sampbias, a method for quantifying geographic sampling biases in species distribution data

Alexander Zizka[1,2], Alexandre Antonelli[3,4,5], Daniele Silvestro[3,4,6]

1. German Centre for Integrative Biodiversity Research Halle-Jena-Leipzig (iDiv), University of Leipzig, Deutscher Platz 5e, 04103 Leipzig, Germany

2. Naturalis Biodiversity Center, Leiden University, Leiden, Darwinweg 2, 2333 CR Leiden The Netherlands

3. Gothenburg Global Biodiversity Centre, University of Gothenburg, Box 461, 405 30 Gothenburg, Sweden

4. Department for Biological and Environmental Sciences, University of Gothenburg, Box 461, 405 30 Gothenburg, Sweden

5. Royal Botanic Gardens Kew, TW9 3AE, Richmond, Surrey, United Kingdom

6. Department of Biology, University of Fribourg, Ch. du Musée 10, 1700 Fribourg, Switzerland

Abstract

Geo-referenced species occurrences from public databases have become essential to biodiversity research and conservation. However, geographical biases are widely recognized as a factor limiting the usefulness of such data for understanding species diversity and distribution. In particular, differences in sampling intensity across a landscape due to differences in human accessibility are ubiquitous but may differ in strength among taxonomic groups and datasets. Although several factors have been described to influence human access (such as presence of roads, rivers, airports and cities), quantifying their specific and combined effects on recorded occurrence data remains challenging. Here we present *sampbias*, an algorithm and software for quantifying the effect of accessibility biases in species occurrence datasets. *Sampbias* uses a Bayesian approach to estimate how sampling rates vary as a function of proximity to one or multiple bias factors. The results are comparable among bias factors and datasets. We demonstrate the use of *sampbias* on a dataset of mammal occurrences from the island of Borneo, showing a high biasing effect of cities and a moderate effect of roads and airports. *Sampbias* is implemented as a well-documented, open-access and user-friendly R package that we hope will become a standard tool for anyone working with species occurrences in ecology, evolution, conservation and related fields.

Keywords

Collection effort, Global biodiversity Information Facility (GBIF), Presence only data, Road-side bias, Sampling intensity

Background

Publicly available datasets of geo-referenced species occurrences, such as provided by the Global Biodiversity Information Facility (www.gbif.org) have become a fundamental resource in biological sciences, especially in biogeography, conservation, and macroecology. However, these datasets are typically not collected systematically and rarely include information on collection effort. Instead, they are often compiled from a variety of sources (e.g. scientific expeditions, census counts, genetic barcoding studies, and citizen-science observations). Species occurrences are therefore often subject to multiple sampling biases (Meyer et al. 2016).

Sampling biases that may affect the recording of species occurrences (presence, absence and abundance, Isaac and Pocock 2015, Boakes et al. 2010) include the under-sampling of specific taxa ("taxonomic bias", e.g., birds *vs.* nematodes), specific geographic regions ("geographic bias", i.e. easily accessible *vs.* remote areas), and specific temporal periods ("temporal bias", i.e. wet season *vs.* dry season). In particular geographic sampling bias—the fact that sampling effort is spatially biased, rather than equally distributed over the study area—is likely to be widespread in all non-systematically collected datasets of species distributions.

Many aspects can lead to sampling biases, including socio-economic factors (i.e. national research spending, history of scientific research; www.bio-dem.surge.sh, Meyer et al. 2015, Daru et al. 2018), political factors (armed conflict, democratic rights; Rydén et al. 2019), and physical accessibility (i.e. distance to a road or river, terrain conditions, slope; Yang et al. 2014, Botts et al. 2011). Especially physical accessibility by people is omnipresent

as a bias factor (e.g. Lin et al. 2015, Kadmon et al. 2004, Engemann et al. 2015), across spatial scales, as the commonly used term "roadside bias" testifies. In practice, this means that most species observations are made in or near cities, along roads, paths, and rivers, and near human settlements. Relatively fewer observations are expected to be available from inaccessible areas in e.g. a tropical rainforest or a mountain top. Since the recording of different taxonomic groups poses different challenges, geographic sampling bias and the effect of accessibility may differ among taxonomic groups (Vale and Jenkins 2012).

The implications of not considering geographic sampling biases in biodiversity research are likely to be substantial (Rocchini et al. 2011, Barbosa et al. 2013, Yang et al. 2013, Kramer-Schadt et al. 2013, Shimadzu and Darnell 2015, Meyer et al. 2016). The presence of geographic sampling biases is broadly recognized (e.g. Kadmon et al. 2004), and approaches exist to account for it in some analyses—such as for species-richness estimates (Engemann et al. 2015) species distribution models (Beck et al. 2014, Varela et al. 2014, Warren et al. 2014, Boria et al. 2014, Fourcade et al. 2014, Fithian et al. 2015, Stolar and Nielsen 2015, Monsarrat et al. 2019), occupancy models (Kery and Royle 2016), and abundance estimates (Shimadzu and Darnell 2015). In contrast, few attempts have been made to explicitly quantify the overall bias (Hijmans et al. 2000, Kadmon et al. 2004) or to discern and quantify different sources of bias (Fithian et al. 2015, Fernández and Nakamura 2015, Ruete 2015). To our knowledge, no tools exist for comparing the strength of bias factors or datasets. We define as *bias factors* any anthropogenic or natural features that facilitate human access and sampling, such as roads, rivers, airports, and cities.

It is unrealistic to expect that accessibility bias in biodiversity data will ever disappear even

after more automated observation technologies are developed. It is therefore crucial that researchers realise the intrinsic biases associated with the data they deal with. This is the first step towards estimating to which extent these biases may affect their analyses, results, and conclusions. Any study dealing with species occurrence data should arguably assess the strength of accessibility biases in the underlying data. Such a quantification can also help researchers to target further sampling efforts.

Here, we present *sampbias*, a probabilistic method to quantify accessibility bias in datasets of species occurrences. *Sampbias* is implemented as a user-friendly R-package and uses a Bayesian approach to address three questions:

1) How strong is the accessibility bias in a given dataset?

2) How strong is the effect of different bias factors in causing the overall accessibility bias?

3) How is accessibility bias distributed in space, i.e. which areas are a priority for targeted sampling?

Sampbias is implemented in R (R Core Team 2019), based on commonly used packages for data handling (`ggplot`, Wickham 2009, `forcats`, 2019, `tidyr`, Wickham and Henry 2019, `dplyr`, Wickham et al. 2019, `magrittr`, Bache and Wickham 2014, `viridis`, Garnier 2018), handling geographic information and geo-computation (`raster`, Hijmans 2019, `sp`, Pebesma and Bivand 2005, Bivand et al. 2013) and statistical modelling (`stats`, R Core Team 2019). *Sampbias* offers an easy and largely automated means for biodiversity scientists and non-specialists alike to explore bias in species occurrence data, in a way that is comparable across

datasets. The results may be used to identify priorities for further collection or digitalization efforts, improve species distribution models (by providing bias surfaces in the analyses), or assess the reliability of scientific results based on publicly available species distribution data.

Methods and Features

General concept

Under the assumption that organisms exist across the entire area of interest, we can expect the number of sampled occurrences in a restricted area, such as a single biome, to be distributed uniformly in space (even though, of course, the density of individuals and the species diversity may be heterogeneous). With *sampbias* we assess to which extent variation in sampling rates can be explained by distance from bias factors.

Sampbias works at a user-defined spatial scale, and any dataset of multi-species occurrence records can be tested against any geographic gazetteer. Reliability increases with increasing dataset size. Default global gazetteers for airports, cities, rivers and roads are provided with *sampbias*, and user-defined gazetteers can be added easily. Species occurrence data as downloaded from the data portal of GBIF can be directly used as input data for *sampbias*. The output of the package includes measures of the sampling rates across space, which are comparable between different gazetteers (e.g. comparing the biasing effect of roads and rivers), different taxa (e.g. birds *vs.* flowering plants) and different data sets (e.g. specimens *vs.* human observations).

Distance calculation

118 *Sampbias* uses gazetteers of the geographic location of bias factors (hereafter indicated with

119 B) to generate a regular grid across the study area (the geographic extent of the dataset).

120 For each grid cell i, we then compute a vector $X_i(j)$ of minimum distances (straight aerial

121 distance, "as the crow flies") to each bias factor $j \in B$. The resolution of the grid defines the

122 precision of the distance estimates, for instance a 1x1 degree raster will yield approximately

123 a 110 km precision at the equator. Due to the assumption of homogeneous sampling and a

124 computational trade-off between the resolution of the regular grid and the extent of the study

125 area (for instance, a 1 second resolution for a global dataset would become computationally

126 prohibitive in most practical cases), *sampbias* is best suited for local or regional datasets at

127 high resolution (c. 100 – 10,000 m).

Quantifying accessibility bias using a Bayesian framework

129 We describe the observed number of sampled occurrences S_i within each cell i as the result of

130 a Poisson sampling process with rate λ_i. We model the rate λ_i as a function of a parameter

131 q, which represents the expected number of occurrences per cell in the absence of biases,

132 i.e. when $\sum_{j=1}^{B} X_i(j) = 0$. Additionally, we model λ_i to decrease exponentially as a function

133 of distance from bias factors, such that increasing distances will result in a lower sampling

134 rate. For a single bias factor the rates of cell i with distance X_i from a bias is:

$$\lambda_i = q \times \exp\left(-wX_i\right)$$

135 where $w \in \mathbb{R}^+$ defines the steepness of the Poisson rate decline, such that $w \approx 0$ results in a

136 null model of uniform sampling rate q across cells. In the presence of multiple bias factors

137 (e.g. roads and rivers), the sampling rate decrease is a function of the cumulative effects of

138 each bias and its distance from the cell:

$$\lambda_i = q \times \exp\left(-\sum_{j=1}^{B} w_j X_i(j)\right) \quad (1)$$

139 where a vector $\mathbf{w} = [w_1, ..., w_B]$ describes the amount of bias attributed to each specific factor.

140 To quantify the amount of bias associated with each factor, we jointly estimate the parameters

141 q and $\mathbf{w}$ in a Bayesian framework. We use Markov Chain Monte Carlo (MCMC) to sample

142 these parameters from their posterior distribution:

$$P(q, \mathbf{w}|\mathbf{S}) \propto \prod_{i=1}^{N} Poi(S_i|\lambda_i) \times P(q)P(\mathbf{w}) \quad (2)$$

143 where the likelihood of sampled occurrences S_i within each cell $Poi(S_i|\lambda_i)$ is the probability

144 mass function of a Poisson distribution with rate per cell defined as in Eqn. (1). The

145 likelihood is then multiplied across the N cells considered. We used exponential priors on

146 the parameters q and $\mathbf{w}$, $P(q) \sim \Gamma(1, 0.01)$ and $P(\mathbf{w}) \sim \Gamma(1, 1)$, respectively.

147 We summarize the parameters by computing the mean of the posterior samples and their

148 standard deviation. We interpret the magnitude of the elements in $\mathbf{w}$ as a function of the

149 importance of the individual biases. We note, however, that this test is not explicitly intended

150 to assess the significance of each bias factor (for which a Bayesian variable selection method

¹⁵¹ could be used), particularly since several bias factors might be correlated (e.g. cities, and

¹⁵² airports). Instead, these analyses can be used to quantify the expected amount of bias in the

¹⁵³ data that can be predicted by single or multiple predictors in order to identify under-sampled

¹⁵⁴ and unexplored areas.

¹⁵⁵ We summarize the results by mapping the estimated sampling rates (λ_i) across space. These

¹⁵⁶ rates represent the expected number of sampled occurrences for each grid cell and provide a

¹⁵⁷ graphical representation of the spatial variation of sampling rates. Provided that the cells are

¹⁵⁸ of equal size, the estimated rates will be comparable across data sets, regions, and taxonomic

¹⁵⁹ groups. Analysing different regions, biomes, or taxa in separate analyses allows to account

¹⁶⁰ for differences in over sampling rates, which are not linked with bias factors. For instance,

¹⁶¹ the unbiased sampling rate q is expected to differ between a highly sampled clade like birds

¹⁶² and under-sampled groups of invertebrates, but their sampling biases ($\mathbf{w}$) might be similar

¹⁶³ across the two groups.

Example and Empirical validation

¹⁶⁵ A default *sampbias* analysis can be run with few lines of code in R. The main function

¹⁶⁶ `calculate_bias` creates an object of the class `"sampbias"`, for which the package provides

¹⁶⁷ a plotting and summary method. Based on a `data.frame` including species identity and

¹⁶⁸ geographic coordinates. Additional options exist to provide custom gazetteers, a custom grain

¹⁶⁹ size of the analysis, as well as some operators for the calculation of the bias distances. A

¹⁷⁰ tutorial on how to use *sampbias* is available with the package and in the electronic supplement

¹⁷¹ of this publication (Appendix S1).

To exemplify the use and output of *sampbias*, we downloaded the occurrence records of all mammals available from the island of Borneo (n = 6,262, GBIF.org 2016), and ran *sampbias* using the default gazetteers as shown in the example code below, to test the biasing effect of the main airports, cities and roads in the dataset. The example dataset is provided with *sampbias.*

We found a strong effect of cities on sampling intensity, a moderate effect of roads and airports and negligible effect of rivers (Fig. 1). All models predict a low number of collection records in the centre of Borneo (Fig. 2), which reflects the original data, and where accessibility means are low (Figure S1 in Appendix S2). The empirical example illustrates the use of *sampbias*, for detailed analyses or a smaller geographic scale, higher resolution gazetteers, including smaller roads and rivers and a higher spatial resolution would be desirable. Results might change with increasing resolution, since roads and rivers might have a stronger effect on higher resolutions (facilitating most the access to their immediate vicinity), whereas cities and airports might have a stronger effect on the larger scale (facilitating access to a larger area).

```r
library(sampbias)


#a data table with species identify, longitude, and latitude
example.in <- read.csv(system.file("extdata",

                                   "mammals_borneo.csv",

                                   package="sampbias"),

                       sep = "\t")
```

```
#running sampbias

example.out <- calculate_bias(x = example.in,

                              res = 0.05,

                              buffer = 0.5)



#summary

summary(example.out)

plot(example.out)



#projecting the bias effect in space

proj <- project_bias(example.out)

map_bias(proj)
```

Data accessibility

Sampbias is available under a GNU General Public license v3 from https://github.com/azi

zka/sampbias, and includes the example dataset as well as a tutorial (Appendix S1) and a

summary of possible warnings produced by the package (Appendix S3).

Acknowledgements

Author contributions

All authors conceived this study, AZ and DS developed the statistical algorithm and wrote the R-package, AZ and DS wrote the manuscript with contributions from AA.
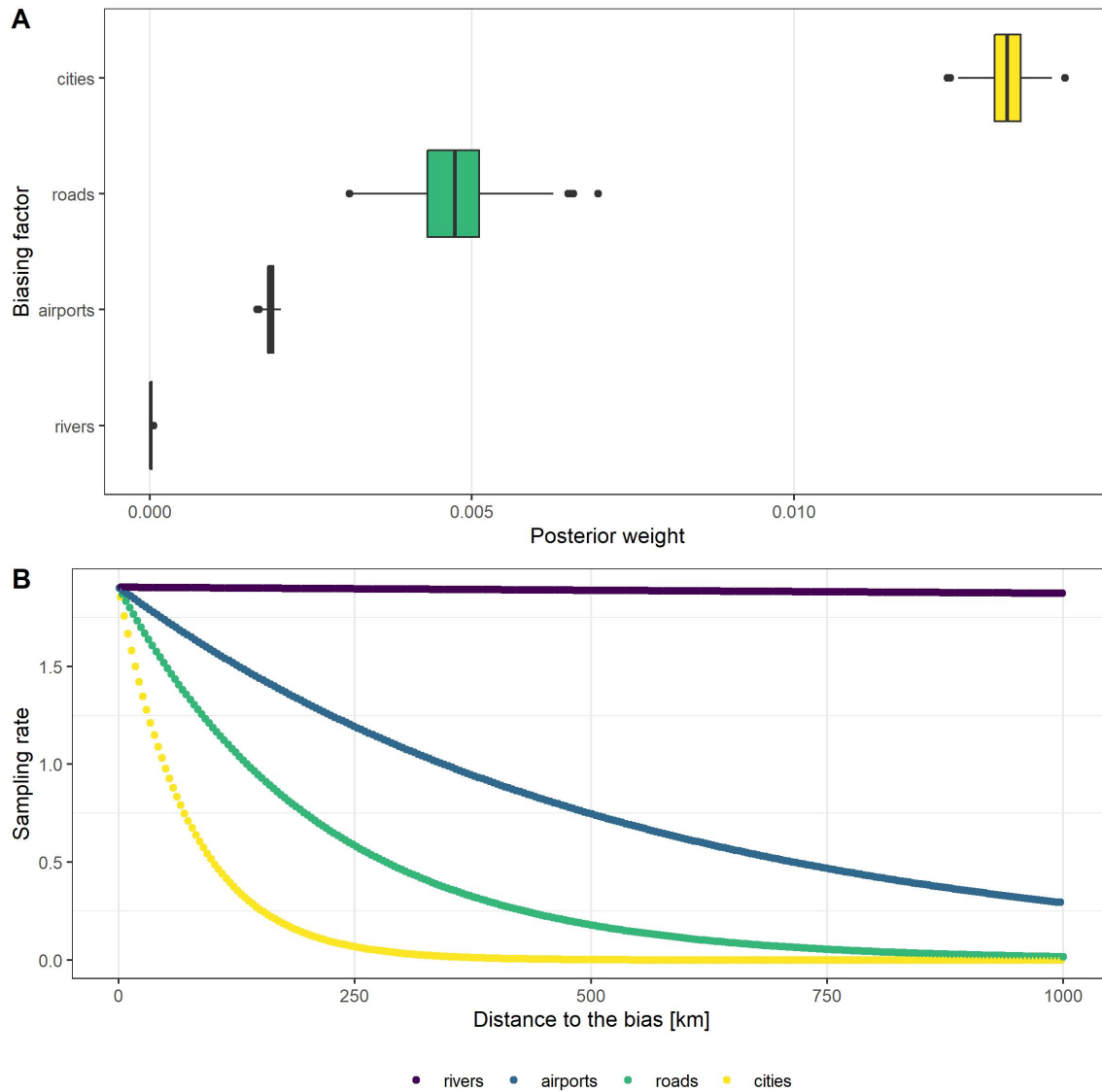
Figures

Figure 1: Results of the empirical validation analysis, estimating the accessibility bias in mammal occurrences from Borneo). A) bias weights (w) defining the effects of each bias factor, B) sampling rate as function of distance to the closest instance of each bias factor (i.e. expected number of occurrences) given the inferred *sampbias* model. At the study scale of 0.05 degrees (c. 5km) *sampbias* finds the strongest biasing effect for the proximity of cities and roads.
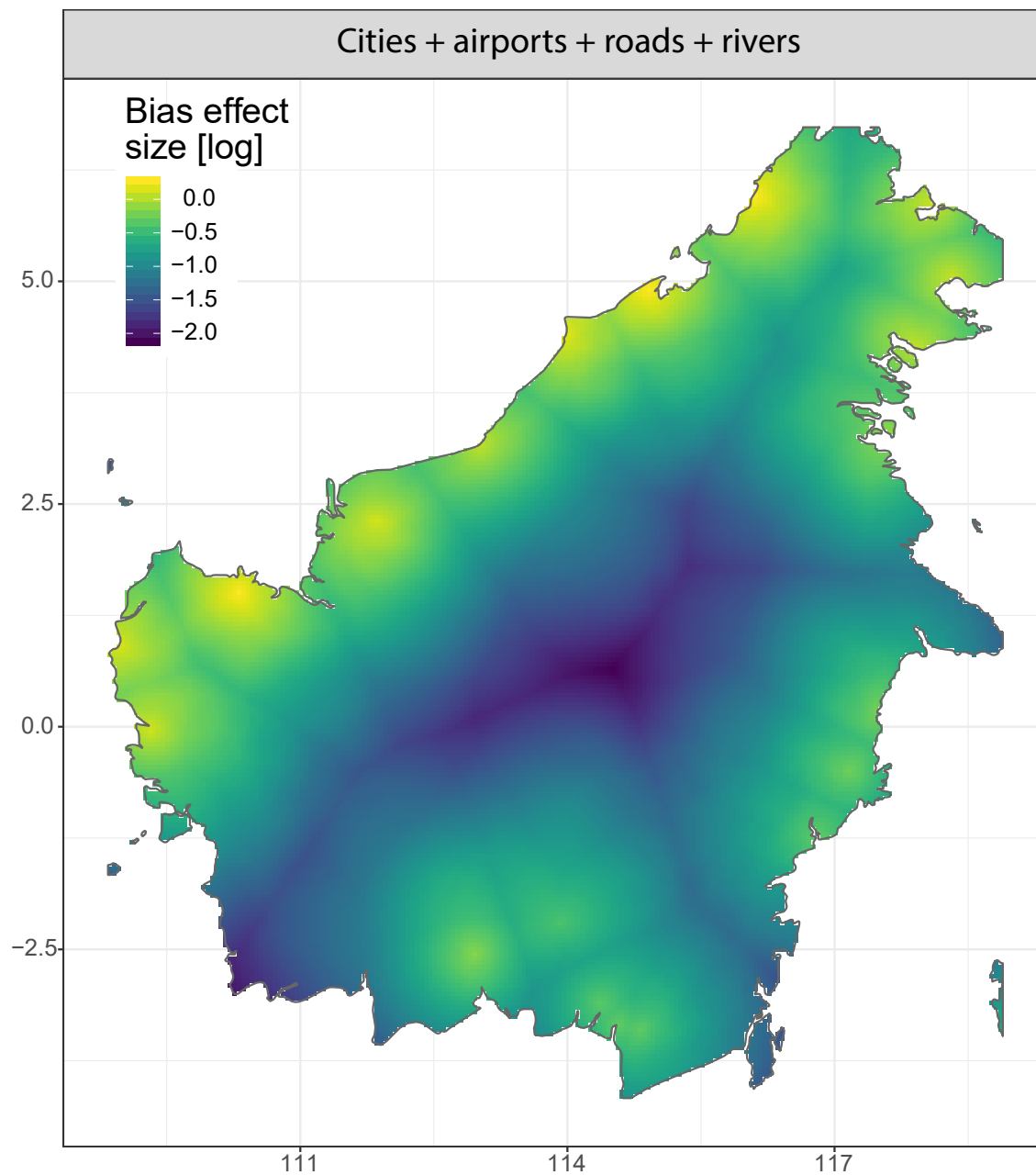
Figure 2: Spatial projection of the estimated sampling rates in an empirical example dataset of mammal occurrences on the Indonesian island of Borneo (downloaded from www.gbif.org. GBIF.org, 2016). The colours show the projection of the sampling rates (i.e. expected number of occurrences per cell) given the inferred extitsampbias model. The highest undersampling is in the centre of the island.

Supplementary material

Appendix S1 - Tutorial running *sampbias* in R

Appendix S2 - Supplementary Figure S1

Appendix S3 - Possible warnings and their solutions

References

Bache, S. M. and Wickham, H. 2014. magrittr: A Forward-Pipe Operator for R.

Barbosa, A. M. et al. 2013. Species-people correlations and the need to account for survey effort in biodiversity analyses. - Diversity and Distributions 19: 1188–1197.

Beck, J. et al. 2014. Spatial bias in the GBIF database and its effect on modeling species' geographic distributions. - Ecological Informatics 19: 10–15.

Bivand, R. S. et al. 2013. Applied spatial data analysis with R, Second edition. - Springer.

Boakes, E. H. et al. 2010. Distorted views of biodiversity: Spatial and temporal bias in species occurrence data. - PLoS Biology 8: e1000385.

Boria, R. A. et al. 2014. Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. - Ecological Modelling 275: 73–77.

Botts, E. A. et al. 2011. Geographic sampling bias in the South African Frog Atlas Project: Implications for conservation planning. - Biodiversity and Conservation 20: 119–139.

Daru, B. H. et al. 2018. Widespread sampling biases in herbaria revealed from large-scale digitization. - New Phytologist 217: 939–955.

Engemann, K. et al. 2015. Limited sampling hampers "big data" estimation of species richness in a tropical biodiversity hotspot. - Ecology and Evolution 5: 807–820.

Fernández, D. and Nakamura, M. 2015. Estimation of spatial sampling effort based on

presence-only data and accessibility. - Ecological Modelling 299: 147–155.

Fithian, W. et al. 2015. Bias correction in species distribution models: pooling survey and collection data for multiple species. - Methods in Ecology and Evolution 6: 424–438.

Fourcade, Y. et al. 2014. Mapping species distributions with MAXENT using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. - PLoS ONE 9: e97122.

Garnier, S. 2018. viridis: Default color maps from 'matplotlib'.

GBIF.org 2016. (08 September 2016) GBIF occurrence download, doi.org/10.15468/dl.7fg4zx.

Hijmans, R. J. 2019. geosphere: Spherical Trigonometry.

Hijmans, R. et al. 2000. Assessing the geographic representativeness of Genebank collections: The case of Bolivian wild potatoes. - Conservation Biology 14: 1755–1765.

Isaac, N. J. B. and Pocock, M. J. O. 2015. Bias and information in biological records. - Biological Journal of the Linnean Society 115: 522–531.

Kadmon, R. et al. 2004. Effect of roadside bias on the accuracy of predictive maps produced by bioclimatic models. - Ecological Applications 14: 401–413.

Kery, M. and Royle, J. A. 2016. Applied hierarchical modeling in ecology - Analysis of distribution, abundance and species richness in R and BUGS: Volume 1: Prelude and Static Models. - Academic Press, Elsevier.

Kramer-Schadt, S. et al. 2013. The importance of correcting for sampling bias in MaxEnt species distribution models. - Diversity and Distributions 19: 1366–1379.

Lin, Y.-p. et al. 2015. Uncertainty analysis of crowd-sourced and professionally collected field data used in species distribution models of Taiwanese moths. - Biological Conservation 181: 102–110.

Meyer, C. et al. 2015. Global priorities for an effective information basis of biodiversity distributions. - Nature Communications 6: 8221.

Meyer, C. et al. 2016. Multidimensional biases, gaps and uncertainties in global plant occurrence information. - Ecology Letters 19: 992–1006.

Monsarrat, S. et al. 2019. Accessibility maps as a tool to predict sampling bias in historical biodiversity occurrence records. - Ecography 42: 125–136.

Pebesma, E. J. and Bivand, R. S. 2005. Classes and methods for spatial Data: the sp Package. - R News 5: 21–41.

R Core Team 2019. R: A language and environment for statistical computing.

Rocchini, D. et al. 2011. Accounting for uncertainty when mapping species distributions: The need for maps of ignorance. - Progress in Physical Geography: Earth and Environment 35: 211–226.

Ruete, A. 2015. Displaying bias in sampling effort of data accessed from biodiversity databases using ignorance maps. - Biodiversity Data Journal 3: e5361.

263 Rydén, O. et al. 2019. Linking democracy and biodiversity conservation: Empirical evidence

264 and research gaps. - Ambio: 15pp.

265 Shimadzu, H. and Darnell, R. 2015. Attenuation of species abundance distributions by

266 sampling. - Royal Society Open Science 2: 140219.

267 Stolar, J. and Nielsen, S. E. 2015. Accounting for spatially biased sampling effort in presence-

268 only species distribution modelling. - Diversity and Distributions 21: 595–608.

269 Vale, M. M. and Jenkins, C. N. 2012. Across-taxa incongruence in patterns of collecting bias.

270 - Journal of Biogeography 39: 1744–1744.

271 Varela, S. et al. 2014. Environmental filters reduce the effects of sampling bias and improve

272 predictions of ecological niche models. - Ecography: 1084–1091.

273 Warren, D. L. et al. 2014. Incorporating model complexity and spatial sampling bias into

274 ecological niche models of climate change risks faced by 90 California vertebrate species of

275 concern. - Diversity and Distributions 20: 334–343.

276 Wickham, H. 2009. ggplot2 - Elegant graphics for data analysis. - Springer.

277 Wickham, H. 2019. forcats: Tools for working with categorical variables (Factors).

278 Wickham, H. and Henry, L. 2019. tidyr: Tidy messy data.

279 Wickham, H. et al. 2019. dplyr: A grammar of data manipulation.

280 Yang, W. et al. 2013. Geographical sampling bias in a large distributional database and its

281 effects on species richness-environment models. - Journal of Biogeography 40: 1415–1426.

282 Yang, W. et al. 2014. Environmental and socio-economic factors shaping the geography of

283 floristic collections in China. - Global Ecology and Biogeography 23: 1284–1292.