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Quantifying the effect of forest edge on tropical fauna using explainable ecoacoustics metrics

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1 Tropical forests are biodiversity hotspots but increasingly fragmented by human
2 activities, multiplying forest edges that alter microclimates and species dynamics.
3 While edge effect on plants is well documented, its impact on fauna remains less ex-
4 plored. Ecoacoustics provides a non-invasive and passive approach to monitor faunal
5 communities, yet the complexity of soundscapes and the opacity of machine learning
6 tools often limit ecological interpretability. Here, we show that acoustic diversity
7 in New Caledonian ultramafic forests exhibits a detectable edge effect, with sound-
8 scapes converging towards homogeneity starting 100 m from the forest edge. Using
9 passive acoustic monitoring and 59 ecoacoustic indices, we combined machine learn-
10 ing, Representational Similarity Analysis, and explainable statistical methods from
11 psychophysics. Results reveal a significant correlation between distance to edge and
12 acoustic diversity, particularly pronounced during day-time. Indices such as NDSI,
13 Hf, and SKEWf contributed most to detecting the effect, whereas some other in-
14 dices added noise rather than informative signal. These findings match the botanical
15 threshold described by [Blanchard *et al.* \(2023\)](#) and highlight both the promise and
16 limitations of indice-based ecoacoustics. By integrating explicability methods, we
17 offer a transparent framework to disentangle complex ecological signals, advancing
18 ecoacoustics as a pertinent tool for studying forest fragmentation and guiding biodi-
19 versity conservation.

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20 I. INTRODUCTION

21 In a global context of unprecedented environmental change, natural ecosystems are un-
22 dergoing profound and rapid transformations. The acceleration of global warming and the
23 intensification of human activities through deforestation, urbanization and exploitation of
24 resources are major pressures on biodiversity globally (IPBES, 2019). Forests are reservoirs
25 of biodiversity and are therefore a biological conservation priority (Aerts and Honnay, 2011).
26 Yet, around 10 million hectares of forest disappear annually worldwide (FAO, 2022), chang-
27 ing their structure and affecting their biodiversity. This phenomenon largely contributes to
28 the fragmentation of forests leading to the increase in edge zones, the ecological interfaces
29 between dense forest and open environments. On a global scale, more than 70% of forest
30 areas are located within one kilometer of an edge, and 19% of tropical forests within 100 me-
31 ters (Haddad *et al.*, 2015). Edges are transition zones known to cause significant changes in
32 the microclimate, such as an increase in temperature and a decrease in humidity in the first
33 few meters of the forest (Ewers and Banks-Leite, 2013). These environmental alterations can
34 influence the composition, abundance and behavior of species, thus profoundly modifying
35 the dynamics of biological communities (Haddad *et al.*, 2015). This phenomenon is known
36 as the edge effect, defined as a positive or negative variation in the abundance or frequency
37 of a species near the edge, in response to altered environmental conditions and the influence
38 of species or resources from adjacent environments (Driscoll *et al.*, 2013). In Amazonian
39 forests, the edge effect on vegetation has already been studied and has been shown to induce

40 profound and lasting changes in forest ecosystems, affecting plant community structure, tree
41 demographic dynamics, and species distribution ([Laurance *et al.*, 2011](#)).

42 An emblematic example of forest fragmentation is New Caledonia. It is recognized as
43 one of the world's 36 biodiversity hotspots, with an exceptional rate of endemism, reaching
44 over 74% for plants ([Morat *et al.*, 2012](#)). This biological uniqueness is particularly marked
45 in forests on ultramafic soils, i.e., forests that develop on soils rich in heavy metals. These
46 unique environments are home to remarkable biodiversity but are under increasing pressure
47 from human activity such as mining ([Birnbaum *et al.*, 2023](#)). New Caledonia holds around
48 25% of the world's nickel reserves, and mining accounts for over 90% of the territory's
49 exports ([institut de la statistique et des études économiques de Nouvelle-Calédonie, 2023](#)).
50 This activity leads to rapid deforestation, particularly in the south of the island where
51 mining exploitation is intensive ([Losfeld *et al.*, 2015](#)). In this context, it is crucial to better
52 understand the impact of the edge effect on the diversity of forests on ultramafic soils in New
53 Caledonia, in order to assess the consequences of forest fragmentation on local biodiversity.
54 To meet this goal, as part of the RELIQUES project (fRagmentation des forEts sur substrats
55 uLtramafIQUES de Nouvelle-Calédonie) (CNRT, 2022), supported by CIRAD and IRD, a
56 first study was carried out in the south of New Caledonia on the response of floristic diversity
57 to the edge effect ([Blanchard *et al.*, 2023](#)). By combining data on plant composition and
58 canopy structure, this study highlighted clear variations between the first few meters from
59 the edge and areas beyond 100 meters, suggesting a marked ecological gradient linked to
60 fragmentation. However, edge effect studies in general, and the one in New Caledonia in
61 particular, focused on flora (e.g., ([Laurance *et al.*, 2011](#))), and more research considering

62 edge effect on fauna are needed. As part of the project RELIQUES, the work presented
63 in this paper complements the floristic analysis conducted by (Blanchard *et al.*, 2023) by
64 focusing on the fauna.

65 **A. Understanding the impact of the edge effect on the fauna’s dynamic using**
66 **ecoacoustics**

67 Being able to decipher the mechanisms linking fauna’s dynamics to forest density prop-
68 erties necessitates effective monitoring methods that can be applied on a large scale. The
69 ecoacoustic approach (e.g., (Sueur and Farina, 2015)) offers continuous data over long peri-
70 ods of time on a very fine temporal and spatial scale. The recording and analyzing of the
71 sounds of the environment allows a better understanding of interactions between species,
72 their distribution, and the impact of environmental disturbances on biodiversity, ecolog-
73 ical dynamics and the overall functioning of ecosystems (Ross *et al.*, 2023). A specific
74 application of this ecoacoustic approach is the global analysis of the soundscape of a natural
75 environment. This soundscape, defined by the link between a landscape and the sounds that
76 compose it ((Krause, 1987); (Pijanowski *et al.*, 2011)), is divided into three distinct cate-
77 gories: biophony, which groups together all the sound signals emitted by living organisms,
78 geophony, which corresponds to sounds from natural but non-abiotic sources and anthro-
79 pophony, which includes sounds of human origin unless speech and vocalizations. These
80 three components provide a complete picture of sounds from an ecosystem, and therefore, to
81 some extent, of the composition and state of that ecosystem. In this study, we analyse the

82 soundscapes of New Caledonian ultramafic forests to assess whether forests edge influences
83 the acoustic diversity of the local fauna.

84 The analysis of soundscapes can be complex due to the multitude and the interdepen-
85 dency of acoustic parameters such as frequency, amplitude, temporal patterns contained in
86 the recorded data. To address this issue, we relied on acoustic indices, which were developed
87 to summarize and quantify soundscape characteristics. A synthesis of these indices has been
88 proposed by (Sueur *et al.*, 2014) and updated by (Buxton *et al.*, 2018). These indices aim
89 to quantify different characteristics of the soundscape, such as spectral complexity, ratios
90 between frequency bands, frequency richness, entropy or even the temporal organization of
91 signals (Bradfer-Lawrence *et al.*, 2025). The application of these indices has proved useful
92 in various ecological contexts. (Krause and Farina, 2016), for example, highlighted a de-
93 crease in acoustic complexity, measured by the Acoustic Complexity Index (ACI) (Pieretti
94 *et al.*, 2011) which captures temporal variation in sound intensity within frequency bands
95 that reflects the richness of biological activity, in a Californian forest subjected to climatic
96 disturbances, signaling a decline in avian biodiversity. Similarly, (Gasc *et al.*, 2018b) were
97 able to monitor the resilience of a desert ecosystem after a fire, by observing the recovery
98 of animal sound signals using the Bioacoustic Index (BI) (Boelman *et al.*, 2007) which esti-
99 mates biotic activity by quantifying acoustic energy in frequency ranges typically occupied
100 by animal sounds. However, a growing number of studies suggest that acoustic indices, when
101 used in isolation, have limited value for monitoring biodiversity, reporting inconsistent per-
102 formance and variable effect sizes when correlated with biodiversity measurements (Alcocer
103 *et al.*, 2022). The results obtained in a certain geographical area would not be reproducible

104 in another area. They would also be difficult to generalize (Sethi *et al.*, 2023) and would
105 suffer from poor ecological interpretability. From a methodological point of view, this has
106 led to increasing interest in approaches that consider multiple indices simultaneously.

107 **B. Explaining black-box statistical methods in meaningful ecoacoustic indices**

108 Analytical approaches from the fields of multivariate statistics and artificial intelligence
109 can integrate several indices at once and detect complex relationships between acoustic in-
110 dices and ecosystem properties (Thoret *et al.*, 2020). However, these methods are often
111 criticized for their opacity. While they allow to conclude that there is relevant information
112 in the acoustic data, it remains challenging to determine which acoustic features drive their
113 predictions or correlation. To overcome this challenge, our study combine advanced statis-
114 tical methods with explicability techniques specifically designed to address the “black box”
115 nature of these approaches. Following the framework proposed by (Thoret, 2023; Thoret
116 *et al.*, 2024, 2021a), we apply explicability methods that help identify the most influential
117 acoustic indices along the distance-to-edge gradient. By incorporating these innovative ap-
118 proaches, our study contributes not only to the understanding of acoustic responses to the
119 distance to edge but also promotes the development of more transparent and generalizable
120 methods in ecoacoustics, an important need in the field.

121 **II. MATERIAL AND METHODS**

122 The acoustic dataset was first prepared to ensure that it accurately reflects the biological
123 component of the soundscape and was organized into hourly intervals. Then, we employed

124 a multi-index approach to evaluate the overall impact of edge distance on acoustic diversity.
125 Finally, we used explicability methods to determine which indices contributed most to the
126 observed patterns, revealing which acoustic indices are most important for understanding
127 ecological responses to the edge.

128 **A. Study sites selection**

129 We selected a large remnant of rain forest at low altitude on ultramafic soils, situated
130 in the southern part of New Caledonia, in the Kuebini Valley region. This kind of low
131 altitude forested area is among the most threatened forest remnants in New Caledonia, as it
132 represents biodiversity relict and conservation refugia, of previously larger forested blocks,
133 that has been fragmented by old past wildfires. This kind of forest is among the most affected
134 by the fragmentation and represent refugia for numerous endemic plants and related fauna,
135 which have all been filtered by harsh conditions from ultramafic (low nutriment, high level
136 of heavy metals in environment). It is situated in Plaine des lacs region where it represents
137 one of the largest patches of free access rain forest. We monitored a total of 30 forested plots
138 (1). For each site, the distance to the forest edge was determined thanks to the analysis of
139 high-resolution satellite images (Blanchard *et al.*, 2023). Sites were selected to represent six
140 distances from the forest edge: 10, 20, 40, 100, 200, and 300 meters.

141 **B. Passive acoustic monitoring**

142 At each site, a SM4 recorder device (Wildlife Acoustics©) was installed on a trunk
143 at 1.50 m from the ground, near the center of the previously established botanical plot

Acoustic edge effect of biophony

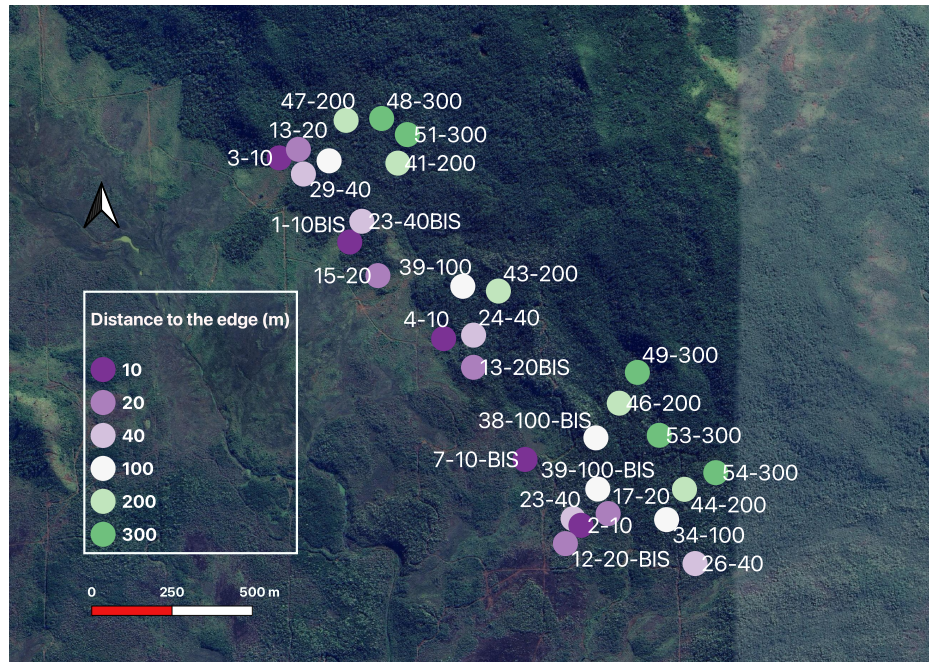


FIG. 1. The 30 sites selected for acoustic surveys. $22^{\circ}13'00''$ S - $166^{\circ}57'00''$ E and $22^{\circ}13'56''$ S - $166^{\circ}58'00''$ E, Kuebini region, southern New Caledonia. Each site is associated to a color point reflecting the distance to the edge and a label corresponding to a unique site name.

144 (Blanchard *et al.*, 2023). The left microphone was systematically oriented towards the north
145 to ensure consistency in the recordings. The device was programmed to record a 1-minute
146 sequence every 10 minutes, to capture variations in the soundscape throughout the day.
147 The recording program was configured as follows: sampling frequency 48000 Hz, gain 16
148 dB, pre-amplification 26 dB, high-pass filter 220 Hz. All devices were set to UTC+11 (local
149 time) and deployed for at least three weeks, with a minimum target of six consecutive days
150 of favorable weather conditions (no rain or strong wind). Three recording sessions were
151 carried out with ten microphones installed per session in order to have a balanced collection
152 of recordings from the six distances for each session. The first recording session ran from

153 18 November 2021 to 7 December 2021, the second from 7 December 2021 to 10 February
154 2022, and the third from 30 June 2022 to 28 July 2022. The three sessions generated a
155 total of 141755 audio files, respectively 17103, 85161 and 39491 files for each session. The
156 variation in the number of files per session is explained by challenges encountered in the field,
157 including weather conditions for collecting the acoustic sensors. Audio files were initially
158 recorded in WAV and then stored in the lossless compression FLAC (Free Lossless Audio
159 Codec) format. This collection is available under the project name RELIQUES from the
160 IMBE sound library (<https://ecophony.imbe.fr>).

161 **C. Acoustic indices calculation**

162 For each audio file, we extracted 59 acoustic indices using the *all_spectral_features()* and
163 *all_temporal_features()* functions in the Python scikit-maad library (Ulloa *et al.*, 2021). These
164 indices provide a fine-grained quantification of the soundscape’s characteristics, based on
165 several signal dimensions: frequency, time, energy, regularity, and spectral diversity. Spectral
166 indices describe how acoustic energy is distributed across the frequency spectrum. For
167 example, the Acoustic Diversity Index (ADI) measures the distribution of energy between
168 frequency bands, while the Acoustic Evenness Index (AEI) reflects the dominance of a limited
169 number of frequencies. Others, such as the Number of Peaks (NBPEAKS), count energy
170 peaks in the spectrum, while spectral entropy measures (e.g., HPairedShannon, HSimpson,
171 Hrenyi) quantify the complexity or predictability of frequency distribution. Temporal indices
172 describe signal variations over time. The Acoustic Complexity Index (ACI), for example,
173 measures rapid changes in intensity, often associated with animal vocalizations. Temporal

174 Entropy (Ht) provides information on signal variability over time, while indices such as
175 Signal-to-Noise Ratio (SNR) indicate overall energy and signal clarity. This multi-index
176 approach forms the basis of our assessment of acoustic variations along the distance-to-edge
177 gradient. All indices are analysed together, without a priori selection, in order to explore
178 these variations exhaustively.

179 **D. Acoustic disturbance filtering**

180 Acoustic indices, although very useful for analyzing soundscapes, are very sensitive to
181 geophonic or anthropophonic sounds, which could bias the analyses. These elements are
182 likely to modify the spectral structure of the signal and can therefore distort the calculation
183 of acoustic indices. To reduce these identified acoustic biases, acoustic files with microphone-
184 related technical malfunctions were manually discarded. We assumed that no significant
185 anthropophonic sound affected our study area due to its isolation; however, a significant
186 proportion of recordings remained affected by acoustic disturbances of environmental origin,
187 mainly due to geophonic sources such as rain and wind. To discard acoustic recordings
188 containing geophony, we developed an automatic classification model for detecting recordings
189 containing wind or rain.

190 **Training dataset.** 660 audio files were randomly selected from the whole database.
191 These files were manually labeled based on direct listening and visual observation of the
192 spectrogram, to indicate the presence or absence of rain and wind. This step provided a
193 reference training dataset from allowing to develop and evaluate the effectiveness of various
194 filtering methods.

195 **Development of the model.** We developed a dedicated machine learning classification
196 model, inspired by the work of (Stowell, 2022) on the automatic detection of geophony in
197 acoustic recordings. The labeled dataset (660 files) was randomly divided into a training
198 set (80%) and a test set (20%). Acoustic indices were standardized using *StandardScaler()*
199 to ensure comparability across the variables beforehand. A dimensionality reduction was
200 applied through principal component analysis (PCA), retaining components that explained
201 99% of the total variance. A Support Vector Classifier (SVC) with a nonlinear kernel, a
202 Radial Basis Function (RBF), was trained. RBF's hyperparameters, the regularization pa-
203 rameter C, and the kernel parameter gamma, were optimized to maximize the generalization
204 of the SVM using *GridSearchCV* in a five-fold stratified cross-validation scheme (*Stratified-*
205 *KFold*). Intuitively, these two parameters control the influence of individual training points
206 in the radial basis function (RBF) kernel. The couple of values gamma and C leading to the
207 highest generalization on the held out set was finally retained.

208 **Testing.** To obtain an estimate of the model's performance and its ability to generalize
209 to new data, the whole process (data splitting, training, cross-validation, and testing) was
210 repeated 100 times with different random partitions between the training and test sets.
211 The average balanced accuracy over the 100 repetitions is used as the final indicator of
212 model performance. Balanced accuracy corresponds to the average between sensitivity (the
213 rate of correct detection of acoustic nuisance) and specificity (the rate of correct detection of
214 nuisance-free recordings). The classifier achieved a balanced accuracy of 94% on the training
215 data and 85% on the test sample. This corresponds to a specificity of 90% and a sensitivity
216 of 80%. This enabled us to effectively filter out recordings with acoustic nuisance from our

217 entire database (141755 files), allowing us to remove 60493 files containing acoustic nuisance
218 and thus constituting an essential preliminary step in ensuring the reliability of subsequent
219 analyses of acoustic diversity as a function of distance from the edge.

220 **E. Hourly clustering**

221 After filtering out recordings with acoustic disturbances, we investigated the hourly struc-
222 turing of soundscapes. It has been established that the acoustic profiles of an ecosystem
223 vary throughout the day ([Francomano *et al.*, 2020](#)), particularly in relation to the activity
224 rhythms of species in New Caledonian forests on ultramafic soils ([Gasc *et al.*, 2013](#)). An-
225 alyzing these temporal patterns is essential to identify periods that concentrate the most
226 informative acoustic signals, and to ensure that potential edge effect is not masked by daily
227 fluctuations in biological activity. To identify possible hourly groupings, we first calculated
228 the average of each acoustic index per hour by aggregating all available recordings. An
229 unsupervised classification was then performed using the K-means algorithm, preceded by
230 data normalization to ensure fair weighting of indices.

231 Clustering analysis revealed two distinct groups. The first cluster corresponds to a diurnal
232 (“Day”) period, from 5 a.m. to 6 p.m., closely aligned with sunrise and sunset in the study
233 area, while the second cluster represents a nocturnal (“Night”) period, from 6 p.m. to 5
234 a.m. (2). This partition highlights the strong daily structuring of the soundscapes and was
235 therefore used as a temporal framework for subsequent analyses.

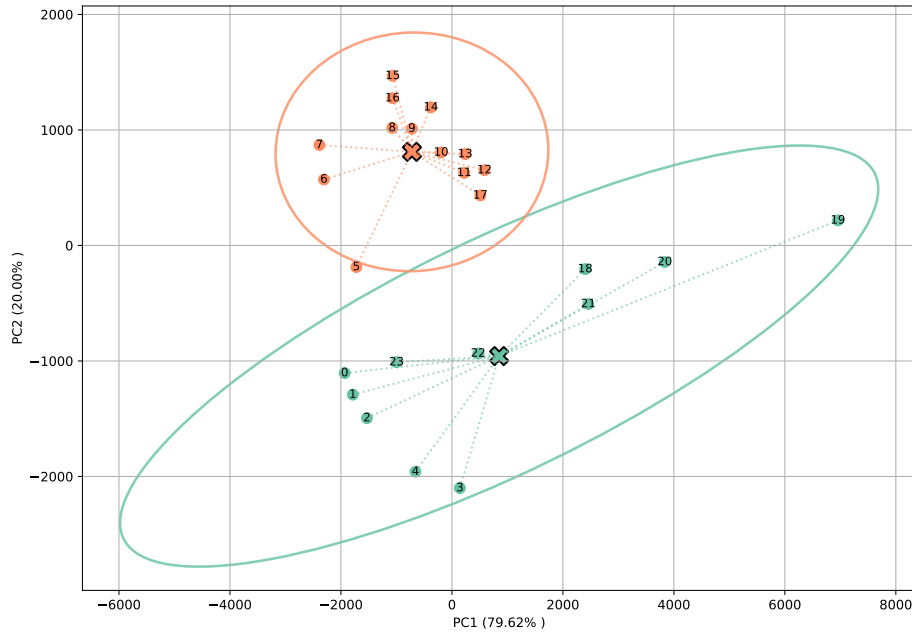


FIG. 2. PCA on K-means clustering results. In blue, the “night-time” cluster, In orange, the “day-time” cluster. For each cluster, the center of gravity is represented by a cross and the 95th percentile calculation by an ellipse.

236 F. Representational Similarity Analysis

237 Initially designed to compare neuronal activation patterns, the Representational Simi-
238 larity Analysis (RSA) introduced by (Kriegeskorte *et al.*, 2008) allows analysis of complex
239 structures in multidimensional data sets such as distances matrices. Here we apply this
240 method to evaluate the detection of an edge effect by analyzing the correlations between three
241 dissimilarity matrices designed to quantify different aspects of variation between recordings.

242 For each pair of recordings, the Euclidean distance was calculated from normalized acous-
243 tic indices, producing an acoustic dissimilarity matrix. Two additional matrices were con-
244 structed to represent explanatory variables: a “Distance to edge” matrix, indicating the

Acoustic edge effect of biophony

245 absolute difference in distance to edge for each pair of points, and a binary "Site" matrix,
246 where 0 indicates recordings from the same site and 1 from different sites (3). By correlating
247 the upper triangular part of these matrices with each other, RSA can be used to assess the
248 extent to which acoustic similarity between recordings reflects a particular ecological factor.
249 More specifically, partial correlations were calculated between the acoustic dissimilarity ma-
250 trix and the "Distance to edge" matrix, using the "Site" matrix as a control variable. This
251 approach isolates the effect of edge distance on acoustic diversity while accounting for the
252 spatial structure of recordings. The analysis can be applied to different time intervals by
253 pre-filtering the relevant matrices, allowing exploration of edge effects over the course of the
254 day.

255 To build the dataset, six days were randomly selected per site among those with complete
256 recordings covering all precipitation-free time intervals to create a balanced dataset. This
257 choice is based on the work of (Gasc *et al.*, 2018a), which indicates that six days are generally
258 enough to characterize the acoustic diversity of a given point in New Caledonian forests of
259 the same area. For each day selected, acoustic indices were averaged over eight three-hour
260 intervals (00-03 h, 03-06 h, ..., 21-24 h). This protocol could theoretically generate a total
261 of 1440 records (30 sites \times 6 days \times 8 intervals). However, to preserve the homogeneity of
262 the dataset, we excluded site 17 due to an insufficient number of valid days, and only four
263 days could be retained for sites 2, 7bis and 29. This gave us a final total of 1368 records
264 that we structured along four hierarchical dimensions: distance to edge, site, day and time
265 interval.

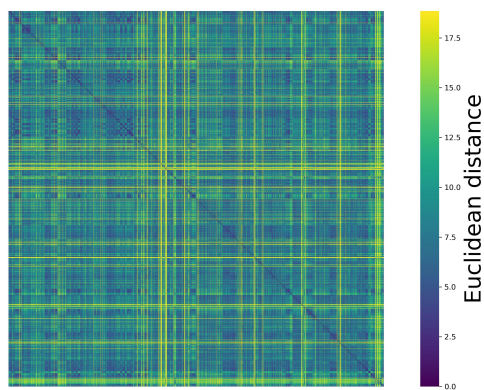
266 In addition, we investigated at which distance the edge effect is fading. Practically, we
267 investigated at which distance a significant acoustic variation can be detected based using
268 this acoustic dissimilarity matrix. This complete matrix was divided into sub-matrices, each
269 corresponding to recordings from a single distance from the edge. A Pearson correlation was
270 performed between each pair of sub-matrices to assess the similarity of structure between
271 the sites of different distances.

272 **G. Unveiling relevant ecoacoustic indices of RSA with the “bubbles” method**

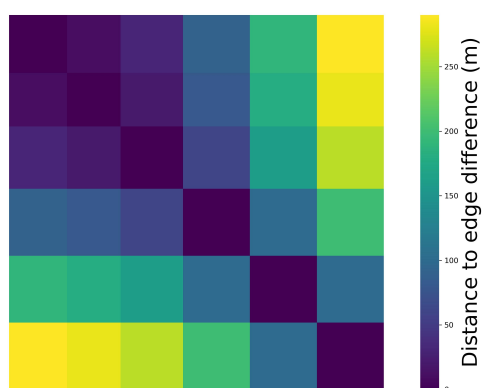
273 The RSA method used here is effective in detecting an edge effect based on acoustic
274 characteristics, in this case, ecoacoustic indices. However, it can be described as opaque,
275 as we do not know precisely which indices are decisive or to what extent each contributes
276 to the detection of this effect. It therefore remains difficult to understand exactly which
277 information embedded in the ecoacoustic indices is the most relevant in the sense of RSA
278 correlations.

279 To improve interpretability of the results, certain methods from the cognitive sciences
280 and psychophysics have recently been adapted to the analysis of machine learning models
281 such as classifiers (Thoret et al., 2021, 2023, 2024) and can be applied to RSA (Giamundo
282 *et al.*, 2025). This is the case of the “bubbles” method developed by (Gosselin and Schyns,
283 2001) in the field of visual perception, to identify the elements of a visual stimulus used by
284 an observer to make a decision, for instance recognizing the gender of someone from their
285 face. The principle consists of randomly masking the stimulus, leaving only small areas
286 called “bubbles” visible so that only certain portions of the information are accessible on

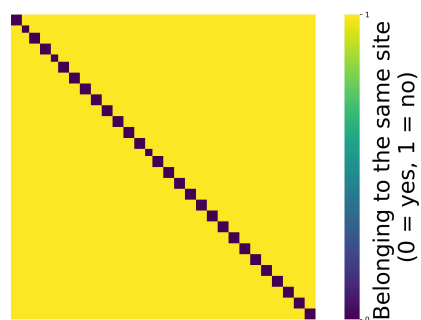
Acoustic edge effect of biophony



A



B



C

FIG. 3. Dissimilarity matrices used in the RSA. (A) “Acoustic” matrix, (B) “Distance to edge” matrix, (C) “Site” matrix.

287 each trial. The principle consists of randomly masking the stimulus, leaving only small areas
288 called “bubbles” visible so that only certain portions of information are accessible on each
289 trial. Repeating this procedure makes it possible to estimate which features are most often
290 associated with correct decisions. Applied to ecoacoustics, each feature corresponds to an
291 acoustic index, and its contribution to RSA correlations can be evaluated by perturbing the
292 index vector and testing its effect on correlation scores.

293 In practice, we introduce multiplicative noise by randomly removing 15 indices at each
294 iteration and recalculating the partial correlation between the acoustic dissimilarity ma-
295 trix and the “Distance to edge” matrix, controlling for “Site”. After 10000 iterations, the
296 resulting distribution of correlation coefficients identifies which indices are most decisive
297 in detecting the edge effect, while accounting for redundancy and collinearity common in
298 ecoacoustic indices.

299 **III. RESULTS**

300 We first analysed the structuring of acoustic diversity with RSA to characterize patterns
301 of homogeneity in deeper forest areas and to evaluate the existence of an edge effect. We
302 then assessed the contrasted contributions of ecoacoustic indices to this effect, identifying
303 the most informative indices and comparing their influence between daytime and nighttime
304 soundscapes.

305 **A. Influence of forest edge on acoustic diversity**

306 **1. Homogeneity of acoustic structures in deeper forest areas**

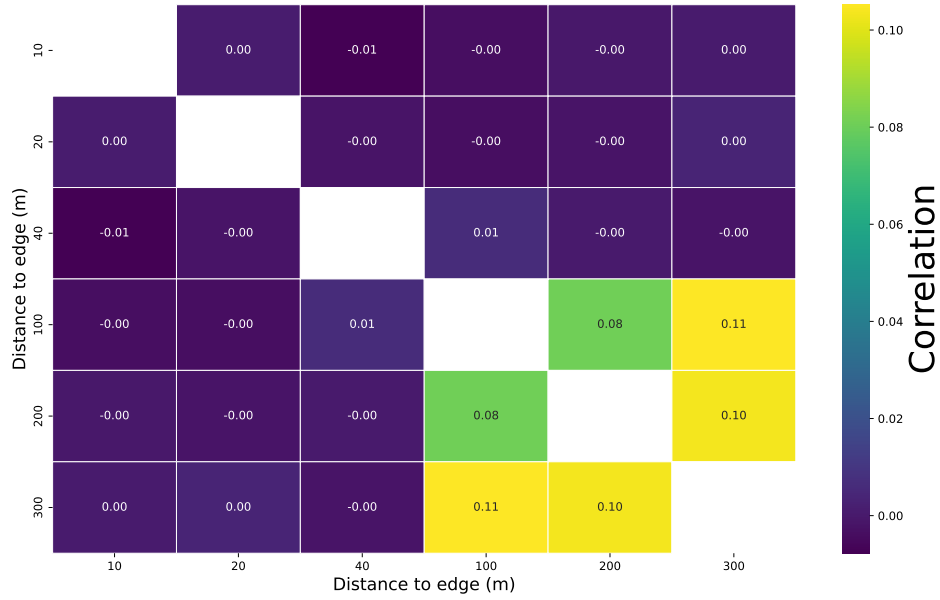
307 The results suggest a stronger similarity between the acoustic diversity structures at
308 distances of 100 m, 200 m, and 300 m, indicating a certain homogeneity of the soundscapes
309 in these deeper areas of the forest. A complementary analysis was carried out by separating
310 the data according to daytime (05:00-18:00) and night-time (18:00-05:00) periods and showed
311 that the average relationship for distances of 100, 200, and 300 m was 0.063 during the day,
312 compared with 0.033 at night (4).

313 **2. Significant edge effect on acoustic diversity**

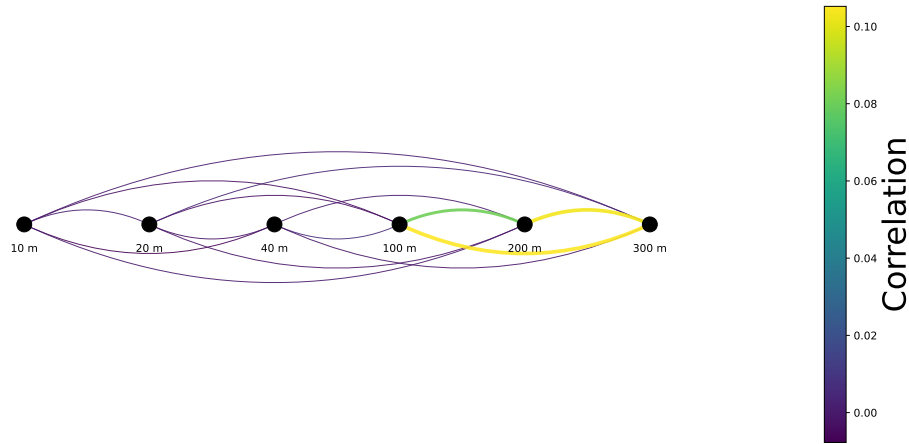
314 Results show a significant correlation between the acoustic dissimilarity matrix and the
315 “Distance to edge” matrix: $r = 0.0228$ (CI95% [0.0206; 0.0247], $df = 933658$), which is
316 still higher than would be expected under the null hypothesis. This correlation reaches r
317 $= 0.0267$ (CI95% [0.0220, 0.0306], $df = 269742$) for the day-time data, while $r = 0.0201$
318 (CI95% [0.0157, 0.0242], $df = 193750$) for the night-time data.

319 Although the magnitude of these correlations is low, their statistical significance indi-
320 cates that distance from the edge exerts an influence on the structure of perceived acoustic
321 diversity. These results suggest the existence of an edge effect, albeit a moderate one. It is
322 also possible that the real impact of this effect is partially masked by other factors, such as
323 local environmental variations, biological dynamics that are independent of the edge, or the
324 presence of certain uninformative acoustic indices that introduce noise into the data.

Acoustic edge effect of biophony



(A)



(B)

FIG. 4. Average correlations between acoustic dissimilarity submatrices according to distance to edge represented by (A) a matrix and (B) a diagram.

325 Overall, our results indicate that distance from the forest edge affects acoustic diversity.
326 Partial correlation analysis of the three matrices reveals a significant relationship, stronger
327 during daytime, while analysis of only the acoustic dissimilarity matrix shows that sound-

328 scape structures become more homogeneous beyond 100 m, highlighting a detectable edge
329 effect.

330 **B. Contrasted contributions of ecoacoustic indices on the edge effect detection**

331 Results show that among the 59 indices included in the analysis, 32 contributed positively
332 to the observed correlation while 27 displayed negative weights (5). The most informative
333 indices include NDSI (0.2281), Hf (0.2241), HPairedShannon (0.2136), and SKEWf (0.2005).

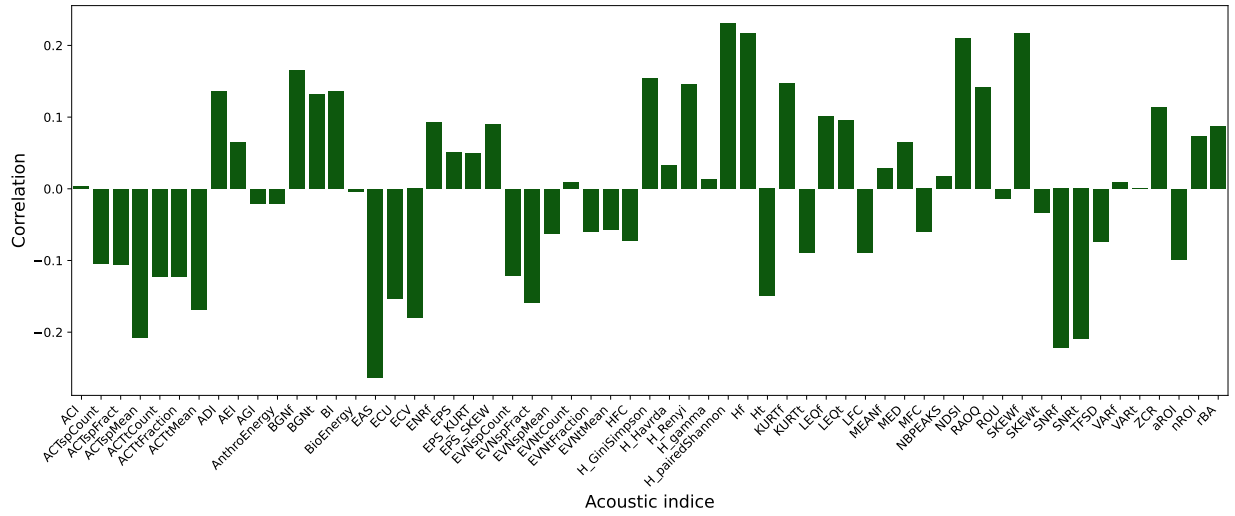
334 By removing these 27 negative indices and recalculating the partial correlation we obtain
335 a coefficient of $r = 0.0555$ (CI95% [0.0523, 0.0563], $df = 933658$), a significant improvement
336 compared to the initial score ($r=0.0228$).

337 Analysis reveals distinct profiles in the importance of the acoustic indices between the
338 daytime and nighttime periods (5). When only the indices with a positive contribution are
339 retained for each time interval, the partial correlation reaches a coefficient of $r = 0.0448$
340 (CI95% [0.0410, 0.0490], $df = 269742$) for the day-time, compared with $r = 0.0564$ CI95%
341 [0.0526, 0.0603], $df = 193750$) for the night-time period.

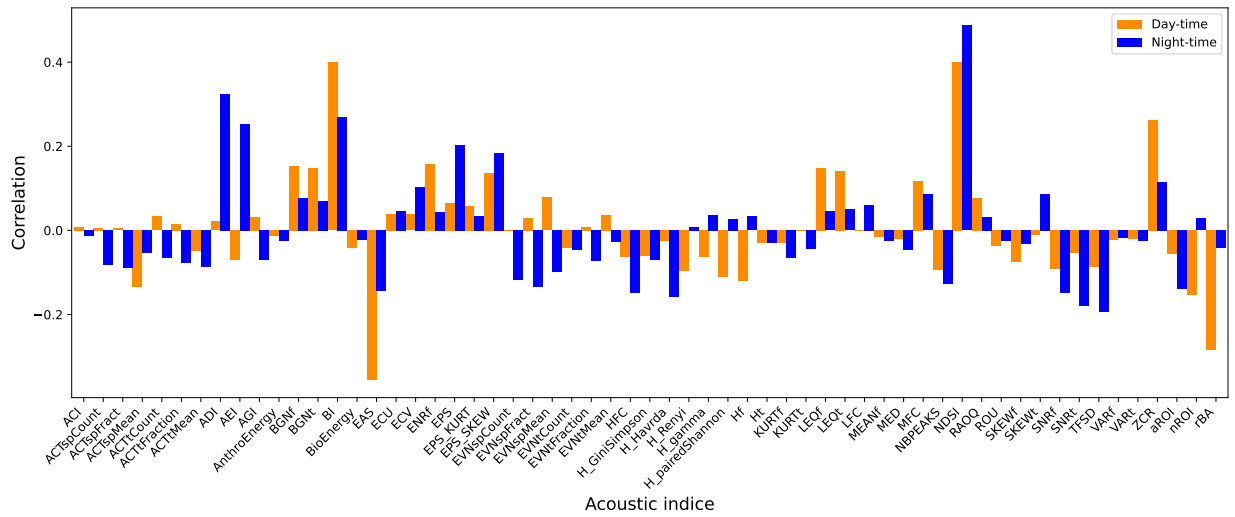
342 **IV. DISCUSSION**

343 This study aimed to assess whether an edge effect on fauna acoustic diversity in forests
344 on ultramafic soils in New Caledonia can be detected. Methods from ecoacoustics were
345 combined with multivariate statistics and explainability techniques. A wide range of eco-
346 acoustic indices was calculated from recordings collected at various distances from the edge.
347 These measurements were first used to filter out undesirable recordings with a machine

Acoustic edge effect of biophony



(A)



(B)

FIG. 5. Histogram of the importance of each index in the partial correlation between the acoustic dissimilarity matrix and the “Distance to the edge” matrix, controlling for the site effect. (A) Results obtained by analysing the entire dataset, (B) Results obtained by analysing separately data collected during the “day-time” represented in orange and the “night-time” in blue.

348 learning classifier trained to detect rain. The relationship between acoustic diversity and
 349 distance from the edge was then quantified and characterized. The contribution of different

350 indices was unveiled using correlations between dissimilarity matrices and an explicability
351 method based on reverse correlation. The main finding of our study was to reveal, in New
352 Caledonia forest context, a significant edge effect for animal communities using a biophony
353 analysis, with a detected acoustic activity threshold at 100 meters from forest edge. From a
354 methodological standpoint, this study exemplifies the interest of combining all indices with
355 an explainable pipeline to identify which indices contributed most to detecting this effect
356 and highlighted differences between daytime and nighttime patterns.

357 **A. An acoustic edge effect consistent with botanical patterns**

358 The analysis of the acoustic dissimilarity matrices revealed an overall sound structure
359 that was not very similar between the different distances to the edge of the forest, suggesting
360 strong acoustic heterogeneity at the edge of the forest. However, the sites located at 100, 200,
361 and 300 meters show positive correlations between them ($r =$ approximately 0.1), indicating
362 a gradual homogenization of the soundscape beyond 100 meters. These results are consistent
363 with the botanical observations of (Blanchard *et al.*, 2023), which also suggest a diminishing
364 edge effect beyond this distance in terms of floristic diversity. They are also in line with the
365 work of (Laurance *et al.*, 2011) on tropical forests, where a similar threshold, around 100
366 meters, was identified for the richness and composition of plant communities. Our result,
367 therefore, supports the existence of a genuine edge effect on faunal activity, perceptible
368 in the overall structure of the soundscape, the intensity of which seems to decrease with
369 distance, potentially reaching a plateau of homogeneity in the deeper areas of the forest.

370 This homogenization can be interpreted as a return to more stable ecological conditions that
371 are less subject to abiotic or human disturbance at the edges.

372 **B. Other factors contribute to the acoustic diversity**

373 Partial correlation analysis of the dissimilarity matrices was used to isolate the effect of
374 distance from the edge on acoustic dissimilarity, controlling for the site effect. The results
375 show a weak but significant correlation ($r = 0.02$) when all the acoustic indices are considered.
376 This result suggests that the acoustic structure is influenced by factors other than simple
377 distance from the edge, or that some of the indices considered introduce noise that masks a
378 clearer relationship.

379 In order to identify the most informative contributions of the indices, the bubble and
380 reverse correlation methods were used. Excluding indices with a negative impact (values
381 below 0) more than doubled the partial correlation compared to the initial value, showing
382 that some indices can add more noise than information in a specific context. This improve-
383 ment indicates a significant improvement in the analysis, thanks to a data-driven selection
384 of indices.

385 These results show the importance of selecting indicators beforehand: not all indicators
386 are equally sensitive to the ecological phenomena under study. Their redundancy or sensi-
387 tivity to noise can alter the quality of the relationships observed, so they must be discarded
388 in order to improve the accuracy of the acoustic analyses. In addition, the information pro-
389 vided by the acoustic indices may vary according to the time interval: the indices used to

390 detect a correlation between acoustic dissimilarity and distance from the edge vary according
391 to the time of day.

392 Finally, an additional avenue of analysis would be not to exclude the indices associated
393 with a negative impact, but to include them as inverse contributors in the detection of the
394 edge effect. These indices could provide useful ecological information and taking them into
395 account could refine the overall interpretation of the prediction system.

396 **C. On the interest of combining numerous ecoacoustic indices**

397 The analyses conducted in this study reveal that certain acoustic indices have a high
398 explanatory power with regard to distance from the forest edge. This is particularly the
399 case for the NDSI (Normalized Difference Soundscape Index), Hf (spectral entropy) and
400 SKEWf (spectral asymmetry) indices. Conversely, more commonly used indices such as
401 the ACI (Acoustic Complexity Index) and BI (Bioacoustic Index), which are widely used in
402 ecoacoustic literature, show little contribution here. This divergence highlights an important
403 limitation of approaches based on a small number of indices chosen a priori: they risk
404 obscuring acoustic dimensions that are nevertheless informative in a specific context. The
405 approach adopted here, based on an exhaustive analysis integrating all indices at once and
406 then distilled by explanatory method, allows the selection of truly relevant indices without
407 prior assumptions. However, this ‘data-driven’ approach is not free from bias: some rare
408 indices or those strongly correlated with others may be unfairly excluded. Furthermore,
409 indices considered informative in a given context (e.g. forests on ultramafic soils in New
410 Caledonia) are not necessarily transferable to other ecosystems; this remains to be tested.

411 Thus, combining traditional and explainable approaches appears to be a complementary
412 strategy for refining the ecological relevance of the indices selected.

413 **D. Explicability and interpretability of models in ecoacoustics**

414 One of the major contributions of this work lies in the use of explainability methods to
415 interpret the results produced by classification methods that are often considered opaque. In
416 the context of ecoacoustics, these models can detect complex relationships between acoustic
417 indices and ecological variables, but without necessarily providing keys to understanding the
418 underlying mechanisms. This is precisely where explainability comes in: by applying the
419 bubble method, it was possible to open the ‘black box’ and determine which acoustic cues
420 are to provide high correlations between matrices. This has not only given us a better under-
421 standing of how the soundscape is organized in relation to distance from the forest edge but
422 also revealed which acoustic components convey relevant ecological signals. Explainability
423 is, therefore, a powerful methodological response to the problem of tool opacity, reconnecting
424 the statistical performance of models to a more graspable ecological interpretation.

425 **E. Limitations**

426 This work has made it possible to characterize the presence of an edge effect on the
427 acoustic soundscape within the Caledonian forests, but several limitations and possible
428 improvements should be highlighted. First, all analyses were based on a single acoustic
429 representation: ecoacoustic indices. Although this innovative approach allows sound infor-
430 mation to be condensed into synthetic measurements, it remains reductive compared to the

431 spectro-temporal richness contained in the raw signals. Direct use of representations such
432 as spectrograms, modulation spectra (Chi *et al.*, 2005; Elliott and Theunissen, 2009; Thoret
433 *et al.*, 2021b) or joint-time frequency scattering (Andén *et al.*, 2019) could reveal finer signa-
434 tures, increase the degree of interpretability by making information associated with distance
435 from the edge more intuitive. Finally, this study focuses solely on the acoustic gradient
436 associated with distance from the edge. A comparative analysis with other gradients, such
437 as botanical gradients (Blanchard *et al.*, 2023), should further refine our understanding of
438 the relationship between distance from the edge, the ecological content of the environment,
439 and acoustic variability. This dual perspective, floristic and acoustic, structural and func-
440 tional, would provide an integrated framework for evaluating the ecological impact of forest
441 fragmentation in New Caledonia.

442 V. CONCLUSION

443 This study explored the effect of distance from the forest edge on acoustic diversity in
444 ultramafic forests in New Caledonia. Thanks to the analysis of ecoacoustic indices geome-
445 try with Representational Similarity Analysis, a significant edge effect has been observed.
446 Thanks to an explainable approach, the indices related to this edge effect, NDSI, HPaired-
447 Shannon , Hf and SKEWf have been unveiled. They seem particularly prominent during
448 the daytime, suggesting an increased influence on the daytime acoustic activity of species.

449 Furthermore, a convergence of acoustic profiles is observed beyond 100 meters from the
450 forest edge, which is consistent with the results obtained by botanical studies conducted in
451 the same area.

452 Several avenues for further development can be envisaged. First, the use of artificial
453 intelligence models has optimized the processing of a massive dataset, in particular through
454 the automatic filtering of disturbed recordings. Second, the explainability method currently
455 applied to acoustic indices could be extended to the direct analysis of spectrograms. Such an
456 approach would make it possible to identify the precise frequency signatures that characterize
457 different distances from the forest edge. Next, a more detailed hourly analysis, incorporating
458 biological rhythms (such as bird singing periods), could reveal more subtle edge effects that
459 may be masked in aggregated analyses.

460 Extending the protocol to other ecosystems, with more points per distance, would allow
461 the robustness and transferability of the results to be tested. The goal is to develop auto-
462 mated, reliable and non-invasive monitoring tools to monitor ecological fragmentation via
463 soundscapes.

464 Finally, this approach opens broader prospects in the field of conservation, particularly
465 in areas that are difficult to access. Acoustic monitoring, a non-intrusive and automatable
466 method, could be particularly relevant in environments such as the marine environment,
467 where traditional ecological monitoring methods are costly or logistically limited.

468 In this sense, the approach developed here could contribute not only to the ecological
469 management of Caledonian forests, land-use planning and the preservation of endemic bio-
470 diversity, but also to a broader transformation of ecological monitoring tools in contexts
471 marked by challenges of resilience to increasing anthropogenic and climatic pressures.

472 Finally, in the context of Human Auditory Ecology ([Lorenzi *et al.*, 2023](#)), this study
473 raises the question of the auditory perception of distance to the edge is interesting in itself.

474 This question would be of great interest to be addressed with regard to the knowledge in
475 spatial hearing. Such a context may help decipher how humans might have learned to use
476 acoustic information from natural auditory scene in order to infer information about their
477 environment.

478 **VI. CONFLICT OF INTEREST**

479 The authors declare no conflict of interests.

480 **VII. DATA AVAILABILITY**

481 Data can be accessed upon reasonable request.

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Acoustic edge effect of biophony

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