



Protecting bias: Across time and ecology, open-source bat locality data are heavily biased by distance to protected area



Marina Fisher-Phelps^{a,*}, Guofeng Cao^{b,c}, Rebecca M. Wilson^a, Tigga Kingston^a

^a Department of Biological Sciences, Texas Tech University, Lubbock, TX 79409, USA

^b Department of Geosciences, Texas Tech University, Lubbock, TX 79409, USA

^c Center for Geospatial Technology, Texas Tech University, Lubbock, TX 79409, USA

ARTICLE INFO

Keywords:

Distribution models
Bias correction
Method bias
MaxEnt
Chiroptera
Southeast Asia

ABSTRACT

Open-source species locality data are widely used in species distribution modeling but may be spatially biased by uneven sampling effort across a species' range. Spatial biases may vary across ecological trait groups if traits affect associations with landscape features and capture probability. Furthermore, spatial biases may change across time as research priorities, funding, and methodologies change, which may confound modeling of temporal changes in distributions. We used locality records from 93 bat species from the Global Biodiversity Information Facility to characterize the differential contribution of bias variables to spatial bias and how contribution varied across ecological trait groups. Next, we examined how historical changes in protected area proliferation, economic development, and sampling method advancement affected protected area and university biases. Roosting and foraging traits influenced spatial bias, but distance to protected areas was the greatest contributor to spatial sampling bias in a pooled model and 8 out of 10 ecological trait group models. Over time, distance to protected areas significantly decreased following protected area proliferation, but economic improvement did not influence distance to universities. Sampling method advancements increased protected area bias for two out of three foraging groups. Although sampling effort has increased over time, effort is becoming more biased towards protected areas, which may not encompass the entirety of species' ranges or allow for equal sampling across taxa. Characterizing spatial bias differences among species and across time clarifies underlying causes of spatial bias, information that can be leveraged to improve spatial bias correction.

1. Introduction

Biodiversity researchers have urged the global scientific community to prioritize biological data acquisition to improve knowledge of species distributions and better support conservation assessments (Guralnick and Hill, 2009; Wilson, 1988). Despite advances in the digitization, collation, and mobilization of species distribution data, precise, accurate, and well-distributed locality data are still lacking for most taxa. As a consequence, the availability of high-quality species distribution data lags behind the availability of explanatory environmental data such as topography, land cover, and climate (Beck et al., 2012; Costello et al., 2013; Jetz et al., 2012). Open-source locality data underpin the majority of recent presence-only species distribution models, which predict and map the probability of species occurring across a defined area using presence records (versus those models that use presence and absence) and maps of environmental conditions (Elith et al., 2006). Species distribution models have become a popular tool in ecological and conservation research because they provide geographic

range estimates for data deficient species and can model distributional changes caused by anthropogenic landscape changes and climate change (Guisan et al., 2013; Porfirio et al., 2014; Rebelo and Jones, 2010; Wilson et al., 2011). However, when source data are collected and/or collated using an unsystematic method, they may have temporal or spatial biases (Ballesteros-Mejia et al., 2013; Boakes et al., 2010; Isaac and Pocock, 2015; Newbold, 2010; Yang et al., 2014).

Spatial biases can negatively affect presence-only species distribution models (Barry and Elith, 2006; Phillips et al., 2009; Rondinini et al., 2006; Syfert et al., 2013) because species presence probabilities become more heavily influenced by sampling effort than species ecology. Thus it has become standard practice to correct for spatial biases in presence data, but prevalent techniques (e.g., spatial filtering and background manipulation) do not require knowledge of the extent, magnitude, or causes of spatial bias. For example, spatial filtering is a random process whereby the number of records found within a certain size grid cell is limited to a predetermined number. Background manipulation changes pseudo-absences in the model to match biases

* Corresponding author.

E-mail address: m.fisher-phelps@ttu.edu (M. Fisher-Phelps).

seen in similarly distributed but non-target species (Dormann et al., 2007; Phillips et al., 2009). Spatial filtering and background manipulation both assume that all locality data are similarly biased throughout space and time, and that all biases negatively affect distribution modeling. This may be a false assumption. For example, Kadmon et al. (2004) found that plant localities occurred more frequently near roads but that this bias did not have a significant effect on distribution models.

In species distribution models, spatial bias generally arises when sampling extent and effort are influenced by geographic features. Geographic causes of spatial sampling biases have been intensively studied. Unsurprisingly, features that promote researcher presence, such as protected areas, road access, cities, population density, university presence have been shown to increase density of sampling localities and species inventory completeness (Botts et al., 2011; Ficetola et al., 2014; Freitag et al., 1998; Kadmon et al., 2004; Martin et al., 2012; Reddy and Dávalos, 2003; Yang et al., 2014). In contrast, ecological causes of spatial bias have been less studied. Ecological traits may influence spatial sampling bias, as traits can affect capture rates and location. For example, in Freitag et al. (1998), small terrestrial mammal locality data were biased towards roads whereas large mammals and bats were more biased by distance to protected area. Schmidt-Lebuhn et al. (2013) documented that plant morphology, flowering phenology, and invasion history biased collecting by researchers. Thus we can see that ecology has an effect on taxonomic and spatial sampling biases but hypotheses that explore the connection between ecology, methodology, and biases have not been tested.

Temporal variation in spatial biases is a direct reflection of how sampling extent, effort, and methodology changes through time. Methodological advancements pave the way for an increase in the magnitude, geographic extent, and taxonomic diversity of sampling effort. New methods allow for sampling in previously inaccessible areas and data deficient species to be captured or observed. However, methodological improvements may also lead to taxonomic biases in sampling effort if methods have differential capture success across taxa, trait groups, or environments (Kingston, 2013). For example, MacSwiney et al. (2008) found that current capture methods fail to sample major portions of the bat fauna, including an entire foraging group, because of differential capturability caused by ecological trait differences among species and habitat differences across the landscape. Furthermore, drivers of temporal changes in spatial bias are also poorly understood. This is important because temporal variation in spatial structure of data can result in a reduction of accuracy in the description of a species' niche space (Aguar et al., 2015; Hortal et al., 2008), and this has consequences for tests of temporal hypotheses regarding distribution shifts (Lobo et al., 2007). Hypothesized causes of the temporal variation in data structure are researcher preference (Lobo et al., 2007), ecological niche bias (Aguar et al., 2015), and clustering around protected areas (Boakes et al., 2010), but these have not been explicitly tested.

Our overall objective was to characterize the origins of spatial sampling bias and how those origins are affected by ecology and geography and change over time. First, we hypothesized that the sources of spatial bias origins should vary across ecological trait groups. We used MaxEnt (maximum-entropy) modeling to assess the differential contribution of ease-of-access features and human demography to ecological trait group models. We selected six related variables (distance of the sampling locality to nearest protected area, distance to university, distance to road, population density, night-time light intensity, and land cover) to encompass well-known and expected causes of spatial bias. Second, we hypothesized that temporal changes in protected area conservation, economic development, and sampling method advancement would affect spatial sampling bias by increasing or decreasing distance to protected areas and universities. Lastly, we hypothesized that changes in bat sampling methods may lead to temporal changes in taxonomic bias in sampling effort because methods

have differential capture success across taxa, trait groups, or environments.

We investigated spatial sampling bias in Southeast Asian bat species, a mammalian order underutilized in species distribution research (Razgour et al., 2016). Compared to other taxa examined for spatial bias, such as butterflies and birds, bats are cryptic, traditionally “uncharismatic”, and normally require specialist knowledge to catch and identify. Consequently, bats lack historical documentation by naturalists and lag behind other taxa (e.g. birds) in current efforts to monitor species through citizen science projects (but see Jones et al., 2013). It has been hypothesized that these factors contribute to temporal and spatial changes in biases; however since bats have not been influenced by these factors, we theorized that this taxon may exhibit different spatial bias patterns. Indeed, Freitag et al. (1998) found that sampling of African bats exhibited similar spatial bias to that of large carnivores rather than similar-sized terrestrial mammals, but the cause of this pattern was not examined further. Finally, bats in Southeast Asia are of conservation concern due to rapid deforestation and unregulated hunting. It is predicted that 53% of bat species in this region will go extinct by 2100 if there is not a reduction in threats (Lane et al., 2006). A lack of regional data on bat distributions is considered a major conservation impediment (Kingston, 2010), so developing accurate species distribution model is critical for conservation planning.

2. Methods

2.1. Locality data collation and study species

Bat locality data were downloaded from the Global Biodiversity Information Facility (GBIF) (www.gbif.org, accessed April 2015) and limited to the 11 Southeast Asian countries of Malaysia, Indonesia, Philippines, Brunei, Thailand, Cambodia, Myanmar, Laos, Vietnam, Singapore, and Timor-Leste (Fig. 1). Data without date information or missing or obviously erroneous geographic coordinates were excluded from analysis, which yielded 27,347 records representing 248 species with a temporal range of 1887–2015. Location and species duplicates were removed for analyses resulting in 1471 species independent unique locations.

Currently, there are at least 340 species of bats known in Southeast Asia (Kingston, 2013; Simmons, 2005); however we did not use all species in the analysis. We selected species from the top five most abundant genera (in GBIF) in each family or subfamily and then further reduced selection to the five or six most abundant species in each genus. We chose this selection procedure to create a more manageable list of species (93) that still covered the spectrum of bat taxonomic and ecological diversity (Table A.1).

2.1.1. Ecological trait groups

We organized bat localities into categories based on roost preferences, foraging ecology, and anthropogenic association. Record and species prevalence across ecological trait groups was relatively even except for open-space foragers (Fig. A.1), which are the hardest ecological group to capture because they fly too high to be caught in nets. Categorizations were based on ecological information provided in IUCN Red List Assessments (2016) and expert opinion. Bats in Southeast Asia can be grouped by natural roost preference, as those that roost exclusively in caves, those in tree cavities and foliage, and those that can use either (generalists). For foraging ecology, we first separated plant-visiting bats from insectivorous species, and then split the insectivorous bats into groups based on their ability to capture prey in cluttered environments (such as the dense vegetation of a rainforest) (Schnitzler and Kalko, 2001). Plant-visiting foragers are a separate group, as they do not have the same connection between morphological characteristics and clutter navigation because they predominantly use sight to forage and lack laryngeal echolocation. Thus, we examined four foraging categories: cluttered-space (hunting insects inside dense

Download English Version:

<https://daneshyari.com/en/article/5741896>

Download Persian Version:

<https://daneshyari.com/article/5741896>

[Daneshyari.com](https://daneshyari.com)