

Everything you always wanted to know about gene flow in tropical landscapes (but were afraid to ask)

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The bulk of the world's biodiversity is found in tropical regions, which are increasingly threatened by the human-led degradation of natural habitats. Yet, little is known about tropical biodiversity responses to habitat loss and fragmentation. Here we review all available literature assessing landscape effects on gene flow in tropical species, aiming to help unravel the factors underpinning functional connectivity in the tropics. We map and classify studies by focus species, the molecular markers employed, statistical approaches to assess landscape effects on gene flow, and the evaluated landscape and environmental variables. We then compare qualitatively and quantitatively landscape effects on gene flow across species and units of analysis. We found 69 articles assessing landscape effects on gene flow in tropical organisms, most of which were published in the last five years, were concentrated in the Americas, and focused on amphibians or mammals. Most studies employed population-level approaches, microsatellites were the preferred type of markers, and Mantel and partial Mantel tests the most common statistical approaches used. While elevation, land cover and forest cover were the most common gene flow predictors assessed, habitat suitability was found to be a common predictor of gene flow. A third of all surveyed studies explicitly assessed the effect of habitat degradation, but only 14 of these detected a reduced gene flow with increasing habitat loss. Elevation was responsible for most significant microsatellite-based IBR effects and a single study reported significant isolation by non-forested areas in an ant. Our study reveals important knowledge gaps on the study of landscape effects on gene flow in tropical organisms, and provides useful guidelines on how to fill them.

1 **Everything you always wanted to know about gene flow in tropical**
2 **landscapes (but were afraid to ask)**

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17 **Abstract**

18 The bulk of the world's biodiversity is found in tropical regions, which are increasingly
19 threatened by the human-led degradation of natural habitats. Yet, little is known about tropical
20 biodiversity responses to habitat loss and fragmentation. Here we review all available literature
21 assessing landscape effects on gene flow in tropical species, aiming to help unravel the factors
22 underpinning functional connectivity in the tropics. We map and classify studies by focus species,
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27 published in the last five years, were concentrated in the Americas, and focused on amphibians or
28 mammals. Most studies employed population-level approaches, microsatellites were the preferred
29 type of markers, and Mantel and partial Mantel tests the most common statistical approaches
30 used. While elevation, land cover and forest cover were the most common gene flow predictors
31 assessed, habitat suitability was found to be a common predictor of gene flow. A third of all
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33 detected a reduced gene flow with increasing habitat loss. Elevation was responsible for most
34 significant microsatellite-based IBR effects and a single study reported significant isolation by
35 non-forested areas in an ant. Our study reveals important knowledge gaps on the study of
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37 fill them.

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45 **Introduction**

46 About two-thirds of all known species occur in tropical forests and the majority of the world's
47 most threatened biodiversity hotspots are in the tropics (Myers et al., 2000; Brown, 2014).
48 Extinction rates from habitat loss and fragmentation are acute in the region, and the degradation
49 of essential ecosystem functions and services are threatening billions of people living in tropical
50 countries (Bradshaw, Sodhi & Brook, 2009). However, the vast majority of studies assessing
51 biodiversity responses to habitat degradation have been undertaken in temperate regions due to a
52 lower investment in research and development in tropical countries (Collen et al., 2008; Barlow
53 et al., 2018). For instance, a recent analysis of 182 studies describing links between biodiversity
54 and ecosystem function (Clarke et al., 2017) found that only 13% were carried in the tropics, and
55 nearly half of these (42%) were conducted in a single country (Costa Rica). There is thus a
56 pressing need to reduce the knowledge gap concerning the impact of the degradation of natural
57 habitats on tropical biodiversity.

58 Community-level approaches assessing biodiversity responses to habitat degradation have
59 focused on measuring changes in species richness, composition, and the abundance of indicator
60 species (Morin, 2009). While these metrics underpin ecosystem function, they may not always be
61 the best proxies to detect rapid responses to habitat loss and fragmentation. Local species
62 extinctions may occur after long periods of time since the onset of disturbance (Jackson & Sax,
63 2009), whereas species abundance can be affected by multiple environmental or demographic
64 factors unrelated to habitat degradation (Ehrlén & Morris, 2015). Moreover, complex inter-
65 specific interactions can make natural communities resilient to environmental change and thus
66 mask the effect of habitat degradation on community composition (Devictor, Julliard & Jiguet,
67 2008). Instead, population-level metrics based on genetic information can offer a higher
68 resolution to detect rapid responses to environmental change (Manel & Holderegger, 2013a). For
69 instance, changes in genetic diversity and gene flow patterns in response to recent landscape
70 modification have been found across several species (Balkenhol et al., 2016; DiLeo & Wagner,
71 2016), although tropical organisms have been rarely assessed (Storfer et al., 2010a).

72 Even though the effects of habitat loss and fragmentation on genetic diversity have been
73 reviewed extensively (Aguilar et al., 2006, 2008; Keyghobadi, 2007; Vranckx et al., 2012; Lino et
74 al., 2018; Schlaepfer et al., 2018), there is an important knowledge gap regarding general
75 landscape effects on gene flow (DiLeo & Wagner, 2016). By influencing the willingness of an
76 organism to cross a particular environment, the physiological or fitness costs of moving through
77 it, or all these factors simultaneously, the resistance imposed by landscape structure on the

78 dispersal of organisms can ultimately affect genetic differentiation and patterns of gene flow
79 (Zeller, McGarigal & Whiteley, 2012; Balkenhol et al., 2016). To understand which landscape
80 features impose a greater resistance on gene flow, landscape geneticists first create resistance
81 surfaces for landscape variables of interest, then use these surfaces to estimate cost or resistance
82 distances between sampling locations, and finally regress measures of gene flow on these
83 resistance distances (Spear, Cushman & McRae, 2016). Significant associations between gene
84 flow metrics and landscape resistance distances are taken for evidence of isolation by resistance
85 (IBR), and effect sizes can be considered proxies of functional connectivity (Manel &
86 Holderegger, 2013b).

87 Understanding the factors underpinning functional connectivity across species is essential
88 to design ecological corridors, identify conservation units, assess population threat status,
89 optimize pathogen and invasive specie's management, assist planning of natural heritage systems,
90 and restore threatened populations (Bowman et al., 2016; Waits LP, Cushman SA, 2016).
91 However, no efforts have yet been made to gather, standardize and compare IBR effects across
92 studies and organisms. For instance, landscape genetics is still a your field of research (Manel &
93 Holderegger, 2013b), and the vast majority of landscape genetic studies have focused in a single
94 species (DiLeo & Wagner, 2016; Waits LP, Cushman SA, 2016). So far, gene flow has been
95 shown to be influenced by various factors, including forest cover, land cover, topography, roads,
96 rivers, and climate, but responses vary greatly across species and units of analysis (populations or
97 individuals; see Balkenhol et al. 2016 and references therein).

98 Aiming to unravel the main drivers of functional connectivity in tropical landscapes, here
99 we compiled all studies that assessed landscape effects on gene flow in tropical species so far. To
100 our knowledge, this work represents the first quantitative comparison of such effects across
101 species and units of analysis. We believe this systematic review can help characterize the current
102 knowledge gap on tropical biodiversity responses to habitat degradation, and thereby highlight
103 future research needs.

104

105 **Survey Methodology**

106 ***Dataset***

107 We employed the following search engines to perform a recursive literature search of landscape
108 effects on gene flow in tropical species published by June 2018: Scielo (<http://www.scielo.org>),
109 Portal de Periódicos da Coordenação de Aperfeiçoamento de Pessoal de Nível Superior do
110 Ministério da Educação (CAPES/MEC) (<http://www.periodicos.capes.gov.br/>); Google Scholar

111 (<http://www.scholar.google.com.br>); Web of Knowledge (<http://www.isiknowledge.com>), and
112 Scopus (<http://www.scopus.com>). We used the following combination of keywords and Boolean
113 operators: ("landscape resistance" or landscape or resistance or fragmentation or "land use" or
114 "habitat loss" or deforestation) and (genetic* or "genetic differentiation" or "gene flow" or
115 "genetic distance" or FST or relatedness or kinship). Articles containing at least one of the
116 keywords on each side of the "and" operator were analyzed along with the relevant references
117 therein. Even though this search approach may not be easily replicated (as it involves a
118 substantial effort), it is more likely to minimize omissions than approaches based on the results
119 obtained from search engines alone. We then identified those studies that explicitly related
120 landscape with gene flow metrics in organisms collected between the tropics of Cancer and
121 Capricorn (23.5° north and south of the equator) or within 200km from them. Articles addressing
122 only isolation by geographic distance (IBD) were excluded, as our aim was to survey studies that
123 specifically incorporated landscape effects on gene flow in addition to geographic distance. We
124 then gathered all available information on the focus species, study site, ecosystem, the extent of
125 the study area, the unit of analysis employed, sample size, types and number of genetic markers
126 employed, study objectives, resistance metric employed, statistical methods, landscape or
127 environmental predictors assessed, and the effects reported.

128

129 ***Comparing landscape effects on gene flow across studies***

130 We performed both qualitative and quantitative comparisons of landscape effects on gene flow
131 across studies. For the former, we grouped studies by the landscape or environmental factors
132 assessed and the focus taxonomic group, and summarized the reported effects on gene flow. For
133 the quantitative comparison we selected a subset of our dataset containing only studies that: i)
134 Explicitly reported correlation or regression coefficients, calculated from at least three samples,
135 and ii) Employed nuclear microsatellite markers to measure gene flow, given that measures of
136 genetic differentiation obtained with different genetic markers are not directly comparable across
137 studies (Wan et al., 2004; Allendorf, Luikart & Aitken, 2013). We then separated the studies
138 fulfilling these requirements in two groups according to the units of analysis employed: Those
139 using population-level metrics of genetic differentiation (F_{ST} or D_{est}), and those using individual-
140 level metrics of genetic distance (Rousset's a , relatedness and kinship; Dataset S3). An effect size
141 approach was used to compare isolation by resistance (IBR) within both types of studies
142 (individual and population-level). Correlation coefficients were first normalized using the
143 Fisher's z-transformation (z), and standard errors (se) were calculated as following:

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145
$$z = \frac{1}{2} \ln\left(\frac{1+r}{1-r}\right)$$

146
$$se = \frac{1}{\sqrt{N-3}}$$

147

148 Where r is the correlation coefficient, \ln the natural logarithm and N the number of pairwise
149 comparisons (between individuals or populations). Effect sizes were then calculated dividing the
150 normalized correlation coefficients and standard errors (z/se) (Ellis, 2010). Effect sizes of
151 regression coefficients were calculated dividing them by their respective standard errors. To
152 facilitate comparisons between population-level and individual-level metrics of genetic
153 differentiation we inverted the sign of relatedness and kinship estimates, thus representing genetic
154 dissimilarity. We also calculated 95% confidence intervals for all effect sizes and retrieved the
155 statistical significance (p -values) of IBR effects reported in the original studies. We note that
156 effect sizes were only used for comparative purposes, and that as in previous reviews (DiLeo &
157 Wagner, 2016), small sample sizes did not allow performing a formal meta-analysis.

158

159 **Results**

160 We found a total of 69 articles assessing landscape effects on gene flow in tropical organisms
161 (Dataset S1 in Supplemental Information), most of which were undertaken in the Americas (Fig.
162 1). We recorded 154 target species belonging to eight major taxonomic groups, from which
163 amphibians contained the largest number of species and mammals the highest number of papers
164 (Fig. 2). Most focus species were terrestrial and only three exclusively aquatic species were
165 evaluated. The majority of studies analyzed a single species, but nine publications evaluated two
166 or more. Three studies contributed with more than 40% of all recorded species (Wang, Glor &
167 Losos, 2013; Paz et al., 2015; Jaffé et al., 2016). The oldest study found in our literature search
168 (Trénel et al., 2008) investigated the impact of contemporary Andean landscape features on the
169 spatial genetic structure of a palm tree. After this work, we observed a jump in the number of
170 publications from 2013 onward (Fig. 3).

171 The surveyed studies often had overlapping objectives, which comprised assessing
172 contemporary and historical effects of climate on gene flow (Trénel et al., 2008; Ramírez-
173 Barahona & Eguiarte, 2014); predicting gene flow with habitat suitability models (Poelchau &
174 Hamrick, 2012; Guarnizo & Cannatella, 2013; Paz et al., 2015); assessing landscape and climatic

175 effects on gene flow (Hohnen et al., 2016; Lanes et al., 2018); identifying dispersal routes
176 (Andraca-Gómez et al., 2015; Cleary, Waits & Finegan, 2017; Thatte et al., 2018) and barriers to
177 gene flow (Robertson, Duryea & Zamudio, 2009; Boff et al., 2014; Oliveira et al., 2017); and
178 evaluating the impact of habitat fragmentation on gene flow (Balkenhol et al., 2013; Joshi et al.,
179 2013; de Campos Telles et al., 2014; Carvalho et al., 2015; Ruiz-Lopez et al., 2015).

180 Five types of molecular markers were found across all studies (Fig. 4), and only five
181 publications used more than one type of marker (usually microsatellites and mtDNA).
182 Microsatellites were the most frequently used markers, with more studies using them than
183 publications using all other markers combined. More than 70% of all studies were performed at
184 the population-level and only five studies used both population and individual-level approaches
185 (Dataset S1). Electrical resistance (ER) was the most common resistance metric employed, and
186 Mantel and partial Mantel test the most common statistical methods used to relate genetic with
187 resistance distances (Fig. 5).

188 Landscape and environmental predictors of gene flow included elevation (altitude, terrain
189 ruggedness and slope), land cover, forest cover, habitat suitability (derived from species
190 distribution models), water (rivers, streams and the ocean), precipitation, roads and temperature
191 (Fig. 6, Dataset S1). Only six out of 22 studies considering elevation, four out of 22 studies
192 evaluating land cover, four out of 21 studies assessing forest cover, and 14 out of 17 studies
193 relying on habitat suitability models reported an effect on gene flow (Table S1). Most plant and
194 amphibian studies used habitat suitability models to generate resistance surfaces, but no
195 amphibian study analyzed forest cover, precipitation, roads or temperature independently; no bird
196 study used habitat suitability models; no plant study assessed the effect of water bodies; no reptile
197 or plant study addressed the effect of roads; and no mammal study considered temperature (Fig.
198 6).

199 The effect of habitat loss on gene flow was assessed in 25 studies and 39 species (Dataset
200 S2). From these, only 14 studies detected a reduction of gene flow with increasing habitat loss in
201 three plants, five mammals, one amphibian, two birds and one insect. Remarkably, most insects
202 were unaffected by habitat loss. Only 11 articles reported microsatellite-based IBR effects,
203 comprising 25 species (Dataset S3). Whereas IBD drove most significant effects across this group
204 of studies, individual-level studies ($N = 14$ effects; Fig. 7) showed larger effect sizes than
205 population-level ones ($N = 78$ effects; Fig. 8). Two individual-level IBR effects were significant
206 (revealing isolation by elevation in a bird and an ant, Fig. 7), and three significant IBR effects

207 were identified in population-level studies (revealing isolation by elevation in a plant and a bee,
208 and isolation by non-forested areas in an ant, Fig. 8).

209

210 **Discussion**

211 Despite the extraordinary levels of biological diversity comprised in the tropics, the study of
212 landscape effects on gene flow in tropical organisms only began to gain general attention in the
213 past five years. Still, published studies are mainly concentrated in the Americas and most of them
214 have focused on amphibians or mammals. The majority of studies were performed at the
215 population-level, electrical resistance was the most common resistance metric employed,
216 microsatellites were the most frequently employed type of molecular marker, and Mantel and
217 partial Mantel tests the most common statistical approaches used. While elevation, land cover and
218 forest cover were the most common gene flow predictors assessed, habitat suitability was found
219 to be a common predictor of gene flow. A third of all surveyed studies explicitly assessed the
220 effect of habitat degradation on gene flow, and only 14 studies detected a reduced gene flow with
221 increasing habitat loss. Finally, individual-level microsatellite-based IBR effects showed higher
222 effect sizes than population-level ones, elevation was responsible for most significant effects and
223 a single study reported significant isolation by non-forested areas in an ant.

224 One of the main aims of the field of landscape genetics has been to understand how landscape
225 characteristics shape patterns of functional connectivity (Manel & Holderegger, 2013b), a subject
226 that has been addressed by many studies undertaken in temperate regions (Balkenhol et al.,
227 2016). Here we show that the study of landscape effects on gene flow in tropical organisms has
228 lagged behind, and that published studies are concentrated in the Americas, as are general
229 research effort on biodiversity in human-modified tropical forests (Gardner et al., 2009;
230 Schlaepfer et al., 2018). Moreover, we found that amphibians and mammals were over
231 represented in our surveyed studies, and most studies outside the Americas focused on mammals
232 (Figs. 1 and 2), reflecting taxonomic biases in biodiversity data and societal preferences (Troutet
233 et al., 2017). Our results thus highlight how little we still understand about landscape effects on
234 gene flow in the tropics, and call for more studies on unrepresented taxonomic groups, tropical
235 areas outside the Americas, and exclusively aquatic organisms.

236 Most of the surveyed studies used microsatellite markers, despite the not so recent shift
237 towards genotyping by sequencing (GBS) triggered by next generation sequencing technologies
238 (Allendorf, Hohenlohe & Luikart, 2010; Benestan et al., 2016). For instance, microsatellite
239 genotyping is still cheaper than GBS, and cross-amplification of SSR markers in related species

240 often reduces the cost of developing species-specific markers (Storfer et al., 2010b). However,
241 SNPs are rapidly becoming the new standard in population and landscape genomic studies, due to
242 their genome-wide coverage and analytical simplicity (Morin, Luikart & Wayne, 2004).
243 Moreover, sequencing costs have fallen dramatically (Shendure et al., 2017), and GBS
244 approaches (such as RAD-sequencing) allow an affordable high-coverage sequencing of a
245 representation of the genome and the discovery of thousands of SNPs in organisms lacking a
246 reference genome (Rowe, Renaut & Guggisberg, 2011; Hohenlohe, Catchen & Cresko, 2012).
247 Perhaps the most important obstacle preventing the widespread adoption of GBS is the
248 complexity of bioinformatic processing (pre-processing of sequence data) and working with very
249 large datasets (Johnson, 2009), but we believe that a much higher resolution coupled with the
250 possibility to study both neutral and adaptive genetic variation are worth the effort (Rodriguez et
251 al., 2015; Lanes et al., 2018).

252 Electrical resistance was the most common resistance metric employed, revealing its ample
253 adoption as a general predictor of animal and plant gene flow (McRae & Beier, 2007).
254 Additionally, we found that Mantel and partial Mantel tests were the most widely used statistical
255 approaches to relate landscape and environmental characteristics with gene flow, even though
256 better methods are available (Prunier et al., 2015; Richardson et al., 2016). The limitations of
257 Mantel tests have been thoroughly discussed (Guillot & Rousset, 2013; Zeller et al., 2016), and
258 include high type-I error rates (i.e. false positives), a limit of two predictor variables that can be
259 simultaneously analyzed (in partial Mantel tests), and the absence of a maximum-likelihood
260 framework that allows for model selection (Shirk et al., 2010; Shirk, Landguth & Cushman,
261 2018). Maximum likelihood population effects (MLPE) are particularly appealing mixed-effects
262 models for use landscape genetic studies because they allow implementing multiple regressions
263 that account for the non-independence of pairwise distances within a likelihood framework
264 (Clarke, Rothery & Raybould, 2002) compatible with model selection based on information
265 criteria such as AIC (Jaffé et al., 2016; Row et al., 2017; Shirk, Landguth & Cushman, 2018).

266 Most surveyed studies assessed gene flow responses to few landscape and environmental
267 variables, from which elevation, land cover and forest cover were the most common. For
268 instance, no plant study assessed the effect of water bodies; no reptile or plant study addressed
269 the effect of roads; and no mammal study considered temperature. Again, these findings suggest
270 data and societal preferences (Troudet et al., 2017), although the more limited availability of
271 environmental layers in tropical compared with temperate regions must be highlighted too.
272 Making available more spatially explicit environmental data in the tropics could certainly help

273 broaden the scope of future efforts to capture landscape effects on gene flow (Collen et al., 2008;
274 Barlow et al., 2018). The surveyed studies were nevertheless able to quantify functional
275 connectivity (Balkenhol et al., 2013; Carvalho et al., 2015; Ruiz-Lopez et al., 2015), propose
276 ecological corridors (Atickem et al., 2013; Yumnam et al., 2014), assess threat status (Lanes et
277 al., 2018), evaluate restoration effectiveness (Moraes et al., 2018), and forecast the impact of
278 future climate and environmental changes on gene flow (Thomassen et al., 2009; Velo-Antón et
279 al., 2013; Thatte et al., 2018). Interestingly, several studies found an effect of habitat suitability
280 on gene flow, suggesting that habitat suitability models are useful when proposing ecological
281 corridors or forecasting the impact of future climate on gene flow (Franklin & Miller, 2009).
282 Additionally, elevation was responsible for most significant microsatellite-based IBR effects
283 (Figs. 7 and 8), a result that suggests elevation is an important mediator of functional connectivity
284 in tropical landscapes (Worboys, Francis & Lockwood, 2010).

285 Despite global concerns with the negative effects of habitat degradation on tropical
286 biodiversity (Barlow et al., 2018), only 25 studies have so far explicitly assessed the effect of
287 habitat degradation on gene flow. From these, only 14 found reduced gene flow with increasing
288 habitat loss, and a single microsatellite-based study reported a significant isolation by non-
289 forested areas in an army ant (Fig. 8). In contrast to other flying insects where both females and
290 males disperse, army ant queens are permanently wingless, so gene flow is restricted and mainly
291 driven by male dispersal (Jaffé, Moritz & Kraus, 2009; Pérez-Espona, McLeod & Franks, 2012).
292 These findings suggest that the effect of habitat loss on gene flow is difficult to detect, as species
293 with extremely restricted dispersal are more likely to show large effect sizes and thus be less
294 susceptible to type-II errors (false negatives).

295 Many sources of variation could have influenced the detection of landscape effects on gene
296 flow, including species-specific differences in dispersal ability and reproductive systems,
297 historical processes underpinning genetic differentiation, different sample sizes, the resolution of
298 the spatial data (grain size), the extent of the study area, sampling design, and time-lags in the
299 responses to landscape changes (Anderson et al., 2010; Balkenhol et al., 2016; Schlaepfer et al.,
300 2018). However, small sample sizes, limited information on the natural history of most studied
301 species and inconsistencies in the way data was reported across studies preclude a quantitative
302 assessment of the impact of these factors on our observed effect sizes (Dataset S3). Even though
303 the majority of the surveyed studies employed population-level approaches, individual-level
304 studies showed higher effect sizes, a finding that reinforces that individual-level analyses based
305 on continuously distributed samples are more powerful and appropriate for landscape genetic

306 studies (Landguth et al., 2010; Balkenhol et al., 2016). Additionally, studies that account for the
307 underlying population structure or inter-population variations in effective population size (N_e) are
308 more likely disentangle landscape from drift effects on gene flow (Prunier et al., 2017). This is
309 because population-level metrics of genetic connectivity like the frequently used F_{ST} actually
310 measures the balance between genetic drift on the one hand, and migration on the other. To the
311 best of our knowledge, none of the analyzed studies accounted for variations in N_e between
312 sample units when modeling IBR. This can be done by employing different distance metrics
313 [such as conditional genetic distance (Dyer, Nason & Garrick, 2010)], by restricting IBR models
314 to sample units belonging to the same genetic cluster (i.e. with the same N_e), by including a
315 random effect specifying the nature of pairwise genetic distances (from sample units belonging to
316 the same or different genetic clusters), or through gravity models that explicitly incorporate N_e or
317 other node-level proxy of population size (DiLeo & Wagner, 2016; Zero et al., 2017).

318

319 **Conclusions**

320 Our study reveals important knowledge gaps regarding landscape effects on gene flow in tropical
321 organisms, which prevent making cross-species generalizations. However, general patterns of
322 genetic connectivity provide important insights into common barriers to gene flow or responses
323 to land use changes (Poelchau & Hamrick, 2012; Wang, Glor & Losos, 2013; Paz et al., 2015;
324 Jaffé et al., 2016; Lanes et al., 2018). Such knowledge is particularly important to inform
325 conservation actions seeking to safeguard ecosystem function, and not only target species (Manel
326 & Holderegger, 2013b). Our work nevertheless provides some useful guidelines to help fill these
327 knowledge gaps: 1) Increased efforts are needed to study unrepresented taxonomic groups and
328 tropical areas outside the Americas, as well as generate more spatially explicit environmental data
329 in the tropics; 2) The adoption of genotyping by sequencing and individual-level approaches
330 could substantially increase statistical power and shed light into both neutral and adaptive
331 patterns of genetic variation; 3) Using mixed effect MLPE models to relate genetic and spatial
332 data, could minimize type-I errors, result in more accurate parameter estimates (which account
333 for multiple landscape and environmental predictors), and help establish a common model-
334 selection framework across landscape genetic studies (Row et al., 2017; Shirk, Landguth &
335 Cushman, 2018); 4) Explicitly modeling the impact of historical processes underpinning genetic
336 differentiation, the resolution of the spatial data, and possible time-lags (DiLeo & Wagner, 2016;
337 Waits LP, Cushman SA, 2016), could help provide more confidence in landscape effects on gene
338 flow and make IBR estimates comparable across studies.

339

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343

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Figure 1

Sampling locations of the surveyed studies.

Taxonomic groups are indicated by colors and the unit of analysis by shapes (triangles indicate individual-level studies and circles population-level ones). Horizontal dotted lines represent the Tropic of Cancer, the Equator and the Tropic of Capricorn respectively, from North to South.

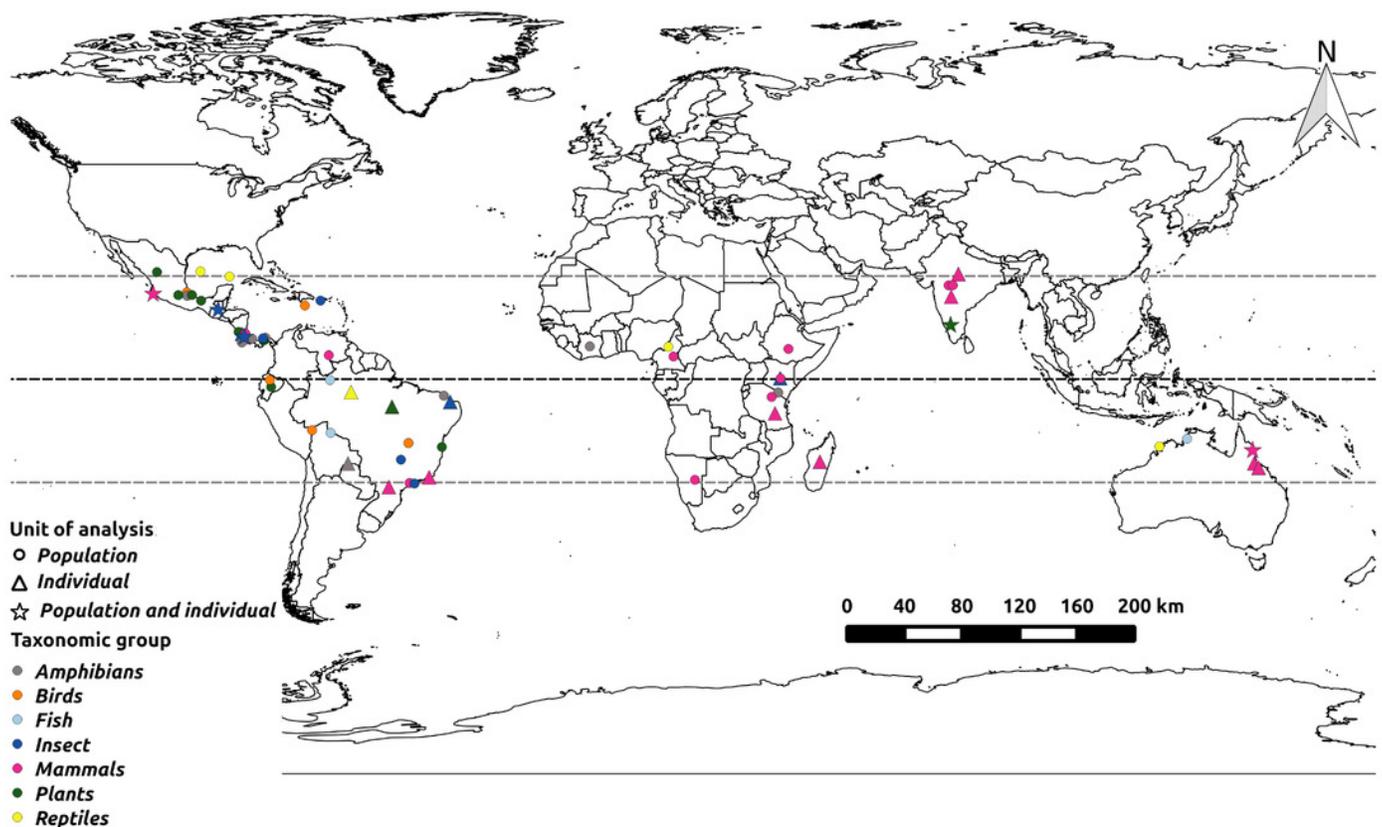


Figure 2

Number of species assessed and number of publications for each taxonomic group.

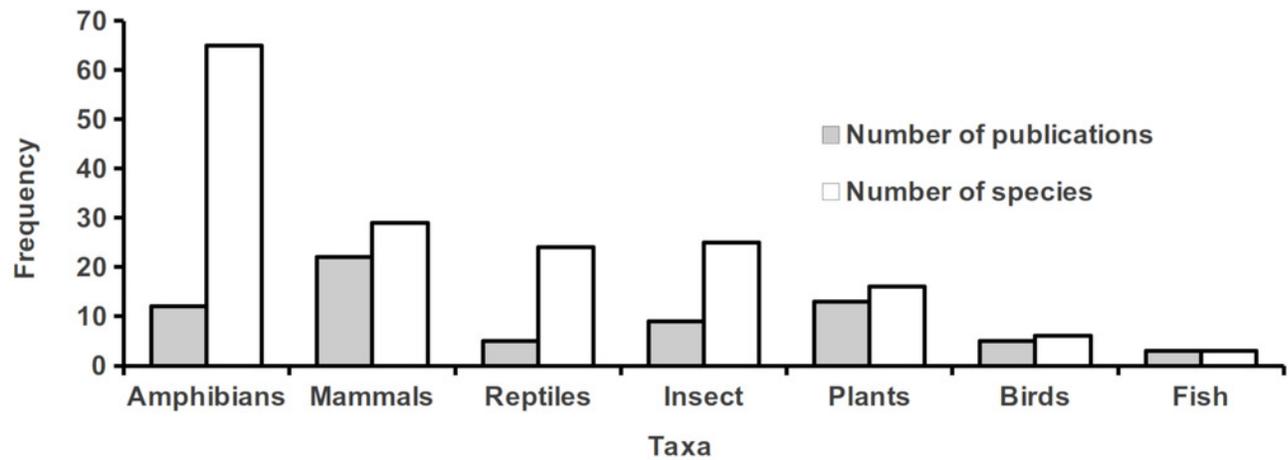


Figure 3

Number of studies assessing landscape effects on gene flow in tropical organisms, published between 2008 and 2018.

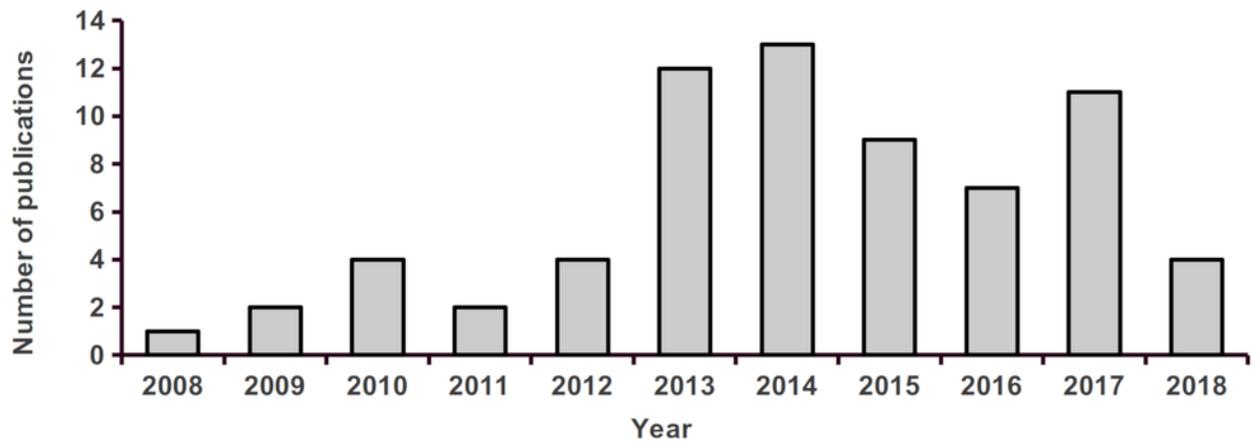


Figure 4

Proportion of studies using different types of genetic markers to assess landscape effects on gene flow in tropical organisms.

Microsatellites, AFLPs and SNPs refer to nuclear DNA. Mitochondrial DNA (mtDNA) and Chloroplast DNA (cpDNA) are specified as such.

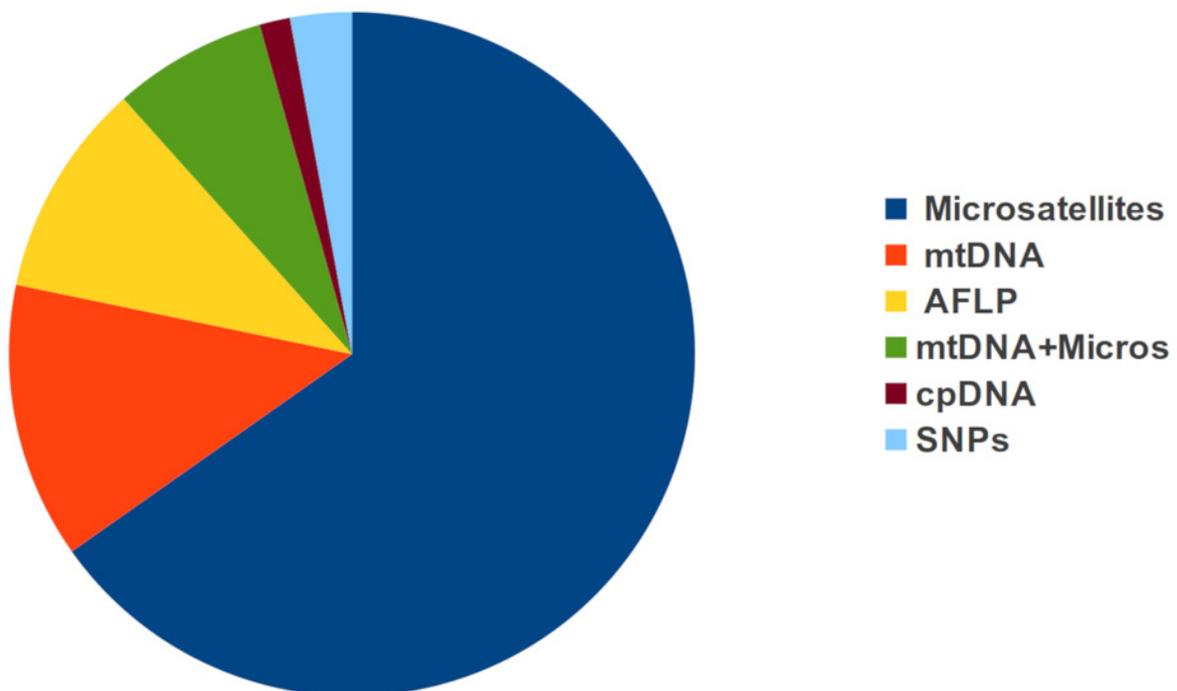


Figure 5

Number of studies using different statistical approaches to assess landscape effects on gene flow in tropical organisms.

Full methods names, by order of appearance on the figure are: Mantel and Partial Mantel tests, Maximum likelihood population effects (MLPE) models, generalized dissimilarity models (GDM), redundancy analyses (RDA), multiple regression on distance matrices (MRDM), generalized linear models (GLM), linear mixed-effect models (LMM), Monte Carlo permutation matrix regression technique (MCPMRT), matrix regression approach (MRA), Random Forest Analysis (RFA), Structural equation modelling (SEM), and Linear Model with Permutation (LMP).

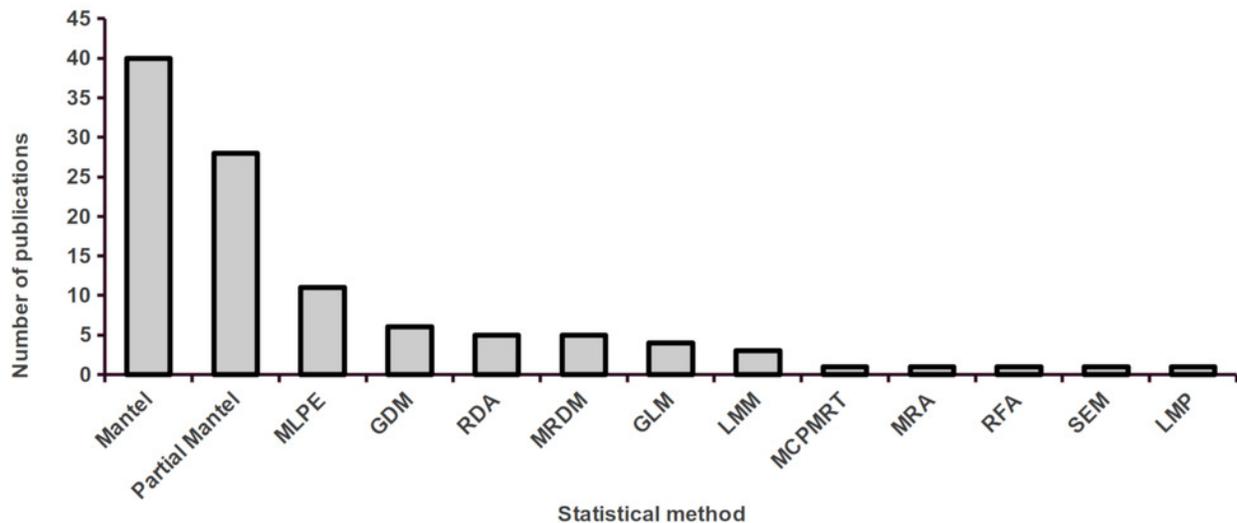


Figure 6

Number of studies focusing on different landscape effects on gene flow for each taxonomic group.

See Dataset S1 for details on the reported effects.

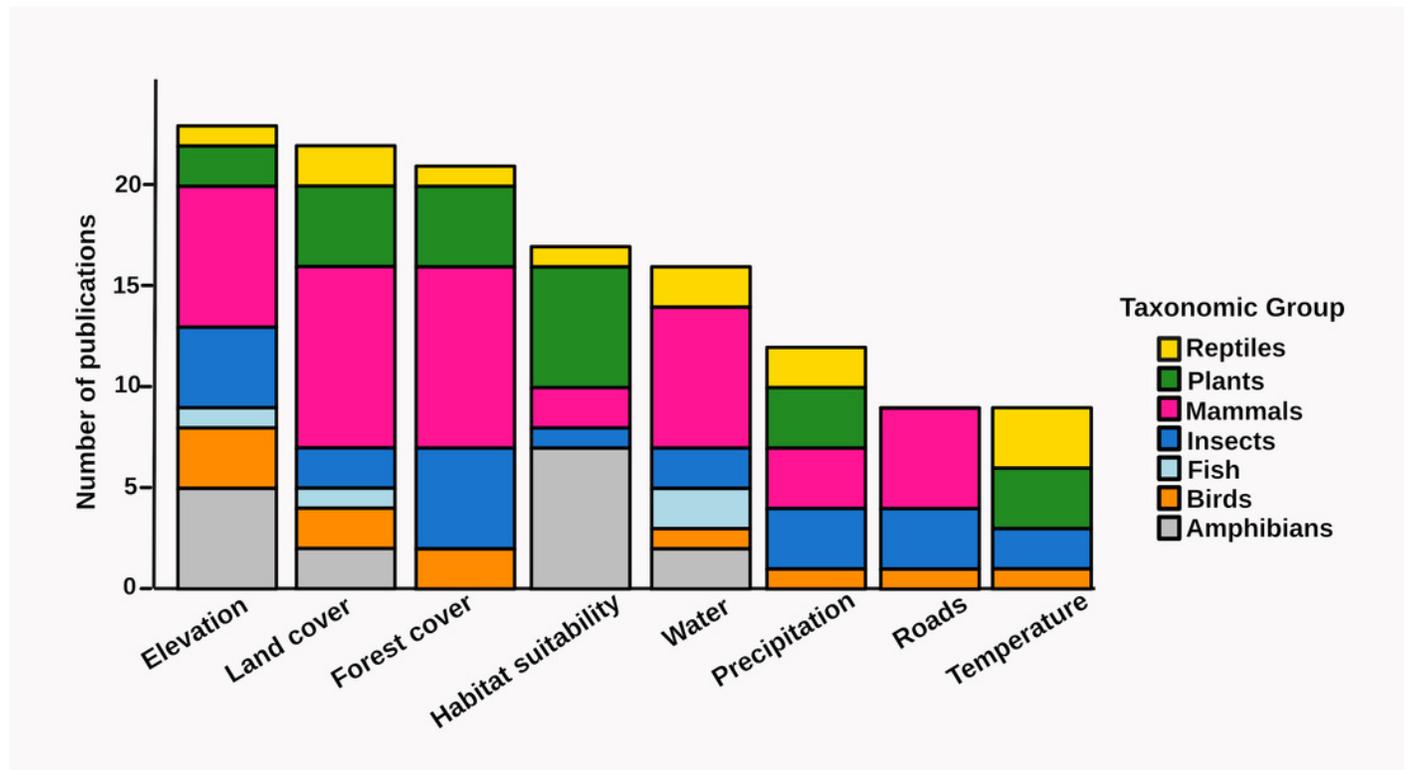


Figure 7

Individual-level effect sizes for isolation by geographic distance (a), isolation by elevation (b) and isolation by forest cover (c).

Dots represent effect sizes and colors indicate taxonomic groups. Significance of the effects reported in the original articles is also highlighted.

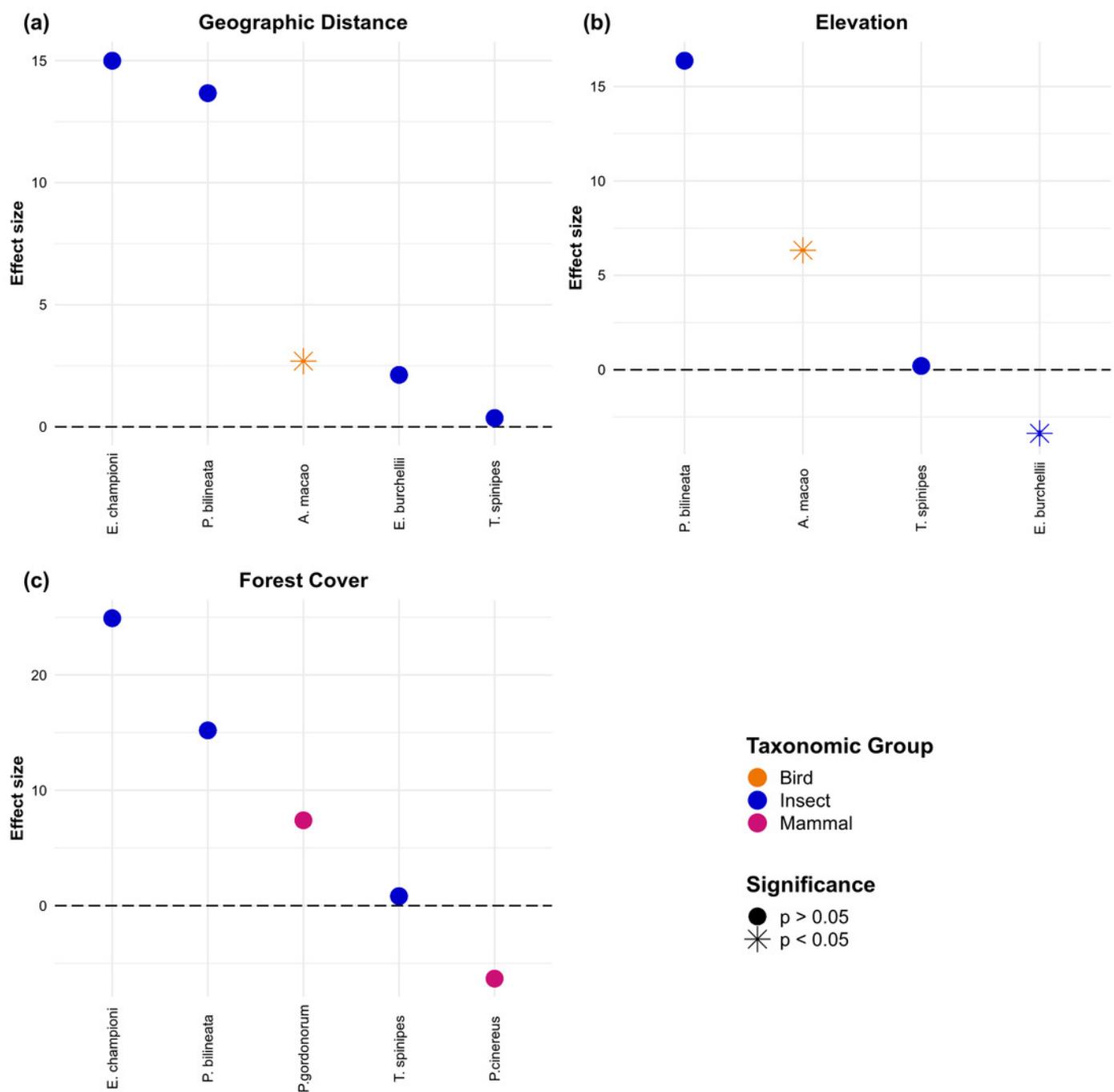


Figure 8

Population-level effect sizes for isolation by geographic distance (a), elevation (b), precipitation (c), temperature (d) and forest cover (e).

Dots represent effect sizes and colors indicate taxonomic groups. Significance of the effects reported in the original articles is also highlighted.

