

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 **Abstract**

- 12 1. Habitat loss represent a major threat to biodiversity, however, the modulation of their effects
13 by the non-habitat matrix surrounding habitat patches is still undervalued. The landscape
14 matrix might change community assembly in different ways. For example, low-quality
15 matrices can accentuate environmental filtering by reducing resource availability and/or
16 deteriorating abiotic conditions but they may also over limit dispersal of organisms and
17 make communities more prone to ecological drift.
- 18 2. To understand how matrix quality modulates the effects of habitat loss, we quantified the
19 relative importance of environmental filter and ecological drift in bird communities across
20 more local (400 m buffer around sampling sites) and broader (2 km focal landscapes)
21 gradients of habitat loss embedded in low- and high-quality matrices. We used a trait-based
22 approach to understand habitat loss filtering effects on forest specialist and habitat generalist
23 bird occurrences.
- 24 3. We found that low-quality matrices, composed mainly of low-productive pasturelands,
25 increased the severity of habitat loss filtering effects for forest specialist birds, but only at
26 the landscape scale. Bird occurrences were in general higher in high-quality matrices, i.e.,
27 more heterogeneous and with low-contrasting edges, indicating the role of the matrix quality
28 on attenuating species extinction risks at the landscape scale, probably due to mass effect.
29 Moreover, forest specialists presented a strong negative response to habitat loss filtering
30 across different functional traits, while generalists presented a high variability in traits
31 response to habitat loss.
- 32 4. *Synthesis and applications:* We raised evidence in supporting that landscape habitat loss
33 filtering may be relaxed or reinforced depending on the quality of the matrix, evidencing
34 that matrix quality has a strong impact in modulating community assembly processes in

35 fragmented landscapes. In practical terms, it means that improving matrix quality may help
36 in maintaining the high diversity of birds even without any increase in native forest cover.

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

39 **Introduction**

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

50 Determining the matrix effects on community assembly processes in human-dominated
51 landscapes faces two main challenges: how to disentangle community assembly processes at
52 different spatial scales, and how to characterize the matrix context in landscapes. First, community
53 assembly processes in acting differently at local and landscape scales may result in different
54 metacommunity arrangements (Leibold et al., 2004), which evidence the foreseen patterns of
55 multidimensionality and scale-dependency of species richness and biodiversity changes (Chase et
56 al., 2018). One approach to disentangle community assembly processes is the use of species traits to
57 elucidate mechanisms by which communities respond to environmental gradients (McGill et al.,
58 2006). Such trait-environment associations proved to be critical in understanding how ecological
59 processes affect biodiversity across scales (Newbold et al., 2013, 2014; Suárez-Castro et al., 2018).
60 Therefore, trait-focused approaches may show how local environments and landscapes constrain
61 diversity (Tschardt et al., 2012), for example when the matrix influences trait diversity in habitat
62 patches (Boesing et al., 2018a; Häkkilä et al., 2017).

63 Second, a prolific way to characterize matrix context is by its quality for a target group of
64 organisms. Matrix quality is taxon and context-dependent, but in general, it may be assumed as the
65 structural similarity of the matrix with the native habitat (Prevedello & Vieira, 2010). For instance,
66 landscapes with high-quality matrices can maintain greater amounts and diversity of resources
67 (Dunning et al., 1992; Pardini et al., 2009) which can be used occasionally by species living in
68 habitat patches (spillover; Blitzer et al. 2012). High-quality matrices can also facilitate species
69 movement across the landscape leading to higher landscape connectivity (Antongiovanni &
70 Metzger, 2005; Fahrig, 2007). Consequently, landscapes with high-quality matrices may support
71 more species than the ones with matrices of lower quality (Carrara et al., 2015; Reider et al., 2018).

72 The matrix may change how habitat loss and fragmentation modulate community assembly
73 processes through its effects on (1) organismal movements (Biz et al., 2017; Fahrig, 2007; Watling
74 et al., 2011), (2) the availability of supplementary or complementary resources in the landscape
75 (Boesing et al., 2021; Dunning et al., 1992), and (3) abiotic edge conditions of habitat patches
76 (Saunders et al. 1991, Pardini et al. 2009, Pfeifer et al. 2017). When movements of organisms
77 among habitat patches are heavily limited by the matrix, dispersal may be limited and, together with
78 habitat loss, will lead to small and functionally isolated communities, which are more prone to
79 ecological drift (Horváth et al., 2019; Siqueira et al., 2020), i.e., random fluctuations of species
80 abundances in the community leading or not to random local extinctions (Vellend et al. 2010).
81 When matrix decreases resource availability in the landscape and/or accentuate unfavorable abiotic
82 condition inside habitat patches (edge effects), habitat loss may be an even more severe
83 environmental filter, selecting only those species able to persist under these harsher conditions
84 (Chase, 2007). By modulating these three mechanisms, matrix quality changes how habitat loss and
85 fragmentation alter the relative importance of the assembly processes of dispersal (potentially
86 leading to ecological drift) and environmental filtering. Moreover, given the scale-dependent nature

87 of ecological communities (Chase et al., 2018), only a multiscale combined with a trait-based
88 approach (Suárez-Castro et al., 2018) may help to identify the relative strength of such processes
89 across both local and landscape scales.

90 Bird communities are an excellent model system to investigate the effects of matrix quality
91 on community assembly after habitat loss because it is a key factor determining birds' movements
92 and resource use in anthropogenic landscapes (Barros et al., 2019; Boesing et al., 2018a; Deikumah
93 et al., 2013; Kennedy et al., 2010). Birds are especially mobile organisms, which allows them to
94 actively search and respond to pulses of resources in ways not generally possible for other
95 vertebrates, allowing them to leave areas in which resources are no longer sufficient and relocate to
96 more productive locations (Whelan et al., 2008). In addition, birds have large variety of responses
97 to landscape modification: while in general habitat-specialist species are highly intolerant to human-
98 modified environments, habitat generalists are less restrictive and more resilient to use different
99 kinds of environments (Boesing et al., 2021; Morante-Filho et al., 2016).

100 In this study, we investigated whether and how matrix quality modulates the relative
101 importance of assembly processes in bird communities across gradients of habitat loss. First, we
102 hypothesize that the relative contribution of the assembly processes of habitat loss filtering and
103 ecological drift will depend on (1) how dispersal is limited and (2) the harshness of the
104 environmental filtering by matrices of different qualities. If bird dispersal is heavily limited by low-
105 quality matrices, habitat loss will create small and isolated communities more prone to drift, which
106 in turn will relatively decrease the importance of habitat loss filtering compared to landscapes with
107 high-quality matrices. However, if the main effects of a low-quality matrix are in decreasing
108 resource availability and/or deteriorating abiotic conditions in habitat patches, habitat loss will be an
109 even more severe filter, increasing the relative importance of habitat loss filtering compared to
110 high-quality matrix landscapes. Second, given that matrix quality is an element of the landscape, we

111 expect that the effects of habitat loss filtering on species traits will be stronger at the focal landscape
112 scale than at the local scale – i.e. the amount of forest nearby the sampling point (hypothesis of
113 landscape moderation of trait selection; Tschamntke et al. 2012). We compared results between
114 forest specialist and habitat generalist birds. Since specialists are considered more sensitive to
115 habitat loss (Carrara et al., 2015; Pardini et al., 2009), habitat loss filtering should be stronger and
116 negative for them. As habitat generalists are commonly less affected by habitat loss or can even
117 increase in abundance (Nordberg & Schwarzkopf, 2018), we predict a positive or null relationship
118 of their traits to habitat loss.

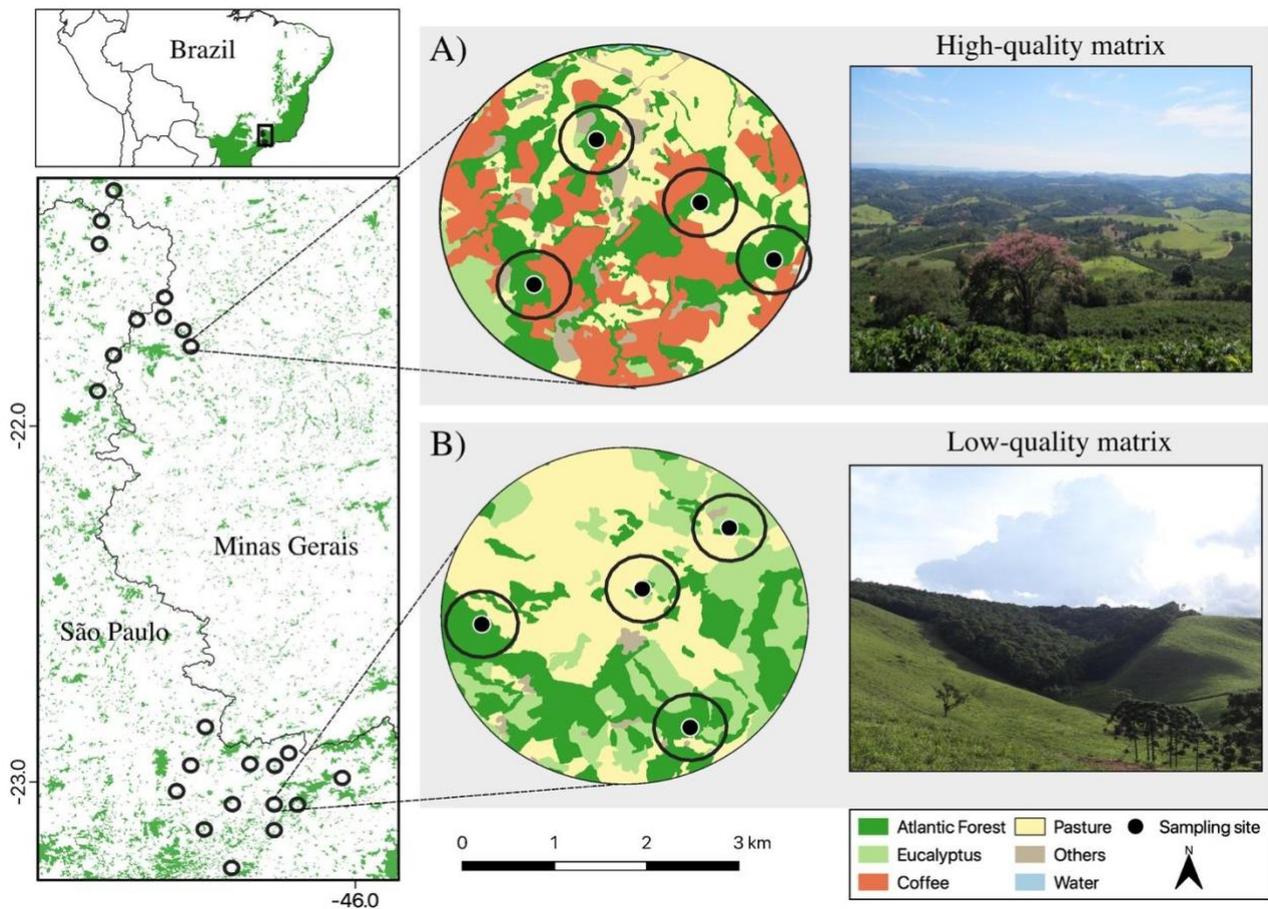
119 To test our hypotheses and predictions, we modeled the occurrence of bird species in sets of
120 landscapes from two regions with contrasting matrix qualities using hierarchical models that are
121 commonly used to analyze trait-environment associations (Jamil et al., 2013; ter Braak, 2019), for
122 disentangling scale-dependent community assembly processes (Ovaskainen et al., 2017), and to sort
123 out niche and drift effects on species abundances (Mortara, 2016). We used variance partitioning of
124 the models (Nakagawa & Schielzeth, 2013) to compare the relative importance of processes across
125 assemblages. Habitat loss effects across scales were investigated by both habitat loss overall effect
126 in birds' occurrences and trait filtering effects as the variation of the effects of forest cover on
127 species with different traits (interaction terms). We also evaluated how much (in percentage) of the
128 species response to habitat loss is explained by their traits to understand how species traits are
129 filtered in landscapes under different matrix contexts.

130

131 **Methods**

132 **Study areas**

133 The study was carried out in the Atlantic Forest of southeastern Brazil (Fig. 1). The entire
134 region retains less than 30% of the original forest cover, and most of the forest is confined in small
135 patches (< 50 ha) in different stages of regeneration (Rezende et al., 2018). Our study landscapes
136 were constrained across two regions (far apart 90 km) retaining similar biophysical characteristics
137 and bird species pool, but with different agricultural matrix compositions. These matrices were
138 denominated as high and low quality considering the perspectives or requirements of forest
139 dependent bird species. Higher quality is associated with a more heterogeneous landscape and low-
140 contrasting edges that provide more resources and facilitate the movement of forest species across
141 the landscape. The northwest region (henceforth ‘high-quality matrix’) is mainly composed of a
142 mosaic of sun-coffee, sugar cane plantations, and pastures, resulting in a more heterogeneous
143 matrix. Coffee plantations cover around 46% of the matrix and it is usually located adjacent to
144 forest edges, creating low-contrasting edges at the patch scale (Fig. 1A). The southeast region
145 (henceforth ‘low-quality matrix’) is largely dominated by low-productive pastures and low diversity
146 of other land use types, and so it is composed of a more homogeneous matrix. Additionally, the
147 huge structural difference between pastures and forests creates high-contrasting edges at the patch
148 scale (Fig. 1B). See Appendix 2 for comparisons of land use composition of landscapes at both
149 regions.



150

151 **Figure 1:** Location of the study area (left upper panel) within the Atlantic Forest biome (in green)
 152 with 23 studied landscapes in southeastern Brazil (left lower panel). We show two 2 km radius
 153 landscapes with 27% of native forest cover, but in (A) with a high-quality matrix – more
 154 heterogeneous with a high proportion of sun coffee plantations; and in (B) with a low-quality matrix
 155 mostly composed of low-productive pastures. In each landscape 4 local-scale sampling points of
 156 400 m radius buffer (black dots).

157 We used the landscape selection approach of Pasher et al. (2013) to select independent focal
 158 landscapes that span a gradient of landscape-level forest cover, while controlling for potentially
 159 confounding factors, as altitude (ranging from 800-1300 m.a.s.l), soil type (ferric red latosol or
 160 argisol soil), presence of large highways and water reservoirs. We selected 10 and 13 focal
 161 landscapes (2 km radius, 1256 ha each) in the high-quality (ranging from 7-46% of forest cover)
 162 and low-quality matrix (12-55% of forest cover) regions, respectively. In each landscape, we placed
 163 4 sampling sites (total 96 sites) in forest patches spaced a minimum of 800m apart (1591 ± 621 m)

164 in a way to cover different ranges of local forest cover inside the same focal landscape. For each
165 selected forest patch, we randomly selected a point along the forest-matrix interface and placed a
166 sampling site within the forest patch at the end of a 100 m transect always oriented to the center of
167 the forest patch. The matrix type of the closest edge was always a coffee plantation in high-quality
168 landscapes and pasture in low-quality landscapes. All selected forest patches at both regions were
169 similar in structure and composed of intermediate to advanced second-growth forest with a well-
170 established canopy, free from cattle disturbance in the understory and, located within private
171 properties. See Appendix 1 and Boesing et al. (2018a) for more details about the area selection
172 procedure.

173 **Bird sampling and traits selection**

174 In each sampling site, we performed a 50 m fixed radius point count and recorded all bird
175 species detected visually or aurally during a 15 min sampling period. Studies in tropical regions
176 indicate that 10 min point counts are sufficient to record 90% of tropical bird species (Esquivel et
177 al., 2008). Each site was visited four times, between January–April and August–November of 2014
178 (N=368), by the same experienced ornithologist (ALB) and both regions were sampled
179 simultaneously (more details in Appendix 1).

180 To be recorded, bird individuals needed to be perched or singing inside the radius of
181 detection: species flying above the canopy or flying through the sample area were not recorded
182 (Bibby et al., 2000). All point counts were performed in the four hours after sunrise and in the last
183 hour before sunset. Each point count was sampled in different times during the morning and
184 evening periods in order to give the same chance of detection for all species (Esquivel et al., 2008).
185 To increase the detectability of more cryptic and rare species, each point count was replicated four
186 times, between January–April and August–November of 2014 (23 landscapes, 92 sampling sites, n

187 = 368 point counts) and both regions were sampled simultaneously. Some of the records are
188 deposited at: <https://xeno-canto.org/contributor/ETMICIBVME>.

189 Bird traits selection followed the framework proposed by Luck et al. (2012). First, we listed
190 the potential traits based on current knowledge on bird traits related to extinction-proneness due to
191 habitat loss, land use, or environmental change (references in Appendix 2). Then, we selected traits
192 based on the (1) data availability; (2) experts' knowledge (ALB); and (3) the empirical relationship
193 among traits (correlations). Finally, we selected five groups of response traits that are known to
194 affect individual fitness by influencing growth, reproduction, or survival of the species on human-
195 modified landscapes: hand-wing index (HWI), body size, nest type, diet, and foraging stratum.
196 These traits were represented by eight operational variables described in detail in Appendix 2.

197 We kept separate analyses for forest specialist and habitat generalist birds (henceforth just
198 specialists and generalists) given that habitat specialization is very important for understanding the
199 effects of habitat loss and fragmentation (Kupsch et al., 2019; Pandit et al., 2009). Moreover, as
200 both groups of species presented similar ranges of trait values on our data (Appendix 2), we also
201 investigated if the same trait differs in response to habitat loss depending on species habitat
202 specialization. We considered forest specialists those species that depend on forest environments for
203 breeding and survival, and habitat generalists those that rely on different habitat types, including
204 forests, to survive (Del Hoyo, 2014). We appealed afterwards for a bird expert revision (Scott
205 Robinson, Univ. of Florida) to guarantee the quality of our classification. We also excluded
206 predators to conform our assemblages to the definition of a horizontal community without trophic
207 interactions (*sensu* Loreau, 2010) and due to the biased method of point counts for detection of such
208 species.

209 **Modeling**

210 We modeled bird occurrences with hierarchical linear models commonly used to analyze
 211 trait-environment associations and disentangle scale dependency in community assembly processes
 212 (Jamil et al., 2013; ter Braak, 2019). We used a binomial generalized linear mixed model (logit link
 213 function) with the number of detections of each of n species (four visits) in each of m sites as
 214 response variable (Miller et al., 2018). In each species-site combination (Y_i , where i goes from 1 to
 215 $n \times m$ observations), we assigned predictors of the n species-level trait and the m site- and
 216 landscape-level forest cover (Miller et al., 2018). Our model is described by:

$$217 \quad Y_i \sim \text{Binomial}(4, p)$$

$$218 \quad \text{logit}(p) = (\alpha + a_{\text{spp}[i]} + b_{\text{site}[i]} + c_{\text{landscape}[i]}) + (\beta_1 + d_{\text{spp}[i]}) \text{forest}_{\text{cover}_{\text{site}[i]}} +$$

$$219 \quad (\beta_2 + e_{\text{site}[i]} + f_{\text{landscape}[i]}) \text{trait}_{\text{spp}[i]} + \beta_{12} \text{trait}_{\text{spp}[i]} \times \text{forest}_{\text{cover}_{\text{site}[i]}} + \quad (1)$$

$$220 \quad g_{\text{site}[i] \times \text{spp}[i]} + h_{\text{landscape}[i] * \text{spp}[i]}$$

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

$$227 \quad Y \sim \text{trait} * \text{forest_cover} + (\text{forest_cover} | \text{species}) + (\text{trait} | \text{site}) +$$

$$228 \quad (\text{trait} | \text{landscape}) + (1 | \text{landscape} : \text{species}) + (1 | \text{landscape} : \text{site})$$

229 The fixed effects in the logit link function are the main effects of habitat loss and trait
230 $(\alpha, \beta_1, \beta_2)$ and habitat loss filtering effects through traits (interaction term β_{12}). We used the
231 percentage of forest cover at both local and landscape scales as response variables to denote habitat
232 loss and we found no collinearity between these variables (Appendix 2). We are particularly
233 interested in: (1) the main effects of habitat loss, i.e., how steep is the decrease in occurrence
234 probability of all birds when habitat is lost, and (2) the interaction effect of habitat loss with traits,
235 i.e., how species with different traits respond to habitat loss. However, these effects are not
236 statistically easily separable from the main effects of trait in terms of variance explained (R^2 ,
237 Johnson 2014). As we show below, we kept the whole structure of fixed effects in interpreting
238 marginal R^2 as a general interpretation of habitat loss effects. Nevertheless, we also compared the
239 estimates of habitat loss main effects among assemblages and across scales and calculated the
240 importance of the traits in explaining habitat loss filtering (equation 2, below) to interpreting habitat
241 loss filtering effects through traits.

242 Species random effects are the variation among species in their overall abundances (random
243 intercept, $a_{spp[i]}$) and response to habitat loss (random slope, $d_{spp[i]}$) regardless of its trait values.
244 They express the idiosyncratic response of each species to habitat loss and their differences in
245 overall abundances. Trait-site and trait-landscape random interactions (random intercepts: $b_{site[i]}$,
246 $c_{landscape[i]}$, and slopes: $e_{site[i]}$, $f_{landscape[i]}$) deal with the trait-mediated response to non-
247 measured environmental gradients at local and landscape scales, respectively. This is a solution to
248 "account for any interaction that the observed trait has with any unobserved environmental
249 gradient" (ter Braak, 2019).

250 We included two additional random effects of site-species ($g_{site[i] \times spp[i]}$), and landscape-
251 species interactions ($h_{landscape[i] \times spp[i]}$) to express that the occurrence probability of the same

252 species may vary among sites and landscapes, regardless of the species identity, its traits, and the
 253 habitat loss gradients. This term expresses a random variation in species occurrences probabilities
 254 across sites and landscapes. The site-species interaction term is the so-called Observation Level
 255 Random Effect (OLRE), which allows for extra variance among observations. OLRE is generally
 256 used to deal with overdispersion in data modeling with the exponential family distributions
 257 (Harrison, 2015). For species occurrences, overdispersion is frequently associated with individuals'
 258 aggregations in space (e.g. Ozgul et al., 2009). In this sense, at the community level, we can assume
 259 that the spatial aggregation expressed by these terms is a result of differential dispersal, which may
 260 be a limitation or excess of dispersal. Dispersal limitation of individuals among patches and
 261 landscapes may lead to ecological drift (*sensu* Vellend 2010). Although it is expected that these
 262 terms express ecological drift (Mortara, 2016), we cannot ensure that all the variances apportioned
 263 in these terms are exactly differential dispersal. However, because we have carefully handled many
 264 possible niche processes (or selection *sensu* Vellend 2010) in the model, probably, these terms do
 265 not include other processes than random variation in species occurrence probabilities. At least, if
 266 differential dispersal among patches and landscapes is an important process, it will be expressed in
 267 these two random effects and not in the other terms.

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

$$271 \quad C_{\beta} = 1 - \frac{d_{spp[i]}(res)}{d_{spp[i]}(total)} \quad (2)$$

272 $d_{spp[i]}(res)$ is the variance of the random species slope from the model with forest cover and trait
 273 main effects (β_2) and the trait-environment interaction (β_{12}); $d_{spp[i]}(total)$ is the same variance
 274 term for the model without trait-environment interaction but with the main effects. This proportion

275 explains how much of the effect of habitat loss on each species can be explained by their trait
 276 values.

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

284

285 **Table 1:** Definitions and ecological interpretations of the statistical terms of the hierarchical linear
 286 model (equation 1). Code syntax follows *lme4* R package.

Model terms	Code	Description
$\alpha; \beta_1; \beta_2; \beta_{12}$	trait*env	Fixed effects: main effects of habitat loss and traits, and habitat loss filtering effects through traits (interaction terms) at both local and landscape scale.
$a_{spp[i]}; d_{spp[i]}$	(env 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 habitat loss 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 habitat loss conditions.

287
 288

289 **Data analysis**

290 We ran the model described above for each low and high-quality matrix landscapes and for
291 forest specialists and habitat generalists separately (hereafter assemblages) to better interpret and
292 compare overall and marginal R^2 s among assemblages. We analyzed the data in two steps. First,
293 given that ecological responses can be affected by processes acting at different spatial scales, we
294 selected the best scale for the effect of local forest cover (Appendix 2), which was the percentage of
295 local forest cover measured at 400 m buffer radius around each site (Fig. 1). Second, we ran
296 separate models for each species trait (equation 1) including local and landscape forest cover (2 km
297 radius around the centroid of the landscapes) as predictors of habitat loss. We finally combined 4
298 traits with the highest explanatory power for all datasets (main diet, proportion of lower strata use,
299 body mass, and nest type) in one model to predict the trait's response to habitat loss and to compare
300 the marginal R^2 of each model term. The combined traits models did not show collinearity and the
301 traits were not correlated among species (Appendix 3).

302 Considering that the two regions with high- and low-quality matrix landscapes may present
303 different pools of species, we performed a robustness analysis with only the species that occurred at
304 both regions with high- and low-quality landscapes. The results from the combined models with
305 only the subset of species were very similar to the models with all species in each assemblage
306 (Appendix 4), discarding any potential effect of biogeography or other sources of variation in
307 species composition in our results. All data analysis was performed using R (version 4.0, R Core
308 Team 2019) with *lme4* package (Bates et al., 2015) for modeling, and *DHARMA* (Hartig, 2018) for
309 quantile residuals diagnostic (Appendix 3).

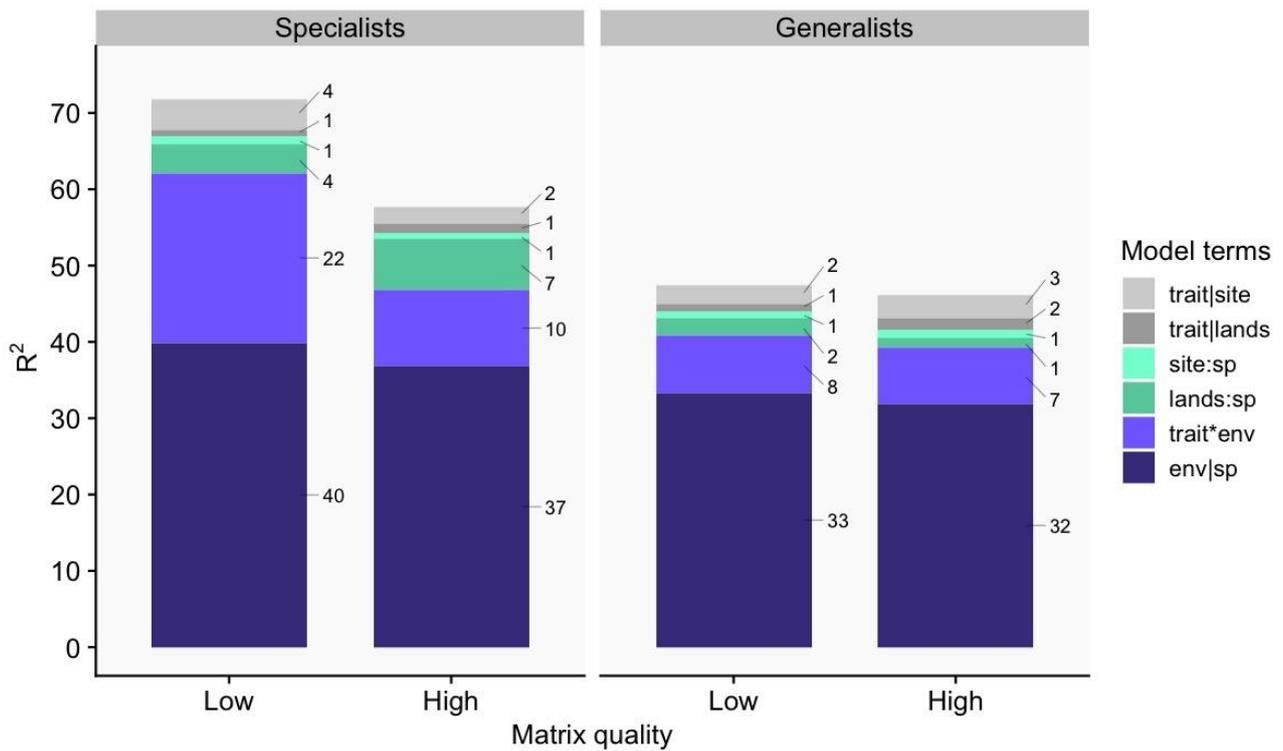
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311 **Results**

312 In our modeling approach, the R^2 s of the fixed effects – trait, habitat loss, and filtering
313 effects at both local and landscape scales – were the variance component that presented the most
314 marked differences between assemblages (Fig. 2). It was 2.2 times higher for the specialists in the
315 low-quality than in the high-quality matrix landscapes (22 and 10%, respectively), and it was up to
316 3 times higher for specialists than for both generalist assemblages (7-8%). It means that habitat loss
317 effects alone and habitat loss filtering effects were much stronger for the specialist birds in low-
318 quality matrix landscapes. Moreover, overall R^2 for specialists in low-quality matrix landscapes
319 captured most of the variability in bird's occurrence (72%), followed by specialists in high-quality
320 matrices (58%) (Fig. 2). Overall R^2 for generalists was smaller and similar across landscapes
321 regardless of matrix quality (46-47%).

322 The R^2 for the terms that account for random variation in species occurrences across sites
323 (*site:sp*), were very low (1%) for all assemblages. However, the R^2 for random variation in species
324 occurrences at the landscape scale (*lands:sp*) was larger for the specialists in high-quality matrices
325 than for the specialists in low-quality matrices. This term was also larger for specialists (4-7%) than
326 generalists (1-2%).

327 The terms that express the variation among species in their overall abundances and
328 responses to habitat loss regardless of their traits (random intercept and slope: *env/sp*) presented the
329 highest marginal R^2 for all assemblages, ranging from 32 to 40%, and being about 1.3 higher for the
330 specialists than for the generalists. Similarly, marginal R^2 of the terms that express the effects of
331 species traits associated with unmeasured environmental variables (*trait/site* and *trait/land*) were
332 very low, and together they varied between 3 to 5% in all assemblages.



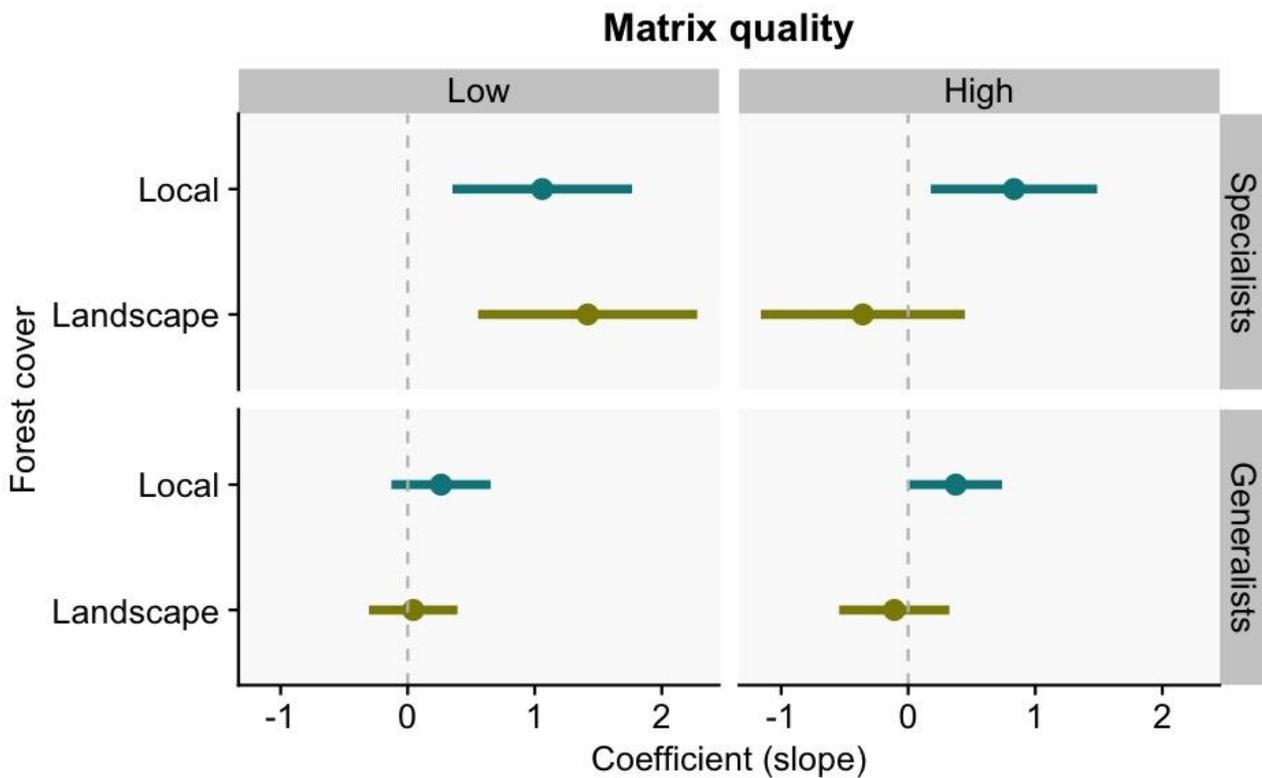
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334 **Figure 2:** Overall and marginal R^2 s for the models with combined traits (body mass, type of nest,
 335 main diet, percentage of lower strata use) for habitat generalist and forest specialist birds in high
 336 and low-quality matrix landscapes.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

338

In comparing habitat loss effects across scales, we found that the effects of both local and
 339 landscape habitat loss in bird occurrence were stronger for the specialists in low-quality matrix
 340 landscapes (Fig. 3). While local forest cover presented similar and positive effects on bird
 341 occurrences for specialists in both high- and low-quality matrix landscapes, landscape forest cover
 342 presented a strong effect only for specialists in low-quality matrix landscapes, where this effect was
 343 larger than for local forest cover. As expected, the effects of habitat loss for generalists were

344 generally weaker and irrelevant at any scale.



345

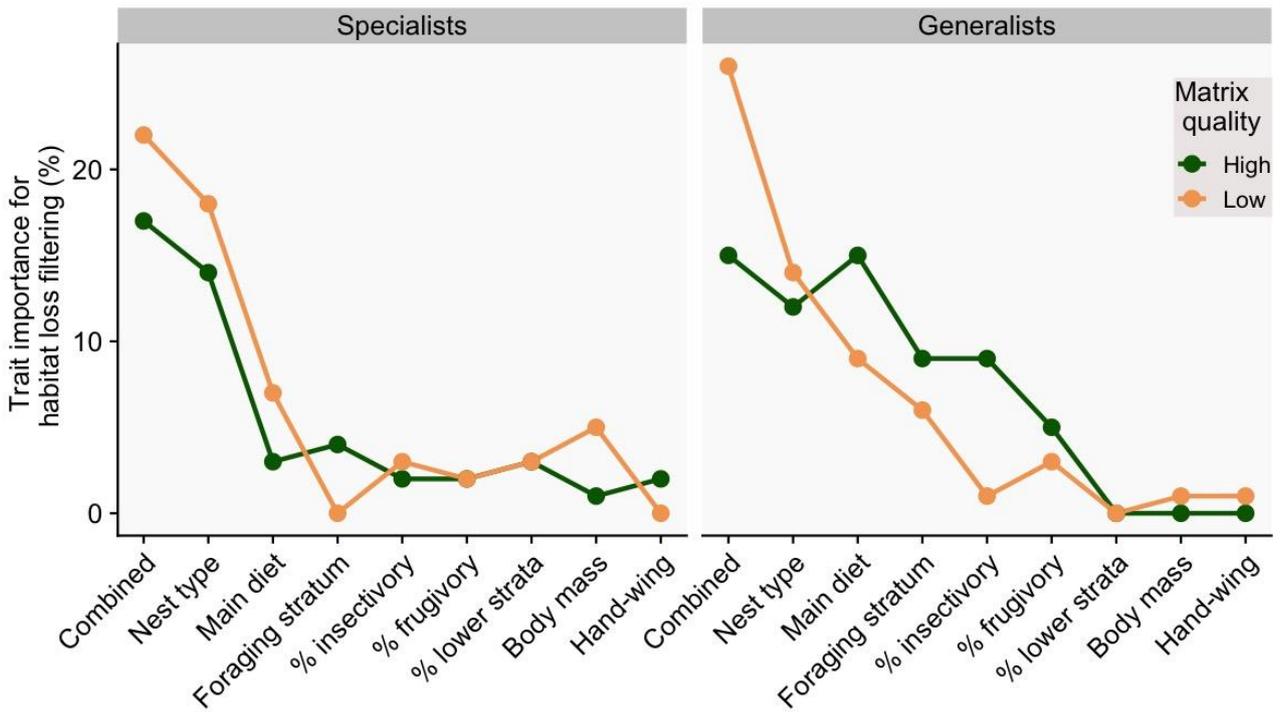
346 **Figure 3:** Slope coefficients (and 95% confidence intervals) of local and landscape forest cover for
347 forest specialist and habitat generalist birds in different matrix quality landscapes. These are results
348 for the combined traits model. See Appendix 3 for a table of all coefficients estimated for each
349 assemblage.

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

356 Bird occurrence probabilities were in general higher for the assemblage in high-quality
357 compared to low-quality matrix landscapes (Fig. 5). For specialists, all the traits were associated
358 with a decrease in occurrence probabilities with habitat loss. For generalists, trait-habitat loss

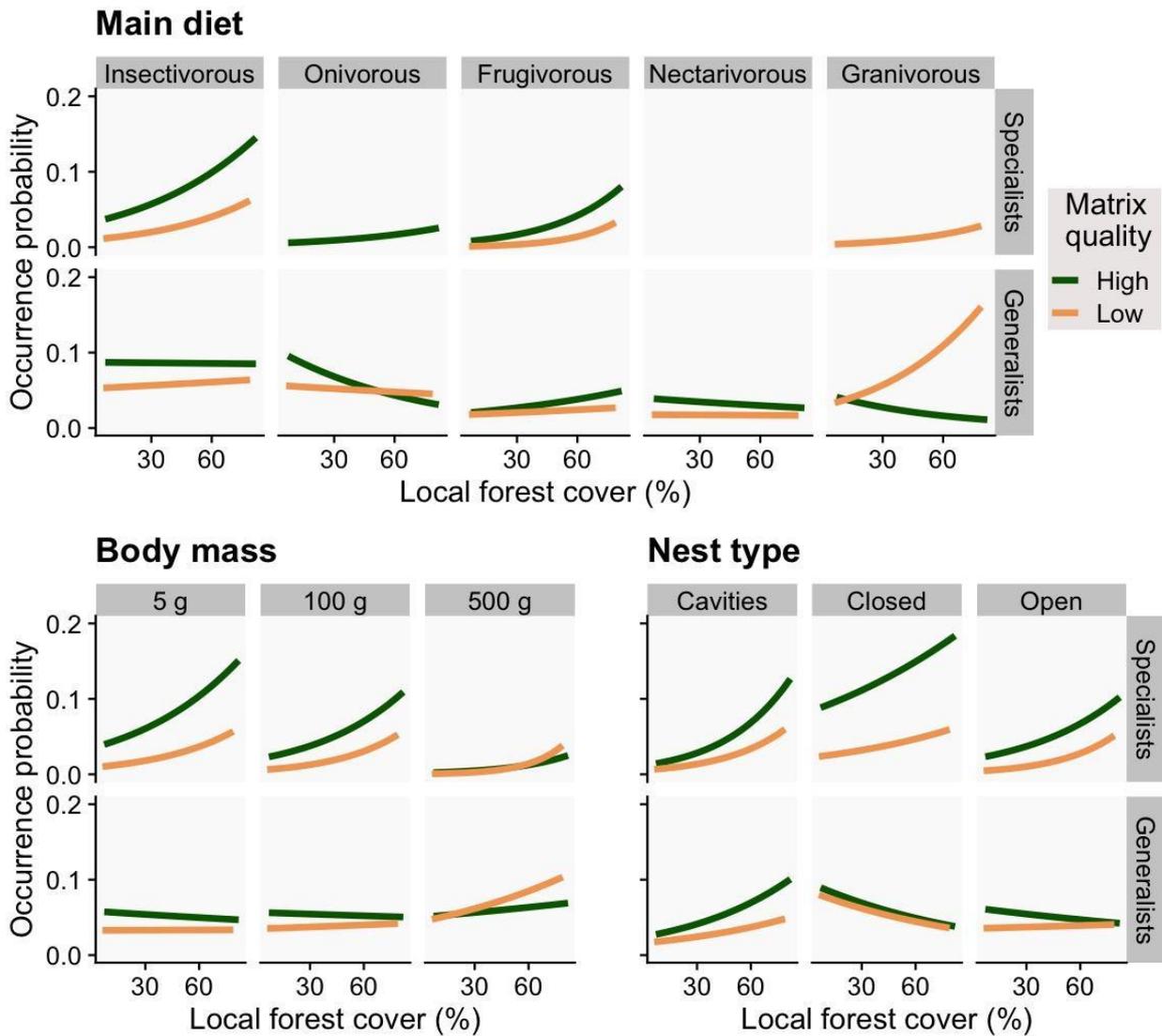
359 relationships changed according to the trait. For example, generalists of closed nests responded
 360 positively to habitat loss, while those that nest in cavities responded negatively and generalists of
 361 open nests almost did not change with habitat loss (Fig. 5). Nevertheless, occurrence probabilities
 362 of frugivores, species that build nests in cavities, and large birds decreased with habitat loss
 363 regardless of the matrix type and habitat specificity (Fig. 5).

364



365

366 **Figure 4:** Importance of species traits in explaining habitat loss filtering (equation 2) for forest
 367 specialists and habitat generalist birds according to matrix quality. Trait importance was calculated
 368 for each trait in separate models and for the combined model, which includes, nest type, main diet,
 369 body mass, percentage of lower strata use, and hand-wing index.



370
 371 **Figure 5:** Predicted occurrence probability of species with local forest cover (400 m buffer; %) according to main diet, body mass, and nest type for forest specialists and habitat generalists in both
 372 high (green lines) and low-quality matrices (yellow lines). For the predictions, landscape forest
 373 cover was fixed at 30%.
 374

375

376 Discussion

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

380 mainly of low-productive pasturelands, increased the severity of habitat loss filtering effects for
381 forest specialist birds (Fig. 2), with habitat loss effects at the landscape scale (Fig. 3) and habitat
382 loss filtering effects through species traits (Fig. 4) being much stronger in those landscapes. In high
383 quality-matrix landscapes (more heterogeneous and with low-contrasting edges), birds' occurrences
384 were in general larger with more random variation among landscapes. Both results indicate the role
385 of matrix quality in attenuating extinction risks in the landscape, allowing species that would have
386 been extinct due to habitat loss in high-quality matrices. Moreover, forest specialists presented a
387 stronger response to habitat loss filtering, displaying a consistent negative relationship of all traits
388 (diet, nest type, foraging stratum, and body size) with local habitat loss, while generalists presented
389 a high variability in traits response to habitat loss (Fig. 5).

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

391 We found that matrix quality modulates habitat loss effects only for specialist birds at the
392 landscape scale. Local habitat amount effects on birds were not dependent on the quality of the
393 matrix. At the landscape scale, filtering processes are usually related to the selection of species
394 according to landscape composition and configuration (Dufлот et al., 2014; Suárez-Castro et al.,
395 2018). Landscapes composed of low-quality matrices decrease the availability of supplementary
396 and complementary resources in the matrix (Boesing et al., 2021; Dunning et al., 1992) and/or
397 deteriorate abiotic conditions in habitat edges (Pardini et al., 2009; Pfeifer et al., 2017; Saunders et
398 al., 1991). These two mechanisms together with habitat loss create an even more severe
399 environmental filter for the communities, selecting only those species able to persist under new
400 harsh conditions (Chase, 2007). Our results for the specialists support this hypothesis of lower-
401 quality matrices increasing severity of habitat loss filtering by showing: (1) a 2-times larger relative
402 importance of habitat loss, traits, and filtering effects, with consequently (2) a stronger habitat loss
403 effect, and (3) higher importance of traits in habitat loss filtering. In addition, there is evidence in

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

407 Additionally, landscapes composed of low-quality matrices would hinder dispersal among
408 patches or decrease the survival rate of dispersing individuals (Biz et al., 2017; Fahrig, 2007;
409 Watling et al., 2011). By that, dispersal limitation would create functionally isolated communities
410 more prone to ecological drift (e.g., Baselga et al. 2015, Siqueira et al. 2020), which, in turn, would
411 decrease the relative importance of species and trait filtering effects by habitat loss. However, our
412 results pointed to the other direction, as we found that habitat loss filtering through traits was
413 stronger in low-quality matrix landscapes. We believe that in our study system, dispersal limitation
414 is not an issue for the forest birds in both matrix landscapes, as the marginal R^2 s for the differential
415 dispersal (Fig. 2, *lands:sp* term) were relatively low. However, the differential dispersal term was
416 higher in relative importance (R^2) for the specialists in the high-quality matrix, indicating that there
417 may be not a limitation but possibly an excess of dispersal in high-quality matrices, which
418 corroborates earlier findings (Boesing et al., 2018b, 2021). High-quality matrix landscapes with
419 higher dispersal rates, more resource availability, and milder edge effects may be preventing
420 extinctions of isolated populations by migration of individuals from other patches (*mass effect* in
421 metapopulation theory, Leibold et al. 2004). This mechanism would weaken the deleterious effects
422 of habitat loss, allowing the survival of species that are not optimally suited for the new
423 environmental conditions (Chisholm et al., 2011; Leibold & Loeuille, 2015).

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

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

427 stronger filtering effects in low-quality matrix landscapes as discussed above. We found that
428 specialist birds with certain traits, e.g., small-sized, insectivorous, or birds with closed nests, were
429 more prone to extinction due to habitat loss in landscapes embedded in low-quality matrices than
430 species with the same traits in high-quality matrices (Fig. 5). This indicates further that habitat loss
431 has different filtering effects (stronger or weaker) over species traits depending on the quality of the
432 matrix. Such changes might be related to effects of the matrix changing specific niches required by
433 different species in-patches, mostly via edge-effects on both biotic and abiotic patterns (Murcia,
434 1995). For instance, species that make nests in cavities or build closed nests are safer against
435 parasitism and predation (Sibly et al., 2012), which are among the most impacting drivers of bird
436 populations' decline in fragmented landscapes (Cavitt & Martin, 2002). As nest
437 predation/parasitism often increases with edge effects (Murcia, 1995), it is stronger in landscapes
438 with highly contrasting matrices, i.e., lower quality.

439 Because we were able to compare the same set of traits for habitat generalist and specialist
440 species, we can understand better why habitat loss and fragmentation do not necessarily lead to loss
441 of functional diversity (Boesing et al., 2018a), change in functional traits (de Coster et al., 2015), or
442 even functional homogenization (Nordberg & Schwarzkopf, 2018). If specialists are replaced by
443 generalists with similar trait values, functional differences cannot be easily observed, and thus no
444 apparent functional differences are seen, as often reported (Boesing et al., 2018a; de Coster et al.,
445 2015). However, we also found that species with some specific traits (such as nest type and body
446 size) were always negatively impacted by habitat loss. This finding raises the point that not all
447 habitat generalist species succeed in fragmented landscapes, and that some key functions and/or
448 species may be indeed lost with no substitution of traits when specialists are replaced by generalists.
449 Overall, our results reinforce the evidence that habitat loss and matrix harshness promote abiotic

450 environmental changes inside habitat patches which make species with specific traits to be more
451 prone to extinction than others under different matrix conditions in the landscapes.

452 **Theoretical and practical implications**

453 Despite a long-standing global research effort into understanding how habitat loss and
454 fragmentation influence species loss, and at which spatial scale species loss is observed (Horváth et
455 al., 2019), there is still a considerable debate on which mechanisms are more important (Fahrig,
456 2017; Fletcher et al., 2018). Our findings raised evidence supporting that habitat loss is a strong
457 filtering process that often leads more vulnerable species to extinction (Pardini et al., 2017), but
458 with a considerable influence of the matrix in modulating filtering processes. We have evidenced
459 the importance of the matrix quality in modulating habitat loss effects at the landscape scale,
460 weakening or strengthening its severity on species filtering (Chase, 2007). Matrices of low quality
461 accentuate habitat loss filtering in fragmented landscapes through its relatively larger effects in
462 altering resource availability and edge effects, more than movement limitation. Consequently, the
463 larger severity of habitat loss filtering in low-quality matrix landscapes decreases the relative
464 importance of ecological drift on those assemblages.

465 Statistical quantification of the effects of dispersal and ecological drift is still an unresolved
466 methodological problem with many caveats (Vellend et al., 2014). Our framework builds on the
467 idea of handling possible effects of differential dispersal through terms that would take the extra
468 variability of the data (overdispersion) produced by differences in species occurrences across sites
469 and landscapes (Mortara, 2016). This way, we saw that dispersal limitation in low-quality matrices
470 leading to ecological drift is not the only possible outcome after habitat loss and fragmentation.
471 High rates of dispersal in high-quality matrix landscapes can even override environmental filtering
472 by allowing species to occupy habitat patches where their intrinsic growth rate would be otherwise

473 negative (Chase et al., 2020). To our knowledge, this is the first empirical evidence that a not
474 limited dispersal in high-quality matrices may result in mass effects in bird metacommunities in
475 fragmented landscapes, although its effects are relatively small in comparison with environmental
476 filtering.

477 In practical terms, improving matrix quality in fragmented landscapes is a key action aiming
478 to restore and achieve more sustainable landscapes (Arroyo-Rodríguez et al., 2020; Leite et al.,
479 2013), especially in places where conservation practices and restoration are constrained by
480 economic and political conflicts, are costly-demanding, and requires strategic planning (Metzger et
481 al., 2021). In this sense, converting low-productive pastures into more heterogeneous environments
482 through tree enrichment and creation of stepping-stones (Prevedello et al., 2018; Silva et al., 2020),
483 or converting such pastures (even if partially) into less contrasting land uses (such as diversified
484 crops, perennial crops and tree plantations) can increase matrix quality, minimizing the severity of
485 habitat loss and fragmentation for forest birds (Ruffell et al., 2017). In our study areas, the
486 conversion of abandoned and unproductive pasturelands into silviculture in the last decades was
487 responsible for the increase in second-growth native forests (Calaboni et al., 2018). We conclude
488 that restoration and economic practices improving matrix quality may help in maintaining the high
489 diversity of birds in the Atlantic Forest even without any increase in native forest cover.

490

491 **Supporting information**

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

493 APPENDIX 2: Forest cover at local and landscape scales

494 APPENDIX 3: Additional models results and diagnostic

495 APPENDIX 4: Additional models results for species that occur at both high and low-quality
496 matrix landscapes

497 **Authors' contributions:** M.S.L., A.L.B., and P.I.P. conceived the project. A.L.B. and J.P.M
498 delineated the sampling design. A.L.B. collected the data. M.S.L. and P.I.P. analyzed the data and
499 wrote the manuscript. All authors provided substantial revisions and comments on the manuscript.

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510 **Data archiving:** All data and code used in the analysis are available in Zenodo Repository
511 <http://doi.org/10.5281/zenodo.5516704> (Leite, 2021) with the published version of the GitHub
512 repository. The original data is also available from the Dryad Digital Repository
513 <http://dx.doi.org/10.5061/dryad.37s4h> (Boesing et al., 2017).

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