

1 **Global drivers of avian haemosporidian infections vary across**
2 **zoogeographical regions**

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82 **Running title**

83 Global drivers of avian haemosporidian prevalence

84

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95 purposes only and does not imply endorsement by the U.S. Government.

96

97 **Data availability statement**

98 The bird infection data used in this study are available as Supporting Information Table S1. R
99 code to retrieve publicly available environmental and species trait data, and perform the analysis
100 is available from <https://github.com/konswells1/Global-haemosporidian-prevalence>.

101

102 **Biosketch**

103 We have worked as a team to characterize local and regional datasets of avian haemosporidian
104 assemblages for a global synthesis. This study represents the efforts of a broad range of
105 researchers from different disciplines: ecologists, entomologists, molecular biologists,
106 ornithologists, and parasitologists interested in factors that shape the prevalence and distribution
107 of parasitic organisms in avian hosts worldwide.

108

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127 **Author contributions**

128 AF, KW, and NJC conceived the idea, designed the research, analysed the data, and wrote the
129 manuscript; the remaining authors contributed with avian tissue collection, sample screening,
130 data curation, and funding reagents and field expeditions. All authors contributed critically to the
131 manuscript drafts and gave final approval for publication.

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134 **Abstract**

135 **Aim:** Macroecological analyses provide valuable insights into factors that influence how
136 parasites are distributed across space and among hosts. Amid large uncertainties that arise when
137 generalizing from local and regional findings, hierarchical approaches applied to global datasets
138 are required to determine whether drivers of parasite infection patterns vary across scales. We
139 assessed global patterns of haemosporidian infections across a broad diversity of avian host

140 clades and zoogeographical realms to depict hotspots of prevalence and to identify possible
141 underlying drivers.

142 **Location:** Global.

143 **Time period:** 1994-2019

144 **Major taxa studied:** Avian haemosporidian parasites (genera *Plasmodium*, *Haemoproteus*,
145 *Leucocytozoon*, and *Parahaemoproteus*).

146 **Methods:** We amalgamated infection data from 53,669 individual birds representing 2,445
147 species worldwide. Spatio-phylogenetic hierarchical Bayesian models were built to disentangle
148 potential landscape, climatic, and biotic drivers of infection probability while accounting for
149 spatial context and avian host phylogenetic relationships.

150 **Results:** Idiosyncratic responses of the three most common haemosporidian genera to climate,
151 habitat, host relatedness, and host ecological traits **indicated** marked variation in host infection
152 rates from local to global scales. Notably, host ecological drivers, such as migration distance for
153 *Plasmodium* and *Parahaemoproteus*, exhibited predominantly varying or even opposite effects
154 on infection rates across regions, whereas climatic effects on infection rates were more consistent
155 across realms. Moreover, infections in some low-prevalence realms were disproportionately
156 concentrated in a few local hotspots, suggesting that regional-scale variation in habitat and
157 microclimate may influence transmission in addition to global drivers.

158 **Main conclusions:** Our hierarchical global analysis supports regional-scale findings showing the
159 synergistic effects of landscape, climate, and host ecological traits on parasite transmission for a
160 cosmopolitan and diverse group of avian parasites. Our results underscore the need to account
161 for such interactions, as well as possible variation in drivers across regions, to produce the robust
162 inference required to predict changes in infection risk under future scenarios.

163

164 **Keywords:** avian malaria, avian migration, disease hotspot, disease macroecology,
165 haemosporidian prevalence, host-parasite interaction, infection probability, parasite
166 macroecology, *Plasmodium*, spatio-phylogenetic models

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175 **Introduction**

176 A growing consensus based on theory and empirical evidence suggests that global change
177 will impact the worldwide distributions and burdens of vector-transmitted pathogens that infect
178 humans (Lafferty, 2009; Ryan, Carlson, Mordecai, & Johnson, 2019; Mordecai, Ryan, Caldwell,
179 Shah, & LaBeaud, 2020). Likewise, climate change and anthropogenic landscape modification
180 are predicted to alter the geographic range of non-human pathogens, such as avian malaria
181 parasites (Benning, LaPointe, Atkinson, & Vitousek, 2002; Loiseau et al., 2012, 2013; Pérez-
182 Rodríguez, de la Hera, Fernández-González, & Pérez-Tris, 2014), whereby infection patterns of
183 avian hosts in natural environments are often driven by an interplay of regional changes in biotic
184 and abiotic conditions (Fecchio et al., 2019). Anticipating spatial or temporal shifts in infection
185 risk requires reliable estimates of prevalence across habitats under different anthropogenic

186 disturbance levels and climatic gradients (Stephens et al., 2016; Weiss et al., 2019). The
187 synergistic effects of such drivers on the broadest levels of host taxonomic and community
188 organisation are poorly described for the majority of non-human parasites.

189 Mean temperatures are expected to increase unevenly across the globe in the coming
190 decades (Wehner, 2020). For example, nights are expected to be warmer in continental interiors
191 than in coastal regions (Wehner, 2020), and extreme temperature ranges are expected to decrease
192 at high-latitudes and increase within subtropical regions (Fischer, Lawrence, & Sanderson,
193 2011). As the effects of climate-driven temperature change will not be spatially uniform, average
194 global warming could alter disease transmission rates and shift the geographic ranges of many
195 parasitic organisms with different modes of transmission (Altizer, Ostfeld, Johnson, Kutz, &
196 Harvell, 2013; Loiseau et al., 2013). For example, optimal temperatures for reproduction of
197 *Plasmodium* malaria parasites within invertebrate vectors are a critical prerequisite for successful
198 transmission to humans (Mordecai et al., 2013). The existence of thermal niches that promote
199 vector activity means that distributions of many vector-borne pathogens may extend into new
200 geographical regions as temperatures change (Ryan et al., 2019). In Africa, for example, where
201 average temperatures are expected to increase between 3°C and 4°C by 2100 (roughly 1.5 times
202 the global mean response; Christensen et al., 2007), hotspots for human malaria risk are
203 predicted to shift toward higher elevations and the relative burdens of dengue fever over malaria
204 are expected to increase across the Sub-Saharan region (Mordecai et al., 2020). Given that
205 temperature might predominately influence infection risk for vector-transmitted pathogens,
206 future climate warming will be an important force driving the prevalence of many human and
207 wildlife diseases (Benning et al., 2002; Lafferty, 2009; Loiseau et al., 2013; Cable et al., 2017).

208 For those parasites infecting multiple host species, spatial heterogeneity in infection
209 probability across host communities may change in response not only to climate filters, but also
210 to changing host species distributions (e.g., host richness) that provide new ecological
211 opportunities for a parasite to expand its host range and increase its local prevalence (Canard et
212 al., 2014; Wells & Clark, 2019). Inevitably, transformation of natural habitats for urban
213 development and agriculture is creating widespread change in habitats and microclimates,
214 leading to shifts in host and vector species pools, thereby impacting parasite transmission
215 (Ferraguti, Hernández-Lara, Sehgal, & Santiago-Alarcon, 2020). This human-induced habitat
216 modification is occurring unevenly across regions and most rapidly within tropical and
217 subtropical grasslands, savannahs, and shrubland ecosystems (Williams et al., 2020).

218 At the avian host-species level, functional traits, such as preferred foraging habitat or
219 dependence on forested habitats (e.g., higher vegetation density), and foraging height, can
220 influence rates of vector exposure for a given avian host, leading to heterogeneous infection
221 probabilities across avian species (Garvin & Greiner, 2003; Clark, Drovetski, & Voelker, 2020).
222 However, assessing the influence of host and parasite traits on infection rates across host
223 communities requires careful consideration of species' evolutionary histories. Traits that
224 influence avian host immune responses and potentially restrict parasite invasion, such as body
225 size (Ruhs, Martin, & Downs, 2020), are often phylogenetically conserved (Minias, 2019).
226 Accordingly, one would expect greater variation in infection rates among rather than within host
227 clades. Furthermore, avian life-history strategy is known to influence haemosporidian prevalence
228 (Lutz et al., 2015; Barrow et al., 2019; Ellis, Fecchio, & Ricklefs, 2020). For example, larger and
229 migratory avian species are more often infected by haemosporidian parasites, due to their
230 propensity to harbor a broader diversity of parasite lineages or by being exposed to a higher

231 abundance and diversity of vectors and, in turn, to vector-transmitted parasites (Filion, Eriksson,
232 Jorge, Niebuhr, & Poulin, 2020; de Angeli Dutra, Fecchio, Braga, & Poulin, 2021).

233 Avian haemosporidian parasites of the genera *Plasmodium*, *Haemoproteus*,
234 *Parahaemoproteus*, and *Leucocytozoon* comprise a diverse group of vector-transmitted parasites
235 (Valkiūnas, 2005; Galen et al., 2018). They infect blood cells of a wide range of avian hosts
236 across all zoogeographic regions (Valkiūnas, 2005). The parasite genera *Plasmodium*,
237 *Haemoproteus*, *Parahaemoproteus*, and *Leucocytozoon* are predominantly transmitted by
238 mosquitos (Culicidae), hippoboscid flies (Hippoboscidae), biting midges (Ceratopogonidae), and
239 black flies (Simuliidae), respectively (reviewed by Santiago-Alarcon, Palinauskas, & Schaefer,
240 2012). The life histories of these dipteran vectors depend on temperature and on the presence of
241 either running or standing water (Valkiūnas, 2005; Santiago-Alarcon et al., 2012). Blackfly
242 larval development and *Leucocytozoon* sexual reproduction do not appear to be highly
243 constrained by low temperature (Valkiūnas, 2005; Fecchio et al., 2020). In contrast, the expected
244 optimum temperature range of 13-28°C for *Plasmodium* sexual reproduction and mosquito
245 activity suggests some constraint on the transmission of avian malarial parasites along latitudinal
246 or elevational gradients, despite *Plasmodium*'s global distribution (Valkiūnas, 2005; Santiago-
247 Alarcon et al., 2012; Atkinson et al., 2014).

248 Haemosporidian parasites exhibit broad variation in prevalence, but the drivers of this
249 variation across zoogeographical realms and among avian clades are only partially understood
250 from region-level studies. In recent years, numerous studies have explored haemosporidian
251 infection rates in birds across habitat gradients under different regional land use or climate
252 conditions but with no consistent predictor identified across studies (e.g., Lutz et al., 2015;
253 Ishtiaq, Bowden, & Jhala, 2017; Harvey & Voelker, 2019; Santiago-Alarcon et al., 2019; Ellis et

254 al., 2020; Gupta, Vishnudas, Robin, & Dharmarajan, 2020). Mounting evidence that various
255 landscape and climate conditions, as well as host and vector species attributes, may drive avian
256 haemosporidian infections calls for global approaches to disentangle abiotic and biotic drivers
257 and anticipate macroecological patterns of parasite spread under current and future conditions.

258 To explore macroecological patterns of avian haemosporidian prevalence, we compiled
259 global-scale infection data from 53,669 birds sampled from 141 avian families and 48 countries
260 dispersed across 10 zoogeographical realms. First, we used 14 biotic and abiotic factors known
261 to influence infection rates of haemosporidian parasites from multiple regional-scale studies to
262 identify the drivers of infection probability for each parasite genus. Second, we assessed whether
263 estimated effects of these drivers vary across zoogeographical realms. Third, we tested whether
264 parasite prevalence varies among and within avian host clades. Our use of Bayesian hierarchical
265 spatio-phylogenetic modelling to estimate prevalence at the broadest levels of host taxonomic
266 and community organization across 10 zoogeographical realms, coupled with information on
267 host species traits, allowed us to assess empirically how recent anthropogenic landscape
268 transformations and climatic gradients synergistically drive the prevalence of a multi-host
269 vector-transmitted group of parasites worldwide.

270

271 **Materials and methods**

272 *Host-parasite data*

273 To compile a representative global data set, we amalgamated field data from an
274 international network of collaborators. We iteratively screened the available literature for studies
275 reporting haemosporidian parasite prevalence. We screened the MalAvi database, the dominant
276 public repository for avian malaria and related parasites (Bensch, Hellgren, & Pérez-Tris, 2009),

277 for studies reporting haemosporidian infection and parasite sequences in bird assemblages with
278 reasonably sample sizes (> 100 individuals and > 5 host species). The raw capture data,
279 including presence-absence records of infections and geographical coordinates of surveyed birds,
280 were then requested from authors of relevant studies (see **Supporting Information Appendix**
281 **S1** for further details). The compiled infection data can be accessed in **Supporting Information**
282 **Table S1**.

283 Any compiled dataset is a finite and biased sample, given that study locations are chosen
284 by researchers according to interest and logistic constraints rather than comprising a truly
285 random sample. Nonetheless, we believe that our dataset provides a reasonable sample for
286 exploring global patterns of haemosporidian infection in birds as it covers all major geographical
287 regions (see **Supporting Information Table S2** for an overview of sample sizes from different
288 zoogeographical regions). Moreover, our dataset includes $\sim 24\%$ of all known bird species (2,445
289 out of $\sim 10,000$ species recognized in Jetz, Thomas, Joy, Hartmann, & Mooers, 2012) and, to the
290 best of our knowledge, covers the majority of areas surveyed for haemosporidian parasites in
291 birds to date (**Supporting Information Figure S1**).

292 Bird species names from field data were revised and assigned to families according to the
293 taxonomy used by Birdtree.org (Jetz et al., 2012). To generate a family-level phylogenetic tree,
294 we randomly selected five species-level fossil-calibrated trees from a phylogenetic posterior
295 distribution estimated from multiple genetic loci for the majority of extant bird species (Jetz et
296 al., 2012). We calculated the pairwise mean Euclidean distance from all combinations of species
297 for each pair of bird families and then converted the resulting distance matrix into a phylogenetic
298 dendrogram using functions in the *ape* and *phylogram* R packages (Paradis, Claude, & Strimmer,
299 2004).

300

301 ***Parasite detection and identification***

302 Blood or tissue samples (liver or muscle) from all individuals were screened for
303 haemosporidian infection by PCR, following standard protocols for amplifying a fragment of the
304 parasite cytochrome-*b* gene (*cyt-b*). See **Supporting Information Appendix S1** for a detailed
305 description of the molecular detection of parasites.

306 Detected haemosporidian parasites were classified as *Haemoproteus*, *Leucocytozoon*,
307 *Parahaemoproteus*, or *Plasmodium* following the lineage identification protocol from the
308 MalAvi database (Bensch et al., 2009). We characterised each individual bird with respect to
309 each parasite genus as infected, not infected (screened with relevant primers but no lineage
310 detected) and missing (when the sample was not screened for the genus *Leucocytozoon* or when
311 separation of parasites of the genera *Haemoproteus* and *Plasmodium* was not achieved via
312 sequencing).

313

314 ***Host traits, climatic, and environmental data***

315 Relevant climatic variables at sample locations were obtained from the WorldClim
316 database of gridded climate data at a 0.01 degree resolution (Fick & Hijmans, 2017; <http://worldclim.org/version2>). We used annual mean temperature (bio1), annual rainfall (bio12), rainfall of
317 driest month (bio14), and rainfall seasonality (coefficient of variation in rainfall over the year,
318 bio15) to characterize aspects of climate previously shown to be associated with haemosporidian
319 occurrence (Fecchio et al., 2019; Clark et al., 2020). Elevation for all locations was quantified
320 using Shuttle Radar Topography Mission (SRTM) data, accessible through the *raster* package in
321 R. We classified the proportion of cover with forest and wetland in buffers of 10 km radius
322

323 around sample locations based on Copernicus landcover data from 2010 (map version 2.07;
324 <https://cds.climate.copernicus.eu>). We downloaded the normalized difference vegetation index
325 (NDVI) for the year 2010 in buffers of 10 km radius around all sampling locations from the
326 Terra Moderate Resolution Imaging Spectroradiometer (MODIS, MOD13Q1 version 6,
327 <https://lpdaac.usgs.gov/products/mod13q1v006/>) and calculated the mean and 1 standard
328 deviation of NDVI as measures of the vegetation density and its annual fluctuation.

329 We defined local species richness of terrestrial birds based on a published map that
330 summarizes bird species richness from BirdLife International range maps
331 (<https://biodiversitymapping.org/>). Zoogeographical realm characterisation followed Holt et al.
332 (2013), who delineated realms for birds by integrating the distributions and phylogenetic
333 relationships of 10,074 bird species (see Holt et al., 2013).

334 We obtained species-level host traits from the EltonTraits v1.0 database (Wilman et al.,
335 2014). In particular, we considered host body mass and the proportion of time individuals forage
336 in the upper canopy, following previous trait-based analyses (Clark et al., 2020; Fecchio et al.,
337 2020; Fillion et al., 2020). For species with missing attributes in this database, values for the
338 closest relative were used instead. We also included migration distance, extracted from Dufour et
339 al. (2020), as a covariate. Species' migration distances were estimated from distribution maps
340 (distance between midpoints of breeding and wintering ranges). As ages of individual birds were
341 not available for all datasets, we did not include this trait in our model. We tested the 14
342 covariates for collinearity and found no strong correlation between predictor variables (all
343 pairwise Spearman's $|r| < 0.7$).

344

345 **Spatio-phylogenetic statistical modelling of multi-host infection patterns**

346 To identify key drivers of infection of birds by haemosporidian parasites, while
 347 accounting for possible spatio-temporal and phylogenetic patterns underpinning the global
 348 dataset, we used a Bayesian statistical model to jointly estimate the posterior distributions of
 349 fixed parameters (host traits and environmental data as described above) and random effect
 350 parameters. This approach enabled us to reduce possible bias of modelled random effects in our
 351 multiple-species system, including the spatial clustering of samples (i.e., multiple host
 352 individuals captured under the same climate and habitat conditions), phylogenetic relationships
 353 of multiple species (i.e., bird species belonging to different families, which vary in sampling
 354 intensity and are unevenly clustered among sampling locations), temporal bias (i.e., samples
 355 collected in different years), and possible statistical interactions between these factors and
 356 zoogeographical region (i.e., when the effect of a factor differs across regions).

357 We assumed that infection Y of any sampled bird individual i with one of the
 358 haemosporidian genera p was a random draw from the true underlying parasite prevalence φ
 359 conditional on location l and host species identity h :

360

$$361 \quad Y_{i,p} = \sim \text{Bernoulli}(\varphi_{i,l,h}) \quad (\text{eqn. 1})$$

362

363 Within our generalized linear mixed-effect model (GLMM) framework, $\varphi_{i,l,h}$ was
 364 modelled further with a suitable link function (e.g., logit-link) and regressed against a range of
 365 location- and host-specific covariates (X_i and X_j ; see descriptions in paragraph above), which we
 366 considered as fixed effects. In multi-species models, phylogenetic relationships likely influence
 367 conclusions on infection patterns, as closely related species often exhibit similar infection rates.
 368 We considered phylogenetic relationship of host species at the family-level as a random effect.

369 We considered four different model structures of increasing complexity to model $\text{logit}(\varphi_{i,l,h})$ (see
 370 equations 2-5). First, in addition to the fixed effects, we considered sampling year, sampling
 371 source (τ_S with the three categories blood, muscle, and liver), and phylogenetic position as
 372 additional random effects, resulting in a phylogenetic GLMM (phyl-cov-GLMM) given as
 373

$$374 \quad \text{logit}(\varphi_{i,l,h}) \sim \beta_i X_{i,l} + \beta_j X_{j,h} + \gamma_y + \tau_S + v_F \quad (\text{eqn. 2})$$

375
 376 Here, β_i and β_j are the respective coefficient estimates for fixed effects, and γ_y is a
 377 random effect estimate based on sampling year. The random effect for phylogenetic relationships
 378 of different host species (v_F) is based on an inverse phylogenetic variance-covariance matrix
 379 derived from the pair-wise distance relationships (i.e., each sampled bird individual is
 380 characterised by its distance relationship in terms of its family to that of any other sampled bird
 381 individual), which can be expressed as latent Gaussian Markov random fields in Bayesian
 382 frameworks (we used the default ‘generic0’ option in the INLA package in R, which set the log-
 383 Gamma hyperparameter prior to a shape parameter of 1 and a rate of 0.00005). This option is
 384 equivalent to assuming that parameter estimates are derived from multivariate Gaussian
 385 distributions with (zero) means as hyper-parameters and spatially structured covariance matrices
 386 based on the underpinning dependence structure of distance/similarity relationships.

387 As our data set included samples from different zoogeographical realms with distinct host
 388 species assemblages, we tested a second model by including zoogeographical realm as a random
 389 effect (π_r), extending our basic phylogenetic GLMM (regional phyl-GLMM):

$$390 \quad \text{logit}(\varphi_{i,l,h}) \sim \beta_i X_{i,l} + \beta_j X_{j,h} + \gamma_y + \tau_S + \pi_r + v_F \quad (\text{eqn. 3})$$

392

393 Because captures of multiple host individuals at the same sampling locations in field
 394 surveillance leads to spatial pseudo-replication, we included a spatial random effect (u_l) in a
 395 fourth model, resulting in a spatio-phylogenetic GLMM (spatio-phyl-GLMM) given as:

396

$$397 \quad \text{logit}(\varphi_{i,l,h}) \sim \beta_i X_{i,l} + \beta_j X_{j,h} + \gamma_y + \tau_S + \pi_r + v_F + u_l \quad (\text{eqn. 4})$$

398

399 As an additional extension of the model, the fifth structure we explored included possible
 400 varying coefficient estimates for the fixed effects, assuming that because of the global scale of
 401 the study, drivers of infection probabilities (denoted as fixed effects) might vary across
 402 zoogeographical realms. Without loss of generality of the GLMM concept, we can assume that
 403 the fixed effect coefficient estimates β_i and β_j are not constant across zoogeographical realms,
 404 and they allow for possible deviation by modelling coefficients for each zoogeographical realm
 405 based on baseline values β_{0i} and β_{0j} , respectively. Moreover, random deviation from these values
 406 across samples from different zoogeographical realms r , result in a spatio-phylogenetic varying
 407 coefficient GLMM (spatio-phyl-varcoef-GLMM) given as:

408

$$409 \quad \text{logit}(\varphi_{i,l,h}) \sim (\beta_{0i} + \xi_{i,r}) X_{i,l} + (\beta_{0j} + \xi_{j,r}) X_{j,h} + \gamma_y + \tau_S + \pi_r + v_F + u_l \quad (\text{eqn. 5})$$

410

411 where $\xi_{i,r}$ and $\xi_{j,r}$ are vectors of random effects ($r = 1, \dots, R$) defining a stochastic process with a
 412 specified Gaussian model over the $R = 10$ zoogeographical realms covered in this study.

413 In addition to the models described above, we fitted an intercept-only model to derive estimates

414 of overall infection probability. We also fitted GLMMs with either realm or location as a random

415 effect to derive location- and region-specific estimates of infection probabilities. We do so to
416 identify possible regional/local hotspots (average high infection probabilities). For model fitting
417 and inference, we used the Integrated Nested Laplace Approximation (INLA) as a
418 computationally efficient way to solve such latent Gaussian spatial models (Rue, Martino, &
419 Chopin, 2009; Lindgren, Rue, & Lindström, 2011). The INLA program models covariance for a
420 random effect using a precision matrix (the inverse of a covariance matrix), taking advantage of
421 sparse structures for efficient computation (Rue et al., 2009). For all random effects based on
422 groupings (i.e., year, region, and region-level varying coefficients), we fitted first-order random
423 walk models (Gaussian Markov Random Field, specified by a zero mean multivariate Gaussian
424 probability density function).

425 For fitting the spatial random effect, u_i , we used the Stochastic Partial Differential
426 Equation (SPDE) approach, as implemented in INLA, to model spatial effects using a Gaussian
427 field based on a Matérn correlation function and a spatial triangulate mesh around sampling
428 locations (Bakka et al., 2018). Setting the minimum allowed distance between points (cut-off) to
429 0.1 degree of latitude and the largest allowed triangle edge length (max edge) to 3 resulted in a
430 mesh of 38,305 triangles, with the smallest edge lengths and finest mesh resolution adjacent to
431 sampling locations (**Supporting Information Figure S2**).

432 Continuous predictor variables were standardized to unit variance before analysis. For
433 fixed effects, we used penalized complexity priors (using the ‘pc.prec’ option in the INLA
434 settings), which penalize any departure from the base model and constrain coefficients to zero if
435 there is insufficient support in the data otherwise. Such priors are commonly used for
436 regularization of regression coefficients in multiple regression models (Simpson, Rue, Riebler,
437 Martins, & Sørbye, 2017).

438 For model comparison and validation, we computed deviance information criteria (DIC)
439 for each candidate model (Spiegelhalter, Best, Carlin, & van der Linde, 2002). We also
440 computed conditional predictive ordinates (CPO) as cross-validation criteria, which estimate for
441 each observation a probability of obtaining the observed value when the model is fitted using all
442 data apart from the left-out observation; larger values indicate a better model fit to the data,
443 whereas small values indicate a poorer model fit.

444 We present results as posterior means and 95% credible intervals (CIs) and considered
445 CIs that did not overlap with zero or with each other in pairwise comparisons as ‘significantly
446 different’. Despite the overall large sample size, group-specific estimates can be burdened by
447 substantial uncertainty (i.e., when few individuals for a certain location or host clade have been
448 sampled). We considered group-level estimates to be meaningful only if the width of the
449 respective CI was smaller than 10%.

450

451 **Results**

452 *Strong spatial variation in haemosporidian infection probability coincides with strong* 453 *phylogenetic variation among host clades*

454 The estimated global average infection probability of birds with haemosporidian parasites
455 differed among parasite genera: *Leucocytozoon* (13.2%, CI: 12.8 – 13.7%, n = 26,635 screened
456 birds, intercept-only model), *Plasmodium* (12.8%, CI: 12.5 – 13.1%, n = 53,669),
457 *Parahaemoproteus* (13.8%, CI: 13.5 – 14.1%, n = 53,669), and *Haemoproteus* (0.7%, CI: 0.6 –
458 0.8%, n = 53,669). Whereas the low overall infection probability for *Haemoproteus* can be
459 explained by this genus being mostly restricted to Columbidae (doves and pigeons) and
460 Fregatidae (frigatebirds), the similar infection probabilities for the other three haemosporidian

461 genera may reflect their ability to infect a broad spectrum of avian clades (**Supporting**
462 **Information Figure S3**). Among the 141 avian host families surveyed, those with the highest
463 average infection probabilities were all songbirds (Passeriformes): Paridae, Corvidae, and
464 Oriolidae for *Leucocytozoon*; Zosteropidae and Melanocharitidae for *Parahaemoproteus*; and
465 Parulidae, Turdidae, and Conopophagidae for *Plasmodium*, according to the lower CI estimates
466 of phylogenetic effects (**Supporting Information Figure S3**).

467 Infection probabilities differed considerably among zoogeographical realms (**Figure 1**,
468 **Supporting Information Table S2**). For the three most common haemosporidian genera
469 (*Leucocytozoon*, *Parahaemoproteus*, and *Plasmodium*) infection probabilities were highest in the
470 Saharo-Arabian realm, with lower CI estimates $\geq 24\%$. *Leucocytozoon* infection probabilities
471 were lowest in the Neotropical, Oceanian, and Panamanian realms. *Parahaemoproteus* infection
472 was lowest in the Australian, Neotropical, and Sino-Japanese realms. *Plasmodium* infection was
473 lowest in the Australian, Oceanian, Oriental, and Sino-Japanese realms (all respective upper CIs
474 $< 10\%$ from GLMMs with region as random effects, **Figure 1**). Given its restriction to doves and
475 frigatebirds, the prevalence of *Haemoproteus* was $< 5\%$ (respective upper CIs) in all realms
476 except for Oceanian and estimated to be highest in the Palearctic and Oceanian realms (both
477 lower CIs $\geq 2.3\%$).

478 We found considerable spatial variation in average infection probabilities across locations
479 within regions (GLMM with locations as random effects), although estimates with acceptable
480 uncertainty (credible intervals $\leq 10\%$) occurred in only 45 – 104 of the 1,630 sampling locations
481 (**Figure 2**). Using these location-based estimates, four currently recognisable local hotspots of
482 *Haemoproteus* infection were identified in the Neotropical realm, with infection rates exceeding
483 2% (respective lower CIs $\geq 2\%$). Hotspots (locations with highest lower CIs) for *Leucocytozoon*

484 and *Parahaemoproteus* were dispersed across different zoogeographical realms:
485 *Parahaemoproteus* in the Palearctic and Australian realms with lower CIs $\geq 25\%$ and
486 *Leucocytozoon* in Afrotropical, Nearctic, and Palearctic with lower CIs $\geq 13\%$). Hotspots of
487 *Plasmodium* occurred in the Nearctic realm (three locations with lower CIs $\geq 21\%$).

488

489 ***Drivers of global infection probability***

490 Models that included phylogenetic and spatial effects and accounted for varying fixed-
491 effect coefficients (spatio-phyl-varcoef-GLMM, equation 5) provided the best fit to the observed
492 data and strongest predictive power according to both the DIC and CPO criteria (**Supporting**
493 **Information Table S3**). We therefore report results from this model unless stated otherwise. We
494 note however, that phylogenetic effects were burdened by high uncertainties, indicating the
495 challenges of disentangling phylogenetic effects from spatial and climatic covariates
496 (**Supporting Information Figure S3**).

497 Infection probabilities exhibited idiosyncratic associations with host traits, landscape
498 variables, and climate conditions at the global scale. Among the 14 covariates used in the
499 analyses, 11 exhibited ‘global average’ coefficient estimates for which CIs did not overlap with
500 zero (**Figure 3, Supporting Information Table S4**). As overall *Haemoproteus* prevalence was
501 extremely low (370 infections out 53,669 screened birds) and constrained to two host families
502 (Columbidae and Fregatidae), this parasite genus was not considered in the following analysis.

503 Local bird species richness showed a positive effect on infection probability for
504 *Leucocytozoon* (odds ratio, OR 1.83, CI 1.26 - 2.56) and *Parahaemoproteus* (OR 1.32, CI 1.09 -
505 1.59). Infection probability increased with increasing host body mass for *Leucocytozoon* (OR
506 1.25, CI 1.11 - 1.41), *Parahaemoproteus* (OR 1.62, CI 1.47 - 1.79), and *Plasmodium* (OR 1.36,

507 CI 1.24 - 1.48). Infection probability increased among bird species spending more time foraging
508 in the canopy for *Leucocytozoon* (OR 1.13, CI 1.05 - 1.22) and *Parahaemoproteus* (OR 1.26, CI
509 1.18 - 1.35), but decreased for *Plasmodium* (OR 0.88, CI 0.81 - 0.95). *Leucocytozoon* infection
510 probability increased with host migration distance (OR 1.19, CI 1.07 - 1.32). Higher proportions
511 of wetland cover at different sites increased infection probability for *Plasmodium* (OR 1.35, CI
512 1.03 - 1.79), but decreased infection probability for *Parahaemoproteus* (OR 0.53, CI 0.37 - 0.78)
513 and *Leucocytozoon* (OR 0.52, CI 0.29 - 0.95). Elevation increased infection probability for
514 *Leucocytozoon* (OR 1.47, CI 1.14 - 1.9), but decreased infection probability for *Plasmodium* (OR
515 0.65, CI 0.53 - 0.80). Infection probability for *Leucocytozoon* (OR 0.33, CI 0.20 - 0.53) was
516 considerably lower at sites with higher rainfall during the driest month and decreased with
517 increasing rainfall seasonality (OR 0.59, CI 0.43 - 0.80). At locations with higher annual rainfall,
518 infection probability increased for *Leucocytozoon* (OR 1.83, CI 1.15 - 2.91), but decreased for
519 *Plasmodium* (OR 0.75, CI 0.58 - 0.97). Sites with higher proportions of forest cover and
520 vegetation density exhibited increased probability of infection by *Parahaemoproteus* (OR 1.31,
521 CI 1.02 - 1.70) and *Plasmodium* (OR 1.44, CI 1.05 - 1.97), respectively. Annual mean
522 temperature, annual fluctuation in vegetation density, and distance to equator showed no evident
523 covariation with infection probability (i.e., CIs overlapped with zero) for any of the three parasite
524 genera (**Figure 3**).

525 Varying coefficient estimates revealed that several covariate effects, notably mostly host
526 ecological traits rather than environmental predictors, differed across zoogeographical realms
527 (see **Supporting Information Table S5** for variance estimates in coefficients). Two host traits
528 and one environmental driver exhibited opposing effects on the probability of parasite infection
529 across zoogeographical realms: local bird species richness had a positive effect on infection

530 probability for *Parahaemoproteus* in the Afrotropical, Palearctic, and Sino-Japanese realms and
531 a negative effect in the Saharo-Arabian realm (**Figure 4**). Migration distance was associated with
532 increased *Parahaemoproteus* infection probability in the Neotropical, Saharo-Arabian, and Sino-
533 Japanese realms, but with decreased infection probability in the Nearctic and Oriental realms
534 (**Figure 4**). Likewise, migration distance was associated with increased *Plasmodium* infection in
535 the Neotropical, Oceanian, and Oriental realms, but with decreased infection probability in the
536 Nearctic realm (**Figure 4**). Annual fluctuation in vegetation density was associated with
537 increased infection with *Leucocytozoon* in the Nearctic realm but with decreased infection in the
538 Palearctic realm (**Figure 4**). In addition, host body mass (infection with *Leucocytozoon* and
539 *Parahaemoproteus*), canopy foraging frequency (infection with *Parahaemoproteus* and
540 *Plasmodium*), and proportion of wetland cover (infection with *Leucocytozoon*), all varied across
541 realms according to variance in coefficient estimates (**Figure 4, Supporting Information Table**
542 **S5**).

543

544 **Discussion**

545 Understanding large-scale variation in parasite prevalence and spread is of increasing
546 importance in a changing world, where counteracting disease emergence and outbreaks pose a
547 global challenge. Using a global database of infections by four genera of a cosmopolitan group
548 of vector-transmitted blood parasites of birds, we show that infection probabilities for each
549 parasite genus vary considerably across zoogeographic realms and avian host families. Our
550 hierarchical global analysis identified key drivers of infection probability that differed in their
551 magnitudes and directions among parasite genera. In particular, we found that bird richness and
552 host attributes may have rather different impacts on infection risk in different zoogeographical

553 realms, whereas climate and habitat conditions are more likely to influence infection risk
554 consistently across zoogeographical realms. Multiple global hotspots of avian haemosporidian
555 infection emerge from our results with strong variation in infection probabilities within realms,
556 indicating that prevalence in avian hosts responds to regional factors as well as broad-scale
557 global drivers such as latitudinal ecological/climatic gradients. Accounting for environmental
558 context in synergy with biotic drivers, such as species ecological traits and host species assembly
559 patterns, is critical for understanding variation in infection probability and conditions that enable
560 parasites to spread.

561

562 *Hotspots of haemosporidian infection probability*

563 Disease hotspots are not necessarily stable over time and may result from high frequency
564 of local spillover event from alternative hosts species. A key challenge in disease ecology is to
565 identify traits of alternative host species (phylogenetically related or not) that might make them
566 competent reservoirs of pathogens and increase local prevalence (Jones et al., 2008). Here we
567 identified locations with the greatest infection risk of a vector-transmitted parasite and host traits
568 that potentially increase local prevalence. Notably, our macroecological analyses of infection
569 probability identified hotspots for haemosporidian parasites dispersed across different
570 zoogeographical regions, some well outside the known biodiversity hotspots for most free-living
571 organisms in the tropics. Unlike the pantropical distribution of human malaria hotspots, our map
572 on global infection risk depicts hotspots for avian malaria in the Nearctic region and for
573 *Parahaemoproteus*, a related avian malaria parasite, in the Palearctic region.

574 The longstanding and much-debated hypothesis that infection risk increases toward the
575 equator (Jones et al., 2008; Stephens et al., 2016, Allen et al., 2017) was not supported in our

576 synthesis for vector-transmitted parasites. Tropical regions support higher bird diversity in
577 comparison to temperate regions (Duchêne & Cardillo, 2015), and thus haemosporidian parasites
578 from tropical regions may have a higher diversity of available “niches” to exploit. Furthermore,
579 the greater diversity of both avian and vector host species in the tropics could lead to increased
580 diversity within individual hosts through lineage sharing and host shifting (Ricklefs et al., 2014).
581 While surprising, the observed absence of a latitudinal gradient in infection probability for the
582 three most prevalent haemosporidian parasites matches what was found for lineage diversity at a
583 global scale (Clark, 2018). Clark (2018) demonstrated that more diverse communities of
584 haemosporidian parasites do not necessarily occur in tropical regions and suggested that
585 macroevolutionary factors, such as propensity of parasites to shift hosts locally, or timing of
586 diversification, are more important drivers of local parasite diversity. Whether haemosporidian
587 prevalence is correlated with lineage diversity and the propensity of these parasites to shift
588 among hosts at different rates across latitude has yet to be investigated.

589 Our findings suggests that haemosporidian infection probabilities emerge not only from
590 general global drivers such as climate, avian host richness, and, possibly, migratory flyways that
591 determine macroecological patterns of community assembly, but also from region-scale habitat
592 and climate variation.

593

594 ***Spatial distribution of avian hosts overshadows phylogenetic signal in infection probability***

595 Host phylogenetic position has been associated with variation in haemosporidian
596 prevalence in avian communities and host clades (Barrow et al., 2019; Clark et al., 2020). Our
597 study confirms these previous findings in terms of a strong phylogenetic signal in bird infection
598 patterns with haemosporidian parasites. However, after accounting for both phylogeny and the

599 location of the collected samples, we found considerable uncertainty in the phylogenetic signal at
600 a global scale, indicating that strong phylogenetic signal inferred from a pooled sample (i.e.,
601 without taking spatial context/covariance into account) can be misleading. This uncertainty in
602 phylogenetic signal can be especially pronounced at a large scale, in which distinct local host
603 assemblages and samples are likely to include closely related individuals/species, which in turn
604 may generate phylogenetic ‘pseudoreplicates’ at the same locations.

605 Recognizing that avian haemosporidian prevalence is highly variable within and among
606 host clades, and that it is spatially clustered, as we have shown here, provides a new framework
607 for outlining region-specific predictions of infection risk by multi-host vector-transmitted
608 parasites. This is particularly true for areas undergoing rapid climate change, anthropogenic
609 landscape transformation, and shifting host species assemblages. We believe that these patterns
610 point to strong synergistic effects of host traits, landscape features, and climatic filters driving
611 infection patterns.

612

613 ***Idiosyncratic drivers influence differences in global infection risk among haemosporidian***
614 ***genera***

615 A central finding of our analysis was not only the identification of host traits driving
616 infection probability for the three most prevalent haemosporidian genera, but also how their
617 effects vary across zoogeographic realms. We showed that bird species which migrate longer
618 distances are more likely to be infected by *Leucocytozoon* worldwide. As most long-distance
619 migrants spend part of their annual cycle breeding in temperate regions, where black fly vectors
620 are more diverse and abundant (Currie & Adler, 2008), there would be much higher potential for
621 *Leucocytozoon* transmission in long-distance migrants than in resident tropical species.

622 Migration distance influenced infection probability in opposing directions across
623 zoogeographical realms for the genera *Plasmodium* and *Parahaemoproteus* (see results and
624 Figure 4). These inverse trends in infection risk for vector transmitted parasites in response to
625 migration patterns warrant future research into underlying mechanisms. Perhaps one of the
626 interesting aspects to consider (if relevant data become available) could be the spatial context of
627 parasites transmission, given the possibility that transmission in migratory birds may take either
628 place in the wintering or breeding area but not necessarily in both. This is especially relevant
629 given the multifaceted environmental changes, which are likely to amplify the anticipated
630 changes in bird migration and community assembly (Visser et al., 2009; Howard et al., 2020)
631 and hence the future infection risk with haemosporidian parasites.

632 Avian hosts inhabiting sites with a higher proportion of wetland cover and denser
633 vegetation are at greater risk of *Plasmodium* infection. The probability of a bird being infected
634 with *Parahaemoproteus* consistently increased with proportion of forest cover, while it
635 decreased in sites with higher proportions of wetland cover. When anthropogenic landscape
636 changes create structures capable of collecting rainwater (e.g., artificial lakes, mining pits, rice
637 fields) or change the course or flooding regime of rivers (e.g., dams, irrigation systems), such
638 changes in water availability may increase infection of birds with avian. Conversely, reduction in
639 forest cover may diminish the local transmission of *Plasmodium* and *Parahaemoproteus* among
640 avian hosts, but whether tree cover removal has a direct effect on vector capacity or parasite
641 capacity to shift between hosts at large spatial scales has yet to be investigated.

642 We found that higher annual rainfall is associated with decreased prevalence of
643 *Plasmodium* but increased prevalence of *Leucocytozoon*. Furthermore, *Leucocytozoon* infection
644 risk decreases at sites with substantial rainfall during the driest months and sites with pronounced

645 variation in rainfall throughout the year. The relationship between rainfall and prevalence
646 suggests that the expected disruption of precipitation patterns due to anthropogenic impacts on
647 global climate (Wehner, 2020) may affect prevalence of avian haemosporidian genera
648 differentially in the future. The magnitude of this impact may vary by region owing to
649 biogeographic structure in realized host specialization of haemosporidian lineages (Fecchio et
650 al., 2019).

651 Elevation emerged as a predictor of *Plasmodium* and *Leucocytozoon* infection probability
652 at a global scale, although with an opposite effect for each parasite genus. Our global dataset
653 allowed us to determine the probability of a bird being infected across an elevation gradient
654 ranging from sea level to ~4,700 meters elevation across 10 zoogeographic realms, while
655 simultaneously controlling for other climatic characteristics known to constrain vector
656 development, activity, and abundance (e.g., temperature and moisture level), as well as parasite
657 reproduction (temperature). This approach consistently demonstrated that the probability of an
658 individual bird being infected with *Plasmodium* decreases with elevation across the globe,
659 presumably because of constraints in parasite development and transmission by mosquito vectors
660 at higher elevation sites (Atkinson et al., 2014). Although we showed that *Leucocytozoon*
661 infection probability increased with elevation, presumably owing to the affinity of black fly
662 vectors for colder sites at high elevations, hotspots of *Leucocytozoon* prevalence were also
663 scattered across lowland bird assemblages.

664 Generally, with the currently available empirical evidence being mostly constraint to
665 vertebrate host infections, correlative approaches as employed in this study allow limited insights
666 into which species and interactions in the vertebrate-host-pathogen transmission cycle are most
667 sensitive to environmental change, warranting future research into specific host-vector

668 associations and host preferences. This is especially relevant for ectothermic arthropod vectors,
669 for which host preferences and biting rates are sensitive to climate and land use changes (Rose et
670 al., 2020).

671

672 **Conclusions**

673 Our spatio-phylogenetic analysis revealed that infection probability of haemosporidian
674 parasites varies across zoogeographical realms and avian host clades owing to broad-scale and
675 possibly also regional-scale variation in environmental conditions and host assemblages. A novel
676 aspect of our study was to determine the drivers and hotspots of infection probability for each
677 haemosporidian genus on a global scale rather than at population or community levels.

678 Importantly, we found that infections in some low-prevalence realms were disproportionately
679 concentrated in local hotspots, suggesting that regional-scale modifications in habitat and
680 microclimate (and perhaps also the way host species assemble in response to strong habitat
681 modification) may increase transmission at a regional scale. However, the synergistic effect of
682 environmental drivers, such as precipitation, vegetation density, and proportion of forest and
683 wetland cover, along with host community and assembly attributes on prevalence of multi-host
684 pathogens across realms, underscores the importance of considering biogeographic patterns in
685 host-parasite systems. At the same time, we suggest that the scattered distribution of local
686 infection hotspots demonstrates that local processes, such as strong habitat modification and the
687 resulting shifts in host species assemblages, can produce unexpected increases in parasite
688 prevalence, emphasising that disease outbreak may be difficult to predict from generalizable
689 large-scale patterns such as climate alone.

690

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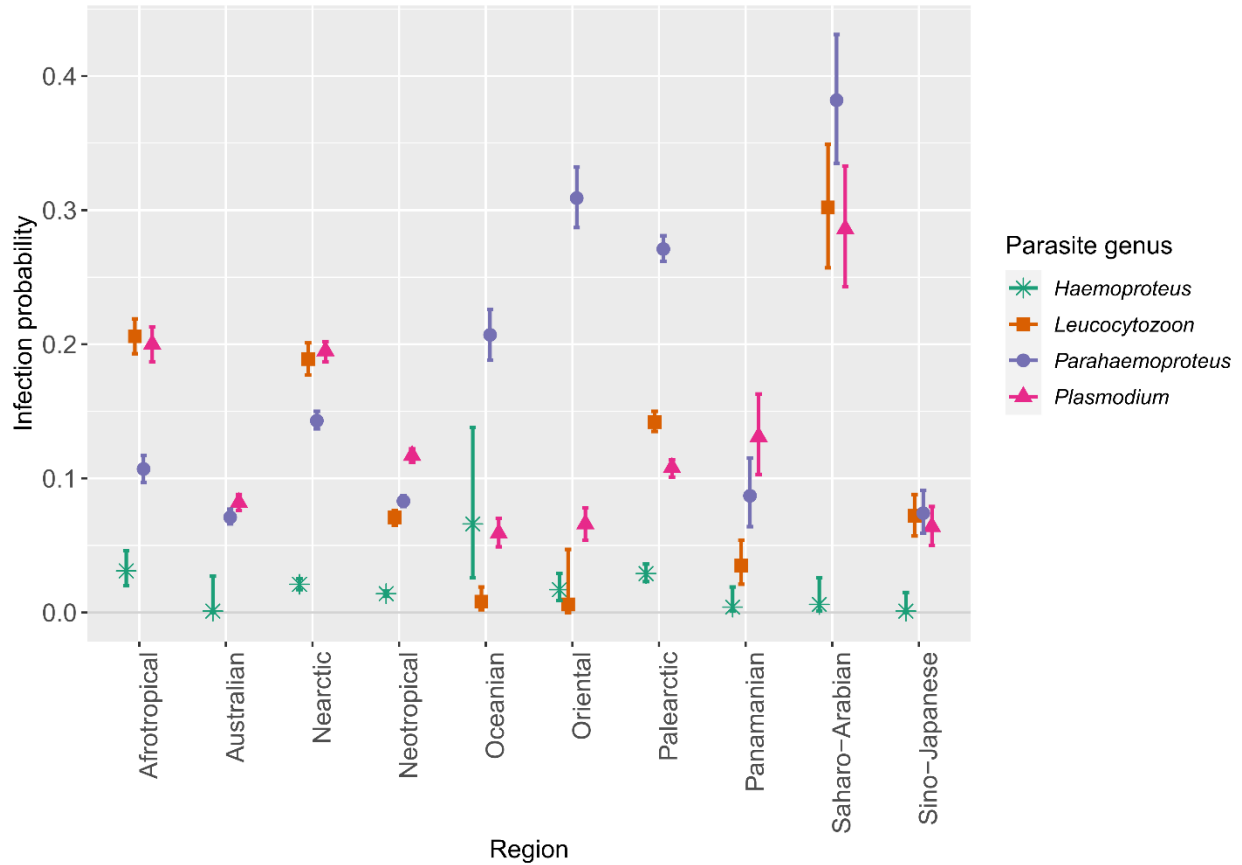
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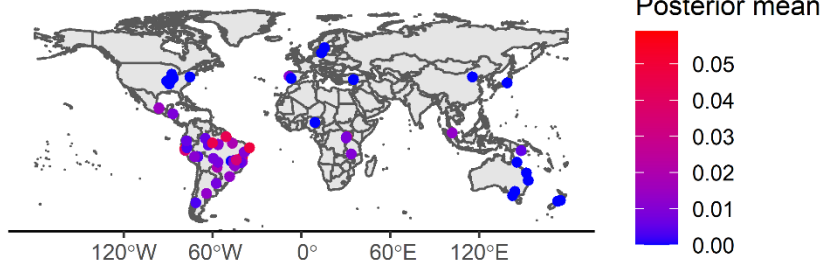
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887 **Figure 1.** Region-specific estimates of average infection probabilities of birds for four
 888 haemosporidian genera, based on 53,669 sampled bird individuals (estimates from GLMM with
 889 region as a random effect). Error bars depict 95% credible intervals, reflecting uncertainty
 890 related to sample sizes in different regions.

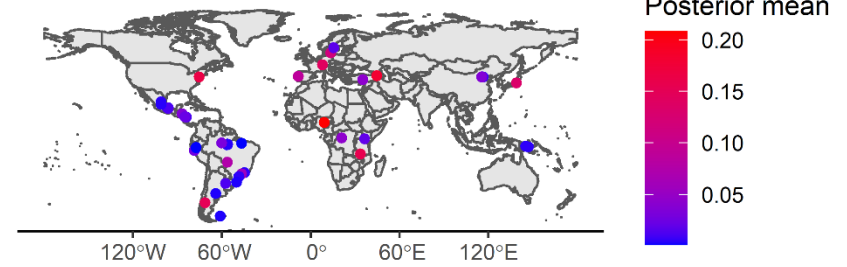
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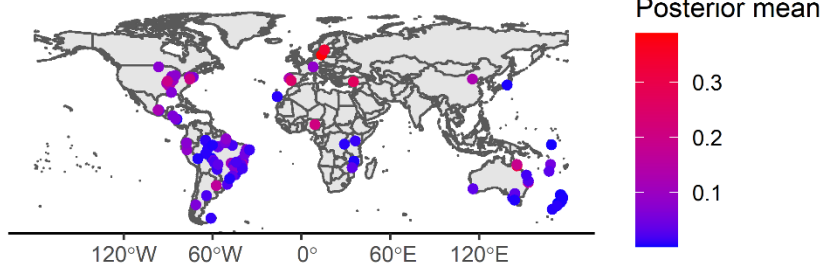
Haemoproteus



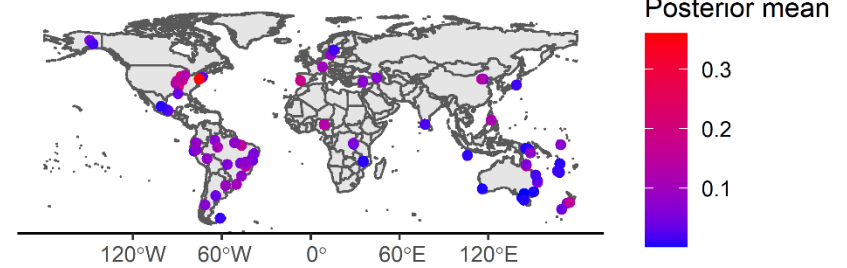
Leucocytozoon



Parahaemoproteus



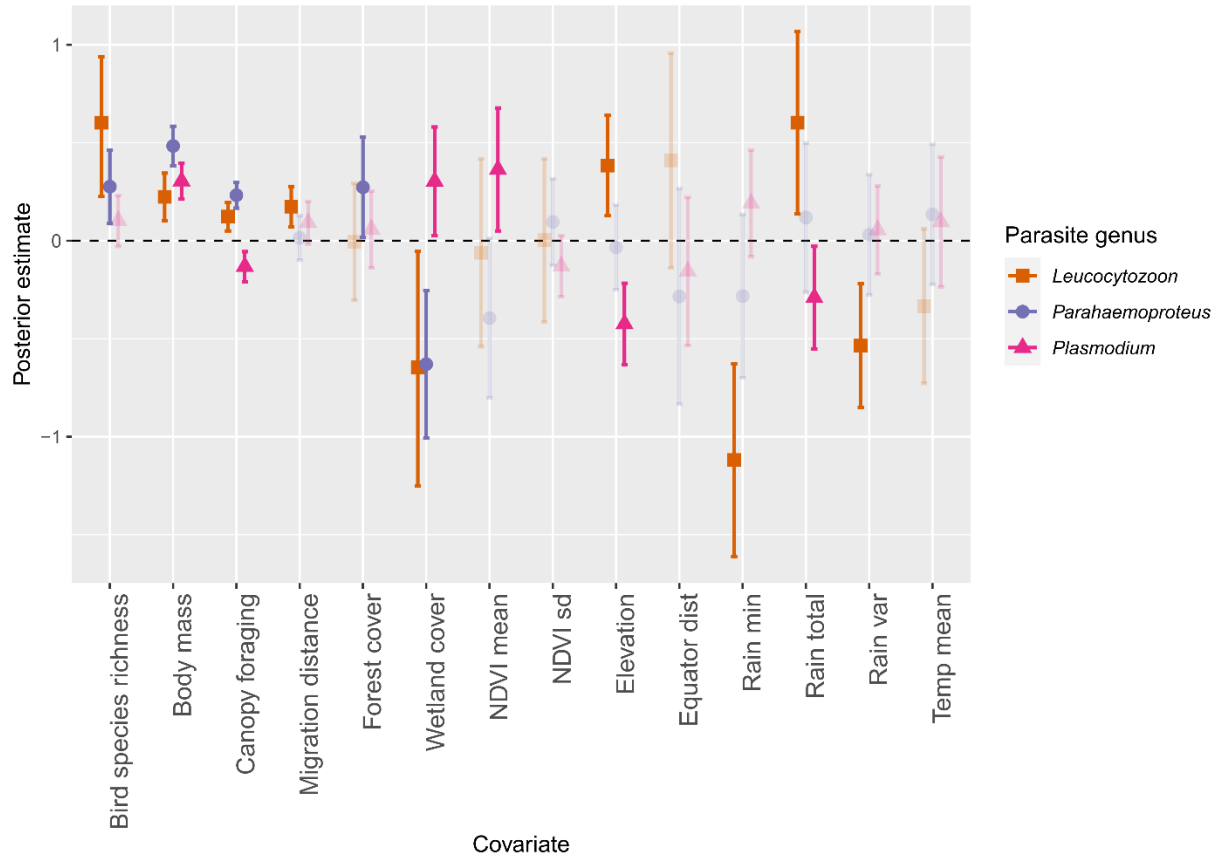
Plasmodium



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894 **Figure 2.** Estimated average parasite prevalence at different locations, shown only for locations with $\leq 10\%$ uncertainty in estimates

895 according to the size of 95% credible intervals.



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897 **Figure 3.** Estimates of the ‘global average’ effects of different drivers on variation in the
 898 infection probability of the three most common avian haemosporidian genera (based on scaled
 899 covariates). Points depict posterior means of the fixed effect estimates from a spatio-
 900 phylogenetic varying coefficient model, and vertical lines indicate 95% credible intervals. For
 901 each parasite genus, the covariates that overlap with zero are shown in light bars.

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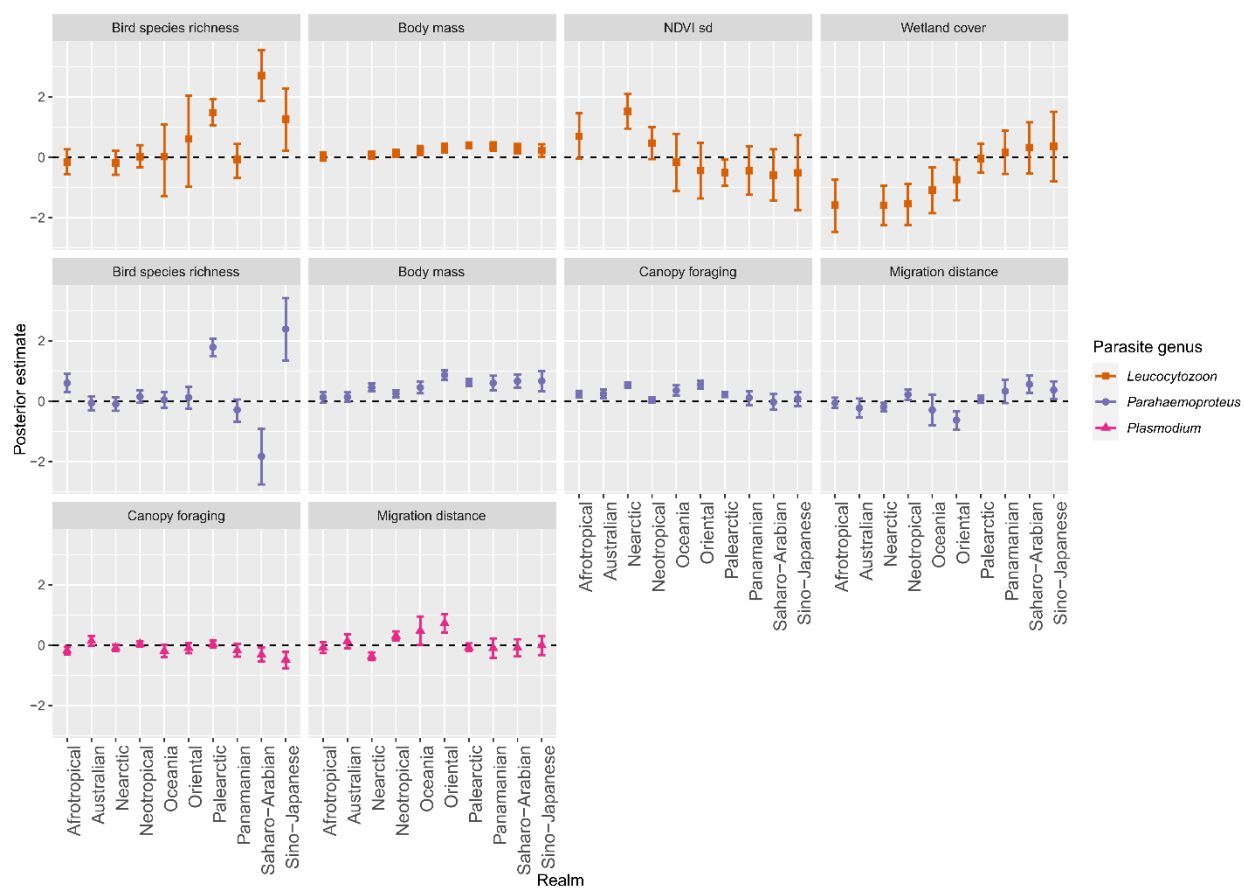
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909 **Figure 4.** Varying coefficient estimates for variables with distinct effects across zoogeographical

910 realms. Points depict the posterior mean of the regional-level effect estimates from a spatio-

911 phylogenetic varying coefficient model, and vertical lines indicate 95% credible intervals.

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