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## Anticipating species distributions: Handling sampling effort bias under a Bayesian framework



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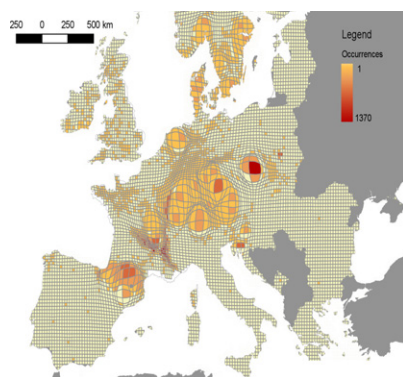
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### HIGHLIGHTS

- Invasive species can modify the structure and function of ecosystems.
- Reliable anticipation of species invasions relies on the quality of input data.
- Sampling effort bias leads to an over- or under-estimation of species occurrence.
- We propose methods to consider sampling effort bias in species distribution modeling.
- We demonstrate the power of incorporating uncertainty in species distribution models.

### GRAPHICAL ABSTRACT



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### ABSTRACT

Anticipating species distributions in space and time is necessary for effective biodiversity conservation and for prioritising management interventions. This is especially true when considering invasive species. In such a case, anticipating their spread is important to effectively plan management actions. However, considering uncertainty in the output of species distribution models is critical for correctly interpreting results and avoiding inappropriate decision-making. In particular, when dealing with species inventories,

**Abbreviations:** DIC, Deviance Information Criterion; MCMC, Markov Chain Monte Carlo; PPD, posterior probability distribution; SDM, species distribution model.

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and avoiding inappropriate decision-making. In particular, when dealing with species inventories, the bias resulting from sampling effort may lead to an over- or under-estimation of the local density of occurrences of a species. In this paper we propose an innovative method to i) map sampling effort bias using cartogram models and ii) explicitly consider such uncertainty in the modeling procedure under a Bayesian framework, which allows the integration of multilevel input data with prior information to improve the anticipation of species distributions.

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## 1. Introduction

Anticipation has recently become a central topic in ecological fields such as food science (Lobell et al., 2012), community ecology (Keddy, 1992; Bacaro et al., 2008), species distribution modeling (Willis et al., 2009), landscape ecology (Tattoni et al., 2017), and biological invasion science (Rocchini et al., 2015). Anticipatory methods are also crucial for developing effective management practices to deal with invasive species (Rocchini et al., 2015).

Invasive species can modify the structure and functioning of ecosystems, altering biotic interactions and homogenizing previously diverse plant and animal communities over large spatial scales, ultimately resulting in a loss of genetic, species and ecosystem diversity (Winter et al., 2009). The annual economic impact of invasive species has been estimated at over 100 billion dollars just within the USA (NRC, 2002), an order of magnitude higher than those caused by all natural disasters put together (Ricciardi et al., 2011); some authors go as far as to claim that the economic impact of invasive species is incalculable (Mack et al., 2000).

Given the massive negative economic and ecological effects of invasive species, a robust method for predicting species' distributions is crucial for an early assessment of species invasions and effective application of appropriate management actions (Malanson and Walsh, 2013).

Investigating how biodiversity is distributed spatially and temporally across the globe has long been a central theme in ecology (Gaston, 2000) and the methods developed to answer this question have become key tools for biodiversity monitoring (Ferretti and Chiarucci, 2003; Chiarucci et al., 2011). For example, species distribution models (SDMs) have been used to map the current distribution of a single species (Rocchini et al., 2011), model the potential distribution of native and invasive species (Rocchini et al., 2015), investigate the statistical performance of different models to infer the distribution of species under various ecological conditions (Elith and Graham, 2009; Guisan and Zimmermann, 2000), test the transferability in space of modeled distribution patterns (Heikkinen et al., 2012; Randin et al., 2006), predict long term changes to species distributions (Pearman et al., 2008) and make inferences on future biodiversity scenarios (Engler et al., 2009; Pompe et al., 2008), evaluate the potential of satellite imagery bands as predictors of biodiversity patterns (Mathys et al., 2009), analyse spatial autocorrelation in species distributions (Carl and Kühn, 2007; Dormann, 2007), and understand biogeographical patterns (Sax, 2001).

In combination with remote sensing products (e.g. Feilhauer et al., 2013; Rocchini, 2007) and current global data sets on in situ species observations, SDMs have become the method of choice for monitoring biodiversity at multiple spatial and temporal scales. However, the strength of this combination depends on the careful selection and application of integrative modeling approaches, in combination with a thorough assessment of uncertainty in both data inputs and modeling methods.

Reliable anticipation of species invasions depends on the quality of input data on one hand and robustness of the predictive SDM on the other. As an example, Rocchini et al. (2011) demonstrated theoretically that input data arising from biased species distribution maps could potentially lead to unsuitable management strategies. In

addition, Elith and Leathwick (2009) demonstrated that, given the same input data set, different SDMs might lead to dissimilar results (see also Bierman et al., 2010; Manceur and Kühn, 2014).

The aim of this manuscript is to propose coherent and straightforward methods to explicitly account for uncertainty when mapping species distributions in the light of anticipating the spread of invasive species. In particular we will cover i) explicitly mapping uncertainty in sampling bias, ii) mitigating uncertainty in data through prior beliefs and Bayesian inference and iii) reporting uncertainty in species distribution maps through Markov Chain Monte Carlo methods. The findings of this manuscript should be of particular interest to landscape managers and planners attempting to predict the spread of species and deal with errors in species distribution maps in a straightforward manner.

## 2. Mapping input uncertainty related to sampling effort bias

In anticipating species distributions a first step is to ensure that the information indicating where species are present is bias-free or, at least, that the uncertainty of input data is explicitly taken into account in further modeling steps.

One of the main problems with field data on species distributions is related to "sampling effort bias" (Rocchini et al., 2011), namely the bias inherent in some areas being under-sampled with respect to others. Quantifying and mapping the uncertainty derived from variation in the number of observations due to sampling effort can be achieved using cartograms (Gastner and Newman, 2004), in which the shape of spatial objects (e.g. polygons and cells) is directly related to a determined property, in our case to uncertainty.

Cartograms build on the standard treatment of diffusion theory by Gastner and Newman (2004), in which the current spatial density of a population is given by

$$J = v(r, t)p(r, t) \quad (1)$$

where  $v(r, t)$  and  $p(r, t)$  are the velocity and density of the spread of the population under study, respectively, at position  $r$  and time  $t$ .

Cartograms facilitate the visualization of spatial uncertainty in the data by varying the size of each polygon according to the density of information contained (e.g. number of observations and variation). As an example, we show a cartogram of the distribution of *Abies alba* Miller overlapping a grid to the set of records obtained from the Global Biodiversity Information Facility (GBIF, <http://www.gbif.org>, Fig. 1). GBIF offers free and open access to hundreds of millions of records from over 30,000 species datasets which are collated from around the world and stored with a common Darwin Core data standard. The cartogram was developed using the free and open source software ScapeToad (<http://scapetoad.choros.ch/>). Since cells with a higher number species occurrences might be biased by the effort spent visiting them, in Fig. 1, the shape of each cell is determined by the number of times it was visited (i.e. number of different dates recorded in GBIF for the species in that cell). From now on, we will refer to this as sampling effort. The colour represents the spatial distribution (density of occurrences, sensu Beck et al., 2014) of the species in each cell. Therefore, cartograms allow uncertainty to be

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