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# The sound of the illegal: Applying bioacoustics for long-term monitoring of illegal cattle in protected areas

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ABSTRACT

Passive acoustic monitoring coupled with automated signal recognition software has been widely used in recent years as an effective and affordable tool for wildlife monitoring and to combat illegal activities within protected areas. Here, we evaluate this technique to monitor the patterns of illegal cattle occurrence in the Brazilian Pantanal over a complete annual cycle. We aim to provide one of the first assessments of the performance of automated signal recognition software to detect ungulates. Cattle occurrences reached their maximum during the end of the dry season when lowland areas provide excellent pastures for cattle. In contrast, cattle occurrences were very low during the rainy season when the study area was seasonally inundated. Automated software was an efficient tool that was able to detect approximately three-quarters of cow calls within the recordings. Passive acoustic monitoring can be used to direct patrols to areas where illegal activities, such as cattle and poaching or logging, have been confirmed, which could be a method that would be especially well suited for remote areas, such as tropical forests. Future studies should evaluate whether there is a relationship between cattle grazing intensity and its associated impacts on wildlife and flora. Rapid advances in automated recognition and the recent development of low-cost recorders foresee a new era of acoustic ecology for improved conservation in the short term.

## 1. Introduction

Cattle farming for beef production is one of the main agricultural activities in Brazil, with the second largest cattle herd in the world (c. 212 million heads, MAPA, 2011). The Brazilian Pantanal supports a rich variety of wildlife and has been an important production area with extensive cattle herds since the late 1800s (Eaton et al., 2017; Junk et al., 2006). Approximately 95% of the Brazilian Pantanal is private and cattle ranches occupy >80% of the biome (Seidl et al., 2001). Traditionally, the Pantanal has been occupied by family ranches (called "fazendas") (Cavalcanti and Gese, 2010), where low-density cattle ranching has been considered an ecologically sound and sustainable management method (Junk et al., 2006; Scherer-Neto et al., 2019). However, over the past decades, cattle ranches in the Pantanal have decreased in size as the land is divided among family members (Cavalcanti et al., 2012). This division meant habitat fragmentation and an increase in human movements. Furthermore, many ranchers have increased their herd sizes (Cavalcanti et al., 2012) and have begun to practice several harmful ranching activities to provide new pastures for their cattle, such as deforestation, conversion of natural habitats to planted pasture, and grazing in protected areas (Devine et al., 2020; Eaton et al., 2017).

Several studies in the Pantanal have shown that intensive, and even traditional, cattle ranching practices may have a serious negative impact on the environment (Trolle, 2003), such as habitat destruction to provide pastures (Walker et al., 2013), simplification of forest vegetation (Santos, 2011), altering the space of use of frugivores (Keuroghlian et al., 2015), and decreasing faunal composition diversity (Eaton et al., 2017). Currently, cattle ranching is legally prohibited in formally protected areas of Brazil. However, protected tropical areas are critically underfunded and managers have few mechanisms in place to enforce

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environmental laws (Bruner et al., 2004). Therefore, there is a need for cost-effective and efficient approaches to provide routine monitoring to protect against illegal cattle ranching. In recent years, some studies have developed automated scalable methods to detect and count cattle through images collected with unmanned aerial vehicles (Shao et al., 2020) or high-resolution images (Laradji et al., 2020). Such automated methods have the advantage of avoiding disturbances to habitats and threatened species within protected areas. Under these assumptions, the use of other non-invasive methods that are able to detect the presence of cattle and collect detailed information on the grazing patterns of cattle in protected areas and in their buffer zones should be evaluated. Among the non-invasive techniques available for terrestrial wildlife monitoring, the use of passive acoustic monitoring coupled with automated signal recognition software has increased significantly in recent years (reviewed by Sugai et al., 2019).

Passive acoustic monitoring is based on the detection of sounds produced by wildlife through the use of autonomous recording units that are programmed to record during periods of interest, followed by recording interpretation (manual or automated). Despite the widespread use of passive acoustic monitoring, few studies have validated the use of this technique for terrestrial mammals (Sugai et al., 2019). However, in recent years, there have been great advances in evaluating the use of this methodology for remotely monitoring several Cervidae species (Enari et al., 2017, 2019; Volodina et al., 2022, Avots et al., 2022), including evaluations regarding its feasibility for tracking their movements through the use of microphone arrays (Salem et al., 2021) and the use of on-deer acoustic recording devices to assess the foraging behavior of the species (Northrup et al., 2019). Recently, one study also tested, for the first time, the application of autonomous recording units coupled with automated signal recognition for cattle monitoring (Karmiris et al., 2021), which opens the door for monitoring the occurrences, grazing activities, and impacts of livestock on the environment over large spatial and temporal scales.

The use of automated signal recognition software is essential for collecting detailed information on grazing patterns, which is one of the main advantages of passive acoustic monitoring. However, to our knowledge, only a few studies have evaluated the effectiveness of automated signal recognition software for detecting ungulates, such as one for monitoring Sika Deer (*Cervus nippon*, Enari et al., 2019), one for Red Deer (*Cervus elaphus,* Avots et al., 2022), and another for livestock (cattle and goats/sheep, Karmiris et al., 2021). In these studies, the automated recognition approach did not detect a large proportion of target signals. For example, only 19% of cow calls were detected by Karmiris et al. (2021). The low proportion of vocalizations detected by automated software may reduce the use of that technique in future research. However, some of the particular properties of cow calls (e.g., call length, low frequency range, and low interindividual variation) suggest that automated recognition should be a reasonable technique to monitor cattle occurrences. It is worth highlighting that Karmiris et al. (2021) used the same statistical model and the same signal parameters to detect three different types of vocalization: cow mooing, sheep/goat bleating, and livestock bells (see Table 1 in Karmiris et al., 2021). The introduction of vocalization-specific parameters into the models could theoretically improve the performance of automated software. Therefore, there is still plenty of room for validation and detailed research on the use of automated signal recognition software to monitor cattle and ungulates.

Here, we used passive acoustic monitoring coupled with automated signal recognition software to monitor the occurrence of illegal cattle over a complete annual cycle in a private area in the Brazilian Pantanal. We aimed to (1) provide a fair assessment (e.g., using cow-specific parameters in the models) of the use of passive acoustic monitoring and automated signal recognition software as a feasible technique for detecting ungulates, (2) collect data with fine spatial and temporal resolution that reflect the grazing patterns of illegal cattle in the monitored protected area, and (3) analyze whether there were differences in the diel or seasonal patterns of cattle occurrences. We hypothesized that the number of cow occurrences would be maximum during the dry season and that these would decrease during the flood period when most of the Brazilian Pantanal is inundated.

**Table 1**
Acoustic measurements (mean ± SD, and range) of 55 cow calls recorded in the study area using a Song Meter SM2 recorder.

| Minimum Frequency (Hz) | Maximum Frequency (Hz) | Duration (s) |
|---|---|---|
| 229.9 ± 172.9 (91–656) | 1381.7 ± 520.4 (281–2581) | 1.13 ± 0.33 (0.46–2.48) |

## 2. Methods

### 2.1. Study area

The study was carried out at four sites located in the northeastern part of the Brazilian Pantanal (Park SESC Baía das Pedras, Poconé, Mato Grosso, Brazil, Fig. 1). It is a private area that hosts the “Pantanal research base” of the Federal University of Mato Grosso. The area is adjacent to the protected Private Reserve of Natural Heritage SESC Pantanal, and the management of Park SESC Baía das Pedras is similar to that carried out in such protected areas; therefore, cattle activity is prohibited within both parks. Despite continuous monitoring and the fact that illegal cattle are removed as often as possible from private areas, ranchers from neighboring farms usually cut fences to enter both protected and private areas. The area is seasonally inundated for half of the year (October–April), while it experiences a pronounced dry season from May to September (Junk et al., 2006). The four selected sites, dominated by a mosaic of forested and savanna areas, were separated by 846, 1379 and 1708 m (Fig. 1). The average annual rainfall ranges between 1000 and 1500 mm, and the mean annual temperature is approximately 24 °C.

### 2.2. Acoustic monitoring

We deployed an acoustic recorder (Song Meter SM2 recorder, Wildlife Acoustics) at each site. The Song Meters were active from 8 June 2015 to 31 May 2016 and programmed to record (.wav format) the first 15 min of each hour. The sampling rate was 48 kHz, with 16 bits per sample resolution. The devices were checked weekly to download data and change batteries. A total of 32,023 15-min recordings (8006 h of recording) were collected (8044 at Station A, 8075 at Station B, 7782 at Station C, and 8122 at Station D).

Karmiris et al. (2021) proved, using Kaleidoscope Pro, which is the same automated signal recognition software that we used (see next section), that cow calls were only automatically detected at a maximum distance of up to 50 m and estimated the effective survey area of the recorders, which was different from ours, to be approximately 0.2 ha for cow calls. Based on the large distances between our acoustic monitoring stations (minimum of 846 m), we assume that there is no risk of recording the same herd from two different stations at the same time.

### 2.3. Acoustic data analyses

We used Kaleidoscope Pro 5.3.9 (Wildlife Acoustics) to scan the acoustic dataset, which is an efficient automated software for acoustic analyses. The Kaleidoscope output includes all the regions of interest (i.e., candidate sounds, ROIs hereafter) that meet the desired signal parameters. The five signal parameters required to run acoustic analyses are the following: maximum intersyllable gap (ms), minimum and maximum detection lengths (s), and minimum and maximum frequencies (Hz). The maximum intersyllable gap defines the maximum allowable time between two vocalizations to be considered a unique vocalization (i.e., vocalizations separated by more space than the one

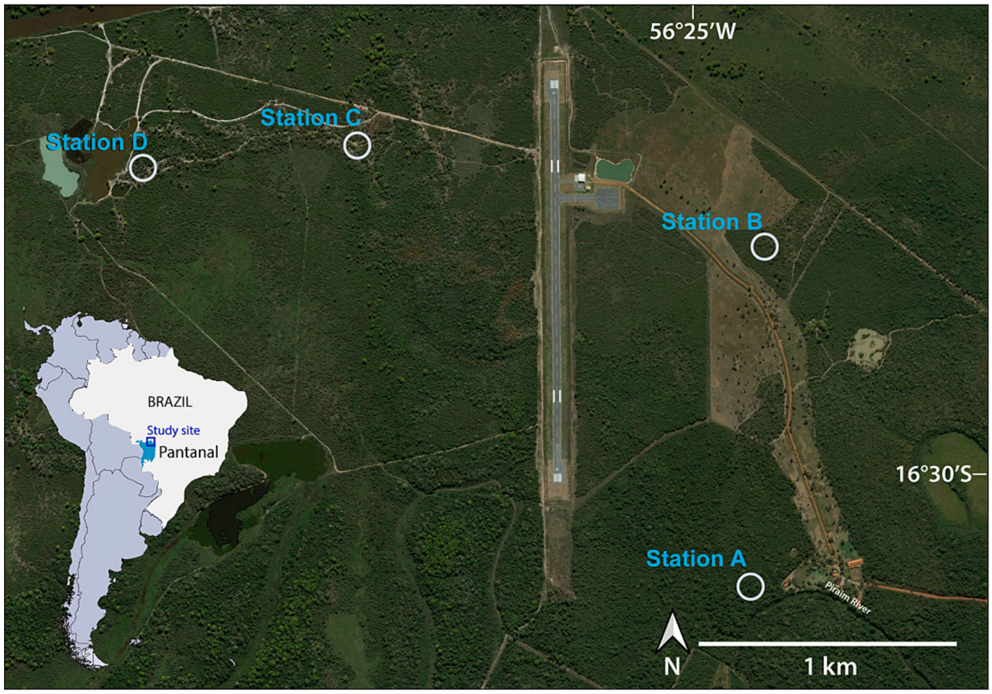


**Fig. 1.** Locations of the four acoustic monitoring stations in the Brazilian Pantanal (Poconé municipality, Mato Grosso, Brazil). The inset shows the location of the study area (blue square) in Brazil. Scale bar: 1 km. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

introduced will be considered two separate vocalizations).

To introduce adequate parameters in Kaleidoscope, we measured, with a Raven Pro 1.6 (Bioacoustics Research Program, 2019), 55 cow calls recorded in the study area and using the same recorder (Song Meter SM2) (Fig. 2). Based on our results (Table 1), the signal parameters introduced were as follows: maximum intersyllable gap: 0.5 s; minimum and maximum detection length: 0.3 and 5 s; and minimum and maximum frequency: 100 and 1800 Hz. The maximum intersyllable gap was set to 0.5 s to detect a single vocalization when there were overlapping individuals. Similarly, the maximum detection length was set to 5 s, which is double the maximum length obtained for an independent cow call (see Table 1), to allow the software to detect overlapping individuals as a single vocalization.

The ROIs identified by Kaleidoscope were automatically grouped by k-means clustering into groups of similar sounds using the cluster analysis function of Kaleidoscope. ROIs within the clusters were also automatically shortened by similarity, and therefore, clusters are mainly composed of sounds of the same species, while the first ROIs of each cluster are the best examples of the sounds within that cluster. The "maximum distance from cluster center to include outputs in cluster.csv" parameter was set to its maximum (2.0), which maximized the number of ROIs detected by Kaleidoscope. Such a parameter can be used as a threshold to filter those sounds that are more dissimilar within a cluster. We opted to use the maximum value since we wanted to detect as many cows as possible, even if it may increase the number of false positives (Pérez-Granados and Schuchmann, 2020b). The FFT window was set to 10.67 ms (5.33 by default). We considered a larger value since a larger FFT will have more resolution for frequency analyses, especially at lower frequencies, on which cows vocalize. Indeed, for vocalizations at lower frequencies, a larger FFT window may provide more desirable results in the cluster analysis process.

The maximum number of states was set to 8 (within the default values), while the "Maximum distance to cluster center for building clusters" was fitted to be 0.3, which can range from 0 to 1 (0.5 default value). A lower value will cause more clusters to be formed, but with fewer signals per cluster, which should facilitate the creation of clusters with more similar sounds. Finally, the maximum number of clusters to be formed was set to 1000 (500 default value) to ensure that the maximum number was not reached during the analyses.

Finally, we verified each ROI to remove mislabeled sounds from the final database. First, we labeled each group of sounds (created by Kaleidoscope) as "Cow" or "Others" based on whether there was a cow call within the first 50 candidate sounds in each group of sounds (see Pérez-Granados and Schuchmann, 2020a). The group of sounds "Others"

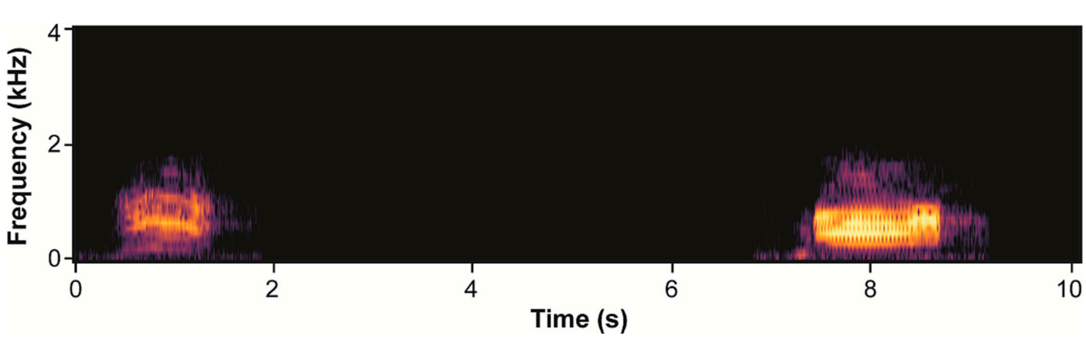


**Fig. 2.** Spectrogram of two typical cow calls in the Brazilian Pantanal.

was removed from the analyses, while we verified (acoustically and/or visually) each ROI within the cluster "Cow" to remove false positives.

The recognizer's performance was evaluated by measuring its recall rate and precision (Knight et al., 2017). The recall rate was estimated by dividing the number of cow calls detected by Kaleidoscope by the number of cow calls present in the sound recordings and is interpreted as an index of the percentage of calls that the recognizer is able to detect (Knight et al., 2017). The number of cow calls in sound recordings was estimated by the same experienced observer who visually and acoustically checked 200 selected recordings (100 recordings with known presence, 25 per site, and 100 randomly selected recordings from those recorded between 4 p.m. and 6 p.m.). During the review process, the observer had no information about the date, hour, or station identification. The precision was estimated by dividing the number of cow calls detected by the software by the total number of ROIs within the "Cow" cluster (Knight et al., 2017; Pérez-Granados and Schuchmann, 2020a) and can be interpreted as an index of the percentage of ROIs correctly labeled by Kaleidoscope.

### 2.4. Statistical analyses

We fitted a generalized linear mixed model (GLMM, Gaussian error structure) to identify diel variations in cow occurrence in the study area. We introduced the number of cow calls detected per hour at each station as the response variable, while the recording hour (24 levels) was included in the models as a fixed effect, and the station (4 levels) was included as a random factor. A second GLMM was run considering the number of cow calls detected per month at each station as the response variable, month (12 levels) as a fixed effect, and station (4 levels) as a random factor. In both GLMMs, the station was considered a random factor to control for variation due to the site, and Tukey's post hoc test was run to identify the hour or month with the highest cow occurrence. All statistical analyses were performed in R 3.6.2 (R Development Core Team, 2019). Packages 'lme4' (Bates et al., 2015), 'lmerTest' (Kuznetsova et al., 2014), and 'multcomp' (Hothorn et al., 2008) were used for the construction of GLMM to calculate the significance of fixed effects and for post hoc comparisons, respectively.

## 3. Results

A total of 1,793,193 sounds matched the parameters introduced in Kaleidoscope, but only 19,873 ROIs (12 clusters, 4.3% of the total clusters created, 1.1% of all ROIs detected) were within the "Cow" category. We identified 1892 true positives (cow calls) within the "Cow" category, which gives a recognizer precision of 9.5% (1892 cow calls within the 19,873 candidate sounds). The recall rate of the recognizer was 74.5% (257 cow calls detected by Kaleidoscope of the 345 calls annotated in the 200 15-min recordings of the validation dataset, with no cow calls detected in the randomly selected recordings).

Cows were detected at the four acoustic monitoring stations, although the number of cow calls detected per station ranged between 91 (Station A) and 1317 (Station D, Table 2). Cow calls were detected in 493 different recordings on 195 different days, which means that cows were detected on 54.5% of the monitoring days (195 out of 358 days) (see summary in Table 2).

### 3.1. Diel and seasonal activity pattern

Vocalizing cows were detected at each recording time, although the diel pattern of calling activity showed a clear activity peak prior to sunset (Fig. 3, see Supplemental Table S1 for the number of calls detected per hour at each acoustic monitoring station). The peak in calling activity occurred at 17:00 (463 cow calls, 24.5% of the total), although this increase in calling activity was extended from 16:00 to 18:00 (976 calls, 51.6% of the total). There was a second lower peak of vocal activity around sunrise, with 112 calls detected at 06:00 (5.9% of the total). The GLMM showed that cow calling activity varied by hour (Table 3) and that the highest calling activity occurred at 18:00 (see Supplemental Fig. S1 for Tukey's post hoc comparison).

The seasonal calling activity of the cows also showed a clear, unimodal pattern with a call activity peak that occurred at the end of the dry season (Fig. 4, 1,379 calls detected during the period from July to September, 72.9% of the total). However, we found large differences between stations on the seasonal scale (see Supplemental Table S2 for the number of calls detected per hour at each acoustic monitoring station). At two of the monitored stations (e.g., Stations A and B) we detected the presence of cows during all monitored months, while at Stations C and D, cow detections were limited to nine and six months, respectively. Interestingly, at Station D, which was the station with the highest number of detected calls, we detected no cow calls from October to April. According to GLMM, the calling activity varied by month (Table 3), with a call activity peak occurring in August (see Supplemental Fig. S2 for Tukey's post hoc comparison).

## 4. Discussion

In this study, we describe and analyze the occurrences of illegal cattle over a complete annual cycle in a private area located within the Brazilian Pantanal and validate the use of automated signal recognition software as an effective tool for long-term monitoring of the occurrence of illegal cattle. We found a clear seasonal pattern of cattle occurrences in the study area. As the dry season advanced and the water levels fell, cattle were moved more frequently into the private area, with a maximum occurring at the end of the dry season (July, August), which is one of the main periods when cattle feed is limited (de Abreu et al., 2010). This result is in agreement with previous studies that analyzed the spatial movements of cattle within the Pantanal (Cavalcanti and Gese, 2010; Eaton et al., 2011). With the start of the rainy season, when the study area is seasonally inundated, there was a clear decrease in cattle occurrences. In fact, cattle were barely detected between January and May at three of the four acoustic monitoring stations (see Supplemental Table S2). This finding could be explained because in the study area most farmers have two properties (de Abreu et al., 2010): one in the lowlands of Pantanal, which is an area with excellent pastures where cattle graze during the dry season, and the other in the high region (non-flooded), where cattle are moved before the lowlands are flooded (de Abreu et al., 2010; Scherer-Neto et al., 2019).

We are aware that native pasturelands in the Pantanal are spatially heterogeneous (Eaton et al., 2011) and that we conducted acoustic monitoring within a limited area, so some of our generalizations may require further research and careful analysis based on cattle occurrences and local conditions. We also detected a clear cattle occurrence peak

**Table 2**
Summary of cow calling activity during an annual cycle in the Brazilian Pantanal (Poconé municipality, Mato Grosso, Brazil). Calling activity was monitored through passive acoustic monitoring from 8 June 2015 to 31 May 2016 at four acoustic monitoring stations. Hours are expressed as UTC (−4).

| Station | Calls | Recordings detected | Days detected | First detection | Last detection | Most active hour | Most active day | Most active month |
|---|---|---|---|---|---|---|---|---|
| A | 96 | 70 | 57 | 9 June | 20 May | 1800 | 6 January | August |
| B | 256 | 144 | 105 | 12 June | 31 May | 1800 | 26 May | May |
| C | 223 | 99 | 63 | 8 June | 4 March | 1800 | 2 September | August |
| D | 1317 | 180 | 75 | 11 June | 30 May | 1700 | 27 August | July |

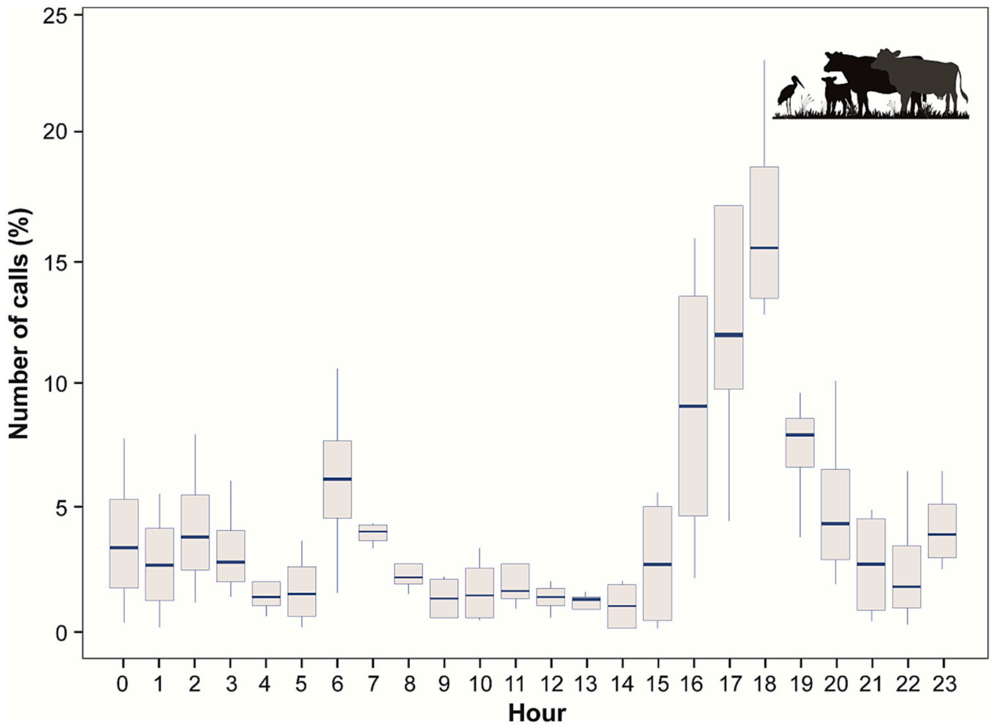


**Fig. 3.** Box plot showing the diel variation in the calling activity pattern of illegal cattle in the Brazilian Pantanal. Calling activity was monitored through passive acoustic monitoring from 8 June 2015 to 31 May 2016 at four acoustic monitoring stations. The hours are expressed in winter local time (UTC -4).

**Table 3**
Results of the variance partitioning analysis performed to test the effect of recording time and month on the diel and the seasonal pattern of vocal activity of cows in the Brazilian Pantanal. The effect of recording hour and month on the vocal activity of the species was assessed with two independent generalized linear mixed models using the mean number of calls (log-transformed) detected per recording time (or month, with all stations pooled), recording time (or month) as a factor and station as a random factor. Vocal activity was monitored using passive acoustics from 8 June 2015 to 16 June 2016 at four acoustic monitoring stations.

| Variable | Sum Sq | Mean Sq | df | Den df | F | *P* |
|---|---|---|---|---|---|---|
| Hour | 50.37 | 2.19 | 23 | 69 | 3.24 | <0.0001 |
| Month | 64.70 | 5.88 | 11 | 36 | 3.34 | <0.0001 |

around sunset, and further research should try to elucidate whether the detected diel pattern is related to changes in cattle vocal activity over the day (i.e., cows call more often around sunset) or because farmers introduce cattle into the private area more often during the last hours of the day. However, the fact that cows were often heard at night (see Supplemental Table S1) suggests that cattle were left unattended for long periods, so the detected pattern may be related to the cattle's preferences to call around sunset.

In this study, we tested the use of automated signal recognition software to detect illegal cattle through non-invasive techniques. The presence of illegal cattle was confirmed on 195 of the 358 monitoring days (> 54%), indicating that grazing occurrences are a common phenomenon in the study area. Karmiris et al. (2021), using a different recorder, found that cow calls were detected by Kaleidoscope Pro at distances of up to 50 m and that the effective survey area of the recorder was approximately 0.2 ha. Therefore, cattle may have crossed (or grazed in) the study area in several instances without being detected due to the low effective detection radius of the recorder. The presence of cattle may compromise some of the research and conservation programs that have been implemented in the Park SESC Baía das Pedras, such as the cultivation of native plants for forest recovery after fire (Wetlands International, 2021).

Our study provides strong evidence on the effectiveness of using automated signal recognition software for detecting ungulates (see Avots et al., 2022). The method we followed required manual validation of the ROIs detected by Kaleidoscope Pro, which is time consuming and could be a clear limitation for further research. However, we only reviewed ROIs within clusters with a high probability of containing cow vocalization, which reduced the number of ROIs to be reviewed by up to 98.9%. Furthermore, Kaleidoscope Pro was able to automatically detect 74.5% of cow calls within the validation dataset, which was a recall rate that was nearly four times higher than previously published for cattle detection research when using the same software (19.1%, Karmiris et al., 2021) and was also higher than the results of an algorithm developed to detect goat / sheep calls (21.2%, Karmiris et al., 2021) and three different Sika Deer vocalizations (range 2–70%, Enari et al., 2019). A recent study using the Red Deer as a study species obtained recall rates of approximately 90% for the five supervised machine learning algorithms tested, suggesting that the creation of sophisticated models could clearly improve the detection of ungulate vocalization.

A previous study aimed at detecting cow calls also employed Kaleidoscope Pro (Karmiris et al., 2021), so the differences found between our study and the one carried out by Karmiris et al. (2021) are probably due to the parameters used in the software. The parameter that may better explain the differences among studies is the "maximum distance from cluster center to include outputs in cluster.csv", which was set at 0.5 by Karmiris et al. (2021) and at its maximum value (2) in our case. This parameter ranges from 0 to 2, and larger values result in larger numbers of detected target signals, but they also slightly increase the number of false misclassified signals. Pérez-Granados et al. (2020) proved that the recognizer precision decreased from 54.3% to 49.7% when setting the parameter to 0.5 or 2, respectively, while the number of detected signals increased from 6218 to 9896 (an increase of 59%) when using a value of 2 instead of 0.5. Therefore, selecting a higher value in our case would have allowed us to detect a larger proportion of target signals, which thus partly explains the differences between studies.

Another parameter that may explain the differences between studies

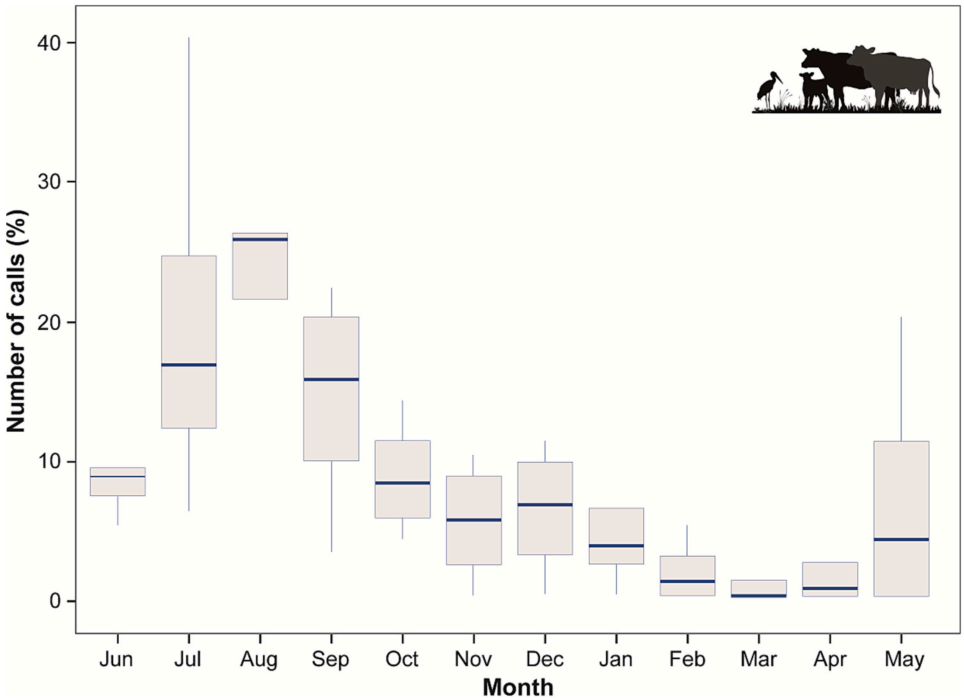


**Fig. 4.** Box plot showing the seasonal variation in the pattern of illegal cattle calling activity over an annual cycle in the Brazilian Pantanal. Calling activity was monitored through passive acoustic monitoring from 8 June 2015 to 31 May 2016 at four acoustic monitoring stations.

is the FFT window size. We opted for a larger FFT window size, which should improve the resolution at lower frequencies on which cows vocalize. Finally, while Karmiris et al. (2021) used the same settings for detecting the three ungulate species (e.g., their minimum frequency introduced for detecting cow vocalization was much higher, 500 Hz, than the mean minimum frequency measured in our dataset, approximately 250 Hz), we fitted cow-specific parameters in the model, which could also partly explain why our model detected a much larger number of cow vocalizations.

The precision of our recognizer could be considered low (9.5%) and was indeed much lower than that previously developed for cattle (57.3%, Karmiris et al., 2021) or Red Deer (> 90% for five models tested, Avots et al., 2022). The low precision had no impact on our results since every false-positive was manually removed. The higher precision obtained by Karmiris et al. (2021) could be partly explained by the fact that they monitored the presence of cattle in Greek mountain areas outside of the breeding period, when wildlife vocal activity is reduced. Karmiris et al. (2021) also used a different recording device, which may also partly explain some of the differences found between studies (see Pérez-Granados et al., 2019; Rempel et al., 2013). However, we monitored the presence of cattle in the Pantanal, one of the most diverse biomes on Earth, over a complete annual cycle, which will likely increase the number of putative sounds that are similar to cow calls (e.g., jaguar roars) and therefore may decrease the recognizer precision. It is true that a low precision recognizer, such as the one we developed, may preclude the future use of passive acoustic monitoring for cattle monitoring at large spatial and temporal scales due to the large amount of time needed to remove misclassified signals. However, we removed only 17,981 false positives in addition to scanning 32,023 15-min recordings (i.e., 2.24 false positives per recording hour), which is an effort that can be considered low and manageable when considering the high recall rate obtained in our dataset.

Future studies that aim to decrease the error rate of algorithms developed using Kaleidoscope may create advanced recognizers after manually labeling the events. Likewise, more research should evaluate the feasibility of using more sophisticated methods for automated cattle detection, such as convolutional neural networks or deep learning (Gupta et al., 2021; Stowell et al., 2019). Indeed, the development of supervised machine learning algorithms has already proven to be very effective for ungulate detection (Avots et al., 2022).

The presence of cattle in protected areas is a serious environmental issue that can compromise conservation efforts. The proposed technique may serve as an early detection system to assist managers in directing patrols to areas where the presence of illegal cattle has been confirmed, which is a method that is especially well suited for remote areas and sites that are difficult to access, such as the Pantanal (Enari et al., 2019). Indeed, the technique could be used for near-real-time monitoring by transmitting acoustic data to a server (i.e., via wi-fi, see Brunoldi et al., 2016; Baumgartner et al., 2019) and lead to permanent removal of cattle from the monitoring area. Acoustic data may also be scanned to detect other illegal anthropogenic activities, such as poaching or illegal hunting (e.g., Astaras et al., 2017; Burivalova et al., 2021; Dobbins et al., 2020). New low-cost recorders for long-term acoustic monitoring are becoming increasingly available (<100 $, e.g., Hill et al., 2018; Karlsson et al., 2021), which, together with rapid advances in automated signal recognition software, foresee a new era for acoustic ecology with the deployment of autonomous recording units at large spatial scales for improved conservation in the short term. We hope that our study may encourage further research on this topic.

## 5. Conclusions

Our results provide support for the use of passive acoustic monitoring coupled with automated signal recognition software to combat illegal grazing. Here, we used that technique to provide quantitative data at large spatial and temporal scales on the occurrence of cows within a protected area. The developed method could be easily adapted to remotely detect the presence of cows, as well as other illegal anthropogenic activities, in other areas. One novelty of our study is the use and the evaluation of automated software for monitoring ungulates, since the use of this technique for monitoring non-flying mammals has been limited (only 6% of the studies focused on that group, see review in Sugai et al., 2019). Further research should improve our knowledge about the circumstances for which automated software might be useful to monitor non-flying mammals, together with the evaluation of more sophisticated automated detection software.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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