



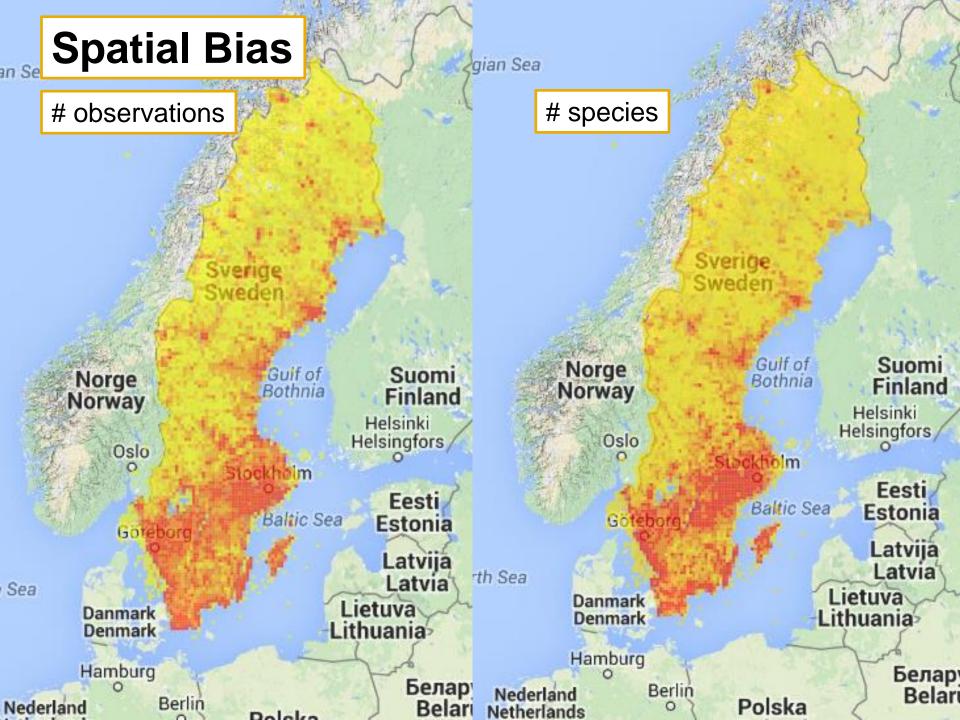
#### **Ignorance scores**

Where and when is data enough?

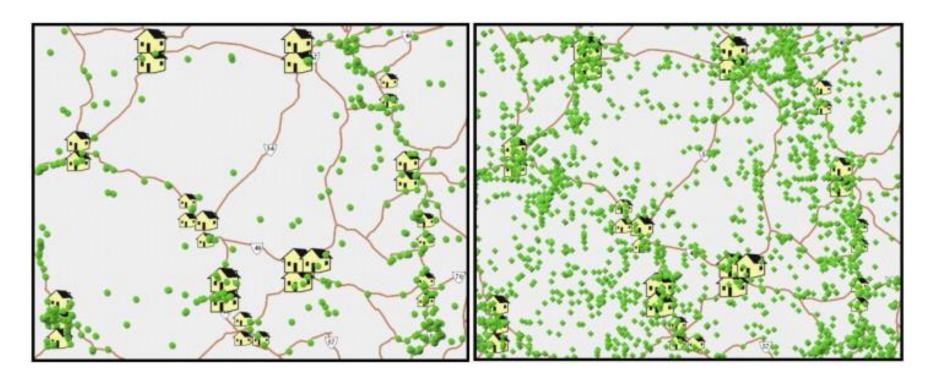
Alejandro **Ruete**, PhD Alejandro @greensway.se

# The greatest enemy of knowledge is not ignorance; it is the illusion of knowledge

**Daniel J. Boorstin** 



#### Non-homogeneous sampling



Presence-only data for butterflies (left) and mammals (right), central Mexico.



#### **Ignorance Maps**

One solution (out of many) <u>alejandroruete.github.io/lgnoranceMaps</u>

Biodiversity Data Journal 3: e5361 (2015)





#### **Exploring ignorance in space and time**

Where and when is data enough? A simple algorithm for fast implementations and comparable results.





STORY

UPDATES



Ignorance of GBIF data on European Amphibians summarized per ecoregion



#### SUBMITTED TO



2016 GBIF Ebbe Nielsen Challenge

WINNER First Prize

#### CREATED BY

# Describe your contribution E.g., I worked on the backend and cleaned up



Alejandro Ruete
Conservation biologist and
Population ecologist.
Analyst. Passionate
photographer.

#### **Approach**

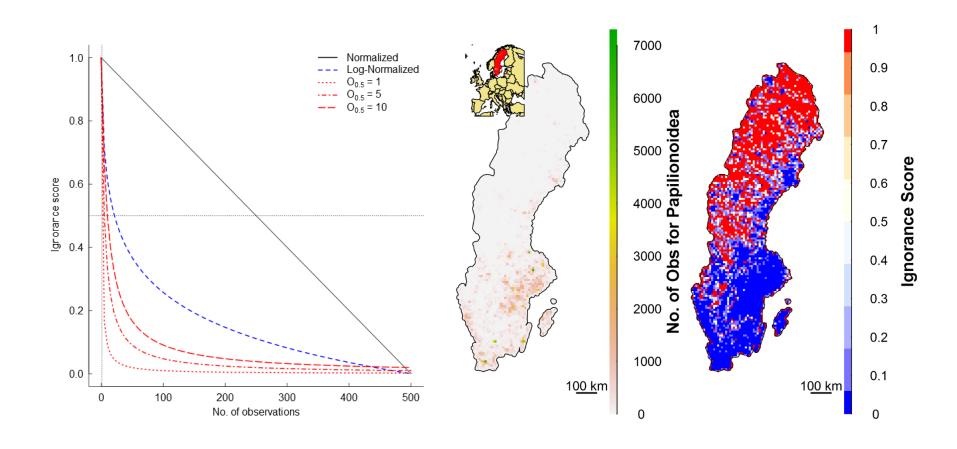
- Based "mainly" on presence-only data
- It is not a model, it is a TRANSFORMATION
- Report of the spatial distribution of sampling effort (or lack of it)
- Least possible number of assumptions
- Generality: inform users to analyse raw data
- Scalability
- Comparability
- Low computational requisites

#### A few assumptions are needed

- Observers are assumed to be fond of or specialist on one or more taxonomic groups (e.g. family, order) and follow roughly the same methods
- REFERENCE TAXONOMIC GROUPS will share similar bias, and are surrogate for sampling effort (Phillips et al. 2009, Ponder et al. 2001).
- The lack of reports of any species from the RTG at a particular location is likely due to a lack of observers, rather than to the total absence of species.

#### **Algorithms**

Transformation of the number of observations (N) per space-time unit into a scale of knowledge

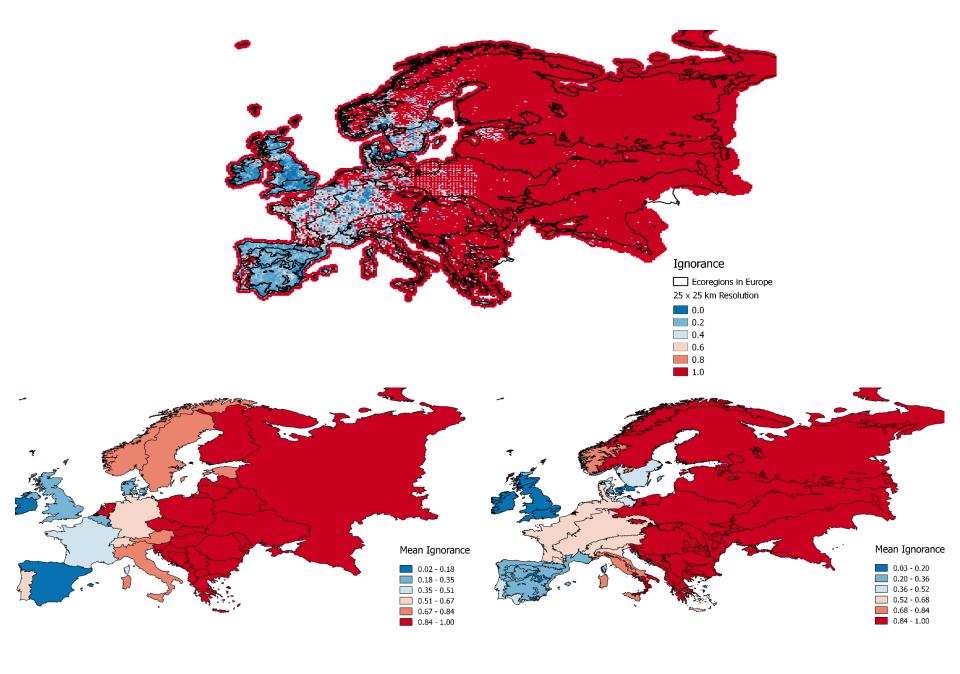


#### Half-ignorance algorithm

$$I_i = \frac{O_{0.5}}{N_i + O_{0.5}}$$

## Let's take a look

## Let's take another look



#### Why this approach?

- Quick. There are several approaches\* but too computationally intensive.
- E.g. approaches like completeness are best at estimating how much is left to be observed.
   However, it requires identifying inventories.
- Independent of any expectation on richness.

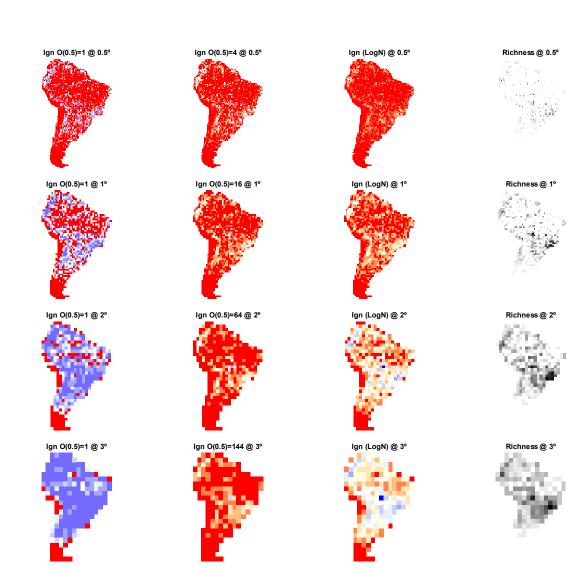
<sup>\*</sup> e.g. Hill 2012, Jeppsson et al. 2010, Ponder et al. 2001, Prendergast et al. 1993, Schulman et al. 2007, Snäll et al. 2011, Sousa-Baena et al. 2014, Stropp et al. 2016

#### **Scalability**

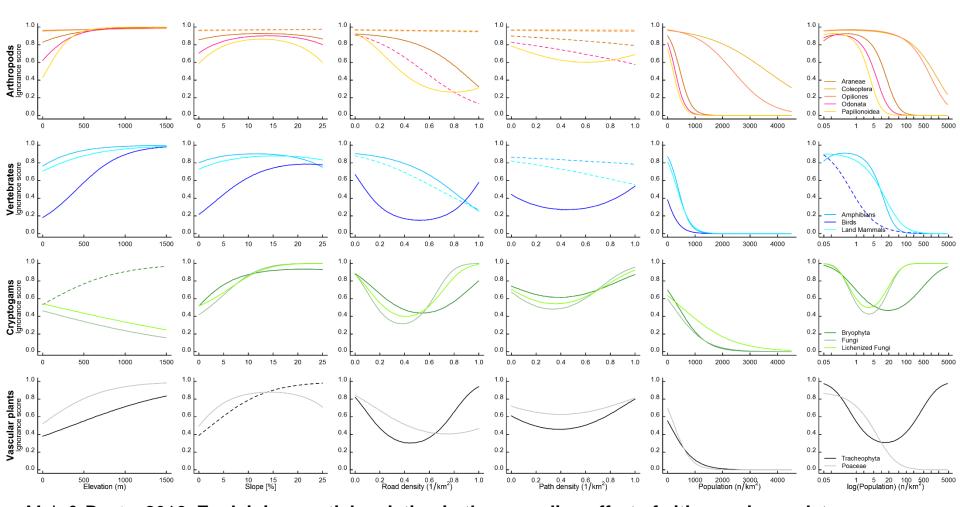


586 beetle species

MSc. J.L. Silva Dr. F. Z. Vaz-de-Mello Coleção Zoológica - Setor de Entomologia. Universidade Federal de Mato Grosso. Cuiabá/Mato Grosso/Brasil.

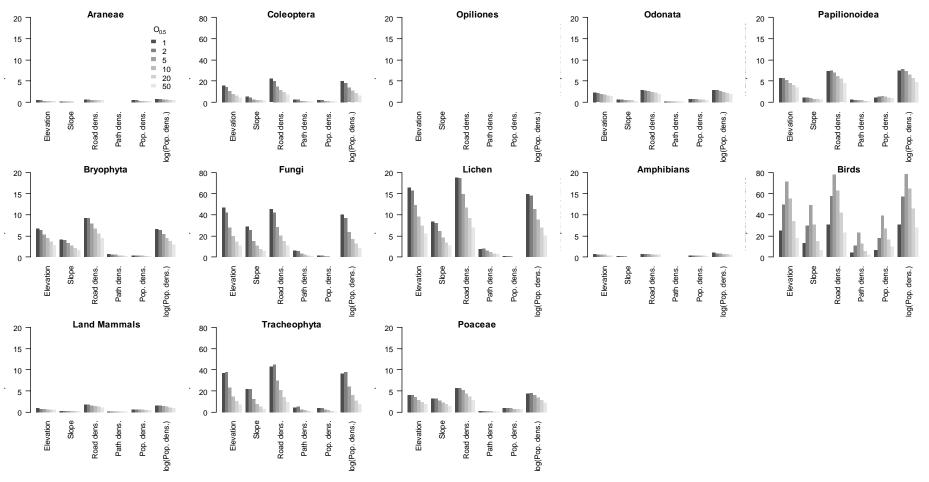


#### One layer to control them all



Mair & Ruete. 2016. Explaining spatial variation in the recording effort of citizen science data across multiple taxa PLoS ONE 11(1): e0147796.

#### Explained Deviance (%) per RTG per variable



Mair & Ruete. 2016. Explaining spatial variation in the recording effort of citizen science data across multiple taxa PLoS ONE 11(1): e0147796.

#### **Applications**

- Consultants performing environmental impact assessments (e.g. ignorance maps as precautionary statements)
- 2. Observers (e.g. interested in undersampled locations)
- 3. Researchers (this is the juicy part!)

#### **Applications:** Species distributions

- generate pseudo-absences
- mask out areas of high uncertainty from other raster layers derived from the raw data
- accurate assessment of species richness (ongoing work)
- ignorance maps as confidence or "All-in-one" bias layers for background sampling (e.g. MaxEnt)

# Knowing what you ignore you already know a lot

### Thank you for your attention

**Questions?** 

