Identification of Tropical Dry Forest Transformation in the Colombian Caribbean Region Using Acoustic Recordings through Unsupervised Learning

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***Abstract*—Passive Acoustic Monitoring (PAM) is one of the alternatives to monitoring endangered ecosystems. PAM uses acoustic recordings of monitored sites to understand the dynamics of communities, and landscape transformation, among other ecological indicators. PAM studies of landscape transformation have applied machine learning techniques using discrete labels for transformation states (i.e., high, medium, low). However, a site does not necessarily belong to a discrete label but can be between two transformation states. Thus, discretely labeling a degraded site while ignoring intermediate states is biased. Due to the natural variability of soundscape, multiple groups that describe different patterns are a requirement for clustering recordings that can belong to specific transformations. This paper proposes an unsupervised methodology based on clustering to identify the ecological transformation. Our proposal does not use transformation labels, either selecting the variables or training the models. This allows to find sites with intermediate states and associate different clusters to a specific level of ecological transformation. Similar groups of recordings were found and linked with ecological transformation using Gaussian Mixture Models (GMMs) in three periods of the day: morning (5-8), day (8-17), and night (17-5). We evaluated 13 Clustering Internal Validation Indices (CIVI) to know which one establishes the number of clusters associated with ecological transformation. Acoustic Indices (AIs) operated as variables to provide information on the acoustic complexity of the sites. We use the Dependence Guided Unsupervised Feature Selection (DGUFS) method to select the most relevant AIs. With data collected from 2015 to 2017, we tested the proposal in a Tropical Dry Forest ecosystem located in the Bolivar region of northern Colombia. Results showed that it is possible to identify the ecological transformation with an F1 score of 0.86 using the Scattering Distance (SD) index as CIVI. In the paper, we evidenced that it is possible to identify the ecological transformation not limited to known a-priori discrete labels.**

Index Terms*—Machine learning, Ecoacoustics, Soundscape, Clustering.

I. INTRODUCTION

One of the emerging ways to complement ecosystem monitoring studies is Passive Acoustic Monitoring (PAM) [1]. PAM involves acoustic soundscape recordings that incorporate information from geophony (earth-related sounds such as rain and thunder), biophony (animal sounds), and anthrophony (human and machine sounds). The acoustic data are used in Machine learning algorithms taking advantage of the rich information from soundscape estimating species richness [2], occupancy models [3], temporal trends of species [4], among others.

In particular, an emerging field in PAM is the study of the acoustic signature of ecosystem transformation [1]. The understanding of ecological transformation can help with conservation policies and restoration strategies, especially for endangered ecosystems [5]. Previous studies have demonstrated the effectiveness of Acoustic Indices (AIs) to determine the transformation of sites [6] and cover types [7]. So far, PAM works that have analyzed the transformation [8] and changes in habitats [9] have used supervised machine learning methods.

Ecological transformation labels used by supervised PAM methodologies are based on discrete pre-classification of health states by satellite imagery [5]. These transformation labels do not take into account community dynamics [10] and do not consider intra-class variability and the intermediate states in which sites could be. Then, supervised methodologies do not let data provide new information on site-specific variability associated with acoustic community dynamics. Some PAM methodologies have used clustering to give information about disturbances [11], geophonic, anthrophonic, biophonic activities [12], temporal patterns and cover types [5]. However, no studies have analyzed the soundscape to identify ecological transformation with unsupervised methodologies. Therefore, we propose a fully unsupervised methodology to identify ecological transformation and analyze acoustic gradients in each site using acoustic patterns.

Given that fine-tuning of parameters (number of clusters) under an unsupervised approach is a complex task, clustering validation indices have emerged to evaluate the resulting partitions [13]. There are two types of criteria in the cluster validation indices: The external, which compares results with existing classes (expected labels), and the internal, which compares results with similarity metrics (no labels usage) [14]. As in our proposal, we need to find information on the ecological transformation gradients, we use the Clustering Internal Validation Indices (CIVIs). However, these indices have drawbacks such as sensitivity to noisy datasets or overlapping classes, where each index gives different results regarding the recommended number of clusters [15]. Moreover, internal validation indices' performance is context-dependent [15], which implies that evaluations should be conducted at each application to select the index with the best performance. Nevertheless, to our knowledge, all clustering PAM studies have only considered one cluster validity index, and they did not implement an evaluation to select the adequate validity index for the particular study case. We integrate into our proposal an unsupervised feature selection of AIs, and an evaluation of 13 CIVIs to determine partitions that give complementary information to the ecological transformation models. Therefore, we propose a fully unsupervised automatic methodology to analyze the acoustic patterns related to ecological transformation gradients in a tropical dry forest.

The structure of the article is as follows. In Section II , we describe the proposed methodology and the used data. Results are given in Section III, and discussed in Section IV. Finally, conclusions are drawn in Section V.

II. Materials and Methods

A. Study site

The data used in this work were provided by the Alexander Von Humbold Institute. The acoustic recordings were acquired from 2015 to 2017 in the Colombian Caribbean region, in the department of Bolivar through a Global Environment Facility (GEF) project. The study sites correspond to a tropical dry forest ecosystem, which is an ecosystem distributed below 1000 m.a.s.l. highly seasonal in its rainfall with dry periods of at least three months. In the locality of Arroyo Grande (Bolivar), twelve sites were sampled along a landscape transformation gradient for over 1 week to reach a total of 2476 recordings. The recordings were obtained using Wildlife Acoustics' SM2 and SM3 recorders which were programmed to record 5-min every 10 minutes during 5 continuous days and stopping to record 5 days periodically. Prior to field campaigns and after a landscape transformation analysis was conducted, each site was classified as high, medium and low transformation. High transformation are sites with a low proportion of retained forest and high proportion of lost forest between 2000 and 2016.Low transformation are sites with a high proportion of retained forest and a low proportion of lost forest. The medium transformation are sites between theses two extremes. These labels were used to compare results of unsupervised algorithms and internal validation indices through the external validation index F1 score (explained in Table III).

B. Unsupervised methodology for transformation identification

For the unsupervised identification of ecological transformation, we propose the methodology presented in Figure 1. Our methodology follow these steps: First, calculate the AIs and select the most representative indices through the DGUFS method explained in section II-B2. With the selected AIs, train a GMM for each day period varying the number of clusters (see subsection II-B3). We tested 13 CIVIs (see Table I) to set the number of clusters. We found that the CIVI SD gives more information related to ecological transformation (see section III). We explain each step in the next subsections:

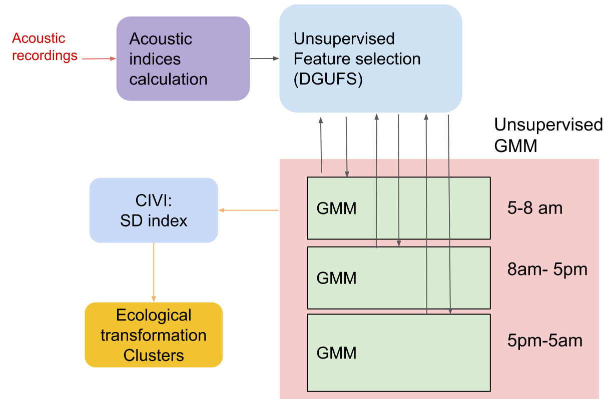

Fig. 1. Automatic unsupervised identification of ecological transformation through acoustic recordings Methodology.

1) Soundscape metrics : Acoustic Indices (AIs) are mathematical functions designed to estimate the acoustic complexity from communities to soundscapes. As equivalent to biodiversity indices in ecology, acoustic indices are indices that emphasize diversity of acoustic elements (similar to species) in a community (alpha (α) diversity), or indices that emphasize the similarity between two areas in terms of shared acoustic elements (beta (β) diversity) [16].

In this work, we focused on the α AIs to characterize the sound of each study site. We used the most popular AIs: Acoustic Complexity Index (frequency- time): 'ACIft' [17], Acoustic Diversity Index: 'ADI' [18], Acoustic Complexity Index (time- frequency): 'ACItf' [17], Bioacoustic index:'B' [19], Temporal Entropy: 'TE' [16], Entropy of spectral maxima: 'ESM' [20], Normalized Difference Soundscape Index: 'NDSI' [21], Ratio of biophony to anthrophony: 'P' [22], Median of amplitude envelope: 'M' [23], Number of peaks: 'NP' [23], Mid-band activity: 'MID' [20], Frequency Background Noise: 'BNF' [24], Temporal Background Noise: 'BNT' [24], Musicality Degree: 'MD' [25], Frequency Modulation: 'FM' [26], Spectral Flatness 'SF', Root Mean Square 'RMS', Crest Factor 'CF', Spectral Centroid 'SC', Spectral Bandwith 'SB', 'Tonnets', Signal Noise Ratio 'SNR' [27]. Also, we calculate the ADI index in each of the 1-11 frequency bands. These indices measure characteristics of the audios related to acoustic complexity. All these AIs were implemented in a user interface application available in [28] . Some of these indices have been used to classify in a supervised way sites by ecological transformation [6], cover types [7], quantify ecosystem changes over time [29] and study the ecological integrity [30].

The behaviors of the soundscape could vary in the hours of the day. Sanchez [30] showed that the relationship between AIs and ecological integrity can vary between different periods of the day. Rendon Hurtado [31] proposed three periods with different patterns of the sound: morning (5-8), day (8-17) and night (17-5). We used these periods to create three clustering models, one for each period.

2) Unsupervised feature selection method: Usually, feature selection in PAM studies has been done based on expert knowledge [29], [30], [32]. However, there are feature selection methods such as the wrapper methods that do not use the data labels. Wrapper methods help to improve the quality of clustering algorithms results based on unsupervised criteria [33]. The Dependence Guided Unsupervised Feature Selection (DGUFS) [34] is a wrapper method that enhances the interdependence among original data, cluster labels and selected features using the L_2 norm [34]. In this work, we use the DGUFS to select the most informative AIs. As a result, we obtain an $\boldsymbol{x}$ vector with the selected features.

3) Unsupervised transformation level model: To determine the transformation level of a site, we use the Gaussian Mixture Models (GMM) algorithm in an unsupervised way. As input features for the clustering, we use the selected AIs. GMM establishes a $P(x)$ distribution of nc clusters for the $\boldsymbol{x}$ feature vector;

$$P(\boldsymbol{x}) = \sum_{i=1}^{nc} \frac{1}{(2\pi)^{\frac{D}{2}} |\boldsymbol{\Sigma_i}|^{\frac{1}{2}}} exp[-\frac{1}{2} * (\boldsymbol{x} - \boldsymbol{\mu_G i})' * \boldsymbol{\Sigma_i}^{-1} (\boldsymbol{x} - \boldsymbol{\mu_G i})] \tag{1}$$

where $\boldsymbol{\mu_{Gi}}$ and $\boldsymbol{\Sigma_i}$ are GMM mean and covariance matrices of the data, respectively. The data is the matrix containing all estimated vector AIs for all training audios. D is the number of features (i.e., number of selected AIs). The algorithm parameters are denoted as $\lambda = (\boldsymbol{\mu_{Gi}}, \boldsymbol{\Sigma_i})$. To determine these parameters, we used the Expectation-Maximization (EM) algorithm refining the parameters using the log-likelihood in the data distribution. One of the characteristics of the GMM is that it requires the number of clusters. If we choose a number of clusters larger than the number of original transformation labels, then several clusters could belong to one transformation state (i.e. high, medium, low) providing information on intra-transformation patterns. We determine the number of clusters evaluating 13 CIVIs presented in the sub-section II-B4. The F1 score results were used as a benchmark to compare the unsupervised approach using CIVIs. We also tested other clustering algorithms (K-means, Gkmeans, DBscan, Fuzzy-Cmeans, Hidden Markov Model with Gaussian Mixture Model emissions (GMMHMM)) to contrast the results.

4) Cluster validation indices (CVIs): The task of finding clusters using unsupervised algorithms depends on the relative nature of the data [15]. CIVIs are proposed to select the best clustering according to a specific criteria [13]. However, CIVIs have certain drawbacks such as low performance due to noise and outliers in data [13], validating the clustering result for large data-sets involves a high computational cost [35], lack of stability and sensitivity to data-set size, and a number of features [14]. Furthermore, different clustering validation indices often recommend different partitions for the same data-set (with a different number of clusters) [36]. Performing comparisons between cluster validation indices would increase the robustness of the application using unsupervised learning. CIVIs are useful to compare solutions up to a limit that depends on the nature of the data. Therefore, the best solution must be found, according to each application. Comparing several CIVIs is relevant because each index can give information about clusters with different soundscape properties. Then, as we searched for partitions related to ecological transformation, we included a comparison of 13 CIVIs. We compared the behaviors of the CIVI presented in Table I with the external validation index F1, also presented in the table.

III. Results

The 35 AIs mentioned above were calculated for each recording and standardized (0 to 1 values). We obtain the following AIs using the DGUFS method: 'ACIft', 'ACItf', 'BETA', 'NDSI', 'P', 'M', 'NP', 'MID', 'BNF', 'MD', 'FM', 'SF', 'RMS', ' SC', 'Tonnets'. Six clustering algorithms were tested by performing a grid search by tuning each algorithm with a different number of clusters (grid search from 2 to 80 clusters). Table II presents a comparison of clustering algorithms using the F1 score. The results show that GMM has the best performance for transformation identification. Then, we selected GMM as the proposed clustering algorithm in our methodology.

TABLE II
Clustering algorithms comparison using the F1 score external clustering validation index.

	Kmeans	Gkmeans	Dbscan	**GMM**	Fuzzy cmeans	GMM HMM
Maximum F1 score test data	0.8	0.79	0.5	**0.84**	0.79	0.74

GMM was used to cluster audios in each period (morning, day, and night). Figure 2 shows the F1 score varying the number of clusters from 2 to 80 for each period of the day. Stabilization of the F1 score was achieved at cluster numbers 53, 55 and 57 in the morning, daytime and evening periods.

TABLE I
COMPARED VALIDATION INDICES

Name	Equation	Principle	Reference
F1 score	$F1 = \frac{tp}{tp+\frac{1}{2}(fp+fn)}$	External validation index F1 score corresponds to the harmonic mean. tp represents the true positive, fp the false positives and fn the false negatives	[37]
Silhouette	$S = \sum_1^M (s(\boldsymbol{x_i}))$, $a(\boldsymbol{x_i}) = \frac{1}{\vert A\vert} \sum_{\boldsymbol{x_j}} d(\boldsymbol{x_i}, \boldsymbol{x_j})$ $b(\boldsymbol{x_i}) = \underset{B \epsilon K, B \neq A}{min} \frac{1}{\vert B\vert} \sum_{\boldsymbol{y_j} \epsilon B} d(\boldsymbol{x_i}, \boldsymbol{y_j})$ s($\boldsymbol{x_i}$)= b($\boldsymbol{x_i}$)-a($\boldsymbol{x_i}$)/max(b($\boldsymbol{x_i}$),a($\boldsymbol{x_i}$))	Silhoette (S) computes which data points fall properly withing the cluster. K is the number of centroids and M is the total number of data. A and B are clusters, $\boldsymbol{x_i}$ and $\boldsymbol{y_j}$ are points in A and B, respectively. $a(\boldsymbol{x_i})$ is the average dissimilarity of the object x_i. $b(\boldsymbol{x_i})$ is the minimum average dissimilarity of the point $\boldsymbol{x_i}$	[35]
Calinksy	$CH = \frac{M-k}{k-1} \frac{\sum_{A \epsilon K} d(\boldsymbol{c_A}, \bar{X})}{\sum_{A \epsilon K} d(\boldsymbol{x_i}, \boldsymbol{c_A})}$	The ratio between clusters variance and within clusters variance, where M is the number of data, d is the distance and $\boldsymbol{c\_A}$ is the centroid of cluster A and $\bar{X}$ is the mean of all data.	[38]
SD	Scat= (1/$\boldsymbol{nc}$) $\sum_{i=1}^{K} \frac{\Vert\sigma(\boldsymbol{c_i})\Vert}{\Vert\sigma(\boldsymbol{X})\Vert}$ $Dis = \frac{(max\Vert\boldsymbol{c_a}-\boldsymbol{c_b}\Vert)}{(min\Vert\boldsymbol{c_a}-\boldsymbol{c_b}\Vert)} * \sum_{k=1}^{K} \left(\sum_{z=1}^{nc} \vert\vert\boldsymbol{c_a} - \boldsymbol{c_b}\vert\vert\right)^{-1}$ $SD = Scat + Dis$	Sum of the average scattering ($Scat$) and average separation between clusters (Dis).	[39]
S_Dbw	$\sigma = \frac{1}{K} \sqrt{\sum_{k=1}^{nc} \vert\vert\boldsymbol{v}(k)\vert\vert}$ $R_{kk'} = \frac{\gamma_{kk'}(\boldsymbol{H}_{kk'})}{max(\gamma_{kk'}(\boldsymbol{G}^k), \gamma_{kk'}(\boldsymbol{G}^{k'}))}$ $\varsigma = \frac{2}{K(K-1)} \sum_{k<k'} R_{kk'}$ $\delta = \frac{\frac{1}{K} \sum_{k=1}^{k} \vert\vert\boldsymbol{v}(k)\vert\vert}{\vert\vert\boldsymbol{v}\vert\vert}$ $S_{Dbw} = \varsigma + \delta$	The S_Dbw relies on the notion of density belonging to two clusters. $\boldsymbol{v}$ is the vector of clusters variances . $\gamma_{kk'}$ is the number of points of clusters C_k and $C_{k'}$, $\boldsymbol{G^k}$ and $\boldsymbol{G^{k'}}$ are the clusters barycenters, $\boldsymbol{H_{kk'}}$ are the midpoints, and ς is the between cluster density.	[35]
PC	$PC = \frac{1}{M} \sum_{A \epsilon K} \sum_l^M \boldsymbol{w_{A,l}^2}$	The Partition Coefficient (PC) is the sum of the squared individual fuzzy membership $\boldsymbol{w_{i,j}}$ by the number of total data.	[40]
GStr	$oi_{rex,A} = min_{j=1,\ldots,k,j \neq A}(\tau_{Aj} - \Lambda_{corr,A} - \Lambda_{corr,j})$ $oi_{str,A} = min_{j=1,\ldots,k,j \neq A}(\tau_{Aj} - \Lambda_{ext,A} - \Lambda_{ext,j})$ $G(oi, \Lambda) = \frac{\sum_{j=1}^{k} oi_{Aj} \Vert A_j\Vert}{\sum_{j=1}^{k} \Lambda_{Aj} \Vert A_j\Vert}$ $G_{str} = G(oi_{str}, \Lambda_{ext})$	G_{str} is the strict version of G (in the 50% of the points). τ is the distance between each pair of clusters. $\Lambda_{cor,A}$ is the median of distances of a point and its cluster that embraces exactly the 50% of the points. $\Lambda_{ext,j}$ ensures that, at least, 75 percent of the samples fall within the extended volume boundary. G uses the five determinant elements that are necessary to draw a summarized representation of the dataset geometry: number of spheres k , sphere center c_j , sphere separation oi_j, and sphere mass A_j.	[15]
Grex	G$_{ext} = G(oi_{rex}, \Lambda_{cor})$	G_{ext} is the strict version of G (in the 75% of the points)	[15]
Gmin	G$_{min} = min_{j \epsilon k} \left(\left\{\frac{oi_{str,j}}{\Lambda_{ext,j}}\right\}\right)$	G_{min} is the minimum relation of the strict overlap index $oi_{str,j}$ and the median of the external distances $\Lambda_{cor,A}$	[15]
CE	$CE = -\frac{1}{M} \sum_{A \epsilon K} \sum_l^M \boldsymbol{w_{A,l}} log_\alpha \boldsymbol{w_{A,l}}$	The Classification Entropy index (CE) is the sum of the entropies of $\boldsymbol{w_{i,j}}$ scores. Good partition is expected to show low entropy values. α is the base of the logarithm. In our work, we use the natural logarithm.	[15]
Xie Beni	$XB = \frac{\sum_{A \epsilon k} \sum_M^l \boldsymbol{w_{A,l}}^\beta d(\boldsymbol{x_l}, \boldsymbol{c_A}^2)}{M min_{A,B \epsilon K} \left\{d(\boldsymbol{c_A}, \boldsymbol{c_B})^2\right\}}$	Xie Beni index is defined as the ratio of compactness and separation of a hard or fuzzy partition. $\beta = 2$ is used in our work.	[14]
DI	$\delta(A, B) = min_{x_i \epsilon A, y_j \epsilon B} \left\{d(\boldsymbol{x_i}, \boldsymbol{y_j})\right\}$ $\Delta(A) = max_{\boldsymbol{x_i}, \boldsymbol{x_j} \epsilon A} d(\boldsymbol{x_i}, \boldsymbol{x_j})$ $DI = \frac{min_{A \epsilon k}\left\{min_{B \epsilon, B \neq A} \delta(A,B)\right\}}{max_{A \epsilon K} \Delta(A)}$	Dunn Index (DI) is defined as the minimal ratio between the distance of the closest points between clusters, and largest clusters diameter (the most separated objects withing a cluster)	[41]

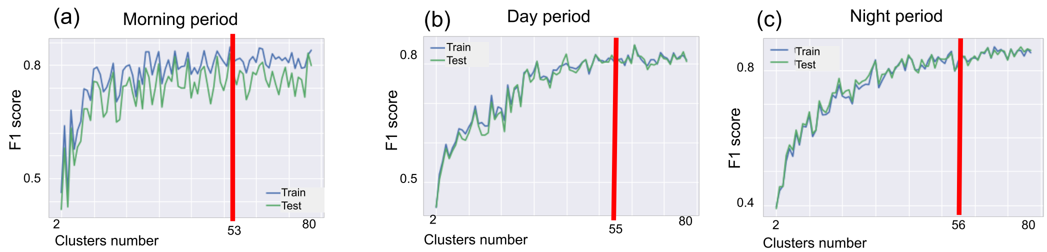

Fig. 2. F1 score varying the number of clusters with the GMM algorithm in each period (a) morning period (5-8), (b) day period (8-17), and (c) night (17-5). The results suggest that the stabilization (red line) is obtained with the cluster numbers of 53, 55 and 56 in each period

These results show that it is not enough to have only three discrete categories (high, medium, low). A large number of clusters is required to identify the transformation. Since our objective was the automatic and unsupervised identification of ecological transformation, we estimated the CIVIs explained in Table I, with the clustering obtained varying the number of the cluster in each GMM model. Table III shows the recommended number of clusters of the CIVIs in each day period.

TABLE III
RECOMMENDED NUMBER OF CLUSTERS FOR EACH CIVI VARYING THE NUMBER OF CLUSTERS FROM 2 TO 80 USING GMM AS CLUSTERING ALGORITHM

Indice	Daily periods		
	5-8 (morning)	8-17 (day)	17-5 (night)
F1 score (stabilization)	53	55	56
Silhouette	2	2	2
Calinksy	2	3	3
Davies	21	10	23
SD	61	62	44
S_Dbw	2	2	2
PC	2	2	2
GStr	7	7	2
Grex	1	1	2
Gmin	2	2	2
CE	2	2	2
Xie Beni	79	74	79
DI	2	2	2

We expected three groups representing the three transformation labels. However, the partitions found with a number of clusters of 3 did not correspond to the ecological transformation (see Calinksy index performance in Figure 3).

IV. Discussion

In this work, it was proved that it is possible to build GMM models to identify the tropical dry forest transformation in a completely unsupervised way. Our proposal includes automatic feature selection and a selection of adequate partitions. Our proposal was tested in the Bolivar region in northern Colombia. Figure 3 presents a comparison of the best performance clustering validation indices.

The Calinksy index suggests a lower number of clusters in each period (morning:2, day:3, night:3). These are the number of labels of previously categorized transformations. The low

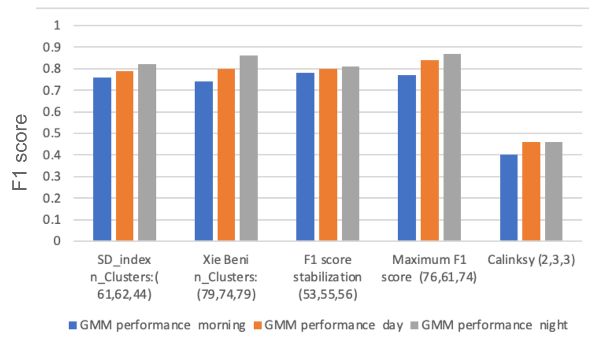

Fig. 3. F1 score using CIVIs: SD index, Xie Beni index, F1 score stabilization, and Calinksy. In each approach the parenthesis show the number of the recommended clusters for each day period

performance of Calinksy index (max F1=0.47) shows that there exist acoustic nuances that describe more variability than the preliminary discrete categories of the transformation.

Only the Xie Beni index and SD index recommended a number of clusters that correspond to ecological transformation using as a metric the external F1 score (F1<0.75). The Xie Beni index suggests 79 clusters for the morning model, 74 for the day model, and 79 for the night period. These number of clusters permit to identify the ecological transformation with a high f1 score (see Figure 3). The behavior of the Xie Beni index (see Figure 4) establishes that the adequate cluster number corresponds to the minimum value (0 in this case). Then, we tested the behavior of the index with different limits: 30, 80, and 200, obtaining the number of clusters 29, 79, and 197, respectively for each threshold. The Xie Beni value decreases when the number of clusters increases. These results suggest that Xie Beni values tend to grow when the number of clusters grows without reaching stabilization. This problem had already been mentioned in the literature by Rita de Franco et al. [42] and Singh et al. [43], who made a modification of the index. However, these CIVIs were proposed for fuzzy clustering algorithms. For this reason, we do not use them in our study.

The SD recommends cluster numbers 61, 62, and 44, which are much closer to the external performance stabilization (F1 score stabilization in Figure 2). Thus, using the unsupervised Gaussian mixtures approach and with the use of the SD,

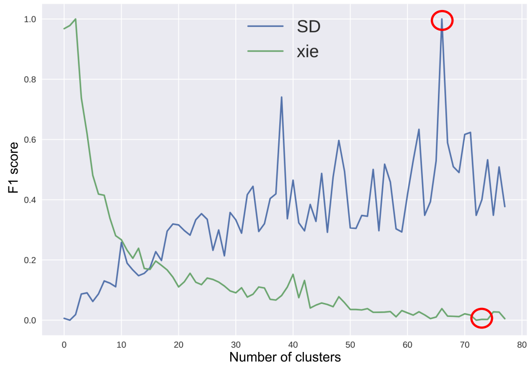

Fig. 4. Comparison of the SD (blue) and Xie Beni (green) behaviors in the morning period, varying the number of clusters in the GMM algorithm. Where the recommended partitions are the maximum value for the SD and the minimum value Xie Beni index (red points in the graph).

it is possible to identify the ecological transformation of ecosystems through sound.

In order to identify the meaning of the intermediate clusters not included in the discrete labels, the behavior of AIs means in some found clusters are shown in Figure 5.

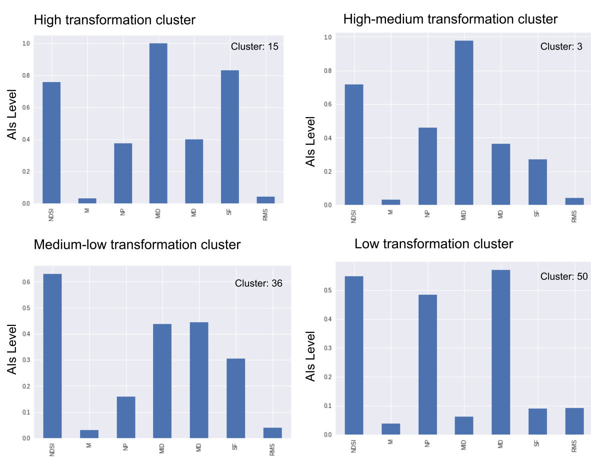

Fig. 5. AIs mean in different clusters that represents different ecological transformation levels. Clusters 13, 3, 36 and 50 represents high, high-medium, medium-low, and low transformation levels, respectively

Analyzing acoustic indices using machine learning techniques increases results interpretation regarding ecological aspects which cannot be achieved with other techniques such as deep learning. For example, in Figure 5, it is evident that the NP index increases as the transformation decreases. This behavior was expected since this index is related to the biodiversity of a site. On the other hand, the graph shows intermediate clusters (high-medium and medium-low transformation), which would not have been found using a supervised approach. These clusters show AIs with intermediate values between high and low transformation.

V. Conclusions

This paper shows a methodology to identify tropical dry forest transformation in a completely unsupervised way. Having an unsupervised approach allows not only to have an adequate identification of 3 discrete states (high, medium, low) but also to find intermediate states. Results show that it is possible to determine the ecological transformation by sound in an unsupervised manner in a tropical dry forest. In addition, in the field of clustering validation, more work should be done on the task of finding CIVIs specially designed for this type of application.

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