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The scale of effect depends on operational definition of forest cover-evidence from terrestrial mammals of the Brazilian savanna

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1 **The scale of effect depends on forest definition – evidence from terrestrial**
2 **mammals of the Brazilian savanna**

3

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41

42 **Keywords**

43 Scale of response; Tree cover; Spatial scale; Multi-scale model; Mammal; Herbivore; Brazil

44

45

46 **Abstract**

47 *Context* The underlying mechanisms determining the scale at which species interact with their
48 environment are still poorly known.

49 *Objective* We investigated the spatial extent at which landscape structure affects the occurrence of
50 four species of terrestrial mammal herbivores in the Brazilian savannas and tested whether those
51 scales could be explained by species ecological traits and habitat definition.

52 *Methods* Using maps of forest cover, camera trapping and occupancy modelling, we determined the
53 relations between three landscape metrics (percentage of forest cover, patch density and edge
54 density) and the occurrence of four species. To determine the optimal scale of effect for each
55 species, we computed landscape metrics at different spatial extents (from 0.5 to 10 km radius) from
56 camera trap locations and for three forest maps, considering different definitions of what is a
57 “forest” (minimum of tree cover of 25, 50 or 75% per pixel).

58 *Results* The occupancy models revealed scales of effect of 0.5 to 2 km, and those scales overlapped
59 highly among species. However, the strength of the effect depends highly on how forest is defined,
60 being stronger when forest was defined with greater tree cover, particularly for forest-dwelling
61 species.

62 *Conclusions* Besides biological traits, the way habitat is defined shapes our ability to detect scale of
63 effects. Thus, if we want to properly identify scales of effect for multiple species, it is necessary not
64 only to adopt a multi-scale approach, but also to use multiple definitions of habitat, considering
65 particularities of how each species interact with their environment.

66

67 **Introduction**

68

69 Identifying the spatial scale at which species respond to landscape structure, or the scale of effect
70 (Jackson and Fahrig 2012) has become an important scientific challenge when investigating
71 species-environment relationships (Fahrig et al. 2011; Redon et al. 2014; Miguet et al. 2016, 2017).
72 As species might respond to a specific landscape attribute at a particular scale, studies have pointed
73 out the importance to consider multiple spatial scales when investigating the effects of habitat
74 change on species (Levin 1992). This is particularly relevant in the understanding of mechanisms
75 underlying the erosion of biodiversity, especially the mechanisms for which human activities shape
76 land use and land cover changes (Newbold et al. 2015; Püttker et al. 2020). Knowing the scale at
77 which species respond to landscapes should help decision-makers in designing management plan to
78 maintain and restore biodiversity and their habitats (Haines-Young 2009).

79 From an ecological standpoint, optimal spatial extents are mainly determined by the scale at
80 which ecological processes are expected to operate for the studied organisms. Huais (2018) argued
81 that ecologists do not usually know *a priori* which are those optimal spatial extents, mainly due to a
82 lack of a full understanding of the underlying biological processes (Jackson and Fahrig 2015).
83 However, several studies have clarified the link between spatial scale and the ecological responses
84 of species under investigation (Levin 1992; Saab 1999; Crawley and Harral 2001; Chase and
85 Leibold 2002; Leibold et al. 2004; Rahbek 2005; Gabriel et al. 2010; Delsol et al. 2018). For
86 instance, the effect of spatial extent has been particularly investigated in habitat selection (Fortin et
87 al. 2008) and animal movement (Fryxell et al. 2008). For large mammal herbivores, Mayor et al.
88 (2009) have reported spatial scales at which ecological and behavioural mechanisms underlying
89 habitat selection should be investigated. Analysing the activities of animals at fine scales (i.e., 1 –
90 100 m) allows to investigate bite, feeding site and patch selection, while studies at local scales (100
91 m – 10 km) allow the understanding of habitat selection and home range, and finally, research at
92 broader, regional scales (>10 km) are relevant for migration and (meta)population dynamics
93 comprehension (Johnson 1980; Danell et al. 2006).

94 Without knowing *a priori* what is the appropriate scale of study, landscape ecologists
95 commonly assess landscape variables at multiple scales to select the scale that yields the best
96 species-landscape relationship (e.g. Brennan et al. 2002; Holland et al. 2004; Holland and Yang
97 2016; Melo et al. 2017; Huais 2018). Different methods or statistical analyses have been proposed
98 in the literature to test for the effect of landscape features on species attributes (e.g., richness,
99 abundance, composition) at different spatial scales and to extract their goodness of fit through an
100 appropriate criterion index (e.g., correlation and determination coefficients or AIC). Spatial scales
101 are usually tested by varying spatial extent (e.g., the size of a buffer zone) over which the habitat

102 predictor variable (i.e., a landscape metric) is measured. The scale of effect is commonly derived by
103 plotting the spatial scale (e.g., buffer size) against goodness of fit. This is sometimes challenging
104 because there is a common lack of knowledge on 1) the suitable landscape metrics to investigate the
105 ecological processes, and 2) the appropriate grain extent at which their relationships should be
106 assessed.

107 Biological/ecological traits of species including for instance body size, dispersal distance,
108 home range and habitat specialisation may affect the scale of effect (Miguet et al 2016). Those traits
109 are particularly relevant when they are indicators of animal mobility, a key biological feature which
110 determines the relationship between species attributes and their surrounding space (Bowman et al.
111 2002). Although the empirical studies are not all in agreement, we might expect that the scale of
112 effect would be larger for larger-bodied species because they are more mobile with higher dispersal
113 distance and home range than smaller-bodied species (Jackson and Fahrig 2012; Miguet et al 2016).
114 Thus, when investigating the effect of landscape features on species occurrence, a general guideline
115 for empirical studies is to consider a radius of a landscape to be 4 – 9 times the median dispersal
116 distance or 0.3 – 0.5 times the maximum dispersal distance of a species. Thornton and Fletcher
117 (2014) in their meta-analysis on birds reported a positive correlation between body size and the
118 spatial scale at which species responded to landscape variables. Finally, the scale of effect may
119 differ between specialist and generalist species of similar body-size although this literature is sparse
120 and not in agreement on whether habitat specialists would exhibit a larger or smaller scale of effect
121 (Boscolo and Metzger 2009; Chaplin-Kramer et al. 2013). Comparisons of habitat generalists and
122 specialists have the added difficulty in consistently defining habitat for the different groups.

123 Landscape features, related to both land use and land cover composition and spatial
124 configuration, could also affect the scale of effect. Particularly, the type of maps of land use and
125 land cover that are used as an input to derive patch-based landscape metrics may influence the
126 assessments of scale of effect. This issue is especially relevant in tropical areas dominated by
127 vegetation gradients (ranging from herbaceous layers with sparse trees to shrubland and forested
128 areas, including degraded forests or regenerating forests) where the definition of landscape units can
129 be arbitrary, and low thematic resolution in land cover maps (e.g., a small number of classes) may
130 lead to an overly simplified representation of reality that may not adequately represent how species
131 perceive their environment (Comber et al. 2005; Rocchini et al. 2013). Moreover, the definition of
132 what is a “forest,” for instance, is vague, ambiguous and highly subjective (Bennett 2002) where
133 gradients in tree cover exist. Indeed, hundreds of different definitions of “forest” coexist (Chazdon
134 et al. 2016), and obviously, none of these use a species perspective. While Hansen et al. (2010) used
135 25% of tree cover to map forest cover, Defries et al. (2001) defined forest cover as greater than 60%
136 tree cover. Although using different percent tree cover would thus select different amount of

137 canopy, it could also affect the type of vegetation that would be considered. In tropical and
138 subtropical zones of Africa, Australia and South America, Hirota et al. (2011) reported that percent
139 tree cover in savannas was about 20% and contrasted with 80% in forested areas. While mammal
140 species might respond differently to forest cover (Royo and Carson 2005; Young et al. 2013;
141 Chamailé-Jammes et al. 2016; Ferreguetti et al. 2017; Zimbres et al. 2018), the question whether
142 the percent tree cover used to map forest cover affects the scale of effect of landscape metrics on the
143 occurrence of species has never been studied. This might be critical when modelling the presence of
144 forest dwelling species in complex mosaic of vegetation types such as in Brazil's Cerrado including
145 forests, savannas and grasslands (Bonanomi et al. 2019).

146 The aim of this study is to investigate the scale of effect in four common species of
147 terrestrial mammal herbivores, the Azara's agouti *Dasyprocta azarae*, the collared peccary *Pecari*
148 *tajacu*, the brown brocket deer *Mazama gouazoubira*, and the south American tapir *Tapirus*
149 *terrestris*, using camera traps in the Brazilian Cerrado. First, we studied how the occurrence of
150 those species responded to three landscape metrics commonly used to describe landscape
151 composition (FC: percent of forest cover) and configuration (PD: patch density and ED: edge
152 density) (Lidicker 1999; Bastian et al. 2006; Bennett et al. 2006; Lu et al. 2013; Lowicki 2017).
153 These metrics have also been useful to explain mammal community distribution in Brazil (Mares et
154 al. 1986; Arévalo-Sandi et al. 2018; Bovendorp et al. 2019; Püttker et al. 2020). Second, we
155 investigated whether the definition of forest cover (i.e. 25, 50, or 75% of tree cover) affected the
156 detection of scale of effect of the landscape features on the occurrence of species. Finally, as the
157 four studied species differ in their body-size, dispersal and home range and forest specialisation
158 (Table 1), we investigated whether the scale of effect varied among species with different
159 biological/ecological traits.

160 We ran occupancy models for each species at 8 spatial extents from 0.5 to 10 km using 3
161 different maps of forest cover. We extracted the Akaike Information Criterion (AIC) for each model
162 and examined whether species exhibited scale of effects. We hypothesized that mobility largely
163 determines the relationship between landscape features and occurrence of the studied species. We
164 therefore predicted that larger species with higher dispersal range and home range would exhibit a
165 larger scale of effect than smaller species. In this context, the scale of effect of the South American
166 tapir should be larger than the brown brocket deer and the collared peccary, with the smallest scale
167 of effect in the Azara's agouti. Regarding forest definition (that shaped both land use and land cover
168 composition and spatial configuration), we predicted a stronger or clearer scale of effect in the two
169 forest-dwelling species, the Azara's agouti and collared peccary, when considering high tree cover
170 (e.g., 75%) compared to medium-low tree cover (50 – 25%).

171

172 **Methodology**

173

174 Study site

175 The Bodoquena Plateau region (20°25'29.28" to 21°44'19.72" S and 56°52'24.46" to 56°17'23.36"
176 W) is located in the state of Mato Grosso do Sul, Brazil (Fig. 1a). It is characterized by a mountain
177 chain (altitude 450 – 800 m) with a tropical climate (annual temperature varies between 20 and
178 22°C and rainfall between 1300 and 1700 mm). The study area is within the range of the Cerrado
179 biome (Brazilian savanna) in the region inside and around the *Serra da Bodoquena* National Park
180 (SBNP). The vegetation comprises a mix of alluvial semi-deciduous and submontane deciduous
181 forest (dry forest), wetlands, regenerating areas and agriculture including pastures and crops
182 (Oliveira and Marquis 2002; Klink and Machado 2005). SBNP represented an important protected
183 area due to acting as an ecological corridor of biodiversity and by maintaining remnants of Atlantic
184 Forest in the area. During the last decades, Cerrado has been experiencing a rapid agricultural
185 expansion (Rausch et al. 2019), leading to fragmentation (Strassburg et al. 2017).

186

187 Forest cover, landscape metrics and spatial extent

188 Landscape metrics were computed using forest maps derived from the Global Forest Change
189 project's products (Hansen et al. 2013). We used the "2000 percent tree cover" (TC) product, which
190 corresponds to the proportion of trees per pixel, i.e. the canopy closure for all vegetation taller than
191 5 m in height. This global product is derived from the analysis of time series of Landsat images
192 with a 30 m spatial resolution. We additionally used the "Forest loss year" product from the Global
193 Forest Change project to remove all deforested areas between 2001 and 2017 (year of field
194 collection; see below) from the forest class in the TC, i.e., TC was set to 0 for deforested areas.
195 Based on this updated TC map, we then produced three forest maps for 2017 applying three
196 thresholds of percent tree cover (25, 50, and 75%) (Fig. 2).

197 Each of the three forest maps was then used to derive three landscape metrics: one metric of
198 landscape composition, forest cover (FC), and two additional metrics of landscape configuration,
199 patch density (PD) and the edge density (ED). FC is the proportion of pixels classified as forest in a
200 given area. PD measures the number of forest patches per km² and ED is the total length of all
201 edges of forest patches divided by the buffer area. These three metrics were calculated using the
202 *ClassStat* function from the *SDMTools* package (VanDerWal et al. 2014) in R 3.6.2 (R Development
203 Core Team 2019). Although a large range of landscape metrics could have been explored, we
204 limited this to three variables in our study as (1) they are commonly used in the literature and (2)
205 they allowed an assessment of forest cover and fragmentation in the Cerrado in 2017 when we

206 collected data in the field (Bonanomi et al. 2019). We checked that these three metrics were not
207 significantly correlated.

208 We calculated ED, PD and FC at different scales, here considered as radii from the sampled
209 areas (i.e. buffer radius of 500, 750, 1000, 1500, 2000, 3000, 5000 and 10000 m). The range of
210 spatial extents allowed the investigation of local and dispersal movements of species (Miguet et al.
211 2016) and have been used to explain habitat selection in terrestrial herbivorous mammals (Johnson
212 1980; Danell et al. 2006). We chose to exclude two smaller buffer sizes, 100 and 250 m, as the
213 small number of pixels from Landsat images (30 m spatial resolution) did not provide enough
214 information to assess accurately PD, ED and FC (Strahler et al. 1986; Woodcock et al. 1987).

215 Finally, landscape variables showed scaling relations suggesting that they could be predicted
216 over a wide range of spatial extents in our study area and remained quite constant beyond a buffer
217 radius of 3 km (Electronic Appendices Table S1 and Fig. S1)

218

219 Data from mammal species

220 We deployed a set of 193 camera traps (Reconyx-hyperfire HC500 and Bushnell-trophy Cam HD) in
221 a gradient of forest cover loss in the study area (Fig. 1b). Each camera trap was in the same location
222 on two different periods of 20 consecutive days between May 2016 and December 2017. They were
223 positioned 40 cm above the ground on the nearest tree of a computer-generated random point with a
224 10° inclination towards the ground. To increase detection of animal movement and maximise
225 identification of species, frame rate interval was set up at 3 seconds with 3 pictures per event. At the
226 end of the sampling period, SD cards were extracted and analysed visually using Wild.ID (TEAM
227 Network 2019). Each sampled picture was checked by two observers to reduce misidentification. In
228 this study, we focused on four species of terrestrial mammals typical from Cerrado: Azara's agouti,
229 collared peccary, brown brocket and South American tapir. Their ecological traits including body
230 size, home range, habitat use, diet and dispersal distance are presented in Table 1.

231

232 Occupancy models

233 Creating large buffers around the locations of the 193 camera traps led to spatial overlaps and thus
234 pseudoreplication. To tackle this issue, we used the Focus program (Holland et al. 2004) to conduct
235 a plot-buffer related sampling using 10 000 iterations on the 193 camera trap locations to select a
236 set of spatially independent locations. Based on the retrials, Focus-2.0 randomly selected one
237 combination of 57 independent locations allowing to increase buffer size up to 2 km (Fig. 1b). As
238 the aim of our study was to understand the response of the occurrence of mammal species to the
239 landscape metrics at wide range of different scales, we chose to use this combination to investigate
240 scaling relations beyond 2 km, i.e. 3, 5 and 10 km although some minimal overlapping existed

241 between several neighbouring buffers. Indeed, beyond 2 km, Focus-2.0 would have reduced the set
242 of combinations to 30 camera traps for which occupancy models failed to converge. Thus, we kept
243 the set of 57 selected locations and we then assessed each landscape metric described above at each
244 buffer size and run occupancy models.

245 To investigate the effect of the landscape features (measured for the 8 buffer sizes and 3
246 percent threshold of tree cover) on the occurrence of the four mammal species, we run occupancy
247 models using the *unmarked* R package (Fiske and Chandler 2011). For each of the 57 camera traps
248 and focal species, we implemented a data set of 40 sampled days in which we indicated when the
249 studied species was detected (coded as 1) vs. non-detected (coded as 0). Then, from the 40 sampled
250 days, we built a matrix of 8 sampling occasions of 5 consecutive days each (as in Niedballa et al.
251 2015). Following this method, 13 camera traps (i.e., 23%) have detected the presence of Azara's
252 agouti, 15 (26%) of collared peccary, 13 (23%) of brown brocket deer and 25 (44%) of South
253 American tapir. Over the combination of 57 camera traps, there was a reasonable chance to detect
254 the selected species. Our study assumed that we did have false detections and the absence of
255 detection of a focal species over one period indicated that sites were truly unoccupied during the
256 sampling period or species were very scarce at the sampled sites during the survey.

257 We used the species detection information to investigate the effects of spatial extent of
258 habitat covariates on the probability of species occupancy. We ran occupancy models for which
259 occupancy probability Ψ at each camera trap location and the detection probability p were modelled
260 as a linear function of covariates x_i using logit link functions (see Niedballa et al. 2015 for details).
261 We ran models for each buffer size and species. First, we determined for each species how the
262 probability of detection p should be implemented in null models. We used a stepwise approach
263 starting with a model $\Psi(.)p(.)$ where both occupancy and detection probabilities were constant (i.e.,
264 fixed as 1). As density of understory and weather could affect detection probability around the
265 camera traps, we created two covariates called visibility (contrasting open vs. dense understory) and
266 weather (contrasting rainy vs. dry season). Then we ran three other models $\Psi(.)p(x_i)$ to test whether
267 covariates x_i including visibility around camera trap and weather, or both, affected detection
268 probability p with occupancy probability Ψ constant. We compared these four models of detection
269 ($\Psi(.)p(.)$, $\Psi(.)p(\text{visibility})$, $\Psi(.)p(\text{weather})$, $\Psi(.)p(\text{visibility}, \text{weather})$) using AIC and selected the
270 model with the lowest AIC and ΔAIC higher than 2 with the closest competing model. Finally, from
271 this selected (null) model of detection, we tested the effects of landscape metrics on occupancy
272 probability Ψ at each of the 8 buffer sizes and three landscape metrics calculated from the three
273 forest cover maps (25, 50 and 75%). Thus, for each landscape metric, we ran 8 models that we
274 compared using AIC and null models. All models showing $\Delta\text{AIC} < 2$ from the best fitted models
275 had similar statistical supports. Estimates (\pm SE) of landscape metrics with their P-values affecting

276 occupancy probability were extracted from the best candidate models. Statistical analyses were
277 performed using R 3.6.2 (R Development Core Team 2019).

278

279 **Results**

280

281 Performance of models run at different spatial extents highlighted scale of effects of landscape
282 metrics on the occurrence of three species. Indeed, buffer sizes that showed the strongest statistical
283 supports (i.e. $\Delta AIC < 2$) ranged from 500 to 1500 m in ED (Fig. 3a) and 500 to 2000 m in FC (Fig.
284 3i) in Azara's agouti, from 500 to 750 m in FC in collared peccary (Fig. 3j) and 750 m in PD in
285 brown brocket deer (Fig. 3g) when percent tree cover was higher than 75% (Electronic appendix
286 Table S2). For the other situations in the three species, we did not detect a scale of effects as null
287 models including only covariates on detection probability p provided similar statistical models than
288 candidate models including covariates affecting occupancy probability Ψ (Electronic appendix
289 Table S2). The South American tapir did not exhibit any scale of effect for the three landscape
290 metrics (Fig 3d, h, l).

291 When the threshold of the percent tree cover used to map forest, cover decreased (from 75 to
292 50% and from 50 to 25%), we observed 3 different patterns from the performance of models at the
293 different buffer sizes (Electronic appendices Table S2-4). The range of selected buffer sizes (i.e. the
294 scale of effect) (1) remained similar as for instance in FC in collared peccary, (2) decreased as in
295 Azara's agouti in ED, or (3) was no longer consistent in PD in brown brocket deer (Table 2).
296 Although a range of selected models emerged at 50% tree cover in PD in Azara's agouti, we did not
297 detect any significant effect of this variable (i.e., $P > 0.05$, Table 2). Thus, we did not consider this
298 result as robust. Altogether, our analyses suggest that the species exhibit a stronger scale of effect
299 when considering high tree cover (e.g. 75%) compared to medium-low tree cover (50 – 25%).

300 Finally, regarding the estimate (β) \pm SE associated with the significant effect of each
301 landscape metric extracted from the candidate models with the lowest AIC (buffer size indicated
302 with * in Table 2), the occurrence of Azara's agouti and collared peccary increased with FC, brown
303 brocket deer with PD, and Azara's agouti with ED when the threshold on percent tree cover was
304 75%. When this threshold decreased, the trend did not change in FC as in collared peccary although
305 the strength of the effect felt to nearly significant value in Azara's agouti (Table 2).

306

307 **Discussion**

308

309 Scales of effects varied among mammal species from the Brazilian savannahs, and this variation
310 could be partially explained by species traits, but most importantly, was strongly influenced by how
311 we define forests.

312 The scale of effect of Azara's agouti ranged from 500 to 2000 m (for FC and ED), while for
313 collared peccary it ranged from 500 to 750 m (FC), and for brown brocket deer it was 750 m (PD).
314 The South American tapir did not exhibit any scale of effect on the three landscape metrics. Thus,
315 the spatial extents that have been detected suggest that ecological and behavioural mechanisms
316 underlying the scale of effects occurred at local scale and were associated with habitat selection and
317 home range as reported in medium and large-body-sized herbivore species (Johnson 1980; Danell et
318 al. 2006). These results also suggest that a range of spatial extents (from 500 to 2000 m in this
319 study) should be considered rather than a particular buffer size in the scale of effect of landscape
320 metrics on species occurrence (Moraga et al. 2019). The ability of some species to live or use
321 fragmented sites depended on their biological traits such as body size (Cardillo et al. 2005),
322 ecological requirements (Miguet et al. 2016) or their ability to cross harsh habitats (Pires et al.
323 2002). We predicted that scale of effect would be larger for larger-bodied species because they are
324 more mobile, tend to be move farther and their home range are higher than smaller-bodied species
325 (Bowman et al. 2002; Jackson and Fahrig 2015). From performance of models with 75% tree cover,
326 we did not detect that scale of effect was larger in the largest studied species, the South American
327 tapir, and the scale of effect overlapped highly among the Azara's agouti, collared peccary and
328 brown brocket deer. Thus, body-size as indicator or animal mobility may not be a very strong
329 predictor of the scale of effect in our four studied tropical herbivorous species. The effect of the
330 dispersal distance on the scale of effect need to be tested on a wide range of species including
331 micromammals to address overall conclusions.

332 Contrary to the two studied generalist species, the South American tapir and brown brocket
333 deer, the two forest-dwelling species, the Azara's agouti and collared peccary, exhibited a scale of
334 effect on FC. These results might show that species that are more generalist in their habitat
335 requirements might not be limited by forest cover using agricultural landscape with open areas to
336 achieve their ecological requirements (e.g., food). A previous study in Brazilian Amazon reported
337 that the lowland tapir was one of the species with a high ability to survive in more altered
338 environments including regeneration areas with food opportunities (Teixeira-Santos et al. 2020).
339 The lack of scale of effect on the occurrence of the South American tapir might also be observed if
340 the response is not scale dependent (Martin and Fahrig 2012) or the landscape heterogeneity does
341 not allow to investigate pattern at a larger scale in species with high dispersal range (> 3km for this
342 species, Table 1). As in our study area, landscape variables remain quite fixed beyond a buffer
343 radius of 3 km (Electronic Appendices Table S1 and Fig. S1), the opportunity to detect scale of

344 effect beyond this distance might be limited. Finally, as the effect of ecological traits might interact
345 to explain the scale of effect of forest cover on species occurrence (as for instance the studied
346 smaller bodied size species were the forest-dwelling ones), more studies are needed to clarify the
347 role of uncorrelated traits in a larger range of species.

348 Landscape features might affect the scale of effect on species occurrence. Lyra-Jorge et al.
349 (2010) reported that two large and highly mobile carnivores, *Puma concolor* and *Chrysocyon*
350 *brachyurus*, were best explained by edge density of the native vegetation at a coarse scale of 2 km.
351 Our analyses showed that species that mainly use forest edges, the Azara's agouti and the collared
352 peccary, exhibited a scale of effect on metrics associated to landscape configuration such as ED and
353 PD. Regolin et al. (2017) reported that the richness of carnivores community increased with forest
354 cover and decreased with landscape fragmentation. Bogoni et al. (2018) showed that large
355 herbivores decreased when native vegetation cover, forest fragment size, and the largest
356 neighbouring patch of remnant forest decreased. Here, as the studied species exhibited different
357 patterns of scale of effect with the landscape metrics, our results supported previous studies
358 showing that landscape composition and configuration are both important drivers in shaping
359 occurrence of terrestrial mammals in native forests (Ochoa-Quintero et al. 2015; Regolin et al.
360 2017). Unfortunately, among the four selected species, we do not have one mammal species that did
361 not require forest.

362 While different percentages of tree cover have been used in the literature to map forest cover
363 (Defries et al. 2001; Hansen et al. 2010), studies were reporting that occurrence of terrestrial
364 mammal species was affected by forest cover (Chiarello 2000; Michalski and Peres 2007) and
365 vegetation types (Lyra-Jorge et al. 2010). However, few studies have examined whether the percent
366 tree cover used to map forest cover affect the scale of effect of landscape metrics on the occurrence
367 of species. Overall, our analyses showed that species exhibited a stronger scale of effect when
368 considering high tree cover (e.g., 75%) compared to medium-low tree cover (50 – 25%). Thus, the
369 detection of scale of effect varies with habitat definition. While the percent tree cover used to map
370 forest cover shaped patch-based landscape metrics and thus the assessment of land use and land
371 cover composition and spatial configuration, it also determines our ability to detect the correct scale
372 of effects for species. This is a new and important result, which implies that before using multiple
373 sizes of buffers to test the scale of effects, we need a previous and decisive step, which is to define
374 correctly habitat types of species. However, defining properly what is an “habitat” is challenging,
375 particularly for species living in complex mosaic of vegetation types including forests, savannas
376 and grasslands (Bonanomi et al. 2019) showing for instance environment gradients. Several
377 percentages of tree cover have been used in the literature to map forest cover (Defries et al. 2001;
378 Hansen et al. 2010). Although changing the percent tree cover allows to select different amount of

379 canopy, it also affects the type of vegetation and thus habitat for species (Hirota et al. 2011). These
380 results are particularly important in the current landscape dynamics occurring in the Cerrado. In the
381 last decades, agriculture expansion at the expense of native vegetation dramatically increased
382 landscape fragmentation (Strassburg et al. 2017) and the need to investigate the mechanism
383 underlying the response of biodiversity to the erosion of native vegetation (e.g., forest cover) has
384 been a critical topic for conservation purposes in Brazil (Pardini et al. 2010; Martensen et al. 2012;
385 Banks-Leite et al. 2014; Ochoa-Quintero et al. 2015).

386

387 Implications for conservation and land planning

388 Although the spatial extent (scale) at which landscape attributes are measured has a substantial
389 impact on inferred species–landscape relationships, the way that habitats are defined has a critical
390 impact on the scale of effect analysis. As mammal species might respond differently to forest cover
391 (Chamailé-Jammes et al. 2016; Zimbres et al. 2018), the question whether forest cover (i.e., percent
392 tree cover) has been appropriately selected to link landscape metrics on the occurrence of species
393 appears as the first main concern to avoid failure in conservation initiatives. Here we recommend
394 using and testing multiple definitions of habitats to assess the ecological requirements of studied
395 species. Although 75% tree cover seems to be a good proxy of forest cover to study the forest-
396 dwelling species in our study area, this might also be the case for other variables of landscape
397 composition that are characterised by a continuous gradient such as agriculture or urbanisation.
398 Moreover, from a conservation perspective, it is critical to test multiple scales at which species
399 respond to the landscape variables. In the Cerrado, we recommend that initiatives examining spatial
400 arrangement of landscape attributes of forest cover in relation to populations in terrestrial mammals
401 (from small to large body sized species) should consider buffer sizes from 500 to 2000 m. However,
402 the puzzle is far more complicated with questions regarding communities. No management
403 approach based on a single scale would benefit all species (Crouzeilles and Curran 2016; Bhakti et
404 al. 2018). It might be important to analyse a large range of species and set targets for each one using
405 specific scales. This should be relevant in the context of systematic planning approaches and
406 multiscale management based on the responses of multiple species (Neel et al. 2004). Thus, using
407 multiple definitions of habitats and scales is critical as most initiatives of ecological zoning,
408 biodiversity prioritizing or ecosystem restoration use landscape units that have a particular meaning
409 in terms of land use dynamics and planning (usually justified by physical constraints) but not in
410 terms of functional responses of the organisms.

411

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425

426

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637 2836

Studied species	Adult body mass (kg)	Home range (ha)	Dispersal range (m)	Habitat use	References
Azara's agouti	2.9	1.34 – 2.45	100 – 500	Forest/ edges	Aliaga-Rossel et al. 2008 ; Jansen et al. 2012 ; Cid et al. 2013
Brown brocket deer	21	2.7 – 348	750 – 1 000	Forest/ open area	Duarte et al. 2012 ; Pires et al. 2018
Collared peccary	22	24 – 800	500 – 1 000	Forest/ edges	Bodmer 1991; Fragoso 1998; Judas and Henry 1999; Keuroghlian et al 2004
South American tapir	225	0.1 – 100	> 3 000	Forest/ open area	Bodmer 1989; Emmons and Feer 1997; Pires et al. 2018

Figure captions

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650

651 Fig. 1 Map of the study site, Bodoquena, state of *Mato Grosso do Sul*, Brazil (a) and forest cover
652 including the location of camera traps (b). Camera traps selected to run occupancy models (see
653 methods) are highlighted in red.

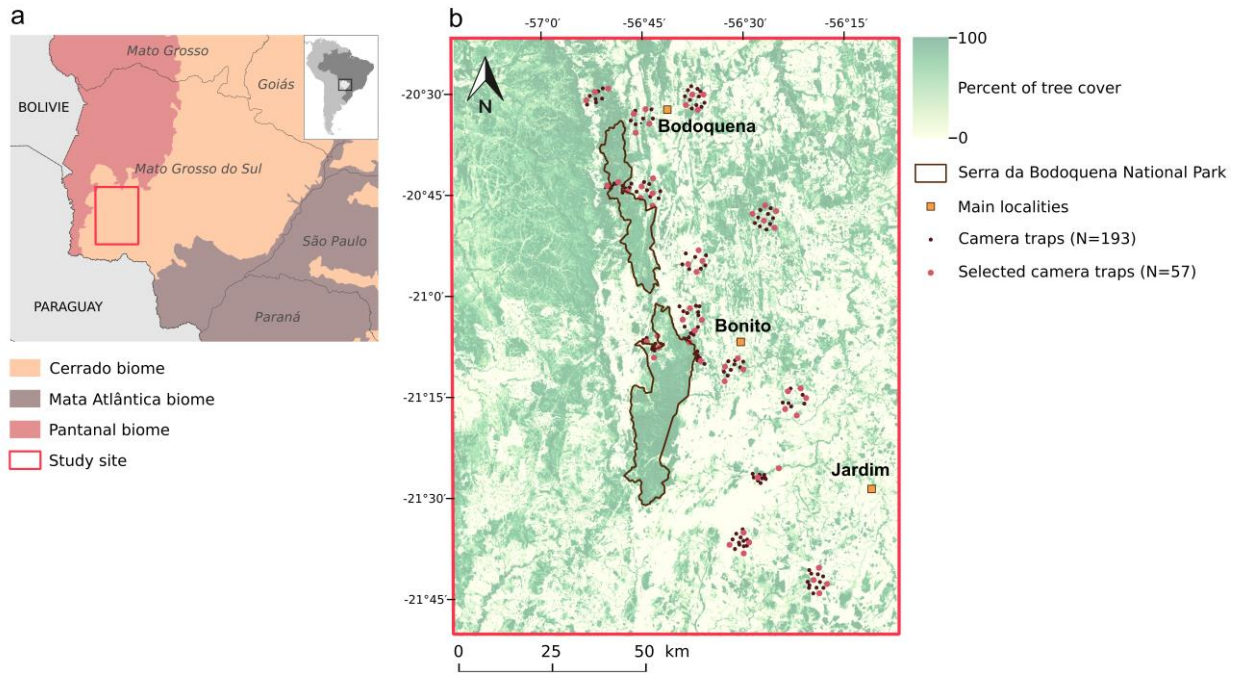
654

655 Fig. 2 Example of forest cover assessed for different threshold of “forest” definition (minimum tree
656 cover per pixel of 25, 50 and 75%) around one camera trap at two buffers sizes, 3000 m (blue disc)
657 and 500 m (red disc). Forest pixels are represented in green.

658

659 Fig. 3 Comparison of model performance for the effect of landscape metric for forests defined with
660 a 75% of tree cover per pixel. The grey triangle is the null model in which occupancy probability is
661 fixed as 1. The scale of effect is detected from spatial extent (i.e. the range of buffer sizes) for which
662 $\Delta AIC \leq 2$ included the smallest AIC without the null model (black dots).

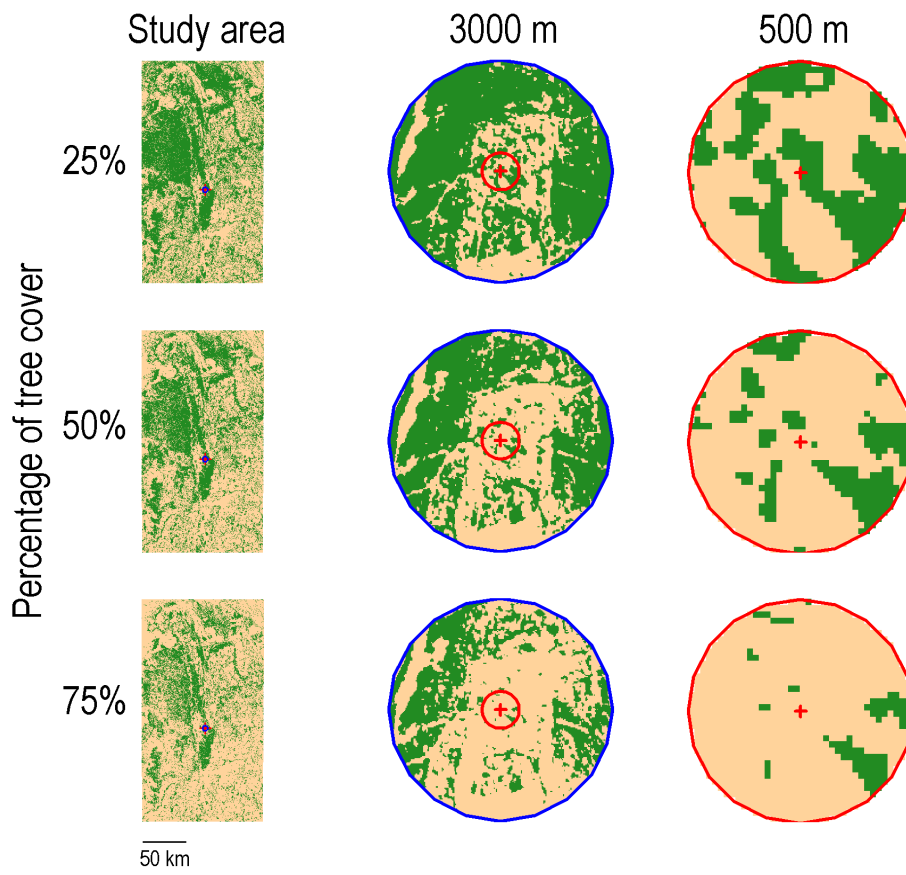
663
664 Fig.1
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666

667 Fig. 2

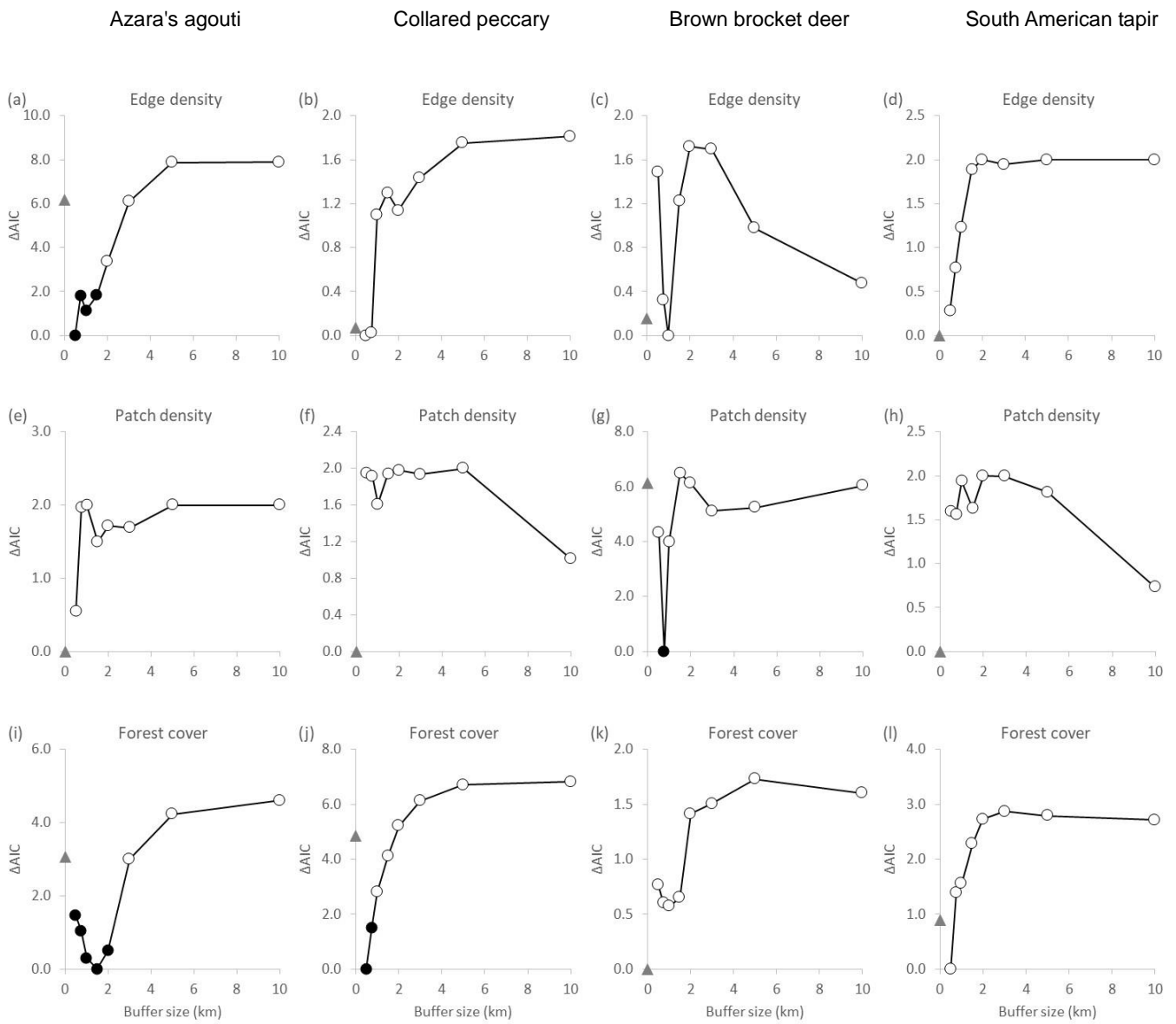
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671 Fig. 3

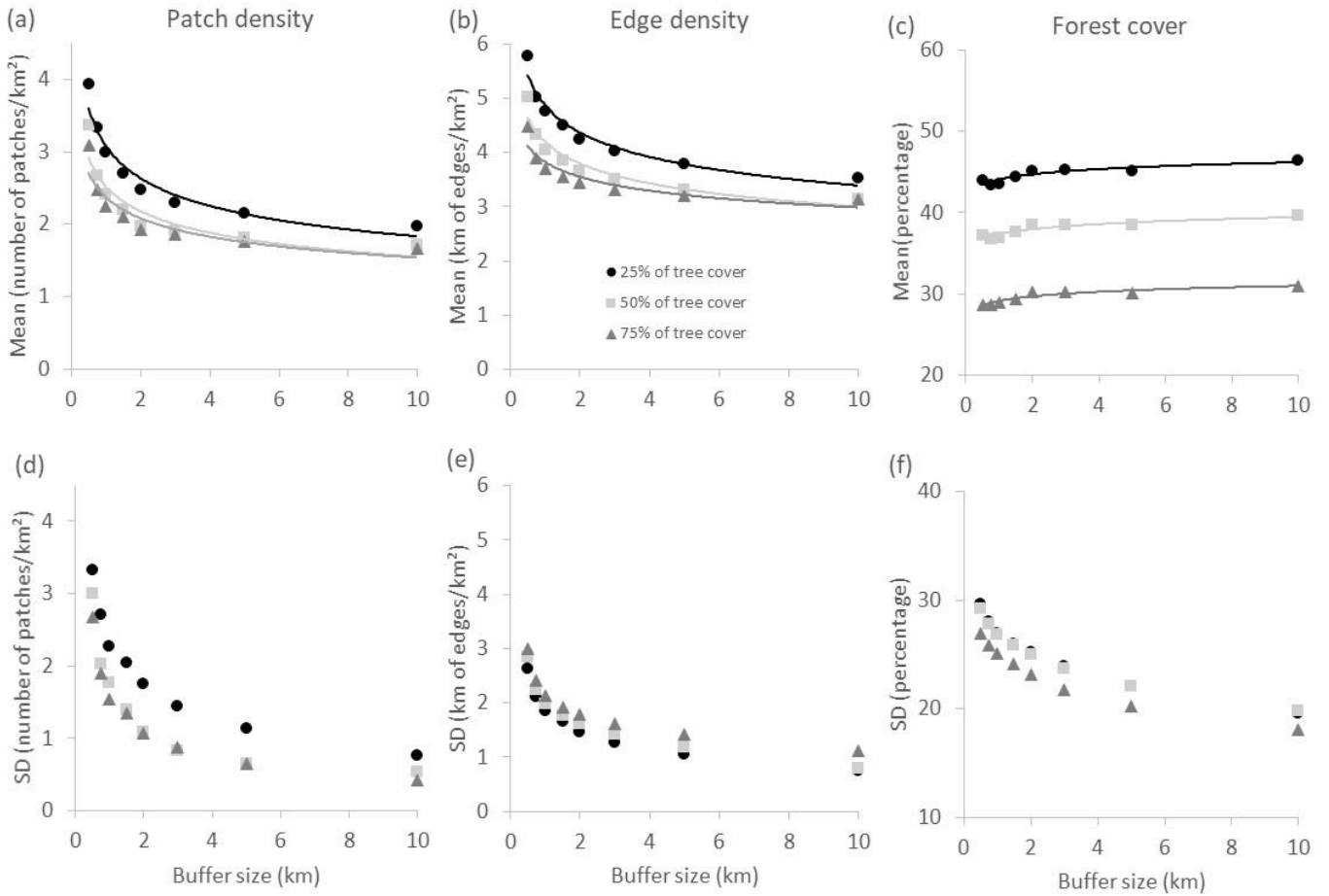
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Electronic appendices

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677

678 Fig. S1 Scaling relations with spatial extent (buffer size) of the mean values of landscape metrics,

679 patch density (a), edge density (b), forest cover (c) and their standard deviation (SD) (d, e, f)

680 assessed around our camera traps at three different percent tree cover per pixel (25, 50 and 75%)

681 (See Table S1 for the statistics of the relationships in a, b and c).

682

683

684 Table S1. Shape of the relationship between buffer size (x) and landscape metrics (y) including
 685 patch density PD, edge density ED and the percent forest cover (FC) assessed at three percent tree
 686 cover per pixel (25, 50 and 75%). *** indicates that P value < 0.001.

687
 688

Landscape metric	Percent tree cover per pixel	Relationship	Equation	R ²
Patch Density	25%	Power***	$y=3.082x^{-0.226}$	0.94
	50%	Power***	$y=2.520x^{-0.211}$	0.87
	75%	Power***	$y=2.372x^{-0.189}$	0.87
Edge Density	25%	Power***	$y=4.868x^{-0.157}$	0.96
	50%	Power***	$y=4.196x^{-0.145}$	0.92
	75%	Power***	$y=3.823x^{-0.108}$	0.86
Forest Cover	25%	Logarithm***	$y=0.917\ln(x)+44.058$	0.81
	50%	Logarithm***	$y=0.915\ln(x)+37.312$	0.86
	75%	Logarithm***	$y=0.804\ln(x)+29.143$	0.89

689
 690

691 Table S2. Performance of occupancy models predicting the occurrence of four species of terrestrial
692 mammals (Azara's agouti *Dasyprocta azarae*, collared peccary *Pecari tajacu*, brown brocket deer
693 *Mazama gouazoubira*, and South American tapir *Tapirus terrestris*,) in the Brazilian Cerrado
694 hotspot across buffer size (from 500 to 10000 m) considering 75% as the threshold of tree cover.
695 Model structure mentions how occupancy probability Ψ at the camera trap i and the detection
696 probability p were implemented. Analyses were carried out separately for each species and
697 landscape metric including edge density, ED, patch density, PD, and the percentage of forest cover,
698 FC. Buffer size is indicated in m. AIC is the Akaike criterion. Models of similar statistical supports
699 with $\Delta AIC < 2$ from the minimum model are in bold.
700

Azara's agouti					Collared peccary				Brown brocket deer				South American tapir			
Landscape metric	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC
ED	Null	p (weather + visibility) $\Psi(1)$	152.43	6.18	Null	p (visibility) $\Psi(1)$	173.54	0.07	Null	p (visibility) $\Psi(1)$	145.56	0.16	Null	p (weather + visibility) $\Psi(1)$	231.04	0.00
	500	p (weather + visibility) $\Psi(ED)$	146.25	0.00	500	p (visibility) $\Psi(ED)$	173.47	0.00	500	p (visibility) $\Psi(ED)$	146.89	1.49	500	p (weather + visibility) $\Psi(ED)$	231.32	0.28
	750	p (weather + visibility) $\Psi(ED)$	148.06	1.80	750	p (visibility) $\Psi(ED)$	173.50	0.02	750	p (visibility) $\Psi(ED)$	145.73	0.33	750	p (weather + visibility) $\Psi(ED)$	231.81	0.77
	1000	p (weather + visibility) $\Psi(ED)$	147.39	1.13	1000	p (visibility) $\Psi(ED)$	174.57	1.10	1000	p (visibility) $\Psi(ED)$	145.40	0.00	1000	p (weather + visibility) $\Psi(ED)$	232.27	1.23
	1500	p (weather + visibility) $\Psi(ED)$	148.08	1.83	1500	p (visibility) $\Psi(ED)$	174.77	1.30	1500	p (visibility) $\Psi(ED)$	146.63	1.23	1500	p (weather + visibility) $\Psi(ED)$	232.93	1.89
	2000	p (weather + visibility) $\Psi(ED)$	149.63	3.38	2000	p (visibility) $\Psi(ED)$	174.61	1.13	2000	p (visibility) $\Psi(ED)$	147.12	1.72	2000	p (weather + visibility) $\Psi(ED)$	233.04	2.00
	3000	p (weather + visibility) $\Psi(ED)$	152.34	6.09	3000	p (visibility) $\Psi(ED)$	174.91	1.44	3000	p (visibility) $\Psi(ED)$	147.10	1.70	3000	p (weather + visibility) $\Psi(ED)$	232.99	1.95
	5000	p (weather + visibility) $\Psi(ED)$	154.12	7.87	5000	p (visibility) $\Psi(ED)$	175.22	1.75	5000	p (visibility) $\Psi(ED)$	146.38	0.98	5000	p (weather + visibility) $\Psi(ED)$	233.04	2.00
	10000	p (weather + visibility) $\Psi(ED)$	154.13	7.88	10000	p (visibility) $\Psi(ED)$	175.28	1.81	10000	p (visibility) $\Psi(ED)$	145.88	0.47	10000	p (weather + visibility) $\Psi(ED)$	233.04	2.00
	Null	p (weather + visibility) $\Psi(1)$	152.43	0.00	Null	p (visibility) $\Psi(1)$	173.54	0.00	Null	p (visibility) $\Psi(1)$	145.56	6.13	Null	p (weather + visibility) $\Psi(1)$	231.04	0.00
500	p (weather + visibility) $\Psi(PD)$	152.98	0.54	500	p (visibility) $\Psi(PD)$	175.49	1.95	500	p (visibility) $\Psi(PD)$	143.78	4.35	500	p (weather + visibility) $\Psi(PD)$	232.63	1.59	
750	p (weather + visibility) $\Psi(PD)$	154.40	1.97	750	p (visibility) $\Psi(PD)$	175.46	1.91	750	p (visibility) $\Psi(PD)$	139.42	0.00	750	p (weather + visibility) $\Psi(PD)$	232.60	1.56	
1000	p (weather + visibility) $\Psi(PD)$	154.43	2.00	1000	p (visibility) $\Psi(PD)$	175.15	1.61	1000	p (visibility) $\Psi(PD)$	143.41	3.99	1000	p (weather + visibility) $\Psi(PD)$	232.98	1.94	
1500	p (weather + visibility) $\Psi(PD)$	153.93	1.50	1500	p (visibility) $\Psi(PD)$	175.49	1.94	1500	p (visibility) $\Psi(PD)$	145.92	6.49	1500	p (weather + visibility) $\Psi(PD)$	232.67	1.63	
2000	p (weather + visibility) $\Psi(PD)$	154.15	1.71	2000	p (visibility) $\Psi(PD)$	175.52	1.98	2000	p (visibility) $\Psi(PD)$	145.54	6.12	2000	p (weather + visibility) $\Psi(PD)$	233.04	2.00	
3000	p (weather + visibility) $\Psi(PD)$	154.12	1.69	3000	p (visibility) $\Psi(PD)$	175.48	1.93	3000	p (visibility) $\Psi(PD)$	144.53	5.11	3000	p (weather + visibility) $\Psi(PD)$	233.04	1.99	
5000	p (weather + visibility) $\Psi(PD)$	154.43	2.00	5000	p (visibility) $\Psi(PD)$	175.54	2.00	5000	p (visibility) $\Psi(PD)$	144.66	5.24	5000	p (weather + visibility) $\Psi(PD)$	232.85	1.81	
10000	p (weather + visibility) $\Psi(PD)$	154.43	2.00	10000	p (visibility) $\Psi(PD)$	174.55	1.01	10000	p (visibility) $\Psi(PD)$	145.46	6.03	10000	p (weather + visibility) $\Psi(PD)$	231.77	0.73	
FC	Null	p (weather + visibility) $\Psi(1)$	152.43	3.07	Null	p (visibility) $\Psi(1)$	173.54	4.84	Null	p (visibility) $\Psi(1)$	145.56	0.00	Null	p (weather + visibility) $\Psi(1)$	231.04	0.89
	500	p (weather + visibility) $\Psi(FC)$	150.83	1.46	500	p (visibility) $\Psi(FC)$	168.70	0.00	500	p (visibility) $\Psi(FC)$	146.33	0.77	500	p (weather + visibility) $\Psi(FC)$	230.15	0.00
	750	p (weather + visibility) $\Psi(FC)$	150.40	1.03	750	p (visibility) $\Psi(FC)$	170.20	1.49	750	p (visibility) $\Psi(FC)$	146.16	0.60	750	p (weather + visibility) $\Psi(FC)$	231.54	1.39
	1000	p (weather + visibility) $\Psi(FC)$	149.66	0.30	1000	p (visibility) $\Psi(FC)$	171.50	2.80	1000	p (visibility) $\Psi(FC)$	146.13	0.57	1000	p (weather + visibility) $\Psi(FC)$	231.71	1.56
	1500	p (weather + visibility) $\Psi(FC)$	149.37	0.00	1500	p (visibility) $\Psi(FC)$	172.83	4.13	1500	p (visibility) $\Psi(FC)$	146.21	0.65	1500	p (weather + visibility) $\Psi(FC)$	232.44	2.28
	2000	p (weather + visibility) $\Psi(FC)$	149.87	0.50	2000	p (visibility) $\Psi(FC)$	173.92	5.22	2000	p (visibility) $\Psi(FC)$	146.97	1.41	2000	p (weather + visibility) $\Psi(FC)$	232.88	2.73
	3000	p (weather + visibility) $\Psi(FC)$	152.37	3.00	3000	p (visibility) $\Psi(FC)$	174.83	6.13	3000	p (visibility) $\Psi(FC)$	147.06	1.51	3000	p (weather + visibility) $\Psi(FC)$	233.02	2.87
	5000	p (weather + visibility) $\Psi(FC)$	153.60	4.23	5000	p (visibility) $\Psi(FC)$	175.41	6.71	5000	p (visibility) $\Psi(FC)$	147.29	1.73	5000	p (weather + visibility) $\Psi(FC)$	232.94	2.79
	10000	p (weather + visibility) $\Psi(FC)$	153.97	4.61	10000	p (visibility) $\Psi(FC)$	175.52	6.82	10000	p (visibility) $\Psi(FC)$	147.16	1.60	10000	p (weather + visibility) $\Psi(FC)$	232.87	2.72

701

702 Table S3. Performance of occupancy models predicting the occurrence of four species of terrestrial
703 mammals (Azara's agouti *Dasyprocta azarae*, collared peccary *Pecari tajacu*, brown brocket deer
704 *Mazama gouazoubira*, and South American tapir *Tapirus terrestris*,) in the Brazilian Cerrado
705 hotspot across buffer size (from 500 to 10000 m) considering 50% as the threshold of tree cover.
706 Model structure mentions how occupancy probability Ψ at the camera trap i and the detection
707 probability p were implemented. Analyses were carried out separately for each species and
708 landscape metric including edge density, ED, patch density, PD, and the percentage of forest cover,
709 FC. Buffer size is indicated in m. AIC is the Akaike criterion. Models of similar statistical supports
710 with $\Delta AIC < 2$ from the minimum model are in bold.
711

Azara's agouti					Collared peccary				Brown brocket deer				South American tapir			
Landscape metric	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC
ED	Null	p (weather + visibility) $\Psi(1)$	152.43	2.89	Null	p (visibility) $\Psi(1)$	173.54	0.00	Null	p (visibility) $\Psi(1)$	145.56	1.43	Null	p (weather + visibility) $\Psi(1)$	231.04	0.00
	500	p (weather + visibility) $\Psi(ED)$	149.54	0.00	500	p (visibility) $\Psi(ED)$	175.12	1.58	500	p (visibility) $\Psi(ED)$	145.48	1.35	500	p (weather + visibility) $\Psi(ED)$	232.32	1.27
	750	p (weather + visibility) $\Psi(ED)$	151.63	2.08	750	p (visibility) $\Psi(ED)$	175.08	1.54	750	p (visibility) $\Psi(ED)$	144.80	0.67	750	p (weather + visibility) $\Psi(ED)$	232.29	1.25
	1000	p (weather + visibility) $\Psi(ED)$	152.15	2.61	1000	p (visibility) $\Psi(ED)$	175.53	1.98	1000	p (visibility) $\Psi(ED)$	144.50	0.37	1000	p (weather + visibility) $\Psi(ED)$	232.89	1.85
	1500	p (weather + visibility) $\Psi(ED)$	151.83	2.29	1500	p (visibility) $\Psi(ED)$	175.51	1.97	1500	p (visibility) $\Psi(ED)$	145.58	1.44	1500	p (weather + visibility) $\Psi(ED)$	233.00	1.95
	2000	p (weather + visibility) $\Psi(ED)$	152.35	2.80	2000	p (visibility) $\Psi(ED)$	175.30	1.76	2000	p (visibility) $\Psi(ED)$	146.10	1.97	2000	p (weather + visibility) $\Psi(ED)$	233.04	2.00
	3000	p (weather + visibility) $\Psi(ED)$	153.49	3.95	3000	p (visibility) $\Psi(ED)$	175.43	1.89	3000	p (visibility) $\Psi(ED)$	145.26	1.13	3000	p (weather + visibility) $\Psi(ED)$	232.96	1.92
	5000	p (weather + visibility) $\Psi(ED)$	154.09	4.55	5000	p (visibility) $\Psi(ED)$	175.43	1.89	5000	p (visibility) $\Psi(ED)$	144.87	0.74	5000	p (weather + visibility) $\Psi(ED)$	233.00	1.96
	10000	p (weather + visibility) $\Psi(ED)$	154.25	4.71	10000	p (visibility) $\Psi(ED)$	175.18	1.64	10000	p (visibility) $\Psi(ED)$	144.13	0.00	10000	p (weather + visibility) $\Psi(ED)$	232.41	1.37
	PD	Null	p (weather + visibility) $\Psi(1)$	152.43	2.05	Null	p (visibility) $\Psi(1)$	173.54	0.00	Null	p (visibility) $\Psi(1)$	145.56	1.83	Null	p (weather + visibility) $\Psi(1)$	231.04
500		p (weather + visibility) $\Psi(PD)$	154.27	3.88	500	p (visibility) $\Psi(PD)$	175.43	1.88	500	p (visibility) $\Psi(PD)$	143.73	0.00	500	p (weather + visibility) $\Psi(PD)$	233.03	1.99
750		p (weather + visibility) $\Psi(PD)$	153.96	3.58	750	p (visibility) $\Psi(PD)$	174.24	0.70	750	p (visibility) $\Psi(PD)$	144.95	1.22	750	p (weather + visibility) $\Psi(PD)$	233.01	1.97
1000		p (weather + visibility) $\Psi(PD)$	152.87	2.49	1000	p (visibility) $\Psi(PD)$	174.45	0.91	1000	p (visibility) $\Psi(PD)$	146.62	2.89	1000	p (weather + visibility) $\Psi(PD)$	232.17	1.12
1500		p (weather + visibility) $\Psi(PD)$	152.24	1.85	1500	p (visibility) $\Psi(PD)$	174.35	0.80	1500	p (visibility) $\Psi(PD)$	147.06	3.33	1500	p (weather + visibility) $\Psi(PD)$	232.55	1.51
2000		p (weather + visibility) $\Psi(PD)$	150.38	0.00	2000	p (visibility) $\Psi(PD)$	175.07	1.53	2000	p (visibility) $\Psi(PD)$	146.83	3.10	2000	p (weather + visibility) $\Psi(PD)$	233.04	2.00
3000		p (weather + visibility) $\Psi(PD)$	151.52	1.13	3000	p (visibility) $\Psi(PD)$	175.35	1.81	3000	p (visibility) $\Psi(PD)$	146.92	3.19	3000	p (weather + visibility) $\Psi(PD)$	232.87	1.83
5000		p (weather + visibility) $\Psi(PD)$	153.40	3.01	5000	p (visibility) $\Psi(PD)$	175.30	1.75	5000	p (visibility) $\Psi(PD)$	146.28	2.55	5000	p (weather + visibility) $\Psi(PD)$	232.75	1.71
10000		p (weather + visibility) $\Psi(PD)$	153.43	3.05	10000	p (visibility) $\Psi(PD)$	175.54	2.00	10000	p (visibility) $\Psi(PD)$	147.44	3.71	10000	p (weather + visibility) $\Psi(PD)$	231.83	0.79
FC		Null	p (weather + visibility) $\Psi(1)$	152.43	3.28	Null	p (visibility) $\Psi(1)$	173.54	3.45	Null	p (visibility) $\Psi(1)$	145.56	0.00	Null	p (weather + visibility) $\Psi(1)$	231.04
	500	p (weather + visibility) $\Psi(FC)$	149.15	0.00	500	p (visibility) $\Psi(FC)$	170.09	0.00	500	p (visibility) $\Psi(FC)$	145.80	0.25	500	p (weather + visibility) $\Psi(FC)$	230.63	0.00
	750	p (weather + visibility) $\Psi(FC)$	150.26	1.11	750	p (visibility) $\Psi(FC)$	170.80	0.71	750	p (visibility) $\Psi(FC)$	145.68	0.12	750	p (weather + visibility) $\Psi(FC)$	231.54	0.91
	1000	p (weather + visibility) $\Psi(FC)$	149.31	0.16	1000	p (visibility) $\Psi(FC)$	171.95	1.86	1000	p (visibility) $\Psi(FC)$	145.82	0.26	1000	p (weather + visibility) $\Psi(FC)$	231.88	1.25
	1500	p (weather + visibility) $\Psi(FC)$	149.44	0.29	1500	p (visibility) $\Psi(FC)$	173.02	2.93	1500	p (visibility) $\Psi(FC)$	145.79	0.23	1500	p (weather + visibility) $\Psi(FC)$	232.60	1.97
	2000	p (weather + visibility) $\Psi(FC)$	150.31	1.16	2000	p (visibility) $\Psi(FC)$	173.87	3.78	2000	p (visibility) $\Psi(FC)$	146.62	1.07	2000	p (weather + visibility) $\Psi(FC)$	232.95	2.31
	3000	p (weather + visibility) $\Psi(FC)$	152.47	3.32	3000	p (visibility) $\Psi(FC)$	174.78	4.69	3000	p (visibility) $\Psi(FC)$	146.72	1.17	3000	p (weather + visibility) $\Psi(FC)$	233.02	2.38
	5000	p (weather + visibility) $\Psi(FC)$	153.63	4.48	5000	p (visibility) $\Psi(FC)$	175.39	5.31	5000	p (visibility) $\Psi(FC)$	146.99	1.44	5000	p (weather + visibility) $\Psi(FC)$	232.95	2.32
	10000	p (weather + visibility) $\Psi(FC)$	154.00	4.85	10000	p (visibility) $\Psi(FC)$	175.50	5.42	10000	p (visibility) $\Psi(FC)$	146.96	1.40	10000	p (weather + visibility) $\Psi(FC)$	232.88	2.25

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714

715 Table S4. Performance of occupancy models predicting the occurrence of four species of terrestrial
 716 mammals (Azara's agouti *Dasyprocta azarae*, collared peccary *Pecari tajacu*, brown brocket deer
 717 *Mazama gouazoubira*, and South American tapir *Tapirus terrestris*,) in the Brazilian Cerrado
 718 hotspot across buffer size (from 500 to 10000 m) considering 25% as the threshold of tree cover.
 719 Model structure mentions how occupancy probability Ψ at the camera trap i and the detection
 720 probability p were implemented. Analyses were carried out separately for each species and
 721 landscape metric including edge density, ED, patch density, PD, and the percentage of forest cover,
 722 FC. Buffer size is indicated in m. AIC is the Akaike criterion. Models of similar statistical supports
 723 with $\Delta AIC < 2$ from the minimum model are in bold.

724

Azara's agouti					Collared peccary				Brown brocket deer				South American tapir			
Landscape metric	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC	Buffer size	Model structure	AIC	ΔAIC
ED	Null	p (weather + visibility) $\Psi(1)$	152.43	0.87	Null	p (visibility) $\Psi(1)$	173.54	0.00	Null	p (visibility) $\Psi(1)$	145.56	1.92	Null	p (weather + visibility) $\Psi(1)$	231.04	0.00
	500	p (weather + visibility) $\Psi(ED)$	151.57	0.00	500	p (visibility) $\Psi(ED)$	175.50	1.96	500	p (visibility) $\Psi(ED)$	145.42	1.78	500	p (weather + visibility) $\Psi(ED)$	232.87	1.83
	750	p (weather + visibility) $\Psi(ED)$	152.81	1.24	750	p (visibility) $\Psi(ED)$	175.54	1.99	750	p (visibility) $\Psi(ED)$	143.64	0.00	750	p (weather + visibility) $\Psi(ED)$	232.79	1.75
	1000	p (weather + visibility) $\Psi(ED)$	153.75	2.18	1000	p (visibility) $\Psi(ED)$	175.36	1.82	1000	p (visibility) $\Psi(ED)$	144.16	0.53	1000	p (weather + visibility) $\Psi(ED)$	233.04	2.00
	1500	p (weather + visibility) $\Psi(ED)$	153.89	2.32	1500	p (visibility) $\Psi(ED)$	175.39	1.85	1500	p (visibility) $\Psi(ED)$	146.32	2.68	1500	p (weather + visibility) $\Psi(ED)$	232.68	1.64
	2000	p (weather + visibility) $\Psi(ED)$	153.95	2.38	2000	p (visibility) $\Psi(ED)$	175.49	1.95	2000	p (visibility) $\Psi(ED)$	147.01	3.37	2000	p (weather + visibility) $\Psi(ED)$	232.99	1.95
	3000	p (weather + visibility) $\Psi(ED)$	154.27	2.70	3000	p (visibility) $\Psi(ED)$	175.31	1.77	3000	p (visibility) $\Psi(ED)$	146.82	3.19	3000	p (weather + visibility) $\Psi(ED)$	232.98	1.94
	5000	p (weather + visibility) $\Psi(ED)$	154.41	2.85	5000	p (visibility) $\Psi(ED)$	175.46	1.92	5000	p (visibility) $\Psi(ED)$	146.21	2.58	5000	p (weather + visibility) $\Psi(ED)$	232.92	1.88
	10000	p (weather + visibility) $\Psi(ED)$	154.43	2.86	10000	p (visibility) $\Psi(ED)$	175.41	1.87	10000	p (visibility) $\Psi(ED)$	146.23	2.60	10000	p (weather + visibility) $\Psi(ED)$	231.68	0.63
	PD	Null	p (weather + visibility) $\Psi(1)$	152.43	0.00	Null	p (visibility) $\Psi(1)$	173.54	0.56	Null	p (visibility) $\Psi(1)$	145.56	0.00	Null	p (weather + visibility) $\Psi(1)$	231.04
500		p (weather + visibility) $\Psi(PD)$	154.21	1.78	500	p (visibility) $\Psi(PD)$	175.17	2.18	500	p (visibility) $\Psi(PD)$	147.01	1.46	500	p (weather + visibility) $\Psi(PD)$	233.03	1.99
750		p (weather + visibility) $\Psi(PD)$	154.39	1.95	750	p (visibility) $\Psi(PD)$	173.04	0.06	750	p (visibility) $\Psi(PD)$	147.30	1.74	750	p (weather + visibility) $\Psi(PD)$	232.69	1.65
1000		p (weather + visibility) $\Psi(PD)$	154.09	1.65	1000	p (visibility) $\Psi(PD)$	174.04	1.06	1000	p (visibility) $\Psi(PD)$	147.54	1.99	1000	p (weather + visibility) $\Psi(PD)$	233.39	2.35
1500		p (weather + visibility) $\Psi(PD)$	152.91	0.48	1500	p (visibility) $\Psi(PD)$	172.98	0.00	1500	p (visibility) $\Psi(PD)$	147.53	1.97	1500	p (weather + visibility) $\Psi(PD)$	233.04	2.00
2000		p (weather + visibility) $\Psi(PD)$	152.71	0.28	2000	p (visibility) $\Psi(PD)$	173.10	0.12	2000	p (visibility) $\Psi(PD)$	147.55	2.00	2000	p (weather + visibility) $\Psi(PD)$	232.52	1.48
3000		p (weather + visibility) $\Psi(PD)$	153.32	0.89	3000	p (visibility) $\Psi(PD)$	174.65	1.67	3000	p (visibility) $\Psi(PD)$	147.56	2.00	3000	p (weather + visibility) $\Psi(PD)$	231.96	0.92
5000		p (weather + visibility) $\Psi(PD)$	153.62	1.19	5000	p (visibility) $\Psi(PD)$	174.72	1.74	5000	p (visibility) $\Psi(PD)$	147.41	1.86	5000	p (weather + visibility) $\Psi(PD)$	231.46	0.42
10000		p (weather + visibility) $\Psi(PD)$	153.82	1.39	10000	p (visibility) $\Psi(PD)$	175.46	2.47	10000	p (visibility) $\Psi(PD)$	146.94	1.38	10000	p (weather + visibility) $\Psi(PD)$	232.47	1.43
FC		Null	p (weather + visibility) $\Psi(1)$	152.43	3.88	Null	p (visibility) $\Psi(1)$	173.54	2.41	Null	p (visibility) $\Psi(1)$	145.56	0.00	Null	p (weather + visibility) $\Psi(1)$	231.04
	500	p (weather + visibility) $\Psi(FC)$	148.55	0.00	500	p (visibility) $\Psi(FC)$	171.13	0.00	500	p (visibility) $\Psi(FC)$	145.76	0.21	500	p (weather + visibility) $\Psi(FC)$	231.49	0.44
	750	p (weather + visibility) $\Psi(FC)$	150.32	1.76	750	p (visibility) $\Psi(FC)$	171.57	0.44	750	p (visibility) $\Psi(FC)$	145.58	0.03	750	p (weather + visibility) $\Psi(FC)$	232.01	0.97
	1000	p (weather + visibility) $\Psi(FC)$	149.82	1.27	1000	p (visibility) $\Psi(FC)$	172.33	1.20	1000	p (visibility) $\Psi(FC)$	145.62	0.06	1000	p (weather + visibility) $\Psi(FC)$	232.26	1.22
	1500	p (weather + visibility) $\Psi(FC)$	150.08	1.53	1500	p (visibility) $\Psi(FC)$	173.21	2.08	1500	p (visibility) $\Psi(FC)$	145.58	0.02	1500	p (weather + visibility) $\Psi(FC)$	232.88	1.83
	2000	p (weather + visibility) $\Psi(FC)$	150.91	2.35	2000	p (visibility) $\Psi(FC)$	173.94	2.81	2000	p (visibility) $\Psi(FC)$	146.44	0.88	2000	p (weather + visibility) $\Psi(FC)$	233.03	1.98
	3000	p (weather + visibility) $\Psi(FC)$	152.55	4.00	3000	p (visibility) $\Psi(FC)$	174.82	3.69	3000	p (visibility) $\Psi(FC)$	146.45	0.89	3000	p (weather + visibility) $\Psi(FC)$	233.04	1.99
	5000	p (weather + visibility) $\Psi(FC)$	153.57	5.02	5000	p (visibility) $\Psi(FC)$	175.41	4.28	5000	p (visibility) $\Psi(FC)$	146.73	1.17	5000	p (weather + visibility) $\Psi(FC)$	232.91	1.87
	10000	p (weather + visibility) $\Psi(FC)$	153.98	5.42	10000	p (visibility) $\Psi(FC)$	175.51	4.38	10000	p (visibility) $\Psi(FC)$	146.84	1.28	10000	p (weather + visibility) $\Psi(FC)$	232.85	1.81

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