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Do acoustic indices correlate with bird diversity? Insights from two biodiverse regions in Yunnan Province, south China

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ABSTRACT

Human activities are affecting biodiversity to a greater extent than ever. Consequently, tools that can efficiently monitor changes in communities are becoming increasingly important. In the case of birds and other vocalizing animals, it has been suggested that passive acoustic methods can be used for this purpose. Multiple acoustic indices have been developed recently, to be used as proxies for species diversity. Preliminary results have been promising. Yet, before the indices can be applied widely, it is necessary to understand better how well they reflect the communities to be monitored, and how they perform under diverse environmental conditions. Here, we tested seven of the available indices, on sound recordings made in two biodiverse regions in Yunnan Province, south China. We assessed each index's performance by measuring its correlation to bird species richness and diversity, estimated using point-count surveys. Each survey was conducted by an expert observer, at the same time each recording was made, and for the same duration. We also tested whether the performance of the indices was affected by levels of environmental dissimilarity between the sites sampled. We found that although no index showed a very strong correlation with species richness or diversity, three indices (the acoustic entropy, acoustic diversity and acoustic evenness indices) performed consistently better that the other four, showing moderate correlations. The levels of environmental dissimilarity among the sites did not seem to affect the performance of any of the indices tested, suggesting consistency − an important property for the indices to have. We conclude that although the acoustic indices have the potential to be used for passive acoustic monitoring, perhaps they need to be refined further before they can be applied widely. Meanwhile, they should be tested in more environments to reveal fully their potential and limitations.

1. Introduction

Humans are modifying landscapes at unprecedented rates, often with detrimental effects on biodiversity (Sala et al., 2000). To assess the extent to which species are affected by it is important to develop reliable monitoring tools that can cover large temporal and spatial scales at a low cost. Recent advances in the field of ecoacoustics (Sueur and Farina, 2015) suggest that for vocalizing animals, these monitoring requirements could be realized using acoustic methods (Acevedo and Villanueva-Rivera, 2006; Bardeli et al., 2010; Depraetere et al., 2012; Tucker et al., 2014; Borker et al., 2015; Roca and Proulx, 2016).

Acoustic methods have been already used successfully to answer a range of ecological and conservation questions (Laiolo, 2010; Blumstein et al., 2011; Sueur et al., 2014; Sueur and Farina, 2015; Grant and Samways, 2016). For example, they have been used to map the occupancy range and territory of chimpanzees and birds (Furnas and Callas, 2015; Kalan et al., 2015; Kalan et al., 2016), to study the behaviour and estimate the abundance of elephants (Wrege et al., 2017), to assess the species richness of insect communities (Roca and Proulx 2016), to study how individual birds use habitat (Kirschel et al., 2011), and to estimate bird diversity (Celis-Murillo et al., 2009; Sedlacek et al., 2015). Indeed, much of the recent research in acoustic methods has been focused on birds (Gasc et al., 2016), for multiple reasons: birds are abundant and therefore are part of most acoustic communities (Bardeli et al., 2010), many birds vocalize prolifically and thus can be captured easily by the acoustic sensors, and birds provide many ecosystem services and are

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thus good indicators of ecosystem health (Sekercioglu, 2006).

Acoustic methods have obvious advantages over the traditional surveying methods since acoustic devices can potentially collect data for longer periods, in a less intrusive way, and at a lower cost (Bardeli et al., 2010). In some cases, comparisons have shown that acoustic surveys can be more accurate than traditional surveys, as researchers have been found to detect more species when listening to the sounds in the laboratory than when surveying the birds in the field (Celis-Murillo et al., 2009). The methods of measuring biodiversity acoustically generally follow two directions. The first has been concerned with the identification of different species, often those with very distinct calls, through computer aided signal processing. This approach generally requires the compilation of a library of bird songs from the species of interest, and the development of pattern recognition algorithms, which identify the acoustic fingerprints of those species. This method, thus far, has been applied only to a small number of species (Bardeli et al., 2010), and unfortunately it can quickly become impractical for monitoring whole communities, when a large number of species needs to be considered.

The second direction for evaluating biodiversity acoustically aims at estimating the richness of a community, without the identity of the species being consequential. It is based on the assumption that higher species richness translates into higher acoustic complexity (Sueur et al., 2014). Hence, by measuring the complexity of an acoustic community one can infer the diversity of the community. However, processing large amounts of acoustic data remains a challenge. One way the data can be processed is by having experienced ornithologists listen to the sounds, or segments of the sounds (Zhang et al., 2016) to identify the species recorded. Processing the acoustic data in the laboratory, however, often takes longer than it would take if surveys were conducted in the field (Wimmer et al., 2013). Moreover, the retained dependency on experienced observers maintains the risk of measurement bias and keeps the survey costs high. Consequently, to unlock the full potential of acoustic monitoring methods, it is useful to develop efficient automated processing techniques.

Automated techniques for estimating diversity can be technically challenging for multiple reasons: species vocalizing simultaneously make the task complicated (Zhang et al., 2016), often unwanted sounds mask the species to be recorded, and spatial and temporal variations in the geophysical conditions of an area affect the characteristics of the recordings (Darras et al., 2016). In spite of the difficulties, several attempts have been made to develop algorithms that measure the diversity of an acoustic community, with promising results (Sueur et al., 2014). For example, Boelman et al. (2007) developed the bioacoustic index (BIO), which estimates acoustic complexity by measuring variations in signal intensity (amplitude). The index was tested in a reserve in Hawaii and was found to correlate with the abundances of birds (Boelman et al., 2007). Sueur et al. (2008b) developed the acoustic entropy index (H), which is the product of the spectral and temporal entropies of the recorded sounds, measured using the Shannon-Wiener diversity index. They tested the index at two coastal forests in Tanzania and found that it correlated (logarithmically) with the number of vocalizing animal species (Sueur et al., 2008b). Similarly, Depraetere et al. (2012) introduced the acoustic richness (AR) index. Depraetere et al. (2012) noticed that in regions with low signal-to-noise ratios (e.g., temperate regions with low species diversity and high anthropogenic noise), the inclusion of the spectral entropy may result in biased results (Depraetere et al., 2012). Therefore, they based the acoustic richness index on the temporal entropy of the sound, while also taking into account the overall amplitude (Depraetere et al., 2012). The index was tested in three woodland habitats in a protected area in France and was found to correlate positively with the species richness of birds (Depraetere et al., 2012).

Villanueva-Rivera et al. (2011) developed the acoustic diversity index (ADI), which similarly to the acoustic entropy index uses the Shannon-Weiner index to estimate acoustic complexity. ADI divides spectrograms into multiple frequency bands and calculates the diversity in the proportions of each band occupied by sounds above a certain amplitude threshold, usually −50 dB relative to full scale (dBFS). The same information is used to calculate the acoustic evenness index (AEI), also developed by Villanueva-Rivera et al. (2011), which is measured using the Gini coefficient, and is therefore negatively related to ADI (Villanueva-Rivera et al., 2011). Pieretti et al. (2011) added the acoustic complexity index (ACI), which estimates the diversity of an acoustic community by measuring the variations in intensities within a recording, based on the assumption that animal sounds, unlike anthropogenic noises, usually vary considerably in sound intensity. The index divides recordings into multiple frequency bins and temporal subsets, and calculates the differences in the intensities of adjacent sounds, with the final ACI value being the grand total of those differences. The index was tested in a national park in northern Italy and was found to correlate with the number of bird vocalizations. Kasten et al. (2012) introduced the normalized difference soundscape index (NDSI), which although not designed to assess the levels of animal diversity, but instead to measure anthropogenic disturbance (by calculating the ratio of anthropogenic sounds to sounds generated by biological organisms), was found to correlate with the presence of birds (Fuller et al., 2015).

Despite these promising results, before the indices can be widely adopted for monitoring purposes, it is important to understand better how accurately they reflect the communities to be monitored, and how they perform under diverse environmental conditions. The indices are all relatively recent, and thus only a handful of studies have assessed their efficacy to date. In one of those studies, Fuller et al. (2015) found that out of all the indices they tested − in a fragmented forested landscape in Australia − H and NDSI correlated the most with the species richness of birds. Machado et al. (2017) measured several of the above indices in a protected area in Central Brazil and found that although NDSI did not correlate strongly with bird species richness, it reflected well the presence of anthropogenic disturbance. Machado et al. (2017) also found the ADI was the most appropriate proxy for the bird species richness in their area. Harris et al. (2016), who also tested some of the same indices but in a marine environment, found that H and ACI were good proxies for the biodiversity in fish reef communities.

Currently, it is uncertain how widely applicable and consistent these relationships are. Furthermore, it is unclear to what extent dissimilar levels of abiotic and biotic conditions affect the efficacy of the indices. For example, the acoustic entropy's logarithmic relationship to species richness suggests that the index's efficacy may be reduced in highly diverse areas. Different conditions affect not only the number of species present and their vocalizations, but also the acoustic properties of an area (Darras et al., 2016). Therefore, the question arises whether the scale of the survey influences which index is most applicable: specifically, should it matter whether the survey is all conducted within a small area, or whether different environments with different bird communities are sampled over a wider region? Here, we tested the acoustic entropy, acoustic diversity, acoustic evenness, acoustic richness, acoustic complexity, bioacoustic index, and NDSI at two forested and highly biodiverse regions in Yunnan Province, in south China, located approximately 290 km apart and at different elevations. We measured each index's correlation to bird species richness and diversity, estimated using conventional point-count surveys conducted by an expert observer at the same time as the recordings. Further, we tested whether the indices perform better when the analysis included only samples with similar environments and similar species compositions, compared to analyses in which samples with dissimilar environments and compositions are also included. The selected study regions provide optimal conditions for answering these questions, as they capture a wide range of environments due to their large altitudinal and land-use gradients, and host a large number of species. Earlier applications of the indices involved mostly small scale, low-diversity systems.

2. Methods

2.1. Study regions and sites

We conducted this study in two regions of Yunnan Province, the province of China that has the most biodiversity (Yang et al., 2004). The first study region was located in the Xishuangbanna Dai Autonomous Prefecture, the most southern prefecture of Yunnan, within a 15 km radius from the Xishuangbanna Tropical Botanical Garden (XTBG, 21°55′N, 101°15′E), a research center of the Chinese Academy of Sciences (CAS) that is located in the town of Menglun. The landscape consists of rubber plantations with some small fragments of tropical rainforest and some larger protected reserves. Surveys in this region were carried out at forty-seven of the study sites established by Liu and Slik (2014), in which they studied the effects of forest fragmentation on trees. Sites were located within 23 forest fragments of varying sizes, ranging from 0.9 to 13872.9 ha; elevation ranged from 541 and 1477 m asl.

The second sampling region was located in Jingdong County, of Yunnan Province, within a radius of 10 km from the Ailaoshan Station for Subtropical Forest Ecosystem Studies (24°32′N, 101°01′E), also a CAS research station, situated within the Ailaoshan National Nature Reserve. The landscape is dominated by subtropical primary forest, although there are scattered patches of secondary forest, as well as patches of forests dominated by pine trees (*Pinus yunnanensis* and *Pinus kesiya var. langbianensi*), and also farmlands nearby. To ensure that the performance of the indices was tested in diverse environments, fifty study sites were selected belonging to four different land-use types: fifteen sites were located in relatively undisturbed forest, twelve sites in disturbed broadleaf forest, thirteen in pine forest, and ten in farmlands. The elevation ranged from 1570 to 2616 m asl. Pine forest sites dominated the lower elevations (< 2020 m asl), while relatively undisturbed sites occurred at higher elevations (> 2390 m asl).

2.2. Data collection

To ensure that the acoustic data were directly comparable to the data collected using the point-count surveys, we made the recordings at the same time as observing the birds. SKD was the observer at Xishuangbanna and LK was the observer at Ailaoshan. Both observers had experience in identifying birds in their regions of more than two years and hence were experts about the respective avifaunas. During the point-count surveys, all individuals heard or seen within a 15-min time period and a radius of 50 m were recorded and identified to the species level. The acoustic data were recorded using an omnidirectional microphone (Sennheiser ME62), mounted on a tripod at breast height and placed next to the observer, attached to a Marantz Professional recorder (Model PMD 661), at a sampling rate of 44.1 kHz (16 bits, one-channel). The data were saved in a waveform audio file format (wav). The microphone was switched on the moment the point-count survey commenced, and switched off, 15 min later, when the survey ended.

Each site at Xishuangbanna was surveyed twice, once during the wet season and once during the dry season, resulting in 94 samples. The wet season survey was carried out between June and August 2014, and the dry season survey between November and December of 2014. Each site at Ailaoshan was surveyed once, in November of 2015, resulting in 50 samples. In total, 144 samples were collected at 97 sites (Table 1). At both regions, the minimum distance between the sites was 250 m. All surveys were conducted in the morning, between 07:00 and 10:45 AM, when the birds were most active. Upon arrival to the site, observers waited two minutes before they started each survey, to minimize possible bias due to disturbance.

2.3. Data analysis

Data were analysed using the R programming language (R Core Team, 2016). The bird species richness was calculated using the *specnumber* function in the "vegan" package (Oksanen et al., 2016). The diversity was calculated using the *diversity* function, in that same package, and using Shannon-Weiner index. All acoustic indices, except AR and ACI, were calculated using the *multiple_sounds* function in the "soundecology" package (Villanueva-Rivera and Pijanowski, 2016), using the default settings. ADI's and AE's default maximum frequency is set to 10 kHz, while the size of the frequency bands is set to 1 kHz. The maximum frequency of the BIO index is set to 8 kHz, while its minimum frequency is set to 2 kHz. In the case of NDSI, anthropogenic sounds are defined as all sounds between 1 and 2 kHz, while biological sounds as those between 2 and 11 kHz. AR and ACI were calculated using the corresponding functions (*AR* and *ACI*) in the "seewave" package (Sueur et al., 2008a). In *AR*, the default settings were used. In *ACI*, which allows for frequency limits to be set, the frequency was set between 2 and 10 kHz to mirror the settings of most of the other indices. To measure the correlations between each index and the bird species richness and diversity, the Pearson's correlation coefficient was used. Analyses were run separately for each region and season (i.e. Xishuangbanna wet season, Xishuangbanna dry season, and Ailaoshan), resulting in six correlation values for each index tested.

Table 1
Number of samples collected in each region, categorized according to the sites' environmental similarity. There were 47 sites at Xishuangbanna and 50 sites at Ailaoshan. Sites at Xishuangbanna were surveyed twice, once during the wet season and once during the dry season, while sites at Ailaoshan were surveyed once, resulting in 144 samples in total.

Xishuangbanna				Ailaoshan		
Size	Fragments	Sites	Samples	Habitat	Sites	Samples
Small	14	17	34	Relatively undisturbed forest	15	15
Medium	6	15	30	Disturbed forest	12	12
Large	3	15	30	Pine forest	13	13
				Farmland	10	10

For the second part of the analysis, in which we compared each index's performance in similar vs. dissimilar environments, we first grouped the sites into categories based on their environmental similarity (Table 1). Sites at Ailaoshan were grouped according to their land-use type, and sites at Xishuangbanna according to the size of their fragment. In Xishuangbanna, fragments of dissimilar size had different environmental conditions because of differences in plant composition, canopy height, and structural complexity (SKD, personal observation). To capture these environmental differences, we grouped fragments into three categories: small (< 100 ha, n = 17 sites), medium (100 ha < x < 1000 ha, n = 15 sites) and large (> 1000 ha, n = 15 sites). To ensure that the fragments selected for this part of the analysis were most distinct, we removed all sites located in medium sized fragments. In total, there were 82 remaining sites, resulting in 114 samples, representing six different environments (i.e. in Ailaoshan, relatively undisturbed forest, disturbed forest, pine forest, farmland; in Xishuangbanna, small fragments, and large fragments).

Using the 114 samples, we created six datasets of incrementally increased environmental dissimilarity. Each dataset was composed of one hundred sets, and each set consisted of ten separate, randomly selected, samples. In the most environmentally similar dataset, each set was drawn only from samples that belonged to the same type of environment. For example, the first set could be made of ten samples all collected in small fragments, while the second set could be made from ten samples all collected in pine forest. The other datasets differed in that the sets could be made from samples in different environments, with the number of environments increasing for each dataset: the sets in the second dataset could be made of samples that belonged to two environments, and so forth, until the sixth dataset, which could draw on samples from any of the six environments. To generate each of the hundred sets, in each dataset, we followed a two-step process. First, we randomly selected from which environments the samples would be drawn from − following the appropriate rules for the dataset as to the number of environments − and then we randomly selected ten samples from those specific environments. This process ensured that not all of the hundred sets, in each dataset, would come from the same combinations of environments. We chose to limit our number of samples within each set to ten, because a higher number would have prevented us from having samples from one environment only. For example, there were only ten farmland sites; similarly, other land-uses had a small number of sites too.

For each of the generated sets, we measured the Pearson's correlation coefficient between each of the seven acoustic indices and the species richness of birds (as diversity, in the first analysis, had similar results with species richness). To obtain an overall estimate for each acoustic index for each of the six datasets, we averaged the resulting hundred coefficients. To assess the variation in our results, we measured the corresponding standard deviations. To assess the extent to which different environments translated into differences in species composition, we ran a non-metric multidimensional scaling (NMDS) analysis using the *metaMDS* function in the "vegan" package (Oksanen et al., 2016).

3. Results

3.1. Summary of the bird surveys using point counts

In total, 106 bird species were recorded at Xishuangbanna, 78 during the wet season and 92 during the dry season (Supplementary material Appendix A). Out of those, 64 were recorded during both seasons. At Ailaoshan 98 species were recorded in total. 22 species were recorded in both regions (Supplementary material Appendix A). On average, sites at Xishuangbanna had 13.34 species ($s = 3.41$) during the wet season, and 13.32 species ($s = 4.99$) during the dry season. Primary forest sites at Ailaoshan had 10.93 species ($s = 5.12$), secondary forest sites had 11.33 species ($s = 3.08$), pine forests had 11.00 species ($s = 1.83$), and farmlands had 11.80 species ($s = 2.57$).

The results of the NMDS analysis confirmed that Ailaoshan and Xishuangbanna have distinct bird communities (Fig. 1). Moreover, at Ailaoshan there are clear differences in the composition of species across sites belonging to different land-use types. The distinction is not as prominent at Xishuangbanna, although the results do confirm that there is some difference between the compositions of species at sites in small fragments versus those in large fragments.

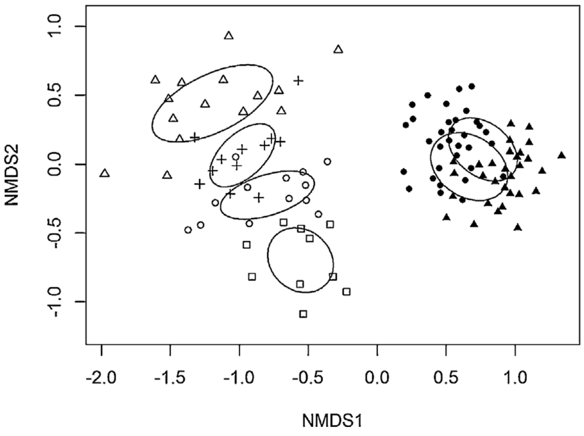

Fig. 1. Results of the non-metric multidimensional scaling (NMDS) analysis, showing the differences in species compositions between the sites at the two regions and within the six environments. Ailaoshan: △ = Relatively undisturbed forest; + = Disturbed forest; ○ = Pine forest; □ = Farmland; Xishuangbanna: ● = Small Fragments; ▲ = Large Fragments. Ellipses represent one standard deviation from the centroid of each environment.

3.2. Indices' performance

Species richness of birds correlated highly with diversity, ranging from 0.84 (at Ailaoshan) to 0.97 (at Xishuangbanna during the wet season). Consequently, their relationships with the acoustic indices were very similar (Table 2). However, the relationships between the acoustic indices and the number of bird species (and diversity) varied considerably depending on the index examined, the region, and the season (Table 2, Figs. 2 and 3 for the relationship between species richness and the indices). Three indices, though, consistently ranked higher than the rest. These were the acoustic entropy, the acoustic diversity, and the acoustic evenness indices (Table 2). Acoustic entropy was the best index, in terms of the strengths of the correlations, in both seasons in Xishuangbanna, whereas acoustic diversity and acoustic evenness were best in Ailaoshan (positive correlation for acoustic diversity, negative for acoustic evenness). The other four indices performed poorly in at least one survey. The correlation between the acoustic richness index and the bird diversity was in all occasions in the opposite direction of that expected (i.e., negative instead of positive). Both the bioacoustic index and the normalized difference soundscape index had poor or negligible correlations during the wet season in Xishuangbanna ($r_{richness} = -0.34$ and -0.01 for BIO and NDSI, respectively; the correlations were in the opposite direction than expected). The acoustic complexity index had a weak correlation in all three surveys ($r_{richness} \leq 0.21$), and was negative for species richness during the dry season in Xishuangbanna ($r_{richness} = -0.03$).

3.3. Differences in index performance between similar and dissimilar environments

When the different levels of environmental similarity were tested, the correlation coefficients between each of the seven acoustic indices and the species richness of birds were very similar, and the corresponding standard deviations were large (Table 3). The substantial overlap between the correlation coefficients of each dataset indicated that there were no significant differences between the different kinds of datasets. As expected from the results in the section above (3.2), the acoustic entropy, acoustic diversity, and acoustic evenness performed better than the other four indices (Table 3).

4. Discussion

Overall, the correlations between the seven indices tested and the bird species richness were lower than what would be expected if the indices were to be used effectively to monitor bird communities. Currently, measuring the diversity of animals using acoustic methods is likely to still require the input of experienced observers, who would have to listen to the recorded sounds and identify the species manually (Darras et al., 2016; Zhang et al., 2016), hence spending a lot of time and effort (Wimmer et al., 2013).

4.1. Indices' performance

Of all the indices examined, acoustic entropy (Sueur et al., 2008b), acoustic diversity and acoustic evenness (Villanueva-Rivera et al., 2011) performed the best. Machado et al. (2017) also found that the acoustic diversity index performed well in their area, and that it was highly correlated with the acoustic evenness and the acoustic entropy indices (the corresponding spearman correlations were −0.999 and 0.703). All three indices divide sounds into multiple frequency bands and involve a measurement of the diversity of the acoustic signal (Sueur et al., 2008b; Villanueva-Rivera et al., 2011), and this is likely to be a key feature to be measured when estimating the complexity of the acoustic communities.

Our results, as far as the acoustic entropy index being among the best performers, are in accordance also with the findings of Fuller et al.

Table 2

The results of the Pearson's correlation analyses, measuring the relationship between each acoustic index and the species richness and diversity of birds at each region and season. Correlations at Xishuangbanna were based on 47 sites, surveyed once during each season, and at Ailaoshan on 50 sites. (W) stands for wet season and (D) for dry season. S stands for avian species richness and H′ stands for Shannon-Weiner avian diversity. H = acoustic entropy index, ADI = acoustic diversity index, AE = acoustic evenness index, AR = acoustic richness index, ACI = acoustic complexity index, BIO = bioacoustic index, NDSI = normalized difference soundscape index.

Region/Season	H		ADI		AE		AR		ACI		BIO		NDSI	
	S	H′	S	H′	S	H′	S	H′	S	H′	S	H′	S	H′
Xishuangbanna (W)	0.51	0.49	0.35	0.36	−0.40	−0.39	−0.46	−0.45	0.21	0.16	−0.34	−0.29	−0.01	−0.01
Xishuangbanna (D)	0.59	0.66	0.55	0.62	−0.54	−0.61	−0.24	−0.24	−0.03	0.06	0.23	0.20	0.54	0.60
Ailaoshan	0.36	0.30	0.56	0.47	−0.57	−0.46	−0.08	−0.10	0.04	0.06	0.37	0.22	0.35	0.27

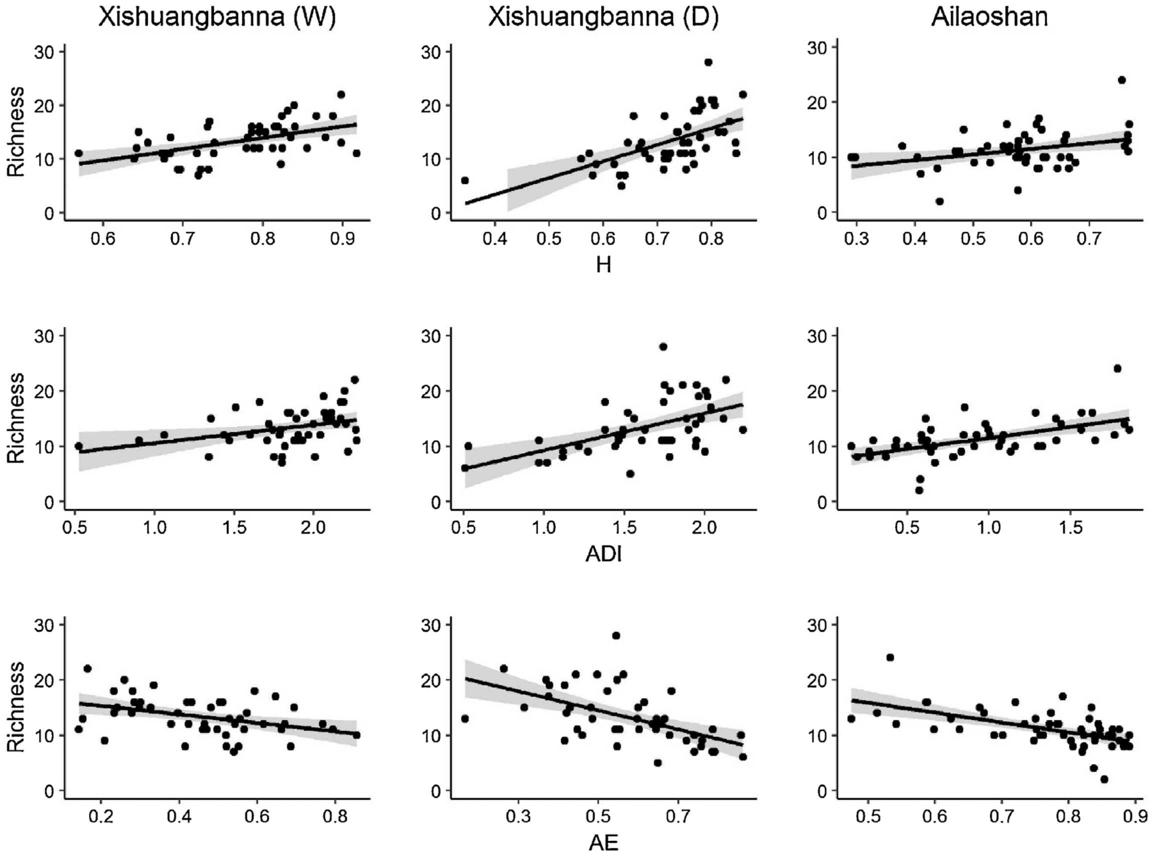

Fig. 2. Scatterplots showing the relationship between the three best performing acoustic indices and the bird species richness at each region and season. Lines represent the linear regression slope and shaded areas indicate the 95% confidence intervals. Abbreviations as in Table 2.

(2015); however, in their study they found that NDSI also correlated with bird presence. In our case, NDSI did not show any consistent patterns. Although the correlation was relative high for the surveys at Xishuangbanna during the dry season, the corresponding correlation for the wet season was much lower and in the opposite direction (Table 2). Perhaps this is because NDSI does not measure species richness per se, and its results depend on the levels of anthrophonies (1–2 kHz) relative to the levels of biophonies (2–11 kHz). Theoretically, varying levels of anthropogenic noise can result in dissimilar NDSI values even when species richness is relatively constant. Contrariwise, relatively larges differences in species richness can result only in small changes in NDSI if the anthropogenic noise does not vary much, and is especially low. Consequently, the index may not accurately reflect the richness of the bird communities under these conditions. This may explain why it can perform imperfectly in some situations, as in our case at Xishuangbanna during the wet season, where most of the NDSI values were clustered around the positive end of the spectrum (the median value was 0.85), indicating very low levels of human-related sounds, but failing to reflect the variation in bird species (Fig. 3).

Surprisingly, the acoustic richness index, which was found to correlate positively with bird species richness in temperate environments (Depraetere et al., 2012), showed the opposite trend in our case. For our data, in general the higher the bird richness the lower the value of this index was (Fig. 3). It should be mentioned that the index was designed for environments with low species diversity and low signal-to-noise ratios. On the contrary, our regions are highly diverse, and although there were some cases of high levels of anthropogenic noise, the signal-to-noise ratio in our recordings is most probably higher than in temperate regions with high human presence.

The acoustic complexity index also performed ineffectively at our sites, although it has been shown to perform well in some other areas (Pieretti et al., 2011). For example, Farina et al. (2011) used the acoustic complexity index to analyse the soundscape of a landscape in Eastern Liguria in Italy, dominated by maqui vegetation, and found that it related to the presence and activity of the birds − although the exact correlation was not assessed. Harris et al. (2016) found that the acoustic complexity index correlated highly with the animal diversity and evenness in reef fish communities. The acoustic complexity index,

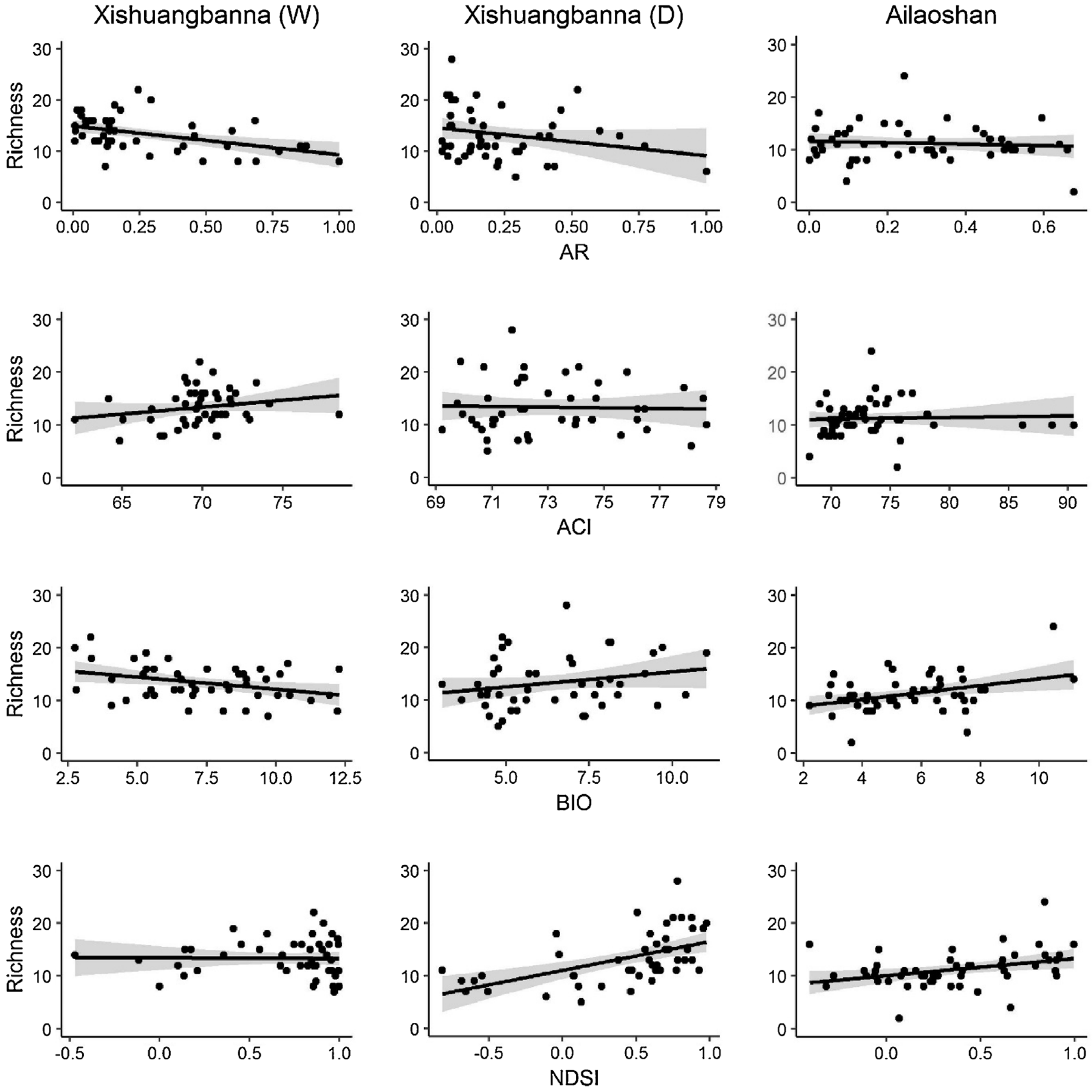

Fig. 3. Scatterplots showing the relationship between the rest of the acoustic indices and the bird species richness at each region and season. Lines represent the linear regression slope and shaded areas indicate the 95% confidence intervals. Abbreviations as in Table 2.

however, is thought to be sensitive to certain anthropogenic noises and geophonies, such wind and rain (Depraetere et al., 2012), and this may partly explain the low correlations in our case. Although we avoided conducting the surveys during bad weather conditions, such as heavy rain, it is likely that our acoustic data have been contaminated to a certain level by geophysical sounds, such as mild winds and drizzles, which could have varying intensities. In addition, some variable anthropogenic sounds may have influenced our results, especially at sites within and near farmlands, near roads, and near human settlements. Yet, these type of conditions are typical of field studies, and probably unavoidable, and therefore for the indices to be used under natural conditions these limitations need to be overcome. Researchers have already emphasized the need for developing algorithms to filter unwanted noise more effectively and/or flag sound segments with low

Table 3
Averaged ($\bar{x}$) Pearson's correlations coefficients and standard deviations (s), showing the relationship between each acoustic index and the species richness of birds when the six datasets of varying levels of environmental similarity were tested. Abbreviations as Table 2.

Number of environments	H		ADI		AE		AR		ACI		BIO		NDSI	
	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s
1	0.40	0.23	0.54	0.16	−0.58	0.18	−0.10	0.34	0.07	0.34	0.19	0.29	0.36	0.31
2	0.44	0.24	0.57	0.16	−0.59	0.18	−0.10	0.34	0.03	0.30	0.22	0.29	0.45	0.29
3	0.39	0.25	0.55	0.18	−0.59	0.19	−0.06	0.33	0.07	0.31	0.22	0.26	0.32	0.34
4	0.40	0.25	0.55	0.17	−0.59	0.18	−0.06	0.35	0.03	0.29	0.23	0.30	0.37	0.32
5	0.40	0.24	0.54	0.16	−0.57	0.18	−0.07	0.35	0.11	0.34	0.23	0.28	0.42	0.32
6	0.43	0.23	0.56	0.17	−0.59	0.18	−0.10	0.37	0.09	0.29	0.20	0.32	0.41	0.32

signal-to-noise ratios (Gasc et al., 2013; Bedoya et al., 2017).

The bioacoustic index correlated only weakly with the bird communities (≤ 0.37) and the correlation was even negative at Xishuangbanna during the wet season. It should be noted here that the algorithm used for the bioacoustic index, available in the "soundecology" package, is a modified version of the original one presented by Boelman et al. (2007), and therefore should not be expected to give the same results (Villanueva-Rivera and Pijanowski, 2016). The index is calculated by estimating the total area under a spectrum curve in an amplitude-frequency plot and relies in differences in the maximum intensities (across all frequencies sampled) to detect differences in animal communities. At our sites, which are very diverse, differences in maximum intensities may not represent accurately differences in species richness. It is also possible that the low correlations can be attributed to some extent to sounds generated by non-avian organisms. Although, the large majority of the vocalizing animals in our samples were birds, they were occasions in which insects were recorded too, such as cicadas (Cicadidae spp.) and crickets (Gryllidae spp.). Machado et al. (2017) also found that the bioacoustic index performed inconsistently.

It is possible that some of the disparity between the results obtained using the seven indices and the point-count surveys is due to covering different acoustic spaces. A key assumption in our study is that the radius covered by the point-count surveys and the microphone was the same (i.e. 50 m). We believe that in forested environments such as ours the assumption is valid. Previous research has shown that acoustic surveys are usually effective within a 50 m threshold (Sedlacek et al., 2015). However, we must acknowledge that there could have been some variation − especially at Ailaoshan where we sampled different types of land-uses − because acoustic spaces have been shown to be affected by land-use types and vegetation structure (Darras et al., 2016).

4.2. Differences between similar and dissimilar environments

Darras et al. (2016) also question whether differences between sites in their environmental and structural characteristics make such an impact on the sampled acoustic space that it would "influence acoustic diversity indices", since "sites with higher sound transmission would have a higher chance of yielding a higher acoustic diversity". If this effect is large, studies that cover a wide range of environments could find weaker correlations. Further, it is not known whether some of the indices are influenced by environmental variance in ways that others are not.

Despite including quite distinct environments − such as open farmland versus closed-canopy forest that had distinct bird communities (as per Fig. 1) − our study did not show significant differences between simulations that included environmental differences and those that did not. All the indices acted in the same way in this exercise. This suggests that results from the acoustic indices obtained in dissimilar environments or at different scales are comparable. This is an important property for indices to have; their performance needs to be consistent at large scales and under different environmental conditions. It is possible that including more distinct environments, such as deserts versus rainforests, could produce different results; however, most studies using acoustic complexity indices to estimate biodiversity will be conducted in areas without such extreme variation. Our results should be interpreted with some caution though, because the large numbers of species at our study regions meant that several sites within a region had dissimilar composition despite their environmental similarity, potentially affecting the results. In the future, it would also be useful to have structural data from the sites that quantify the environmental effects more precisely. Also, it is possible that the results may have been influenced to some extent by inter-observer bias, since the two regions were surveyed by different observers. However, we are confident that any such effect is small enough not to have affected our conclusions. When the data from the two regions are analysed independently, the results are qualitative the same (Supplementary material Appendix B).

4.3. Conclusions

Although our results support the idea that the acoustic indices have the potential to be used for monitoring bird communities (Sueur and Farina, 2015), the relatively low correlations, and the somewhat inconsistent performances of the indices reported in the literature, suggest that there are still limitations to be overcome before they can be widely adopted. However, the field of ecoacoustics is advancing rapidly (Sueur and Farina, 2015) and major improvements are to be expected as these indices are refined and more are developed (Sueur et al., 2014). Additionally, acoustic equipment is improving too, and becoming more affordable, suggesting that automated passive monitoring of vocalizing animal communities may become a common practise in the near future (Bobryk et al., 2016). In our study, we did not use autonomous recording units, which are becoming increasingly common (Merchant et al., 2015; Joshi et al., 2017). It would be interesting to evaluate in future studies whether the type of equipment used influences the results. In the meantime, it is important that researchers continue to test the available indices and technology, under different conditions and in dissimilar environments, to understand better their efficacy and reveal their capabilities and limitations.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2017.07.017.

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