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2 Using the multivariate Hawkes process to study interactions between multiple
3 species from camera trap data

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19 Open Research: Data and code (Nicvert et al., 2023) are available on Figshare at

20 <https://doi.org/10.6084/m9.figshare.24552157.v3>.

21 **Keywords**— African savanna; camera trap; interaction network; inter-specific interactions; multivariate
22 Hawkes process; reactive response; Snapshot Safari; spatio-temporal interactions

Abstract

Inter-specific interactions can influence species' activity and movement patterns. In particular, species may avoid or attract each other through reactive responses in space and/or time. However, data and methods to study such reactive interactions have remained scarce and generally limited to two interacting species. Nowadays, the deployment of camera traps opens new opportunities but adapted statistical techniques are still required to analyze interaction patterns with such data. We present the multivariate Hawkes process (MHP) and show how it can be used to analyze interactions between several species using camera trap data. Hawkes processes use flexible pairwise interaction functions, allowing us to consider asymmetries and variations over time when depicting reactive temporal interactions. After describing the theoretical foundations of the MHP, we outline how its framework can be used to study inter-specific interactions with camera trap data. We design a simulation study to evaluate the performance of the MHP and of another existing method to infer interactions from camera trap-like data. We also use the MHP to infer reactive interactions from real camera trap data for five species from South African savannas (impala *Aepyceros melampus*, greater kudu *Tragelaphus strepsiceros*, lion *Panthera leo*, blue wildebeest *Connochaetes taurinus* and Burchell's zebra *Equus quagga burchelli*). The simulation study shows that the MHP can be used as a tool to benchmark other methods of inter-specific interactions inference and that this model can reliably infer interactions when enough data is considered. The analysis of real data highlights evidence of predator avoidance by prey and herbivore-herbivore attraction. Lastly, we present the advantages and limits of the MHP and discuss how it can be improved to infer attraction/avoidance patterns more reliably. As camera traps are increasingly used, the multivariate Hawkes process provides a promising framework to decipher the complexity of interactions structuring ecological communities.

1 Introduction

Inter-specific interactions affect many aspects of ecological communities. For instance, they influence ecosystem services (Valiente-Banuet et al., 2015), species assembly via biotic filtering (Ovaskainen et al., 2017) and the behavior of interacting species. In particular, interactions are one of the factors that structure the way in which animal species move in the landscape and adjust their habitat choices or activity times (Palmer et al., 2022). Mobile animals can respond to interactions by avoiding or seeking proximity with individuals of other species, depending on the positive or negative outcome of the interactions. For instance, prey can avoid their predators (Say-Sallaz et al., 2019), competing species can avoid each other (Cornhill et al., 2022; Searle et al., 2021), or herbivores can forage together to reduce predation risk or increase access to preferred foraging resources (Beaudrot et al., 2020). In this paper, we will use the term “interaction” to refer to the attraction or avoidance of a species by another one, even though “interaction” also refers to the underlying process to the attraction/avoidance pattern.

These interactions (as defined above) can occur in space and/or time, at different scales. Species can adjust their space use in response to the expected distribution of other species (proactive spatial interaction, Palmer et al., 2022). Species can also alter their daily activity patterns (e.g. Karanth et al., 2017) in response to other species (proactive temporal interaction). However, some species could also exhibit a reactive response to the presence of other species, i.e. change their behavior in response to the actual presence of a species sometime before at a given location (e.g. Karanth et al., 2017; Parsons et al., 2016). This type of response could be mediated, for instance, by olfactory (Cornhill and Kerley, 2020; Kuijper et al., 2014) or auditory cues (Hettena et al., 2014). Investigating these reactive interactions is particularly promising as it allows us to identify fine-grained patterns that could be missed by approaches aggregating data in space or in time (Cusack et al., 2017; Frey et al., 2017; Parsons et al., 2022).

Investigating such fine-scale responses is very challenging, as it requires an intensive sampling effort to monitor multiple species in space and time. In this context, camera traps open new opportunities to study the spatial and temporal activities of multiple species (Caravaggi et al., 2017). Camera trap arrays allow for

72 the collection of multiple species occurrences and, therefore, the monitoring of entire communities for large
73 areas continuously in time (Pardo et al., 2021). Hence, camera traps can produce massive amounts of data
74 and offer new possibilities to study interactions between several species at multiple scales. Moreover, they
75 are relatively cheap and easier to set up than classical fieldwork survey techniques (e.g. transects),
76 especially for rare or elusive species or in remote areas. As camera traps become more affordable and
77 automated species identification methods from pictures are being developed with deep learning, camera
78 trap data (and other passive sensors data) will likely become more abundant in the future (Caravaggi et al.,
79 2017).

80 With camera trap data, interspecific interactions are mostly studied at a broad spatial or temporal scale. To
81 do this, data are often aggregated so that either the spatial or the temporal aspect is completely ignored.
82 There are two main approaches for this purpose: comparing species' daily activities patterns (Ridout and
83 Linkie, 2009) or spatial occupancy patterns (e.g. with the multispecies occupancy model of Rota et al.,
84 2016). Such methods provide a measure of the proactive attraction or avoidance strategy, with species
85 adapting their space or time use in anticipation to other species' presence or absence (Palmer et al., 2022).

86 However, other approaches have combined spatial and temporal aspects to infer reactive
87 attraction/avoidance strategies (frequently called *spatio-temporal interactions* in the literature (Karanth
88 et al., 2017; Murphy et al., 2021; Niedballa et al., 2019; Prat-Guitart et al., 2020)). Most methods using
89 camera trap data quantify only the temporal aspect of reactive interactions: therefore, we will call the
90 inferred patterns *reactive temporal interactions*. The majority are based on the computation of time
91 intervals between the detections of two species at a given place (e.g., Harmsen et al., 2009): here, we call
92 this family of methods *inter-event times methods*. The distribution of time intervals can then be contrasted
93 according to the order of appearance of species (Parsons et al., 2016; Prat-Guitart et al., 2020) or
94 summarized by a statistic that is compared to values obtained under a null model (usually data permutation,
95 Cusack et al., 2017; Galindo-Aguilar et al., 2022; Karanth et al., 2017; Murphy et al., 2021). For a
96 comparison of different approaches to infer reactive temporal avoidance with time interval measures, see

97 [Niedballa et al. \(2019\)](#). Other more recent approaches use point processes, which allow us to integrate
98 temporal dependence in a model-based framework ([Kellner et al., 2022](#); [Schliep et al., 2018](#)).

99 Although all methods described above are useful to study reactive interactions, they usually focus on pairs
100 of species and can therefore be unsuitable for studying complex interaction networks. For instance, these
101 methods can identify spurious interactions between two species if other species are involved in the
102 interaction network but not considered in the analysis. Moreover, they summarize the effect of a species on
103 another one by a single value (e.g., the median of the time interval, [Karanth et al., 2017](#)), thus ignoring the
104 multiscale and possibly time-dependent changes in the attraction/avoidance patterns (but see [Cusack et al.,](#)
105 [2017](#)).

106 In this paper, we propose the multivariate Hawkes process (MHP) ([Hawkes, 1971](#); [Lambert et al., 2018](#)) as
107 a modeling framework to infer reactive interactions between multiple species from passive sensors such as
108 camera traps. Hawkes processes belong to the family of point processes which allow for the analysis of
109 species capture events in continuous time, thus avoiding any data aggregation procedure. In Hawkes
110 processes, species' interactions are modeled as pairwise interaction functions which depend on the time
111 elapsed between species detections. The MHP used in this article is generative and offers the possibility to
112 simulate occurrence data, given parameters specification. It also comes with an inference procedure which
113 allows to adjust the pairwise interaction functions from observed data. It deals properly with indirect effects
114 caused by species interaction chains, thus minimizing the risk of inferring spurious interactions. We believe
115 that this model is a useful conceptual framework which is well-suited for assessing reactive temporal
116 interactions between species. We first present the Hawkes process and how it can be used to analyze camera
117 trap data. Then, we describe the MHP used in this article, which was developed by [Lambert et al. \(2018\)](#)
118 and implemented in the R package `UnitEvents` ([Albert et al., 2021](#)). We then show how this model can be
119 used to simulate data to evaluate the performance of statistical methods or to infer interactions from camera
120 trap data. We also apply the MHP on real camera trap data from the Snapshot Safari monitoring program
121 ([Pardo et al., 2021](#)) to infer reactive temporal interactions between five mammal species. Finally, we

122 discuss on the usefulness of the MHP and the perspectives on how to develop this model further.

123 **2 Material and methods**

124 All analyses were performed using R statistical software (v4.3.0; [R Core Team, 2023](#)) and the code and data
125 ([Nicvert et al., 2023](#)) are available at <https://doi.org/10.6084/m9.figshare.24552157.v3>.

126 **2.1 Model: the multivariate Hawkes process (MHP)**

127 Hawkes processes are a family of point processes used to describe dependencies between punctual events.

128 These processes belong to the class of self-exciting point processes for which the probability of occurrence

129 at time t depends on the previous events occurrences. The first Hawkes process was introduced in 1971 by

130 Alan G. Hawkes ([Hawkes, 1971](#)). Originally applied to model aftershocks following earthquakes (e.g.

131 [Ogata, 1988](#)), Hawkes processes have been applied in various fields ([Reinhart, 2018](#)), for instance to model

132 crime recurrence in cities ([Mohler et al., 2018](#)), the evolution of prices on the stock market ([Hawkes, 2018](#))

133 or the transmission of action potentials in a network of neurons ([Reynaud-Bouret et al., 2013](#)). Theoretical

134 properties of Hawkes processes have also been thoroughly studied, and numerous extensions have been

135 proposed.

136 Throughout this article, we define an occurrence as a detection of an individual at a camera at a given time,

137 and we do not take imperfect detection into account. To describe the model, we consider data on the

138 occurrences of S species collected on C cameras. In our framework, the data collected on C cameras are

139 seen as C independent realizations of the MHP. Let T_m^{li} denote the m -th instant of punctual occurrence for

140 species i at camera l . Let N_i^l be the total number of occurrences for species i at camera l . We model the

141 occurrence times $(T_m^{li})_{m=1\dots N_i^l, i=1\dots S, l=1\dots C}$ as C realizations of a MHP.

142 To model punctual occurrences, point processes use a latent intensity function, which is a measure of the

143 rate at which events occur in time. When modeling species occurrences from camera trap data, the intensity

144 for a given species represents the rate at which this species occurs at a camera. For species i , the intensity

145 $\lambda_i^l(t)$ at camera l is formally defined as (Daley and Vere-Jones, 2003):

$$\lambda_i^l(t) = \lim_{\delta \rightarrow 0} \frac{\mathbb{P}\{n_{[t, t+\delta]}^{li} > 0\}}{\delta} \quad (1)$$

146 where $n_{[t, t+\delta]}^{li}$ is the number of points occurring between times t and $t + \delta$ for species i at camera l and δ is
 147 an infinitesimally small amount of time. Informally, the intensity of a point process multiplied by a small
 148 amount of time can be viewed as the probability that there will be at least one point occurring around time t .
 149 In this article, we use the R package `UnitEvents` (Albert et al., 2021), available at
 150 https://sourcesup.renater.fr/frs/?group_id=3267, to simulate and infer MHPs. `UnitEvents` is only available
 151 on Linux and Mac OS. However, in the code and data repository for the article (Nicvert et al., 2023), we
 152 provide a Dockerfile allowing to run the analyses from any operating system (including Windows).
 153 `UnitEvents` implements the MHP described in Lambert et al. (2018). In this framework, the intensity of
 154 species i seen on camera l for a Hawkes process with S interacting species is written as:

$$\lambda_i^l(t) = \left(\nu_i + \sum_{j=1}^S \sum_{m \mid T_m^{lj} < t} f_{j \rightarrow i}(t - T_m^{lj}) \right)_+ \quad (2)$$

155 where $\lambda_i^l(t)$ represents the intensity for species i (as defined above) at camera l . ν_i is a positive parameter,
 156 the *background rate*: it represents the basal intensity of species i (in time^{-1} , e.g., day^{-1}) unrelated to
 157 previous occurrences. For instance, ν_i would be low for a rare species and higher for a common species.
 158 $f_{j \rightarrow i}$ is the *interaction function* which represents the influence of an occurrence of species j on species i as
 159 a function of time delay: positive values of $f_{j \rightarrow i}$ represent an attraction of species i by species j , negative
 160 values represent a repulsion and null values independence. In the case $j = i$, the function $f_{i \rightarrow i}$ represents
 161 the interaction between individuals of the same species i . In that case, we will call $f_{i \rightarrow i}$ the *auto-interaction*
 162 *function*: it could reflect for instance the fact that some species are solitary or gregarious. $f_{j \rightarrow i}$ are defined
 163 as piecewise constant functions with K time bins of equal length δ :

$$f_{j \rightarrow i} = \sum_{k=1}^K a_{j \rightarrow i}^k \mathbf{1}_{(k-1)\delta, k\delta]} \quad (3)$$

164 where $\mathbf{1}_{(k-1)\delta, k\delta]}$ denotes the indicator function between delays $(k-1)\delta$ and $k\delta$. The K coefficients $a_{j \rightarrow i}^k$
 165 represent the average number of occurrences of species i gained (if positive) or suppressed (if negative) by
 166 an occurrence of species j in the k -th interval after this occurrence of species j .

167 In this framework, $f_{j \rightarrow i}$ can take negative values, thus allowing to model repulsive effect of species j on
 168 species i . As the intensity λ_i^l must be positive by definition, Equation (2) includes a positive part $(\cdot)_+$.
 169 However, for mathematical reasons, in the following developments we will assume that the negative values
 170 of $f_{j \rightarrow i}$ are never too strong so that the intensity never becomes negative, and the positive part is not
 171 needed. To enforce this assumption, the repulsion terms can only be as strong as the other terms making up
 172 the total intensity.

173 Figure 1 illustrates a realization of a MHP with five species (measured at a single camera) simulated with
 174 `UnitEvents`. In this example, some species attract each other (see the interaction network on Figure 1a)
 175 with the same decreasing discrete exponential interaction function with $K = 12$ time bins of width $\delta = 4$
 176 hours (Figure 1b). The background rate is the same for all species and is fixed to 0.2 occurrences day^{-1} .
 177 The right panel (Figure 1c) shows the simulated species occurrences and associated intensities over time.
 178 When nothing happens, the intensity is fixed at the background rate. When an attracting species occurs, the
 179 intensity of the attracted species peaks, making an occurrence more likely. For instance, each occurrence of
 180 species s_1 gives rise to a peak in the intensity of s_2 . Moreover, when several attracting events occur, the
 181 interaction functions add up, which makes the occurrence of the target species even more likely.

182 2.2 Model inference

183 The inference procedure implemented in the `UnitEvents` package is a fast and scalable LASSO-penalized
 184 (least absolute shrinkage and selection operator) least-squares criterion. It allows to estimate a single MHP
 185 from C realizations (in our setting, this corresponds to C cameras).

186 Let $(\beta_1, \dots, \beta_S)$ denote the parameters of interest for each species $i=1, \dots, S$. Each β_i is a vector of size
 187 $1 + SK$ containing the background rate of species i (ν_i) and the parameters of the interaction functions
 188 targeted to this species i for the S species and the K bins: $\beta_i = (\nu_i, (a_{j \rightarrow i}^k)_{j=1 \dots S, k=1 \dots K})$. Each β_i is
 189 estimated as:

$$\widehat{\beta}_i = \arg \min_{\beta_i} \text{LASSO}(\beta_i) \quad \text{where} \quad \text{LASSO}(\beta_i) = \underbrace{-2 \sum_{l=1}^C \mathbf{b}_i^{lT} \beta_i + \beta_i^T \sum_{l=1}^C \mathbf{G}^l \beta_i}_{\text{least-squares}} + \underbrace{2 \mathbf{d}_i^T |\beta_i|}_{\text{penalization}} \quad (4)$$

190 where T denotes transposition and $|\beta_i|$ is the vector containing the absolute values of the coordinates of β_i .
 191 \mathbf{b}_i^l is an observable vector of size $1 + SK$. If camera l is active between times α_l and η_l , then

$$\mathbf{b}_i^l = \left(N_i^l, \left(\int_{\alpha_l}^{\eta_l} n_{[t-k\delta, t-(k-1)\delta]}^{lj} dn_t^{li} \right)_{j=1 \dots S, k=1 \dots K} \right). \quad (5)$$

192 Its first value is the total count of species i observed on camera l . The other values represent the total
 193 occurrence counts of the species j observed in the k -th bin before the occurrences of species i at camera l .
 194 \mathbf{G}^l is also an observable matrix defined as:

$$\mathbf{G}^l = \int_{\alpha_l}^{\eta_l} \mathbf{c}_t^l \mathbf{c}_t^{lT} dt \quad (6)$$

195 where \mathbf{c}_t^l is a vector of size $1 + SK$ defined as $\mathbf{c}_t^l = \left(1, \left(n_{[t-k\delta, t-(k-1)\delta]}^{lj} \right)_{j=1 \dots S, k=1 \dots K} \right)$. Its first value
 196 is 1 and other values represent the occurrence counts of species j occurring on camera l in the k -th bin
 197 before time t .

198 The term $2\mathbf{d}_i^T |\beta_i|$ of Equation (4) corresponds to the LASSO penalization: it can make some parameter
 199 values shrink to zero and thus avoid overparameterization. The strength of this LASSO penalization is
 200 controlled by the weights vectors \mathbf{d}_i , which are computed from the data and tuned by a unique user-chosen
 201 parameter γ (equation derived from Lambert et al. (2018) adapted from Hansen et al. (2015)):

$$\mathbf{d}_i = \sqrt{2\gamma \log(S + S^2K) \sum_{l=1}^C \int_{\alpha_l}^{\eta_l} \mathbf{c}_t^{l^2} dn_t^{li} + \frac{\gamma \log(S + S^2K)}{3} \max_{l=1 \dots C} \left(\sup_{t \in [\alpha_l, \eta_l]} |\mathbf{c}_t^l| \right)}. \quad (7)$$

202 The choice of a suitable value for γ is crucial for model selection, because γ ensures that only relevant
 203 nonzero parameters are kept in the model. However, choosing a good value for γ is difficult: it has been
 204 evaluated by simulations in Lambert et al. (2018) and Hansen et al. (2015), and we proceeded likewise in
 205 this article.

206 In the current implementation of `UnitEvents`, three flavors of the LASSO penalization are available. We
 207 choose the "Bernstein Vanishing LASSO" (BVL), where the penalization in Equation (4) is first applied to
 208 discard weak interaction parameters. Then, the estimates of the remaining non-null parameters are obtained
 209 by minimizing the least-squares criterion. Lastly, an additional step is introduced to remove parameters
 210 smaller than a data-computed threshold (see Lambert et al., 2018, for details and justification).

211 In the implementation of `UnitEvents`, the bins width δ and the number of bins K for the interaction
 212 functions are fixed by the user, who also needs to choose a value of γ a priori. The other parameters
 213 (interaction functions coefficients $a_{j \rightarrow i}^k$ and background rates ν_i) are fitted as described before.

214 **2.3 Simulation study**

215 We generated camera trap-like data under the MHP and used these simulated data to (i) evaluate the
 216 performance of a method and (ii) tune the penalization parameter for inference on real data.

217 **2.3.1 Simulation parameters**

218 For these two objectives, we conducted two sets of simulations in the same conditions. We considered an
 219 interaction network with five species $s_{i=1 \dots 5}$ where s_1 attracts s_2 and s_2 attracts s_3 and s_4 (network from
 220 Figure 1a). This network represents a difficult case as an inference method should detect direct interactions,
 221 but not spurious indirect interactions (e.g., $s_1 \rightarrow s_3$) and identify that species s_5 is not interacting with
 222 others. In this simulation, we define the true interactions by decreasing exponential functions until two days:

$$f(t) = \begin{cases} a \exp\left(-\frac{\ln(2)}{0.5}t\right) & \text{if } t < 2 \\ 0 & \text{if } t \geq 2 \end{cases} \quad (8)$$

223 where a is the interaction strength. The half-life of this function is the denominator of the decrease rate, so
 224 that this function will reach half of its initial value at $t = 0.5$ day. The interaction strength a for the true
 225 model varied from 0.01 to 1 day⁻¹. Here, the interaction strength represents the maximum intensity of the
 226 pairwise interaction function for $t = 0$. An analogous interaction function is shown in Figure 1b with $a = 1$
 227 and with discrete bins. The background rate was fixed at 0.1 day⁻¹ for all species.

228 The simulated trapping length varied from 20 to 500 trapping days for each camera over 25 cameras
 229 (making up to 12 500 trapping days in total). For each condition, 30 different data sets were generated to
 230 evaluate the variability of the inference.

231 We evaluated the performance of the inference by computing the true positive and true negative rates. The
 232 true positive rate is the proportion of inferred nonzero interactions over the count of true nonzero
 233 interactions. The true negative rate is the proportion of inferred null interactions over the count of true null
 234 interactions.

235 **2.3.2 Evaluating a method to infer reactive temporal interactions**

236 We illustrated how synthetic data generated with the MHP can be used to evaluate the performance of a
 237 method to infer inter-specific interactions, considering the inter-event times method of [Murphy et al.](#)
 238 (2021). We applied the method of [Murphy et al. \(2021\)](#) on simulated data (simulation settings are
 239 described in Section 2.3.1). This method consists in computing the median time between directed pairwise
 240 species occurrences (excluding pairs from the same species) for observed and randomly permuted data (999
 241 permutations). The permutation procedure involved randomly changing the cameras' labels of species
 242 occurrences (for details, see [Murphy et al., 2021](#)). Finally, the statistical significance of interactions was
 243 estimated by comparing the median time for observed and permuted data. We used a significance threshold
 244 of 5 % with a Holm correction for multiple testing.

245 **2.3.3 Choice of the penalization parameter**

246 To choose the best penalization parameter γ in the context of interactions inference, we used a simulation
247 approach (simulation settings are described in Section 2.3.1). We inferred MHPs with different values of γ
248 (between 0.3 and 1) from the simulated datasets. For the inference parameters, we chose $K = 12$ bins of
249 width $\delta = 4$ hours (2 days in total, corresponding to the length of the simulated interactions functions).
250 Then, we defined any inferred interaction function as null if all bins were zero over the function's support,
251 and non-null if at least one bin was not null.

252 **2.4 Application: analysis of interactions between five species in the African** 253 **savanna**

254 We used the MHP to infer interaction functions between five species of the southern African savanna:
255 impala *Aepyceros melampus*, greater kudu *Tragelaphus strepsiceros*, lion *Panthera leo*, blue wildebeest
256 *Connochaetes taurinus* and Burchell's zebra *Equus quagga burchelli*.

257 **2.4.1 Data collection**

258 Camera trap data were collected as part of the long-term Snapshot Safari monitoring program (Pardo et al.,
259 2021). Snapshot Safari is a network of camera trap grids set up in more than 30 locations in southern
260 Africa. The camera trap design consists in grids of 5 km² in each location, in which cameras were fixed at
261 about 50 cm high. Cameras were automatically triggered by motion or heat using passive infrared sensors.
262 Each camera was programmed to take a series of three images within 1–5 seconds of each other by day, and
263 only one image by night to minimize disturbance occasioned by white flash. For this analysis, we focused
264 on six camera trap grids in the savanna biome in northern South Africa: the Associated Private Nature
265 Reserves (around Kruger National Park), Kruger National Park, Madikwe Game Reserve, Pilanesberg
266 National Park, Somkhanda Game Reserve and Venetia Limpopo Nature Reserve (see Figure 2).

267 **2.4.2 Data pre-processing**

268 Pictures were classified by citizen science using the Zooniverse platform (www.zooniverse.org), where
269 pictures were available online and annotated by more than 150 000 volunteers (see [Pardo et al., 2021](#), for
270 more details).

271 For this analysis, we filtered out cameras where capture events were too rare (less than 2 pictures in total or
272 less than 1 picture every 30 days on average). We did not filter for independence between occurrences of
273 the same species. However, since the Hawkes model does not allow two capture events to occur
274 simultaneously, if two or more individuals of different species were seen on the same capture event, their
275 occurrence time was randomly shifted from one minute in advance to one minute later. For multiple
276 individuals of the same species seen simultaneously, the occurrences of the individuals were counted as a
277 single event (i.e. an occurrence corresponds to an individual or a group of individuals of a given species).
278 After the filtering procedure, there were 72 703 occurrence events (corresponding to 70 409 unique
279 pictures) collected on 179 cameras in total. Cameras were active during 503 ± 224 (sd) days on average
280 (min: 19 days, max: 851 days), amounting to 90 176 trapping days on all cameras. All pictures were taken
281 between June 2017 and November 2019.

282 **2.4.3 Parameters inference**

283 We inferred the parameters of a MHP using interaction functions defined by $K = 6$ bins of $\delta = 6$ hours (36
284 hours in total). This parametrization should allow us to capture the dynamics of reactive temporal
285 interactions with enough granularity while keeping a relatively low number of parameters to estimate to
286 allow reliable inference. Using results of the simulation study (see Section [3.1.2](#)), we decided to set the
287 value of the penalization parameter γ to 0.5.

288 **3 Results**

289 **3.1 Simulation study**

290 **3.1.1 Evaluating a method to infer reactive temporal interactions**

291 We used data simulated under the MHP to evaluate the method of [Murphy et al. \(2021\)](#). As expected, the
292 ability to detect interactions (true positive rate) increases with the strength of the interactions (Figure 3).
293 Provided the interaction strength a is big enough (at least 0.1 day^{-1}), the ability to detect interactions
294 increases with the number of trapping days, which indicates that a significant sampling effort is required to
295 infer interactions from camera trap data (at least 300 trapping days for 25 cameras when the interaction
296 strength is above 0.2 day^{-1}). More surprisingly, when the interaction strength is high (at least 0.5 day^{-1}), the
297 true negative rate decreases with increasing sampling effort. This indicates that the method wrongly detects
298 interactions between non-interacting species. Additional investigations (Appendix S1: [Section S1](#)) show
299 that these errors mainly concern the detection of spurious indirect interactions between species involved in
300 interaction chains (e.g., $s_1 \rightarrow s_3$).

301 **3.1.2 Choice of the penalization parameter**

302 The simulation study to find suitable values for the penalization parameter γ led to the results shown in
303 Figure 4. Unsurprisingly, the ability to detect true interactions (true positive rate) increases with the
304 number of trapping days and the strength of interactions. When the penalization is too low ($\gamma = 0.3$; top
305 row), the model tends to identify interactions between non-interacting species (reducing the true negative
306 rate) but this problem vanishes when sampling effort increases. On the other hand, a high penalization
307 ($\gamma = 1$; bottom row), moderately improves the true negative rate, but more importantly dramatically
308 hampers the ability to detect non-null interactions for small interaction strengths. A value of $\gamma = 0.5$ seems
309 to be a good compromise allowing to efficiently detect true interactions when their strength is not too small
310 (at least 0.1 day^{-1}) but avoiding the identification of false interactions. It gives good results especially when

311 the sampling lasts more than 400 trapping days per camera. Hence, we decided to use a penalization
312 parameter of $\gamma = 0.5$ to infer the parameters of a MHP from real data (see Section 3.2). Lastly,
313 supplementary analyses show that the spurious interactions are randomly distributed and not biased towards
314 indirect interactions as with the inter-event times method (Appendix S1: Section S1).

315 **3.2 Analysis of real data**

316 We fitted a MHP using the occurrence data of five species (impala, greater kudu, lion, blue wildebeest and
317 Burchell's zebra) collected with camera traps. Adjusting the model only took a few seconds on a personal
318 computer. The resulting interaction functions are shown in Figure 5 and the inferred background rates in
319 Appendix S1: Section S2.

320 Background rates represent the basal intensity for each species, independently of the others. They vary
321 greatly between species, with impala having a much higher background rate than other species (impala:
322 0.212 day^{-1} ; zebra: 0.040 day^{-1} ; kudu: 0.035 day^{-1} ; wildebeest: 0.022 day^{-1} and lion: 0.003 day^{-1}). As
323 expected, they are strongly related to the total occurrence count of each species.

324 Regarding the interaction functions, the inferred parameters highlight a strong auto-attraction for the first
325 bin (0-6h), varying between 1.5 and 2.25 day^{-1} depending on the species. Regarding the cross-species
326 interaction functions, many herbivores are attracted to each other. Impalas follow or avoid kudus
327 (depending on the delay), wildebeests and zebras; zebras follow impalas, kudus and wildebeests;
328 wildebeests mainly follow zebras. Other interactions between herbivores are negligible. These
329 herbivore-herbivore interactions are composed of a short-term attraction (during the first six hours after an
330 occurrence) and of a medium-term attraction (twelve to thirty-six hours after an occurrence), except
331 impalas that are not attracted by zebras on the short-term. Additionally, impalas seem to avoid kudus six to
332 twelve and thirty to thirty-six hours after an occurrence. We notice that these interactions are asymmetrical
333 (impalas and zebras follow other species much more than they are followed). Regarding prey-predator
334 interactions, lions do not follow or avoid any other species. Zebra and impala seem to avoid lion in the next

335 6 hours following an occurrence of this predator. Finally, the inferred interactions are relatively robust to a
336 change in bin width, as we show in Appendix S1: [Section S4](#), where we performed the inference on the
337 same dataset with different bins widths (3 and 9 hours).

338 **4 Discussion**

339 It is now well established that identifying the signature of inter-specific interactions from species
340 occurrence data is generally difficult ([Blanchet et al., 2020](#); [Popovic et al., 2019](#)). However, camera trap
341 data provide additional information (time and order of occurrence of species) that can help to relate
342 occurrence patterns to underlying inter-specific interactions. In this context, the Hawkes model provides a
343 new theoretical framework to analyze species occurrences sampled in continuous time using camera traps.
344 This model aims to predict the probability of occurrence of a given species at a given time taking into
345 account the previous occurrences for several species. By considering the exact time at which species occur,
346 this model provides a detailed picture of species reactive temporal interactions under the form of interaction
347 functions (here, the term “interaction” refers to the attraction/repulsion pattern). These functions allow a
348 multiscale description of interactions as they characterize how the interaction strength varies with time,
349 contrary to other methods that provide a single measure of attraction/avoidance. Moreover, these functions
350 are directed: the inferred interactions can be asymmetrical, as expected for ecological interactions. The
351 toolbox associated to this model offers the possibility to generate data and design simulation studies or to
352 infer parameters from real data.

353 We used the multivariate Hawkes process to generate camera trap-like datasets with different properties
354 (sampling effort, strength of interactions) and showed how these simulated data can be used to evaluate the
355 performance of a method or to tune inference parameters. Both simulation studies demonstrate that camera
356 trap data can be used to detect reactive temporal interactions between species but this requires a substantial
357 sampling effort, especially when the strengths of interactions are low. In our simulation setup (five species,
358 background rates of 0.1 day^{-1} and only attractions), results suggest that at least one year of sampling with

359 25 cameras is required to obtain reliable inference, and this holds only if the interaction is strong enough
360 (interactions of strength 0.01 day^{-1} are not reliably detected in our simulations). These requirements would
361 probably be higher if more species were considered, especially for rare species (smaller background rate).
362 Hence, we agree with [Schliep et al. \(2018\)](#) that more data are needed to estimate reliable reactive
363 interaction patterns than to estimate species occupancy. In this context, the MHP provides a powerful
364 simulation tool to design and assess the quality of sampling protocols in camera trap studies by adopting a
365 virtual ecologist approach ([Zurell et al., 2010](#)). The simulation study also highlights the limits of methods
366 focusing on pairs of species to analyze interactions between multiple species. By focusing only on two
367 species at a time, these approaches are not able to disentangle direct interactions from indirect effects due to
368 other species in interaction chains (Appendix S1: [Section S1](#)). Moreover, the correction for multiple testing
369 we applied in our study was not sufficient to eliminate these spurious interactions, and we can assume that
370 this issue is more important in the literature when no correction is considered. As a consequence,
371 inter-event times methods tend to overestimate the number of interactions, especially when their strength is
372 high or the sampling effort increases. However, such spurious interactions were inferred only when we
373 simulated quite strong interactions, and more investigations would be needed to estimate the range of
374 interaction strengths we can expect in natural conditions. On the contrary, the Hawkes process used here is
375 multivariate by nature, so it works on all species simultaneously and thus allows to identify interactions
376 between two species conditionally to the other species, similar to graphical models in the context of
377 co-occurrence analysis ([Popovic et al., 2019](#)). This modeling approach thus provides a better picture of the
378 interaction network of the whole community.

379 The real dataset analysis shows how the MHP can be used to infer reactive interactions between five
380 mammal species from the African savanna. In our example, since we defined an occurrence as the presence
381 of an individual or a group of individuals, the values of the interaction functions represent the number of
382 individuals or groups of individuals that are attracted/repulsed by other occurrences, and the typical group
383 size to consider depends of the species. We identified strong auto-attractions for all species but also

384 attractions between different herbivores and avoidance of lion by two herbivore species (impala and zebra).
385 Whereas it could be tempting to interpret these results as behavioral responses of species to an underlying
386 interaction (e.g. avoidance in response to predation), the Hawkes model only characterizes
387 attraction/avoidance patterns and particular care should be taken when interpreting these results, especially
388 since no covariates were included in this analysis. We discuss these different interpretations of the observed
389 patterns in terms of ecological processes below and we make suggestions to improve the MHP to untangle
390 the different hypotheses.

391 We identified auto-attractions for all species, indicating that the occurrence of a given species increases the
392 probability to have another occurrence of the same species at the same place. This could be due to the same
393 individual lingering in front of the camera, especially since no independence filter was applied (although
394 cameras are configured to pause for one minute between trigger events), or this could reflect sociality
395 among individuals, as an individual or a group may attract other individuals for gregarious species. This
396 could also stem from habitat selection processes, so that numerous subsequent occurrences could be
397 observed at cameras located in species' preferred habitats. Lastly, circadian rhythms impose physiological
398 constraints on the activity times of each species and thus could increase their occurrence rate at certain
399 times of the day. When they are not taken into account, as is the case here, circadian rhythms could affect
400 the interaction functions in the short term (0-6h) and also induce a 24-hour periodicity in the interaction
401 functions. This issue is clearly illustrated using simulated data (see Appendix S1: [Section S3](#)) and could
402 partly explain the short-term (0-6h) auto-attraction, and probably most of the weak auto-attraction observed
403 around 24h for impala, kudu, wildebeest and zebra (Figure 5).

404 Regarding the cross-species interactions, we observed attraction patterns between some herbivores, which
405 could be explained by four mechanisms. First, temporal niche convergence could induce attraction between
406 species when they are active at the same time of day and if they also share the same location. In our
407 example, the four herbivore species are diurnal with crepuscular activity peaks. However, if the apparent
408 attraction was due to shared circadian rhythms, we would probably observe a symmetry of interaction

409 functions (i.e., if $s_1 \rightarrow s_2$ is not null, $s_2 \rightarrow s_1$ is also not null) as the order of appearance of species at a
410 camera during the activity time would be random. This is not always the case in the example depicted here,
411 for instance between zebra and kudu. Second, species sharing the same kind of preferred environment
412 might show apparent attraction. However, as for the temporal niche, this spatial niche should induce a
413 symmetrical interaction pattern. Third, the apparent attraction between species could be due to
414 mixed-species grouping strategy, whereby some species forage together in mixed groups. Such groups are
415 thought to mitigate predation risk and/or to improve access to resources (Beaudrot et al., 2020). Moreover,
416 when it comes to predation risk, in addition to the dilution effect (a simple number game), there is a possible
417 benefit to being associated with more vulnerable species (Fitzgibbon, 1990). This implies a directionality
418 in the choices of association, an asymmetry well captured by the MHP. In our analysis, some species are
419 attracted by others in the first hours following an occurrence (impala follows kudu and wildebeest; zebra
420 follows wildebeest, kudu and impala; and wildebeest follows zebra). Interestingly, these associations have
421 been described in the literature (Meise et al., 2019; Pays et al., 2014; Schmitt et al., 2014). Finally, another
422 mechanism that could explain interactions between herbivore species is grazing succession (Bell, 1971),
423 which describes a strategy by which species sequentially use the same grazing area: less selective species
424 come first (non-ruminants and species with higher body mass), followed by more selective species (smaller
425 ruminants). In our results, some herbivore species are attracted with a delay (impala following zebra, kudu
426 and wildebeest; wildebeest following zebra; zebra following wildebeest and impala). Impala following
427 other (bigger) species and wildebeest following the non-ruminant zebra are compatible with the grazing
428 succession theory (Bell, 1971). However, the temporal scale of this potential grazing succession occurs at a
429 temporal scale much shorter than the one classically described (McNaughton, 1976, 1985).

430 Regarding the apparent avoidance of lions by zebras and impalas, here again this could stem from temporal
431 niche divergence (lion is a nocturnal species whereas impala and zebra are diurnal). This apparent
432 repulsion could also reflect a strategy of impala and zebra to minimize predation risk by reactively avoiding
433 lions, i.e. responding to actual cues of lions presence (olfactory or auditory cues for instance) at a fine

434 spatio-temporal scale, as documented for zebras ([Courbin et al., 2016](#)).

435 As discussed with the real dataset analysis, a major challenge remains linking attraction/repulsion patterns
436 identified by the MHP to underlying ecological processes. To date, the implementation used in this paper
437 cannot include covariates to model variations in species' background occurrence rates. This calls for two
438 major improvements: first, we could include temporal covariates to account for the variation of species
439 occurrence rate through the day according to their diel cycle. Second, we could include environmental
440 covariates to account for species habitat preferences across the landscape. Works such as [Fujita et al.](#)
441 [\(2018\)](#) for temporal covariates or [Carstensen et al. \(2010\)](#) for temporal and environmental covariates could
442 be helpful in this perspective. Further developments include accounting for the imperfect detection by
443 camera traps, which is known to be an important issue ([Burton et al., 2015](#)). In this regard, [Kellner et al.](#)
444 [\(2022\)](#) recently developed an occupancy model with a detection process occurring in continuous time with
445 a Markov-modulated Poisson process, and a similar approach could be envisioned with the MHP.

446 Here, we inferred a MHP from camera trap data, but this modeling approach could be extended to other
447 types of passive sensors collecting occurrence data in continuous time (e.g., microphones, hydrophones)
448 that are increasingly used to monitor biodiversity. In particular, using a spatially explicit extension of the
449 Hawkes process (first described by [Ogata, 1998](#), in the context of earthquakes occurrences) could be
450 especially suited to include a spatial dependency between camera traps or to analyze GPS collar data and
451 estimate interaction functions in time and space.

452 The Hawkes process could also be used for other applications than estimating inter-specific interactions, for
453 instance to study behavioral synchrony within a group (e.g. [Pays et al., 2012](#)) or to infer animal social
454 networks from occurrence data (e.g. [Jacoby et al., 2016](#)).

455 Even if more developments are required to improve ecological inference, we contend that the MHP and
456 other point processes methods offer an adapted theoretical framework for the analysis of time-continuous
457 occurrence data while contributing to an explanation of interactions among herbivores and between
458 herbivores and predators.

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6 Conflict of interests

The authors declare no conflict of interest.

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7 Figure captions

Figure 1: Example of a realization of a multivariate Hawkes process. (a) shows the interaction network between five species (each arrow represents a non-null interaction function). In this example, all auto-interaction functions $f_{i \rightarrow i}$ are null. (b) shows the shape of the interaction functions ($K = 12$ time bins of width $\delta = 4$ hours) corresponding to arrows in the interaction network (a). (c) shows a realization of the Hawkes process with the interaction network and the interaction functions shown in (a) and (b). For this simulation, the background rate was set to 0.2 occurrences day^{-1} for all species. For each species i , the above panel shows the intensity λ_i and the bottom panel shows the species occurrences. Each time an attracting species occurs, the intensity for the attracted species peaks and then decreases as dictated by the interaction function shape.

Figure 2: Study sites. Six protected areas were surveyed with camera traps for this study: the Associated Private Nature Reserves (APN), Kruger National Park, Madikwe Game Reserve, Pilanesberg National Park, Somkhanda Game Reserve and Venetia Limpopo Nature Reserve. Data © OpenStreetMap contributors.

Figure 3: Evaluation of an inter-event times method (Murphy et al., 2021). Panels represent different interaction strengths (maximum value of the interaction function). The x-axis represents the sampling length and the y-axis represents the performance: true positive rate (full dots, continuous line) or true negative rate (circles, dashed line). Points indicate values for the 30 repetitions, lines joins the medians, and the colored area represents the 2.5th and 97.5th percentiles.

Figure 4: Performance of the inference with the multivariate Hawkes model. In columns, the interaction strength (maximum value of the interaction function). In rows, the different values of the penalization parameter γ . The x-axis represents the sampling length and the y-axis represents the performance (true positive rate or true negative rate). Lines, points and colors have the same meaning as for Figure 3.

Figure 5: Inference of interactions from real data using the multivariate Hawkes model. The top plot shows the auto-interaction functions (between occurrences of the same species). The bottom plot shows

641 cross-species interactions, where the intensity of species in rows is affected by species in columns. The
642 horizontal dashed line represents zero. Note that the y-axis scale is different between auto- and
643 cross-species interactions. Silhouette images from [PhyloPic](#) by Lukasiniho (wildebeest), Margot Michaud
644 (lion), Robert Hering (kudu), Zimices (zebra) and an unknown author (impala).

8 Figures

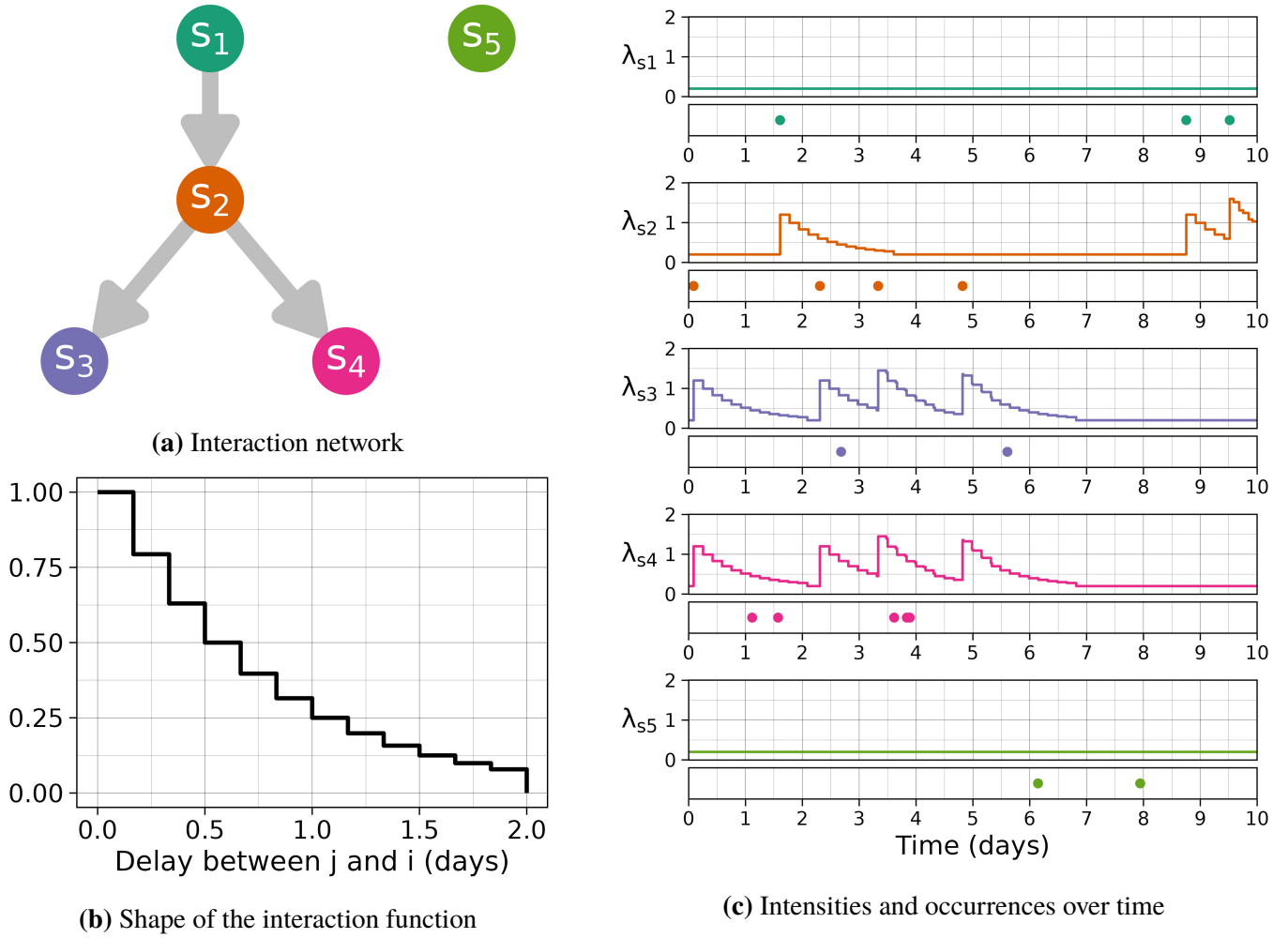


Figure 1

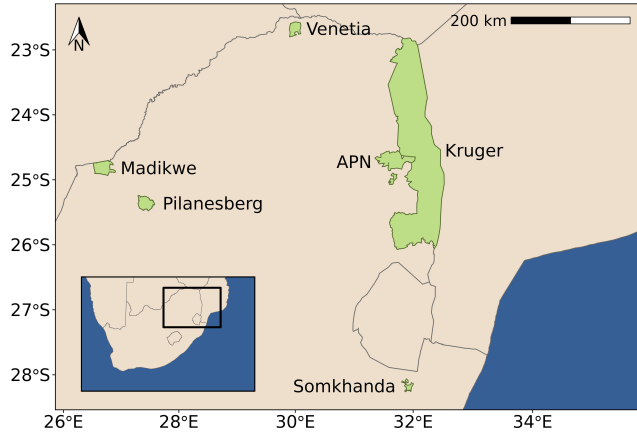


Figure 2

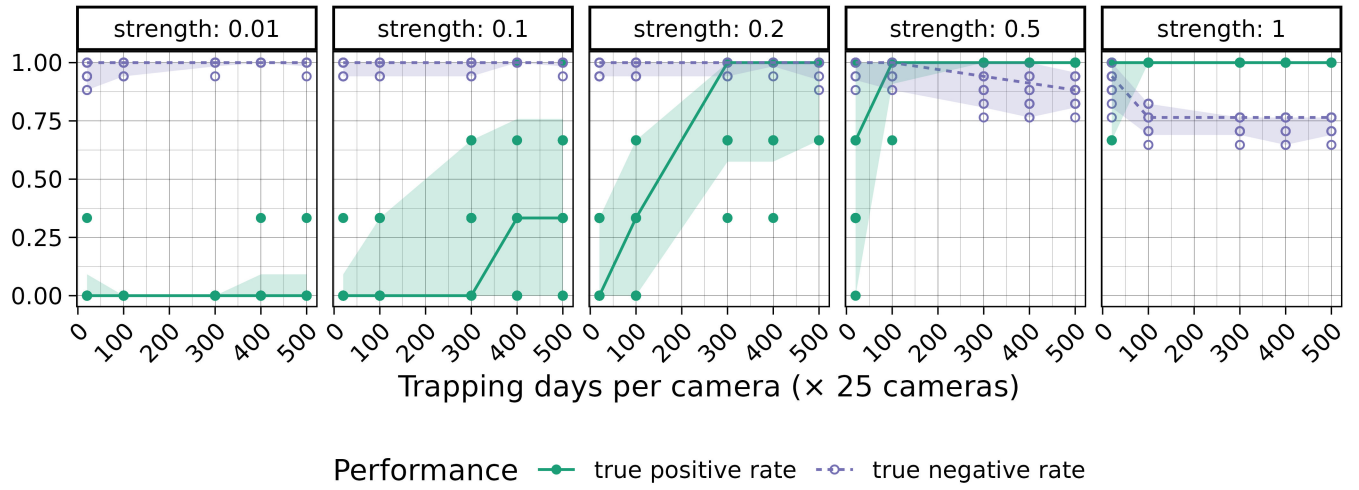


Figure 3

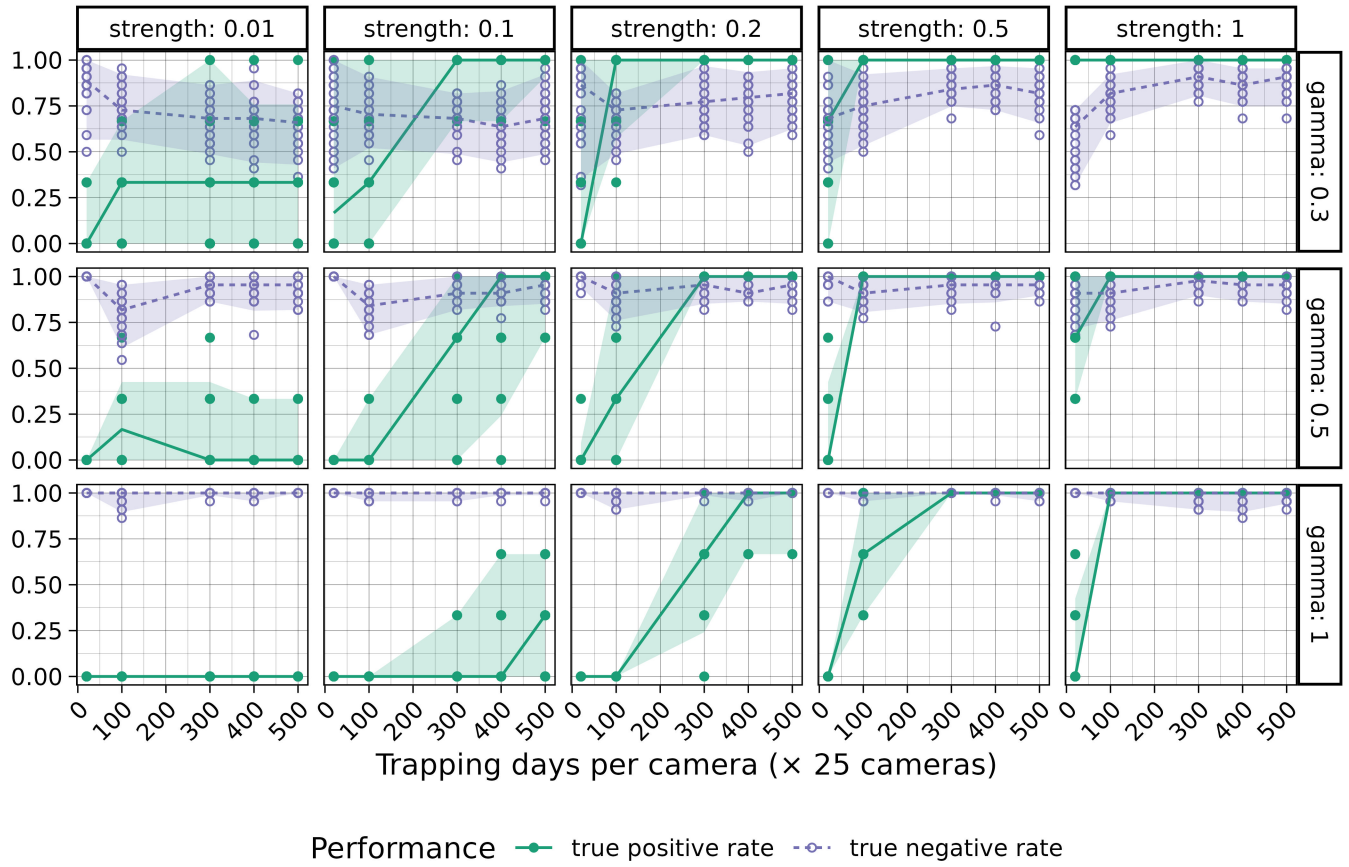
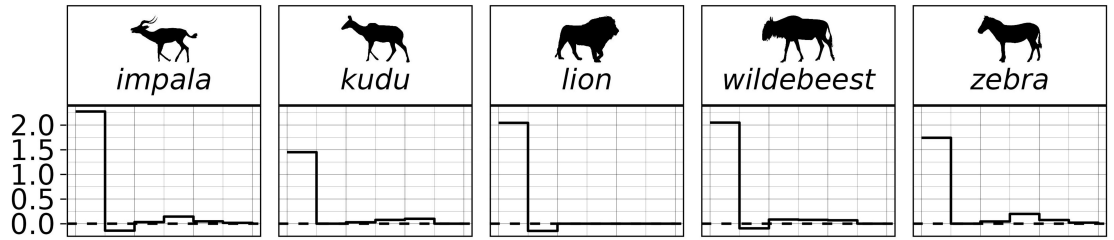


Figure 4

Auto-interactions



Cross-species interactions

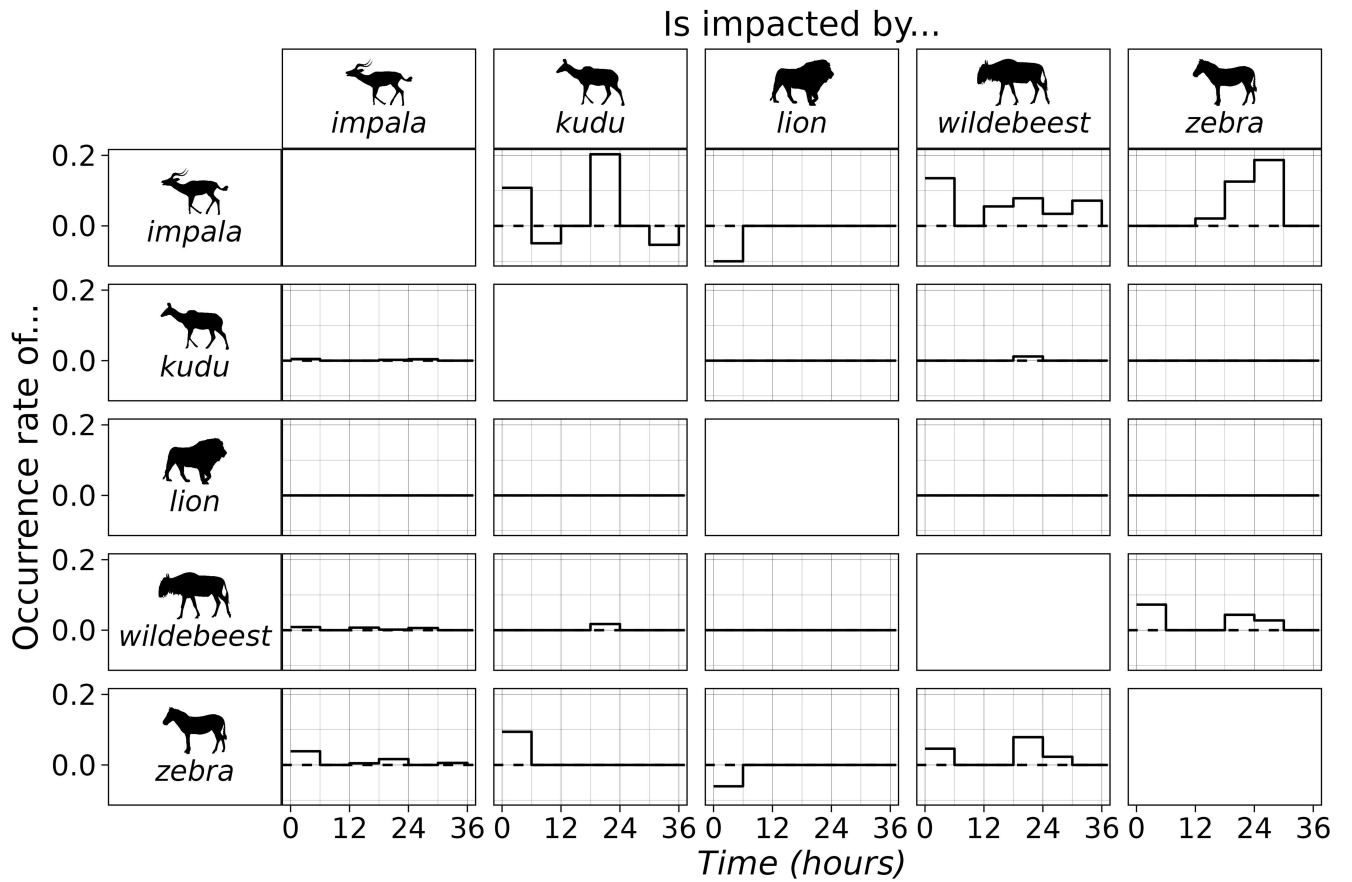


Figure 5