jones et al., 2019), manual inspection and tagging species or groups of interest (Ferreira et al., 2018) or using non-index based metrics (like amplitude and frequency) direct from sound files (Furumo and Aide, 2019). Despite the variety of ways to analyze sound data, single index approach is still one of the most common approaches. As previously stated, single index data can be problematic because they cannot be consistently interpreted across different taxonomic groups or environments. For example, studies using ACI have shown that this index was positively correlated with bird species (Jorge et al., 2018; Mitchell et al., 2020), but also rain and wind (Duarte et al., 2015). Acoustic entropy has been found to have higher values in biodiversity rich habitats (Sueur et al., 2008), although higher values in quiet recordings and lower values in recordings dominated by insects have also been documented (Bradfer-Lawrence et al., 2019). Other studies have also tried to find a direct relationship between one index and one taxonomic group (Brown et al., 2019; Indraswari et al., 2020) but this relationship often does not hold across environments. From these findings we can conclude that a single index provides only a crude or obscure representation of biodiversity and is context-dependant. However, in our study, we have developed, validated and tested a new workflow that can be used in different terrestrial environments. This is particularly important because with recent advances in development of cost-effective ecoacoustic technology, passive acoustic recording is becoming a commonplace ecological survey approach worldwide. It is important that analytical tools are developed to meet this need, and are transferable across environments, providing standardized outputs for comparison or benchmarking.

An alternative to analyzing single index data is to combine indices, but this has been rarely attempted. One study used clusters to combine indices and classify major soundscape components (Phillips et al., 2018). However, their method still relies on listening to many recording minutes, which is extremely time-consuming and usually not feasible for large datasets. Another study combined indices using RF models to predict avian species richness (Buxton et al., 2018) and revealed that acoustic entropy and ACI were among the best predictors of avian biodiversity. But still, their aim was to link indices to a specific taxonomic group. Our approach is different because it

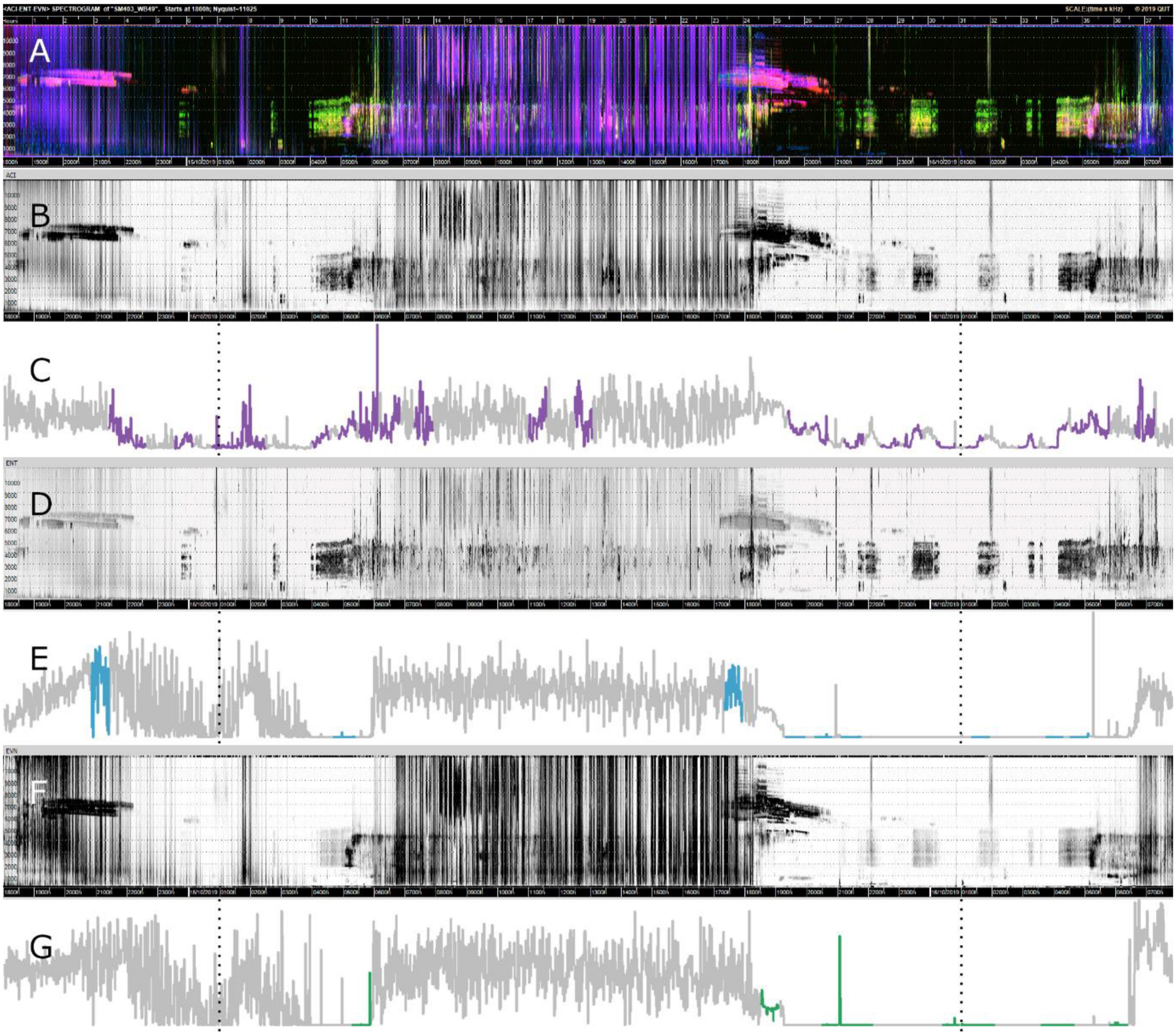

FIGURE 4 | Visualizations of data from Bowra. The dotted lines are marking midnight. **(A)** False-color Spectrogram; **(B)** ACI gray-scale spectrogram; **(C)** ACI time-series and motifs (purple); **(D)** ENT gray-scale spectrogram; **(E)** ENT time-series with motifs (blue); **(F)** EVN gray-scale spectrogram; **(G)** EVN time-series with motifs (green).

shifts the focus from the index itself, to instead examine what is being captured by it. While often the focus of an ecological study is a target species or taxonomic group, soundscapes can provide valuable insights on processes (such as geophony and anthropophony) that may influence biodiversity. Until now, no analytical approach exists that can efficiently extract soundscape components in a semi-supervised and transferable way.

Using index-based spectrograms for visual inspection of recordings, we were able to accurately assign sound labels to motifs, extrapolating these labels to the whole data. Although a certain level of generalization was required when using multiple indices and automated classification techniques, this approach represents a progression from single indices and the manual identification of sounds or calls. Along with the generalization required, there were also issues with misclassifications by the algorithm. Nevertheless, inspection of misclassified motifs showed that, for example, some of them that were not classified as wind, did have wind present. The labeling process was based on the most predominant sound, which does not exclude the possibility of having more than one sound present at a given motif. In fact, the presence of more than one soundscape component is quite common, and for the SERF data here presented an additional label had to be created to address multiple dominant sounds in one motif. Ecosystems are complex and biodiversity is subject to a variety of influencing factors that will change according to geography and its features (Gaston, 2000). This variation challenges the use of automatic analyses, and it also makes it harder to compare different contexts. Nevertheless,

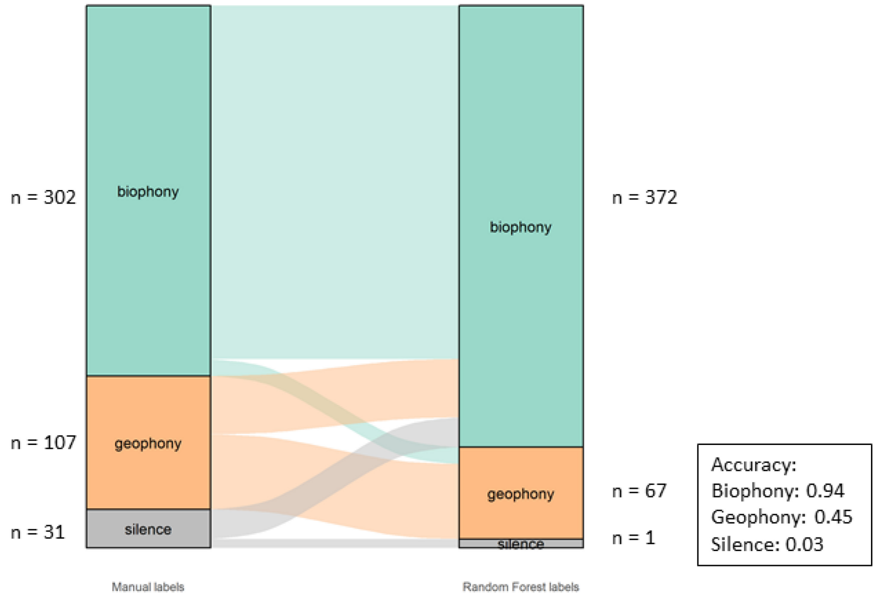

FIGURE 5 | Alluvial graph showing proportions and number of motifs of manual labels on the left-hand and model labels on the right-hand side for the component in the Bowra dataset. The lines in the middle going from manual to model labels indicate the misclassification. The accuracy per class is also shown in the figure.

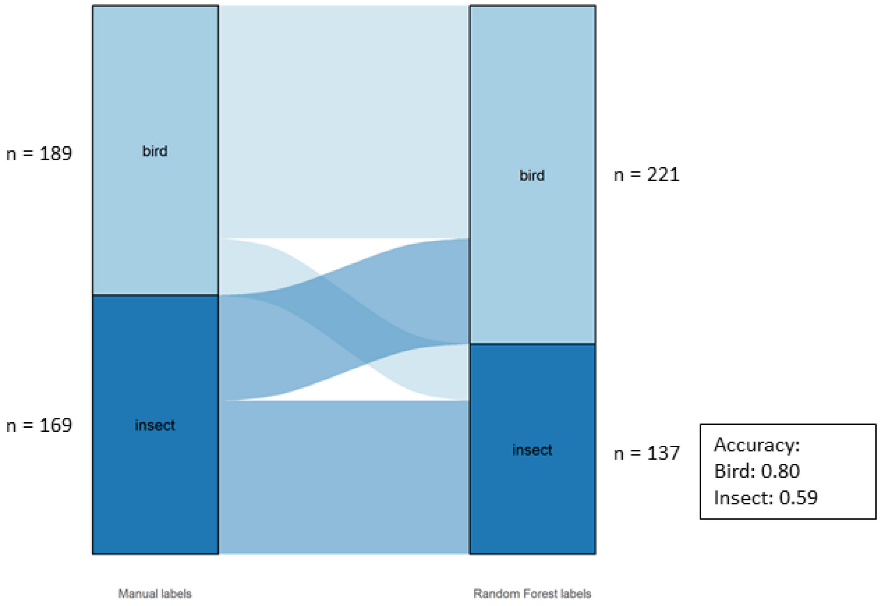

FIGURE 6 | Alluvial graph showing proportions and number of motifs of manual labels on the left-hand and model labels on the right-hand side for the classes in the Bowra dataset. The lines in the middle going from manual to model labels indicate the misclassification. The accuracy per class is also shown in the figure.

it is necessary to establish a baseline for analysis so recordings can be effectively used for environmental and temporal comparisons. Moreover, it highlights the importance of the label process that provides the researcher with the opportunity to adjust the method to the context.

As the two study sites were in different ecoregions (Bowra is classified under the Temperate Grasslands, Savannas and Shrublands while SERF is Temperate Broadleaf and Mixed Forest (Environment Australia, 2000), it was expected that their soundscapes would vary due to the distinct biodiversity, ecology, and environmental conditions. Besides expected differences, the SERF dataset had 10% more minutes than Bowra, but 43% more motifs. Potential explanations include that SERF has a more complex soundscape, or more likely that the increase may be attributed to the lack of wind at SERF relative to Bowra, resulting in more minutes with signal and less noise.

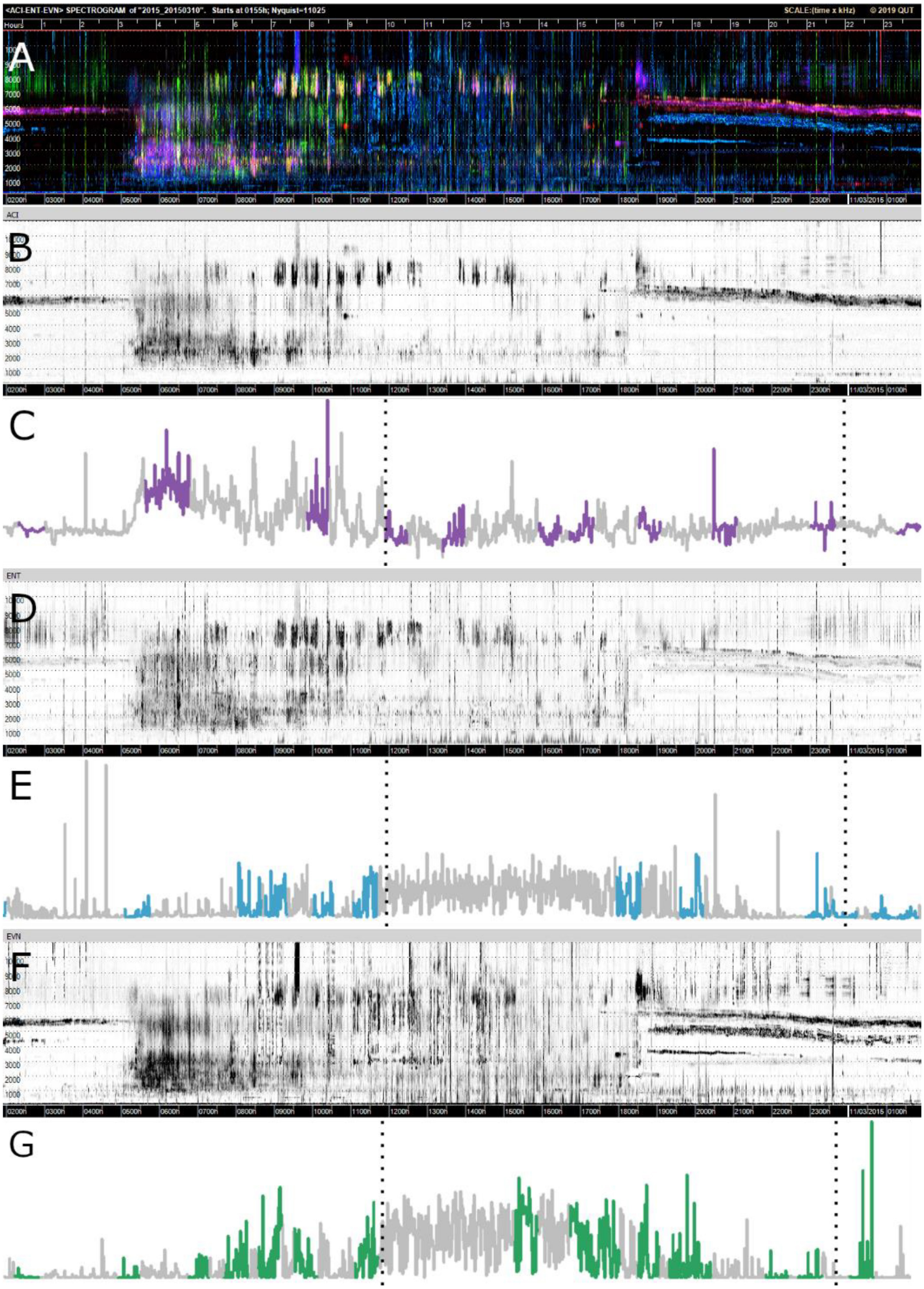

FIGURE 7 | Visualizations of data from 1 day (10/03/2015) of SERF dataset. The dotted lines are marking midday and midnight as reference. **(A)** False-color Spectrogram; **(B)** ACI gray-scale spectrogram; **(C)** ACI time-series and motifs (purple); **(D)** ENT gray-scale spectrogram; **(E)** ENT time-series with motifs (blue); **(F)** EVN gray- scale spectrogram; **(G)** EVN time-series with motifs (green).

Although soundscapes are known to vary between different environments, major soundtopes (Farina, 2014) were still expected to be found in both ecosystems (e.g., dawn and dusk choruses). Daily cycles were evident across the month at SERF, although variation could still be detected. This reflects environmental processes which also vary naturally across days. For example, areas near urban settlements, such as SERF, traffic noise can exhibit differences between weekdays and weekends.

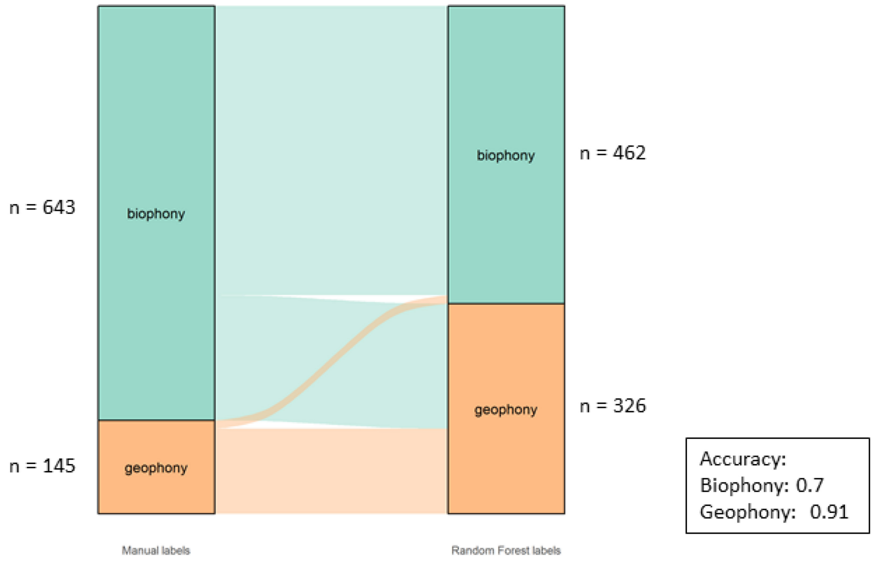

FIGURE 8 | Alluvial graph showing proportions and number of motifs of manual labels on the left-hand and model labels on the right-hand side for the components in the SERF dataset. The lines in the middle going from manual to model labels indicate the misclassification. The accuracy per Class is also shown in the figure.

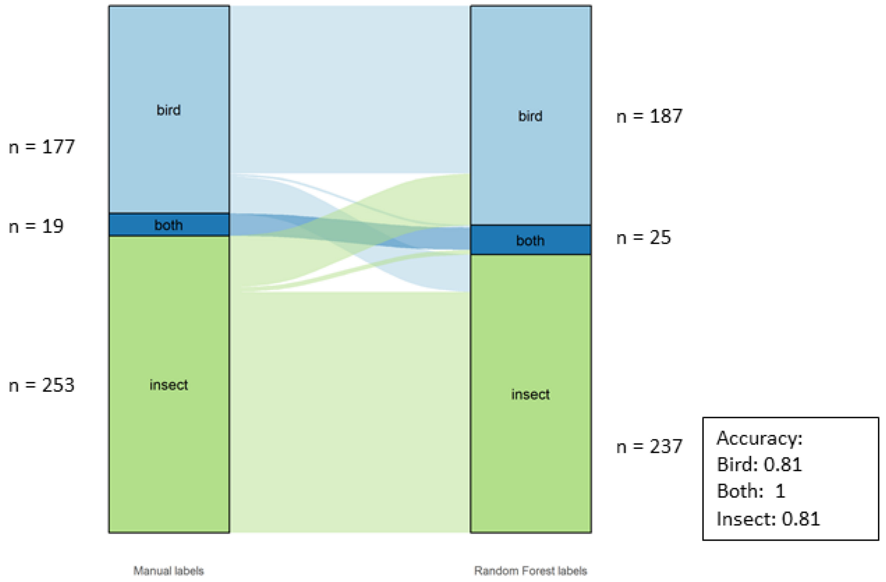

FIGURE 9 | Alluvial graph showing proportions and number of motifs of manual labels on the left-hand and model labels on the right-hand side for the classes in the SERF dataset. The lines in the middle going from manual to model labels indicate the misclassification. The accuracy per Class is also shown in the figure.

Biophony is also expected to change in response to temperature, rainfall, sunlight, and many other environmental factors that influence animal behavior (Pijanowski et al., 2011). The differences found here among and within ecosystems emphasizes again the importance of labeling motifs by a researcher before running the algorithm. Each recording will have distinct features that need to be addressed before data analysis. Furthermore, it provides an opportunity for the researcher to understand patterns and to become acquainted with the data specific to the site. It is also important to keep in mind that like other sampling methods, acoustic surveys are a snapshot of the moment in which the recordings were made. In order to track changes and effectively use this method as a biodiversity monitoring tool, it is important to establish sampling schemes that can capture different moments in time so that natural variation can be examined (Metcalf et al., 2020), as well as man-made impacts.

The labels in this study were generalized, however, future research could attempt to create more specific categories. At the same time, we argue that keeping upper levels of categories is important for model optimization, but it also might be useful when comparing results across datasets and studies. For example, every environment might have different species assemblages but similar patterns of biophony. For this reason, we believe the method presented here will help standardize analyses in ecoacoustics research. Another improvement that can be done is to assign more than one soundscape category per motif, creating a rank of sound presence. In this way, the misclassifications could be measured more accurately and potentially improved.

CONCLUSION

Ecoacoustics is a promising tool which is widely used to monitor biodiversity, and it has increased even more with the advent of acoustic indices. Nevertheless, until now there has been no consensus on how to transform acoustic indices into broad, transferrable ecological information, especially when combining indices. It is crucial to have an approach that standardizes and enables rapid assessment of terrestrial soundscapes. Although the analysis presented here treats indices separately as independent time series, there is no distinction between them for classification. This is important because it addresses the narrow assumption that each index serves as a good proxy for measuring specific taxonomic groups, and that these relationships will hold in different contexts. By combining different analysis techniques (time-series motif discovery and RF model classification), we were able to label grouped minutes of recordings translating acoustic indices into important components of the soundscape. We tested this approach on two datasets acquired using different recording devices and from different environments, providing strong evidence that this method can capture important temporal patterns in insect and bird biodiversity, as well as environmental geophonic sounds across environments. Given the global biodiversity loss that we are currently facing in the Anthropocene (Johnson et al., 2017), it is even more important that monitoring and methods of analysis are developed allowing to track changes in biodiversity.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://doi.org/10.5281/zenodo.4784758.

AUTHOR CONTRIBUTIONS

MS, SF, and BL conceived the ideas. MS and DT collected the data. MS and BL designed the methodology and analyzed the data. All authors contributed to data interpretation, drafts, critical revision and gave final approval for submission.

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Perspectives on the Ecological Role of Geophysical Sounds

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Humans categorize unwanted sounds in the environment as noise. Consequently, noise is associated with negative human and ecological values, especially when it is derived from an anthropogenic source. Although evidence confirms that many machine-generated anthropogenic sounds have negative impacts on animal behavior and communication, natural sources of non-biological sound, such as wind, rain, running water, and sea waves (geophonies) have also been categorized as noise and are frequently dismissed or mischaracterized in acoustic studies as an outside factor of acoustic habitats rather than an integrated sonic component of ecological processes and species adaptations. While the proliferation of machine-generated sound in the Biosphere has become an intrusive phenomenon in recent history, geophony has shaped the Earth's sonic landscapes for billions of years. Therefore, geophonies have very important sonic implications to the evolution and adaptation of soniferous species, forming essential ecological and semiotical relationships. This creates a need to distinguish geophonies from machine-generated sounds and how species respond to each accordingly, especially given their acoustic similarities in the frequency spectrum. Here, we introduce concepts and terminology that address these differences in the context of ecoacoustics. We also discuss how Acoustic Complexity Indices (ACIs) can offer new possibilities to quantifiably evaluate geophony in relation to their sonic contest.

Keywords: ecoacoustics, geophonies, noise, natural quiet, sonic signature

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INTRODUCTION

Environmental sounds represent an important phenomenon that is integral to the functioning of ecological systems (Gage and Farina, 2017). Natural and human-generated sounds are deeply interwoven with the ecological processes and patterns driven by biotic and abiotic relationships (Sueur and Farina, 2015; Gage and Farina, 2017). As such, these sounds are integrated elements within semiotic interactions, as well as measurable indicators of ecological relationships and environmental degradation (Krause et al., 2011; Pijanowski et al., 2011; Farina, 2014; Fuller et al., 2015; Krause and Farina, 2016; Mullet et al., 2016).

The global decline of biodiversity in the wake of expanding human development (United Nations [UN], 2019b), resource depletion (United Nations [UN], 2019a), and climate change (IPCC, 2021) has driven ecologists to examine these relationships in traditional and novel ways. The emerging field of Ecoacoustics has revealed the important role sound plays in ecological relationships (Farina, 2014; Farina and Gage, 2017). These discoveries have expanded the field of ecology to new frontiers with an increasing degree of relevance in the scientific community (Xie et al., 2020). Accordingly, ecoacoustics has added to the growing literature on bioacoustics, environmental impacts of machine-generated sounds on wildlife communities (Shannon et al., 2016; Jerem and Mathews, 2021), and the use of sounds as proxies for assessing environmental quality (Botteldooren et al., 2006; Booi and van den Berg, 2012).

A great deal of work has focused on the impact machine-generated sounds (technophony) have on soniferous species (Jerem and Mathews, 2021). As a result, it is a common practice in acoustic studies to separate the different sound sources of biophony (e.g., bird songs and calls) from the technophonic sounds of machines where biophonies are the singular soundscape component evaluated against the presence of "noise." Noise, in this context, is generally considered the technophony of every machine-generated signal that interferes with animal communication and/or causes a change in animal behavior and/or physiology (Tafalla and Evans, 1997; Barber et al., 2010). Technophony is an emergent component of many sonic environments and has a significant influence on the occupancy and habitat selection of many species (Mullet et al., 2017a).

The study of noise impacts on animals follows a long-standing "human-vs.-nature" paradigm that emphasizes the separation of human actions from non-human, natural processes (Barr, 1972). However, it is not unusual for the natural phenomenon of geophony (e.g., geophysical sounds generated by wind, rain, running water, sea waves) to be lumped together with technophony as "noise" (Klump, 1996; Brumm, 2010; Koper and Plön, 2012; Luther and Gentry, 2013; Bunkley et al., 2015) despite the differential semiotic interpretations wild animals likely have of these two sonic components. In these cases, animal sounds (biophony) are evaluated against a more generic "background noise" (Luther and Gentry, 2013), "ambient noise" (Ryan and Brenowitz, 1985), or "environmental noise" (Kight and Swaddle, 2011), often associated with geophysical sounds. Currently, the sonic-ecological relevance of geophonies remain ambiguous in acoustic studies even though they are present in every terrestrial and aquatic environment in some form. Furthermore, there exists a confusing characterization of geophony as having both negative acoustic qualities in the form of "environmental noise" and positive acoustic qualities in the form of "natural quiet" (Mace et al., 2004; Manning et al., 2007, 2018; Lynch et al., 2011). The indistinction between geophony and noise, along with the lack of reporting the role geophony plays in bioacoustics and ecoacoustics studies, are leaving an unavoidable gap in our understanding of sonic-ecological relationships.

In this paper, we clarify the distinction between noise, geophony, and natural quiet in order to establish a common language that serves to mitigate continued confusion in the ecoacoustics literature. We also discuss the active role geophony plays in ecological processes and the relevance of geophony in species evolution, communication, and habitat selection. We emphasize the need to establish clear reasoning for combining or separating geophonies from technophonies in acoustic studies and provide an example of how acoustic indices can be useful tools to address geophony in acoustic analysis.

ETYMOLOGY OF NOISE, GEOPHONY, AND NATURAL QUIET IN ECOACOUSTICS

As with any new field of science, there is a need to establish an etymology to properly describe its subjects and theoretical philosophies while building upon and/or clarifying language commonly used and accepted in the literature. Ecoacoustics has put a great deal of effort into creating a cohesive vocabulary of terms that explicitly describes its subjects and theories (Sueur and Farina, 2015; Mullet et al., 2017a; Farina et al., 2021a; Farina and Li, 2021). This endeavor has been an evolving process as new ideas, hypotheses, and philosophies emerge. Our intent here is to clarify, introduce, and define terminology associated with noise and geophony for future ecoacoustic investigations.

Noise and Technophony

The origins of the word noise are largely uncertain, but at least date back to the Greek period. Linguistically, noise is a derivative of the Greek word "nautes" (sailor) and the Latin word "nausea," meaning disgust, annoyance, discomfort, or seasickness. Other origins have come from the Latin "noxia," which means hurting, injury, or damage. Contemporarily, noise is broadly defined as unwanted sound. Yet, more specifically, the Oxford English Dictionary describes noise as a sound that is especially loud or unpleasant, causing disturbance or confusion among other sounds, and contains no meaningful information. Noise is inherently negative and subjectively defined by human perception.

Notably, the linguistic roots of noise from the pre-industrial age clearly indicate that unwanted sounds were not originally associated with the sounds of machines. However, over the past two centuries, the proliferation of steam and combustion engines and electronics have introduced new anthropogenic sounds into the environment (Pivato, 2011). As machine-generated sounds made their way through human society, from the workplace to the home and across the globe from agriculture to air and sea travel, machine-generated sounds have become a novel intrusive and detrimental affliction to human and environmental health (Goines and Hagler, 2007; Jerem and Mathews, 2021).

Consequently, the impact of machine-generated sounds on the environment has become an increasingly popular subject of investigation (Jerem and Mathews, 2021) with considerable evidence of its negative influence on animal behavior (Brumm and Slabbekoorn, 2005; Habib et al., 2007), community ecology (Francis et al., 2009), and species habitats (Nowacek et al., 2007; Barber et al., 2010; Chan et al., 2010; Slabbekoorn et al., 2010; Mullet et al., 2017a). Because of their human origin, machine-generated sounds fit within the ecoacoustics category of anthropophony, but more exclusively under the subcategory of technophony (Mullet et al., 2016). This separation is based on the difference between the biological and cultural sounds that humans have been making for millennia (e.g., music, song, language) with the more recent sounds generated by machine technology. Anthropophony of the former has evolved complex semiotic relationships in human societies and nature, while the latter generates sounds with generally no semiotic intent or relevance. This distinction is important because noise is an anthropocentric term often used to define machine sounds as unwanted sounds. This likely stems from how humans perceive the sonic relationship with the environment by distinguishing what is natural from what is unnatural in both human culture and ecologically (Booi and van den Berg, 2012; Gomes et al., 2021).

Because of this, it is vital to be aware that by using the term noise, without explicit definition, the researcher is inherently assuming the sonic element is also unwanted by their non-human animal subjects without providing evidence to support their assumptions. This results in implicit bias of a study's design and confounds ecological interpretation. Therefore, there must be a clear definition in the ecoacoustics literature for the word noise. We suggest that noise be generally defined as machine-generated sound (technophony) that is unwanted or undesirable to humans. In this way, studies of "noise" impacts to wildlife must also clarify why or provide evidence that the variable of noise is "unwanted" to their study subjects (see Barber et al., 2010; Luo et al., 2015; Jerem and Mathews, 2021).

Conversely, technophony, as a distinct soundscape component, is an important contribution to acoustic habitats with significant ecological implications outside human perceptions (Mullet et al., 2017a). Similar to the soundscape component of biophony being ecologically distinguished by the sounds of soniferous species, technophony in the environment can also be distinguished by the presence of human technological sounds. Yet, technophonies cannot be reliably defined as unwanted sounds in non-human animals. The term noise (as defined above) does not adequately apply to the perspective of a non-human animal, but the term technophony still remains relevant. This is because non-human animals do not interpret the meanings of or differentiate between technophonic sources with the same semiotic mechanisms as the human originators. Nevertheless, the presence of technophony within the soundscape still plays an important role in animal behavioral ecology.

We recognize that technophony takes on a variety of characteristics in nature depending on its source. We propose three categorizes of technophony to generalize how it more commonly occurs in the environment. These categories include *continuous technophony, ephemeral technophony,* and *abrupt technophony*. Continuous technophony is characterized as constant machine-generated sound(s) in the environment, occurring over long temporal periods with little or no change. Some typical sources of continuous technophony include oil compressors, highway traffic, and airport traffic. Ephemeral technophony is not constant but occurs intermittently over temporal periods where environments experience a gap between machine-generated sound disturbance events. Ephemeral technophony sources include helicopter and airplane flybys, intermittent vehicle sounds on roads less-frequented than highways, and motorboats. Finally, abrupt technophony is derived from short temporal bursts of machine-generated sounds that do not persist over time. Examples of abrupt technophony sound sources are gunshots, explosions, and pile drivers. These three categories of technophony can also be applied to noise when presented from an anthropocentric perspective.

Geophony

Since the Earth and its atmosphere were formed 4 billion years ago, geophysical sounds have shaped the sonic environment. It was under these sonic conditions where the biological sounds of organisms in marine, freshwater, and terrestrial environments began their long and extensive process of evolution into the diverse animal orchestra we hear today. Concurrently, the Earth's own geomorphological evolution influenced the formation of sonic environments, acoustic habitats, and acoustic communities. It is reasonable to suggest that geophony is an inescapable, and integrated, semiotic component to the sonic environment, species evolution, and ecological processes. Because of this close relationship between biological organisms and geophysical sounds, it is inappropriate to combine geophony with noise without explicitly identifying the reasoning to do so. By dismissing the relevance of geophony in ecoacoustics studies or combining geophony with noise, one dismisses and misinterprets the fundamental nature of soundscapes and ecological relationships (Gomes et al., 2021).

Geophony has been clearly defined to be sounds generated by the Earth and its geophysical events (Pijanowski et al., 2011; Farina, 2014; Farina et al., 2021a). However, like technophony, geophony can be placed into three general categories that include *continuous geophony, ephemeral geophony,* and *abrupt geophony*. Continuous geophony includes those geophysical sounds that persist for long periods of time in the landscape. Perfect examples of continuous geophony include continuous free-flowing rivers and streams and sea waves. Ephemeral geophony consists of the geophysical sounds that do not persist in nature but occur intermittently over time, such as, the sounds of wind, rain, and ephemeral streams. Abrupt geophony are geophysical sound events that occur suddenly and in short time. Earthquakes, landslides, avalanches, and volcanic explosions are abrupt geophonic sound sources.

Sonic Signature

Sonotopes are distinct assortments of biophony, geophony, and technophony embedded within every portion of a land mosaic that vary in space, time, source, and intensity (Farina, 2014; Farina et al., 2021a). Such variability operates at different temporal and spatial scales and is sensed differently among species. In the presence of biophony, technophony, and certain geophony, each sonotope possesses a unique sonic ambience we call a sonic signature. We generally define *sonic signature* as the ever-present ambient sounds that form the sonic foundation of a sonotope. The sonic signature forms the primary occupied acoustic niche that soniferous species must sonically compete with in the most fundamental of ways (**Figure 1**). The Earth's primordial sonic signatures likely played significant roles in the evolution of animal sounds. The late Professor Stuart H. Gage (pers. comm. Michigan State University) described the sonic

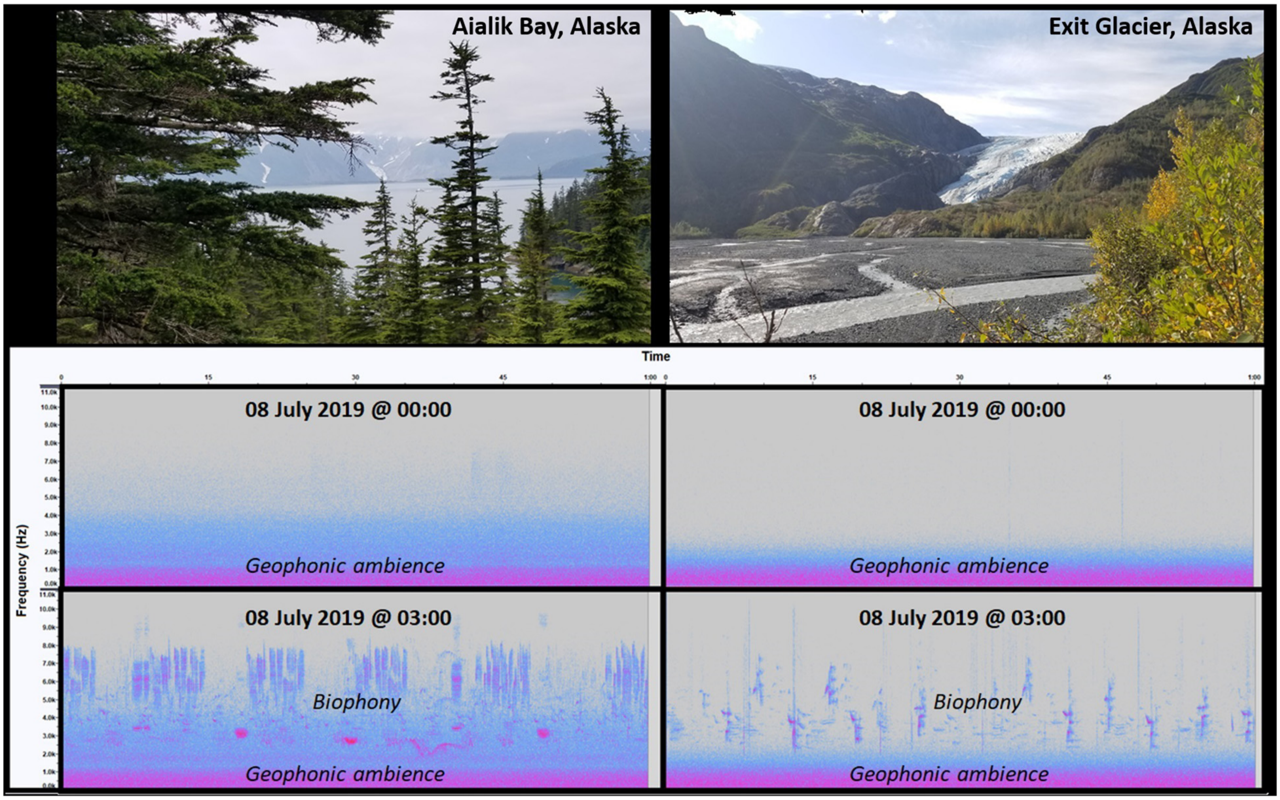

FIGURE 1 | Spectrogram comparison between two subarctic sonotopes located in Aialik Bay (coastal) **(A)** and Exit Glacier (interior) **(B)** of Kenai Fjords National Park in south-central Alaska (60° N; 150° W) on 08 July 2019 at 00:00 and 03:00, illustrating the presence of geophonic ambiences, respectively, characterized by the sounds of waves and a glacial creek, that occur in the absence of biophony, ephemeral/abrupt geophony, and anthropophony at 00:00 and in the presence of biophony during the dawn chorus at 03:00. Note that the geophonic ambience of the coastal sonotope possesses a different sonic signature given the range of low-frequency spectra than that at the interior sonotope, including differences in the intensity and composition of biophonies at higher frequencies between locations.

signature as the primeval sound of the Earth, the geophonic sounds that remain when all else is absent.

A sonic signature can be the result of a single or combination of sound sources (e.g., wind, running water, sea waves). The nature of a sonic signature determines its impact on the ecology of animals, all of which are species-specific. Based on this perspective, it is reasonable to hypothesize that the recurrent sounds of a sonotope's sonic signature have a role in the characterization and selection of a species' habitat (e.g., Tonolla et al., 2010, 2011; Mullet et al., 2017b; Decker et al., 2020; Linke et al., 2020) and therefore, provides a baseline of ambient sounds for a species' semiosis, as well as a quantifiable subject of ecoacoustics investigations (Putland et al., 2017).

Subarctic environments can exhibit periods of time when biophonies, technophony, and ephemeral/abrupt geophonies are not present within the acoustic space (**Figure 1**). In this case, there still exists an ambient background of low-frequency, low-sound energy geophony that is continuous and ever-present. This phenomenon of geophonic ambience contrasts sharply with time periods when the acoustic space becomes occupied by biophonies, ephemeral/abrupt geophonies, and technophony but still remains a primary component of individual sonotopes (**Figure 1**). Thus, geophonic ambience creates a sonic signature that shapes the composition of acoustic habitats.

We acknowledge that sonic signatures are not exclusively geophysical sounds. In fact, the heavily developed metropolitan regions of the world possess a sonic signature of technophonic ambience often produced by vehicle traffic. Similarly, finer-scaled urban sonotopes may have their own unique sonic signature depending on sound sources of the underlying ambience. Examples of these finer-scaled sonotopes are airports and manufacturing plants. Both geophony- and technophony-based sonic signatures are important ecological components to understanding biophonies and animal behavior.

Distinguishing Noise From Geophony

In order to understand the ecological role geophony plays in the environment, one must recognize the implications that research presents when combining geophony with technophony under the moniker of "noise." We have provided pragmatic reasons why geophony is not noise (i.e., unwanted sounds) in an ecological sense. However, we recognize that intense geophonic sources (e.g., waterfalls, torrents, sea waves) may be considered unwanted sounds from a human perspective, especially when assessing the acoustic qualities of an area for listening to biophonies.

This highlights an important distinction to make when using the term noise to describe geophonies and technophonies. We first must acknowledge that the continuous and homogenous sounds of sonic signatures from a human perspective appear as uninformative "noise" but, in fact, the geophonic ambience of a sonotope most likely serves as a critical form of information in animal communication and habitat selection. Secondly, intense geophonic and technophonic sounds possess true and ecologically relevant attributes in the form of masking effects on certain sound sources. Masking can simply be described as one sound interfering with the detection of another sound. The ecological implications of this phenomenon have been demonstrated by the low-frequency sounds (1–4 kHz) of roads and oil compressor fields effecting the ability of some organisms to hear vocalizing cohorts that call within the same frequency range (Ortega, 2012; Ortega and Francis, 2012). Intense geophonic sounds (e.g., high wind events) have also been problematic for detecting and discerning low-frequency biophonies (Mullet et al., 2016).

We suggest that researchers identify the types of geophony and technophony that may influence the results of their acoustic investigations. By doing so, the results of acoustic studies can be interpreted in the context of geophonies as a distinct sonic variable independent of technophony and as an ecological driver of species adaptations and evolution. We recommend that researchers avoid characterizing natural geophonic ambience as unwanted sound (i.e., environmental noise, ambient noise, background noise) (Codarin et al., 2009) for the purpose of avoiding confusion between an anthropocentric perception and one determined by animal semiotics. However, we recognize that animal avoidance behavior to technophony (Luo et al., 2015), geophony (Hayes and Huntly, 2005), and even biophony (Stanley et al., 2016) provides a rare opportunity to characterize some sound sources as unwanted sounds from an animal's perspective.

Natural Quiet

As noise expands to nearly every corner of the Earth, there has become increased interest to locate the world's quietest places (Cox, 2014). Only recently has natural quiet become a term used in bioacoustics and ecoacoustics literature (Mace et al., 2004; Votsi et al., 2014; Mullet et al., 2017b). Natural quiet is simply defined as a period of time when noise does not disturb natural sounds (Manning et al., 2007). This vague definition obviously suggests that natural quiet is composed of any form of biophony and geophony but also implies that there is some level of sound amplitude identified by some receiver as "quiet." More importantly, natural quiet, like noise, is a human construct. Humans easily identify natural sounds as separate from human sounds, but quiet lends itself to a more technical and often subjective definition we will not elaborate on here. Natural quiet within the human domain consists specifically of natural sounds identified according to non-human categories and quiet can be defined according to a relative measure of human perception (i.e., decibels) (e.g., Ambrose, 2006).

Natural quiet does not mean "silence," the complete absence of sound. Although uncommon in the literature, silence has been misused to describe natural sounds (Pfeifer et al., 2020) or used interchangeably with natural quiet (Hempton and Grossmann, 2009). The distinction between natural quiet and silence is important in order to avoid confusing audible-sensorial phenomena with the absence thereof. In fact, sounds are ever-present in nature because of the myriad of sound-producing interactions that occur at micro- and macro-scales of ecosystem processes (Smucker et al., 2006; Tornel et al., 2010; Fuller et al., 2015; Wall et al., 2017).

The sensitivity of a receiver to these sounds depends on their audible range of detection and the frequency and sound energy emitted by these processes. This suggests that sounds that occur outside a receiver's audible range are of less significance to its ecology than sounds they can hear. Yet, the frequency spectrum is not continuously occupied by sounds within a receiver's range of hearing. As illustrated in **Figure 1**, sounds are absent within a given frequency spectrum (e.g., 5,000–11,000 Hz) over a 1-min period at midnight (00:00). By definition, these vacant frequencies are silent to the receiver (i.e., SM4 Song Meter standard microphone, Wildlife Acoustics, Inc., Maynard Massachusetts) despite the microphones capability to detect sound events within this range. In this case, an argument can be made that silence does exist, but only in the context of the receiver. Therefore, the absence of sounds can be considered species-specific and unique by an individual's threshold of hearing. Unfortunately, this example is not what is insinuated as silence in the literature, nor is it considered to explain the sonic characteristics of natural quiet.

There has been some effort to measure natural quiet as a quantifiable variable (Lynch et al., 2011). This has stemmed from an interest in empirically characterizing undeveloped, wild landscapes in the context of human sonic experiences in nature. This approach emphasizes the anthropocentric perspective of what is considered natural (i.e., non-human sounds) and quiet (e.g., some baseline decibel level). Although this approach has benefited the preservation of natural soundscapes and expanded our understanding of human-nature connections through sound, natural quiet in this context provides very little relevance to understand ecological processes. We propose that the term natural quiet explicitly refer to the interpretation of a soundscape's acoustic qualities based on human perception and cultural definitions of "natural" and should not be applied to ecoacoustics studies intended to explain ecological processes where human perception is not the focus.

In an ecological context, it is important to acknowledge the absence of sounds within frequency spectra as an important characteristic of sonic environments. Regrettably, most bioacoustic and ecoacoustic studies have narrowly focused on the occupancy of multiple frequency spectra by biophony to describe the biodiversity of life in many parts of the world (Bertucci et al., 2016; Raynor et al., 2017; del Castillo Domínguez et al., 2021; Dröge et al., 2021; Farina et al., 2021b). Similarly, many studies have concentrated on the occupancy of acoustic partition to test the Acoustic Niche Hypothesis (Krause, 1993) as a viable explanation of sonic-animal ecology and evolution (Villanueva-Rivera, 2014; Bignotte-Giró and López-Iborra, 2019). However, the evidence of a "silent acoustic niche"

(**Figure 1**) reverses the emphasis of interest to understand the sonic environment where the absence of biophony, geophony, and anthropophony are just as vital to understanding natural ecological processes. The opposing perspective of silent acoustic niches in the context of occupied acoustic niches is increasingly important as many ecosystems face catastrophic declines in biodiversity due to climate change, and human impacts (Krause et al., 2011; Krause and Farina, 2016). We recommend that more work be done on this subject.

GEOPHONY AS A DRIVER OF ADAPTATION AND HABITAT SELECTION AND A COMPONENT OF ECOSYSTEMS

Despite evidence that supports the effect geophonies have on the sonic behavior of marine (Brumm and Zollinger, 2011; Holt and Johnston, 2014; Guazzo et al., 2020; Helble et al., 2020) and terrestrial animal vocalizations (Brumm and Slater, 2006; Preininger et al., 2007; Brumm and Naguib, 2009; Samarra et al., 2009; Vargas-Salinas et al., 2014) and species evolution (Ryan and Brenowitz, 1985; Brumm and Slabbekoorn, 2005), there still exists a gap in our understanding the natural selection process of geophony in animal evolution, more specifically in terrestrial systems. Boeckle et al. (2009), for instance, found rock-kipper frogs (*Staurois latopalmatus*) in habitats with continuous geophony from waterfalls emitted higher frequency calls and had smaller body sizes than cohorts where geophony was not as sonically pronounced. Zhao et al. (2017) demonstrated the role of geophony in mate selection among little torrent frogs (*Amolops torrentis*). They observed that females selected males that emitted higher frequency calls in areas where the geophony from streams had high sound amplitude. Males that emitted lower frequency calls in quieter environments were less likely to acquire a mate.

The literature that exists strongly suggests that geophony in marine and terrestrial systems has a significant role in the habitats animals select to inhabit in a landscape. It has been established that the composition and patterns of soundscapes are directly linked to the temporal and spatial arrangements of landscapes (Fuller et al., 2015; Mullet et al., 2016). Thus, sonotopes and their unique sonic signatures are essential components to the homogenous ecotopes that occur across the landscape. In this context, the temporal and spatial configuration of geophony is a fundamental sonic element of a species' habitat that exists within an ecotope. Mullet et al. (2017a) describe the ecological relationships between animal behavior and habitat selection in their seminal Acoustic Habitat Hypothesis.

Since geophony is generated by the vibrations of the physical environment (e.g., sound of wind from rustling leaves, sound of waves from the crashing of ocean water, sound of rain impacting vegetation); the sources, acoustic characteristics, and semiotics of geophony vary temporally and spatially depending on climatic conditions, geomorphology, and vegetation. As an example, the continuous geophony of a river will have differential sonic and semiotic significance based on the distance a sound-dependent species is from the source. However, the manner in which geophony attenuates from the river is also dependent on the geomorphology and vegetation communities of the land surrounding it. In this case, geophony becomes subject to the composition and structure of the physical and biological environment creating unique sonotopes and acoustic habitats across a heterogenous, riparian landscape.

The many forms geophony can take in both its source and intensity are the consequences of complex geophysical phenomena. The characteristics of geophony across spatial scales can be influenced by elevation gradients, topography, global and microclimate dynamics, and successional stages of vegetation communities. Similarly, geophonies express temporal variation too, depending on its source (e.g., river sounds compared to rain showers), geographic region, time of day, and season. Some good examples of spatial and temporal differences in geophony are evident in the seasonal patterns of rainfall constituting the Amazon's wet and dry season (Sombroek, 2001) compared to the more extreme seasonal differences in geophony of south-central Alaska's boreal forests with rainy summers and actively flowing streams (Mullet, 2020) to winters with prolonged periods of ambient geophony interspersed with intense wind events over frozen lakes, rivers, and tundra (Mullet et al., 2016). The Amazon's wet season comes with increased geophony from rain but also marks the height of the breeding period for many songbirds that coincides with food availability (Stouffer et al., 2013). Similarly, the biophony of south-central Alaska increases considerably in summer months as the geophony of rushing water and rain dominate the soundscape (Mullet, 2020) while most soniferous species migrate or become dormant over winter (Mullet et al., 2016). These geophonically-related ecological processes are not only a product of geography, geomorphology, and vegetation, but their seasonality is also a result of the Earth's planetary tilt toward the Sun.

It is reasonable to hypothesize that the scale of ecological factors contributing to geophony are naturally integrated into the evolution and adaptation of animals and the dynamic complexities of Earth system processes. Subsequently, these relationships impact the manner in which sound-dependent species instinctually and cognitively select and occupy habitats. Even more so, the effects of anthropogenic climate change are having profound impacts on physical and biological systems (Rosenzweig et al., 2008). As a result, the attributes of geophonies at fine and coarse scales are likely changing temporally and spatially in a way that can alter the natural selection process they have on animal communities and species distributions. This underlines the importance of including geophony as a key subject in ecoacoustics studies.

GUIDANCE FOR THE STUDY AND ANALYSIS OF GEOPHONY

It is important for us to extend our competency of ecoacoustics in order to better understand the ecological resiliency of the sonic environment and its relationships to natural processes and human activity. As we have expressed earlier, the inclusion of geophony in ecoacoustics investigations is paramount to embodying a holistic knowledge of ecology. In fact, the full characterization of soundscapes can contribute to a greater breadth of knowledge than the narrow perspective of simply describing biophony or noise impacts to soniferous species and communities.

We are aware of the objective difficulties that exist to currently discern, measure, and evaluate geophony in ecoacoustic studies (see methods by Mullet et al., 2016). Nevertheless, including information concerning the characteristics and dynamics of geophonies in ecoacoustics greatly enhances the description of the sonic environment in which species operate and disclose their ecological relationships. To do this, it is necessary to create new, and improve on current, ecoacoustic tools that can be applied in ecoacoustics methodologies.

Geophonies, like many environmental sounds, can be efficiently detected and recorded using autonomous recording stations (ARS). This method enables a researcher to standardize their sample rate and recording intervals while allowing the recording device to run unattended for long-periods of time, generating a broad temporal sample of geophonic events. The temporal sampling period is dependent on the research question (see Buxton et al., 2016; Krause and Farina, 2016; Mullet et al., 2016, 2017b; Mullet, 2020 for examples), but we recommend 1-min as a sufficient recording interval. Sonic data collected by ARS are often generated as a digital waveform (wav) file which can be processed into a metric or index using the computation of an algorithm suitable to answer the focused research question.

Geophonies are often characterized by more continuous patterns when compared to the ephemeral nature of biophonies, like bird calls. In fact, wind and rain events last longer than a few seconds or minutes compared with the short duration of bird calls. Only insects exhibit continuous biophonies but are typically discernable within a specific frequency spectra. Contrarily, geophonies often span a wide range of frequencies depending on the source and over longer time intervals (30 s to hours). Their sonic patterns are typically more homogenous than most technophonies and biophonies. In order to adequately describe such processes, the frequential and temporal resolution with which data are analyzed should be fixed accordingly.

Few studies have approached the investigation of geophonies in terrestrial environments especially focusing on the capacity of ecoacoustic metrics to filter out geophonic events. Mullet et al. (2016) for instance, resolved to listening to thousands of sound recordings to parse out and quantify geophonies from biophonies and technophonies. This challenge has not been lost on other investigators (Bedoya et al., 2017; Sánchez-Giraldo et al., 2020). While terrestrial ecoacoustic studies have struggled with this issue in recent years, a more abundant literature testifies to the interest in and analysis of geophonies in marine systems that have measured the effect of rainfall (Medwin et al., 1992; Ma and Nystuen, 2005; Amitai and Nystuen, 2008; Ferroudj et al., 2014) and wind (Pensieri et al., 2015; Cauchy et al., 2018) on underwater sounds. While our expertise lies within terrestrial soundscapes and acoustic analyses applicable to these systems, we recognize that marine bioacoustics and ecoacoustics methods could prove useful.

Unlike studies that apply multiple acoustic indices to quantify and explain biophonies, we propose the Acoustic Complexity

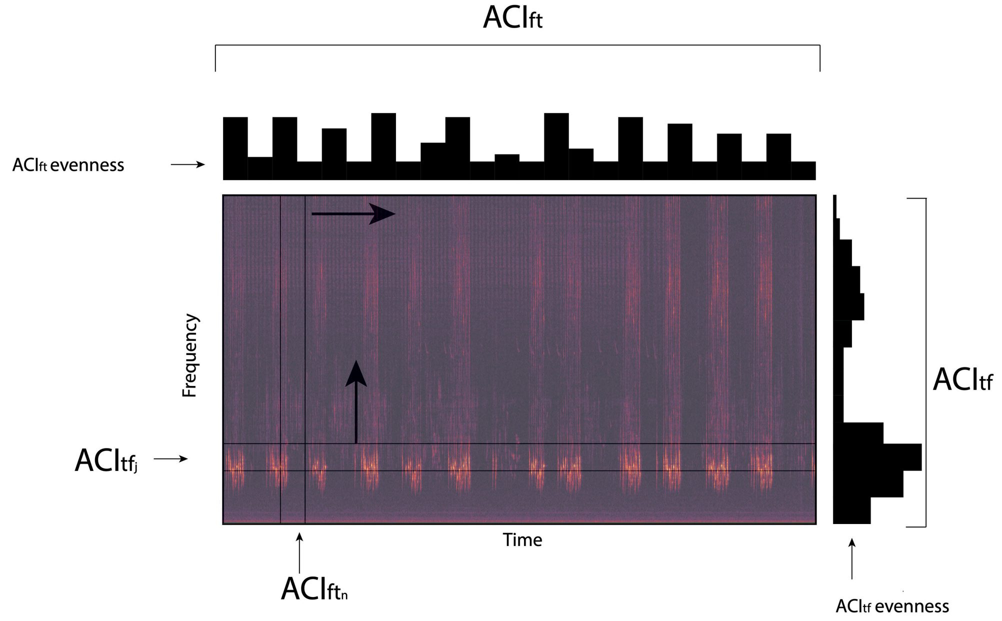

FIGURE 2 | Graphical representation of four Acoustic Complexity Indices (ACIft, ACIft$_{evenness}$, ACItf and ACItf$_{evenness}$) that are used to generate sonic codes in the analysis of ecoacoustic events in a sound recording. ACIft measures the sound energy across the frequency spectra within selected segments of time (ACIftn), while ACIft$_{evenness}$ calculates the distribution of sound energy within the frequency spectra across all time segments. ACItf measures the sound energy within specified frequency intervals (ACItfj) across the recording period (time), while ACItf$_{evenness}$ calculates the distribution of sound energy across all frequency intervals over the recording period.

Indices (ACIs) (Pieretti et al., 2011; Farina et al., 2016) as a convenient set of metrics, powered by the recent SonoScape software (Li and Farina, 2021) that operates at multiple scales, offering the possibility to sample sound recordings at different temporal resolutions to extract the ecoacoustic events of geophony and to filter sonic signals according to an energetic threshold.

In brief, the main performance of ACI enables the measures of sonic information based on the difference that occurs between successive intensity pitches and operates at every temporal scale of a sampling regime. Sonic energy can be measured across time for any frequency interval given the study's sample rate. Four ACI metrics (ACI$_{\mathrm{tf}}$, ACItf$_{\mathrm{evenness}}$, ACI$_{\mathrm{ft}}$, and ACIft$_{evenness}$) can be employed to measure sonic information across frequencies at any predetermined temporal interval (Li and Farina, 2021; **Figure 2**). In this way, ACI$_{tf}$ measures the sonic information within a single frequency interval while ACItf$_{evenness}$ calculates the distribution of ACI$_{\mathrm{ft}}$ across multiple frequency intervals. The amount of sonic information included across frequencies is measured by ACI$_{\mathrm{ft}}$ with ACIft$_{evenness}$ used to calculate the distribution of ACI$_{\mathrm{ft}}$ values along a specified temporal interval (**Figure 2**).

Geophonic events (e.g., an isolated gust of wind or period of rain) can be classified within the SonoScape software using the combination of ACI$_{\mathrm{ft}}$, ACIft$_{\mathrm{evenness}}$ and ACItf$_{\mathrm{evenness}}$ that returns a sonic code that ranges from "000" to "999" (Farina et al., 2018). A sonic code of "000" is equivalent to "no sonic signal," whereas a sonic code of "999" represents a sonic signal that completely saturates the entire frequency spectra and time sequence. Heavy rain and strong wind events are often characterized by a sonic code of 999. Sonic codes are obtained for every time interval a wav file is sub-divided into.

For instance, if we process a wav file of 300 s at a resolution of 1 s, we obtain 300 codes, one for each second interval. If we reduce the temporal resolution to calculating indices at intervals of 6 s, we obtain 50 codes, and so on. Sonic code values are strongly affected by the temporal resolution (i.e., time interval) chosen by the analyst because the temporal dimensions potentially delimit the field of existence of an ecoacoustic event. This is true if one desires to capture abrupt geophonic events like thunder. In this case, the sonic matrix must be appropriately segmented into intervals of 2–3 s for the event to be detected within the sonic code calculation. Similarly, the ephemeral geophony of wind or sea waves may require 10–30 s, while the continuous geophony of sonic signatures spread across long temporal scales. For rain, the time interval depends on whether the sonic events are short- or long-duration rain showers.

The usefulness of ACI for identifying, quantifying, and parsing out geophonies from biophonies and technophonies lends itself to the manner in which the indices of sonic events are calculated based on their occurrence within frequency spectra and over time intervals. The diverse, but unique, nature of geophonies can be relatively easy to distinguish from biophonies. However, we recognize that the similarities in sonic characteristics between sonic signatures of continuous geophony (e.g., rivers) and continuous technophony (e.g., highways) or the ephemeral occurrence of intermittent passing cars at less-traveled roadways and wind events may confuse ACI results. More investigation is underway to address these issues. Although we recognize that other scientists are addressing the issues of geophony in acoustic analysis (Bedoya et al., 2017; Sánchez-Giraldo et al., 2020), there appears to be open opportunities to explore ACI beyond biophonies to measure and quantitatively interpret geophonies within sonic environments.

CONCLUSION

The geophonies of Earth have been an evolutionary driver of animal physiology and communication across a diverse array of extant and extinct species. Given their ever-present influence on the sonic environment, animal behavior, and human experience, we suggest that geophonies must occupy a more central position in the study and understanding of ecological processes. This is even more important now that the expansive impacts of anthropogenic climate change to the Biosphere present exceptional risks to displacing and reconfiguring sonic events, if not driving many soundscapes to extinction (Sueur et al., 2019). Among these are certainly the geophonies that are directly associated with Earth's processes. Unfortunately, these changes have already begun, and we must strive to obtain a higher standard of ecoacoustics research (Krause and Farina, 2016).

As we currently explore the surface of Mars (Leighton, 2021), we have acquired the first recordings of Martian geophony. This scientific achievement may give us insights to the role geophony has played in Earth's primordial history, or perhaps, a peak into Earth's distant future. Our pursuit of knowledge to understand the ecology of our own world must not negate the fundamental elements and phenomena that have shaped its existence. The quest to understand geophony among the myriad of biological and anthropogenic sounds can only open new doors to discovery here on Earth. We invite further research on this subject to generate a more holistic understanding of their semiotic relationships.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

AF and TM developed the theoretical basis of this manuscript and contributed equally to the literature review, writing, and revisions of the manuscript. TB, DB, and TT provided institutional support and the motivation to develop and publish this work. PL contributed to technical support for data processing. All authors contributed to the successful completion and publication of this article and collectively approved the submitted version.

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– Staff of Kenai Fjords National Park

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Key Issues for Realizing Open Ecoacoustic Monitoring in Australia

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Many organizations are attempting to scale ecoacoustic monitoring for conservation but are hampered at the stages of data management and analysis. We reviewed current ecoacoustic hardware, software, and standards, and conducted workshops with 23 participants across 10 organizations in Australia to learn about their current practices, and to identify key trends and challenges in their use of ecoacoustics data. We found no existing metadata schemas that contain enough ecoacoustics terms for current practice, and no standard approaches to annotation. There was a strong need for free acoustics data storage, discoverable learning resources, and interoperability with other ecological modeling tools. In parallel, there were tensions regarding intellectual property management, and siloed approaches to studying species within organizations across different regions and between organizations doing similar work. This research contributes directly to the development of an open ecoacoustics platform to enable the sharing of data, analyses, and tools for environmental conservation.

Keywords: ecoacoustics, open data, open science, monitoring, conservation, standards

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INTRODUCTION

Australia has incredible fauna biodiversity, across a sparsely populated landscape, with many species under threat. Ecoacoustics offers a much-needed approach to large-scale threatened species and biodiversity monitoring. Yet there remain challenges to realizing this important vision both in Australia and globally. This paper presents an investigation into how ecoacoustics monitoring might be scaled-up to complement other ecological monitoring methods in the face of global biodiversity loss.

Passive acoustic monitoring offers the advantages of non-invasive, long-duration sampling of environmental sounds, including biodiversity, can detect cryptic species (Znidersic et al., 2020), estimate species richness (Xie et al., 2017), evaluate ecosystem health (Deichmann et al., 2018), and be used to model a species' spatial distribution (Law et al., 2018). However, the ease with which large amounts of data can be collected complicates storage, analysis, and interpretation of results. Despite the development of new computing and visualization techniques (Eichinski and Roe, 2014; Phillips et al., 2017; Towsey et al., 2018; Truskinger et al., 2018), ecoacoustics research is currently hampered by bottlenecks in analysis and data management (Gibb et al., 2019). One challenge includes the amount of time, effort, and expertise needed to create labeled datasets with which to produce and evaluate automated call recognizers (McLoughlin et al., 2019). The use of automated methods of call identification to produce these datasets can greatly reduce the time compared to manual methods, but also increase the likelihood of false positives and negatives (Swiston and Mennill, 2009). The skillsets of computing science and ecology are also rarely held by the same person (Mac Aodha et al., 2014) leading to potential misalignments between data collection and data management protocols even in close collaborations (Vella et al., 2020). Scaling up ecoacoustics research will require a considerable effort to address the lack of standardization for acoustic data and metadata collection (Roch et al., 2016; Gibb et al., 2019), as well as the development of communities and platforms that enable the sharing of annotated datasets and tested species detection techniques. Enabling acoustic data categorization by citizen scientists also holds great promise (Jäckel et al., 2021). For example, citizen scientists engaging with Hoot Detective [a collaboration between the Australian Acoustic Observatory (A2O), the Australian Broadcasting Commission, Queensland University of Technology, and the University of New England, for National Science Week] have at the time of writing identified 2,624 native owl calls (Noonan, 2021). In the following, we focus on the Australian context, however, the challenges and opportunities that are identified are likely to be applicable in others.

A key initiative in ecoacoustics data collection, management and analysis has emerged in Australia, namely the Australian Acoustic Observatory (A20).[1] The A2O (Roe et al., 2021), is a continent-wide acoustic sensor network collecting data from 360 continuously operating sensors. This and the Ecosounds platform,[2] which manages the ecoacoustics data, visualization and analysis of negotiated research collaborations, are both using the open-source Acoustic Workbench software (Truskinger et al., 2021) available on GitHub. Other ecoacoustics data management is enabled by the Terrestrial Ecosystem Research Network (TERN[3]) project, which houses ecoacoustics data collected from TERN SuperSites: long-term research sites collecting a range of environmental data, including acoustic data. Another platform of note is the Atlas of Living Australia (ALA[4]), which aggregates a wide range of environmental data (i.e., observance records), but does not currently support the ingest of audio annotation observance records in a standardized form (Belbin and Williams, 2016). Finally, the Ecocommons[5] platform promises to support a wide range of ecological modeling and a analysis needs, including those of ecoacoustics, through access to curated datasets, tools, and learning materials. While this suggests extensive support for ecoacoustics data management and analysis, in practice, ecoacoustics research continues to rely upon *ad hoc* approaches. For example, while many organizations in Australia, including universities, governments, non-government agencies such as Birdlife International, are collecting acoustic data, driven by the increasing availability of low-cost recorders, subsequent analysis tools are being developed on an individual/region basis. While recognizer development is a valid area of investigation, in this paper we focus instead on what is needed to effect smoother data interchange and improve the scale at which ecoacoustics analyses can be conducted. One means of addressing these aims is through the sharing of resources and expertise. Making ecological data open has obvious benefits, such as the re-use of datasets to answer new research questions, and the possibility of new discoveries through meta-analysis of disparate datasets (Chaudhary et al., 2010; Cadotte et al., 2012). Open data also enables local and specific data to address questions dealing with larger spatial and temporal scales (Hampton et al., 2013), and creates the impetus to make data findable, accessible, interoperable and reusable (FAIR, Wilkinson et al., 2016). One way data can be made findable is through linked data (structured data which is interlinked with other data, so it becomes more useful through semantic queries) (Bizer et al., 2011). Sharing data also opens the possibility of networking and collaboration with other researchers in and across fields. However, the movement toward open ecological data has been slow, due in part to concerns about time investment not being returned, lack of data standards, missing infrastructure, intellectual property issues, amongst others (Enke et al., 2012). Data also has a financial value, and can be withheld out of fear of losing research funding (Groom et al., 2015). The reluctance to share data for the reason of poor investment return is being slowly overcome through systems of reward and attribution (Heidorn, 2008), though these may be most effective within academic fields. While some infrastructure and standards have been developed for some forms of ecological practice, these are still in development for the management of ecoacoustics data and metadata.

Though there is also value in standards being applied to other natural or anthropogenic sounds, it should be noted that this paper focuses on biophony and ecoacoustics applications for biodiversity monitoring. Ecoacoustics standards development promises to promote understanding of long-term biodiversity trends by making acoustic data and metadata transfer across different platforms and software possible. Data and metadata standardization also goes hand-in-hand with the development of standardized approaches to ecoacoustic survey and study design. Currently, research on this topic has identified key applications (Sugai et al., 2019), approaches based on ecological research aim (Gibb et al., 2019), project specific guides (Roe et al., 2021) and some comprehensive guidelines, however, ones that do not yet provide guidance on best practice (Browning et al., 2017), or instead, focus on specific uses, such as the production of indices (Bradfer-Lawrence et al., 2019). Standardization would promote collaborative and collective efforts to collect verified call data for neglected taxa and regions (e.g., tropical terrestrial biomes). Centralized sound libraries containing consensus data and metadata standards (e.g., date/time of recording, geographic location, recording parameters, sensor position) (Roch et al., 2016), would also improve the accessibility and comparability of reference sound libraries (Mellinger and Clark, 2006). However, the movement toward standardization, as in most interdisciplinary endeavors is slow and full of friction (Edwards et al., 2011), making human-centered methods a useful approach (Vella et al., 2020).

An open science approach to ecoacoustics research should greatly increase the availability of biodiverse data annotations and call recognizers, and with standards, can maximize conservation

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[1] https://acousticobservatory.org

[2] https://www.ecosounds.org/

[3] https://www.tern.org.au/

[4] https://www.ala.org.au/

[5] https://www.ecocommons.org.au/

outcomes through sharing limited resources for monitoring. However, the steps to achieving this are unclear. This study seeks to produce an overview of current practices, analytic techniques, and available metadata schemata, as well as produce a grounded understanding of how these are implemented (or not) across a range of organizations with a focus on conservation, land management, and research. Consequently, this research was largely driven by a human-centered approach to technology design with a series of online workshops conducted with a wide range of ecoacoustics practitioners. This paper concludes with a series of recommendations to guide the development of open ecoacoustics both within the Australian context and internationally.

MATERIALS AND METHODS

The overall aim of this research was to inform the development of an open ecoacoustics platform and linked resources to scale-up ecoacoustics monitoring both nationally and internationally. As such, the study focused on current resources and practices utilizing exploratory review and online workshops.

Our choice to conduct workshops with a wide range of ecoacoustics practitioners was driven from a human-centered approach to technology design. We believe it necessary to do this kind of scoping with real users in a real-world context as the rich data provided by this approach provides insight into how to design for adoption and accessibility.

Review

We conducted a review of available ecoacoustic hardware, software tools and field-wide standards to better our understanding of common practices, availability of techniques and tools, and limitations related to the management and analysis of ecoacoustic data. An additional aim of the review was to identify common data formats, metadata fields, and analysis related to ecoacoustic data to inform the development of a metadata schema. We conducted a search of the literature and included reviews of the field of bioacoustics and ecoacoustics, and searched literature on bioacoustic and ecoacoustic related software using the following search terms: “ecoacoustics,” “bioacoustics,” “review,” “automated processing,” “long duration recording,” “metadata,” “analysis software,” “call recognizers,” “detection algorithm,” “recognizer performance,” “repository,” “standards.” The search of the literature was conducted between May and August 2021 and involved searching Google Scholar and the Queensland University of Technology’s Library for the above keywords. Advanced search terms included articles from 2019 to present. These publications referred to other relevant literature, which was also included. We also accessed technical guides of the hardware and software tools identified and created summary tables of the information found. Existing standards for ecoacoustic analysis procedures and the ingesting of metadata were identified. This review also informed the development of materials for the following workshops with ecoacoustics researchers, and organizations that were incorporating this research method into their programs.

Workshops

Online workshops were conducted from 25 June to 1 September 2021, under QUT Human Ethics Clearance 2021000353. We recruited participation from partner organizations and end users. In this study, we are reporting upon the end user workshops only. These workshops were carried out across two sets:

1. Current Practices: The first user workshop aimed to understand how users work and interact with their current data, tools, and technologies; explore how current activities are performed with the support of current technologies; and identify issues faced within those current practices and potential solutions to those issues.
2. Requirements Gathering: The second user workshop aimed to map out an “ideal” open ecoacoustics platform; gather requirements that would increase accessibility and improve the user experience; produce a skeleton training plan; and list IP conditions.

Participants

End users ($N = 23$) were recruited from ten organizations within Australia who were largely responsible for or focused on conservation management, protecting endangered species, and conducting ecological and environmental research. They included universities, conservation advocacy groups, and State government departments. Wherever possible, participants were placed in workshops with others from the same organization.

The first set of workshops had twenty participants drawn from nine groups (Australian Wildlife Conservancy, Birdlife Australia, Charles Sturt University, Department of Biodiversity, Conservation and Attraction (Western Australia), Department of Primary Industries, Parks, Water and Environment (Tasmania), Griffith University, James Cook University, Museums Victoria, and University of Melbourne. In total, eight workshops were conducted, and each workshop ran for approximately 2 h.

The second set of workshops had eleven participants from six groups (Australian Wildlife Conservancy, Bush Heritage, James Cook University, Museums Victoria, University of Melbourne, and Birdlife Australia). In total, five workshops were conducted (each between 1 and 2 h in length) and included eight participants who had also participated in the first set.

Participants varied greatly in their familiarity with ecoacoustics data collection, management, and analysis. This was most likely due to the participants holding different roles within organizations (e.g., project manager vs. project officer), as well as these organizations having different sets of capacities, funding models, and priorities (e.g., universities vs. conservation advocates).

Procedure

Each workshop was 2 h in duration, was run via Zoom and Miro (an online, collaborative whiteboard tool), and was audio and video recorded. At least two members of the research team were present during the workshops, with one running the workshop and the other taking notes. At the conclusion of each workshop, screenshots and photos were taken of the mapping activities completed in Miro and the spreadsheet template.

Workshop 1—Current Practices

At the beginning of each workshop participants were asked to introduce themselves, their role, the organization they were from and the aims of that organization, and their interest in the project. We then explored their current practices around ecoacoustics research, data collection and analysis.

As part of this exploration, we created a spreadsheet template of some of the functional aspects of common software, tools and platforms used in the workflow of ecoacoustic data management and analysis. We asked participants to use this template to identify the tools they were using in their analysis process, as well as better understand how they use them and some of the pain points associated with them. Once this was complete, we then ran a brainstorming session which explored this workflow to highlight issues and potential solutions within that workflow.

Workshop 2—Requirements Gathering

At the beginning of each workshop, participants were asked to introduce themselves. They were then immediately shown a Miro board with a selection of ecoacoustics study designs. They were asked if there were any that we hadn't captured, and which were more important to them.

Following this they were shown example ecoacoustics use cases (one of these is presented in **Figure 1**), and this used to prompt discussion of their own use cases. These were listed and then reproduced in a similar format to that of **Figure 1**, i.e., they captured the flow of ecoacoustics data from the field, survey through to data management, analysis, and use (see pink boxes in **Figure 1**). Discussion followed from the construction of this use case.

Once a use case was completed, it was duplicated. Participants were then asked to think about how they would like this process modified and where. Prompts included thinking about what platforms or tools would remain essential; what parts of the research process they would like to outsource; how they'd like to manage data storage. The duplicated use case was changed as necessary, and notes taken. These use cases were also used to frame discussion about training resources (what was needed, ideal delivery system, and formats); data sharing (data sensitivities, what conditions would be necessary to enable sharing). Lastly, participants were asked if there were any use cases that were worth considering in the future.

Workshop Data Analysis

The analyzed dataset includes audio transcripts, Miro board outputs, and facilitator notes taken during the workshop. Audio transcripts and facilitator notes were analyzed in Nvivo, Release 1.5. All data went through a deductive coding process driven by particular areas of research focus, which were used as deductive codes when analyzing data from both workshop 1 and 2. These codes included tools and technologies; current research practices and activities; data collection, management, and analysis; standards; education and training; relationships; needs and expectations; and challenges.

Authors 1, 2, and 3 each individually analyzed the Workshop 1 audio transcripts and facilitator notes. Following this, they met to discuss their initial analysis and examine the Miro board outputs. All insights from this process were captured in Miro, where they then conducted deductive coding to collate participant findings within codes created from predetermined research questions. These insights were used to inform Workshop 2. Author 1 conducted deductive coding of the outputs of Workshop 2 utilizing both the initial codes and the codes created from the data from Workshop 1, collecting insights from this process also in Miro. At the conclusion of both workshops, a final round of discussion amongst Authors 1, 2, 3, and 4, was conducted using data from both workshops to determine the contents of the final themes.

RESULTS

Review Findings

This review was conducted with the aim of promoting standardization across ecoacoustics research. Standardizing data should reduce some of the frictions of interoperability between analysis programs and the harvesting of metadata from audio recordings. In turn, by making analyses and comparisons between analyses easier, data standardization should also encourage the development of standardized protocols. The following outlines the state of current guidelines and standards for acoustic recorders, data, analysis tools and techniques, and acoustic annotation. Following this is an overview of interoperability between tools; methods for evaluating recognizer

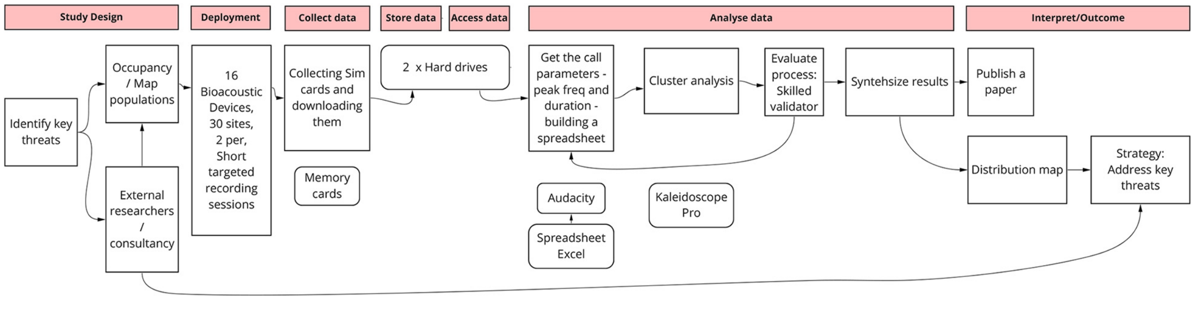

FIGURE 1 | An example ecoacoustics use case showing the flow of data between multiple organizations. The research group *QUT Ecoacoustics* accesses data from an ecoacoustics portal *the A2O* which is then shared with the *Hoot Detective* citizen science project.

performance; available acoustic repositories and registries; and finally, a summary of the key findings and gaps.

Standards for Acoustic Recorders

We reviewed the technical specifications and available metadata fields for acoustic sensor devices Song Meter 4, Song Meter SM4 Bat FS, Song Meter Mini, Song Meter Mini Bat, Song Meter Micro from Wildlife Acoustics, Inc.,[6] BAR-LT from Frontier Labs,[7] AudioMoth, μMoth from Open Acoustic Devices[8] (Hill et al., 2018), Swift from Cornell Lab,[9] and Bugg.[10] Detailed information is supplied as **Supplementary Material**, but in brief we found that for all sensor devices except Bugg, technical specifications were easily accessible either on the website, in linked technical guides and user documents or related publications. A metadata standard for audio collected by BAR-LT sensor includes a comprehensive list of terms of key recorder and recording attributes, however this standard is not adopted by other sensor devices and is not in a format readily transferable to other devices. Whilst there are a wide variety of audio recorders available, there are no common standards between manufacturers, particularly those related to metadata standards that capture: timestamps including UTC offsets; location stamps; gain; serial numbers for sensors, microphones, and memory cards; microphone type; firmware version; temperature; battery level. The Wildlife Acoustic devices share a proprietary standard which has been reversed engineered (i.e., a program was written to interpret the information present in audio headers[11]), however, this method is less efficient and potentially less accurate than working from a common standard. In addition to technical specifications of the audio sensor, it is important that metadata relating to environmental and ecological factors is accounted for in statistical analysis (Browning et al., 2017). It is therefore recommended that any relevant environmental or ecological metadata (e.g., rainfall, temperature, phenological events) be collected in addition to audio.

Standards for Data

Biodiversity Information Standards (TDWG, originally called Taxonomic Database Working Group)[12] have developed such as Darwin Core (Wieczorek et al., 2012) and Audubon Core (GBIF/TDWG Multimedia Resources Task Group, 2013) that have the overall aims of facilitating the sharing of information about biodiversity and representing metadata originating from multimedia resources and collections respectively. The intent of Audubon Core is to inform users of the suitability of the resource for biodiversity science application—a feature that would be desirable in an ecoacoustics standard. The Audubon Core standard contains several vocabulary terms relating specifically to audio resources and helps to promote the integration of existing standards by drawing vocabulary from other standards such as Darwin Core, Dublin Core (DCMI, 2020) and others. The standard, however, does not contain metadata terms that directly capture metadata pertaining to audio analysis and results and as such would need to be extended upon to capture all of the metadata fields that could be desired in an ecoacoustics standard. The metadata structuring rules named "Tethys," developed by Roch et al. (2016) more adequately address metadata fields that are not currently captured by existing systems and that are specific to bioacoustic research design, analysis and quality control (Roch et al., 2016). These include terms relating to the fields of project, quality control, description of analysis method and algorithm used, and a description of annotation effort and annotation boundaries Whilst "Tethys" is a good example of a published standard of practice capturing metadata beyond just segments of audio in time, the schema is difficult to adopt outside of the Tethys Metadata Workbench. Drawing upon the example of "Tethys," standards for ecoacoustic data should not only capture metadata about the recording itself, but metadata about the project, deployment (including survey design), recordings, objects annotated (including annotation effort and parameters) and analysis (including description of methods, algorithms, parameters, results and performance statistics). By applying standards to data in this way, comparisons and analyses of data would be easier and the development of standardized protocols would be encouraged (Roch et al., 2016).

Analysis Tools and Techniques

The entire analysis workflow of an ecoacoustics project can include various stages, such as collection of data, storage of data, manual analysis of data, automatic analysis of data, documentation of methods, and sub-sampling analysis effort. This review focused on common analysis software and does not represent a comprehensive list of analysis software, nor of the latest automated approaches to data processing. For example, the Practical AudioMoth Guide (Rhinehart, 2020) contains a list of software targeted at or used by bioacoustics researchers and that is either stable, currently in active development or recently released as of 2020.[13] Darras et al. (2020) reviewed software tools built specifically for ecoacoustics and find limited software that can perform all of the data processing tasks required and Priyadarshani et al. (2018) reported 19 software tools, of which 3 were no longer in use as of 2020 (Darras et al., 2020). Browning et al. (2017) list 19 software packages and tools for analysis of acoustic recordings, including a brief summary of each software and status of availability. It is important to note that software is continually updating, with new methods of analysis emerging in the literature.

We reviewed a range of free and proprietary software (some requiring a license), consisting of cloud-based, locally run, server run, command line based or software with graphical user interfaces. The list of software reviewed includes: Audacity, Kaleidoscope Lite and Kaleidoscope Pro (Wildlife Acoustics, 2019), Raven Lite (K. Lisa Yang Center for Conservation Bioacoustics, 2016) and Raven Pro

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[6] https://www.wildlifeacoustics.com

[7] https://frontierlabs.com.au

[8] https://www.openacousticdevices.info

[9] https://www.birds.cornell.edu/ccb/swift/

[10] https://www.bugg.xyz/

[11] https://github.com/riggsd/guano-spec

[12] http://www.tdwg.org

[13] https://github.com/rhine3/audiomoth-guide/blob/master/resources/analysis-software.md

(K. Lisa Yang Center for Conservation Bioacoustics, 2011), AviaNZ (Marsland et al., 2019), Rainforest Connection (RFCx) Arbimon (Aide et al., 2013), Ecosounds, Biosounds (Darras et al., 2020), and BioAcoustica (Baker et al., 2015). The reviewed software also includes popular command line run packages such as bioacoustics (Marchal et al., 2021), monitoR (Hafner and Katz, 2018), and seewave (Sueur et al., 2008). All the software reviewed have some form of visual data inspection capacity and all software have analysis capabilities to varying degrees. Most have annotation capabilities, with approximately half having recognizer building capacity and only a few with recognizer tuning and testing capabilities. Few have detection review capabilities, and standards for evaluating recognizer performance are inconsistent across software. Furthermore, in the literature, there is a lack of consensus on the best approach to evaluating recognizer performance (see section "Evaluating Recognizer Performance").

Of the above software, we highlight the following four software with qualities that promise to assist with realizing scalable ecoacoustics in being capable of the management and visualization of soundscape-level acoustic data, whilst also being able to support multiple kinds of analyses: Ecosounds, BioSounds (Darras et al., 2020), AviaNZ (Marsland et al., 2019), and RFCx Arbimon (Aide et al., 2013). The Ecosounds website is a key platform for the management, access, visualization and analysis of environmental acoustic data through the open-source and freely available Acoustic Workbench software—which the website hosts. In addition, the Ecosounds website acts as a repository of environmental recordings, and any annotations made are downloadable and available as.csv files making annotation outputs readable across multiple software. An advantage of the Ecosounds platform is that it is cloud based and supports the visualization and navigation of long duration and continuous recordings.

Similar to Ecosounds, BioSounds is an open-source, online platform for ecoacoustics which can manage both soundscape and reference recordings, be used to create and review annotations and also perform basic sound measurements in time and frequency (Darras et al., 2020). On the platform, recordings can be collaboratively analyzed and reference collections can be created and hosted (Darras et al., 2020). However, a major limitation of BioSounds is that at present, it does not have the capacity to develop species-specific recognizers and therefore lacks the capacity to develop efficient solutions for automatic analysis of long duration datasets—something which has been identified as one of the major barriers for the expansion of terrestrial acoustic monitoring (Sugai et al., 2019).

Another open-source and freely available software for automatic processing of long-duration acoustic recordings is AviaNZ (Marsland et al., 2019). This software facilitates the annotation of acoustic data, provides a preloaded list of species (based on New Zealand bats and birds for annotation IDs) and facilitates the building and testing of recognizers whilst providing performance metrics and statistics. AviaNZ can import annotations made with other software as well as export any lists of annotations or verified detections, therefore more readily interfacing with other software. In addition, pre-built detectors (for several New Zealand species of bats and birds) are available for use in AviaNZ and any filters (recognizers) created by users using AviaNZ can be uploaded for use on the platform, facilitating the sharing of resources among users.

RFCx Arbimon[14]'s free, cloud based analytical tool can be used to upload audio (and bulk upload.csv files), visualize, store, annotate, aggregate, analyze, and organize audio recordings (Aide et al., 2013). RFCx Arbimon's analysis capabilities includes automated species identification and soundscape analyses—functions that support the analysis of both bioacoustic and ecoacoustic audio data.

Our review findings support that, of the software available for data processing, none support the entire workflow or can perform all data processing tasks required by ecologists when analyzing large acoustic data sets (Darras et al., 2020).

Approaches to Annotations

There are many reasons why practitioners may choose to annotate sound data collected from the monitoring program, and these may depend on the aims of the study or program and range from being taxa dependent to purpose specific. Whilst there is no single approach to annotation, common approaches usually include start and stop times of the sound event in either time, frequency, or both, such as by the drawing of a box on a spectrogram around the event. In addition to the creation of annotations, some software can compute an array of acoustic parameters of signals of interest, which can be exported for use in statistical analyses (Rountree et al., 2020). Raven Pro software, for example, has over 70 different measurements available for rectangular time-frequency selections around signals of interest. As such, there is no standard approach to annotations. Depending on what the annotation was trying to capture/measure and what software was used to complete the annotation, variable metadata about the annotation may be available. Uniquely, the "Tethys" metadata schema introduced by Roch et al. (2016) provides an example of a structure that aims to capture annotation effort—that is, what proportion of detections were made systematically "OnEffort" and which detections were made opportunistically "OffEffort." Specifying the analysis effort with "Tethys" includes denoting which portions of the recording were examined, as well as the target signals were being detected ("Effort") (Roch et al., 2016). Considering the analysis effort is especially relevant when considering the number and frequency of annotations made. Considering this effort can prompt questions such as: what portion of the data were analyzed?; were all calls found, or were only one call per site/per day identified?; given the analysis effort, can the species truly be declared absent from the recordings? (Roch et al., 2016). Given the varying approaches to annotation, it would be useful to understand the level of effort and a description of the protocols used to create annotations. This could be done through the creation of a standard that offers different levels of certification of the annotation made, ranging from: (0) unknown or unstructured; (1) a protocol was followed, (2) a protocol was

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[14] https://arbimon.rfcx.org/

followed and verified and finally, (3) a protocol was followed and verified, but by multiple people.

Interoperability

With no single, unified approach to analysis of ecoacoustic data, ideally, components of analysis tools will be able to interoperate. Within the reviewed software, aspects of interoperability have been identified due to the capacity of software to ingest data of a certain format, as well as export data in a certain format. For example, Kaleidoscope Pro can create CSV format output files of detections and verified detections, and AviaNZ are RFCx Arbimon can import annotations from software in CSV or Excel format. Ecosounds can export upon request: annotations, acoustic indices and recognizer events detected CSV files. Raven Pro can export.txt format files of annotations and detection measurements, and the MonitoR packages can export sound data as text files—all of which can be imported by Audacity. The Seewave package can also import audio markers exported by Audacity. Whilst there exists some degree of interoperability due to common data formats of underlying audio data, translational issues are likely to arise when file formats are not supported; the exact structure and semantics of annotations varies between tools and additional scripts are needed; or when there is difficulty accessing and sharing resources and tools.

Evaluating Recognizer Performance

Without consistent metrics to quantify performance, it can be difficult to compare performance of analysis techniques across studies and across techniques. In addition, Browning et al. (2017) report that classification errors for proprietary software are often inadequately reported. It is desirable that recognizer performance metrics are included with any reporting of use of a recognizer, and that details of the construction of the recognizer are included (Teixeira et al., 2019). Whilst there are a range of metrics that can be used to evaluate classification performance and compare performance across studies, four agreed upon key metrics recommended by Knight et al. (2017) and Priyadarshani et al. (2018) are: precision, recall, accuracy, and F1 score (the harmonic mean of precision and recall). Calculating these four metrics for each automatic classification task allows users to contrast performance results of analyses and studies of potentially vastly different designs by using common metrics of assessment. One promising tool in development, *egret* (Truskinger, 2021), can be used to report efficacy of recognizers and publish the results in a standard format by evaluating precision, recall, accuracy metrics. By promoting such standards in future, comparison of studies that previously would not have been possible due to different approaches in assessing and reporting classification metrics, will become possible.

Available Archives

The need for more extensive and detailed collections of labeled ecoacoustic data to support automated call recognition has been identified (Gibb et al., 2019). These can take the form of registries (that register the various locations of data), repositories, and reference libraries We define a repository as software capable of storing annotations for large acoustic datasets—the annotations of which are particularly important for supervised machine learning tasks (McLoughlin et al., 2019). Of the above reviewed software, Ecosounds, BioSounds, AviaNZ, and RFCx's Arbimon have the capacity to also act as a repository. Separate to repositories are reference libraries, for example Macauly sound library,[15] Xeno-Canto[16] (mainly oriented for birds) and BioAcoustica (Baker et al., 2015) and Zenodo[17] Whilst reference libraries and repositories offer potentially high quality reference material, often certain taxonomic groups, habitats and regions are data deficient (Browning et al., 2017). Further limitations of reference libraries and repositories is that currently recordings of single species prevail over soundscape recordings (Gibb et al., 2019; Abrahams et al., 2021). If these potentially data rich repositories and reference libraries are to be used in the development, testing, comparison and validation of machine learning methods for ecoacoustic applications, then standardized methods of describing these datasets will ensure that they are both findable to researchers and assessable for fitness and inclusion into studies.

Key Findings and Identification of Gaps

This review finds that there is no one best approach or best choice of analysis techniques or best software that can be used in the processing of ecoacoustic data. Few freely available, open-source analysis tools available unify the multiple steps of the ecoacoustics workflow. Whilst there is some evidence of interoperability among software, few software have the capacity to share analysis and annotations. Some key reference libraries and repositories exist, however there is a lack of availability of strongly labeled datasets (in both publications and repositories) due to the absence of clear standards and the effort required to create such datasets. Few software that have the capacity to manage soundscape level data by visualizing large amounts of acoustic data also have the capacity to develop and test species-specific recognizers. Of the metadata schemas reviewed, none contain enough ecoacoustics-specific terms to capture the level of data that practitioners, moving forward, may wish to track. Finally, whilst conventions for annotations exist, there is yet to be a standard approach to annotations which is likely to continue to impact upon the reusability of labeled training datasets using in machine learning classification tasks.

Workshop Findings

Our workshop revealed tensions around data management and identified a range of analytic pain points. Participants reported a need for help locating learning resources that describe the most appropriate software, analytic techniques, and processes. We also identified a range of considerations for encouraging ecoacoustics data openness, and interoperability challenges.

Data Management and Analysis

Common practices around data storage included the collection of data on hard drives and memory cards, and their subsequent

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[15] www.macaulaylibrary.org

[16] www.xeno-canto.org

[17] https://zenodo.org

storage on the same. Backup of data could include duplication onto more hard drives, and very occasionally, cloud storage. Cloud storage costs were mitigated by making use of free services such as Arbimon.

Effort was expended creating consistent file structures when data was collected from different recorders (with different associated metadata); as well as when porting data between software with different data fields (see **Figure 2** for an example workflow from Workshop 2). Participants would make use of multiple software and platforms to access the functionality they needed. While simple scripts could address these, less computer science savvy users were not always able to easily produce these. *Ad hoc* workarounds were developed that might negatively impact reuse of data, for example the division of large sound files into 1-min segments to expedite analysis. This practice destroys associated metadata necessary for archiving and produces a set of files that might negatively impact the performance of any hosting platform (decreasing the likelihood that a platform might accept this data at a later date).

Recognizer development was similarly hampered, both in terms of learning the best techniques to apply, applying these techniques, annotation of datasets, and verification. Users from conservation advocacy groups reported, in some cases, that analyses being outsourced to contractors to overcome some of these issues. Many participants identified that expert validation was particularly important, especially when monitoring critically endangered species. Most users trained recognizers with datasets specific to regions and because of regional variation in species' calls, recognizer re-use in other regions may be limited or challenging. Anascheme (Gibson and Lumsden, 2003) was identified as a potential solution because it had developed "regional keys," a signature for a species across different regions. Participants reported a strong desire for a "toolkit" of recognizers from many regions, however there was also a need for these recognizers to be associated with metadata or "notes" describing the process through which the recognizer was developed.

Finally, citizen science was seen as a possible solution to the bottleneck in the generation of annotated datasets, but existing platforms have not been optimized for audio tasks. For example, Zooniverse (Simpson et al., 2014) and Arbimon (Aide et al., 2013) were being used for annotation and verification of identifications but were not well suited to audio analysis or segmentation.

Training and Education

Finding training for new techniques was described as a "black box," or opaque, by one participant. Participants sought training information and help from hardware manufacturers (e.g., Wildlife Acoustics, 2019), software forums, authors of academic papers on ecoacoustics, and through their networks. Knowledge varied across groups, with the university groups reporting greater confidence in their ability to choose and carry out the most appropriate analysis technique for their research question and data. Conservation advocacy groups were interested in being able to enable community groups to work on their own projects, as well as to upskill land managers, but had limited capacity (time, money, staff) to learn ecoacoustics analysis techniques. Choice of tool was driven by cost, familiarity, recommendation, and any additional benefits (e.g., free data storage, such as with Arbimon).

Participants identified a need for advice on best practice, across a range of areas including:

- Guidelines on data collection procedures including how to design monitoring programs to best use acoustics with other techniques in the field
- Choice of monitoring tools
- Ideal recording parameters for the target species or habitat
- How to prepare and analyze data, including the best techniques for developing recognizers
- The kinds of metadata that should be collected
- How to compare different types of data in a meaningful way

Specific examples were preferred that showed how people have tackled problems. Some mechanism for triaging analytic techniques based on data type and research question was also seen as desirable. Participants also demonstrated varied levels of confidence and capacity for learning the programming skills necessary for some analytic and data management tasks, with universities being better equipped than conservation advocacy groups. Developing user interfaces and tools that account for users with low levels of programming experience or the time

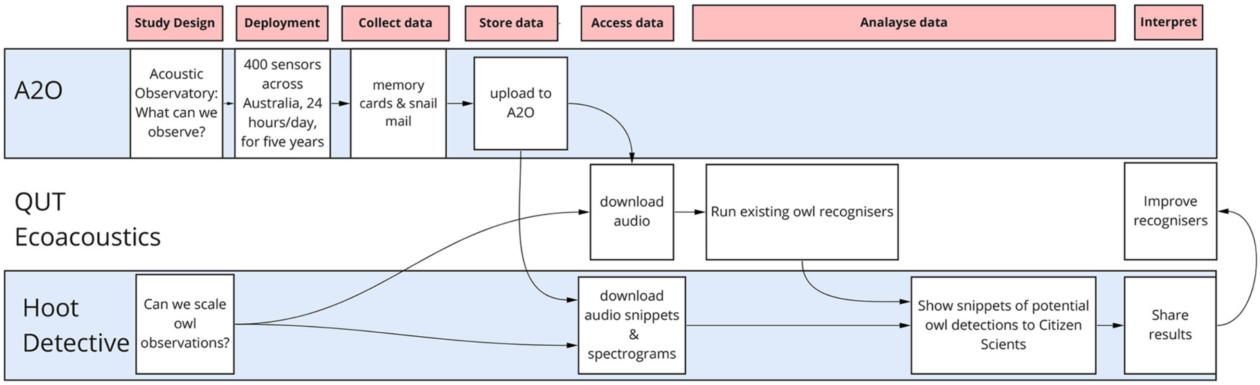

FIGURE 2 | Example workflow of species occupancy detection.

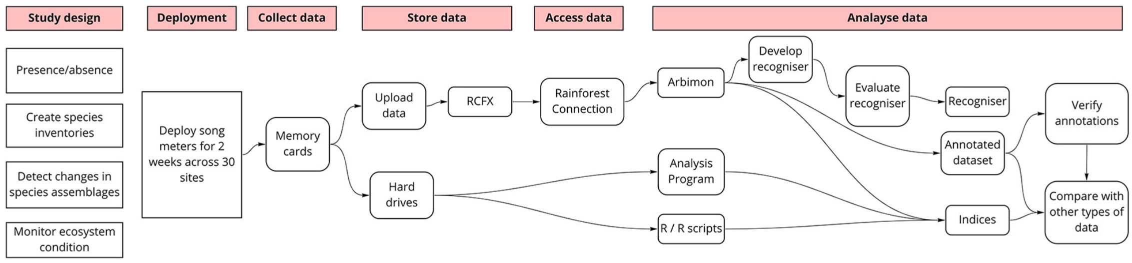

FIGURE 3 | Workflow for ecosystem condition analysis using ecoacoustics data.

to learn these may supplant the need for some forms of technical training.

Workshops were the preferred format for the delivery of ecoacoustics training and education, though it was noted that attending live events was challenged by fieldwork commitments. Workshops were seen as a way to collaborate across disciplines (ecology, computer science) to solve current problems. Having materials online and always available was considered necessary, particularly for organizations operating with limited resources and those engaging in seasonal fieldwork. Forums were desirable as this would allow researchers to ask questions and seek expert advice.

Interoperability

Participants reported using analysis tools including RFCx Arbimon, Audacity, Kaleidoscope Lite and Pro, Raven Lite and Pro, various R scripts including MonitoR, Seewave and more. It was recognized that being able to relate acoustics data to other forms of data provided much needed context. Consequently, there was a strong desire to be able to input ecoacoustics data into other ecological modeling tools, for example to relate acoustic data to environmental variables such as water level, habitat structure, or vegetation, or to spatially and temporally model species occupancy. **Figure 3** shows a current practice in which indices and verified annotations are compared with other types of data using an analysis process with multiple streams. Interoperation with other platforms such as Atlas of Living Australia (Belbin and Williams, 2016) was also seen as desirable.

Hardware outputs, e.g., file formats, were not always well suited to analytic software requirements and the need for common data interchange formats was recognized. Issues were identified with the upload and download of audio from analytic platforms.

Intellectual Property and Sharing

Participants reported a lack of awareness regarding other groups' ecoacoustics projects, with siloing of information sometimes experienced within groups operating across multiple regions. There was a strong desire to discover and use acoustic data and/or recognizers that others had developed as this would minimize the labor costs of monitoring and increase their overall ability to monitor environments.

Various barriers to sharing this data were identified. Participants universally stated a reluctance to share data on sensitive species (e.g., critically endangered), and noted that partnership agreements with academics, landowners, commercial companies, and Indigenous communities may also impact sharing. Less anticipated was the disclosed reluctance to share data that might be leveraged for philanthropic funding by another organization. In the space of not-for-profit conservation advocacy, this funding is directly tied to being able to show novel or innovative outcomes that might engage the public, and organizations were in competition for these funds. Another barrier to sharing large acoustic datasets was the possibility of it containing human voices and an inability to automatically detect them.

Methods to encourage sharing included producing clear guidelines and licensing agreements for sharing and copyright of data. Levels of access were also explored that might give users more control over who could access the data, and when. Associated location data would in some cases need to be obscured (e.g., private land, sensitive species). Intellectual property agreements would need to account for relationships between universities, other not-for-profit organizations, community groups, Indigenous communities, and commercial enterprises.

DISCUSSION

Realizing scalable ecoacoustics monitoring is hampered by some of the problems common to emerging fields. These include a lack of consensus regarding the best techniques to apply to a given research problem, and a lack of infrastructure to accommodate the specificities of data use and management. This study combined a review and workshops with ecoacoustics practitioners, to identify key issues for scaling up ecoacoustics monitoring programs. Contributing factors were identified by both the review and the workshop methods. These include a lack of standardization in methods, poor software and platform interoperability, difficulty finding training resources and best practice examples, and a lack of ecoacoustics data storage infrastructure available to a wide range of ecoacoustics practitioners. Of these, some practitioners were impacted more than others, with university-led users having greater access to expertise, as well as high-performance computing and data storage. Specific data sensitivities were also identified that impact how data sharing would be negotiated. The next section discusses these points and offers recommendations across the areas of enabling the sharing of data and metadata; standardization and other improvements to ecoacoustics data analysis workflows; and knowledge and skill acquisition for a range of actors. Finally, we make recommendations to ensure that ecoacoustics research becomes increasingly open and FAIR (Wilkinson et al., 2016).

Registries and Repositories

Making datasets and call recognizers searchable through either a registry or repository would enable the field of ecoacoustics to greatly expand its analytic capacity, by allowing recognizers to be re-used, and by increasing the number of cross-region and longitudinal comparisons that can be made (Hampton et al., 2013). Repositories also contribute to the wider ecoacoustics landscape by reorienting research toward openness, as they represent successful negotiations around intellectual property rights, and the fields' long-term aspirations. The movement toward open data requires a critical mass, where the most common and basic operations are documented, open, and standard.

We propose a method for sharing recognizers and evaluation datasets. Each recognizer made should be published to a source code repository, like a GitHub repository. This model allows researchers to publish recognizers openly by default while also allowing for private repositories (useful for embargo situations). Users can also maintain sovereignty for their recognizers (as they are version controlled), group recognizers together by project or organization, and generate DOIs automatically through services like Zenodo. Training and test datasets, depending on their size, can be published with the recognizers, or linked from the repository by using tools like Git LFS[18] or the increasingly popular DVC toolset, which is used to track datasets for experiments (Kuprieiev et al., 2021). Tools like egret (Truskinger, 2021) can be used to report efficacy of recognizers and publish the results in a standard format. Template recognizer repositories can be set up and published along with guides to make this process easier for beginners.

Standardization and Interoperability

Standards would also greatly support interoperability between software and platforms. Our review of metadata standards reveals there are few dedicated environmental audio standards, and none that are open and accessible. Whilst Tethys is the best example of a metadata schema containing fields that go beyond just technical specifications of acoustic sensor devices and ecological and environmental data accompanying recordings, we suggest that the most sustainable and responsive model for standards development is open—something that Audubon Core excels at. Further, we believe that linked data and formal ontologies, while important, aren't useful in day-to-day scientific work. We propose that linked data standard (such as Dublin Core, and the extensions relevant to us, like Biodiversity Information Standards, Audubon Core, and the annotations interest groups) are most important to technical implementers, like archives, software, device manufactures and other actors that need to share data or otherwise interoperate. Not one of our workshop participants mentioned linked data, ontologies, or other technical minutiae, however, this is explained by the lack of participants with a background focused on structuring information so that it is searchable, persistent, and linked to other data.

Currently ecoacoustics practitioners are using a wide range of acoustic editing and analytic tools to complete analysis. Whilst some software may focus on targeting one or a few analysis functions within the ecoacoustic workflow, key challenges remain in managing soundscape level data. In particular, the capacity to develop or test species-specific recognizers, and to upload and visualize large amounts of acoustic data challenges practitioners. Issues also emerge when porting data between software to access additional functionality. Ideally, there needs to be more integration of a suite of analysis functions tools into software to perform a greater proportion of the acoustic analysis workflow. Alternatively, translational software that assists with software interoperability could address some of these issues. There is also a need to compare ecoacoustics data with other forms of data (e.g., to conduct spatial modeling). Although there are *ad hoc* approaches to achieve this (see Law et al., 2018), these analyses would be greatly aided by free, non-proprietary, cloud-based tools. While there are some software that meet one or more of these requirements, few can capture all three criteria in a way that can be scaled-up.

Opening up ecoacoustics data necessarily requires consideration of interoperability with existing data platforms, and for this to include publishing to or allowing access to audio data and derived data (e.g., annotations or calculated statistics from audio data). These are opportunities where translational tools can help scientists transfer their data between platforms using formal data standards, for example, to enable annotations of acoustic events to be uploaded as observance records to the Atlas of Living Australia. Similarly, existing citizen science platforms (e.g., Zooniverse) that are not currently well suited to acoustics data categorization and annotation could benefit from generalized tools for working with audio. Working with these platforms to enhance their capacity to utilize acoustic data will greatly aid the development of automated methods of detection and raise the profile of ecoacoustics more broadly.

Best Practice and Training

Relatedly, ecoacoustics training resources aimed at undergraduate ecology and land management courses would greatly aid the development and the standardization of methods in the field. As an emerging field, best practice is a work-in-progress. To date, no comprehensive guide to ecoacoustic survey and study design exists, though promising directions are indicated (Browning et al., 2017; Bradfer-Lawrence et al., 2019; Gibb et al., 2019; Sugai et al., 2019). However, there is currently enough collective knowledge to provide worked examples of how to approach a number of research questions with ecoacoustics methods. File organization, sensor deployment, sensor settings, relevant field data needed for collection, dealing with audio files, recommendations for storage, and many other topics are all worthwhile publishing. The goal should be broad adoption of easy-to-use best practices that are easy to understand. With this

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[18] https://git-lfs.github.com/

platform of practices set up, the goal will be to have these *de facto* standards coalesce into true standards. Suggested data formats and layouts, become *de facto* standards through adoption, and critical mass will lead to tools that interoperate with these formats, which will realize gains for the community. Similarly, to the recognizer registry proposed above, there will be need for public contribution, version tracking, citable, and transparency when developing these standards of practice. A wiki platform or a source code repository are ideal choices if consumers see a website first, and editors can be onboarded in a friendly manner.

In addition to best practices, there is value in creating more formal training resources. Based on our participants' responses we can suggest that training resources need to be free for not-for-profits, on-demand, modular, facilitate interactive learning (questioning/answering), and tied to research questions. Ideally, any educational material recommends the use of software. Currently, with a plethora of analysis software, tools, and techniques available, there is no clear guide to what technique/software to apply when, or to which ecological problem. Of the software reviewed, categories of analysis software ranged from being locally installed, run from the cloud or a server, with either command line or Graphic User Interface interaction. Some software is paid and requires a license, whereas others are freely available. The choice of analysis software and technique will largely depend on requirements such as whether the software is free, whether it can handle large amounts of acoustic data, whether it can perform analysis to the desired level and whether it is accessible to the user. We recommend that formal training resources recommend software that is open-source and caters for a range of technical experience—allowing for simple and effective analyses with little to no code, scaling up to resources supporting advanced programming (like deep learning research).

Open Ecoacoustics

Addressing these components—registries and repositories, standardization and interoperability, best practices, and training—will allow ecoacoustics monitoring to practically scale up. Collectively, these improvements will also make ecoacoustics methods more accessible for less well-resourced actors such as not-for-profit conservation organizations. These groups are well-versed in the promotion of conservation initiatives as well as community engagement and—together with improvements in ecoacoustics citizen science methods—these groups have the potential to greatly influence the public imagination. This in turn, can support the movement toward gaining widely accessible open ecoacoustics data repositories. However, the changes suggested above do not entirely address the challenges of open ecoacoustics. As such, we make the following recommendations for promoting open ecoacoustics research:

- Publication of ecoacoustics research should require submission of data to an appropriate repository.
    - ○ Recognizers or other classification tools should be published as per the recognizer repository concept.
    - ○ Original audio recording data should be placed in a suitable archive, such as an Acoustic Workbench instance or RFCx's Arbimon.
- Opportunities for decentralized community collaboration should be produced, particularly for best practices and guides.
- Ecoacoustics leaders and organizations should place an emphasis on open by default research and data. Options for sensitive data or proprietary intellectual property agreements need to continue to exist but should be communicated as the exception to the rule.
    - ○ Particularly for vulnerable species, archives of data must be transparent in their dissemination of said data and build trust with stakeholders when storing data. Options for embargos and fine-grained access control are paramount. These levels of access are to be reviewed periodically.
    - ○ Some forms of metadata must remain open regardless of data sensitivities, e.g., project name, what type of data was collected, who collected it, and how it was collected may be negotiated stay open so that data remains searchable, but users may wish for greater levels of control regarding the where and when.
- Ecoacoustic platforms (software, archives, and hardware) must work cooperatively on formal data standards and interoperation.
- Ecoacoustic archives must invest persistent identifiers for their data collections. Datasets need to be associated with Digital Object Identifiers (DOIs), other research related persistent identifiers, and citing data must become commonplace.

Limitations

We did not review every available tool, technique, or software relating to ecoacoustics. Further review of existing survey and study designs that synthesize commonalities would also be valuable. Obvious next steps include systematically reviewing the literature and supplementing this with a broad survey of common practices, worldwide. However, we are confident, based upon similarities with the workshop findings, that the current review does provide a representative illustration of the types of techniques currently used in the ecoacoustics field.

The workshop participants from organizations conducting conservation research and/or land management. We did not recruit participants from industry (e.g., forestry, agriculture, mining), or commercial environmental consultants. It seems likely that these groups may have different needs for intellectual property protection that would impact open data agreements. Further research in this direction could consider how commercial and conservation-focused ecoacoustics interact and how data openness and protections might be achieved. Additionally, participation in the workshops was limited to Australian ecoacoustics practitioners. Australia is unique in its environmental conditions and species, and some of the problems our participants face may not be faced by ecoacoustics practitioners elsewhere. Though the opposite is also true, and the specificities of what is needed to realize scalable ecoacoustic monitoring in other parts of the globe requires further investigation.

While the workshop participants mentioned complexities with the development of call recognizers with training data from species of different regions to their target species, we did not follow up with an in-depth account of how they tackled this technically. Clearly, there is a need for tools and techniques that can address regional variation in calls, and this remains a design challenge that could be further explored through a canvasing of current techniques.

CONCLUSION

This study of current ecoacoustics practices, tools, and standards highlights the key obstacles for realizing scalable ecoacoustic monitoring for conservation and suggests ways to move forward. Strategies have been identified that address the challenges identified by workshop participants, and the gaps established by the review. Amongst these are the continued development of formal standards by platforms and the establishment of open-source best practices for scientists and related stakeholders (e.g., land managers in charge of deployment). Additionally, the development and production of training and learning materials is needed to guide the next generation of ecoacoustics researchers. Recognizer repositories and registries should be established with a focus on open-by-default methods and practices. This will be supported by the publication of data along with research being strongly encouraged by organizations and journals, and a focus on FAIR data—that is findable, accessible, interoperable, and reusable (Wilkinson et al., 2016)—and persistent identifiers for said data.

There is massive potential for the ecoacoustics field to influence biodiversity research and conservation, as well as computing techniques in related fields (e.g., bioinformatics). With the aforementioned suggestions implemented, the field of ecoacoustics can continue to grow into an established science.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because we do not have ethical permission to share raw, anonymized human data (interview transcripts) publicly. Requests to access the datasets should be directed to corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the University Human Research Ethics Committee (UHREC), Queensland University of Technology. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

KV, TC, and AG contributed to the method, data collection, analysis, first draft, and final edits. AT contributed to the analysis, first draft, and final edits. SF and PR contributed to the research design, final edits, and project funding. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2021.809576/full#supplementary-material

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METHODS
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Using a Novel Visualization Tool for Rapid Survey of Long-Duration Acoustic Recordings for Ecological Studies of Frog Chorusing

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Continuous recording of environmental sounds could allow long-term monitoring of vocal wildlife, and scaling of ecological studies to large temporal and spatial scales. However, such opportunities are currently limited by constraints in the analysis of large acoustic data sets. Computational methods and automation of call detection require specialist expertise and are time consuming to develop, therefore most biological researchers continue to use manual listening and inspection of spectrograms to analyze their sound recordings. False-color spectrograms were recently developed as a tool to allow visualization of long-duration sound recordings, intending to aid ecologists in navigating their audio data and detecting species of interest. This paper explores the efficacy of using this visualization method to identify multiple frog species in a large set of continuous sound recordings and gather data on the chorusing activity of the frog community. We found that, after a phase of training of the observer, frog choruses could be visually identified to species with high accuracy. We present a method to analyze such data, including a simple R routine to interactively select short segments on the false-color spectrogram for rapid manual checking of visually identified sounds. We propose these methods could fruitfully be applied to large acoustic data sets to analyze calling patterns in other chorusing species.

Keywords: acoustic monitoring, Ecoacoustics, frog chorusing, acoustic data analysis, acoustic data visualisation, chorus detection

INTRODUCTION

Passive acoustic monitoring is now a standard technique in the ecologist's toolkit for monitoring and studying the acoustic signals of animals in their natural habitats (Gibb et al., 2019; Sugai et al., 2019). Autonomous sound recorders provide significant opportunities to monitor wildlife over long time frames, and at greater scale than can be done physically in the field. Recording over extended periods and locations provides insight into species' activity patterns, phenology and distributions (Nelson et al., 2017; Wrege et al., 2017; Brodie et al., 2020b), and allows for the study and monitoring of whole acoustic communities (Wimmer et al., 2013; Taylor et al., 2017). Continuous and large-scale acoustic monitoring has become feasible as technological advances have provided smaller, cheaper recording units with improved power and storage capacities. However, the large streams of acoustic data that can be collected must be mined for ecologically meaningful data, and so the problem of scaling of observations has been translated into a problem of scaling data analysis (Gibb et al., 2019). Ecologists using acoustic approaches require effective and efficient sound analysis tools that enable them to take advantage of the scaling opportunities in large acoustic data sets.

Often, computer-automated approaches to detecting and identifying the calls of target species, such as pattern recognition and machine learning, are put forward as the solution to analyzing big acoustic data (Aide et al., 2013; Stowell et al., 2016; Gan et al., 2019). However, developing automated detection pipelines requires a high level of signal processing, computational and programming expertise, as well as considerable time and effort in labeling call examples to train classifiers, and then test and refine their performance (e.g., Brodie et al., 2020a). Unsupervised machine learning methods circumvent the need for labeled data but still require a large amount of data, and considerable time and expertise, to compute learning features and interpret the results (Stowell and Plumbley, 2014). Long-duration field recordings often contain intractable amounts of noise and variability in the quality of calls, and achieving accurate species identification is challenging in large-scale studies or studies of multiple species (Priyadarshani et al., 2018). The focus of automated acoustic analysis has been on detection of individual calls, but this granularity of data is often not what is required in studies of population chorusing activity, and call detections are instead aggregated into calls per unit of time. The time and effort in developing automated species detection methods to create results of limited practical use means this approach is not feasible in many studies and monitoring programs. Thus, manual sound analysis continues to be used in the majority of ecological studies using acoustic methods (Sugai et al., 2019), while automated call detection methods continue to be developed and improved (e.g., Ovaskainen et al., 2018; Marsland et al., 2019; Brooker et al., 2020; Kahl et al., 2021; Miller et al., 2021).

The manual approach to analyzing environmental sound recordings for studies of vocal animals, is to inspect each sound file using specialized software with both spectrogram and playback functions (e.g., Audacity[1]; Raven, Cornell Lab of Ornithology). An observer familiar with the calls of target species will typically scan the spectrogram visually for candidate sounds, and may use playback to confirm the species when uncertainty exists. In this way, an expert observer does not need to playback and listen to the entire recording to analyze it and identify the species present. This can be more efficient than designing automated call recognizers for short-term studies where there are few target species. However, manual analysis of sound recordings becomes impractical for large-scale studies (long-term or many species). As a consequence, many acoustic surveys are still designed with restricted sampling regimes that permit manual analysis. By programming recording units to record for a limited time at regular intervals throughout the study period, the temporal and spatial scale of surveys can still be kept large while keeping manual analysis feasible. Restricted sampling regimes have disadvantages over continuous recordings, however, such as a reduced likelihood of detecting rare species or species that vocalize infrequently (Wimmer et al., 2013), as well as a narrower temporal sampling resolution, which may miss ecological patterns of interest. Therefore, techniques that allow analysis of long, continuous audio recordings that do not rely on statistical techniques that are beyond the expertise of many users (e.g., machine learning), and that do not restrict the amount of time sampled, are required.

Recent developments in computational approaches to the analysis of environmental sound recordings have led to software tools being made available that generate visual representations of sound recordings at scales of 24-h or more. Towsey et al. (2014) developed a method of representing a long sound file in a single spectrogram that can be viewed whole on a standard computer monitor screen. This was achieved by using acoustic indices, which are numerical summaries of the sound signal calculated at coarse time scales, and which can be considered a form of data compression (Sueur et al., 2008; Pieretti et al., 2011). The compressed spectrograms were generated using three different acoustic indices calculated at 1-min resolution and mapping the values to three color channels (red, green, and blue) to form a "false-color" spectrogram. The sound content of the recording is reflected in the visual patterns which highlight dominant sound events. While these false-color spectrograms were devised to visualize general patterns in the soundscape, exploration of the patterns revealed that the calls of some species could be identified in the images (Indraswari et al., 2018; Towsey et al., 2018b). An example of a false-color spectrogram for a recording used in this study is presented here (**Figure 1**).

This manuscript presents a method of using long-duration false-color spectrograms to navigate and sample a large set of environmental recordings to detect species in a chorusing frog community. The impetus for applying this method was to collect data on the chorusing phenology and nightly chorusing activity of frog species at multiple breeding sites. We present simple R (R Core Team, 2021) routines for generating false-color spectrograms and for interactive selection of time segments to automate the process of finding and opening the segments of interest in the audio for manual analysis. We also test the accuracy of an observer, after some learning experience, to visually identify the frog species present at the study sites from patterns on the false-color spectrograms. Our aim is to outline and describe a protocol that will be useful to ecologists looking for an easily implemented method of navigating acoustic recordings and identifying the calls of target species.

MATERIALS AND METHODS

Acoustic Recordings

Long-duration sound recordings were made at frog breeding sites near Townsville, north Queensland, Australia (19.357° S,

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[1] https://www.audacityteam.org

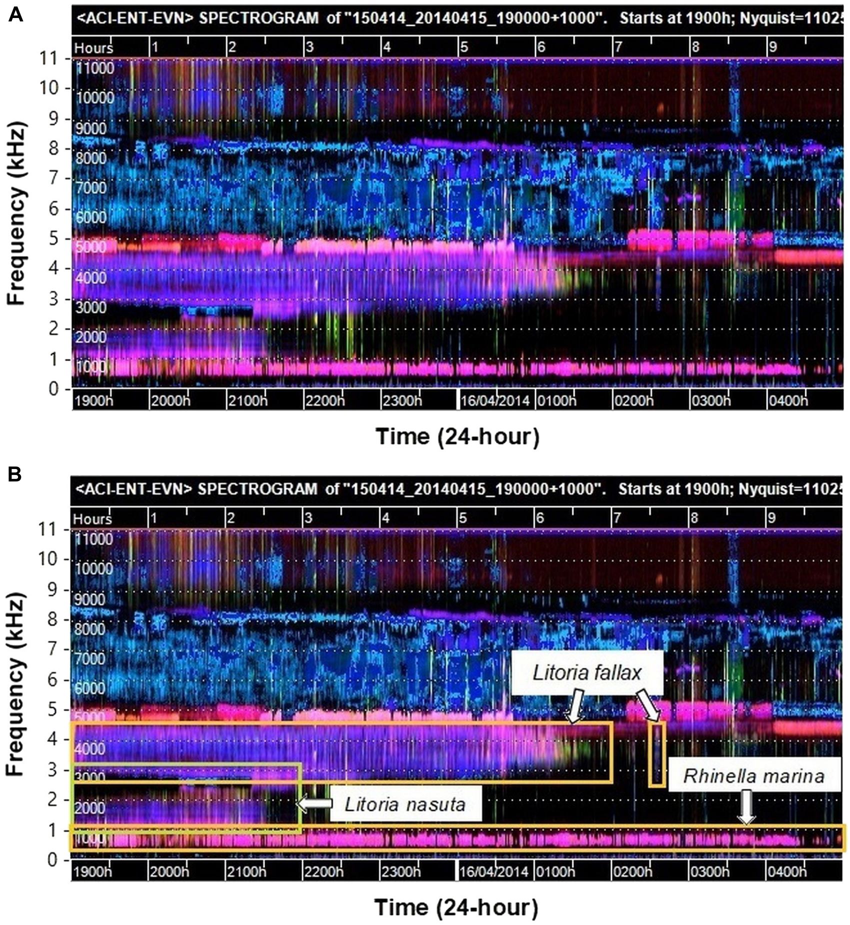

FIGURE 1 | (A) Example false-color spectrogram of a recording used in this study with chorusing of three frog species dominant. The frog choruses show as pink and purple tracks below 4.5 kHz. Sporadic birds calls occur (green/yellow), and insect choruses are prominent as pink and blue tracks above 4 kHz. The horizontal dotted lines delineate 1000 Hz frequency intervals (labeled in kHz on the axis outside the figure for clarity). Colors are derived from three acoustic indices (Acoustic complexity – red; Entropy – green; and Event count – blue) which are defined in the text. **(B)** The same false-color spectrogram image with the chorusing frog species identified inside the labeled boxes.

146.454° E). Recording units (HR-5, Jammin Pro, United States) were set to record continuously at 10 sites each night throughout a 19-month period from October 2012 to April 2014. Recorders were housed in water-proof metal boxes with external microphones in plastic tubing, and recordings were made in MP3 file format (128 kbps bit rate; 32000 Hz sampling rate). The study area is in a tropical savanna ecoregion and frogs in this habitat are nocturnal, so recordings were only made during the night. Most recordings were between 10- and 13-h duration, typically commencing between 1800 and 1930 h and ending after sunrise. The number of nights recorded at each site during the study period ranged from 375 to 473 nights (audio was not obtained for all nights because of recording equipment failure). At the end of recording period we had collected 3,965 nightly recordings totaling approximately 46930 h of audio.

Generation of False-Color Spectrograms

False-color spectrograms were produced using the QUT Ecoacoustics Audio Analysis Software v.17.06.000.34 (Towsey et al., 2018a) following the methods detailed in Towsey et al. (2015) and Towsey (2017). Audio recordings were divided into 1-min segments, re-sampled at a rate of 22,050 samples per second and processed into standard spectrogram form using a fast-Fourier transform with Hamming window and non-overlapping frames of 512 samples per frame (~23.2 ms per frame). Acoustic indices were calculated for each minute segment in each of 256 frequency bins from 0 to 11025 Hz (bandwidth ~43.1 Hz). False-color spectrograms can be produced using a combination of any three of the calculated acoustic indices, which are mapped to red, green and blue colors. We used the default combination of indices output by the software – the acoustic complexity index (ACI), spectral entropy (ENT) and acoustic events (EVN) (**Table 1**). This combination of acoustic indices best displays biotic sounds of interest in the false-color spectrograms, because they are minimally correlated and highlight different features (Towsey et al., 2018b).

The analysis to calculate acoustic indices and produce false-color spectrograms for our large set of recordings was done by the

TABLE 1 | Definitions of acoustic indices used in composing false-color spectrograms, calculated for each minute in each frequency bin (Towsey et al., 2014; Towsey, 2017).

Acoustic index	Description
Acoustic complexity index (ACI)	The average relative change in sound amplitude from one frame to the next.
Entropy (ENT)	A measure of temporal concentration of acoustic energy.
Event count (EVN)	The number of acoustic events exceeding 3 dB.

QUT Ecoacoustics Research Group's data processing lab using multiple computers which were dedicated to research analyses. However, the QUT Ecoacoustics Audio Analysis program is available as open source software and can be run on a personal computer. The program is downloaded as an executable file and run from the command line which provides flexibility for scripting and batch processing on different platforms (Truskinger et al., 2014). R code to run the open source version on multiple sound files in a single process is provided on GitHub (Brodie, 2021). When tested on a desktop PC (16 GB RAM, Intel(R) Core(TM) i7-7700 CPU @ 3.60 GHz) and running analyses in parallel, a 12-h recording took on average 7 min to analyze. For large data sets where this rate of output is inadequate, dedicated high-peformance computing facilities or professional support may be required.

Navigation and Inspection of False-Color Spectrograms

The QUT Ecoacoustics Audio Analysis software output a set of files for each separate audio file including the raw acoustic index values in CSV files, and the false-color spectrograms as PNG image files. All the PNG image files of the ACI-ENT-EVN indices combination were placed into a single directory for each site for ease of navigation through each set of images. Each pixel on the false-color spectrogram images represented 1 min on the time scale and approximately 43 Hz frequency range. A time scale is included on the image displaying the time since the start of the recording or, if a valid date and time is included the audio filenames, the time of the recording. Therefore, the position of a pixel on a false-color spectrogram informs the time position within the audio recording (x-axis), and the approximate frequency range (y-axis). We used the XnView image viewer application (v 2.43[2]) to view the PNG image files, as this application displays the position coordinates of the mouse pointer on the image. This allowed identification of the precise point, in number of minutes, from the start of the recording.

The patterns in the false-color spectrograms reflect the dominant sound sources in each time segment and frequency bin. Learning to relate visual patterns to sound events was done by identifying potential sounds of interest on the false-color spectrogram images and then manually inspecting the corresponding minute in the audio file to identify potential sound sources. We used Audacity audio software (see text footnote 1) for playback of the raw audio and viewing in standard spectrogram format.

R Routines for Efficient Analysis

Although sound analysis software packages such as Audacity can open and display long sound files, opening and navigating long recordings is inefficient when short segments from many separate recordings need to be analyzed. We made the analysis more efficient using R routines in the RStudio environment (RStudio, 2021) to slice short segments of the recordings at specified time points using the "Audiocutter" function in the QUT Ecoacoustics Audio Analysis software (Towsey et al., 2018a). The R routines included user-defined functions to select and cut audio segments using two alternative methods of selection:

(i) direct user input - the user entered the start minute (the *x*-value identified on the false-color spectrogram image) and desired length of audio segment as variables into the R script;
(ii) interactive selection – the user invoked a function from the R 'imager' package (Barthelme, 2021) which opened a graphic window displaying the false-color spectrogram and prompted the user to select the desired minute(s) (*x*-value) interactively on the image (the 'grabPoint' function to select a single *x*-value, or the "grabRect" function to select a range of *x*-values).

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[2] https://www.xnview.com/en

TABLE 2 | Results of accuracy test of visual identification of frog species in 321 test minutes using false-color spectrograms.

Species	Minutes present	Correct (TP)	Incorrect (FP)	Missed (FN)	Not present (TN)	Precision TP/(TP + FP)	Recall (sens) TP/(TP + FN)	Specificity TN/(TN + FP)
Rhinella marina	132	125	1	7	189	99.2%	94.7%	99.5%
Litoria fallax	149	140	3	9	172	97.9%	94.0%	98.3%
Litoria nasuta	100	88	3	12	221	96.7%	88.0%	98.7%
Limnodynastes convexiusculus	30	28	0	2	291	100.0%	93.3%	100.0%
Limnodynastes terraereginae	21	17	2	4	300	89.5%	81.0%	99.3%
Limnodynastes peronii	15	13	0	2	306	100.0%	86.7%	100.0%
Litoria rubella	7	4	0	3	314	100.0%	57.1%	100.0%

Minutes present, number of randomly selected minutes in which the species was confirmed to be calling; TP, True positive; FP, False positive; FN, False negative; TN, True negative.

The user input was then passed to the "Audiocutter" function which cut the selected minute(s) from the audio file and opened the selected segment in the Audacity program. The R code files have been made available on GitHub (Brodie, 2021).

Validation of False-Color Spectrograms as a Species Identification Tool

To validate that the false-color spectrograms were a reliable tool for visual identification of the frog species in this data set, a random selection of minutes was analyzed by an observer (SB) before being validated by inspecting the raw audio. Fifty false-color spectrograms (i.e., for recordings of different nights) from three sites were chosen which had not been previously analyzed. A random selection of up to 20 one-minute segments was made from each spectrogram using a random number generator. The presence of frog species was predicted for each randomly selected minute in each recording solely from visual inspection of the false-color spectrogram and prior to any inspection of the audio file. The visually based predictions were then validated by inspecting the corresponding audio segment using the Audacity program. A total of 321 separate minutes were randomly selected for validation, and the identification precision, recall and specificity metrics were calculated for each species identified. The frog species present at the study sites aggregate at water bodies to breed and males call in choruses. We did not distinguish between times when only one individual was calling and more than one individual was calling, since the ultimate aim is to use calling or chorusing as an indicator of breeding activity. It should be noted that this test was performed after the observer (SB) had gained some familiarity with the species' patterns in the false-color spectrograms of the data set, and had an expert level of ability to identify the calls of the frog species present in the raw audio.

RESULTS

Using the false-color spectrograms as a visual guide to the sound content of long environmental recordings, we were able to efficiently collect data on the presence and timing of chorus activity of multiple species of frogs in a large set of acoustic recordings. This method greatly reduced the manual listening effort required when compared to scanning entire recordings and increased the detectability of species over a method using a restricted sampling regime of regular time intervals. The time taken to survey the nightly recordings using the R routine to select, cut and open short segments of audio ranged from a few seconds (on nights with no frog chorusing) to 90 min (a full 13-h continuous recording with 11 species of frogs identified and extensive chorus activity). The average time taken to survey each night was 14 min.

In the test of species identification accuracy, 9 false-positive identifications were made, and 39 false-negative identifications (species missed) out of a total of 454 occurrences of any frog species (**Table 2**). As a result, precision (the percentage of correct identifications) was very high for all species present. Recall (the percentage of actual species occurrences detected) was high for the most common species, but low for *Litoria rubella* which was present in only 7 of the minutes selected for validation.

Inspection of the possible reasons for the identification errors revealed that other noises in the same frequency band caused the false-positive detections (**Table 2**). *Litoria fallax* and *Litoria nasuta* were falsely detected occasionally because they were confused with visual patterns made by splashing water. *L. fallax* was also falsely detected in one instance when insect noise was present. *L. fallax* has a call in the frequency range 2–6 kHz, which overlaps with some insect sounds. *L. nasuta* was falsely detected in one instance when *L. rubella* was calling, and once when *L. fallax* was calling. *L. nasuta* has a short, broadband call in the frequency range 1–4 kHz which entirely overlaps the calls of *L. rubella* and partly that of *L. fallax*. *Rhinella marina,* which has a long, low-frequency call made up of a trill of rapid pulses, was misidentified only once when rapid dripping of water onto the recorder housing created a similar pattern on the false-color spectrogram. In two instances, *R. marina* was mistakenly identified as *L. terraereginae.* The calls of these two species overlap in the frequency range of approximately 500–900 Hz. False-negative identifications (species missed) occurred either because the missed species was obscured by other dominant noise (vehicles, wind, other frogs or insects) or because the calls were very faint and distant, very short bouts or one individual calling at a very slow rate.

DISCUSSION

Visualization of long sound recordings is an innovative approach for providing insight into the acoustic structure of environmental soundscapes, and to aid detection of wildlife vocalizations. We found that false-color spectrograms generated using acoustic indices were a reliable and accurate method of identifying the chorus activity of individual species in a large community of chorusing frogs. A routine using the R programming environment was developed that automates searching and opening segments of sound files after interactive selection on the false-color spectrogram image. This method provided an easily implemented and practical tool for biological researchers to explore and navigate sound recordings for species of interest, and provides opportunities for increasing the scale of acoustic analysis with open-source software tools. False-color spectrograms allowed easy identification of which recordings contained large amounts of vocal activity and those that did not. For example, recordings with no frog chorusing had false-color spectrograms with very little color pattern in the frequency range below 4 kHz (e.g., **Figure 2**). This allowed us to quickly eliminate nights with no frog chorus activity without the need to manually check the audio file, and focus on those recordings with high vocal activity (e.g., **Figure 3**).

The use of visualization as a tool to analyze long recordings in ecological studies was developed independently by several researchers (Wiggins and Hildebrand, 2007; Towsey et al., 2014) but, despite its demonstrated usefulness, it has not been applied extensively in practice. Wiggins and Hildebrand (2007) first devised a method of visualizing sound recordings by averaging

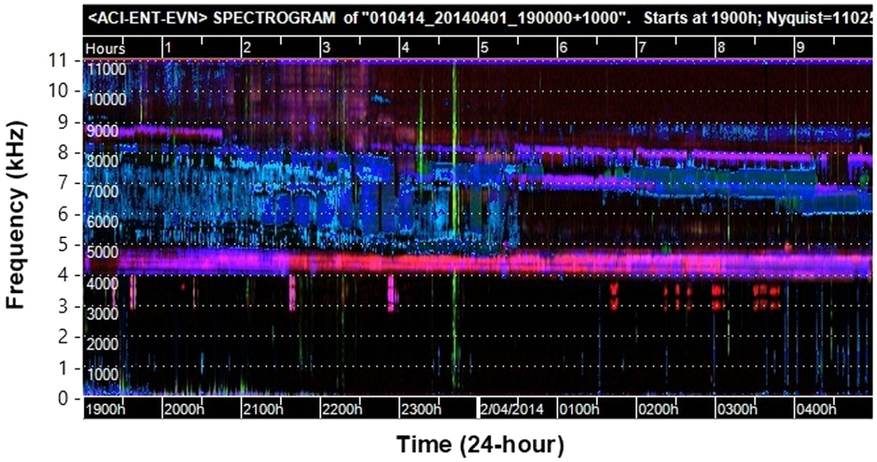

FIGURE 2 | False-color spectrogram of a recording used in this study showing a night with no frog vocal activity. The dominant sounds are insect choruses above 4 kHz. The occasional pink and red tracks at 3–4 kHz are also insects. Sporadic sounds below 3 kHz which occur include wind, passing vehicles and occasional bird calls. The obvious green broadband mark at approx. 23:40 hrs is made by water birds splashing and flapping wings close to the microphone. The horizontal dotted lines delineate 1,000 Hz frequency intervals (labeled in kHz on the axis outside the figure for clarity).

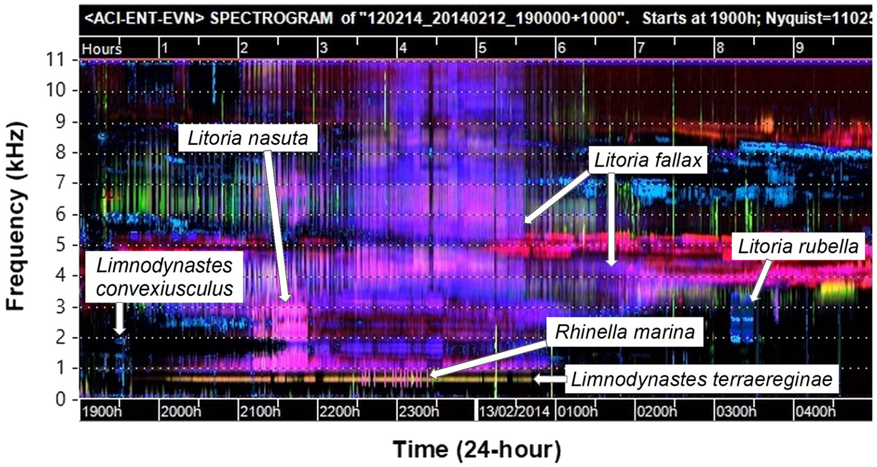

FIGURE 3 | False-color spectrogram of a recording used in this study which features the choruses of six frog species calling simultaneously. The horizontal dotted lines delineate 1,000 Hz frequency intervals (labeled in kHz on the axis outside the figure for clarity). Patterns are sometimes obscured by other dominant species but can be distinguished at other times.

spectral power values over chosen time frames to generate compressed spectrograms. Their method was implemented in the MATLAB programming environment using the Triton software package (Wiggins, 2007) which also facilitates navigation to specific segments of the raw audio for manual analysis. Published examples have applied visualization using the Triton package in marine environments, for which it was designed, to detect whale calls (Soldevilla et al., 2014) and describe marine soundscapes (Rice et al., 2017), but it has also been used in freshwater environments to detect chorusing of an underwater-calling frog (Nelson et al., 2017), and in terrestrial environments to detect chimpanzee vocalizations (Kalan et al., 2016).

The false-color spectrograms developed by Towsey et al. (2014), Towsey et al. (2015), and demonstrated here, progressed the concept of soundscape visualization, by using acoustic indices that highlight biological sounds. The method of visualization using three color channels based on different metrics enables display of more complex patterns, and highlights a greater variety of sound sources than using the single spectrogram power values. False-color spectrograms have been used in ecological studies to describe and compare soundscapes, by using the visual images to detect the dominant sounds in the environment (Dema et al., 2018; Campos et al., 2021). Several studies have shown the calls of individual species can be detected visually using false-color spectrograms. Towsey et al. (2018b) and Znidersic et al. (2020) were able to visually detect the presence of cryptic marsh birds. Brodie et al. (2020b) used the method to confirm the nightly presence of invasive toad calling activity.

The general advantage of visualization of environmental recordings is that it allows rapid detection of candidate sounds of interest without relying on complex computational methods, and reduces the effort required to manually scan sound files. While previous published studies have used false-color spectrograms for detecting species presence and characterizing soundscapes, here we have demonstrated the method can scale to studies of communities of chorusing frogs over extended time periods and multiple locations. The constant choruses of several frog species left unique traces on the false-color spectrograms which, in many instances, could be confidently identified without the need to analyze the raw audio, decreasing further the manual analysis required. Manual inspection of the audio, either by listening or viewing the standard spectrogram, was still required for many of the recordings where the noise source of presence of a frog species was unclear. Therefore, there is a limit to the scalability of using this method for very large data sets.

The high precision and specificity of frog species identification achieved in the test cases (**Table 2**) reflects the low rate of false-positive detections. That is, patterns on the false-color spectrograms were only very occasionally incorrectly identified as another species. The majority of identification errors were missed species' presence, in cases where the frog calls were distant and low-quality in the recording, or there was a low rate of calling. Low-quality, background calls will always be difficult to detect regardless of the method used. The accuracy results presented here are better for the 5 species that are shared with a previous study investigating the use of automated classification using acoustic indices and machine learning (Brodie et al., 2020a). This suggests that even with considerable time and effort to label training data and train classification models, automated methods may still not perform as desired, and manual methods such that presented here may be more suitable.

Our aim in this study was not to compare the accuracy of species identification using false-color spectrograms with automated detection methods, as these are different approaches to data reduction and analysis of acoustic data. The use of false-color spectrograms to survey acoustic recordings for target species can reduce the amount of manual analysis required, but still requires significant manual effort and time to learn to identify patterns of interest. In addition, computing time to calculate acoustic indices and generate the images is considerable for large data sets. Automated species detection for environmental sound recordings is a rapidly advancing field, however, may not be feasible or practical for all acoustic studies. The most successful automated detection algorithms are for species with well-described calls which are distinct from the calls of other species (e.g., Walters et al., 2014 for bats; reviewed in Kowarski and Moors-Murphy, 2020 for fin and blue whales) or for which large sets of training data are available (e.g., Kahl et al., 2021; Miller et al., 2021). Nonetheless, the challenge of automating analysis of acoustic data is far from solved for many research questions. Automated animal call detection is now the domain of computer scientists and computational experts, and there is considerable time and expertise required in developing accurate detection algorithms. Further, recent reviews have revealed that the majority of studies utilizing automated call detection methods incorporate manual human intervention in post-processing stages, such as manual validation and cleaning of call detection results (Sugai et al., 2019; Kowarski and Moors-Murphy, 2020). There are inevitable trade-offs in time, cost and effort when researchers decide whether to utilize automated or manual methods in their acoustic data analysis.

Several factors combine to render frog choruses visually distinct and readily identifiable on the false-color spectrograms. Frog choruses tend to be persistent through time, often continuing for several hours, and are the dominant sound at breeding sites during breeding periods. Frog calls are repetitive and consistent in structure within species, but vary in both structure and frequency range among species. This method of using visualization to analyze long-duration audio is, therefore, highly suited to monitoring frog communities where species form persistent, loud choruses at breeding sites. This approach would also be applicable to other chorusing species, such as soniferous insects. Sounds that occur over short periods may also be visible on the false-color spectrograms but are less obvious than patterns that extend through a large portion of the recording. Some nocturnal birds that call continuously for at least a few minutes, such as owls and cuckoos, can also be identified (Phillips et al., 2018; personal observation). Short bursts of sounds may also be highlighted on the false-color spectrograms if they are louder than other sounds in the same minute segment, so this technique of detecting sounds is not limited to species with long-duration calls. However, it became clear from our experience analyzing this data set that the representation of sounds in the false-color spectrograms is dependent on other sounds present in the same minute segment and frequency band. The loudest sounds in each segment are highlighted so that the choruses of several frog species were sometimes obscured, or masked, in periods of high chorus activity dominated by other frog species. On the other hand, soft short calls may be identified in other periods when there are no competing noises in the same frequency range (Znidersic et al., 2020; personal observation). We found that the masking by dominant frog species could be somewhat overcome by using long, continuous recordings rather than shorter, intermittent recordings. Having a complete, continuous recording for each study night meant we could detect most of the chorusing frog species at some point in the false-color spectrogram when masking was reduced. Whether false-color spectrograms are a suitable tool for the detection of a species depends on the likelihood of capturing calling individuals within range of the microphone and the level of competing noise in the target frequency range.

A further advantage to the approach described is that all software used was open source and does not require a specialized platform. The QUT Ecoacoustics Audio Analysis program[3] automatically performs all processing of raw audio, calculation of acoustic indices and generation of the false-color spectrograms. Some knowledge of running programs from a command-line environment is required, but user input requirements are limited to defining the input and output files, with some configuration options. The interactive selection functions were implemented in

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[3] https://github.com/QutEcoacoustics/audio-analysis/releases

R using R Studio (Brodie, 2021), and are simple to run for users with basic knowledge of the R programming environment. R is now widely used in ecological research (Lai et al., 2019) and easily accessible for most researchers.

The false-color spectrograms can be a useful tool to analyze long recordings, even without the R routine program, simply by manually opening the corresponding sound file and navigating to the time-point of interest indicated on the false-color spectrograms. The interactive R routine was created to increase time efficiency, as shorter sound files are quicker to open than longer files, and when opened can be immediately inspected without having to navigate through a long recording to the relevant time point. In addition to increased efficiency, the R routine reduces the risk of human error. When dealing with large sets of sound files there is a risk of choosing the wrong file if many files have similar names with the same date, or of navigating to the wrong time point in long recordings.

Although automated methods of identifying species in acoustic data is an advancing field of research, many researchers continue to use manual analysis methods in acoustic monitoring studies. Our aim in this paper was to demonstrate a work-flow including the practical application of false-color spectrograms (Towsey et al., 2014) as a navigation aid to streamline the manual analysis of acoustic data. The process described here takes this innovative method of visualizing sound and incorporates it into an efficient routine for detecting the chorusing of multiple species of frogs in large acoustic data sets. The accuracy achieved in identifying multiple species of frogs from field recordings taken at different times and locations confirms this can be a reliable method of species detection and identification. Used as a means to quickly scan the content of recordings for target sounds, the amount of manual analysis is greatly reduced. There is potential for its use in increasing the coverage of ecological monitoring programs, particularly where automated methods of analysis are not practical or feasible. In describing and outlining our process of utilizing false-color spectrograms to analyze long-duration recordings, we seek to make this method accessible and practical for use by other researchers using acoustic monitoring methods.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

SB and LS conceived the ideas and designed methodology. MT conceived and designed the original methodology of audio visualization with false-color spectrograms with input from PR. SB developed and wrote the R routines with input from SA-A. SB collected and analyzed the data and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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Temporal Soundscape Patterns in a Panamanian Tree Diversity Experiment: Polycultures Show an Increase in High Frequency Cover

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In this ecoacoustic study we used the setting of a tropical tree diversity planted forest to analyze temporal patterns in the composition of soundscapes and to test the effects of tree species richness on associated biodiversity measured as acoustic diversity. The analysis of soundscapes offers easy, rapid and sustainable methods when assessing biodiversity. During the last years the quantification of regional or global acoustic variability in sounds and the analysis of different soundscapes has been evolving into an important tool for biodiversity conservation, especially since case studies confirmed a relationship between land-use management, forest structure and acoustic diversity. Here we analyzed soundscapes from two seasons (dry and rainy season) and aurally inspected a subset of audio recordings to describe temporal patterns in soundscape composition. Several acoustic indices were calculated and we performed a correlation analysis and a non-metric multidimensional scaling analysis to identify acoustic indices that: (i) were complementary to each other and such represented different aspects of the local soundscapes and (ii) related most strongly to differences in acoustic composition among tree species richness, season and day phase. Thus, we chose "High Frequency Cover," "Bioacoustic Index," and "Events Per Second" to test the hypothesis that acoustic diversity increases with increasing tree species richness. Monocultures differed significantly from polycultures during night recordings, with respect to High Frequency Cover. This index covers sounds above 8 kHz and thus represents part of the orthopteran community. We conclude that increasing tree species richness in a young tropical forest plantation had positive effects on the vocalizing communities. The strongest effects were found for acoustic activity of the orthopteran community. In contrast to birds, orthopterans have smaller home ranges, and are therefore important indicator species for small scale environmental conditions.

Keywords: ecoacoustics, tree diversity experiment, high frequency cover, acoustic diversity, soundscape, temporal patterns

INTRODUCTION

Habitat loss, agricultural activities, global warming and the introduction of exotic species lead to massive decreases of biodiversity all over the world (Sala et al., 2000; Cardinale et al., 2012; IPBES, 2019b). With habitat loss being a major driver of species loss and deforestation still increasing dramatically in the tropics (Brooks et al., 2002; IPBES, 2019a), afforestation is an important and widely used tool for restoring ecosystems and mitigating climate change. Although evidence shows that tree species mixtures can improve multi-functionality in forest (van der Plas et al., 2016, 2017), particularly forest productivity and Carbon storage (Potvin and Gotelli, 2008; Potvin et al., 2011; Ammer, 2019; Guillemot et al., 2020), most areas pledged for afforestation are currently set to become monocultures (Lewis et al., 2019). Monocultures are likely less suited than natural secondary forests or mixed-species plantations for promoting and restoring associated biodiversity (Perfecto et al., 1997; Ampoorter et al., 2020). Increasing tree species richness in plantations might have multiple consequences for the associated fauna, by providing a broader range of food sources for both generalists and specialists herbivores, which could scale up to higher trophic levels (Brose, 2003; Potts et al., 2003; Castagneyrol and Jactel, 2012; Pekin et al., 2012; Ebeling et al., 2018). Additionally, changes in tree species richness has consequences for microclimatic conditions that could affect both diversity and abundance of the animal communities as well as temporal activity patterns (Walker, 1975a,b; Akutsu et al., 2007; Checa et al., 2014; Kunz et al., 2019; Campos-Cerqueira et al., 2020; Burivalova et al., 2021).

Biodiversity assessments in species rich tropical regions are time and resource consuming. This is particularly true for arthropods, as species identification for arthropods can take years and demand expert knowledge in taxonomy. But also for well-known taxonomic groups such as birds sampling is time, money and labor intensive. During the last decade passive acoustic monitoring and ecoacoustic methods have been proven a useful and rapidly expanding tool for fast detection of biodiversity trends, especially in response to land-use change (Burivalova et al., 2018, 2019, 2021). Acoustic surveys do have the advantages of being rapid, sensitive to multiple taxa, non-invasive and easy to apply over large areas and long term periods simultaneously at multiple locations (Sueur et al., 2008). Soundscapes are driven by the composition of different vocalizing communities and thus follow their respective vocal activity patterns resulting in specific diurnal and seasonal soundscapes patterns. However, for tropical habitats, little is known about such acoustic temporal patterns, as most ecoacoustic studies so far have focused on temperate regions (Scarpelli et al., 2020). The majority of tropical ecoacoustic studies focused on diurnal patterns indicate that insects dominate most of the diurnal soundscape, leaving a rather small "empty" acoustic niche for birds at dawn and dusk (Aide et al., 2017). In mature tropical forests these dawn and dusk periods result in an overall soundscape saturation peak, with soundscape saturation being defined as the proportion of active acoustic frequency bins within a recording (Burivalova et al., 2018). Much less is known on seasonal acoustic trends in the tropics, which likely relate to changes in precipitation and humidity, often driven by the alternation of dry and rainy seasons (Rankin and Axel, 2017; Opaev et al., 2021). Additionally, some studies indicate that disturbances and changes in microclimate might interact with the diurnal and seasonal (acoustic) activity patterns of the tropical fauna (Akutsu et al., 2007; Checa et al., 2014; Campos-Cerqueira et al., 2020; Burivalova et al., 2021; Fontúrbel et al., 2021).

Phenological acoustic activity patterns can be studied by the application of ecoacoustic methods and its large variety of acoustic indices that have been developed so far (Sueur et al., 2014; Eldridge et al., 2018; Oliveira et al., 2021). In the past, these indices have been successfully used as proxies for various aspects of ecosystem biodiversity and as tools for conservation (Sueur et al., 2008; Pekin et al., 2012; Fuller et al., 2015; Buxton et al., 2016, 2018; Mammides et al., 2017; Burivalova et al., 2018; Gasc et al., 2018; Turner et al., 2018; Shaw et al., 2021). These findings suggest that habitat heterogeneity positively affects acoustic diversity and thus also species richness, at least for vocalizing taxonomic groups. Habitat gradients that were tested in previous ecoacoustic studies were sometimes substantial. Dröge et al. (2021) for example confirmed good relationships between acoustic indices and land-use types, testing a gradient from rice paddies to old growth forests. In the present study we wanted to test how changing a single habitat parameter, that is tree species richness, effects the acoustic composition and temporal dynamic of the acoustic community during the diurnal cycle in both the dry and wet seasons. Experimental plantations are an ideal platform for testing such a question as all other environmental variables can be kept rather constant. This research took advantage of the Sardinilla planted forest, set up in Panama in 2001 to study the effects of tree species richness on ecosystem functions (Scherer-Lorenzen et al., 2005). Here we performed acoustic monitoring in plots with different tree species richness ranging from monocultures to five-species polycultures to test our hypothesis that acoustic diversity increases with increasing tree richness. Based on previous studies highlighting the dominance of insects in tropical soundscapes and given the small size of the research plots we further hypothesized that particularly orthopteran vocalizations should increase with increasing tree species richness (Aide et al., 2017; Campos-Cerqueira et al., 2020).

Above and beyond testing the effect of tree species richness on acoustic diversity, our objectives were to examine how tree species richness effected acoustic patterns through different seasons and day phases and which acoustic indices can be used to capture complementary acoustic patterns.

MATERIALS AND METHODS

Study Site

The Sardinilla planted forest is part of the global research network TreeDivNet, which aims to quantify the relation between tree species richness and ecosystem functioning (Paquette et al., 2018). The experimental site of Sardinilla is located in the central north of Panama (9°19′30′′N, 79°38′00′′W) at an altitude of 70 m. The area's original forest was logged in the early 1950's. After 2 years of agriculture, land-use turned into pasture. The total experimental area covers approximately nine hectares (Scherer-Lorenzen et al., 2007).

The tree plantation included six native tree species that form a gradient from fast-growing pioneers to slow long-lived tree species. Planted fast-growing species were *Cordia alliodora* [(Ruiz and Pav.) Oken] and *Luehea seemannii* (Triana and Planch.), whereas intermediate-growing species were *Anacardium excelsum* [(Bertero and Balb. ex Kunth) Skeels] and *Hura crepitans* (L.). *Cedrela odorata* (L.) and *Tabebuia rosea* [(Bertol.) Bertero ex A.DC.] were chosen as slow-growing tree species. In total, there were 24 plots of 45 m by 45 m consisting of twelve monoculture plots (two per species), six three-species mixtures (one per growth rate category) and six identical six-species plots (Potvin and Gotelli, 2008). One tree species, *Cordia alliodora,* failed to establish. We thus considered the realized species richness (5, 3, 2, and 1) rather than the original richness (6-3-1) (**Figure 1**). In 2017, after 16 years of growth, a data collection campaign took place during which we set up automatic recording devices to monitor acoustic diversity. The recording period ranged from 30 March 2017 to 11 June 2017, covering parts of the dry and the rainy season. The dry season in Sardinilla lasts from end of December to April followed by 8 months of rainy season, which is reflected in monthly precipitation sums of Sardinilla ranging from 48 to 70 mm in March over 115–142 mm in April up to 306–344 mm in May and 290–339 mm in June 2017 (Hydrometeorology Management of ETESA, 2017). Days were differentiated into four phases: dawn (05:30–09:00), day (09:10–15:50), dusk (16:00–19:30) and night (19:40–05:20).

Recording Methods

Recordings were made in all five-species plots, all three- and two-species plots and five monoculture plots (one for each species) using prototypes of the SET-Recorders (Soundscape Explanatory Terrestrial, Lunilettronik, Fivizzano)[1]. One monoculture (*Hura crepitans*) and two five-species plots were excluded from further analysis as recordings stopped after just a few recording minutes. Thus, in total we analyzed data from 14 plots (four 4 monocultures, 3 two-species, 3 three-species, and 4 five-species). The autonomous recorders were equipped with omnidirectional microphone capsule [EMY-63M/P, sensitivity (0 dB = 1 V/Pa. 1 kHz): dB −38 ± 3, signal to noise ratio: >60 dB, input voltage of the ADC: 0.75 Vrms (personal communication with Lunilettronik Coop.)]. The microphone gain was manually set to +25 dB. The signals were sampled at 48 kHz with a 16 bits digitization, recording for 1-min every tenth minute during 24 h a day. This recording schedule allowed us to cover the whole diurnal cycle, while at the same time covering an extended time period from the dry season into the rainy season. The devices were installed on a tree in the center of the plots, positioned at 1.7 m height always facing south, away from the main wind direction. To assess the quality of the audio data the first and last recordings per recording period were listened to.

Aural Classification of Audio Files

Adapting the protocol developed by Gasc et al. (2018), we randomly selected a subsample of our recordings – 10 audio files per day phase (4), season (2) and richness level (4), resulting in 320 audio files in total. First author SM listened to each

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[1] http://www.lunilettronik.it/prodotto/set-soundscape-explorer-terrestrial/

FIGURE 1 | Images of two plots of the Sardinilla planted forest. *Left*: Example of a five-species mixture; *right*: example of a monoculture with *Luehea seemannii*. Photographs are curtsey of Matthias Kunz and were taken in the middle of each plot, on June 10th 2017.

of these audio files and visualized the spectrogram classifying them according to the three soundscape categories biophony, geophony, and anthropophony (Pijanowski et al., 2011). It was possible that the same audio file contained several of these categories. Furthermore, SM noted for all recordings containing biophony the presence and absence of different vocalizing animal groups, that were anurans, birds, cicada, insects vocalizing in mid-frequency ranges (4–8 kHz) and insects vocalizing in high-frequency ranges (8–24 kHz); again it was possible to assign several subcategories to the same audio file. The presence of other soundscape components such as wind, rain, planes, cars, barking dogs, human voices, and other identifiable sounds was also noted, but we did not use this information for further analysis. In accordance with Gasc et al. (2018) the duration of each category and subcategory as well as the range of song types were recorded. As only birds differed very slightly in that respect among tree species richness levels we refrained from presenting that data.

Calculation and Selection of Acoustic Indices

In total we calculated different acoustic features using "Analysis Program" (Towsey et al., 2018) and the Bioacoustic Index (Boelman et al., 2007). Data preprocessing involved the package "stringr" (Wickham, 2019). We used "High Amplitude" and "Clipping Index" to identify recordings with very loud wind and rain noises and excluded all recordings with values > 0 from further analysis. False-Color-Spectrograms (Towsey et al., 2014, 2018) were produced to identify periods with strong rain and wind, which were additionally excluded from further analysis. We assumed that strong rain and strong wind events were identical for all plots. This method allowed us to identify the exact start of the rainy season in that year as being the 15 April 2017.

After calculating acoustic indices, a correlation analysis and a non-metric multidimensional scaling (NMDS) analysis to select acoustic indices for further analysis (see Supplementary for further details) were performed. This served to identify indices that were most complementary to each other and thus were most likely to capture different soundscapes components during the different day phases and seasons (Towsey et al., 2014; Phillips et al., 2018). The selection was based on the following criteria (i) acoustic indices should not be significantly correlated among each other (**Supplementary Figures 1–11**); (ii) selected acoustic indices should relate to the NMDS axis that separate the different day phases, seasons and mixture levels (**Supplementary Figures 12–14**).

Based on these criteria, "High Frequency Cover", "Bioacoustic Index," and "Events Per Second" were selected for analysis. "High Frequency Cover" describes the "fraction of noise-reduced spectrogram cells that exceed 3 dB in the high-frequency band" (8–24 kHz) (Towsey, 2018). The "Bioacoustic Index" is calculated as the "area under each curve included all frequency bands associated with the dB value that was greater than the minimum dB value for each curve. The area values are thus a function of both the sound level and the number of frequency bands used by the" fauna (Boelman et al., 2007). "Events Per Second" represents a "measure of the number of acoustic events per second, averaged over the same noise-reduced 1-min segment. An event is counted each time the decibel value in a bin crosses the 3-dB threshold from lower to higher values" (Towsey, 2018). Insect sounds that cover a frequency band for the whole duration of the audio file (e.g., monotonous stridulations) are not counted as an acoustic event.

Statistical Methods

Statistical analyses were performed using R 4.0.2 (R Core Team, 2020). For the selected acoustic indices, we model diurnal patterns per season using generalized additive models (GAMs) and tested if parameter estimates for tree species richness level were significant. Tree species richness level (Mix) and season were included as factors, time of the day as smoother and "PlotID" as a random effect. Tropical acoustic communities show diurnal and seasonal activity patterns, to test this we added interaction terms for tree species richness level and season, as well as an additional smoother interaction term for time of day and season. GAMs were calculated using the "mgcv" package

TABLE 1 | Model specifications and output for High Frequency Cover.

High frequency cover

Family: Beta regression (26.985)
Link function: logit

Formula:
HighFreqCover ~ mix × season + s(ToD, by = mix, $k = 50$, bs = "cc") + s(ToD, by = season, $k = 50$, bs = "cc") + s(PlotID, bs = "re," $k = 10$)

R^2 adj = 0.275; Deviance explained = 32.8%; −REML = −2.0008e + 05; Scale est. = 1; n = 101,846

Parametric coefficients

	Estimate	Std. error	*z* Value	Pr(>|*z*|)
SR1: Monoculture dry season (intercept)	−2.98	0.09	−34.73	<0.001***
SR2 – two tree species	0.61	0.13	4.67	<0.001***
SR3 – three tree species	0.47	0.13	3.62	<0.001***
SR5 – five tree species	0.30	0.12	2.49	<0.05*
Season rain	−0.21	0.01	−20.00	<0.001***
SR2:rain	0.04	0.01	2.83	<0.01**
SR3:rain	0.02	0.01	1.13	>0.2 n.s.
SR5:rain	−0.003	0.01	−0.22	>0.8 n.s

Approximate significance of smooth terms

	edf	Ref.df	Chi.sq	*p*-Value
s(ToD):SR1	12.26	48	77.75	<0.001***
s(ToD):SR2	7.26	48	18.23	<0.001***
s(ToD):SR3	11.16	48	49.23	<0.001***
s(ToD):SR5	2.33	48	2.66	<0.001***
s(ToD):seasondry	23.44	48	685.762	<0.001***
s(ToD):seasonrain	34.06	48	619.562	<0.001***
s(PlotID)	9.98	10	4,041	<0.001***

Mix: tree species richness level (SR1, SR2, SR3, and SR5 for 1, 2, 3, and 5 tree species), season: dry and rainy season, ToD, Time of day (hour).
*Significant levels are given as: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, ·$p > 0.1$.*

TABLE 2 | Model specifications and output for Bioacoustic Index.

Bioacoustic index

Family: Scaled $t(3.383, 0.364)$
Link function: identity
Formula:
BioAcousticlog $\sim$ mix $\times$ season + s(ToD, by = mix, $k = 50$, bs = "cc") + s(ToD, by = season, $k = 50$, bs = "cc") + s(PlotID, bs = "re", $k = 10$)
R^2 adj = 0.224; Deviance explained = 23%; −REML = 73,683; Scale est. = 1; $n = 101{,}846$

Parametric coefficients

	Estimate	Std. error	*z* Value	Pr(> |*z*|)
SR1: Monoculture dry season (intercept)	4.62	0.073	63.05	$<0.001^{***}$
SR2 – two tree species	0.30	0.112	2.70	$<0.01^{**}$
SR3 – three tree species	0.001	0.112	0.01	>0.900 n.s.
SR5 – five tree species	−0.01	0.104	−0.07	>0.900 n.s.
Season rain	0.211	0.006	33.78	$<0.001^{***}$
SR2:rain	−0.20	0.010	−21.53	$<0.001^{***}$
SR3:rain	0.12	0.010	13.42	$<0.001^{***}$
SR5:rain	−0.03	0.010	−3.78	$<0.001^{***}$

Approximate significance of smooth terms

	edf	Ref.df	Chi.sq	*p*-Value
s(ToD):SR1	9.03	48	83.99	$<0.001^{***}$
s(ToD):SR2	22.62	48	243.03	$<0.001^{***}$
s(ToD):SR3	20.59	48	348.08	$<0.001^{***}$
s(ToD):SR5	0.24	48	0.24	$<0.001^{***}$
s(ToD):seasondry	39.28	48	2,355.94	$<0.001^{***}$
s(ToD):seasonrain	42.44	48	3,270.66	$<0.001^{***}$
s(PlotID)	9.99	10	8,437.77	$<0.001^{***}$

Mix: tree species richness level (SR1, SR2, SR3, and SR5 for 1, 2, 3, and 5 tree species), season: dry and rainy season, ToD: Time of day (hour).
Significant levels are given as: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{\cdot}p > 0.1$.

TABLE 3 | Model specifications and output for Events Per Second.

Events Per Second

Family: negative binomial (158034.093)
Link function: log
Formula:
EventsPerSecondsqrt $\sim$ mix $\times$ season + s(ToD, by = mix, $k = 50$, bs = "cc") + s(ToD, by = season, $k = 50$, bs = "cc") + s(PlotID, bs = "re", $k = 10$)
R^2 adj = 0.26; Deviance explained = 22.7%; −REML = 83,641; Scale est. = 1; $n = 101{,}846$

Parametric coefficients

	Estimate	Std. error	*z* Value	Pr(> |*z*|)
SR1: Monoculture dry season (intercept)	−1.15	0.178	−6.450	$<0.001^{***}$
SR2 – two tree species	0.79	0.272	2.904	$<0.01^{**}$
SR3 – three tree species	0.33	0.272	1.220	>0.200 n.s.
SR5 – five tree species	0.14	0.252	0.239	>0.500 n.s.
Season rain	−0.35	0.024	−14.377	$<0.001^{***}$
SR2:rain	−0.002	0.031	−0.070	>0.900 n.s.
SR3:rain	−0.01	0.033	−0.279	>0.700 n.s.
SR5:rain	−0.16	0.032	−4.861	$<0.001^{***}$

Approximate significance of smooth terms

	edf	Ref.df	Chi.sq	*p*-Value
s(ToD):SR1	8.13	48	144.431	<0.001 ***
s(ToD):SR2	13.54	48	303.000	<0.001 ***
s(ToD):SR3	9.61	48	347.404	<0.001 ***
s(ToD):SR5	0.002	48	0.002	<0.001 ***
s(ToD):seasondry	30.84	48	3,617.442	<0.001 ***
s(ToD):seasonrain	31.80	48	3,906.556	<0.001 ***
s(PlotID)	9.97	10	3,279.162	<0.001 ***

Mix: tree species richness level (SR1, SR2, SR3, and SR5 for 1, 2, 3, and 5 tree species), season: dry and rainy season, ToD, Time of day (hour).
Significant levels are given as: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{\cdot}p > 0.1$.

(Wood, 2011). Model diagnostics were assessed graphically and a specific distribution family was necessary for each acoustic index. Respective model specifications can be found in **Tables 1–3**. For graphical outputs we use the packages "ggplot2" (Wickham, 2016) and "tidymv" (Coretta, 2021).

RESULTS

Temporal Patterns and Soundscape Composition

Aural Inspection

The number of recordings containing biophony did not change substantially across day phases and season, as biophony was recorded in almost all recordings that were aurally inspected (**Figure 2**). Both geophony and anthropophony appeared mostly during the day and rarely at night, but were overall less frequent than biophony. The most common geophony sounds were light wind and rain, as recordings with heavy rain and strong wind were excluded from the recordings. Anthropophony consisted of sounds from planes, undefinable machinery, nearby constructions, vehicles, and chainsaws.

Distinct patterns were found between day – when birds and non-biophony sounds were dominating the soundscape – and night – with orthopterans occupying a large frequency band (**Figure 3**). Other sound sources in the Sardinilla planted forest included insects vocalizing in mid-frequency ranges (4–8 kHz, mainly crickets), anuran (dominating the range just below the crickets) and cicada (rare events, overlapping with crickets in the frequency domain). Bird vocalizations were recorded from dawn until dusk, and dominated the day recordings. This dominance resulted from a reduced number of recordings with vocalizations from anurans and insects rather than an increase in bird activity. Thus, the aural inspection did not indicate a clear peak of bird vocal activity at dawn and dusk, as can be observed in temperate or boreal biomes. There was no observable seasonal trend for birds. Anurans were least active during the day but this activity increased in the rainy season. Insects singing in mid–frequency ranges were also least active during the day, with a slight increase

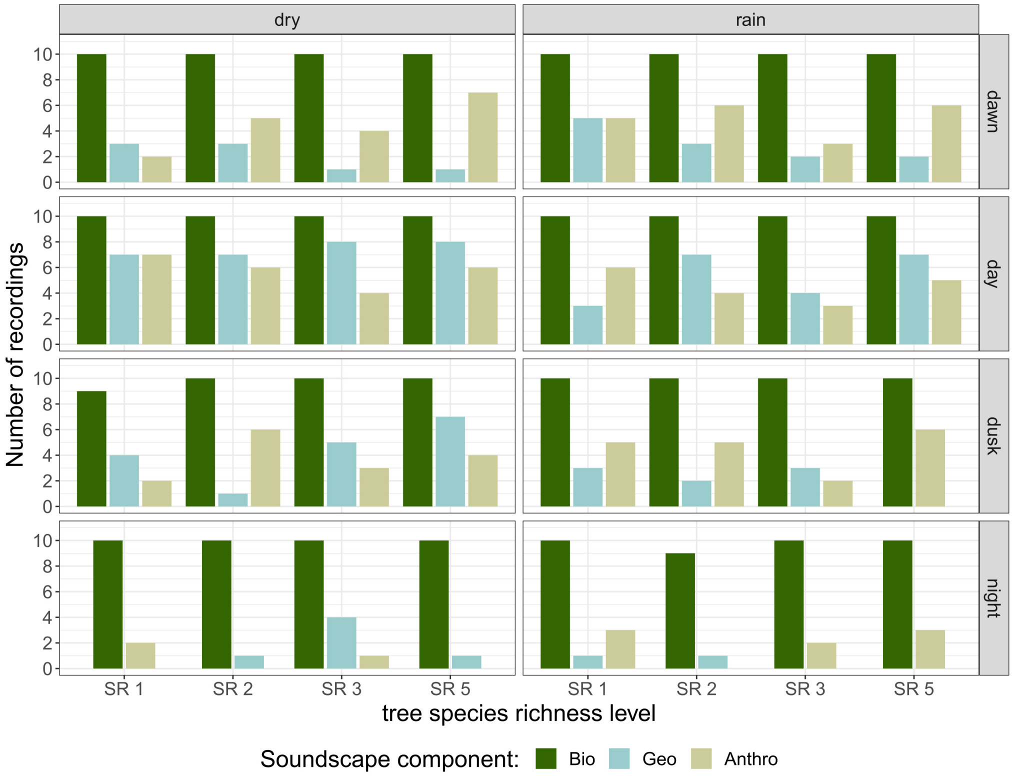

FIGURE 2 | Soundscape composition of recordings in terms of biophony, geophony, and anthropophony. Number of recordings for each category from the 320 recordings that were aurally classified, per season, day phase, and tree species richness level. Recordings could contain more than one soundscape component.

in the rainy season. Insects singing at high frequency ranges showed clear activity peaks at dusk and night with no strong seasonal patterns. Cicadas were not common to observe, and showed an irregular pattern with a slight higher frequency of observations during day and dusk in the dry season.

Comparison of Acoustic Indices

The correlation analysis revealed that acoustic indices could be grouped into four clusters (**Supplementary Figure 1**). Cluster 1 consisted of Entropy of Average Spectrum and Entropy of Variance Spectrum. These indices showed higher values at night compared to day, with only slight differences among rainy and dry season (**Supplementary Figures 2, 3**). These indices were negatively correlated with indices from cluster 2 and 4 and were therefore not included in further analysis. Cluster 2 consisted of Acoustic Complexity Index, Mid Frequency Cover and Bioacoustic Index. All indices showed distinct dawn peaks and different patterns between dry and rainy season (**Supplementary Figures 4–6**). From this cluster we chose the Bioacoustic Index for further hypothesis testing, also based on results from an NMDS analysis (**Supplementary Figure 12**). The Bioacoustic Index showed peaks at dawn and dusk, slightly lower values during the day and lowest values at night (**Figure 4**). During the rainy season, the patterns for these indices changed: index values increased throughout the day, but particularly at midday, resulting in less pronounced peaks at dawn and dusk. Thus, the Bioacoustic Index corresponded to anuran and bird acoustic activity patterns identified in the aural inspection. Cluster 3 consisted of High Frequency Cover and Spectral Density. These indices also showed higher values at night compared to day (as cluster 1, **Supplementary Figures 7, 8**). From this cluster we chose High Frequency Cover for further analysis. High Frequency Cover was designed to represent the orthopteran community that predominantly communicates in high frequencies, while few other vocalizing animal groups occupy this frequency range. Peaks at night for High Frequency Cover, as well as a slight reduced High Frequency Cover in the rainy season (**Figure 5**) could be verified by the aural inspection (section "Aural Inspection" and **Figures 3**, **5**). Cluster 4 consisted of Low Frequency Cover, Events per Second and Temporal Entropy. These indices showed strong peaks during the day, without peaks at dawn and dusk, and very low values at night (**Supplementary Figures 9–11**). Dry season had higher peak values than the rainy season. From this cluster Events Per Second was chosen for further analysis (**Figure 6**).

Effects of Tree Species Richness on Temporal Patterns of Acoustic Indices

There was a significant lower High Frequency Cover in monocultures at night, compared to polycultures (**Figure 5**), and parametric coefficients for polycultures were significantly different from the monocultures (**Table 1**). Polycultures did

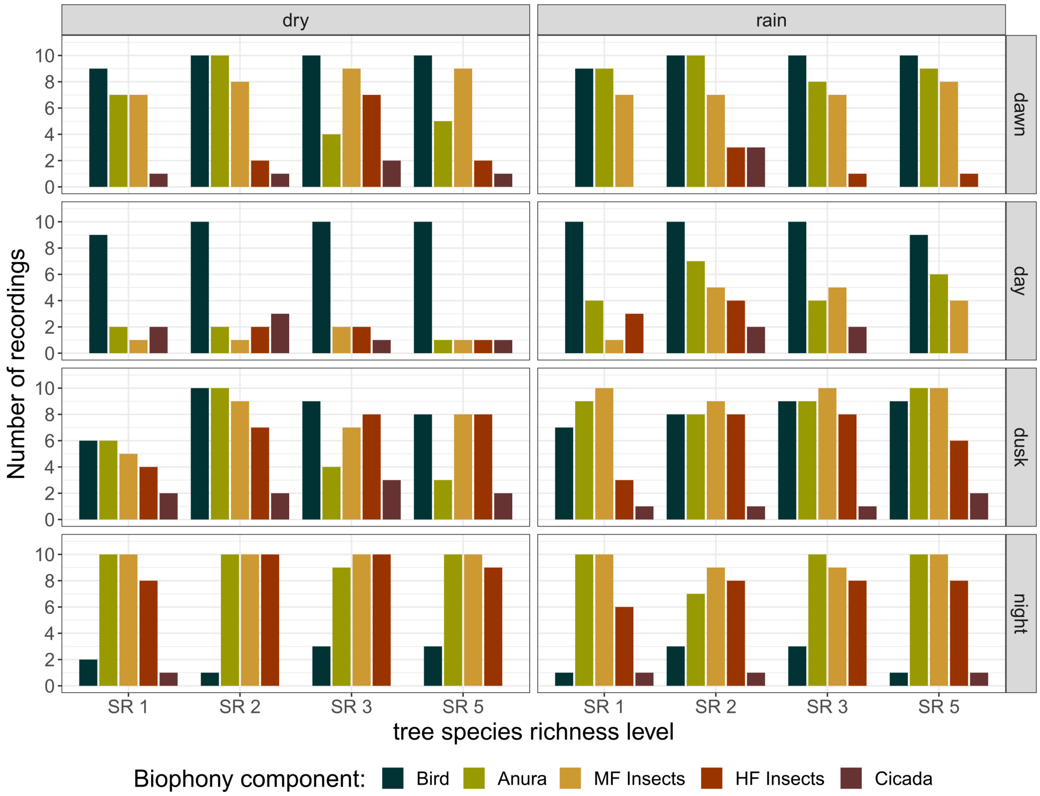

FIGURE 3 | Detailed biophony composition analysis, from the 320 recordings that were aurally classified, per season, day phase, and tree species richness level. Recordings could contain more than one biophony component. All recordings containing biophony were classified according to presence of birds, anurans, insects vocalizing in mid-frequency ranges (4–8 kHz, MF Insects), insects vocalizing in high-frequency ranges (8–24 kHz, HF Insects) and cicadas.

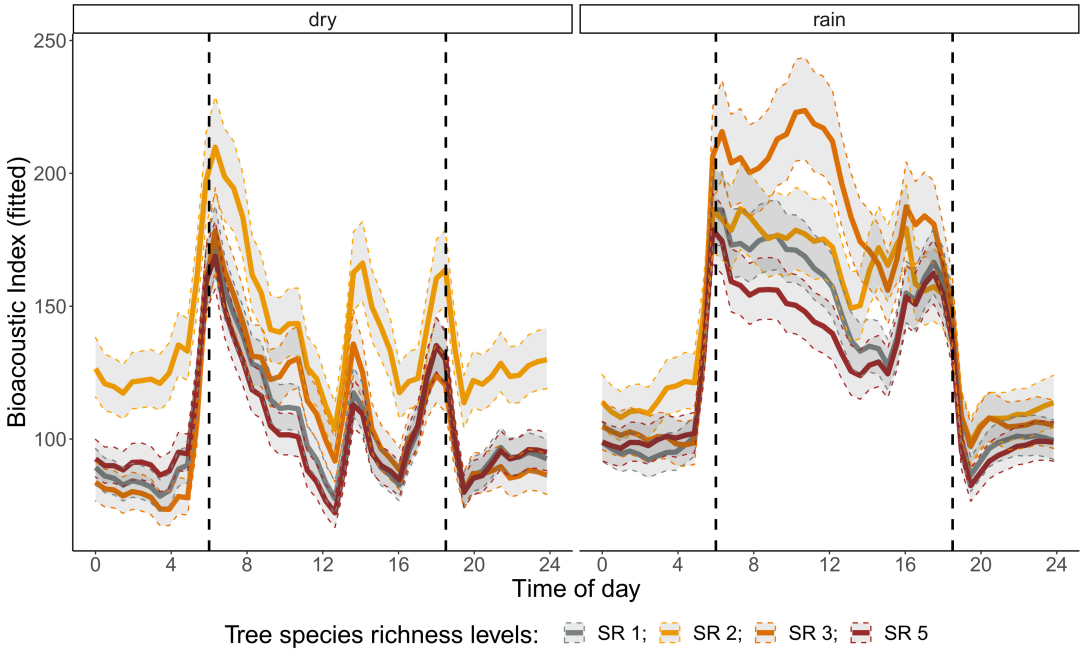

FIGURE 4 | Fitted values for bioacoustic index over a diurnal cycle (time of day) per season (dry and rainy season) and tree SR level. Dashed vertical line indicate sunrise (ca. 06:00) and sunset (around 18:30).

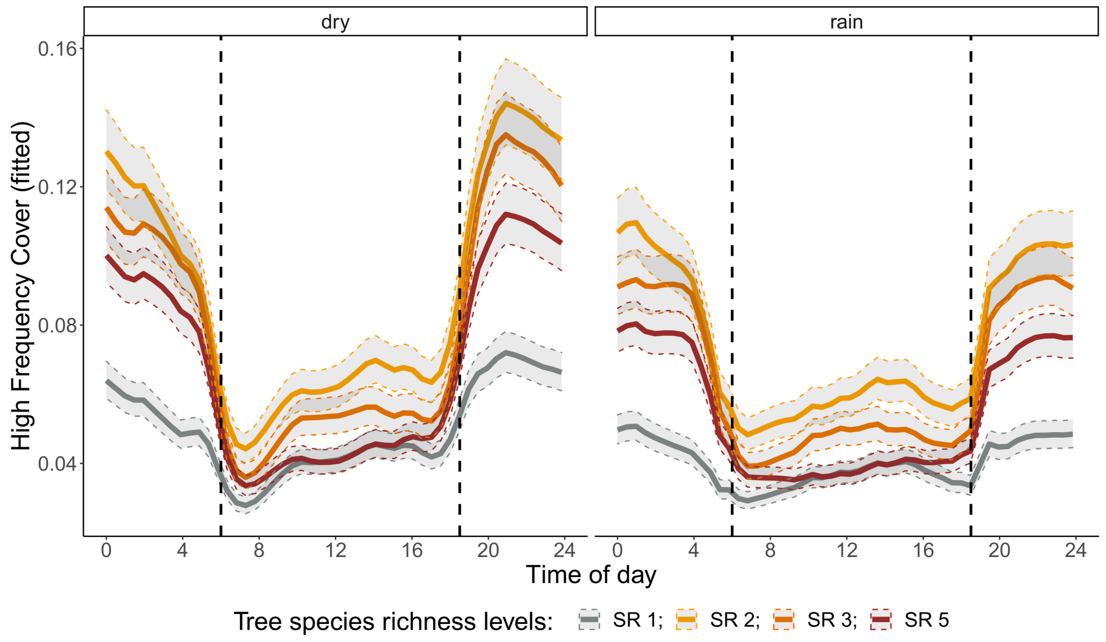

FIGURE 5 | Fitted values for high frequency cover over a diurnal cycle (time of day) per season (dry and rainy season) and tree species richness level (SR). Dashed vertical line indicate sunrise (ca. 06:00) and sunset (around 18:30).

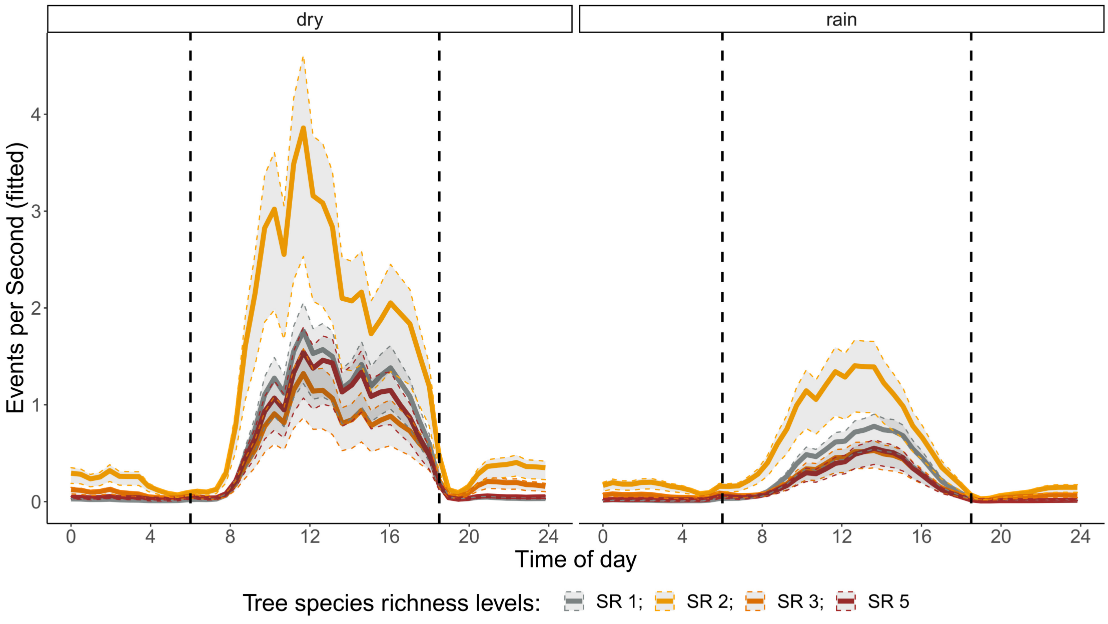

FIGURE 6 | Fitted values for events per second over a diurnal cycle (time of day) per season (dry and rainy season) and tree SR level. Dashed vertical line indicate sunrise (ca. 06:00) and sunset (around 18:30).

not differ from each other, but two-species mixtures showed a slight but significant lower decrease of High Frequency cover in the rainy season than the other plots (**Table 1**). In the dry season the parametric coefficients for two-species mixtures were significantly higher than for the other mixture levels in terms of the Bioacoustic Index, and differences were most pronounced at night (**Figure 4** and **Table 2**). In the rainy season the three-species mixtures showed higher values than the other plots at midday. For Events Per Second the two-species mixtures showed parametric coefficients significantly different from the monocultures while the other polycultures did not (**Table 3**), and had a significantly higher day peak during the dry season.

Differences among two-species mixtures and the other tree species richness levels were less pronounced but still significant during the rainy season (**Figure 6**).

DISCUSSION

Indices to Capture Temporal Patterns of Acoustic Diversity

Different acoustic indices capture different aspects of the soundscape. By choosing non-redundant indices, it is possible to capture complementary patterns in the soundscape, and attribute them to specific groups in the acoustic community (Buxton et al., 2018; Eldridge et al., 2018; Phillips et al., 2018). Since acoustic community composition and dynamics vary among different biomes in interaction with local geophony and anthropophony, it may be necessary for each ecoacoustic study to identify its own unique set of indices to describe soundscape composition. Ross et al. (2021) tested several acoustic indices within different sonic conditions for their performance in capturing biological meaningful patterns and sensitivity in respect to noise. Most commonly used indices showed sensitivity to various confounding sound sources (Ross et al., 2021). Even though they came up with very useful practical recommendation for the suitability of different indices in different sonic conditions, studies in other biomes identified different sets of acoustic indicators to best describe their specific soundscape (Fuller et al., 2015; Ng et al., 2018; Turner et al., 2018; Carruthers-Jones et al., 2019; Oliveira et al., 2021).

If we understand acoustic indices as an integrative measure of biodiversity that reflects the soundscape composition and particularly the acoustic communities as a whole in response to human activity and ecological gradients (Pijanowski et al., 2011; Farina, 2014; Farina and Gage, 2017) we also have to understand that a single acoustic index will rarely correspond only to a single vocalizing animal group (Retamosa Izaguirre et al., 2021). This is probably especially true in the tropics as different vocalizing animal groups often vocalize at the same time (Eldridge et al., 2018) and could explain why in our study the temporal patterns of the chosen acoustic indices did not match the patterns of a single vocalizing animal group perfectly well. This is in line with other studies, mostly on birds, that have shown an often significant but weak correlation of acoustic indices with bird richness (Moreno-Gómez et al., 2019; Dröge et al., 2021). Even though recent studies indicate that such correlations might be improved if species richness is based on bioacoustic identification from acoustic recordings rather than point-count assessments (Shaw et al., 2021). In contrast, studies focusing on the relationship of acoustic indices with parameters that describe ecological condition such as vegetation structure, vegetation complexity, habitat type, land-use intensity and/or distance to the nearest road often report acoustic indices to be good indicators (Tucker et al., 2014; Fuller et al., 2015; Burivalova et al., 2018; Ng et al., 2018).

By the selection process we applied and by analyzing different temporal acoustic niches, we could identify three complementary indices that allowed us to test effects of tree species richness on different vocalizing communities. As Metcalf et al. (2020) argued, the interpretability of acoustic indices can be greatly improved by calculating them in ecological meaningful time and frequency bins. But even then, given the integrative properties of acoustic indices in capturing soundscape components, interpretability of acoustic index patterns might not be very straight forward. Aural inspection of a subset of recordings supported the interpretability in our study. Nevertheless, aural inspection only indicated the presence or absence of certain vocalizing groups across day phases and season, while acoustic indices respond also to diversity, distance and abundances of vocalizing animal groups.

High Frequency Cover in our study matched the temporal acoustic activity patterns identified for orthopteran vocalizing in high frequencies, and was therefore a useful tool to identify effects of tree species richness on this insect community. The Bioacoustic Index is frequently used in ecoacoustic studies and it was designed to specifically pick up bird vocalization patterns (Boelman et al., 2007). In our study it seemed to be driven both by bird and anuran vocalizations. While aural inspection of recordings did not suggest a change in activity patterns of birds in our study, the increase in Bioacoustic Index during the rainy season might be mainly driven by an increase in anuran activity. Also Boullhesen et al. (2021) found a very good relationship between the Bioacoustic Index and frog vocal activity patterns and frog species richness. Opaev et al. (2021) found a similar increase of Bioacoustic Index with increasing humidity just before the monsoon season, which they associated with the onset of the breeding season for both birds and anurans. In a study of different forest types in the Valdivian temperate rainforests of southern Chile, Fontúrbel et al. (2021) observed a clear peak of bird vocalizations at dawn only in old- growth forest, while it peaked at noon in plantations, and in the afternoon in logged forests and showed a variable pattern in secondary forest, suggesting that daily activity peaks of birds could depend on forest understorey and forest structure. Our data showing that birds were active throughout the day from dawn until dusk and dominated the soundscape at noon is coherent with the observations made in Chilean plantations.

Events Per Second was correlated with Low Frequency Cover and Temporal Entropy and showed a clear peak during the day, but no peaks at dawn and dusk. This might have related to an increase in geophony and anthropophony during the day recordings (**Figure 2**), which should both be related to Low Frequency Cover (Gage and Axel, 2014; Shaw et al., 2021). The two-species mixtures were a result of establishment failure of *Cordia alliodora*. Which could have resulted in higher wind noises in these plots due to lower stand density and might explain partly that these plots showed significantly higher values for Events Per Second throughout the day, in comparison to the other plots. Additionally, Events Per Second might relate to a dominance of birds while insects showed a reduced activity. This would relate also to the fact that Events Per Second is reduced in the rainy season when the dominance of birds is also reduced due to an increase in anuran activity.

Since the high frequency ranges - in most environments we can think of - are occupied exclusively by orthopterans (and sometimes bats), the usefulness of High Frequency Cover can probably be generalized to other ecosystems and habitats. The situation is more complex in mid-frequency ranges where more than one vocalizing animal group is active. Other studies have addressed the advantages and disadvantages of different acoustic indices under different environmental conditions, and useful overviews can be found, for example, in Bradfer-Lawrence et al. (2019), Zhao et al. (2019), Ross et al. (2021), Sánchez-Giraldo et al. (2021), and Shaw et al. (2021).

Effects of Tree Species Richness

High Frequency cover, revealed a positive effect of polycultures on insect acoustic activity that might relate to abundance of this vocalizing insect group. This confirmed our hypothesis that planting polycultures has positive effects on associated biodiversity, specifically manifested within the orthopteran community due to their small home ranges. Birds in contrast are likely to be more mobile and their home ranges might not be restricted to a single plot. A recent meta-analysis revealed that bird diversity in plantations is lower than in natural forests but that overall faunal diversity, including birds, benefits from planting a mix of native tree species (Bohada-Murillo et al., 2020; Wang et al., 2021)

An increase in tree species richness could increase orthopteran abundance and diversity via an improved variety of food sources, especially for specialist plant consumers. A mechanism that is modulated by trophic interactions, as was shown for grassland ecosystems (Siemann, 1998; Ebeling et al., 2018). In forests these relationships were often studied under the objective of testing tree species richness effects on herbivore damage on trees (associational resistance hypothesis, Jactel et al., 2021), and not how it would affect orthopteran diversity. Still, there is evidence that herbivore arthropod diversity and abundance is related to tree diversity and that this relationship between plant diversity and consumer diversity might be particularly strong in the tropics (Becerra, 2015). Given that many orthopteran are highly host tree specific, the effect of tree species identity has to be considered as well (Novotny and Basset, 2005).

Another mechanism could be the indirect effect of tree species richness on microclimate and microhabitats. In a global meta-analysis, canopy cover, which affects microclimate, was the most important driver of faunal biodiversity (Wang et al., 2021). How microclimate can change the acoustic communities was addressed by Campos-Cerqueira et al. (2020) and Burivalova et al. (2021). In their study selective logging resulted in microclimatic changes that decreased humidity in the logging gaps. This had impacts on amphibians and understory specialist birds, and certain insect groups. Anurans are driven by the presence of microhabitats and waterbodies while tree species richness itself is likely less important (Duellman, 1988; Oda et al., 2016). In our study we found tree species richness effects on Bioacoustic Index, suggesting that anuran and maybe also bird activity was positively related to two-species mixtures in the dry season and three-species mixtures in the rainy season.

The sensitivity of insects to land-use induced habitat and microclimatic changes could make them very suitable indicators for disturbance regimes in tropical forests (Akutsu et al., 2007; Campos-Cerqueira et al., 2020). These studies highlight the urgency for including insects into biodiversity assessments. While acoustic identification of insects in the tropics poses a significant challenge, acoustic indices can give valuable insights in temporal activity changes, and indicate changes in abundance and diversity (Oliveira et al., 2021). Thus, acoustic monitoring has great potential to become an important additional monitoring tool which is crucial particularly for tropical ecosystems (Lamarre et al., 2020). In our study, differences in microclimate among plots might be a result of the different tree species richness levels, that result from differences in above ground space use efficiency (Sapijanskas et al., 2014). Additionally, the failure of one tree species resulted in larger canopy openings of some plots, mainly the two-species mixture. If insects profit from canopy gaps this could explain why two-species mixture often showed the highest acoustic activity.

CONCLUSION

In this study we showed that planting polycultures increased orthopteran acoustic activity at night, and this may be related to an increase in abundance and maybe also richness of this taxonomic group. Given the small scale of the plots and the young age of the planation this would indicate that this animal group is most sensitive to these small scale habitat differences in our experimental forest plantation, making them important indicator species for monitoring ecosystem changes. Additional to direct effects of tree species richness and tree species identity, variations in microclimate most likely drive the observed differences in acoustic patterns across season and day phases. We have shown that ecoacoustics can provide valuable insights in studying the interaction between forest features, associated biodiversity and acoustic activity patterns in the tropics where these interactions are far less studied than in temperate regions.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

SM, MS-L, and CP designed the study. SM analyzed the data with support from OM and LO and wrote the manuscript. All authors read, commented on, and approved the final version of the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2022.808589/full#supplementary-material

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frontiers in Ecology and Evolution

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Sounding the Call for a Global Library of Underwater Biological Sounds

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Aquatic environments encompass the world's most extensive habitats, rich with sounds produced by a diversity of animals. Passive acoustic monitoring (PAM) is an increasingly accessible remote sensing technology that uses hydrophones to listen to the underwater world and represents an unprecedented, non-invasive method to monitor underwater environments. This information can assist in the delineation of biologically important areas via detection of sound-producing species or characterization of ecosystem type and condition, inferred from the acoustic properties of the local soundscape. At a time when worldwide biodiversity is in significant decline and underwater soundscapes are being altered as a result of anthropogenic impacts, there is a need to document, quantify, and understand biotic sound sources–potentially before they disappear. A significant step toward these goals is the development of a web-based, open-access platform that provides: (1) a reference library of known and unknown biological sound sources (by integrating and expanding existing libraries around the world); (2) a data repository portal for annotated and unannotated audio recordings of single sources and of soundscapes; (3) a training platform for artificial intelligence algorithms for signal detection and classification; and (4) a citizen science-based application for public users. Although individually, these resources are often met on regional and taxa-specific scales, many are not sustained and, collectively, an enduring global database with an integrated platform has not been realized. We discuss the benefits such a program can provide, previous calls for global data-sharing and reference libraries, and the challenges that need to be overcome to bring together bio- and ecoacousticians, bioinformaticians, propagation experts, web engineers, and signal processing specialists (e.g., artificial intelligence) with the necessary support and funding to build a sustainable and scalable platform that could address the needs of all contributors and stakeholders into the future.

Keywords: soundscape, bioacoustics database, artificial intelligence, biodiversity, passive acoustic monitoring, ecological informatics

BACKGROUND

Aquatic (i.e., marine, brackish, and freshwater) environments encompass the world's most extensive habitats, rich with sounds produced by a diverse range of animals. Advances in data acquisition, storage and processing that enable increased recording durations at reduced costs, and easier logistics of sensor deployment and retrieval, have made passive acoustic monitoring (PAM) a more accessible and feasible tool than ever before (Lindseth and Lobel, 2018; Chapuis et al., 2021; Wall et al., 2021). Combined with an increasing appreciation of the ecological importance of acoustic cues to almost all aquatic fauna, these advances have expanded the field of underwater bioacoustic and ecoacoustic research to increasing numbers of researchers and organizations (Lindseth and Lobel, 2018). The result has been an almost exponential increase in the volume of aquatic PAM data being collected around the world, in conjunction with increases in soundscape research (Lindseth and Lobel, 2018; Mooney et al., 2020; Duarte et al., 2021). Researchers now routinely collect substantially more PAM data, on an increasing number of taxa, and in more locations than ever before, from freshwater to marine, from shallow waters to the deep, and from tropical to polar regions (Wall et al., 2021). Higher sampling frequencies and longer deployment durations mean that datasets may now easily exceed terabytes in size and years in duration, potentially containing millions of sounds and hundreds of different types (Waddell et al., 2021; Wall et al., 2021). This makes manual classification of underwater sounds by experts—the traditional method of verifying call presence and source identification—increasingly difficult (Mooney et al., 2020; Waddell et al., 2021).

PAM is already used for a multitude of biological applications. Examples include monitoring, characterizing and delineating underwater soundscapes, and investigating aquatic communities (e.g., Desjonquères et al., 2015; Erbe et al., 2015; Menze et al., 2017; Mooney et al., 2020; Stanley et al., 2021); documenting the distribution and migration patterns of the great whales (e.g., Risch et al., 2014; Tsujii et al., 2016; Davis et al., 2020; Warren et al., 2021); characterizing the spatial and temporal responses of fish choruses to environmental drivers like temperature, salinity, lunar phase, tide, and time of sunset (e.g., Barrios, 2004; Rountree et al., 2006; Parsons, 2010; Straight et al., 2015; Rice et al., 2016; McWilliam et al., 2017; Parsons et al., 2016; Karaconstantis et al., 2020; Linke et al., 2020); understanding how animals change their behavior and distribution in response to climate change (Gordon et al., 2018), anthropogenic noise sources (e.g., Thompson et al., 2013; Cerchio et al., 2014; Erbe et al., 2019; Meekan et al., 2021), algal blooms (e.g., Rycyk et al., 2020) and extreme weather events like hurricanes (e.g., Locascio and Mann, 2005; Fandel et al., 2020; Boyd et al., 2021; Schall et al., 2021); understanding how prey change their sound production rates or behaviors with the presence of predators (e.g., Luczkovich and Keusenkothen, 2007; Hughes et al., 2014; Bailey et al., 2019; Burnham and Duffus, 2019); and how noise and propagation conditions can affect communication spaces (e.g., Alves et al., 2016; McKenna et al., 2021). This wide range of uses for PAM is expanding with developments in technology, providing a great volume of easily accessible data on aquatic life.

With an increase in the use of PAM, there is increasing awareness of the impacts the acoustic environment (i.e., frequency-dependent propagation loss) can have on characteristics of recorded sound. For example, the same humpback whale song may produce different received spectra in two spatially separated recordings, depending on propagation conditions, and appear as two different types of calls. Sound production mechanisms (e.g., directionality of the source signal) can also influence recorded sound characteristics, such as the azimuth-dependent received spectra of some odontocete calls (Lammers and Au, 2003). Together with the impact of signal-to-noise ratio (SNR) on the clarity of a sound sample, these factors all affect the reproducibility of signals, which needs to be considered when assessing the sound samples provided to, and by, a sound library.

Underpinning much of this work is the ability to identify or characterize sound sources either to assess them individually or understand their contribution to the overall soundscape (Mooney et al., 2020; McKenna et al., 2021). We are beginning to understand how these biological sounds, together with anthropogenic and geophysical sounds that make up the local soundscape (Schafer, 1969, 1977; Southworth, 1969; Krause, 2008; Hildebrand, 2009), can collectively provide information on physical habitats, biodiversity, and aquatic ecosystem health (Mooney et al., 2020). PAM is proving to be one of the most effective ways to monitor visually elusive but vocal species in aquatic environments, which can potentially aid in more effective conservation management, such as spatio-temporal zoning measures found in marine park areas or fishery closures (Coquereau et al., 2017; Nikolich et al., 2021). At a time when global biodiversity is in significant decline (Sala and Knowlton, 2006; Worm et al., 2006; Marques, 2020) and increasingly impacted by climate change (e.g., Poloczanska et al., 2013; Sydeman et al., 2015), there is a need to document and understand as many sound sources in the ocean as possible, potentially before they disappear.

There are 126 marine mammal species, approximately 35,000 known species of fish, and nearly 250,000 documented species of marine invertebrates in the world (Froese and Pauly, 2021; World Register of Marine Species, 2021), and the number of known soniferous (actively sound-producing) species underwater is consistently increasing (see **Figure 1** for spectrograms of example sounds). There are even a handful of reports of sound produced by birds underwater (e.g., Thiebault et al., 2019). It is thought that all aquatic mammal species exhibit soniferous behavior underwater and reports have so far confirmed this trait for almost all of them (e.g., Mellinger and Clark, 2006; Richardson et al., 2013). Calls of many marine mammal species are often distinctive and can even show significant variability among individuals (e.g., Janik and Sayigh, 2013; McCordic et al., 2016; Bailey et al., 2021). Additionally, as comparatively large and charismatic species, mammals can often be verified as the source of a sound with nearby surface sightings or from studies of animals in human care (e.g., Rogers et al., 1996).

Overall, validated sounds have been attributed to a much lower proportion of species from the speciose groups of aquatic invertebrates and fishes, than for marine mammals. Whereas almost all marine mammals are confirmed to produce sounds underwater, this behavior has been validated for fewer than 100 species of aquatic invertebrates (e.g., Popper et al., 2001; Coquereau et al., 2016) and approximately 1,000 fish species (Kaatz, 2002; Parmentier et al., 2017; Bolgan et al., 2020a; Looby et al., 2021; Rice et al., 2022); however, the former includes members of Alpheidae, the "snapping shrimp" family with over 500 species and the latter represents over two-thirds of fish families, implying many more species are soniferous (Parmentier et al., 2021). Fishes and invertebrates are typically more difficult to validate in the field than mammals (e.g., Sprague and Luczkovich, 2001; Riera et al., 2017), though visual confirmation is on occasion achieved (e.g., Lobel, 1992, 1996, 1998, 2001; Allen and Demer, 2003; Lobel et al., 2010; Parsons et al., 2013a) or inferred by weight-of-evidence from the species present at the time of recording and their behavior (e.g., Tricas and Boyle, 2014; Pyć et al., 2021), or by localization (e.g., Parsons et al., 2009; Mouy et al., 2018). Sound travels much farther than light underwater and efficiently through turbid waters that often prohibit visual source validation more than a few meters from an observer or camera, or even ranges of centimeters in turbid environments (Harvey et al., 2004; Jones et al., 2019). This is particularly problematic when the source in question is "small and cryptic," found within an assemblage of several species', at great depth, or within complex habitat. Moreover, many fish and invertebrate species are predominantly nocturnal, rendering simultaneous visual and audio observations arduous or impossible (e.g., Spence, 2017). Thus, while some sources have been confirmed, the majority of fish and invertebrate sounds and choruses remain anonymous, uncharacterized and largely unreported, as they do not comprise sounds of a project's target species. Recordings taken under controlled conditions (e.g., within tanks or aquaria) can provide confirmation of species' sound production (e.g., Sprague and Luczkovich, 2001) as well as other information on sound-producing behavior that could be challenging to collect in the field (e.g., Montie et al., 2017; Riera et al., 2018); however, assessment of the acoustic characteristics and behavioral context of these sounds requires additional consideration. The material, dimensions and background noise within a constrained environment, for example, affect the received signal (e.g., Akamatsu et al., 2002). Additionally, soniferous behavior may be affected by captivity, such as the acclimation time, surroundings and number of other individuals within the environment, among other factors (e.g., Holt and Johnston, 2014). The nature and extent of the effects of captivity has on recorded sounds and overall acoustic behavior may vary between species and potentially even individuals (e.g., Bolgan et al., 2020b,c).

Although substantial work has been conducted on freshwater species, predominantly on fishes and initially in aquaria (Gerald, 1971; Desjonquères et al., 2020; Grabowski et al., 2020; Linke et al., 2020; Roca et al., 2020; Rountree and Juanes, 2020; Higgs and Beach, 2021), the majority of efforts to record aquatic biological sounds have historically focused on the marine environment (Greenhalgh et al., 2020). Freshwater recordings present a variety of complexities that are less common in the marine environment, such as terrestrial, aerial and water-surface sounds from birds, insects, and road or air traffic (Erbe et al., 2018; Linke et al., 2020; Rountree et al., 2020; Leon-Lopez et al., 2021).

In addition to the difficulties in identifying soniferous species, there is also potential variability in sound types and characteristics of sound production for a given species (e.g., McIver et al., 2014; Parsons and McCauley, 2017; Bolgan et al., 2020c). There are very few species where the entire suite of calls has been captured and even at a single location, full repertoires are rarely confirmed or reported. Further, numerous taxa are cosmopolitan, either as wide-roaming individuals, such as the great whales, or as broadly distributed species, such as many fishes. Some of these global (and regional) travelers exhibit dialects, or completely different signal structures among regions, several of which evolve over time (e.g., Parmentier et al., 2005; Garland et al., 2011; **Figure 1**).

Alongside active sound production for the purported purpose of communication, many aquatic species produce "passive sounds" as a by-product of other life-functions, such as eating, swimming, and crawling (e.g., Fish, 1948; Moulton, 1958, 1960, 1963, 1964; Uno and Konagaya, 1960; Mallekh et al., 2003; Radford et al., 2008; Rountree et al., 2018; Ajemian et al., 2021; Tricas and Boyle, 2021; **Figure 1**). These passive sounds may be less acoustically complex or distinct than active sounds; however, they still provide important contributions to the soundscape and have demonstrated ecological signal potential in select circumstances (Banner, 1972; Connor et al., 2000; Tricas and Boyle, 2014; Rountree et al., 2018). Thus, while collating global records of known sound production may be feasible to accomplish (e.g., for fishes; Looby et al., 2021), because of the variation in sound within and among species and individuals, the effort required to collect and maintain representative sounds for every species is a continuous and laborious process. Further, even when unidentifiable biological sounds are described in detail, there remains no global system with which to attempt to

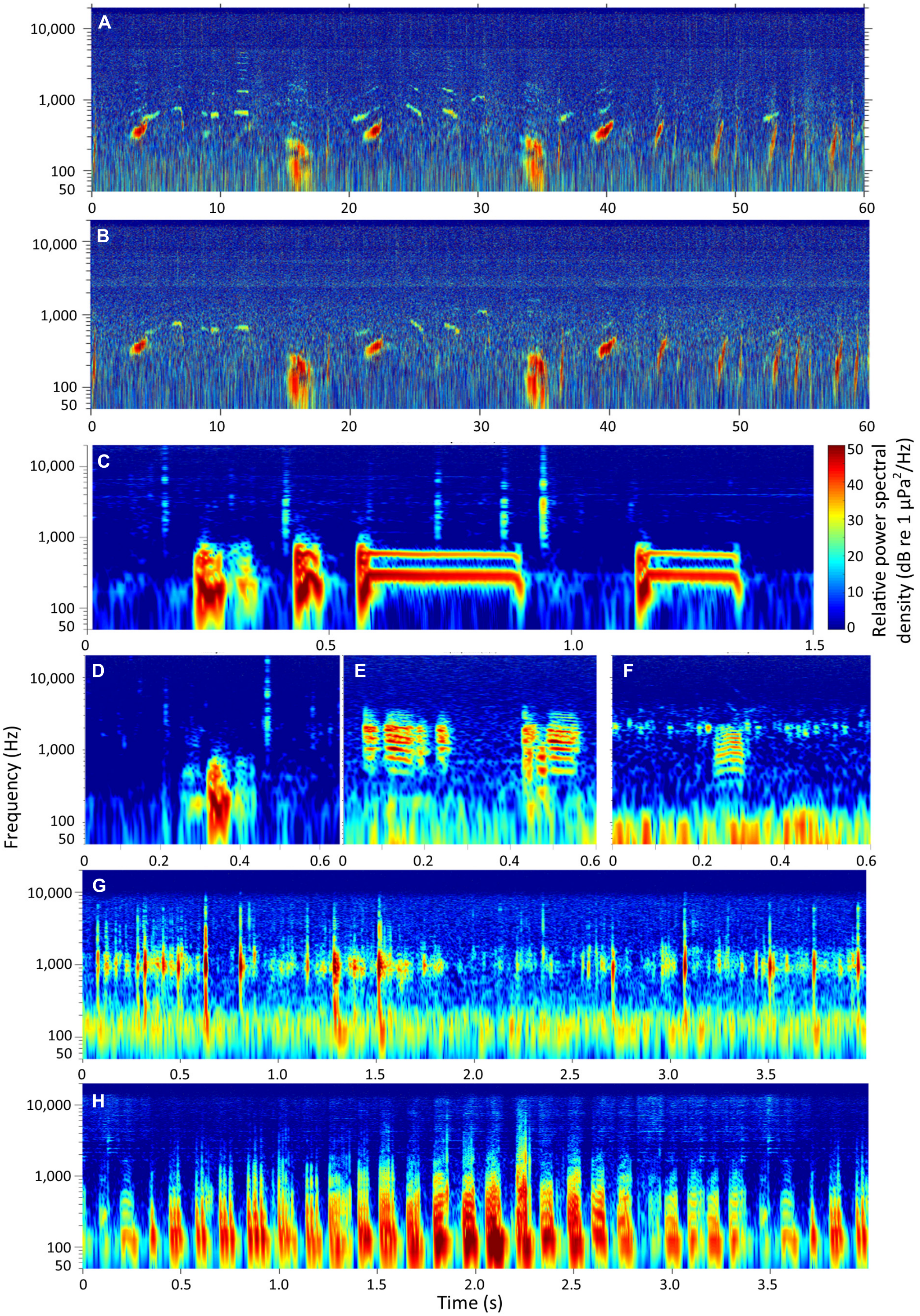

FIGURE 1 | Example spectrograms produced (1,024 point-long Hanning window, 0.9 overlap, frequency display 50–20,000 Hz, relative received levels) from: two simultaneous recordings of a humpback whale (*Megaptera novaeangliae*) song in **(A)** 20 m and **(B)** 40 m depth waters off Okinawa, Japan, (recording locations separated by ≈500 m, note the lack of high-frequency energy in **B**); **(C)** a complex call and **(D)** a single grunt sound from gulf toadfish (*Opsanus beta*); **(E)** two sounds from a 20–30 cm-long sooty grunter (*Hephaestus fuliginosus*); **(F)** one sound from a 7 cm-long spangled grunter (*Leiopotherapon unicolor*); **(G)** 4 s of sounds made a crawling kina urchin (*Evechinus chloroticus*) and **(H)** 4 s of sounds produced by a New Zealand paddle crab (*Ovalipes catharus*). Power spectral density axes in each spectrogram are relative and span 50 dB re 1 μPa^2/Hz. Spectrograms are for comparative purposes and, as such, recording conditions and methods are not provided. All recordings sampled at 44.1 ksps except that producing panel **(E)**, which was sampled at 48 ksps.

characterize or identify them (Anderson et al., 2008; Rountree et al., 2020).

Although some of these sources are obvious, pervasive, and readily observed in long-term recordings, many more are rare and of lower amplitude, often going undetected unless the observer is specifically searching for them (Mooney et al., 2020). Many studies are conducted with single- or limited-species objectives, although these recordings are often filled with a great diversity of sounds. Collectively there are now multi-millions of recording hours around the world that could potentially be assessed for a plethora of both known and, to date, unidentified biological sounds. Only recently have studies begun to address the groupings of such sounds, in the field of acoustic community ecology (Desiderà et al., 2019; Bolgan et al., 2020a; Di Iorio et al., 2021).

SOUND LIBRARIES

The provision of audio samples is an important activity as it is often difficult for a researcher to confirm that a sound they have recorded is the same as one that has been previously identified, based on a description in a journal or website. This is particularly true if the two were recorded under different environmental conditions. A library provides first-hand examples for comparison, preferably with a spectrogram that has clear annotations describing the specific time and frequency range of the target signals, along with sufficient metadata to facilitate comparison between user and library samples, to maximize the use of the library. The audio-visual combination provides the user with a good understanding of the call type (under the recorded conditions). This combination can be particularly important for high-biodiversity systems such as coral reefs, where even a short recording can pick up multiple animal sounds.

Several independent libraries of biological sounds, many of which either contain aquatic examples, or have an underwater focus, have been established around the world (see **Table 1** for selected examples). Existing libraries often focus on species of interest that are targeted by the host institute's researchers and are often recorded from a particular phylum or more restricted taxon, with a smaller selection of opportunistically recorded species. A few libraries describe many known sound sources from a region as the basis for an article describing reported species distribution in the region, including standardized characteristics of each sound type for the species, with a link to a website where the sounds can be downloaded (e.g., Erbe et al., 2017). Other libraries are national and may be incrementally expanded by contributions of a handful of researchers with associated papers outlining sounds as they are observed (**Table 1**). The *FishSounds* website project, for example, began with a systematized, global review of fish species examined for sound production (with or without documented sonifery) in the peer-reviewed and gray literature, which is now being expanded to include representative recordings of fish sounds contributed by researcher donations of known and unknown fish species (Looby et al., 2021). This is a significant step; however, this library currently only accepts recordings of fish sounds that can be associated with some form of published reference.

In general, existing libraries are "silos"—lacking the cohesiveness that a taxa-independent global library or network could provide. Moreover, PAM is not a traditional method of categorizing or preserving information on diversity. Thus, keeping such libraries up to date has not been a focus and, in recent years, many libraries have lagged in their updates. Sustainability and accessibility of a sound collection is critical, particularly when it is tied to a single researcher, rather than a host institution.

Finally, few libraries identify what is missing from their catalogs. While this is a more complex task for fish and invertebrates, examples like Cornell University's Macaulay Library have a list of target species for which they have fewer than 10 recordings. As our list of confirmed sources and known soniferous species increases, so does the ease with which the unconfirmed sources can be identified via a "weight of evidence" approach.

Here, we provide justification for the creation of a global bioacoustics platform that integrates and expands on existing libraries by describing five critical characteristics of such a program and what its extensions can bring to acoustic research and monitoring. The benefits of a global sound library include: (1) a full inventory of known underwater sound sources; (2) a baseline of unidentified biological sounds; (3) the foundation for a training platform for detection and classification algorithms (at both a source and soundscape level); (4) standardized metadata for understanding how, when, and where the recordings were made; and (5) an open-access (including for citizen science/public users) database to make aquatic biological sounds more accessible to the general public and allow them to upload sounds and add to the dataset (see **Figure 2**, for a conceptual diagram of such a potential integrated library). In addition to these benefits, the global sharing of such an expansive database—from potentially numerous contributors—holds the potential for multiple broadscale collaborations on regional and international trends of PAM detections. Similar efforts have been achieved in related fields, like acoustic telemetry (e.g., Hussey et al., 2015; Sequeira et al., 2019; Lédée et al., 2021; Matley et al., 2021), and visual censusing of marine fauna (e.g., Langlois et al., 2020), fostered by open forums and working groups to develop such research. We also discuss some of the technical challenges in developing this platform, historical hurdles that may have prevented previous attempts at such global data sharing environments, and a potential way forward for building this resource.

The discussion presented in this paper originated within the "Working Group on Acoustic Measurement of Ocean Biodiversity Hotspots" of the International Quiet Ocean Experiment (Boyd et al., 2011), an international program of research, observation and modeling formed to better characterize and understand ocean sound fields and the effects of sound on marine life. This collaboration was then expanded to include authors that are involved in the development, presentation and maintenance of existing underwater bioacoustics repositories;

TABLE 1 | Example biological sound libraries with recordings of mammal, fish, avian and invertebrate sounds.

Title (host)	Weblink (citation)	Details
Audio Gallery (Discovery of Sound in the Sea)	https://dosits.org/galleries/audio-gallery/ (Vigness-Raposa et al., 2012)	Sound samples of 44 marine mammal, 29 fish and 4 invertebrate species from around the world
Fish Sounds (University of Rhode Island)	http://www.gso.uri.edu/fishsounds/ (Fish and Mowbray, 1970)	155 sound samples of 153 fish species from the Western North Atlantic (Fish and Mowbray, 1970)
The SOUND Table (FishBase)	https://www.fishbase.de/topic/List.php?group=sounds (Kaschner, 2012)	121 sound samples of 90 fish species, mostly from the Western North Atlantic (Fish and Mowbray, 1970)
Macaulay Library (Cornell University)	https://www.macaulaylibrary.org/ (Macaulay Library, 2021)	1,189,562 sound samples of 10,056 bird species and 2,674 non-bird species
Marine Mammals of Australia and Antarctica (Curtin University)	http://cmst.curtin.edu.au/research/marine-mammal-bioacoustics/ (Erbe et al., 2017)	Sound samples of 43 marine mammal species from Australasia
Ocean Networks Canada (Sound Cloud)	https://soundcloud.com/oceannetworkscanada/albums (Ocean Networks Canada, 2021)	60 sound samples of marine mammal and fish species from Canada
Watkins Marine Mammal Sound Database (Woods Hole Oceanographic Institution)	https://cis.whoi.edu/science/B/whalesounds/index.cfm (Sayigh et al., 2016; Watkins Marine Mammal Sound Database, 2021)	About 15,000 sound samples of 55 marine mammal species, as well as about 1,600 full soundscape recordings, mainly collected during the career of William Watkins
Sonothèque (Muséum National d'Histoire Naturelle)	https://sonotheque.mnhn.fr/ (Sonothèque, 2018)	19,589 sound samples of wildlife species, including marine mammals and fishes, predominantly collected by Bernie Krause with additional contributors
British Library Sound Archive (The British Library)	https://sounds.bl.uk/Environment (The British Library, 2021)	240,000 sound samples of 10,000 bird, mammal, amphibian, reptile, fish, and invertebrate species from around the world
Voices in the Sea (University of California San Diego)	http://voicesinthesea.ucsd.edu/ (Voices in the Sea, 2018)	Sound samples of 33 Cetacean and 10 Pinniped species
FishSounds (MERIDIAN)	https://www.fishsounds.net (Looby et al., 2021)	240 sound samples of 130 fish species
MobySound	mobysound.org (Heimlich et al., 2021)	Sound samples of 25 Cetacean and 2 Pinniped species
Animal Sound Archive (Museum für Naturkunde in Berlin)	https://www.tierstimmenarchiv.de/ (Tierstimmenarchiv, 2021)	120,000 sound samples of any wildlife, including invertebrates, marine mammals, and fishes
FonoZoo (Museo Nacional de Ciencias Naturales Madrid)	http://www.fonozoo.com/ (FonoZoo, 2021)	11,656 sound samples of 1,620 species, including invertebrates, marine mammals, amphibians and fishes

i.e., an overall partnership that represents various stakeholder groups—including bio- and ecoacousticians, and research specialists of a variety of taxa and ecosystems. All of these authors are aware of the benefits a global library of underwater biological sounds offers to the scientific, environmental management and public sectors. This paper, however, is not meant to dictate the exact form such a global underwater biological sounds library should take, but is meant to renew and revitalize discussion on the topic, present some of the many considerations such an effort would require, and describe a possible path forward for us or others to undertake as opportunities and interests arise. A more detailed discussion of such a program, involving a wider network of contributors, is planned through upcoming stakeholder engagement and scoping workshops.

CHARACTERISTICS OF A GLOBAL LIBRARY OF UNDERWATER BIOLOGICAL SOUNDS

Applications of an Inventory of "Known" Sounds

Creating a reference library of aquatic sounds from known origins will broaden our reference list for confirming the sources of sounds that appear in recordings and help expand our knowledge of aquatic acoustic diversity, as well as our understanding of taxonomic biodiversity and ecology. Bringing known sounds together in a unified depository or single platform with links to multiple existing databases facilitates easy comparison among species, locations, species repertoires, and recording methodologies.

Studies often focus on a single or a limited number of species and, therefore, so does a project's data analysis. Although the advent of multi-species automated detection platforms has brought significant advances in the terrestrial environment (Potamitis, 2014; Sueur and Farina, 2015; Farina et al., 2018; Kahl et al., 2021), such analyses are currently lagging behind in the underwater environment. The potential to process each dataset for sources beyond the focal species is rarely undertaken due to the funding and effort required as well as a lack of individual knowledge about all the different sounds and sources that exist. Easing this burden requires a collective effort to detect, identify, characterize, and collate sources. A global reference library of underwater biological sounds would increase the ability for more researchers in more locations to broaden the number of species assessed within their datasets and to identify sounds they personally do not recognize. Such access would ultimately lead to a description and catalog of acoustic biodiversity around the globe, and an increased understanding of acoustic ecology. A global database could serve broader questions, like determining universal trends in underwater sound production,

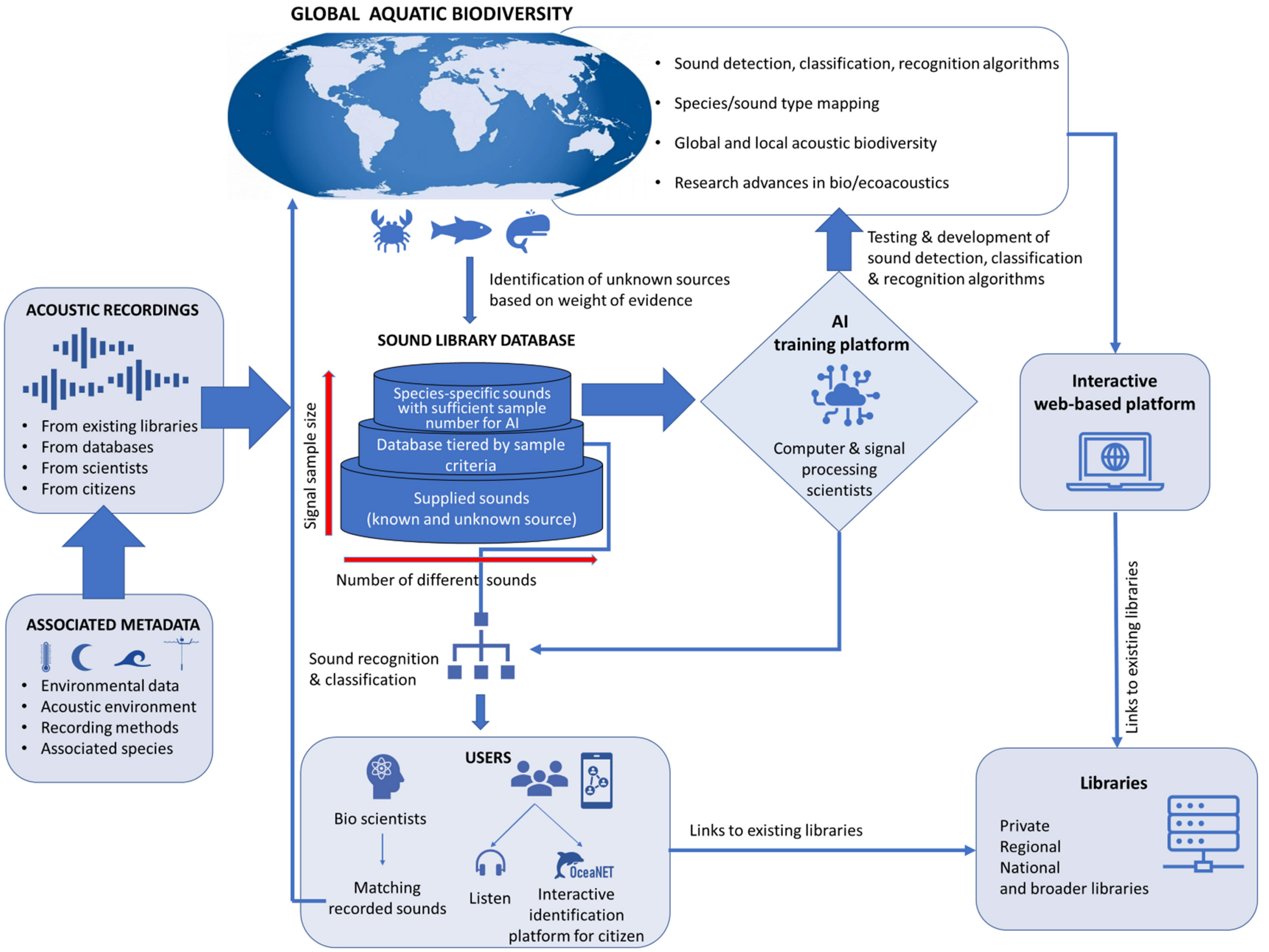

FIGURE 2 | Conceptual diagram of the basic structure and data flow within a potential global integrated library and database sharing platform.

while individual, specialized repositories could continue to inform and detail other topics, such as documenting the presence of soniferous species in a particular region.

Spatiotemporal Species Mapping

The expansion of PAM data collection has increased our understanding of spatiotemporal patterns of individual species' presence and acoustic behavior. As a result, reported distributions of these species are being expanded. Even some of the great whales are being found in places they were not expected (Allen et al., 2021), and occasionally a new species (Rosel et al., 2021) or a new sound (Rice et al., 2014; Cerchio et al., 2020) is discovered. This fact could prove vital for soniferous fauna, as our ever-changing climate ensures that many species are modifying their distributions and broadening or reducing their ranges (e.g., Scheinin et al., 2011; Ramirez et al., 2017; Bonebrake et al., 2018). Biologically important areas can be mapped; spawning grounds, essential fish habitat, and migration pathways can be delineated (e.g., Luczkovich et al., 1999; Rountree et al., 2006; Mann et al., 2009; Morano et al., 2012a; Schärer et al., 2014; Bertucci et al., 2015; Lammers and Munger, 2016; Karaconstantis et al., 2020); the timing of reproductive activities can be associated with the environment (e.g., Mann and Grothues, 2008; Parsons, 2010; McWilliam et al., 2017; Zarada et al., 2019); and displacement from preferred habitats due to anthropogenic activities and noise, such as that from shipping lanes and exploration surveys, can be mapped (e.g., Tyack, 2008; Castellote et al., 2012; Rako et al., 2013). These and other questions can be queried on broader scales if we have a global catalog of sounds.

Comparisons of Signal Structure

Comparison of sounds from a single species across broad areas and times provides the ability to understand signal diversity and evolution, and to gain insights into species ecology (e.g., Tellechea et al., 2010). Fin whale (*Balaenoptera physalus*) calls, for example, differ among populations (Delarue et al., 2009) between the Northern and Southern hemispheres (Gedamke and Robinson, 2010; Širović et al., 2013, 2017; Aulich et al., 2019), as well as over seasons (Morano et al., 2012b). Pilot whales (*Globicephala melas*), on the other hand, produce similar call types across the hemispheres even though populations' home ranges do not (or no longer) cross the equator, raising interesting questions about their acoustic ecology and evolution (Courts et al., 2020). Fishes may also develop "dialects," such as the different acoustic characteristics of agonistic sounds produced by the skunk anemonefish (*Amphiprion akallopisos*) in Madagascar compared with those in Indonesia (Parmentier et al., 2005). Cultural evolution of humpback whale (*Megaptera novaeangliae*) song has been observed across ocean basins, providing greater understanding of population interactions across the Pacific Ocean (Garland et al., 2011) and around the coast of Australia (Allen et al., 2018). Call structure, and source spectra of blue (*Balaenoptera musculus*) and pygmy blue whales (*Balaenoptera musculus brevicauda*) around the world evolve through time, with peak frequencies changing each year (e.g., McDonald et al., 2009; Gavrilov and McCauley, 2012), such that detection algorithms developed in 1 year may not be successful some years later; thus, keeping libraries up to date aids classification efforts. Sound production between similar species within a taxonomic family can also be compared, such as those of mulloway (*Argyrosomus japonicus*) and black jewfish (*Protonibea diacanthus*) in Australia (Parsons et al., 2012, 2013b, 2016) with those of French meagre (*A. regius*) in Europe (Lagardère and Mariani, 2006; Bolgan et al., 2020b), or those of various species of toadfishes in the Pacific, Indian, and Atlantic oceans (Thorson and Fine, 2002; Rice and Bass, 2009; Mosharo and Lobel, 2012; Alves et al., 2016; Staaterman et al., 2018; Pyć et al., 2021), to better understand the variation within families.

Acoustic Communities

There is increasing evidence that the study of acoustic communities, based on acoustic characteristics of the sounds emitted by animal communities, provides ecologically relevant information (Francis et al., 2009; Farina and James, 2016; Desiderà et al., 2019; Mooney et al., 2020). Soundscapes provide unique opportunities to investigate the biodiversity and community of soniferous species, frequency and temporal niche partitioning, and organism-environment relationships (Ruppe et al., 2015; Di Iorio et al., 2021; McKenna et al., 2021). However, this field is in its infancy and requires a catalog of identified sounds to develop reliable and time-efficient classification techniques that will be necessary for describing the acoustic communities and relating them to the underlying animal assemblages (Mooney et al., 2020).

Environmental Noise

Anthropogenic noise, such as that from vessels, exploration, construction, and aerial vehicles (Reine et al., 2014; Newhall et al., 2016; Pangerc et al., 2016; Erbe et al., 2018; Chion et al., 2019; McCauley et al., 2021; Parsons et al., 2021), is a growing pollutant in the underwater environment and high ambient noise levels, such as those found in areas of intense human activity, inhibit signal detection (Hildebrand, 2009; Duarte et al., 2021). If the observer knows a target species' signal characteristics, these sounds may be more easily detected, but without prior knowledge of either presence or structure of sounds, listening through the noise can be difficult. This has been highlighted by the recent COVID "anthropause" experienced at various aquatic locations around the world (e.g., Bates et al., 2021; De Clippele and Risch, 2021; Dunn et al., 2021; Gabriele et al., 2021; Ryan et al., 2021), where removal of the anthropogenic component of some soundscapes has provided an opportunity to observe sounds (and therefore presence) of marine fauna that might otherwise be lost in the noise (e.g., Pine et al., 2021). However, it is not just anthropogenic noise that limits acoustic detection of marine fauna. The ocean is naturally noisy and geophysical noise (such as from wind and ice) exceeds anthropogenic noise in many regions and seasons (e.g., Farcas et al., 2020; Erbe et al., 2021; Sertlek, 2021). The number and intensity of storms and extreme weather events are expected to increase with climate change (e.g., Cheal et al., 2017), inevitably contributing further noise to the underwater environment (e.g., Zhao et al., 2014; Ashokan et al., 2015; Zhang et al., 2018). A reference library of sounds, as well as detection algorithms, would significantly ease the detection of sounds in low SNR environments.

Assisting Unknown Source Identification

A sound catalog can provide a reference for comparison with unknown sounds to assist in their source identification, potentially through an online tool, within the library. The associated metadata that accompanies recordings (discussed below) may also contribute to a weight-of-evidence approach in identifying sound sources. Sainburg et al. (2020), demonstrated the use of unsupervised learning to assemble acoustic signals displaying similar spectral-temporal modulation features into groups. Such exploratory data analysis tools will assist in identification of sound sources; however, their design and functionality may be dependent on the amount of data (general and source-specific acoustic data and validation data), the distribution of the source signal and potential sources, and the characteristics of the signal, among other factors. In selected species, where sound production has not yet been confirmed, it may be possible to use signals reported from a closely related species to assist in detecting sounds or choruses from the targeted species. Calls produced by terapontid fish species, for example, are often similar, but not all species within the family have been reported to produce sound (Parmentier et al., 2016; Looby et al., 2021). Although not definitive, sound production by related species can provide evidence toward soniferous behavior, though caution is warranted as species that appear morphologically similar can be acoustically different, such as Ophidiformes (Mann et al., 1997; Parmentier et al., 2006, 2010).

Basis for Machine Learning Development

A library of reference sounds requires only a handful of examples for each individual sound type. In contrast, a dataset for training artificial intelligence (AI) requires a far larger number of signals, ideally several thousands of examples (e.g., Madhusudhana et al., 2020, used > 11,000 replicates of the same call type to build robust detectors). The library itself can be of benefit as it provides the basis from which the AI datasets can be developed either through providing numerous examples for directly training models, or for facilitating event mining from previously collected data streams (Xie et al., 2008; Zhang et al., 2013). For example, Miller et al. (2021) initiated an open-access library of annotated recordings to train and evaluate automated detectors of Antarctic blue whale and fin whale (*B. physalus*) calls. The library was designed to include recordings from a broad range of instruments, locations, environmental conditions, and years, to ensure that robust detectors can be developed and tested across a suite of recording conditions. However, given the scope of this library initiated through the Southern Ocean Research Partnership Fin and Blue Whale Acoustics Group (Van Opzeeland et al., 2014), it is unlikely to be extended to other regions and taxa.

As the number of samples of a given sound type reaches critical mass, and recordings of them are also sufficiently rich in signals recorded under different conditions (e.g., SNR, acoustic environment, recording methods), that sound type can be flagged as available for the development of detection algorithms. Indeed, presenting the information on current sample numbers within each sound type could promote contributors to target them, increasing the likelihood of collectively bringing the dataset up to the required level. If it can be achieved, a library that includes an entire species' sound repertoire will assist in validating detection algorithms and provide the ability to expand these algorithms to datasets where the call type was not the original target for analysis, and conduct this on a global, rather than local scale. For species that produce sounds that change with time, historical data and continual updating of the library could assist in predicting future evolution (Gavrilov and McCauley, 2012).

Database of Unknown Sounds

A database of unidentified sounds is, in some ways, as important as one for known sources; as the field progresses, new unidentified sounds will be collected, and more unidentified sounds can be matched to species. These sounds and the times and locations of their recording can form a basis for future identification and ease mapping of the species' distribution once the source has been confirmed. Given the increasing rate of data collection, it is better to start building a map of these sounds as soon as possible. The library can also provide evidence to help test hypotheses of source species for unknown sounds if there are sufficient recording locations that can be compared to distribution maps of potential source species (e.g., those produced from catch data or visual census).

Although the analysis of acoustic communities benefits from a baseline of cataloged sounds, most sound sources that contribute to the soundscape remain uncertain and most libraries only archive signals with known species' identity. In addition, we know more about the sounds of endangered or commercially important species than those of commonly encountered species (Luczkovich et al., 2008; Popper and Hawkins, 2019). This knowledge gap has impeded effective use of underwater soundscapes in monitoring marine biodiversity, but much information on acoustic ecology can still be gleaned from categorized sound types of unknown origin (Le Bot et al., 2015; Rountree et al., 2019; Bertucci et al., 2020; Bolgan et al., 2020a; Di Iorio et al., 2021). A library to archive unknown sounds and their recording times and locations will be crucial for guiding future studies of marine bioacoustics and biodiversity. This is especially important in areas that are rarely investigated or where source identification is particularly problematic, such as the twilight and midnight zones, where a description of unknown sounds can give us insights on biodiversity in the deep ocean (e.g., Mann and Jarvis, 2004; Rountree et al., 2012; Lin et al., 2019).

Platform for Training Deep-Learning Applications

Signal- and image-processing techniques have been used in the temporal and spectral domains to automatically detect and quantify fauna sounds. For example, click detectors operating on waveforms have been applied to recordings of dolphins and porpoises (e.g., Sostres and Nuuttila, 2015), belugas (Le Bot et al., 2015), sperm whales (Madhusudhana et al., 2015), beaked whales (e.g., Yack et al., 2010; Le Bien, 2017), and snapping shrimp (e.g., Bohnenstiehl et al., 2016; Du et al., 2018). Matched-filtering of spectrograms has been used to detect highly stereotypical sounds of some whales and fishes (e.g., Mellinger and Clark, 1997; Ricci et al., 2017; Madhusudhana et al., 2020; Ogundile and Versfeld, 2020). Information entropy detectors have been applied to aberrant (non-stereotypical) tonal sounds (Erbe and King, 2008). Detectors are further applied to wavelets and the cepstral domain as well (e.g., Alias et al., 2016; Noda et al., 2016; Malfante et al., 2018). Machine and deep learning (AI) methods have been increasingly used to classify and detect sources in multiple applications (e.g., Lin et al., 2017; MacAodha et al., 2018; Bergler et al., 2019; Stowell et al., 2019).

There have been considerable advances in the fields of facial and voice recognition that have advanced public use of phone-based apps to identify music, plants, and the calls of frogs and birds (Kahl et al., 2021). However, this success has been largely due to the enormity of the respective databases from which AI algorithms can be trained, a goal that has only recently become possible in the aquatic environment and only for selected call types. The sheer enormity of data now collected in many underwater acoustic studies, together with the myriad of signals often present and the extreme amount of time required to search these records in more "standard" methods, means there is a clear opportunity for AI to improve efficiency and extract more information from these datasets. Increasingly, neural networks and other AI methods are being used to detect marine mammals in historical recordings such as of humpback whales across the Hawaiian archipelago (Allen et al., 2021), and multiple cetacean species along the west coasts of Canada and Australia (Mellinger and Clark, 2006). Detections of pulse trains, typically based on previously identified or grouped inter-pulse timing (the time between pulses of sound) are being successfully applied to count the number of echolocating individuals and fish sounds within datasets (Bahoura and Simard, 2010; Le Bot et al., 2015; Ibrahim et al., 2018).

Many machine learning techniques have been developed under the framework of AI (e.g., Shamir et al., 2014). Application of these techniques has begun to coalesce and recent studies now extract multiple features to detect the different types of signals, such as Malfante et al. (2018), who tested 84 extracted features to detect and characterize four general classes of fish sounds: (1) impulsive (pulses with signal separation > 1 s); (2) trains of > 15 pulses audible as either a single tone or a series of knocks in quick succession; (3) wide-band signals of 10–30 s in duration; and (4) short signals with harmonic structure. Each of these sound types required the detection of different features and individual machine learning. The recent development of deep learning has significantly reduced the work required in feature extraction (Shiu et al., 2020; Kahl et al., 2021; Waddell et al., 2021) and even made end-to-end learning feasible, in which AI models automatically learn features from raw audio to perform signal detection and classification. Successful examples include avian calls (Bravo Sanchez et al., 2021), odontocete clicks (Luo et al., 2019; Roch et al., 2021), and frog calls (Xie et al., 2020). Hand-selected features, such as peak frequency and frequency bandwidth measured manually or automatically, are no longer a necessity.

Developing a global database that can assist in modifying or developing algorithms in the underwater environment holds significant potential for detecting, classifying, and quantifying spatiotemporal distribution and abundance of aquatic fauna. Such a global database of known and unknown sound sources can benefit both supervised and unsupervised machine learning. Supervised machine learning is effective when training data of detection/classification targets are available. However, most underwater biodiversity assessments are unable to make sure all sound sources are already covered in the training database. Unsupervised machine learning may help discover the structure of sound categories from a substantial number of unlabeled recordings and reduce the effort required in manually annotating signal types and characteristics (Frasier et al., 2017; Phillips et al., 2018; Lin et al., 2021; Ozanich et al., 2021). Deep-learning models that have learned the structure of labeled and unlabeled recordings archived in this global database will be adaptable to other applications, via transfer learning (Yosinski et al., 2014). Therefore, this global library will benefit the detection and quantification of signal types, which may be added to a suite of acoustic metrics, to be used collectively as scene classifiers, to routinely characterize the soundscape.

Any AI model must learn the difference between target signals and background noise. Voice recognition techniques often begin with clean recordings and synthesize training data by adding noise to the known reference (Lu et al., 2013; Xu et al., 2015). These are then used to train models to extract speech from recordings that contain real noise and target signals in long-term recordings. Such data augmentation techniques have proven effective in improving the performance of AI models and have been widely applied in speech and music enhancement models (see review in Lin and Tsao, 2020). Recordings of biological sounds with high SNR will therefore be crucial to the development of a marine fauna AI database. The ultimate goal of an AI algorithm is that it can accurately classify sounds through any or all recordings of any duration and noise level.

An audio database for training AI models requires large numbers of recordings for one species or sound type of unknown origin. The goal of building such a database is to train a model that can effectively recognize species-specific or sound type acoustic features. This requires signals that have been recorded and processed to a certain set of criteria. Although it is difficult to assess how many recordings will be needed, in general the greater the number of sound samples and the higher the sound quality, the more reliable and precise the automatic classification becomes, as the algorithm learns and improves its performance with increasing data availability (Zhong et al., 2020). For species with more complex vocal repertoires, greater amounts of training data further improve classification. Thus, the prerequisite to apply these techniques is a robust and representative training dataset, which is what the library we propose here could provide.

Citizen Science

AI has facilitated the development of many highly popular image-based animal, plant and music recognition applications (apps). Possibly the best known is iNaturalist,[1] though other more taxonomically focused applications are emerging (e.g., Merlin BirdID,[2] WikiAves).[3] The iNaturalist app started as a crowd-sourced community, where people uploaded animal or plant photos to be identified by other users, and has become a place where images are identified by artificial intelligence. In the biological sounds space, FrogID[4] and BirdNet[5] have shown the possibility of using machine learning with signal processing to allow researchers and citizen scientists alike to identify frogs and birds by recording calls with a phone (Rowley et al., 2019; Kahl et al., 2021).

Much like BirdNet and FrogID, a library of underwater biological sounds and any automated detection algorithms would be useful not only for the scientific, industry and marine management communities, but also for users with a general interest. Acoustic technology has reached the stage where a hydrophone can be connected to a mobile phone so people can listen to fishes and whales in the rivers and seas around them. Therefore, sound libraries are becoming invaluable to citizen scientists and the general public, with signal-processing automated detection algorithms supporting the decision networks behind apps like FrogID and BirdNet for someone to record a sound and identify the source. FrogID has over 50,000 recordings uploaded for the > 240 species of frogs in Australia, and the Cornell Lab of Ornithology's BirdNet app has been downloaded over 1,000,000 times and has records of 3,000 species of bird calls across 40 countries (Kahl et al., 2021). As evidence of this type of application moving into the underwater world, the River Listening app,[6] which began in Australia (Barclay et al., 2018), encourages the general public to record sounds in rivers and coastal waters to listen to the sounds of fishes. Further, Chapuis et al. (2021) showed the utility of waterproof recreational recording systems (such as GoPros) to collect information on underwater soundscapes and in particular, recording and cataloging biological sounds, while Lamont et al.

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[1] https://www.inaturalist.org/

[2] https://merlin.allaboutbirds.org/

[3] https://www.wikiaves.com.br/

[4] https://www.frogid.net.au/

[5] https://birdnet.cornell.edu/

[6] https://www.riverlistening.com/

(2022) highlighted how low-cost alternative hydrophones and recording systems (such as the Hydromoth) are becoming increasingly available to scientists and the general public. These types of systems can provide valuable PAM data; however, the calibration, variability in sensitivity and directionality, and low signal-to-noise ratios mean additional considerations must be made, to be able to use the data within the library, in particular, for sound analysis purposes.

Increased sampling efforts from citizen scientists could be invaluable for the detection of vocal fauna in coastal and inland waters. For example, FishBase[7] uses community input to provide information on each species (Froese and Pauly, 2021), while Redmap (Range Extension Database & Mapping project)[8] is more explicit, inviting the general public to spot, log, and map marine species that are uncommon in Australia, or along particular parts of the coast to monitor changes in species distribution. Future online libraries, such as the Open Portal to Underwater Soundscapes (OPUS)[9] would be expected to facilitate public contributions, similar to WhaleFM,[10] a citizen science project that focused on categorization of call types produced by two cetacean species.

Metadata and Functionality

Creating a library with established metadata and information criteria will help standardize the format in which signals are reported, optimize use of the library, and ease future classifications of sounds (Frazao et al., 2019). It is important to provide guidelines on all the pertinent information that could be provided by a person collecting the original recording and that should be included when it is presented, for example, as a static spectrogram on a library website (Parsons, 2010; Warren et al., 2018; Frazao et al., 2019; Looby et al., 2021; Miller et al., 2021). Such metadata standardization can also build confidence in the library's utility and attract support from national bodies for its application, such as the ADEON noise reporting standards (e.g., Ainslie et al., 2017). Each criterion may not be required for entry of a sample into the library, but the level of information supplied determines the level of potential use of a sample within the database. There are three criteria that determine how useful a recording could be to the database and how it could fit with known information about the species and its soniferous behavior around the world. These relate to the information available about the recording and the source species:

- Metadata pertaining to the specific recording (e.g., recording equipment and pre-amplifier used, calibration, model, and sensitivity; recording settings such as gain, sampling rate, number of bits and duty cycle; recording methodology such as deployment configuration; environmental conditions such as depth and bottom characteristics; location and timing), and how it is presented (e.g., un-/calibrated waveform, spectrum with specified window lengths, resolution, FFT/DFT size, and overlap, or the code and settings associated with a plugin automatically generating visualizations of the recording). Recordings taken under controlled conditions (e.g., within tanks or aquaria) have additional acoustic and behavioral considerations and therefore require additional metadata, such as the tank material and dimensions, acclimation time and number of other individuals present.
- Information about the source species in general, such as recording-specific information (e.g., behavioral context if concurrent visual observations were made); more general information may be supplied by the contributor or updated by the host, through continued review of literature (e.g., known distribution, auditory ability, known sound types and their characteristics, and sound production mechanism and typical behavioral contexts associated with sound production, if known). This information provides context to place calls into a species' known behaviors.
- Associated information about the location relative to the broader region (e.g., description of community species composition, habitat, and local soundscape information). This information provides a broader picture of how the local environment may have affected the animal producing the sound.

Defining these requirements, their level of detail, and the final platform design requires the collective expertise of biologists (who have experience related to the potential numbers and types of sounds a species may exhibit), acousticians (who appreciate the impact that propagation losses, sampling methods, and processing techniques may have on the characteristics of the audio clips), signal processing experts (who develop and apply detection, classification, and recognition algorithms, and who can detail the needs of turning example signals into a database for automated detection), and data scientists/database developers (who can develop a scalable and searchable database that can be effectively used and accessed by a broader user community).

In such a way, data are optimized at a quality that is useful for future applications, such as AI development or global-scale meta-analyses and reviews of sound production. Users would benefit from not only the sounds themselves, but the associated metadata about the sounds (Teixeira et al., 2019; Kahl et al., 2021; Lin et al., 2021) and, if there are multiple recordings, a classification of the sound type in which it fits (Sainburg et al., 2020). This information can assist in categorization of an unknown sound and provide context around the recording from an environmental, methodological, or behavioral perspective. However, the level of data made available in the library for each species and each recording depends on the information provided by the contributor, and researchers from fields with different objectives, backgrounds, and experiences, who typically report information in different ways. The most common example in bioacoustics is the classification of signals by phonetic description (onomatopoeia), such as the "thwop," "muah," and "boop" of humpback whale social sounds (Recalde-Salas et al., 2020), and various onomatopoeic descriptions of species-specific and unidentified fish sounds (e.g., Tavolga, 1971; Thorson and Fine,

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[7] https://www.fishbase.us/home.htm

[8] https://www.redmap.org.au/

[9] https://epic.awi.de/id/eprint/53610/

[10] https://whalefm.wordpress.com/

2002; Staaterman et al., 2018; Waddell et al., 2021). Such calls may also be reported in a physics-focused context that include categories of frequency- or amplitude- modulated or continuous-wave signals (Erbe et al., 2017).

Finally, the library and its potential as an AI database would benefit from a scalable design that allows frequent expansion and a web platform that can be continually updated. The database would include a user-friendly interface to investigate data and upload sounds, with automated quality control. Presentation of the data is also a consideration, not only with respect to the variety of signals, but also individual recording locations and their temporal distributions. Data portals, such as the interactive maps of the North West Atlas in Australia,[11] allow viewers to choose any study site in a map and view a synopsis of species composition and a video snapshot of the site, along with environmental data. This could also be achieved from an acoustic perspective. For example, the data portal of the Integrated Marine Observing System[12] allows viewers to peruse long-term spectrograms of recording sites for a user-defined period. An interactive map that can incorporate all these options becomes a user platform for the acoustic data. OPUS is a recent initiative driven by the International Quiet Ocean Experiment that is currently under development and includes some of these functions. This program was created to share underwater soundscapes through audio and synchronized spectral visualizations at staggered temporal resolution. It allows viewers to select locations from a map and explore local soundscapes while also logging events of interest, thereby inviting the public to participate in creating overall logs with acoustic events that can support further processing of the data.

HISTORIC HURDLES AND CHALLENGES

This is not the first time a global approach to data sharing has been suggested in underwater acoustics research. In recent years, multiple international research and blue economy-focused workshops have repeatedly identified the need for global sharing of data, technology, and best practices, to grow techniques and ensure that economic, environmental, and social benefits, developed through the application of knowledge, are realized to the benefit of all (e.g., World Wildlife Fund [WWF], 2017; European Commission, 2018). Most recently, the emergence of COVID-19 has provided a perfect example of the need for international transparency and collaboration to maximize research opportunities and rapidly respond to urgent needs, and it has highlighted how achievable this approach is with modern technology (Apuzzo and Kirkpatrick, 2020). In an acoustics forum, among other workshops, the special sessions of the Acoustical Society of America [ASA] (2018) identified that there are "an increasing number of applications of machine learning methods in ocean acoustics, particularly when working with large data sets" and discussions focused on data access, code-sharing, and reproducible research.

An integrated sound sharing platform begins with three main areas of development to focus and pool efforts: large-scale archives of annotated and unannotated audio data, the open-access reference library of identified and unidentified sound sources, and data mining processes, including AI algorithms. Acoustic repositories and data portals, such as OPUS and IMOS, are becoming increasingly common. Importantly, initiatives such as the allocation of 15 petabytes for a passive acoustic data portal by the National Center for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA; United States of America) illustrate the growing appreciation and realization of this need at the national scale (Wall et al., 2021).

Reference libraries have existed on various scales for many years and advances in technology are quickly increasing their ability to expand and integrate user contributions. The Detection Classification, Localization and Density Estimation (DCLDE) and the Detection and Classification of Acoustic Scenes and Events (DCASE) workshop series (2003–2022 and 2013–2022, respectively) have focused on data mining and analytical approaches. These groups have been the main producers of public datasets to advance machine learning applications of biological sounds in the ocean (Frazao et al., 2019) and the workshops regularly provide training sets to test detection algorithms under different conditions (e.g., various frequency-dependent SNR and propagation losses).[13] Their outputs have shown what is achievable from data-sharing of comparatively "small" platforms (previously up to 10 TB), which complement the sharing of open-source code that individuals are increasingly providing with the publication of analytical works (e.g., Bergler et al., 2019; Bermant et al., 2019; Madhusudhana et al., 2020; Lin et al., 2021). Together these activities highlight the potential for applications of data-sharing of acoustic information to be applied to larger repositories that are now more achievable with cloud-based options, such as AI for Social Good,[14] or government supported platforms, such as the NCEI.

Although the development of a global integrated and open-access underwater sound reference library, repository and sharing platform has been suggested previously, despite these discussions and the increasing appearance and support for individual components of such a program, it has not been fully realized on an international level. The main barrier to creating an international database of aquatic bioacoustics may be as simple as sourcing adequate funding to achieve such a sizable task, due to a lack of awareness of the value and importance of the product among organizations with the financial resources to support its creation and continuation.

To make a global underwater sound library a success, broader engagement, buy-in, and support of the scientific community will be needed, as well as providing incentives for individuals to contribute their sounds and algorithms to the library (e.g., Bradbury et al., 1999; Gaunt et al., 2005). There are several non-trivial hurdles to establishing this buy-in. Firstly, researchers often need to be convinced about the value of open and accessible science that may counterbalance more individualistic

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[11] https://northwestatlas.org/nwa/map/gallery

[12] https://portal.aodn.org.au/search

[13] http://www.soest.hawaii.edu/ore/dclde/dataset/

[14] https://ai.google/social-good/

benefits associated with their intellectual property and therefore encourage contribution of recorded sounds to a repository; this parallels the ongoing broader scientific cultural change toward promoting data sharing and accessibility. A repository that provides a way to have example sounds as citable data (such as through providing a DOI number) further motivates individuals to contribute by ensuring they receive appropriate future credit for their original recordings; however, this is matched with the consideration that in some cases, contribution may require signing over copyright and access rights for that acknowledgment. Secondly, a repository needs to reduce burdens for individuals to contribute sounds and provide a system that can easily ingest audio and relevant metadata (Bradbury et al., 1999). A third challenge is raising the awareness that many individual archives are not as permanent as individuals think; analog media often degrades over time (Gaunt et al., 2005) and hard drives are not immune from failure, so depositing sounds in a sustainable repository is an urgent need, particularly for older recordings. One example of such archiving is the recovery and digitization of the fish sound recordings taken by Fish and Mowbray (1970), as described in Rountree et al. (2002). Launching a new library is particularly taxing as it requires building the interest of potential contributors to maximize their donations, while having limited outputs to offer initially. This could be alleviated by integrating efforts from existing libraries and archives, rather than initiating an entirely new database, which will also increase the library's appeal to potential funding sources.

There may also be more nebulous factors that have limited the provision of appropriate funding, including the likely duration of the program (i.e., including long-term planning and on-going resources to maintain the platform) and facilitating the repeated meeting of numerous global partners needed to identify and agree on its structure and criteria. Securing the longevity of the program is vital to the usefulness of the platform as libraries that are not scalable, well-maintained, and continually updated can quickly become redundant or outdated. The world's increasing awareness around the environmental costs of data storage and processing mean that consideration of carbon neutrality will also be a key factor in the design and longevity of the program.

Passive acoustic research is now, it appears, rapidly approaching a nexus point. The changing environment and decreasing biodiversity are compelling the documentation of baseline acoustic observations. Technical advances associated with data collection and an increasing number of researchers and institutes collecting PAM data are providing the ability to create bioacoustic databases. Concurrently, awareness of the importance of acoustic cues to aquatic fauna, the impacts of noise on them and the potential for acoustic communities to provide an indication of ecosystem health has reached a stage where PAM is becoming appreciated as a mainstream data source across more species and ecosystems than ever. Finally, public interest and access to user applications means citizen scientists can drive widespread knowledge sharing. Now is the time to facilitate that progress by gathering the acoustic, ecological, and bioinformatic community together to realize an aquatic-sounds sharing platform.

FUTURE STEPS

The development of an international platform for sharing acoustic data is non-trivial and requires identifying and describing a number of inter-dependent factors including: (1) sources and protocols for securing and maintaining significant funding at national and international levels; (2) global interdisciplinary collaboration and stakeholder consultation to develop and agree on criteria for data supply and reporting and system configuration that produce the most useful, yet user-friendly, environment; (3) an appropriate scalable platform on which the facility can be hosted; (4) an open forum to facilitate open access and common development of AI algorithms; (5) continual system management and quality assurance; (6) establishment and agreement on the use of data and metadata standards; and (7) on-going promotion and engagement to ensure maximum use, such as open working groups to foster international collaborations focused on global spatiotemporal trends in detected aquatic fauna. These are multidisciplinary tasks requiring input from bio- and eco-acousticians, bioinformatics experts, AI engineers, web engineers, and stakeholders. To begin our journey along this shared pathway, we recommend a multi-disciplinary workshop to detail all the requirements for developing an appropriate library/database to fulfill the needs of all that may wish to access it and to detail the resources needed to support the work. Such an effort is critical and timely as we enter the UN Decade of Ocean Science for Sustainable Development.

AUTHOR CONTRIBUTIONS

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Is It Time for Ecotremology?

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Our awareness of air-borne sounds in natural and urban habitats has led to the recent recognition of soundscape ecology and ecoacoustics as interdisciplinary fields of research that can help us better understand ecological processes and ecosystem dynamics. Because the vibroscape (i.e., the substrate-borne vibrations occurring in a given environment) is hidden to the human senses, we have largely overlooked its ecological significance. Substrate vibrations provide information crucial to the reproduction and survival of most animals, especially arthropods, which are essential to ecosystem functioning. Thus, vibroscape is an important component of the environment perceived by the majority of animals. Nowadays, when the environment is rapidly changing due to human activities, climate change, and invasive species, this hidden vibratory world is also likely to change without our notice, with potentially crucial effects on arthropod communities. Here, we introduce ecotremology, a discipline that mainly aims at studying substrate-borne vibrations for unraveling ecological processes and biological conservation. As biotremology follows the main research concepts of bioacoustics, ecotremology is consistent with the paradigms of ecoacoustics. We argue that information extracted from substrate vibrations present in the environment can be used to comprehensively assess and reliably predict ecosystem changes. We identify key research questions and discuss the technical challenges associated with ecotremology studies.

Keywords: ecotremology, monitoring, hidden biodiversity, vibroscape, vibrational communication

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INTRODUCTION

Our awareness of sounds in natural and urban environments has led to the recognition of soundscape ecology (Pijanowski et al., 2011a) and ecoacoustics (Sueur and Farina, 2015). These two interdisciplinary research fields in an non-invasive way increase the understanding of ecological processes and ecosystem dynamics through acoustic monitoring that can assess biodiversity and human impact on terrestrial, freshwater and marine ecosystems (reviewed in Linke et al., 2018; Miksis-Olds et al., 2018; Sugai et al., 2019). However, in contrast to the prevailing general belief that organisms mainly rely on information provided by air-borne or underwater sounds, research over the past decade suggests that substrate-borne vibrations are one of the most prevalent sources of environmental information (Cocroft et al., 2014; Hill et al., 2019). Vibrational signaling is the most common and taxonomically widespread form of mechanical communication (Cocroft and Rodríguez, 2005; Cocroft et al., 2014). Animals can also perceive and use vibrational information available in the environment outside of the communication context, for example to detect prey, host or predators (Virant-Doberlet et al., 2019). Substrate vibrations can provide relevant information about the environment for plants (Appel and Cocroft, 2014; Mescher and Pearse, 2016) and bacteria (Reguera, 2011). The increased awareness of the importance of substrate vibrations to organisms has recently led to the definition of biotremology (see **Table A1**), a new field of animal behavior research (Hill and Wessel, 2016; Hill et al., 2019).

Here, we aim to expand biotremology beyond behavioral studies by promoting the concepts of vibroscape and ecotremology. We argue that information on substrate vibrations present in the environment can be useful to comprehensively assess ecosystem functions and propose more effective conservation plans in the future. We first introduce the concepts of vibroscape and ecotremology, highlighting the similarities and differences to soundscape and ecoacoustics. We then identify the key research questions that should be addressed, and finally, we discuss some challenges associated with ecotremology studies and possible applications. In line with our own research and existing literature, we focus primarily on terrestrial habitats.

VIBROSCAPE AND ECOTREMOLOGY—THE CONCEPTS

Sound and Vibration

Our intent here is not to delve into the physics of sound and vibration, but to briefly discuss some conceptual issues relevant to understanding the nature of mechanical information in the environment that can be used for ecosystem assessment and surveys.

For the purpose of ecosystem monitoring, the separation between sound and vibration may be surprisingly difficult. Sound and vibration are two terms so commonly used in everyday life that they are generally accepted as distinct. However, the terminology and definition of sound and vibration may differ between physicists, mechanical engineers and biologists (Cremer et al., 2005; Hill, 2008; Hill and Wessel, 2016; Mortimer, 2017; Strauß et al., 2021). Here we follow the biological definition of sound where detection mechanism is important (Hill, 2009; Hill and Wessel, 2016). Both sound and vibration are at the source generated by mechanical vibrations and the energy is transferred through the surrounding medium (air, liquid or solid) by mechanical waves characterized by particle oscillation (Cremer et al., 2005; Hill, 2008, 2009; Caldwell, 2014). In more fluid homogenous media like air and water, mechanical waves propagate as longitudinal compressional (pressure) waves with particle oscillations in the direction of wave propagation and are primarily detected by pressure (or pressure difference) receivers known as ears [but see exceptions in fish (Popper and Hawkins, 2018)]. In solids, various types of mechanical waves relevant to animal behavior propagate at the interface between two media (surface-borne waves) and are received by mechanoreceptors detecting the particle displacement perpendicular to the direction of wave propagation (Hill, 2008, 2009; Hill and Wessel, 2016; Hill et al., 2019; Strauß et al., 2021). Here, we refer to the former as sound and the latter as vibrations. Energy is also transferred across the interface between two media: the mechanical waves propagating through the air induce particle oscillations in the solid medium with which the air is in contact. Thus, the same source (e.g., a stridulating bushcricket sitting on a plant) simultaneously generates mechanical waves in both surrounding media (air and solid, i.e., plant or ground), both directly by mechanical vibrations of the body and indirectly by a transfer of energy between the two media (Caldwell, 2014; Hill and Wessel, 2016; **Figure 1**).

The propagation of substrate vibrations through the environment is more complex than the propagation of air- or water-borne sound. First, a vibrating source induces in the substrate several different types of mechanical waves simultaneously, while the substrate geometry and material composition influence their transmission properties and frequency dependence (see e.g., Michelsen et al., 1982; Aicher and Tautz, 1990; Barth, 1998; Hill, 2009; Polajnar et al., 2012; Mortimer, 2017; Hawkins et al., 2021). In addition, differences in physical properties within and between plants, with and between soil types, and with and between ground covers make the propagation of vibrations through the habitat highly difficult to predict (Hill, 2009; Elias and Mason, 2014; Strauß et al., 2021). Although the substrate can be any solid surface or object in the environment, the most relevant natural substrates from the perspective of ecosystem monitoring are plants and ground, including river- and seabed (Cocroft and Rodríguez, 2005; Roberts and Elliott, 2017; Hawkins et al., 2021). In the literature, vibrations propagating through the ground are often referred as seismic (e.g., Arnason et al., 2002). The environment has a major impact on the transmission and detectability of vibrational signals: geometry (size and shape) and physical characteristics (density, elasticity) impact signal attenuation and distortion (Hill, 2009; Elias and Mason, 2014; Mortimer, 2017). Although substrate vibrations are generally considered as a short range communication channel, the active space of arthropod vibrational signals on a shrub or tree has been shown to extend up to several meters (McVean and Field, 1996; Barth, 2002). The effective range of seismic signals can even cover kilometers as demonstrated by long-range seismic communication in elephants (Günther et al., 2004; Narins et al., 2016). From the plant on which an insect emits signals, vibrational signals are transmitted to neighboring plants via touching leaves, stems and roots (Šturm et al., 2019) and also across smaller air-gap between plants that are not physically connected (Eriksson et al., 2011; Gordon et al., 2019).

Soundscape and Vibroscape

Substrate-borne vibrations are ubiquitous in nature (Hill, 2009). Analogous to soundscape (Pijanowski et al., 2011a), vibroscape has been defined as a collection of all vibrations emanating from the environment, that includes biological, geophysical and anthropogenic components (Šturm et al., 2019).

Except some high intensity anthropogenic and geophysical sources (e.g., train, earthquake), vibroscape is hidden from

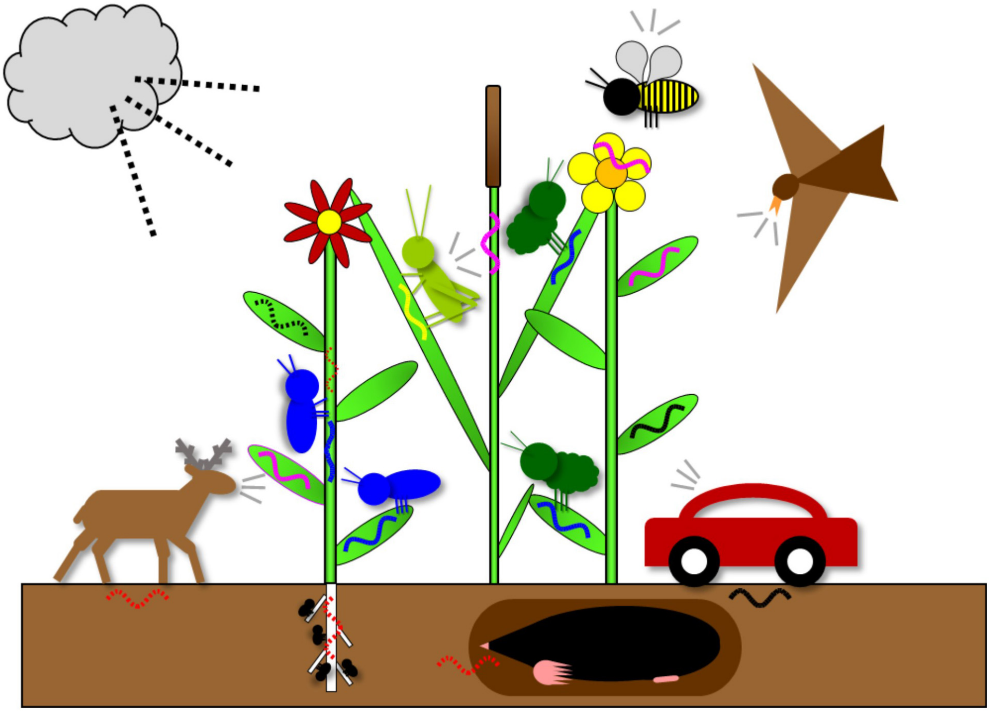

FIGURE 1 | Schematic presentation of sources that can contribute to a vibroscape recorded in a hay meadow habitat. The main source of biological vibrations are vibrations emitted by animals, either during intraspecific vibrational communication (blue waves), or as an incidental by-product of other activities [red dotted waves, vibrations induced by locomotion (walking deer, digging mole, walking insect) and feeding (insect nymphs on the roots)]. Biological component also includes directly (yellow wave, stridulating grasshopper) or indirectly induced vibrational components of air- borne animal sounds (pink waves: stridulating grasshopper, singing bird, calling deer, wing buzzing bee). The main source of geophysical vibrations is wind (black dotted wave). Anthropogenic vibrations (directly and indirectly induced) (black waves) are represented by a car. Other sources not shown (e.g., animals communicating with vibrational signals underground, landing of insects on the plant, rain) also contribute to vibroscape.

human senses and we need to understand it primarily from the perspective of organisms decoding the vibrational information present in the environment. Taking this perspective is challenging due to the size disparity between humans and organisms relying on substrate vibrations, from tiny fruit flies (Drosophilidae) to large elephants. Species-specific ability to generate and detect substrate vibrations results in different spatial scales. For example, for an insect, vibroscape can represent a meadow area of 50 square centimeters, whereas for elephants it can cover an area of several square kilometers.

Regardless of spatial scale, the vibroscape potentially includes more contributing sources than soundscape. It incorporates the sources which may be located above or below ground and may induce vibrations directly by body movements or indirectly by producing sound, whereas only the air-borne component of sound-producing sources contributes to the terrestrial soundscape (**Figures 1**, **2**). Vibroscape characteristics and vibrational communities are largely unexplored but first analyses indicate that terrestrial vibroscapes are dominated by frequencies below 2 kHz. This frequency band includes wind vibrations (geophysical vibrations), human-generated vibrations (anthropogenic vibrations), as well as animal signals (biological vibrations) (Šturm et al., 2019, 2021; **Figure 2**). It is currently estimated that more than 240,000 arthropod and vertebrate species use vibrational signaling in various intraspecific interactions (Cocroft and Rodríguez, 2005; Uhl and Elias, 2011; Narins et al., 2016).

Ecoacoustics and Ecotremology

The importance of substrate vibrations in communication and survival of most animals has now been well established (Hill, 2009; Cocroft et al., 2014; Virant-Doberlet et al., 2019). However, the ecological significance of vibroscape has been so far largely overlooked (Šturm et al., 2019, 2021). While ecoacoustics studies sources of air- or water-borne sounds as indicators of ecological processes (Sueur and Farina, 2015), ecotremology aims at recording, monitoring and understanding the vibrations that emanate from natural environments. The theoretical framework on which ecoacoustics is based–the acoustic niche hypothesis (ANH) and the acoustic adaptation hypothesis (AAH) (Sueur and Farina, 2015)–provides the foundation for ecotremology as well. Ecotremology opens up the possibility of monitoring a wide variety of arthropod species that are essential for ecosystem functioning and conservation, but are not accessible through other non-invasive methods. Considering vibroscape is a unique way to monitor neglected but crucial animal biodiversity found in grasslands and bushlands, ecotremology also gives the

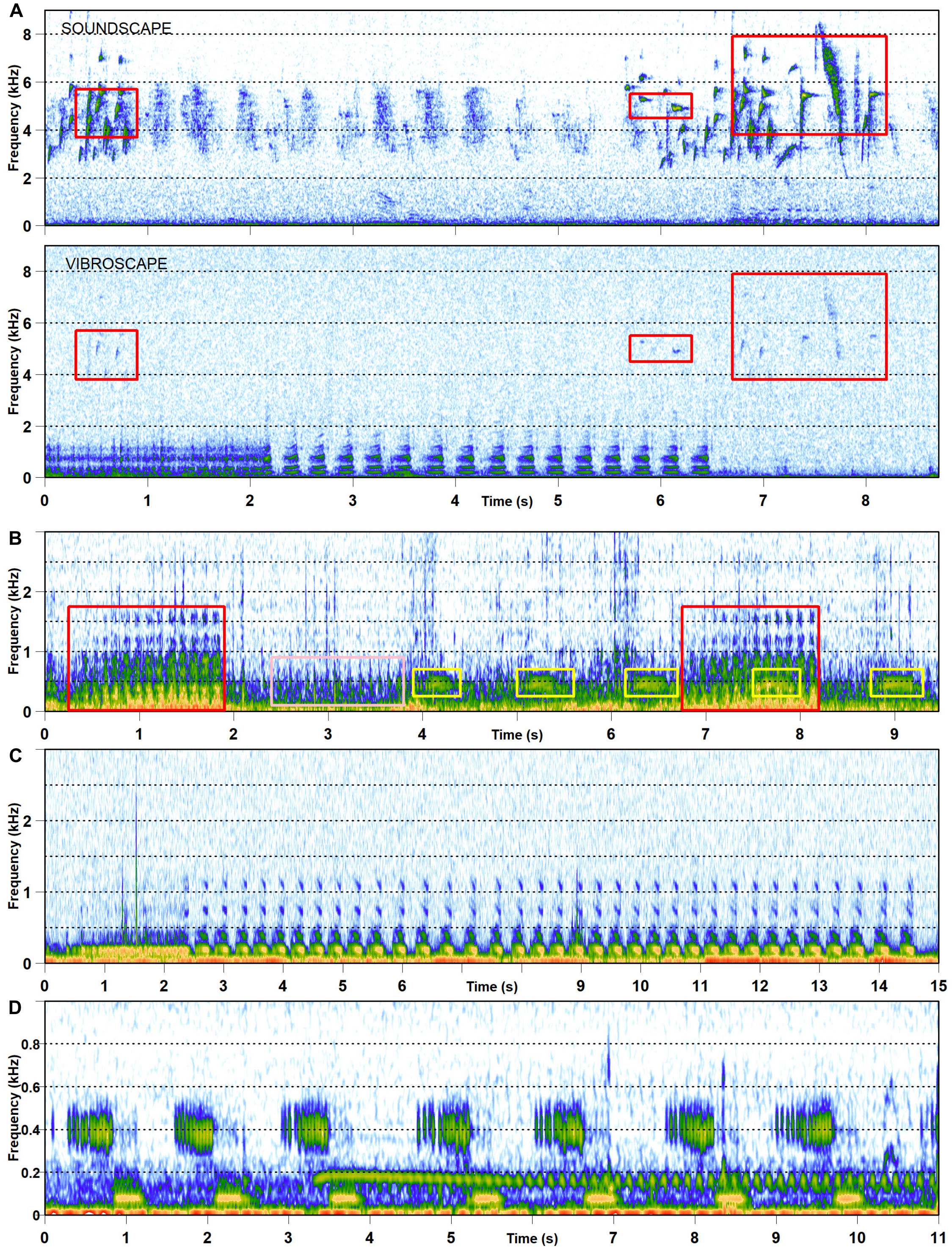

FIGURE 2 | Visualizations of the vibroscape recorded by laser vibrometer in the form of spectrograms. **(A)** Simultaneous recording of soundscape (above) and vibroscape (below) from Bistra (Slovenia) meadow on July 6, 2021. Vibroscape was recorded on wild strawberry (*Fragaria vesca*). Red frames indicate bird songs of European goldfinch (*Carduelis carduelis*) observed on both channels; **(B)** Vibroscape recorded on herbaceous plant hedge bedstraw (*Galium mollugo)* in a hay meadow at Bistra (Slovenia) on July 7, 2018. Frames of different color indicate different types of vibrational signal (species unknown). Note strong constant background vibrational noise induced by wind in the frequency range up to 1 kHz. **(C)** Vibroscape recorded from a spider web (from f. Lyniphidae) includes vibrational signals of the *Aphrodes bicincta* in a hay meadow at Bistra (Slovenia) on July 14, 2020. **(D)** Vibroscape recorded on a dogwood bush (*Cornus sanguinea)* at Bistra on June 20, 2019 (signallers unknown). All spectrograms obtained with the R package seewave (Sueur et al., 2008).

opportunity to approach in a passive way the ecology of unique populations, communities and landscapes.

ECOTREMOLOGY—KEY RESEARCH QUESTIONS TO BE ADDRESSED

The research questions and applications of ecotremology are largely the same as those of ecoacoustics (Sueur and Farina, 2015; Farina and Gage, 2017; Farina, 2018; Linke et al., 2018). However, because vibroscape studies are still in their infancy and due to some fundamental differences between environmental sound and vibration, several specific research questions should be addressed first.

Spatial and Temporal Variation in Vibroscape

The extent and significance of spatial and temporal variation are fundamental questions that should be resolved before the implementation of ecotremological ecosystem monitoring, reflecting our lack of personal experience of the natural vibratory world. Due to heterogeneity of the substrate that affects damping and selective frequency filtering, the amplitude of emitted vibrational signals may be reduced below detection level 10 cm away from the plant on which an arthropod is signaling. As a consequence, the recorded vibroscape may change substantially and unpredictably over a few centimeters (Šturm et al., 2019, 2021). In such a situation, any vibration sensor will pick up signals from an area that is several order of magnitude smaller than with microphones, downscaling the spatial range of observation.

Vibroscape may be plant species-specific due to the geometry and transmission properties of the plant, and the plant-dwelling animals that can be host specific inside and on the plant. Furthermore, spatial position of individual plant within the habitat may crucially influence the recorded vibroscape due to neighboring plants with their specific characteristics or abiotic conditions (e.g., sunny or shady, wind-exposed or sheltered position) (Šturm et al., 2021).

Vibroscape composition also shows substantial diel and seasonal changes (McNett et al., 2010; Šturm et al., 2021). To develop adequate sampling design, studies of signal transmission on different substrates within the natural habitats, including sediments in aquatic environments (Roberts and Elliott, 2017; Hawkins et al., 2021) along with a comprehensive analysis of variation in vibroscape characteristics over short distances within a single field-site and long-term 24-h recordings are vital.

In comparison with ecoacoustic studies, vibroscape monitoring lags far behind due to technical challenges associated with field recordings (Šturm et al., 2019) and several technical issues should be resolved before a general ecotremological approach can be developed. Autonomous vibration recorders for vibroscape monitoring are currently not available and the cost of equipment for registering substrate vibrations over an array of multiple sensors, as usually deployed for soundscape analyses, may be a limiting factor and solutions should be sought to develop inexpensive vibroscape recording approaches.

While affordable seismic sensors such us geophones are available (e.g., Reinwald et al., 2021), recording from substrates like plants requires a different recording approach. Portable laser vibrometers are the most sensitive and avoid the problem of mass loading, but are costly and complex. However, there are other less expensive sensors available (Nieri et al., 2022). Although accelerometers are likely to be less suitable to reliably attach to herbaceous plants and grasses, they currently hold the most promising solution for recording with an array of sensors.

Characterization of Vibroscape and Vibrational Communities in Different Habitats and Ecosystems

The only existing vibroscape study focused on a temperate hay meadow at a single site (Šturm et al., 2021). Before generalizations can be made, comprehensive comparative studies of vibroscape recorded on different substrates and in different habitats and ecosystems, including aquatic environments, are needed, not only to characterize the biological component as mentioned above, but also the contributions of geophysical and anthropogenic components.

Ecotremology appears as a challenging field of research. First of all, the number of sources is relatively high, implying an additional level of complexity due to rich communities. Second, due to the complex pattern of vibration propagation through solids under field conditions, the degradation of signals is unpredictable with particularly important frequency and temporal changes (Michelsen et al., 1982; Casas et al., 2007; Polajnar et al., 2012; Mortimer, 2017; Brandt et al., 2018; Šturm et al., 2019). Third, ecotremology cannot refer to a public sample libraries as they exist for bird, amphibian or mammal sounds. The lack of a library hinders the manual or automatic identification of vibrational sources. The establishment of a comprehensive public library of vibrational signals that would include not only reference signals recorded in the laboratory, but also signals recorded on different natural substrates under different field conditions, is essential to the implementation of ecotremological studies. Ideally, such library should also include vibrational components of air-borne sounds and incidental vibrations.

Selection pressures pertinent to AAH and ANH, respectively, associated with evolutionary constraints on acoustic signals (e.g., Sueur and Farina, 2015; Farina and James, 2016; Krause and Farina, 2016) are also relevant to the processes underlying the observed structure and complexity of vibroscape. Because the effects of the physical environment on the evolution of vibrational signals and signaling strategies are especially strong (Cocroft et al., 2010; Endler, 2014), studies of the structure and dynamics of vibrational communities are likely to provide good model systems for the effects of adaptation and competition on partitioning of the communication channel (Šturm et al., 2021).

Relation Between Soundscape and Vibroscape

Although vibroscape includes also the vibrational component of air-borne sounds, it is not possible to predict vibroscape richness and structure of a particular habitat from its soundscape characteristics (Šturm et al., 2021). The variety of potential sources contributing to the vibroscape composition (**Figure 1**) might also suggest that the vibroscape could be richer than the soundscape. However, this is not necessarily the case and the relation certainly depends on habitat, season and diel dynamics. Simultaneous recordings of soundscape and vibroscape should determine complementary mechanical information available in the environment and provide crucial information for appropriate sampling design.

Link Between Vibroscape Composition and Ecosystem State

Vibroscape has remained "out of sight, out of mind" until recently and there is no existing information about the composition and structure of vibroscape in the past. Current natural vibrational communities may already have been altered due to habitat loss and fragmentation, biological invasion, climate change and anthropogenic noise. Although there is so far no information on the impact of human activities on vibroscapes, field studies of the effects of anthropogenic vibrations showed negative effects on animal behavior (Shier et al., 2012; Day et al., 2019; Phillips et al., 2020; Mortimer et al., 2021; Roberts and Howard, 2022). The recording of pristine and disturbed vibroscapes appears as a prerequisite for future work; however, there is also a need to build reference libraries and baseline information to assess the possible future changes of vibroscapes.

Acoustic indices are often used to characterize soundscape and acoustic communities or to find proxies of local biodiversity (e.g., Sueur et al., 2014; Gasc et al., 2015; Buxton et al., 2018; Eldridge et al., 2018). In ecotremology, the relationship between rich biological vibroscape component and ecosystem state has not yet been established and is not likely to be straightforward. Indices developed to characterize soundscape might not be directly applicable to vibroscapes. In addition, the indices have been shown to be sensitive to background noise when soundscape monitoring has a low signal-to-noise ratio (e.g., Desjonquères et al., 2015). As a preliminary test, we compared the hay meadow vibroscape recorded at different times of the day, when vibrational signaling activity was the highest (mid-day) and the lowest (midnight). We could not find any consistent correlation between aurally and visually determined richness and abundance of vibrational signals and spectral entropy *Hf*, Acoustic Complexity Index *ACI* (both calculated in frequency range from 200 Hz to 4,000 Hz), the envelope energy *M*, Acoustic Entropy Index *H* and Acoustic Complexity Index *ACI* (both calculated in frequency range from 0 to 20,000 Hz). However, this initial work does not preclude that other indices might perform better and could be used for a rapid vibroscape assessment in the future.

DISCUSSION

In contrast to terrestrial soundscapes, which can be perceived and recorded in everyday life humans have no personal experience with natural vibroscapes. The sensory barrier that isolates the vibroscapes from human perception greatly limits both popular and scientific interests in vibroscape. However, there is no good reason to assume a forest soundscape is more important than a meadow vibroscape. Recordings of deep-sea soundscapes have proved that previously inaccessible sounds can greatly attract the attention of large audiences, including scientists, artists and citizens (Duarte et al., 2021). The development of low-cost and reliable recording equipment suitable for long-term unsupervised field-recordings in research programs, but also for opportunistic recordings is necessary to increase interest in this hidden form of biodiversity.

As in ecoacoustic studies, vibroscape recordings may generate a large amount of raw data reaching several TB very quickly (Šturm et al., 2019). Manual identification is highly time-consuming, so that large datasets cannot be thoroughly processed by a small number of observers and automated species identification and diversity assessment is needed. At present, manual identification and assignation of vibrational signals by listening and visualization of spectrograms is still challenging due to unpredictable changes in signal structure during transmission, high levels of vibrational noise overlapping the frequency range of vibrational signals, and the lack of reference libraries. The great majority of vibrational signals are unknown, so it can be challenging for an inexperienced listener to distinguish signals from incidental vibrations caused by locomotion or feeding (Šturm et al., 2019). Computational methods for automatic classification and identification of vibrational signals have not yet been tested on field recordings (Korinšek et al., 2019; Šturm et al., 2019, 2021). Nevertheless, even taking into account specific challenges encountered in vibroscape recordings, automatic identification of signals should be possible using recent AI techniques such as convolutional neural networks applied to spectrogram images (Stowell et al., 2019). This option will be possible only if the identification models can be trained with annotated datasets. This again underlines the need of expert and shared libraries.

Seismology is a well-established discipline (e.g., Lecocq et al., 2020) and therefore it is not surprising that it has already provided the first applications of ecotremology in monitoring elephants either by vibrational component of their infra-sound vocalizations or by incidental vibrations induced by locomotion (Wood et al., 2005; Mortimer et al., 2018; Parihar et al., 2021; Reinwald et al., 2021). The latter approach also allows differentiating between large mammal species (Wood et al., 2005). Substrate vibrations created by gunshots could also be invaluable in monitoring poaching (Mortimer et al., 2018).

Monitoring plant-dwelling arthropods provides more challenging application, but nevertheless a preliminary study showed that species-specific vibrational signals of insect pests could be identified in the vibroscape recorded in the vineyard (Akassou, 2021). Monitoring insects through vibroscape analysis could provide important information on the dynamics of insect populations that have been shown to be in severe decline, threating the state of ecosystems and, as consequence, human society (e.g., Wagner, 2020; Miller, 2021; Wagner et al., 2021).

CONCLUSION

Vibrational signaling is the most common form of mechanical communication. Although substrate vibrations provide a rich and reliable source of information to the majority of animals, humans have so far overlooked vibroscape as an essential element of the natural environment that can have important effects on ecological processes and ecosystem dynamics. Several key technical challenges will have to be resolved, before such approach can be implemented in the monitoring. We believe that with the increased awareness about vibroscape and the growing research interest and demand for technical solutions, the implementation of ecotremological monitoring will be feasible within the next decade. We encourage researchers, artists and citizens to incorporate ecotremology into their projects to gain better awareness and knowledge of hidden vibroscapes.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work, and approved it for publication.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX

TABLE A1 | Table of relevant terms as used in the main text with their definitions.

Term	Definition	References
Vibration	Different types of waves on the boundary between two distinct media	Hill and Wessel, 2016
Biotremology	The study of mechanical communication by surface-borne waves	Hill and Wessel, 2016
Vibroscape	A collection of biological, geophysical and anthropogenic vibrations emanating from a given landscape	Šturm et al., 2019
Ecotremology	Discipline studying substrate-born vibrations for unraveling ecological processes	This paper
Sound	Purely longitudinal wave in homogeneous medium	Hill and Wessel, 2016
Bioacoustics	Study of the production, transmission and reception of animal sounds	Mcloughlin et al., 2019
	Study of mechanical communication by acoustic waves	Hill and Wessel, 2016
Soundscape	Collection of biological, geophysical and anthropogenic sounds that emanate from a landscape and which vary over space and time	Pijanowski et al., 2011b
Ecoacoustics	Ecological investigation and interpretation of environmental sound	Sueur and Farina, 2015

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A Convolutional Neural Network Bird Species Recognizer Built From Little Data by Iteratively Training, Detecting, and Labeling

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Automatically detecting the calls of species of interest in audio recordings is a common but often challenging exercise in ecoacoustics. This challenge is increasingly being tackled with deep neural networks that generally require a rich set of training data. Often, the available training data might not be from the same geographical region as the study area and so may contain important differences. This mismatch in training and deployment datasets can impact the accuracy at deployment, mainly due to confusing sounds absent from the training data generating false positives, as well as some variation in call types. We have developed a multiclass convolutional neural network classifier for seven target bird species to track presence absence of these species over time in cotton growing regions. We started with no training data from cotton regions but we did have an unbalanced library of calls from other locations. Due to the relative scarcity of calls in recordings from cotton regions, manually scanning and labeling the recordings was prohibitively time consuming. In this paper we describe our process of overcoming this data mismatch to develop a recognizer that performs well on the cotton recordings for most classes. The recognizer was trained on recordings from outside the cotton regions and then applied to unlabeled cotton recordings. Based on the resulting outputs a verification set was chosen to be manually tagged and incorporated in the training set. By iterating this process, we were gradually able to build the training set of cotton audio examples. Through this process, we were able to increase the average class F1 score (the harmonic mean of precision and recall) of the recognizer on target recordings from 0.45 in the first iteration to 0.74.

Keywords: bird monitoring, ecoacoustics, deep learning, biodiversity, species recognition, active learning

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INTRODUCTION

Surveys of birds belonging to various functional groups over time can give farmers information about the health of the ecosystems on their farms. It is in the interest of cotton farmers to improve biodiversity and ecosystem function on their farms: healthy ecosystems may improve productivity of the farms in the long term through pest suppression (Garcia et al., 2020) and there is an increasing demand for environmentally sustainable products (Kumar et al., 2021). Monitoring avian diversity is also valuable in order to document their response to changes in their environment over time, particularly in regard to weather events and climate change (Both et al., 2010).

Monitoring the presence of a particular bird species in a location traditionally requires an ecologist to periodically visit the location, stay for a period of time to make observations, often returning repeatedly to account for the intermittent nature of bird presence (Newell et al., 2013). In recent years audio recordings have been used to lessen the time burden on ecologists: rather than multiple trips to the location, a recorder can be deployed and the data collected periodically, a less frequent and quicker task than the on-site surveys (Acevedo and Villanueva-Rivera, 2006; Wimmer et al., 2013). Surveys can be then done by listening to the audio recordings at a time that suits the ecologist. While this decreases the total work somewhat, there is still a large time burden involved with listening to the audio. Passive acoustic monitoring is increasingly being applied to monitor Australian birds particularly in conservation contexts (e.g., Leseberg et al., 2020; Teixeira et al., 2021).

Automated detection of bird species can dramatically speed up this process. Creating a machine learning model for species recognition requires access to training examples; how many training examples depends on the difficulty of the recognition task. Furthermore, the training examples should be as close as possible to the audio that will be encountered when the recognizer is deployed. A mismatch between training data and the unlabeled inference data encountered at deployment is an issue encountered in many machine learning scenarios and is known as dataset shift or domain shift (Dockès et al., 2021; Kouw and Loog, 2021; Stacke et al., 2021). This can arise from regional variation in call types, or a difference in background noise profiles due to vegetation or other local conditions. It is also likely that the types of confusing signals found in the deployment location will be different from those encountered in the training data, such as machinery, traffic or other anthropogenic sound, or different types of non-target animal vocalizations.

There are two issues that arise from this: firstly, having a mismatch between the training data and the deployment location could cause the recognizer accuracy to suffer when deployed, and secondly, without examples from the deployment location in the test set, the accuracy of the recognizer at deployment is not known, as the only accuracy measurements available are for the non-deployment location. This is often problematic because in real world applications, labeled recordings from the study location may not exist. This can be partly alleviated by sourcing the training and testing data from a wide variety of locations as this is likely to increase generalizability of the model, however it is not a replacement for having labeled recordings from the deployment location.

In this paper, we describe our approach to training a deep learning convolutional neural network (CNN) detector of seven species of interest in Australian cotton farms, referred to as the target species: Australasian Pipit (*Anthus novaeseelandiae*); Golden-headed Cisticola (*Cisticola exilis*): Mistletoebird (*Dicaeum hirundinaceum*); Rufous Whistler (*Pachycephala rufiventris*); Australian Boobook (*Ninox boobook*); Striated Pardalote (*Pardalotus striatus*); and Striped Honeyeater (*Plectorhyncha lanceolata*). **Figure 1** shows spectrograms of example vocalizations from each of these species.

These species were chosen based on several criteria. Firstly, they cover multiple functional groups of interest—insectivores, frugivores, nectarivores, and predators. Secondly, they are known to occur across multiple cotton growing regions within Australia (Smith et al., 2019). They are expected to be present in numbers where changes in the frequency of their presence will be detectable: i.e., not so common that they are always present no matter if the health of the ecosystem deteriorates or improves, but and not so rare that they never occur. Finally, they have reasonably distinguishable calls, compared to some other candidates.

The challenge was that we started with no labeled examples of these species in recordings from cotton regions. Using recordings from other regions we built a recognizer that was able to find enough of the target species that it could be used to optimize the process of manually labeling cotton recordings to build the training dataset. This process was iterated, with each iteration adding more examples from cotton regions.

Related Research

For the last decade or more, interest in using acoustics for ecological monitoring has been steadily increasing, bolstered by a drop in the price for recording hardware and storage (Roe et al., 2021) and more recently by advances in automated analysis (Xie et al., 2019). For a number of years, deep learning techniques have dominated these automated analysis approaches (Gupta et al., 2021). In the 2018 Bird Audio Detection challenge a competition for classifying 10-s audio clips as containing a bird or not, the highest performing entries were all convolutional neural networks, with the most accurate results achieved using a transfer learning setup, with both resnet50 and inception models (Lasseck, 2018).

Deep learning models, and machine learning models in general, are trained on one set of examples, and tested on a different set, referred to as the test set. Much published research uses datasets where the training data and test data are drawn from the same datasets (Narasimhan et al., 2017; Xu et al., 2020). While this is valuable and interesting for exploring different algorithms, in many real-world ecological applications the model will be deployed in new environments. Other research tests models on datasets not used in training (Stowell et al., 2019), which is a much more challenging test of generalizability of the models.

This paper describes challenges related to this ability for the model to generalize from one dataset to another. Most of the literature presents an academic exercise in increasing accuracy on an available test dataset. There is little research published on how to approach the situation where the species recognizer is to be deployed for a real-world ecological purpose but data from that deployment location does not exist.

The main approach we took is an active learning approach. Generally speaking, active learning involves the model making predictions on unlabeled examples, selecting the most informative of these for labeling based on a query strategy, querying an oracle for the label, and then updating its weights based on this new training example (Cohn et al., 1994; Wang et al., 2019). This technique has been proposed in a number of ecoacoustics studies: Kholghi et al. (2018) adopted this approach

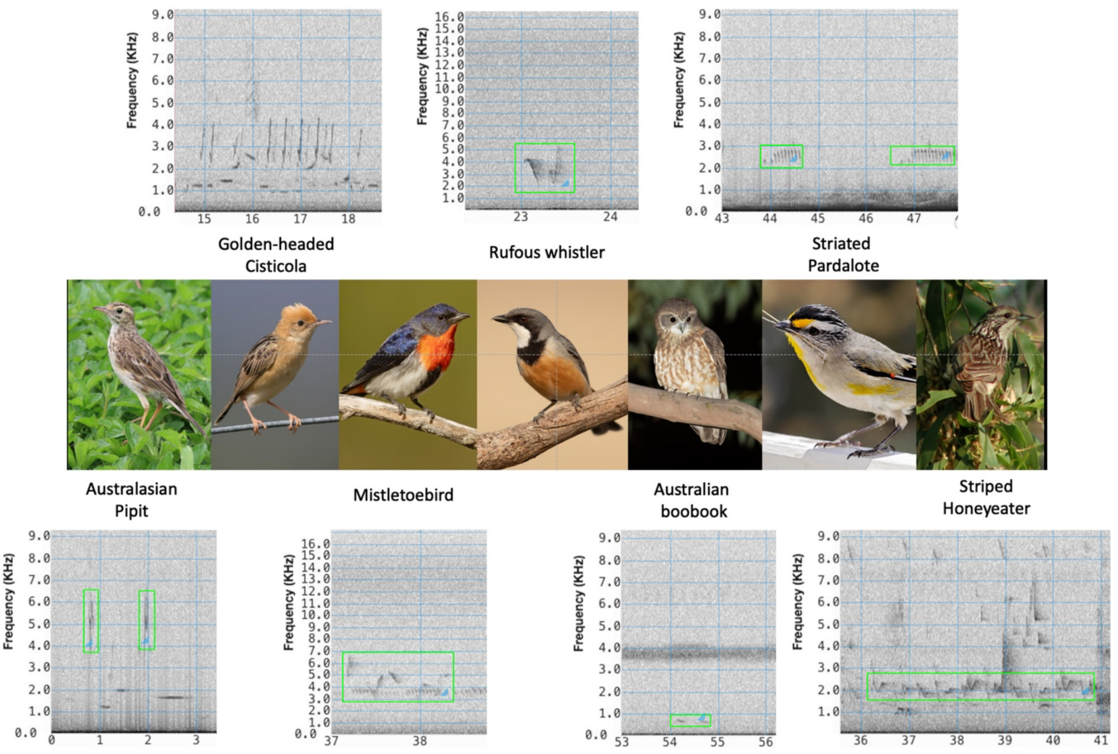

FIGURE 1 | Target species and their vocalizations. Australiasian Pipit, photo credit: https://commons.wikimedia.org/wiki/User:Summerdrought; https://creativecommons.org/licenses/by-sa/4.0/; Golden-headed Cisticola, Mistletoebird, Rufous Whistler, Australian Boobook, photo credit: https://commons.wikimedia.org/wiki/User:JJ_Harrison; https://creativecommons.org/licenses/by-sa/4.0/legalcode. Striated Pardalote, photo credit: https://en.wikipedia.org/wiki/User:Fir0002; https://creativecommons.org/licenses/by-nc/3.0/legalcode. Striped Honeyeater, photo credit: https://commons.wikimedia.org/wiki/User:Aviceda; https://creativecommons.org/licenses/by-sa/3.0/legalcode.

to speed up labeling audio for soundscape classification. Qian et al. (2017) assessed the performance of active learning for classifying a library of bird calls. These studies, however, are made on constrained artificial tasks, and tend to focus on the mathematics of the query strategy for selecting new samples.

This paper describes our experience in applying an active learning approach to developing species recognizers for our biodiversity monitoring project, using a mismatched initial labeled dataset. As well as describing the network architecture and active learning query strategy, we describe the progression of how the dataset grew, and how the accuracy metrics for each target species changed accordingly.

MATERIALS AND METHODS

Dataset Building Through Verification of Results

Data Sources

Original Dataset

Ecosounds[1] is a website built using the QUT Ecoacoustics Workbench (Truskinger and Cottman-Fields, 2017) and serves as a repository for annotated ecological audio recordings. It contains several datasets for which we had permission to use, and which served as a starting point. These recordings were from a variety of locations in eastern Australia, but none of which were cotton regions. This dataset consisted of recordings with vocalizations annotated with time and frequency bounds of variable length. The numbers of examples for each species from this dataset is shown in **Table 1**.

In addition to examples of the target species, a varied selection of negative examples was also included in the training data.

TABLE 1 | Number of initial recordings from other regions.

Label	Count
Australasian Pipit	1
Golden-Headed Cisticola	9
Mistletoebird	383
Nothing	174
Other	503
Rufous Whistler	5,000
Australian Boobook	464
Striated Pardalote	2,380
Striped Honeyeater	144

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[1] www.ecosounds.org

Examples from every non-target species available to us was included. The class containing non-target species events is referred to as "other."

Cotton Recordings

We deployed Song Meter SM3 recorders (Wildlife Acoustics) on Australian cotton farms in the Narrabri region of northern New South Wales in early 2020, and the St George, Miles and Dalby regions of southern Queensland in late 2020 and early 2021, shown in **Figure 2** and **Table 2**. The recorders were programmed to record for 2 h starting just before dawn and 1 h during dusk at 24 kHz and default gain settings. Ecosounds was used to store and later annotate these cotton recordings.

Convolutional Neural Network Verification Workflow

Figure 3 illustrates the workflow to build the dataset so that it contains examples from the cotton recordings.

Initial Labeling of Cotton Recording

Two species were under-represented in the non-cotton dataset: Australasian Pipit and the Golden-headed Cisticola. Recognizers were built for these species, using the QUT Ecoacoustic Analysis Programs software (Towsey et al., 2020). These do not use learned features or machine learning but rather use human-designed features with thresholds manually set based on human knowledge about the call structure. The results of these recognizers were used to filter the cotton recordings. Combined with some random manual sampling, this provided sufficient examples to initiate training of the CNN, however, due to the high number of false positives and scarcity of the target species, it was a slow and inefficient exercise. A recognizer was also built for Australian Boobook as this was an easier task due to the simple call structure and quieter time (night) when they are active. Through this process, a variety of examples for the negative classes as well as a handful of examples for other target species were found. The numbers for each species are show in column T1 of **Table 3**.

FIGURE 2 | Cotton regions where recordings were taken. Imagery (C)2021 Landsat/Copernicus, Data SIO, NOAA, U.S. Navy, NGA, GEBCO, Imagery (C)2021 TerraMetrics, Map data (C)2021 Google.

TABLE 2 | Recording period for training data.

Region	Number of Sites	Period	Total hours
Narrabri	12	March 2020	249
St George	2	December 2020–March 2021	331
Miles	2	December 2020–March 2021	317

Training and Verification

Using a dataset comprised of both these initial cotton annotations and the non-cotton annotations, the CNN was trained. Then the following steps were performed repeatedly.

- The long unlabeled recordings were segmented into non-overlapping 4 s segments which were each then classified as belonging to one of the seven positive classes or on of the two negative classes. As well as the predicted class, the network also provides the probability for every class.
- These predictions and probabilities were then used to select the subset that was most likely to contain examples of the target species. Links to find these segments on ecosounds were generated.
- An expert avian ecologist then correctly annotated the selected segments.
- The dataset was recreated from all available annotations, including these new additions.

This kind of iterative process is known as active learning. New examples are added to the training set by selecting them based on the estimated new information they will add to the classifier.

Query Strategy for Selection of Segments for Verification

For the initial iterations, there were low numbers of detections for the positive classes. For many of the classes none of the segments were classified as that class. As these were unlabeled segments, it was not possible to know whether this was because there were few individuals of those species present in those recordings or the recall for those species was very low.

A protocol for selection of the subset for human verification was designed with the goals of (a) increasing the number of examples of each of the target species (b) correctly labeling the segments that the classifier was least sure about.

Firstly, for each species we included the 20 examples with the highest probability for that class. In cases where there were fewer than 20 segments classified as that class, we still selected the top 20 examples using the probabilities output by the CNN. That is, a particular segment might be the highest scoring for one species even if that probability is lower than the probability for another species. An example with a very high probability that is verified to be correct may only marginally improve the recognizer performance. This is because, for the particular variations of the vocalization that is added to the training set, the network is already performing well. However, if it turns out that these high probability predictions were incorrect, then it is very valuable to include them as training examples to rectify

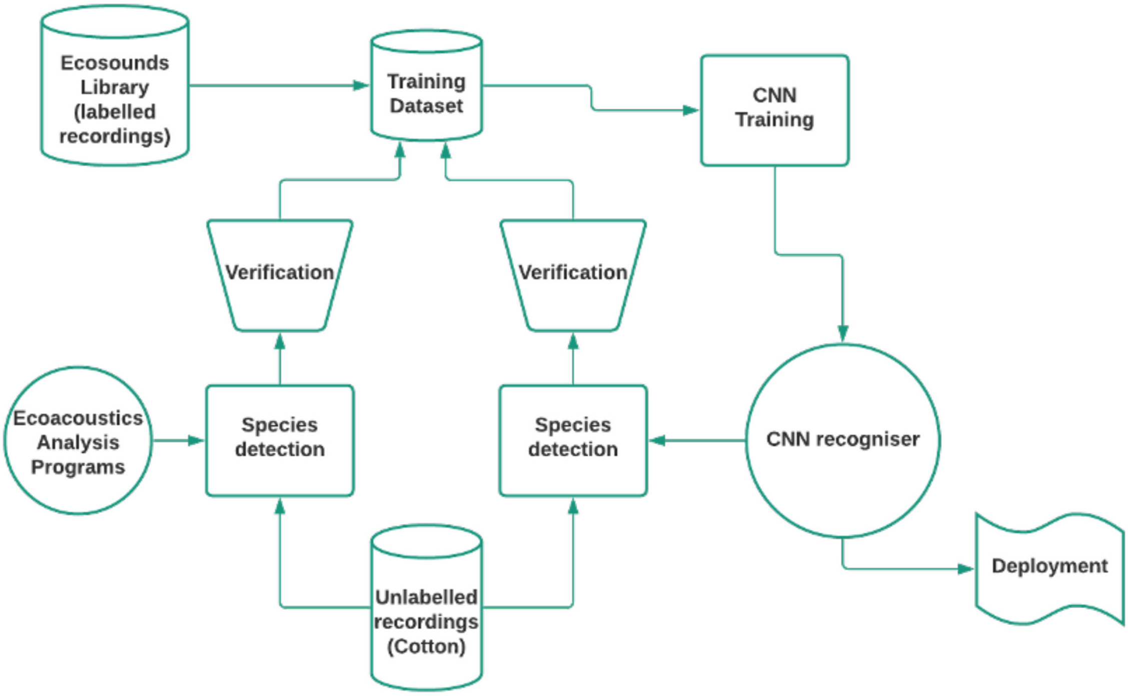

FIGURE 3 | Iterative workflow for verifying classification results.

these mistakes in subsequent iterations. Furthermore, an example that the recognizer correctly identifies is often the case that other examples are present nearby in the recording that may not have been detected. These can be easily manually scanned for and added by navigating in the Ecosounds interface.

Secondly, for each species, we included for verification the 10 examples that were classified as that class (or fewer if there were fewer than 10 detections) but had the *lowest* probability of belonging to that class—those that the CNN was least sure about. These are likely to contain interesting and unique confusing sounds, and are therefore valuable to include in the dataset.

Thirdly, for each species we included a random selection of 10 segments that were classified as belonging to that class (or fewer if there were fewer than 10 detections). This can be used to get an idea of the precision for each class.

TABLE 3 | Number of examples from cotton region recordings for each class at each iteration T1 to T8.

Label	T1	T2	T3	T4	T5	T6	T7	T8
Australasian Pipit	59	59	59	59	60	62	85	101
Golden-Headed Cisticola	156	156	156	156	268	294	399	426
Mistletoebird	2	2	2	7	24	34	57	68
Nothing	8	91	91	224	344	404	447	500
Other	990	1,207	1,291	1,329	1,692	1,847	1,893	1,923
Rufous Whistler	12	12	12	12	51	82	84	89
Australian Boobook	534	536	536	547	557	564	564	568
Striated Pardalote	3	3	3	5	5	15	15	15
Striped Honeyeater	3	3	3	9	48	75	102	108

For the "other" and "nothing" classes, we did the same, but with only five examples between them. The reason for this lower number, is that examples of these classes are very easy to find and are likely to be included through false positive detections of the bird species.

This resulted in a maximum of 300, 4-s segments to verify on each iteration. However, the actual number may be fewer, as the same segments can be included in more than one selection, especially where there were few or no detections for some species.

Incorporation of Verified Samples Into the Dataset

For each of these, links were generated to view and listen to the segments on the Ecosounds website, with some padding to give more context. These verified segments now have annotations that are then incorporated into the training/testing.

To ensure that the accuracies for the model trained on different stages of the dataset were comparable with each other, the model is retrained from scratch (i.e., transfer learning from the initial weights provided by the model, described in the next section), rather than fine tuning the previously trained model.

We repeated this process a total of eight times. **Table 3** shows the number of examples from cotton regions after each iteration.

Convolutional Neural Network Architecture and Data Preprocessing

Convolutional Neural Network Architecture

The CNN architecture that was chosen is Resnet34 (He et al., 2015). It is a deep convolutional neural network designed for image classification, but which has been shown to perform well when trained on ecological audio (Lasseck, 2018). It is a model that has been tested in many applications and the model parameters pre-trained on a large image dataset are available to allow transfer learning. The input to this architecture is a square image of size 224 × 224 pixels. The network was implemented and trained using the FastAI python library (Howard and Gugger, 2018), built on Pytorch.

The output of the final fully connected layer is passed through a softmax function to give a probability for each class. In addition to a class for each of the seven target species, there is one for events that were not vocalizations from the target species labeled as "other," and one for segments that only contain background noise, labeled as "nothing." Collectively these two classes will be referred to as "negative examples." The decision to separate the negative class into "other" and "nothing" was made due to the likely ease of determining the difference of discriminating between these two and the potential usefulness of being able to filter silent segments for applications like random sampling in the future.

The CNN does not localize the vocalization to a region within the input segment, but simply selects which of the classes the segment belongs to. We chose to use a single class architecture, meaning that it assumes that only one of the target species will be present, with the probabilities for all the classes adding to one. While this assumption may not necessarily always be true, we did not come across any examples in cotton recordings where this was the case. In the event that it does occur the pipeline for extracting training examples from our library is set such that it would include separate overlapping examples for the two species. While this would necessarily cause the accuracy on one of the two species to suffer slightly, it happened so infrequently that it was deemed to be worth the benefit of the simplified architecture as well as the dataset curation that a single class classifier brings.

Audio Preprocessing

The annotations from which the training set was generated were of variable length, due to the variable length nature of the vocalizations. The CNN network requires a fixed size input. While this could be achieved through simply squashing the image down, as is common in standard image recognition, the nature of spectrograms means this is unlikely to be appropriate. Instead, a fixed duration segment of the variable length segment was cropped at random from the longer variable length segment as the input to the network. A different random crop was taken each time the image was fed into the network. To allow for this random cropping, for each annotation, a 1 s padding was added before and after the full second marks that enclose the annotation, or if the annotation was less than 4 s, the annotation was centered in a 6 s clip with the boundaries on the nearest whole second. For these short events, when cropped randomly, the resulting 4 s segment contains the entire vocalization. This is illustrated in **Figure 4**.

The call library contains recordings at a variety of different sample rates. For the resulting spectrogram images to be comparable with each other, the inputs to the CNN should all be at the same sample rate. For this reason, all recordings were resampled to 16,000 Hz. Below are some considerations in choosing the frequency to resample to.

Because the number of rows of the spectrogram is fixed, lowering the top frequency gives a higher frequency resolution. However, it may not be desirable to down-sample too far. By including at least some of the frequency band above the top frequency of the target calls, more information is available to the CNN. For example, it may be that some acoustic event resembles the target species vocalization within the low frequency band, but also extends into the high frequencies, and this is the information that can be used to successfully discriminate.

Up-sampling is likely to be detrimental, and so the common frequency to resample to must be equal to or lower than the lowest frequency of the testing/training sets. Up-sampling will introduce artificial blank space at the top of the spectrogram, which could bias the network if certain classes are more likely to occur in those recordings. That is, the network might make an association between up-sampled audio and a given class.

Spectrogram Generation

For each variable length audio segment, a mel-scale spectrogram was generated. With 16 kHz audio, a short time Fourier transform (STFT) hop length is 286 samples to fit the desired 224-pixel width of 4 s of spectrogram. We found this works well with a window size of 512 samples with overlap of 226 samples (44%). A high pass of 100 Hz was applied to remove very low background noise. The python librosa package was used to produce a mel-scale spectrogram. The mel-scale increases the frequency resolution for low frequencies and reduces it for high frequencies.

The amplitude was converted to a log scale, a common practice for audio processing, and more closely represents the way that the ear processes sound. That is, a certain difference in amplitude between two low amplitude sounds will be more noticeable than the difference in amplitude between two high amplitude sounds. These log amplitude values were then normalized between 0 and 255 to produce the pixel color. Normalizing over very short duration audio can have drawbacks. If the segment is very quiet or contains only background noise, this background noise is unnaturally amplified. However, this does not seem to cause the performance of the network to suffer and is a simple way to scale to pixel values.

Resnet was originally designed for red-green-blue (RGB) color images, with the input a 224 × 224 × 3 tensor. The spectrogram is a two-dimensional grid of log amplitude values. These values of the pixels can be mapped to a three-dimensional array using a number of different color mapping schemes, for example red for high values and blue for low values. This kind of color mapping is often used when visualizing spectrograms for human viewers as it can be aesthetic, since loud events stand out from the background as a different color. We opted for a simpler grayscale mapping where the spectrogram is duplicated to each of the three color channels, as it is easier to implement, and there does not appear to be any evidence in the literature that grayscale is worse. The computational overhead for redundant layers on the input is negligible.

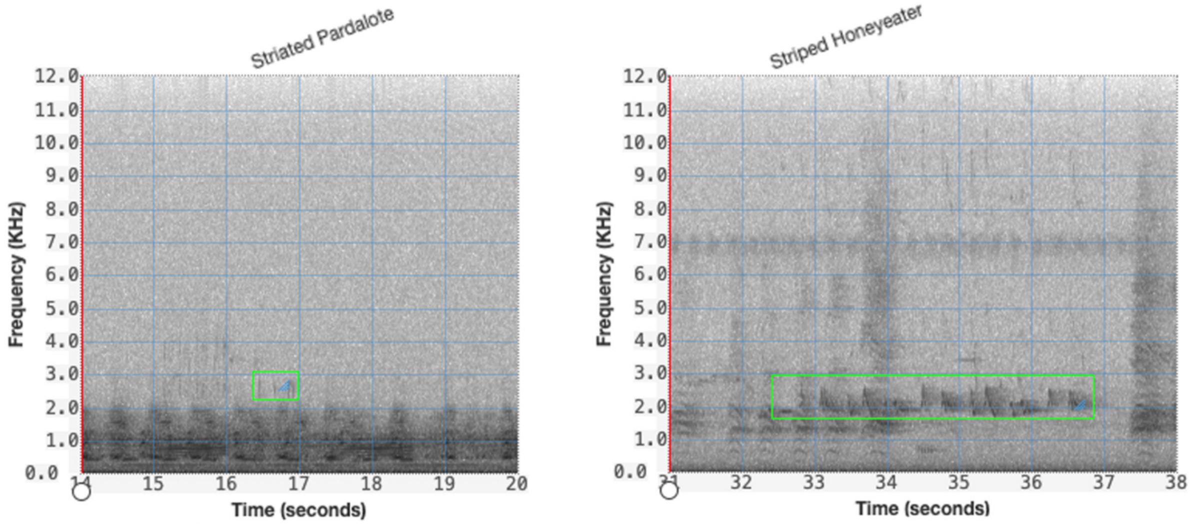

FIGURE 4 | Segmentation of variable length audio, for both short (left) and long (right) annotations showing green bounding box of the time and frequency limits of the annotation.

Spectrograms were pre-generated rather than generated on the fly as part of the pipeline. This accelerates the training process as spectrograms can be generated once rather than every epoch.

Data Augmentation

Training was performed on spectrograms of 4-s clips. Four seconds was chosen for a number of reasons. Vocalizations of the target species can be longer than 4 s, and the audio segment needs to be long enough that it captures enough of the vocalization to distinguish the class. However, it cannot be too long as this will increase the likelihood that other sounds will be included, and very short vocalizations would comprise a very small proportion of the overall size of the spectrogram image. The duration also needs to be reasonable to fit a square spectrogram image.

The training examples were of variable length depending on the duration of the example vocalization. On each epoch of training, a random 4 s segment was taken from the variable length segment. This trains the network to discriminate calls no matter which point of time they appear in the 4 s segment, that is the recognizer is time invariant.

Training examples were also blended with negative examples taken from cotton regions from the training set. Negative examples were selected, multiplied by between 0.1 and 0.3 randomly then added to the augmented training example before normalization, which has the effect of audio-mixing on the spectrogram images. This effectively synthesizes new training examples with not only more variety of background sounds, but background sounds that appear in the soundscape where the recognizer will be eventually deployed.

All data augmentation was performed on the fly for each batch of forward propagation on the training set, and the number of training examples mentioned in this paper does not include the contribution of augmentation.

Training

Examples were randomly allocated as either training (85%) or testing (15%). This was done deterministically for each file by taking a cryptographic hash of the id for the annotation mod 100 and splitting it according to the resulting value. This has the advantage of easily ensuring that a particular example would always belong to the same part of the split, which potentially allows for finetuning of the model produced by the previous iteration of the verification loop (although we chose not to do this so that the results could be compared between each iteration) without cross contamination between training and test sets. The drawback is that for classes with very few examples, the proportion of training examples can end up being greater or less than 85%. Often in machine learning there is a third dataset split, the validation set, which is used to calculate metrics to inform hyperparameter tuning during the course of training, however, this was not applicable to our design.

To prevent the massive class imbalance in the dataset from biasing the CNN, care was taken in training so that on each epoch the network used the same number of examples from each class. This was achieved by repeating examples from classes that had few examples. Thus, the only class that had its examples fed into the network exactly once per epoch was the class with the most examples (Rufous Whistler). Training continued for four epochs, as this was when the test set error rate stopped showing improvement.

RESULTS

After each iteration of training, metrics were calculated on the test set. For each class the precision (the fraction items predicted to belong to the class which were correct), and recall (the fraction of items that belong to the class which were predicted as belonging to that class) were calculated, as well as the F1 score, the harmonic

TABLE 4 | Metrics for classification on test set for **i**teration 1, 5, and 8.

	Precision	Recall	F1	Count	Precision	Recall	F1	Count
	T1 cotton				**T1 all**			
Australasian Pipit	0.8	0.667	0.727	6	0.667	0.667	0.667	6
Golden-Headed Cisticola	0.529	0.529	0.529	17	0.529	0.529	0.529	17
Mistletoebird	0	0	0	1	0.864	0.844	0.854	45
Nothing	0.333	0.333	0.333	3	0.774	0.923	0.842	26
Other	0.917	0.935	0.926	154	0.806	0.816	0.811	239
Rufous Whistler	0.5	0.667	0.571	3	0.98	0.984	0.982	740
Australian Boobook	1	0.988	0.994	83	0.981	0.963	0.972	162
Striated Pardalote	0	0	0	1	0.95	0.942	0.946	380
Striped Honeyeater	0	0	0	0	1	0.8	0.889	20
Accuracy	0.903	0.903	0.903	268	0.935	0.935	0.935	0.935
Macro average	0.453	0.458	0.453	268	0.839	0.83	0.832	1,635
Weighted average	0.898	0.903	0.9	268	0.935	0.935	0.935	1,635
	T5 cotton				**T5 all**			
Australasian Pipit	0.8	0.667	0.727	6	0.8	0.667	0.727	6
Golden-Headed Cisticola	0.711	0.75	0.73	36	0.692	0.75	0.72	36
Mistletoebird	0.714	0.625	0.667	8	0.86	0.827	0.843	52
Nothing	0.711	0.771	0.74	35	0.725	0.862	0.787	58
Other	0.909	0.895	0.902	256	0.855	0.827	0.841	341
Rufous Whistler	0.6	0.857	0.706	7	0.979	0.992	0.986	754
Australian Boobook	1	0.988	0.994	85	1	0.945	0.972	164
Striated Pardalote	0	0	0	1	0.953	0.963	0.958	380
Striped Honeyeater	0.4	0.286	0.333	7	0.864	0.704	0.776	27
Accuracy	0.871	0.871	0.871	0.871	0.932	0.932	0.932	0.932
Macro average	0.649	0.649	0.644	441	0.859	0.837	0.845	1,818
Weighted average	0.874	0.871	0.872	441	0.933	0.932	0.932	1,818
	T8 cotton				**T8 all**			
Australasian Pipit	0.8	0.8	0.8	10	0.8	0.8	0.8	10
Golden-Headed Cisticola	0.824	0.848	0.836	66	0.812	0.848	0.83	66
Mistletoebird	0.8	0.75	0.774	16	0.812	0.867	0.839	60
Nothing	0.772	0.863	0.815	51	0.779	0.905	0.838	74
Other	0.922	0.902	0.912	276	0.856	0.837	0.846	361
Rufous Whistler	0.714	0.909	0.8	11	0.979	0.989	0.984	741
Australian Boobook	0.988	0.988	0.988	85	0.987	0.957	0.972	164
Striated Pardalote	0	0	0	1	0.963	0.947	0.955	380
Striped Honeyeater	0.846	0.688	0.759	16	0.929	0.722	0.813	36
Accuracy	0.891	0.891	0.891	0.891	0.931	0.931	0.931	0.931
Macro average	0.741	0.75	0.743	532	0.88	0.875	0.875	1,892
Weighted average	0.892	0.891	0.891	532	0.932	0.931	0.931	1,892

Metrics are calculated for both all test examples and test examples from cotton.

mean of the precision and recall. We also determined the overall accuracy, which is the fraction of items that were predicted correctly, however, since our dataset was so unbalanced, this may give an over-optimistic picture, as classes that contributed most to the accuracy because they had a lot of examples also tended to have higher precision and recall. We prefer to summarize by averaging precision, recall and F1 across the classes with each class weighted equally. This macro average of F1 score was deemed the most important metric for the overall performance of the recognizer.

Table 4 lists all the metrics for the recognizer after the first and last iteration of training, as well as the middle iteration to give a sense of the progress. The macro average F1 score increased from 0.45 to 0.74 between the first iteration (T1) and the final iteration (T8). Also included are the confusion matrix for T1 and T8 in **Figure 5**.

The results differed for each of the classes, depending on the ease of discriminating species calls, the number of examples in both cotton and non-cotton, and the abundance of the species in the unlabeled cotton recordings used to build the dataset.

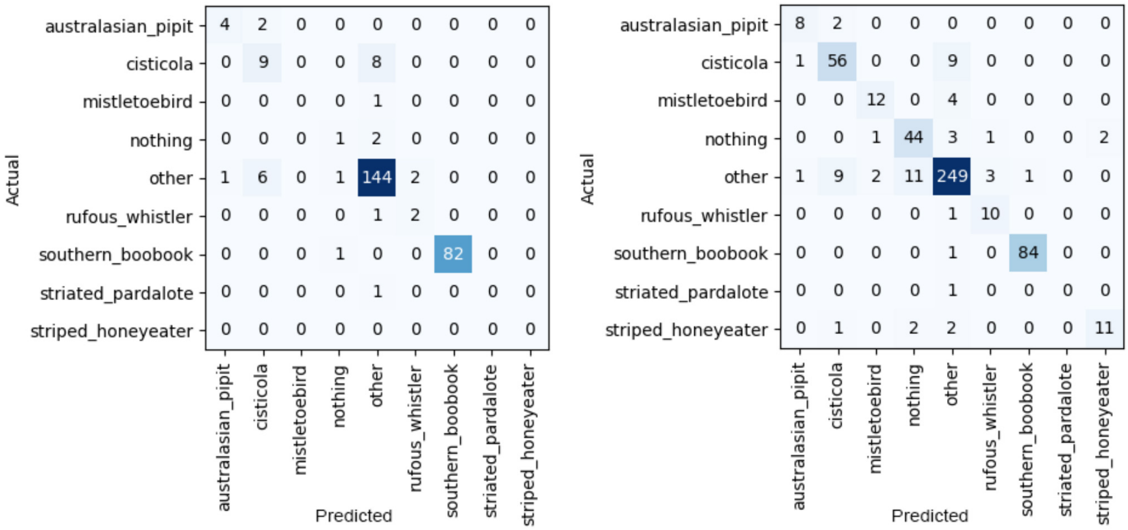

FIGURE 5 | Confusion matrix for T1 (left) and T8 (right).

The Rufous Whistler was an interesting example. Initially we had thousands of examples from non-cotton regions, but only 12 from cotton regions, three of which were included at random in the test set. The initial precision and recall over the entire test set was very high (F1 score of 0.98), however this did not generalize to cotton with 0.5 precision and 0.67 recall, although with such a small number the recall especially may be heavily influenced by random variation. For the 5th iteration (T5) we had added 39 new examples and the precision and recall increased to 0.6 and 0.86, respectively. Finally, for the 8th iteration there were a total of 89 examples, with the precision and recall increasing to 0.71 and 0.91, respectively. This improvement is interesting since, although the number of examples of Rufous Whistler in cotton increased more than sevenfold, this still comprised less than 2% of the examples.

The Australian Boobook and the "other" class showed no improvement, as they were already performing quite well with the initial cotton examples that were added through the verification of non-machine-learning Ecoacoustics Analysis Programs detections. The Australian Boobook was the least challenging of the seven target species because it is active at night when there are fewer confusing sounds. The recall of the "other" class lowered slightly as the dataset was built. This might be because the sheer variety of events that belong to the "other" means that, although we were adding misclassified confusing events into the training set for "other," we were also adding confusing events to the test set that were not necessarily similar to those added training examples. Regardless, this slight drop in recall for the negative classes has no impact on the usefulness of the model as a species detector.

Some species were not found in great numbers using the verification loop workflow. The Australasian Pipit initially had 59 examples from cotton, which was increased to 101. The reported recall in cotton for the Australasian Pipit was initially 0.68, meaning that it should have been able to detect this species in the unlabeled recordings. It is possible that Australasian Pipits were not present or not particularly active during the time period during which the recordings were made. This species was largely absent from the non-cotton recordings, however, there were enough found through the early laborious efforts to create some initial examples.

The Striated Pardalote initially only had three examples from cotton region recordings, with over 2,000 from non-cotton recordings. The is eventually increased to 15 examples, however due to the way that training, and test data was split, only one example was included in the test set. The recall on non-cotton recordings was quite high at 0.93, and therefore we would have expected to find more examples in cotton if they were present.

The Striped Honeyeater was one of the species with the best improvement. It initially had only three examples from cotton recordings, none of which ended up in the test data, and so metrics could not be calculated. At T5 the number of examples had increased to 48, and the F1 score from the model trained on this was 0.3. By T8 the number of examples had grown to 108 and the F1 score increased to 0.76.

The overall macro average F1 of the test set of all recordings also increased from 0.83 to 0.88. This was initially surprising, since the overall number of new examples from cotton recordings added was only a fraction of the total recordings. However, for some classes, namely Australasian Pipit, other, nothing, and Striped Honeyeater, the proportion of new examples added between T1 and T8 was high.

It can be seen that the first few iterations were relatively unsuccessful in finding new examples across many of the species, and then the rate of finding new examples started to accelerate. One explanation for this might be that early on there were many incorrect detections of target species that were labeled as "other" on verification. It wasn't until the after this initial addition to the training set of confusing sounds present only in the deployment location that the model was able to reduce false positive rate enough for target species to begin to be added.

DISCUSSION

Example of Data Mismatch

A potential cause for mismatch is a systematic bias in the labeled recordings. For example, our labeled Australian Boobook recordings, which were made at night, were often accompanied by cicadas stridulating. Our negative set of recordings of class "other" was designed to include a wide variety of calls by sampling from the full range of annotations. However, this did not happen to contain many annotations of cicadas. This led to the CNN learning to associate the presence of cicadas with Australian Boobooks and therefore produced many false positive Australian Boobook detections where cicadas were present. In this example, the one iteration of verifications remedied this; these false positives were added to the training set and the precision for Australian Boobooks increased.

Bias Introduced Through Feedback

A limitation of using results from a classifier to find more training examples is that it may be missing a certain variety of call type that were never included and therefore it continues to miss. While we can estimate the proportion of detections of each class that were correct (precision), which gives the false positive rate, it is not possible to measure the proportion of each class in unlabeled recordings that were found (recall), as only a small fraction of the analyzed duration is verified, meaning we can't know the false negative rate. We tried to address this as best as we could by doing some random sampling of segments in close temporal proximity to any true positive detection. This is because it is likely that individuals or members of the group will call repeatedly, and this approach had some success on occasion. However, the expertise of the ecologist doing the verifications is important here, as their knowledge of the habits of the different species at different seasons, times of day and vegetation types informed their decision to dedicate time to this search.

Acceptable F1 Scores for Drawing Conclusions

The main purpose of this classifier is to detect differences in species richness among the target species over long periods of time, drawing on the aggregations of many individual predictions of 4-s segments. It is possible to compare the presence of a particular species between two sets of many recordings even with a number of errors, as this process of aggregation removes the impact of the individual errors. In theory, as long as the errors are made in a consistent way across the two sets of recordings being compared, any F1 score above that of random guessing (0.11 for a nine-class classifier) could still be useful if aggregated across enough data. Of course, in reality, the errors will not necessarily be random or consistent. For example, there may be a sound source that causes confusion present in one of the sets of recordings and not the other. Most of our target species ended with F1 scores around 0.8–0.9, which should be enough to compare sets of recordings on aggregate, even with the potential of these confusing sounds not being spread evenly across the recordings.

CONCLUSION

Through an iterative process of training, classifying unlabeled recordings, verifying and retraining, we were able to build a dataset for the cotton regions of eastern Australia that can be used to train a convolutional neural network to achieve a macro average F1 score across seven target species of birds plus two negative classes of 0.74%. This F1 score would likely continue to improve with further iterations. In the future, this ecoacoustic analytical approach will be deployed with the aim of monitoring changes in the mean proportion of functional guilds of birds in response to on-farm vegetation management in cotton growing regions of Australia, providing valuable information to assist the cotton industry in preserving biodiversity.

DATA AVAILABILITY STATEMENT

Data for this research was provided by several sources and not all of them have given permission for the data to be made publicly available. Requests to access the datasets should be directed to the corresponding author (philip.eichinski@qut.edu.au).

AUTHOR CONTRIBUTIONS

PE: coding and running the CNN and other software scripts required for this research and writing the manuscript. CA: creation of the dataset by labeling audio examples and fieldwork making recordings. PR: advising on data collection, labeling and curation strategies, and planning the manuscript structure. SP: advising on data collection, labeling and curation strategies, planning the manuscript structure, and leading the project. SF: designing the study, fieldwork making recordings, planning the manuscript structure, and editing. All authors contributed to the article and approved the submitted version.

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Relative Importance for Lincoln's Sparrow (*Melospiza lincolnii*) Occupancy of Vegetation Type versus Noise Caused by Industrial Development

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Anthropogenic noise can create an acoustic environment detrimental for animals that communicate using acoustic signals. Currently, most studies of noise and wildlife come from traffic noise in cities. Less is known about the effects of noise created by industry in natural areas. Songbirds far from cities, but influenced by industry, could be affected by noise, but also are likely to be impacted by changes in vegetation conditions related to industrial development. We described the importance of industrial noise (from facilities and transportation) on occupancy of Lincoln's Sparrow (*Melospiza lincolnii*) relative to habitat change caused by vegetation alteration and edge effects. Lincoln's Sparrows naturally breed in varying seral stages and types of boreal forest. To test the influence of industrial noise, we selected three areas in Northern Alberta, Canada with high, medium, and low levels of industrial development and varying road density. At each area, we deployed a systematic arrangement of autonomous recording units (280 units in total, separated by 600 m) for 3 consecutive days. To measure noise, we developed a method that used the relative noise values extracted from the recordings of 8 frequency-octave bands. We obtained three noise measurements: noise with high energy in the low part of the spectrum (mean 0.5–1 kHz), masking level noise (mean 2–8 kHz), and noise in all frequency octave bands (mean 0.5–16 kHz). Proportion of chronic noise sources explained the highest variation of noise in the environment, and less by traffic noise. We found Lincoln's Sparrow had a higher occupancy in areas with higher proportion of industrial disturbances, shrubs and grass, and decreased in noisy areas. Masking level noise had a negative effect on Lincoln's Sparrow occupancy in areas with industrial disturbances, relative to areas with similar changes in vegetation structure, but no noise. Masking noise could indicate limitation in communication as noise increases. Our study amplifies the findings of others that future research should consider not only anthropogenic changes to vegetation in human-altered landscapes, but also human-caused changes to acoustic environments.

Keywords: anthropogenic noise, noise tolerance, occupancy, songbird, vegetation structure, *Melospiza lincolnii*

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INTRODUCTION

Anthropogenic noise is a selective pressure on species occupancy, especially for animals that rely on acoustic signals for communication. It has been reported for birds additional responses in terms of species richness, productivity, and abundance. The main driver for the decreases in all these population parameters is the elevated traffic and ambient noise in urban environments (Reijnen et al., 1996; Stone, 2000). In general, species richness and densities of breeding birds decrease close to roads with high traffic volume or in noisy parts of cities (Reijnen et al., 1996; Forman et al., 2002; Perillo et al., 2017; Carral-Murrieta et al., 2020). Other kinds of noise might similarly degrade the quality of habitat for songbirds (Bayne et al., 2008; Francis et al., 2009; Nenninger and Koper, 2018).

Certain types of anthropogenic noise are more likely to overlap spatially and temporally with the morning singing times of songbirds (Slabbekoorn and Ripmeester, 2008). Whereas urban and traffic noise are intermittent, with variation throughout time, industrial noise typically produces constant noise. This means that urban noise can be more or less likely to overlap temporally with the morning singing times of songbirds depending on latitude and time of year. This variation may provide some flexibility to birds in terms of when to sing in order to communicate effectively. By contrast, industrial noise typically produces constant noise across all times of day and year (Bayne et al., 2008; Francis et al., 2009). For example, in the boreal forest of Canada, compressor stations, injection wells, and processing facilities from the oil sands industry creates constant noise (Northrup and Wittemyer, 2013; Nenninger and Koper, 2018) adjacent to breeding bird habitat. Moreover, many forms of chronic industrial noise occur at low frequencies (0–2.5 kHz) with high amplitude levels (75–90 dB at the source), reaching as much as 105 dB at the largest industrial facilities (MacDonald et al., 1996). Despite the potential large effect of such noise in natural areas, chronic noise from compressor stations and processing facilities in conjunction the vehicle traffic to maintain these types of equipment has been less studied than the intermittent traffic noise in urban environments (Slabbekoorn and Ripmeester, 2008; Francis, 2015; Halfwerk and Slabbekoorn, 2015; Shannon et al., 2016).

The limited comparisons of birds in quiet versus noisy areas created by industrial development in wilderness areas have shown species-specific responses. Previous work in Alberta's boreal forest found lower densities for all birds combined, lower densities for some common species, and reduced occupancy rates for a number of species close to noisy compressor stations relative to silent well sites with similar vegetation disturbance (Bayne et al., 2008). However, not all species showed negative effects, and some showed trends toward being more abundant near noisy compressor stations (Bayne et al., 2008). Similarly, bird assemblages in noisy areas of New Mexico differed in comparison with quiet sites, which were associated with high acoustic masking of certain species close to generators (Francis et al., 2009). A major difference was that the western scrub-jay (*Aphelocoma californica*), a nest predator, decreased in sites with anthropogenic noise. In turn, lower predation rates for other bird species were observed in noisy areas suggesting a potential benefit of noise for some species (Francis et al., 2009, 2012). For secondary cavity-nesting birds, some species had higher occupancy close to noisy generator, while others had lower occupancies (Kleist et al., 2017). Clearly, the effects of anthropogenic noise on birds are variable and complex, indicating that more studies are needed to understand why species react differently to intermittent and chronic noise in otherwise natural ecosystems, and why some species do or do not react to noise (Francis and Barber, 2013).

The habitat requirements of a species is one potential source of variation that may influence how noise impacts birds. It is well documented that vegetation type influences habitat selection by birds (MacArthur et al., 1962; MacArthur, 1964), but these effects may differ among seral stages. Most of the species studied by Bayne et al. (2008) that were more sensitive to industrial noise also tended to prefer mature forest. Whether species that use early seral habitat and prefer edges react to noise is not well understood. If the human disturbance that creates noise also changes vegetation structure and composition (i.e., through edge effects and creating new early seral vegetation patches), then responses to noise may be confounded by the presence of more suitable habitat closer to noisy areas. Thus, similarly to cities, noisy areas in remote locations may attract more tolerant species (or "urban exploiters" *sensu* Blair, 1996; McKinney, 2002). Sensitive species that cannot use disturbed or edge vegetation may simply be filtered out by loss of habitat rather these species avoiding noisy areas *per se* (Blair, 1996; Cardoso et al., 2018). In the boreal forest near industrial facilities associated with oil and gas extraction, there is considerable variation in the state of the vegetation related to natural processes as well as human disturbances, which make it possible to separate the relative importance of habitat change versus noise (Venier and Pearce, 2007; Venier et al., 2014; Dabros et al., 2018).

A fundamental challenge in summarizing studies that purport to study how birds respond to noise is that in some studies, direct measures of noise are not quantified (i.e., Bayne et al., 2008). Instead, surrogate variables (i.e., distance to noise source, noisy vs. quiet, traffic volume) are often used. Quantification of noise measurements are needed to separate the relative importance of noise relative to changes in habitat conditions caused by the disturbances that create noise. At the same time, there are many ways to measure noise and there has been very limited assessment of how birds react to different ways of quantifying noise (Scobie et al., 2016).

An additional factor that is rarely addressed in noise impact studies is the possibility that vegetation conditions interact with noise transmission by altering sound absorption (Martens and Michelsen, 1981). Low-frequency sounds can transmit farther distances in open areas, while denser vegetation can provide a vertical obstruction to the sound waves that can mitigate the distance anthropogenic noise travels (Truax, 1978; Rossing and Fletcher, 2004). Whether different vertical obstructions related to vegetation type make the surrounding habitat more or less suitable for some songbird species because of differences in the way noise transmits in different vegetation types remains poorly studied.

Lincoln's Sparrow (*Melospiza lincolnii*) is a common songbird that breeds in many different vegetation types in Alberta's boreal forest (Alberta Biodiversity Monitoring Institute [ABMI], 2020). Previous work suggests they are more likely to be found near relatively quiet pipelines and well sites with disturbed vegetation than mature forest (Bayne et al., 2016). Studying a species that prefers disturbed areas provides a unique way to test the importance of noise because we know their habitat requirements are met in areas where industrial development is occurring. An additional factor that can mediate the occupancy of the species could be its vocal features. In general, songbirds with low-frequency songs are less abundant or showed lower occupancy in noisy sites than those with higher frequency vocalizations (Proppe et al., 2013; Francis, 2015). Lincoln's Sparrow songs range from 1.5 to 7.5 kHz (Cicero and Benowitz-Fredericks, 2000; **Figure 1C**); therefore, its songs are partially overlapping with anthropogenic noise that usually concentrates at low frequencies (<2 kHz; Lohr et al., 2003). We addressed this topic with four primary objectives to: (1) develop a cost-effective way of quantifying noise levels from industrial activities that could be used to statistically separate the effects of noise from vegetation disturbance caused by energy development in natural areas; (2) determine how vegetation structure influences noise transmission in the boreal forest; (3) assess if occupancy of Lincoln's Sparrow was influenced by noise, vegetation disturbance, or both; and (4) test if different ways of quantifying noise (noiseLOW, noiseHIGH, noiseALL) altered our conclusions.

MATERIALS AND METHODS

Study Area

Our study area was located in the boreal forest in Alberta, Canada (**Figure 1A**), where there is active presence of the energy industries. It is dominated by upland boreal forest with variation in industrial disturbances that creates areas of forest regeneration, edges, seismic lines, among others. It is known that Lincoln's Sparrow inhabit disturbed areas in the boreal forest (Bayne et al., 2016), providing an opportunity to explore changes in occupancy given the habitat relative to industrial noise. Based on our objectives, we performed the following tests: (1) the influence of vegetation, noise sources, and disturbances on industrial noise (response variable), and (2) the effect of industrial noise on Lincoln's Sparrow occupancy (response variable).

The data were collected in June 2015 using autonomous recording units (ARUs) deployed at different areas of disturbances created by the oil sands industry in Northern Alberta, Canada. According to the Alberta Biodiversity Monitoring Institute (ABMI) human footprint classification system[1], these areas vary considerably in levels of human footprint with some areas containing industrial infrastructure such as processing facilities and compressor stations. All sites also included roads, well sites (active and abandoned), and seismic lines (Dabros et al., 2018; **Figure 1A**).

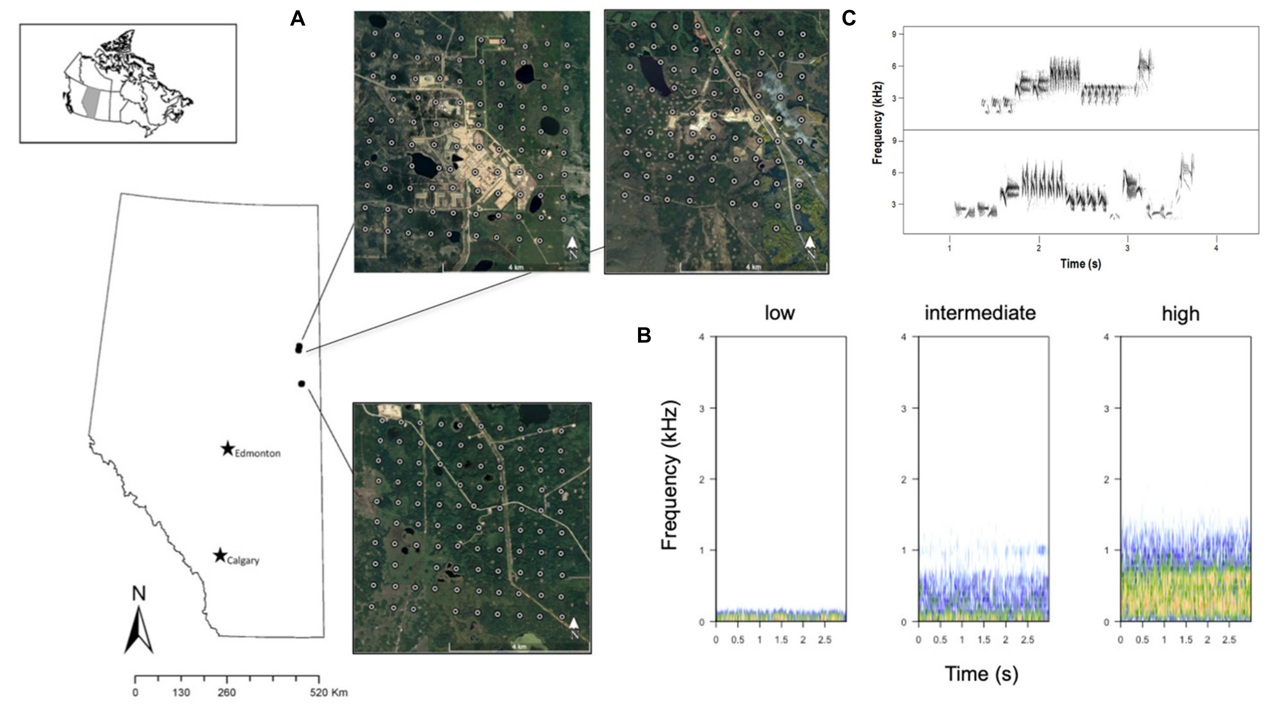

FIGURE 1 | (A) Sample design. Autonomous digital recorders deployed 600 m apart in three areas of industrial disturbances in Northern Alberta, Canada. Upper areas correspond to high and medium industrial settings. Lower area corresponds to low industrial settings. **(B)** Spectrograms of noise variation at a specific station in the low, intermediate, and high industrial settings areas. **(C)** Spectrogram of two Lincoln's Sparrow songs showing the different elements in the song.

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[1] www.abmi.ca

In the sampling design, we selected three large areas in which to sample a gradient of industrial disturbances. We defined site as an area of multiple ARUs (n = 98, 83, and 99 ARUs at each of three sites) and a station as one ARU deployed within the site. ARUs were located in grids 600 m from the adjacent recorders, comprising an area of 3,600 ha (**Figure 1**). The ARUs were originally laid out in systematic grids of 100 units, but recording failures reduced the actual number. These areas comprised a systematic design that was random in location with respect to roads and distance to various noise sources (**Supplementary Figure 1**).

Acoustic Survey

Recordings were collected with SM2 and SM3 recorders (Wildlife Acoustics) with two omni-directional microphones (SMM-A1 sensitivity: −4 ± 3 dB, 0 dB = 1 V/pa at 1 kHz). Previous to their deployment, we tested the sensitivity of each microphone using an Extech 94 dB sound calibrator. We ensured all ARUs had microphones with gain gaps between the left and right less than 4 dB (Lankau, 2015). We stored all the recordings in SD cards in stereo format (WAV) at a sampling rate of 44.1 kHz and 16-bit resolution. We defined the recording time to be 10 min long at 0500 h, which matches the highest peak of vocal activity of most boreal birds. We attached ARUs to trees with wood screws at 1.5 m height, facing North, for 3–4 consecutive days from May 25 to July 6, 2015. Most of the acoustic data analyzed were from recordings collected in June, which corresponds to the breeding season of the study species.

A group of five expert transcribers in songs and calls of Alberta birds identified the songs and calls in each 10 min recording for the 3 days of the acoustic surveys. We saved all detections including location of the site, weather (presence of rain or wind), and industrial noise classified as low, intermediate, or high, in a database (**Figure 1B**). We excluded windy and rainy recordings. This classification index provided a reference of noisy and quiet stations at each site at which we then measured noise levels more precisely as described below.

Site Variables

Quantitative Noise Measurements

We defined industrial noise as the sounds generated by industrial equipment, such as machinery, trucks, wells, and compressor stations. This type of noise concentrates the highest amplitude levels in the low frequencies of the acoustic spectrum at less than 2,000 Hz (Nemeth and Brumm, 2010; Luther and Gentry, 2013). We obtained noise measurements in two different ways. First, we used Raven Pro (2019) 1.6 (Cornell Lab of Ornithology 2019) to extract noise values manually at each recording by Natalie V. Sánchez, measuring 1 s sections in the power spectra window of the recordings (Hann window type, 700 samples, and a discrete Fourier transform size of 2,048 samples with a temporal overlap of 50%). We did this at times without bird vocalizations at both the beginning (within minute 0–1) and the end (within minute 9–10) of each 10 min recording. From each 1 s section of the recording, we extracted the relative values of amplitude (average amplitude in FSdB, Raven Pro user manual) for six 1/3-frequency octave bands (500, 1,000, 2,000, 4,000, 8,000, and 16,000 Hz). We defined the low and high frequency limits for each 1/3-frequency octave band following values reported in the literature (Sueur, 2018).

Given that we had recordings for 3 consecutive days at the same ARU stations and the majority of industrial noise is constant, we expected noise levels would be similar between days. We tested this assumption with a repeated measures ANOVA by analyzing noise level over the 3 sample days for five stations that were randomly selected at each site. Average noise levels did not vary between days ($F_{2,267} = 0.344$; $P = 0.709$; **Supplementary Figure 2**). Consequently, in the following analysis, we only included the average noise level obtained as described above from the six frequency octave bands, which we extracted from the recording on a single day that was selected randomly. It is important to clarify that the ARUs and the microphones were not calibrated to obtain absolute measurements of amplitude, thus noise levels should be viewed as relative amplitude values where the noisy sites had the highest noise values and were closer to 0 while quieter places had more negative values.

We classified the noise measurements from Raven Pro into three noise types: (1) noiseLOW measured low frequency sounds with concentrated energy in 500 and 1,000 Hz frequency octave bands; (2) noiseHIGH was defined as the average values of relative decibels from 2,000 to 8,000 Hz, which is more likely to directly interfere with communication by masking bird songs in the maximum peak of hearing of most passerine birds (Okanoya and Dooling, 1988; Dooling et al., 1992) including our study species (Cicero and Benowitz-Fredericks, 2000); and finally, (3) noiseALL included all frequency octave bands (measurements from 500 to 16,000 Hz). This last measurement can be interpreted as a measurement of total noise since it includes all the frequency octave bands.

The second method was calculated using Kaleidoscope Pro (version 5.2; Wildlife Acoustics Inc., Concord, MA, United States). This was used to obtain measurements of nineteen 1/3 frequency octave bands (from 19.7 to 2,000 Hz). These are the same octave-bands settings used by Marín-Gómez et al. (2020) to assess the effects of anthropogenic noise on occupancy by owls. Both methods showed a high correlation at 500 Hz ($r = 0.81$, $P < 0.0001$) and 1,000 Hz ($r = 0.83$, $P < 0.0001$) (**Supplementary Figure 3**). Given the strong correlation, we decided to only use the noise values obtained with Raven Pro in our subsequent analyses since we were more confident those values did not include biotic sounds.

Vegetation

At each station, we calculated the proportion of vegetation within a 150 m radius buffer from the Alberta Vegetation Inventory (AVI). We extracted proportion of conifer forest, deciduous forest, mixed-wood forest, grass, and shrubs. When assessing if noise transmission was influenced by vegetation conditions, we grouped plant species into three categories as follows: (1) **conifer:** high density conifer stands dominated by black spruce (*Picea mariana*); (2) **mixedwoods:** medium density deciduous forest dominated by trembling aspen (*Populus tremuloides*) or mixed-woods of trembling aspen and white spruce (*Picea glauca*); and

(3) **open** areas containing shrubs and/or grass. We used ArcGIS 10.6.1 (Environmental Systems Research Institute, Inc., Redlands, CA, United States) to calculate the buffer and to extract the proportion of vegetation.

We extracted the proportion of the 150 m radius buffer that was conifers and mixedwoods by age class (0–19, 20–40, 41–100, and more than 100 years old). Class 20–40 years did not have any values in the three study areas. Therefore, we collapsed 0–19 to 20–40 to a new category 0–40. Then, we created a new categorical variable called "age" with three levels: **young** forest (0–40 years), **mature** (40–100 years), and **old** forest (more than 100 years). Each ARU was placed in an age class based on the age class most common in the buffer. Human disturbance variables were extracted from a 150 m buffer (around each station) using the Human Footprint Inventory GIS layer (see text footnote 1).

Statistical Analysis

Factors Influencing Noise Levels

Our sites were selected based on the amount of energy sector disturbance visible from satellite imagery. Thus, prior to ARU deployment we did not know if noise levels actually differed between sites. To test if our designations of low, moderate, and high footprint sites actually had different noise levels, we used an ANOVA to test if the average noise levels were significantly different between sites (each ARU was treated as a replicate). We ran three separate ANOVAs using noiseLOW, noiseHIGH, and noiseALL, as the response variable. In addition, we tested whether the noise measurements using all the frequency octave-bands had differences in relative amplitude between the sites. We compared the average slopes of noise measurements (response variable) between the three sites (fixed effect), using all the frequency octave bands measurements (obtained with Raven Pro) with a Generalized Linear Mixed Model (GLMM).

We then assessed whether the various noise metrics were associated with different types of energy sector footprint. Using generalized linear models with a Gaussian distribution and identity link, we tested six hypotheses about what the various noise metrics were measuring (see **Table 1** for model structure): (1) they described general noise in the environment caused by nuisance factors that vary in some unknown way as a function of forest composition (conifer, mixedwood, open) and age (young, mature, old), but not energy sector footprint (hereafter vegetation); (2) they were correlated with the proportion of total energy footprint within a 150 m buffer (proportion of area disturbed by abandoned well, active well, facility, road, seismic line, and pipeline) with no designation of the type of noise that each footprint is likely to create; (3) they were correlated with purported chronic noise sources like oil sands processing facilities, compressor stations, and active injection wells; (4) they were correlated with intermittent noise sources like roads, abandoned wells, pipelines, and seismic lines that are used to access the energy network via trucks and off-highway vehicles; (5) if both chronic or intermittent contributed to our noise measurement in an additive way; and (6) if chronic versus intermittent noise contributed to noise measurements in an interactive way. Natural variation in environment (vegetation) was included in all models.

Occupancy Models

We estimated the factors influencing Lincoln's Sparrow occupancy using the single-season occupancy model framework (MacKenzie et al., 2002). The model estimates the occupancy (psi) and the detection probability (p) based on the detection history of singing birds of 3 consecutive days recorded per station. We generated 42 models that allowed us to test the following hypotheses: (a) any variation in Lincoln's Sparrow occurrence was simply due to detection error caused by time of sampling (Day of year, hereafter DOY); (b) natural vegetation conditions are the primary driver of occupancy; (c) any type of energy development (footprint) creates altered habitat conditions that influence Lincoln's Sparrow occupancy; (d) linear features (proportion of area disturbed roads, seismic lines, and pipelines) create edge habitat preferred by Lincoln's Sparrow; (e) polygonal features (active well, abandoned well, facility) create early seral open habitat preferred by Lincoln's Sparrow; and (f) both linear and polygonal features create habitat for Lincoln's Sparrow but at different rates.

To these six basic model structures, we added the three different noise measurements (noiseLOW, noiseHIGH, and noiseALL) to see if we observed different responses on the occupancy side of the equation (24 models). Finally, we evaluated whether the three noise metrics influenced detection across all models under the premise that noise may influence our ability to observe Lincoln's Sparrow, even when present, because of reduced ability to aurally detect them because of the noise. Day of year was included on the detection side of all models.

TABLE 1 | Model structure and description of the variables included in the respective model to test the noise hypotheses.

Model structure	Description of the variables
Noise ∼ vegetation	Vegetation = proportion of conifers + mixedwood + open + age (young + mature + old)
Noise ∼ footprint + vegetation	Footprint = proportion of energy footprint (excluding vegetation)
Noise ∼ chronic + vegetation	Chronic noise footprint = proportion of chronic noise sources (facilities + compressor stations + active injection well sites)
Noise ∼ intermittent + vegetation	Intermittent noise footprint = proportion of intermittent noise sources (roads + abandoned wells + pipelines + seismic lines)
Noise ∼ chronic + intermittent + vegetation	
Noise ∼ chronic × intermittent	

Forest age is a categorical variable.

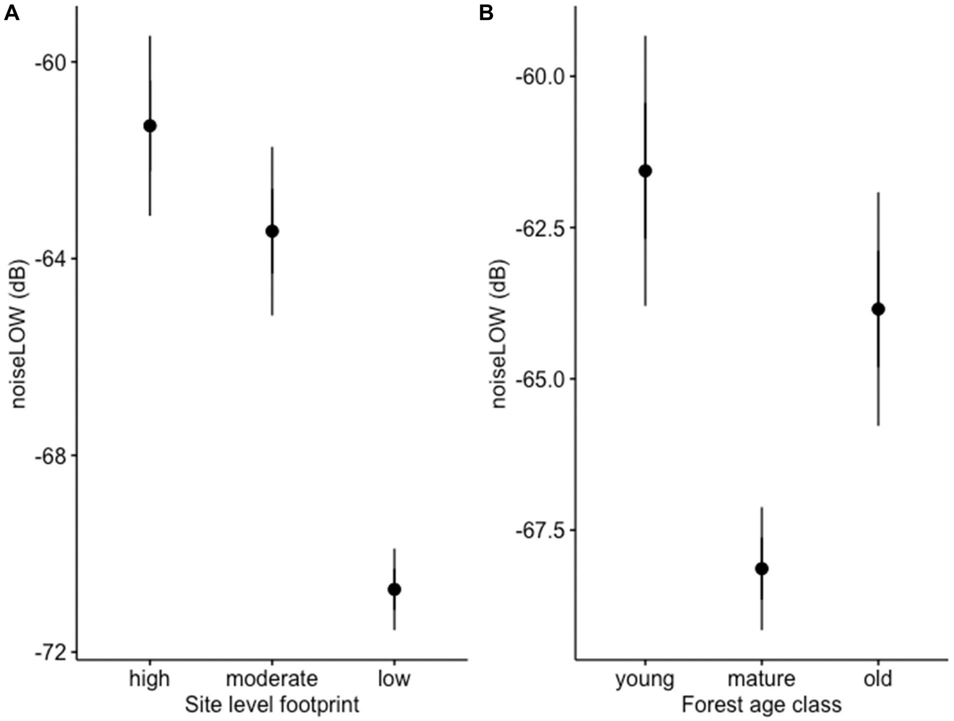

FIGURE 2 | (A) Predicted noise level for noiseLOW at the high, intermediate, and low footprint sites. **(B)** Predicted average noise levels for noiseLOW in young, mature, and old forest ARU locations. Error bars are 95% CI.

Time of day was controlled by our experimental design that standardized recording times. The models were ranked using Akaike Information Criteria (AIC, Burnham and Anderson, 2002). The best model had the lowest AIC value. All the occupancy models and model selection analyses were performed with the software RStudio (version 1.4.1106) and the R package "unmarked" (Fiske and Chandler, 2011).

RESULTS

Factors Influencing Noise Levels

We analyzed recordings from 280 stations at sites that we *a priori* ranked as having high, moderate, and low levels of energy footprint. There were significant differences in average noise for noiseLOW ($F_{2,277} = 44.5$, $P < 0.0001$), noiseHIGH ($F_{2,277} = 15.9$, $P < 0.0001$), and noiseALL ($F_{2,277} = 36.9$, $P < 0.0001$), among sites. *Post hoc* Tukey's test for noiseLOW found that the low footprint site had lower noise levels than the moderate (difference: −9.42; −11.88, −06.96 95% CI) or high footprint site (difference: 7.28; 4.71, 9.85 95% CI). Moderate and high footprint sites were similar in term of noise (difference: −2.14; −4.71, 0.43 95% CI) (**Figure 2A**). noiseLOW contains the higher values of noise; therefore, we considered that this metric reflected the stronger differences between sites. The linear regression of the log transformed relative amplitude values including all the frequency octave bands also showed differences between the slope of both the high site and the intermediate site with the low site (**Table 2** and **Figure 3**).

The three noise metrics were correlated. The correlation coefficient (r) for the three noise metrics was: noiseLOW vs. noiseHIGH = 0.71, noiseLOW vs. noiseALL = 0.95, noiseHIGH vs. noiseALL = 0.88. The model that best predicted the variation in all three noise measurements was the one including the variables Chronic Noise footprint × Intermittent Noise footprint (**Table 3**). The AIC weight for this model was 0.99 for three noise metrics. Given the correlation between noise metrics, it was not surprising that the same model was selected as having the best fit, but there were some distinct differences in beta estimates (**Table 4**). Across all models, age of forest showed the same effect on noise level with the lowest noise level in mature forests. Based on 95% confidence intervals, this was lower than old forests, which had intermediate noise levels. Young forest had the highest noise levels and the 95% CI do not overlap with mature forest, but did overlap with old forest (**Figure 2B**).

TABLE 2 | Linear regression analysis adjusted testing the differences between measurements of frequency octave band slopes between sites (high, moderate, and low levels of noise).

	β	SE	df	*t*-value	*p*-value
High-moderate	−4.96	0.25	1084	0.71	0.4796
Moderate-low	−4.46	0.25	1090	4.02	<0.0001
High-low	−1.98	0.13	1180	4.83	<0.0001

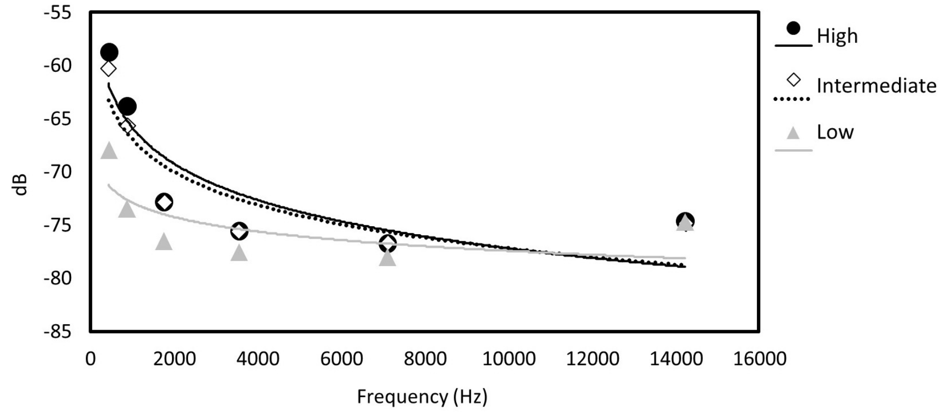

FIGURE 3 | Relative measurements of sound amplitude measured from recordings for the six frequency octave bands per site using Raven Pro software. Sites are represented by symbols and fitted lines. High industrial disturbances, black dots and line; moderate footprint, hollow diamonds and dotted line; low disturbances, gray triangles and line.

There was a variation in how proportion of forest had an influence on the different noise measurements. For noiseLOW, conifer and mixedwood had beta values that included zero based on 95% CI, and the more open habitat had the loudest noiseLOW scores (**Figure 4**). For noiseALL, conifer had beta values that included zero indicating no change in noiseALL controlling for other variables. NoiseALL increased as mixedwood increased, but not as steeply as in open vegetation (**Figure 4**). When there is an natural open area surrounding a chronic noise source, noiseALL reached at the ARUs is higher than in less open areas (**Figure 5**). NoiseHIGH showed a very different pattern. Conifer and open had 95% CI that included zero while there was an increase in noiseHIGH as mixedwood increased (**Figure 4**).

In all models, the interactive model between chronic noise footprint and intermittent noise footprint was a far better fit than the additive model. The patterns were the same across all noise metrics (**Figure 6**). When the proportion of chronic noise footprint increased and intermittent noise footprint was low, noise was the highest. NoiseHIGH and noiseLOW represented the higher levels of noise considering chronic noise and intermittent noise sources (**Figure 6**).

TABLE 3 | Results from AIC comparisons of generalized linear models that predict how the three noise metrics respond to various models of vegetation conditions (vegetation = conifer, mixedwood, and open as continuous variables, and age class as categorical variable) and type of energy footprint (Chronic noise = facilities + active well + road; Intermittent noise = abandoned well + seismic line + pipeline), and total footprint (footprint).

Models	nPars	AIC noiseALL	AIC noiseLOW	AIC noiseHIGH
Chronic × intermittent + vegetation	9	1482.3	1880.4	1390.1
Chronic + intermittent + vegetation	8	1502.1	1896.6	1406.5
Chronic + vegetation	7	1504.5	1902.0	1405.0
Intermittent + vegetation	7	1563.9	1949.9	1458.6
Footprint + vegetation	7	1502.1	1895.0	1410.2
Vegetation	6	1567.8	1956.8	1457.9

nPars, number of parameters.

Occupancy Models

Lincoln's Sparrow was detected at 123 of 280 stations (at 55 of 98, 45 of 83, and 23 of 99 stations grouped as sites: high, moderate, and low industrial sites, respectively); the naïve occupancy estimate was 0.48. Along the noise gradient, Lincoln's Sparrow occupancy was best explained by proportion of total disturbances, proportion of open areas, and masking noise levels (noiseHIGH) in the range 2,000–8,000 Hz frequency octave bands (**Table 5** and **Figure 7**). The beta estimates of the best model indicated a positive effect of the total footprint, and open areas. Lincoln's Sparrow had higher occupancy in sites with greater proportion of industrial settings, regenerating vegetation, such as grass and shrubs, and young forest stands (**Figures 7A,B,D**). Masking noise (noiseHIGH) showed change on Lincoln's Sparrow occupancy, decreasing as noise increased. However, there is a high variation in the occupancy estimate as noise increased (**Figure 7C**).

Variation in occupancy was observed within the three noise measurements. For noiseLOW frequency octave bands (500 and 1,000 Hz) and noiseALL, predicted occupancy was positive as noise increased and it changed to neutral when we included vegetation and footprint as predictors. A different pattern was observed using masking noise (2,000–8,000 Hz; noiseHIGH); it changed from slightly positive to neutral with vegetation, and to a slight negative response when we included vegetation and footprint as predictors (**Table 6** and **Figure 8**).

DISCUSSION

In recent years, wildlife responses to noise have been an area of active investigation with the main focus being urban environments (Francis and Barber, 2013; Shannon et al., 2016;

TABLE 4 | Model parameters from the best-fitting models that predict the three different noise metrics as a function of vegetation and energy footprint variables.

	noiseALL	noiseLOW	noiseHIGH
Conifer	0.40 (−2.10, 2.87)	0.88 (−4.16, 5.92)	0.20 (−1.90, 2.30)
Mixedwood	1.81 (0.05, 3.56)*	2.05 (−1.53, 5.62)	2.26 (0.77, 3.74)*
Open	2.82 (0.14, 5.50)*	7.99 (2.53, 13.44)*	0.32 (−1.95, 2.59)
Young vs. mature	−1.12 (−2.18, −0.06)*	−2.26 (−4.42, −0.09)*	−0.83 (−1.72, 0.08)
Young vs. old	0.38 (−1.03, 1.80)	0.98 (−1.91, 3.87)	0.04 (−1.16, 1.24)
Mature vs. old	2.28 (0.89, 3.67)*	4.78 (1.99, 7.57)*	1.26 (0.26, 2.55)*
Chronic	11.05 (8.84, 13.26)*	20.61 (16.12, 25.10)*	8.52 (6.65, 10.39)*
Intermittent	12.16 (6.87, 17.45)*	26.17 (15.40, 36.93)*	7.09 (2.61, 11.58)*
Chronic × intermittent	−40.49 (−57.44, −23.53)*	−75.06 (−109.59, −40.54)*	−31.48 (−45.86, −17.10)*
Intercept	−74.10 (−75.27, −72.92)*	−69.14 (−71.55, −66.73)*	−77.17 (−78.18, −76.17)*

*95% CI are shown in brackets. *95% CI not overlapping cero.*

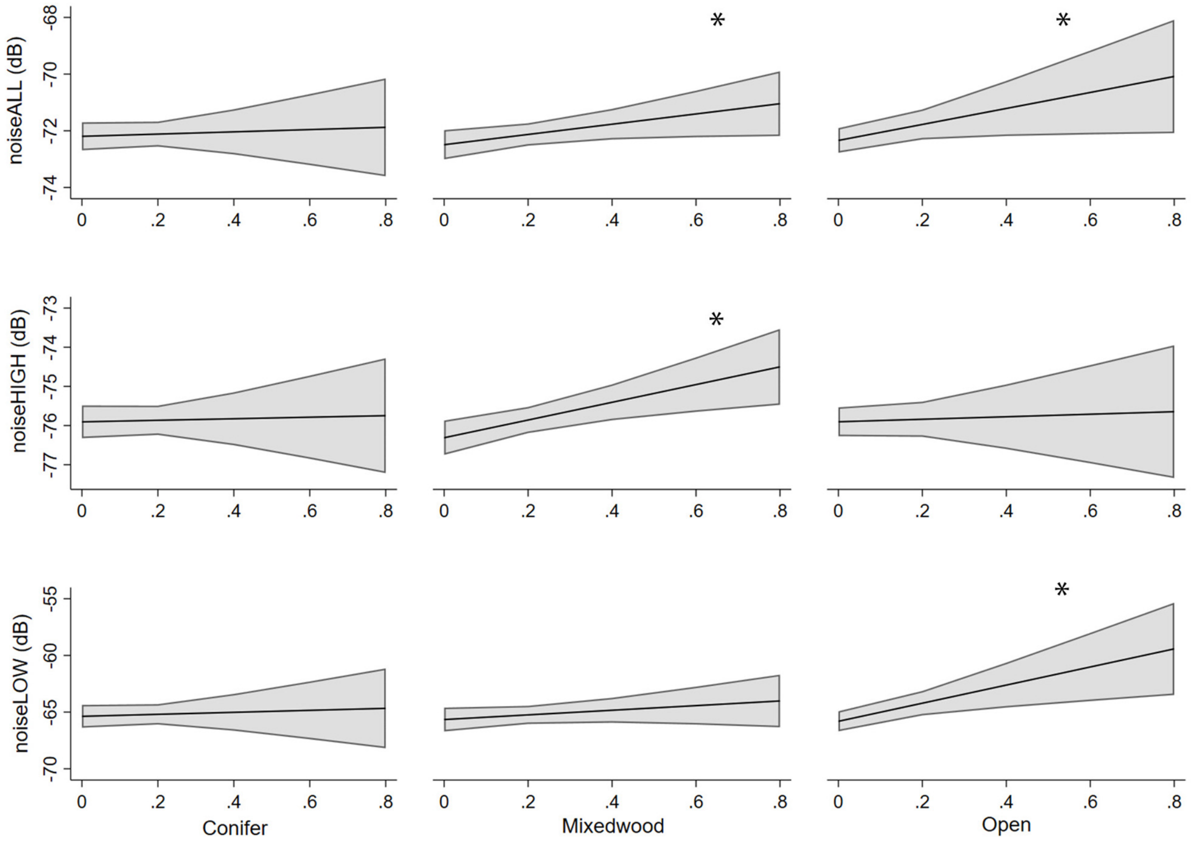

FIGURE 4 | Predicted noise levels from the three noise metrics with increasing proportions of conifer, mixedwood, and open habitats. Error bands are 95% confidence intervals. *Indicates a significant relationship.

Ciach and Fröhlich, 2017), while industrial sites and the noise associated to their activities remain understudied (Habib et al., 2007; Francis et al., 2011b). Our approach to directly measure noise with ARUs and compare it to the occupancy of a disturbance tolerant species addresses this knowledge gap by separating the effects of vegetation structure and industrial noise in a remote area undergoing energy development. We found that industrial activities, specifically facilities and certain roads, increased the levels of noise in the environment. We also found that Lincoln's Sparrow occupancy responded to a gradient of noise variation showing a tendency to decrease as masking noise increases in conditions with similar levels of disturbance to vegetation.

The idea that the energy industry and the noise generated by its activities have negative effects on songbird occupancy comes from the few previous studies that compared noisy to non-noisy industrial areas (Bayne et al., 2008; Francis et al., 2011a). A potential drawback of this dichotomous approach to anthropogenic noise is the lack of opportunity to understand bird responses to continuous variation in levels of noise. For example, intermediate levels of noise may be less detrimental than an extreme noisy vs. non-noisy contrast. In this study, we had 280 ARU stations describing a gradient of industrial noise levels at different sources as well as distances to those noise sources. Similarly, Marín-Gómez et al. (2020) studied the variation of occupancy for an owl species in a gradient of noise in an urban area, finding that levels of noise in the −60 and −40 dB ranges (relative amplitude levels at the frequency octave bands under 2,000 Hz) influenced occupancy, but values below −60 dB elicited no effect. Here, we assessed three different quantitative measurements of noise that were not previously considered as explanatory predictors of bird occupancy inhabiting the boreal forest in the context of industrial noise. Frequency octave bands from 2,000 to 8,000 Hz and low frequency octave bands (500 and 1,000 Hz) concentrated the higher levels of sound energy (from −60 to −40 dB), which were also the ones predicting changes in occupancy by our study species.

Measuring Noise and Factors That Influence Noise Levels

Although there are potential limitations of using ARUs to measure noise levels, we found strong relationships between energy sector footprint and our noise metrics. The large sample size allowed us to test multiple hypotheses about how noise may spread in complex environments with relationships that are somewhat dependent on the metric of noise used. There are numerous processes affecting sound propagation, such as attenuation and reverberation due to vertical objects (Wiley and Richards, 1978, 1982; Naguib and Wiley, 2001). Here, the proportion of open areas was positively associated with higher noise levels recorded at a given ARU. *A priori* we expected that open habitats might have higher noise levels because of fewer obstructions. Sound propagates spherically, and energy decreases with square of distance from the source (6 dB for each doubling of distance), but when sound encounters dense trees there is often a greater decrease (as high as 5–10 dB) for each doubling of distance (Naguib and Wiley, 2001). The known impediment to sound caused by vegetation makes it surprising that proportion conifers or proportion mixedwood were not important predictors of sound intensity. This may have occurred because other kinds of vegetation also absorbed sound. While there is often an inverse correlation between the proportion conifer or proportion mixedwood with proportion open, that correlation was not strong in our study area ($r = -0.04$, $r = -0.12$). Another unexpected result was that mixedwood was positively related with the noiseHIGH metric, but this may have resulted spuriously if the locations where particularly high frequency noises occurred were disproportionately located in mixedwoods. Further assessments of noise propagation are needed to more completely understand the role of vegetation structure in such areas.

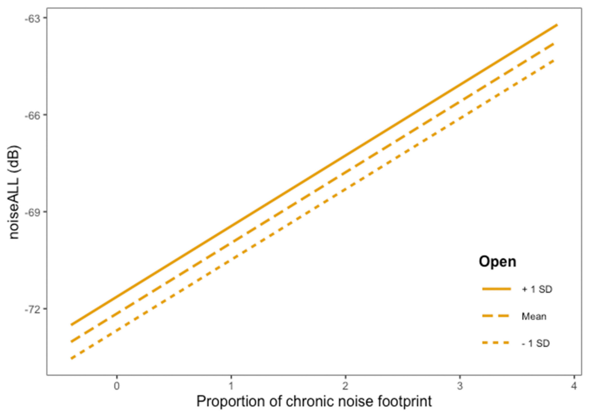

FIGURE 5 | Graphical representation of model predictions of the relationship between noiseALL and proportion of footprint though to create chronic noise as influenced by proportion of open habitat. Proportion of chronic footprint is centered to observe in detail changes in values higher than the mean.

The use of measurements in different octave bands to evaluate occupancy by Lincoln's Sparrow was key to understand at which frequencies in the acoustic spectrum noise caused the strongest effect. Controlling for vegetation and energy footprint was an important component of understanding the impacts of noise, which could otherwise be confounded with habitat type. While Lincoln's Sparrow can clearly be found in areas with noise, this species likely does not prefer noisy sites *per se*, but rather prefers habitat types in early seral stages that tend to be closer to noise sources (best occupancy model including noiseHIGH, total footprint, and open areas). Our noise metrics obtained from un-calibrated recordings on ARUs can benefit the study of noise in the wild because it allows for comparisons in diverse spatial settings with realistic variation in environmental noise. By measuring noise directly over several frequencies with Wildlife Acoustic SM2 recorders, we reduced variation between measurements that could otherwise be caused by equipment type. With the improvements of recording devices (especially microphones), modern equipment can eliminate some of the sounds made by the devices themselves to strengthen the inferences that can be made about noise effects. By recording ARU makes, models, and settings, researchers can support robust comparisons of these types of noise measurements across studies.

The interaction between chronic noise and intermittent noise for the three noise metrics shows the complexity of measuring noise along an industrial gradient. High chronic noise was driven by the presence of large industrial facilities, active wells, and compressor stations. Thus, the noise received by the ARUs in our study was more likely to be a function of relatively few noise sources. As the proportion of intermittent noise increased, total noise increased even with low footprints from chronic noise sources. Interestingly, at high levels of chronic noise, intermittent noise from roads did not add much to the total noise levels we observed. One reason for this could be that our method of measuring noise level was not able to properly measure the cumulative effects of noise (Sueur, 2018). The major highway and multi-lane gravel roads that take workers from the highway to the oil sands facilities generated much of the intermittent noise in our study area. However, traffic speeds are generally lower close to oil sands facilities to support greater safety, which

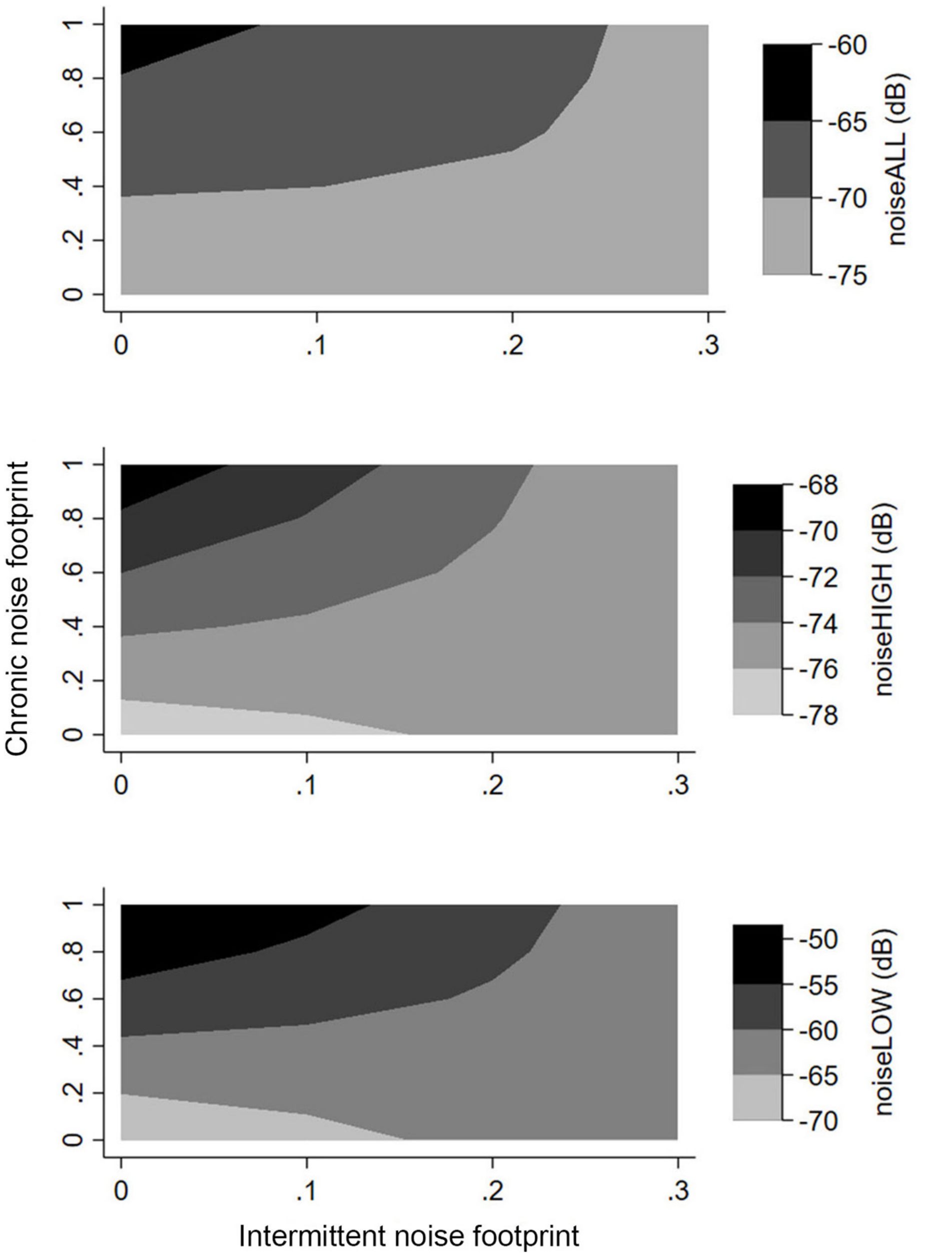

FIGURE 6 | Change in noise metrics represented in 3-D contour plots showing predicted noise level as an interactive function of proportion of area covered by footprint thought to generate chronic noise vs. proportion of area covered by footprint thought to generate intermittent noise. Graphs shows for noiseALL, noiseLOW, and noiseHIGH.

differs from the generally positive effect on noise of traffic speed (Parris and Schneider, 2009). While not reported here, we also modeled the distance to facilities and roads as noise predictors, but these models did not fit as well as the proportion metrics, suggesting a cumulative noise effect is occurring that cannot easily be measured with distance to variables.

Lincoln's Sparrow Response

Generally, songbirds with low-frequency songs are less abundant in noisy sites than those with higher frequency vocalizations (Proppe et al., 2013; Francis, 2015). This is why most studies that have assessed noise have focused on low-frequency anthropogenic noise. Therefore, we expected that Lincoln's Sparrow would occupy sites with moderate-high levels of noise because their songs are generally less masked above 2,000 Hz. In addition, sparrows have shown acoustic flexibility in their songs that may allow them to better adjust to anthropogenic noise by altering their vocalizations (Wood and Yezerinac, 2006; Gentry and Luther, 2017). Occupancy models including noiseLOW or noiseALL as predictors, suggested that Lincoln's Sparrow

TABLE 5 | Occupancy and detection probability models (AIC values) explaining Lincoln's Sparrow variation.

Set	Psi (occupancy)	p (detection)	NO noise	noiseALL	noiseLOW	noiseHIGH
1	No control variables	DOY	832.577	823.597	818.518	831.002
	Vegetation	DOY	806.22	805.088	800.969	808.221
	Vegetation + footprint	DOY	784.065	785.9411	784.538	**783.587**
	Vegetation + linear	DOY	801.990	802.658	800.0418	803.895
	Vegetation + polygon	DOY	785.686	786.806	784.473	786.177
	Vegetation + polygon + linear	DOY	790.293	792.042	790.151	789.483
2	No control variables	DOY + NOISE	832.577	825.297	821.794	831.2069
	Vegetation	DOY + NOISE	806.22	803.757	802.126	807.0216
	Vegetation + footprint	DOY + NOISE	784.065	785.721	784.552	785.745
	Vegetation + linear	DOY + NOISE	801.990	799.646	798.101	802.793
	Vegetation + polygon	DOY + NOISE	785.686	787.592	786.971	787.361
	Vegetation + polygon + linear	DOY + NOISE	790.293	791.357	790.499	792.146

We performed the models in two sets: (1) Models including only Date of Year (DOY) in the detection side, and (2) Models including DOY + Noise variables in both, the occupancy and the detection probability side of the models. Noise variables included: noiseLOW (average 500–1,000 Hz frequency octave bands), noiseHIGH (average 2,000–8,000 Hz frequency octave bands), and noiseALL (average 500–16,000 Hz frequency octave bands). Vegetation = (conifers, mixedwood, open, age), and energy footprint variables (Linear features = pipelines, seismic lines, roads; Polygonal features = well sites, facilities, compressor stations; Footprint = total footprint) are included as explanatory predictors of habitat preference. Model with the lowest AIC (best model) is bolded.

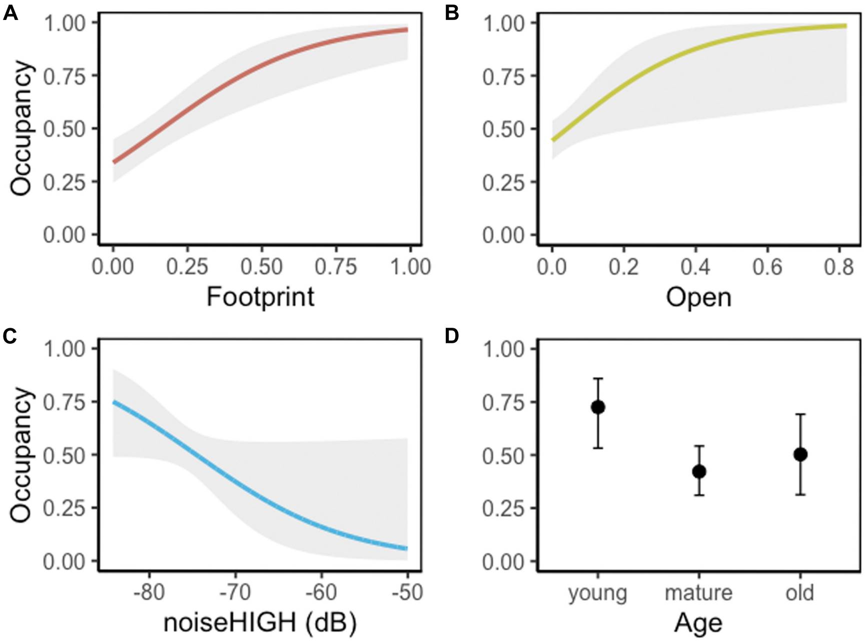

FIGURE 7 | Lincoln's Sparrow occupancy predicted values (95% CI, gray shade) explained by **(A)** proportion of footprint, **(B)** proportion of open areas (grass and shrubs), **(C)** industrial noise values (average dB from 2,000 to 8,000 Hz frequency octave bands), and **(D)** forest age class. Confidence intervals for noise are shown in **Figure 8**.

occupancy increased with noise; nevertheless, these were not the best predictors. These results could be interpreted as Lincoln's Sparrow can live in noisy areas and either do not experience or have adapted to negative effects of noise on their communication. The best fitting occupancy model suggested that natural variation that made for suitable habitat was more important than the effects of noise. However, the negative effect of occupancy of high frequency industrial noise (noiseHIGH) warrants further investigation, and suggests that noise may have impacts even on species that is otherwise highly tolerant to human disturbance.

The generality of our results may depend on whether the noise levels we monitored were sufficient to inhibit aural communication in Lincoln's Sparrow or whether the birds adapted their songs to be able to communicate in areas with noise. Lincoln's Sparrow songs can be masked by industrial noise as there is an overlap in the low frequency syllables of their song with industrial noise under 2,000 Hz, with syllables ranging between 1.5 and 8 kHz (Cicero and Benowitz-Fredericks, 2000; Sockman, 2009). Therefore, acoustic flexibility of Lincoln's Sparrow song features could be a possible adaptation for living

TABLE 6 | Beta estimates (±SE) of best occupancy model including the three different noise metrics. The best model included noiseHIGH.

	Parameters	noiseALL	noiseLOW	noiseHIGH
Psi	Conifer	−0.33 (0.95)	−0.32 (0.95)	−0.36 (0.96)
	Open	5.30 (2.20)	5.49 (2.20)	**5.48 (2.39)**
	Mixedwood	−0.67 (0.68)	−0.72 (0.68)	−0.35 (0.67)
	Old	0.19 (0.48)	0.11 (0.48)	0.32 (0.47)
	Young	1.21 (0.44)	1.21 (0.44)	**1.28 (0.44)**
	Footprint	3.98 (1.16)	3.82 (1.15)	**4.08 (1.04)**
p	DOY	0.003 (0.01)	0.003 (0.1)	0.005 (0.1)

DOY, Day of Year. Bold numbers indicate variables affecting Lincoln's Sparrow occupancy (see ***Figure 7****).*

in noisy areas, as described for other sparrow species exposed to similar industrial noise (Curry et al., 2018). However, in other work, we showed that Lincoln's Sparrow did not shift the minimum frequency of its song in this environment (Sánchez, 2021). By contrast, some other species have been shown to shift the frequencies of their songs in response to anthropogenic noise (Slabbekoorn and Peet, 2003; Proppe et al., 2011; Cardoso, 2014; Roca et al., 2016).

This study is one of the first to directly use noise measurements to predict occupancy of a wild songbird in the context of chronic industrial noise and to do so in an environment that consists mainly of natural habitat. Another important feature of our study was to measure noise at multiple octave-bands, which resulted in a non-biased method to characterize the noise along an industrial gradient, giving a quantitative description of noise rather than a categorical human judgment. This method can be used to test potential limitations in communication in songbirds and will be valuable for song transmission experiments that test masking and song degradation for species exposed to noise. Understanding masking noise and how it influences song degradation over space are key biological issues related to chronic industrial noise that require more investigation. We found a negative effect of high frequency noise on Lincoln's Sparrow occupancy in a gradient of industrial noise; therefore, this result suggests a potentially deleterious effect of noise that interferes with communication, and not of other noise types. Future studies will be needed to understand the effects of noise on communication, physiological state, and reproductive success. For terrestrial passerines and especially for Neotropical migrants who find new conditions for reproduction every year in Northern Latitudes, understanding the multiple environmental factors that could diminish quality of breeding territories requires attention for conservation actions.

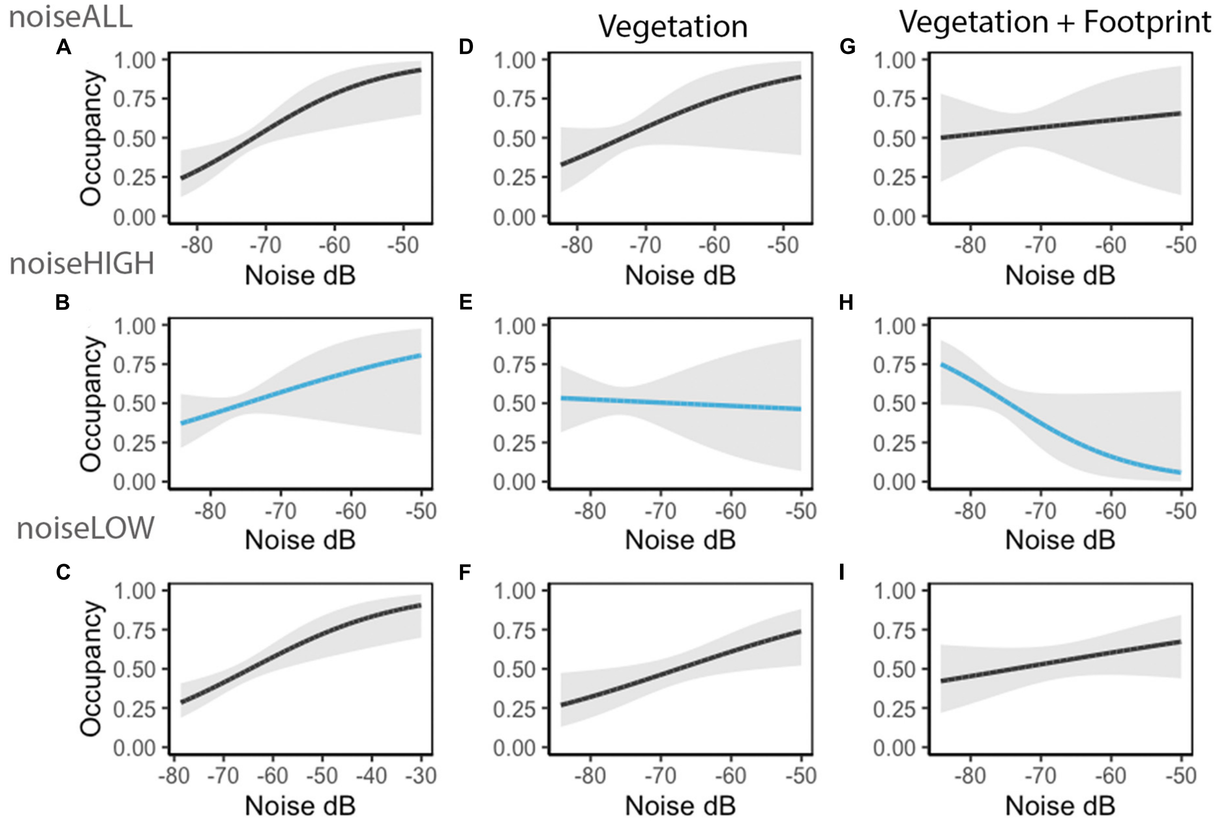

FIGURE 8 | Lincoln's Sparrow occupancy predicted values (95% CI, gray shade) changed with each noise metric. Each row represents three set of models: noise as unique predictor, and when additional variables are included (e.g., noiseALL, noiseALL + vegetation, and noiseALL + vegetation + proportion of footprint). Each row shows how Lincoln's Sparrow occupancy estimates varied by noiseALL **(A,D,G)**, noiseHIGH **(B,E,H)**, and noiseLOW **(C,F,I)**.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Ethical review and approval was not required for the animal study because the study relied solely on the use of autonomous recording units placed in the field to collect acoustic data. No animals were captured, handled, housed, manipulated, or followed.

AUTHOR CONTRIBUTIONS

NS and EB conceived the idea. NS acquired the data and wrote the first draft with input from EB and CS. NS, LS, RH, and EB analyzed the data. All authors contributed to interpreting the results and writing the final draft.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2022.810087/full#supplementary-material

Supplementary Figure 1 | Spatial distribution of average noise levels in the three study sites.

Supplementary Figure 2 | Noise measurements at 3 survey days.

Supplementary Figure 3 | Correlation of 500 Hz and 1000 Hz noise levels using Raven Pro and Kaleidoscope Pro.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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What Do We Mean by “Soundscape”? A Functional Description

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The concept of soundscape was originally coined to study the relationship between humans and their sonic environment. Since then, several definitions of soundscapes have been proposed based on musical, acoustical and ecological perspectives. However, the causal mechanisms that underlie soundscapes have often been overlooked. As a consequence, the term “soundscape” is frequently used in an ambiguous way, alternatively pointing to objective realities or subjective percepts. Through an interdisciplinary review, we identified the main biotic and abiotic factors that condition non-anthropogenic terrestrial soundscapes. A source-filter approach was used to describe sound sources, sound propagation phenomena and receiver’s characteristics. Interdisciplinary information was cross-referenced in order to define relationships between factors, sound sources and filters. Those relationships and the associated references were organized into a functional block diagram. This representation was used to question the different uses and meanings of the soundscape concept found in the literature. Three separate categories were then suggested: distal soundscape, proximal soundscape and perceptual soundscape. Finally, practical examples of these different categories were described, in relation to the diagram. This new systemic approach to soundscapes should help ecoacousticians, bioacousticians, psychoacousticians and environmental managers to better understand soundscapes and protect natural areas in a more significant way.

Keywords: soundscape, environmental factors, sound sources, sound propagation, distal soundscape, proximal soundscape, perceptual soundscape

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INTRODUCTION

The concept of soundscape, which has been widely used in different scientific contexts during the last decades (Kang and Aletta, 2018), was originally introduced in by Southworth (1969) who was studying the perception of urban acoustic environment. Southworth first defined the soundscape as “the quality and type of sounds and their arrangements in space and time.” Schafer later popularized the term (Schafer, 1977). Through the study of the history of human soundscapes, Schafer exposed the rising emergence of noise pollution as a potential threat to human health and culture. Although Schafer did not have any scientific evidence at the time, he feared that the growth of what he called “low-fidelity soundscapes” at the expense of “high-fidelity soundscapes” would alter man’s relationship with nature and decrease his concern for ecosystem well-being. Later, with the emergence of soundscape ecology (e.g., Pijanowski et al., 2011) and more recently ecoacoustics (e.g., Sueur and Farina, 2015), the concept of soundscape evolved to designate an acoustic space that could be studied within the frame of ecology. Today, many studies show that the concerns of Schafer were justified and that soundscapes play a significant role in our understanding of natural environments, as well as our own well-being (Ratcliffe, 2021).

However, the definition of soundscape still appears as vague and ambiguous. Pijanowski et al. (2011) defined the soundscape as "the collection of biological, geophysical and anthropogenic sounds that emanate from a landscape and which vary over space and time reflecting important ecosystem processes and human activities." Although this definition appears to be consensual and shared, at least in 2011, by Pijanowksy's co-authors, the soundscape concept is actually associated with a wide variety of objects. As Farina and Pieretti (2012) noted, "The landscape can be defined in several ways according to the epistemological basis adopted and the discipline."

In his seminal book Soundscape Ecology (2014), Farina proposed several definitions of the soundscape, two of them being: "an acoustical composition that results from the voluntary or involuntary overlap of different sounds of physical or biological origin" and "the acoustic context produced and, in turn, perceived in different ways by both animals and humans." The first definition is parsimonious with that of Pijanowski, but the second explicitly relates the soundscape to perception of the acoustic environment. Farina will later make the distinction between the vibroscape, which represents all the vibrations present in an area, and the soundscape, that he finally defined as "the part of the vibroscape perceived as sound by an organism" (Farina et al., 2021). However, contemporary literature relates the vibroscape to substrate-borne sounds only (Šturm et al., 2022). Still, Farina's last definition of soundscape suggests that animals play an active role in building the soundscape as an intellectual construct, which matches the definition from the International Standardisation Organisation (ISO, 2014) where the soundscape results from the listener's understanding of an acoustic environment. Moreover, incorporating auditory perception aspects into the soundscape puts an emphasis on cognitive constraints that were not included in Pijanowski's definition.

Barchiesi et al. (2015) presented the soundscape as an equivalent of the "acoustic scene", designating the sound produced by the environment. In the context of acoustic scene classification, the acoustic scene pulls away from Pijanowski's holistic soundscape and rather describes the sounds that arrive to an observer. Celis-Murillo et al. (2009) went further and suggested that a recording contained all the information that was embedded in a soundscape, and that a 360° display was a faithful replication of this soundscape. The idea that the soundscape and its recording are one and the same is common in soundscape composition. According to Westerkamp (2002), a soundscape may be understood as the result of the juxtaposition of environmental sound recordings that provide an "artistic, sonic transmission of meanings about place, time, environment and listening perception." In soundscape composition, the ecological origin of sounds that is emphasized in Pijanowski's definition has been replaced by the "meaning" that people attribute to the sounds. In Payne et al. (2009), merged both objective and subjective aspects of soundscapes into their own definition: "Soundscapes are the totality of all sounds within a location with an emphasis in the relationship between individual's or society's perception of, understanding of and interaction with the sonic environment." However, this definition does not state whether the object of study is a physical (thus, external) phenomenon, or a perceptual (thus, internal) understanding of complex acoustic assemblages.

As Farina et al. rightfully said, "ecoacoustic research to date has focused predominantly on the development of tools for environmental monitoring, rather than theoretical and conceptual development and explication" (Farina et al., 2021). Some clarification could be obtained by identifying the causes and effects behind the soundscape concept. The description of the ecological factors that influence the production of sound sources and alter their acoustic qualities should help to better understand the dynamic relationship between sound sources, sound propagation, and sound perception. The causes and effects could be organized according to the principles of information theory, in which communication is the result of a source that generates a signal which passes through a transmission channel and conveys information to the receiver (Shannon and Weaver, 1949; see Reza, 1994). This approach allowed speech production and later animal communication research to tackle animal vocal communication through the source-filter theory. The source-filter theory decomposes vocal sound production into a larynx (the source) and a supralaryngeal vocal tract (the filter) (Lindblom et al., 2010; Taylor et al., 2016). Following these principles and taking a bioacoustic perspective, animal vocal production can be considered as a source signal that is filtered a first time by the acoustic particularities of the environment, and a second time by the auditory system of the receiver. In ecoacoustics, biophony and geophony may be considered as a collection of sound sources, and sound propagation and auditory perception as two different kinds of acoustic filters operating one after the other.

Here we aim at clarifying the terrestrial soundscape concept by listing and drawing the interactions between the causes and effects that explain non-anthropogenic soundscapes so that original ecological interactions, without human pressures, can be underlined. Soundscapes, as ecological phenomenons, were born and structured in non-anthropogenic environments. Although it is appropriate to say that anthropophony today represents a prevalent part of soundscapes around the world, including natural protected areas (Barber et al., 2011; Buxton et al., 2017), anthropophony is not indispensable to the clarification of the soundscape concept. Consequently, a source-filter approach was used, combined with an interdisciplinary review, in order to describe cause and effect relationships regarding biophony and geophony only. A systematic functional block diagram was then built in order to clarify factors, sources and filters. This description helped to unravel the soundscape conundrum. The resulting causal cartography offered a tool to deliberate on which meaningful concepts were hidden behind the soundscape polysemy. All of this led to the definition of three distinct soundscape categories: the distal soundscape, the proximal soundscape and the perceptual soundscape.

METHODS

Studying Terrestrial Non-anthropogenic Acoustic Environments

Only non-anthropogenic terrestrial environments were considered in this study. Often referred to as “natural” or “pristine,” these environments do not contain any trace of human activity, that is any trace of anthropogenic sounds, also called “anthropophony.” It is acknowledged that this selection is a double simplification. However, terrestrial and marine soundscapes have been studied independently since the origin of soundscape ecology and ecoacoustics because air and water have different acoustic properties. In addition, excluding the anthropophony opens the possibility to focus on primary ecological processes that have occurred before the development of modern industries and the consequent rise of anthropophony.

Source-Filter Approach and Categories

In a source-filter approach, source signals (input) go through a filtering process, giving rise to a final signal (output). The properties of sources and filters depend on external or environmental factors which can affect the output signal properties (**Figure 1**). Soundscape components were therefore classified into environmental factors, sound sources and acoustic filters. Environmental factors were themselves divided into five categories: temporal factors, spatial factors, abiotic factors, biotic factors and acoustic factors. Sound sources were the primary sonic objects before considering any environmental alteration. Biotic sound sources were grouped into biophony and abiotic sound sources were grouped into geophony. Acoustic filters were separated into sound propagation filters, which depend on environmental conditions, and receiver filters, which depend on the receiver’s characteristics (i.e., location, structure) and acoustic sensitivity (i.e., auditory capacities).

Interdisciplinary Literature Review

Environmental factors, sound sources and acoustic filters were listed and their relationships stated by conducting an interdisciplinary literature review on non-anthropogenic terrestrial soundscapes. The review covered animal behavior, animal physiology, community ecology, landscape ecology, meteorology, climatology, environmental acoustics, soundscape ecology, ecoacoustics and psychoacoustics. Because birds were overrepresented in papers dealing with biophony (Shannon et al., 2016), we cannot rule out a possible bias toward this taxonomic group when identifying the cause and effect mechanisms. Still, it is important to note that birds are, with insects, the main contributors to non-anthropogenic terrestrial soundscapes compared to amphibians and mammals (e.g., Phillips et al., 2018).

Semantics

As the literature review was interdisciplinary, several concepts were named differently according to the disciplines. Terms were therefore chosen by applying the following criteria in order of priority: (1) the term that was the least ambiguous, (2) the term that was the most shared by the scientific community, and (3) the term that would be the most understandable by the ecoacoustic community.

Functional Block Diagram

Functional block diagrams (FBD) are logic models that represent each object as a block, linked to one or more blocks by an arrow or different connectors (Papazoglou, 1998). FBDs, which are used in systems engineering, ecology modeling and risk management, help to visualize the relationships between objects, as well as specifying the nature of these relationships. Since each block represents a potential cause or effect, the construction of FBDs helps to consider any important causal links or objects in the literature. Here, each environmental factor, sound source and acoustic filter was represented as a block, which was connected to other blocks with directional arrows to symbolize cause and effect relationships. Using a color-blind safe color palette named “Okabe-Ito”, we colored the boxes according to their categories. The source-filter approach consisted in a linear approach that was translated into a linear diagram to be read from left to right.

ENVIRONMENTAL FACTORS

Temporal Factors

Temporal factors take into account time changes at different scales. Animal and geophysical sounds produce acoustic variations at time scales ranging from milliseconds to minutes. **Day hour** has direct and indirect influences on animal behavior, known as diel activity (Balakrishnan, 2016; Phillips et al., 2018; Gil and Llusia, 2020). **Lunar cycle** is also known to regulate animal behavior, in particular for acoustic communication (Grant et al., 2013; York et al., 2014). **Seasons** through weather variations regulate yearly animal activity, known as phenology (Suthers et al., 2016; Phillips et al., 2018), and affect the composition of local species assemblages.

Spatial Factors

Spatial factors correspond to abiotic factors that are specifically linked to the **geographical location** of the soundscape, that is its geospatial coordinates. **Topography** and ground **surface** can impact sound propagation with obstacles and elevation inducing ground effects and sound scattering (cf. section “Acoustic Factors”).

Abiotic Factors

Climate regulates animal and vegetal biotic factors. Climate mostly depends on the studied area geographical location and the season.

Weather produces geophonic sound sources, impacts vegetation and alters animal behavior and distribution

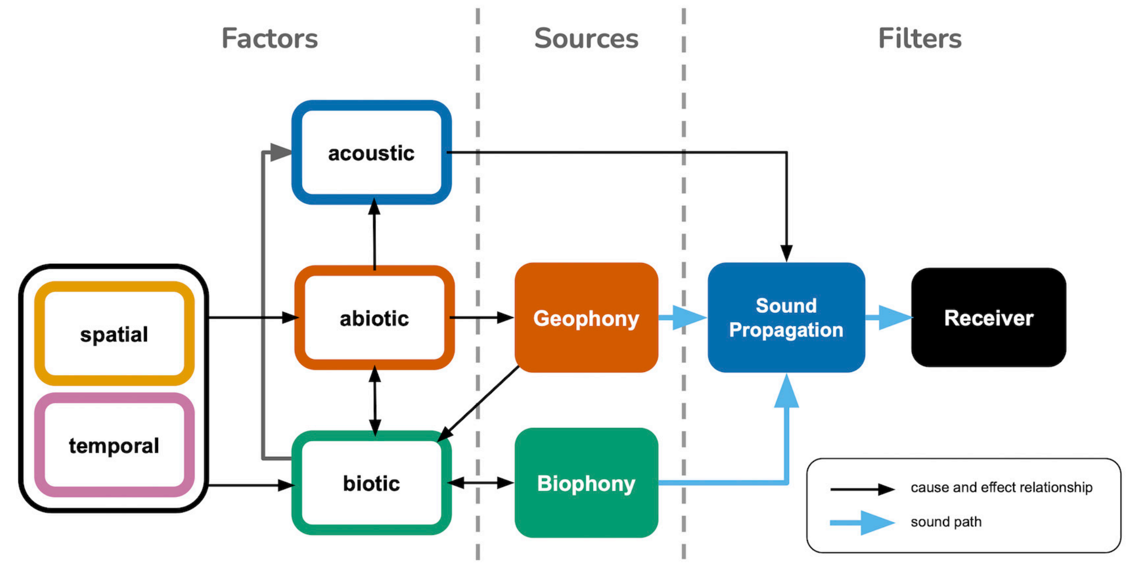

FIGURE 1 | Simplified soundscape functional block diagram. Environmental factors, sound sources and acoustic filters are represented through a source-filter approach. The influence of geophony and biophony on biotic factors introduce feedback loops that partially explain the complexity of soundscape dynamics.

(Birch, 1957; Thuiller et al., 2008; Elkins, 2010). Rain also alters hydrologic landscape sounds such as rivers. Wind can produce a salient acoustic meteorological effect that generates amplitude fluctuations when it occurs in open areas such as meadows (cf. section "Acoustic Factors" and "Sound Propagation").

Climate and weather, along with vegetation (cf. section "Biotic Factors"), influence the **local microclimate**, which can be described by the temperature, humidity and sun irradiance of a given area. Local microclimates influence animal behavior (Gil and Gahr, 2002), as well as acoustic meteorological effects such as atmospheric absorption (cf. section "Acoustic Factors").

Biotic Factors

Biotic factors cover a large range of phenomena from physiological characteristics to ecological relationships. Here, we curated a list of biotic factors that have been frequently cited in the literature regarding biophony production and/or sound propagation. The first three factors (vegetation, acoustic community, and acoustic behavior) describe species and their intrinsic traits, whereas the last three factors (population density, territory distribution and trophic interactions) account for the complexity of intraspecific and interspecific dynamics.

Vegetation, either herbaceous or woody, affects the sound propagation. The thickness, geometry and porosity of plant components (stems, trunks, leaves) impact sound propagation through acoustic scattering and ground effects (cf. section "Acoustic Factors"). Vegetation is also a core determinant of the local microclimate, especially in closed habitats. The presence of vegetation near an open habitat can have an influence on wind currents and create specific sound speed profiles (Forrest, 1994).

In ecology, a community is an assemblage of species found in a given area and sharing the same resource. In soundscape ecology and ecoacoustics, an **acoustic community** is an assemblage of species sharing the same acoustic space (Gasc et al., 2015; Farina and James, 2016). Species assemblages vary geographically and can evolve through time depending on the season, environmental change and migration (Morin, 2009). Acoustic communities are the main elements of the biophony. Species assemblages are therefore crucial to obtain a good knowledge of local species dynamics.

Acoustic behavior is a behavior expressed by an individual emitting a sound. In terrestrial habitats, most animals produce intentional sounds for intraspecific communication. The information encoded in these signals includes courtship, territory defense, alarm, distress, kin contact, and parent-offspring interactions (Bradbury and Vehrencamp, 2011). Incidental sounds are mainly due to locomotion including walk and flight during, among others, habitat exploration, foraging, and prey escape. However, incidental sounds can appear as intentional and the line between the two can be blurry (Clark, 2016).

Population density is the number of acoustically active individuals in a given area and represents the abundance of sounds produced locally (Dawson and Efford, 2009; Thomas and Marques, 2012). On an ecological level, population density depends on population dynamics which are affected by trophic interactions and the species intrinsic rate of increase (Hanski and Gilpin, 1991).

Territory distribution is the position in space of any animal which can participate in biophony in a given area. Whereas the location of abiotic factors can be identified from topographical sources, the position of animals varies greatly due to individual movements in relation with the defense of their territory and with the exploration and exploitation of their home range (Birch, 1957). The position and trajectory of each biophonic animal is necessary to assess the spatial dynamics of the soundscape.

Trophic interactions are the core of inter-specific relationships in a given ecosystem. Trophic interactions are also influenced by abiotic factors (Rosenblatt and Schmitz, 2014). Fundamental trophic interactions such as prey-predator and plant-animal interactions considerably influence animal behavior and incidentally affect biotic sound sources through acoustic behavior (Siemers and Schaub, 2011; Medina and Francis, 2012).

Acoustic Factors

Ground effects describe the reflection of sound waves on the ground, which changes the distance that the sound wave can travel. This phenomenon produces destructive (attenuation) or constructive (amplification) interferences depending on the phasing of the resulting sound waves. Ground effects can therefore have a significant impact on sound propagation, especially at low frequencies (Embleton, 1996; Swearingen and White, 2007; Tarrero et al., 2008). The composition of the different layers determines the ground impedance which is responsible for the reflection. The magnitude of ground effects also depends on the sound source distance to the ground (Ellinger and Hödl, 2003).

Sound scattering occurs when sound wavelength is smaller than the dimension of surrounding objects such as tree trunks and foliage. Sound scattering consists of absorption, refraction and reverberation (reflection). Scattering impacts more high frequencies than low frequencies. Sound scattering depends on forest characteristics including tree density, foliage density, leaf shape, and rock configuration (Swearingen and White, 2007; Tarrero et al., 2008) and is more significant in closed habitats than in open habitats.

Meteorological effects regroups all abiotic and biotic phenomenons that impact sound propagation due to climate and weather. Humidity can facilitate atmospheric absorption. Ambient temperature which is linked to the canopy structure and solar irradiance changes sound speed (Swearingen and White, 2007). The combination of temperature fluctuations and wind currents can cause atmospheric turbulence that results in irregular amplitude fluctuations (cf. section "Sound Propagation") (Embleton, 1996; Larom et al., 1997). Meteorological effects are more prominent in open habitats and for long distance communication.

SOUND SOURCES

Geophony

Geophony is produced by abiotic sources (**Figure 2**). Here, we divide geophonic sounds into two main categories: weather sounds, like rain and wind, and hydrologic sounds, like waterfalls and rivers. Such sounds are dominated by relatively broadband and transient sounds (Lewicki, 2002; Theunissen and Elie, 2014). Other geophonic sound sources that have a low rate of occurrence and have been less studied, such as thunder, forest fire or seismic activity were not considered here. Still, it is important to state that such geophony can, during a certain timeframe, have a pervasive impact on soundscapes.

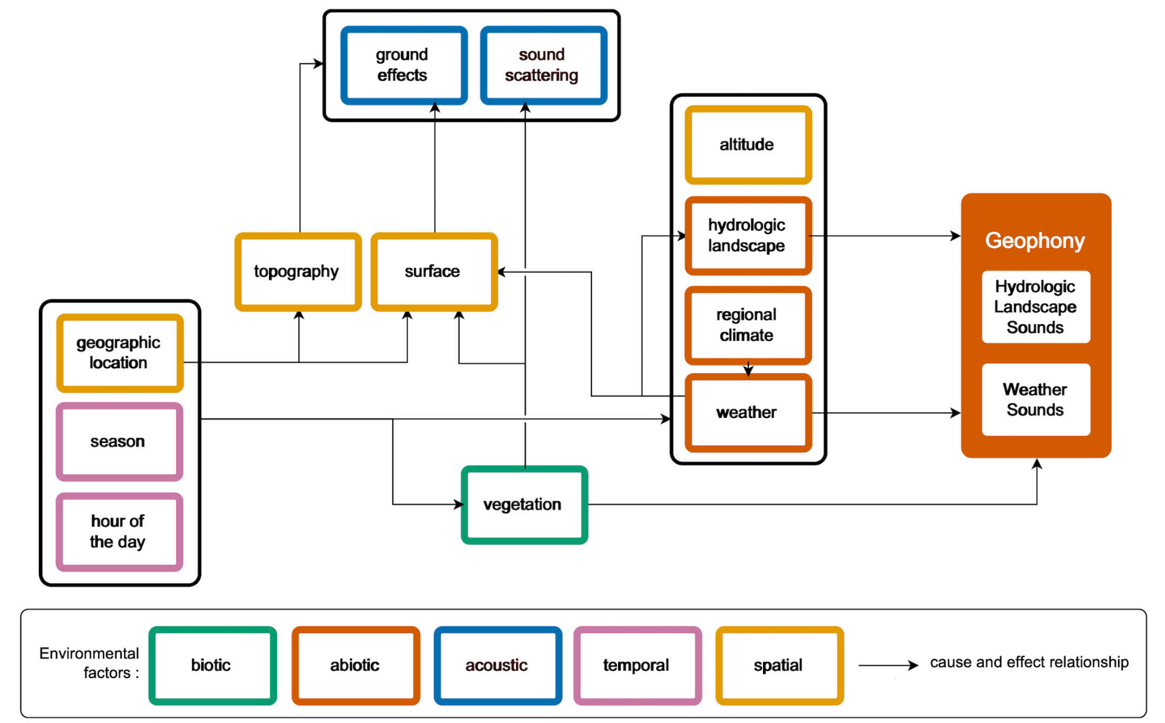

FIGURE 2 | Detailed soundscape functional block diagram: focus on geophony.

Weather sounds depend on meteorological variables, but also on biotic factors. The occurrence and power of weather sounds, like the force of the wind or the intensity of rain, are linked to climatic and meteorological factors, whereas the textural quality of weather sounds depends on the physical elements of the landscape with which weather phenomena interact. For example, the interaction between wind force (linked to abiotic factors) and tree foliage (linked to biotic factors) design wind sound. Similarly, leaf shape and soil texture change rain sound. During episodes of storms, high wind or heavy rain can generate a significant broadband noise that can alter animal behavior at various levels (Lengagne and Slater, 2002; Brumm, 2004; Tishechkin, 2013; Farji-Brener et al., 2018; Geipel et al., 2019).

Hydrologic sounds are produced by endemic moving bodies of water such as rivers or waterfalls. Unlike weather sounds, hydrologic landscape sounds are pervasive, although their presence and quality can depend on climatic and meteorological factors. A small stream can disappear during the dry season, whereas a river can become a prevalent sound source during a rainy day. The noise produced by rivers can have an impact on species territory distribution (Gomes et al., 2021).

Biophony

Biophony is produced by biotic sources, either intentionally or incidentally. Animals are the main sources of biophony. Each biophonic sound results from the species-specific behavior of an individual positioned in the landscape. Biophony encompasses a large variety of sounds that are themselves produced by a large variety of sound production systems (e.g., vocalization, stridulation, percussion): biophonic sounds range from periodic (as in the case of pure tones) to almost noisy sounds, may be stationary or fluctuating and range from narrowband to broadband sounds (Hauser, 1996; Tembrock, 1996; Bradbury and Vehrencamp, 2011).

Recent studies in sensory neuroscience that aimed to assess the acoustic statistics of natural scenes and isolated biological sounds suggest that most recorded animal vocalizations, that is to say animal sounds emanating from a vocal apparatus with vocal chords, are dominated by relatively slow amplitude modulations (below ∼10 Hz) with fine harmonic structure (Nelken et al., 1999; Lewicki, 2002; Theunissen and Elie, 2014). However, other frequent events such as stridulations have rather sudden onsets, often with fast fluctuations, and these studies still need to be extended to larger and more diverse sound databases. Biophony involves numerous types of biotic and abiotic factors, different modalities of these factors for each species, and complex internal dynamics such as prey-predator interactions with feedback loops (**Figure 3**).

Ambient Sounds

Ambient sounds, usually referred to as "background sounds," "background noise," "ambient noise" or "silence," are the result of the combination of two types of sounds: external ambient sounds and internal ambient sounds. As their common appellation suggests, ambient sounds are often considered as background sounds, meaning that they are mostly understood as inherently undesirable sounds. Most of today's terrestrial ecoacoustic literature intends to remove ambient sounds instead of studying them for their intrinsic qualities. But ambient sounds are not only a significant component of soundscapes, they also constitute the main, if not only, source of sound during periods of reduced biotic and abiotic activity such as nights or winters (e.g., Grinfeder et al., 2022).

External ambient sounds, also called "environmental noise," consist in a mixture of biophonic and geophonic signals that are too attenuated and/or distorted to be separated and identified (Forrest, 1994). External ambient sounds are usually described as showing most energy below about 2 kHz, but it remains unknown to which extent biophony and geophony, respectively, influence the acoustic nature of external ambient sounds. However, one can make the assumption that biophonic and geophonic ambient sounds should occur on different parts of the amplitude spectrum, follow different periodicities, and overall possess distinguishable features.

Internal ambient sounds are sounds that are produced by the receiver's body and can only be perceived by it. For animals, internal ambient sounds can have neural, vascular or pulmonary origins. For artificial recorders, internal ambient sounds are mechanical or electronic sounds that result from the recorder's physical configuration and operation.

ACOUSTIC FILTERS

Sound Propagation

During sound propagation, the acoustic characteristics of the environment filter the signal and produce attenuation and distortion (**Figure 4**). This filter can be characterized by a transfer function which captures the shape of a known signal after its transmission through the habitat. Signal attenuation and distortion may reduce the amount of information encoded or limit the transmission of the information over a specific distance, usually known as the active space.

Attenuation is the decrease of intensity of a sound traveling through a medium. Attenuation is mainly due to spreading loss and atmospheric absorption (cf. section "Acoustic Factors"). Sound attenuation is frequency dependent, with a greater effect on high frequencies (Wiley and Richards, 1978; Forrest, 1994). Moreover, ground effects can generate shadow zones that drastically attenuate sounds in areas that can be close to the source (Roberts et al., 1981).

Distortion mainly results from sound scattering and meteorological effects (cf. section "Acoustic Factors"). Time, amplitude and frequency alteration of sounds can occur such that temporal smearing or amplification can be observed after transmission. Temporal smearing, mainly due to reverberation, may mask high rate amplitude modulation. Irregular amplitude fluctuations, due to atmospheric turbulence, may mask low rate amplitude modulation (Richards and Wiley, 1980).

Receiver

A receiver is a system which operates a transduction of acoustic energy into mechanical or electrical energy. The receiver acts as a filter which can be defined with a transfer function.

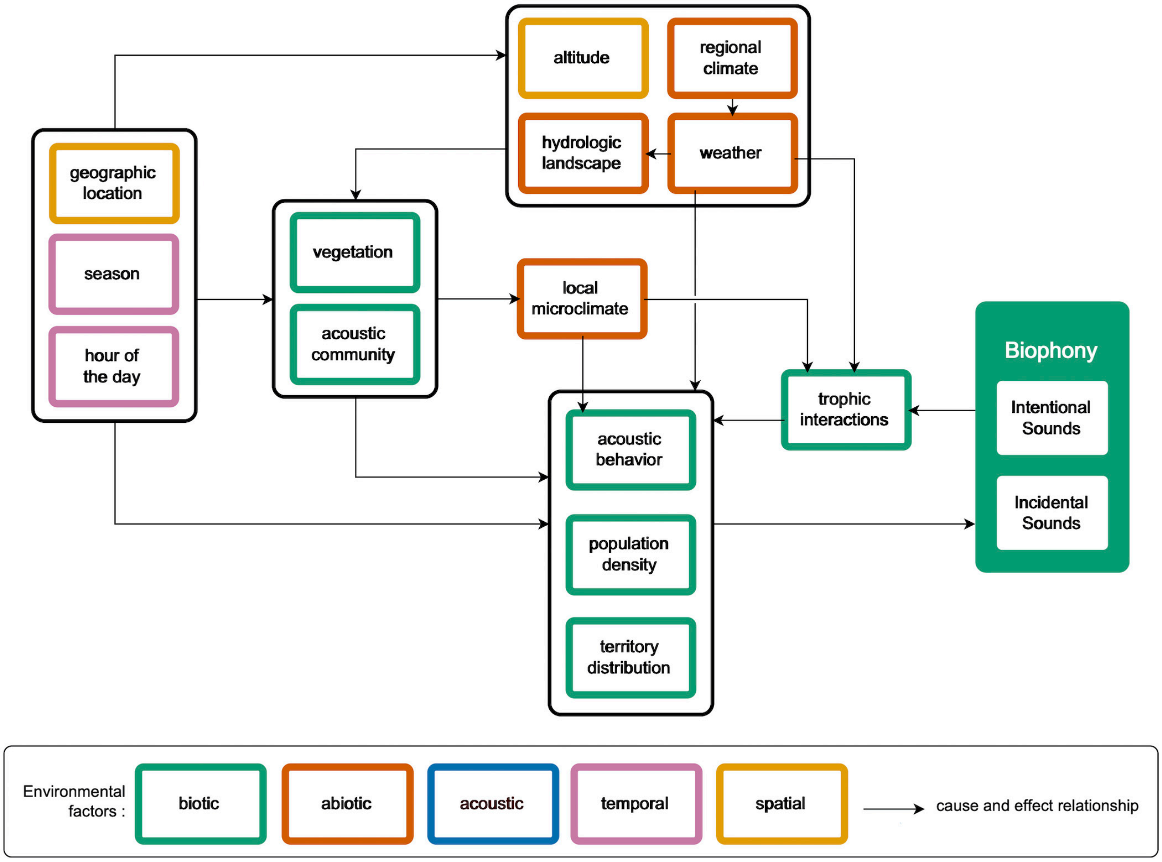

FIGURE 3 | Detailed soundscape functional block diagram: focus on biophony.

A receiver can be an animal, including a human, or a machine, in particular a microphone. The characteristics of the receiver include observational condition and transduction. Here, we consider the receiver as a passive observer of the soundscape. Consequently, the receiver does not retroactively act on factors, nor does it influence the sound sources.

Observation conditions consist of the position, orientation, structure (e.g., head, neck and torso for humans) and movement of the receiver's body.

Transduction is constrained by the amplitude dynamic range, integration time and frequency response of the transducer. Each species and each individual may have specific transduction properties.

BUILDING OPERATIONAL DEFINITIONS

Operational definitions are warranted to specify the scientific value and usefulness of the soundscape concept. Such definitions should allow to formulate qualitative and quantitative hypotheses and predictions that could guide scientific investigations through experimental designs (Popper, 1959). As indicated below, we adopted a source-receiver approach and distinguished between different categories of soundscape events according to the configuration and nature of the potential receivers and their relationship to sound sources. Each category represents a different kind of possible semantic relationship to the soundscape and the three categories should be considered as complementary rather than contradictory (**Figure 5**).

Three Categories of Events

During the construction of the FBD, the question of the specific placement of "soundscape" arose several times. The soundscape was first placed after the receiver, implying that the soundscape was the result of the recording or perception of filtered sound signals. However, this choice seemed unsatisfying because of its inconsistency with other soundscape definitions such as Pijanoswky's one. Three potential locations for the soundscape concept were identified on the diagram: (1) in the area of biophony, geophony and sound propagation blocks, (2) before the receiver block, and (3) after the receiver block. The first location corresponds to Pijanowski's definition and consists of an "external" but purely theoretical event. The second location is similar to Barchiesi's definition, consists of an "external" event that is not theoretical and represents the sonic information that is transformed by the environment but not yet recorded by a microphone or perceived by an observer. The third location corresponds to Farina's definition where the soundscape is more

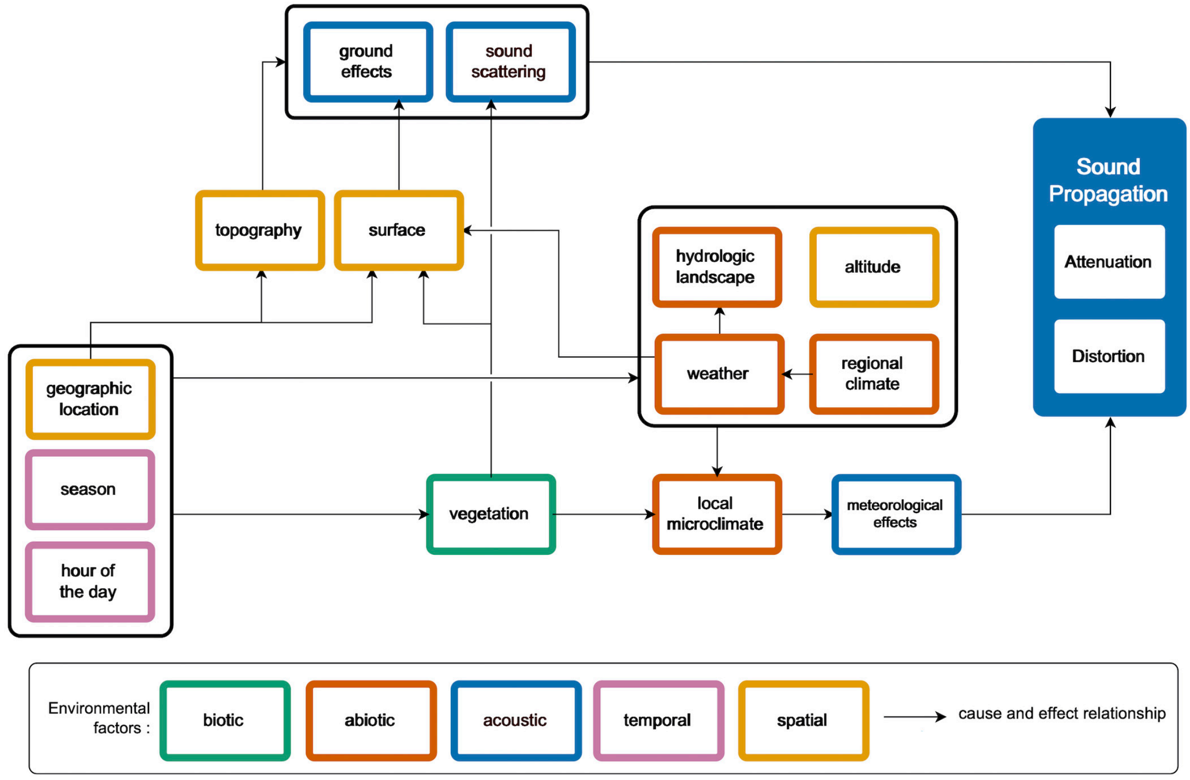

FIGURE 4 | Detailed soundscape functional block diagram: focus on sound propagation.

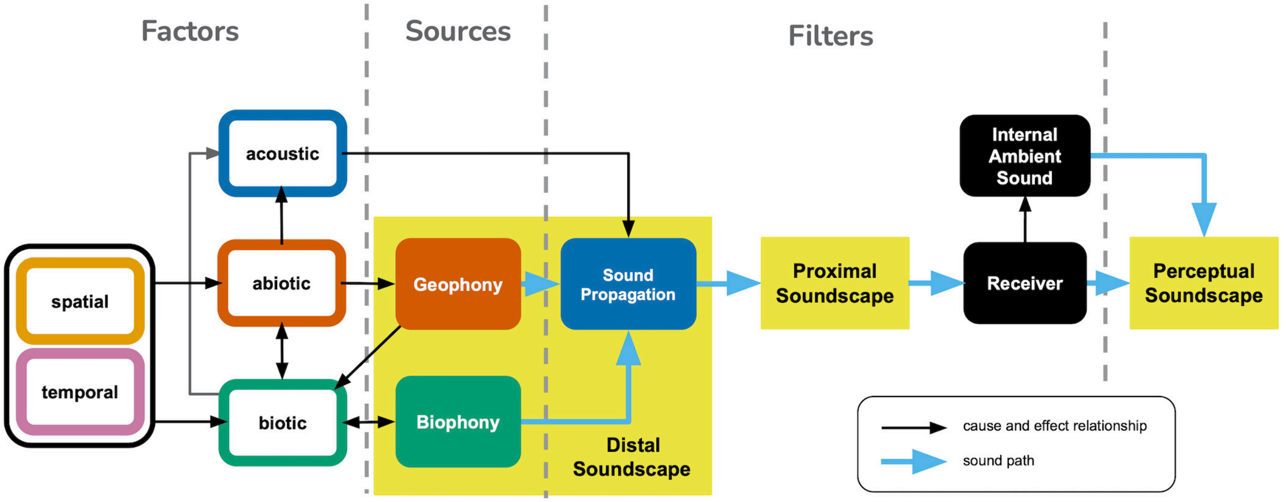

FIGURE 5 | General soundscape functional block diagram. The distal soundscape is closer to environmental factors and their influence on sound production and propagation. The proximal soundscape is located just before the receiver and represents an ideal point of observation which includes external ambient sounds. The perceptual soundscape is the soundscape representation that the receiver progressively builds through its psychoacoustic apparatus. Compared to **Figure 1**, the "internal ambient sound" block was added in order to clarify the perceptual soundscape category.

subjective and consists of an "internal" event that can be attributed to a perceptual representation.

Farina et al. (2021) were the first to differentiate soundscape categories that they called "soundscape epithets." The latent soundscape is "a portion of vibroscape that is not perceived by a particular individual as sound but that can be heard by others." This concept (or any equivalent) does not seem to be included in ecoacoustic research yet. The sensed soundscape is "the portion of the acoustic information that a particular organism is sensitive to but are not necessarily integrated into a physiological or behavioral reaction." Finally, the interpreted soundscape is "the subset of soundscape that makes a difference to the organisms." This distinction between sensed and interpreted soundscape matches, to some extent, the hierarchy made by psychophysicists between low-level (i.e., sensory) and high-level (i.e., cognitive) processing stages. However, these soundscape epithets do not integrate the external-oriented uses of the soundscape concept. This led us to believe that there was a need to introduce a different operational categorization of the soundscape concept, aimed at discriminating the different usages present in the literature.

In the second half of the 20th century, psychologists and philosophers made the distinction between distal, proximal and perceptual events. A distal event is an event as it is produced at the source, far from the observer. A proximal event is an event as it arrives at the receiver and after it has been altered by its propagation from the distal location. Finally, a perceptual event is an event as it has been processed by the observer to link successive proximal events into a singular interpretation (Cooper, 1992). We followed this three-fold partition to divide the soundscape concept into three separate categories. This opened the possibility to draw a parallel between previous soundscape definitions and a new nomenclature of soundscape into distal soundscape, proximal soundscape and perceptual soundscape.

The Distal Soundscape

Landscape ecology, which can be considered as a parent of soundscape ecology, studies ecological invariant patterns of interest that emerge from a collection of singular events (McGarigal and Urban, 2001). Since a landscape event cannot be assimilated to a singular signal, it would be more accurate in this context to consider a soundscape event as a collection of sound signals in a prespecified area. This spatial and temporal distribution of sound signals is theoretical because no observer can receive at the same time the total acoustic information that occurs in a given area. It is the collection and identification of invariant spatial and temporal patterns, such as the bird dawn chorus, that gives external clues about the soundscape dynamics. Consequently, when we consider the soundscape as the acoustic equivalent of the landscape, we consider the distal soundscape.

This definition can still be seen as vague because the acoustic scale of the sound signals has not been defined. Should the sound of a worm moving in the soil be considered when studying the distal soundscape at the scale of vertebrates? Or more generally, what is the time period used to study the distal soundscape? The patterns that soundscape ecologists observe only occur at a specific time, frequency and amplitude range, which is often implied but rarely stated. These ranges define the acoustic scale of the distal soundscape and complete the spatial scale of the defined area. However, the acoustic scale is altered by acoustic factors which will alter the accessibility of sound information (cf. section "Sound Propagation"). In contrast with conventional distal events, the distal soundscape should therefore encompass sound propagation in order to correctly reflect its complexity. The distal soundscape is therefore defined as the spatial and temporal distribution of sounds in a prespecified area, in relation to sound propagation effects. When described, a distal soundscape should be associated with a specific time period and a specific acoustic range. This soundscape category can be represented by an acoustic cartography or a thorough description of the sound patterns that occur in a specific area.

The Proximal Soundscape

In visual psychophysics, the "ambient optic array" represents a visual point of observation (Gibson, 2014). Whereas the perception of the ambient optic array (the "visual scene") should change from one observer to another, the ambient optic array remains consistent and represents all the potential information that can be retrieved by any observer at any point in time. Barchiesi et al. (2015) suggested that the acoustic scene could be thought of as an acoustic equivalent of the ambient optic array, but this would be a matter of interpretation. In order to clarify this, we suggest using the notion of proximal soundscape in this context. Where the distal soundscape requires the survey of all the potential effects of sound propagation that can occur on a given area, the proximal soundscape is the effective filtering of these sound signals at one point in space. Although there is only one distal soundscape for a given area, there is a multiplicity of proximal soundscapes occurring in the same area, corresponding to every potential receiver position. The proximal soundscape is therefore defined as the collection of propagated sound signals that occurs at a specific point in space. This soundscape category can be represented by an "ideal" recording with a limitless acoustic scale (cf. section "The Distal Soundscape") and no internal ambient sound (cf. section "Ambient Sounds").

The Perceptual Soundscape

A perceptual event consists of acquiring proximal events through time and/or space, and linking them into a dynamic "internal" representation. Consequently, a perceptual event is a subjective representation built by the observer, suited for a given task, in order to make sense of the acquired information. For any living observer, the analysis of a proximal soundscape involves multiple sensory and cognitive processes operating in a sequential and/or parallel fashion. These processes (or computations) take time. Some are automatic and fast, and others are more controlled and slow (see Neuhoff, 2004). Over the past century, research in auditory psychophysics, neuroscience and cognitive psychology has shown that the auditory processing of complex acoustic mixtures such as proximal soundscapes requires – among other things – the segregation of these scenes into "streams" or "auditory objects" on the basis of simultaneous and sequential grouping mechanisms (e.g., Bregman, 1990; Moore and Gockel, 2012; Młynarski and McDermott, 2019), and the computation of acoustic attributes such as pitch, loudness, timbre and dynamic patterns (e.g., Moore, 2012; Thoret et al., 2020). Auditory processing of proximal soundscapes also involves bottom-up attentional processes that enhance the sensory representation (the "salience") of certain acoustic events (these events "pop out"; Kayser et al., 2005; Huang and Elhilali, 2017; Filipan et al., 2019) as well as memory and decision processes. Recent work in brain imaging (Irwin et al., 2011) reveals the existence of two distinct neural processing pathways recruited by soundscapes: (i) an auditory bottom-up analysis pathway (from the auditory periphery to the cortical centers) and (ii) an emotional processing pathway involving two central structures well known in emotional response. The observer eventually constructs a more elaborate "cognitive representation" that results from deeper (e.g., semantic) processing. This cognitive representation may finally be stored in episodic and semantic autobiographical memory (e.g., Tekcan et al., 2015).

Since there is a multiplicity of proximal soundscapes, there is an infinite number of perceptual soundscapes, depending on the receiver's nature, observation conditions and processing stages. The perceptual soundscape is therefore defined as the individual subjective interpretation of a proximal soundscape. This soundscape category can be represented in many ways depending on the processing stage that is considered.

APPLICATIONS AND IMPLICATIONS

In this section, we propose applications of the distal, proximal and perceptual soundscape concepts. Each application refers to the global functional diagram (**Figure 6**).

Soundscape Recordings

Soundscape recordings are the fundamental material of soundscape ecology and ecoacoustics. Microphones receive a proximal soundscape that is then transformed by an analog to digital converter into a digital audio file. The digital signal is afterward converted into a given numerical representation thanks to specific mathematical operations. This can lead to different visual representations including waveforms, amplitude spectra, or spectrograms.

Due to the holistic dimension of distal soundscapes, it is not possible to consider a unique point of recording as an accurate reproduction of a distal soundscape. In other words, an infinity of soundscape recordings is theoretically required to properly assess a distal soundscape. Consequently, the use of the expression "soundscape recording" in this context can be inappropriate. However, it is reasonable to assume that a limited set of recordings provide a partial approximation of the distal soundscape and can be defined as a "distal soundscape recording." Despite the fact that such apparatus could not encompass all the sounds that occur in a given area, the identification of sound patterns across recordings can give general but useful clues about spatio-temporal sound dynamics (e.g., Rodriguez et al., 2014).

For proximal soundscapes, soundscape recordings can be considered as an approximation of the absolute sonic object that proximal soundscapes represent. Since soundscape recordings are limited by their acoustic scale (cf. section "The Distal Soundscape"), it is important to note that soundscape recordings give an incomplete representation of the information available at a given point of observation. Soundscape recordings are often limited to the audible frequency range of humans, 20 Hz to 20 kHz, missing potentially important information in the infrasonic and ultrasonic domains.

With regard to perceptual soundscapes, soundscape recordings convey acoustic information that stimulates the sensory organ (e.g., the cochlea for humans) but only a fraction of it is taken into account by the sensory system of the observer, each species showing a unique "listening bandwidth" and spectro-temporal resolution. For those reasons, soundscape recordings should not be confused with perceptual soundscapes, even with "low-level" perceptual representations.

Consequently, any subsequent processing stage of the former soundscape recording, whether it is sonic or numerical, can also be seen as some form of soundscape recording or representation. This is why the use of "soundscape recording" in this context should be accompanied by the explicit soundscape category in question, that is "distal soundscape recording" or "proximal soundscape recording". When referring to the subjective experience, the term "perceptual soundscape" should be used.

Distal Soundscapes and Temporal Patterns

As presented in **Figure 5**, the distal soundscape is the soundscape that is the least affected by filtering processes, which allows the study of sound sources and their relationship with environmental factors. Distal soundscape can therefore be useful to reveal the processes that drive the diel and seasonal patterns of biophony and geophony. If we take the example of a temperate cold forest, diel patterns can be predicted by assessing the relationship between biotic factors such as birds' circadian rhythms and temporal factors such as moon and annual cycles. As shown in Grinfeder et al. (2022), yearly patterns can be predicted by combining biotic factors such as vegetation seasonal cycle and weather abiotic factors such as temperature, snowfall, rainfall and wind. In this study, the description of invariant features (i.e., the periodicity of a selection of acoustic sources) in a specific area (i.e., the same habitat) were used as evidence for the description of the forest's distal soundscape dynamics.

Proximal Soundscapes and the Listening Experience

Whereas distal soundscapes are often used to describe sounds at an ecological scale, proximal soundscapes are usually considered as means to change the individual experience of the sonic environment. The work of Bernie Krause consists of recording natural non-anthropogenic environments in order to study their composition and reproduce the sonic, subjective experience of listening in non-anthropogenic areas through soundscape composition (Krause, 2015). Here, the task focuses not on studying the ecological dynamics of the soundscape but on using observation points as references to produce a work of art to share with an audience. The information that is retrieved from these references is the type of sound sources (geophony and biophony), as well as potential sound propagation effects if needed. Since soundscape composition aims at inspiring "environmental listening awareness" (Westerkamp, 2002), soundscape composers allow themselves to take creative liberties. However, linking sound sources and acoustic filters to the corresponding environmental factors could help building

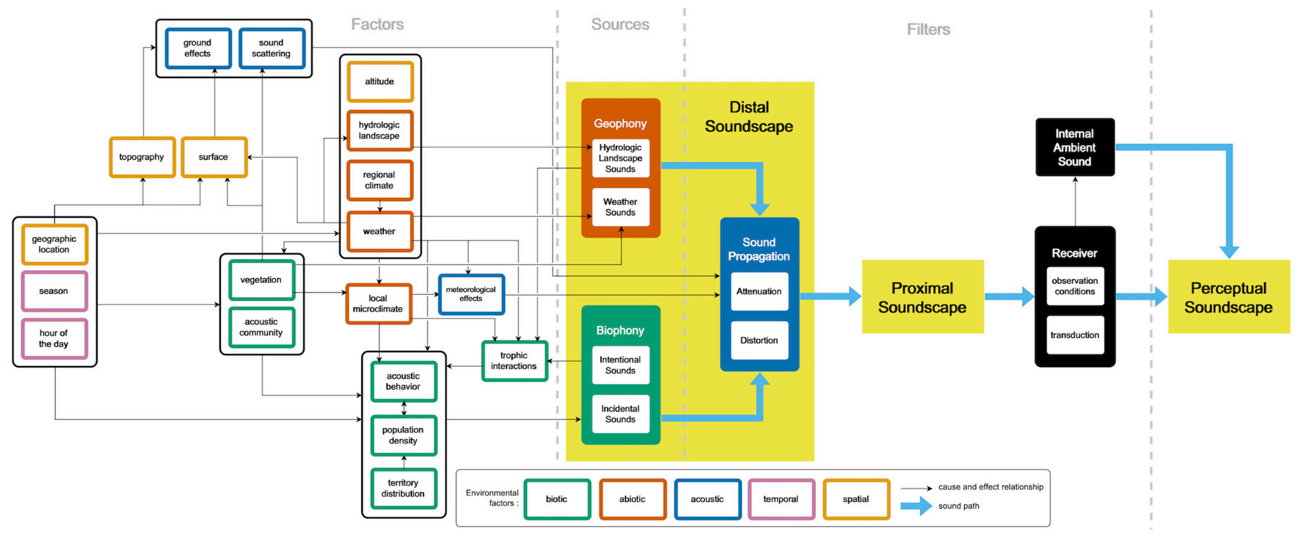

FIGURE 6 | Detailed soundscape functional block diagram. The complex entanglement of the different types of environmental factors reveals the underlying complexity of soundscapes. This diagram can be used as a graphical display of current soundscape related knowledge, or as a tool to evaluate the potential impact of environmental change on non-anthropogenic terrestrial soundscapes.

proximal soundscape "reconstructions", which are consistent with validated ecological knowledge. The reconstruction of proximal soundscapes could then be improved, going beyond the raw superposition of bird song recordings (Gasc et al., 2015; Zhao et al., 2019; Morrison et al., 2021). Such a tool would provide a new kind of ecoacoustic ground-truth that may be useful to rigorously evaluate biodiversity indexes among others.

Perceptual Soundscapes

Tympanic ears appeared about 210–230 million years ago (Grothe and Pecka, 2014). It is thus reasonable to assume that through selective adaptation, the auditory system of many species has evolved to develop and optimize a capacity to analyze soundscapes, efficiently detect biological sound sources and discriminate levels of biodiversity in close environments (e.g., Webster et al., 2017). Indeed, soundscapes provide crucial information about potential resources, preys, predators, mates and habitat structure.

As discussed in section "The Perceptual Soundscape," the existence of a multiplicity of perceptual processing stages within the observer's auditory and cognitive system makes the conception of a singular comprehensive example of perceptual soundscape difficult. In addition, the understanding of perceptual soundscapes has more often been the source of speculations based on landscape ecology, such as the hypothesis of the "cognitive soundscape" (Farina, 2014; Barchiesi et al., 2015), rather than a source of objective data production. Cognitive psychology and neurosciences can be used to draw operational hypotheses aiming to assess basic aspects of soundscape perception and test the respective roles of low- and high-level auditory mechanisms (Theunissen and Elie, 2014). For instance, are we humans able to discriminate between soundscapes associated with distinct habitats - which represent a specific combination of environmental factors - or temporal factors such as seasons or moments of the day? The answer is probably "yes" but information about the capacities of human listeners is clearly lacking. Many other questions arise. Are biological sound sources processed differently from geophonic sound sources? To which extent are we able to distinguish levels of biodiversity with our ears? These questions among others pave the way for an entirely new research program in the cognitive sciences of audition.

CONCLUSION

Despite the ambiguity that the soundscape concept has been carrying since Schafer's seminal work, there is an opportunity to distinguish three distinct but complementary categories. The distal soundscape is the spatial and temporal distribution of sounds in a prespecified area, in relation to sound propagation effects. The proximal soundscape is the collection of propagated sound signals that occurs at a specific position in space. The perceptual soundscape is the individual subjective interpretation of a proximal soundscape. By explicitly clarifying soundscape definitions, we hope to make soundscape ecology more operational. The soundscape, which is often summarized as a simple collection of individual sounds, underlies a complex association of sound sources and acoustic filters that are affected by an array of environmental factors. We hope that the graphical display of these relationships can help ecologists and environment managers to formulate relevant scientific hypotheses, anticipate the ecoacoustic impact of anthropogenic and non-anthropogenic environmental changes and guide conservation policies.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

EG designed research, conducted the literature review, developed the conceptual framework, and the qualitative model. CL, SH, and JS contributed to the conceptual framework and the qualitative model. All authors wrote the manuscript.

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