

1       **ANTHROPOGENIC DISTURBANCE INCREASES DISEASE EMERGENCE RISK**  
2       **THROUGH PREDICTABLE CHANGES IN PARASITE COMMUNITY STRUCTURE**

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30 **ABSTRACT**

31 Niche theory predicts specialists will be more sensitive to environmental perturbation compared  
32 to generalists, a hypothesis receiving broad support in free-living species. Based on their niche  
33 breadth, parasites can also be classified as specialists and generalists, with specialists infecting  
34 only a few and generalists a diverse array of host species. Here, using avian haemosporidian  
35 parasites infecting wild bird populations inhabiting the Western Ghats, India as a model system,  
36 we elucidate how climate, habitat and human disturbance affects parasite prevalence both  
37 directly and indirectly via their effects on host diversity. Our data demonstrates that  
38 anthropogenic disturbance acts to reduce the prevalence of specialist parasite lineages, while  
39 increasing that of generalist lineages. Thus, as in free-living species, disturbance favors parasite  
40 communities dominated by generalist vs. specialist species. Because generalist parasites are  
41 more likely to cause emerging infectious diseases, such biotic homogenization of parasite  
42 communities could increase disease emergence risk in the Anthropocene.

43 **INTRODUCTION**

44 The Anthropocene has been characterized by large, and often rapid, alterations of natural  
45 environments driven by human-mediated factors acting at various scales – from local habitat  
46 modification to global climate change (Corlett 2015; Laurance 2019). Many species have been  
47 unable to adapt sufficiently to cope with the such anthropogenic changes to their environment  
48 leading to species loss at local and global scales (Young *et al.* 2016; Radchuk *et al.* 2019; Turvey  
49 & Crees 2019 ). However, community disassembly is not a random process, with species loss  
50 often following certain general principles with specialists being more sensitive to environmental  
51 perturbations (e.g., habitat loss and climate change) compared to generalists (Swihart *et al.* 2003;  
52 Kellermann *et al.* 2009; Slatyer *et al.* 2013), leading to the biotic homogenization of natural

53 communities globally (McKinney & Lockwood 1999; Olden 2006; Olden & Rooney 2006;  
54 Clavel *et al.* 2010; Li *et al.* 2020 ). While not universal (Williams *et al.* 2006; Colles *et al.* 2009),  
55 the increased sensitivity of specialists to endangerment has been demonstrated in many taxa (Safi  
56 & Kerth 2004; Kotiaho *et al.* 2005; Shultz *et al.* 2005; Walker 2006; Boyles & Storm 2007; Essl  
57 *et al.* 2009; Saupe *et al.* 2015; White & Bennett 2015; Liang *et al.* 2019; Colléony & Shwartz  
58 2020). Biotic homogenization is of particular concern because the generalist species that thrive in  
59 human-dominated landscapes are also more likely to harbor greater diversity of parasites,  
60 including those can infect humans (Gibb *et al.* 2020; Ostfeld & Keesing 2020). Thus, human-  
61 mediated landscape modification can affect disease dynamics by favoring host communities that  
62 are dominated by generalist species (Gibb *et al.* 2020; Ostfeld & Keesing 2020). However, the  
63 effects of such human pressures on parasite community structure remains unclear.

64         Like free-living species, parasites can also be categorized as specialists and generalists,  
65 based on their niche breadth, with specialist parasite lineages infecting only one or few related  
66 host species, and generalists infecting broad diversity of hosts (Cooper *et al.* 2012; Gupta *et al.*  
67 2019). This dichotomization of parasites is particularly important from the perspective of human  
68 and wildlife health because generalist parasites are more capable of switching to new hosts, and  
69 are thus more likely to be associated with emerging infectious diseases (EIDs) (Timms & Read  
70 1999; Ewen *et al.* 2012; Hatcher *et al.* 2012; Farrell *et al.* 2013; Johnson *et al.* 2015a). While  
71 there is some evidence that generalist parasites are less prone to extinction (Woolhouse *et al.*  
72 2001; Cooper *et al.* 2012), and it has been hypothesized that generalist parasites are more likely  
73 to adapt to relatively common generalist hosts (Ostfeld & Keesing 2020), the question of  
74 whether human-mediated changes to the environment favor parasite communities dominated by  
75 generalist vs. specialist species, as in the case of free-living communities, remains an open one.

76 Here we test this question using avian haemosporidian parasites as a model system. Answering  
77 this question is critical because generalist parasites are capable of rapidly switching to new host  
78 species (Wells & Clark 2019), and thus the biotic homogenization of parasite communities will  
79 increase the risk disease emergence.

80 Avian haemosporidian parasites are vector-borne pathogens of birds belonging to several  
81 genera including *Haemoproteus* and *Plasmodium* (Valkiūnas 2005). We have previously shown  
82 that in bird communities inhabiting an important biodiversity hotspot – the Western Ghats,  
83 Southern India (Fig. 1a) – these genera differ in host breadth, with genetic lineages of  
84 *Haemoproteus* being host-specialists while *Plasmodium* lineages are host-generalists (Gupta *et*  
85 *al.* 2019), as seen in other bird communities (Fallon *et al.* 2005). Indeed, *Plasmodium* infections,  
86 unlike *Haemoproteus*, have been responsible for epidemic mortalities in wild bird populations on  
87 some oceanic islands (Warner 1968; Valkiūnas 2005; Niebuhr *et al.* 2016), because being  
88 generalists *Plasmodium* lineages are more likely to emerge in novel host communities (Gupta *et*  
89 *al.* 2019). Here, using data from a sample of >1000 birds of 28 species inhabiting the Western  
90 Ghats (Table S1), we show that, the parasite community structure is predictably influenced by  
91 anthropogenic disturbance, after controlling for effects associated with the environment (i.e.,  
92 climate and terrain) and host community structure. Specifically, our results indicate that  
93 anthropogenic pressure acts to reduce the prevalence of specialist parasite lineages, while  
94 increasing the prevalence of generalist lineages. Such biotic homogenization of parasite  
95 communities is a novel mechanism that can contribute to the increased risk of disease emergence  
96 in human-dominated landscapes, and thus has broad implications of human and animal health.

97 **METHODS**

98 **Field and laboratory methods**

99 The study area was located in the southern 600 km of the Western Ghats (Fig. 1a). Field  
100 sampling was carried out between 2011-2013, across the four major geographical regions  
101 separated by three biogeographic barriers—Chaliyar River valley, Palghat Gap, and Shencottah  
102 Gap (Fig. 1a). For our analyses we used samples from 28 species of birds (N = 1172) captured  
103 during the pre-monsoon season (January-May) at 42 sites (700-2500 m above sea level) across  
104 our study area (Fig. 1a; Supplementary Table 1). Procedures for bird mist-netting and blood  
105 collection have been described previously (Gupta *et al.* 2019). Parasite detection was carried out  
106 by sequencing 478 bp of the Haemosporidian cytochrome-b gene using genomic DNA extracted  
107 from individual bird blood samples. All lab and field methods followed those described  
108 previously in Gupta *et al.* (2019).

109 **Environmental and ecological variables**

110 One of the main objectives of this study was to elucidate how climate, landscape and human  
111 disturbance affected parasite prevalence, both directly and through their effects on host diversity.  
112 Environmental data were downloaded from publicly available datasets. We obtained the  
113 bioclimatic variables from <http://chelsa-climate.org/bioclim/>. Landscape variables included: (a)  
114 Terrain: Elevation, slope and roughness extracted from elevation data  
115 (<http://www.earthenv.org/DEM>) using the R package RASTER (HIJMANS *ET AL.* 2015), and water  
116 flow-accumulation from <https://www.hydrosheds.org/page/hydrorivers>; (b) Canopy height:  
117 <http://lidarradar.jpl.nasa.gov>; (c) Landcover data: Obtained from authors of a published dataset  
118 (Roy *et al.* 2015). We then used the package RASTER to calculate the proportions of 10 major  
119 habitat types (i.e., cropland, degraded habitat, grassland, gregarious forest, locale-specific forest,

120 mixed forest, plantation, settlements, shrub and savannah and water); (d) Anthropogenic  
121 disturbance: Included distance from protected areas (calculated as the distance from the nearest  
122 boundary with negative values falling inside and positive outside protected areas, respectively)  
123 using data from <http://datasets.wri.org/dataset/64b69c0fb0834351bd6c0ceb3744c5ad>. We also  
124 used a Indian population dataset (<http://www.ciesin.columbia.edu/data/india-census-grids/>) to  
125 calculate an index of human proximity following Alexander et al. (Alexander & Wint 2013).  
126 Apart from the environmental variables we also used two host ecological variables, including  
127 host phylogenetic and functional diversity. Host diversity measures were calculated using the  
128 alpha diversity function implemented in the R package BAT (Cardoso *et al.* 2014), with  
129 phylogenetic diversity using phylogenetic distances between the bird species and functional  
130 diversity using the Gower distance between species based on ecological traits associated with  
131 feeding strata, sociality, habitat, and genetic connectivity. Details of all variables used at given in  
132 Table S2.

### 133 **Statistical analyses**

134 All statistical analyses were carried out using R ver. 4.0.0 (The R Foundation for Statistical  
135 Computing 2019), and all statistical tests and reported *P* values are two-sided. A complete list of  
136 R packages used for analyses are given in Table S3. All analyses were carried out at the scale of  
137 the individual site (Table S1). We pooled samples across multiple years because we found no  
138 significant effect of year (*Haemoproteus*:  $\chi^2 = 9.281$ ; *P* = 0.158; *Plasmodium*:  $\chi^2 < 0.001$ ; *P* =  
139 1.000). Our major objective was to test for differences in the factors affecting infection risk with  
140 specialist vs. generalist parasites. Thus, we first classified each Haemosporidian lineage as a  
141 specialist or generalist using a randomization test to evaluate if the diversity of hosts the lineage  
142 was found to infect was lower or higher than random expectation, respectively (see

143 Supplementary Methods). All further analyses were carried out only using the parasite lineages  
144 that were clearly classified as specialists or generalists.

145 To test for the direct and indirect effects of the various predictor variables on parasite  
146 infection risk we used a hybrid approach that combined random forests, a powerful machine  
147 learning algorithm, and Structural Equation Models (SEMs). Thus, prior to building the SEM we  
148 reduced the list of predictor variables using random forests models (RFMs) as suggested by  
149 Duffy et al. (Duffy *et al.* 2016). Random forests models were implemented in the R package  
150 RANGER (Wright & Ziegler 2017). All RFMs were run using 100,000 trees and we optimized the  
151 model parameters (mTry, Min. node size, Split rule) using a 10-fold cross-validation procedure  
152 implemented in the trainControl function from the R package CARET (Kuhn 2008). All RFMs  
153 also included the number of birds sampled in each trap site as case weights to control for  
154 potential sample size effects. We initially included all environmental variables for all RFMs, and  
155 also added host-related variables for the parasite-related RFMs. Thus, initially environmental  
156 factors (i.e., terrain, climate, habitat and disturbance) were included in the RFMs to predict host  
157 ecological variables (host phylogenetic/functional diversity). In turn, parasite-related variables  
158 (parasite phylogenetic diversity and infection risk) were assumed to be driven by direct effects of  
159 environmental variables and the indirect effects of these variables through their effects on host  
160 ecology. For each RFM, we first fit the full random forest model with all variables (Table S2),  
161 and estimated the variable importance values (Wright & Ziegler 2017). We then used a forward  
162 step-wise selection starting from the most important variable, and adding variables in decreasing  
163 order of importance. At each step a variable was added if it's correlation with variables included  
164 in the model until that step was  $\leq 0.7$  and if addition of the variable increased the coefficient of  
165 determination ( $R^2$ ) for the whole model. Model validation was done using three repetitions of a

166 10-fold cross validation procedure to maximize the  $r^2$  value of the whole model using 75% of the  
167 data to train the model and 25% to assess model prediction accuracy (Kuhn 2008). In order to  
168 calculate the relative importance of each of the four main variable groups (i.e., terrain, climate,  
169 habitat and ecology; Table S2) we calculated the weighted mean of the number of times  
170 variables in each group were used to split trees in the random forest (see  
171 <https://stats.stackexchange.com/questions/92419>).

172 To better understand the mechanisms driving the spatial variation in infection risk, we  
173 modeled the direct and indirect effects between the variables identified by the RFMs using  
174 structural equation models (SEMs), which are a powerful statistical approach wherein a set of  
175 mutually interconnected equations are used to evaluate the causal relationships among a set of  
176 variables (Shipley 2016). SEM analyses was implemented in the R package PIECEWISESEM  
177 (Lefcheck & Freckleton 2015). Initially, we included as predictors all variables retained in the  
178 final random forest models of host- and parasite-related variables (see details above). We  
179 included both main and quadratic effects to model potential non-linear effects between the  
180 variables, and  $z$ -transformed these variables to obtain standardized model coefficients. We then  
181 sequentially dropped variables if dropping the variable from a specific model reduced the overall  
182 Akaike Information Criterion (AIC) of the SEM model (Shipley 2013), and if the removed path  
183 was not considered to be a significant missing path (Lefcheck & Freckleton 2015). Final model  
184 acceptance was based on the Fisher's  $C$  statistic, with a model being accepted if the associated  $P$ -  
185 value  $> 0.05$  (Shipley 2016). Final path diagram was plotted using the R package diagram, and  
186 the strength of specific paths was assessed visually using partial residual plots using the R  
187 package VISREG (Breheny & Burchett 2017).

188 **RESULTS**

189 We identified a total of 47 unique parasite lineages infecting the birds in our study area, and  
190 found that 28 of 29 *Haemoproteus* lineages were host specialists and 2 of 18 *Plasmodium*  
191 lineages were host generalists, with the diversity of hosts infected by the remaining 17 lineages  
192 not differing significantly from random expectation (Table S4). All further analyses were carried  
193 out only using the 30 parasite lineages that were clearly classified as specialists or generalists.  
194 We found that the RFMs generally performed well, and the models for infection risk explained  
195 >70% of the variance amongst sampling sites in both parasites (*Haemoproteus*:  $r^2= 0.794$ ;  
196 *Plasmodium*:  $r^2= 0.707$ ; Fig. 1b and c; Table S5 and S6). Interestingly, in both *Haemoproteus*  
197 and *Plasmodium*, the majority of the total variance explained was due to host (61% and 49%,  
198 respectively) and landscape (21% and 26%, respectively) related factors, and least to climate  
199 (18% and 25%, respectively) (Fig. 1d). Our final RFMs revealed that there was considerable  
200 spatial variation in infection risk associated with *Haemoproteus* (Figure 1e) and *Plasmodium*  
201 (Figure 1f).

202 To better understand the mechanisms driving the spatial variation in infection risk, we  
203 modeled the direct and indirect effects between the variables identified by the RFMs using an  
204 SEM. Our final SEM (i.e., reduced) model testing the hypothesized direct and indirect effects of  
205 our predictor variables fit the data well with no significant missing paths ( $\Delta AIC_{REDUCED-FULL} = -$   
206  $875$ ; Fisher's  $C = 130.651$ ;  $DF = 166$ ;  $P = 0.98$ ; Table S7). The SEM revealed distinct paths  
207 affecting infection risk with specialist (*Haemoproteus*) vs. generalist (*Plasmodium*) parasites  
208 (Figure 2a and b; Table S8). Critically, human-mediated disturbance (distance to protected areas  
209 and human population proximity) affected infection risk in opposing ways through direct effects  
210 and mediation via host-related variables (Figure 2a and b).

211 To dissect the SEM results we focus on each of the primary variables in the model  
212 sequentially. Our analyses revealed that that BIO05 (maximum temperature of warmest month)  
213 had a negative effect on both functional host diversity ( $\beta \pm SE = -0.261 \pm 0.120$ ;  $P = 0.037$ ) and  
214 phylogenetic host diversity ( $\beta \pm SE = -0.306 \pm 0.139$ ;  $P = 0.034$ ) (Fig 2a and b; Table S8). We  
215 also found that anthropogenic disturbance, as measured by distance from protected areas,  $PA_{DIST}$   
216 reduced both functional ( $\beta \pm SE = -0.229 \pm 0.113$ ;  $P = 0.049$ ) and phylogenetic ( $\beta \pm SE = -0.669$   
217  $\pm 0.132$ ;  $P < 0.001$ ; Fig. 2c) host diversity. Thus, the biotic homogenization of host communities  
218 occupying human-modified habitats is a characteristic of the bird communities in the Western  
219 Ghats, as in other natural communities globally (McKinney & Lockwood 1999; Clavel *et al.*  
220 2010).

221 Our analyses also revealed some interesting differences in factors affecting parasite  
222 diversity. Thus, we found that BIO02 (mean diurnal temperature range) had significant non-  
223 linear effects on the phylogenetic diversity of both *Haemoproteus* (Fig. 2d; Main  $\beta \pm SE = -$   
224  $0.080 \pm 0.199$ ;  $P = 0.689$ , Quadratic  $\beta \pm SE = -0.288 \pm 0.136$ ;  $P < 0.041$ ) and *Plasmodium* (Fig.  
225 2e; Main  $\beta \pm SE = -0.528 \pm 0.162$ ;  $P = 0.002$ , Quadratic  $\beta \pm SE = -0.657 \pm 0.118$ ;  $P < 0.001$ ).  
226 Alternatively, we found that BIO05 only affected the diversity of the generalist (*Plasmodium*)  
227 parasites (Fig. 2f; Main  $\beta \pm SE = -0.054 \pm 0.158$ ;  $P = 0.736$ , Quadratic  $\beta \pm SE = -0.348 \pm 0.144$ ;  $P$   
228  $< 0.021$ ). Importantly, we found that host phylogenetic diversity had a positive effect on  
229 phylogenetic diversity for specialist (*Haemoproteus*) parasites (Figure 2g;  $\beta \pm SE = 0.683 \pm$   
230  $0.163$ ;  $P < 0.001$ ), but did not affect phylogenetic diversity for generalist (*Plasmodium*) parasites.

231 With respect to infection risk we found a significant direct positive effect of parasite  
232 diversity in the case of both *Haemoproteus* (Fig. 2h;  $\beta \pm SE = 0.323 \pm 0.067$ ;  $P < 0.001$ ) and  
233 *Plasmodium* (Fig. 2i;  $\beta \pm SE = 1.115 \pm 0.338$ ;  $P = 0.001$ ). We also found that while the host

234 functional diversity had a significant direct negative effect on infection risk of the generalist  
235 (*Plasmodium*) parasite (Fig. 2j;  $\beta \pm SE = -0.789 \pm 0.289$ ;  $P = 0.006$ ), but had no effect on  
236 infection risk of the specialist (*Haemoproteus*) parasite. This difference between *Plasmodium*  
237 and *Haemoproteus* could be because *Plasmodium*, as a generalist parasite, is likely affected by  
238 host spatial proximity (and thus levels of niche overlap), but, as a specialist, *Haemoproteus* is  
239 primarily affected by host phylogenetic relatedness (Gupta *et al.* 2019). Of most importance, we  
240 also found opposite effects of anthropogenic disturbance on infection risk associated with  
241 specialist and generalist parasites. In the case of the specialist parasite *Haemoproteus*, infection  
242 risk was negatively affected by human population proximity (Figure 2k;  $\beta \pm SE = -0.284 \pm$   
243  $0.111$ ;  $P = 0.011$ ) but a positive association was observed in the case of the generalist,  
244 *Plasmodium* parasites (Figure 2l;  $\beta \pm SE = 0.899 \pm 0.327$ ;  $P = 0.006$ ).

245         Taking into consideration direct and indirect effects, distance to protected areas had a  
246 significant negative total effect on infection risk for *Haemoproteus* [ $\beta_{TOT} = -0.027$ ; 95 %  
247 confidence interval (CI): -0.059, -0.013] but a significant positive total effect on infection risk  
248 for *Plasmodium* risk ( $\beta_{TOT} = 0.014$ ; CI: 0.002, 0.036) (Fig. 3). Additionally, human population  
249 proximity had a significant negative total effect on infection risk for *Haemoproteus* ( $\beta_{TOT} = -$   
250  $0.057$ ; CI: -0.172, -0.018), but a significant positive effect on *Plasmodium* risk ( $\beta_{TOT} = 0.061$ ; CI:  
251  $0.037, 0.116$ ) (Figure 3). These opposing effects of anthropogenic pressure on infection risk in  
252 the case of specialist vs. generalist parasites is, at least partially, mediated by the opposing  
253 effects of host diversity on infection risk. Thus, while host diversity had a positive total effect on  
254 *Haemoproteus* infection risk ( $\beta_{TOT} = 0.048$ ; CI: 0.025, 0.09), it had a negative effect in the case  
255 of *Plasmodium* ( $\beta_{TOT} = -0.046$ ; CI: -0.077, -0.014) (Fig. 3). While all the SEM analyses were  
256 carried out at the scale of each host population, qualitatively similar results were obtained with

257 lineage-level analyses also (Table S9; Fig. S1). Specifically, we found that as diversity of hosts a  
258 parasite lineage could infect increased (i.e., as parasites became more generalist), the effect of  
259 host diversity on observed parasite prevalence changed from being positive (i.e., an amplification  
260 effect) to being negative (i.e., a dilution effect). Similar patterns were also found in the case of  
261 the standardized prevalence calculated based on the host community composition (i.e., expected  
262 prevalence). Thus, our data indicate that host species that tend to be found in high diversity host  
263 communities (i.e., specialist hosts) are less competent hosts for generalist parasites (i.e.,  
264 *Plasmodium*) compared to those in low diversity host communities (i.e., generalist hosts).

## 265 **DISCUSSION**

266 Darwin’s “Tangled Bank” (Darwin 1909) is one of the most common images brought to mind  
267 when envisioning ecological systems comprised of a complex network of interacting species, and  
268 the functional integrity of this tangled bank can severely compromised by the recent and rapid  
269 modifications to global environments (Lau & terHorst 2020). Parasites form an integral part of  
270 all ecological networks, and comprise a large, albeit relatively uncharacterized, portion of global  
271 biodiversity (Dobson *et al.* 2008; Okamura *et al.* 2018). Thus, there is an increasing recognition  
272 of the need to incorporate them into biodiversity conservation plans (Gomez & Nichols 2013;  
273 Dougherty *et al.* 2016). Indeed, parasites – especially specialist parasites that are closely  
274 dependent upon a very narrow set of host species – may be especially prone to extinction risk  
275 (Galetti *et al.* 2018; Thompson *et al.* 2018; Moir & Brennan 2020), and ignoring such species  
276 coextinctions can lead to gross underestimation of global extinction rates (Koh *et al.* 2004;  
277 Strona & Bradshaw 2018). Here we show that the loss of host diversity will negatively impact  
278 the diversity of specialist, but not generalist, parasites. Thus, our data supports the idea that  
279 specialist parasites can be especially sensitive indicators of ecosystem health (Hudson *et al.*

280 2006), because these parasites are not only more sensitive to environmental perturbations but  
281 also to co-extinction caused by loss of specific host species on which they depend (Dunn *et al.*  
282 2009; Colwell *et al.* 2012). The increased endangerment of specialist vs. generalist species is not  
283 unexpected, and has been shown to be common across numerous free-living taxa globally. Such  
284 non-random loss of species has critical impacts on ecosystem function through the biotic  
285 homogenization of ecological communities (McKinney & Lockwood 1999; Olden 2006; Olden  
286 & Rooney 2006; Clavel *et al.* 2010; Li *et al.* 2020 ).

287         Defaunation in the Anthropocene can have dramatic impacts on multiple ecosystem  
288 services including nutrient and energy cycling, and can also directly impact disease dynamics  
289 (Dirzo *et al.* 2014). Specifically, biotic homogenization due to non-random species loss has been  
290 shown to alter disease dynamics by changing the relative abundance of competent vs. non-  
291 competent hosts in a community (Johnson & Thielges 2010; Johnson *et al.* 2013; Johnson *et al.*  
292 2015b). For example, it has been found that the most competent host species (i.e., the ones most  
293 likely to be infected) also tend to be generalists (i.e., the ones most likely to persist in low  
294 diversity communities) in many well-characterized host-parasite systems, such as West Nile  
295 virus infections in bird communities and *Borrelia burgdorferi* infections in small mammal  
296 communities (Ostfeld & Keesing 2012). In such systems increasing host diversity reduces host  
297 community competence – host species abundance weighted by its competence to transmit  
298 infection (Johnson *et al.* 2015b) – leading to a strong dilution effect. Here we have shown that  
299 such a dilution effect is more likely to be evidenced in the case of generalist vs. specialist  
300 parasites. Specifically, our data reveal that loss of host biodiversity can increase infection risk  
301 associated with the generalist parasite (*Plasmodium*) because low diversity communities are  
302 more likely contain host species that are competent to harbor and transmit the parasite (Fig. S1c

303 and d). Consequently, as in other disease systems, we show that host species-specific traits (e.g.,  
304 levels of niche specialization) can jointly affect endangerment and infection risk (Ostfeld &  
305 Keesing 2012; Johnson *et al.* 2015b).

306 Interestingly, while the effects of anthropogenic disturbance on the structure of free-  
307 living communities has received much attention, relatively little attention has been paid to  
308 understanding how such disturbances impact parasite community structure. While our analyses  
309 do address this question, we lack data on the vectors that transmit the Haemosporidian parasites  
310 in our study system. This remains a critical missing piece of the puzzle because *Haemoproteus*  
311 and *Plasmodium* are transmitted by different vectors; biting midges (e.g., *Culicoides spp.*) and  
312 mosquitoes (e.g., *Culex quinquefasciatus*), respectively (Valkiūnas 2005). Thus, differences in  
313 the prevalence of these two parasites genera could be driven by underlying differences in the  
314 effects of anthropogenic disturbance on their respective vector populations. However,  
315 irrespective of the underlying mechanism, our data strongly supports the hypothesis that, as in  
316 free-living species (McKinney & Lockwood 1999; Clavel *et al.* 2010), human-mediated  
317 disturbance can favor parasite communities dominated by generalist vs. specialist species.  
318 Clearly this finding has critical implications for human health also. For example, a recent study  
319 has shown that species most likely to transmit pathogens to humans are also those that tend to  
320 thrive in human-dominated landscapes (Gibb *et al.* 2020; Ostfeld & Keesing 2020). Thus,  
321 anthropogenic disturbance can increase the risk of disease emergence in human populations. Our  
322 results add another dimension to this idea, and reveals that anthropogenic disturbance also tends  
323 to favor generalist vs. specialist pathogens. Because generalist parasites are more commonly  
324 associated with emerging infectious diseases (Shaw *et al.* 2020), such biotic homogenization of  
325 parasite communities could increase disease emergence risk in human-dominated landscapes.

326 To conclude, using data collected from >1000 birds belonging to 28 species across the  
327 Western Ghats, we show that parasite community structure is strongly influenced by  
328 anthropogenic disturbance and host community structure, after controlling for effects associated  
329 with the environment (e.g., climate). Our data reveal that the effects of anthropogenic  
330 disturbance favors parasite communities that are dominated by generalist vs. specialist species, in  
331 keeping with expectations based on niche theory. These results have broad implications for our  
332 understanding of disease dynamics in the Anthropocene. Specifically, the biotic homogenization  
333 of parasite communities driven by anthropogenic disturbance has the potential to mediate some  
334 ongoing debates in disease ecology. For example, high parasite diversity has been considered to  
335 be a sign of a healthy ecosystem (Hudson *et al.* 2006), while at the same time disturbed  
336 ecosystems are the ones with increased risk of disease emergence (Ostfeld & Keesing 2017;  
337 Ostfeld & Keesing 2020). Our data resolves this apparent paradox by revealing that undisturbed  
338 ecosystems are likely to have a high diversity of specialized parasites which are highly  
339 susceptible to being lost because they can only infect one or a few related host species.  
340 Alternatively, disturbed ecosystems tend to primarily retain generalist parasites, which are more  
341 robust to disturbance because they can infect multiple species, a characteristic which also  
342 increases their ability to cause EIDs. These results have critical implications for public health  
343 policy because they provide a clear mechanistic understanding of why disease emergence risk is  
344 highest in areas facing rapid human-mediated landscape modifications (Allen *et al.* 2017; Gibb *et*  
345 *al.* 2020; Ostfeld & Keesing 2020).

346 **ETHICAL APPROVAL**

347 This research was carried out in accordance with bird sampling permits granted by the Forest  
348 Departments of Kerala and Tamil Nadu, and institutional animal ethics clearance from the  
349 National Centre for Biological Sciences

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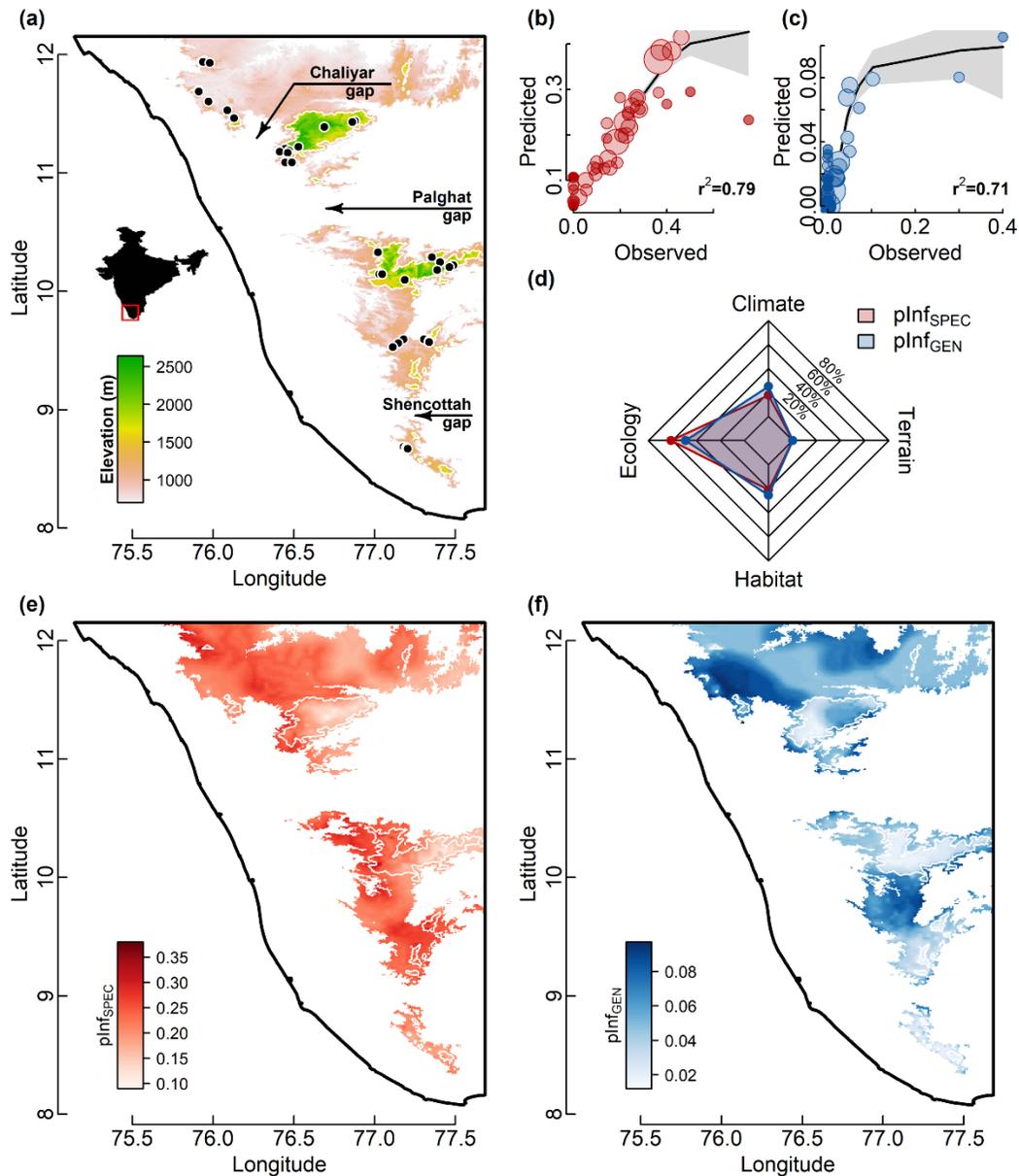
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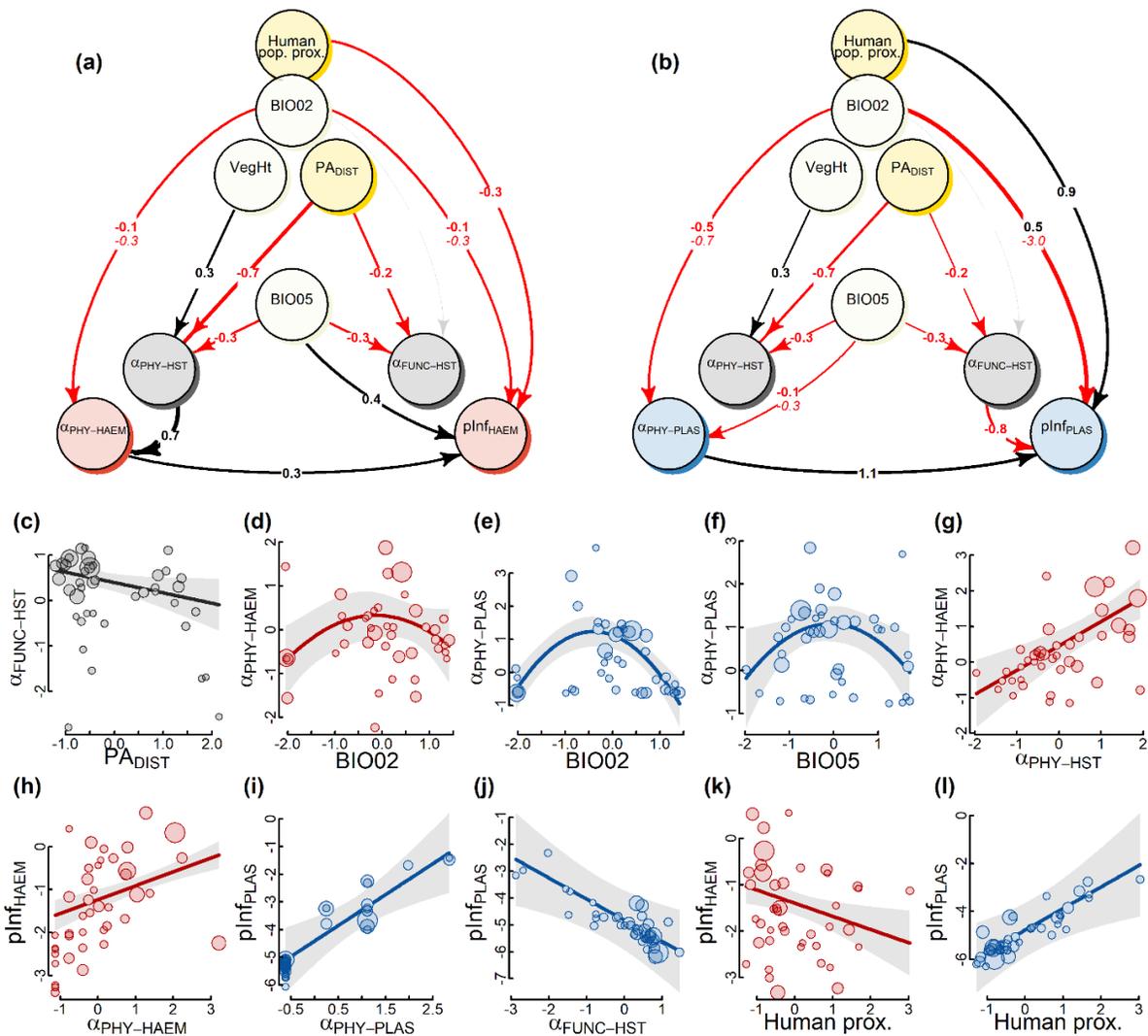
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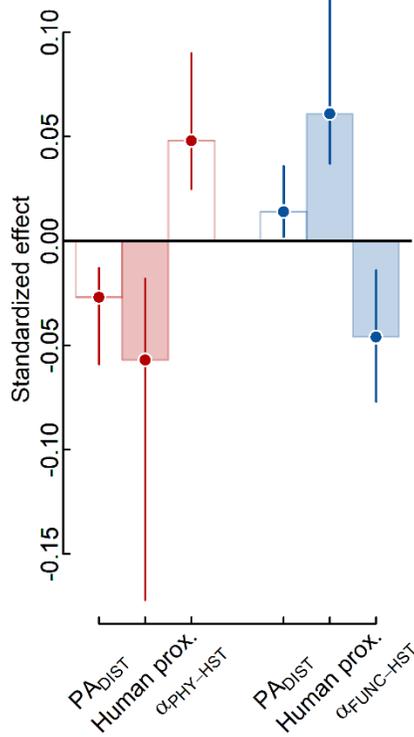
532

533 **Figure 1.** Study area and random forests model results of infection risk. (a) Study area map  
 534 showing sample site locations (circles) in four geographical regions which are separated by three  
 535 biogeographic barriers (the Chaliyar, Palghat and Shencottah gaps). All analyses were based on a  
 536 sample of birds ( $N = 1172$ ) captured at the 42 sites (Table S1). Random forest model  
 537 performance in predicting: (b) *Haemoproteus* infection risk ( $pInf_{HAEM}$ ) and (c) *Plasmodium*  
 538 infection risk ( $pInf_{PLAS}$ ). (d) Relative importance of variables grouped into four major categories  
 539 (climate-, terrain-, habitat-, and host-related factors) in predicting  $pInf_{HAEM}$  (red polygon) and  
 540  $pInf_{PLAS}$  (blue polygon). Random forest model predictions of the effects of climate, terrain,  
 541 habitat and ecological factors on infection probability of: (e) *Haemoproteus* ( $pInf_{HAEM}$ ) and (f)  
 542 *Plasmodium* ( $pInf_{PLAS}$ ).



543

544 **Figure 2.** Modeling the drivers of parasite infection risk. Structural equation model for: (a)  
 545 *Haemoproteus* infection risk (pInf<sub>HAEM</sub>), with direct or indirect effects of mean diurnal  
 546 temperature range (BIO02), maximum temperature of warmest month (BIO05), vegetation  
 547 height (VegHt), distance to protected areas (PA<sub>DIST</sub>), human population proximity (Human pop.  
 548 prox.), host phylogenetic diversity (α<sub>PHY-HOST</sub>), host functional diversity (α<sub>FUNC-HOST</sub>), and  
 549 *Haemoproteus* phylogenetic diversity (α<sub>PHY-HAEM</sub>); (b) *Plasmodium* infection risk (pInf<sub>PLAS</sub>),  
 550 direct or indirect effects of BIO02, BIO05, VegHt, PA<sub>DIST</sub>, Human pop. prox., α<sub>PHY-HOST</sub>, α<sub>FUNC-</sub>  
 551 <sub>HOST</sub>, and *Plasmodium* phylogenetic diversity (α<sub>PHY-PLAS</sub>). In the flow diagrams, circles indicate  
 552 variables (with model *r*<sup>2</sup> values, if applicable). Arrows indicate significant positive (black lines)  
 553 or negative (red lines) relationships, with standardized coefficients for main (bold) and quadratic  
 554 (italic) effects. (c-n) Partial residual plots for SEM paths for variables associated with the host  
 555 (gray symbols), *Haemoproteus* (red symbols) and *Plasmodium* (blue symbols). Points represent  
 556 trap sites scaled by relative sample size, with predicted fits (colored lines) and 95% confidence  
 557 intervals (CIs; gray bands). All analyses were based on a sample of birds (N = 1172) captured at  
 558 42 sites across the study area (Figure 1A; Table S1).



559

560 **Figure 3.** Indirect (white bars), direct (colored bars) and total (circles) effects of distance to  
 561 protected areas (PA<sub>DIST</sub>), human population proximity (HPP), and either host phylogenetic ( $\alpha_{PHY-}$   
 562 HOST) or function ( $\alpha_{FUNC-HOST}$ ) diversity on infection risk for *Haemoproteus* (red symbols) and  
 563 *Plasmodium* (blue symbols), respectively. Error bars are 95% CIs.