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Investigating Acoustic Similarities of Auditory Elephant Deterrents to Optimize Current Techniques

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ABSTRACT

One of the primary reasons elephants are endangered is human-elephant conflict (HEC), the opposition that occurs between elephants and the humans living nearby. The violence that erupts in settings of HEC, such as crop fields, often results in both human and elephant deaths as both species struggle to coexist. Many methods are being researched to mitigate HEC, including playing audio playbacks that trigger flight responses in elephants near crop fields and reduce chances of contact and destruction. Habituation to these stimuli creates the demand for a greater number and more types of auditory deterrents, but it would be unethical and inefficient to immediately jump to tests with crop fields without first verifying these playbacks are at least somewhat effective. Thus, this paper aims to analyze currently used auditory deterrents to determine if any acoustic similarities exist between them, and create a generalization for what characteristics make up an effective auditory deterrent. The results will help optimize current playbacks and help create a threshold of characteristics to use before future testing, to reduce habituation and human-elephant conflict.

Introduction

Over the past few decades, elephant numbers have rapidly declined due to the expansion of humans into the forest habitat of African and Asian elephants. In the country of Côte d'Ivoire, for example, elephant numbers have dropped from an estimated 1,790 savannah elephants and 3,050 forest elephants during pre-colonial times to merely 270 elephants in 2020 (Kouakou et al., 2020). Chen et al. found that an Asian elephant population in southwestern China lost 62% of their habitat within three decades, with increasing extinction rates due to anthropogenic pressures (2021). This reduction in elephant populations can more specifically be attributed to three main factors: poaching, habitat fragmentation, and human-elephant conflict (HEC).

HEC often hurts both human and elephant species as they struggle for survival. Elephants are confined to smaller areas to live in while people set up farms around their habitats. This creates a clash between humans and elephants as elephants turn to these crops for food, and farmers deem elephants a threat to their crops and income. Mackenzie et. al found food insecurity and disease to be higher in households that experienced crop raiding, as well as lower scholastic achievement for children who grew up in these households (2012). Fernando et al. reported the major threat to elephants in Sri Lanka was the immigration of humans into their lands, with the elephant deaths related to this stemming mostly from gun shots by farmers (2011). As HEC levels continue to increase, there is an urgent need for a solution to help humans and elephants coexist.

Currently, there are a variety of techniques being used to combat HEC. A literature review published in 2003 breaks these down into nine main categories: traditional methods, disturbance methods, killing elephants, translocation, repellent methods, physical barriers, compensation schemes, wildlife utilization schemes, and land use planning (Nelson et al.). Notable work among the "repellent method" category includes the discovery of African elephants being deterred by playbacks of disturbed bee sounds (King et al., 2007), which makes way for these bee sounds to be used as an auditory deterrent for elephants. Thuppil et al.'s study found 90% of crop raiding attempts were deterred through their active infrared system playing tiger growls (2015). Wijayagunawardane et al. found that there was a flight response 65% of the time when matriarchal family group vocalizations were being played (2015). However, this field is relatively niche, and no studies to the best of our knowledge have explored efficiency and reliability of auditory deterrents.

Auditory deterrents can be further justified by an elephant's hearing abilities. Indian elephants can hear frequencies ranging from 17 hertz to 10.5 kilohertz (Heffner & Heffner, 1980). In Langbauer et al.'s study, it was found that elephants responded to playbacks at 1.2 and 2.0 kilometers away from the testing site, as well as that males responded more frequently than females (1990). Because crop raiding is often done by male elephants to gain reproductive advantage over other male elephants (Thuppil 2012), auditory deterrents can help target the right group more efficiently. The distance they can hear also helps rationalize the use of auditory deterrents because farmers or other users could space out where speakers for the audio playbacks are placed and where the crop fields are. Additionally, distance would give farmers or other users an easier transition into using auditory deterrents because backup methods may be placed closer to the crop fields in case the sounds do not work as intended. Yet, no studies to the best of our knowledge have tried to identify why these specific auditory deterrents worked better than others.

While these results are promising, there is still a risk of habituation to the sounds being played. Goodyear found that when the pots and pans were used as an auditory deterrent, one elephant's distress returned to near normal levels by the second trial, only showing stress on Trial 9 afterward (2015). Though habituation varies between individuals, the effectiveness of each auditory deterrent will significantly decrease each time the subject is exposed. This hints towards either finding more auditory deterrents that can be used and cycled out each farming season, or that auditory deterrents need to be adjusted to be more effective.

Yet, it would be unethical and inefficient to immediately jump to field tests of these auditory deterrents without first verifying these playbacks are at least somewhat effective. If the stimuli tested do not work, crop fields would be destroyed, not to mention unnecessary stress caused to both the humans and elephants involved. Thus, in this paper we aim to quantitatively analyze previously used auditory playbacks to look for similar acoustic characteristics between them. Through gaining a deeper understanding of what makes these audio playbacks effective at deterring elephants, we aim to help optimize further field testing and provide key baseline levels of an effective auditory deterrent to look for before further study.

Methods

This project involved three main methods: calculating acoustic characteristics, performing linear regression, and generalizing the results. These procedures are outlined in detail below.

Calculating Acoustic Characteristics

In order to analyze audio playbacks, various authors were contacted who performed studies in this field. From this process, we were able to retrieve ten audio files total. The first two files were from Dr. Lucy King from her study "African elephants run from the sound of disturbed bees" (2007), which were a 30 second recording of bees and a ten second recording of white noise. The other eight files were provided by Dr. Thuppil from his studies from 2012, 2013, and 2015. These include leopard growls (10 second and 17 second files), tiger growls (21 second and 36 second files), lion growls (two 25 second files), and human shouts (97 second and 93 second files). We considered the white noise to be a control due to its low efficiency during Dr. King's study, while all other playbacks to be auditory deterrents. [Include here whether all the sounds were considered deterrents]. All files were converted to .wav format using cloudconvert.com. We analyzed all audio files using the R statistical programming language (version, accessed through RStudio Cloud). Each audio file was made into an object using the 'tuneR' package (ADD CITATION), and then the 'soundgen' analyze function was run for each object. The analyses we performed included novelty analysis, pitch tracking, roughness analysis, loudness analysis, and formant analysis. The results were copied onto a spreadsheet for later reference. Each analysis was performed independently, keeping other analyses constant due to file size and memory constraints within RStudio. For example, if loudness characteristics were being retrieved for a specific round of analysis, the other analyses such as pitch tracking and roughness analysis were kept false, NULL, or 0. We used the summary characteristics which soundgen retrieved by looking at the overall audio playback, and used the mean values for each acoustic characteristic because we believe that it best represents the characteristic.

Out of the 114 characteristics that we were able to retrieve, we filtered them based on importance and relevance before moving forward to linear regression. The table below outlines the characteristics we decided to move forward with.

Table 1. Different acoustic characteristics used for study. Descriptions obtained from soundgen manual at https://cran.r-project.org/web/packages/soundgen/soundgen.pdf. CPP's description was obtained through soundgen's vignette at
https://cran.r-project.org/web/packages/soundgen/vignettes/acoustic_analysis.html#cepstrum

Name of Function	Name of Characteristic	Description
flux	Feature-Based Flux	"The rate of change in acoustic features such as pitch, HNR, etc. (0 = none, 1 = max)"
pitchDom	Lowest Dominant Frequency Band	"...domThres (0 to 1) to find the lowest dominant frequency band, we do short-term FFT and take the lowest frequency with amplitude at least domThres"
peakFreq	Peak Frequency	"...the frequency with maximum spectral power (Hz)"
amFreq	Frequency of Amplitude Modulation	"The frequency of amplitude modulation (amFreq, Hz) is calculated as the highest peak in the smoothed AM function"
specCentroid	Spectral Centroid	"...the center of gravity of the frame's spectrum, first spectral moment (Hz)"
quartile25	25% Quartile of Spectrum of Voiced Frames	N/A
quartile50	50% Quartile of Spectrum of Voiced Frames	N/A
quartile75	75% Quartile of Spectrum of Voiced Frames	N/A
harmHeight	Harmonics Height	"...how high harmonics reach in the spectrum, based on the best guess at pitch"
HNR	Harmonics-to-Noise Ratio	"...a measure of harmonicity returned by soundgen:::getPitchAutocor"

Name of Function	Name of Characteristic	Description
ampl	Amplitude Envelope	N/A
amDep	Depth Of Amplitude Modulation	"...amplitude modulation (AM) depth, %. 0: no change; 100: AM with amplitude range equal to the dynamic range of the sound" "...ratio of this peak [highest peak in the smoothed AM function] to the median AM over amRange"
Loudness	N/A	"...a vector of loudness in sone per STFT frame" "...the subjective loudness of each sound is estimated by getLoudness, which assumes frequency sensitivity typical of human hearing" "... getLoudness estimates how loud a sound will be experienced if it is played back at an SPL of SPL_measured dB. The most meaningful way to use the output is to compare the loudness of several sounds analyzed with identical settings or of different segments within the same recording."
harmEnergy	Harmonics Energy	"...the amount of energy in upper harmonics"
pitch	Fundamental Frequency	"a numeric vector of f0 values in Hz or a dataframe specifying the time (ms or 0 to 1) and value (Hz) of each anchor, hereafter "anchor format". These anchors are used to create a smooth contour of fundamental frequency f0 (pitch) within one syllable"
entropy	Spectral Flatness/Wiener Entropy	"Weiner entropy of the spectrum of the current frame. Close to 0: pure tone or tonal sound with nearly all energy in harmonics; close to 1: white noise"
specSlope	Spectral Slope	"the slope of linear regression fit to the spectrum below cutFreq (dB/kHz)"
f1_freq	Frequency of First Formant	N/A
roughness	N/A	"the amount of amplitude modulation"
CPP	Cepstral Peak Prominence	"... cepstrum is a way to find periodicity in the spectrum … Cepstral Peak Prominence or CPP. This is the ratio of the highest cepstral peak (presumably corresponding to f0) to the trend line over cepstrum - basically, it shows whether cepstrum has a clear peak."

Performing Linear Regression and Principal Component Analysis

Once the acoustic characteristics were calculated for each auditory deterrent, we plotted them to visually identify any similarities among the auditory deterrents and specific acoustic characteristics. The rest of the analysis was done using R. We plotted each characteristic as a function of efficiency through scatter plots, and used the 'lme4' package (Bates et al. 2015) to calculate a linear regression including the correlation coefficient and the p-value. For this study, we decided to use the Adjusted R^2 value to reduce chances of overfitting data. If the correlation coefficient was greater than 0.4, the acoustic characteristic was noted down to be accounted for later. If the value could be rounded to 0.4, the p-value was checked to determine if the acoustic characteristic should be noted. We noted down any characteristics with p-values of 0.05 or below in this category.

We performed another round of linear regressions that included only the bees, white noise, lion files, and tiger files. This was to reduce the chances of confounding variables in the study due to the differences in study design. King et al. placed the auditory deterrents 10 meters away from the elephants tested and Thuppil et al. placed only the lion and tiger files ten meters away from the subjects. Any acoustic characteristics with correlation coefficients of 0.4 were also noted down from these linear regressions.

We also performed principal component analysis using all ten audio files and the characteristics that were obtained through the methods outlined in the calculating acoustic characteristics section. This was to identify if the audio playbacks were similar in any way with their acoustic characteristics.

Generalizing Results

After finding significant characteristics that contributed to an auditory deterrent's effectiveness, we wanted to calculate recommendations for the most effective values of these characteristics. To create the generalizations, we used a weighted average approach. First, we added up the decimal values of all the efficiencies used and set them equal to a value denoted sum. We then divided the efficiency of the first auditory deterrent by sum and set this equal to the weightage of the specific auditory deterrent. We repeated this process until the weightages for all the auditory deterrents were calculated. To calculate weighted average, we multiplied the first noted characteristic values of the auditory deterrents by their respective weightages and calculated the sum of these values, then divided this value by the total number of auditory deterrents. This process was repeated for each noted characteristic to find the weighted average for each.

Results

We were able to calculate acoustic characteristics for a majority of the auditory deterrents A total of 114 acoustic characteristics were acquired for at least one of the auditory deterrents. Some of the analyses in the analyze function were unable to run, including the novelty analysis that only outputted values for one lion file and the two leopard files. We believe this might be due to the file sizes or the structure of the audio playbacks. The resulting values were visually plotted through bar charts, shown in Figure 1 for the mean Wiener entropy of these playbacks and the mean flux, two characteristics that clearly display how white noise contrasts all other audio playbacks. Feature-based flux was about two times higher than the various other sounds, while white noise seems to be about seven times higher in mean Wiener entropy than most other auditory playbacks.

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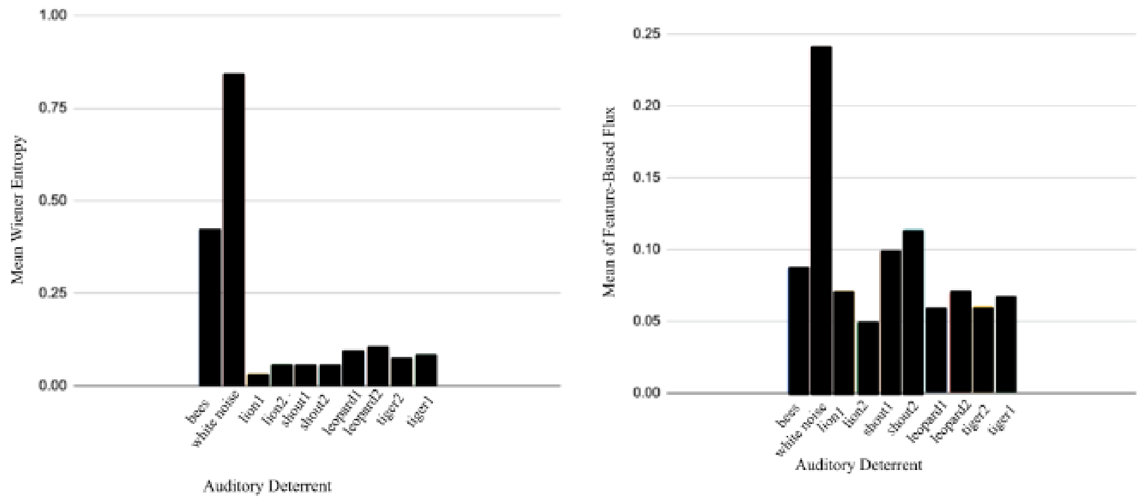

Figure 1. Examples of acoustic characteristics for each auditory deterrents. Bar chart displaying audio playbacks vs. mean Wiener entropy (left) and bar chart displaying audio playbacks vs. mean feature-based flux (right).

The mean peak frequency was also significantly higher in white noise, at more than seven times higher than the audio playbacks with shouting and more than 51 times higher than felid growls like lion sounds.

The scatter plots we made were fairly clustered around certain specific values. Figure 2 shows some of these patterns, with the lowest dominant frequency band characteristic exhibiting a linear relationship with the higher efficiency playbacks while roughness was random. The Adjusted R^2 of the lowest dominant frequency band of the audio playbacks was found to be 0.5107, while the Adjusted R^2 of roughness was -0.1082.

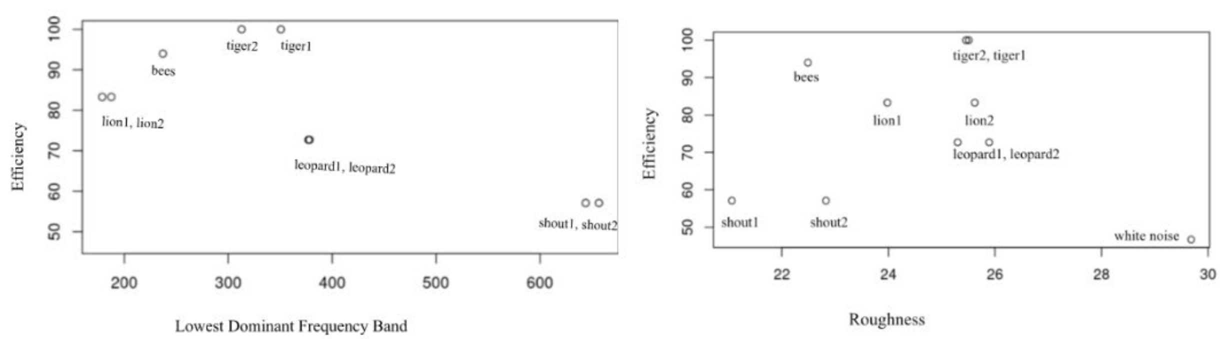

Figure 2. Acoustic characteristics of various auditory deterrents plotted against efficiencies of deterrents. Scatter plots of lowest dominant frequency band in Hertz vs. efficiencies (left) and roughness in percentage vs. efficiencies (right) of each audio playback.

After performing all rounds of linear regression, the acoustic characteristics found significant for efficiency were noted in the table below. Their weighted average was also calculated and noted in Table 2.

Table 2. Acoustic characteristics determined significant by Adjusted R^2 values and p-values. Characteristics with Adjusted R2 values lower than 0.4 were compared with p-values before deciding if they were significant.

Name of Acoustic Characteristic	Adjusted R^2	p-value	Recommended Value for Effectiveness
Lowest Dominant Frequency Band	0.5107	0.0184	344.7551 Hz
Loudness	0.5476	0.0087	11.4357 dB
25% Quartile	0.4325	0.0231	438.5812 Hz
Peak Frequency	0.3557	0.0404	376.7834 Hz
Depth of Amplitude Modulation	0.3739	0.0472	-11.6774%
Flux	0.4278	0.0239	0.0732

For the analysis performed with only the audio playbacks placed about ten meters away during testing, the correlation coefficients and p-values were increased. As a comparison, the lowest dominant frequency band characteristic had an Adjusted R^2 value of 0.8797, while roughness had an Adjusted R^2 value of 0.4941. This can be seen through Figure 3, with a clear linear relationship occurring with the audio playbacks placed 10 meters away during testing. Due to the closer proximity of values for most of the characteristics in this second round of analysis, many were determined to be significant based on efficiency. They are outlined in Table 3.

Table 3. Acoustic characteristics determined significant by Adjusted R^2 values and p-values of audio playbacks placed 10 meters away during testing.

Name of Characteristic	Adjusted R^2	p-value	Recommended Value for Effectiveness
Fundamental Frequency	0.6351	0.0357	247.0620 Hz
Harmonics to Noise Ratio	0.8113	0.0090	2.7451
Harmonics Height	0.6652	0.0298	923.9781
75% Quartile	0.6234	0.0382	1922.9680 Hz
50% Quartile	0.7789	0.0125	618.7998 Hz
25% Quartile	0.8216	0.0080	190.5374 Hz
Spectral Centroid	0.6443	0.0338	1382.5815 Hz
Roughness	0.4941	0.0723	N/A
Frequency of Amplitude Modulation	0.5222	0.1033	33.6172 Hz
Peak Frequency	0.8322	0.0071	125.2522 Hz
Flux	0.7577	0.0151	0.0432
Lowest Dominant Frequency Band	0.8797	0.01183	165.4009 Hz
Root Mean Square of Amplitude Per Frame	0.7061	0.0226	0.0573

We were also able to perform principal component analysis, whose results can be found in Figure 3.

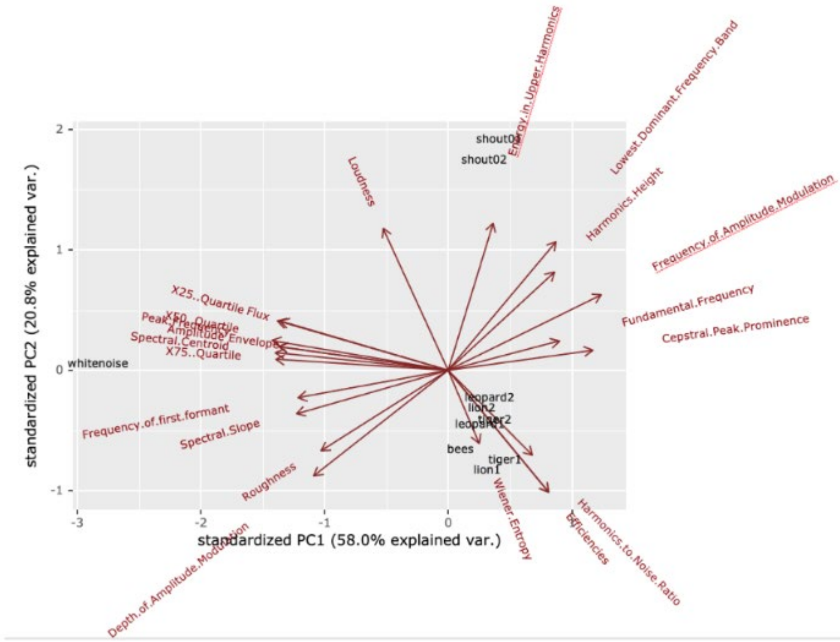

Figure 3. A biplot displaying principal component analysis done on all the audio playbacks and their acoustic characteristics.

Discussion

Figure 3 shows the biplot of principal component analysis, which helps visually display the similarities between the leopard, lion, tiger, and bee sounds due to their proximity. The white noise appears to be an outlier, which proves the higher efficiency playbacks appear to be acoustically similar. Additionally, the auditory deterrents with high efficiency (such as the bee, leopard, tiger, and lion sounds) are all clustered together, implying their acoustic similarities. The human shout playbacks, which had low efficiency, and the white noise (control deterrent) playbacks are away from this cluster, which further supports the idea that the high efficiency auditory deterrents have similar acoustic characteristics.

The Fundamental Frequency is a clear example of the white noise differing in its acoustic characteristics; however it is uncertain whether this difference can be attributed to efficiency due to the similarity of tiger, leopard, and lion growls. This is because all of the highly efficient sounds were felid growls, and so the recommended values for acoustic characteristics may be skewed towards being more similar to felid growls rather than being efficient. This creates the need for more research in the area to determine if other inefficient sounds that do not subjectively sound similar to felid growls would still produce the same results.

Conclusion

To summarize, all audio playbacks were similar on the basis of lowest dominant frequency band, loudness, 25% quartile, peak frequency, depth of amplitude modulation, and flux, and these characteristics were found to be significant towards efficiency. Through a weighted average approach, we were able to create recommended values for effective auditory deterrents, while using linear regression to verify the similarities between the auditory deterrents used. We hope this research can be used by farmers, researchers, or ecologists as a reference of acoustic characteristic values that they should aim for when selecting or testing auditory deterrents and minimize the chance of error with crop fields and elephants. Nonetheless, we believe more research must be done to understand how these predicted values play out in real-world scenarios. Thus, this makes way for studies in habituation of auditory deterrents and elephants, as the values retrieved here can be used to determine how effective this research is at reducing habituation. We hope that the general methods used here can be applied in a variety of contexts to understand how to mitigate human-wildlife conflict, such as acoustic deterrents for deterring fish from fishing nets.

Limitations

Though we tried getting rid of external factors, there are many confounding variables that could have affected our results. For example, King et al. found one group of elephants tested did not respond to the bee sounds played, interpreted as the group not remembering or encountering bees [2007]. There would need to be more research in this area to determine if elephants only respond to sounds that they have encountered before and have gained a negative connotation of or if elephants can be deterred with any sounds. Additionally, there were only six sounds placed ten meters away (bees, white noise, lion files, and tiger files), meaning that correlation coefficient could have been skewed by the small sample size and similarities in subjective pitch. Thus, it is important to consider testing various distances to determine if ten meters is really optimal or if these values are correlated due to other reasons.

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References

Bates D, Mächler M, Bolker B, Walker S (2015). "Fitting Linear Mixed-Effects Models Using lme4." Journal of Statistical Software, 67(1), 1–48. doi: 10.18637/jss.

CHEN, Y., SUN, Y., ATZENI, L., GIBSON, L., HUA, M., LI, K., SHI, K., & DUDGEON, D. (2021). Anthropogenic pressures increase extinction risk of an isolated Asian elephant (Elephas maximus) population in southwestern China, as revealed by a combination of molecular- and landscape-scale approaches. *Integrative Zoology*. https://doi.org/10.1111/1749-4877.12534

Goodyear, S., & Schulte, B. (2015). Habituation to Auditory Stimuli by Captive African Elephants (Loxodonta africana). *Animal Behavior and Cognition*, *2*(4), 292–312. https://doi.org/10.12966/abc.11.01.2015

Fernando, Prithiviraj, et al. "Current status of Asian elephants in Sri Lanka." Gajah 35 (2011): 93-103. http://dx.doi.org/10.5167/uzh-59037

Heffner, R., & Heffner, H. (1980). Hearing in the Elephant (Elephas maximus). *Science*, *208*(4443), 518–520. https://doi.org/10.1126/science.7367876

King, L. E., Douglas-Hamilton, I., & Vollrath, F. (2007). African elephants run from the sound of disturbed bees. Current Biology, 17(19), R832-R833. https://doi.org/10.1016/j.cub.2007.07.038

Kouakou, J. L., Gonedelé Bi, S., Bitty, E. A., Kouakou, C., Yao, A. K., Kassé, K. B., & Ouattara, S. (2020). Ivory Coast without ivory: Massive extinction of African forest elephants in Côte d'Ivoire. *PLOS ONE*, *15*(10), e0232993. https://doi.org/10.1371/journal.pone.0232993

LANGBAUER JR, W. R., Payne, K. B., Charif, R. A., Rapaport, L., & Osborn, F. (1991). African elephants respond to distant playbacks of low-frequency conspecific calls. Journal of Experimental Biology, 157(1), 35-46. http://dx.doi.org/10.1242/jeb.157.1.35

Mackenzie, C. A., & Ahabyona, P. (2012). Elephants in the garden: Financial and social costs of crop raiding. *Ecological Economics*, *75*, 72–82. https://doi.org/10.1016/j.ecolecon.2011.12.018

Ngama, S., Korte, L., Bindelle, J., Vermeulen, C., & Poulsen, J. (2016). How Bees Deter Elephants: Beehive Trials with Forest Elephants (Loxodonta africana cyclotis) in Gabon. PLOS ONE, 11(5), e0155690. doi: 10.1371/journal.pone.0155690

Thuppil, V., & Coss, R. G. (2012). Using threatening sounds as a conservation tool: evolutionary bases for managing human–elephant conflict in India. Journal of International Wildlife Law & Policy, 15(2), 167-185. https://doi.org/10.1080/13880292.2012.678794

Thuppil, V., and R. G. Coss. 2013. Wild Asian elephants distinguish aggressive tiger and leopard growls according to perceived danger. Biology Letters 9:20130518. http://dx.doi.org/10.1098/rsbl.2013.0518

Thuppil, V., & Coss, R. (2015). Playback of felid growls mitigates crop-raiding by elephants Elephas maximus in southern India. Oryx, 50(2), 329-335. https://doi.org/10.1017/S0030605314000635

Wijayagunawardane, M. P., Short, R. V., Samarakone, T. S., Nishany, K. M., Harrington, H., Perera, B. V. P., ... & Bittner, E. P. (2016). The use of audio playback to deter crop-raiding Asian elephants. Wildlife Society Bulletin, 40(2), 375-379. https://doi.org/10.1002/wsb.652