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Acoustic heterogeneity of tropical dry forest based on identification of landscape transformation

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Acoustic heterogeneity of tropical dry forest based on identification of landscape transformation

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Abstract

The Colombian Tropical Dry Forest (TDF) is an important ecosystem due to its high levels of endemism. This ecosystem is currently under threat due to deforestation generated by cattle, mining, and urban development since more than 200 years. Therefore, it is urgent the need to carry out conservation activities which require to understand the ecological heterogeneity and the states of the sites. Traditionally, environmental conservation experts measure it through direct observation, but these methods are invasive to the study landscapes. A proficient alternative is the passive acoustic monitoring with the use of computational tools. However, there are no acoustic methods to determine the heterogeneity using successional states of sites. This document proposes a new method to automatically identify the transformation in separate sites within areas in the Colombian TDF. The methodology follows 5 steps: First, establish if the recording has a high noise level. If is a noisy recording, it is not analysed. Second, calculate the selected acoustics indices for the recording. Third, based on the recording hour the stage of daily acoustic patterns is selected. Four, Use GMM models to identify the transformation type. Five, calculate the proposed acoustic heterogeneity index. To achieve this, we did an analysis of acoustic variables to determine the most informative. It was proposed to include two new variables spectral centroid and spectral band-with, since these help to better identification of succesional states. Also, it was exploring the acoustic patterns found 3 stages with similar behavior: morning (5-8), day(8-17), and night (17-5). Our proposal was tested with a data-set provided by Alexander Von Humboldt Institute. This data-set consists of a group of acoustic recordings recorded in two local sites: La Guajira and Bolivar. The method to identify the transformation level achieved an F1 score of 92% and 90% for La Guajira and Bolivar regions. We use the Acoustic Heterogeneity index to create maps that allow to see similarities among the studied sites. Also, we found that the method can detect special sites that can be associated with anomalies in the landscapes. As far as the authors know, this proposal is the first method to find heterogeneity in ecosystems that perform high capabilities to create informative maps about the site states using acoustic indices analysis.

En memoria de Fausto y Vanesa.

"Si la vida es solo un sueño pasajero, el despertar es lo que realmente nos arroja al vacío"

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Nomenclature

Abbreviations

AH	Acoustic Heterogeneity
EM	Expectation-Maximization
ESM	Entropy ofspectral Maxima
GMM	Gaussian Mixture Models
KS	Kolmogorov-Smirnov
MAP	Maximum A Posteriori
MD	Musicality Degree
MID	Mid-band activity
NDSI	Normalised Difference Soundscape Index
PAM	Passive Acoustic Monitoring
PSD	Power Spectral Density
SB	spectral bandwidth
SC	Spectral Centroid
SF	Spectral Flatness

TDF Tropical Dry Forest

UBM Universal Background Model

Mathematical nomenclature

α Estimated techno-phony index

β Bio-acoustics index

$\hat{\Sigma}_i$ GMM covariance Matrix

λ Parameters of GMM

μ Median

$\mu_G i$ vector mean of GMM

f Spectrum specific frequency value

k Frequency index

M Number multi-modal Gaussian densities

$M_t[n]$ Fourier transform magnitude

n Frequency bin

N_f Total number of frequency bins

Nr the number of recordings in site i

P_f Spectrum Values of each frequency f

S Number of study sites

s Site index

t Time frame

Tm Number of transformation levels

U_j	Maximum value in the frequency bin j
W	Welch's power spectral density estimate
w	Cell in the spectrogram
$w_G i$	GMM mixture weights
$X(k)$	Normalized spectrum magnitude in the k index

Chapter 1

Introduction

1.1 Problem description and justification

The population growth generate accelerated rates of natural ecosystems degradation. In particular, the Tropical Dry Forest (TDF) of Colombia has only 8% of its original distribution, which makes it one of the most fragmented ecosystems in the country (Moreno and Goméz, 2019). It is due to ranching land large stretches, and deforestation for farming exploration since colonial times. TDF has unique flora and fauna components with high levels of endemisms and Beta diversity, whereby it is urgent the need to carry out conservation plans (Mendoza, 1999). In order to identify the landscape transformation effects and thus make better decisions in conservation actions, it is necessary to develop efficient and high biological methods, finding explicit spatial models of connectivity (Dickson et al., 2018; McRae et al., 2008). The functional connectivity can be understood as the degree to which the landscape facilitates movement between resource patches Bélisle (2005), and landscape heterogeneity can be defined as "the complexity and/or variability of a system property in space and/or time" Li (1995). Landscape heterogeneity research is fundamental, as it has implications, in the habitat selection, movement of organisms (Wiens et al., 1993), and the management and conservation of natural ecosystems (Moreno and Goméz, 2019).

Traditionally conservation experts determine the connectivity models by direct observation creating species inventories, which require a large amount of money and time and also perturbs the studied sites (Pimm et al., 2015). However, the technological revolution of the last years has resulted in the invention of alternatives to trade off the disadvantages of traditional methods. One of these alternatives is Passive Acoustic Monitoring (PAM) that studies wildlife and its environments by using soundscape. The soundscape is the composition of three sound sources : Geo-phony (Geology sounds like rain, wind, etc), Biophony (Biological sounds by animals), and Anthro-pophony (human sounds, like engines, human voice, etc). All of these sound are distributed along the spectrum, indeed they vary according to the seasons and the day time (Villanueva-Rivera et al., 2011).Then, PAM uses acoustic recordings placed in the interest sites for hours, days, or months, storing data. This data need to be processed to extract ecological information. Nowadays, PAM is becoming a useful tool for ecological surveys, and an alternative for the traditional monitoring of ecosystems because it does not generate significant disturbances in the studied environments (Napoletano et al., 2011a).

Given the sound landscape's complexity and the need to analyze large amounts of ecoacoustic data, representative acoustic metrics are necessary to identify biological characteristics in recordings. Researchers have developed acoustic indices inspired by ecological measures to quantify the biological content of sounds (Doohan et al., 2018). These indices estimate energy distribution and complexity of ecological systems, and help to extract ecosystems information: species richness, equality among communities, acoustic niches, and sound heterogeneity (Towsey et al., 2014a).

There is still a long way to go to understand the relationship between soundscapes and biodiversity. In special the understanding of landscapes heterogeneity has too many implications for the management and conservation of natural ecosystems (Bormpoudakis et al., 2013). Understand the heterogeneity among sites is fundamental to promote the maintenance of habitat quality to avoid the extinction of species (Moreno and Goméz, 2019).

There are two definitions to understand the perturbation state of the ecosystems. The first one is the permanency: it helps to conceive the ecosystems ability to persist in the original state despite disturbances (Hutson and Schmitt, 1992). The second one, the transformation is the capability for an ecosystem to become another (Folke et al., 2010). The identification of permanency and transformation in an ecosystem are helpful to guide environmental conservation policies. As far as the authors know, there are not proposals to automatically determine the heterogeneity between sites using their transformation and acoustics. Integrating acoustic indices can offer information to better understand the heterogeneity between sites of an ecosystem, and it would be the first step to create methods that allow determining connectivity within an landscape.

Therefore, in this work it was proposed a methodology that associating the changes in the ecosystem transformation of forest cover, allows to automatically identify heterogeneity between different sites in the TDF of Colombia. Results search to generate maps that can achieve an idea of connectivity between the forest remnants and increase the characterization of the protected areas to facilitate the persistence of rare species in the tropical dry forests of Colombia.

1.2 Objectives

1.2.1 General Objective

To develop a methodology to identify the heterogeneity among areas in TDF through acoustic recordings and to associate the heterogeneity with ecosystem changes.

1.2.2 Specific Objectives

1. To identify acoustic variables that allow discriminating TDF areas.
2. To propose a methodology to define transformation levels using classification methods.
3. To propose a methodology to associate changes in the ecosystem with the TDF areas based on the results of classification methods.
4. To validate the proposed method with the TDF-IAVH database

Chapter 2

Literature review

The understanding of the heterogeneity of a region helps to improve our knowledge about the biology of disturbance, the movement of organisms, dispersal decisions (Clobert et al., 2009), habitat choice (Vermeij et al., 2010) or even evolution (Maan and Seehausen, 2011). Also, it could provide information on species dynamics in landscapes (Pijanowski et al., 2011). Likewise, landscape acoustic patterns allow to understand key acoustic events (Farina et al., 2016). In this chapter a brief review of state of art is presented in what concerns to the studies of heterogeneity using the soundscape.

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2.1 Eco-acoustic and bio-acoustic analysis

The soundscape is the collection of biological, geophysical, and anthropogenic sounds that make up a specific site (Pijanowski et al., 2011). Animals such as birds, mammals, amphibians, and fishes produce sounds that reflect aspects of their behaviors including reproduction, predation, and migration (Hill, 2008). The acoustic community is defined as a group of species that produce sounds (Farina et al., 2016). These sounds can be used to quantify changes according to a disturbance since some communities such as birds change their acoustic behavior in a certain habitat (Doyon et al., 2005). Also, they are related to the quality of the environment (Pijanowski et al., 2011). On the other hand, sounds can provide evidence of current ecological conditions (Joo et al., 2007) and be indicators of environmental health (Gregory and van Strien, 2010).

Some acoustic communities produce more sounds during the day (e.g. songbirds, insects) or at night (e.g. insects, frogs, bats, snapping shrimps). However, other animals deviate from this pattern, such as cicadas that sing when the temperature is maximum (Sueur and Sanborn, 2003). Then, acoustic signals are heterogeneous in time and space (Blackman et al., 2014) and are recorded through sound recorders that are displayed in the interest sites for hours, days, or months. Consequently, these data need to be processed to extract ecological information. Eco-acoustics is the discipline that research ecosystems through sound signals. This is a good alternative to direct observation methods due to it is a passive alternative and it does not generate significant changes in studied environments (Napoletano et al., 2011b).

2.2 Acoustic indices

In the PAM field, there is a need to identify representative variables that permit a complete characterization of soundscapes. Researchers have faced this by the use of signal physical variables as well as the development of acoustic indices. Similar to ecological measurements, acoustic indices have been divided into alpha indices and beta indices. Alpha (within communities) and beta indices (between groups) were designed to describe phases of biological communities. Acoustic indices are related directly to biodiversity aspects such as species vocal activity and do not need a particular species detection (Borker et al., 2019). Alpha acoustic indices estimate acoustic diversity in a single site, and Beta gives information on how communities or acoustic landscapes differ between different sites or times (Sueur, 2018). Despite acoustic indices are unstable due to their noise sensitivity, the multivariate analysis has served to detect disturbed habitats (Gómez et al., 2018), and explore the variations of different tropical ecosystems (Sueur, 2018).

2.3 Daily acoustic patterns

Studies show that species considered indicators of ecosystem health such as birds (Deichmann et al., 2017), insects (Aide et al., 2013), and frogs (Boullhesen et al., 2019) do not present sound peaks in the same hours. Some species produce peaks at sunrise and sunset, and others in the hours of the day or night (Wimmer et al., 2013; Towsey et al., 2014a). These peaks vary according to study site, daily hour, and season of the year (Towsey et al., 2014a). Animal sounds change throughout the year. Some species sing immediately after sunrise while during the day they remain with low activity, and start singing after sunset (Farina et al., 2013). Fuller et al. (2015) studied patches of subtropical forests. He found that the acoustic indices NDSI, H, and AEI represent the configuration of the soundscape where NDSI and H show relationships with the richness of bird species, H and ADI may indicate that these indices are sensitive to nocturnal activity (insect activity). In Deichmann et al. (2017), the composition of the soundscape was analyzed based on activity peaks. The study shows that for this area, there is a peak of activity during the night from approximately 6 p.m. to 6 a.m., with less noise activity during the day (approximately 8:00 a.m. to 4:00 p.m.). They also use the hours of sunrise 5 a.m.-8 a.m., and sunset 5 p.m.-8 p.m. as peaks for counting bird species. For the Wimmer et al. (2013) and Towsey et al. (2014b) work, an open forest with small areas of tropical forest was studied. Both studies showed that from 05:15 a.m. to 08:14 a.m. are the hours in which the greatest number of bird species can be detected. The Towsey et al. (2014b) study used acoustic indices, and false-color spectrum's to determine species richness at different times of the day. This work shows that the songs of species such as crows can be identified in the 24 hours of the day.

Despite the acoustic patterns that have been widely studied, the works are based only on particular species and habitats. Acoustic patterns vary according to the place conditions such as the location, the weather, and the disturbances (Pijanowski et al., 2011). The reason being of this is since the sounds of different species are distributed in the day according to their acoustic niches (Krause, 1993) to avoid the overlapping of sounds (Planqué and Slabbekoorn, 2008). In consequence, due to these differences between soundscapes, it is not possible to generalize the temporal patterns of acoustic behaviors. For that reason its relevant that the study of the heterogeneity must be linked to the soundscape daily patterns.

2.4 Heterogeneity methods

In the monitoring of ecosystems, in particular, the TDF is important to design effective conservation strategies. Ambient sound heterogeneity can be interpreted as a source of environmental heterogeneity (Bormpoudakis et al., 2013).

There are several works in dynamics of landscape using ecoacoustic information. Some studies have focused on detecting the changes due to impacts according to a certain disturbance during a study period. As the quantification of shelterwood logging influence on soundscapes due to natural resources exploitation (Deichmann et al., 2017; Doser et al., 2020; Gasc et al., 2018). Gómez et al. (2018) have shown that it is possible to automatically identify cover types using sound recordings. Likewise, Duque-Montoya (2019) work used unsupervised ways to measure the transformation but with lower accuracy in the TDF case of study. In these approaches, machine learning is used to analyze acoustic indices to estimate the health of sites but not the heterogeneity of a system.

On the other hand, studies have worked to detect sites with different landscape characteristics using acoustic dissimilarities. Hayashi et al. (2020) identify significant differences in location and time factors between oil palm plantations and surrounding forests. Similarly, Villanueva-Rivera et al. (2012) identified the relationship between acoustic diversity and metrics of the vertical forest. Studies like Bormpoudakis et al. (2013) found ambient sound heterogeneity using self-organizing maps clustering, and the relation with habitat types and Burivalova et al. (2019) measure the acoustic heterogeneity based on the quantifying of soundscape saturation and a maximum power of spectrum.

These works show that soundscapes are related according to their landscape and level of transformation. Therefore habitats types and successional states of the ecosystems have started to be identified using soundscape. However, in what the author knows, none of these works have into account the transformation levels to determine the heterogeneity of landscapes. Complementing the heterogeneity studies with transformation information have a great potential in which connectivity studies relate. In conclusion, automatic tools to identify the heterogeneity based on the transformation state could achieve environmental retrieval monitoring studies.

Chapter 3

Proposed methodology to heterogeneity estimation

We proposed a methodology to estimate the acoustic heterogeneity based on the transformation due to perturbations of each site. The proposed method is showed in figure 3.1, which consists of 5 steps. First, to exclude the noisy recordings using Bedoya et al. (2017) method explained in the subsection 3.2.1. Second, calculating the selected acoustics indices for the recordings. In the subsection 3.2.2 is presented the study to select the most informative indices. Third, to select the recording hour stage. Temporal pattern analysis was carried out to identify the stages of the day for the TDF (see section 3.3). In four step, implement GMM models to identify the level (high, medium or low) of ecosystem transformation. The GMM models were estimated using the training recordings (labeled with the transformation level of the site). A GMM was estimated for each transformation and for each hour stage (morning 5-8, day 8-17, and night 17-5). Then, for each recording a model to estimate the transformation level is used. The hour of the recording establishes the model selected. To train the GMM models the Expectation-Maximization algorithm was used. With each recording indices, the Log-likelihood is estimated. The transformation level can be determined using the maximum log-likelihood for each GMM. Finally, calculate the acoustic heterogeneity between the interesting sites. To achieve these groups the n log-likelihood values are used for each site to obtaining a kxn matrix (were k is the number of log-likelihood transformation levels). From these matrices calculate the acoustic heterogeneity degree explained in section 3.5.

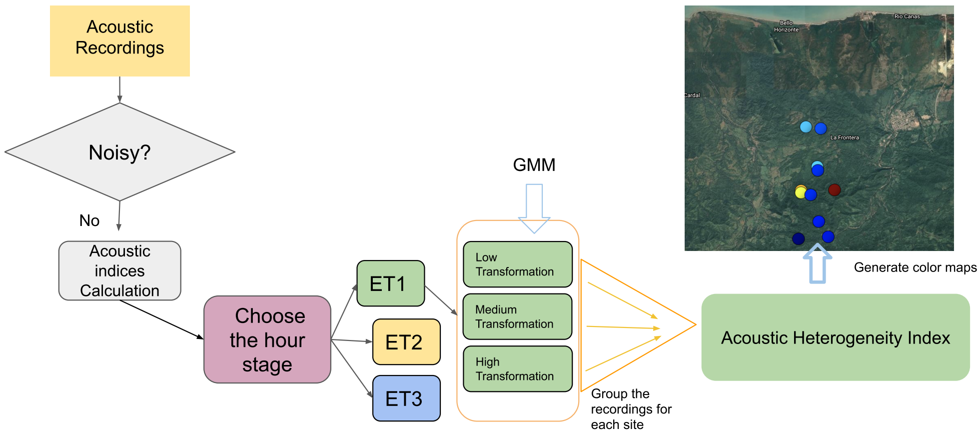

Figure 3.1: Acoustic heterogeneity identification method

Contents

3.1 Data and materials

The database was provided by Alexander Von Humboldt Institute (IAVH). This dataset was recorded at TDF areas in the Caribbean region of Colombian Cañas river and the Arroyo river basins as show in the fig 3.2. Two regions were analyzed in this work: Cesar, San Juan Nepomuceno in Bolívar, and Mingueo, La Guajira. Bolívar's recordings were obtained in the middle stream river, Cesar in the Garupal river, and Guajira in the reed's river. The recordings were obtained from December 2015 to March 2017. TDF areas are between 0 and 1000 meters above sea level, with high levels of endemism, high rainfall changes, and dry periods between 3 and 6 months. The study sites in each area were categorized the transformation level gradient (high, medium, low), which was derived from the forest/non-forest analysis in the time series between 1990 and 2012 (IDEAM 2012). The transformation level was labeled according to the proportion of retained and new forests on each sub-watershed. The information was established using geographic information (hydrology, digital elevation models –DEM-, topographic attributes, roads, urban and rural centers, Corine Land Cover vegetation maps, among others) with a grid of 1x1 km2. High transformation refers to sub-watershed with a low proportion of retained or new forest and the highest proportion of lost forest. Low transformation refers to the high proportion of retained or new forest and low proportion of lost forest. The medium transformation refers to the remaining sub-watershed. These labels were assigned by IAVH researchers specialized in vegetation and species of ecosystems. Wildlife acoustics recorders (SM2, SM3) were programmed to record every 10 minutes in 5 continuous days and stop recording 5 days, with a 5 minutes recording duration. We split the recordings for train (70%), test(20%) and validation (10%). The acoustic indices selection (section 3.2.2), the temporal pattern analysis (section 3.3), and the train the GMM models were carried out with train recordings.

With the train recordings it was done the acoustic indices selection (section 3.2.2), and the pattern analysis study (section 3.3), also we train the GMM models.

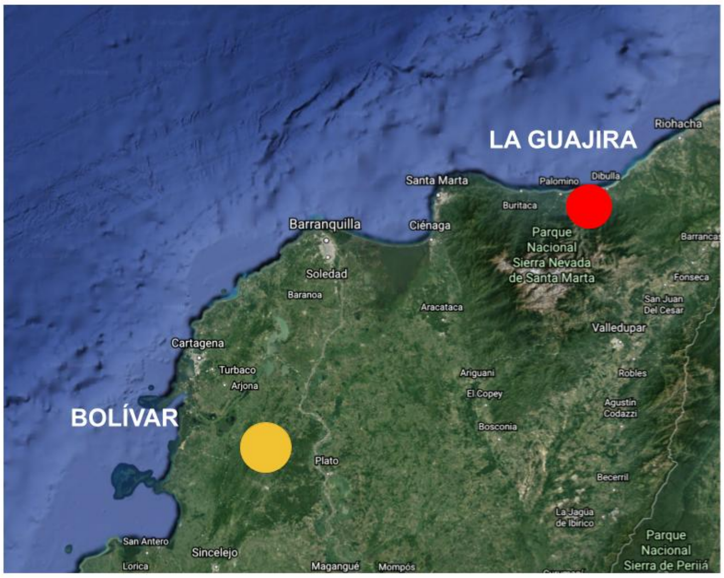

Figure 3.2: TDF Regions analyzed: La Guajira and Bolivar

Using the proposal of automatic noise detection (see section 3.2.1) we identified a 9.58% of noisy recordings. In the figure 3.1 are showed the total number of recordings of each site for Bolivar and La Guajira region.

Table 3.1: Selected Recordings for Bolivar and La Guajira sites

La Guajira	**Records number**	**Bolivar**	**Records number**
12/JSC5069__0_	2279	654-302298__0_	2065
5070MIRALT__0_	2127	/ESPAN5067__0_	1904
12/M0S5067__0_	1746	4/GUAM5070__0_	1447
OLO-302151__0_	1648	123/LAS40-3785	1343
2/POLO5072__0_	1468	3/13-654SM3786	1333
1221/T5M-S3786	1276	654-SM5071__0_	1248
LAS40-5069__0_	1214	4/GUAM5072__0_	1158
61221/T6M-3787	1048	ASILAR5071__0_2	1837
2/MIRAMEDI3788	913	0214/BRA2S3786	683
TM4-302143__0_	683	LOROSM5069__0_	502
/RMT2-5071__0_	617	654-302151__0_	228

The noisy recordings correspond to Power Spectral Density (PSD) high levels and low signal to noise ratio of the initial samples that were discarded in this studio. Finally, the methodology was used with a 28765 number of recordings. Bolivar and La Guajira trained data were split in 80% for the GMM model train and 20% for validation. In Bolivar, the study was carried out with 10998 training recordings and 2749 validation recordings. In the case of La Guajira was used 12015 training recordings and 3003 for validation recordings.

3.2 Signal processing

3.2.1 Noise analysis

One of the most relevant geophonic elements in the ecology field is the rain. It modifies the environment's physical properties (relative humidity) (Busby and Brecheisen, 1997), which influences reproduction patterns and organizational structure in tropical species such as anurans (Saenz et al., 2006) and birds (Gregory and van Strien, 2010). However, to analyze the audio signal, high intensity of rain does allow the identification of songs of the animals.

The method proposed by Bedoya et al. (2017) is a good estimator for detecting recordings with rain and anthropogenic elements. This method is based on PSD. PSD indicates how the power of the signal is distributed in 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. 90% of the rain recordings were located in the 600-1200 Hz frequency band. This bandwidth was used as a parameter in the PSD calculation. To avoid false positives Signal

Noise ratio (SNR) was calculated. SNR establishes a relationship between desired signal power level and background noise power. In this work, we modified the Bedoya et al. (2017) algorithm calculating an automatic noise threshold of PSD using its geometric and arithmetic mean as thresholds following Duque-Montoya and Isaza (2018) method. The thresholds were calculated for each site. In this way, the recordings that pass the PSD threshold are considered with high noise levels and they are not taken into account for this methodology. The acoustic indices were calculated with the not noisy recordings (those that do not exceed the PSD threshold).

3.2.2 Acoustic indices selection

Acoustic communities have complexity, amplitude, and frequency characteristics that vary significantly by wild gradients and regions (Carruthers-Jones et al., 2019). Doser et al. (2020) recommend incorporating multiple attributes to better capture the characteristics of the soundscape and biodiversity. Then it was decided to make a multivariate analysis of indices that allow us to obtain representative characteristics of transformation in the TDF. The acoustic indices were selected in accordance to discriminate between transformation states.

Due that transformation identification was done with a classification algorithm, the most discriminate indices must be found for each transformation, then a boxplot analysis was carried out. It can be see in appendix A and figures 3.3 and 3.4. Using the distribution of the data related to transformation states, seven indices were selected according to the difference of the median for each class (low, medium, high), and the quartile separation. Each index is described in the table 3.2: Spectral Maxima Entropy (ESM), Musicality Degree (MD), Normalized Difference Soundscape

Index (NDSI), Mid-band activity (MID), Spectral Flatness (SF). These indices describe important characteristics of the landscape as Biophony, Antropophony, geophony (Towsey et al., 2014a; Pijanowski et al., 2018).

Table 3.2: Acoustic indices

index	Equation	Description
Spectral Flatness (SF)	$\frac{\sqrt[N_f]{\prod_{N_f}^{j=1} W_j}}{\bar{W}}$	The spectral flatness (SF) estimates how the degree of frequencies in a spectrum are evenly distributed (such as noise). SF is geometric ratio and arithmetic means of a sub-band in the power spectrum (Sueur and Farina, 2015)
Mid-band activity (MID)	$\int_{3500Hz}^{482Hz} P_f$	Area below of the mid-band (482 Hz-3500 Hz) for the values of spectrum P_f, where spectral amplitude exceeds the mean (Sueur and Farina, 2015)
Musicality Degree (MD)	$\frac{\sum_f^{f-1} \frac{log(W_{j+1}^2 - W_j^2)}{log(f_{j+1} - f_j)}}{N_f - 1}$	Measures the signal complexity. W is the Welch power spectral density, f is a specific frequency value (De Coensel, 2007)
Normalised Difference Soundscape Index (NDSI)	$\frac{\beta - \alpha}{\beta + \alpha}$	A normalized measure of biophony ratio to technophony. For pure technophony NDSI=-1 and for pure biophony NDSI=1.β is the bioacoustics index and α is the estimated technophony, which is measured similarly to β for the frequency band between 200 Hz and 1500 Hz (Kasten et al., 2012).
Entropy of spectral Maxima (ESM)	$-\sum_{N_f}^{j=1} U_j log_2 U_j$	The Shannon index applies to frequency maximum values in the spectrogram,in the band between 482 Hz and 8820 Hz (biophony band expanding). If w represents a cell in the spectrogram in the passage of time i and the frequency bin w and Uj is the maximum value in the frequency bin j (Towsey et al., 2014a)

We propose to include the Spectral Centroid (SC) as acoustic index since it helps to measure acoustic activity. SC has been used in Alzheimer's disease diagnosis by electroencephalography studies (Kulkarni and Bairagi, 2017). It is also used in musical genres classification using audio signals

(Tzanetakis and Cook, 2002). From what the authors know, SC had not been used for the acoustic analysis of ecosystems. SC measures the shape and position of the spectrum. Then SC High values equal large amounts of energy, it can be defined as:

$$C_f = \frac{\sum_{n=1}^{N} M_t[n] * n}{\sum_{n=1}^{N} M_t[n]} \tag{3.1}$$

Where $M_t[n]$ is the Fourier transform magnitude in t frame and n frequency bin of the audio signal. In sound landscape analysis terms, this new variable scales linearly by multiplication in the frequency bin n of the numerator, which indicates that it gives greater importance to the higher frequency signals and less importance to lower frequencies. For the use of the SC index its necessary to work with a data-set without outliers. In this work it was excluded a 9.8% of noisy recordings, using the Bedoya et al. (2017) algorithm explained in session 3.2.1. The Spectral Bandwidth (SB) measures spectrum shape but in frequency values terms, and corresponds to the following equation:

$$SB = \sum_{k} X(k)(k - C_f)^2 \tag{3.2}$$

Where k is a non-negative frequency index, and X (k) is the spectrum normalized magnitude in the k index. This variable indicates frequency variations in spectrum scaled with amplitude, so it gives importance to frequencies that vary from the SC. This is useful to take into account the edges that move away from the SC, but it is necessary to pre-filter the signal before using this index since the acoustic indices can be affected by geo-phonic or anthro-phonic noises.

The Outliers were eliminated calculating the noisy recordings using the algorithm presented in session 3.2.1.. to analyze the relevant variables, Violin diagrams analysis were carried out on the acoustic indices in which each index was compared with transformations levels as it was have shown in figures 3.3 and 3.4.

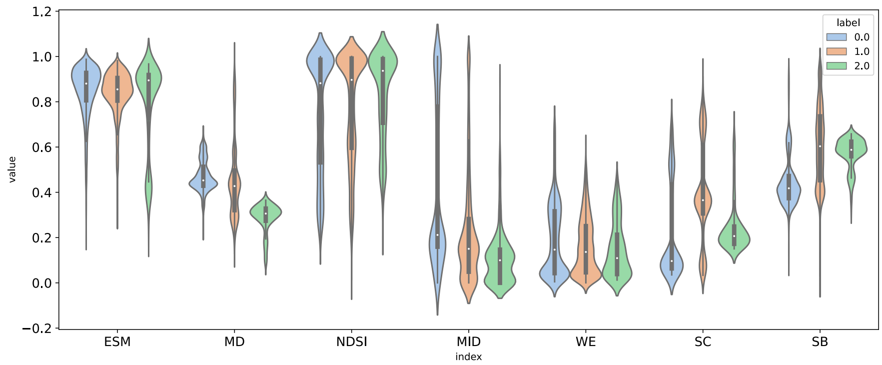

Figure 3.3: Violin plots of calculated acoustic indices for Bolivar where the X axis are the acoustic indices, the Y axis are the levels and the colors represent the transformation state (green:high transformation, orange: medium transformation, and blue: low transformation).

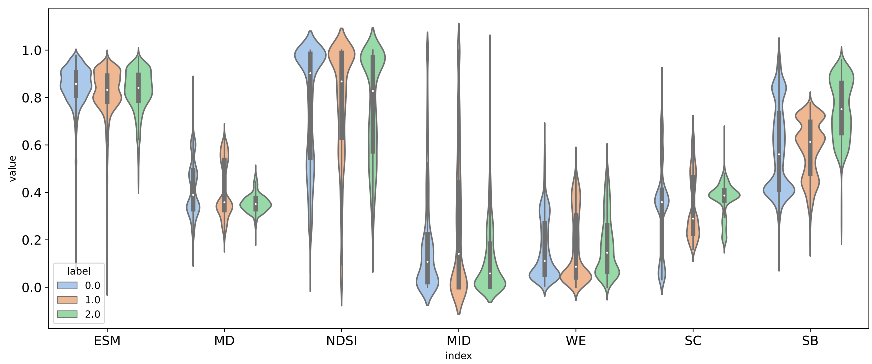

Figure 3.4: Violin plots of calculated acoustic indices for La Guajira, where the X axis are the acoustic indices, the Y axis are the levels and the colors represent the transformation state (green:high transformation, orange: medium transformation, and blue: low transformation).

The MD index presented a similar behavior between the two studies cases (Bolivar and La Guajira). Additionally, MD presented different levels in each transformation label, that is the reason why it was an index to be taken into account for the study. Similarly, Indices such as ESM, NDSI, SC and WE presented good discrimination between two transformation levels as is shown in the same figures. Note that some indices are not homogeneous between two transformation. For example, the NDSI index has high values for high and low transformation at Bolivar, while for La Guajira the NDSI has high values for low and medium transformation. Other indices as the MD present similar behaviors for both regions.

3.3 Day acoustic patterns

Identifying the heterogeneity and landscape transformation in TDF was found valuable to understand the acoustic heterogeneity. However, it was not found information about the daily acoustics patterns on the Colombian TDF. For this reason, it was decided to propose a study to find such temporal patterns. The expected hypothesis was to found similar acoustics behavior among close hours recordings, and high differences with distant hours recordings.

The acoustics indices mentioned above were used to find clusters on a multidimensional space. The indices were estimated for all the training data, and clustering analysis was performed. In this case, it was necessary to use non supervised computational intelligence algorithms to group similar recordings. The clustering method was K-means, which is based on Euclidean distance to partition the data set into local groups (Steinhaus, 1955). From clustering analysis were obtained 7 clusters validated by Silhouettes index (Starczewski and Krzyżak, 2015), that found optimal dispersion data grouping/partition using the mean intra-cluster distance and the mean nearest-cluster distance.

Groups obtained were grouped by the period of the day. It is important to note that the time of the recording was not included in the variables (descriptors analyzed by the cluster). The descriptors for the clustering were only the selected acoustic indices indicating that temporal patterns are identified according to the indices. From temporal analysis were found three periods of prominent activity, morning, day, night allowing for better soundscape characterization. The acoustic indices multivariate analysis is necessary for integration of descriptive elements due each one has particular behaviors infrequency, amplitude, and acoustic complexity.

Each centroid is the most representative element of each cluster and from there the distance is measured to estimate whether a recording is from one cluster or another. The K-means centroid clusters algorithm are present in table 3.3.

Table 3.3: K-means centroids clusters

Index	k0	k1	k2	k3	k4	k5	k6
ESM	0.82	0.95	0.89	0.85	0.90	0.84	0.76
MD	0.38	0.47	0.41	0.39	0.45	0.33	0.59
NDSI	0.71	0.79	0.34	0.50	0.91	0.96	0.94
MID	0.83	0.97	0.65	0.18	0.15	0.09	0.10
WE	0.24	0.63	0.24	0.24	0.17	0.08	0.11
SC	0.34	0.08	0.09	0.36	0.09	0.33	0.57
SB	0.62	0.48	0.45	0.79	0.40	0.60	0.47

Some indices showed stability between clusters, and others showed variations among them. ESM and MD had stability in the clusters. Other indices indicate heterogeneity among clusters, so we notice that each cluster recordings have a relation with some hours.

To identify this relation, histograms of the number of recordings and each day hour are shown in figure 3.5. Graphical analysis indicates that each cluster group recordings correspond to an hour stage (day, night, and morning).

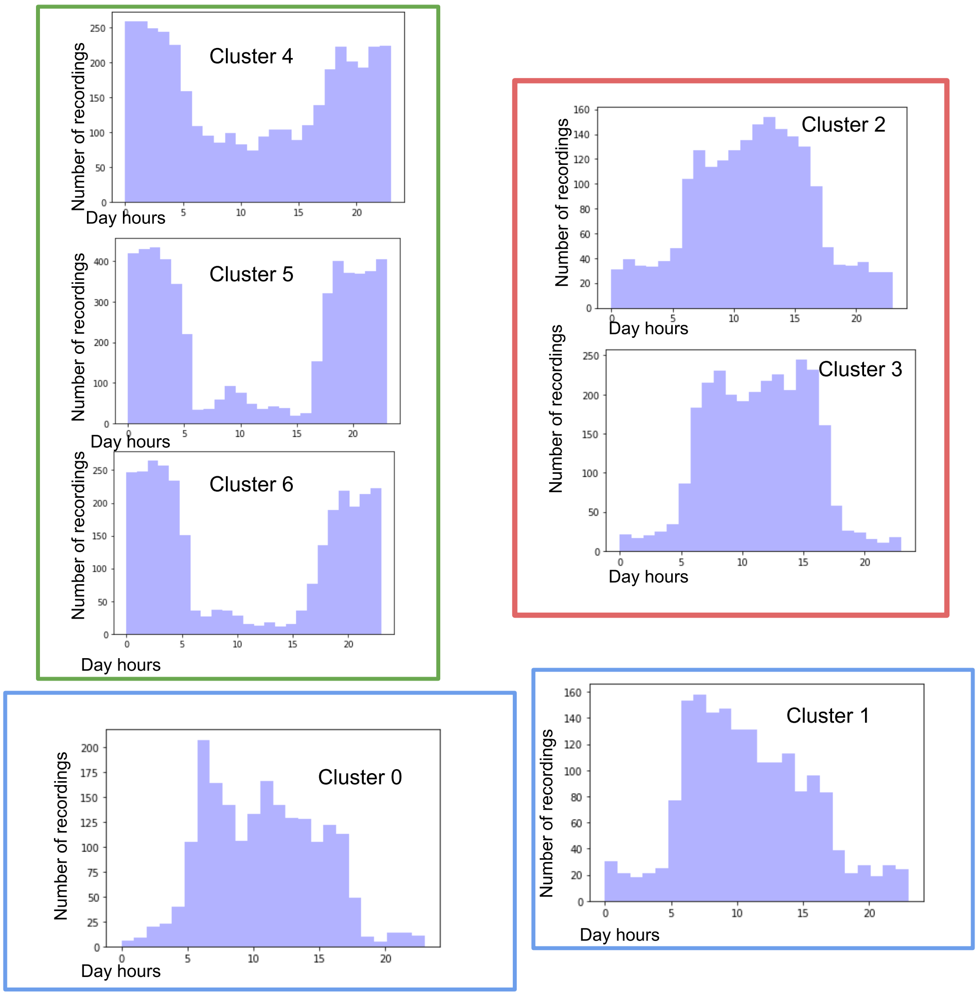

Figure 3.5: K-means clusters histograms: In green the night stage, in red the day stage and in blue the morning stage. The X axis are the hours of the day and Y axis are the number of recordings for each cluster

We grouped the similar clusters labeled by blue, red, and green squares in figure 3.5 and table 3.3. These squares represent 3 stages in which the clusters have similar behaviors among them (intra stages) and different behaviors with other stages (inter stages). The cluster with the same hour stage grouped recordings with hours in common. Then the clustering methods identify sound patrons of temporal heterogeneity in the day. The morning stage (blue square) grouped the clusters 1 and 2 that have the majority of recordings between the 5 and 8 hours. The day stage (red square) grouped the clusters with the majority of recordings between 8 and 17 hours. The night stage (green square) group the majority of clusters with night recordings. Also, similar behaviors were observed in NDSI, MID, WE, SC (yellow labeled on table 3.3) that were the indices with the best discriminative stage behavior. To verify the similarities among the stages, we apply the Kolmogorov-Smirnov statistic Hodges (1958) which finds whether 2 clusters are drawn from different distribution (KKS-test, large values represent that samples are from distinct distribution). The test was applied in cluster pairs (table 3.4), finding that clusters in the same stage belong to the same distribution.

Table 3.4: Kolmogorov-Smirnov (KS) statistic between clusters, column kx,ky represent the 2 samples:cluster x vs cluster y

kx,ky	**KS-test**
4,5	0.108
4,0	0.274
4,6	0.116
4,2	0.252
4,3	0.294
4,1	0.259
5,0	0.383

kx,ky	**KKS-test**
5,6	0.051
5,2	0.327
5,3	0.383
5,1	0.348
0,6	0.379
0,2	0.09
0,3	0.083

kx,ky	**KS-test**
0,1	0.038
6,2	0.367
6,3	0.41
6,1	0.374
2,3	0.055
2,1	0.106
3,1	0.089

To validate the identified the stages analysis, we decided to graph the mean spectrograms of recordings for each cluster which are shown in figure 3.6. Spectrum's indicate notable differences among stages and the similarity among clusters on the same stage (green squares). These behaviors prove that stages were correctly established.

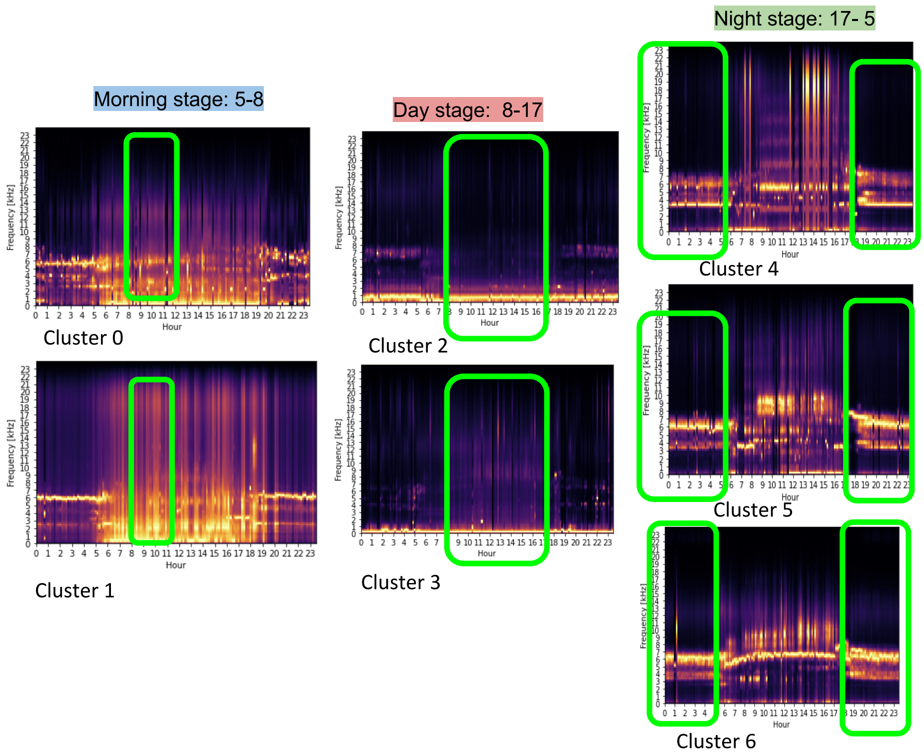

Figure 3.6: Recording mean spectrum's for each Cluster. Where the X axis are the day hour, the Y axis are the frequencies. Colors represent intensity of the power, and the green squares indicate the stage membership

On the other hand, indices captured spectral tendencies are directly related to the entities of the soundscape. The adapted NDSI index has ranged from 0 to +1 (presence in the range 0.5-1.5 kHz vs presence in the range 2-8 kHz). NDSI evidence high values for the night stage (table 3.3). This behavior can be supported by the high intensities in the 3-7 kHz range and lower intensities in the 0-2 kHz range. Clusters spectrum of day stage showed high values in 0-2 kHz frequencies, which describe a behavior similar to Gage et al. (2017), and lower levels in the range 2-8 kHz, that explain the lower NDSI index level. A similar analysis of NDSI shows the relations between the index and the value in the morning stage. The MID index shows the fraction of spectrum cells in the mid-band (0.5 kHz – 3.5 kHz). In the same way as the above analysis, the index presents high values for the morning stage, lower levels for the night stage, and medium values for the day stage.

These levels can be corroborated with spectral activity on the 482 Hz – 3500 Hz. The morning stage sounds can be related to the highest avian acoustic activity (Doser et al., 2020), the day stage describes low community activity, perhaps due to the extreme climate of the TDF (Mendoza, 1999). The activity at the night stage probably is related insects' acoustic activity and anuran communities (Aide et al., 2013). In consequence, for the correct identification and measuring of the heterogeneity, it was necessary to take into account each stage. So, it was proposed to generate a model for each one.

Some indices presented little variations between hours of the day (ESM, MD, SB). Others works present high heterogeneity as NDSI that it had already shown its potential in the (Gage et al., 2017) study. MID evidence that the middle band (1.5 to 2.5 kHz) presents significant differences between day hours. WE and SC prove the discrimination capacity only by two stages. Average spectrum infers that morning (5-8) have entities that cause sounds with high activity from 0 to 8 kHz, and at night there is a high activity from 3 to 7 kHz.

Daylight hours have the most activity from 0 to 2 kHz and a lower activity at frequencies above 3 kHz. This behavior is contrary to what found Burivalova et al. (2019), which found more activity during daylight hours in a tropical forest. These differences among sites check the soundscape spatial heterogeneity at similar day hours. Perhaps this type of activity in the TDF is a consequence of extreme weather that reaches up to 35 degrees Celsius (Mendoza, 1999). It is probably that species in TDF seek to find hours of the day where the weather is not so extreme. However, further research must be performed to validate this assumption. In this ecosystem, the temporal patterns should be studied on a larger time scale (months, years) because that brings changes in information. As a result of the temporally study, we propose to create a GMM model for each hour stage/day acoustic pattern.

3.4 Identification of transformation level

Following the methodology flow, it must be done the noisy recording elimination and the calculation of selected acoustic indices for each recording with the methods explained in the 3.2 session. Next, the transformation is estimated using the three models (morning, day, and night) for Bolivar and Guajira areas. To obtain each model, it was proposed to use Gaussian Mixture Models (GMM) (Reynolds et al., 2000). The GMM allows to establish the general behavior for each transformation level in each hour stage. The distribution is a linear combination of M multi-modal Gaussian densities P(x) ;

$$P(x|\alpha) = \sum_{i=1}^{M} \frac{w_G i}{(2\pi)^{\frac{D}{2}} |\Sigma_i|^{\frac{1}{2}}} exp[-\frac{1}{2} * (x - \mu_G i)' * \Sigma_i^{-1} (x - \mu_G i)] \qquad (3.3)$$

Where $\mu_G i$ and Σ_i are GMM mean and co-variance matrices. With the constraint of $\sum_{i=1}^{M} w_i = 1$,and the parameters are denoted as $\lambda = w_G i, \mu_G i, \Sigma_i$. For the train model stage, GMM parameters were estimated by Expectation-Maximization (EM) that iterative refines the parameters to increase the likelihood to each transformation label. For the GMM training, the number of components must be estimated. Grid-search was used with the purpose to find the optimal number of components for each Gaussian on the two geographical regions, observe the figure 3.7.

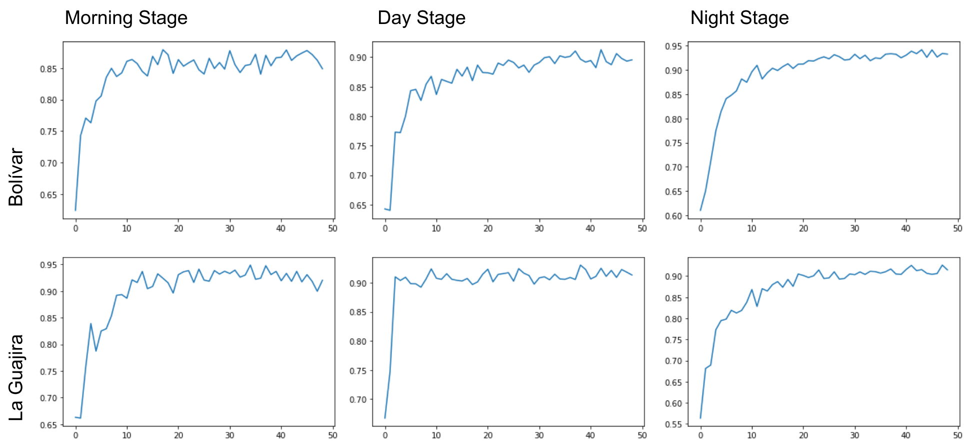

Figure 3.7: Graph of Grid search for the number of components (X axis) and accuracy performance (Y) in each stage for Bolivar and La Guajira

It was used the training set of recordings for train the GMMs with diagonal co-variance matrices. The number of components that show table 3.5 were the best configuration based on train accuracy.

Table 3.5: Number of components in the transformation identification

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

To identify the transformation level, with each new recording (validation recordings), acoustic indices were estimated. To calculate the transformation state for each recording it must choose the maximum log-likelihood value as the new label transformation state. Results are presented in section 4.1

In the study, we generate a unique model for the two study regions. This was implemented through UBM model (see appendix B). However, results for GMM models results were better than UBM models. The GMM models had a performance of 91% for Guajira and 90% for Bolivar, while UBM had

84% accuracy with training data. The comparison of UBM and GMM corroborated that there are acoustic differences between the two geographical regions of study. Therefore it is necessary to work with independent models for each region, just as GMM does. One model per stage was proposed to implement, with 3 stages (morning, day, and night) and 2 regions (Bolivar and La Guajira) in our case. Details of results with validation data are presented in section 4.

3.5 Heterogeneity identification

To estimate acoustic heterogeneity between sites, it was propose an index based on the automatic transformation level identification (see section 3.4). With each validation recording, it was calculated the log-likelihood for each transformation GMM. Therefore, it is a vector of Nr_ixTm, where Nr is the number of recordings in site i and Tm the number of transformation levels. It was proposed to define the Acoustic Heterogeneity (AH) of a site j to another k, as the euclidean distance of median transformation log-likelihoods as show in the equation.

$$AH = \sqrt{(\sum_{i=1}^{Tm}(\mu(Loglikelihood_i(site_j)) - \mu(Loglikelihood_i(site_k)))^2} \tag{3.4}$$

Where Med is the median and i is each transformation. From previous equation, it was created a matrix of SxS which each of elements are the normalized AH between sites, and S corresponds to the number sites. The matrix has to be symmetric, and the diagonal matrix has elements with a value 0, due to the difference in the log-likelihood of the same sites.

Chapter 4

Results and discussion

This section presents the transformation identification results (section 4.1) and the heterogeneity estimation among sites(section 4.2) when using the validation data. The analysis was performed for each interest region: Guajira and Bolivar.

Contents

4.1 Identification of transformation level

Using the validation recordings, the selected acoustic indices were estimated (see section 3.2.2). The transformation for each recording was estimated using 3 GMMs according to the region and hour of recording. Table 4.1 shows the F1 score for each study region.

Table 4.1: Validation classification performance

	Stages	Morning	Day	Night	Without Stages
	Bolivar F1 Score	0.90	0.90	0.87	0.88
	La Guajira F1 Score	0.91	0.89	0.92	0.88

Results confirm that it is necessary to implement different models depending on recording hour (the hour stages analyzed in section 3.3), and results show that proposal allows us to adequately estimate the level of transformation. To estimate the differences between transformations, a centroid analysis for each transformation level was done. The acoustic indices mean are presented in Tables 4.2 and 4.3.

Table 4.2: Mean by transformation for Bolivar

	ESM	MD	NDSI	MID	WE	SC	SB
0	0.84	0.39	0.83	0.31	0.12	0.34	0.53
1	0.82	0.44	0.8	0.26	0.19	0.44	0.66
2	0.87	0.4	0.77	0.43	0.2	0.12	0.45

Table 4.3: Mean by transformation for La Guajira

	ESM	MD	NDSI	MID	WE	SC	SB
0	0.82	0.47	0.74	0.18	0.15	0.34	0.55
1	0.87	0.35	0.79	0.21	0.17	0.29	0.65
2	0.85	0.37	0.73	0.2	0.19	0.32	0.68

There were significant differences in the indices that allow a good discrimination between the transformation levels. The spectral complexities that correspond to the ESM and WE indices tend to vary differently between transformation levels but with similar values for the two regions. The mean of SC showed a similar behavior for the low transformation in both regions. This is due to acoustic communities that sing at the same frequency (SC on Table 4.2). High NDSI values and medium values of MID for two regions (a little more for Bolivar) were linked a high activity in the 2-8 kHz band and little activity in the 482 Hz – 3500 Hz band.

The automatic identification of transformation results demonstrated the improvement of the baseline for the TDF, since the maximum result in the TDF classification of transformation in the previous research was 68% (Duque-Montoya, 2019). The acoustic indices mean showed discriminate characteristics in what transformation states in both regions, which highlights the great potential to work with hour stages and the two news variables (SC, SB), and the potential to find acoustic differences through the day and improve the acoustic heterogeneity analysis of the TDF.

4.2 Acoustic heterogeneity index

Using the validation data, the log-likelihood was calculated per recording using the 3 GMM. Then, according to the region and the hour of each recording, the heterogeneity matrices were calculated (see section 3.5). The tables 4.4 and 4.5 show the Acoustic Heterogeneity in Bolivar and La Guajira regions between one point (column) and each other points (rows). In these tables each cell corresponds to AH between two sites. It was expected to find lower acoustic heterogeneity among two sites with the same transformation level. So green label cells were assigned to the lower values of acoustic heterogeneity that belongs to sites with the same label transformation, and red cells are the sites with the same label transformation but higher acoustic heterogeneity. Also, it was expected that the sites with the same transformation had similarities in soundscape, so it was tried to find relations of AH and close sites.

Puntos		T5M S3786	TM4 302143	M0S 5067	5070 MIRALT	POLO 5072	RMT2 5071	JSC 5069	LAS40 5069	MIRAM EDI3788	T6M 3787'	OLO 302151
	Label	0	0	2	0	1	2	0	1	0	0	1
T5M S3786	0	0,00	0,42	0,67	0,63	1	0,62	0,60	0,47	0,34	0,10	0,52
TM4 302143'	0	0,42	0,00	0,25	0,21	0	0,26	0,26	0,12	0,75	0,50	0,14
M0S 5067	2	0,66	0,25	0,00	0,09	0	0,19	0,21	0,27	1,00	0,75	0,19
5070 MIRALT	0	0,63	0,21	0,09	0,00	0	0,18	0,20	0,24	0,96	0,71	0,19
POLO 5072	1	54,66	0,14	0,17	0,14	0	0,28	0,29	0,11	0,86	0,61	0,08
RMT2 5071	2	0,62	0,26	0,19	0,18	0	0,00	0,03	0,34	0,95	0,71	0,29
JSC 5069	0	0,60	0,26	0,21	0,20	0	0,03	0,00	0,35	0,93	0,69	0,30
LAS40 5069	1	0,47	0,12	0,27	0,24	0	0,34	0,35	0,00	0,77	0,53	0,09
MIRAM EDI3788	0	0,34	0,75	1,00	0,96	1	0,95	0,93	0,77	0,00	0,25	0,84
T6M 3787'	0	0,10	0,50	0,75	0,71	1	0,71	0,69	0,53	0,25	0,00	59.294.192,00
OLO 302151	1	0,52	0,14	0,19	0,19	0	0,29	0,30	0,09	0,84	0,59	0,00

Table 4.4: Acoustic heterogeneity between sites in La Guajira

The heterogeneity values corroborate the method effectiveness. AH index indicates that the majority of sites have a low heterogeneity among sites that were labeled by experts as having the same transformation level and high heterogeneity values with sites that were labeled with different levels. To analyze the results, the power spectrum graph is a good descriptor of the soundscape (Kasten et al., 2012). Then to obtain a better understanding of the behavior of both regions, it was plot the mean spectrum's and their acoustic indices mean values for each transformation. It is showed in figure 4.1 and tables 4.2, 4.3. In the figures, it can easily observe high

site		GUAM 5072	BRA2S 3786	LOROS M5069	4/GUAM 5070	ASILA R5071	654-SM 5071	654-30 2298	3/13-654 SM3786	123/LAS 40-3785	ESPAN 5067	654-30 2151
	label	1	0	2	1	0	2	0	1	1	1	0
GUAM 5072	1	0	0,31	0,12	0,09	0,18	0.16	0,08	0,38	0,87	0,05	0,53
BRA2 S3786	0	0,31	0	0,43	0,38	0,44	0.44	0,32	0,09	0,57	0,29	0,22
LOROS M5069	2	0,13	0,43	0	0,09	0,10	0.05	0,12	0,5	0,99	0,14	0,64
4/GUAM 5070	1	0,09	0,38	0,09	0	0,13	0.13	0,07	0,45	0,94	0,08	0,6
ASILAR 5071	0	0,18	0,43	0,1	0,13	0,00	0.08	0,13	0,52	1,00	0,17	0,65
654-SM 5071	2	0,16	0,44	0,05	0,13	0,81	0	0,15	0.52	1,00	0,17	0,65
654-30 2298	0	0,08	0,32	0,12	0,07	0,13	0.15	0	0,4	0,89	0,05	0,54
3/13-654 SM3786	1	0,38	0,09	0,5	0,45	0,52	0.52	0,4	0	0,49	0,37	0,16
123/LAS 40-3785	1	0,87	0,57	0,99	0,94	1,00	1	0,89	0,49	0	0,9	0,4
ESPAN 5067	1	0,05	0,29	0,14	0,08	0,17	0.18	0,05	0,37	0,9	0	0,5
654-30 2151	0	0,53	0,22	0,64	0,6	0,65	0.65	0,54	0,16	0,4	0,5	0

Table 4.5: Acoustic heterogeneity between sites in Bolivar

differences among the Bolivar and La Guajira regions. La Guajira showed intense activity in range 5-7 kHz for all transformations in the night stage, lower activity in the morning stage in high transformation, and high activity in 7-9 kHz on the day. In the case of Bolivar, it can be observed 3-7 kHz activity in the night, 0-3 kHz activity at morning, and 8-10 kHz activity for all transformations. In accordance with the Duque-Montoya (2019) founds, the general spectrum exposes the similarity between high and medium transformation for both regions. However, if it is done an analysis using the stages, it can be observed that there are several differences between the two transformations for the two regions. Then this segmentation using the temporal patterns permit the better characterization of the ecosystem and classification of the transformation.

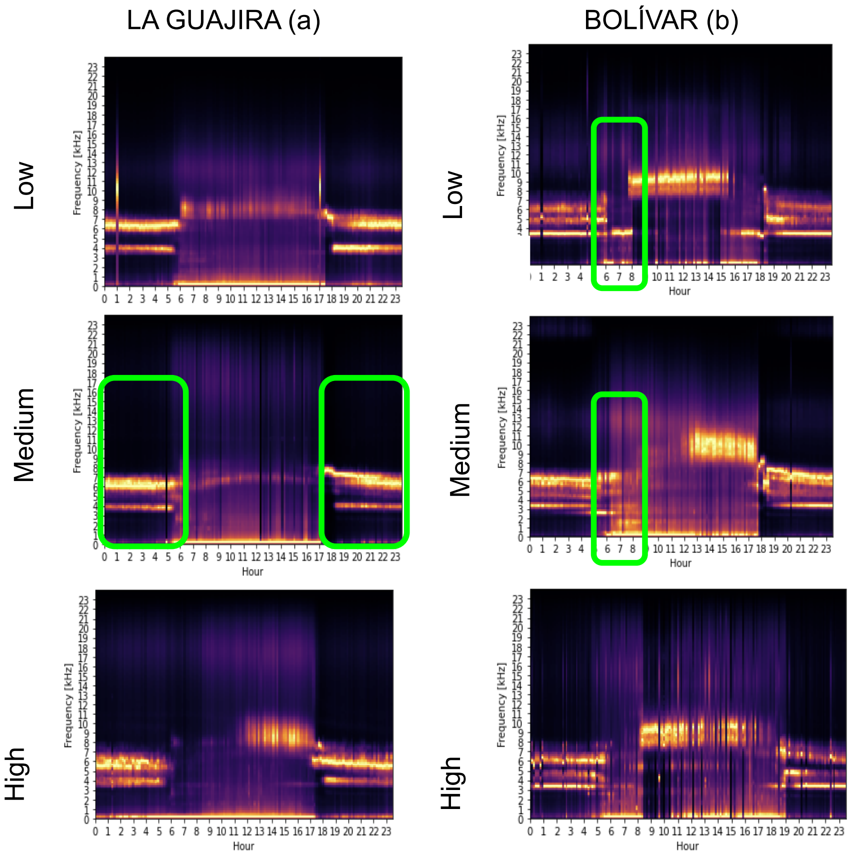

Figure 4.1: Power Spectrum Graph for each transformation in La Guajira (a) and Bolivar (b)

With the acoustic heterogeneity matrix, it can create color/intensity maps to see graphically how it's the behavior on the soundscape as shown in figure 4.2. It could be achieved to take a heterogeneity vector of two sites and convert each value to a color based on a color gradient palette. In the figure 4.2 it can see the heterogeneity sites for the 4 site. Similar to Hayashi et al. (2020) work it was not detected relationships between physical distances and the heterogeneity index. Acoustic dissimilarity should theoretically be consistent with biotic homogenization (McKinney and Lockwood, 1999; Olden et al., 2004). However, the image shows that there is a connectivity line of acoustic similar sites (Follow the blue sites). Also, the mean spectrograms between sites that have high heterogeneity index levels as are the sites highlighted with red and green in the image, it can be see the huge difference between the spectrograms. This suggests the efficacy of our proposed index based on the analysis of acoustic indices for detecting the change and the heterogeneity of two sites.

Zone		4		
	Label	1	LATITUDE	LONGITUDE
0	0	0.54663327	11°11'11.0"N	73°26'32.9"W
1	0	0.13957215	11°11'44.7"N	73°26'07.7"W
2	2	0.1737528	11°12'48.3"N	73°26'3.2"W
3	0	0.1375027	11°11'7.9"N	73°26'18.2"W
4	1	0	11°10'0.9"N	73°26'36.9"W
5	2	0.27793153	11°12'50.8"N	73°26'25.7"W
6	0	0.28700753	11°11'50.3"N	73°26'8.4"W
7	1	0.10612131	11°10'27.2"N	73°26'6.2"W
8	0	0.86368945	11°11'15.2"N	73°25'42.3"W
9	0	0.61457557	11°11'14.2"N	73°26'32.9"W
10	1	0.07787701	11°10'03.9"N	73°25'51.9"W

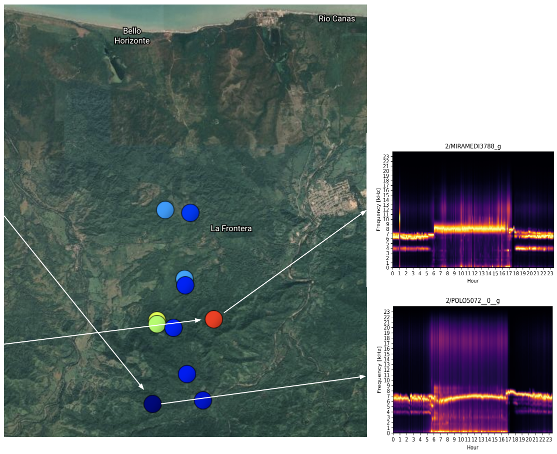

Figure 4.2: Heterogeneity index and generated map for the 2/POLO5072 site

The result of acoustic heterogeneity index for each site was analyzed by means of the average spectrum's. There are certain sites that were tagged with a transformation but the index indicates that they have a greater similarity with others with a different transformation level. For example, the La Guajira Tm4-302143 recorder (figure 4.3), originally labeled with low transformation has a low value of the heterogeneity index with sites with medium or high transformation. At the same time it has a high heterogeneity value with sites with low transformation (miramedi13788 and T6M3787). The guajira Tm4-302143 soundscape is similar to regions with other types of transformation. It can be associated with the fact that the place is in a successional state of transformation Low to Medium transformation. The average spectrogram for the recordings of this location is shown in Figure 4.3, and the indices mean in table 4.6.

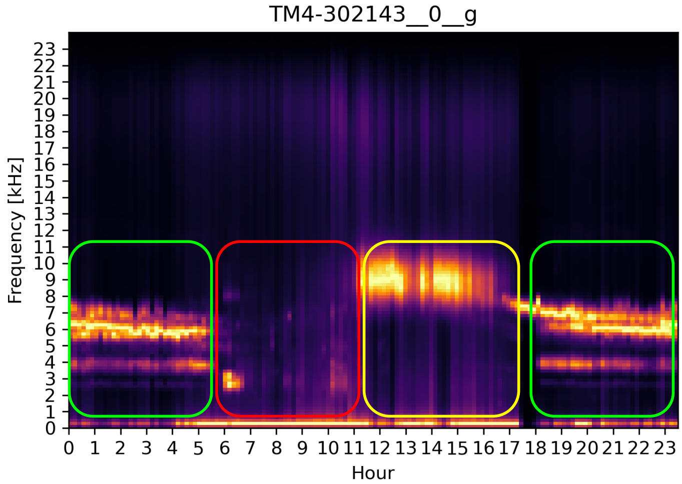

Figure 4.3: Mean spectrum of Tm4-302143 recording. The figure show patterns on the frequency that are close in between (green and red square) and different patterns on distant hours (compare of green and red square).

Table 4.6: Mean spectrum of Tm4-302143

Tm4-302151	ESM	MD	NDSI	MID	WE	SC	SB
La Guajira	0.79	0.36	0.81	0.08	0.12	0.26	0.64

Observe the night stage in figure 4.3 (underlined with green in the image) where there is a high amplitude of 4 to 8 kHz activity. The intensity is higher between 5 and 7 kHz. The spectrum is more similar to the medium transformation if compares with the average spectrum of the medium and low transformation of La Guajira in green squares on figure 4.1. These behaviors of the spectrogram can be correlated with the mean of acoustics indices, where NDSI and ESM show high values, and MID, WE low values (see Table 4.6). This evidence thigh activity and entropy in the 3-8 band that can be interpreted with high biodiversity. Then it is evident that the heterogeneity index allows identifying intermediate levels of transformation that were not expected and associating similar sites (with low heterogeneity) in an appropriate way from the acoustic analysis.

It was done the same analysis for the 3/13-654SM3786 recorder of Bolívar

Table 4.7: Mean spectrum of recorder 3/13-654SM3786$_b$

3/13	ESM	MD	NDSI	MID	WE	SC	SB
La Guajira	0.78	0.57	0.81	0.53	0.14	0.51	0.49

that was originally label as medium transformation. The method showed that this place has high heterogeneity index with sites of the same transformation and low levels of the heterogeneity index with lower transformation. Observe the average spectrum of this recorder (figure 4.4). If it focuses the analysis of the morning time in Bolívar (green labels in figure 4.1), it indicates that frequencies had similar behaviors with low transformation. The average value of the indices (Table 4.7) showed high values of ESM and NDSI, and medium values of MID and MD present different behaviors of medium frequencies than La Guajira region.

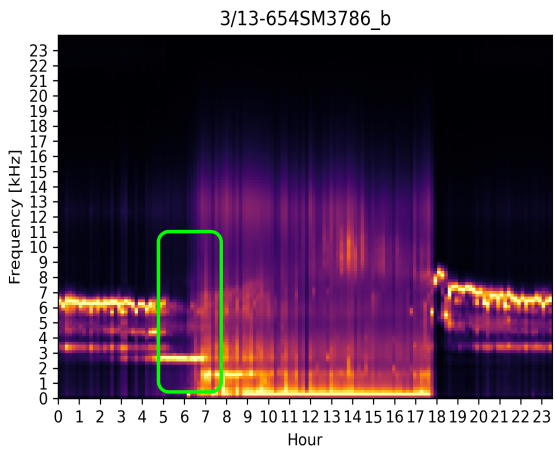

Figure 4.4: 3/13-654SM3786 mean spectrum, in green label the morning stage

The AH index for the LAS40-3785 (Bolivar) presents a special behavior. This site has high values of heterogeneity for the majority of the sites. It was calculated the mean spectrum of LAS40-3785 showed in the figure 4.5. The spectrum display high intensities in the medium spectrum and a power intensity line in the 6-7 kHz frequencies. The characteristics are very different from other Bolivar sites (see figure 4.1). The site's behavior makes that the heterogeneity index was very high for other recordings of the same region. The spectrum indicates that the site can have particular behaviors of the acoustic communities, mostly in the medium frequencies.

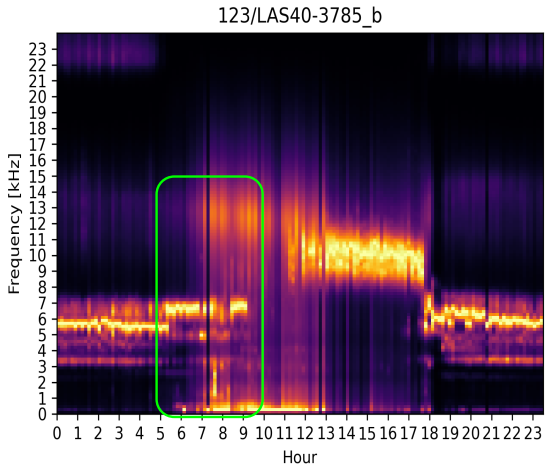

Figure 4.5: LAS40-3785 mean spectrum, in green label the morning stage

Understanding acoustic heterogeneity brings information about environmental health, conservation corridors, and mobility of species. It was found that studied regions (La Guajira and Bolivar) indicate high acoustic differences. This is the first approach to find temporal patterns and measure acoustic heterogeneity in TDF. Also, the generation of Gaussian models provides density distributions that allow finding continuous transformation values. Thanks to this, it was possible to identify transformation levels in some areas that had been mislabeled as the Tm4-302143 site or determine particular behaviors of recordings as LAS40-3785 site.

Chapter 5

Conclusions

The principal contribution of this thesis is the proposal of a methodology that integrates information from different indices to connect the acoustic heterogeneity with the site's transformation levels in an ecosystem. The methodology allows the analysis between sites to capture information related to the acoustic heterogeneity with acoustic indices. This work was tested in two Colombian geographical regions with a dataset of TDF recordings provided by Alexander Von Humboldt Institute.

In what acoustic variables respect we proposed two new variables on the ecoacoustics soundscape analysis: SC and SB. These variables are originally used in music genre classification but here they are useful to the classification of the TDF transformation.

It was proposed a methodology to detect the temporal patterns on ecosystems through unsupervised techniques. For the TDF it was found the existence of 3-hour stages that presented temporal patterns: morning (5-8), day (8-17), and night (17-0). This is the first attempt to study the acoustic patterns in the Colombian TDF ecosystem.

To determine the TDF transformation levels a methodology through acoustic recordings was proposed. We include temporal patterns information for the classification in which it was implemented 3 models (morning, day, and night) in the Bolivar and La Guajira regions. Regarding the transformation classification results, the method was tested in two TDF regions attained a maximum F1 score of 90% for Bolivar and 92% for La Guajira. These results show the high capability of the proposed method since the maximum baseline in the TDF classification of transformation was 68% Duque-Montoya (2019). The differences between this work and other models implemented in the state of the art are the use of local GMM (individually regions) to determine the log-likelihoods of each recording. Also, it was found the use of stages for the classification by hour recordings helps to the better characterization of ecosystems and helps make up for the lack of data in some sites that have only data on determining day hours.

It was proposed a method that allows us to identify and quantify acoustic heterogeneity between sites of TDF. To achieve this, it was used log-likelihoods generated in each pair of sites. The method was validated through the average spectrum. This allows a comparison of soundscape activity and heterogeneity levels behavior. An advantage of this approach is that the algorithm not only evaluates whether the transformation of the forest estimated automatically is similar to the transformation established a priory by field personnel, but also allows evaluating whether the a priory classification is appropriate. This method allows to identify intermediate values transformation and associate sites with similar transformations through the values of the AH index. These results are key for the management of TDF because they not only allow to classify of ecosystems from their acoustics but also allow to evaluate the congruence between different sources of information (acoustics and biological characterizations)

The proposed method is the first step for the development of ecoacoustic studies oriented to find models of connection between geographical points, which can be useful to landscapes monitoring, determining transformation mislabeled zones or 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, the health state of landscapes, and the mobility of species. Species recognition studies are needed to complement the entities related to high amplitude activity and can permit the correlation of acoustic indices with landscape behaviors. Then it is needed to continue the exploration of the characteristics of the soundscape for the development of new tools. These studies will allow correlating communities' presence in the study sites with the hour of the day in the specific hour, as-well as the environmental health.

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Appendices

Appendix A

Acoustic indices Analysis

To choose the acoustic indices, an analysis of box diagrams used in the state of the art was done. Due to the non-normal nature of the data and the need to have interpretive variables, it was decided to work with variables without any type of transformation (It was avoid the power transform methods). The figure A.1 shows the behaviors that some acoustic indices had with the 3 types of transformation. In red we show the indices that can not discriminated the transformation using the mean. In the figure we label with red some acoustic indices that permit to discriminate the transformation using the mean as an example of the discriminative capacity of the indices used in this work (see section 3.2.2) . The analysed indices were the following ones: Acoustic Complexity Index (ACI) (Farina et al., 2011),Median of amplitude envelope (M) Depraetere et al. (2012), Acoustic Diversity Index(ADI) (Towsey, 2013), Crest Factor(CF) (Towsey, 2013), Frequency Modulation (FM) Villanueva-Rivera et al. (2011), Spectral Flatness (SF) (Mitrović et al., 2010), Chroma stf, Rolloff, Zero Crossing rate Ellis et al. (2015), Spectral Band-with and Spectral Centroid (see the table A.1). The 3.2 table shows the indices that were chosen.

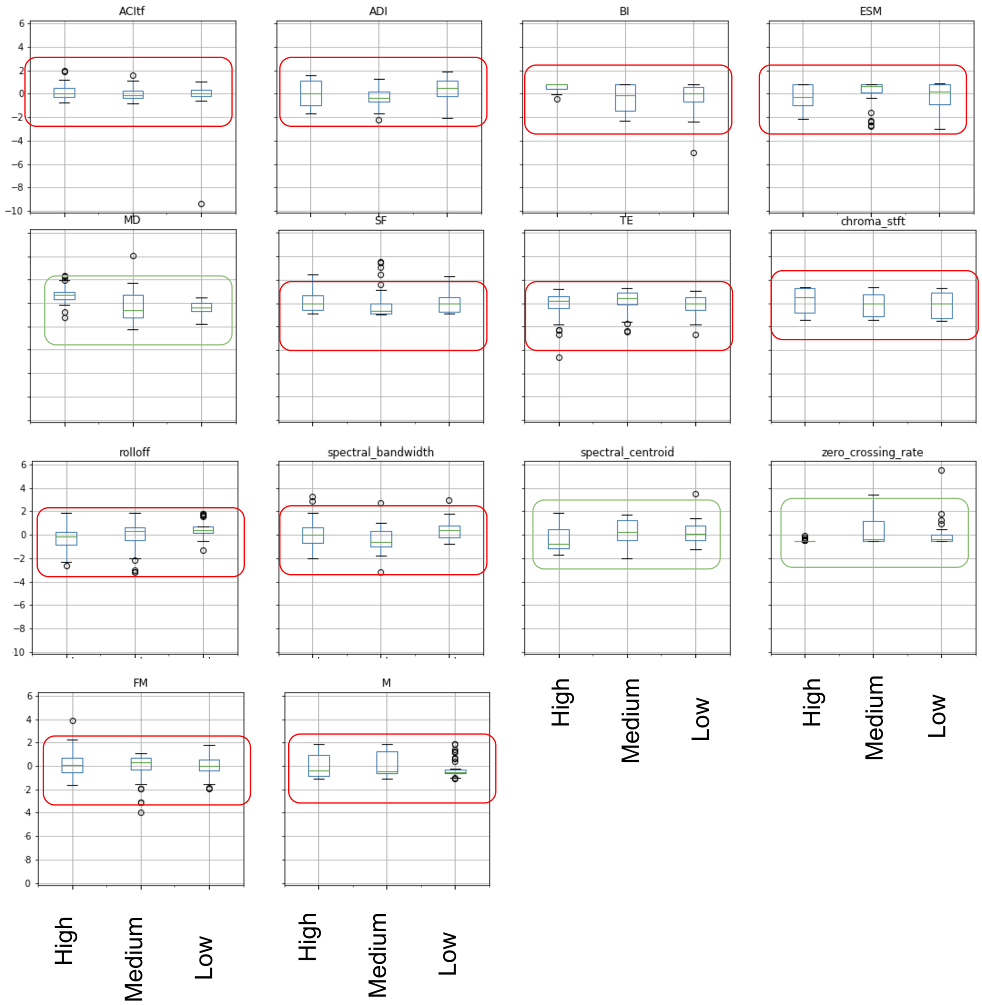

Figure A.1: Acoustic indices boxplots analysis

It is highlighting the discriminative capacity of the proposed SB and SC indices (section 3.2.2).

Appendix B

GMM-UBM approach

In the case of need a general model (a model with several regions), the GMM approach can be not sufficient for the determine the transformation type (Classification process) because the regions have statistical differences in landscape and soundscape. For this type of cases it was propose to use Universal Background Model (UBM)as alternative to classify TDF in a general way. The UBM is a large GMM trained to represent the independent distribution of features. GMM-UBM can be used as the adaptation of a new GMM to GMM-UBM trained model, for finding the new parameters the Maximum A Posteriori estimation was used, that is a form of Bayesian adaptation. There are several's approaches to train a UBM, in this study, we trained individual UBMs in the sub-populations one for each transformation level. We use this approach since it can be effective with unbalanced datasets. The UBM has to be trained with the EM algorithm Reynolds et al. (2000). Each class parameters are adapted to the UBM, and finally, the acoustic indices of new recordings are adapted using MAP estimation. With the new recordings generated GMM, the next step is to find the distance to each class GMM adaptation with the Bhattacharyya distance, and the class with the adapted models shortest distance defines the predicted class. Bhattacharyya (Bha) distance measures the distance between two probability distributions (Young, 1974). If we assume GMM the Bhattacharyya distance is given by:

$$Bha = (1/8)*\sum_{i=1}^{M}(\hat{u}_i - u_i)^T[\frac{\hat{\Sigma}_i + \Sigma_2}{2}]^{-1}(\hat{u}_i - u_i) + (1/2)*\sum_{i=1}^{M} ln\frac{|\frac{\hat{\Sigma}_i+\Sigma_2}{2}|}{\sqrt{|\hat{\Sigma}_i||\Sigma_2|}} - w_b ha \tag{B.1}$$

Where $\hat{u}$ and $\hat{\Sigma}_i$ are UBM mean and covariance matrix. u_i and Σ_i are the mean vector and covariance matrix of the adapted GMM new experimental recordings. Each class distance has to be compared and it is chosen the short distance as the predicted class.

Then an additional performance benchmark was carried out using UBM with Bolivar, Guajira, and Cesar with 50 % of the data. The adaptation for each class was found with 30 % obtaining a High-GMM, Low-GMM, and Medium-GMM. The test was done with recordings adaptation groups with the remaining 20 %. In contrast with the GMM approach, we found an 84% of accuracy. One of the advantages of GMM and UBM is that these models are computationally inexpensive without storage demands (Reynolds et al., 2000). The general model obtained with GMM-UBM is better than the general GMM approach for all the sites but not for individual regions. Although the performance for the GMM-UBM classifier was not as good as using GBM, the former has great potential for use in identifying changes in different zones of a particular ecosystem exposed by the use of Bayesian adaptation. Maybe the lower performance is due to the lack of data for training the model. Both approaches can discriminate among different transformation states in TDF. GMM performs good results, but with the limitation that it only works for each study site with different numbers of components. GMM-UBM works with both zones but with worse performance results.