**Title: Using acoustic indices to monitor vertebrate biodiversity**

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**Abstract**

Acoustic monitoring promises to provide effective biodiversity monitoring that can be used at temporal and spatial scales far greater than standard manual monitoring efforts (ref). The use of acoustic indices as a proxy for traditional biodiversity estimates such as species richness…

Here we show that at the scale of a week, a number of acoustic indices have moderate to strong correlations with species richness, not only of birds, but of all vertebrates…

**Introduction**

***5-6 paragraphs max***

Biodiversity, monitoring, new technologies

Expensive to get estimates of biodiversity using manual methods – audio may be cheaper? (also many taxa vocalise)

Large-scale acoustic monitoring starting (A2O, others?)

Challenges of manual ID (doesn’t scale), automated ID (challenging)

Acoustic indices to capture information about soundscape without species identity (higher complexity soundscape == higher species richness), results mixed

Can indices provide reliable estimates of biodiversity?

Brief summary of what has been done to-date!

How will this study differ?

()

In this study we aimed to test the utility of acoustic indices as a proxy for vertebrate biodiversity.

Specifically, we aimed to test individual acoustic indices as well as models containing multiple acoustic indices for species richness, Shannon’s diversity, and total count.

**Methods**

*Study sites*

We surveyed six sites distributed along the east coast of Australia that form part of the Australian Acoustic Observatory (Roe et al., 2021; Figure 1). Each site contained four 100 x 100 m plots. Plots were arranged in pairs (500–5000 m between pairs), and each pair contained a wet plot (≤50 m from a body of water) and dry plot (≥50 m from a body of water and (500–5000 m from the wet plot). When possible each site was surveyed twice in 2021. Each survey lasted for seven days (excluding setup days), and all four plots within a site were surveyed simultaneously.

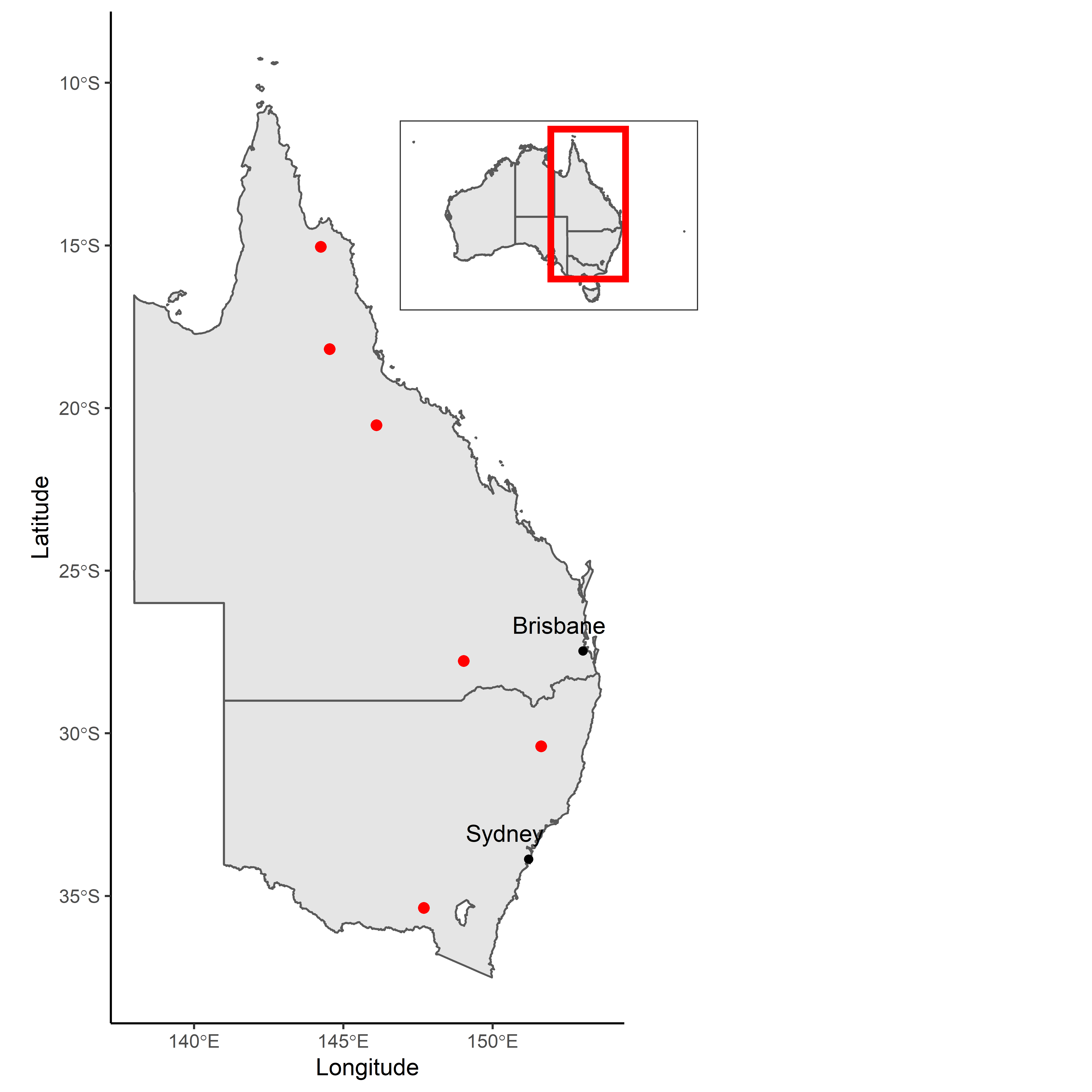


Figure . Map of the six study locations. Each location had 4 plots.

Table . Table of study sites, survey dates, and the total number of surveys with 7 days of matched vertebrate survey and acoustic data.

|  |  |  |  |
| --- | --- | --- | --- |
| Site name | Survey dates - Trip 1 | Survey dates - Trip 2 | Total number of matched surveys |
| Tarcutta | 2021-04-29 – 2021-05-06 | 2021-10-18 – 2021-10-25 | 8 |
| Duval | 2021-04-18 – 2021-04-25 | NA | 4 |
| Mourachan | 2021-05-09 – 2021-05-16 | NA | 3 |
| Wambiana | 2021-07-05 – 2021-07-12 | 2021-11-09 – 2021-11-16 | 7 |
| Undara | 2021-06-03 – 2021-06-10 | 2021-09-29 – 2021-10-06 | 6 |
| Rinyirru | 2021-06-14 – 2021-06-21 | 2021-10-09 – 2021-10-16 | 7 |

*Vertebrate surveys*

For each survey plot, a standardized series of survey and trapping methods to document the vertebrate fauna present was used. All methods were used continuously for 7 days during each survey period and methods were consistent across plots. Each plot contained: two drift fences, 12 arboreal cover boards, four cage traps, and 24 Elliot traps (Figure 2).

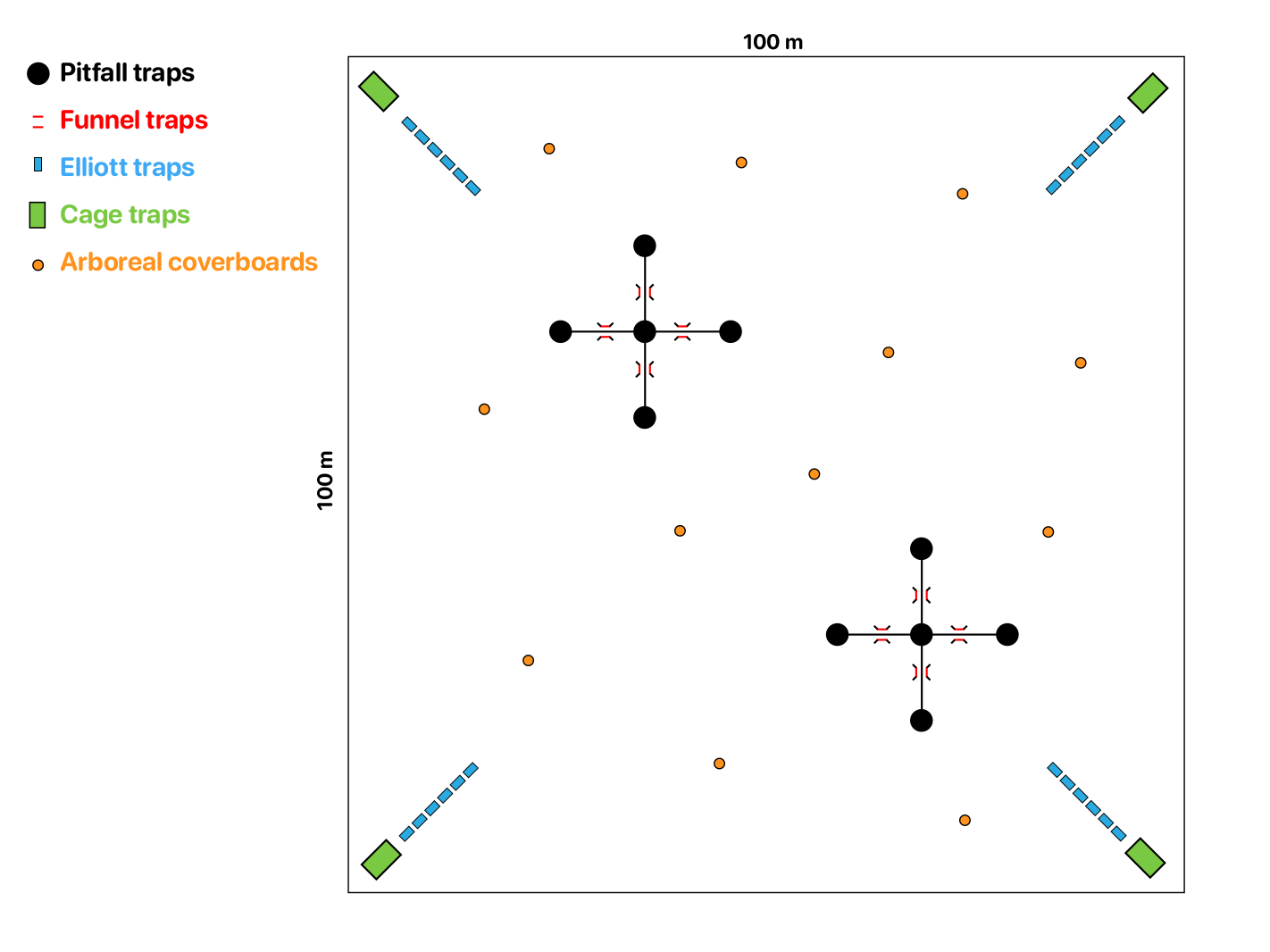


Figure . Approximate layout of the vertebrate trapping methods use on each survey plot.

Drift fences (30 cm tall) were X-shaped, with four 10-m long arms and five 20-L pitfall traps (one in the center and one at the end of each arm). Additionally, each arm contained two funnel traps (18 x 18 x 79 cm; one in the middle of each side of the arm) with an opening on each end (eight funnel traps per fence). To improve capture rates, a “wing” (18 x 50 cm) of fence fabric was placed at a 45° angle to each opening of each funnel trap to guide additional animals into the traps (McKnight, Dean, & Ligon, 2013). To prevent desiccation and overheating, wet sponges were placed in each funnel and pitfall traps, shade cloths were placed over the funnel traps, and all traps were checked twice daily (in the morning and evening).

Arboreal cover boards consisted of foam mats (50 x 50 cm) attached to trees by two elastic straps (Nordberg & Schwarzkopf, 2015). They were placed on 12 haphazardly selected trees and checked every morning. They were placed at the start of each survey period and removed at the end.

Cage traps were 66 x 26 x 25 m and were placed in each corner of the plot (~10 m from the corner at a 45° angle to the plot boundaries). Elliot traps were 8 x 9 x 33 cm and were placed in a line (six per line) starting in each corner ~5 m from the cage trap and ending near the center of the plot (~5 m between each trap). Cage and Elliot traps were baited with bait balls made of peanut butter, oats, and vanilla. Each trap was opened in the evening, checked the following morning, and closed during the day. Camera traps were also deployed at each plot, however vertebrate data from them have not been included here.

In addition to trapping methods, we conducted visual and auditory searches each morning and night. During the searches, two researchers meandered through the plots for 15min recording any animals that were seen or heard. While researchers stayed within the plots, animals seen or heard off the plots were also noted. Morning searches focused on birds, while nocturnal searches used head torches and focused on reptiles and amphibians. During each 7-day survey, researchers rotated among teams and plots to minimize observer bias. Finally, throughout the 7-day surveys, we noted incidental encounters with animals that were seen or heard outside of our 15-minute search periods.

*Audio surveys*

At each survey plot, audio was continuously recorded using acoustic sensors that are part of the Australian Acoustic Observatory (Roe et al., 2021). Each sensor is fitted with a single microphone mounted 1.2-1.8m above the ground, recording continuously at a sampling rate of 22.05kHz in the FLAC file format (FrontierLabs - https://www.frontierlabs.com.au/solar-bar; see Roe et al., 2021 for full details).

*Vertebrate diversity measures*

To compare manual survey results with acoustic indices, we split the data into four taxonomic groupings: all vertebrates (containing all observations regardless of taxa or method of detection), frogs (all frogs detected by any method), birds (only birds observed during the morning birding surveys), and non-avian vertebrates (all taxa other than birds detected by any method). The frogs and birds subsets were chosen because both taxa vocalise and are likely to be detected on acoustic recorders (thus directly testing acoustic indices). The remaining two categories were intended to test the possibility that diversity in acoustic species would be reflective of diversity more generally and, therefore, acoustic indices would be useful for describing the broader vertebrate diversity. For each plot, we calculated species richness (total species observed), Shannon’s diversity (which combines richness and evenness), and the total count of observations for each taxonomic grouping.

*Acoustic indices*

Thirteen acoustic indices were generated from the audio for the entire 7 days (12pm on day of first spotlighting survey – 12pm on the day of last bird survey) at a 1-min resolution using Kaleidoscope Pro (Wildlife Acoustics; version 5.4.1) and QUT Ecoacoustics Audio Analysis Software (M. Towsey, Truskinger, Cottman-Fields, & Roe, 2020; version 20.11.2.0).

Table . List of the 13 acoustic indices generated from the acoustic recordings.

|  |  |
| --- | --- |
| Acoustic Index | Description |
| ADI\* | Acoustic diversity index (Villanueva-Rivera, Pijanowski, Doucette, & Pekin, 2011) |
| AEI\* | Acoustic evenness index (Villanueva-Rivera et al., 2011) |
| BI\* | Bioacoustic index (Boelman, Asner, Hart, & Martin, 2007) |
| NDSI\* | Normalized difference soundscape index (Kasten, Gage, Fox, & Joo, 2012) |
| SH\* | Spectral entropy (Han, Muniandy, & Dayou, 2011) |
| ACT† | Activity (M. W. Towsey, 2017) |
| EVN† | Events per second (M. W. Towsey, 2017) |
| LFC† | Low-frequency cover (M. W. Towsey, 2017) |
| MFC† | Mid-frequency cover (M. W. Towsey, 2017) |
| HFC† | High-frequency cover (M. W. Towsey, 2017) |
| ACI† | Acoustic complexity index (Pieretti, Farina, & Morri, 2011) |
| CLS† | Cluster count (M. W. Towsey, 2017) |
| SPT† | Spectral peak density (M. W. Towsey, 2017) |

\* Indices generated using Kaleidoscope Pro  
† Indices generated with QUT Ecoacoustics Audio Analysis Software

For comparison with the on-ground vertebrate survey data, each acoustic index was aggregated into a weekly value by taking the average of all 1-minute values for certain taxa-specific time periods. For birds, indices were averaged for the daytime (6am-6pm). For frogs, indices were averaged for the nighttime (6pm-6am). For total vertebrate biodiversity and non-avian vertebrate biodiversity, indices were averaged for the entire 7-day dataset. Any time period that had less than 70% of the audio available (e.g. due to hardware failure) was removed from the dataset. This resulted in a total of 35 matched 7-day vertebrate survey and acoustic survey periods (Table 1).

*Statistical analyses*

To determine which individual acoustic indices may be useful proxies for vertebrate biodiversity, bootstrap Spearman’s rank correlation values (and 95% CIs) were calculated for each acoustic index and each biodiversity measure (i.e. species richness, Shannon’s diversity, total count) for the four vertebrate taxonomic groupings.

To determine how well multiple acoustic indices predict vertebrate biodiversity, random forest models were fit to each biodiversity measure using all 13 acoustic indices as predictors. Unbiased random forest models were fit using 1000 trees, and 10 x 3 cross validation was used to estimate predictive performance (R version 3.6.1; party version 1.3.7; caret version 6.0.86). Model performance was evaluated on the out-of-bag samples using normalized RMSE (RMSE/(maximum – minimum response)), scatter index (RMSE/mean response), and R-squared. To determine which acoustic indices contributed most to the predictive accuracy of each model, variable importance for each random forest model was calculated using conditional permutation importance (threshold = 0.95) and scaled by the total (null-model) error using the *permimp* package (version 1.0.1).

**Results**

*Acoustic index correlations*

A number of the acoustic indices tested had moderate to strong correlations (0.5 ≤ rs ≥ 0.8) with the vertebrate biodiversity measures, particularly for birds and all vertebrates, less so for frogs and non-avian vertebrates (Figure 3). In general, acoustic indices had lower correlations with Shannon’s diversity than species richness and total count across all vertebrate groupings examined.

For all vertebrates, species richness had the highest correlation with spectral density (SPD; rs = 0.68) and mid-frequency cover (MFC; rs = 0.67), Shannon’s diversity had the highest correlation with activity (ACT; rs = 0.55), and total count had the highest correlation with the acoustic complexity index (ACI; rs = 0.71) and MFC (rs = 0.69; Figure 3a).

For non-avian vertebrates, many of the acoustic indices tested had low correlations that were not different from zero (Figure 3b). High-frequency cover (HFC; rs = 0.59) and SDP (rs = 0.53) correlated with species richness, and the normalized difference soundscape index correlated with total count (rs = 0.59).

For birds, MFC, SPD, ACI and cluster count (CLS) had the highest correlations with vertebrate biodiversity measures (Figure 3c). Specifically, species richness (rs = 0.7) and Shannon’s diversity (rs = 0.62) had the highest correlation with CLS, and total count had the highest correlation with MFC (rs = 0.77).

For frogs, MFC and SPD had moderate correlations with species richness (rs = 0.53 and rs = 0.56 respectively) and total count (rs = 0.66 and rs = 0.66 respectively), while none of the acoustic indices correlated particularly well with Shannon’s diversity (Figure 3d).

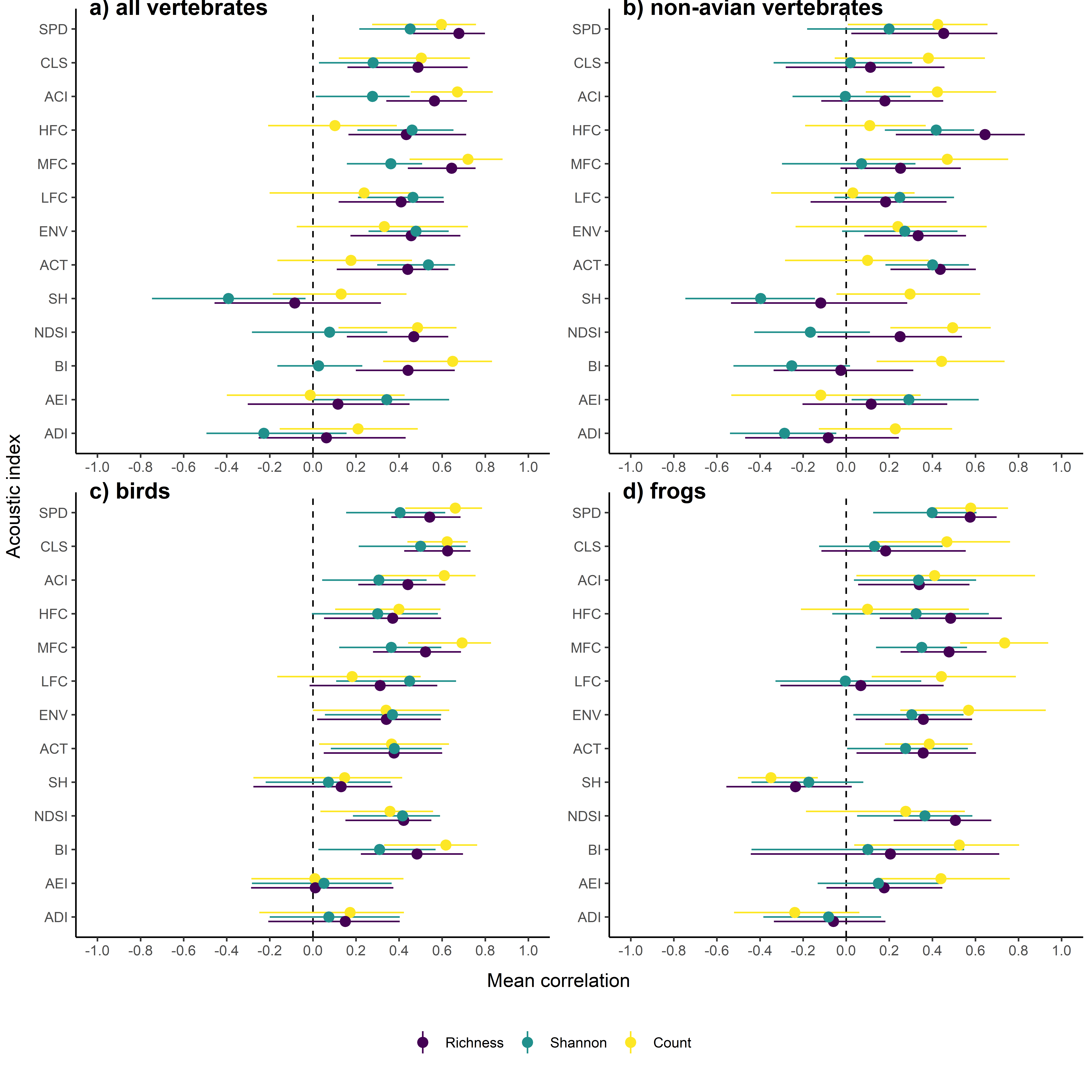


Figure . Bootstrap Spearman’s rank correlation values (±95% CI) of thirteen acoustic indices and three biodiversity measures (species richness, Shannon’s diversity and total count) for a) all vertebrate taxa, b) all non-avian vertebrate taxa, c) birds, and d) frogs.

*Random forest models*

Random forest models for all vertebrate groupings examined, except for frogs, performed well (i.e. low normalised RMSE and scatter index, high R squared; Figure 4). In general, models for frogs had a higher RMSE, higher scatter index, and lower R2 than the equivalent models for the other vertebrate groupings considered (Figure 4). Despite only slightly higher normalised RMSE than models for the other vertebrate groupings, random forest models for frogs had a very high scatter index, particularly for total count (Figure 4b). This is likely due to the high number of survey plots with zero frogs found (n = XX).

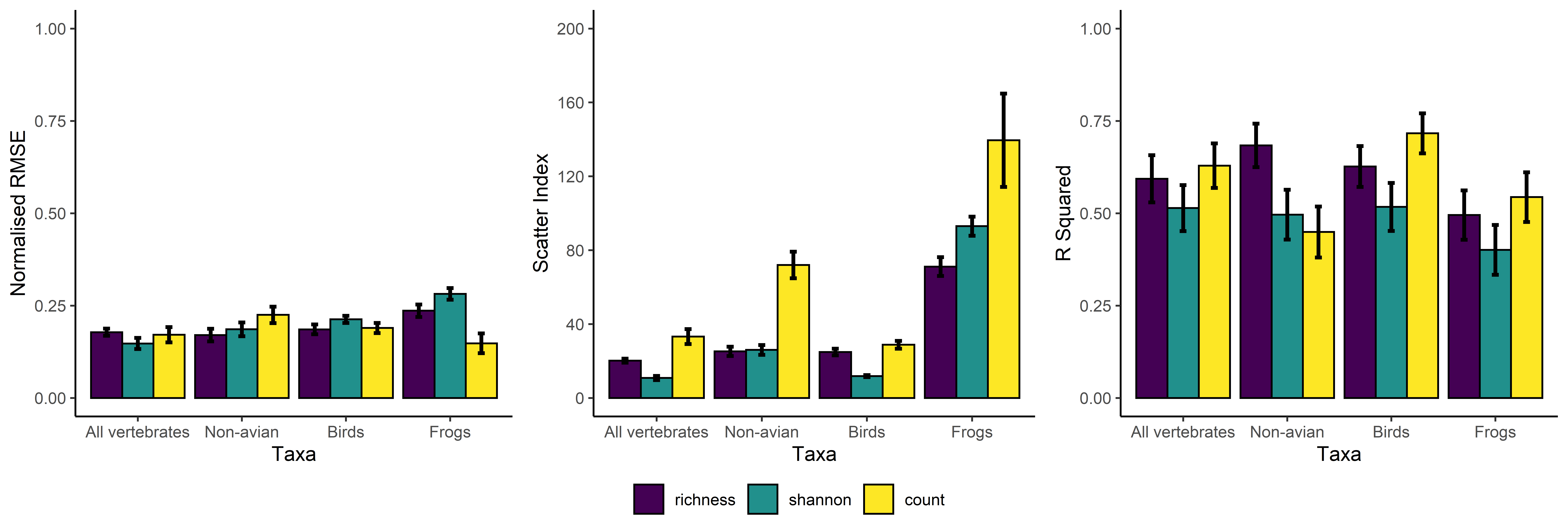


Figure . Mean (±SE) performance of random forest models predicting richness, Shannon’s diversity, and total count of all vertebrates, non-avian vertebrates, birds, and frogs. Performance measured with 10 x 3 cross-validation.

Observed vs predicted plots show that, in general, random forest models were poorest at predicting Shannon’s diversity out of the three biodiversity measures examined (Figure 5), while species richness was predicted best. For species richness and total count, models were more accurate at predicting all vertebrates and birds than the other vertebrate groupings examined.

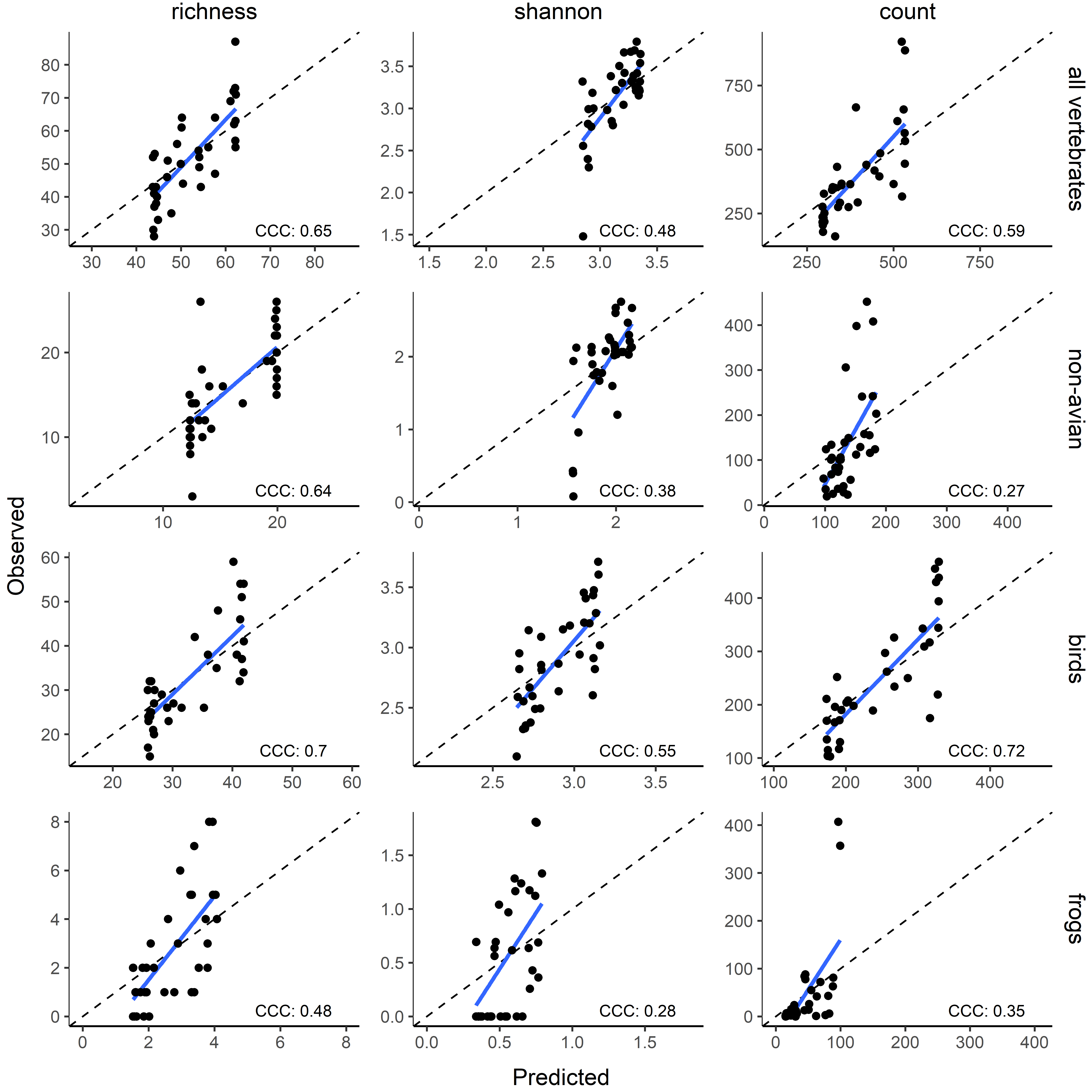


Figure . Comparison of observed biodiversity values and out-of-bag predicted values from each random forest model. The Concordance Correlation Coefficient (CCC) values measure how far the data deviates from the 45 degree line (i.e. perfect prediction).

For all vertebrates, SPD and MFC were the most important acoustic indices for species richness and MFC for total count. (For non-avian vertebrates, only high-frequency cover (HFC) was identified as an important acoustic index for the species richness model.) For birds, the most important acoustic indices to the random forest models were cluster count (CLS) for both species richness and Shannon’s diversity, and mid-frequency cover (MFC) for total count (Figure 6). (For frogs, no single acoustic index was particularly important to model performance, which aligns with random forest models for frogs performing comparatively poorly.)

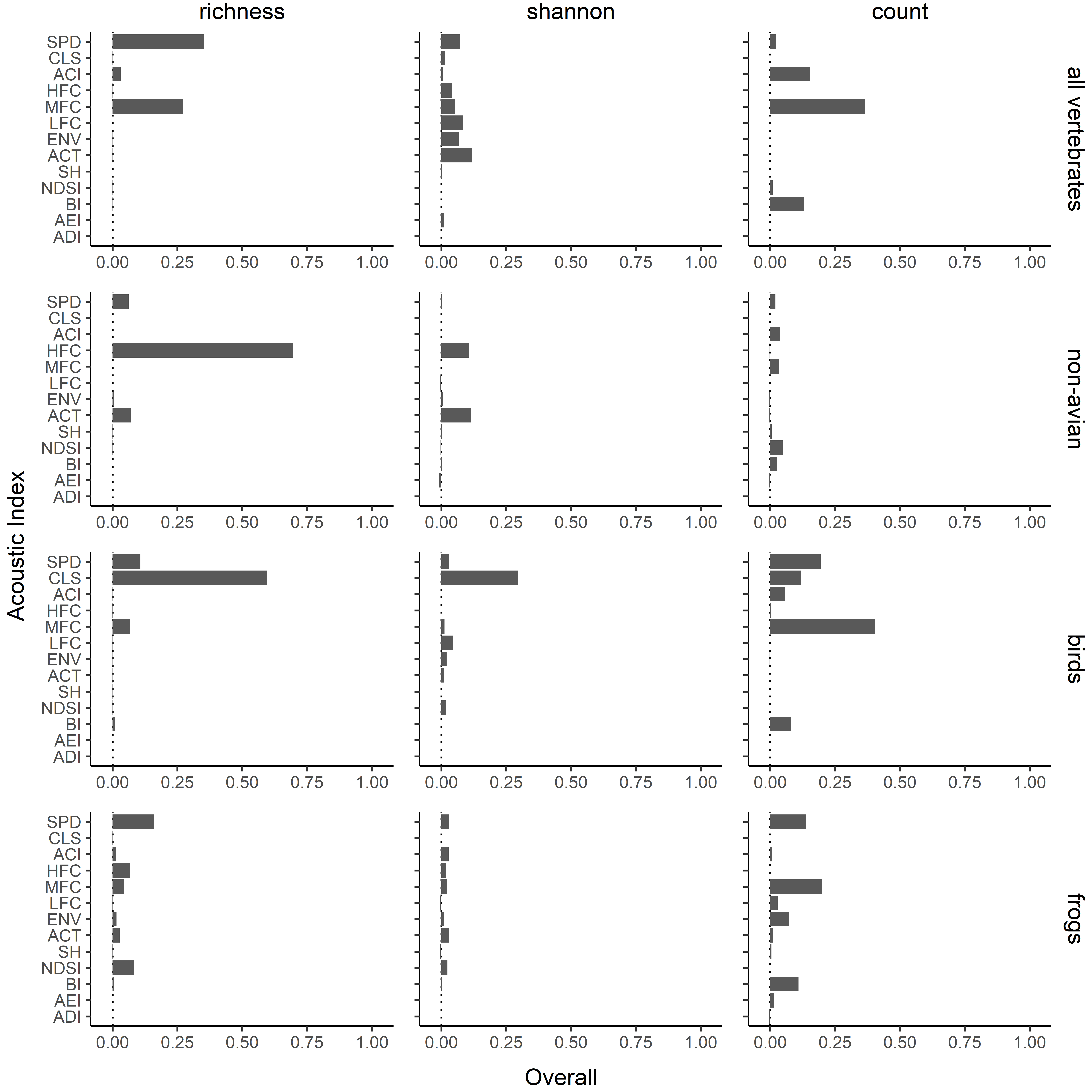


Figure . Variable importance metrics for each random forest model. Values are the mean decrease in accuracy as a proportion of total null-model error from random permutations of each acoustic index.

**Discussion**

A number of acoustic indices correlated well with vertebrate measures from manual surveys, and models incorporating multiple acoustic indices were effective at estimating species richness and total count for birds and all vertebrates.

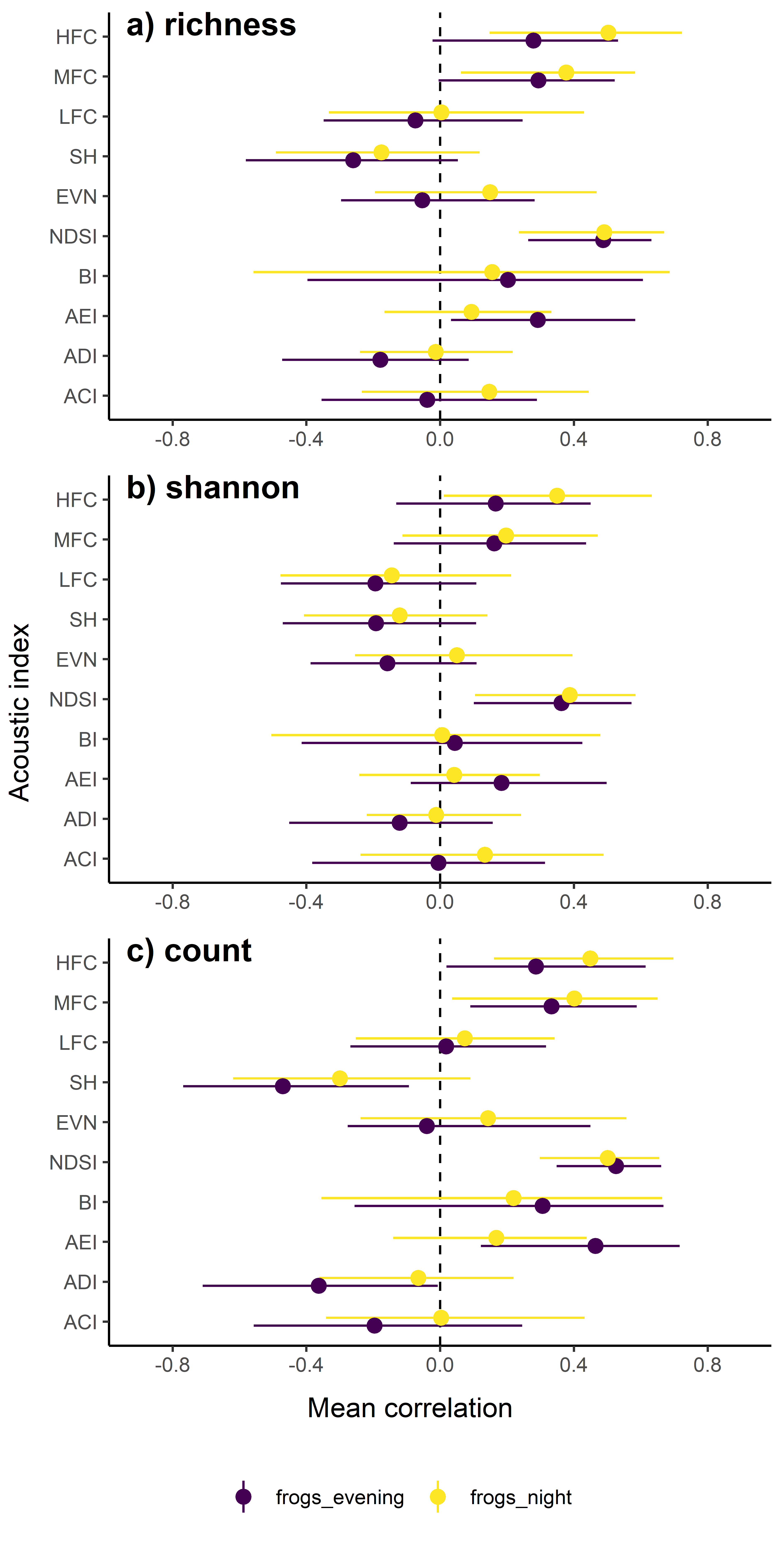
Birds,

CLS, SPD for richness - explain

MFC for total count – makes sense?

Individual indices and multiple index models performed relatively poorly for frogs. Despite frogs being a vocal taxa and …, this is likely due to the seasons sampled. A number of the sites occur in … environment where frog chorusing activity is strongly associated with rainfall events. This is further supported by the number of surveys that had no frogs at all. (Previous studies on acoustic indices and frogs – acoustic indices (ACI, H, Hf, Ht, ADI, AEI, BI) had poor correlation with anuran richness (Moreno-Gómez et al. 2019) – of those same indices tested here we also found low correlations – the two indices with highest correlations MFC and SPD were not used by Moreno-Gómez et al. 2019; random forest models of acoustic indices have been shown to be reliable predictors of species level calling behaviour of frogs at short time scales (e.g. 1 minute; Brodie et al. 2020); )

**Supporting Information**



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