

1 **Matrix quality determines the strength of habitat loss filtering on bird communities at the**
2 **landscape scale**

3

4 **Authors:** Melina de Souza Leite^{1*}, Andrea Larissa Boesing^{1,2}, Jean Paul Metzger¹ & Paulo Inácio
5 Prado¹

6 1. Department of Ecology, University of São Paulo, Rua do Matão 321, T14, São Paulo, SP, 05508-
7 090, Brazil

8 2. Senckenberg Biodiversity and Climate Research Institute (SBIK-F), Georg-Voigt-Straße 14,
9 60325 Frankfurt am Main, Hessen, Germany

10 * Corresponding author: melina.leite@ib.usp.br

11

12 Abstract

- 13 1. Habitat loss and fragmentation represent a major threat to biodiversity, however, the
14 modulation of its effects by the non-habitat matrix surrounding habitat patches is still
15 undervalued. The landscape matrix might change community assembly in different ways.
16 For example, low-quality matrices can accentuate environmental filtering by reducing
17 resource availability and/or deteriorating abiotic conditions but they may also over limit
18 dispersal of organisms and make communities more prone to ecological drift.
- 19 2. To understand how matrix quality modulates the effects of habitat loss, we quantified the
20 relative importance of environmental filter and ecological drift in bird occurrences across
21 both local and landscape gradients of habitat loss embedded in low- and high-quality
22 matrices. We used a trait-based approach to understand habitat loss filtering effects on birds.
- 23 3. We found that low-quality matrices, composed mainly of low-productive pasturelands,
24 increased the severity of habitat loss filtering effects for forest specialist birds, but only at
25 the landscape scale. Bird occurrence was in general higher in high-quality matrices, i.e.,
26 more heterogeneous and with low-contrasting edges, indicating the role of the matrix quality
27 on attenuating species extinction risks at the landscape scale probably due to mass effect.
28 Moreover, forest specialists presented a strong negative response to habitat loss filtering
29 across different functional traits, while generalists presented a high variability in traits
30 response to habitat loss.
- 31 4. *Synthesis and applications:* We raised evidence in supporting that landscape habitat loss
32 filtering may be relaxed or reinforced depending on the quality of the matrix, evidencing
33 that matrix quality has a strong impact in modulating community assembly processes in
34 fragmented landscapes. In practical terms, it means that improving matrix quality may help
35 in maintaining the high diversity of birds even without any increase in native forest cover.

- 36 **Keywords:** community ecology, dispersal, ecological drift, environmental filter, functional traits,
37 landscape structure, trait-environment relationship.

38 **Introduction**

39 Anthropogenic habitat change is one of the most important drivers of biodiversity loss (Díaz
40 et al., 2019). The division of habitats into smaller and more isolated fragments, separated by a non-
41 habitat matrix of human-transformed land cover, alters not only the quantity but also the quality of
42 the habitats in the landscape (Fischer & Lindenmayer, 2007; Haddad et al., 2015). Much has been
43 studied on how habitat loss and fragmentation impact biodiversity in terms of the community and
44 species deterministic responses (environmental filtering) and random demographic events leading to
45 stochastic changes in community composition (ecological drift) (Baselga et al., 2015; Henckel et
46 al., 2019; Pardini et al., 2017). Nevertheless, the role of the landscape matrix in altering these
47 deterministic and random assembly processes and thus the outcome of habitat loss on community
48 composition is still unclear (Kupfer et al., 2006; Pardini et al., 2017).

49 The outcome of habitat loss and fragmentation on biodiversity may depend on how the
50 matrix changes the relative importance of the assembly processes in the remaining habitat patches
51 and the landscape (metacommunities *sensu* Leibold et al. (2004)). This knowledge is critical for
52 mitigating the negative effects of global environmental change (Kohli et al., 2018; Tschardt et al.,
53 2012), especially given the vast diversity of ways humans modify landscapes and create different
54 matrix contexts. However, it faces two main challenges: how to disentangle community assembly
55 processes at different spatial scales, and how to characterize the matrix context in landscapes. First,
56 community assembly processes in acting differently at local and landscape scales may result in
57 different metacommunity arrangements (Leibold et al., 2004), which evidence the foreseen patterns
58 of multidimensionality and scale-dependency of species richness (Chase et al., 2019) and
59 biodiversity changes (Chase et al., 2018). One approach to disentangle community assembly
60 processes is the use of species traits to elucidate mechanisms by which communities respond to
61 environmental gradients (Cadotte et al., 2015; McGill et al., 2006). Such trait-environment

62 associations proved to be critical in understanding how ecological processes affect biodiversity
63 across scales (Gilroy et al., 2015; Newbold et al., 2013, 2014; Suárez-Castro et al., 2018).
64 Therefore, trait-focused approaches may show how local environments and landscapes constrain
65 diversity (Tscharntke et al., 2012), for example when the matrix influences trait diversity in habitat
66 patches (Boesing et al., 2018a).

67 Second, a prolific way to characterize matrix context is by its quality for a target group of
68 organisms. Matrix quality is context-dependent, since each species may perceive the matrix
69 differently, but in general, it may be assumed as the structural similarity of the matrix with the
70 native habitat (Prevedello & Vieira, 2010). For instance, landscapes with high-quality matrices can
71 maintain greater amounts and diversity of resources (Dunning et al., 1992; Pardini et al., 2009)
72 which can be used occasionally by species living in patches (spillover; Blitzer et al. 2012). High-
73 quality matrices can also facilitate species movement across the landscape leading to higher
74 landscape connectivity (Antongiovanni & Metzger, 2005; Fahrig, 2007). Consequently, landscapes
75 with high-quality matrices may support more species than the ones with matrices of lower quality
76 (Carrara et al., 2015; Reider et al., 2018; Stjernman et al., 2019). Even though there is evidence that
77 landscapes with matrices of better quality (e.g., more heterogeneous, less contrasting) permit higher
78 species and trait diversity (Boesing et al., 2018a), the specific mechanisms are still unclear.

79 The matrix may change how habitat loss and fragmentation modulate community assembly
80 processes through its effects on (1) organismal movements (Biz et al., 2017; Fahrig, 2007; Watling
81 et al., 2011), (2) the availability of supplementary or complementary resources in the landscape
82 (Boesing et al., 2021; Dunning et al., 1992), and (3) abiotic edge conditions of habitat patches (*edge*
83 *effects*, Saunders et al. 1991, Pardini et al. 2009, Pfeifer et al. 2017). When movements of
84 organisms among habitat patches are heavily limited by the matrix, dispersal (*sensu* Vellend 2010)
85 may be limited and, together with habitat loss, will lead to small and functionally isolated

86 communities, which are more prone to ecological drift (Horváth et al., 2019; Siqueira et al., 2020).
87 When matrix decreases resource availability in the landscape and/or accentuate unfavorable abiotic
88 condition inside habitat patches (edge effects), habitat loss may be an even more severe
89 environmental filter, selecting only those species able to persist under these harsher conditions
90 (Chase, 2007). By modulating these 3 mechanisms, matrix quality changes how habitat loss and
91 fragmentation alter the relative importance of the assembly processes of dispersal (potentially
92 leading to ecological drift) and environmental filtering. Moreover, given the scale-dependent nature
93 of ecological communities (Chase et al., 2018), only a multiscale combined with a trait-based
94 approach (Suárez-Castro et al., 2018) may help to identify the relative strength of such processes
95 across both local and landscape scales.

96 In this study, we investigated whether and how matrix quality modulates the relative
97 importance of assembly processes in bird communities across gradients of habitat loss. First, we
98 hypothesize that the relative contribution of the assembly processes of habitat loss filtering and
99 ecological drift will depend on (1) how dispersal is limited and (2) the harshness of the
100 environmental filtering by matrices of different qualities. If bird dispersal is heavily limited by low-
101 quality matrices, habitat loss will create small and isolated communities more prone to drift, which
102 in turn will relatively decrease the importance of habitat loss filtering compared to landscapes with
103 high-quality matrices. However, if the main effects of a low-quality matrix are in decreasing
104 resource availability and/or deteriorating abiotic conditions in habitat patches, habitat loss will be an
105 even more severe filter, increasing the relative importance of habitat loss filtering compared to
106 high-quality matrix landscapes. Second, given that matrix quality is an element of the landscape, we
107 expect that the effects of habitat loss filtering on species traits will be stronger at the landscape scale
108 than at the local scale (hypothesis of landscape moderation of trait selection; Tschardt et al.
109 2012). We compared results between forest specialist and forest generalist birds. Since specialists

110 are considered more sensitive to habitat loss (Carrara et al., 2015; Pardini et al., 2009), habitat loss
111 filtering should be stronger and negative for them. As forest generalists are commonly less affected
112 by habitat loss or can even increase in abundance (Devictor et al., 2008; Nordberg & Schwarzkopf,
113 2018), we predict a positive or null relationship of their traits to habitat loss.

114 To test our hypotheses and predictions, we modeled the occurrence of bird species in
115 landscapes with different matrix quality using hierarchical models that are commonly used to
116 analyze trait-environment associations (Jamil et al., 2013; ter Braak, 2019), for disentangling scale-
117 dependent community assembly processes (Ovaskainen et al., 2017; Poggiato et al., 2021), and to
118 sort out niche and drift effects on species abundances (Mortara, 2016). We used variance
119 partitioning of the models (Nakagawa & Schielzeth, 2013) to compare the relative importance of
120 processes across assemblages. Habitat loss effects across scales were investigated by both habitat
121 loss overall effect in birds' occurrences and trait filtering effects. We also evaluated how much of
122 the species response to habitat loss is explained by their traits, to understand how species traits are
123 filtered in landscapes under different matrix contexts.

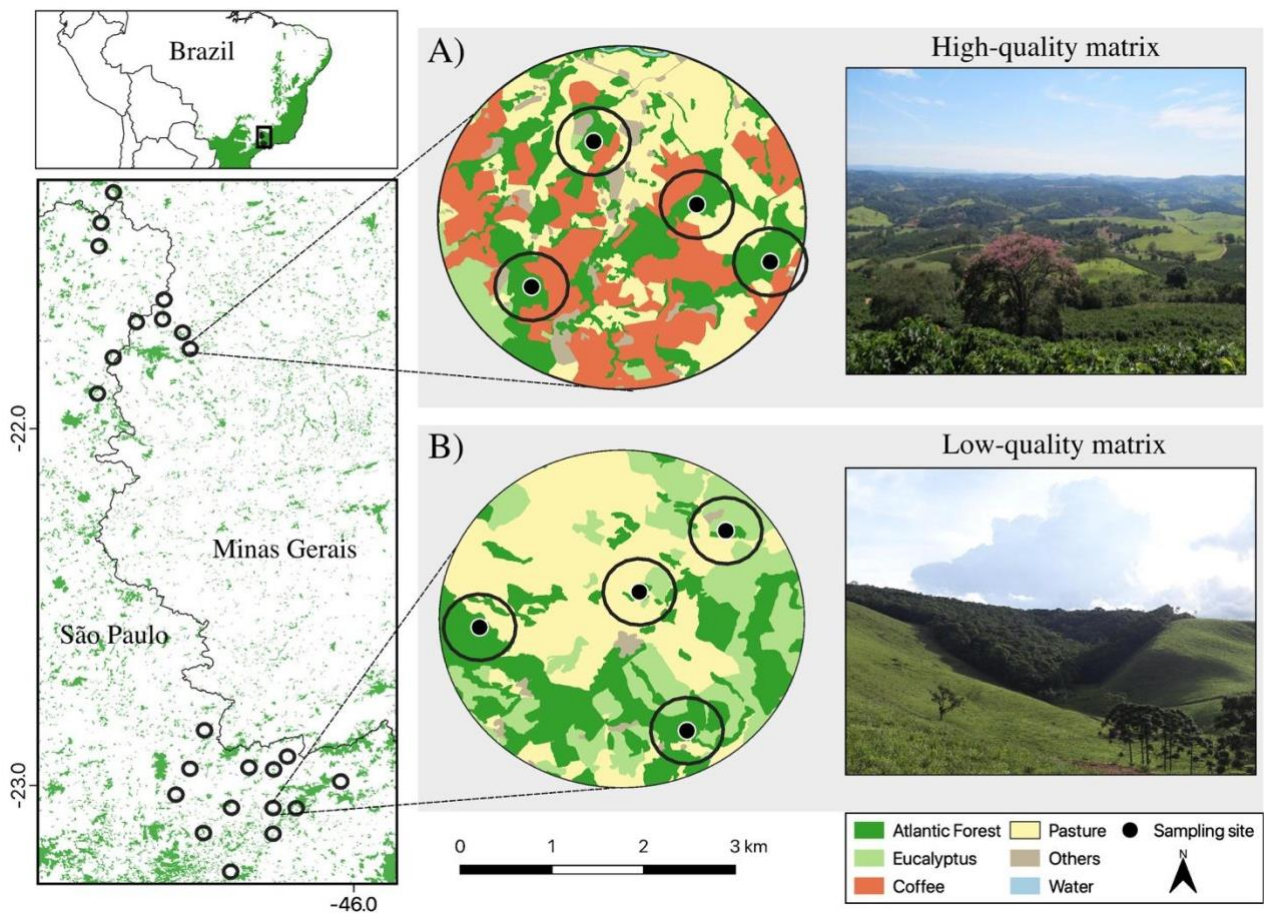
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125 **Methods**

126 **Study areas**

127 The study was carried out in the Atlantic Forest of southeastern Brazil (Fig. 1). Currently,
128 the entire region retains less than 30% of the original forest cover (Rezende et al., 2018), and most
129 of the forest is confined in small patches (< 50 ha) in different stages of regeneration (Ribeiro et al.,
130 2009). Our study landscapes were constrained across two regions (far apart 90 km) retaining
131 similar biophysical characteristics and bird species pool, but with different agricultural matrix
132 compositions (details in Boesing et al. 2018). The northwest region (henceforth 'high-quality

133 matrix') is mainly composed of a mosaic of sun-coffee, sugar cane plantations, and pastures,
 134 resulting in a more heterogeneous matrix. Coffee plantations cover around 46% of the matrix and it
 135 is usually located adjacent to forest edges, creating low-contrasting edges at the patch-scale (Fig.
 136 1A). The southeast region (henceforth 'low-quality matrix') is largely dominated by low-productive
 137 pastures and low diversity of other land use types, and so it is composed by a more homogeneous
 138 matrix. Additionally, the huge structural difference between pastures and forests creates high-
 139 contrasting edges at the patch scale (Fig. 1B).



140

141 **Figure 1:** Location of the study area (left upper panel) within the Brazilian Atlantic Forest biome
 142 (in green) with 23 studied landscapes in southeastern Brazil (left lower panel). We show in (A) a
 143 landscape with 27% of native forest cover and high-quality matrix, which is more heterogeneous
 144 and have a high proportion of sun coffee plantations; and in (B) a landscape with the same forest
 145 cover but low-quality matrix mostly composed by low-productive pastures. Buffers of 400 m radius

146 around sampling sites (black dots) composed the local scale, while the focal 2 km landscape with 4
147 sampling points composed the landscape scale.

148 We selected landscapes that span a gradient of landscape-level forest cover (2 km radius,
149 1256 ha each), while controlling for potentially confounding factors, following Pasher et al. (2013).
150 We selected 10 and 13 focal landscapes in the high-quality (ranging from 7-46% of forest cover)
151 and low-quality matrix (12-55% of forest cover) regions, respectively. In each landscape, we placed
152 4 sampling sites (total 96 sites) in forest patches in a way to cover different ranges of local forest
153 cover inside the same landscape. See Appendix 1 and Boesing et al. (2018a) for more details about
154 the area selection procedure.

155 **Bird sampling and traits selection**

156 In each sampling site, we performed a 50 m fixed radius point count (Bibby et al. 2000) and
157 recorded all bird species detected visually or aurally during a 15 min sampling period. Each point
158 count was visited four times, between January–April and August–November of 2014 (N=368). Both
159 regions were sampled simultaneously. See Appendix 1 for more descriptions about the bird
160 sampling and community.

161 Bird traits selection was similar to the framework proposed by Luck et al. (2012). First, we
162 listed the potential traits based on current knowledge on bird traits related to extinction-proneness
163 due to habitat loss, land use, or environmental change (references in Appendix 2). Then, we
164 selected the traits based on the (1) data availability (considering mainly Wilman et al. 2014,
165 Boesing et al. 2018, Rodrigues et al. 2019); (2) experts' knowledge (ALB); and (3) the empirical
166 relationship among traits (correlations). Finally, we selected four groups of response traits (*sensu*
167 Violle et al. 2007) that are known to affect individual fitness by influencing growth, reproduction,
168 or survival of the species on human-modified landscapes: body size, nest type, diet, and foraging

169 stratum. These traits were represented by seven operational variables described in detail in
170 Appendix 2.

171 The classification of the species concerning their habitat specialization (forest specialists
172 and forest generalists, henceforth just specialists and generalists) could be also considered a life
173 history trait (e.g., Newbold et al., 2013). However, because habitat specialization is very important
174 for understanding the effects of habitat loss and fragmentation (Kupsch et al., 2019; Owens &
175 Bennett, 2000; Pandit et al., 2009), we kept separate analyses for specialists and generalists.
176 Moreover, as both groups of species presented the same range of trait values on our data (Appendix
177 2), we also investigated if the same trait differs in response to habitat loss depending on species
178 habitat specialization.

179 **Modeling**

180 We modeled bird occurrences with hierarchical linear models commonly used to analyze
181 trait-environment associations and disentangle scale dependency in community assembly processes
182 (Jamil et al., 2013; Poggiato et al., 2021; ter Braak, 2019). We used a binomial generalized linear
183 mixed model (logit link function) with the number of detections of each of n species (four visits) in
184 each of m sites as response variable (Miller et al., 2018). In each species-site combination (Y_i , where
185 i goes from 1 to $n \times m$ observations), we assigned predictors of the n species-level trait and the m
186 site- and landscape-level forest cover (Miller et al., 2018). Following the convention of mixed
187 models (Gelman et al., 2007; Miller et al., 2018), our model is described by:

$$188 \quad Y_i \sim \text{Binomial}(4, p)$$

$$189 \quad \text{logit}(p) = (\alpha + a_{spp[i]} + b_{site[i]} + c_{landscape[i]}) + (\beta_1 + d_{spp[i]})forest_{cover_{site[i]}} +$$
$$190 \quad (\beta_2 + e_{site[i]} + f_{landscape[i]})trait_{spp[i]} + \beta_{12}trait_{spp[i]} \times forest_{cover_{site[i]}} + \quad (1)$$

191
$$g_{site[i] \times spp[i]} + h_{landscape[i] * spp[i]}$$

192 where Y_i is the observed occurrence for each of the i species-site combination (species n in site m).
 193 Fixed effects are represented in Greek and random effects in Latin letters. All random effect terms
 194 are represented by a normal distribution with mean zero and their respective estimated variances
 195 $(\sigma_a^2, \sigma_b^2, \sigma_c^2, \sigma_d^2, \sigma_e^2, \sigma_f^2, \sigma_g^2, \sigma_h^2)$. Terms with random intercept and slope have additional parameters
 196 denoting the correlation between them $(\rho_{ad}, \rho_{be}, \rho_{cf})$. The model's formula syntax the *lme4* R
 197 package (Bates et al., 2015) is:

198
$$Y \sim \text{trait} * \text{forest_cover} + (\text{forest_cover} | \text{species}) + (\text{trait} | \text{site}) +$$

 199
$$(\text{trait} | \text{landscape}) + (1 | \text{landscape} : \text{species}) + (1 | \text{landscape} : \text{site})$$

200 The fixed effects in the logit link function are the main effects of habitat loss (represented by
 201 forest cover) and trait $(\alpha, \beta_1, \beta_2$ and habitat loss filtering effects through traits (interaction term
 202 β_{12}). We used the percentage of forest cover at both local and landscape scales as response
 203 variables to denote habitat loss and we found no collinearity between these variables (Appendix 2).
 204 We are particularly interested in: (1) the main effects of habitat loss, i.e., how steep is the decrease
 205 in occurrence probability of all birds when habitat is lost, and (2) the interaction effect of habitat
 206 loss with traits, i.e., how species with different traits will respond to habitat loss. However, these
 207 effects are not statistically easily separable from the effects of trait values in terms of variance
 208 explained (R^2 , Johnson 2014). As we show below, we kept the whole structure of fixed effects in
 209 interpreting marginal R^2 as a general interpretation of habitat loss effects. Nevertheless, we also
 210 compared the estimates of habitat loss main effects among assemblages and across scales and
 211 calculated the importance of the traits in explaining habitat loss filtering (equation 2, below) to
 212 interpreting habitat loss filtering effects through traits.

213 Species random effects are the variation among species in their overall abundances (random
214 intercept, $a_{spp[i]}$) and response to habitat loss (random slope, $d_{spp[i]}$;) regardless of its trait values.
215 They mean the idiosyncratic response of each species to habitat loss and their differences in overall
216 abundances. Trait-site and trait-landscape random interactions (random intercepts: $b_{site[i]}$,
217 $c_{landscape[i]}$, and slopes: $e_{site[i]}$, $f_{landscape[i]}$) deal with the trait-mediated response to non-
218 measured environmental gradients at local and landscape scales, respectively. This is a solution to
219 "account for any interaction that the observed trait has with any unobserved environmental
220 gradient" (ter Braak, 2019).

221 We included two additional random effects of site-species ($g_{site[i] \times spp[i]}$), and landscape-
222 species interactions ($h_{landscape[i] \times spp[i]}$) to express that occurrence probability of the same species
223 may vary among sites and landscapes, regardless of the species identity, its traits, and the
224 environment (habitat loss gradients), i.e. random variation in species occurrences probabilities
225 across sites and landscapes. In our model, the site-species interaction term is the so-called
226 Observation Level Random Effect (OLRE), which allows for extra variance among observations.
227 OLRE is generally used to deal with overdispersion in data modeling with the exponential family
228 distributions (Harrison, 2014, 2015). For species occurrences, overdispersion is frequently
229 associated with individuals' aggregations in space (Elston et al., 2001; Ozgul et al., 2009). In this
230 sense, at the community level, we can assume that the spatial aggregation expressed by these terms
231 is a result of differential dispersal, which may be limitation or excess of dispersal. For instance,
232 dispersal limitation of individuals among patches and landscapes leads to ecological drift (*sensu*
233 Vellend 2010). Although it is expected that these terms express ecological drift (Mortara, 2016), we
234 cannot ensure that all the variances apportioned in these terms are exactly differential dispersal.
235 However, because we have carefully handled many possible niche processes (or selection *sensu*
236 Vellend 2010) in the model, probably, these terms do not include other processes than random

237 variation in species occurrence probabilities. At least, if differential dispersal among patches and
238 landscapes is an important process, it will be expressed in these two random effects and not in the
239 other terms.

240 To express the **importance of traits in explaining habitat loss filtering** we calculated the
241 proportional decrease in the variance of the species random slope of forest cover ($d_{spp[i]}$) when we
242 include the trait-forest cover interaction term (β_{12}) in the model (Jamil et al., 2013):

$$243 \quad C_{\beta} = 1 - \frac{d_{spp[i](res)}}{d_{spp[i](total)}} \quad (2)$$

244 $d_{spp[i](res)}$ is the variance of the random species slope from the model with forest cover and trait
245 main effects (β_2) and the trait-environment interaction (β_{12}); $d_{spp[i](total)}$ is the same variance
246 term for the model without trait-environment interaction but with the main effects. This proportion
247 explains how much of the effect of habitat loss on each species can be explained by their trait
248 values.

249 We computed overall R^2 for the models by the additive variance partitioning method
250 (Johnson, 2014; Nakagawa et al., 2017; Nakagawa & Schielzeth, 2013), which is appropriate for
251 comparing models fit to different data sets because it does not depend on sample size (Ives, 2019).
252 We also apportioned the total variance among the model terms (marginal R^2 *sensu* Ives 2019) to
253 compare the relative importance of processes across assemblages. We calculated the overall and
254 marginal R^2 on the scale of the link function (logit) since it can decouple variance and mean so that
255 the linked scale R^2 can be calculated independent of the population mean (Nakagawa & Schielzeth,
256 2010).

257

258 **Table 1:** Definitions and ecological interpretations of the statistical terms of the hierarchical linear
 259 model (equation 1).

Model terms (equation 1)	Code*	Description
$\alpha; \beta_1; \beta_2; \beta_{12}$	trait*for_cov	Fixed effects: main effects of habitat loss and traits, and habitat loss filtering effects through traits (interaction terms) at both local and landscape scale.
$a_{spp[i]}; d_{spp[i]}$	(for_cov sp)	Random effects: variation among species in their overall occurrences (intercept) and response to habitat loss (slope) regardless of its traits. It is the idiosyncratic response of each species to habitat loss and their differences in overall abundances .
$b_{site\{i\}}; e_{site}; c_{landscape[i]}; f_{landscape[i]}$	(trait site) (trait lands)	Random effects: interaction (random intercept and slope) between trait values and sites/landscapes. It is the possible relationship of the measured trait with any unmeasured environmental variable at the site/landscape level. Trait-mediated response to other environmental gradients at local/landscape scale.
$g_{spp[i] \times landscape}$	(lands:sp)	Random effects: overdispersion term indicating random variation in species occurrences across landscapes , regardless of its traits and environmental conditions.
$h_{spp[i] \times site[i]}$	(site:sp)	Random effects: overdispersion term indicating random variation in species occurrences across sites , regardless of its traits and environmental conditions.

* R syntax code following lme4 package (Bates et al. 2015).

260
261

262 **Data analysis**

263 We ran the model described above for each low and high-quality matrix landscapes and for
 264 forest specialists and generalists separately (hereafter assemblages) to better interpret and compare
 265 overall and marginal R^2 s among assemblages. We analyzed the data in two steps. First, given that
 266 ecological responses can be affected by processes acting at different spatial scales (Jackson &
 267 Fahrig, 2015), we selected the best scale for the effect of local forest cover (details in Appendix 2).
 268 We chose the percentage of local forest cover measured at 400 m buffer radius around each site
 269 (Fig. 1). Second, we ran separate models for each species trait (equation 1) including local and
 270 landscape forest cover (2 km radius around the centroid of the landscapes) as predictors of habitat
 271 loss. We finally combined 4 traits with the highest explanatory power for all datasets (main diet,
 272 proportion of lower strata use, body mass, and nest type) in one model to predict the trait's response
 273 to habitat loss and to compare the marginal R^2 of each model term. The combined traits models did
 274 not show collinearity and the traits were not correlated among species (Appendix 3).

275 All data analysis was performed using R (R Core Team 2019) with *lme4* package (Bates et
276 al., 2015) for modeling, and *DHARMA* (Hartig, 2018) for quantile residuals diagnostic. See
277 Appendix 3 for models' implementation and diagnostic.

278

279 **Results**

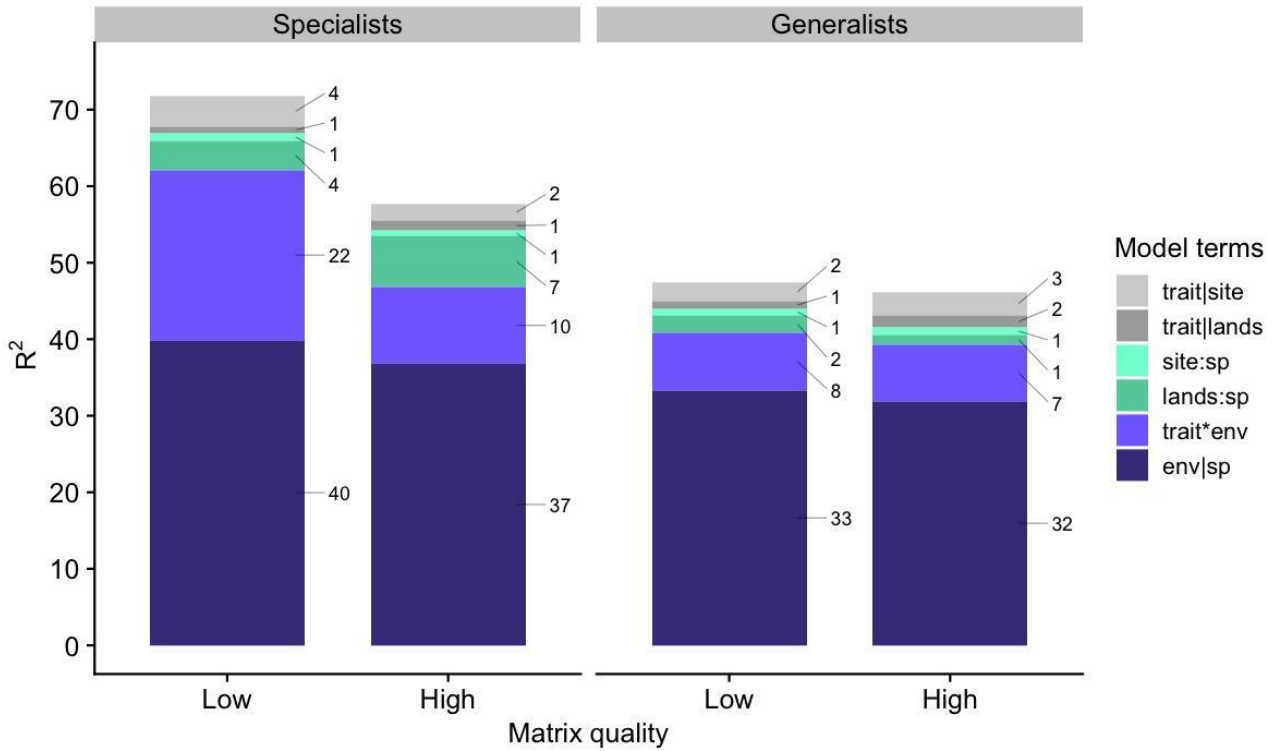
280 In our modeling approach, the R^2 of the fixed effects – trait, habitat loss, and filtering effects
281 at both local and landscape scales – was the variance component that had the most marked
282 differences between specialist assemblages (Fig. 2). It was 2.2 times higher for the specialists in the
283 low-quality than in the high-quality matrix landscapes (22 and 10%, respectively), and it was up to
284 3 times higher for specialists than for both generalist assemblages (7-8%). It means that habitat loss
285 effects alone and habitat loss filtering effects were much stronger for the specialist birds in low-
286 quality matrix landscapes. Moreover, overall R^2 for specialists in low-quality matrix landscapes
287 captured most of the variability in bird's occurrence (72%), followed by specialists in high-quality
288 matrices (58%) (Fig. 2). Overall R^2 for generalists was smaller and similar across landscapes
289 regardless of matrix quality (46-47%).

290 The R^2 for the terms that account for random variation in species occurrences across sites
291 (*site:sp*), were very low (1%) for all assemblages. However, the R^2 for random variation in species
292 occurrences at the landscape scale (*lands:sp*) was almost 2 times larger for the specialists in high-
293 quality matrices than for the specialists in low-quality matrices, and it was much larger for
294 specialists (4-7%) than generalists (1-2%). Therefore, specialists in high-quality matrices have
295 higher random variation in species occurrences among landscapes than in low-quality matrices.

296 The terms that express the variation among species in their overall abundances and
297 responses to habitat loss regardless of their traits (random intercept and slope: *env/sp*) presented the

298 highest marginal R^2 for all assemblages, ranging from 32 to 40%, and being about 1.3 higher for the
 299 specialists than for the generalists. Similarly, marginal R^2 of the terms that express the effects of
 300 species traits associated with unmeasured environmental variables (*trait/site* and *trait/land*) were
 301 very low, and together they varied between 3 to 5% in all assemblages.

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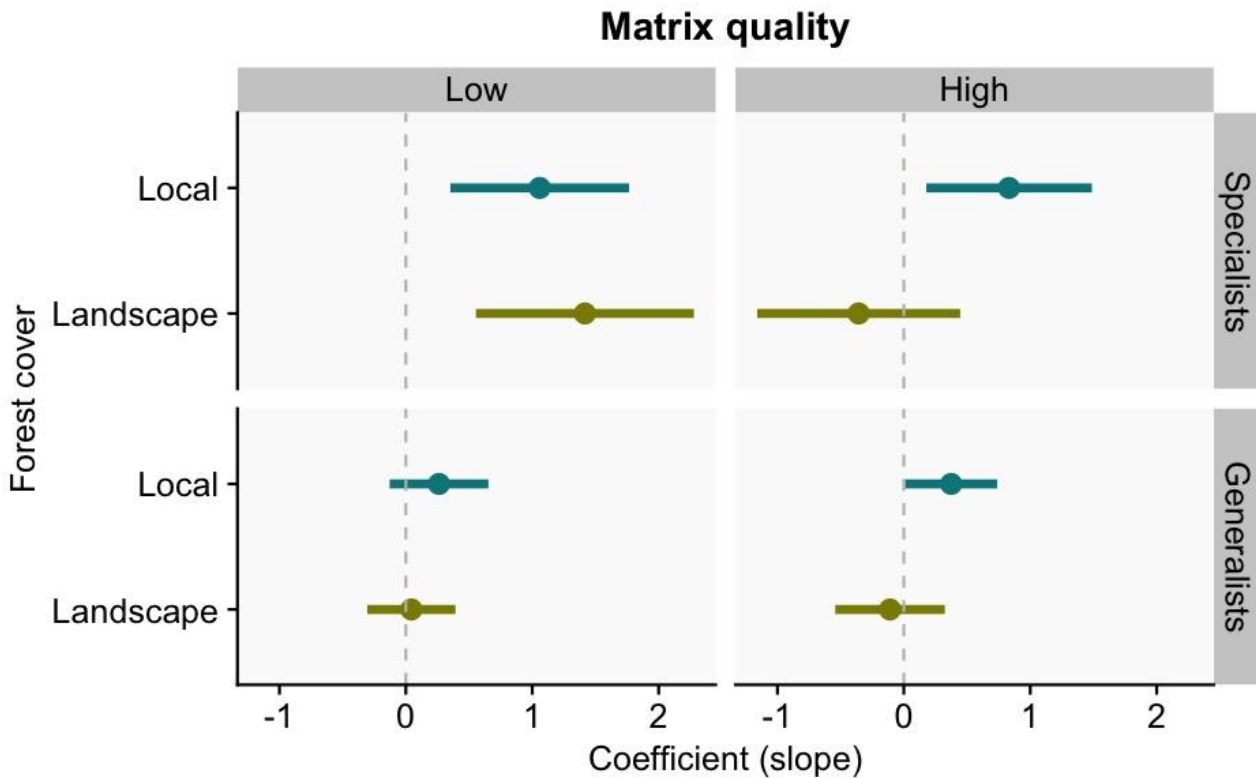


303

304 **Figure 2:** Overall and marginal R^2 s for the models with combined traits (body mass, type of nest,
 305 main diet, percentage of lower strata use) for forest generalist and forest specialists in high and low-
 306 quality matrix landscapes. The number on the right side of each bar indicates the percentages for
 307 each term. See Table 1 for model terms definitions.

308 In comparing habitat loss effects across scales, we found that the effects of both local and
 309 landscape habitat loss in bird occurrence were stronger for the specialists in low-quality matrix
 310 landscapes (Fig. 3). While local forest cover presented similar and positive effects on bird
 311 occurrences for specialists in both high- and low-quality matrix landscapes, landscape forest cover
 312 presented a strong effect only for specialists in low-quality matrix landscapes, where this effect was

313 larger than for local forest cover. As expected, the effects of habitat loss for generalists were
 314 generally weaker and irrelevant at any scale.



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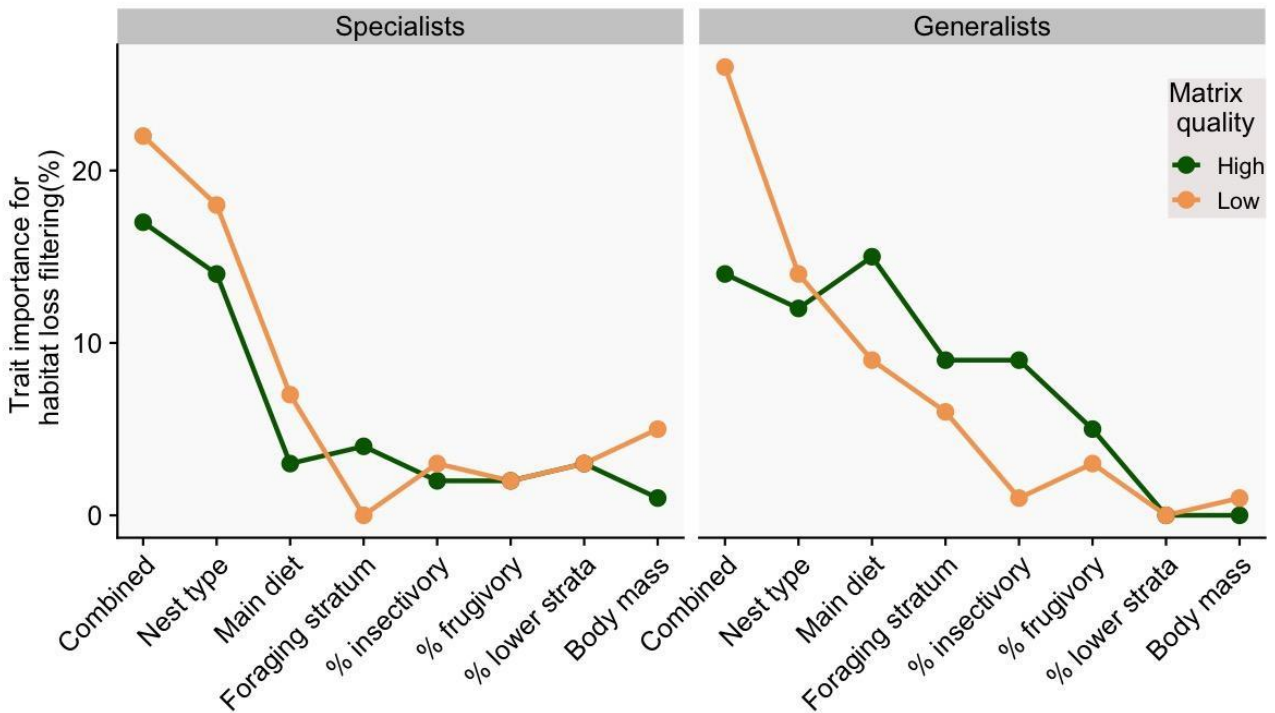
316 **Figure 3:** Slope coefficients (and 95% confidence intervals) of local and landscape forest cover for
 317 specialist and generalist birds in different matrix quality landscapes. These are results for the
 318 combined model (equation 1) with the traits: main diet, nest type, body mass and proportion of
 319 lower strata use. See Appendix 3 for a table of all coefficients estimated for each assemblage.

320 The importance of species traits explaining habitat loss filtering was higher for the
 321 assemblages in low-quality matrices (Fig. 4, combined traits model). Trait importance for the
 322 generalists in low-quality matrix landscapes explained 26% of the variability in species response to
 323 habitat loss. For the specialists, trait importance varied between 17 and 22%, and for the generalist
 324 in high-quality landscapes, it was only 14%. In general, nest type and main diet presented the
 325 highest values of trait importance for the assemblages (Fig. 4).

326 Bird occurrence probabilities were in general higher for the assemblage in high-quality
 327 compared to low-quality matrix landscapes (Fig. 5). For specialists, all the traits were associated

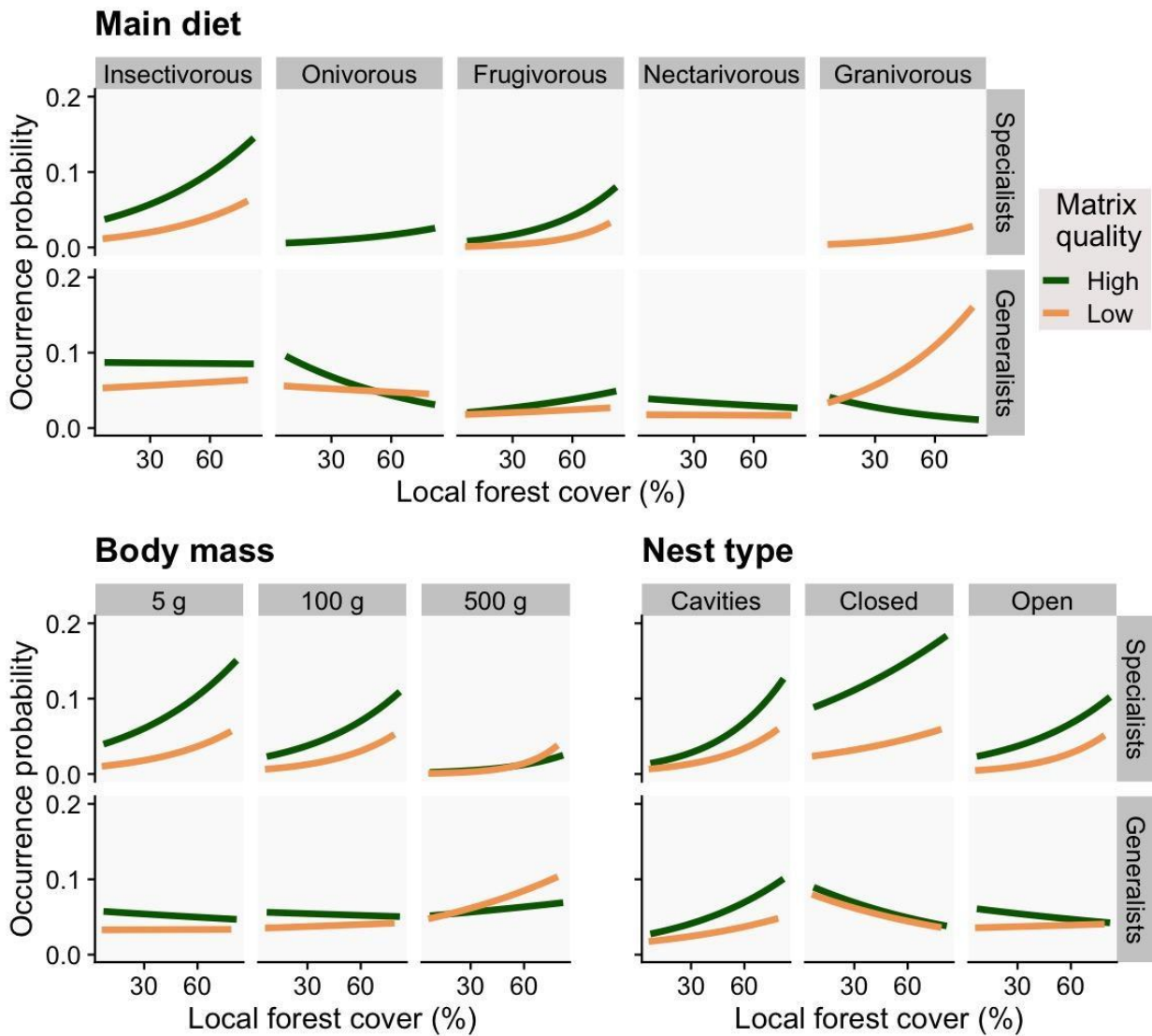
328 with a decrease in occurrence probabilities with habitat loss. For generalists, trait-habitat loss
 329 relationships changed according to the trait. For example, generalists of closed nests responded
 330 positively to habitat loss, while those that nest in cavities responded negatively and generalists of
 331 open nests almost did not change with habitat loss (Fig. 5). Nevertheless, occurrence probabilities
 332 of frugivores, species that build nests in cavities, and large birds decreased with habitat loss
 333 regardless of the matrix type and habitat specificity (Fig. 5).

334



335

336 **Figure 4:** Importance of species traits in explaining habitat loss filtering (equation 2) for forest-
 337 specialists and forest-generalists according to matrix quality. Trait importance was calculated for
 338 each trait in separate models and for the combined model, which includes, nest type, main diet,
 339 body mass, and percentage of lower strata use.



340
 341 **Figure 5:** Probabilities of occurrence of species with local forest cover (400 m buffer; %) according to
 342 main diet, body mass, and nest type for forest specialists and generalists in both high (green
 343 lines) and low-quality matrices (yellow lines). For the predictions, landscape forest cover was fixed
 344 at 30%.

345

346 Discussion

347 Here, we aimed to understand how the quality of the matrix surrounding habitat patches
 348 modulates the relative importance of assembly processes in bird communities across local and
 349 landscape gradients of habitat loss. We found that landscapes with low-quality matrices, composed

350 mainly of low-productive pasturelands, increased the severity of habitat loss filtering effects for
351 forest specialist birds (Fig. 2), with habitat loss effects at the landscape scale (Fig. 3) and habitat
352 loss filtering effects through species traits (Fig. 4) being much stronger in those landscapes. In high
353 quality-matrix landscapes (more heterogeneous and with low-contrasting edges), birds' occurrences
354 were in general larger with more random variation among landscapes (evidence for larger
355 differential dispersal). Both results indicate the role of matrix quality in attenuating extinction risks
356 in the landscape, allowing species that would have been extinct due to habitat loss. As expected,
357 forest specialists presented a stronger response to habitat loss filtering, displaying a consistent
358 negative relationship of all traits (diet, nest type, foraging stratum, and body size) with local habitat
359 loss, while generalists presented a high variability in traits response to habitat loss (Fig. 5).

360 **Matrix quality modulating the relative importance of habitat loss across scales**

361 We found that matrix quality modulates habitat loss effects only for specialist birds at the
362 landscape scale. Local habitat amount effects on birds were not dependent on the quality of the
363 matrix. At the landscape scale, filtering processes are usually related to the selection of species
364 according to landscape composition and configuration (Dufлот et al., 2014; Suárez-Castro et al.,
365 2018). Landscapes composed of low-quality matrices may decrease the availability of
366 supplementary and complementary resources in the matrix (Boesing et al., 2021; Dunning et al.,
367 1992) and/or deteriorate abiotic conditions in habitat edges (Pardini et al., 2009; Pfeifer et al., 2017;
368 Saunders et al., 1991). These two mechanisms together with habitat loss may create an even more
369 severe environmental filter for the communities, selecting only those species able to persist under
370 new harsh conditions (Chase, 2007). Our results for the specialist birds support this hypothesis of
371 lower-quality matrices increasing severity of habitat loss filtering by showing: (1) a 2-times larger
372 relative importance of habitat loss, traits, and filtering effects, with consequently (2) a stronger
373 habitat loss effect, and (3) higher importance of traits in habitat loss filtering. In addition, there is

374 evidence in our study system that the high-quality matrices, especially sun-coffee plantations, are
375 serving as a source of complementary resources for biodiversity due to the movement of organisms
376 from forest patches to the matrix for foraging (*cross-habitat spillover*, Boesing et al. 2018b, 2021).

377 Additionally, landscapes composed of low-quality matrices may hinder dispersal among
378 patches or decrease the survival rate of dispersing individuals (Biz et al., 2017; Fahrig, 2007;
379 Watling et al., 2011). By that, dispersal limitation would create functionally isolated communities
380 more prone to ecological drift (e.g., Baselga et al. 2015, Siqueira et al. 2020), which, in turn, would
381 decrease species filtering effects by habitat loss. However, our results pointed to another direction,
382 as we found that habitat loss filtering through traits was stronger in low-quality matrix landscapes.
383 We believe that in our study system, dispersal limitation is not an issue for the forest birds in both
384 matrix landscapes, as the marginal R^2 s for the differential dispersal (Fig. 2, *lands:sp* term) were
385 relatively low. However, the differential dispersal term was 2 times higher in relative importance
386 (R^2) for the specialists in the high-quality matrix, indicating that there may be not a limitation but an
387 excess of dispersal in high-quality matrices – possibly resulting in source-sink dynamics (Mouquet
388 & Loreau, 2003). High-quality matrix landscapes with higher dispersal rates, more resource
389 availability, and milder edge effects may be preventing extinctions of isolated populations by
390 migration of individuals from other patches (*mass effect* in metapopulation theory, Leibold et al.
391 2004). This mechanism would weaken the deleterious effects of habitat loss, allowing the survival
392 of species that are not optimally suited for the new environmental conditions (Leibold & Loeuille,
393 2015).

394 **Habitat loss filtering depends on the quality of the matrix**

395 The importance of species traits in explaining habitat loss filtering effects was higher for the
396 assemblages in low-quality matrices for both generalists and specialists (Fig. 4), evidencing

397 stronger filtering effects in low-quality matrix landscapes as discussed above. We found that
398 specialist birds with certain traits, e.g., small-sized, insectivorous, or birds with closed nests, were
399 more prone to extinction due to habitat loss in landscapes embedded in low-quality matrices than
400 species with the same traits in high-quality matrices (Fig. 5). This indicates further that habitat loss
401 has different filtering effects (stronger or weaker) over species traits depending on the quality of the
402 matrix. Such changes might be related to further effects of the matrix changing specific niches
403 required by different species in-patches, mostly via edge-effects on both biotic and abiotic patterns
404 (Murcia, 1995). For instance, species that make nests in cavities or build closed nests are safer
405 against parasitism and predation (Sibly et al., 2012), which are among the most impacting drivers of
406 bird populations' decline in fragmented landscapes (Cavitt & Martin, 2002). As nest
407 predation/parasitism often increases with edge effects (Murcia, 1995), it may be stronger in
408 landscapes with highly contrasting matrices, i.e., lower quality. However, this difference among
409 matrices of different quality vanishes in low forest cover (less than 30%) for species that nest in
410 cavities, even though they have higher occurrence probabilities for larger forest cover (~60%) in
411 high-quality matrix landscapes. It may be the case that the lack of suitable nesting cavities under
412 low forest cover amounts have a similarly strong effect on the reproduction of these species in both
413 landscape types, especially for Picidae and Psittacidae families, which require old or dead trees to
414 build their nests (Sick, 1997).

415 Because we were able to compare the same set of traits for forest generalist and specialist
416 species, we can understand better why habitat loss and fragmentation not necessarily leads to loss of
417 functional diversity (Boesing et al., 2018a), change in functional traits (de Coster et al., 2015), or
418 even functional homogenization (Clavel et al., 2011; Devictor et al., 2008; Nordberg &
419 Schwarzkopf, 2018). If specialists are replaced by generalists with similar trait values, functional
420 differences cannot be easily observed, and thus no apparent functional differences are seen, as often

421 reported (Boesing et al., 2018a; de Coster et al., 2015). However, we also found that species with
422 some specific traits (such as nest type and body size) were always negatively impacted by habitat
423 loss. This finding raises the point that not all forest generalist species succeed in fragmented
424 landscapes, and that some key functions and/or species may be indeed lost with no substitution of
425 traits when specialists are replaced by generalists. Overall, our results reinforce the evidence that
426 habitat loss and matrix harshness promote abiotic environmental changes inside habitat patches
427 which make species with specific traits to be more prone to extinction than others under different
428 matrix conditions in the landscapes.

429 **Theoretical and practical implications**

430 Despite a long-standing global research effort into understanding how habitat loss and
431 fragmentation influence species loss, and at which spatial scale species loss is observed (Horváth et
432 al., 2019), there is still a considerable debate on which mechanisms are more important (Fahrig,
433 2013, 2017; Fletcher et al., 2018; Haddad et al., 2015; Hanski, 2015). Our findings raised evidence
434 supporting that habitat loss is a strong filtering process that often leads more vulnerable species to
435 extinction (Banks-Leite et al., 2012; Gilbert et al., 2006; Pardini et al., 2017; Püttker et al., 2015),
436 but with a considerable influence of the matrix in modulating filtering processes. We have
437 evidenced the importance of the matrix quality in modulating habitat loss effects at the landscape
438 scale, weakening or strengthening its severity on species filtering (Chase, 2007). Matrices of low
439 quality accentuate habitat loss filtering in fragmented landscapes through its relatively larger effects
440 in altering resource availability and edge effects, more than movement limitation. Consequently, the
441 larger severity of habitat loss filtering in low-quality matrix landscapes decreases the relative
442 importance of ecological drift on those assemblages.

443 Statistical quantification of the effects of dispersal and ecological drift is still an unresolved
444 methodological problem with many caveats (Vellend et al., 2014). Our framework builds on the
445 idea of handling possible effects of differential dispersal through terms that would take the extra
446 variability of the data (overdispersion) produced by differences in species occurrences across sites
447 and landscapes (Mortara, 2016). This way, we saw that dispersal limitation in low-quality matrices
448 leading to drift is not the only possible outcome after habitat loss and fragmentation. High rates of
449 dispersal in high-quality matrix landscapes can even override environmental filtering by allowing
450 species to occupy habitat patches where their intrinsic growth rate would be otherwise negative
451 (Chase et al., 2020). To our knowledge, this is the first empirical evidence that a not limited
452 dispersal in high-quality matrices may result in mass effects in metacommunities in fragmented
453 landscapes, although its effects are relatively small in comparison with environmental filtering.

454 In practical terms, improving matrix quality in fragmented landscapes is a key action aiming
455 to restore and achieve more sustainable landscapes (Arroyo-Rodríguez et al., 2020; Leite et al.,
456 2013), especially in places where conservation practices and restoration are constrained by
457 economic and political conflicts, are costly-demanding and requires strategic planning (Metzger et
458 al., 2021). In this sense, converting low-productive pastures into more heterogeneous environments
459 via tree enrichment (Prevedello et al., 2018), or converting such pastures (even if partially) in less
460 contrasting land uses (such as diversified crops, perennial crops, or even tree plantations) can
461 increase matrix quality, minimizing the severity of habitat loss and fragmentation for forest birds
462 (Ruffell et al., 2017). In our study areas, the conversion of abandoned and unproductive
463 pasturelands into silviculture in the last decades was responsible for the increase in second-growth
464 native forests (Calaboni et al., 2018). Restoration and economic practices improving matrix quality
465 may help in maintaining the high diversity of birds in the Atlantic Forest even without any increase
466 in native forest cover.

467

468 **Supporting information**

469 APPENDIX 1: Extended methods, bird assemblages, and species trait selection

470 APPENDIX 2: Forest cover at local and landscape scales

471 APPENDIX 3: Additional models results and diagnostic

472 **Authors' contributions:** M.S.L., A.L.B. and P.I.P. conceived the project. A.L.B. and J.P.M
473 delineated the sampling design. A.L.B. collected the data. M.S.L. and P.I.P. analyzed the data and
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485 **Data archiving:** All data and code used in the analysis are available in Zenodo Repository
486 <http://doi.org/10.5281/zenodo.5516704> (Leite, 2021) with the published version of the GitHub
487 repository. The original data is also available from the Dryad Digital Repository
488 <http://dx.doi.org/10.5061/dryad.37s4h> (Boesing et al., 2017).

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