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## Abstract

Biogeographic knowledge of Amazonian amphibians presents significant challenges in spatial and temporal coverage, as well as in the taxonomic refinement of their diversity. Despite recent advances, the spatial distribution of sampling and detailed taxonomic knowledge remain limited, potentially causing biases in our understanding of their diversity and distribution. In this study, we conducted a large-scale analysis using an extensive database with 951 species and 213,072 georeferenced occurrence records, distributed across 24,319 sampling points in the Amazon. This analysis aimed to elucidate potential drivers of sampling biases for Amazonian amphibians in the presence of infrastructure factors (cities, hydroelectric dams, and transmission lines) and accessibility (navigable rivers and roads). Among accessibility factors, we found that rivers were the main facilitators in amphibian sampling. On the other hand, roads did not exert a strong influence as expected, due to the late and limited development of land transportation in the region, which has historically been dominated by river transportation. Among the infrastructure factors, both cities and hydroelectric plants had a moderate influence on sampling. The reason for this is that most cities in the Amazon region were established a few decades ago and have limited infrastructure, especially considering the presence of consolidated research centers. Hydroelectric plants have generated extensive databases due to environmental legislation requirements for their installation, but restricted access to information from these reports limited their use in this study. We conclude that Amazonian amphibian sampling exhibits significant geographic bias, attributable to the uneven distribution of research efforts caused by logistical challenges, including accessibility and infrastructure limitations. Overcoming these obstacles requires coordinated efforts between researchers and decision-makers, as well as investment in research infrastructure and data dissemination initiatives, not only for amphibians, but for all biodiversity in the face of increasing deforestation and climate change.

# 1 **Biases in Amphibian Sampling in the Amazon: Using Infrastructure and Accessibility**

## 2 **Data to Identify Sampling Gaps**

3

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5 in spatial and temporal coverage, as well as in the taxonomic refinement of their diversity.  
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22 exhibits significant geographic bias, attributable to the uneven distribution of research efforts  
23 caused by logistical challenges, including accessibility and infrastructure limitations.  
24 Overcoming these obstacles requires coordinated efforts between researchers and decision-  
25 makers, as well as investment in research infrastructure and data dissemination initiatives, not

26 only for amphibians, but for all biodiversity in the face of increasing deforestation and climate  
27 change.

28 **Keywords:** Amazonian amphibians, biodiversity, Linnean deficit, Wallacean deficit,  
29 macroecology

30

## 31 **Introduction**

32 The synergy between technology and conservation enables scientists and conservationists  
33 to adopt effective approaches to biodiversity and ecosystem conservation (Arts et al., 2015;  
34 Moreto, 2015; Adams, 2019; Toivonen et al., 2019; Vargas-Ramírez & Paneque-Gálvez, 2019;  
35 Sandbrook et al., 2021). Computational simulations allow us to understand global biodiversity  
36 patterns, as well as to identify and monitor species dispersal (Michelot et al., 2016; Borowicz et  
37 al., 2019), and predict the impacts of human activities and climate change on ecosystems  
38 (Hopkiins, 2007; dos Santos et al., 2015; Stropp et al., 2020; Albuquerque et al., 2021; Carvalho  
39 et al., 2023). However, the application and robustness of these models depend on the quality of  
40 the data used, which can be affected by data collection and availability, tabulation, and  
41 taxonomic identification, among other factors (Hortal et al., 2015). Therefore, biodiversity data  
42 has biases and gaps that cannot be overlooked (Boakes et al., 2010; Martin et al., 2012; Beck et  
43 al., 2014; Hortal et al., 2015; Gueta & Carmel, 2016; Anderson et al., 2020; Hughes et al.,  
44 2021).

45 One of the most important barriers observed in biodiversity data for understanding  
46 species distributions is the geographical sampling shortcomings, known as the Wallacean  
47 shortfall (Hortal et al., 2015). This occurs when some regions are sampled more extensively than  
48 others, resulting in uneven knowledge of biodiversity across geographic space (Boakes et al.,  
49 2010; Martin et al., 2012; Amano & Sutherland, 2013; Hortal et al., 2015; Anderson et al., 2016;

50 Pelayo-Villamil et al., 2018; Hughes et al., 2021; Tessarolo et al., 2021; Zizka et al., 2021;  
51 Castro-Souza et al., 2024). Inaccessibility of remote areas, which is common in the Amazonia  
52 basin, due to lack of infrastructure such as roads and cities, or even legal restrictions, such as  
53 bureaucratic hurdles to access Indigenous lands, may contribute to bias in data collection  
54 (Santos et al., 2015; Carvalho et al., 2023). In addition, bias related to accessibility and the  
55 tendency to study charismatic group (e.g. mammals and birds; Troudet et al., 2017) or easily  
56 identifiable species can lead to an underestimation of the real diversity of a region (Diniz-Filho  
57 et al., 2010; Theobald et al., 2015; Amano et al., 2016; Oliveira et al., 2016; Troudet et al., 2017;  
58 Hughes et al., 2021). Therefore, this is one of the reasons that the distribution of some groups  
59 continues to be neglected, contributing to knowledge biases in mega-diverse regions such as the  
60 Amazonia.

61 The Amazon basin hosts the world's largest tropical forest (Vale and Jenkins 2012;  
62 Malhado et al. 2013; Santos et al. 2015) comprising approximately 20% of the planet's terrestrial  
63 diversity (Peres et al. 2023) and has contributed to the extensive exchange of evolutionary  
64 lineages among different regions and biomes over tens of millions of years (Antonelli et al.  
65 2018; Guayasamin et al., 2024). Consequently, it plays a fundamental role in maintaining  
66 biodiversity, ecosystems and regulating global climate (Garda et al. 2010; Aragón 2018; Tigre  
67 2019). However, knowledge about Amazonian biodiversity is still underestimated and  
68 influenced by biases and sampling gaps (Hopkins 2007; Santos et al. 2015; Stropp et al. 2020;  
69 Albuquerque et al. 2021; Carvalho et al. 2023), leading to inefficiencies in public policies for the  
70 conservation of Amazonian biodiversity and ecosystem services. These knowledge gaps arise  
71 from the inaccessibility of remote areas, combined with neglect and/or reduced investments in  
72 research in the Amazon (Carvalho et al., 2023; Stegmann et al., 2024).

73 Records of amphibian distribution in the Amazonia are incomplete (Guerra et al., 2020;  
74 Fouquet et al., 2021), with significant biases and gaps in the geographic sampling.

75 Amphibians are one of the three taxa with the highest species richness among vertebrates  
76 (AmphibiaWeb 2024; Frost 2024). They have a high endemism index, with approximately 77%  
77 in the Atlantic Forest (Vancine et al. 2018) and 82% in the Amazonia (Vacher et al. 2020;  
78 Penhacek et al., in press), and face the highest risk of species extinction (40.7%) (Amaral et al.  
79 2019; Luedtke et al. 2023). Furthermore, amphibians are recognized as important indicators of  
80 environmental changes (Toledo 2009; Becker et al. 2010; Amaral et al. 2019), due to their high  
81 vulnerability to climate change and landscape modification (Amaral et al. 2019; Luedtke et al.  
82 2023). Therefore, amphibians are constantly included in monitoring programs for potentially  
83 polluting enterprises, but these data have restricted access (Vaz-Silva et al., 2015). Making this  
84 data accessible would contribute to understanding their distribution patterns and evaluating the  
85 anthropogenic impacts on biodiversity (Dayrell et al., 2021).

86 Here, we evaluate the spatial distribution of amphibian sampling in the Amazon, testing  
87 the influence of accessibility variables (navigable rivers and roads) and infrastructure (cities,  
88 hydroelectric power plants, and transmission lines) as drivers of geographical biases in  
89 amphibian knowledge. Given the structural and environmental complexity, as well as the vast  
90 territorial extent, we believe that accessibility variables will be the main driver of the  
91 geographical knowledge of sampling, followed by the establishment of cities and hydroelectric  
92 enterprises such as hydroelectric power plants (HPP) and transmission lines (TL). To facilitate  
93 the visualization of sampling patterns, maps were designed to spatially highlight the combined  
94 effects of drivers on the distribution of amphibian sampling in the Amazonia, also showing the  
95 main sampling gaps. The biases and gaps detected here can serve as alerts to the existence of  
96 similar sampling biases in the geographical knowledge of other taxa of terrestrial Amazonian  
97 biodiversity, thus contributing to guidance for future biodiversity research and conservation  
98 actions.

## 100 **Materials and Methods**

### 101 **Study Area**

102           The study covered all the Amazonian boundaries proposed by the WWF (WWF 2019).  
103    Located in northern South America, the Amazon basin covers an area of approximately 6.5  
104    million km<sup>2</sup> and includes nine countries: Bolivia, Brazil, Colombia, Ecuador, Guyana, French  
105    Guiana, Peru, Suriname, and Venezuela (WWF 2019; Tigre 2019). Although its vast territory  
106    contains approximately 50% of all remaining tropical rainforests on the planet, the region also  
107    includes limited areas of non-forest vegetation, such as savannas and seasonally flooded  
108    grasslands (Schuman et al. 2007, Peres et al. 2010, Castuera-Oliveira et al. 2020). The Amazon  
109    basin holds the largest reserves of liquid freshwater, with more than 7,000 tributaries  
110    (HidroSHEDS 2024) and about 20% of the world's freshwater flow (Tigre 2019), which also  
111    serve as important transport routes and accessibility. Regarding mineral resources, the region  
112    has attracted global attention for its vast reserves of aluminum, iron, niobium, and gold, among  
113    others. Mineral extraction has an impact on traditional communities, indigenous peoples, and  
114    biodiversity (Mello et al. 2013), due to the opening of roads (Laurance et al. 2009) and  
115    infrastructure for mining (Siqueira-Gay et al. 2020). Additionally, the vast expanse of arable  
116    land and high rainfall have led to a huge expansion of agribusiness, resulting in forest  
117    fragmentation, soil, air, and water pollution, and threats to biodiversity and ecosystem services  
118    (Fearnside 2015).

119           Our amphibian occurrences database was created from four primary sources (Fig. 1A): I)  
120    "digitally accessible data platforms" (GBIF, SiBBr, SISBIO, Specieslink, and VertNet) collected  
121    until February 2022; II) "peer-reviewed articles," consisting of 150 articles published in  
122    scientific journals containing information on the occurrence of amphibian in the Amazon; III)  
123    "grey literature," which includes technical reports from Environmental Impact  
124    Studies/Environmental Impact Reports, as well as records from rescue and monitoring of

125 amphibians in Hydroelectric Power Plants (HPPs); and IV) "own data," which comprises  
126 personal collections of the authors spanning 15 years, from 2007 to 2022, from southern  
127 Brazilian Amazon (for more details, see Penhacek et al. in press). Our data contain an extensive  
128 database with 163,643 primary records related to 947 species of amphibians.

129 To this database, we added 52,529 records from 98 species collected between 2011 and  
130 2019 during monitoring and rescue programs at four Hydroelectric Power Plants - (HPPs):  
131 Colíder, São Manoel, Sinop and Teles Pires. These data were obtained from the respective  
132 licensing agencies: the Mato Grosso State Secretariat for the Environment - SEMA (Colíder and  
133 Sinop HPPs) and the Brazilian Institute for the Environment and Renewable Natural Resources -  
134 IBAMA (São Manoel and Teles Pires HPPs).

135 The database underwent a filtering process where records identified above the species  
136 level, such as those at the genus (sp), group (gr), related (aff) or confer (cf) levels, were  
137 excluded. Then, the remaining species occurrences were taxonomically updated by joining  
138 synonyms for the most recent valid species names (according to Frost 2024). Subsequently, each  
139 species underwent distribution evaluation using three specialized platforms: AmphibiaWeb  
140 (2024), Frost (2024) and IUCN (2024). For more details on data validation (see Penhacek et al.  
141 in press). Thus, the final database has 213,072 primary records in 24,319 sampling points in the  
142 Amazon, encompassing 951 species (Supplementary Material Worksheet S1).

### 143 **Accessibility and Infrastructure Variables**

144 To understand the drivers (Fig. 1B) of bias in amphibian samplings, we used five  
145 explanatory variables (drivers) related to accessibility (distance to navigable rivers and  
146 highways) and infrastructure (cities, hydroelectric power plants, and power transmission lines).  
147 We used data from the HydroRIVERS database, specifically focusing on rivers classified within  
148 the first five levels of magnitude based on water flow capacity (Lehner and Grill 2013). For  
149 highways, we considered federal, state, and/or municipal roads obtained from the Center for

150 International Earth Science Information Network (CIESIN 2023), Rede Amazônia de  
151 Informação Socioambiental (RAISG 2023), and the Instituto Brasileiro de Geografia e  
152 Estatística (IBGE 2014). We also used information from the following sources: (i) Cities (143  
153 reference urban centers in each location, involving the largest cities in each region), assuming  
154 that they have better infrastructure to support researchers, obtained from Natural Earth Data  
155 (Natural Earth 2023); (ii) Hydroelectric Power Plants (312 Hydroelectric Power Plants, HPPs  
156 and Small Hydropower plants - SHPPs) under construction and/or in operation, obtained from  
157 the Amazon Network of Georeferenced Socio-Environmental Information – RAISG (RAISG  
158 2023); and (iii) power transmission lines (LTs), provided by Arderne et al. (2020). These  
159 shapefiles were incorporated into vector files with a resolution of  $0.05^\circ$  (5 x 5 km in Equator),  
160 containing points representing cities and HPPs/SHPPs, and lines representing the LTs.

161

## 162 **Data Analysis**

163 To assess the influence of accessibility and infrastructure variables on amphibian  
164 sampling, we used the Bayesian analysis proposed by Zizka et al. (2020) to compare the  
165 statistical distribution of observed distances (actual occurrences) with a null model (expected  
166 distribution simulated by random sampling). Initially, we evaluated the weight of each variable,  
167 indicating the intensity of bias generated by the presence of each selected variable in the study  
168 area (Figure 1C). We then calculated the correlation between sampling (number of known  
169 amphibian occurrences per grid) and distance (km) for each bias variable within the study area  
170 (Figure 1D).

171 Finally, we created a spatial projection map that illustrates the combined effects of  
172 accessibility and infrastructure variables on the estimated sampling of amphibian occurrence  
173 records. This map highlights the regions where these variables have a greater effect on sampling  
174 bias, indicating areas that are oversampled (Figure 1E). In this context, we measured the effect

175 based on the variable with the highest bias, combining it in descending order with the other  
176 variables (Supplementary Material Figure S1). These approaches allow us to comprehend the  
177 relative influence of different precursor variables of bias on the sampling of amphibians and  
178 spatially project their combined effects. This is crucial for better understanding the distribution  
179 and representativeness of amphibian occurrence records in the Amazonia, as well as for  
180 identifying areas where sampling effort needs to be optimized.

181 All analysis was carried out in the R Program (R Development Core Team, 2022).  
182 Sampbias biases were analyzed using the sampbias package (Zizka et al., 2020). QGIS 3.4  
183 software (Free, 2023) was used to create all cartographic projections, including the bias maps.

184 Figure 1 here

## 185 **Results**

### 186 **Amphibian sampling distribution in the Amazon**

187 With the robust dataset used here, consisting of over 213,000 occurrence records, our  
188 biogeographic projection (Figure 2) revealed an uneven sampling distribution with oversampled  
189 (biased) and undersampled (knowledge gap) regions for amphibians in the Amazon,  
190 characterizing a strong bias for this taxon in this region.

191 Figure 2 here

### 192 **Sampling bias**

193 Sampling is concentrated and strongly biased towards locations close to rivers, followed  
194 weaklier by highways, urban centers and hydroelectric plants. In contrast, the proximity of  
195 electricity transmission lines (LT) had little influence on sampling (Figure 3).

196 Figure 3 here

197 Amphibian sampling data across the Amazon revealed an uneven distribution, with  
198 oversampled (biased) and under sampled (knowledge gaps) regions (Fig. 4). Oversampled  
199 regions were concentrated especially in the southwest and west regions of the Amazon, near the

200 Andes Mountain Range (southern Peru to northern Ecuador). In the Brazilian Amazon, this bias  
201 was pronounced for almost the entire Madeira River basin in the state of Rondônia, as well as  
202 along the upper and lower Tapajós River basin in the states of Mato Grosso and Pará,  
203 respectively. Other regions, such as the basins of the Tocantins River in the state of Maranhão,  
204 Rio Branco River in the state of Roraima, and along the Amazon River from the confluence of  
205 the Negro and Solimões Rivers in the state of Amazonas to its estuary in the Atlantic Ocean,  
206 also presented biases in amphibian sampling (Fig. 4). In Colombia, sampling was biased towards  
207 the southeast region near the Vaupés department, which borders Brazil. In Guyana, the bias was  
208 observed in the Berbice and Essequibo River basins. Biases were also observed in the  
209 northwestern and eastern regions of French Guiana, throughout the northwestern region of  
210 Suriname, and in the northern region of Venezuela. In addition to these regions, other smaller  
211 areas with sampling biases were observed throughout the Amazonia (Fig. 4).

212 On the other hand, an extensive area is under sampled in the Amazon basin, highlighting  
213 the central-western between the Negro and Solimões River basins, the middle and upper region  
214 of the Xingu River, and the eastern, western, and northern parts of the state of Maranhão,  
215 Amapá, and Pará, in Brazil, respectively (Fig. 4). Additionally, we observed a gap in amphibian  
216 sampling in the entire central and eastern region of Bolivia, the entire eastern extent of Peru, and  
217 the central, northern, and southern regions of Colombia, as well as smaller gaps in the southern  
218 regions of Suriname and French Guiana, and the northwest region of Venezuela (Figure 4).

219 Figure 4 here

## 220 **Discussion**

221 Our study analyzed the sampling bias of Amazonian amphibians using a robust database  
222 that consolidates records for over 11% of global amphibian diversity (Frost 2024). Despite this  
223 extensive database, with more than 213 thousand occurrence records, it represents less than 20%  
224 of the currently available data for amphibians in the Amazonia (Penhacek et al., in preparation).

225 This limitation occurs due to absence of geographical coordinates in species records (Wallacean  
226 shortfall), taxonomic incompleteness (Linnean shortfall) often found in scientific collection  
227 records, digital platforms (e.g., Stropp et al., 2020; Araújo et al., 2022), driven by the high  
228 diversity of cryptic amphibian species existing in the Amazon, combined with the scarcity of  
229 regional taxonomists.

230 Even with the robust and extensive database used in this work, we observed that the  
231 Amazon is not adequately sampled in all its regions. While we observe sampling concentrations  
232 in some regions, mainly on the western edges of the Peruvian and Ecuadorian Amazon and near  
233 large rivers such as the Amazon, Madeira, Tapajos and lower Xingu among others (Fig. 1), there  
234 are extensive areas that are poorly sampled or neglected throughout the Amazon, but mainly in  
235 the southeastern and central western regions of the Amazon (Fig. 4).

236 The extensive territory of the Amazon, often surrounded by almost inaccessible dense  
237 forests, presents challenges for carrying out biological surveys. This increases the sampling  
238 deficit “Wallacean deficits” (Hortal et al. 2015), leading to both oversampling in easily  
239 accessible areas and undersampling in difficult-to-access areas, creating gaps in our  
240 understanding of biodiversity patterns. These gaps found in the Amazon can be attributed to  
241 logistical factors, infrastructure limitations, taxonomic challenges, and landscape changes  
242 caused by human intervention. Overcoming these obstacles will require coordinated efforts,  
243 investments in research and monitoring, and the commitment of countries to United Nations  
244 Sustainable Development Goal 15 (‘Life on Land’) of the 2030 Agenda for Sustainable  
245 Development, aimed at the conservation and sustainability of the region (UN BR 2030).

246 Our results revealed significant sampling biases for Amazonian amphibians related to  
247 accessibility variables (especially rivers) and urban and industrial infrastructure. As expected,  
248 medium and large rivers are the most important factors in amphibian sampling globally in the  
249 Amazon. Similar results have been observed for different taxonomic groups studied in the  
250 Amazon, including plants (Hopkins 2007, Stropp et al. 2020, Araújo et al. 2022), ants

251 (Albuquerque et al. 2021) and multi-taxa (Santos et al. 2015, Oliveira et al. 2016, Carvalho et al.  
252 2023). Despite the differences between taxonomic groups, well-sampled areas are consistently  
253 those close to rivers and cities. These biases may hinder the understanding of the distribution  
254 patterns of Amazonian biodiversity (Daru & Rodriguez, 2023).

255         Due to the recent surge in road paving and construction projects across the Amazon,  
256 along with the consequent need for fauna surveys and impact assessments, during these projects,  
257 we initially believed that highways could be a significant driver of sampling bias, as observed  
258 for different taxonomic groups such as arthropods, vertebrates, and angiosperms (Oliveira et al.  
259 2016; Andrade-Silva et al., 2022). However, investments in infrastructure in the interior regions  
260 of the Amazon are still recent and sporadic (Araújo et al., 2023). Historically, rivers have been  
261 and remain the main means of transportation in the Amazon (Hernández-Fontes, et al., 2021),  
262 especially in low-lying areas and along wide rivers. In these regions, road construction is  
263 considerably hindered by river flooding and soil types, creating significant obstacles to travel  
264 during the rainy season. However, during this period, there is an increase in vocalization,  
265 foraging, and mating activities of amphibian species. (Bastos and Haddad 2007, Ferrão et al.  
266 2024). This leads herpetologists to prefer sampling during this time, due to the greater local  
267 aggregation of species and the increased efficiency in recording amphibian species richness  
268 (Ferrão et al. 2024). Therefore, river accessibility is fundamental for reaching remote areas of  
269 the Amazon, enabling the cataloging of species from these locations (Carvalho et al., 2023; This  
270 study).

271         The distance from cities (Carvalho et al., 2023) and Hydroelectric Power Plant (Dayrell,  
272 et al.2021) are also considered drivers of biodiversidade sampling in the Amazon. However, in  
273 this study, the effect of these variables was smaller compared to that of navigable rivers (Fig. 3).  
274 Cities with populations greater than 100,000 inhabitants tend to have better infrastructure,  
275 including airports, bus terminals and research centers such as universities. Consequently, the  
276 number of researchers and research activities near these cities is typically higher, as observed by

277 Hopkins (2007). Furthermore, sampling in remote and hard-to-reach locations is discouraged  
278 due to the high logistics costs and the limited financial resources allocated per km<sup>2</sup> in the  
279 Amazon, especially in the Brazilian region (Fernandes et al., 2017; Barlow et al., 2018;  
280 Magnusson et al., 2016, 2018; Hopkins, 2019; Carvalho et al., 2023).

281         The construction of Hydroelectric Power Plants (HPPs) and Small Hydropower plants  
282 (SHPPs) has significantly intensified in the Amazon over the past three decades (Brasil, 2024).  
283 Due to their impacts on fauna and flora, and considering the high number n of projects to be  
284 implemented in the Amazon (Cavalcante et al., 2021; Dayrell et al., 2021), the Brazilian Institute  
285 of the Environment and Renewable Natural Resources (IBAMA) approved normative  
286 instruction (IN 146, dated January 10, 2007). This regulation establishes the necessity for  
287 standardized monitoring criteria to assess potential impacts on biodiversity (MMA, 2016). Thus,  
288 a large amount of data on biodiversity has been produced in recent years (e.g., Ávila &  
289 Kawashita-Ribeiro, 2011; Vaz-Silva et al., 2015; Dayrell et al., 2021). These databases have  
290 significant potential in cataloging species and ecological data in previously unexplored or  
291 difficult-to-access regions, with great potential to fill gaps in knowledge about biodiversity.  
292 However, a large portion of the data obtained during these projects is not adequately available,  
293 making it difficult for scientists and decision-makers to obtain and/or use them (Penhacek et al.,  
294 in press). Therefore, the correct identification and deposition of specimens in scientific  
295 collections, standardization of collected data, and the dissemination of results as species list by  
296 environmental agencies would make this information more accessible and useful for researchers  
297 and environmental managers, enhancing the effectiveness of decision-making and conservation  
298 efforts.

299         Our results also reveal that there is regional variation in the effect of variables that  
300 contribute to sampling bias. Although rivers have shown a greater influence on sampling bias  
301 globally across the Amazon, there are extensive sampling gaps in areas with high river density,  
302 particularly along the middle and upper Xingu basin in the southeastern Amazon, and in the

303 basins of the Coquetá, Jupara, Jurua, Napo, Solimoes, Purus, Putumayo rivers, among others, in  
304 the central-western region of the Amazon (Figure 4). Therefore, in each Amazonian region,  
305 different factors may predominantly influence the sampling rate for amphibians.

306         Finality this study revealed the drivers that explain the sampling bias of Amazonian  
307 amphibians, highlighting gaps and challenges in the collection and analysis of biogeographic  
308 data. These significant biases, driven by the proximity of navigable rivers, highways, urban  
309 centers, and hydroelectric plants, affect the interpretation of species distribution patterns  
310 and limit the use of data for predictive modeling, which is essential for biodiversity conservation  
311 plans. Moreover, they undermine our understanding of species dispersal, space-time occupation  
312 patterns and the effects of human activities and climate change on biogeographic patterns. Thus,  
313 the identification of undersampled regions evidenced here, especially in the southwest and  
314 central-west Amazon, highlights the need for targeted efforts to fill these gaps to achieve a more  
315 complete and accurate representation of amphibian diversity in the region. Such efforts are  
316 necessary to protect biodiversity in the Amazon due to the ongoing threats of deforestation and  
317 ongoing climate change.

318

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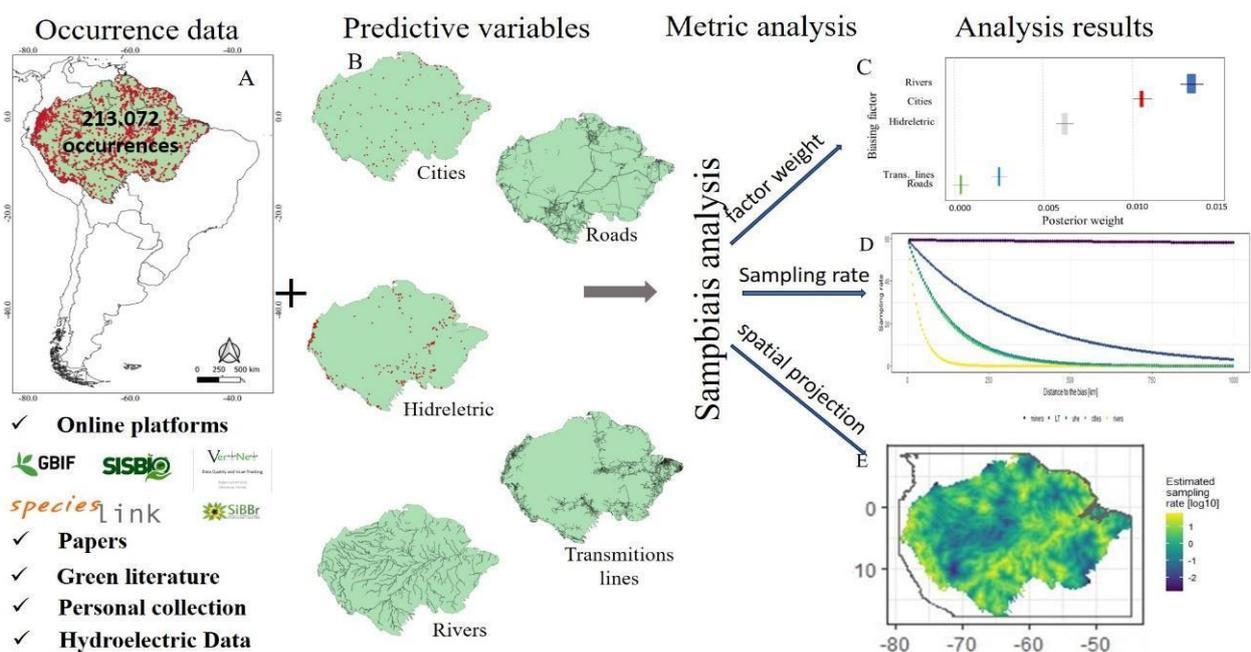
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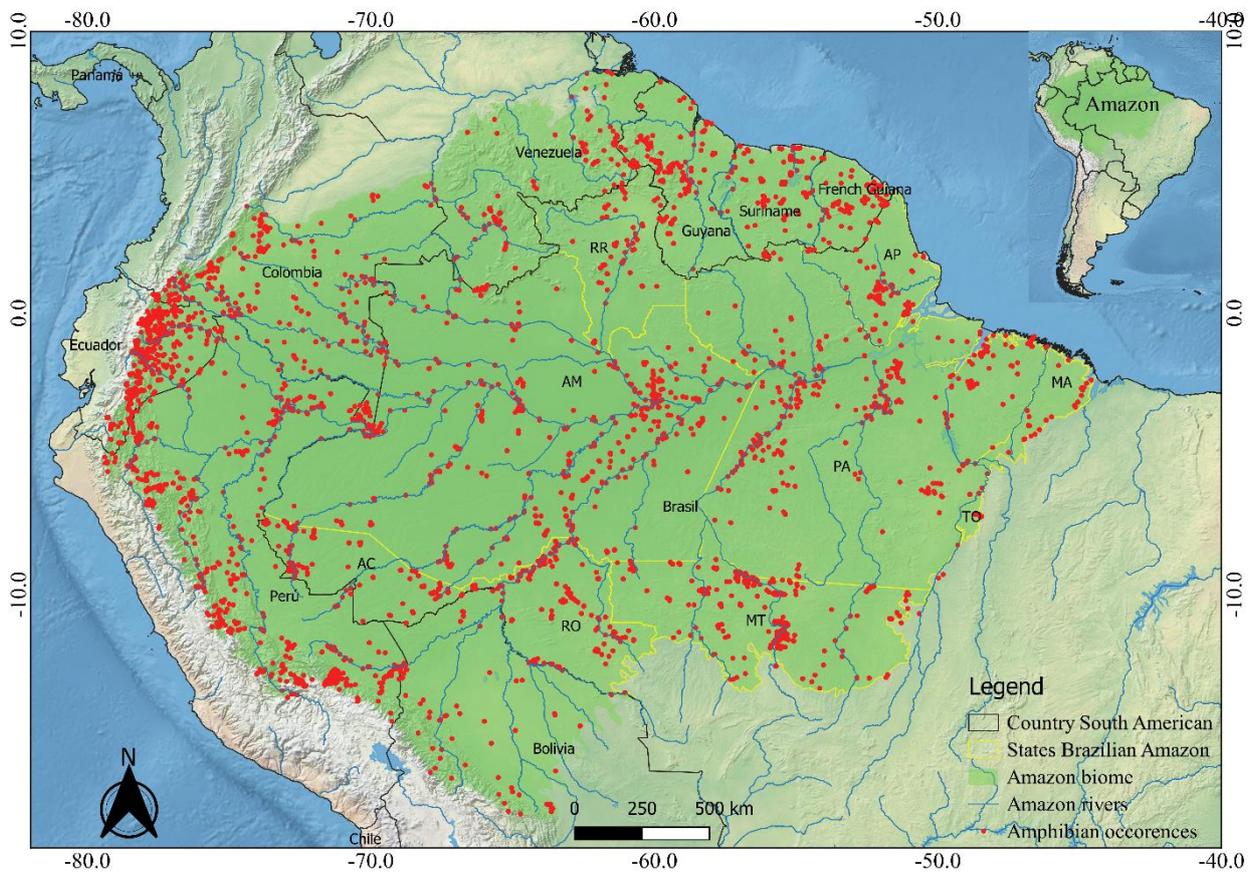
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526 **FIGURAS**



528 **Figure 1.** Methodology for evaluating accessibility and infrastructure drivers in Amazonian  
529 amphibian sampling biases. Occurrences of amphibian records in the Amazon (A); predictive  
530 variables: cities, rivers, hydroelectric plants, roads and transmission lines (B); weights of  
531 variables in sampling bias (C); sampling rate as a function of distance for each variable  
532 (expected number of occurrences) (D) and; spatial projection of the combined bias effect from  
533 accessibility and infrastructure variables (E).

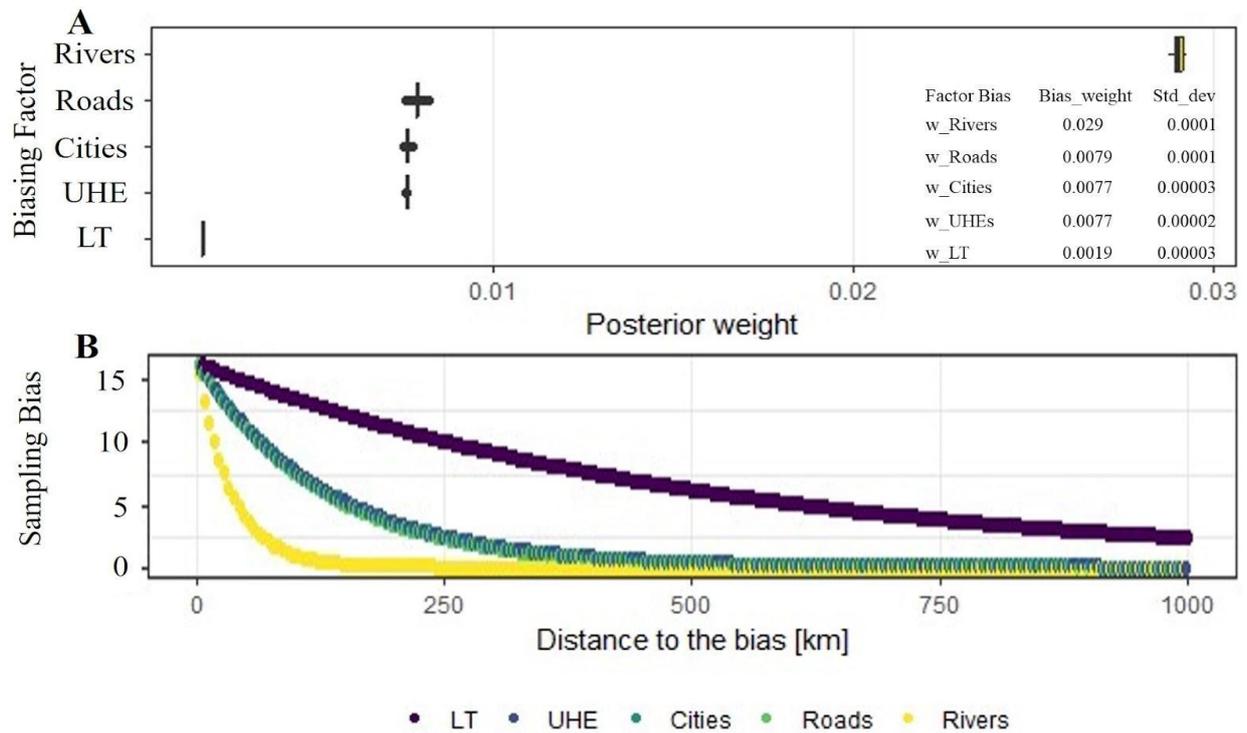
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535

536 Figure 2. Distribution of the 24,319 amphibian sampling points in the Amazon delimited  
537 according to WWF (2019).

538



539

540 Figure 3. Bias in amphibian occurrences in Amazonia related to accessibility and infrastructure

541 variables. The bias weights ( $w$ ) represent the influence of each bias variable, and the Factor Bias

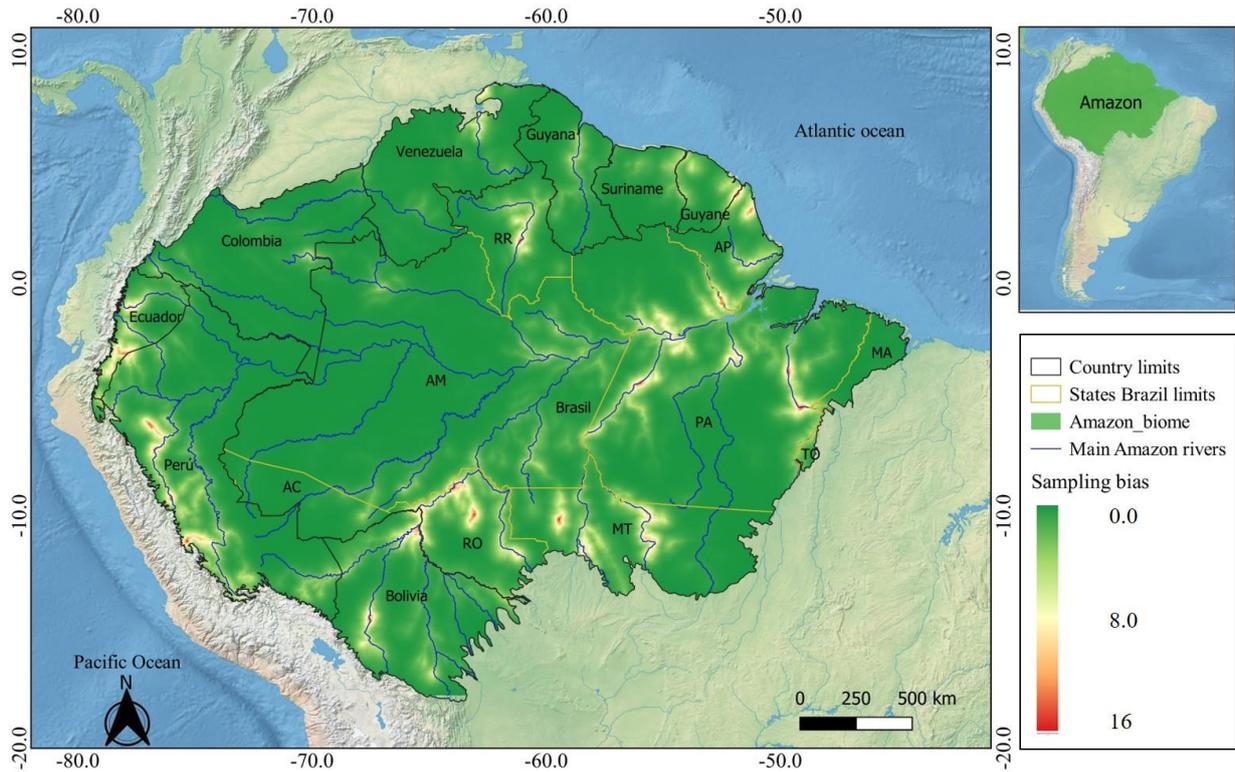
542 refers to the specific variable evaluated (A). Sampling rate as a function of the distance to the

543 closest point of each bias variable (the expected number of occurrences) given the inferred

544 sampbias model (B). At the study scale of 0.05 degrees (about  $5 \times 5$  km), sampbias identified

545 the strongest polarization effect in proximity to rivers, highways, cities, hydroelectric plants, and

546 transmission lines, respectively.



547  
 548 Figure 4. Spatial variation in amphibian sampling intensity across the Amazon basin. Colors  
 549 show the projection of log<sub>10</sub>-transformed sampling rates (i.e., number of sample occurrences per  
 550 cell) when compared to null (stochastic) models. Values close to -3 indicate under sampled areas  
 551 (gaps), while those near 1 indicate oversampled (biased). The acronyms correspond to Brazilian  
 552 states, AC - Acre, AM - Amazonas, AP - Amapá, MA - Maranhão, MT - Mato Grosso, PR -  
 553 Pará, RA - Roraima, RO - Rondônia and TO - Tocantins. Separate effects of the variables can be  
 554 seen in Supplementary Material figure S1.