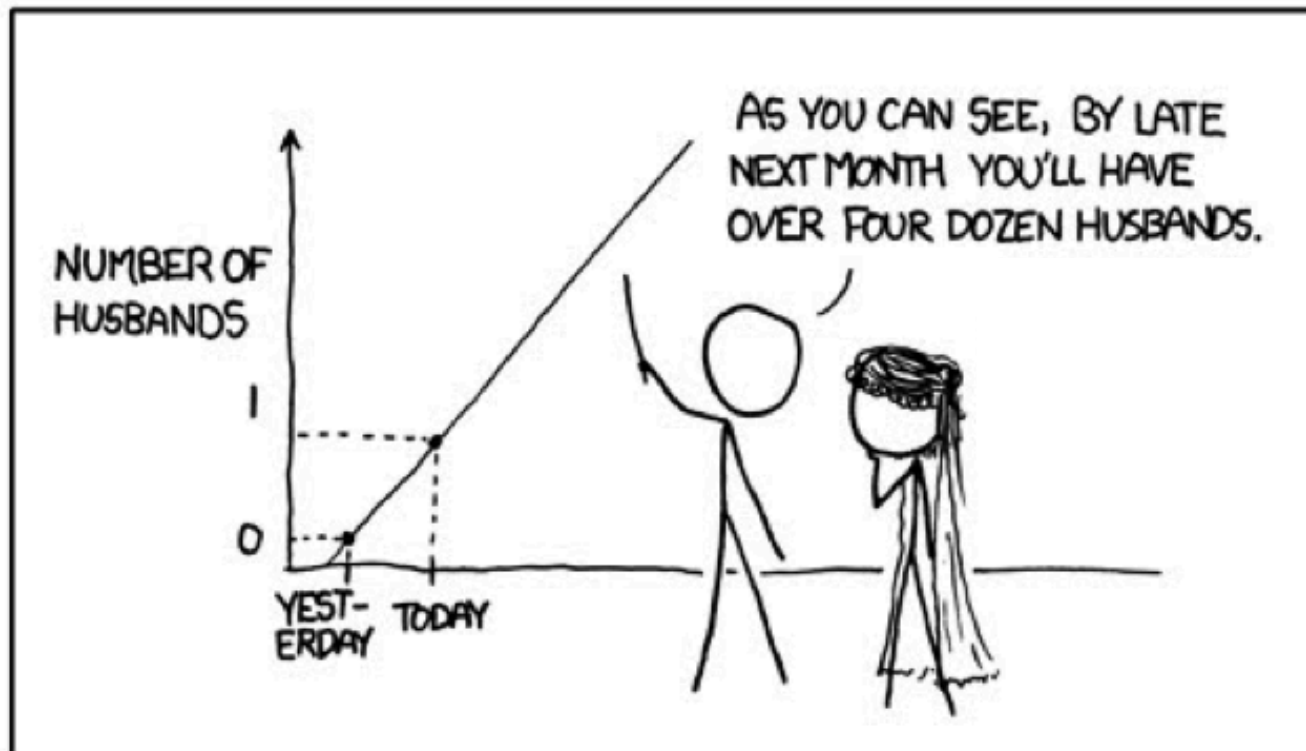
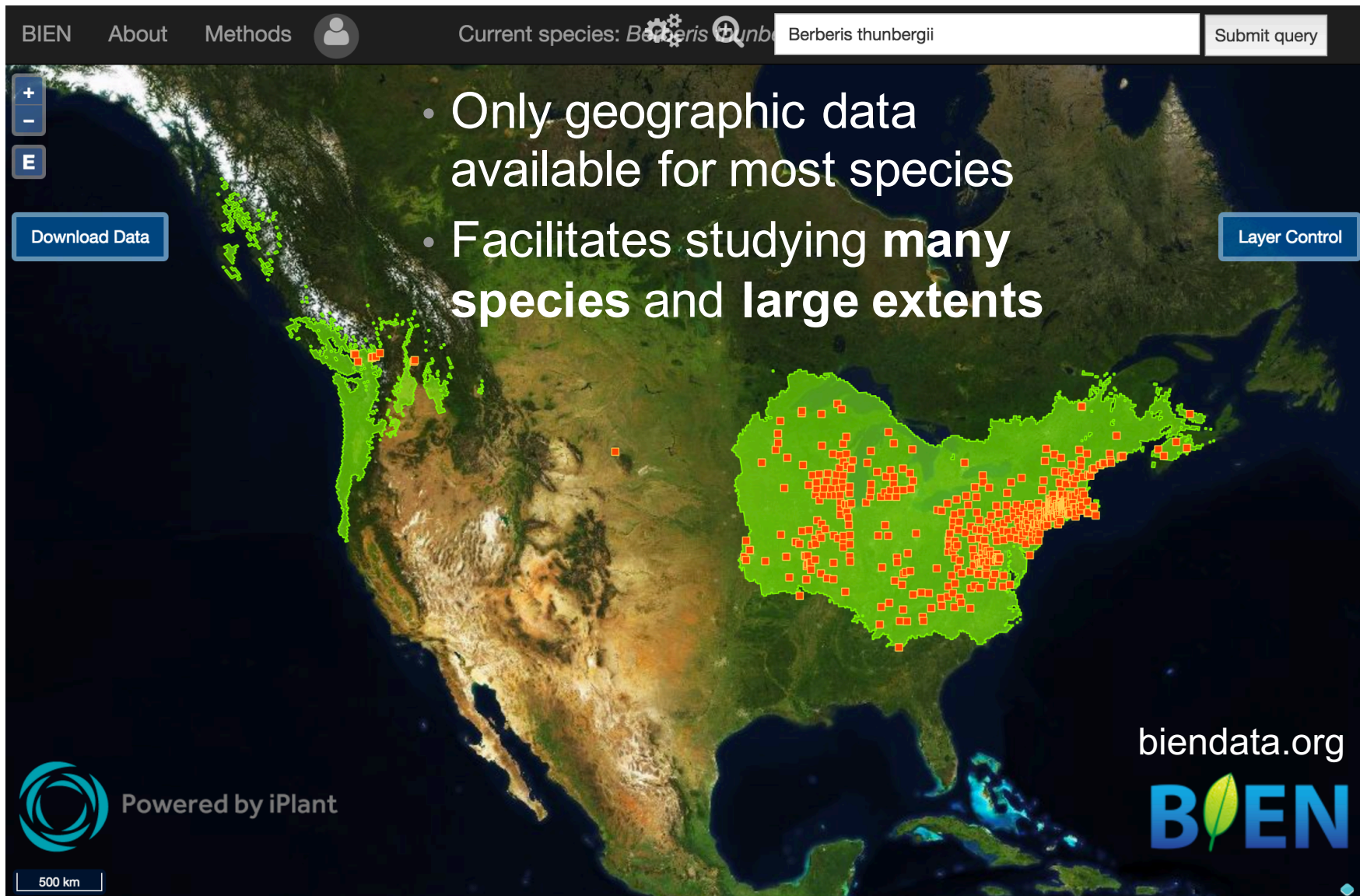


# Forecasting, Extrapolation and Uncertainty

MY HOBBY: EXTRAPOLATING

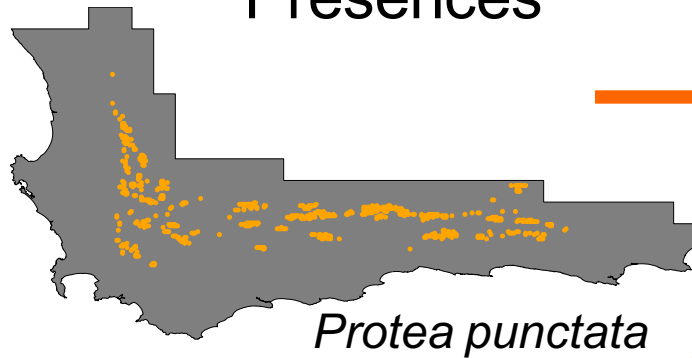


# Occurrence patterns: starting point

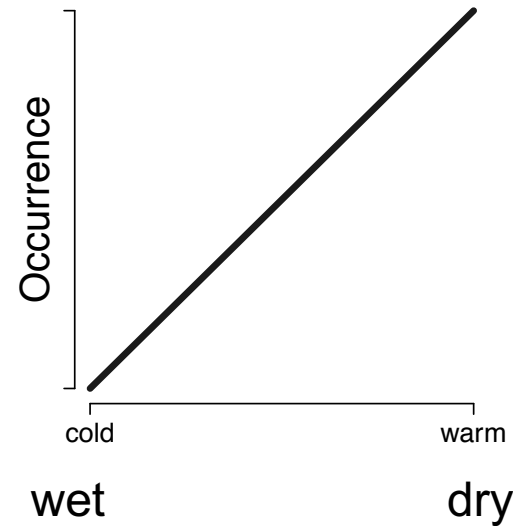
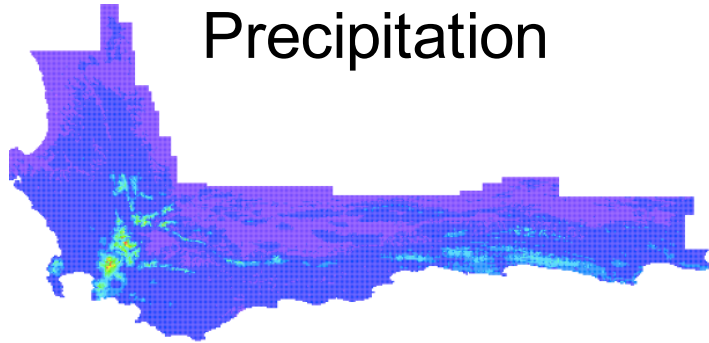


# Occurrence

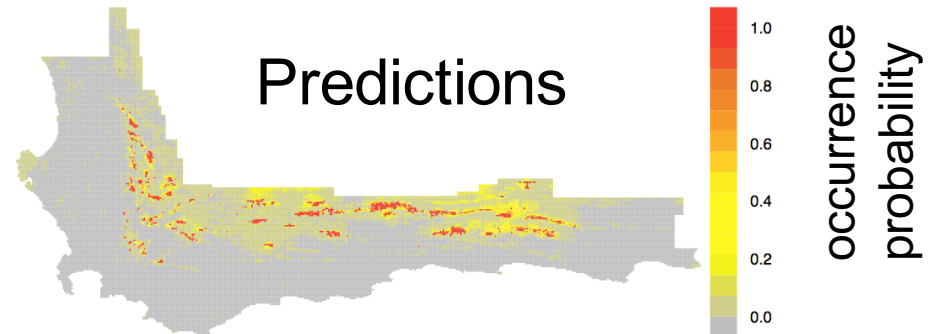
Presences



Annual  
Precipitation



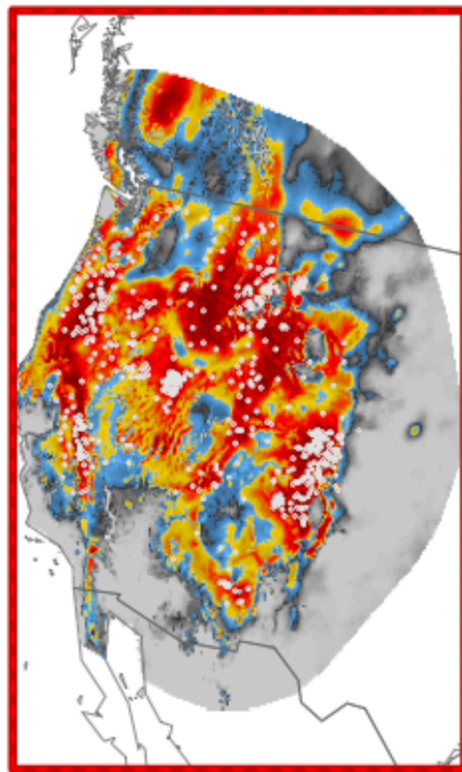
Predictions



- |                    |                                      |
|--------------------|--------------------------------------|
| Maxent Guide:      | Merow et al., 2013, <i>Ecography</i> |
| Maxent v. Maxlike: | Merow et al., 2014, <i>MEE</i>       |
| Complexity:        | Merow et al., 2014, <i>Ecography</i> |
| Minxent:           | Merow et al., 2016, <i>GEB</i>       |
| Expert Maps:       | Merow et al., 2017, <i>GEB</i>       |

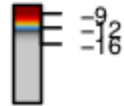
# Future Forecasts

Present

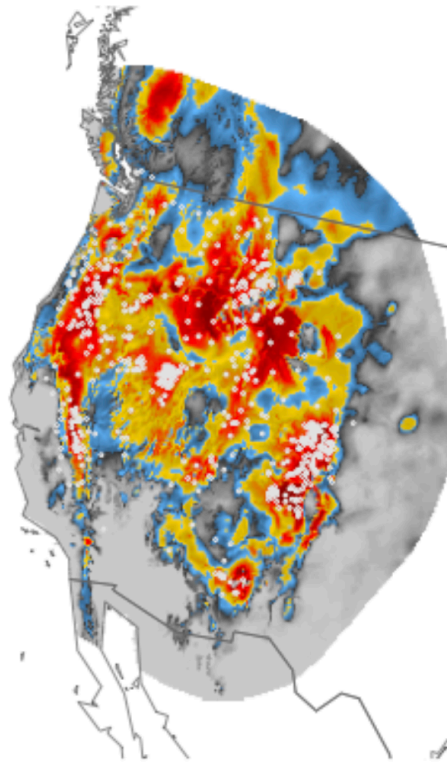


noBias

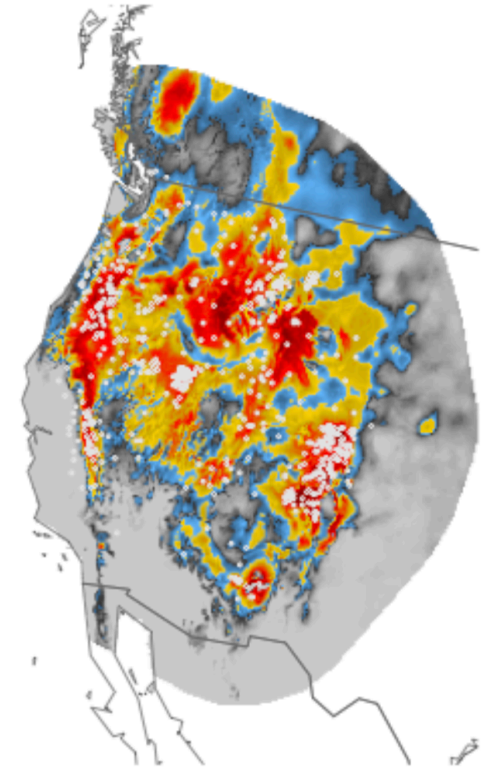
AUC<sub>train</sub> = 0.878  
AUC<sub>test</sub> = 0.81  
AUC<sub>test</sub><sup>lg</sup> = 0.69  
Boyce<sub>test</sub> = 0.391  
TPR<sub>test</sub>(10) = 0.898  
FPR<sub>test</sub>(10) = 0.413  
TPR<sub>test</sub>(5) = 0.947  
FPR<sub>test</sub>(5) = 0.583  
pAUC<sub>test</sub><sup>8-95</sup> = 0.774  
AUC<sub>test</sub><sup>ss</sup> = 0.809  
AUC<sub>test</sub><sup>lg,ss</sup> = 0.689  
log(ROR)



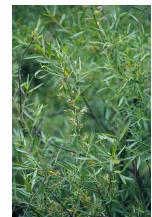
2050: RCP 8.5



2070: RCP 8.5



Salix geyeriana





# Outline

## Case study

## Types of extrapolation

- Environment\*
- Space
- Time

## Uncertainty

- Modeling decisions
- Parameters
- Future Scenarios

Where can  
biology provide  
guidance?



# Case Study

# Projected regional distribution losses of terrestrial vertebrates under different climate and land-use change scenarios

# Goals

Forecast potential range loss for ~20k



---

How do

***land use change and climate change***

contribute to

***EXPECTED RANGE LOSS*** this century?



# Informing IPBES



## International Panel on Biodiversity and Ecosystem Ser

‘provides policymakers with **objective scientific assessments** about the state of knowledge regarding the planet’s **biodiversity, ecosystems** and the benefits they provide to people’

# Informing IPBES



New Results

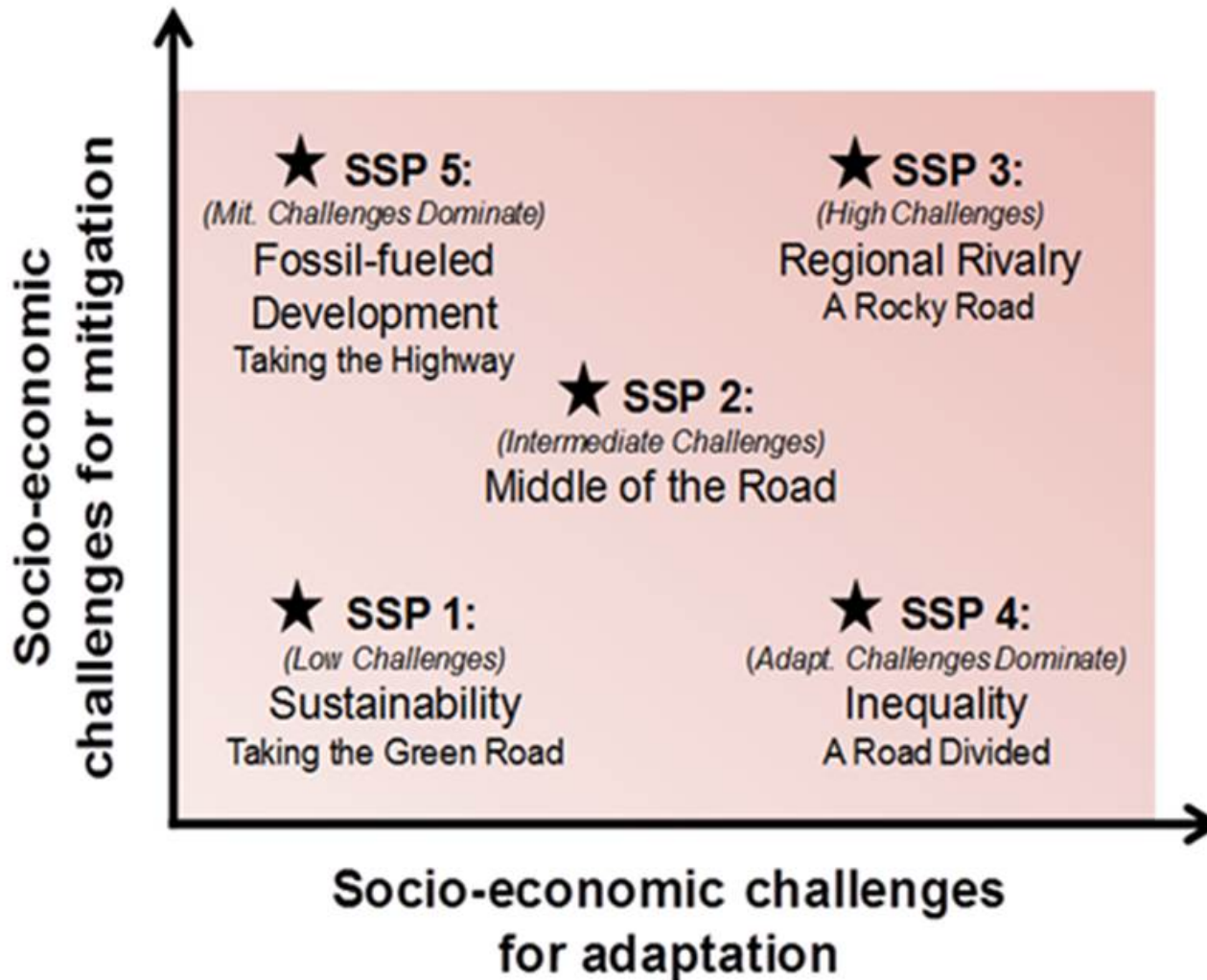
[View current version of this article](#)

## **A protocol for an intercomparison of biodiversity and ecosystem services models using harmonized land-use and climate scenarios**

Hyejin Kim, Isabel M.D. Rosa, Rob Alkemade, Paul Leadley, George Hurtt, Alexander Popp, Detlef van Vuuren, Peter Anthoni, Almut Arneth, Daniele Baisero, Emma Caton, Rebecca Chaplin-Kramer, Louise Chini, Adriana De Palma, Fulvio Di Fulvio, Moreno Di Marco, Felipe Espinoza, Simon Ferrier, Shinichiro Fujimori, Ricardo E. Gonzalez, Maya Gueguen, Carlos Guerra, Mike Hartfoot, Thomas D. Harwood, Tomoko Hasegawa, Vanessa Haverd, Petr Havlik, Stefanie Hellweg, Samantha L.L. Hill, Akiko Hirata, Andrew J. Hoskins, Jan H. Janse, Walter Jetz, Justin A. Johnson, Andreas Krause, David Leclere, Ines S. Martins, Tetsuya Matsui, Cory Merow, Michael Obersteiner, Haruka Ohashi, Benjamin Poulter, Andy Purvis, Benjamin Quesada, Carlo Rondinini, Aafke Schipper, Richard Sharp, Kiyoshi Takahashi, Wilfried Thuiller, Nicolas Titeux, Piero Visconti, Christopher Ware, Florian Wolf, Henrique M. Pereira

**doi:** <https://doi.org/10.1101/300632>

## THE SHARED SOCIO-ECONOMIC PATHWAYS (SSPs)



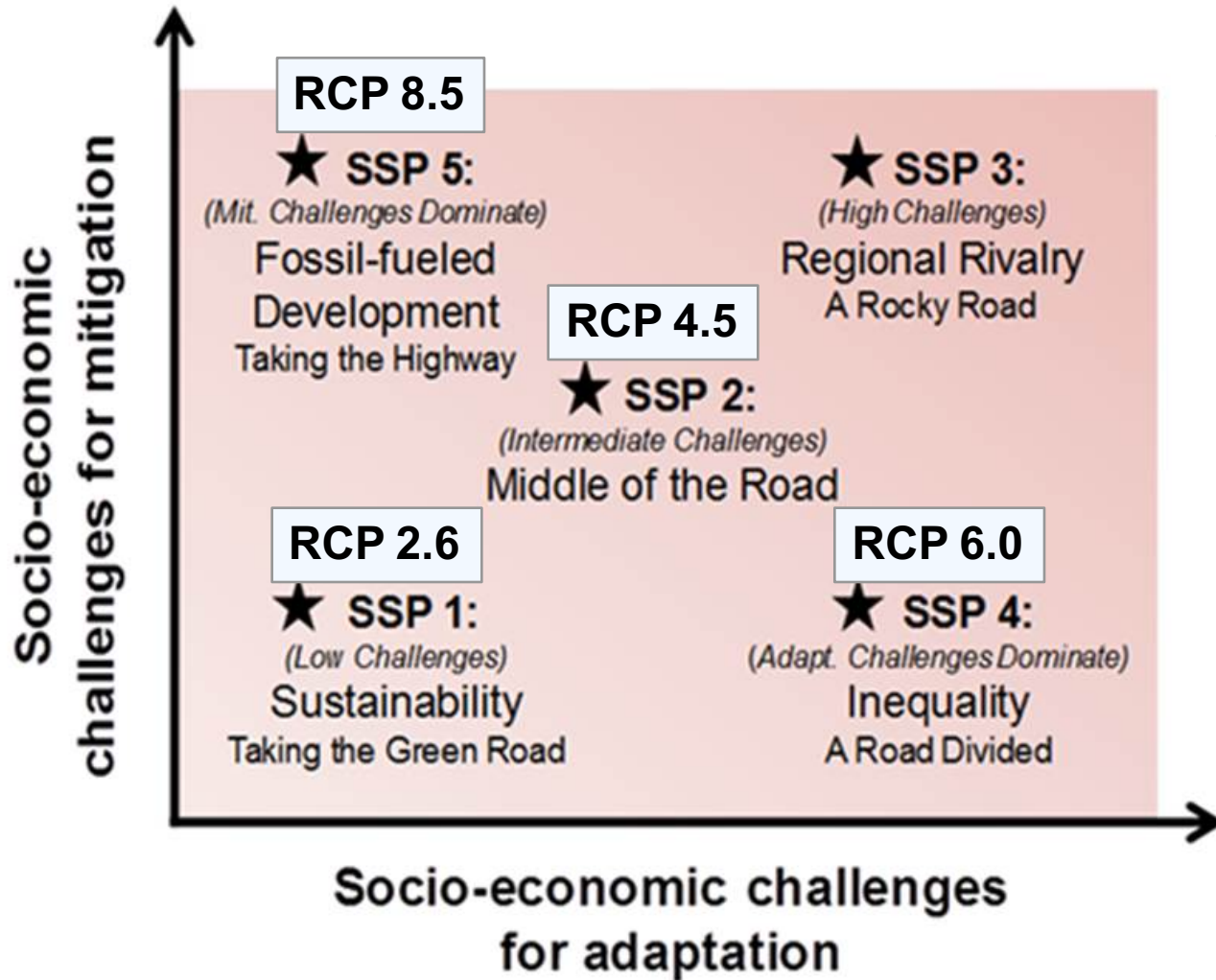
Scenarios of:

- Demographics
- Human development
- Economy and lifestyle
- Policies and institutions
- Technology
- Environment/natural resources

O'Neill et al. 2017 Glob. Env. Change

Land Use Harmonization 2 Project: [luh.umd.edu](http://luh.umd.edu)

# THE SHARED SOCIO-ECONOMIC PATHWAYS (SSPs)



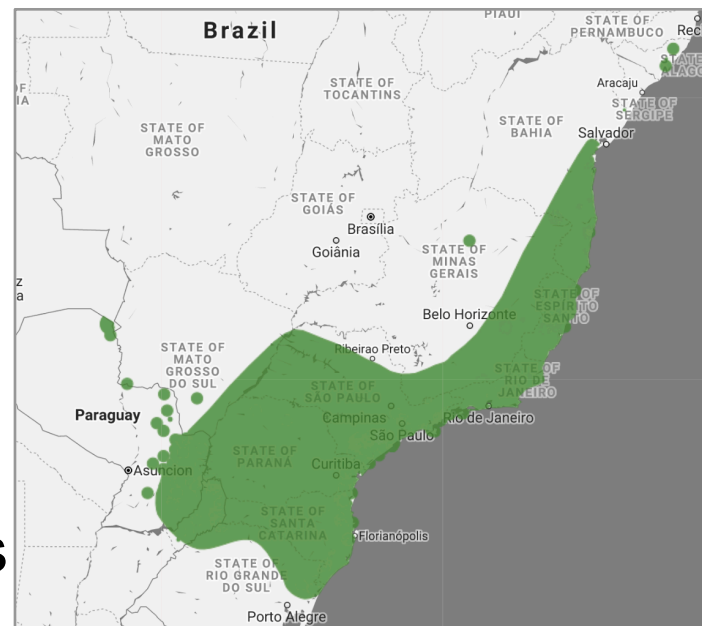
Scenarios of:

- Demographics
- Human development
- Economy and lifestyle
- Policies and institutions
- Technology
- Environment/natural resources



# Inputs

- Expert Maps
  - ~20k amphibians, mammals and birds
- Species habitat preferences
  - forest, agriculture, urban, etc.
- Present and Future Land use maps
  - .25 degree
- Present and Future Climate
- Maxnet
- Grain of predictions: .25 degree

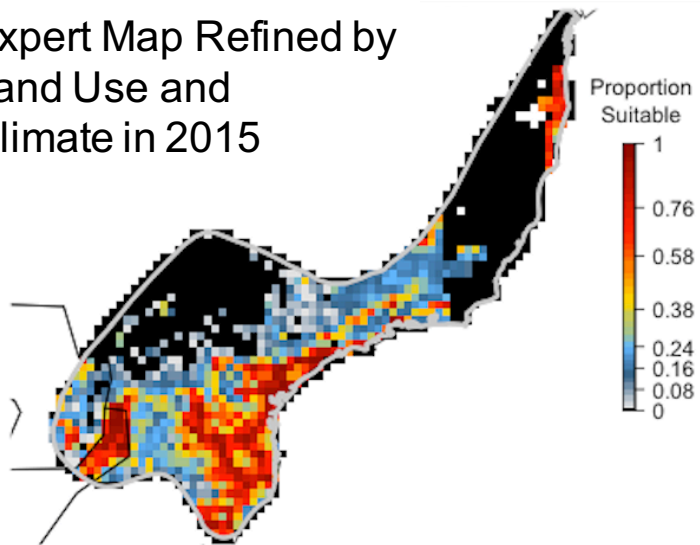


**WorldClim - Global Climate Data**

*Free climate data for ecological modeling and GIS*

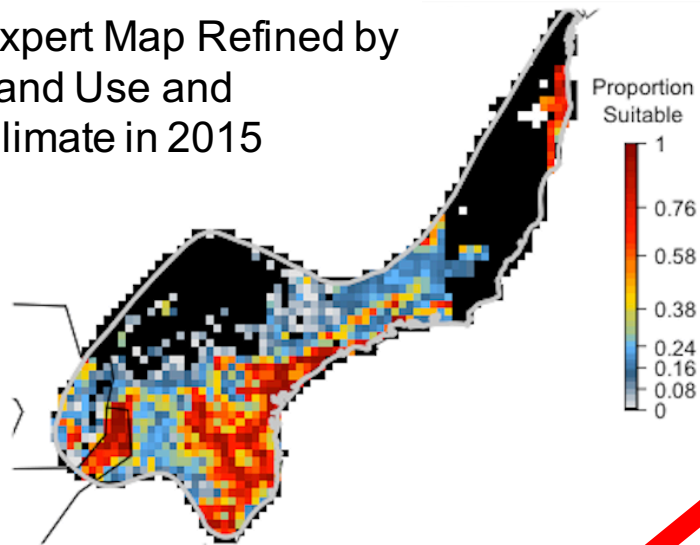
# Partitioning land use and climate losses

Expert Map Refined by  
Land Use and  
Climate in 2015

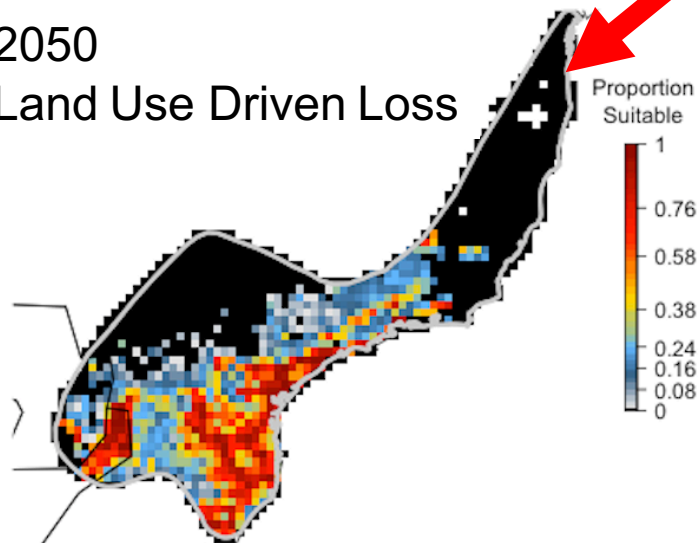


# Partitioning land use and climate losses

Expert Map Refined by  
Land Use and  
Climate in 2015

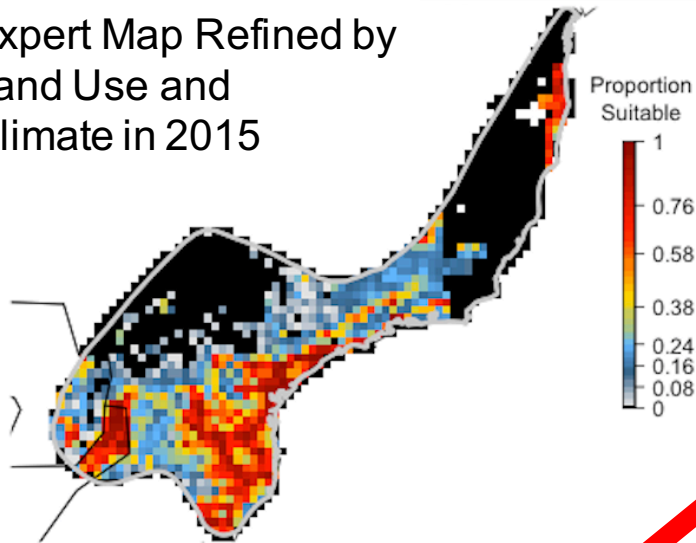


2050  
Land Use Driven Loss

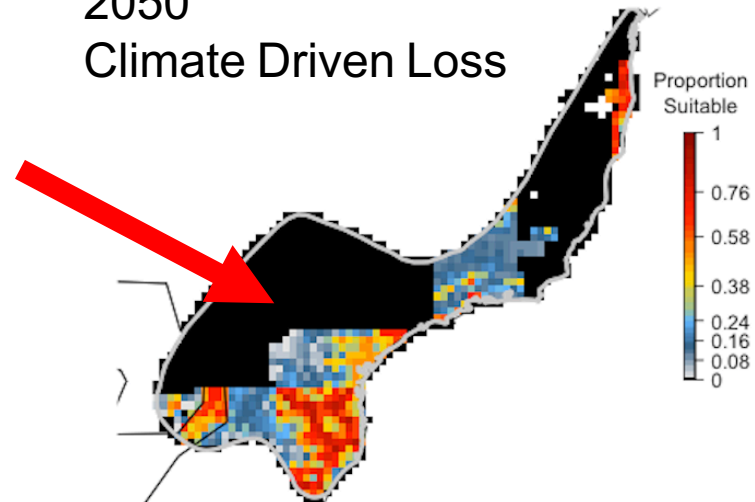


# Partitioning land use and climate losses

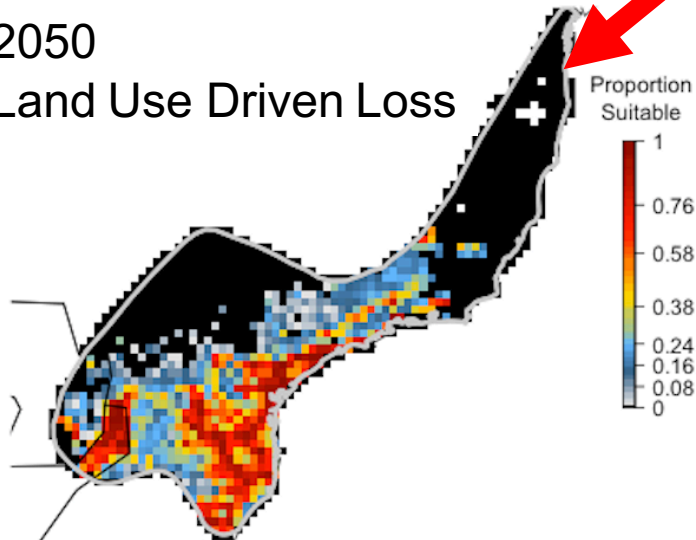
Expert Map Refined by  
Land Use and  
Climate in 2015



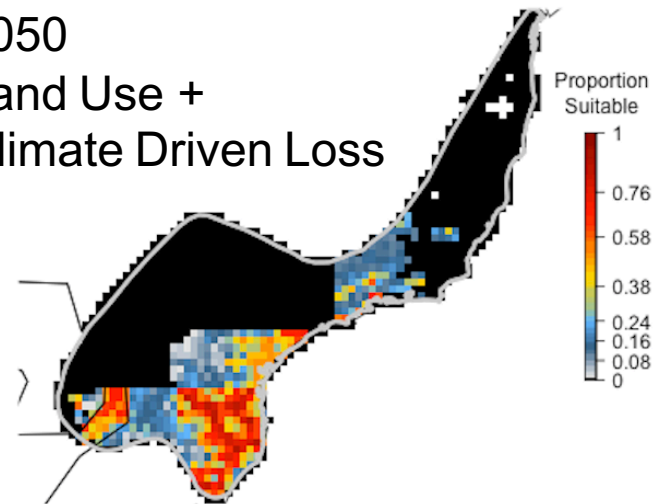
2050  
Climate Driven Loss



2050  
Land Use Driven Loss



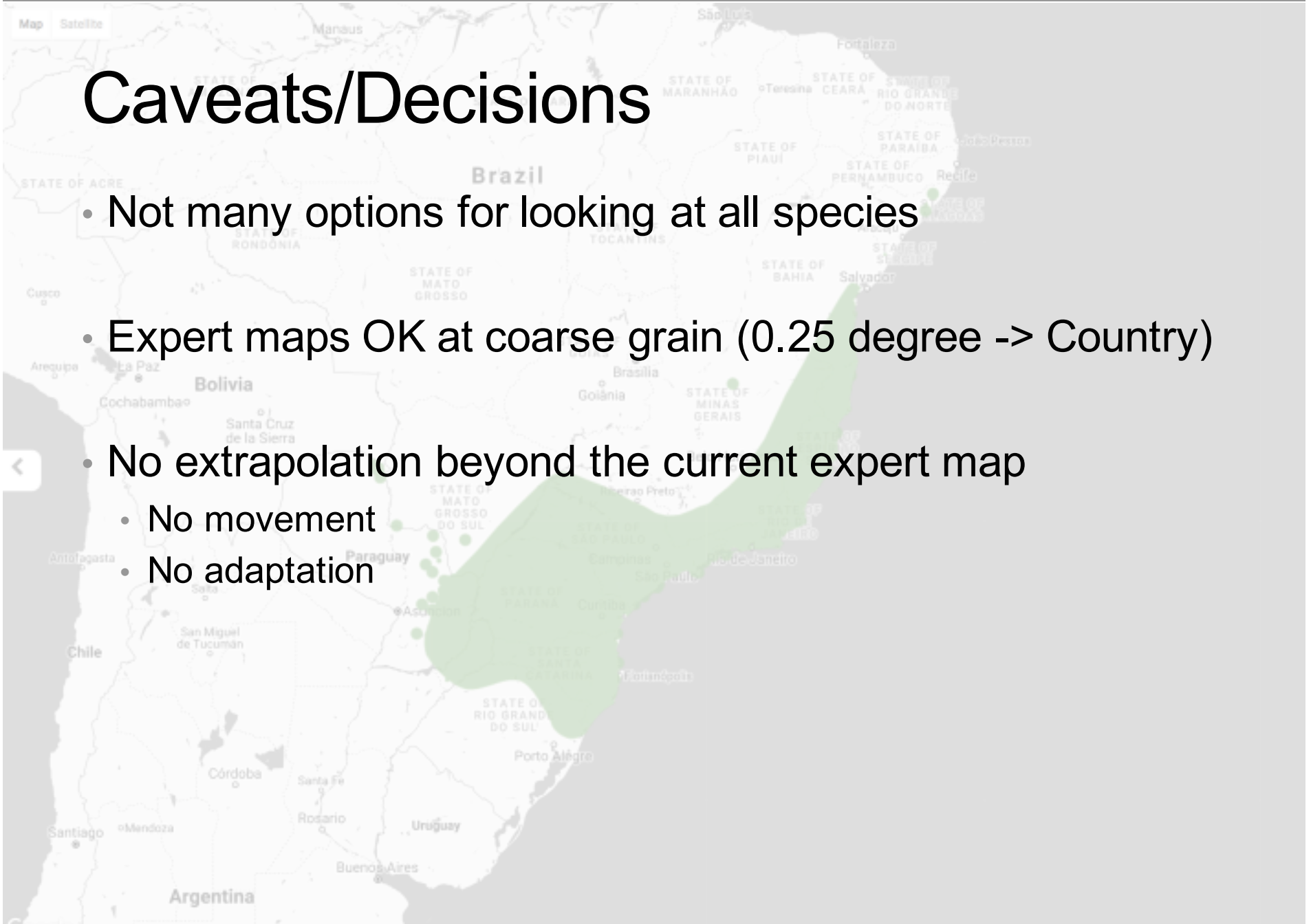
2050  
Land Use +  
Climate Driven Loss



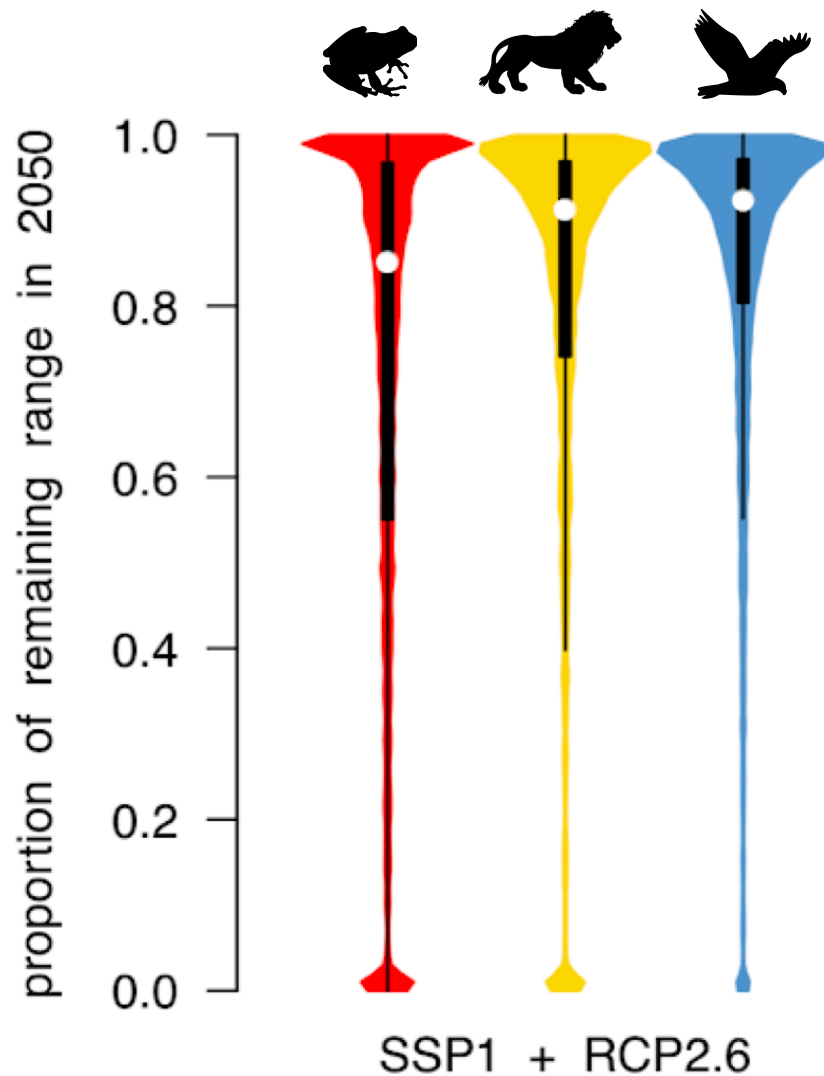


# Caveats/Decisions

- Not many options for looking at all species
- Expert maps OK at coarse grain (0.25 degree -> Country)
- No extrapolation beyond the current expert map
  - No movement
  - No adaptation



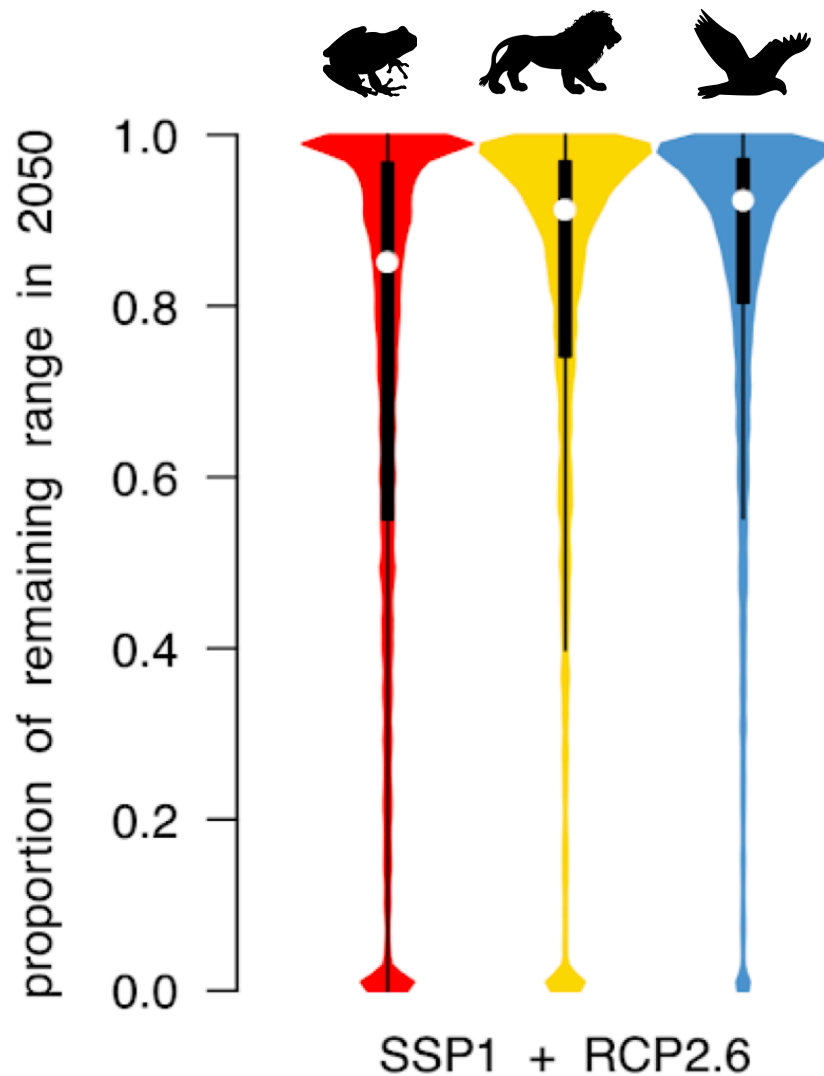
# Expected losses...



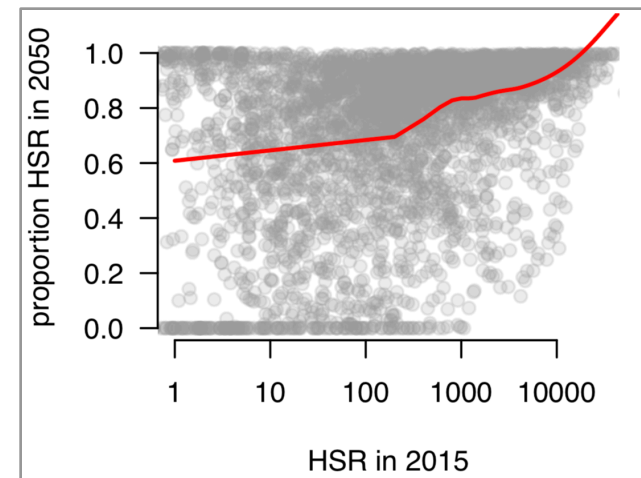
(Biased toward species you can build a model for...)

- Amphibians
- Mammals
- Birds

# Expected losses...

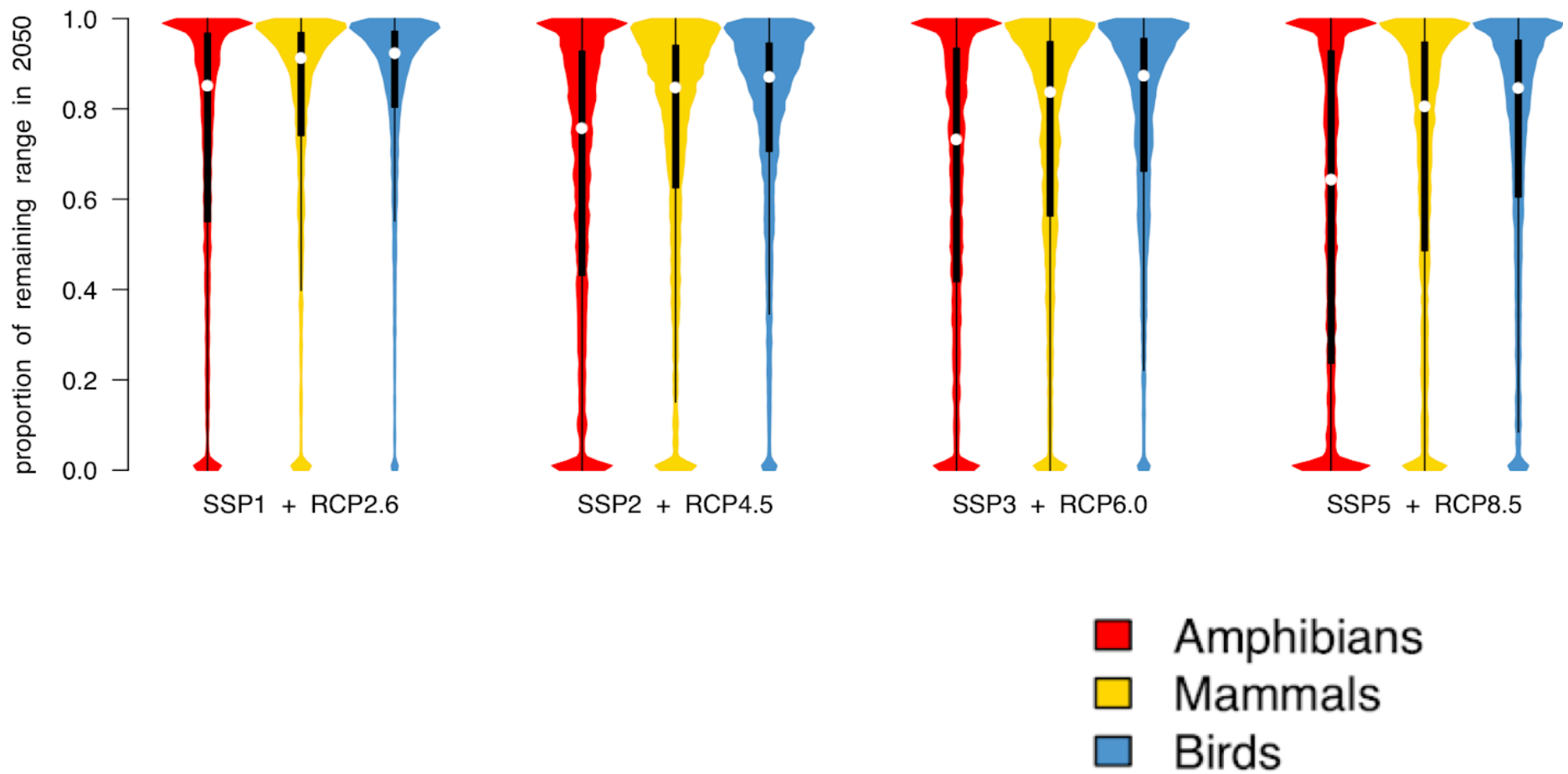


(Biased toward species you can build a model for...)

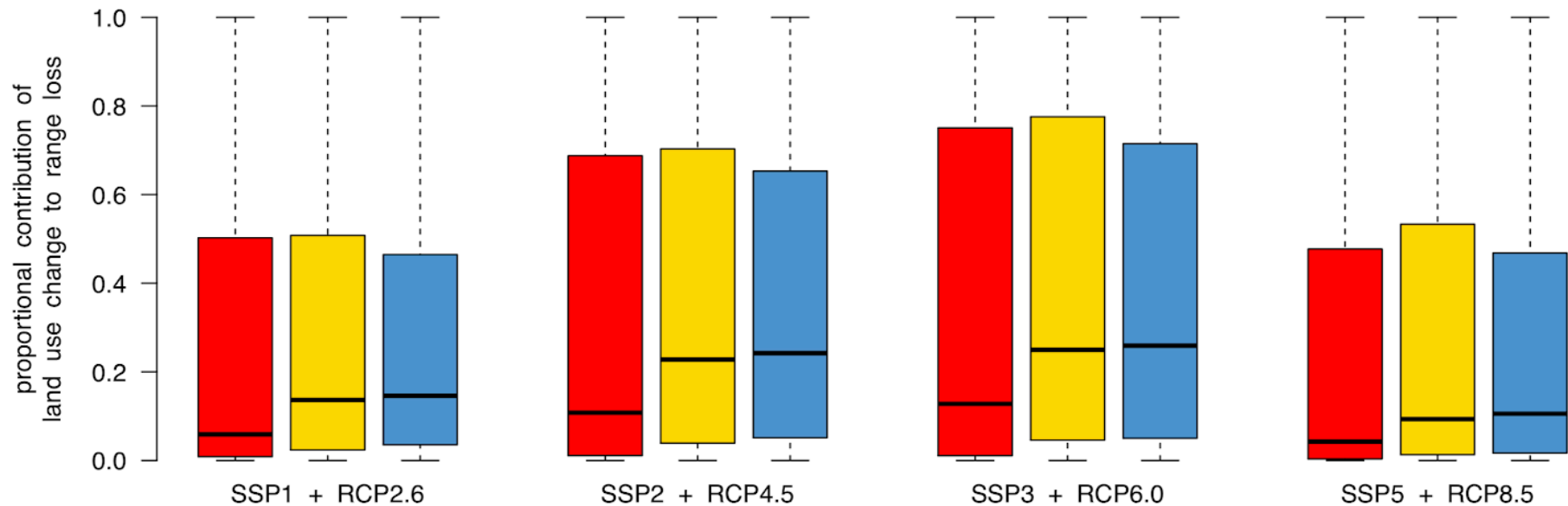


- Amphibians
- Mammals
- Birds

# Consistent trends in expected losses...



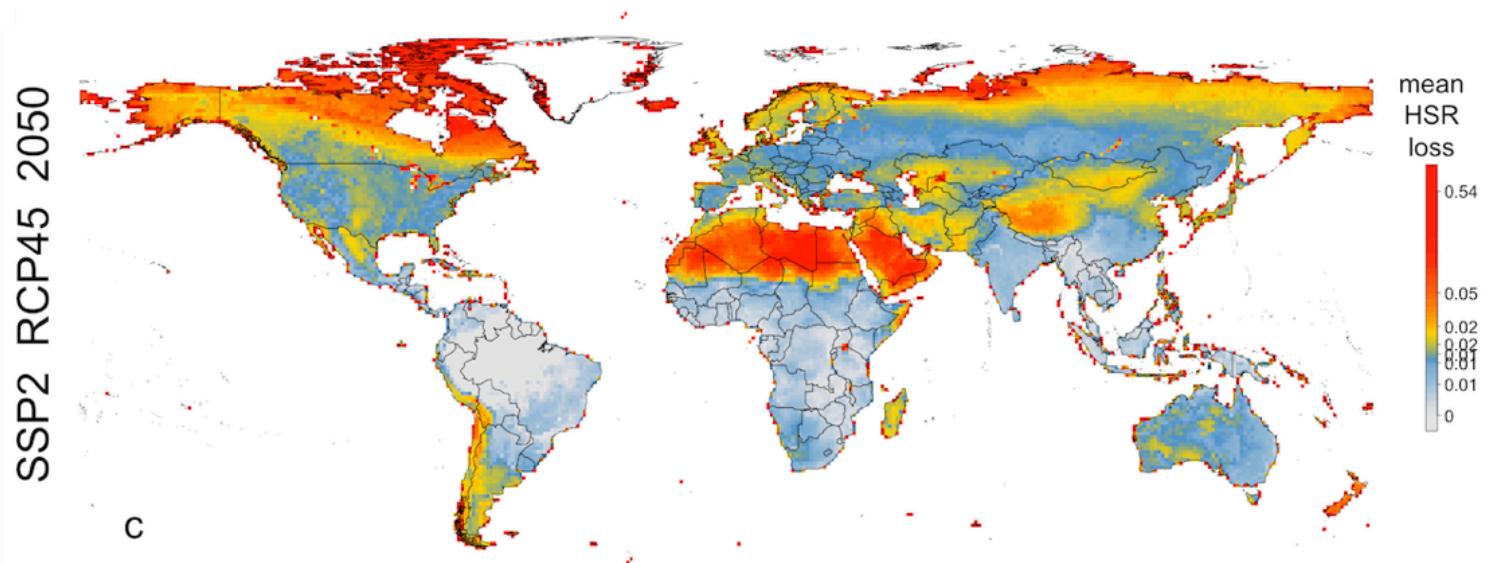
# Climate >> Land Use



- Climate has biggest effect on amphibians



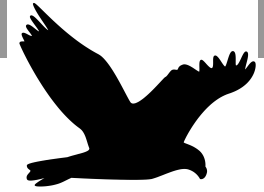
# Local loss



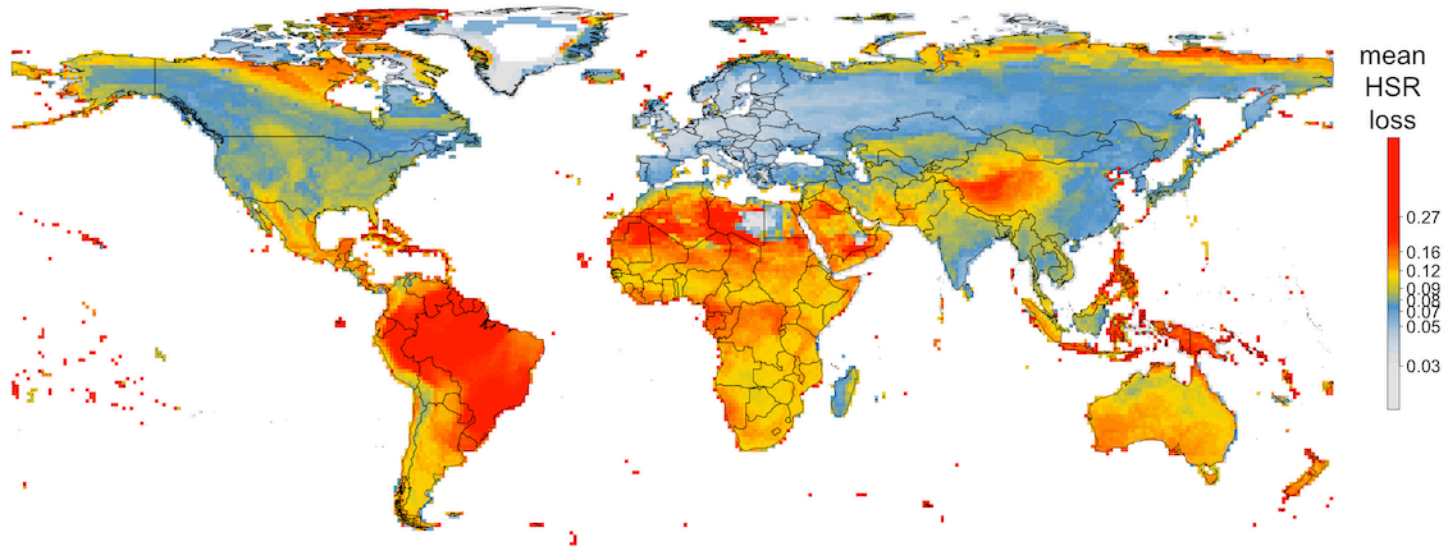
In places that are already hot, or should be cold



# How does global loss compare to local loss?



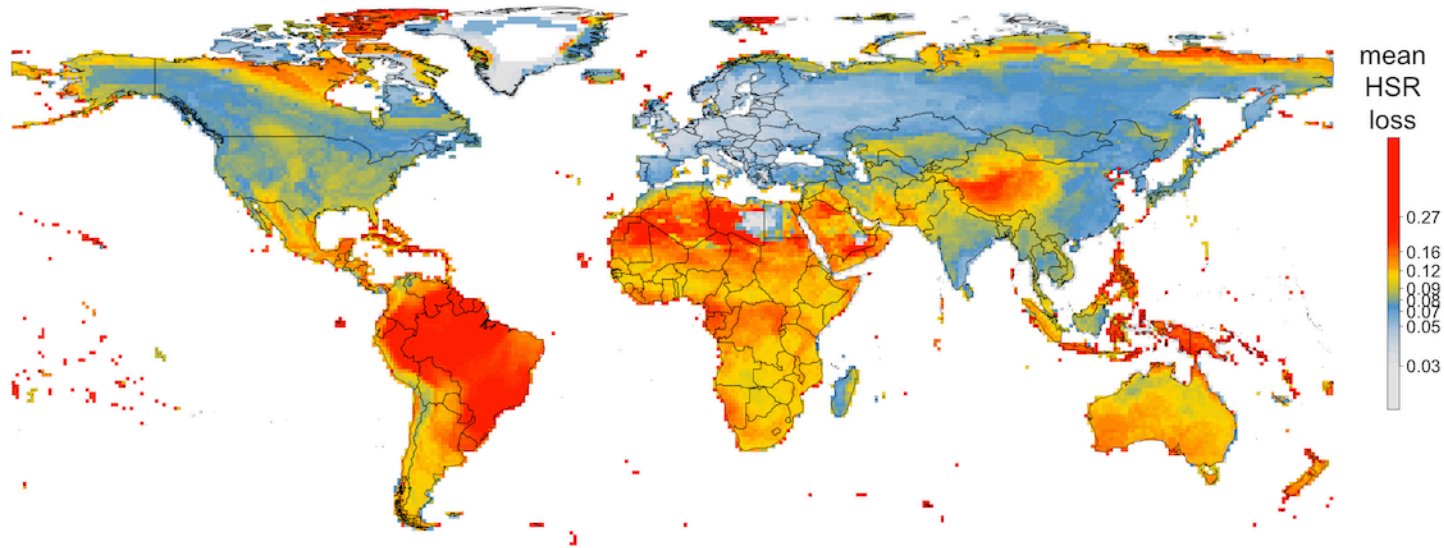
Global loss



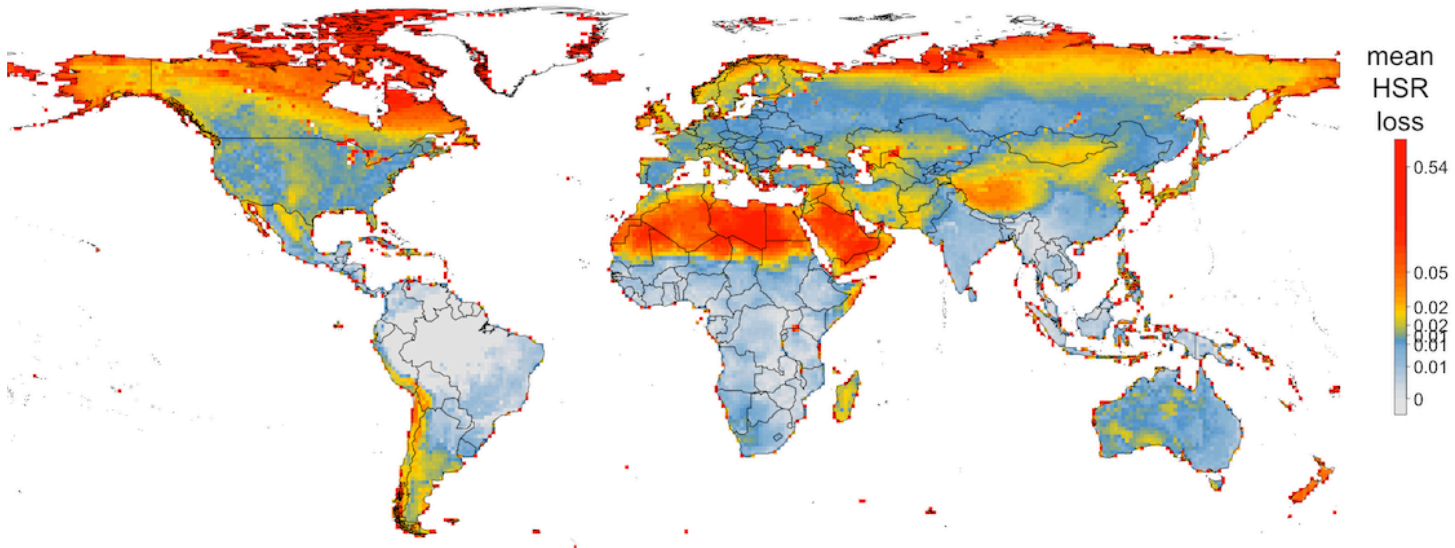
# How does global loss compare to local loss?



Global loss



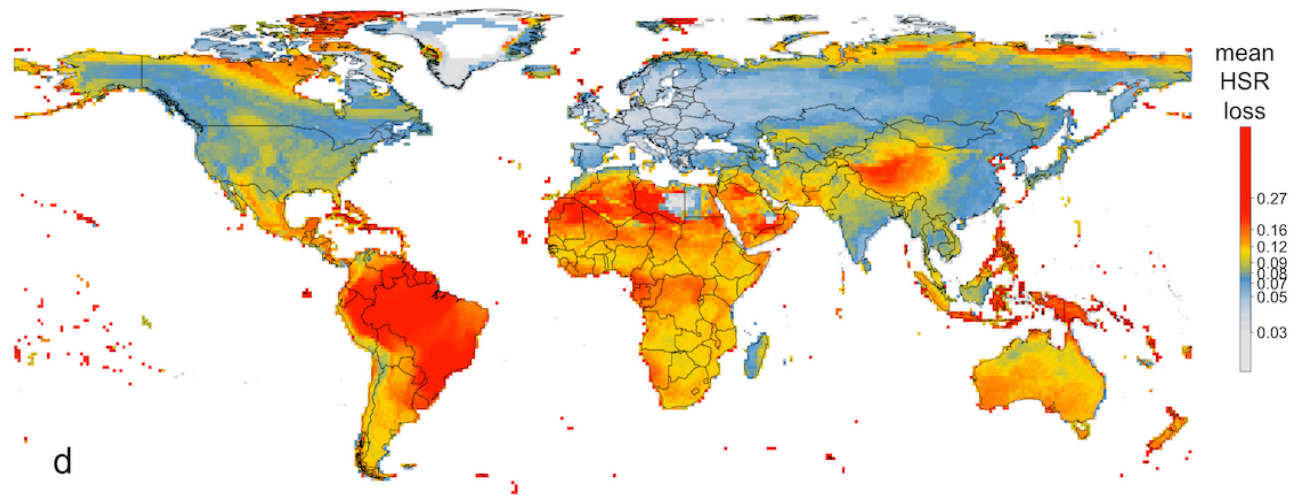
Local loss



# Contribution to climate

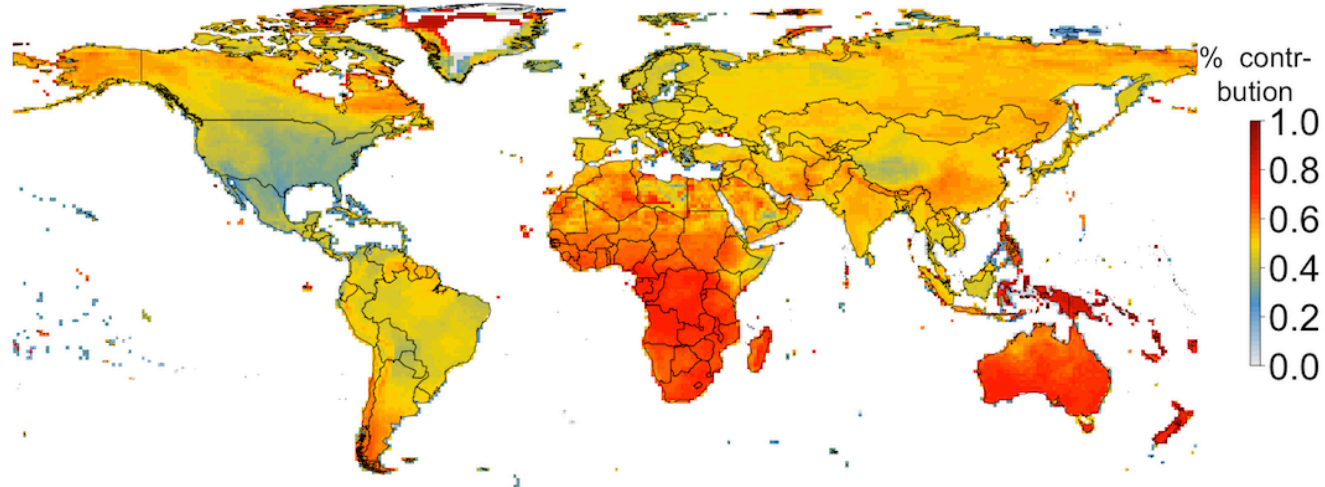


Global loss



Proportional contribution of climate

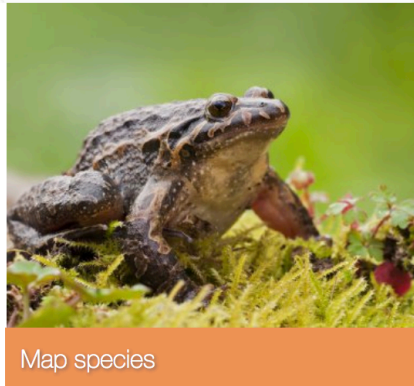
SSP2 RCP45 2050 CLIMATE



# Next steps

- Targeted conservation strategies
  - Low local loss, high global loss, low climate contribution (low risk)
  - High local loss, high global loss, low climate contribution (high risk, high reward)
- Anticipate changing stewardship
- Serve to scientific community
- Serve for policy





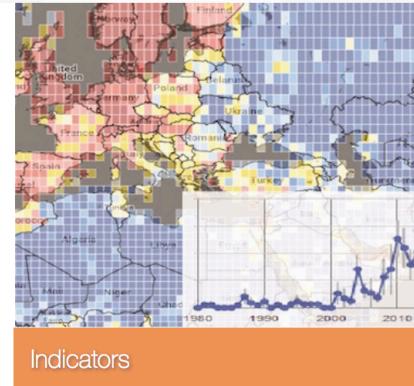
Map species

Views species range map, inventory, and occurrence data



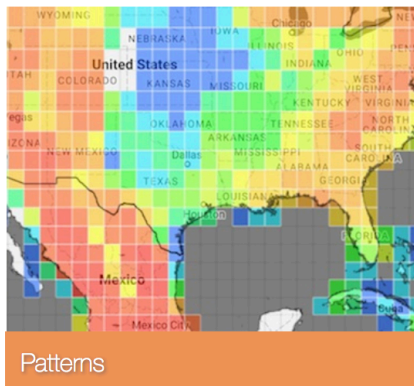
Species by location

Select a location, filter by distance or group, and view a list of species along with source data



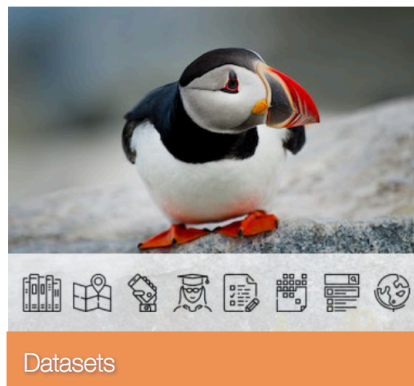
Indicators

Explore trends in biodiversity knowledge, distribution, and conservation



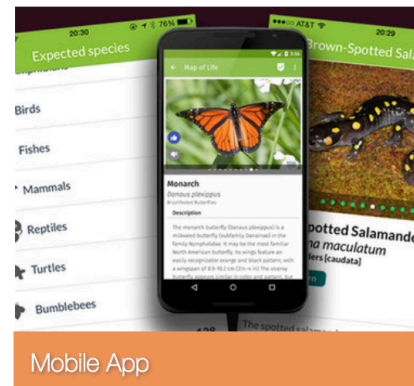
Patterns

Explore richness patterns and biodiversity facets



Datasets

Explore datasets used across MOL



Mobile App

Discover, identify, and record biodiversity worldwide



Shared Socio-Economic Pathway

SSP 2 (RCP 4.5)

Projection Year (Map)

2050

Habitat Regain Assumption

No-regain

Regain

Get habitat projection



Suitable elevation: -500 to 1300 meters

Suitable tree cover: 75 to 100%

Suitable land-cover categories:

Forest

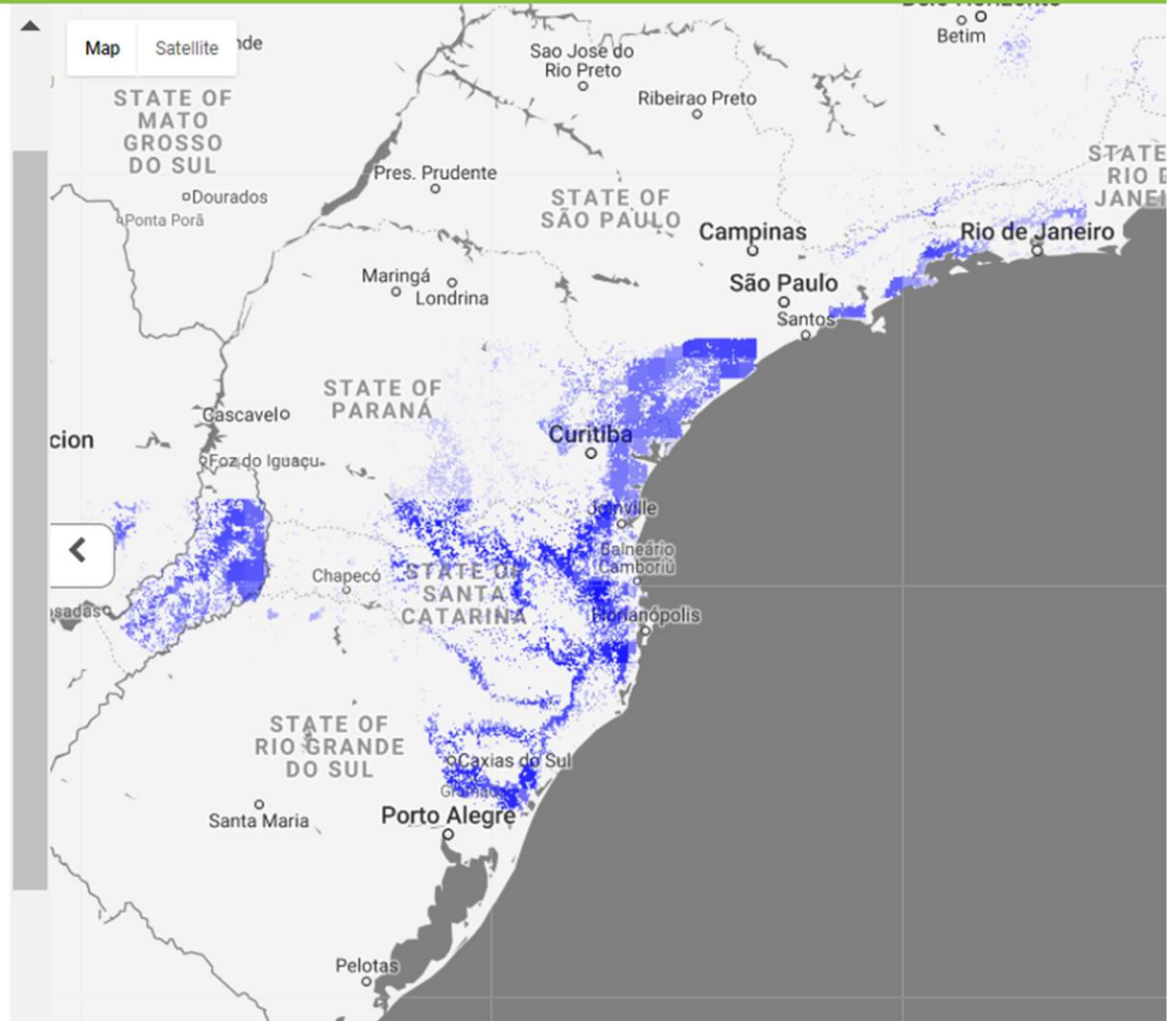
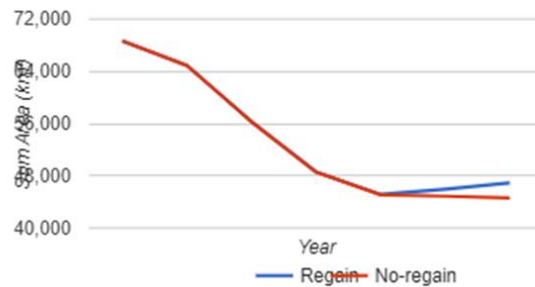
Non-Forest

Managed Land

Urban

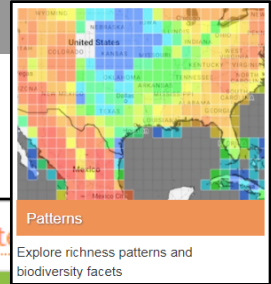
Crop

Suitable Habitat Trend





# Biodiversity Patterns



**MOL MAP OF LIFE**

login/register

Species Locations Indicators Patterns

Overview Biodiversity Facets Background

Map Satellite

Mammals Functional Endemism

Cell area protected:  $\geq 10\%$

Reserve type:  Strict  All

UN environment WCMC

0.40

Google MOL MAP OF LIFE

Map data ©2017 Google, INEGI Terms of Use



# Conclusions

Climate >> land use

Environmental change alone doesn't predict loss

Priorities for loss

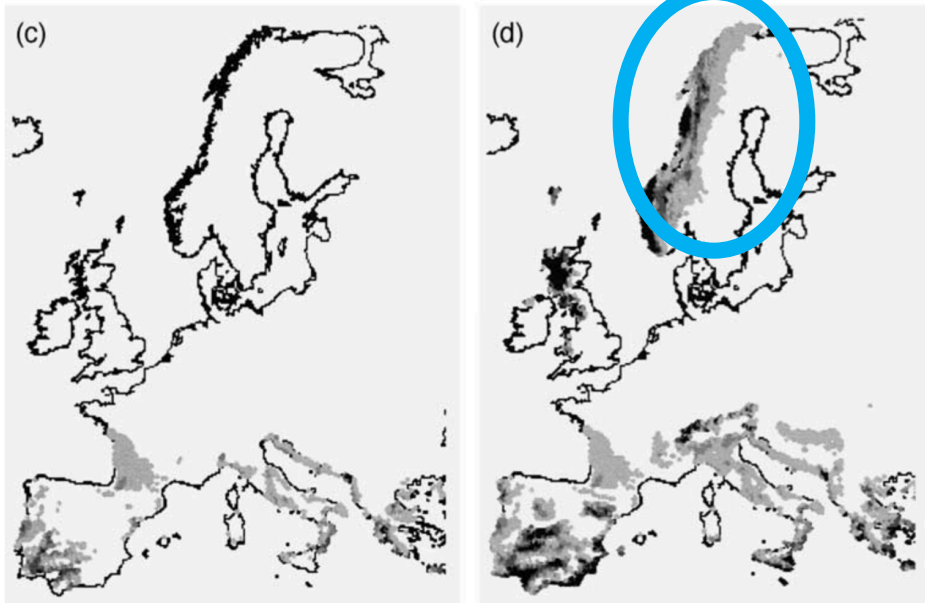


# Environmental Extrapolation

What assumptions were made?

# Extrapolation

clamping



Thullier et al. 2004

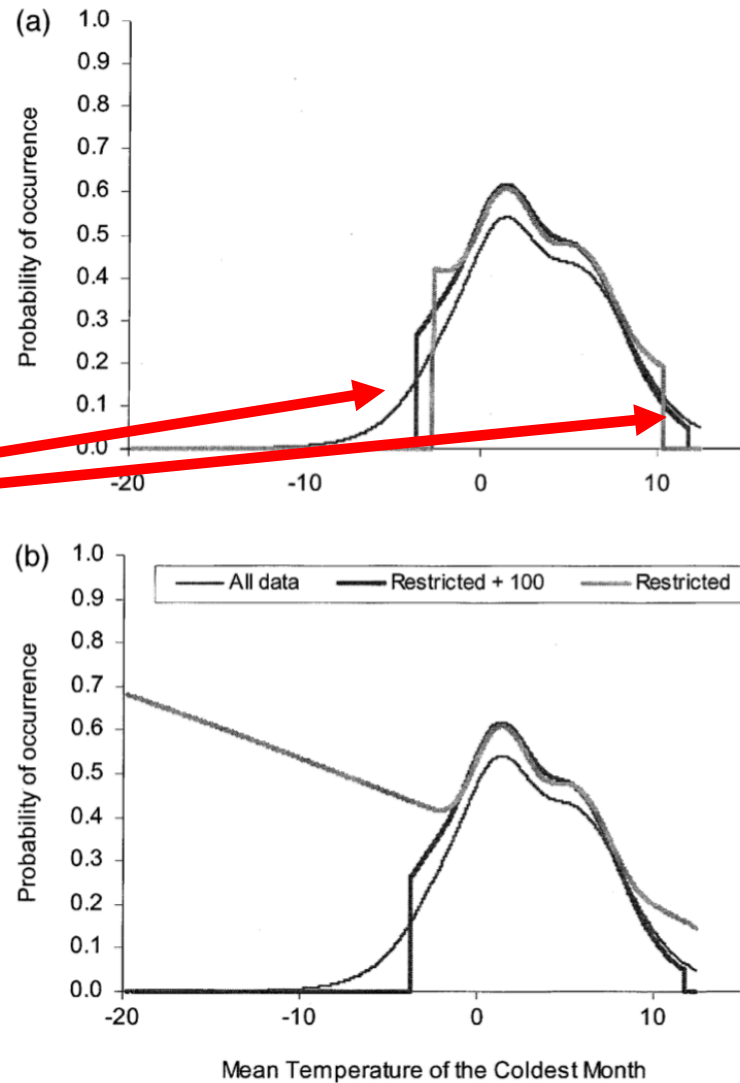
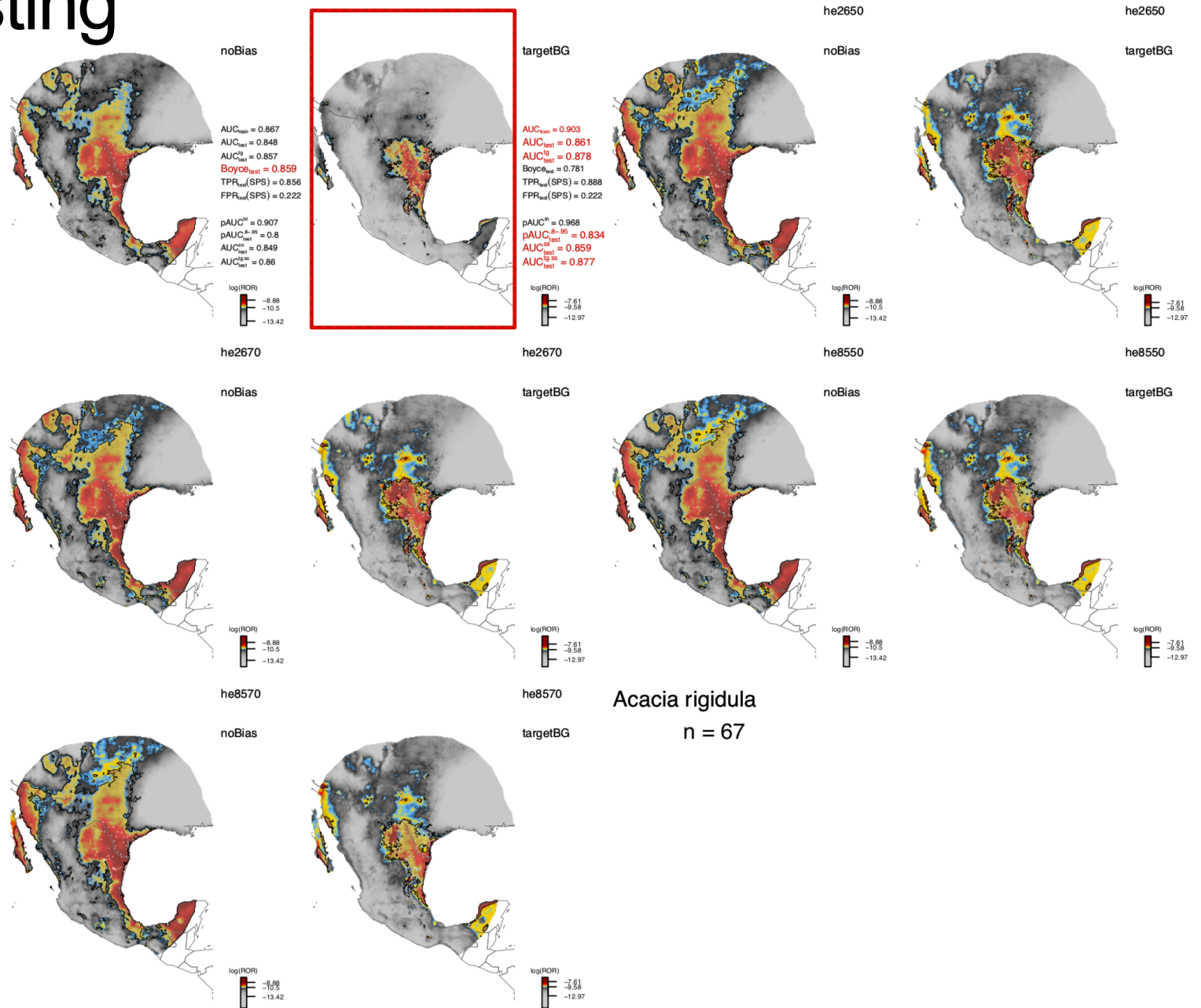


Fig. 2. Projections of response curve of *Quercus crenata* on larger spectrum of climate data at finer resolution. (a) The three models setting probability values equal to zero outside the environmental limits used to calibrate models; (b) Same as (a) but without setting probability values equal to zero outside the environmental limits used to calibrate models for the restricted model.

# Forecasting



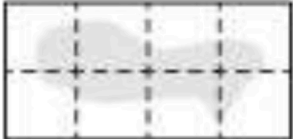
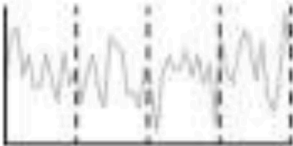

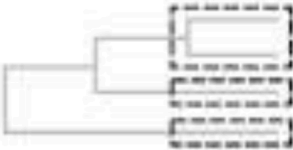


# What can we do about it?

- Don't do it
- Get more data in the range you want to predict
- Cross validation

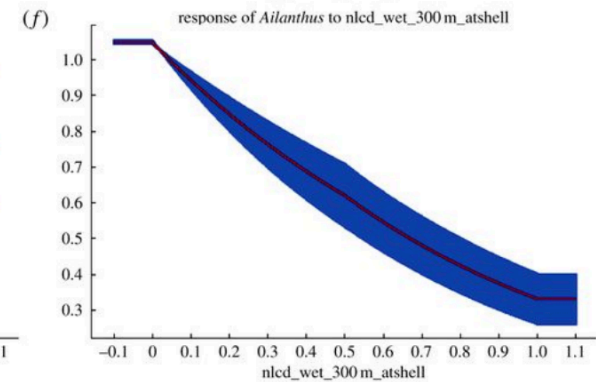
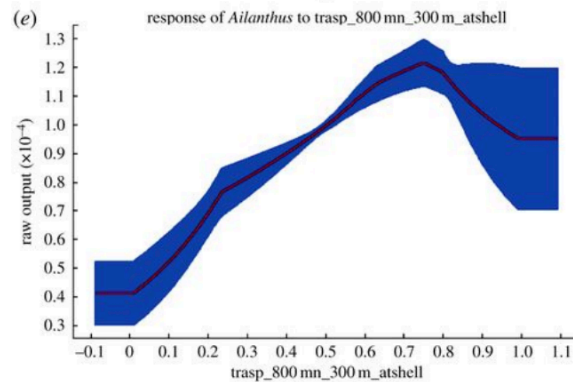
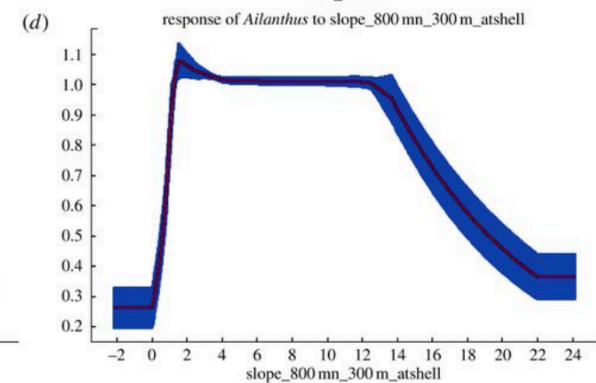
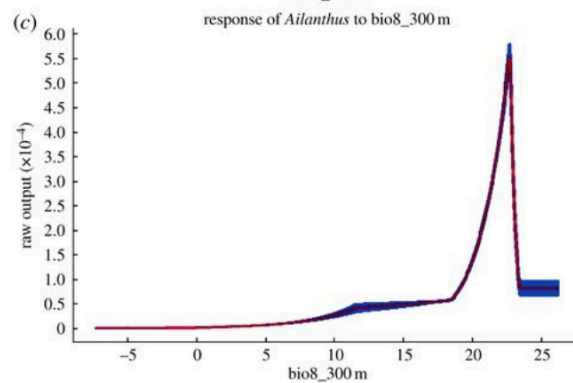


# Cross Validation

Dependence structure	Parametric solution	Blocking	Blocking illustration
Spatial	Spatial models (e.g. CAR, INLA, GWR)	Spatial	
Temporal	Time-series models (e.g. ARIMA)	Temporal	
Grouping	Mixed effect models (e.g. GLMM)	Group	
Hierarchical / Phylogenetic	Phylogenetic models (e.g. PGLS)	Hierarchical	

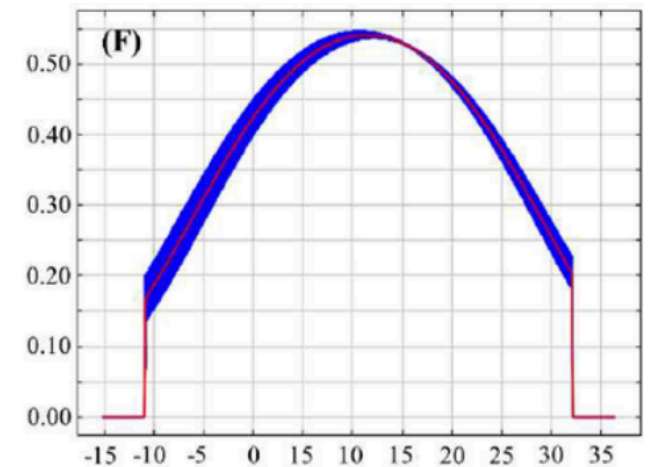
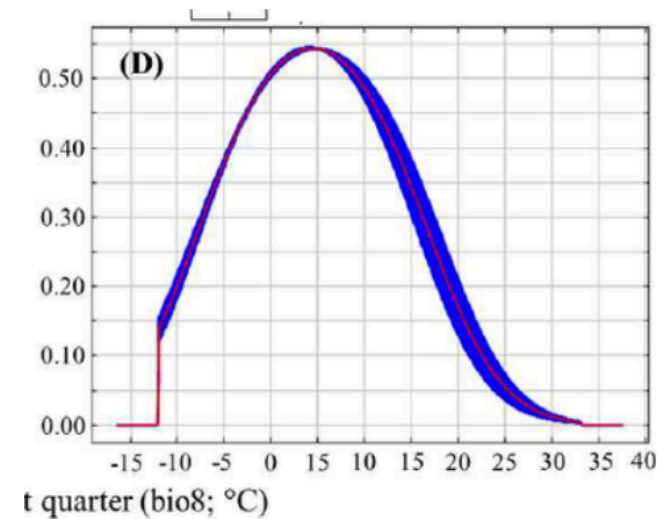
# What can we do about it?

- Don't do it
- Get more data in the range you want to predict
- Cross validation
- **Constrain it**



# What can we do about it?

- Don't do it
- Get more data in the range you want to predict
- Cross validation
- Constrain it
- **Make a heuristic argument that its ok**



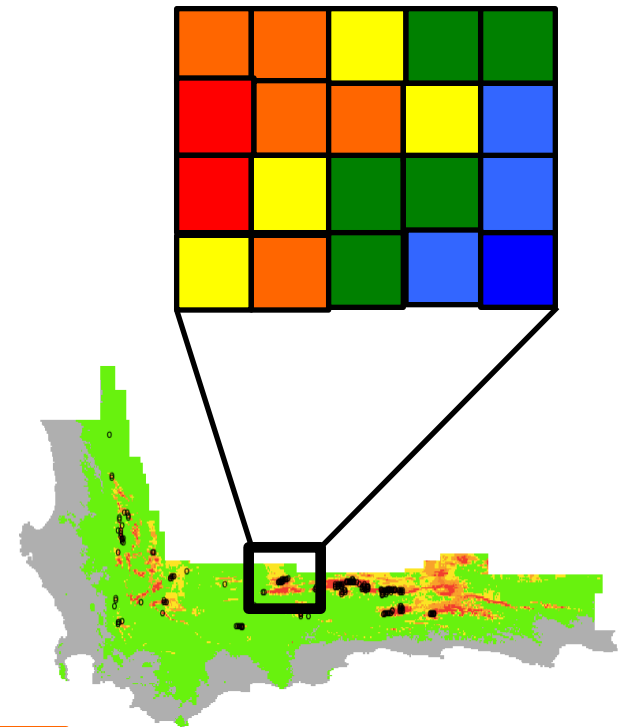
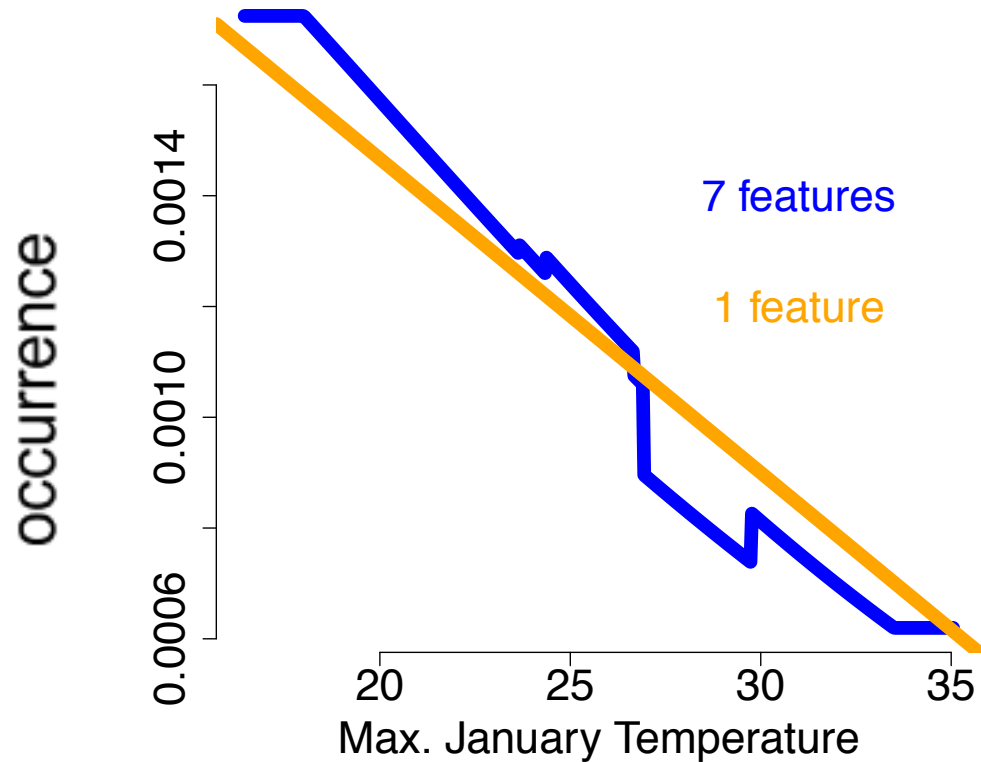
# What can we do about it?

- Don't do it
- Get more data in the range you want to predict
- Cross validation
- Constrain it
- Make a heuristic argument that its ok
- **Make a mechanistic model**
- **Predict another emergent pattern to validate the extrapolation with a different type of data**

---

# Spatial Extrapolation

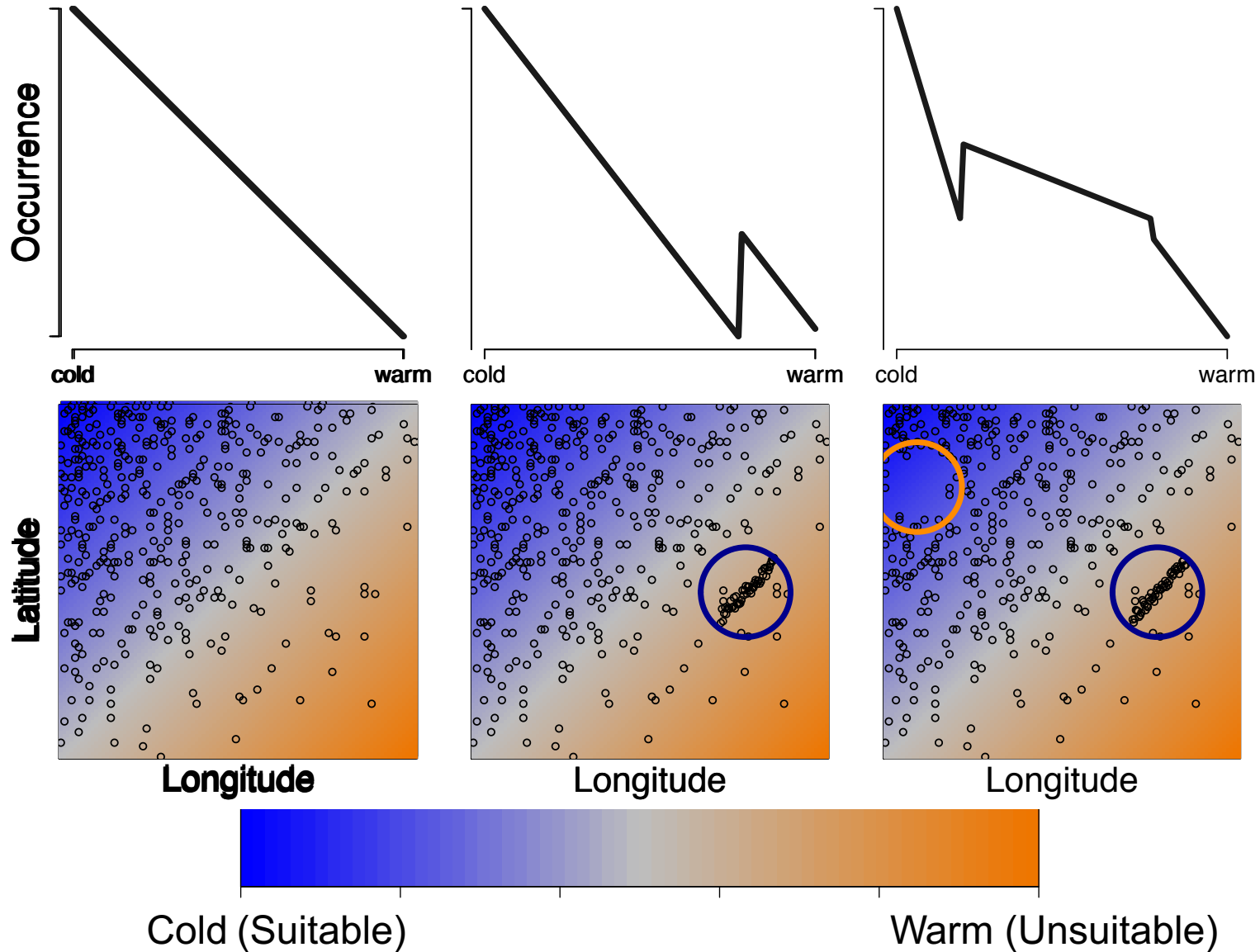
# Two cultures of SDMing



Bumps attributed to environmental response actually arise in geographic space

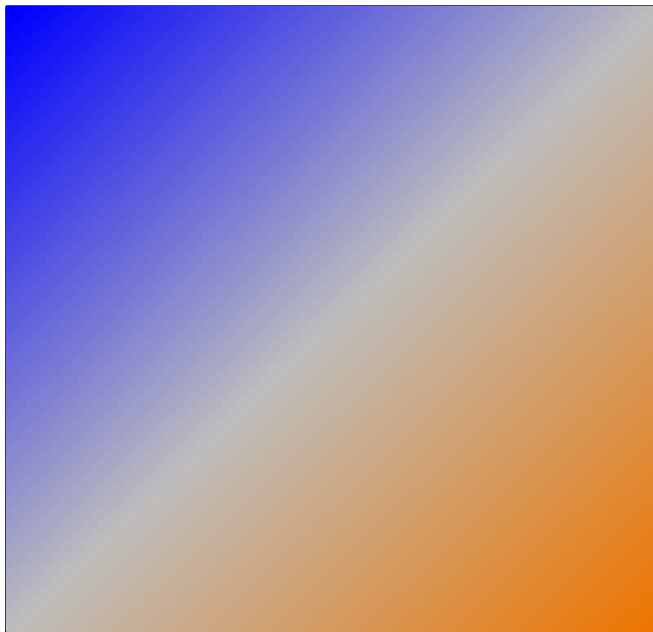


# Spatial Aggregation and Overfitting

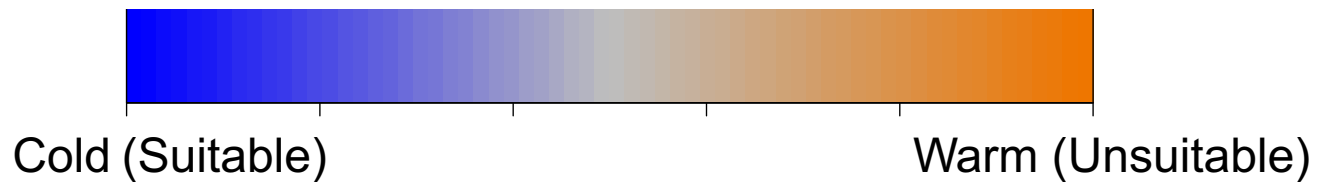
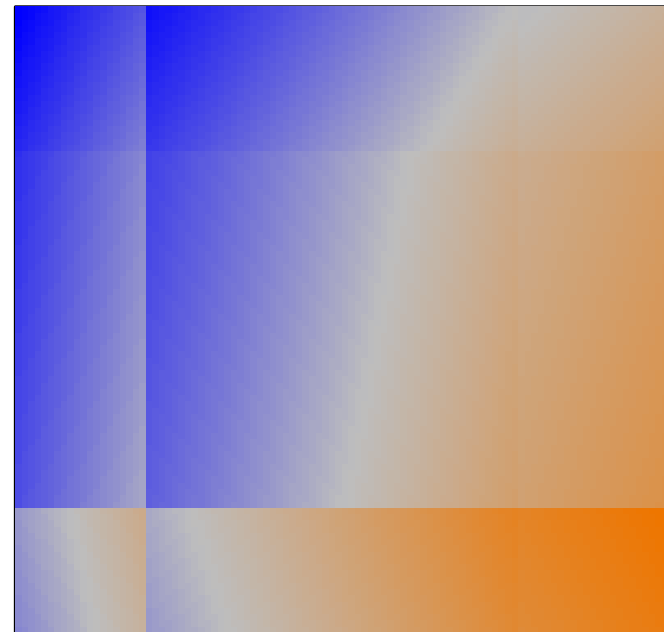


# Overfitting

True Suitability

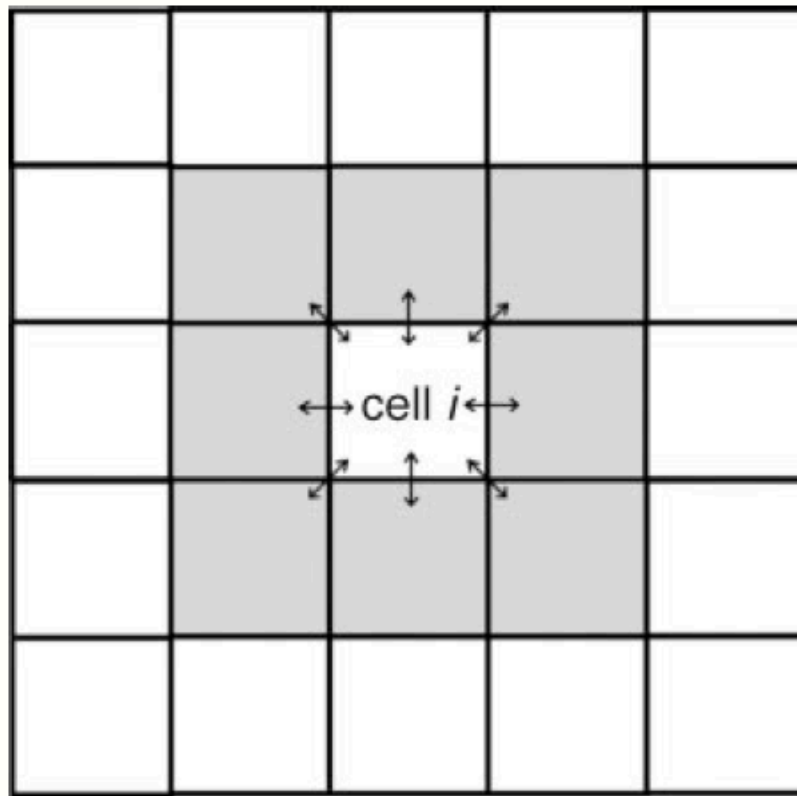


Predicted Suitability



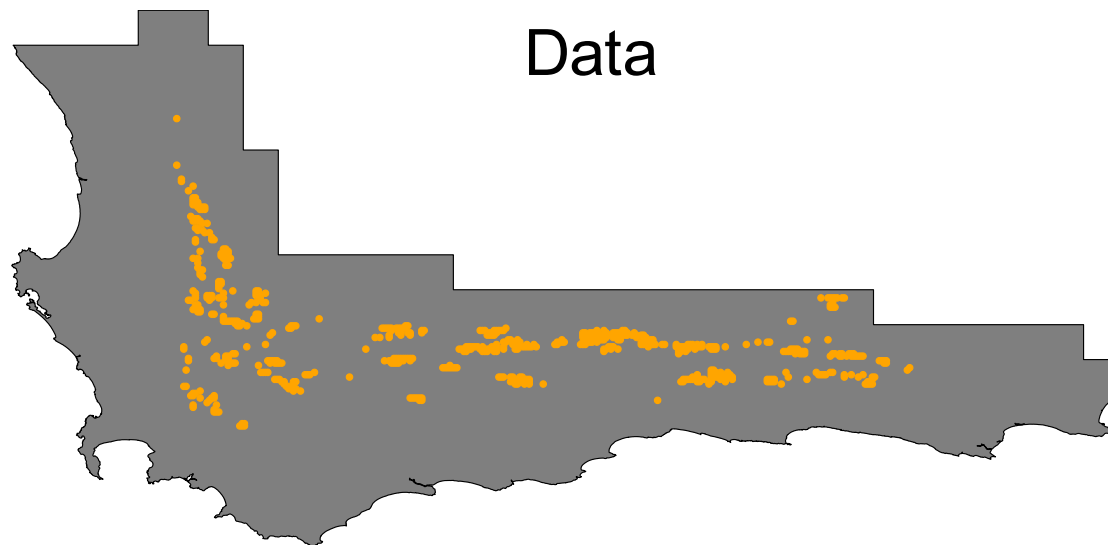
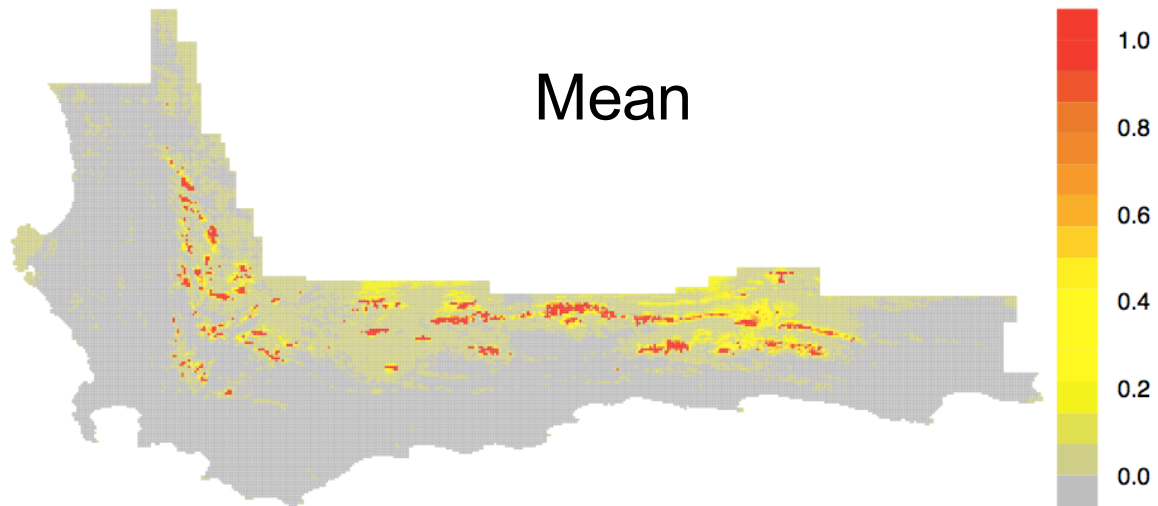
# Bayesian Spatial models

$$\text{logit}(p_i) = X_i\beta + w_i \quad \text{Spatial random intercepts}$$

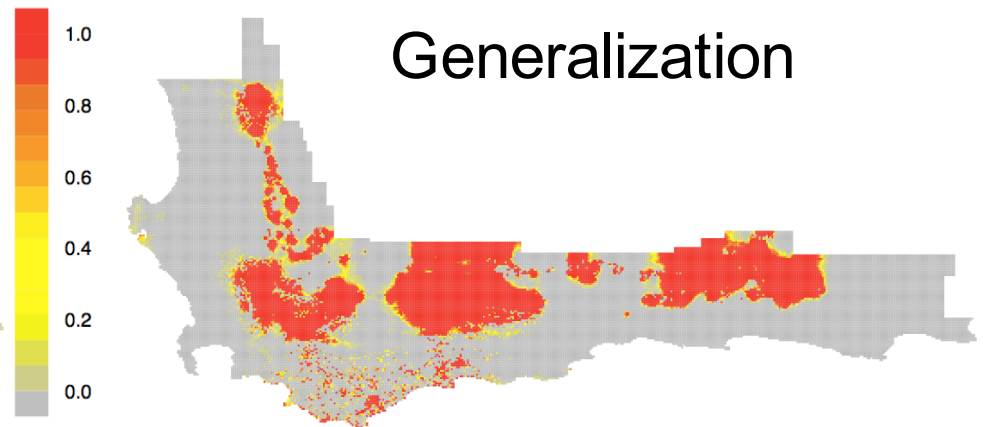
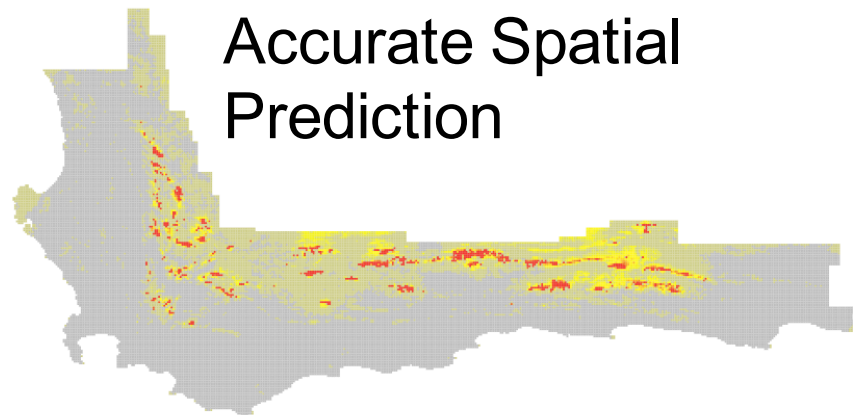
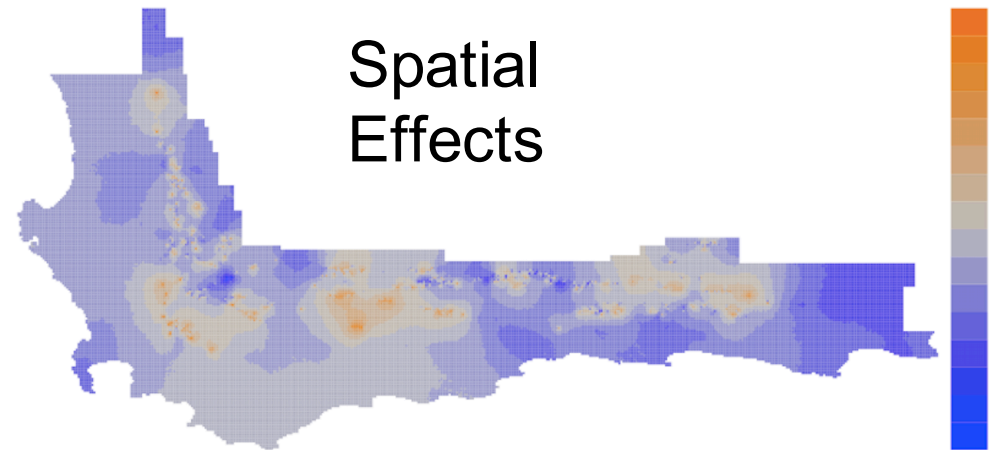
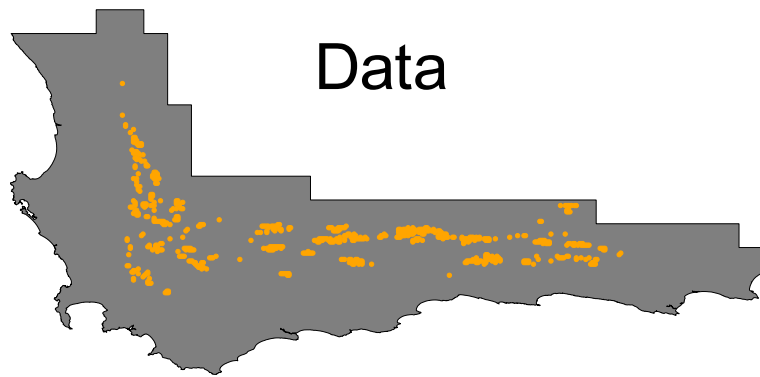


R package: hSDM

# Spatial prediction



# Spatial prediction

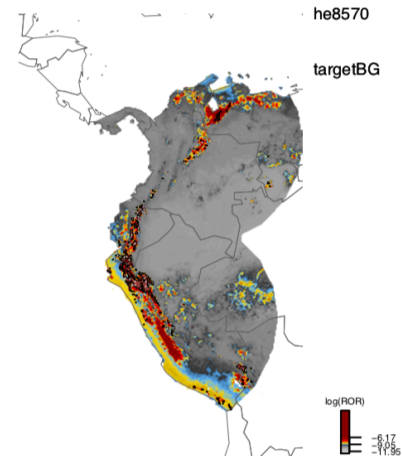
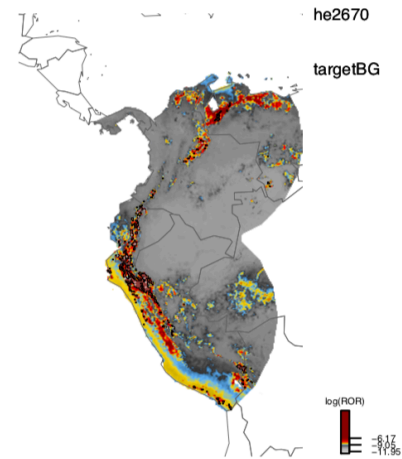
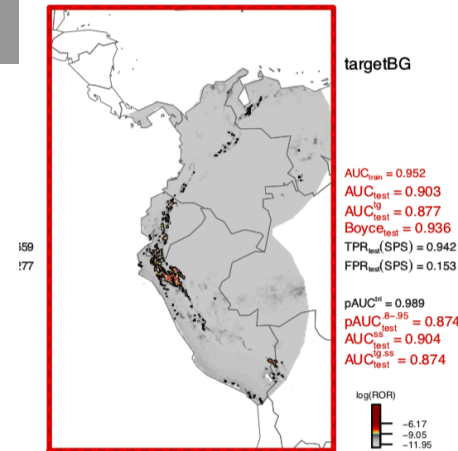




# Temporal Extrapolation

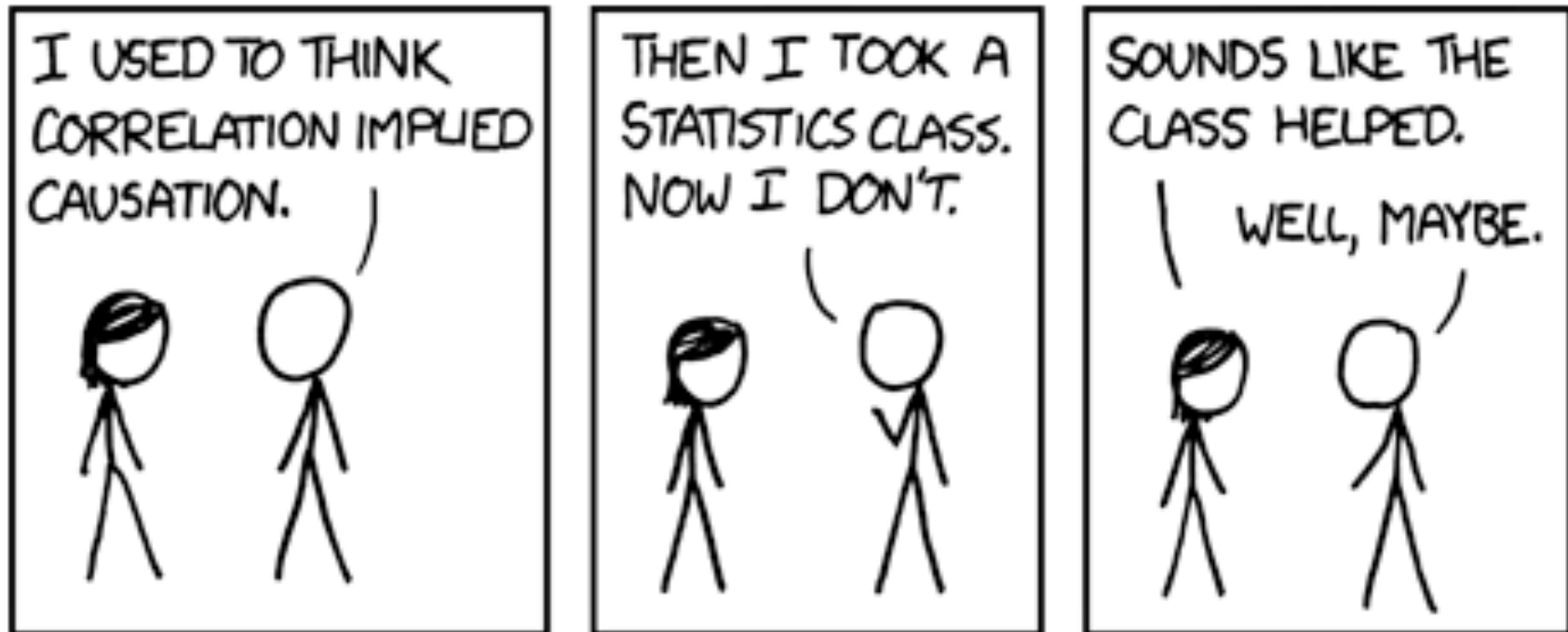
# Temporal extrapolation

Correlative models can only take you so far....



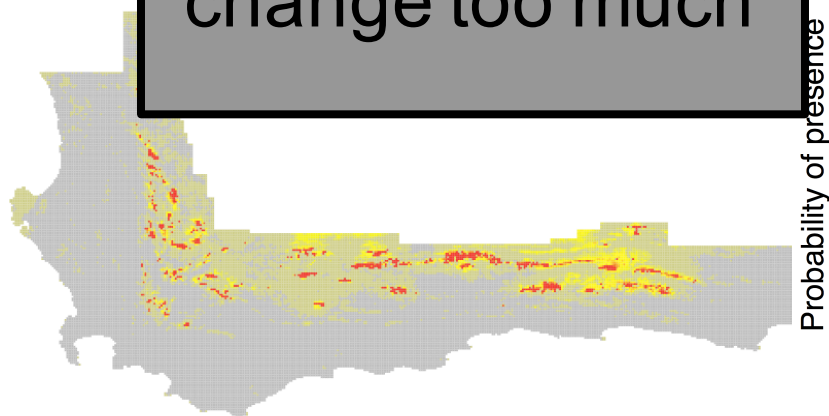
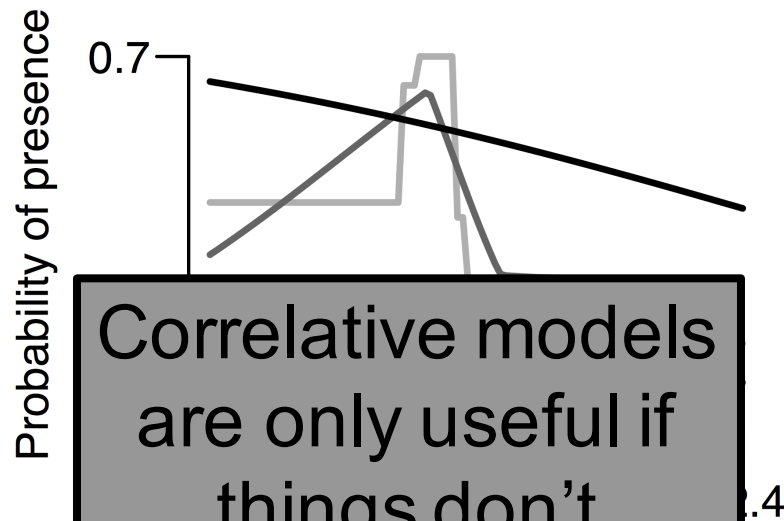
# Forecasting

And the need for mechanism...

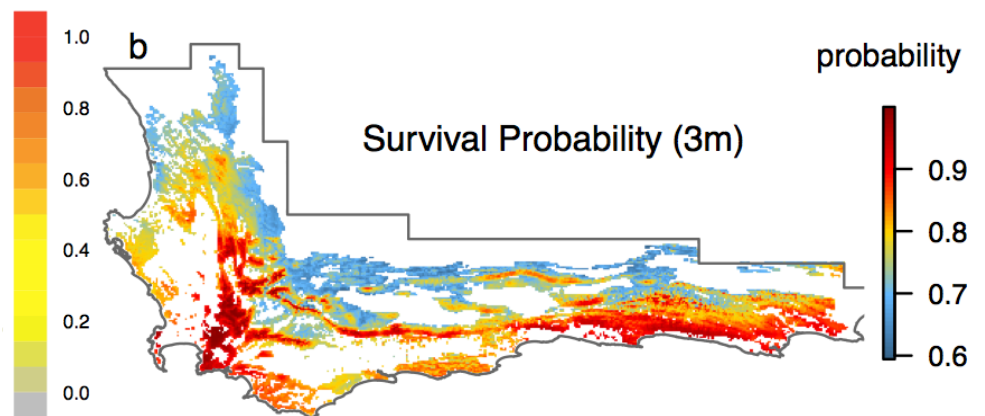
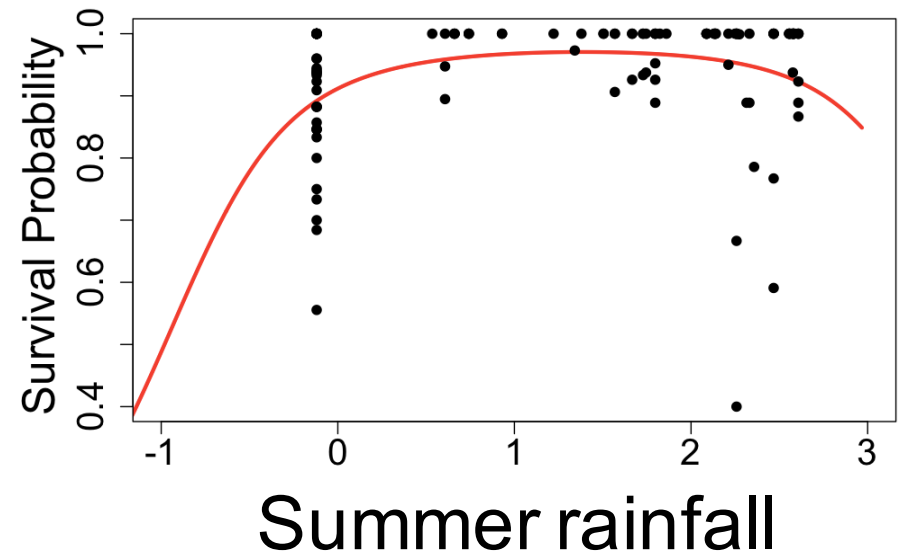




# Correlative



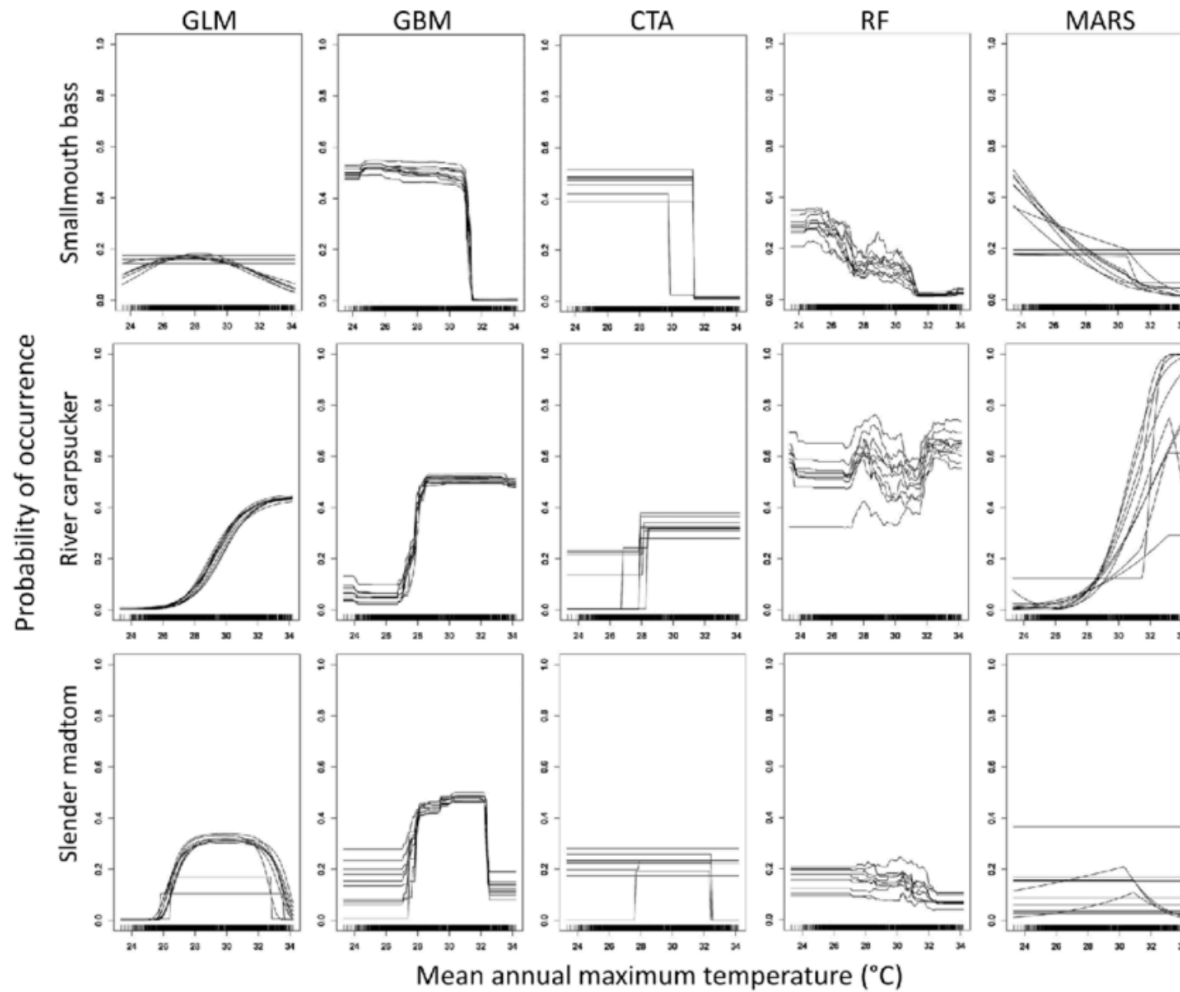
# Mechanistic



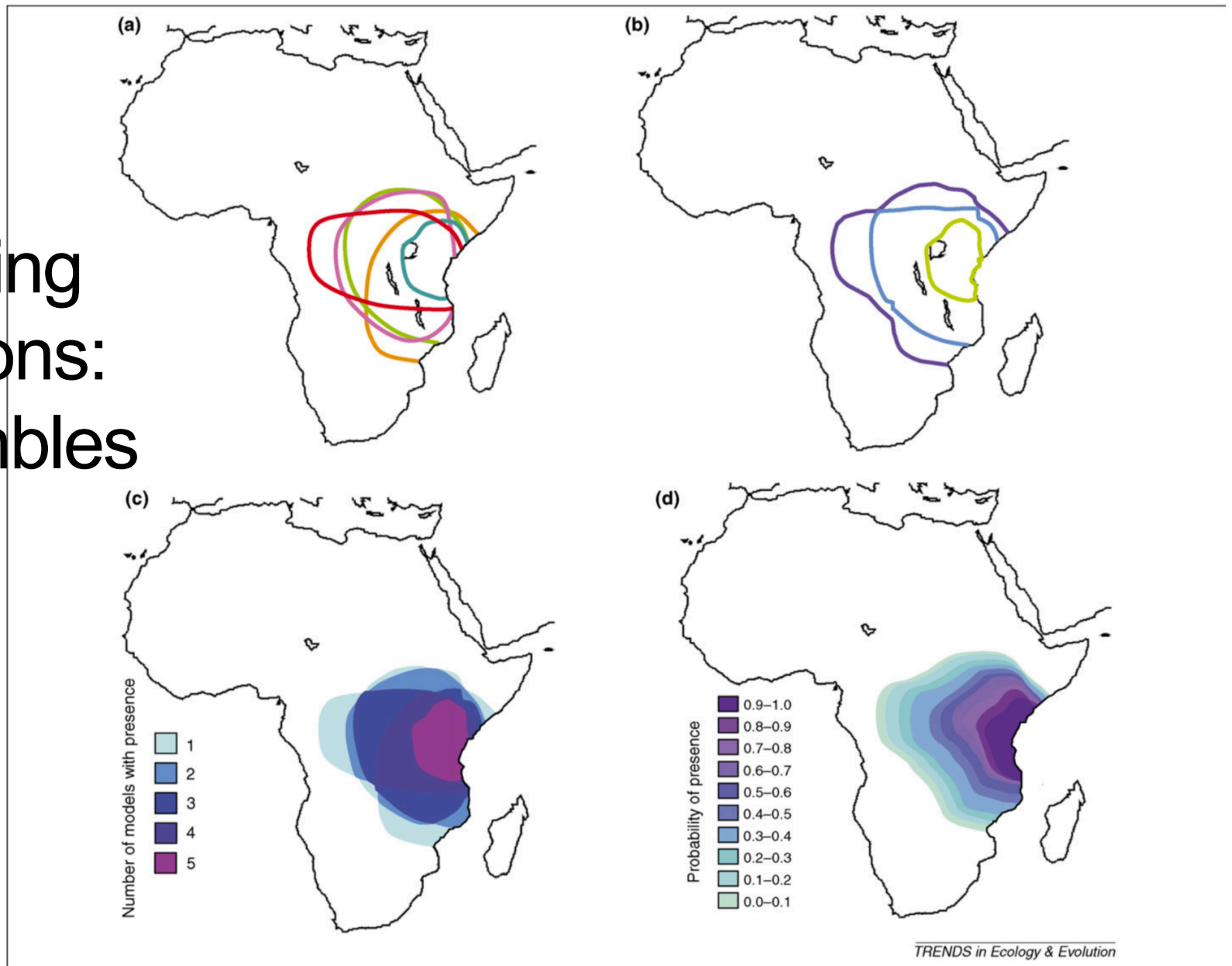
# Uncertainty

- Modeling decisions
- Parameters
- Future Scenarios

# Modeling decisions: algorithms

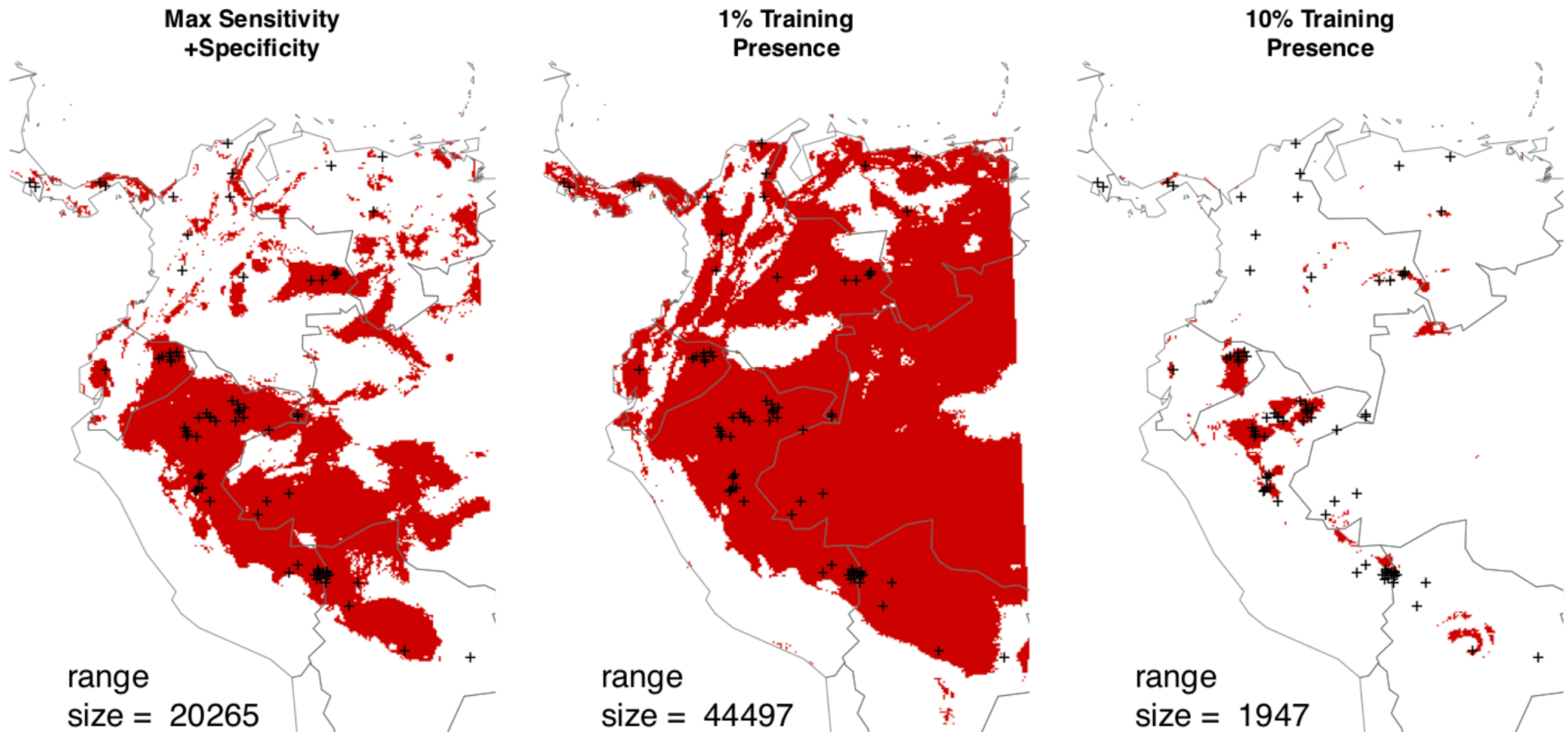


# Modeling decisions: ensembles



**Figure 1.** Examples of alternative approaches to analysing ensemble forecasts using artificial data projected onto the map of Africa: **(a)** Individual results from five hypothetical bioclimatic models (shown by coloured lines) predicting the area occupied by a key species under a climate change scenario (no combination of the ensemble forecast is performed); **(b)** a bounding box showing the area where at least one (purple) or all models (green) predict species presence in the future, and a consensus forecast (blue) showing the area where at least half the models (the median) forecast species presence; **(c)** a frequency histogram, showing the number of models (1–5) forecasting the presence of the species at any point; and **(d)** a probability density function showing the likelihood of species presence estimated from a large ensemble

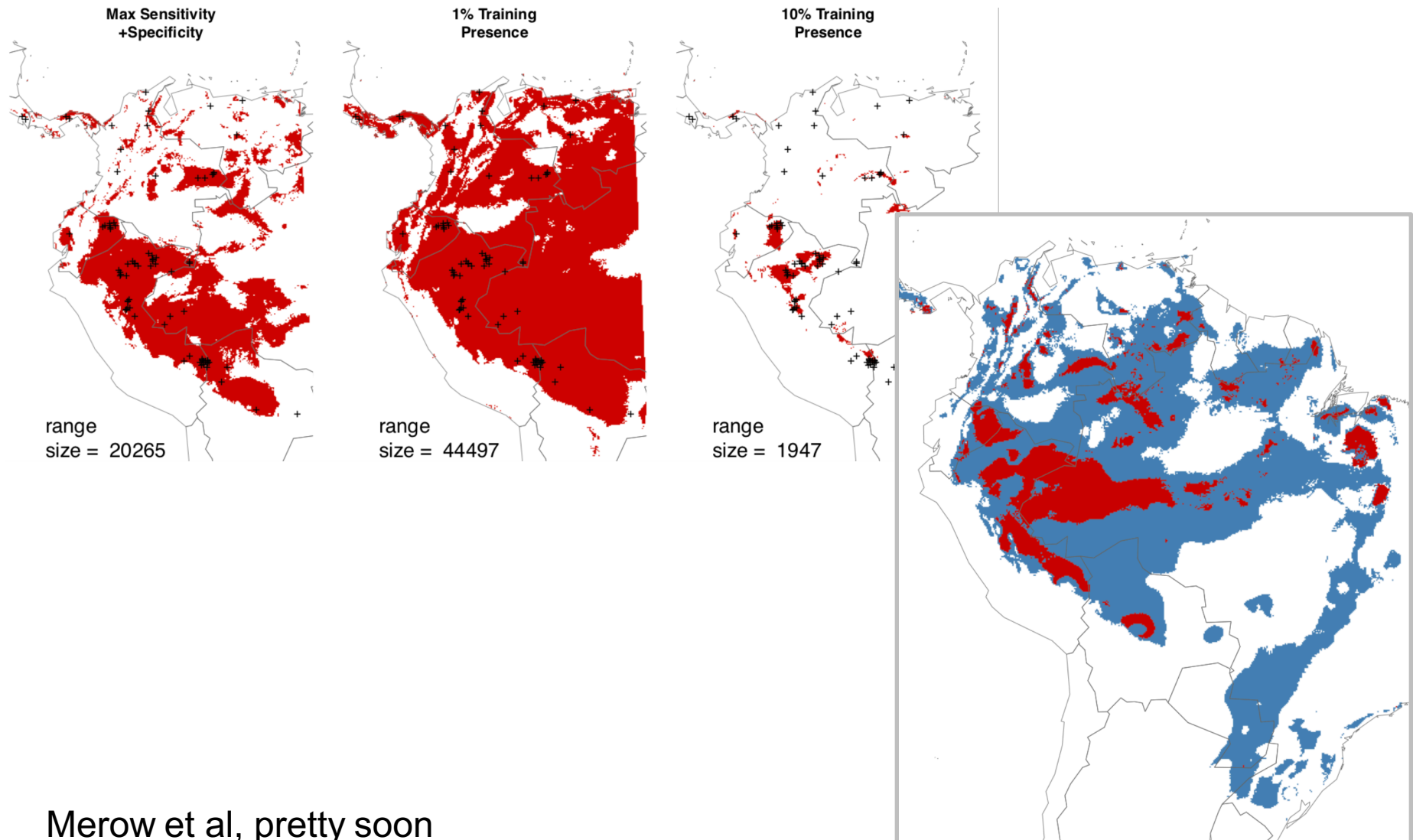
# Modeling Decisions: Binary Maps



Determining the right threshold is dodgy with **presence – only** data

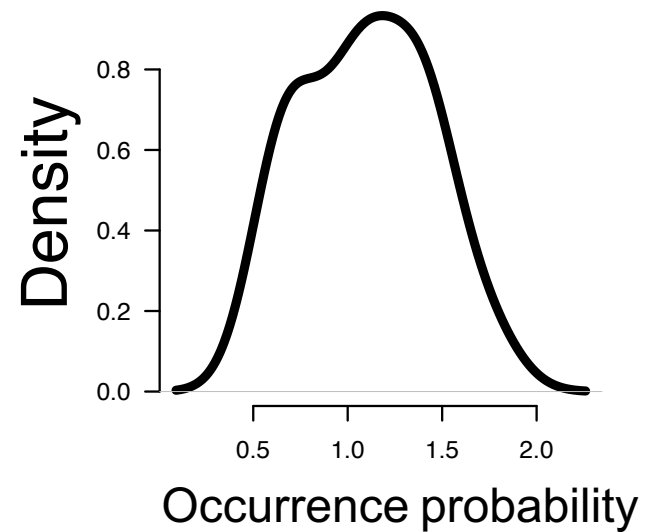
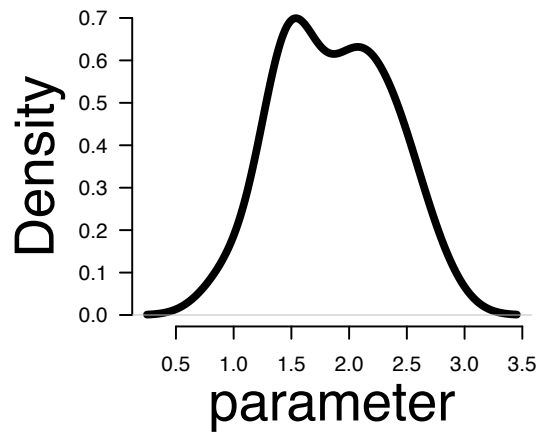
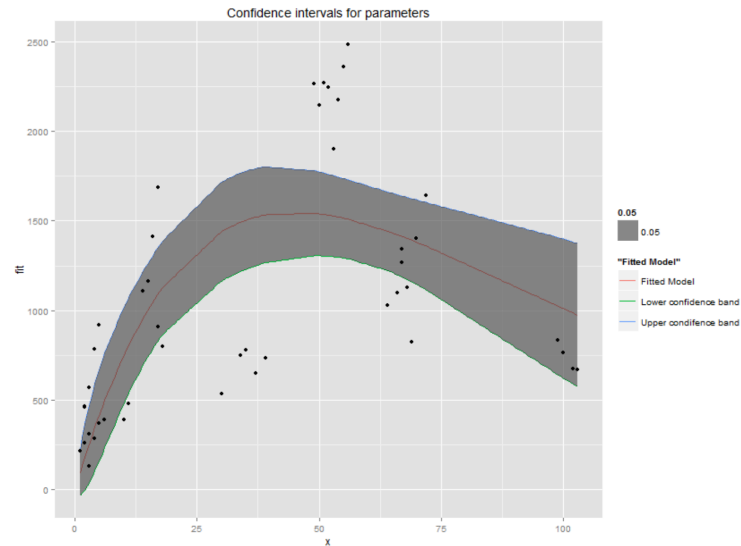
Merow et al, pretty soon

# Modeling Decisions: Binary vs. Trinary Maps



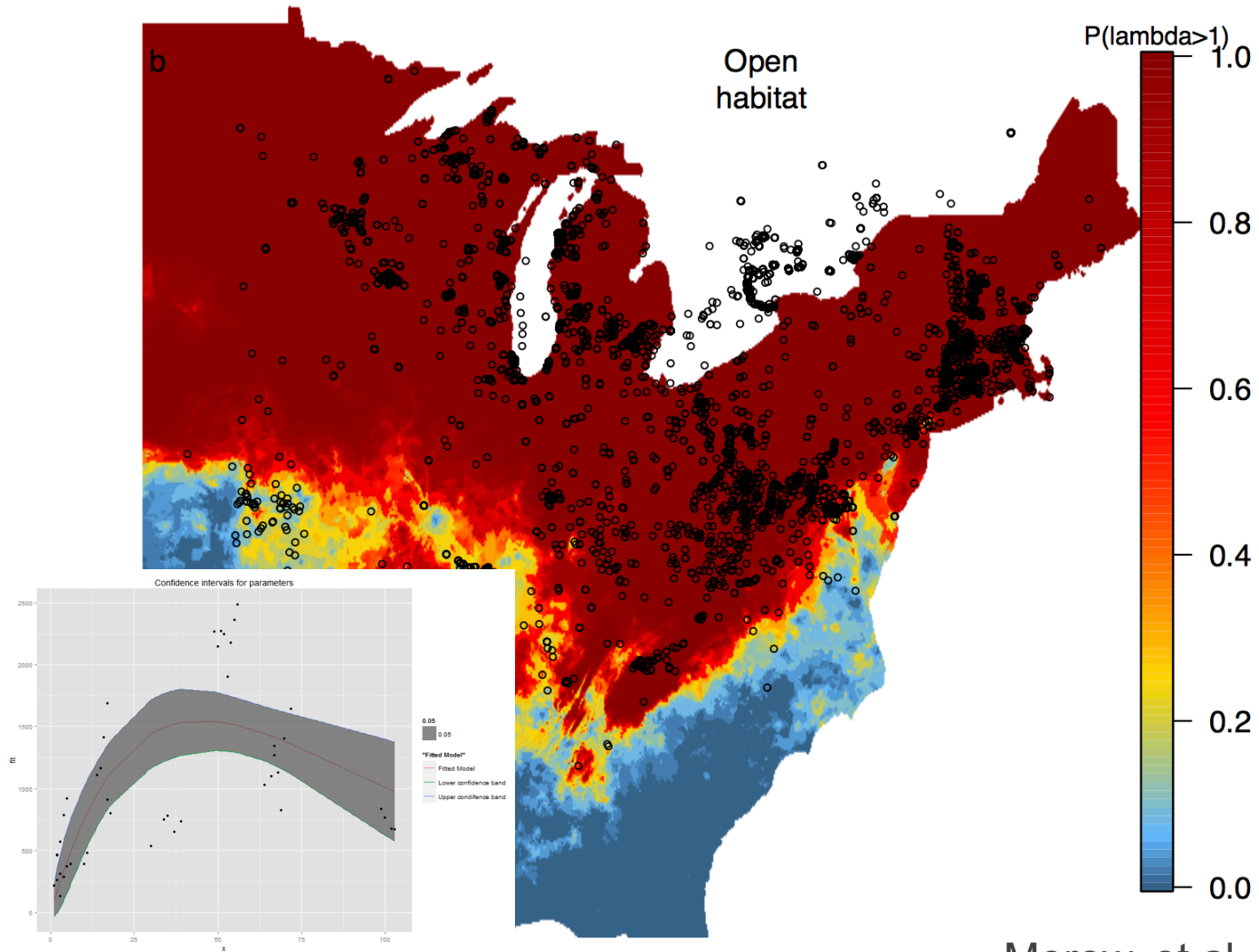
Merow et al, pretty soon

# Parameter Uncertainty





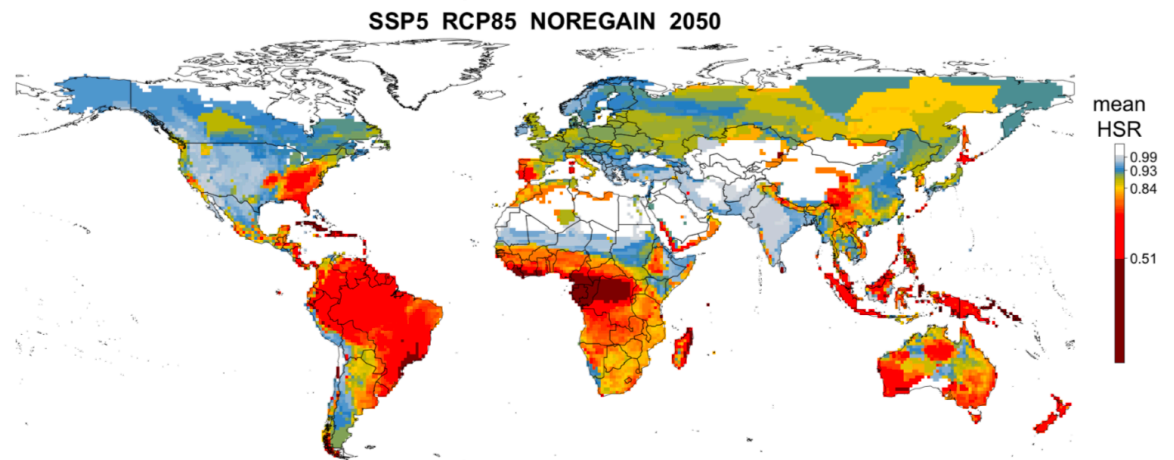
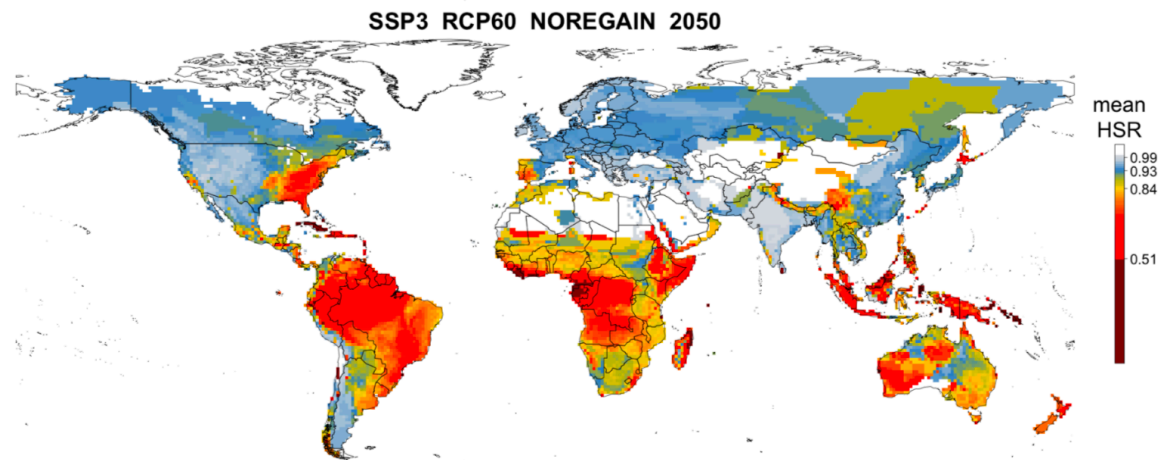
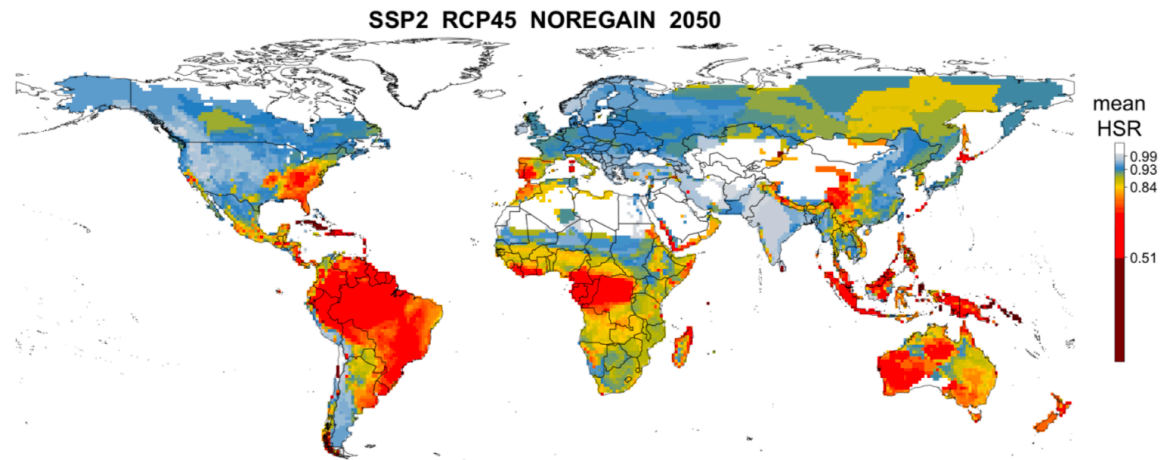
# Parameter Uncertainty



Merow, et al. 2017, PNAS

# Future scenarios

Weather  
Climate  
Land Use  
Disperal



# Concluding thoughts

## **Types of extrapolation**

- Environment
- Space
- Time

Identify the type

## **Uncertainty**

- Modeling decisions
- Parameters
- Future Scenarios

Reduce, report