UNIVERSIDADE ESTADUAL PAULISTA
“JÚLIO DE MESQUITA FILHO”
INSTITUTO DE BIOCIÊNCIAS – RIO CLARO

PROGRAMA DE PÓS-GRADUAÇÃO EM ECOLOGIA, EVOLUÇÃO E BIODIVERSIDADE

PREDICTING BIRD DIVERSITY USING ACOUSTIC INDICES WITHIN THE ATLANTIC FOREST BIODIVERSITY HOTSPOT

LUCAS PACCIULLIO GASPAR

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Orientador: Prof. Dr. Milton Cezar Ribeiro
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“Princípio do Mentalismo: O todo é Mente; o universo é mental.

Princípio da Correspondência: O que está em cima é como o que está embaixo. O que está dentro é como o que está fora.

Princípio da Vibração: Nada está parado, tudo se move, tudo vibra.

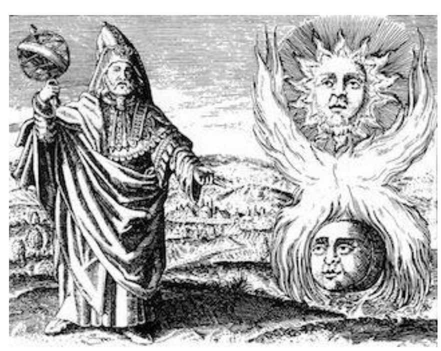
Princípio da Polariadade: Tudo é duplo, tudo tem dois pólos, tudo tem o seu oposto. O igual e o desigual são a mesma coisa. Os extremos se tocam. Todas as verdades são meias-verdades. Todos os paradoxos podem ser reconciliáveis.

Princípio do Ritmo: Tudo tem fluxo e refluxo, tudo tem suas maŕes, tudo sobe e desce, o ritmo é a compensação.

Princípio de Causa e Efeito: Toda causa tem seu efeito, todo o efeito tem sua causa, existem muitos planos de causalidade, mas nada escapa à Lei.

Princípio de Gênero: "O Gênero está em tudo: tudo tem seus princípios Masculino e Feminino, o gênero manifesta-se em todos os planos da criação.”

(O Caibalion - 1908)



RESUMO

A abordagem de índices acústicos em dados oriundos de monitoramento acústico passivo, torna possível sintetizar automaticamente informações de grande volume de dados. Desde o desenvolvimento destes índices, pesquisadores têm tentado entender o quão bem correlacionado é cada índice com os diferentes componentes da paisagem sonora, incluindo biofonias. Demonstramos que os índices acústicos estão mais bem correlacionados com o número de vocalizações de aves do que com a riqueza ou diversidade. Modelos que utilizam dois índices ao invés de apenas um, apresentou melhores correlações com a diversidade acústica de aves. Além disso, observamos que o tipo de ambiente tem influência nestas correlações. Portanto, defendemos o uso de índices acústicos para medir o nível e os padrões de atividade acústica das aves. No entanto, comparações entre pesquisas e inferências ecológicas realizadas a partir deste tipo de dado, precisam de cautela. Isso porque, ao variar o ambiente, também há variação na correlação entre os índices acústicos e os diferentes aspectos da diversidade de aves.

Palavras chave: Monitoramento Acústico Passivo, Ecologia Acústica, Avaliação Acústica, Etiquetamento Manual, PELD.

ABSTRACT

Acoustic indices approach from passive acoustic monitoring data, makes it possible to automatically synthesize information from a large volume of data. Since the development of these indices, researchers have tried to understand how well correlated each index is with the different components of the soundscape, including biophonies. We demonstrated acoustic indices are better correlated with bird number of vocalizations than richness or diversity; models that use two indices instead of just one, have better correlations with bird acoustic diversity and; the environment type has influence in these correlations. So, we defend the use of acoustic indices to measure the level and patterns of birds' acoustic activity. However, the ecological inferences and comparisons made from this data type need caution, since when varying the environment, there is also variation in the correlation between acoustic indices and different aspects of bird diversity.

Keywords: passive acoustic monitoring, ecoacoustics, acoustic surveys, manual labelling, long-term ecological research.

Sumário

1. Introduction

The accelerated conversion of natural areas to anthropic land uses is causing local and regional population declines as well as species extinction. These changes affect both biodiversity and its related ecosystem services (Butchart et al., 2010; Johnson et al., 2017) as well as important ecological functions that maintain the integrity of the ecosystems, such as seed dispersal and pollination (Duarte et al., 2018) . In order to understand how humans affect biodiversity, ecosystem functions and services, we must expand biological monitoring both in time and space, using a wider taxonomic coverage, and yet cost efficient methods (Schmeller et al., 2017) . Remote sensing techniques have been widely used aiming to increase sampling coverage and decrease costs. Also, it is non-invasive and allows large scale monitoring of sensitive and remote areas with difficult access.

Acoustic remote sensing is usually done through Passive Acoustic Monitoring (PAM) and autonomous recording units (ARU - Shonfield and Bayne, 2017) . ARU's can be used in both terrestrial or marine environments, and might record data from a wide spatial range, capturing information from all directions up to 100 m away (Stowell and Sueur, 2020) . The units may be set to record continuously and unattended for long periods of time (Stowell and Sueur, 2020), and are capable of recording soundscape information such as the biophony (sounds produced by animals - (Krause, 1987) ; geophony (abiotic components of a landscape); and anthrophony (sounds produced by human activities and machines) (Pijanowski et al., 2011) . Therefore, audio recordings can be used to obtain a large variety of ecological information on biodiversity, like activity patterns, composition of vocally active species and behavior (Farina et al., 2011) , as well as on the quality and integrity of habitats (Gómez et al., 2018).

Environmental changes are known to modify bird diversity and composition and in fact birds have been used as bioindicators of environmental quality (Furness et al., 1993; Padoa-Schioppa et al., 2006) . Besides, they occur in a great variety of environments and have their taxonomy well known, with extensive literature about behavior and responses to habitat changes. In addition, they are the group of animals which highly contribute to the biophony in soundscapes (Farina et al., 2011), as they vocalize for both inter and intra-specific communication, including reproduction and territory defense (McGregor ·and Peake, 2000) . In this way, birds are a good candidate for monitoring through PAM.

PAM can collect data on a large spatial and temporal scales, making it possible to obtain species composition through manual detection (e.g. Wimmer et al., 2013) . However, although this approach contains accurate information about the species, many other ecologically interesting questions can be answered using the entire volume of recordings obtained, such as large patterns of activity and management of the database. As a result, it is necessary to improve more automated analysis techniques in order to take full advantage of the information contained in the recordings and a macro view of standards (Sueur et al., 2014) .

Acoustic Indices (AI) are one automatic approach used to analyse environmental recordings. They consist of metrics that are calculated by using several spectral and temporal parameters of the sound recordings (Sueur et al., 2014) . These indices are sensitive to signal characteristics such as amplitude variations and the frequency bands it occupies. Some indices were developed aiming to quantify biodiversity and soundscape patterns, based on the acoustic parameters of a soundscape recording (e.g. Villanueva-Rivera et al., 2011; Towsey et al., 2014; Scarpelli et al., 2020) . Therefore, it is generally expected that better preserved environments will present higher levels of biophony and that those signals will be spread across different frequency bands, considering the natural selection acting in the acoustic niche (Farina et al., 2011; Araújo et al., 2020) , despite being insensitive to species composition and functional diversity. But anyway, the acoustic variability can be used as proxies for biodiversity quantification (Sueur et al., 2014b) . In terrestrial environments, AI are being used for rapidly assessing biodiversity (e.g. Sueur et al., 2008) , describing habitat type and spatial heterogeneity (e.g. Bormpoudakis et al., 2013) , characterizing soundscapes (e.g. (Towsey et al., 2014) , quantifying anthrophony (e.g. Buxton et. al. 2017) and monitoring protected areas (e.g. Campos et al., 2021) .

Since the development of AI, their effectiveness to predict biodiversity activity patterns from environmental recordings has been tested in areas with different vegetation structures (Buxton et al., 2018) , climate (Eldridge et al., 2018) , and species composition (Depraetere et al., 2012) . The level of success of translating AI on bird biodiversity estimation has varied between studies and explanatory power varies from low to high. As an example, studies that tested the correlation between bird richness and Acoustic Complexity Index (ACI - Pieretti et al., 2011) have been presenting low positive correlation (Mammides et al., 2017; Jorge et al., 2018) , moderate positive correlation (Eldridge et al., 2018) , moderate negative correlation (Eldridge et al., 2018; Izaguirre et al. 2018; Shamon et al., 2021) , and also no correlation (Dröge et al., 2021) . In the Appendix S1 is presented as a table with previous results about other indices. Knowing that the AI summarizes characteristics of an audio, the divergent results of previous studies may be related to differences in the method of obtaining ecological indices of diversity and data treatment. In addition, different environments have different soundscape patterns, both in species composition and differences in the patterns of other signs, such as geophonies and anthropophonies. Because the patterns are not yet clear, there are still limitations and concerns on the broad use of acoustic indices as a proxy of biodiversity (Mammides et al., 2017) . Therefore, understanding how the AI can be used as surrogate biodiversity measures at wide spatial scales is essential for its application in monitoring programs (Stowell and Sueur, 2020) .

We compared the relative contribution of AI commonly used to measure birds diversity in different types of environments. We used 7 acoustic indices (ACI, BIO, ADI, AEI, AR, Ht, and NDSI) to answer three questions: (1) What is the relative contribution of acoustic indices in explaining bird diversity?; (2) What are the explanatory power gains when combining acoustic indices (i.e bivariate models), compared to single indices (univariate models)?; (3) Does the type of environment have an influence on the strength of these correlations? We hypothesized that (1) bivariate models perform significantly better than univariate models, independent of response variables (Figure 1.A). This is due to the idea that the use of two indices in a complementary way may have a better capacity to capture different characteristics of the data. Regarding the expected differences in the relative contribution of each index in the bivariate models, we believe that some AI will have a certain redundancy between them when combined. (2) From the indices, ACI will have the higher explanatory power in univariate models due to its sensitivity in detecting amplitude variability and having resistance to constant noise, followed by BIO, ADI, AR and

NDSI (Figure 1.A); ADI will be negatively related with response variables, and the others will be positively related (Figure 1.B). In Figure 1.C we represent how bird diversity can behave in bivariate models with two hypothetical explanatory indices. (3) There will be a change in the relationship between AI and bird diversity among the three environments (forest, pasture and swamp). Due to structural differences and similarities, the model with greater explanatory strength for forest will be different, while for pasture and swamps the best model will be coincident.

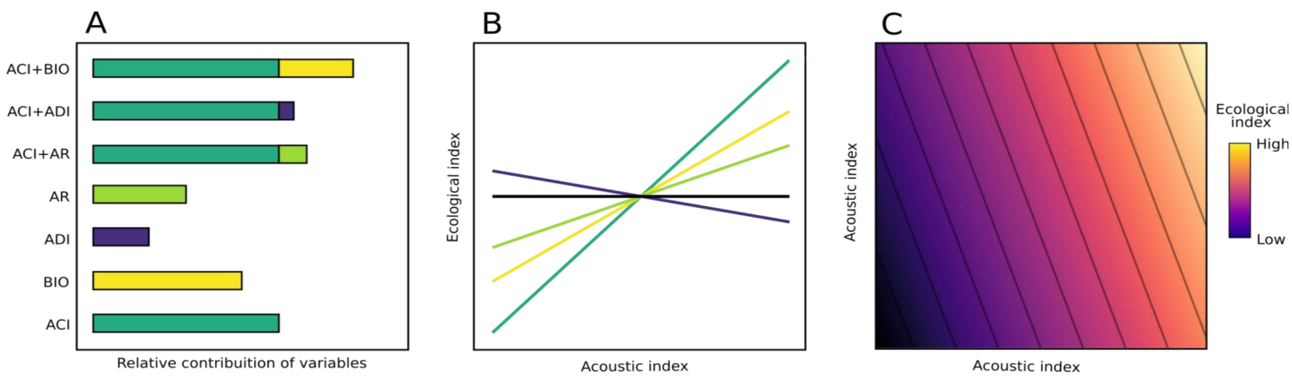


Figure 1 - Expected patterns for acoustic index (univariate or bivariate models) on explaining the bird diversity. A) explanatory power for some acoustic index alone, or combined with other indices; B) expected slopes between bird diversity and acoustic indices (the steeper the slope. the higher the relationship between bird diversity and the indices); c) expected patterns between bird diversity and bivariate acoustic models), where an AI would be a more explication contribution than others. To simplify, only some examples are presented here.

2. Material and Methods

2.1 Study area

The study was conducted in northeastern São Paulo State and the southern portion of Minas Gerais State, Brazil (Figure 2). The region is the focus of a Long Term Ecological Research within the ecological Corridor of Cantareira-Mantiqueira (PELD CCM). This area is of great ecological importance as it connects two large Atlantic Forest remnants: the Cantareira State Park and the Serra da Mantiqueira mountain range (Boscolo et al., 2017) .

The Atlantic Forest is a biodiversity hotspot as it presents high levels of bird richness (620 species, Myers et. al 2000) and endemism (223 species, Vale et al., 2018) , but also because it has been highly deforested and fragmented (Laurance, 2009) . The Atlantic Forest has had its forest cover reduced to about 28% of its original size (Rezende et al., 2018) . The remaining patches are isolated (average distance is 1,440 m), small in size (84% has less than 50 ha), and are under severe edge effects (half of the remnants are less than 100 m from the forest edges - (Ribeiro et al., 2009) . The main land cover types of the study area consist of forest, pasture, agriculture, forestry (mainly *Eucalyptus* plantation), swamps as well as urban and rural buildings (Barros et al., 2019; Boscolo et al., 2017) .

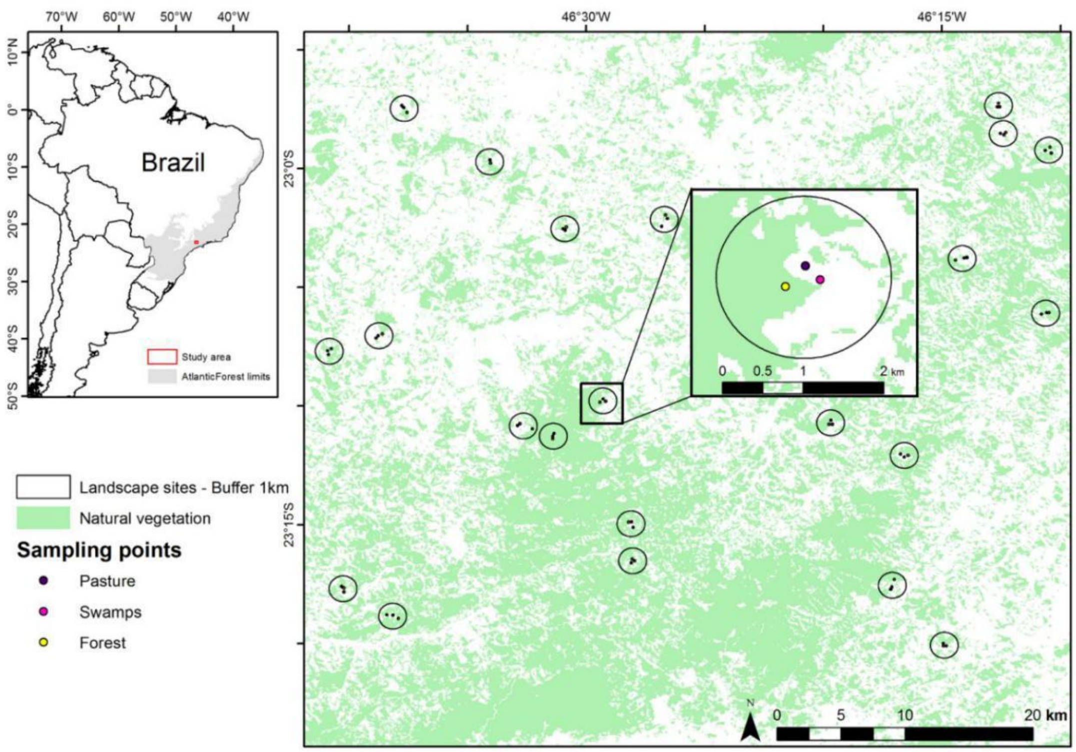


Figure 2 - Landscapes studied in the Cantareira-Mantiqueira ecological corridor, located in the Atlantic Forest biodiversity hotspot in southeastern Brazil. Zoom showing the three different environments (forest, swamp and pasture) sampled in each of the 22 landscapes varying in forest cover gradient (1% - 97%) in a 1km radius buffer.

2.2 Experimental design

We collected audio data in 22 landscapes with varying forest cover (1 to 97%) within 1 km from the sampling site centroids (Figure 2). On each landscape we sampled three different habitat types: forest, pasture and swamp. Habitats were sampled between October 2016 to January 2017 with the following sampling scheme: forests (October to November), swamps (November to December) and pastures (December to January), during 30 sequence days each. The forest sites were at least 50 meters away from the border to the interior of the forest; the pastures were mainly for cattle raising; and the swamps consisted of wetlands, in lower portions of the relief. The sampling period refers to the rainy season in this region, and it matches with the reproductive period of most birds within the Atlantic Forest (Develey and Peres, 2000) . During the sampling period, the average temperature and precipitation were similar between landscapes, thus we assumed that the differences in months did not affect general biodiversity patterns.

2.3 Soundscape recordings

We used Song Meter Digital Field Recorders (SM3; Wildlife Acoustics. Inc. Massachusetts) fixed on tree trunks 1.5 m above ground. The recorders were equipped with two omnidirectional microphones (frequencies 20 Hz to 20 kHz), and the sampling rate was 44.1 kHz, 16 bits and mono mode (to save storage space and battery). For the entire project and the complete sampling scheme we attained a total of 10,343 hours of recordings. The complete sampling effort of each landscape and site (i.e. habitat type) can be found in Appendix S2. Because this study focused only on diurnal birds, with the peak vocal activities in the first hours of the morning, we only used the samples from this period (05:00am until 08:25am).

2.3 Audio subset and species labeling

We created a subset of the recordings by following four steps: (1) we selected five 25-minute files (05:00am, 05:45am, 06:30am, 07:15am, and 08:00am) per day (9,151 files, totalizing 228,775 minutes); 2) from each file we extracted two random minutes, totaling 18,594 minutes; 3) we grouped those minutes into nine packages of 300-random-minutes each (i.e. 2,700 minutes), being 100 minutes for forest, 100 minutes for swamps, and 100 minutes for pastures per package; 4) the packages were sent to bird experts, which labeled the occurrence of bird species on each minute (see scheme on Appendix S3). We detected 137 corrupted, blank minutes that were excluded from the analysis. So, in the end we evaluated 2,563 minutes.

Finally, we had 10,437 classified bird vocalizations from the labels, being 9,437 at species level, 192 at genus levels, and 808 not identified (distant signals or dubious calls). Recordings of unidentified calls were excluded from the analysis. We labeled each species once each minute, regardless of the number of times their vocalizations appeared in it, using the software Raven Pro v.1.5 (Center for Conservation Bioacoustics 2014).

2.5 Acoustic indices

For each minute, we calculate eight AI that has been commonly used to measure bird diversity: (1) Acoustic Diversity Index (ADI); (2) Acoustic Evenness Index (AEI); (3) Acoustic Complexity Index (ACI); (4) Entropy Index (H); (5) Bioacoustic Index (BIO); (6) Acoustic Richness index (AR); (7) Temporal Entropy index (Ht); and (8) Normalized Difference Soundscape Index (NDSI) (description in the Table 1). As there is no consensus on which parameters are best to be followed, we used different frequency and amplitude threshold parameters, such as their combinations, to calculate the indices.

We used Rstudio v.1.414 (R Development Core Team 2016) environment and the *Seewave* (Sueur et al., 2008) (ACI and Ht) and *Soundecology* packages (Villanueva-Rivera et al., 2016) (ADI, AEI, BIO, H, and NDSI) to perform calculations. AR was calculated using the formula (Eq. 1) due to errors in its automatic calculation from Seewave. No pre-processing techniques were applied prior to the calculation of indices as it is important to test how AI performs in different environmental conditions.

$$AR = \frac{(rank\ (Ht)\ x\ rank\ (M))}{(n_{\text{files}})^2} \qquad \text{(Eq.1)}$$

2.6 Models and Statistical analysis

The number of annotated minutes and number of tags varied between sampling points. Therefore, we decided to standardize the sampling effort prior to proceeding with response variable estimations. For this, we made a bootstrap procedure in which 100 sub-samples from the

2,563 annotated files were generated, considering the audio files of each sampling point. Each of these 100 sub-samples consisted of 1,300 random minutes totaling 6,500 groups of 20 minutes each.

Then, we estimated three response variables: bird richness, number of tags, and diversity. In a sub-sample, for richness, we used the number of species noted. Tags number was considered the total of tags in a sub-sample. In order to measure diversity, we used the inverse of Simpson (Chao et al., 2010) . The same groups of minutes (20 minutes) were used for calculating the average of each acoustic index.

We used Generalized Linear Models (GLM's) to test the relationship between bird diversity (species richness, number, and diversity of tags) and AI means as explanatory variables. The models were evaluated according to values of dAIC, wAIC, R^2 and correlation plots. The final models were tested for multicollinear variance inflation factors (VIF), being considered VIF < 10 (Montgomery and Peck 1992). The VIFs analysis selected the same set of acoustic indices (Table 2) to three responses variables (bird richness, number and diversity of tags).

Table 1 - Description of the acoustic indices used for the correlation test with acoustic diversity of diurnal birds within the region of the Long Term Ecological Research within the ecological Corridor of Cantareira-Mantiqueira (PELD CCM), Atlantic Forest, São Paulo, Brazil.

Acoustic indices	**Description**	**Reference**
Bioacoustic (BIO)	A function between spectral amplitude of signals and the number of frequency bands occupied. It is an evaluation of the sound level and the amount of frequency bands used, measuring the abundance of birds.	Boelman et al. (2007)
Acoustic Complexity (ACI)	Since biological sounds have greater variability, whereas anthropogenic or geophonic sounds have less variation. Divides the spectrogram into multiple frequency bins and temporal subsets, and calculates the differences in the intensities of adjacent sounds, being a measure of variability on amplitude intensity.	Pieretti et al. (2011b)
Acoustic Diversity (ADI)	Divides the spectrogram into frequency bands and calculates the signal diversity in each of those bands similarly to a Shannon-Wiener index (Shannon and Weaver 1949). The higher the amount of species emitting sound, the more frequency bands occupied, and the higher the value of the index.	Villanueva-Rivera et al. (2011)
Acoustic Evenness (AEI)	Divides the spectrogram into frequency bands and measures evenness using the Gini coefficient and is negatively related to ADI.	Villanueva-Rivera et al. (2011)
Acoustic Richness (AR)	Based on Temporal Entropy (H) and the median of the overall amplitude (M). Uses the general median and Ht, developed for environments with a high signal-to-noise ratio.	Depraetere et al. (2012)
Total Entropy (H)	Estimated acoustic energy dispersion over the spectrum and it uses spectral and temporal amplitude patterns. The more species in a community, the more distinct signals will be produced.	Sueur et al. (2008)
Temporal Entropy (Ht)	Computed following the Shannon evenness index applied to the amplitude envelope of the temporal series and where the envelope points correspond to the categories.	Sueur et al. (2008)
Normalized Difference Soundscape (NDSI)	Estimates the level of anthropogenic disturbance on the soundscape by computing the ratio of human-generated (anthrophony) to biological (biophony). An estimate of the level of acoustic disturbance in a landscape.	Kasten et al. (2012)

Table 2 - Acoustic indices set selected over VIFs used in final models to test the correlation with bird richness, number and diversity of tags within the region of the Long Term Ecological Research within the ecological Corridor of Cantareira-Mantiqueira (PELD CCM), Atlantic Forest, São Paulo, Brazil. The "x" means absence of amplitude threshold.

Acoustic indices	Frequency range	Amplitude threshold
ADI	300 - 12,000 hz	75db
AEI	1000 - 12,000 hz	50db
ACI	1000 - 12,000 hz	x
BIO-1	1000 - 12,000 hz	x
BIO-2	1000 - 22,050 hz	x
NDSI-1	Antro: 300-1,000hz Bio: 1,000-12,000hz	x
NDSI-2	Antro: 1,000-2,000hz Bio: 2,000-22,050hz	x
Ht	0 - 22,050 hz	x
AR	0 - 22,050 hz	x

3. Results

We analyzed a total of 2,563 minutes. In total, we had 9,629 labels, being 9,278 at species level (199 species) distributed in 53 families and 351 at genus level (18 genus) (Appendix S4). The species with the highest number of detections were *Vireo chivi* (781 minutes), *Zonotrichia capensis* (631 minutes), *Basileuterus culicivorus* (533 minutes), *Cyclarhis gujanensis* (427 minutes), and *Pitangus sulphuratus* (371 minutes).

3.1 Considering generalizations of environments

The acoustic indices models had great correlation with the number of tags (maximum $R^2 = 0.48$), followed by richness (maximum $R^2 = 0.43$), and less with tag diversity (maximum $R^2 = 0.26$). To all response variables, the additive model BIO1+ACI had the best performance (Figure 03; Table 3). The complete results of the models are in Appendix S5. Both in the models that considered the variable environment and in those that did not consider it, the additive models with two acoustic indices, were the best correlations to three response variables. The dAICc results with big differences among the models were probably due to the use of big data as entered (e.g. 6,500 samples). So, because of this, we also used R^2 to obtain an idea about the explaining power of the models.

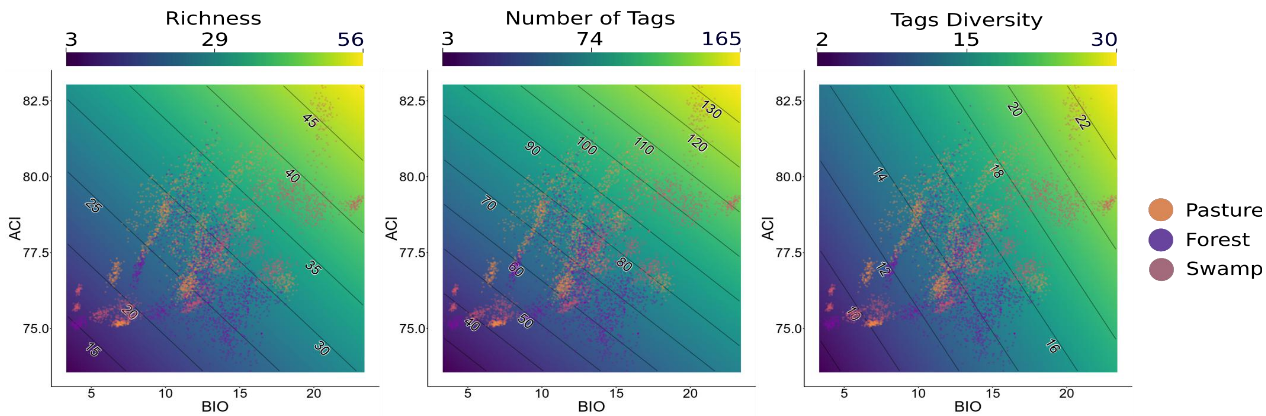


Figure 3 - The best models from GLM analysis using data of all environments, within the region of the Long Term Ecological Research within the ecological Corridor of Cantareira-Mantiqueira (PELD CCM), Atlantic Forest, São Paulo, Brazil.

3.2 Considering each environment separately

In general, different models had greater correlation not only for different environments, but also for different response variables. The best models and correlation power presented some variation among the data from the different environments. Swamp showed greaters results, with $R^2 = 0.76$ to richness (ADI+BIO1); $R^2 = 0.67$ to diversity (ADI+BIO1), and $R^2 = 0.64$ to number of tags (ACI+BIO1). Pasture got a number of tags $R^2 = 0.43$ (BIO1+AR), richness $R^2 = 0.41$ (BIO1+AR), and $R^2 = 0.29$ (BIO1+AR) to tag diversity. Finally, the forest environment showed results of $R^2 = 0.50$ about number of tags (BIO1+NDSI2), $R^2 = 0.25$ to richness (BIO1+ACI), and the smaller value to diversity, $R^2 = 0.14$ (NDSI1+Ht) (Table 4). The complete results are in the Appendix S6.

Table 3 - Four best models results for each response variable and null model. Model variables, dAICc, df (degrees of freedom), wAIC and Explanatory power (R^2) of acoustic indices on explaining bird responses within the region of the Long Term Ecological Research within the ecological Corridor of Cantareira-Mantiqueira (PELD CCM), Atlantic Forest, São Paulo, Brazil. Bird responses are bird richness, number of bird tags and bird tag diversity. The acoustic indices after the symbol "~" were used in the models, which were ranked from the higher dAICc and R^2 values (top) to the lowest (botton) within bird responses. Detailed results are available in Appendix S6.

GLM models	[Delta]AICc	df	wAIC	R^2
Richness~ACI + BIO1 + environment	0	6	1.000	0.43
Richness~BIO1 + AR + environment	474.96	6	<< 0.0001	0.38
Richness~ADI + BIO1 + environment	513.07	6	<< 0.0001	0.38
Richness~ACI + BIO1	605.74	4	<< 0.0001	0.37
Richness~NULL	3622.95	2	0.000	0.00
Tags.Number~ACI + BIO1 + environment	0	6	1.000	0.48
Tags.Number~BIO1 + AR + environment	317.74	6	<< 0.0001	0.46
Tags.Number~ADI + BIO1 + environment	466.09	6	<< 0.0001	0.44
Tags.Number~AEI + BIO1 + environment	468.56	6	<< 0.0001	0.44
Tags.Number~NULL	4274.76	2	0.000	0.00
Diversity~ACI + BIO1 + environment	0	6	1.000	0.26
Diversity~BIO1 + NDSI2 + environment	40.44	6	<< 0.0001	0.25
Diversity~ACI + BIO1	53.97	4	<< 0.0001	0.25
Diversity~BIO1 + NDSI2	67.93	4	<< 0.001	0.25
Diversity~NULL	1921.78	2	0.000	0.00

To the pasture, both acoustic indices in the bivariate model had similar contributions in the explanation in the models, while in the forest data, to richness and number of tags both acoustic indices in the model were similar contributions (Figure 4). But to the diversity, Ht had much more contribution than ACI. In the swamp BIO had a greater contribution in the models than ADI to all responses variables.

Table 4 - Mainly models from GLM results to responses variables from each environment data. Model variables, dAICc, df (degrees of freedom), wAIC and Explanatory power (R^2) of acoustic indices on explaining bird responses within the region of the Long Term Ecological Research within the ecological Corridor of Cantareira-Mantiqueira (PELD CCM), Atlantic Forest, São Paulo, Brazil. Bird responses are bird richness, number of bird tags and bird tag diversity. The acoustic indices after the symbol "~" were used in the models, which were ranked from the higher dAICc and R^2 values (top) to the lowest (botton) within bird responses. Detailed results are available in Appendix S6.

Environment	GLM models	[Delta]AICc	df	wAIC	R^2
Forest	**Richness**~BIO1 + ACI	0	4	1.000	0.25
	Richness~BIO1 + NDSI2	102.89	4	<< 0.0001	0.21
	Tags.Number~BIO1.NDSI2	0	4	1.000	0.50
	Tags.Number~ACI + BIO1	365.63	4	<< 0.0001	0.41
	Diversity~NDSI1 + Ht	0	4	1.000	0.14
	Diversity~ACI + Ht	19.39	4	<< 0.0001	0.13
Pasture	**Richness**~BIO1 + AR	0	4	1.000	0.41
	Richness~ACI + AR	179.76	4	<< 0.0001	0.35
	Tags.Number~BIO1 + AR	0	4	1.000	0.43
	Tags.Number~ACI + AR	109.97	4	<< 0.0001	0.40
	Diversity~BIO1 + AR	0	4	1.000	0.29
	Diversity~AEI + BIO1	110.42	4	<< 0.0001	0.25
Swamp	**Richness**~ADI + BIO1	0	4	1.000	0.75
	Richness~ACI + BIO1	162.05	4	<< 0.0001	0.73
	Tags.Number~ACI + BIO1	0	4	1.000	0.64
	Tags.Number~AEI + BIO1	114.64	4	<< 0.0001	0.62
	Diversity~ADI + BIO1	0	4	1.000	0.67
	Diversity~BIO1 + BIO2	79.91	4	<< 0.0001	0.66

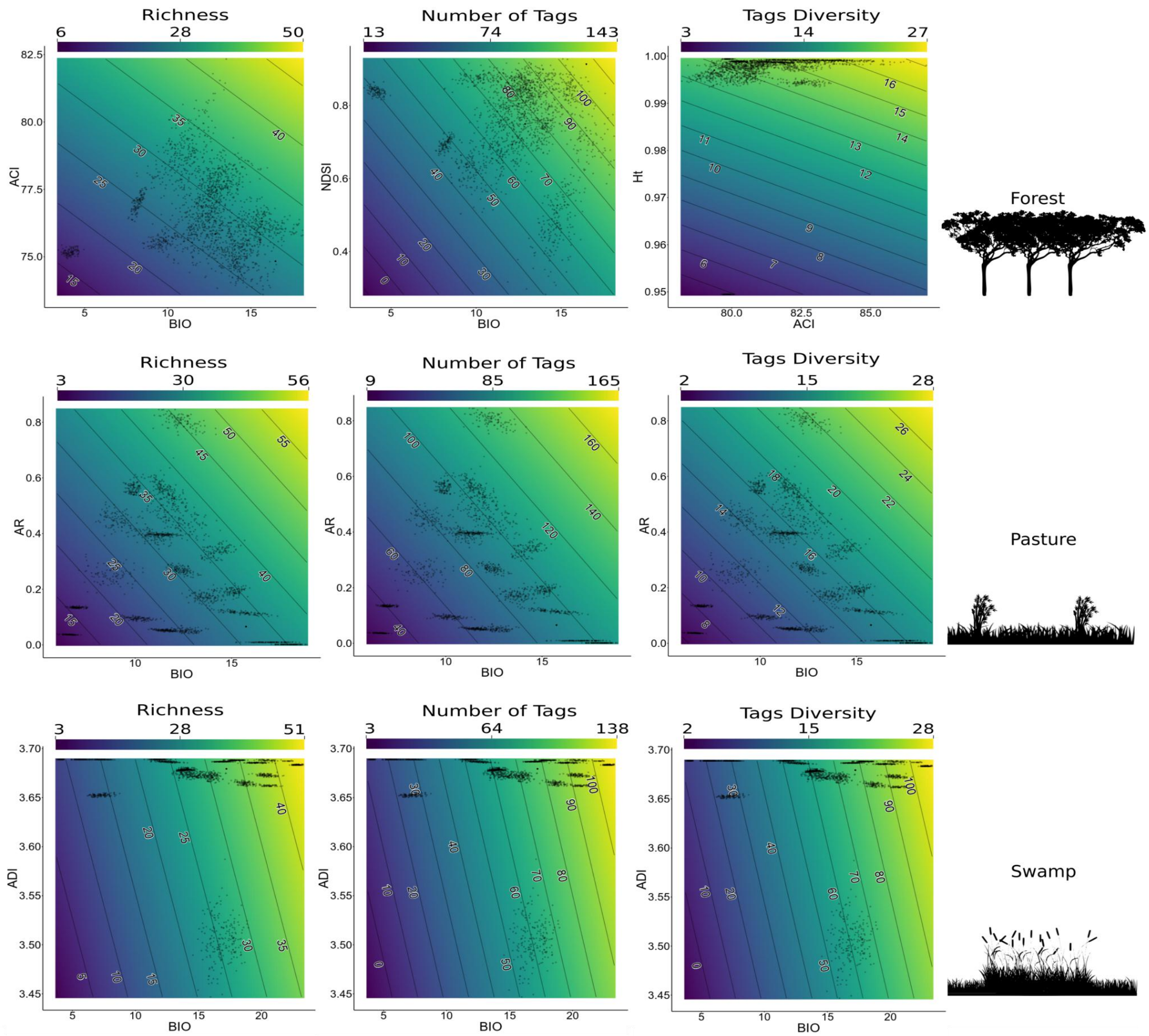


Figure 4 - The best models to each response variable (bird richness, number of tags and tags diversity) to each environment in separate within the region of the Long Term Ecological Research within the ecological Corridor of Cantareira-Mantiqueira (PELD CCM), Atlantic Forest, São Paulo, Brazil. Bird responses are bird richness, number of bird tags and bird tag diversity. All BIO correspond to the BIO1 parameters.

4. Discussion

We investigated how seven most used different acoustic indices were related to the bird's acoustic community in different environments of Atlantic Forest. We were able to demonstrate how the combination of two indices using models better explains diversity of vocalizations than single indices approach to all situations. Also, the environment type has influence in the correlations, being the best correlations were found in the swamps, pasture and forest, respectively. The swamp environment has found greaters results not only for richness (ADI+BIO) but also for the diversity (ADI+BIO) and number of tags (ACI+BIO). To pasture, the BIO+AR was the best model to the three responses variables. Finally, for forests, BIO+NDSI was the best model correlation with number of tags, while BIO+ACI and NDSI+Ht were similar to others, but with low correlation.

The idea of a single index being unable to capture all facets of the diversity of vocalizations was discussed by (Sueur et al., 2014b) by using some few studies (Eldridge et al., 2018; Towsey et al., 2014). Eldridge et al., 2018 discussed the combination of indices that use different strategies to measure aspects of biodiversity. Nevertheless, here we demonstrate that the two indices with the best combined performance measure the different facets of the diversity of birds tested (richness, tag abundance and diversity) were indices with similar theoretical backgrounds. (Towsey et al., 2014) have found that bivariate models (ACI+Spectral diversity) were better than three indices models, even more than four indices models, and a low explanation was added with more indices about bird richness. Here, we used bivariate models, and found the ACI, BIO, AR and NDSI the greater indices, but the ADI, besides important, had less to explain contribution.

The literature presents several inconsistencies in the relationship between AI and measures of bird diversity. This demonstrates that there is a long way to go for the widespread use of AI, mainly about what conclusions can be drawn from them. All these different patterns can be due to several reasons, such as differences in the land uses (e.g. Buxton et al., 2018), climate (e.g. (Eldridge et al., 2018), vocalization patterns (Zhao et al., 2019) and acoustic signals diversity, like anthropogenic noises types (e.g. Ross et al., 2021). In addition, they can also be caused by differences in obtaining ecological measures and data analysis. Here we saw that environments with structural differences and complexity (e.g. forest and pasture) showed different results. In addition, even environments with similar structure, that is, open vegetation (e.g. pastures and swamps) also differed between the results. Despite not being tested, this divergence may be related to the amount of anthropic activities, which tend to be larger closer to the pastures than in the swamp area, where the relief is more rugged and the soil is moist. Therefore, acoustic data obtained in different environments need to be treated separately to more accuracy, since the type of environment will have an influence on the relationship between AI and biodiversity. However, we showed the bivariate model BIO+ACI was the most appropriate model when we considered data from all environments together, however the environment variable was important in all models and not considering it, later analyzes may be superficial and mask the real standards.

The differences can also be a result of ecological and biological processes. Understanding and explaining biodiversity patterns is usually the goal of the majority of studies using PAM and AI, but as there is still a lack of baseline it is hard to compare among different studies and be certain of what is causing variation. Another cause of inconsistency between studies similar to this one, may be related to differences in analyzes. Many of them vary between obtaining ecological variables, such as listening points in the field (e.g Mitchell et al., 2020; Bradfer-Lawrence et al., 2020; Mammides et al., 2017; Retamosa Izaguirre and Ramírez-Alán, 2018) or manual detection of species in the recordings (e.g Buxton et al., 2018; Eldridge et al., 2018; Jorge et al., 2018; Machado et al., 2017; Moreno-Gómez et al., 2019; Shamon et al., 2021) , selecting minutes and considering sample size and also, different statistical tests and presenting the results to test the correlations.

In addition we believe that obtaining ecological variables from the manual detection of species in audio is important, since they will have exactly the same intentions used for calculating AI. We perform bootstrap sampling, that is, draws of sets of minutes with replacement. Thus, there is a standardization of the sampling effort of each collection point and also, different possible combinations of minutes, which decreases the temporal correlation in the data. In addition, for the selection of models we use GLM, considering mainly not only the values of dAIC but also of R^2. This is because, dAIC despite ordering the best models, for large samples the results between the models tend to be discrepant. Since, from R^2 values, in addition to obtaining the best model, we can have an idea of how well related the variables are and the size of the explanation gain that is gained or lost between each model. In addition, based on R^2 values, it is possible to make more concrete comparisons between the different studies that seek to test this relationship in different contexts and possibilite real estimates about biodiversity numbers.

As for the manual detection of species to obtain ecological variables, we use not only the most common richness, but also the amount and diversity of tags. We understand the limitation of the use of quantitative measures from acoustic data, however, it is to verify which aspects of acoustic activity certain AI are more sensitive or less. In addition, in view of the large amount of data collected and labeled species, we believe that it is necessary to move beyond just richness. Here we use the quantity of tags as a next for the quantity of vocalizations and from the richness and number of tags in a given sample we calculate the diversity of tags. In general, our results showed for each response variable there were differences not only in the correlations power, but also for the best correlated models. In the forest and pasture environment, the highest correlation of AI was with the number of tags. In a swamp environment, the greatest correlation was with richness, but also with high diversity values and number of tags. Therefore, in addition to differences in the correlations between AI and bird biodiversity in different environments, they are also correlated differently depending on the ecological variable involved.

5. Conclusions and future directions

We demonstrated acoustic indices are better correlated with bird number of vocalizations than richness or diversity; models that use two indices instead of just one, have better correlations with bird acoustic diversity and; the environment type has influence in these correlations. We defend the use of acoustic indices to measure mainly the level and patterns of acoustic activity. However, the ecological inferences and comparisons made from this data type need caution, since when varying the environment, there is also variation in the correlation between acoustic indices and different aspects of bird diversity. This, mainly due to the absence of information regarding functional diversity, for example. Further studies are needed to test the acoustic indices in different conditions, considering the use of two or more indices for the analyzes. In addition, based on the correlations found, in fact perform prediction tests, relating the values of acoustic indices and how much the estimated diversity of bird species in a given landscape would be.

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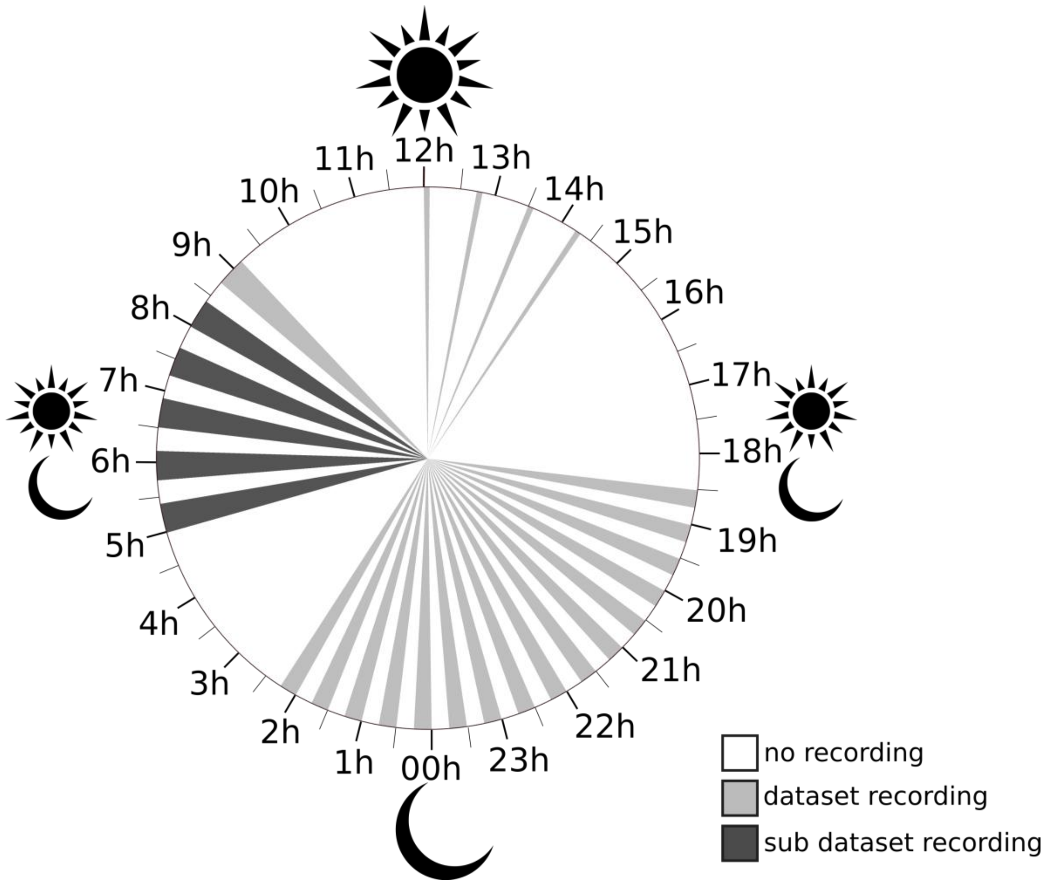
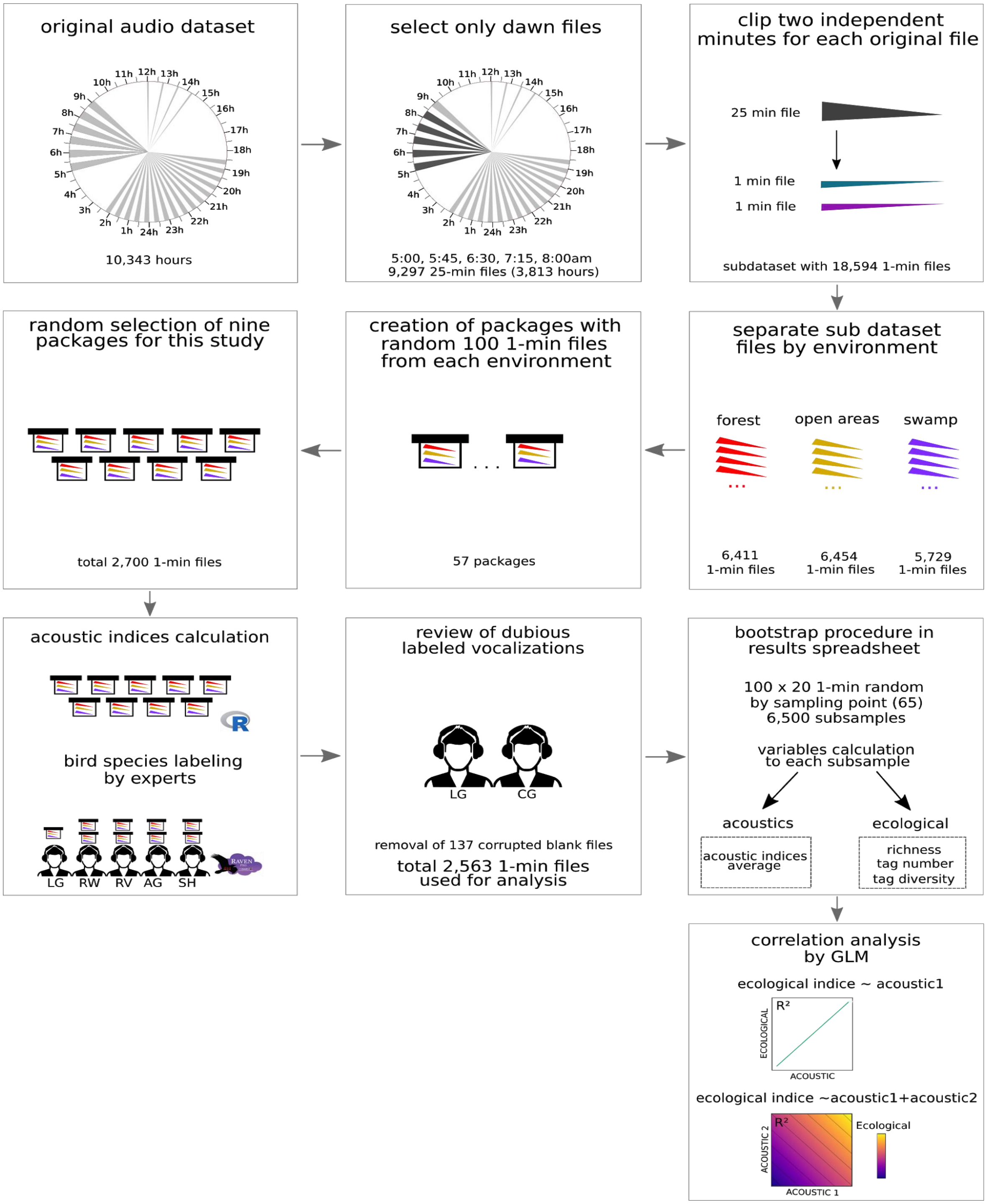
Supplementary Material

Appendix S1 - Programming schedule of audio recorders for data collection.



Appendix S2 - Scheme of the routine to preparing acoustic subdataset.



Appendix S3 - List of species of daytime birds identified by means of manual detection in 2,563 minutes obtained by Passive Acoustic Monitoring in fragmented landscapes of the Atlantic Forest. Names following CBRO 2015 Piacentini et. al (2015) and Conservation Status (IUCN 2020).
* Endemism of Atlantic Forest biome (Vale et al. 2018).

Order	Family	Scientific Name	English Name	Conservation Status	Number of Tags
Tinamiformes	Tinamidae	*Tinamus solitarius*	Solitary Tinamou	NT	3
		Crypturellus obsoletus	Brown Tinamou	LC	17
		Crypturellus parvirostris	Small-billed Tinamou	LC	15
		Crypturellus tataupa	Tataupa Tinamou	LC	83
		Rhynchotus rufescens	Red-winged Tinamou	LC	1
Anseriformes	Anatidae	*Dendrocygna autumnalis*	Black-bellied Whistling-Duck	LC	1
		Cairina moschata	Muscovy Duck	LC	3
Galliformes	Cracidae	*Penelope* sp.			5
Pelecaniformes	Threskiornithidae	*Mesembrinibis cayennensis*	Green Ibis	LC	8
		Theristicus caudatus	Buff-necked Ibis	LC	3
Cathartiformes	Cathartidae	*Coragyps atratus*	Black Vulture	LC	2
Accipitriformes	Accipitridae	*Leptodon cayanensis*	Gray-headed Kite	LC	6
		Rupornis magnirostris	Roadside Hawk	LC	26
Gruiformes	Aramidae	*Aramus guarauna*	Limpkin	LC	1
	Rallidae	*Aramides cajaneus*	Gray-necked Wood-Rail	LC	9
		*Aramides saracura**	Slaty-breasted Wood-Rail	LC	19
		Laterallus melanophaius	Rufous-sided Crake	LC	3
		Mustelirallus albicollis	Ash-throated Crake	LC	1
		Pardirallus nigricans	Blackish Rail	LC	5
Charadriiformes	Charadriidae	*Vanellus chilensis*	Southern Lapwing	LC	118
Columbiformes	Columbidae	*Columbina talpacoti*	Ruddy Ground-Dove	LC	101
		Patagioenas picazuro	Picazuro Pigeon	LC	241
		Patagioenas cayennensis	Pale-vented Pigeon	LC	35
		Patagioenas plumbea	Plumbeous Pigeon	LC	25
		Patagioenas sp.			2
		Zenaida auriculata	Eared Dove	LC	43
		Leptotila verreauxi	White-tipped Dove	LC	163
		Leptotila rufaxilla	Gray-fronted Dove	LC	62
		Leptotila sp.			5

Order	Family	Scientific Name	English Name	Conservation Status	Number of Tags
Cuculiformes	Cuculidae	*Piaya cayana*	Squirrel Cuckoo	LC	10
		Crotophaga ani	Smooth-billed Ani	LC	21
		Guira guira	Guira Cuckoo	LC	36
		Tapera naevia	Striped Cuckoo	LC	34
		Dromococcyx pavoninus	Pavonine Cuckoo	LC	1
Caprimulgiformes	Caprimulgidae	*Lurocalis semitorquatus*	Short-tailed Nighthawk	LC	3
Apodiformes	Apodidae	*Chaetura meridionalis*	Sick's Swift	LC	1
	Trochilidae	*Phaethornis pretrei*	Planalto Hermit	LC	24
		*Phaethornis eurynome**	Scale-throated Hermit	LC	3
		Phaethornis sp.			13
		Eupetomena macroura	Swallow-tailed Hummingbird	LC	6
		Florisuga fusca	Black Jacobin	LC	1
		Chlorostilbon lucidus	Glittering-bellied Emerald	LC	9
		*Thalurania glaucopis**	Violet-capped Woodnymph	LC	2
		Leucochloris albicollis	White-throated Hummingbird	LC	19
		Amazilia lactea	Sapphire-spangled Emerald	LC	9
		Amazilia sp.			6
		Trochilidae sp.			5
Trogoniformes	Trogonidae	*Trogon surrucura*	Surucua Trogon	LC	3
Coraciiformes	Alcedinidae	*Megaceryle torquata*	Ringed Kingfisher	LC	1
Galbuliformes	Galbulidae	*Galbula ruficauda*	Rufous-tailed Jacamar	LC	2
	Bucconidae	*Malacoptila striata**	Crescent-chested Puffbird	NT	8
Piciformes	Ramphastidae	*Ramphastos toco*	Toco Toucan	LC	3
		*Ramphastos dicolorus**	Red-breasted Toucan	LC	3
	Picidae	*Picumnus* sp.			38
		Melanerpes candidus	White Woodpecker	LC	39
		Veniliornis spilogaster	White-spotted Woodpecker	LC	5
		Veniliornis sp.			1
		Colaptes melanochloros	Green-barred Woodpecker	LC	3
		Colaptes campestris	Campo Flicker	LC	98
		Celeus flavescens	Blond-crested Woodpecker	LC	14
		Dryocopus lineatus	Lineated Woodpecker	LC	3
Cariamiformes	Cariamidae	*Cariama cristata*	Red-legged Seriema	LC	62

Order	Family	Scientific Name	English Name	Conservation Status	Number of Tags
Falconiformes	Falconidae	*Caracara plancus*	Southern Caracara	LC	3
		Milvago chimachima	Yellow-headed Caracara	LC	7
		Herpetotheres cachinnans	Laughing Falcon	LC	5
		Micrastur ruficollis	Barred Forest-Falcon	LC	1
Psittaciformes	Psittacidae	*Psittacara leucophthalmus*	White-eyed Parakeet	LC	113
		Eupsittula aurea	Peach-fronted Parakeet	LC	1
		Forpus xanthopterygius	Blue-winged Parrotlet	LC	8
		*Brotogeris tirica**	Plain Parakeet	LC	6
		Brotogeris chiriri	Yellow-chevroned Parakeet	LC	62
		Brotogeris sp.			11
		Pionus maximiliani	Scaly-headed Parrot	LC	18
		Amazona aestiva	Turquoise-fronted Parrot	LC	1
		Psittacidae sp.			5
Passeriformes	Thamnophilidae	*Dysithamnus mentalis*	Plain Antvireo	LC	171
		Herpsilochmus rufimarginatus	Rufous-winged Antwren	LC	61
		Thamnophilus doliatus	Barred Antshrike	LC	1
		Thamnophilus ruficapillus	Rufous-capped Antshrike	LC	3
		Thamnophilus caerulescens	Variable Antshrike	LC	143
		Batara cinerea	Giant Antshrike	LC	3
		*Hypoedaleus guttatus**	Spot-backed Antshrike	LC	60
		*Mackenziaena severa**	Tufted Antshrike	LC	2
		*Myrmoderus squamosus**	Squamate Antbird	LC	19
		Pyriglena leucoptera	White-shouldered Fire-eye	LC	75
		*Drymophila ferruginea**	Ferruginous Antbird	LC	9
		*Drymophila ochropyga**	Ochre-rumped Antbird	NT	2
		*Drymophila malura**	Dusky-tailed Antbird	LC	1
	Conopophagidae	*Conopophaga lineata*	Rufous Gnateater	LC	63
	Grallariidae	*Grallaria varia*	Variegated Antpitta	LC	18
	Rhinocryptidae	*Psilorhamphus guttatus**	Spotted Bamboowren	NT	2
	Scleruridae	*Sclerurus scansor**	Rufous-breasted Leaftosser	LC	2
	Dendrocolaptidae	*Sittasomus griseicapillus*	Olivaceous Woodcreeper	LC	29
		*Xiphorhynchus fuscus**	Lesser Woodcreeper	LC	3
		*Campylorhamphus falcularius**	Black-billed Scythebill	LC	1
		Lepidocolaptes angustirostris	Narrow-billed Woodcreeper	LC	1

Order	Family	Scientific Name	English Name	Conservation Status	Number of Tags
...	Xenopidae	*Xenops rutilans*	Streaked Xenops	LC	13
	Furnariidae	*Furnarius figulus*	Wing-banded Hornero	LC	1
		Furnarius rufus	Rufous Hornero	LC	129
		Lochmias nematura	Sharp-tailed Streamcreeper	LC	21
		*Automolus leucophthalmus**	White-eyed Foliage-gleaner	LC	38
		Anabazenops fuscus	White-collared Foliage-gleaner	LC	1
		Philydor rufum	Buff-fronted Foliage-gleaner	LC	15
		Heliobletus contaminatus	Sharp-billed Treehunter	LC	2
		*Phacellodomus ferrugineigula**	Orange-breasted Thornbird	LC	13
		Certhiaxis cinnamomeus	Yellow-chinned Spinetail	LC	14
		*Synallaxis ruficapilla**	Rufous-capped Spinetail	LC	32
		Synallaxis frontalis	Sooty-fronted Spinetail	LC	4
		Synallaxis spixi	Spix's Spinetail	LC	118
		*Cranioleuca pallida**	Pallid Spinetail	LC	22
	Pipridae	*Chiroxiphia caudata**	Swallow-tailed Manakin	LC	105
	Tityridae	*Schiffornis virescens**	Greenish Schiffornis	LC	12
		Pachyramphus viridis	Green-backed Becard	LC	1
		Pachyramphus validus	Crested Becard	LC	26
	Cotingidae	*Pyroderus scutatus*	Red-ruffed Fruitcrow	LC	3
		*Procnias nudicollis**	Bare-throated Bellbird	VU	55
	Platyrinchidae	*Platyrinchus mystaceus*	White-throated Spadebill	LC	35
	Rhynchocyclidae	*Mionectes rufiventris**	Gray-hooded Flycatcher	LC	26
		Leptopogon amaurocephalus	Sepia-capped Flycatcher	LC	22
		Corythopis delalandi	Southern Antpipit	LC	43
		Phylloscartes ventralis	Mottle-cheeked Tyrannulet	LC	1
		Tolmomyias sulphurescens	Yellow-olive Flycatcher	LC	148
		*Todirostrum poliocephalum**	Gray-headed Tody-Flycatcher	LC	36
		Todirostrum cinereum	Common Tody-Flycatcher	LC	5
		Poecilotriccus plumbeiceps	Ochre-faced Tody-Flycatcher	LC	19
		*Hemitriccus diops**	Drab-breasted Pygmy-Tyrant	LC	1
	Tyrannidae	*Hirundinea ferruginea*	Cliff Flycatcher	LC	1
		Tyranniscus burmeisteri	Rough-legged Tyrannulet	LC	1

Order	Family	Scientific Name	English Name	Conservation Status	Number of Tags
...		*Camptostoma obsoletum*	Southern Beardless-Tyrannulet	LC	91
		Elaenia flavogaster	Yellow-bellied Elaenia	LC	78
		Elaenia obscura	Highland Elaenia	LC	23
		Myiopagis caniceps	Gray Elaenia	LC	2
		Myiopagis viridicata	Greenish Elaenia	LC	3
		Serpophaga subcristata	White-crested Tyrannulet	LC	8
		Attila rufus	Gray-hooded Attila	LC	3
		Legatus leucophaius	Piratic Flycatcher	LC	2
		Myiarchus swainsoni	Swainson's Flycatcher	LC	69
		Myiarchus ferox	Short-crested Flycatcher	LC	18
		Myiarchus tyrannulus	Brown-crested Flycatcher	LC	26
		Pitangus sulphuratus	Great Kiskadee	LC	371
		Machetornis rixosa	Cattle Tyrant	LC	9
		Myiodynastes maculatus	Streaked Flycatcher	LC	164
		Megarynchus pitangua	Boat-billed Flycatcher	LC	31
		Myiozetetes similis	Social Flycatcher	LC	22
		Tyrannus melancholicus	Tropical Kingbird	LC	179
		Tyrannus savana	Fork-tailed Flycatcher	LC	2
		Empidonomus varius	Variegated Flycatcher	LC	26
		Colonia colonus	Long-tailed Tyrant	LC	5
		Myiophobus fasciatus	Bran-colored Flycatcher	LC	47
		Gubernetes yetapa	Streamer-tailed Tyrant	LC	1
		Lathrotriccus euleri	Euler's Flycatcher	LC	48
	Vireonidae	*Cyclarhis gujanensis*	Rufous-browed Peppershrike	LC	427
		*Hylophilus poicilotis**	Rufous-crowned Greenlet	LC	1
		Vireo chivi	Chivi Vireo	LC	781
	Corvidae	*Cyanocorax chrysops*	Plush-crested Jay	LC	18
	Hirundinidae	*Pygochelidon cyanoleuca*	Blue-and-white Swallow	LC	7
		Stelgidopteryx ruficollis	Southern Rough-winged Swallow	LC	4
		Progne tapera	Brown-chested Martin	LC	2
		Progne chalybea	Gray-breasted Martin	LC	1
		Tachycineta sp.			1
	Troglodytidae	*Troglodytes musculus*	Southern House Wren	LC	274
	Donacobiidae	*Donacobius atricapilla*	Black-capped Donacobius	LC	1
	Turdidae	*Turdus flavipes*	Yellow-legged Thrush	LC	2
		Turdus leucomelas	Pale-breasted Thrush	LC	201

Order	Family	Scientific Name	English Name	Conservation Status	Number of Tags
...		*Turdus rufiventris*	Rufous-bellied Thrush	LC	164
		Turdus amaurochalinus	Creamy-bellied Thrush	LC	40
		Turdus albicollis	White-necked Thrush	LC	71
		Turdus sp.			84
	Mimidae	*Mimus saturninus*	Chalk-browed Mockingbird	LC	10
	Passerellidae	*Ammodramus humeralis*	Grassland Sparrow	LC	48
	Parulidae	*Setophaga pitiayumi*	Tropical Parula	LC	82
		Basileuterus culicivorus	Golden-crowned Warbler	LC	533
		Myiothlypis flaveola	Flavescent Warbler	LC	5
		Myiothlypis leucoblephara	White-browed Warbler	LC	267
	Passerellidae	*Arremon semitorquatus**	Half-collared Sparrow	LC	8
		Zonotrichia capensis	Rufous-collared Sparrow	LC	631
	Icteridae	*Icterus pyrrhopterus*	Variable Oriole	LC	2
		Icterus jamacaii	Campo Troupial	LC	1
		Gnorimopsar chopi	Chopi Blackbird	LC	2
		Chrysomus ruficapillus	Chestnut-capped Blackbird	LC	49
		Pseudoleistes guirahuro	Yellow-rumped Marshbird	LC	25
		Agelasticus cyanopus	Unicolored Blackbird	LC	3
		Molothrus bonariensis	Shiny Cowbird	LC	2
	Thraupidae	*Pipraeidea melanonota*	Fawn-breasted Tanager	LC	1
		*Tangara desmaresti**	Brassy-breasted Tanager	LC	1
		Tangara sayaca	Sayaca Tanager	LC	340
		Tangara palmarum	Palm Tanager	LC	4
		Tangara cayana	Burnished-buff Tanager	LC	47
		Tangara sp.			9
		Conirostrum speciosum	Chestnut-vented Conebill	LC	35
		Sicalis flaveola	Saffron Finch	LC	89
		Sicalis luteola	Grassland Yellow-Finch	LC	10
		Volatinia jacarina	Blue-black Grassquit	LC	123
		Coryphospingus cucullatus	Red-crested Finch	LC	3
		*Tachyphonus coronatus**	Ruby-crowned Tanager	LC	140
		Ramphocelus carbo	Silver-beaked Tanager	LC	5
		Tersina viridis	Swallow Tanager	LC	28
		Dacnis cayana	Blue Dacnis	LC	1

Order	Family	Scientific Name	English Name	Conservation Status	Number of Tags
...		*Coereba flaveola*	Bananaquit	LC	57
		Tiaris fuliginosus	Sooty Grassquit	LC	1
		Sporophila lineola	Lined Seedeater	LC	55
		*Sporophila frontalis**	Buffy-fronted Seedeater	VU	1
		Sporophila caerulescens	Double-collared Seedeater	LC	108
		Sporophila leucoptera	White-bellied Seedeater	LC	2
		Sporophila angolensis	Chestnut-bellied Seed-Finch	LC	1
		Sporophila sp.			4
		Emberizoides herbicola	Wedge-tailed Grass-Finch	LC	2
		Saltator similis	Green-winged Saltator	LC	146
		*Saltator fuliginosus**	Black-throated Grosbeak	LC	1
		Thlypopsis sordida	Orange-headed Tanager	LC	2
		Thraupidae sp.			3
	Cardinalidae	*Habia rubica*	Red-crowned Ant-Tanager	LC	31
		Cyanoloxia brissonii	Ultramarine Grosbeak	LC	4
	Fringillidae	*Euphonia chlorotica*	Purple-throated Euphonia	LC	26
		Euphonia cyanocephala	Golden-rumped Euphonia	LC	5
	Passeridae	*Passer domesticus*	House Sparrow	LC	2

Appendix S4 - Model selection results using the General Linear Model (GLM) to data with all environments. Models with $R^2 \leq 0.20$ were disregarded

Bird richness

GLM models	[Delta] AICc	df	weight	r2
Richness~ACI_1000_12000_FFT512 + BIO_1000_12000_FFT512 + environment	0	6	1	0.43
Richness~BIO_1000_12000_FFT512 + AR + environment	474.96	6	<< 0.001	0.38
Richness~ADI_300_12000_75db + BIO_1000_12000_FFT512 + environment	513.07	6	<< 0.001	0.38
Richness~ACI_1000_12000_FFT512 + BIO_1000_12000_FFT512	605.74	4	<< 0.001	0.37
Richness~BIO_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512 + environment	658.39	6	<< 0.001	0.37
Richness~AEI_1000_12000_50db + BIO_1000_12000_FFT512 + environment	774.67	6	<< 0.001	0.36
Richness~BIO_1000_12000_FFT512 + Ht + environment	873.11	6	<< 0.001	0.35
Richness~ADI_300_12000_75db + BIO_1000_12000_FFT512	961.08	4	<< 0.001	0.34
Richness~BIO_1000_12000_FFT512 + BIO_1000_22050_FFT512 + environment	998.84	6	<< 0.001	0.33
Richness~BIO_1000_12000_FFT512 + environment	1001.87	5	<< 0.001	0.33
Richness~BIO_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512 + environment	1003.13	6	<< 0.001	0.33
Richness~ADI_300_12000_75db + ACI_1000_12000_FFT512 + environment	1065.06	6	<< 0.001	0.33
Richness~ACI_1000_12000_FFT512 + BIO_1000_22050_FFT512 + environment	1177.48	6	<< 0.001	0.31
Richness~ACI_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512 + environment	1211.18	6	<< 0.001	0.31
Richness~BIO_1000_12000_FFT512 + AR	1223.65	4	<< 0.001	0.31
Richness~ACI_1000_12000_FFT512 + Ht + environment	1234.96	6	<< 0.001	0.31
Richness~AEI_1000_12000_50db + BIO_1000_12000_FFT512	1267.49	4	<< 0.001	0.31
Richness~ACI_1000_12000_FFT512 + AR + environment	1290.21	6	<< 0.001	0.30
Richness~BIO_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512	1345.58	4	<< 0.001	0.30
Richness~ACI_1000_12000_FFT512 + environment	1347.33	5	<< 0.001	0.30
Richness~ACI_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512 + environment	1348.28	6	<< 0.001	0.30
Richness~AEI_1000_12000_50db + ACI_1000_12000_FFT512 + environment	1349.22	6	<< 0.001	0.30
Richness~ACI_1000_12000_FFT512 + BIO_1000_22050_FFT512	1444.54	4	<< 0.001	0.28
Richness~ADI_300_12000_75db + ACI_1000_12000_FFT512	1504.32	4	0	0.28
Richness~BIO_1000_12000_FFT512 + Ht	1542.72	4	0	0.27
Richness~ACI_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512	1571.49	4	0	0.27
Richness~BIO_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512	1589.03	4	0	0.27
Richness~BIO_1000_12000_FFT512 + BIO_1000_22050_FFT512	1598.63	4	0	0.27
Richness~ACI_1000_12000_FFT512 + Ht	1609.02	4	0	0.27
Richness~BIO_1000_12000_FFT512	1622.76	3	0	0.26
Richness~ACI_1000_12000_FFT512 + AR	1623.80	4	0	0.26
Richness~ACI_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512	1667.78	4	0	0.26
Richness~ACI_1000_12000_FFT512	1688.73	3	0	0.26
Richness~AEI_1000_12000_50db + ACI_1000_12000_FFT512	1690.31	4	0	0.26

Richness~ADI_300_12000_75db + BIO_1000_22050_FFT512 + environment	1923.36	6	0	0.23
Richness~ADI_300_12000_75db + BIO_1000_22050_FFT512	1941.89	4	0	0.23
Richness~N ULL	3622.95	2	0	0.00

Number of Tags

GLM models	[Delta] AICc	df	weight	r2
Tags.Number~ACI_1000_12000_FFT512 + BIO_1000_12000_FFT512 + environment	0	6	1	0.48
Tags.Number~BIO_1000_12000_FFT512 + AR + environment	317.74	6	<< 0.001	0.46
Tags.Number~ADI_300_12000_75db + BIO_1000_12000_FFT512 + environment	466.09	6	<< 0.001	0.44
Tags.Number~AEI_1000_12000_50db + BIO_1000_12000_FFT512 + environment	468.56	6	<< 0.001	0.44
Tags.Number~BIO_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512 + environment	636.75	6	<< 0.001	0.43
Tags.Number~BIO_1000_12000_FFT512 + Ht + environment	902.61	6	<< 0.001	0.40
Tags.Number~BIO_1000_12000_FFT512 + BIO_1000_22050_FFT512 + environment	952.93	6	<< 0.001	0.40
Tags.Number~BIO_1000_12000_FFT512 + environment	953.61	5	<< 0.001	0.40
Tags.Number~BIO_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512 + environment	955.42	6	<< 0.001	0.40
Tags.Number~ADI_300_12000_75db + ACI_1000_12000_FFT512 + environment	1318.21	6	<< 0.001	0.37
Tags.Number~ACI_1000_12000_FFT512 + BIO_1000_22050_FFT512 + environment	1390.49	6	<< 0.001	0.36
Tags.Number~ACI_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512 + environment	1468.36	6	<< 0.001	0.35
Tags.Number~ACI_1000_12000_FFT512 + AR + environment	1513.94	6	0	0.35
Tags.Number~ACI_1000_12000_FFT512 + Ht + environment	1547.28	6	0	0.34
Tags.Number~AEI_1000_12000_50db + ACI_1000_12000_FFT512 + environment	1553.40	6	0	0.34
Tags.Number~ACI_1000_12000_FFT512 + BIO_1000_12000_FFT512	1572.87	4	0	0.34
Tags.Number~ACI_1000_12000_FFT512 + environment	1584.97	5	0	0.34
Tags.Number~ACI_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512 + environment	1585.10	6	0	0.34
Tags.Number~ADI_300_12000_75db + BIO_1000_12000_FFT512	1864.81	4	0	0.31
Tags.Number~AEI_1000_12000_50db + BIO_1000_12000_FFT512	1918.20	4	0	0.30
Tags.Number~ADI_300_12000_75db + ACI_1000_12000_FFT512	2099.27	4	0	0.28
Tags.Number~ADI_300_12000_75db + BIO_1000_22050_FFT512 + environment	2118.81	6	0	0.28
Tags.Number~ACI_1000_12000_FFT512 + BIO_1000_22050_FFT512	2160.58	4	0	0.28
Tags.Number~BIO_1000_12000_FFT512 + AR	2264.20	4	0	0.27
Tags.Number~ACI_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512	2275.08	4	0	0.26
Tags.Number~AEI_1000_12000_50db + ACI_1000_12000_FFT512	2280.09	4	0	0.26
Tags.Number~ACI_1000_12000_FFT512 + AR	2290.77	4	0	0.26
Tags.Number~ACI_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512	2299.79	4	0	0.26
Tags.Number~ACI_1000_12000_FFT512 + Ht	2355.46	4	0	0.26
Tags.Number~ACI_1000_12000_FFT512	2368.62	3	0	0.25
Tags.Number~BIO_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512	2430.88	4	0	0.25
Tags.Number~BIO_1000_22050_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512 + environment	2483.83	6	0	0.24
Tags.Number~ADI_300_12000_75db + BIO_1000_22050_FFT512	2502.94	4	0	0.24
Tags.Number~BIO_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512	2526.65	4	0	0.24
Tags.Number~BIO_1000_12000_FFT512 + BIO_1000_22050_FFT512	2594.70	4	0	0.23
Tags.Number~BIO_1000_12000_FFT512 + Ht	2619.52	4	0	0.22

Tags.Number~BIO_1000_12000_FFT512	2630.26	3	0	0.22
Tags.Number~AEI_1000_12000_50db + BIO_1000_22050_FFT512 + environment	2639.75	6	0	0.22
Tags.number~NULL	4274.76	2	0	0.00

Diversity

GLM models	[Delta] AICc	df	weight	r2
Diversity~ACI_1000_12000_FFT512 + BIO_1000_12000_FFT512 + environment	0	6	1.000	0.26
Diversity~BIO_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512 + environment	40.44	6	<< 0.001	0.25
Diversity~ACI_1000_12000_FFT512 + BIO_1000_12000_FFT512	53.97	4	<< 0.001	0.25
Diversity~BIO_1000_12000_FFT512 + NDSI_AMAX2000_AMIN1000_BMAX22050_BMIN2000_FFT512	67.93	4	<< 0.001	0.25
Diversity~BIO_1000_12000_FFT512 + AR + environment	112.83	6	<< 0.001	0.24
Diversity~BIO_1000_12000_FFT512 + AR	147.78	4	<< 0.001	0.24
Diversity~ADI_300_12000_75db + BIO_1000_12000_FFT512 + environment	202.84	6	<< 0.001	0.23
Diversity~ADI_300_12000_75db + BIO_1000_12000_FFT512	207.36	4	<< 0.001	0.23
Diversity~BIO_1000_12000_FFT512 + Ht + environment	212.12	6	<< 0.001	0.23
Diversity~BIO_1000_12000_FFT512 + Ht	242.16	4	<< 0.001	0.23
Diversity~BIO_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512 + environment	324.32	6	<< 0.001	0.22
Diversity~AEI_1000_12000_50db + BIO_1000_12000_FFT512 + environment	326.04	6	<< 0.001	0.22
Diversity~AEI_1000_12000_50db + BIO_1000_12000_FFT512	333.22	4	<< 0.001	0.22
Diversity~BIO_1000_12000_FFT512 + BIO_1000_22050_FFT512 + environment	354.69	6	<< 0.001	0.21
Diversity~BIO_1000_12000_FFT512 + NDSI_AMAX1000_AMIN300_BMAX12000_BMIN1000_FFT512	364.68	4	<< 0.001	0.21
Diversity~BIO_1000_12000_FFT512 + BIO_1000_22050_FFT512	371.09	4	<< 0.001	0.21
Diversity~BIO_1000_12000_FFT512 + environment	374.80	5	<< 0.001	0.21
Diversity~BIO_1000_12000_FFT512	395.16	3	<< 0.001	0.21
Diversity~NULL	1921.78	2	0	0.00

Appendix S5 - Model selection results using the General Linear Model (GLM) to data to each environment separate. Here considered only the five best models to each response variable.

Forest

GLM models	[Delta]AICc	df	wAIC	R^2
Richness~BIO1 + ACI	0	4	1.000	0.25
Richness~BIO1 + NDSI2	102.88	4	<< 0.001	0.21
Richness~ACI+Ht	105.34	4	<< 0.001	0.21
Richness~NDSI1+NDSI2	182.43	4	<< 0.001	0.19
Richness~BIO1+Ht	208.26	4	<< 0.001	0.18
Tags.Number~BIO1.NDSI2	0	4	1.000	0.50
Tags.Number~ACI + BIO1	365.63	4	<< 0.001	0.41
Tags.Number~BIO+NDSI2	386.14	4	<< 0.001	0.41
Tags.Number~BIO1+ADI	520.50	4	<< 0.001	0.37
Tags.Number~BIO1+AR	613.98	4	<< 0.001	0.34
Diversity~NDSI1 + Ht	0	4	1.000	0.14
Diversity~ACI + .Ht	19.39	4	<< 0.001	0.13
Diversity~AEI+Ht	30.55	4	<< 0.001	0.13
Diversity~AEI+NDSI2	51.43	4	<< 0.001	0.12
Diversity~ADI+Ht	53.92	4	<< 0.001	0.12

Swamp

Richness~ADI + BIO1	0	4	1.000	0.75
Richness~ACI + BIO1	162.05	4	<< 0.001	0.73
Richness~BIO1.BIO2	203.10	4	<< 0.001	0.72
Richness~BIO1 + NDSI1	221.15	4	<< 0.001	0.72
Richness~BIO1 + NDSI2	253.68	4	<< 0.001	0.71
Tags.Number~ACI + BIO1	0	4	1.000	0.64
Tags.Number~AEI + BIO1	114.64	4	<< 0.001	0.62
Tags.Number ~ADI + BIO1	150.65	4	<< 0.001	0.62
Tags.Number~ACI + Ht	158.81	4	<< 0.001	0.61
Tags.Number~BIO1 + NDSI1	204.19	4	<< 0.001	0.61
Diversity~ADI + BIO1	0	4	1.000	0.67
Diversity~BIO1 + BIO2	79.91	4	<< 0.0001	0.66
Diversity~ADI1 +BIO1	0	4	1.000	0.67
Diversity~BIO1 + BIO2	79.91	4	<< 0.001	0.66

Diversity~AEI + BIO1	267.25	4	<< 0.001	0.63

Pasture

Richness~BIO1 + AR	0	4	1.000	0.41
Richness~ACI + AR	179.76	4	<< 0.001	0.35
Richness~BIO1+ADI	200.27	4	<< 0.001	0.35
Richness~ACI+ADI	218.22	4	<< 0.001	0.34
Richness~BIO1 + ACI	261.59	4	<< 0.001	0.33
Tags.Number~BIO1 + AR	0	4	1.000	0.43
Tags.Number~ACI + AR	109.97	4	<< 0.001	0.40
Tags.Number~ACI+ADI	214.20	4	<< 0.001	0.38
Tags.Number~BIO1 + ADI	293.02	4	<< 0.001	0.35
Tags.Number~BIO1 + ACI	364.02	4	<< 0.001	0.33
Diversity~BIO + AR	0	4	1.000	0.29
Diversity~AEI + BIO1	110.42	4	<< 0.001	0.25
Diversity~ACI+AR	189.45	4	<< 0.001	0.23
Diversity~NDSI1 + NDSI2	225.46	4	<< 0.001	0.21
Diversity~BIO1 + NDSI2	262.13	4	<< 0.001	0.20