

Screening large audio datasets to determine the time and space distribution of Screaming Piha birds in a tropical forest



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ABSTRACT

Acoustic monitoring has proved to be an efficient approach to monitor wildlife, notably in environments with limited visibility, such as tropical rainforests. Today, recording equipment allows acoustic data to be gathered in remote areas at wide spatial and temporal scales. The resulting datasets are large and the use of automated processing systems to extract relevant information can greatly facilitate their analysis. Here, we have developed signal processing techniques to reveal the spatio-temporal dynamics of an emblematic bird voice of the neotropical forest: the song of the Screaming Piha (*Lipaugus vociferans*). Using recordings made in a French Guianan lowland forest, with an array of 24 microphones in a three dimensional space, we implemented a detection system based on spectrogram cross-correlation to trace the vocalisations of *L. vociferans*. We tuned the detection system based on the percentage area under the Receiver Operating Characteristic curve, finding a maximum of 95.88%. To strictly minimise false positives, we set the operating point to have 34.9% true positives and 0% false positives. We detected a total of 12,735 songs attributed to the study bird during 25 study days. We found that spatial patterns of lower activity corresponded to a zone having smaller trees and more tree gaps — a known liana forest patch — suggesting that Screaming Piha birds tend to avoid non-mature primary forests. The sampling sites near the creeks had more detections than the sites further away, suggesting that the lek mating arenas might be distributed strategically to be near to a source of water. We also found a marked temporal pattern. The lek was active during the whole day, from sunrise to sunset, with two peaks of activity shifted by more than 2 h from the dawn and dusk chorus. The approach described here can be tested using other conspicuous and stereotyped sounds that occur within a heterogeneous and noisy background. To decipher the complex interacting sounds of the tropical forest, these focal studies on specific acoustic elements should be complemented with community or soundscape analysis, to demonstrate the human impact on the ecosystem and to provide guidelines for natural resource management.

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1. Introduction

Monitoring the dynamics of biodiversity is a key challenge for ecology and biological conservation (Magurran, 2004) or for the new ecoacoustics discipline (Sueur and Farina, 2015). In particular, there is an essential need to map the distribution of species in space and time over local or regional scales and during circadian or longer temporal cycles. To date, this challenge has been mainly tackled with the help of field-based data collected by human observers (Hill et al., 2005). The

emergence of new sampling methods based on remote sensors, which automatically acquire environmental information at a regular rate, can supplement human observations, potentially increasing the accuracy of biodiversity monitoring data (Le Galliard et al., 2012).

One of the most recent and original automatic approaches to track biodiversity changes is based on the detection of sounds produced by animals during communication (Towsey et al., 2014). New audio technology allows us to deploy robust acoustic sensors, which collect data over long periods of time in remote areas. Acoustic monitoring based on these devices has already proved to be an efficient technique that could complement other data acquisition methods, notably in environments with limited visibility (Aide et al., 2013; Farnsworth and Robert, 2007; Frommolt and Tauchert, 2014; McDonald and Fox, 1999; Mellinger et al., 2007; Obrist et al., 2010; Yack et al., 2013). These

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monitoring programmes can produce large volumes of data. The analysis of such unsupervised datasets by human observers is tedious and time-consuming, whereas the implementation of automated or semi-automated signal processing systems can greatly facilitate data management, data visualisation, and data analyses.

In recent years, numerous pattern recognition methods such as Gaussian mixture models (Cheng et al., 2010; Skowronski and Harris, 2006), hidden Markov models (Kogan and Margoliash, 1998), artificial neural networks (Chesmore, 2004) and random forest (Armitage and Ober, 2010; Potamitis, 2014; Briggs et al., 2012), have been applied to acoustic databases to detect and classify animal sounds. All these approaches are valuable advances to improve ecoacoustic monitoring. However, reliable recognition in complex audio scenes remains difficult (Bardeli et al., 2010; Potamitis, 2014; Towsey et al., 2012) because unsupervised recordings can contain significant background noise such as wind and rain, and species may vocalise simultaneously. To improve recognition rates and cover larger areas, Bardeli et al. (2010) proposed the development of a specific algorithm for each target species. The problem of detecting a known signal among noise has been previously studied for radar systems (Skolnik, 2001). One of the resulting methods is cross-correlation (Smith, 2003). This is a widespread approach, as it works as an optimal linear operation for detecting a deterministic signal corrupted by white Gaussian noise (Brunelli, 2009). Cross-correlation gives a measure of similarity between the template and the objective signal at shifted positions. Cross-correlation has been adapted to audio data screening by searching for areas of spectrograms that match with a template. Spectrogram cross-correlation has already been applied to identify the sound produced by a focused species in a multi-source audio recording as illustrated in several marine (Erbe et al., 1999; Mellinger and Clark, 2000) and terrestrial (Borker et al., 2014; Fitzsimmons et al., 2008; Frommolt and Tauchert, 2014; Llusia et al., 2013; Clark and Fristrup, 2009) studies. Moreover, a recent computational study included this technique in a multi-label classification system for the recognition of bird vocalisation (Potamitis, 2015).

Tropical forests pose a great challenge to global biodiversity conservation, as they suffer from destruction and degradation by human activity at exceptional rates (Morris, 2010). Surprisingly, large ecoacoustic monitoring programmes that focus on such tropical environments are rather rare. The coexistence of many tropical species generates a fascinating and complex acoustic environment, described as the soundscape (Pijanowski et al., 2011), which remains poorly understood in its structure and dynamics. Recent studies have revealed rough temporal and spectral properties of the soundscape (Ellinger and Hödl, 2003; Hammer and Barrett, 2001; Pekin et al., 2012; Riede, 1993; Rodriguez et al., 2014; Slabbekoorn, 2004), but the dynamics of the elementary items are still unknown. In order to understand better the emergent patterns of tropical soundscapes, it is necessary to decipher the dynamics of specific acoustic elements, in particular of soundmarks. A soundmark, as defined by Schafer (1993), refers to a unique sound that is specifically distinguished for its qualities by the people of a locality. Species associated with these iconic sounds might provide a focus for rising awareness and action – a flagship species in terms of conservation biology. In the South American tropical forest, the loud and characteristic song of the tropical bird *Lipaugus vociferans* is well known by locals and visitors and is undoubtedly a soundmark.

In a previous study, an array of automated recording systems was established in the primary lowland forest in French Guiana (Rodriguez et al., 2014). A large audio dataset was collected, replete with intricate animal sounds that compete and overlap, creating an overwhelming dataset. This audio dataset was initially parameterised using a global approach, namely, by considering the files as unit samples without trying to identify the species they contained. This first approach provided important insights into the spatio-temporal organisation of the forest soundscape. However, it quickly appeared that analyses at a finer scale were required, to understand better the underlying factors that shape the dynamics of the tropical soundscape. To decrypt the complex

acoustic environment of a tropical forest, we reconsidered our dataset by focusing on a salient acoustic element, the song of *L. vociferans*.

The objectives of this study were (1) to adapt template matching techniques to find the song of *L. vociferans* in the tropical acoustic environment and (2) to generate spatio-temporal maps of the distribution of this species. Here, we present a methodology to implement and tune template-matching techniques on ecoacoustic databases. The results of the acoustic monitoring are confronted with hydrology and vegetation maps through LiDAR data, providing novel ecological information on *L. vociferans*.

2. Material

2.1. Study site

The study site was located in French Guiana at the CNRS Nouragues Research Station (4°05'N; 54°40'W), in a primary lowland rainforest (Fig. 1a). The Nouragues station is located in an inhabited region and is only accessible by river, 60 km from the nearest village, or by helicopter. Close to the equator line, the mean temperature oscillates between 26 °C and 27 °C and the humidity remains high during the whole year, between 80% and 90%. The rainfall is 2861 mm year⁻¹ (average amount of rainfall from 1992 to 2012), with a 2-month dry season (<100 mm month⁻¹) occurring from September to October, and a shorter dry season in March. The study was conducted over 25 days, from 12 November to 6 December 2010, at the beginning of the wet season.

2.2. Acoustic sampling protocol

Sounds were recorded with Song Meter 2 (SM2) systems from Wildlife Acoustics Inc. The SM2 can be programmed to record automatically on a schedule. The device comprised two omnidirectional microphones, an analogue-to-digital converter and a controller inside a waterproof enclosure. Twelve recorders were deployed in a 4 by 3 grid 200 m apart. The grid was formed by linear trails previously named with a letter and a Roman number. Each of our recording sites was named after its corresponding column (K, M, O) and row (XI, XIII, XV, XVII) coordinates (Fig. 1b and c). Each recorder was set to sample the audio at 44.1 kHz at a 16-bit resolution. The left-channel microphone was placed at the canopy level (20 m above the ground) and the right-channel microphone was placed at the understory level 1.5 m above the ground. The devices were programmed to record for 1 min every 15 min during the 24 h day/night cycle. The database used here accounts for 25 days of these recordings and represents a total of 960 h of audio data.

2.3. Study species

Despite its cryptic plumage, the Screaming Piha (*L. vociferans*; hereafter, “Piha”) is one of the most representative species of the neotropical forest. The commonly heard song of this bird is a remarkable soundmark known by anyone who has visited this region (electronic supplementary material, Audio S1). This species is regarded as one of the birds that possesses the loudest song in the world, with a mean sound-pressure level of 111.5 dB re 2.10⁻⁵ Pa estimated at 1 m distance (Nemeth, 2004), and can spend 70% of the day time calling (Snow, 1961). Males gather in leks of around 25 individuals, where they highly compete vocally to mate with selecting females (Tostain et al., 1992). The Piha is common in the primary forest, but is highly sensitive to habitat degradation (Stotz et al., 1996).

The Piha is a suboscine passerine, therefore, it is thought that the song is inherited genetically and hence, stereotyped. Recent studies have shown that small variations in its song can encode individual distinctiveness and bear a lek signature (Fitzsimmons et al., 2008).

Perching on horizontal branches on his territory, the Piha calls with a typical song composed of two parts: (1) varied and quiet introductory notes, *groo groo*, and (2) a louder and highly modulated

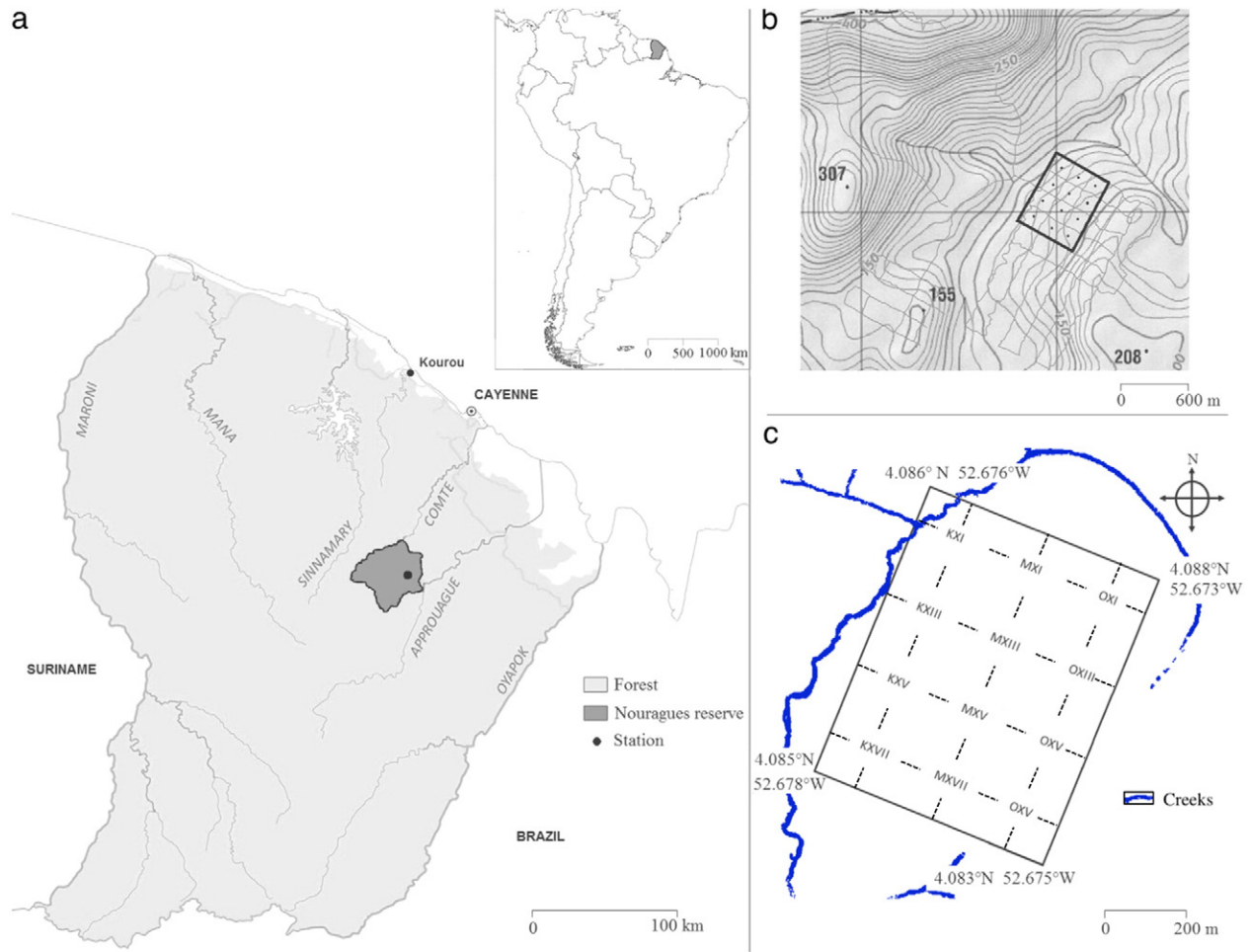


Fig. 1. (a) Location of French Guiana and the Nouragues reserve. (b) Topographical map of the study area. (c) Schematic representation of the study area with the layout of the location of the 12 autonomous recording systems. The sensors were installed at the cross of perpendicular trails, in the understory (1.5 m) and at the canopy level (20 m). Letters and Roman numbers refer to trail names.

whistled *pee-haw*. For our study, we focused only on the louder part of the song. The first syllable, *pee*, is a rapidly ascending frequency modulation from 1.3 to 5.0 kHz. The second syllable, *haw*, can be

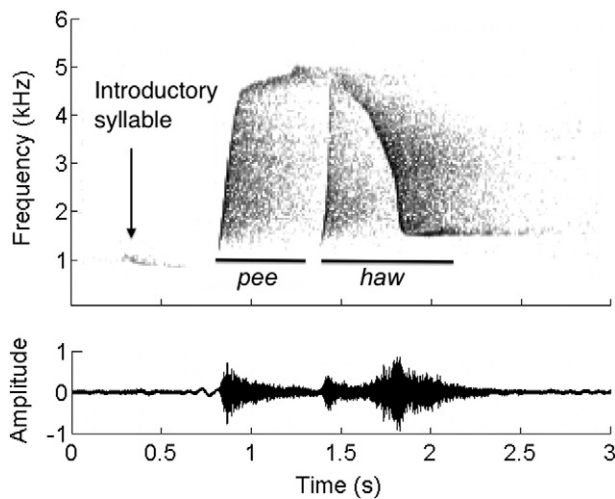


Fig. 2. Spectrogram and waveform of a typical *Lipaugus vociferans* song composed of a two-syllable *pee-haw*. The high-energy regions are at the beginning and at the end of the song, at about 1.5 kHz. The short-time Fourier transform was calculated with a Hamming window of 1024 samples, no zero padding and 50% overlap between windows. A dynamic range of 40 dB was set to display the spectrogram.

considered as being composed of a whistle with three connected parts: an upswing, a downswing and a final constant frequency tune at 1.5 kHz (Fig. 2 and electronic supplementary material, Audio S1). There is also another whistling call, *wee-oo*, made by the birds holding territories, but it is a very occasional vocalisation (Snow, 1961).

2.4. Canopy height detection

An acquisition of small-footprint discrete-return LiDAR (Light Detection and Ranging) was conducted in the Nouragues research area in March 2012 and covered an area of 2400 ha, including our study zone. The acquisition was based on a portable Riegl laser rangefinder (LMS-Q560) mounted on a Falcon aircraft at a speed of approximately 45 m s^{-1} about 400 m above the ground. The system had a multiple returns registering capacity and the mean laser-point density was approximately 20 impulsions per m^2 . We constructed a canopy elevation model, i.e., the maximum local canopy height, using a procedure implemented in FUSION (McGaughey, 2012). The canopy elevation model was constructed at 1-m resolution using a 1-m resolution digital elevation model (DEM) and the “CanopyModel” procedure implemented in FUSION. A 3×3 neighbour window median filter was finally used to smooth the surface and thus avoid local unrealistic maxima or minima. A full description of the LiDAR dataset and of the construction of the DEM and of the canopy model is given in Réjou-Méchain et al. (2015).

The median canopy height (in metres) of the surrounding 1 ha was calculated for each microphone to avoid overlap between neighbouring sample sites (Fig. 3). The median of the canopy height has been shown

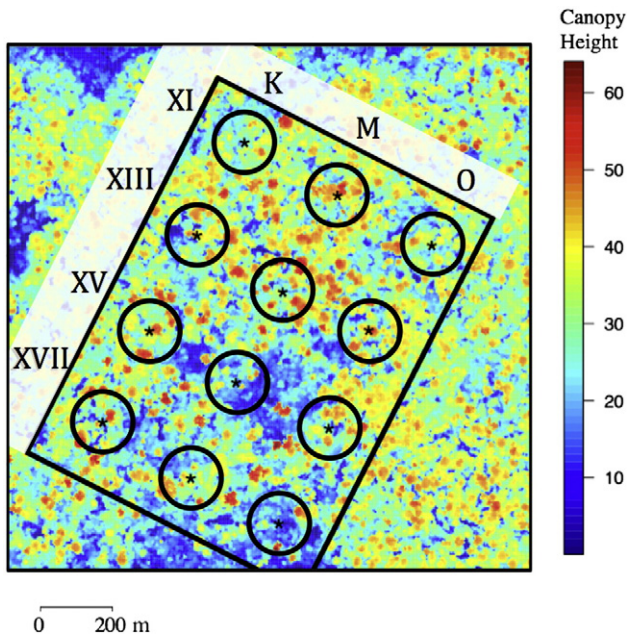


Fig. 3. Height of the canopy of the study site using LiDAR technology. Stars indicate the position of the recorders and circles delimit an area of 1 ha surrounding the recorders where the median tree height was estimated. Letters and Roman numbers refer to trail names.

to be a good proxy for the aboveground tree biomass, and hence of the whole forest structure (Réjou-Méchain et al., 2015).

3. Methods

3.1. Test database

As a first step, we created a test database (training database) to develop a detection system. The acoustic environment in the tropical forest is heterogeneous in space and time. Previous statistical analyses on the recordings showed an acoustic pattern of four main sound environments during one day: (1) a morning period from 1:00 to 9:00, (2) a day period from 9:00 to 18:00, (3) an evening period from 18:00 to 19:00, and (4) a night period from 19:00 to 1:00 (Rodríguez et al., 2014). To tune correctly the detection system, the test database should contain samples with soundscapes from the different time-periods. To account for the temporal variation, we selected one day every four days over the 25 days of study, and for each day, we chose one sample from each time period. To account for the spatial variation, we selected samples from all 12 recording sites. The resulting test database contained 336 files of one minute in length (4 files/day/site \times 7 days \times 12 sites). Two of us (J.S. and J.S.U.) listened with headphones and visually inspected the spectrogram of each file to annotate the occurrence of the Piha's songs in the test database. The open-source software Audacity (<http://audacity.sourceforge.net/>) was used for the manual analysis and annotations. Manually annotations contained Piha songs mixed with sounds produced by other species. The songs due to different Piha individuals vocalising at the same time could also overlap. Within the resulting test database, we found a total of 262 songs of the Piha. We used this material as the ground truth to tune and test the detection system (see Section 3.4).

3.2. Signal processing

Noise is unwanted sound that interferes with the desired signal and as stated in the introduction, noise can be divided into background noise and interference. The recording equipment introduces unwanted energy and distortions; electromagnetic and thermal noise from the electronic circuit (-115 dBV equivalent input noise for the SM2

recorders), and quantisation distortion by the conversion of the signal from analogue to digital. Outdoor recordings always contain a significant amount of background noise that fluctuates in intensity. Geophonic sounds, such as wind and rain, add background noise to the signal as well as incidental anthropophonic noise such as helicopter noise. Interferences are due to sounds produced by other vocalising species, but which are not of interest for the study. In the tropical forest, there is a large number of vocalising species that generate many sounds that can potentially interfere with the targeted signal. In signal detection, the background noise limits the detection range of the system, whereas the interference decreases the accuracy of the system by increasing the false-positive detection rate (Skolnik, 2001). In our study, the target signal is the song of the Piha and all other sounds are regarded as noise. For example, we present a field recording that includes various sources of sounds, including the target signal (supplementary material, Audio S2).

Template matching is a set of techniques used to identify a pattern in a large database. A particular method of implementing template matching is to compute the cross-correlation function. Cross-correlation is performed by sliding a template signal over an objective signal, and calculating a correlation value at each time offset. The output signal is a measure of similarity between the template and the objective signal at a different time-lag. This method has been used in image processing to determine the position of a pattern in an image (Ding et al., 2001).

Audio data can be represented in a matrix by applying the short-time Fourier transform (STFT). The signal is divided into m overlapping windows of n samples and then the n -point discrete Fourier transform (DFT) is calculated for each windowed signal. The results are organised into a $m \times n$ matrix; the frequency frames m , the time frames n and the amplitude as cell values. The matrix is plotted as a colourmap, and the resulting image is called a spectrogram. In audio signal processing, the two-dimensional cross-correlation allows the search for patterns using features in the time and frequency domain.

Normalised cross-correlation (NCC) is an effective method for template matching. This approach is robust to differences in relative signal amplitude between the template and the objective signal, such as those caused by signal absorption (Brunelli, 2009). The two-dimensional normalised cross-correlation (NCC) is calculated by the following equation:

$$NCC(u, v) = \frac{\sum_{x,y} [f(x, y) - \bar{f}_{u,v}] [t(x-u, y-v) - \bar{t}]}{\sqrt{\sum_{x,y} [f(x, y) - \bar{f}_{u,v}]^2 \sum_{x,y} [t(x-u, y-v) - \bar{t}]^2}}$$

where f is the objective matrix and the sum is over the region x, y under the template t shifted at position u, v . $\bar{f}_{u,v}$ denotes the mean value of $f(x, y)$ within the region under the template and \bar{t} is the mean value of the template matrix.

3.3. Template selection

Firstly, we computed the signal-to-noise ratio (SNR) of the 262 Piha vocalisations that occurred in the test database. To calculate this ratio, we used the following equation:

$$SNR_{dB} = 20 \log_{10} \left(\frac{A_{signal}}{A_{noise}} \right)$$

where A is the root-mean-square of the sample. We selected for the background noise 0.7 s before and 0.7 s after the target song. The duration of the background noise (1.4 s) is equal to the mean duration of a Piha vocalisation. The SNR values range from -22 dB to $+22$ dB.

Then, to ensure the detection of nearby vocalisations, we selected the ten samples with the highest SNR (from $+14$ dB to $+22$ dB) and

we standardised them. We aligned the samples in the time domain, starting at 0.2 s before the beginning of the vocalisation and with a total length of 1.6 s, and we normalised each sample between 0 and 1.

Finally, we calculated the mean over the ten standardised samples, to derive a single mean template. This template maintained the most salient parts of the signal and accounted for the small but inevitable variations in the song.

3.4. Tuning the spectrogram parameters

To tune the system, we compared the output of the NCC with manual annotations. The detection task treated showed an uneven distribution between classes, positive outcomes being rare compared to negative outcomes. As discussed in Provost and Fawcett (1997) and Daskalaki et al. (2006), the classification accuracy is an inappropriate performance measure in the particular case of unbalanced outcomes. We therefore used a methodology from signal detection theory, the Receiver Operating Characteristic (ROC) curve together with the Area Under the Curve (AUC) to summarise the rate of false and true detections. ROC curves describe the predictive behaviour of a class independent of class distribution, so they decouple classification performance from these factors (Provost et al., 1997). The AUC has two main advantages when evaluating the performance of a detector: it is threshold-independent and it is invariant to a priori class probabilities (Bradey, 1997).

The main parameters of a spectrogram are the fast Fourier transform (FFT) window length, the overlap between successive FFT windows, the zero padding of the FFT and the shape of the window used. All these parameters change the time–frequency resolution of the spectrogram and therefore, change the result of the detection system. Preliminary observations have shown that the parameters that change the detection performance most drastically are the window length and the overlap between windows. We systematically measured the AUC metric associated with different combinations of these two parameters to find the optimal value. We changed the value of the window length from 128 to 8192 samples by 2^k (where k is an integer from 7 to 13) steps, and the overlap from 0% to 75% by 25% steps. The performance of the system varied by 2.61% and we attained the optimal settings with a 256 window length and 0% overlap (Table 1).

The song of the Piha had a bandwidth of 4 kHz on average, ranging from 1.3 to 5 kHz. Thus, we narrowed our search around the frequencies of the signal of interest. We computed the correlation for different frequency bandwidths with bounds from 1 to 6 kHz by steps of 1 kHz. This ensured that the most suitable frequency band was found, for an optimised performance of the detection system. The performance of the system for the different bands varied by 9.72% and the optimal setting was found for the frequency band from 1 to 6 kHz (Table 2).

3.5. Threshold setting

The corresponding ROC curve of the detection system selected is presented in Fig. 4. The ROC curve displays the true positive rate (TP) of the detection system versus the false positive (FP) rate in relation with a variation of the discrimination threshold. A threshold must be

Table 1

Variation in the system performance with the window FFT size and overlap of the short-time Fourier transform. The evaluation metric is the AUC (area under the curve) as a percentage. The best result is highlighted in bold font.

Overlap	FFT window size (number of samples)						
	128	256	512	1024	2048	4096	8192
0%	94.68	95.88	95.58	94.67	95.03	94.15	93.48
25%	94.27	95.17	95.11	94.83	94.43	94.21	93.27
50%	94.49	95.18	94.78	94.97	94.51	94.16	93.86
75%	94.34	94.99	94.65	94.92	94.64	94.01	93.84

Table 2

Variation in the system performance with the frequency bands of the search. The evaluation metric is the AUC (area under the curve) expressed as a percentage. The best result is highlighted in bold font.

Upper frequency bound (kHz)	Lower frequency bound (kHz)				
	1	2	3	4	5
6	95.88	94.44	91.75	91.14	86.40
5	92.74	91.23	89.40	89.84	
4	90.22	89.06	86.16		
3	89.39	91.43			
2	88.45				

defined to turn the results of cross-correlation into a series of discrete detection events. An event was registered when a peak of amplitude of the cross-correlation exceeded the threshold. The choice of such a threshold depends on the application. Increasing the threshold increases the selectivity of the detection system while lowering the threshold increases the sensitivity.

As the Piha produces a loud song, the array of sensors could capture this sound in more than one recording site. In our particular case, we focused on the detection of the nearby vocalisations to avoid any overlap between neighbouring sites, which could overestimate the number of local vocalisations. We therefore chose a high and selective threshold value of 0.3. With this setting, the metrics of the detection system for the test database were: 0% FP and 34.9% TP. All analyses were programmed with Matlab (The MathWorks, Inc., Natick, MA).

4. Results

Prior to automated analysis, the manual detections were removed from the annotation table. Scanning the complete database took 17.4 h with a laptop running with a 2.8 GHz processor and a 8 GB memory. The detection system found a total of 12,735 Piha songs. From these, 62% of the vocalisations were detected in recordings made by the canopy sensors and the remaining 38% of the recordings were made by the understory sensors. Fewer detections were found in the understory in all recording sites (Fig. 5). The site M-XI had by far the highest number of detections, followed by O-XI and K-XI. In contrast, almost no songs were detected in the recording sites M-XV, O-XV and O-XVII, where the forest had the lowest canopy (Fig. 3) and which corresponds to a zone known to be dominated by lianas (Tymen et al., in press). All the other sites had a relatively low and similar number of detections.

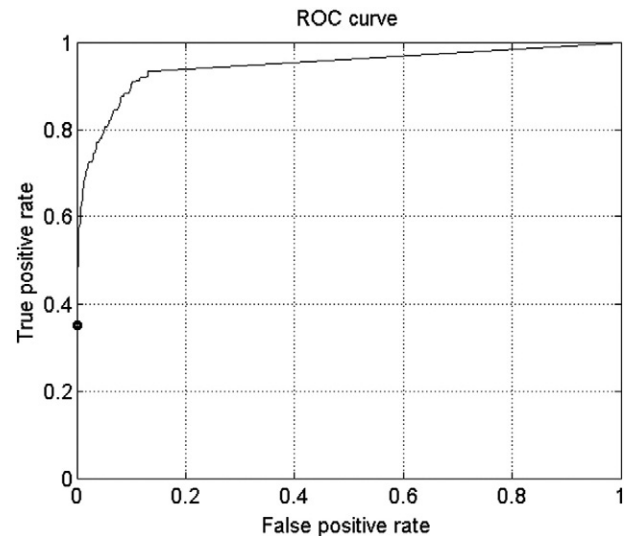


Fig. 4. Receiver Operating Characteristic (ROC) curve of the detection system. The point on the curve indicates the operating point selected: false-positive rate = 0% and true-positive rate = 34.9%.

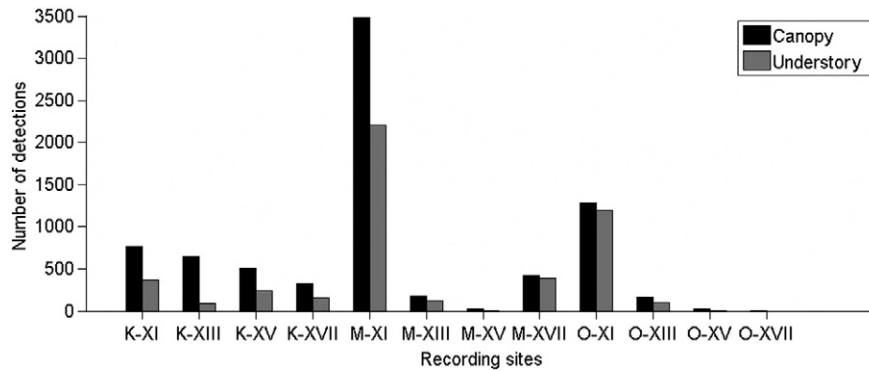


Fig. 5. Barplot of the number of songs detected for each recording site at the understory and canopy levels.

In the time domain, there was a mean \pm SD of 509.4 ± 284.3 songs detected per day over the whole study area (Fig. 6). The maximum activity was reached on the fourth day, with 1405 songs, and the minimum activity on day 23, with 74 songs. Indeed, a decreasing trend was noted from the beginning to the end of the study. A simple linear regression model, with log-transformed response, showed that the number of vocalisations decreased approximately 5% by day (estimate \pm SE: -0.053 ± 0.013 , adjusted $R^2 = 0.4$, $F_{1,23} = 17.09$, $P = 0.0004$). Diagnostics of model validity and stability (Cook's distance, DFBetas, DFFits, and leverage; distribution of residuals plotted against fitted values) did not indicate obvious influential cases, nor deviations from the assumptions of normality and homogeneity of residuals. The understory and the canopy showed almost the same profile of temporal activity, and as observed before, the canopy always had a higher number of detections for each day.

A diurnal activity pattern appeared clearly (Fig. 7): the calling activity began at sunrise (6:15) and increased slowly, reaching a first peak at 8:30. A reduction in the activity, with fluctuations, was observed between 10:00 and 14:45. The peak in activity was observed at 15:30 and then activity decreased progressively until sunset (18:10).

Finally, the complete set of results was summarised in a density plot that combined time (24-h cycle and days), space (horizontal and vertical) and Piha vocal activity (Fig. 8). Zones of high (K-XVII, K-XV, K-XIII, K-XI, M-XI and O-XI) and low (M-XV, O-XV and O-XVII) activity can be observed. In addition, the temporal circadian activity is clearly emerging, showing the activity constrained by the sunrise and sunset dashed lines.

5. Discussion

Assessing and monitoring animal diversity in tropical forests is a challenging task, due to the immense number of co-existing species and the structural complexity of the environment. Acoustic monitoring can offer new tools to remotely detect and locate species of interest in space and time (Blumstein et al., 2011). In addition, acoustics might be involved in the global assessment of communities or

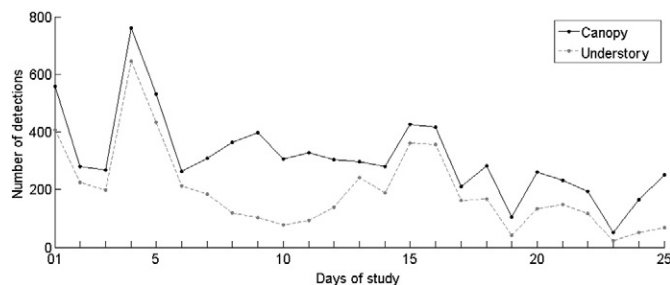


Fig. 6. Sum of the songs detected for the understory and canopy levels for the 25 days of the study.

ecosystems through the development of diversity or landscape indices (Gage and Axel, 2014; Pieretti et al., 2011; Sueur et al., 2008, 2014; Towsey et al., 2014). The sampling protocol used here was designed to define the acoustic dynamics of a patch of a neotropical forest (Rodriguez et al., 2014). This dataset embeds a unique amount of information concerning the behaviour, distribution and ecology of vocalising species. This information should be retrieved using methods adapted to large audio datasets. We therefore took the opportunity of this audio sampling to track one of the most conspicuous sounds of the forest in space and time – the song of the bird *L. vociferans* – the Piha.

5.1. Template matching in complex soundscapes

The Piha sings in an acoustic scene with several other species that can produce sound concomitantly. Detecting the song of the Piha in almost 1000 h of audio was therefore a challenge for signal analysis within large audio data. To achieve this task, we used a relatively standard template-matching approach through spectrogram cross-correlation. Using this technique we could build an objective classification system with a relatively small test database. In addition, we could screen the complete database within an acceptable processing time (<18 h) with a standard laptop. Therefore, we showed that the cross-correlation of spectrogram is a robust and rapid technique to detect soundmarks such as the Piha song. This success was primarily due to the loudness and stereotypy of the Piha song, therefore, we expect that our approach might also perform well with other conspicuous and stereotyped sounds such as some amphibian vocalisations and insect stridulations, thereby opening perspectives in multi-species monitoring approaches.

The performance of spectrogram cross-correlation varies, depending on the focused signal, the background noise, the interferences and the input parameters (spectrogram specifications and the template(s) used). The parameters of spectrogram cross-correlation

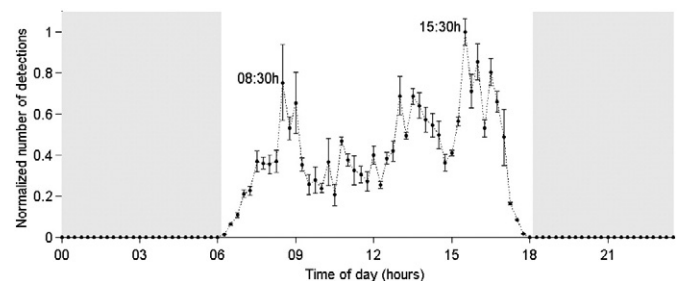


Fig. 7. Circadian evolution of the Piha calling activity. The six recording sites with the highest activity were used to build the trend. The results of each recording site were normalised and then averaged. A final normalisation was performed to show the results from 0 to 1. Filled round marks represent the average and the bars represent the variance between the sites.

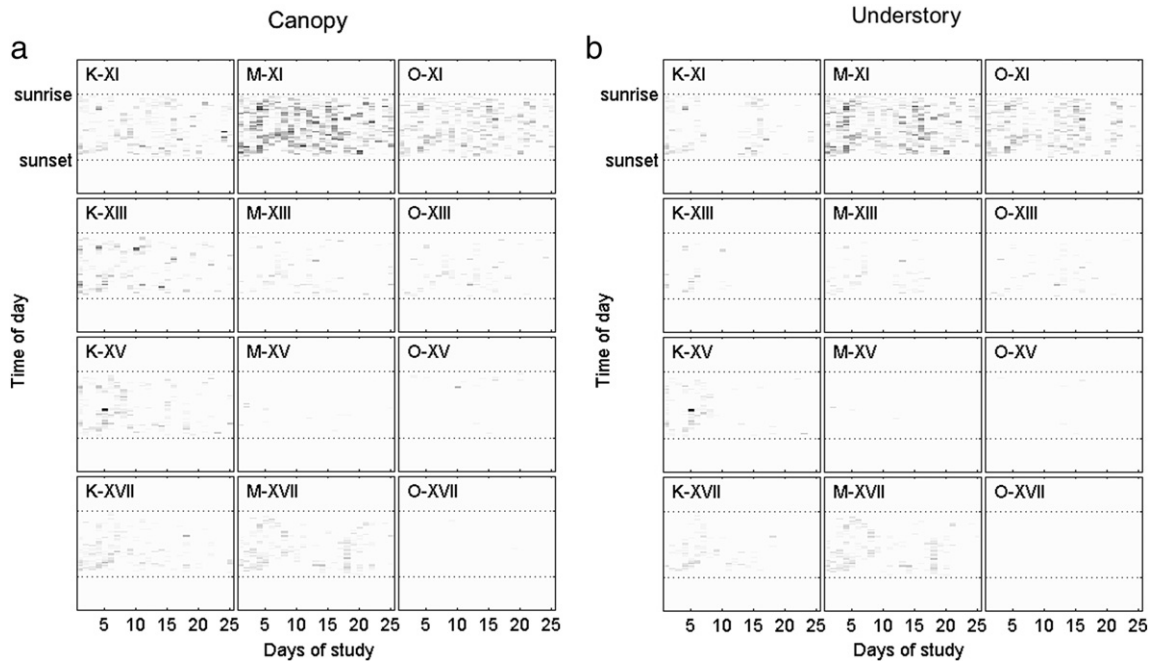


Fig. 8. Representation of the spatio-temporal calling activity in an intensity image for the canopy (a) and understory (b) sensors. Each box represents a recording site. The y-axis represents the 24-h cycle from 0:00 am to 23:45, with sunrise (18:15) and sunset (18:10) indicated by a dashed line. Sunrise and sunset were considered constant during the sampling period (Earth equatorial line). The x-axis follows the activity during each of the 25 days of study. The grey scale of the pixels indicates the number of detections; the darker points represent more detections. The scale ranges from white (0 detections) to black (41 detections).

must therefore be tuned to consider all the sources of variation as we did, by testing the features of the Fourier window, the frequency bandwidth of interest and the detection threshold value. The spectrogram cross-correlation technique is now incorporated into different software, facilitating its handling by non-experts in signal analysis. However, the features that tune the detection system are rarely found in software documentation, which reduces the possibility of reproducibility.

The spectrogram cross-correlation is definitely not universal and other methods should be invoked for less stereotyped songs. As suggested by Towsey et al. (2012), each species might require a specific tool to be identified automatically, making the unsupervised monitoring of several species extremely difficult. The use of more generic features describing intrinsic call structure, such as ridge features (Dong et al., 2015), could provide a better performance and the flexibility to detect species with more variable songs.

5.2. Remote-sensing, behaviour and ecology of the Piha

We initially found that the number of Piha vocalisations detected in the canopy was higher than in the understory. The canopy microphone was placed at a height of 20 m and the understory microphone at 1.5 m. Two facts might explain this vertical difference: (1) Piha singing perches are closer to the canopy than to the ground; and (2) the acoustic properties of the habitat favour signal transmission towards the canopy. Regarding the first alternative, the literature is consistent in defining the perch height of the Piha in about the middle understory and the lower canopy (Stotz et al., 1996; Thiollay, 1994; Thiollay et al., 2001) with estimates between 6 and 16 m or higher (Snow, 1961) or 7 and 25 m (Pearson, 1971). Lower-boundary estimates are consistent, but upper-boundary ones vary significantly between observations. Personal observations (J.S.U.) indicated that the perch height of the Piha was closer to the canopy microphone (i.e., 20 m) in our study site. Regarding the second explanation, the few studies on signal transmission in tropical environments have evaluated signal degradation based on source height (Marten et al., 1977; Morton, 1975) or in specific layers (Ellinger and Hödl, 2003; Jain and Balakrishnan, 2012; Nemeth et al., 2001) but not on receiver height. Therefore, it would be too speculative to draw

conclusion at this point. In summary, given our field observations (see above), it is more likely that the Piha sings closer to the canopy microphone at this specific study site. Transmission experiments and calibration methodologies at ecoacoustic monitoring sites would be needed, however, to confirm this supposition. Some methodological techniques that might be applicable for future studies are presented in the work of Llusia et al. (2011).

Considering a wider spatial scale, the results showed that the recording site M-XI produced by far the highest number of vocalisations (5696), followed by the site O-XI (2476) on all days. The high activity at this site is probably due to the proximity of a lek, where a higher number of individuals were concentrated.

The horizontal spatial activity pattern corresponded to the structure of the canopy estimated by LiDAR techniques. In particular, the sites with the lowest activity had the lowest canopy height. These sites are located in a forest dominated by lianas where canopy openness and dynamics is much greater than in the surrounding tall forest (Tymen et al., in press). This reflects that the habitat of the Piha is the high mature primary forest and confirms observations made by Stotz et al. (1996). In addition, Piha songs were more frequently detected in the recording spots K-XVII, K-XV, K-XIII, K-XI, M-XI and O-XI, which border the main creek. This suggests that the lek mating arenas are distributed strategically near to a source of water for the singing males. However, further analysis and data would be needed to confirm this habitat preference.

Regarding the temporal organisation of the acoustic activity of the Piha, the screening of the database showed a well-defined circadian rhythm over a 12-h period, starting at 6:00 and ending at 18:00. It appears that the Piha avoids calling at dawn and at dusk, at the transition between day and night, when soundscapes with more acoustic activity could be observed (Rodríguez et al., 2014). The morning peak of Piha singing activity appeared more than 2 h after dawn and the afternoon peak of activity was reached two and a half hours before dusk. During the rest of the day, the vocal activity was less intense, but still present, making the Piha a relatively active bird that dominates the day soundscape and confirms its status as a soundmark of the forest.

On a larger temporal scale, the number of detections decreased from the beginning to the end of the study. However, the sampling period of only 25 days, even though important, prevents a seasonal trend from being interpreted. Only longer sampling protocols, in terms of development, over months and possibly years, could provide the required data to establish a seasonal trend for this bird and for the other sounds of the forest.

6. Conclusion

This species-centred study represents a contribution towards biodiversity assessment at a large scale of a taxon-rich ecosystem – the lowland tropical forest. Using data collected in a neotropical forest with a tree-dimension array of 24 microphones and implementing signal processing techniques, we could describe the spatial and temporal distribution of the tropical bird, *L. vociferans*. We provided detailed, objective and quantitative results, which are three crucial qualities for the advancement of biodiversity-monitoring strategies.

This study reused a protocol that aimed to sense the global acoustic features of the forest. It is therefore possible to use the sample dataset to obtain information on tropical forest acoustics at different scales, from populations to communities or landscapes. We advocate the development and use of both bottom-up and top-down approaches for research that deals with individual species of interest through automatic identification, and for research that zooms out on a group of species through the use of diversity indices (Sueur et al., 2014).

The tropical acoustic environment is composed of numerous sounds that interact and remain to be analysed at narrow and wide ranges. Even when the focal point of a study is a particular sound, it is important to remember that this sound occurs in a specific acoustic context that might have shaped the focused sound. Understanding the diversity of sounds in the tropical forest is a more difficult task than to excise individual elements and examine them independently; the scene and its characters should be examined together.

Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.ecoinf.2015.11.012>.

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