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Diel and Annual Patterns of Vocal Activity of Three Neotropical Wetland Birds Revealed via BirdNET

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Abstract: Compared with traditional field techniques, automated and noninvasive bird monitoring techniques, such as passive acoustic monitoring, offer significant advantages. However, the extensive data collected through passive acoustic monitoring can be challenging to analyze and may require the use of machine learning algorithms for efficient processing. BirdNET is a user-friendly and ready-to-use machine learning tool that can recognize more than 6500 wildlife species, including several tropical species. However, the performance of BirdNET in tropical ecosystems has rarely been assessed. Here, we evaluate the effectiveness of BirdNET for monitoring the vocal activity of three Neotropical wetland species from recordings collected over a year in the Brazilian Pantanal: Green Ibis (*Mesembrinibis cayennensis*), Limpkin (*Aramus guarauna*), and Sunbittern (*Eurypyga helias*). BirdNET was able to detect the presence of the three species in 82–92% of the recordings with known presence. Similarly, BirdNET's ability to correctly identify vocalizations was consistently greater than 77% (range 77–98%), confirming its effectiveness for monitoring these three tropical bird species. The peak vocal activity for the three species occurred during crepuscular periods, at the end of the rainy season, and during the receding season, a period when the risk of nest damage from flood pulses is low and food availability is high owing to the large presence of small water bodies. The use of machine learning algorithms such as BirdNET may improve bird monitoring in tropical areas but also facilitate research that improves our knowledge of birds' natural history, which remains unknown for many tropical species.

Keywords: convolutional neural network; Green Ibis; Limpkin; machine learning; Pantanal; Sunbittern

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1. Introduction

In recent decades, the rapid advancement of automated and noninvasive techniques has transformed the methods employed for species and habitat monitoring, and these techniques have swiftly become standard tools in ecology [1]. These cutting-edge approaches empower researchers to increase both the spatial and temporal dimensions of their investigations, facilitating the collection of substantial datasets. Nevertheless, the large datasets often generated through acoustic monitoring present challenges for human surveyors because of the time-consuming, laborious, and difficult manual processing of such data. To circumvent these challenges, machine learning algorithms have emerged as powerful solutions for efficiently processing large acoustic datasets [2–4].

Among the techniques for biomonitoring are passive acoustic monitoring, which has proven to be a useful tool for monitoring various vocally active groups, including anurans, mammals, insects, and birds [5,6]. One of the main disadvantages associated with passive acoustic monitoring surveys is that this technique may easily generate a vast number of recordings, which poses serious challenges or makes it impossible for the visual inspection of or manual listening to audio files (but see [7]). Audio recordings can be automated via machine learning algorithms, which have become essential for managing large volumes of acoustic data [4,8]. State-of-the-art machine learning models can provide highly accurate audio recognition [4,9]. However, the complexity of developing state-of-the-art machine learning models, such as convolutional neural networks [4], can deter their implementation by ecologists, managers, and the public owing to the significant level of informatics and engineering background needed [9]. Fortunately, a new generation of user-friendly and readily accessible machine learning approaches has recently emerged, potentially enhancing the efficacy of automated audio recognition and opening the door to applying automated sound recognition to managers and researchers with limited machine learning backgrounds (e.g., [10–14]).

Among these advances is BirdNET, which is a user-friendly and a ready-to-use machine learning tool that can provide multispecies-labeled output [15] (for a review of its applications, see [16]). BirdNET employs a deep neural network for the automated detection and classification of wildlife vocalizations [15], and the last updated version (v2.4) includes sound recognizers for more than 6500 wildlife species. BirdNET can be easily accessed through various user-friendly interfaces, including a mobile application (see applications of the BirdNET App in [17]) and a web-based platform (BirdNET-API; see [18]). Scientists usually run batch analyses via BirdNET on a GUI interface (e.g., Windows) or via Python through the BirdNET Analyzer [19,20], which is openly accessible on GitHub (https://github.com/kahst/BirdNET-Analyzer, 28 February 2025). The last version of BirdNET also allows users of Raven Pro, an audio software developed by the Cornell Lab of Ornithology [21], to run BirdNET from that software.

In BirdNET, audio recordings are divided into 3-s segments, and multispecies predictions of wildlife species can be made for each segment [15]. BirdNET predictions are accompanied by a quantitative confidence score that ranges from 0 to 1, which reflects the model’s confidence that a given prediction has been accurately recognized [22]. Users are allowed to select a threshold value, enabling the filtering of BirdNET outputs at a desired confidence score threshold. Setting a high confidence score threshold increases the proportion of true positives (correct identifications) in the output but at the cost of reducing the number of predictions reported. Our current knowledge on how setting a confidence score threshold impacts BirdNET performance is limited to a few species and biomes (see [15]; reviewed by [16]), but it is known that the selection of an optimal threshold greatly varies between species and study areas [14,19,23,24].

BirdNET is a promising tool, but its effectiveness for bird monitoring has yet to be extensively assessed (see [25]). For example, a recent review revealed that BirdNET studies (including gray literature) have thus far focused on species inhabiting North America or Europe [16], likely because the first version of the software only included only species from these regions [15]. However, the last update of BirdNET (v 2.4, June 2023) includes several species from the Southern Hemisphere, which offers new opportunities for expanding the use of BirdNET for monitoring tropical bird species. The effectiveness of BirdNET in correctly identifying a few tropical bird species has been recently assessed (see [26]), but its ability to detect the presence of tropical birds has never been assessed.

Here, we aimed to (i) assess the ability of BirdNET to detect the presence of the three target species in sound recordings, (ii) estimate the precision of BirdNET in correctly identifying bird vocalizations, and (iii) determine the optimal confidence score threshold of each species, which may be used as a reliable criterion for considering only BirdNET detections with a high probability of being correct. Additionally, we estimated the computing time needed for scanning a large acoustic dataset collected over a complete annual cycle at three different stations (24,681 15-min recordings analyzed) and the amount of human time needed for verifying the output. Finally, we employed BirdNET detection above the optimal confidence score threshold to (iv) describe diel and seasonal changes in the vocal activity of the three considered species over a year and, therefore, improve our knowledge of the life history of these little-studied species. Our goal was to stimulate further research using BirdNET or other automated audio processing software and to better understand diel and annual variations in the vocal activity of tropical birds, an aspect that has been rarely studied (but see [10,27–29]).

2. Materials and Methods

2.1. Study Species

In this study, we used the Green Ibis (*Mesembrinibis cayennensis*), the Limpkin (*Aramus guarauna*), and the Sunbittern (*Eurypyga helias*) as target species. We selected these species because they are (i) common birds in the Neotropics and well distributed in the Brazilian Pantanal (see next section), (ii) aquatic species and therefore adequate for assessing seasonal changes in vocal activity according to flood pulses [30,31], and (iii) included in the latest version (version 2.4) of BirdNET [15]. Moreover, as wetland species, they are good examples of species living in ecosystems that are logistically complex to monitor owing to the usually damp and boggy substrate and the typically dense yet fragile vegetation structure [11,32].

The Green Ibis (Family Threskiornithidae) typically inhabits, alone or in pairs, wetlands and swampy woods in Central and South America (see extended description in [33]). The species has been cataloged as a resident, although it has been proposed that the species might be able to move from forests in the wet season to open areas in the dry season [33]. Here, we aim to provide new insights into whether the species is present throughout the year in the Brazilian Pantanal and to improve our knowledge of the natural history of the Green Ibis, which are among the top priorities for further research on the species [33]. The vocalization of the species is described "as low rattles ending in a soft, bell-like whistle, or an undulating, throaty whistle" [34], such as "kro, kro, koro, koro" (Figure 1; [35]).

The Limpkin (Family Aramidae) is a resident species locally distributed in freshwater marshes and riparian habitats from southern Florida through to Central and South America [36]. Although females are mainly silent, males have extraordinary vocal habits, especially when several males countercall, which has been described as "one of the weirdest cacophonies of nature" [37]. Winkler et al. [36] proposed that males call the most when pair bonds and territorial activity are greatest and become quieter thereafter. Here, we aim to quantify and analyze its annual vocal activity and provide insights into the suspected partial migration of the species, which is among the top priorities for further research on the species [36]. We used the number of vocalizations detected per recording as a surrogate for the bird abundance around the recorders (i.e., the detected vocal activity rate, reviewed by [38]; see also [39] for migration studies using that metric). Monitoring the species in a seasonal habitat, such as the Brazilian Pantanal, may provide new insights into both drivers, namely the seasonality of vocal activity of the species and their suspected partial migration. Male vocalization is described as a loud call type, such as "kreow" (Figure 1; [36]).

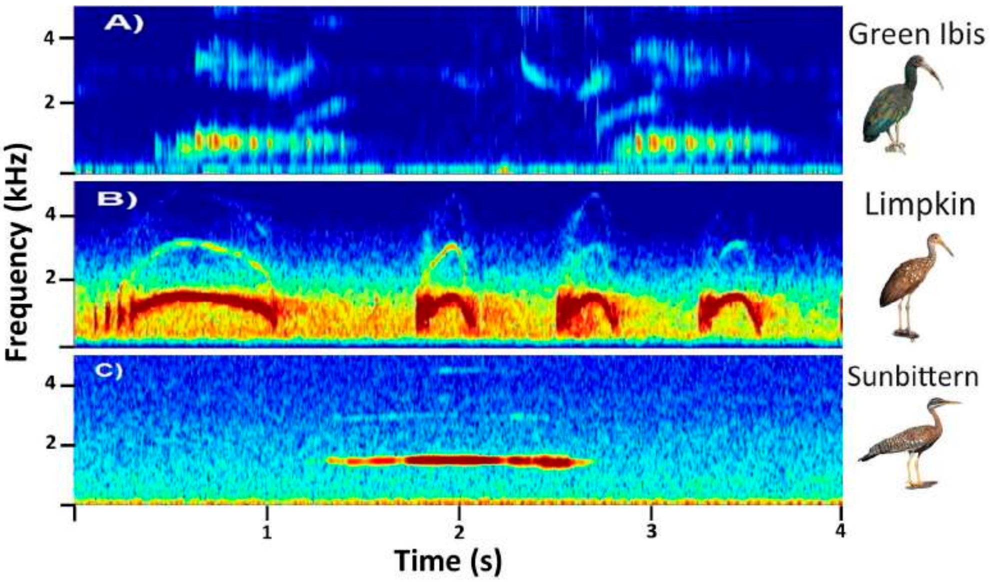

Figure 1. Typical vocalizations of the (**A**) Green Ibis (*Mesembrinibis cayennensis*), (**B**) Limpkin (*Aramus guarauna*), and (**C**) Sunbittern (*Eurypyga helias*) in the Brazilian Pantanal.

The Sunbittern (Family Eurypygidae) is a cryptic bird, except when it displays gold patterns in its wings and tail, and is endemic to the Neotropics. This species occupies forested streams, river sandbars, and forest pools from southern Mexico to southern Brazil [40]. Currently, most of the research on the life history (especially reproduction) of this species has involved captive birds [40]; therefore, there is a need to improve our knowledge about the natural history of this species in the wild [40]. Thomas and Strahl [41] reported that sunbitterns vocalize a clear descending whistled “eeeeeeeeuree” during nest defense interactions (Figure 1). Although the species can utter other vocalization types, the vocalizations predicted (and verified) by BirdNET refer to that descending whistle (Figure 1). Thus, we aimed to assess seasonal changes in vocal activity to provide new insights into the breeding phenology of the species in the Brazilian Pantanal. Likewise, the assessment of new monitoring methods, such as passive acoustic monitoring, might be useful for further research monitoring programs of this species, which is among the top priorities of research on this species [40].

2.2. Study Area

We conducted a field study in the northeastern Brazilian Pantanal (Pantanal Matogrossense), the largest seasonal floodplain in the world. The study area is located near the SESC (Serviço Social do Cómercio) Pantanal Resort (Mato Grosso, Brazil; 16°30′ S, 56°25′ W), which is within the floodplain of the Cuiabá River (Appendix A). This area is seasonally inundated from October–April due to flooding of the Paraguay River within the Pantanal, whereas during May–September, it experiences a pronounced dry season [42]. The vegetation is a mosaic of forest formations and savannas. A more detailed description of the vegetation community and the effects of pulses on the local avian community can be found in [30]. The regional climate is tropical and humid. During the monitored period (June 2015–May 2016; see the Acoustic Monitoring section), according to a weather station located at station A, the rainfall was 1131 mm, and the rainfall regime followed the typical seasonal pattern of the Brazilian Pantanal, with 1025 mm (90.6% of the total) accumulated during the wet season (October–April). The mean temperature during the monitored year was 25.5 °C.

2.3. Acoustic Monitoring

The study was carried out at three acoustic monitoring stations separated by minimum distances of 1600 and 5870 m (Appendix A). The stations were selected to cover the most representative vegetation formations of the Brazilian Pantanal (forest and savannas). Having a large distance between recorders reduces the risk of detecting the same individuals by two different stations. At each acoustic monitoring station, we deployed one Song Meter SM2 recorder (Wildlife Acoustics, Maynard, MA, USA; www.wildlifeacoustics.com, 28 February 2025) that operated daily from 8 June 2015 to 31 May 2016. The recorders were programmed to record (stereo in .wav format) the first 15 min of each hour during the entire study period, with a sampling rate of 48 kHz and 16 bits per sample. Nonetheless, in that study, we scanned only those recordings made during the daytime (see next section). Recorders were checked approximately every two weeks to download the data and to change the batteries. A total of 24,681 15 min recordings (6170 h) were collected (8404 at Station A, 7811 at Station B, and 8466 at Station C). At two out of the three stations, the recorders operated under optimal conditions. However, at station B, there was a malfunction, resulting in the absence of any recordings between 28 January and 15 February 2016.

2.4. Acoustic Data Analyses

The three target species are diurnal; therefore, to expedite the scanning process, we analyzed only those recordings collected during the diurnal period. Daytime was defined as the period between the morning and evening nautical twilight ([43]; see definition of the nocturnal period for the study area in [27]), as extracted from www.timeanddate.com, 28 February 2025. To standardize the number of hours of recordings analyzed per day and to control for seasonal variations in the night length, we used recordings made between 5 a.m. and 7:15 p.m. (UTC-4), which covered the whole year between the morning and evening nautical twilight times (a similar approach was used in [27]).

The selected recordings were analyzed via the “Multiple files” tab in the GUI interface of BirdNET (version 2.4, [15]; https://github.com/kahst/BirdNET-Analyzer, 28 February 2025). BirdNET was run with the following (default) parameters: (i) a confidence score threshold of 0.1, (ii) a sensitivity parameter of 1.0, and (iii) no overlap of prediction segments (0). We used the “Custom species list” option and configured BirdNET to report detections exclusively for the Green Ibis, the Limpkin, and the Sunbittern, thus avoiding the detection of nontarget species (see a similar approach in [11,14]). BirdNET was configured to process one 15 min recording at a time using four CPU threads. The total scanning time was 85 h (c. 2.2% of the total daytime recording time). Notably, we used an Intel(R) Core(TM) i7 (8th Gen, CPU 1.80 GHz, 1.99 GH, 8 GB RAM) with the acoustic recordings stored and analyzed from an external hard drive with USB 3.0. The workflow of BirdNET, including screenshots, is shown in Appendix B.

2.5. Assessment of BirdNET Performance

To evaluate the performance of BirdNET in monitoring tropical birds, we assessed (1) its ability to detect the presence of the species via sound recordings, which may be sufficient for several monitoring programs and research purposes (i.e., occupancy analyses) and (ii) the precision of BirdNET in correctly identifying the vocalizations of the three bird species considered. The percentages of presence detected were estimated by using a test dataset of 200 15-min recordings manually reviewed by a human. The test dataset consisted of 100 15-min recordings equally distributed among the three stations and randomly selected from among those recorded during March–June between 5 a.m. and 8 a.m. (selected for being the recordings with the highest probability of detecting the species; see Results section) and 100 15-min recordings randomly selected from among the whole diurnal acoustic dataset. For each of the 200 15-min recordings, a human annotated whether the Green Ibis, the Limpkin, or the Sunbittern was detected by visual inspection, and, when needed, spectrograms were recorded in Raven Pro 1.6 [21]. Recordings were reviewed blindly without knowledge of the acoustic monitoring station, date, or time of recording. The recordings of the test dataset were also analyzed via BirdNET-Analyzer, and all the recordings with predictions by BirdNET were verified by an expert observer by listening to or by inspecting the spectrogram in Raven Pro 1.6 [21]. The observer confirmed whether the species was present or absent at the timestamp of the 3-s segment predicted by BirdNET. If the species was absent in the first BirdNET prediction, subsequent predictions were reviewed until the presence of the species was confirmed or until the last prediction was checked. If the species was not confirmed or there were no BirdNET predictions, the species was marked as nondetected by BirdNET in the recording file. We estimated BirdNET's ability to detect a species' presence by dividing the number of species presences confirmed via BirdNET by the total number of recordings with known presence (human annotated) in the test dataset.

We also estimated the precision of BirdNET, defined as the proportion of BirdNET predictions correctly classified divided by the total number of BirdNET predictions verified [44]. To estimate the precision, we randomly selected 1000 BirdNET predictions for each species from among the whole BirdNET output by using the "Segments" function in BirdNET-Analyzer. For each prediction, an experienced observer listened to and visually inspected the audio spectrogram at the timestamp of the 3 s segment reported by BirdNET in Raven Pro 1.6 [21] and verified whether the target species was well predicted. The whole output verification process was carried out within 26 h (c. 0.4% of the total recording time).

2.6. Statistical Analyses

The verified predictions described above were used to estimate the confidence score threshold with a 95% probability of correct identification for each species. We followed the approach outlined in [13,14], so we back-transformed BirdNET's confidence scores into its original logit scale via the following equation:

$$\text{Logit score} = \ln(\text{confidence score}/(1 - \text{confidence score}))$$

Next, for each of the three species, we fitted a logistic regression using the correct or incorrect classification of the verified predictions as a response variable and the BirdNET logit-scale prediction score as the independent variable. The logistic regressions provide an equation that enables us to convert BirdNET scores into the probability of a given prediction being correct. For each species, the equations considering a probability of correct identification of 95% were as follows:

$$\text{Threshold} = (\ln\,(\mathrm{p}/(1 - \mathrm{p})) - \alpha)/\beta,$$

where p is the BirdNET score threshold corresponding to that probability (0.95 in our case), α is the intercept of the logistic regression, and β is the slope of the regression.

The identified optimal threshold was used to consider only BirdNET predictions with a high probability of correct identification when describing the diel and seasonal patterns of vocal activity of the three monitored species (see the same approach for bird vocal behavior descriptions in [14,26]). The patterns of vocal activity were described by pooling the data from the three acoustic monitoring stations and were expressed as a percentage of the total vocalizations detected per hour or month.

3. Results

3.1. BirdNET Performance

The presence of the Green Ibis, Limpkin, and Sunbittern was detected by a human in 34, 31, and 26 recordings within the 200 15-min recordings of the test dataset (Table 1). With the aforementioned BirdNET settings, BirdNET was able to detect the presence of the three species in more than 80% of the recordings with a confirmed presence (Table 1). Green Ibis was detected by BirdNET in 28 of the 34 recordings with a confirmed presence (82.3%), although there were 3 recordings with a BirdNET-predicted presence that were not confirmed after verification of the spectrograms (i.e., they were mislabeled recordings). Similar values were achieved for the Limpkin, with 26 of the 31 confirmed presences being detected by BirdNET (83.9%) and 5 mislabeled recordings. For Sunbittern, BirdNET correctly detected the species in 24 of the 26 recordings (92.3% of the recordings with a known presence) and with no mislabeled recordings (Table 1).

Table 1. Confusion matrix of the ability of BirdNET to correctly detect the presence of the Green Ibis, Limpkin, and Sunbittern in sound recordings. The test dataset was composed of 200 15-min recordings that were manually reviewed for each species.

		Green Ibis		**Limpkin**		**Sunbittern**	
		BirdNET		**BirdNET**		**BirdNET**	
		Detected	**Not Detected**	**Detected**	**Not Detected**	**Detected**	**Not Detected**
Human	Presence	28	6	26	5	24	2
	Absence	3	163	5	164	0	174

The BirdNET precision was high for the three species considered. The lowest precision was achieved for the Limpkin, for which 776 of the 1000 verified BirdNET predictions were correctly classified (77.6%), and the highest confidence score for a mislabeled prediction was 0.398 (all predictions with a confidence score higher than this value were correctly classified). The precision for the Green Ibis was 83.1 (831 of the 1000 BirdNET predictions verified to be correctly classified), with the highest confidence score for a mislabeled prediction of 0.663. Finally, BirdNET had a precision of 97.9% in correctly classifying vocalizations of the Sunbittern (979 of the 1000 BirdNET predictions verified to be correctly classified), and the highest confidence score for a mislabeled prediction was 0.373.

3.2. Vocal Activity

The equations considering a 95% probability of correct identification for the Green Ibis and the Limpkin were as follows:

$$\text{Threshold (Green Ibis)} = (\ln (0.95/(0.05)) + 1.333)/13.790;\ p < 0.001$$

$$\text{Threshold (Limpkin)} = (\ln (0.95/(0.05)) + 0.355)/7.494;\ p < 0.001$$

Therefore, the confidence score threshold for considering only detections with a 95% probability of correct identification was 0.440 for the Green Ibis and 0.310 for the Limpkin (Figure 2). Owing to the high precision of BirdNET for correctly detecting the Sunbittern (97.9%), we used the default confidence score of BirdNET (0.1) to describe the vocal activity of the Sunbittern.

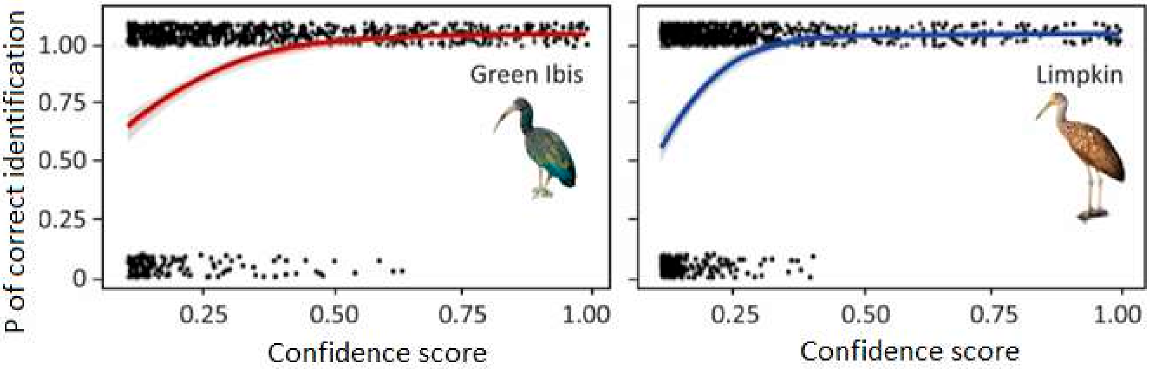

Figure 2. Results of the logistic regression showing the relationship between the probability of a BirdNET prediction being correctly classified and the confidence score of a given prediction for the (**left**) Green Ibis (*Mesembrinibis cayennensis*) and the (**right**) Limpkin (*Aramus guarauna).* Statistical analyses were performed using the BirdNET logit-scale of the prediction score (see methods) as an independent variable, but we represent the original confidence score of BirdNET for graphical purposes. The Sunbittern (*Eurypyga helias*) is not included in the graph since the precision of BirdNET, which uses the default confidence score threshold (0.1), was 97.9%.

3.2.1. Diel Pattern

The diel pattern of vocal activity varied among the three species (Figure 3; for detailed tables of the hourly vocal activity of each species per station, see Appendices C–E). The Green Ibis and the Limpkin showed a bimodal pattern of vocal activity, with peaks of vocal activity around sunrise and sunset and very low vocal activity during the central hours of the day (Figure 3). The Green Ibis showed a much greater vocal activity around sunset (64.1% of the vocalizations detected three hours before sunset versus 24% of the vocalizations detected three hours after sunrise; Figure 3 and Appendix C). However, the vocal activity of the Limpkin was similar around sunrise and sunset (40.6% and 39.2% of the vocalizations detected in the three hours before sunrise and sunset, respectively; Figure 3 and Appendix D). The diel pattern of the Sunbittern differed greatly from those of the other two species. The Sunbittern had peak vocal activity around sunrise (46.5% of the vocalizations detected during the four hours after sunrise); then, it was relatively constant during the day but showed very reduced vocal activity around sunset (Figure 3 and Appendix E).

3.2.2. Seasonal Pattern

The Green Ibis showed a seasonal pattern of vocal activity that differed from that of the other two species (Figure 4). The Green Ibis had peak vocal activity in June (35.7% of the total vocalizations) and secondary, and much smaller, peak vocal activity in January and February (24.5% of the total vocalizations; Appendix F). The Limpkin and the Sunbittern showed similar patterns, with peak vocal activity occurring between March and May during the beginning of the dry season and a second peak of Limpkin vocalizations in October (Figure 4 and Appendices G and H). The percentages of vocalizations detected between March and May, relative to the total vocalizations, were 58.9% and 55.6% for the Limpkin and the Sunbittern, respectively. The three species were detected monthly throughout the year, although very few vocalizations were detected between August and September (range for the three species = 2.3–3.7% of the total vocalizations detected throughout the year; Figure 4). Detailed tables of the monthly vocal activity of each species per station can be found in Appendices F–H.

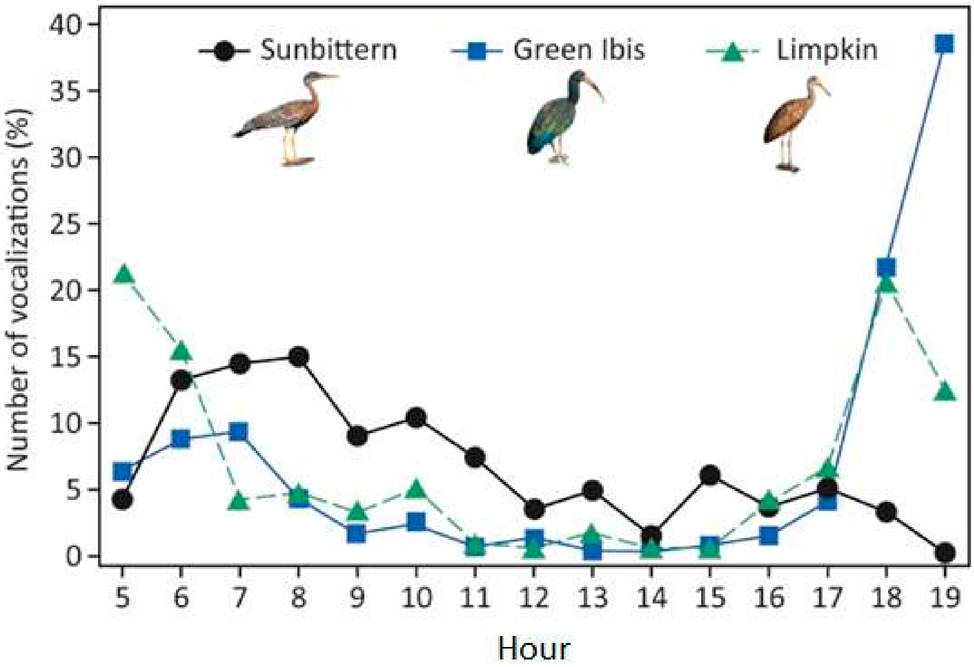

Figure 3. Diel pattern of vocal activity of the Green Ibis (*Mesembrinibis cayennensis*), Limpkin (*Aramus guarauna*), and Sunbittern (*Eurypyga helias*) in Pantanal Matogrossense (Brazil). The diel patterns of vocal activity are expressed as the percentage of calls with respect to the total number of calls detected per hour and station. Hours are expressed in winter local time (UTC-4). Vocal activity was monitored via autonomous recording units from 8 June 2015 to 31 May 2016 at three acoustic monitoring stations. The total number and mean percentage of calls detected per hour at each station and species can be found in Appendices C–E .

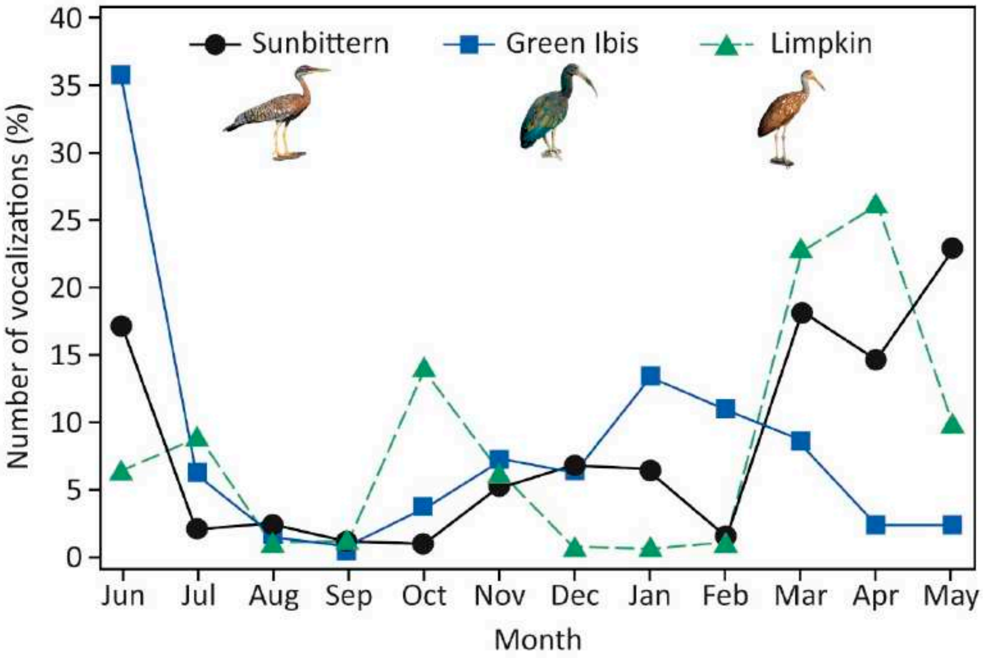

Figure 4. Annual pattern of vocal activity of the Green Ibis (*Mesembrinibis cayennensis*), Limpkin (*Aramus guarauna*), and Sunbittern (*Eurypyga helias*) in Pantanal Matogrossense (Brazil). The annual patterns of vocal activity are expressed as the mean percentage of calls relative to the total number of calls detected per month and station. Vocal activity was monitored via autonomous recording units from 8 June 2015 to 31 May 2016 at three acoustic monitoring stations. The total number and mean percentage of calls detected per month at each station and species can be found in Appendices F–H.

4. Discussion

In this study, we validated the use of BirdNET with default values for detecting the presence of the three target species in sound recordings, with more than 80% of the recordings with known presences being also annotated by BirdNET for all three species; these values are like those proposed for other bird temperate species (e.g., [14]). Although we were unable to provide a robust assessment regarding the ability of BirdNET to detect vocalizations by the target species, our experience from reviewing the test dataset allow us to share some insights as to when BirdNET more frequently failed to detect the presence of the species. Most of the false negatives (recordings of known presences but not those detected by BirdNET) were recordings with few vocalizations by the target species or with individuals vocalizing far from the recorded vocalizations (according to the sound level of the recorded vocalizations). Both factors may reduce the ability of BirdNET to detect and correctly identify bird vocalizations (see [18,24]). Overall, BirdNET showed high precision, with a limited number of mislabeled recordings (i.e., false positives; Table 1). We are aware that the extended recording length (15 min) used in the study may have biased the percentage of presences detected using our technique. The percentage of presences detected would have been lower if the recording length had been shortened owing to the larger probability of detecting at least a single vocalization in longer recordings. In addition, our findings revealed, for the first time, that BirdNET has a compelling ability to detect the presence of tropical bird species in single recordings, making it suitable for describing bird communities and for performing occupancy modeling studies when detection is usually only needed at hourly or daily scales [19] or to describe seasonal patterns of vocal activity. Here, as a preliminary assessment, we evaluated the ability of BirdNET to detect a species' presence and to obtain new ecological insights regarding the target species (see also [26]). The approach we followed was appropriate for reaching our goals with the three species considered, but further research may require the use of different approaches to assess the performance of BirdNET under different circumstances. These approaches may require assessing the recall rate, defined as the percentage of vocalizations automatically detected by BirdNET. Such validations may expand the use of BirdNET beyond simple presence/absence monitoring.

In this study, we demonstrated the ability of BirdNET to correctly identify the vocalizations of three Neotropical bird species from soundscape recordings (collected with omnidirectional microphones; precision > 77% for all species). Surprisingly, the mean precision reported in our study (86.2%) surpassed the overall precision reported for 984 European and North American bird species via focal (i.e., species-specific) recordings (mean precision of 79.0% [15]). It is possible that the distinctive, relatively simple, and relatively unvaried vocalizations of the selected species may partly contribute to the high ability of BirdNET to correctly identify such vocalizations. Nonetheless, it is worth highlighting that the precision values reported here are very similar to those reported for BirdNET in a prior study with other three tropical passerine birds [26]. We found slight variations among species, with precisions ranging from 77.6% for the Limpkin to 97.9% for the Sunbittern. These findings are consistent with those previous studies that stated that BirdNET's precision may vary significantly among species and even within species between studies. For example, the BirdNET precision for correctly identifying the Common Raven (Corvus corax) ranged from 0.29 [19] to 0.66 [45] and 0.94 [46].

In this study, we corroborated the ability of BirdNET to scan large acoustic datasets and to provide valuable insights into ecological processes. To achieve this, we had to estimate the optimal confidence score threshold for each of the three monitored species (following [13]; see a similar approach for birds in [14,22]). This approach allowed us to consider only predictions with a high probability (95%) of being correct to describe the diel and annual patterns of vocal behavior for the three target species. Nonetheless, the use of high confidence score thresholds decreases the percentage of presences and vocalizations detected; therefore, future studies should further examine the impact of using variable confidence score thresholds to detect bird vocalizations (see case studies for two and three bird species in [14,26]).

The Green Ibis and the Limpkin exhibited concentrated vocal activity during the crepuscular periods, with limited output during the day, whereas the Sunbittern showed pronounced vocal activity around sunrise, which remained relatively constant during the day and decreased toward sunset. The number of vocalizations detected would likely be greater if we had extended the study into the night, since the crepuscular patterns found for most species suggest that some of them may also vocalize at night, as has already been found for other nonpasserine diurnal species in the study area (see [27]). The described patterns of vocal activity align with anecdotal descriptions in field guidebooks. For example, Hilty [35] annotated the Green Ibis as being mostly silent while foraging during the day but as exhibiting loud vocalizations at sunset when the birds fly into or leave the roost, potentially explaining the crepuscular vocal behavior found in our study. Similarly, Ingalls [47] described the Limpkin as calling more often in the early morning and evening, with vocal activity reduced at midday. Finally, the diel pattern found for the Sunbittern also corroborates prior descriptions, such as that by Stiles and Skutch [48], who reported that this species is most frequently heard in the morning. Further research should explore the function of vocalizations for the studied species and investigate the relationship between daily vocal activity and climate conditions, an aspect that remains relatively understudied for tropical birds (but see, e.g., [27,49,50]).

In addition to seasonal changes in vocal activity, the three species were detected monthly in the study area, which suggests that they might be residents of the Brazilian Pantanal. Nonetheless, further research using more appropriate methods (e.g., GPS devices) to study the seasonal movements of the species in the study area could improve our knowledge regarding their migratory behavior. Our study also sheds light on the breeding schedules of the three monitored species in the Brazilian Pantanal, providing valuable insights into their natural history, which is very limited (but see [33,36]). Previous research has suggested that limpkins vocalize primarily during pair bonding and territorial defense [36], whereas sunbitterns vocalize more frequently during nest defense interactions [41]; therefore, seasonal changes in their vocal activity may provide insight into their breeding periods. The breeding seasons for the Limpkin and the Sunbittern in the Brazilian Pantanal were similar and, according to the seasonal changes in vocal activity, seemed to occur between March and June, a period that corresponds to the receding season (April–June), when the water level starts to decline [51]. Seasonal changes in the vocal activity of the Green Ibis, which exhibited two periods of vocal activity (January–February, during the flooded period, and July, toward the end of the receding season), suggest that the species may have reproduced twice in the study area, since peaks of vocal activity are commonly associated with breeding attempts (i.e., mate attraction and territory defense) in birds. Nonetheless, we lack observational data to confirm whether the Green Ibis is indeed a double-brooded species, and further field studies are necessary to verify our assumption. The hypothesized breeding periods align with records from the study area, such as the two records of copulations of sunbitterns in the Pantanal wetland, which occurred during the dry season (May–August [52]), and in nearby regions, such as the breeding period hypothesized for the Green Ibis in Colombia and Panama (February–April [53]).

The annual patterns of vocal activity observed in our study differed significantly from those described in the Brazilian Pantanal for various insectivorous (e.g., [10,27,31]) and frugivorous bird species (e.g., [10,31]). The vocal activity of insectivorous and frugivorous species peaked at the beginning of the rainy season (September–October), coinciding with a period of abundant insects and fruits in the Brazilian Pantanal [54,55], which was driven by the onset of rainfall (which occurred in September of the studied year; Figure 2). Our findings suggest that aquatic birds in seasonally flooded ecosystems, such as the Brazilian Pantanal, may exhibit a delayed breeding phenology to mitigate the risk of nest damage caused by flood pulses during the rainy period, as has been observed for the Sunbittern [56]. Hancock et al. [53] proposed that the Green Ibis breeding season typically begins a few months after the onset of the rainy season. Breeding during the receding season, when there are still significant water bodies but at reduced levels, may enhance the foraging success of aquatic species and provide abundant food for chicks, as well as accessible mud for nest construction [41].

5. Conclusions

We demonstrated the effectiveness of BirdNET in accurately detecting and identifying three Neotropical bird species and in monitoring their vocal behavior. Further research should evaluate BirdNETs' performance in correctly identifying a broader range of tropical species, including those with more diverse vocalizations and restricted distributions (i.e., with fewer recordings available in public sound libraries), as these circumstances may decrease the precision of BirdNET. We hope that our assessment will encourage researchers and managers to utilize this readily available tool (available on GitHub or through the learning detector of Raven Pro), which has the potential to generate valuable scientific data, improve bird conservation, and increase public awareness of bird ecology and conservation, including the study of wetland species, which are challenging habitats for bird monitoring.

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Data Availability Statement: The raw databases employed for describing the birds' vocal behavior are published as Appendices A–H. The number of vocalizations detected per hour and month at each acoustic monitoring station for each of the three species can be found in the Appendices A–H.

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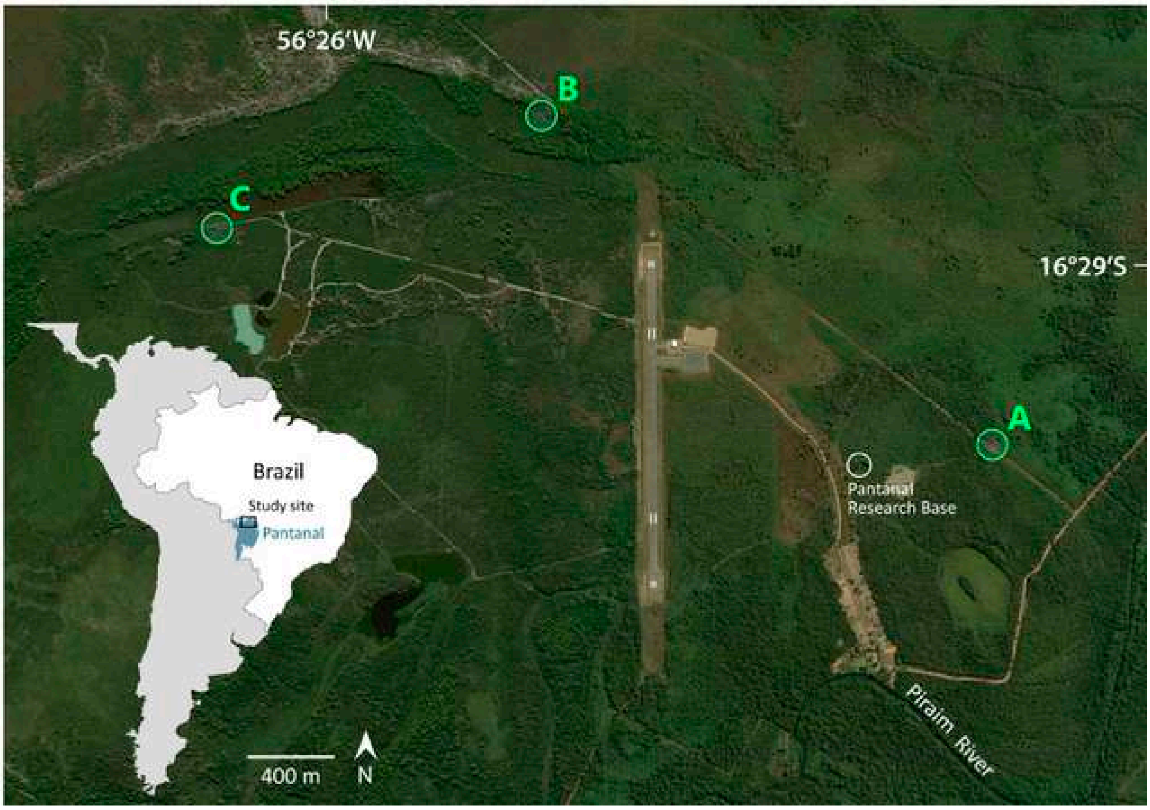
Conflicts of Interest: The authors declare that they have no conflicts of interest.

Appendix A

Locations of the three acoustic monitoring stations in Pantanal Matogrossense (Poconé municipality, Mato Grosso, Brazil). The inset shows the location of the study area (black square) in Brazil.



Appendix B

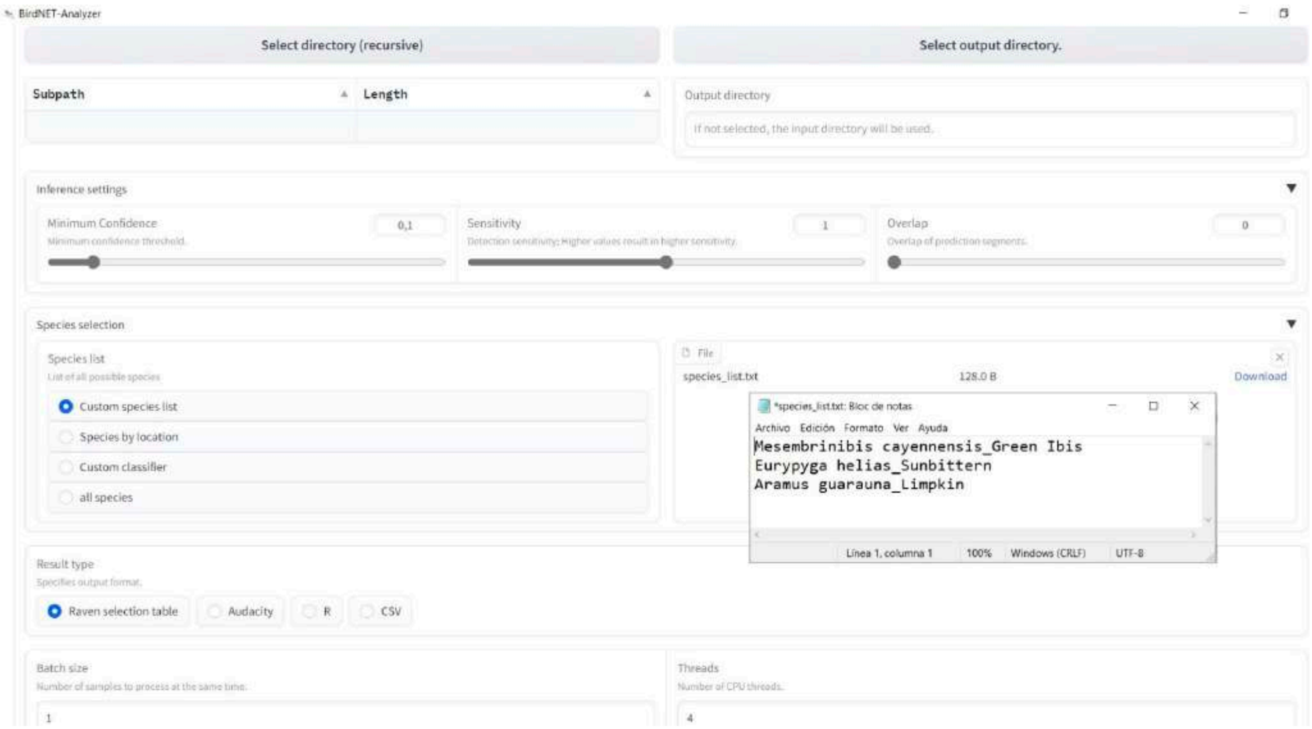
The following page presents the settings introduced in BirdNET. The first two boxes shows the paths to the folders where the audio recordings were stored (Select directory) and where the output was saved (Select output directory).

We used default values for the parameters' minimum confidence, sensitivity, and overlap, which were introduced as follows:

Minimum Confidence: 0.1; Sensitivity: 1; Overlap: 0

In the "Species selection" tab, we applied the "Custom species list" filter, for which we uploaded a text file with the names of the three target species (see caption within the image).

The BirdNET output was saved as a "Raven selection table" and configured to process one sample at a time and to use four CPU threads (default values).



Output directory: If not selected, the input directory will be used.

Minimum Confidence (Minimum confidence threshold.): 0,1

Sensitivity (Detection sensitivity; Higher values result in higher sensitivity.): 1

Overlap (Overlap of prediction segments.): 0

Species list (List of all possible species):
● Custom species list
○ Species by location
○ Custom classifier
○ all species

species_list.txt 128.0 B

*species_list.txt: Bloc de notas

```
Mesembrinibis cayennensis_Green Ibis
Eurypyga helias_Sunbittern
Aramus guarauna_Limpkin
```

Result type (Specifies output format.): ● Raven selection table ○ Audacity ○ R ○ CSV

Batch size (Number of samples to process at the same time.): 1

Threads (Number of CPU threads.): 4

Appendix C

Number of Green Ibis vocalizations detected per hour at three monitoring stations in Pantanal Matogrossense (Brazil). The total number and percentage of vocalizations detected per hour with respect to the total number of vocalizations are also shown. Vocal activity was monitored by acoustic monitoring from 8 June 2015 to 31 May 2016 at three acoustic recording stations.

Hour	Station A	Station B	Station C	Total	%
5	289	18	9	316	6.23
6	333	79	24	436	8.59
7	401	46	18	465	9.17
8	154	28	25	207	4.08
9	40	26	6	72	1.42
10	19	85	18	122	2.40
11	23	0	0	23	0.45
12	44	3	5	52	1.03
13	4	0	2	6	0.12
14	13	0	3	16	0.32
15	7	26	3	36	0.71
16	32	25	13	70	1.38
17	147	16	49	212	4.18
18	653	166	273	1092	21.53
19	8	535	1405	1948	38.40
TOTAL	2167	1053	1853	5073	

Appendix D

Number of Limpkin vocalizations detected per hour at three monitoring stations in Pantanal Matogrossense (Brazil). The total number and percentage of vocalizations detected per hour with respect to the total number of vocalizations are also shown. Vocal activity was monitored by acoustic monitoring from 8 June 2015 to 31 May 2016 at three acoustic recording stations.

Hour	Station A	Station B	Station C	Total	%
5	91	383	423	897	21.08
6	152	94	411	657	15.44
7	53	22	99	174	4.09
8	16	74	103	193	4.54
9	8	1	122	131	3.08
10	130	16	66	212	4.98
11	18	4	8	30	0.71
12	7	2	9	18	0.42
13	50	6	10	66	1.55
14	7	0	7	14	0.33
15	2	3	11	16	0.38
16	46	105	30	181	4.25
17	127	15	132	274	6.44
18	120	232	516	868	20.40
19	2	192	330	524	12.31
TOTAL	829	1149	2277	4255	

Appendix E

Number of Sunbittern vocalizations detected per hour at three monitoring stations in Pantanal Matogrossense (Brazil). The total number and percentage of vocalizations detected per hour with respect to the total number of vocalizations are also shown. Vocal activity was monitored by acoustic monitoring from 8 June 2015 to 31 May 2016 at three acoustic recording stations.

Hour	Station A	Station B	Station C	Total	%
5	263	3	4	270	4.18
6	839	1	3	843	13.05
7	919	1	3	923	14.29
8	959	1	0	960	14.86
9	570	2	6	578	8.95
10	657	2	4	663	10.26
11	468	1	1	470	7.28
12	217	0	1	218	3.38
13	303	2	1	306	4.74
14	87	1	0	88	1.36
15	383	0	1	384	5.95
16	233	0	0	233	3.61
17	319	1	2	322	4.99
18	176	20	4	200	3.10
19	1	0	0	1	0.02
TOTAL	6394	35	30	6459	

Appendix F

Number of Green Ibis vocalizations detected per month at three monitoring stations in Pantanal Matogrossense (Brazil). The total number and percentage of vocalizations detected per month with respect to the total number of calls are also shown. Vocal activity was monitored by acoustic monitoring from 8 June 2015 to 31 May 2016 at three acoustic recording stations. * At station B, there was a malfunction, resulting in the absence of any recordings between 28 January and 15 February 2016.

Month	Station A	Station B	Station C	Total	%
June 2015	112	609	1090	1811	35.70
July 2015	82	16	221	319	6.29
August 2015	13	1	79	93	1.83
September 2015	22	0	4	26	0.51
October 2015	179	0	15	194	3.82
November 2015	345	4	18	367	7.23
December 2015	322	7	2	331	6.52
January 2016	381	239	66	686	13.52
February 2016	380	109	66	555	10.94
March 2016	167	21	251	439	8.65
April 2016	111	13	3	127	2.50
May 2016	53	34	38	125	2.46
TOTAL	2167	1053	1853	5073	

Appendix G

Number of Limpkin vocalizations detected per month at three monitoring stations in Pantanal Matogrossense (Brazil). The total number and percentage of vocalizations detected per month with respect to the total number of calls are also shown. Vocal activity was monitored by acoustic monitoring from 8 June 2015 to 31 May 2016 at three acoustic recording stations. * At station B, there was a malfunction, resulting in the absence of any recordings between 28 January and 15 February 2016.

Month	Station A	Station B	Station C	Total	%
June 2015	2	11	259	272	6.39
July 2015	2	2	380	384	9.02
August 2015	12	2	37	51	1.20
September 2015	17	7	29	53	1.25
October 2015	583	1	15	599	14.08
November 2015	160	6	105	271	6.37
December 2015	7	0	25	32	0.75
January 2016	2	6	23	31	0.73
February 2016	9	4	43	56	1.32
March 2016	14	373	583	970	22.80
April 2016	19	730	364	1113	26.16
May 2016	2	7	414	423	9.94
TOTAL	829	1149	2277	4255	

Appendix H

Number of Sunbittern vocalizations detected per month at three monitoring stations in Pantanal Matogrossense (Brazil). The total number and percentage of vocalizations detected per month with respect to the total number of calls are also shown. Vocal activity was monitored by acoustic monitoring from 8 June 2015 to 31 May 2016 at three acoustic recording stations. * At station B, there was a malfunction, resulting in the absence of any recordings between 28 January and 15 February 2016.

Month	Station A	Station B	Station C	Total	%
June 2015	1098	1	3	1102	17.06
July 2015	139	0	0	139	2.15
August 2015	164	2	0	166	2.57
September 2015	71	0	0	71	1.10
October 2015	69	1	4	74	1.15
November 2015	329	17	1	347	5.37
December 2015	437	1	4	442	6.84
January 2016	415	2	4	421	6.52
February 2016	102	3	0	105	1.63
March 2016	1154	8	6	1168	18.08
April 2016	942	0	3	945	14.63
May 2016	1474	0	5	1479	22.90
TOTAL	6394	35	30	6459	

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