

Automated bird acoustic detection at Las Arrieras Nature Reserve in Sarapiquí, Costa Rica

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Abstract—Ecological characteristics favor high biodiversity on the Caribbean slope of Costa Rica, but this piedmont zone is poorly studied. In birds, the use of automated song and call recognition has progressed to support bird studies about ecology and behavior. We used a Pattern Matching method to label the presence of the Cinnamon Woodpecker, Great-Green Macaw, Red-capped Manakin and Chestnut-backed Antbird to create a random forest model and detect the species' vocalizations to characterize their vocal activity in the reserve. We used Audiomoth recorders. For all acoustic detection models, accuracy, and precision values above 91% were obtained despite the imbalance of positive and negative classes, the value of Unweighted Average Recall was high for each model. Three sites showed the highest number of detections and the number of detections per site varied among species. A preference of use for some sites within the reserve was identified for *A. ambiguus* and *C. mentalis* and a more generalist use for *C. loricatus* and *P. exsul*. For each species, greater acoustic activity was found in the morning hours with less activity in the afternoon hours for some of the species with a peak of activity between February to May. The acoustic detection patterns found agreed with the literature for each species when analyzing the ecological behaviors inside and outside the breeding season of birds in Costa Rica. This acoustic information will improve conservation decision making for the species involved and other species that develop in these ecosystems.

Index Terms—Acoustic detection, Passive acoustic monitoring, Random forest model, Pattern matching, conservation, Costa Rica

I. INTRODUCTION

Biodiversity that occupies the Caribbean Slope of Costa Rica is profoundly diverse [1] and increases towards the foothills that border the southwest of the Central Mountain Range of the country [2]. The irregular topographical conditions of this area favor a high variety of microclimates, constant rainfall, lush and dense vegetation that provides

abundant niches and food resources, and an altitudinal gradient where species migration is common [3], [4].

Despite the number of opportunities for research, the biota that inhabit in this area are poorly studied, due to its limited access to undisturbed habitats and complex logistics for in situ [5]. Based on this, it has been necessary to implement monitoring techniques that facilitate data collection in the field, reduce effort and costs, and also provide effective information in significant amounts to generate knowledge of the remnants of undisturbed forests of the Caribbean foothills where access is possible [6], [7].

Passive acoustic monitoring has been used for a long time to define the acoustic patterns of species with vocal activity. In the past, it was necessary to listen the recordings and to make the acoustic detections manually. Nowadays, computational bioacoustics, the automated detection of soundscape elements have been implemented, making the study and recognition of acoustic patterns easier through sound recognizers [8].

Groups such as birds, amphibians, insects, and bats have been the focus on automatic detection studies using vocalizations [9]. To achieve this, various machine learning approaches have been used and have been successful [10]. On birds, the use of automated recognition is progressing agilely in studies covering various aspects of bird ecology and behavior, including presence-absence studies, population density estimates, monitoring of threatened species, and anthropogenic impacts on populations [11].

The main methods used in acoustic monitoring projects for the automated identification of nature sounds have been Convolutional and Recurrent Neural Networks (CNN) [12], [14], dense and deep CNN [13], Hidden Markov Models, Gaussian Mixture Models, Support Vector Machines [15]. Techniques such as Pattern Matching (PM) and Random Forest Model (RFM) have been the most common classifiers among others algorithms for bird acoustic detection (BAD) [16].

Previous works about bird acoustic detection developed in

the tropical region studied the vocal activity of birds using Hidden Markov Models and achieved 83% to 99% of accuracy and precision [35] and a RFM from Puerto Rico and Costa Rica avifauna that showed precision values between 63% to 97% [27] and a previously executed RFM at Las Arrieras Nature Reserve that revealed scores of 82% to 86% for accuracy and precision of validated recordings. [23].

PM and RFM could be useful and complementary for analyzing and comparing recognition patterns [32]. The RFM has been selected as one of the most accurate machine learning procedures for prediction models of vocalizations in different groups of fauna, mainly birds [33]. This model uses collections of classification and regression trees and simple models to determine predictions for both supervised and unsupervised classifications [34].

Baseline studies on the ecology of birds are of great importance to increase and improve conservation efforts in poorly studied sites. By conducting focal analyses on a set of species, we can get a clear and broad picture of the threats they may face and their natural behaviors. Thus, selected species can function as an "umbrella" to generate inferences about what may be occurring in other species [17], [18].

Some criteria for choosing these key species may include the altitude of migratory species that use a wide range of habitats on their routes and are threatened by fragmentation [19], common insectivorous species that have shown a drastic decrease in their populations in recent years [20] and species that depend on large territories for their subsistence.

The results of acoustic monitoring can provide of vital information on how they might react to habitat changes, alterations in rainfall and temperature patterns due to climate change, and pressure from the expansion of human productive activities [21], [22].

In this study, we apply PM method to label the presence of Cinnamon Woodpecker (*Celeus loricatus*), Great Green Macaw (*Ara ambiguus*), Red-capped Manakin (*Ceratopipra mentalis*) and Chestnut-backed Antbird (*Poliocrania exsul*), a RFM to detect the species vocalizations, and then we use the results to characterize their vocal activity at the reserve.

II. METHODOLOGY

A. Data Collection

The study was conducted in the Caribbean foothills of the Central Volcanic Cordillera, specifically in Las Arrieras Natural Reserve located in Sarapiquí, Heredia, Costa Rica (10°18'44 "N, 85°2'30 "W). These areas maintain a high variety of life zones and allow the establishment of an exceptional biological richness.

The reserve is a site of great importance and conservation interest for the maintenance of populations of endangered or reduced species such as the green macaw (*Ara ambiguus*), the ocellated antbird (*Phaenostictus mcleannani*), the cerulean warbler (*Setophaga cerulea*) and the red-fronted parakeet (*Touit costaricensis*) [23].

Ten Audiomoth recorders were placed in the field to monitor the soundscape at seven sites within the Las Arrieras farm and three sites at the Monasa farm. We placed seven recorders in the understory at 10 meters high (A01, A02, A03, A04, M01 and M03) and three recorders (A05, A07 and M02) in the canopy at 2 meters high to monitor landscape sounds at each site (Figure 1).

Soundscape files were collected in digital wav format, 48 kHz sampling rate and 16-bit resolution using the one-minute methodology at ten-minute intervals for 24 hours at each site from November 2020 to December 2021. A total of 254,179 recordings were uploaded to ARBIMON platform (<https://arbimon.rfcx.org/>) for analysis. [24].

B. Data Processing

Four common species were considered for automated sound detection according to its particular ecological and conservation importance, with a song rate, intensity and structure of vocalization that characterize them as easily detectable species in the region and reserve.

Using the ARBIMON Visualizer tool, sound templates were created for each species from the recordings in the Las Arrieras Nature Reserve. Subsequently, the binary classification RFM feature was chosen, which has shown high efficiency in the analysis of passive acoustic monitoring data for automated identifications [25].

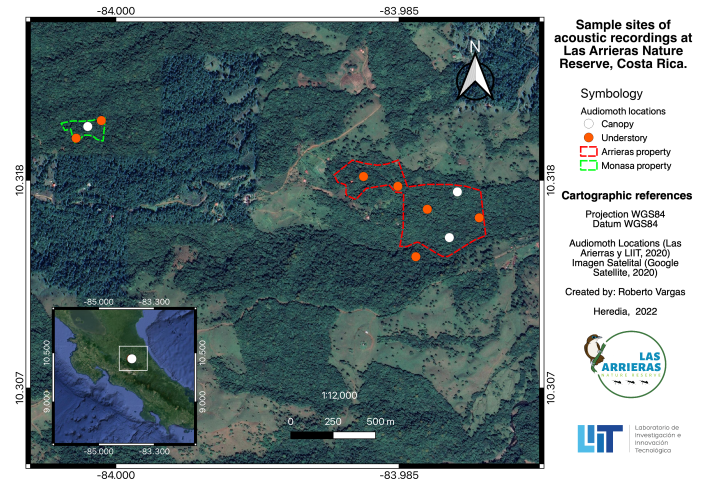


Fig. 1. Location of study sites at canopy and understory in Las Arrieras Nature Reserve

We used ARBIMON Pattern Matching feature through a playlist of 105,776 recordings from 5:00 am to 9:00 am and from 2:00 pm to 6:00 pm. Threshold (value at 0.1) and Maximum Match (five per recording) parameters were used to create multiple Regions of Interest (ROI) and run the validation process to detect acoustic signals with a correlation equal to or higher than the assigned threshold in the spectrogram (time-frequency). [26].

We create 252 tags for *C. loricatus*, 204 tags for *A. ambiguus*, 5093 tags for *C. mentalis* and 1606 tags for *P. exsul*. Subsequently, we validated a maximum number of recordings

for each species where at least on individual was present. In each validation, we used 70% of the data for training and 30% of the data as validation data.

Matching with presence (True Positive or TP) or absence (True Negative or TN) validations are determined by the ROI created by the Pattern Matching feature. ROIs are then created in the "Training Set" feature with the 10 best sounds for each species that will be needed to run the Random Forest model during automated detection.

Using a vector of 12 acoustic statistical features (mean, median, minimum, maximum, standard deviation, maximum-minimum, skewness, kurtosis, hyperasymmetry, hyperkurtosis, histogram and cumulative frequency histogram) the RFM is trained to detect the corresponding species [27].

C. Data Analysis

We describe the performance of the binary classifier (presence or absence of species) by using a confusion matrix. The matrix is composed of columns representing the number of cases or values in a predicted class, while each row represents the values in an actual class.

We used several metrics from recommendations of [28] and previous work of [23] to validate the model using accuracy (Ac), negative predictive value (Npv), precision (Pr), sensitivity or recall (Se), specificity (Sp), Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) and the Unweighted Average Recall (UAR).

The frequency at which the classifier is correct can be determined by the Accuracy.

$$Ac = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

Complementarily, the frequency of positive identifications of the classifier with respect to the presence of the species can be determined by the Precision:

$$Pr = \frac{(TP)}{(TP + FP)} \quad (2)$$

The proportion of identified non-cases among the negative results can be described by the Negative predictive value (Npv):

$$Npv = \frac{(TN)}{(TN + FN)} \quad (3)$$

The ability of the model to find all relevant cases in the data set can be determined by the Sensitivity or recall (Se):

$$Se = \frac{(TP)}{(TP + FN)} \quad (4)$$

To assess the model's ability to predict true negatives we can use Specificity (Sp):

$$Sp = \frac{(TN)}{(TN + FP)} \quad (5)$$

To measure the ability and performance of a classifier to distinguish between classes (positive and negative), the Area Under the ROC Curve (AUC) tool can be used.

Finally, when the model has been created with an unbalanced class classification between positive and negative labels, the use of Unweighted Average Recall (UAR) is recommended to better describe its performance.

$$UAR = \frac{(Se + Sp)}{(2)} \quad (6)$$

The model classification results for each species were processed in the R programming language version 4.0.3 ([29]) using the pROC package ([30]) to analyze the AUC. All plots were created with the ggplot2 package ([31]).

III. RESULTS

A. Models performance

Table I The validations on the RFM performance are summarized in the confusion matrix of the test data set. For each species the value of TP was higher than FP and FN was lower than TN . This allows us to interpret that the model classifier correctly predicts the presence of true positives and true negatives compared to false positives and false negatives.

TABLE I
CONFUSION MATRIX BY SPECIES FOR THE PERFORMANCE EVALUATION OF THE RFM FOR DETECTION OF BIRDS IN LAS ARRIERAS NATURE RESERVE.

Species	Confusion Matrix	Present	Absent
<i>Celeus loricatus</i>	Present	45 (TP)	1 (FN)
	Absent	1 (FP)	29 (TN)
<i>Ara ambiguus</i>	Present	31 (TP)	2 (FN)
	Absent	1 (FP)	30 (TN)
<i>Ceratopipra mentalis</i>	Present	336 (TP)	23 (FN)
	Absent	33 (FP)	1137 (TN)
<i>Poliocrania exsul</i>	Present	224 (TP)	18 (FN)
	Absent	4 (FP)	237 (TN)

The metrics resulting from the classification model are shown in Table II. For each species the accuracy was lower than the precision except for *C. mentalis*. For all species the classifier correctly identified more than 85% of the recordings.

The Npv score was higher in *C. mentalis* compared with the other species, meaning that the proportion of the noncases identified out of all negative test results was very high for this species. The lower score was *C. loricatus* in the model classification.

The Se score shows a high ability of each model to find positive cases. The lowest value for this metric was in *C. loricatus* model.

The high values of the Sp scores shows the high ability of the models to predict true negatives. The lowest value of this metric is also present in *C. loricatus* model.

The scores of the AUC was low on each model. This means that all classifiers were bads in distinguishing between positive and negative classes. Scores varied between 0.51 and 0.57.

TABLE II
VALIDATIONS, ACCURACY (AC), NEGATIVE PREDICTIVE VALUE (NPV), PRECISION (PR), SENSITIVITY (SE), SPECIFICITY (SP), AREA UNDER THE ROC CURVE (AUC) AND UNWEIGHTED AVERAGE RECALL (UAR) OF THE SPECIES AT LAS ARRIERAS NATURE RESERVE.

Species	Validations	Ac	Pr	Npv	Se	Sp	AUC	AUR
<i>Celeus loricatus</i>	252	0.97	0.98	0.97	0.98	0.97	0.55	0.97
<i>Ara ambiguus</i>	204	0.95	0.97	0.94	0.94	0.97	0.51	0.95
<i>Ceratopipra mentalis</i>	5039	0.96	0.91	0.98	0.94	0.97	0.57	0.95
<i>Poliochrana exsul</i>	1606	0.95	0.98	0.93	0.93	0.98	0.56	0.95

The majority of datasets have a class imbalance with a high number of soundfiles not containing any sounds of the species of interest.

In contrast, the UAR shows higher scores because it analyzes true positives and negatives compared to false positives and negatives, which allows correcting for class imbalance in the entire data set analyzed. The lower UAR score was shown in *C. loricatus* model.

The RFM execution time was approximately 42 hours for each species. Each model identified vocalizations for *C. loricatus* in the 6.7%, for *A. ambiguus* in the 5.8%, for *C. mentalis* in the 1.5% and for *P. exsul* in the 5% of total recordings analyzed in the established period of sampling.

B. Acoustic ecology

The classifications results for all models was used to describe the number of detections for each sampling site by species (Figure 2). The information from the detections allows us to study in detail the distribution and acoustic ecology of the avifauna of protected areas (public and private) such as Las Arrieras Nature Reserve.

C. loricatus was highly detected in all sites in both Arrieras and Monasa. The lowest number of detections occurred at the A05 sampling site. *A. ambiguus* was mainly detected at sites A01, A02 and A03 with a higher number of detections in M01.

For *C. mentalis* the main detection sites were A03 and A07, with a highly number of detections in M01. *P. exsul* was detected in significant numbers at all sites with a predominance at A01, A03 and M01. In particular, site A05 presented the lowest number of detections for each of the species analyzed.

Acoustic activity by hour is shown in Figure 3. All species shows an increasing acoustic activity from 5:00 to 7:00 a.m. and decreases towards the morning hours. *C. mentalis* presents a peak of detections around 14:00 hours. *C. loricatus* and *A. ambiguus* shows second peak of acoustic activity between 16:00 and 17:00 hours. *P. exsul* shows a sudden activity that decreases rapidly along the day.

The Figure 4 shows the variations in acoustic detection of each species by month. *C. loricatus* shows an important peak of activity between December 2020 to March 2021 and a second higher number of vocalizations in October 2021 similar to what we found in *P. exsul*. *A. ambiguus* have a high peak of vocalizations in March 2021. Finally, we found a significant number of acoustic detections in *C. mentalis* during the month of March 2021 with a low crest in October 2021.

IV. DISCUSSION

Acoustic community analysis is an emerging approach for characterizing bird biodiversity and as we continue to use these techniques, the precision in the detection of species in the space-time acoustic data will make more accurate and robust models, improving conservation efforts [37]. This study shows the utility of automated techniques for classifying large amounts of nature sound data to understand population trends in time, space, habitat use in soundscapes at sites of conservation importance.

In recent years, the need for experts to identify species in thousands of recordings from a specific study has been reduced. Experts can now spend their time validating automated classification analyses [36] and provide specific information on acoustic ecology and relationships at the population and community levels [37], [38].

All detection models presented high values of precision and accuracy. Metrics such as sensitivity and specificity prove the effectiveness of the models in automatically identifying the species of interest. Since some of the models were created with an imbalance in positive and negative classes, the UAR metric provides a better understanding of model performance. All models perform adequately on the task of detecting vocalizations for each species.

Similar studies regarding acoustic detections of bird vocalizations in tropical ecosystems also found accuracy values higher than 90% for methodologies based on Multiple Instance Learning. However, these values varied between 66% and 92% for techniques such as Convolutional Neural Networks (CNNs), Binary Neural Networks (BNNs) and Pattern Matching based on frequency [12], [13].

According to the AUC, all values for the models of each species was higher than 0.5 that suggests a reasonable discriminating ability to recognize the species [39]. It is recommended to obtain values greater than 0.7, however it depends on multiple variables such as the quality of the acoustic data, the level of noise in the environment, the power of the acoustic signal for each species in the recordings, among others.

In the results of detection of species by hour (Figure 4) we found a relationship with the "dawn chorus" theory, which explains that dawn choruses (increased singing activity) occur in a cyclical manner and therefore it is possible to identify a pattern for each ecosystem with respect to passerine and some non-passerine birds that vocalize at these sites [40]. This consistent increase in song usually begins for the earliest species around the first hours of daylight (6:00 to 7:00 hours),

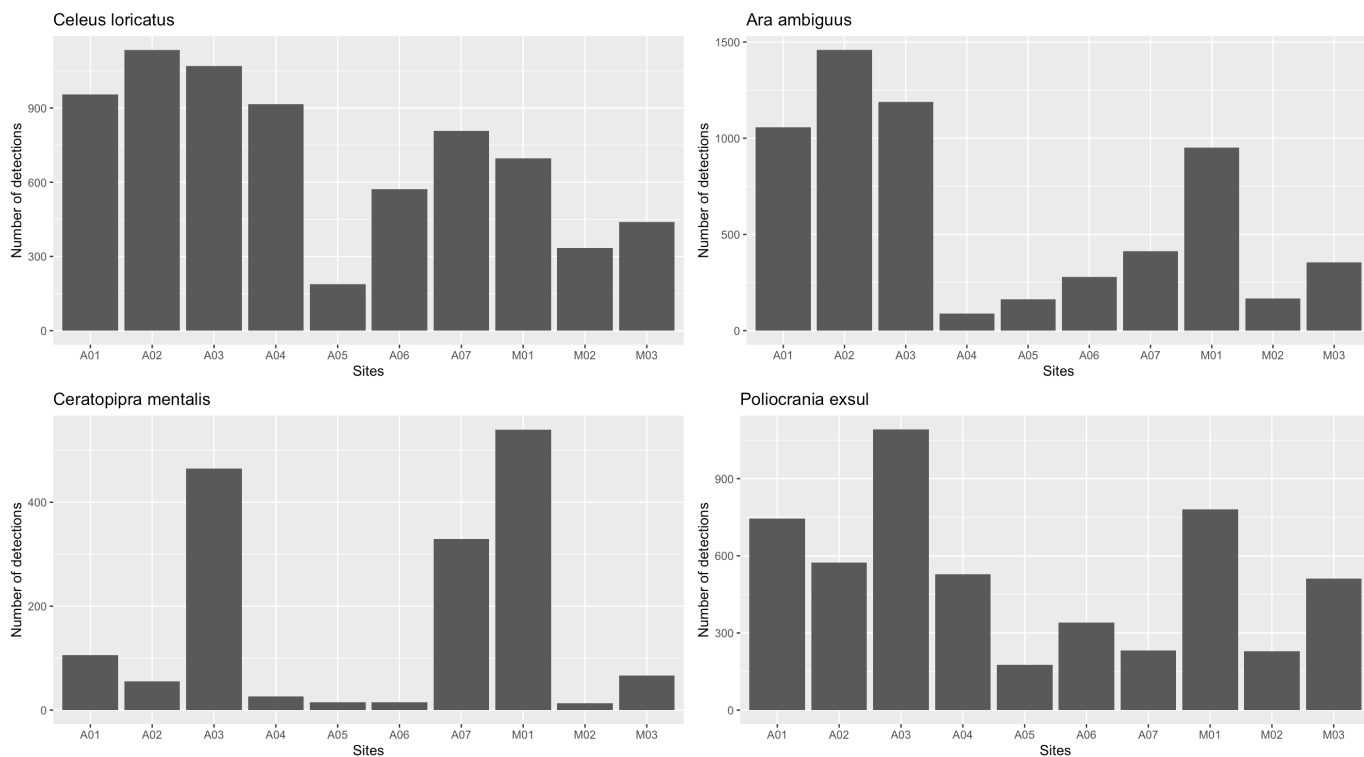


Fig. 2. Detections of species by site at Las Arrieras Nature Reserve. All graphs differ on the scale of the Y axis given the number of detections for each species.

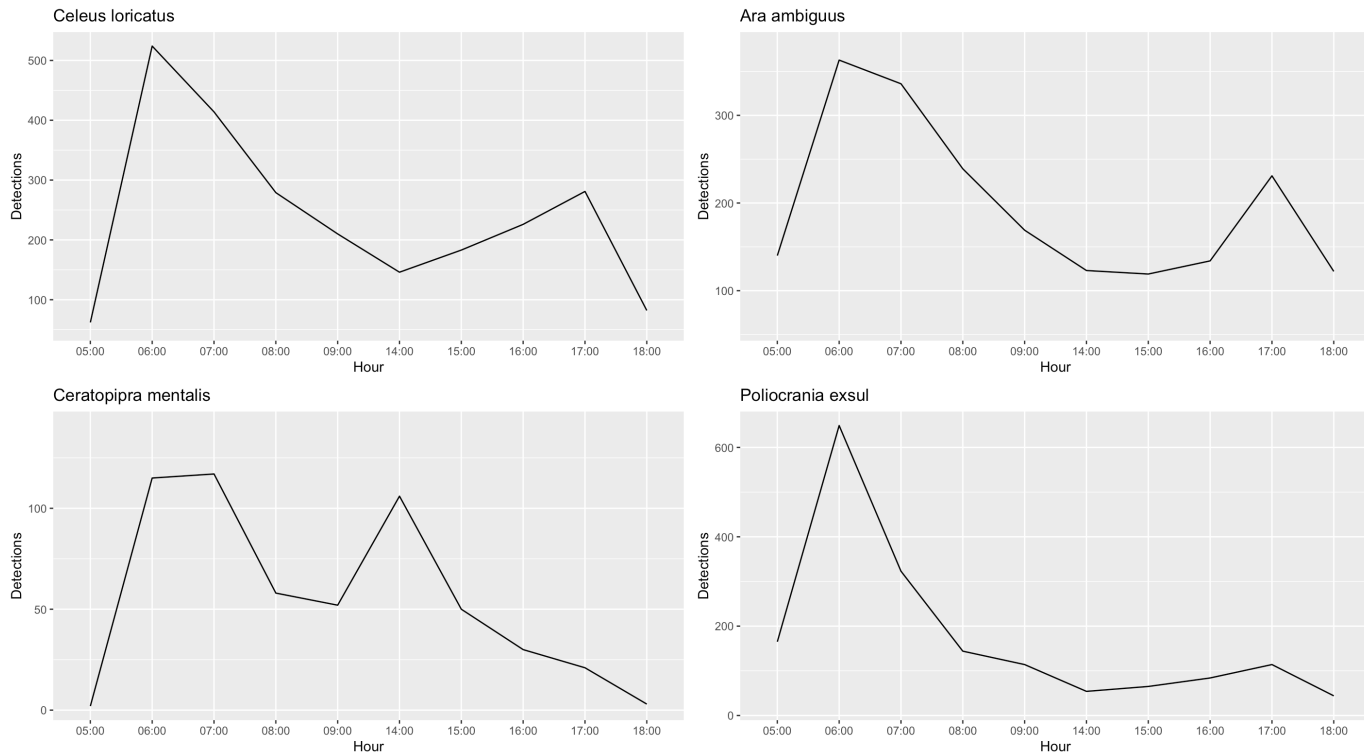


Fig. 3. Detections of species by hour at Las Arrieras Nature Reserve. All graphs differ on the scale of the Y axis given the number of detections for each species

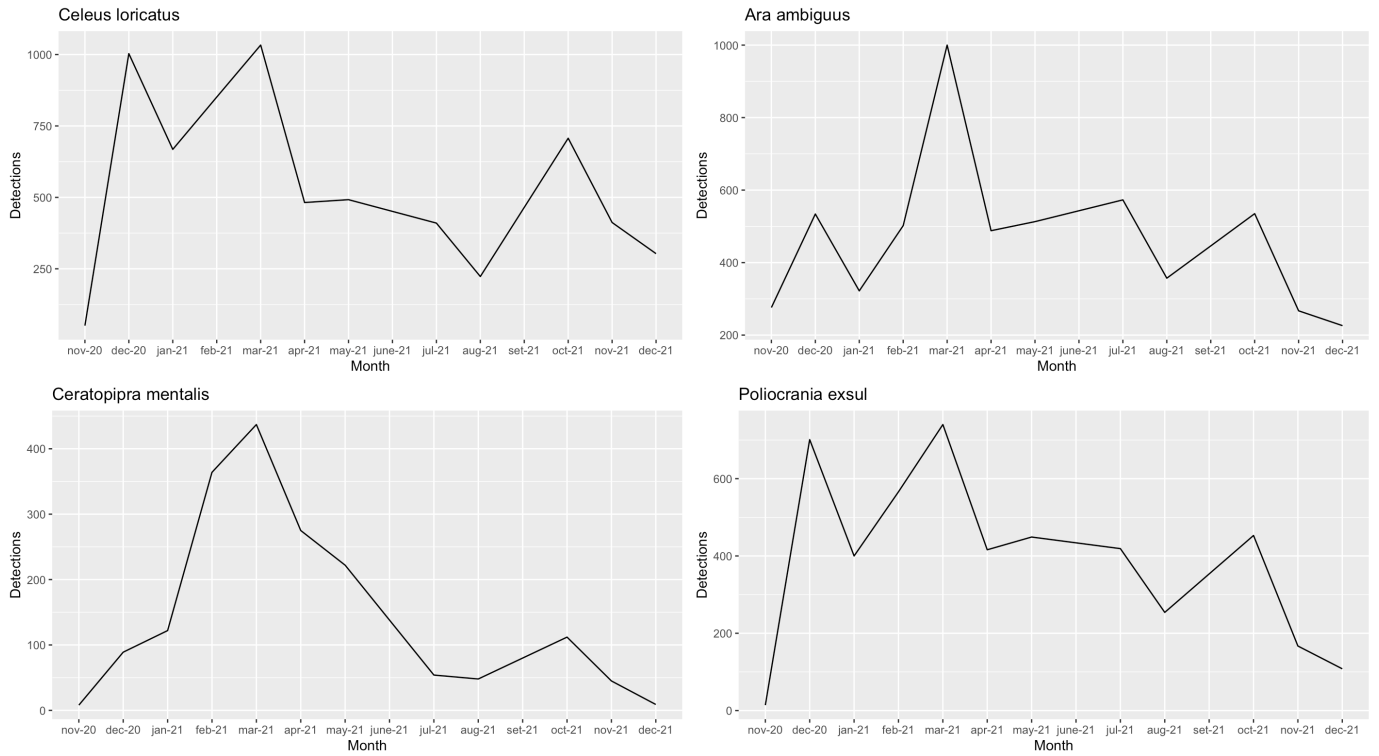


Fig. 4. Detections of species by month at Las Arrieras Nature Reserve. All graphs differ on the scale of the Y axis given the number of detections for each species.

and is continued quite systematically by other species until sometime around sunrise (17:00 to 18:00 hours) [41].

The beginning of the song in the dawn chorus is a specific aspect for each species [42]. During the dawn chorus many species overlap their songs, generating a chorus with specific characteristics that determine the structure of the soundscapes of the different bird communities [43]. Reflecting, probably no other daily cycle comprises so many levels of acoustic complexity between displays of groups of animals [40].

C. loricatus, *C. mentalis* and *P. exsul* belong to the acoustic community of the Arrieras Nature Reserve and form an important part of the structure of the dawn chorus in the ecosystems of the Cordillera Volcanica Central. *A. ambiguus* have particular conservation importance [44] and field observations suggest that the species uses some sites in the reserve as nurseries for juveniles to keep them together while the adults go to feeding areas far from the reserve to return in the afternoons in search of juveniles to take them to the resting sites.

This behavior allows for cohesion in these social groups and could increase the survival of juveniles by keeping them in areas away from predators and roosting sites as happens in other species of the Psittaciformes group [45]. This activity is easily detected by the vocalizations emitted by the adults when they arrive at these sites within the reserve.

Regarding detections by month, the pattern found corresponds to the periods of greatest vocalizations for each species. This is associated with the courtship and breeding period,

which for most birds in Costa Rica is between April and May, and even for some species may occur in more than one period depending on environmental conditions and resources in the ecosystem. [46].

V. CONCLUSIONS

The combination of PM and RFM models is valuable when implementing analyses on large datasets of soundscape recordings that allow automated acoustic detection to understand ecological and behavioral patterns of species such as potential breeding activity in the reserve.

Values for accuracy, precision, and other model metrics for acoustic detections were high and similar to acoustic detection of birds in other tropical studies, however it is important to use different detection methods to compare and improve data processing.

Acoustic monitoring is a tool that allows the determination of behavioral patterns on spatiotemporal scales with which it is possible to generate descriptions and provide recommendations for decision makers that benefit the conservation of Costa Rica's avifauna.

Future research will focus on comparing different approaches to classification and automated detection, selecting the best model for each species in comparison to the RFM used in the present work. Another objective will focus on studying soundscape patterns with acoustic indices and relating them to species detection for the benefit of better conservation decision making in the reserve.

We also consider important to use noise filtering methods since this variable could be affecting the detectability of some species and could be useful for automated detections in the future.

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