Ecological Indicators 140 (2022) 109017

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Automatic acoustic heterogeneity identification in transformed landscapes from Colombian tropical dry forests

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ARTICLE INFO

Keywords:
Acoustic heterogeneity
Landscape transformation
Machine learning
Ecoacoustics
Acoustic indices

ABSTRACT

Tropical ecosystems with high levels of endemism are under threat due to climate change and deforestation. The conservation actions are urgent and must rely on a clear understanding of landscape heterogeneity from transformed landscapes. Currently, passive acoustic monitoring uses the soundscape to understand the dynamics of biological communities and physical components of the sites and thus complement the information about the structures of landscape. However, the link between the analysis and quantification of ecosystem transformation based on acoustic methods and acoustic heterogeneity is just beginning to be analyzed. This document proposes a new beta Acoustic Heterogeneity Index (AHI) that quantifies the acoustic heterogeneity related to landscape transformation. AHI estimates the acoustic dissimilarity between sites modeling membership degrees of mixture models in three transformation states: high, medium, and low. We hypothesized that if acoustic recordings of different habitats are analyzed looking for particular patterns, it is possible to quantify the landscape heterogeneity between sites using sound. To calculate the AHI we propose a methodology of five steps: (1) filtering out recordings with high noise levels, (2) estimating acoustics indices, (3) including temporal patterns, (4) using GMM classification models to recognize habitat transformation levels, and (5) calculating the proposed AHI. We tested the proposal with data collected from 2015 to 2017 for 22 tropical dry forests (TDF) sites in two watersheds of Colombian Caribbean region. The sites were labeled by the level of landscape transformation using forest degradation indicators with satellite imagery. We compared these labels with the predicted transformation of our method showing an F1 score of 92% and 90% in regions of La Guajira and Bolívar respectively. To use AHI interactively, we analized the soundscapes similarities on geographic maps in the study regions. We identified that AHI allows estimating the similarity of points with similar transformations, and where the soundscape provides information about the transition states. This proposal allows complementing landscape transformation studies with information on the acoustic heterogeneity between pairs of sites.

1. Introduction

An essential part of ecological conservation plans is identifying the landscape heterogeneity in highly transformed habitats. We understand landscape heterogeneity as the complexity or variability of landscape features (Malanson and Cramer, 1999). To study the heterogeneity is necessary to compile biodiversity data of planning regions or ecosystems (Worboys et al., 2010). A cost-efficient alternative to study ecosystems is Passive Acoustic Monitoring (PAM), which uses environmental acoustic signals to obtain reliable information on biodiversity and ecosystem health (Napoletano et al., 2011; Krause and Farina, 2016). The soundscape is the collection of biological, geophysical, and anthropogenic sounds that make up a specific site (Pijanowski et al., 2011). Sounds from the soundscape reflect behavior aspects of biotic components and characteristics of the landscape (Hill, 2008; Farina and Fuller, 2014). Thus, the soundscape is usually related to environmental health

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https://doi.org/10.1016/j.ecolind.2022.109017
Received 26 March 2022; Received in revised form 24 May 2022; Accepted 25 May 2022
Available online 30 May 2022

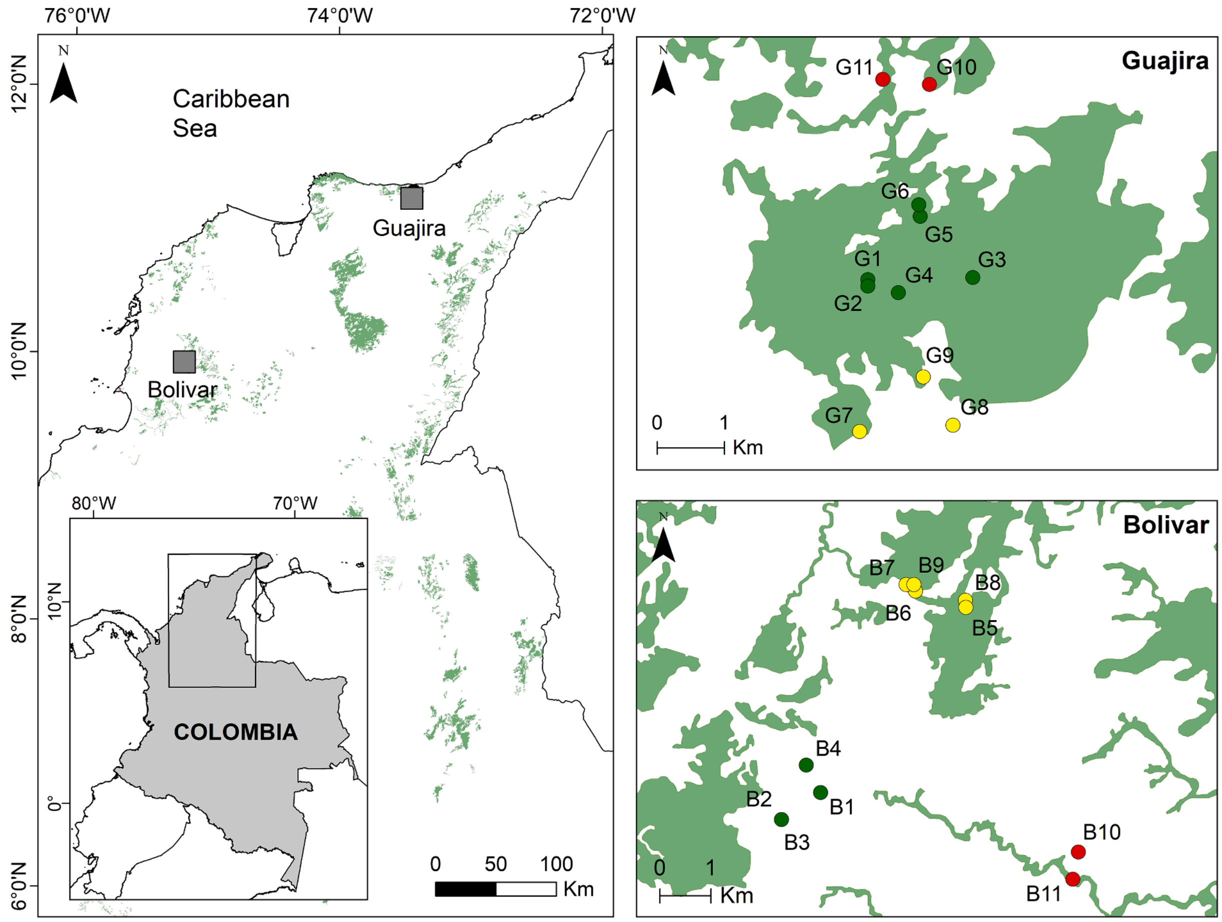

Fig. 1. Study area in the Caribbean region of Colombia. Spatial distribution of samples sites, ecological transformation and land cover of the Dry Forest in the Guajira and Bolivar regions.

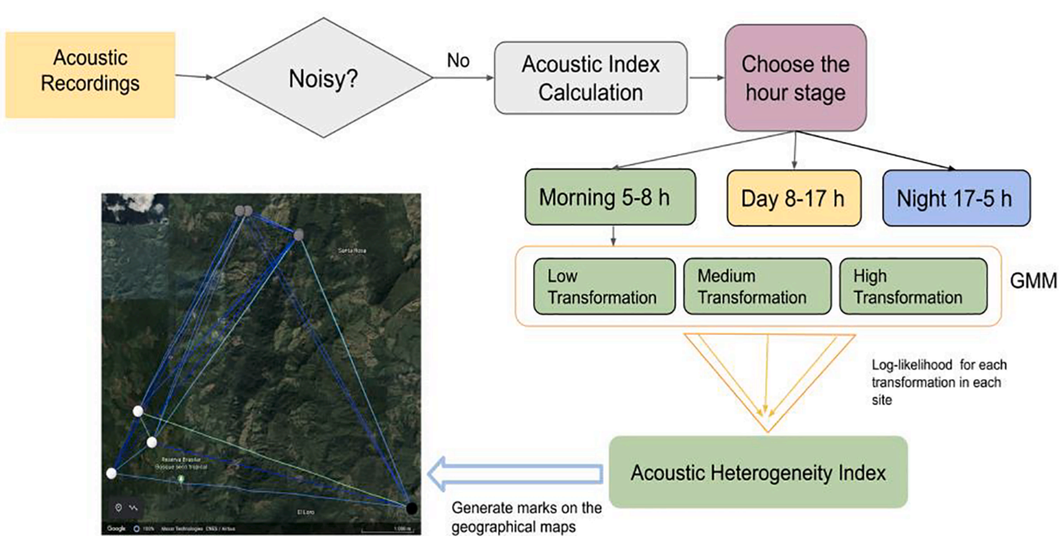

Fig. 2. The method takes the acoustic recordings and filters out the noisy ones. We estimate acoustic indices of the remaining recordings for each stage of the day (see appendix). GMM models for each transformation are calculated in each period. Then, the Loglikelihood at each GMM transformation is used to determine the AHI. Finally, with the AHI we plot marks between each pair of sites to see the relations spatially.

indicators (Gregory and Strien, 2010; Sánchez-Giraldo et al., 2021). PAM helps to monitor these indicators since acoustic recorders collect the sounds for hours, days, or months. Representative variables have been necessary to automatically identify biological characteristics given the large number of collected recordings (Sueur et al., 2014). Researchers have developed two types of acoustic indices to characterize the acoustic communities of animals and soundscapes: alpha (within-group) and Beta (between-group) (Sueur et al.,2014; Towsey et al., 2014). Alpha indices help to understand the amplitude, evenness, richness, heterogeneity of a soundscape in a particular site (Sueur

Table 1
Number of components for each GMM model.

	Morning	Day	Night
Bolívar number of components	28	37	30
La Guajira number of components	22	10	33

Table 2
Validation classification performance.

	Morning	Day	Night	All periods
Bolívar F1 Score Test	0.92	0.90	0.92	–
La Guajira F1 Score Test	0.91	0.89	0.92	–
Bolívar F1 Score Validation	0.90	0.90	0.87	0.88
La Guajira F1 Score Validation	0.91	0.89	0.92	0.88

Table 3
Centroid by transformation for Bolívar.

	ESM	MD	NDSI	MID	WE	SC	SB
Low	0.84	0.39	0.83	0.31	0.12	0.34	0.53
Medium	0.82	0.44	0.80	0.26	0.19	0.44	0.66
High	0.87	0.4	0.77	0.43	0.20	0.12	0.45

Table 4
Centroid by transformation for La Guajira.

	ESM	MD	NDSI	MID	WE	SC	SB
Low	0.82	0.47	0.74	0.18	0.15	0.34	0.55
Medium	0.87	0.35	0.79	0.21	0.17	0.29	0.65
High	0.85	0.37	0.73	0.20	0.19	0.32	0.68

et al.,2014). For example, Alpha indices have been used to link acoustic behaviors to the heterogeneity of local sites (Barbaro et al., 2022; Sánchez-Giraldo et al., 2021), to give information about habitats changes (Gómez et al., 2018; Hayashi et al., 2020; Ospina et al., 2013) and communities behaviors (Pijanowski et al., 2011). On the other hand, Beta acoustic indices help to compare and measure changes in acoustic communities or soundscapes among sites (Sueur et al.,2014).

Some PAM studies have focused on ecosystems disturbance's identification using Alfa and Beta acoustic indices as the quantification of shelterwood logging influence on soundscapes (Doser et al., 2020), acoustic variations in a perturbed site (Deichmann et al., 2017), and ecological transformation quantification (Duque-Montoya and Isaza, 2018).

Some of most used acoustic characteristics are related with spectral profiles and amplitude envelopes (Rodriguez et al., 2014; Sueur et al., 2014), acoustic indices that give frequency information (Barbaro et al., 2022; Sánchez-Giraldo et al., 2021), Power Spectral Density (DSP) among others (Doser et al., 2020; Duque-Montoya and Isaza, 2018). But only a few studies identify soundscape heterogeneity through time and between sites (Barbaro et al., 2022; Sánchez-Giraldo et al., 2021; Burivalova et al., 2018; Rodriguez et al., 2014) exhibiting that acoustic characteristics of landscapes vary throughout day and do not necessarily vary in linearly continuous states with landscape transformations. These studies have begun to use methodologies such automatic noise recording filtering (Duque-Montoya and Isaza, 2018), periods of the days (Barbaro et al., 2022; Doser et al., 2020), and variables relate to entropy of frequencies Rodriguez et al., 2014), frequency modulation, and linear combinations of alfa acoustic indices (Barbaro et al., 2022). However, no study has integrated these methodologies and variables modeling distributions of soundscape keeping in mind the transition states of transformation to analyse the acoustic dissimilarity between pair of sites.

Landscape ecology has matured enormously, and it is progressing towards incorporating new conservation strategies and monitoring schemes (Dickson et al., 2019). Our interest was not to quantify the acoustic heterogeneity in a particular site as the alfa indices do, but to quantify the acoustic heterogeneity between transformed geographical sites (Beta). As we seek to find heterogeneity among sites in transformed TDF, we modele mixture models of the acoustic caracteristics related to transformation levels for each site in the BST. With the models we measure the differences between pairs of sites, and consequently know how heterogeneous the sites are. Therefore, we propose a Beta index called Acoustic Heterogeneity Index (AHI) that integrates the transformation states and diverse acoustic behaviors to automatically identify the acoustic heterogeneity between pair of sites. Finally, we used the proposed index in maps trazing lines of dissimilarity that help to achieve an idea of acoustic heterogeneity patterns in the forest remnants of TDF.

2. Materials and methods

2.1. Study site

The Tropical Dry Forest (TDF) of Colombia has only 8% of its original distribution, making it one of the most threatened ecosystems in the country (Hoyos et al., 2017). Under this scenario is a challenge to protect and restore the TDF landscapes. Between December 2015 and March 2017, the Global Environment Facility (GEF) project was established to characterize biodiversity at TDF remnants along different landscape and successional gradients in Colombia (Hernández et al., 2018). During this project, several TDF remnants were acoustically monitored. Three watersheds along the Caribbean region were included, but in our study only two were analyzed: Rio Cañas (La Guajira) and Arroyo Grande (Bolivar) as show the Fig. 1. The ecosystem in the study areas corresponds to a typical TDF that is distributed between 0 and 1000 m.a.s.l., and it has a strong seasonality marked by rainfall with a dry period of at least three months. Within each watershed, nine forest patches were randomly selected along a combination of two gradients, landscape transformation and forest successional stage. The transformation level was labeled according to the proportion of retained and new forests on each sub-watershed established using a forest/non-forest time series (between 1990 and 2015, IDEAM 2012) of 30 m resolution that was aggregated as percentage of forest lost, gain, and retained for a grid of 1x1 km^2 using vegetation cover on satellite imagery. Three transformation states were defined: high, low, and medium. High transformation refers to sub-watershed with a low proportion of retained or new forest and highest proportion of lost forest. Low transformation indicates high proportion of retained or new forest and low proportion of lost forest. The medium transformation refers to remaining sub-watershed, which is not categorized within high or low transformation. These labels were used to train our classification models and identify the transformation based on audio recordings. Acoustic monitoring of sites in each watershed were carried out using autonomous recorders (Wildlife Acoustics SM2 and SM3 models), which were programmed to record in a frequency of 5-min every 10 min during 5 continuous days and stopping to record 5 days (sites coordinates are shown supplementary material). We split the recordings for the model train (70%), test (20%) and validation (10%).

2.2. Heterogeneity estimation

We proposed the Acoustic Heterogeneity Index (AHI) to estimate the acoustic heterogeneity between sites based on the transformation level of each sampling site. The methodology to calculate the AHI consists of five steps which are presented in Fig. 2.

The first stage consists of excluding noisy recordings using an approach based on Bedoya 2017 method (see details in subsection 2.2.1). Second, to calculate the selected acoustics indices from the recording. In the 2.2.2 section are presented the used acoustic indices. Third, each recording is labeled according to the day period (morning 5–8 h, day 8–17 h, and night 17–5 h). A temporal pattern analysis was done to identify the TDF day intervals (see Supplementary information).

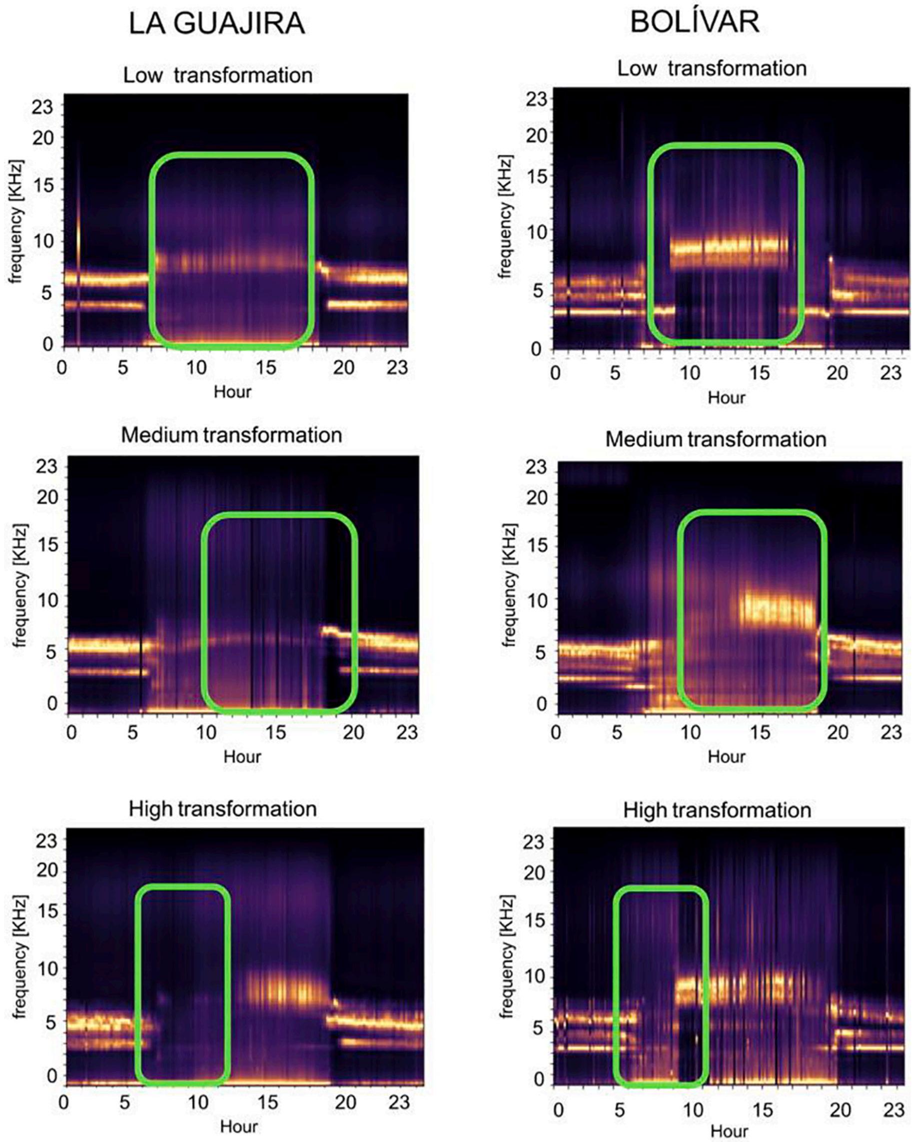

Fig. 3. Daily long-term spectrogram for each landscape transformation in La Guajira (right) and Bolívar (left) regions. In green is evidence the most notable frequency differences between the Guajira and Bolivar sites.

The fourth step (subsection 2.2.3) consist on identify the landscape transformation which is necessary for the AHI calculation. We implemented three GMM with the acoustic indices to automatically identify the ecological transformation level. A GMM was estimated for each transformation (low, medium, and high) in each day period. The temporal patterns established the model selected to classify the audios. To train the GMM models the Expectation-Maximization algorithm is used. For each recording indices the Log-likelihood for each transformation level is estimated. The predicted transformation was determined using the maximum log-likelihood from each recording to each GMM. The last step calculates the AHI between each pair of sites, which is computed using the GMM log-likelihood transformation values explained in subsection 2.2.4.

2.2.1. Noise analysis

The acoustic indices are highly sensitive to noisy recordings (Gregory, 2010; Duque-Montoya and Isaza, 2018; Gómez et al., 2018; Sánchez-Giraldo et al., 2020). In consequence, we decided to automatically detect and exclude noisy recordings. The Power Spectral Density (PSD)-based method proposed by Bedoya et al., 2017 is an adequate estimator for detecting recordings with geophonic and anthropogenic elements. PSD indicates how the signal power is distributed across frequencies. The non-parametric Welch method (Welch, 1967) was implemented to calculate the PSD, which uses the Fast Fourier transform based on short time averages with modified periodograms. The 90% of the rain sounds are distribute in the 600–1200 Hz frequency band (Bedoya et al., 2017), then we used this bandwidth as a parameter in the PSD calculation. To avoid false positive recordings the Signal Noise ratio (SNR) was used. SNR establishes a relationship between desired signal power level and background noise power. In this study, we modified the algorithm calculating an automatic noise threshold of PSD using its median for each analyzed geographical site. In this way, the recordings that pass the PSD threshold were considered with high noise level and were excluded from subsequent analyses.

2.2.2. Acoustic indices calculation

Acoustic communities have complexity, amplitude, and frequency characteristics that vary significantly across regions (Carruthers-Jones et al., 2019). Doser et al. 2020 and Gómez et al., 2018 recommended to incorporate multiple attributes to better capture the characteristics of the soundscape diversity. Futhermore, Barbaro et al., 2022 show the relation of soundscape and the compositionaland configurational

Table 5
AHI between sites in La Guajira region (label 0 low, 1 medium, 2 high transformation).

Sites		G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11
	Transformation	0	0	0	0	0	0	1	1	1	2	2
G1	0	0	0.07	0.33	0.63	0.57	0.63	0.62	0.53	0.54	0.67	0.64
G2	0	0.07	0	0.4	0.55	0.49	0.56	0.55	0.45	0.47	0.6	0.57
G3	0	0.33	0.4	0	0.95	0.9	0.96	0.95	0.85	0.87	1	0.97
G4	0	0.63	0.55	0.95	0	0.06	0.1	0.07	0.13	0.15	0.05	0.1
G5	0	0.57	0.49	0.9	0.06	0	0.11	0.1	0.09	0.12	0.11	0.11
G6	0	0.63	0.56	0.96	0.1	0.11	0	0.17	0.2	0.23	0.09	0.03
G7	1	0.62	0.55	0.95	0.07	0.1	0.17	0	0.11	0.11	0.11	0.17
G8	1	0.53	0.45	0.85	0.13	0.09	0.2	0.11	0	0.05	0.17	0.2
G9	1	0.54	0.47	0.87	0.15	0.12	0.23	0.11	0.05	0	0.19	0.23
G10	2	0.67	0.6	1	0.05	0.11	0.09	0.11	0.17	0.19	0	0.08
G11	2	0.64	0.57	0.97	0.1	0.11	0.03	0.17	0.2	0.23	0.08	0

Table 6
AHI between sites in Bolívar region.

Zone		B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
	Transformation	0	0	0	0	1	1	1	1	1	2	2
B1	0	0	0.73	0.29	0.31	0.15	0.28	0.32	0.24	0.47	0.76	0.65
B2	0	0.73	0	0.5	0.47	0.81	0.98	0.49	0.55	0.43	0.1	0.33
B3	0	0.29	0.5	0	0.07	0.38	0.57	0.06	0.08	0.21	0.54	0.38
B4	0	0.31	0.47	0.07	0	0.39	0.59	0.04	0.09	0.17	0.49	0.34
B5	1	0.15	0.81	0.38	0.39	0	0.23	0.39	0.31	0.53	0.82	0.71
B6	1	0.28	0.98	0.57	0.59	0.23	0	0.59	0.51	0.74	1	0.92
B7	1	0.32	0.49	0.06	0.04	0.39	0.59	0	0.08	0.16	0.52	0.34
B8	1	0.24	0.55	0.08	0.09	0.31	0.51	0.08	0	0.24	0.57	0.41
B9	1	0.47	0.43	0.21	0.17	0.53	0.74	0.16	0.24	0	0.45	0.19
B10	2	0.76	0.1	0.54	0.49	0.82	1	0.52	0.57	0.45	0	0.33
B11	2	0.65	0.33	0.38	0.34	0.71	0.92	0.34	0.41	0.19	0.33	0

heterogeneity through a multivariate analysis of alfa acoustic indices. Then, we decided to make a multivariate acoustic indices analysis. To select the most discriminative indices to identify the transformation level, we applied a box-plot analysis using the median and quartile separation in 22 acoustic indices (see supplementary material). We selected seven indices: Spectral Maxima Entropy (ESM) (Sueur and Farina, 2015), Musicality Degree (MD) (De Coensel, 2007), Normalized Difference Soundscape Index (NDSI) (Kasten et al., 2012), Mid-band activity (MID) (Sueur and Farina, 2015) and Wiener Entropy (WE) (Sueur and Farina, 2015) Spectral Centroid (SC). Futhermore we propose to use Spectral Bandwidth (SB), an index used in automatic identification of musical generes. Some the choose indices help to describe

Table 7
Pearson correlation between the geographical distance and AHI values of study sites.

Sites\Period	Morning	Day	Night
Guajira	0.054	0.25	−0.08
Bolivar	0.27	0.15	0.26

characteristics of landscape as species richness and species diversity with Biophony, Antropophony, and Geophony (Towsey et al., 2014). Also, some of they have been used to describe the relations between landscape configuration and ecological conditions (Barbaro et al., 2022; Dema et al., 2017). To automatic indices estimation we created a computational tool in Python available in: https://udeaeduco-my.sharepoint.com/:u:/g/personal/nestor_rendon_udea_edu_co/Eb_g2fJbQKBLmRHliwXsp5wB7MhSbE8msTvIJ1V1sVEZOg?e=4B7MzX.

2.2.3. Identification of transformation level

With the calculated acoustic indices we use GMM (Reynolds et al., 2000) to estimate the habitat transformation level generated with the filtered audios (session 2.2.1). The GMM permits to establish the general pattern for each transformation level within an acoustic period. The distribution is a linear combination of *M* multi-modal Gaussian densities P(x);

$$P(x|\alpha) = \sum_{\{i=1\}}^{M} \frac{w_{Gi}}{(2\pi)^{\frac{D}{2}}|\Sigma_i|^{\frac{1}{2}}} \exp\left[-\frac{1}{2}*(x-\mu_{Gi})'*\Sigma_{\{i\}}^{\{-1\}}x-\mu_{Gi}\right] \quad (1)$$

where $\mu_G i$ and Σ_i are GMM mean and co-variance matrices of the data respectively. *D* is the number of dimensions (i.e., number of selected indices). With the constraint of $\sum_{i=1}^{M} w_i = 1$, and the parameters are denoted as $\lambda = (w_G i, \mu_G i, \Sigma_i)$. These parameters were estimated by Expectation-Maximization (EM) that iterative refines the parameters to increase the likelihood to each transformation label. In the GMM training, the number of components must be estimated for each model. Grid-search was used with the purpose to find the optimal number of components for each Gaussian's on the two geographical regions. We used diagonal covariance matrices for the training set of recordings GMMs. To identify the transformation level with each new recording (validation recordings) the acoustic indices must be estimated. To calculate the transformation state for each recording we use the maximum log-likelihood value as the new label transformation state. We propose to implement one GMM per period. In our case we found necessary do the analysis with 3 periods:morning, day (see supplementary material).

2.2.4. Acoustic heterogeneity index

To estimate the acoustic heterogeneity between sites, we proposed a Betha indice the Acoustic Heterogeneity Index (AHI) based on the automatic transformation level identification (see section 2.2.3). The goal is to measure the acoustic dissimilarity that exists between each pair of analyzed geographic points (i,j). As the Log-likelihood determines how much a recording belong from high, low, or medium GMM transformation (section 2.2.3) the acoustic similarity between points can be identified according to their proximity to each GMM model. Then for each recording, we calculated the log-likelihood on each transformation GMM. Therefore, the results form a vector of $Nr_i x Tm$, where *Nr* is the number of recordings in site *i* and *Tm* the number of transformation levels. We proposed to define the AHI as the Euclidean distance between the median transformation log-likelihoods of a site j to another k, as it shown equation (2).

$$AHI_{jk} = \sqrt{\sum_{\{i=1\}}^{Tm} \left(\mu\left(Loglikelihood_{i(site_j)}\right)^2 - \mu\left(Loglikelihood_{i(site_k)}\right)^2\right)} \quad (2)$$

where μ is the median and *i* is each transformation state. We created a matrix in which each element corresponds to the normalized AHI between sites. The matrix must be symmetric with dimensions *SxS* in which S corresponds to the number sites and diagonal elements with a 0 value, due to the difference in the log-likelihood of the same sites. To validate the AHI proposal, and to analyze the relation with geographical distances, we used a long-term spectrograms soundscape analysis. The Pearson correlation in the spectrograms given by the equation (3) were evaluated for all sites in both regions (La Guajira and Bolivar).

$$Corr = \frac{\sum_m \sum_n (Amn - \overline{A})(B_{mn} - \overline{B})}{\sqrt{(\sum_m (A_{mn} - \overline{A})^2)(\sum_m (B_{mn} - \overline{B})^2)}} \quad (3)$$

where *A* and *B* being long-term spectrograms of the recordings of two sites, m and n are the matrix positions and $\overline{A}$ and $\overline{B}$ correspond to the

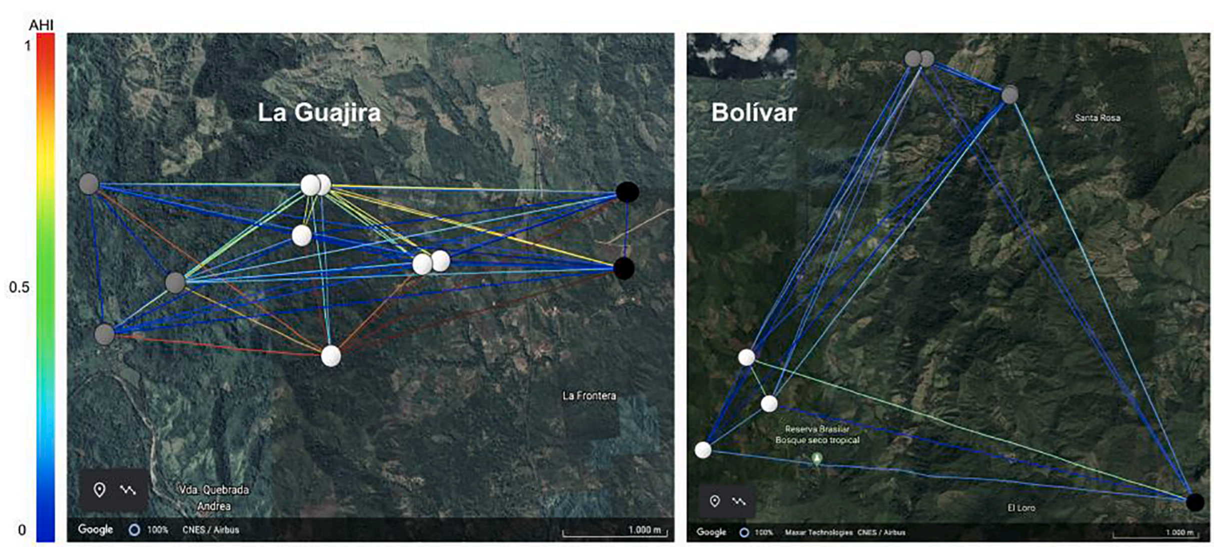

Fig. 4. Acoustic heterogeneity index generated map for La Guajira and Bolivar regions. The map is generated taking the AHI matrix and mapping each value to a color gradient palette (left). Color points are the ecological transformation level white, gray, black correspond to low, medium, high transformation respectively. Lines with hot colors (red) correspond to AHI high values and cold colors (blue) correspond to low values.

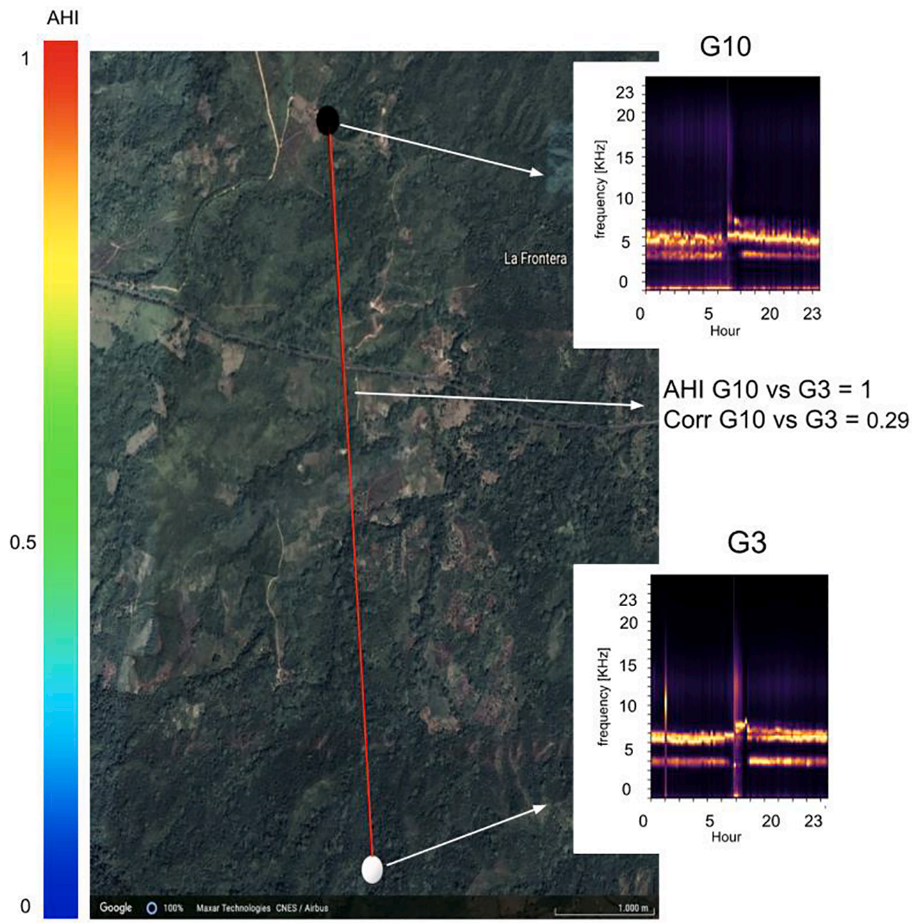

Fig. 5. The figure shows the AHI between sites G10 and G3 in the La Guajira region (red line) and the long-term of both sites (right). The AHI (1) shows high differences between the sites with different transformation level. This behavior is consistent with the low correlation (0.29) between the long-term spectrograms. See the differences in the 4–6 kHz and the 0–2 kHz long-term spectrograms on the figure.

mean long-term spectrogram of the sites. The analysis was done under the hypothesis that two sites with the same transformation are similar acoustically. Then, we interpreted the correlation of two long-term spectrograms with the same transformation less than 0.5 as success and higher than 0.5 as an error. In section 4 we show the validation of the AHI through longterm spectrograms and correlation images.

3. Results

3.1. Classification of the landscape transformation

To identify transformation levels in both regions, we selected the most discriminative acoustic indices. Using the indices, the GMMs were obtained. Through clustering, we evidenced the existence of three-hour periods (see supplementary material) representing temporal patterns in the studied geographical zones: morning (5–8), day (8–17), and night (17–0). We include the temporal patterns information in the classification step in which were implemented 3 models (morning, day, and night) in the Bolívar and La Guajira regions. To obtain the GMMs as wee explain in section 2.2.3 is necessary select the number of components. The Table 1 show the selected components using grid-search.

The Table 2 shows the F1 performance of the classification of landscape transformation for each study region. We remark that variables SC and SB helped us to find acoustic differences through the day and improve the TDF transformation analysis. Test with GMM without SC and SB showed a low F1 score performance of 86 %, and using SC and SB showed an F1 score of 90%.

In Table 2, the fourth column (All periods) correspond to a GMM model created to integrate the two zones (Bolivar and Guajira). F1 score decreased in this case. Results confirm that it is necessary to implement different models depending on the recording hour and geographical zone. To estimate the differences between transformations, an analysis of the transformation centroids was done. The acoustic indices centroids for each transformation are showed in Tables 3 and 4. The centroids correspond to vectors that better represent the patterns in each transformation type.

The spectral complexity (correspond to ESM and WE indices) varies between transformation levels but it has similar values for the two regions. The Spectral Centroids (SC) shows a similar behavior for the low transformation in both regions. Perhaps this is due to acoustic communities that sing at the same frequency (SC on Table 3 and Table 4). However, future studies are necessary to demonstrate this. The sound recordings from each site were analyzed using long-term spectrograms for each daily hour as shown in Fig. 3. NDSI with high values and MID with medium values for the two regions (Bolivar higher than Guajira) show high activity in the 2–8 kHz band and little activity in the 482 Hz – 3500 Hz band (Fig. 3).

In the Fig. 3 it is observe high differences among the long-term spectrograms between La Guajira and Bolivar. La Guajira showed an intense activity in range 5–7 kHz for all transformations in the night period, a lower activity in morning period in high transformation, and high activity in 7–9 kHz on the day. In the case of Bolívar, it can be observed 3–7 kHz activity in the night, 0–3 kHz activity for the morning, and 8–10 kHz activity for all transformations. In accordance with Duque et al. 2018 work, spectrogram gives similarity between high and medium landscape transformation for both regions. However, if it is done

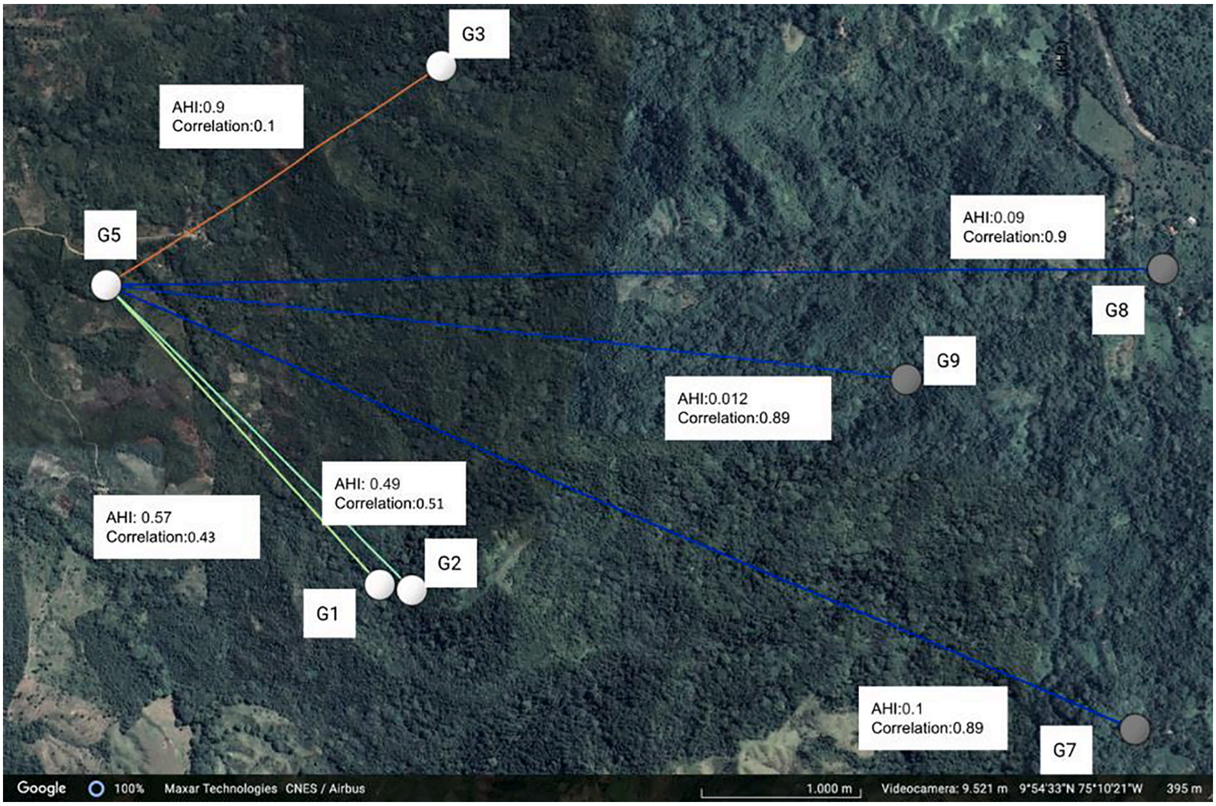

Fig. 6. AHI and spectrogram correlation of site G5 with sites G3, G2, G1 that were tagged with the same transformation (Low) and sites G8, G9, G7 previously tagged with different transformation (medium). The AHI showed the heterogeneity with same transformation places. While for the places that were labeled with different transformation the index showed homogeneity.

Table 8
Pearson correlation among the site G5 and other Guajira's sites. The place shows high correlation with other places from different transformation than the one that was tagged.

Site	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11
G5 Transformation	0	0	0	0	0	0	1	1	1	2	2
Correlation spectrograms	0.43	0.5	0.1	0.94	1	0.89	0.9	0.91	0.88	0.89	0.89

Table 9
Mean spectrum of G5.

G5	ESM	MD	NDSI	MID	WE	SC	SB
La Guajira	0.79	0.36	0.81	0.08	0.12	0.26	0.64

an analysis using hour periods, it can be observed that there are several differences between stransformations for each region. Then, segmentation using temporal patterns (hour period) allowed us to obtain better sites characterization.

3.2. Acoustic heterogeneity between two sites

Using the validation data, the log-likelihood was calculated per recording using GMMs described in section 2.2.3. According to region and hour of each recording, acoustic heterogeneity matrices were calculated (see section 2.2.4). Tables 5 and 6 show the acoustic heterogeneity in Bolívar and La Guajira regions between one site (column) and the other sites (rows). Each cell is the Acoustic Heterogeneity Index (AHI) between two sites. We expected to find lower acoustic heterogeneity among two sites with same transformation level.

Green labels cells were assigned to lower values of AHI (sites with the same transformation label), red cells are the sites with the same transformation label but higher AHI, and white cells are the remaining cells associated with the sites with different transformation.

In the AHI_{jk} analysis, the hypothesis is that pairs of sites with same transformation level have similar acoustic landscape. In results, most of pair of sites show low acoustic heterogeneity if they were labeled by experts in the same transformation level.

3.3. Correlation of AHI and geographical distance

In order to compare the relation between the heterogeneity proposed metric (AHI_{jk}) and the distance between sites (site j and k), we performed a Pearson correlation between AHI matrices and a geographic distance matrix calculate with Vicenti distance (Vincenty, 1975). We not detected direct relationships between geographical distances and the sound characteristics like Hayashi et al. 2020 work. Table 7 shows low correlation values, and therefore, it cannot be assured that there is a relationship between the geographical distance of sites and the AHI.

4. Discussion

With the acoustic heterogeneity index matrix (Table 6 and 7), we created color/intensity marks on geographical maps to graph the dissimilarity between a site and the others as shown in Fig. 4 using the python *simplekml* library. In Fig. 4, the AHIs between all site pairs of

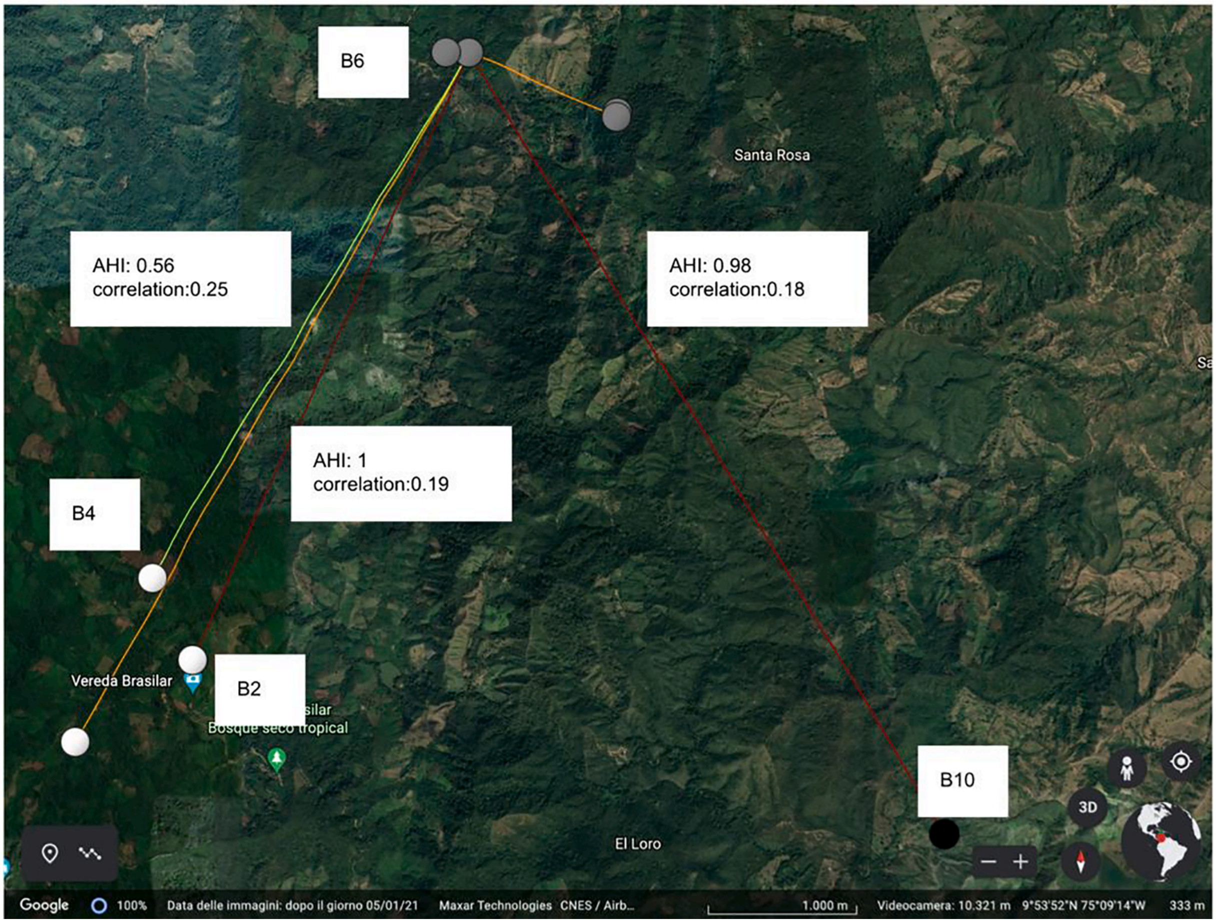

Fig. 7. AHI among B6 and other sites. Note the warm colors which represent high AHI value have low correlation values.

Guajira are represented, with the connection between sites being indicated by a color line.

Acoustic dissimilarity should theoretically be consistent with biotic homogenization (Olden et al., 2004). Our results indicate that there are low AHI values (cold colors: blue, green, yellow) between sites with similar transformation level. Also, estimating the long-term spectrogram between sites that have high AHI levels exhibit big differences (see Fig. 5). This suggests the efficacy of our proposed index based on the acoustic indices for detecting acoustic heterogeneity between two sites.

However, there are certain sites that were tagged with a transformation state but the AHI index indicates that they have a greater similarity with others exhibiting a different transformation level (See red cells in tables 6 and 7). For example, site G5 in La Guajira, originally labeled with low transformation has a low value of AHI with sites with medium or high transformation that means high similarity. At the same time, sites with low transformation have a high heterogeneity value between them (see Fig. 6). Due to the values of AHI, our hypothesis was that the label was in a transition state of Low-medium transformation. This is consistent with what was found by Flower, 2021, revealing a geography that will not necessarily match the obvious landscape or visual geography. We Validate this assumption with Long-term spectrograms correlation for each pair of sites (Fig. 6). If the spectrogram correlations is high there is acoustic similarity, then the acoustic heterogeneity should be low.

To understand high AHI values between sites from the same label transformation, we analyzed the long-term spectrogram correlation between places. A low correlation between the mean spectrograms indicates large sound differences. In Table 8 the correlation between G5 and other sites are showed.

The G5 site was initially labeled by the experts with low transformation (Fig. 6) The spectrogram is more similar to medium transformation if it is compared with long-term spectrograms of medium and low transformation. These sound behaviors can be correlated with the mean of acoustics indices, where NDSI and ESM show high values, and MID, WE low values (see Table 9). This pattern evidence high activity and entropy in the 3–8 band that can be interpreted with high biodiversity. Then, the heterogeneity index allows to identify intermediate levels of transformation that they were not expected. The AHI proposal permits to associate similar sites (with low heterogeneity) in an appropriate way from the acoustic analysis. The acoustic evidence shows that the site can be associated with an acoustic transition degree providing complementary information to describe the landscape transformation. The mean of the acoustic indices of this site are show in Table 9.

We identified a special situation on B6 site (Bolívar region) wih have high AHI with all sites except for B1 site (Fig. 7).

The long-term spectrograms of different transformations and the B6 site are showed in the Fig. 8. This probably can be associated to sites that are in a soundscape special condition: not homogeneous with other sites (high AHI). The long-term spectrogram presented high intensities in the medium frequencies and a power intensity line in the 6–7 kHz frequency band. The behavior was very different for other sites of the same region. The spectrogram indicates that the site has acoustic communities' behavior, mostly in the medium frequencies. Then the AHI allowed finding additional information about the acoustic richness of sites that had not been initially detected when the labeling was done.

In our study, the regions (La Guajira and Bolívar) showed high AHI values. Also, with GMM the method is based in density distributions that allowed finding continuous transformation values. Thanks to this, the method provides additional information related with acoustic

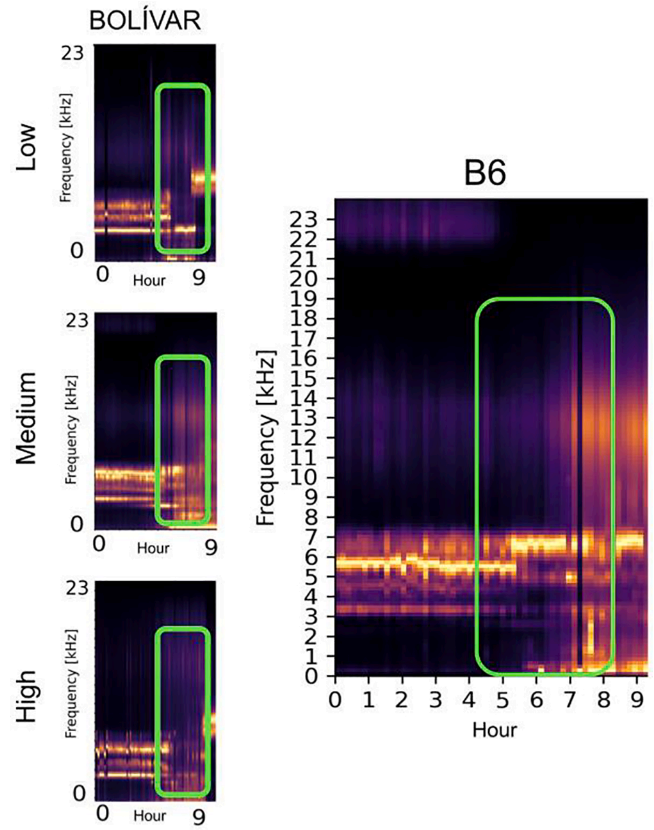

Fig. 8. Bolivar sites vs B6 long-term spectrograms. The site shows high AHI with almost all sites. In color green is evidence the different frequency behaviors between the Bolivar sites.

heterogeneity associated with ecological transformation of sites that could be in transition states.

The proposed methodology allows the analysis of acoustic heterogeneity related to the ecological transformation. According to Big-o notation* (Bae, 2019), the computational complexity of AHI is associated to calculations inside three steps in our proposal: The first step is the detection of the noisy recording having a complexity of $O(c \log(f))$ where c is the block length of each recording, and f is the number of overlapping windows. The c and f are parameters to choose to calculate the Fast Fourier transform required in the PSD estimation (Welch, 1967). In our proposal, f was 128, and c was 1024 for each recording. The second step is the acoustic indices calculation having a complexity type of O(c log.

c). The other step is the GMM model estimation which have a computational complexity of $O(NK)$ for N recordings and K Gaussian components which are more efficient than the other steps. In consequence, the computational complexity relies mostly on the fast Fourier transform parameters. In this work, we analyzed 124,989 recordings of five minutes each. The method was implemented in an intel core i7-6800 k computer with 32 gigabytes of RAM. To analyze an equal or a large number of recordings, we recommend a computer with the same or greater ram. Despite this complexity underlying the AHI methodology, it can be implemented for the analysis of any ecosystem as long as two inputs are available: The discrete transformation categories of each study site (e.g. high, medium and low), and acoustic data of each site.

Finally, the results show that sounds to describe the health of the TDF cannot be understood as something discrete, but rather as a set of sound relationships between various study sites that may share similar elements.

5. Conclusions and future work

We proposed the AHI that allow to quantify the acoustic heterogeneity between geographical points of the TDF. Specifically, the differences between our proposal and other works to quantify the acoustic heterogeneity between different sites (Rodriguez et al., 2014; Burivalova et al., 2018) are the integration of mixture models of transition states transformations through multivariate information from alpha indices related to complexity (ESM and WE) and relationships between frequencies (MID, SC, NDSI, and SB). Also, AHI is based on different ranges of hours that present different patterns of the sound: morning (5–8), day (8–17), and night (17–0). Those strategies allow to identify intermediate values transformation and associate sites with similar transformations through acoustic indices GMM distributions.

Our method not only evaluates whether the forest transformation estimated automatically in a site is similar to the transformation established a priory by field personnel or other alternative methods as remote sensing, but also allows evaluating whether a priory classification is appropriate.

Regarding the transformation classification results, the method was tested in two TDF regions, and it attained a maximum F1 score of 90% for Bolivar and 92% for La Guajira. These results showed the high of the model since the maximum performance in the TDF classification of transformation was 68% (Duque-Montoya and Isaza, 2018). These results are key for the management of TDF because they not only allow to classify ecosystems from their acoustic traits, but also allow to evaluate the congruence between different sources of information (acoustics, remote sensors, biological characterizations).

These models could be useful to landscapes monitoring, determining sites with transition of the transformation, sites with special behaviors, and the development of action plans to slow down ecosystem degradation. The soundscape is a valuable element that can help us to understand the natural landscapes and can serve as a complement to ecological research projects. There is a long way to understanding the ecosystem's soundscape, the relation with the dynamics of the communities, and the health state of landscapes and mobility of species. Species recognition over landscapes is needed to identify the entities related to activity and can permit the correlation of acoustic indices with the biodiversity patterns. Then it is needed to continue the exploration of soundscape for the development of new tools that allow the understanding of landscape transformation. These studies will allow correlating species' presence in the study sites with the specific hour of the day, as-well the environmental health.

CRediT authorship contribution statement

Nestor Rendon: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Susana Rodríguez-Buritica:** Data curation. **Camilo Sanchez-Giraldo:** Writing – review & editing. **Juan M. Daza:** Writing – review & editing, Conceptualization. **Claudia Isaza:** Conceptualization, Supervision, Validation, Writing – review & editing, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by Universidad de Antioquia, Instituto Tecnológico Metropolitano de Medellín, Alexander von Humboldt Institute for Research on Biological Resources, Colombian National Fund for Science, Technology and Innovation, Francisco Jose de Caldas - MINCIENCIAS (Colombia) [Program No. 111585269779], and

ECOSNord program: MESRI (France) et MINCIENCIAS (Colombia) [Cod. 83477. Cto.494-2021].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2022.109017.

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