Transdisciplinary Nature Conservation:

The IUCN Red List of Threatened Species from evaluation to practice

Luca Bütikofer, 15.09.2022

Environmental Data

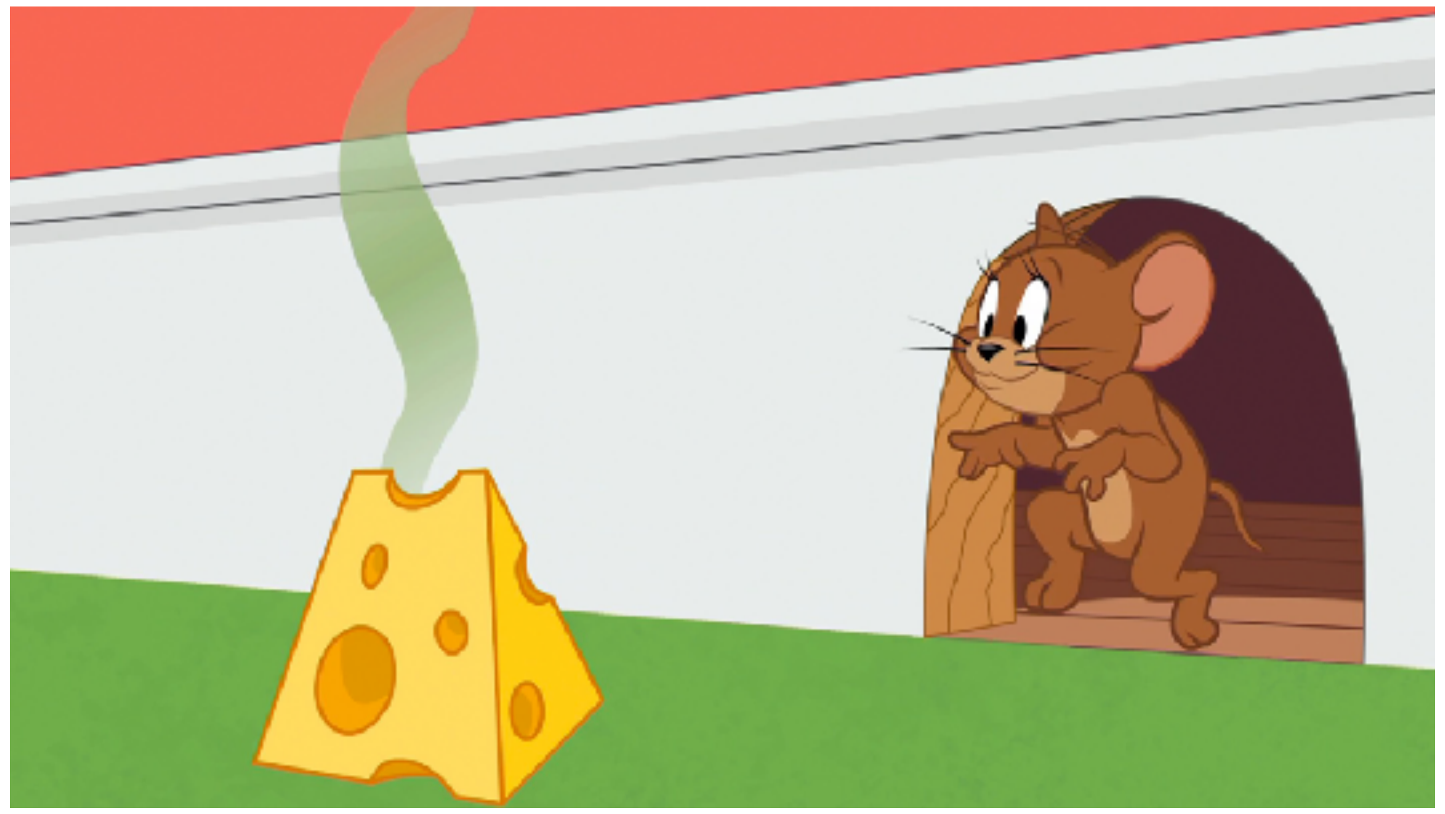
Wallace Component “3 Env Data”

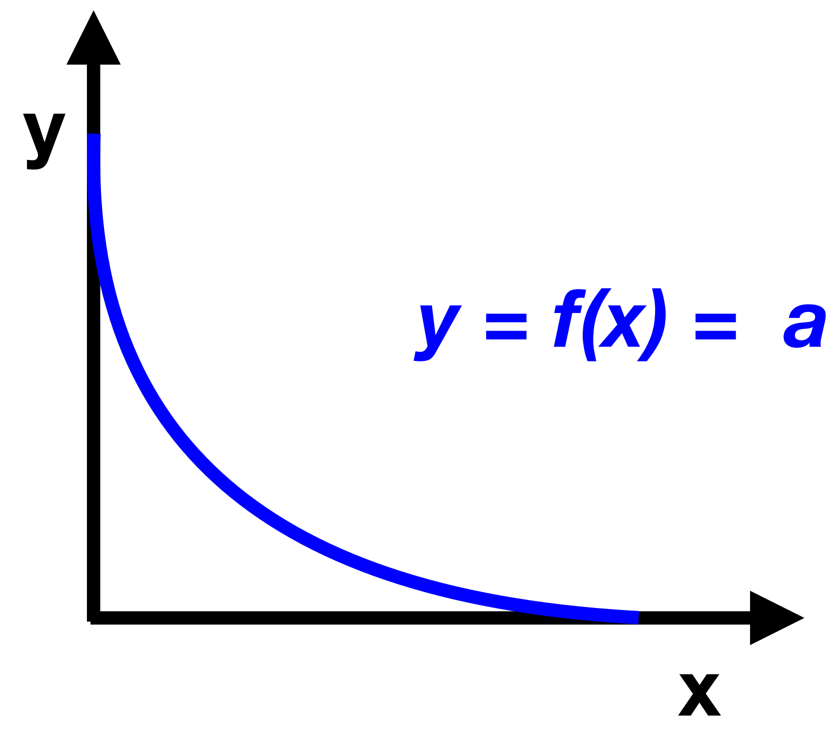
Environmental Data

These are the model's explanatory variables

What explains the distribution of the species?

- y: number of mice observations
- x: proximity to cheese
- a: steepness of decay
- e: 2.71828 (constant)





Environmental Data

These are the model's explanatory variables

What determines the species distribution?

- Typical examples:

Environmental Data

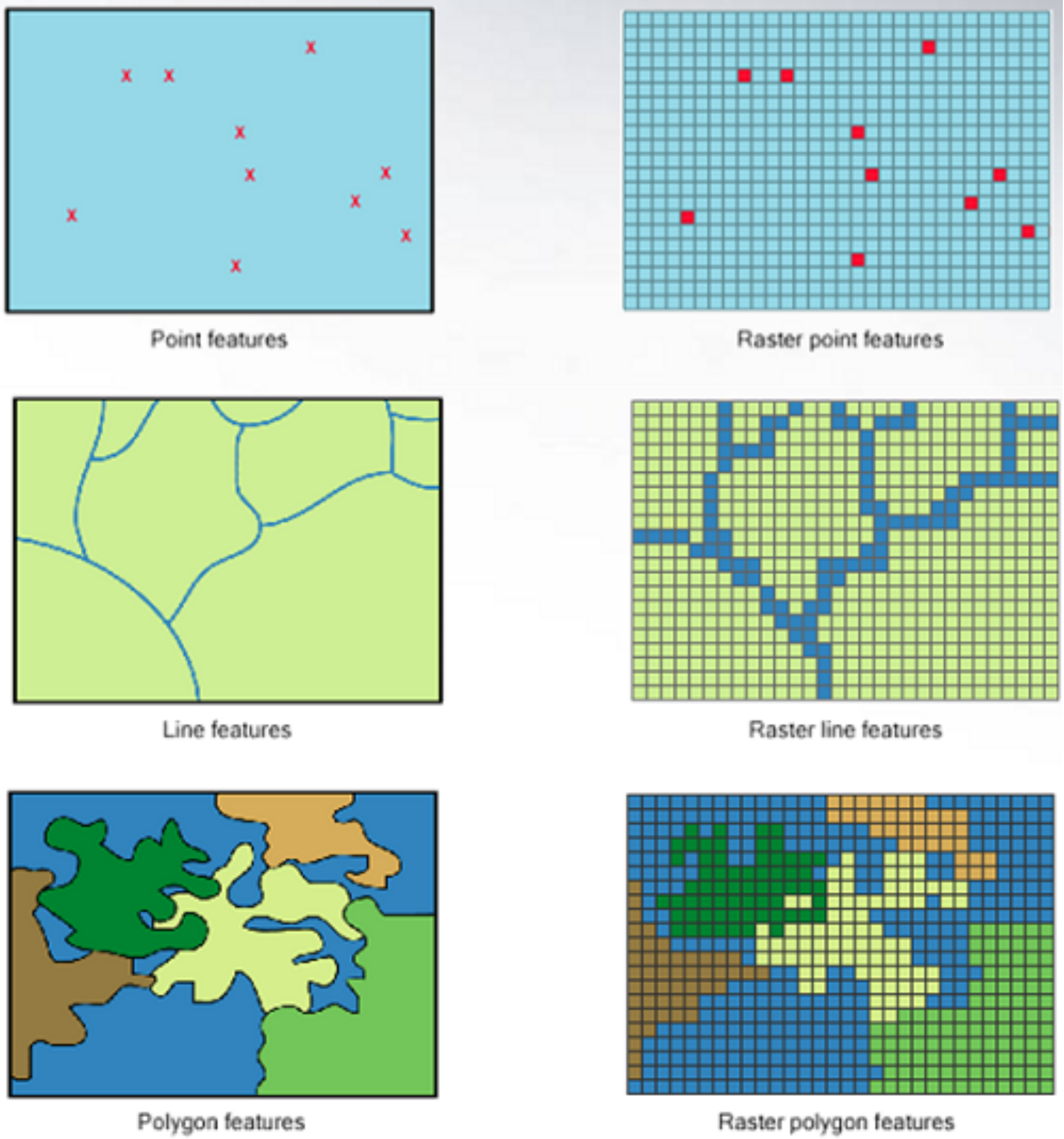
These are the model's explanatory variables

What determines the species distribution?

- Typical examples:
  - Climate
  - Geology
  - Soil
  - Hydrology
  - Land-use / land-cover
  - Distance to…
  - Moving windows

Environmental Data

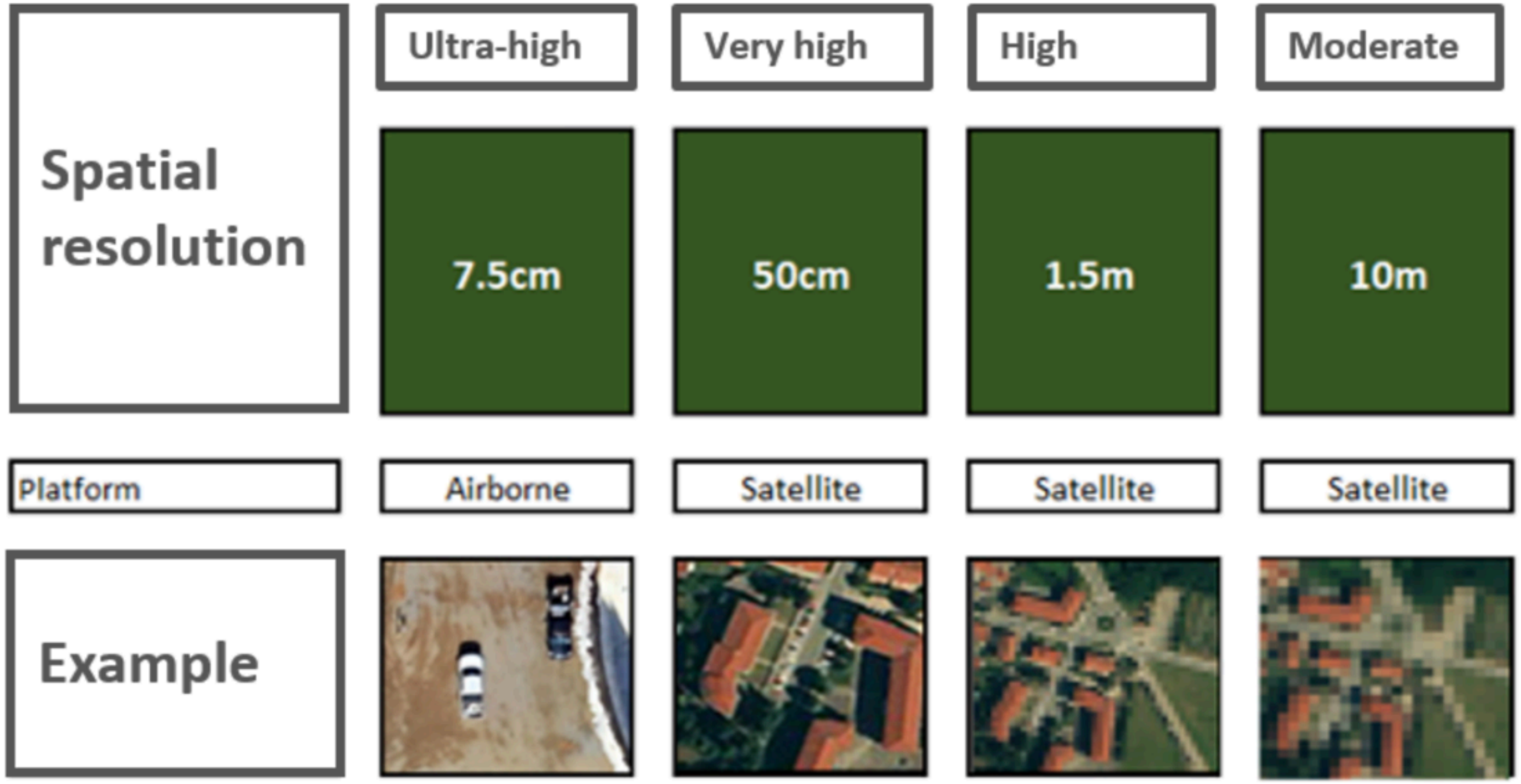
The raster format



Environmental Data

Scale

Work at the **characteristic scale** of the phenomenon you are modelling!



Environmental Data

Scale

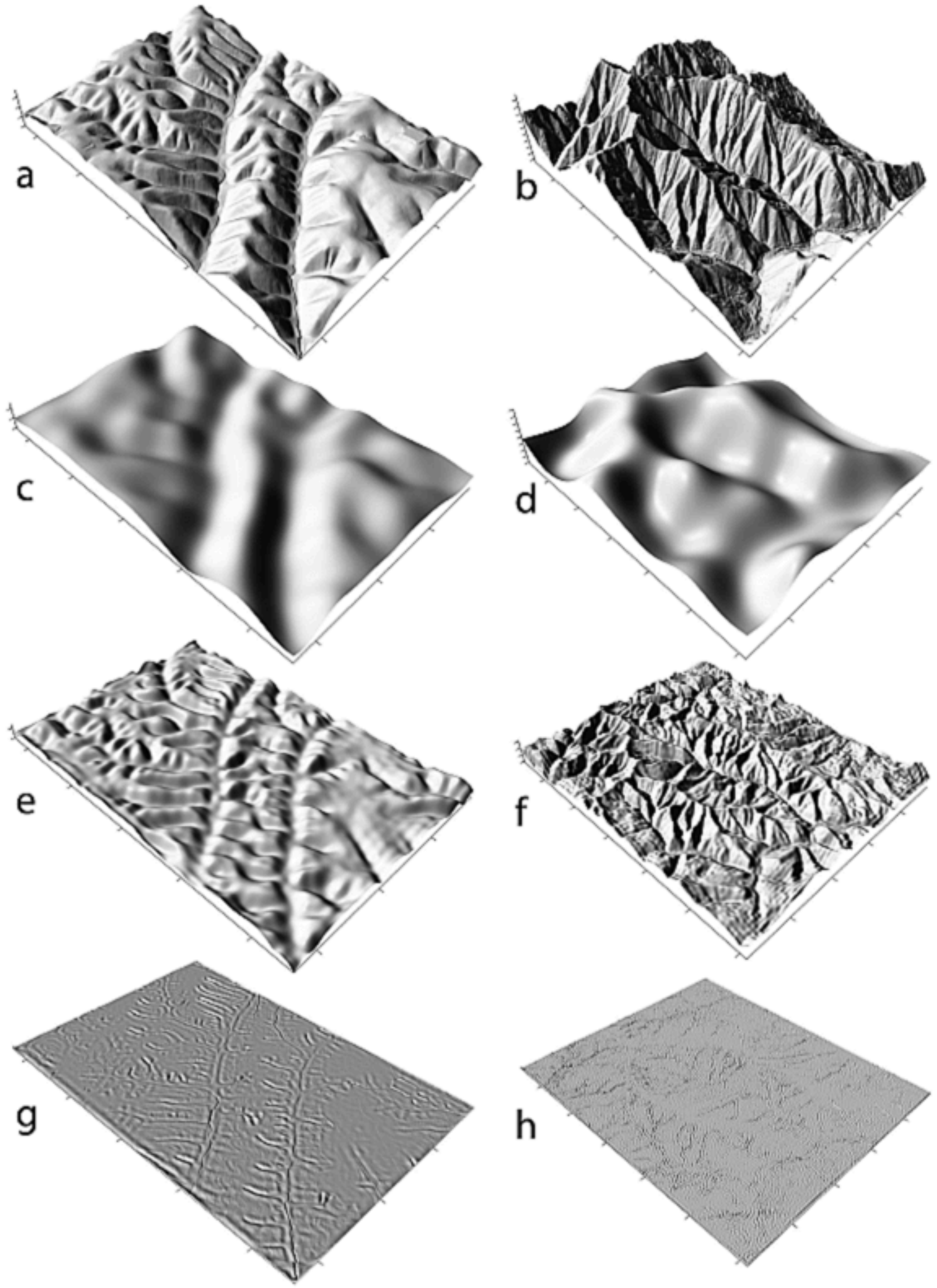
Work at the **characteristic scale** of the phenomenon you are modelling!

Example landscapes:

Large valleys:

Smaller valleys:

Terrain roughness:



JOURNAL OF GEOPHYSICAL RESEARCH
Earth Surface
AN AGU JOURNAL

Free Access

Spectral signatures of characteristic spatial scales and nonfractal structure in landscapes

J. Taylor Perron, James W. Kirchner, William E. Dietrich

First published: 07 October 2008 | https://doi.org/10.1029/2007JF000866 | Citations: 111

Environmental Data

These are the model's explanatory variables

Climate

- WorldClim Bioclims:
- From the monthly temperature and rainfall values to generate more biologically meaningful variables.
- Annual trends (e.g., mean annual temperature, annual precipitation)
- Seasonality (e.g., annual range in temperature and precipitation)
- Extreme or limiting environmental factors (e.g., temperature of the coldest and warmest month, and precipitation of the wet and dry quarters)

BIO1 = Annual Mean Temperature
BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3 = Isothermality (BIO2/BIO7) (* 100)
BIO4 = Temperature Seasonality (standard deviation *100)
BIO5 = Max Temperature of Warmest Month
BIO6 = Min Temperature of Coldest Month
BIO7 = Temperature Annual Range (BIO5-BIO6)
BIO8 = Mean Temperature of Wettest Quarter
BIO9 = Mean Temperature of Driest Quarter
BIO10 = Mean Temperature of Warmest Quarter
BIO11 = Mean Temperature of Coldest Quarter
BIO12 = Annual Precipitation
BIO13 = Precipitation of Wettest Month
BIO14 = Precipitation of Driest Month
BIO15 = Precipitation Seasonality (Coefficient of Variation)
BIO16 = Precipitation of Wettest Quarter
BIO17 = Precipitation of Driest Quarter
BIO18 = Precipitation of Warmest Quarter
BIO19 = Precipitation of Coldest Quarter

Environmental Data

These are the model's explanatory variables

WorldClim - Global Climate Data

Free climate data for ecological modeling and GIS

Contact

WorldClim

WorldClim is a set of global climate layers (gridded climate data) with a spatial resolution of about 1 km^2. These data can be used for mapping and spatial modeling.

The *new* **Version 2.0** is now available (current climate only --- more coming soon)

The old version is **Version 1.4**.
For this version you can get data for past, current and future climates.

Read more

https://www.worldclim.com

Environmental Data
These are the model's explanatory variables

Alternatives to Bioclims

- CHELSA, https://chelsa-climate.org

Home Downloads Daily timeseries Monthly timeseries Bioclimate / Köppen-Geiger Future

Paleo Climate Climate diagrams

CHELSA

Climatologies at high resolution for the earth's land surface areas

Environmental Data

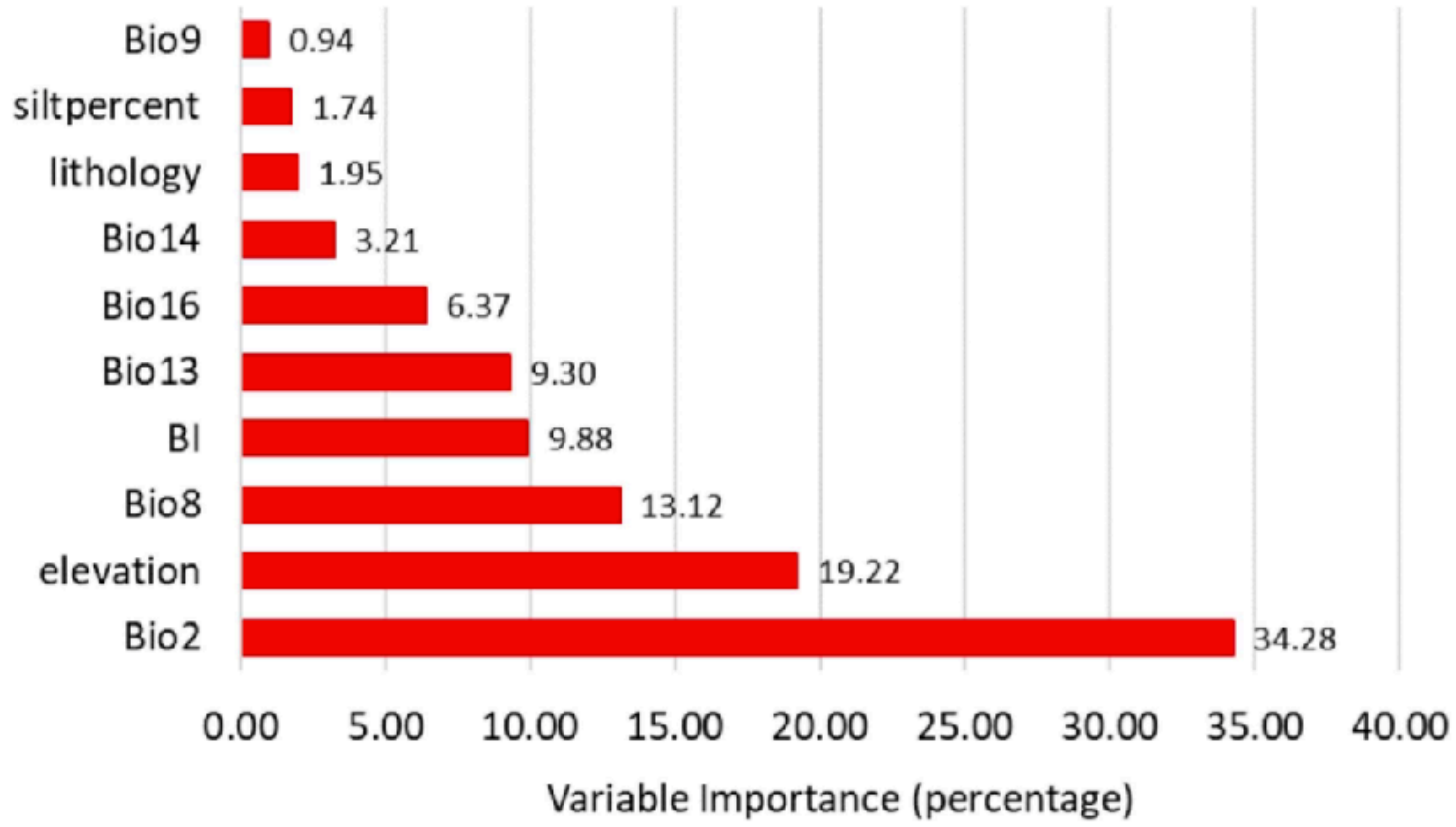
These are the model's explanatory variables

LULC sources

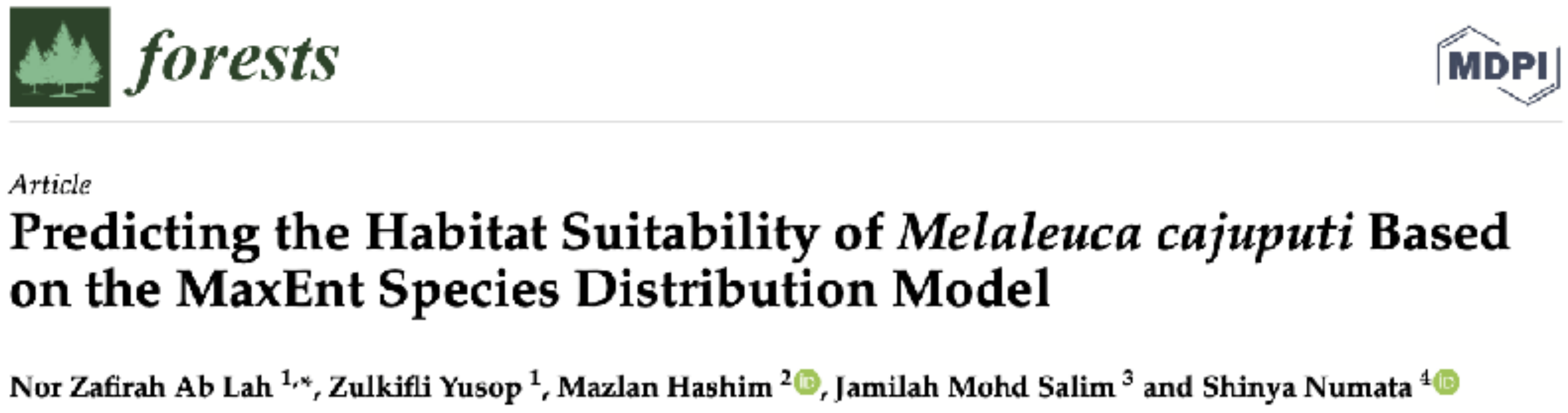
- ESA-CCI-LC, https://www.esa-landcover-cci.org/?q=node/164

Environmental Data

Variables importance, example of Gelam tree (*Melaleuca cajuputi*)—Malaysia



- Bio 2 (mean diurnal range)
- Elevation
- Bio 8 (mean temperature of the wettest quarter)


forests MDPI

Article

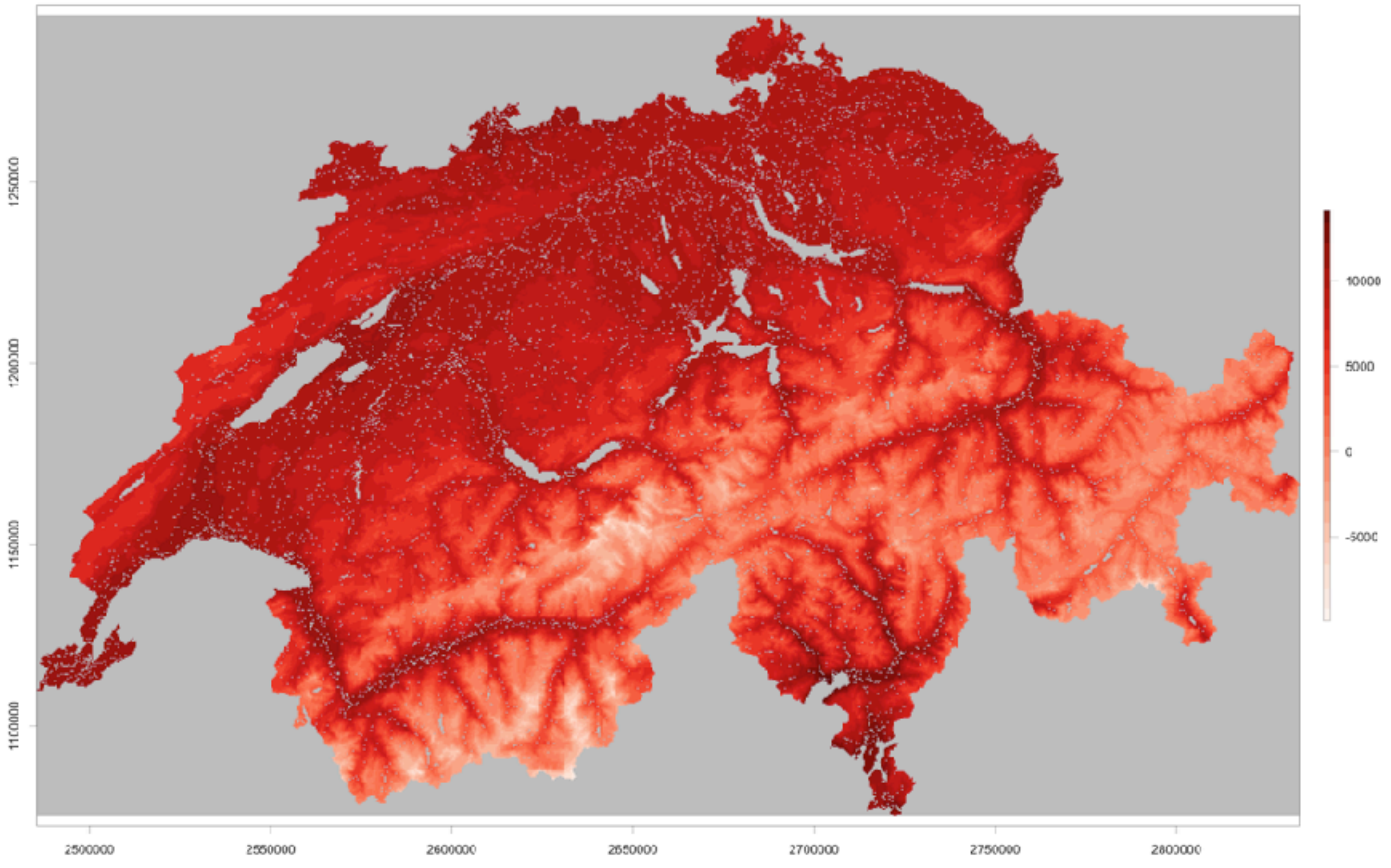
Predicting the Habitat Suitability of *Melaleuca cajuputi* Based on the MaxEnt Species Distribution Model

Nor Zafirah Ab Lah [1,*], Zulkifli Yusop [1], Mazlan Hashim [2], Jamilah Mohd Salim [3] and Shinya Numata [4]

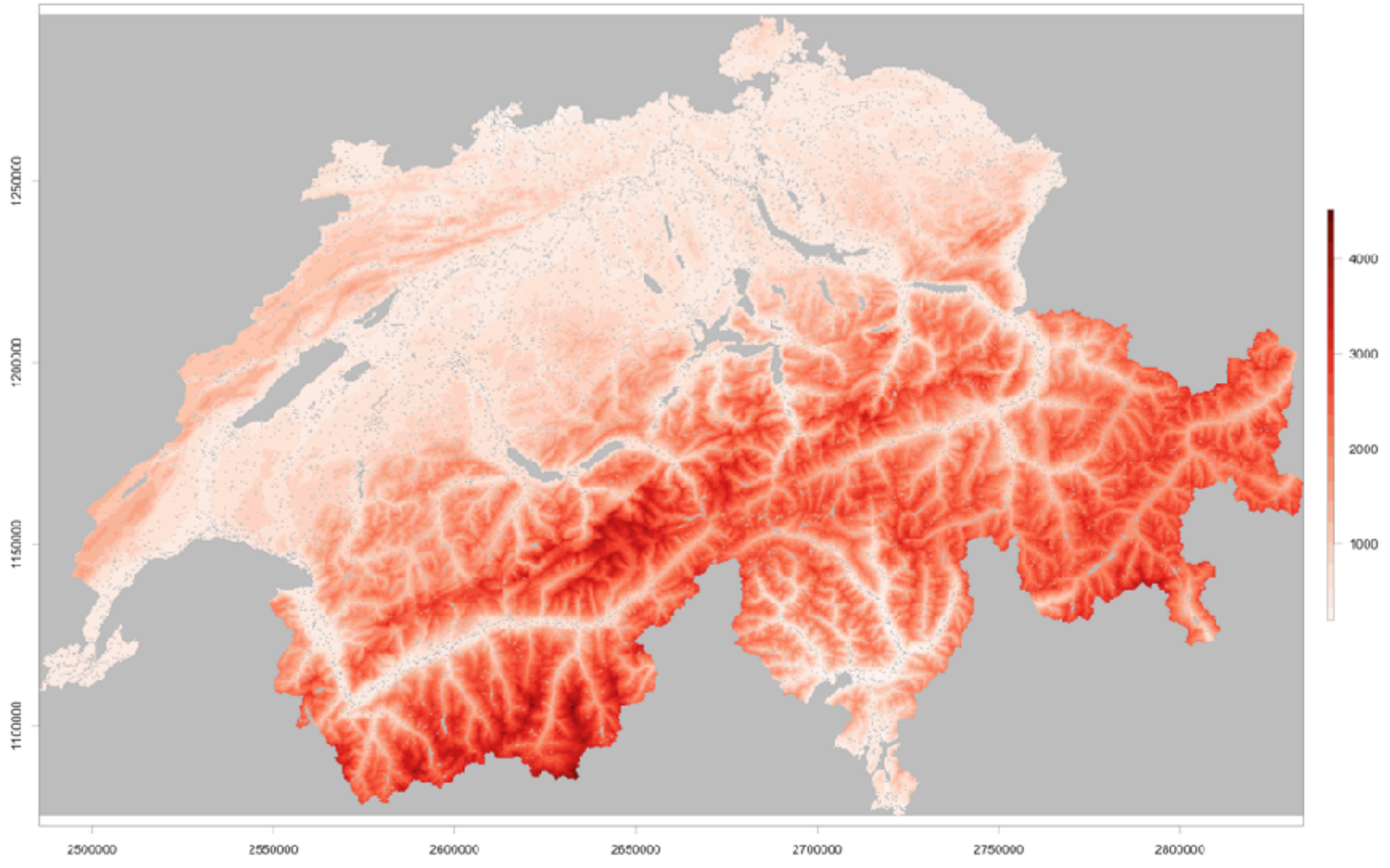
Environmental Data

Variables correlation

Temperature



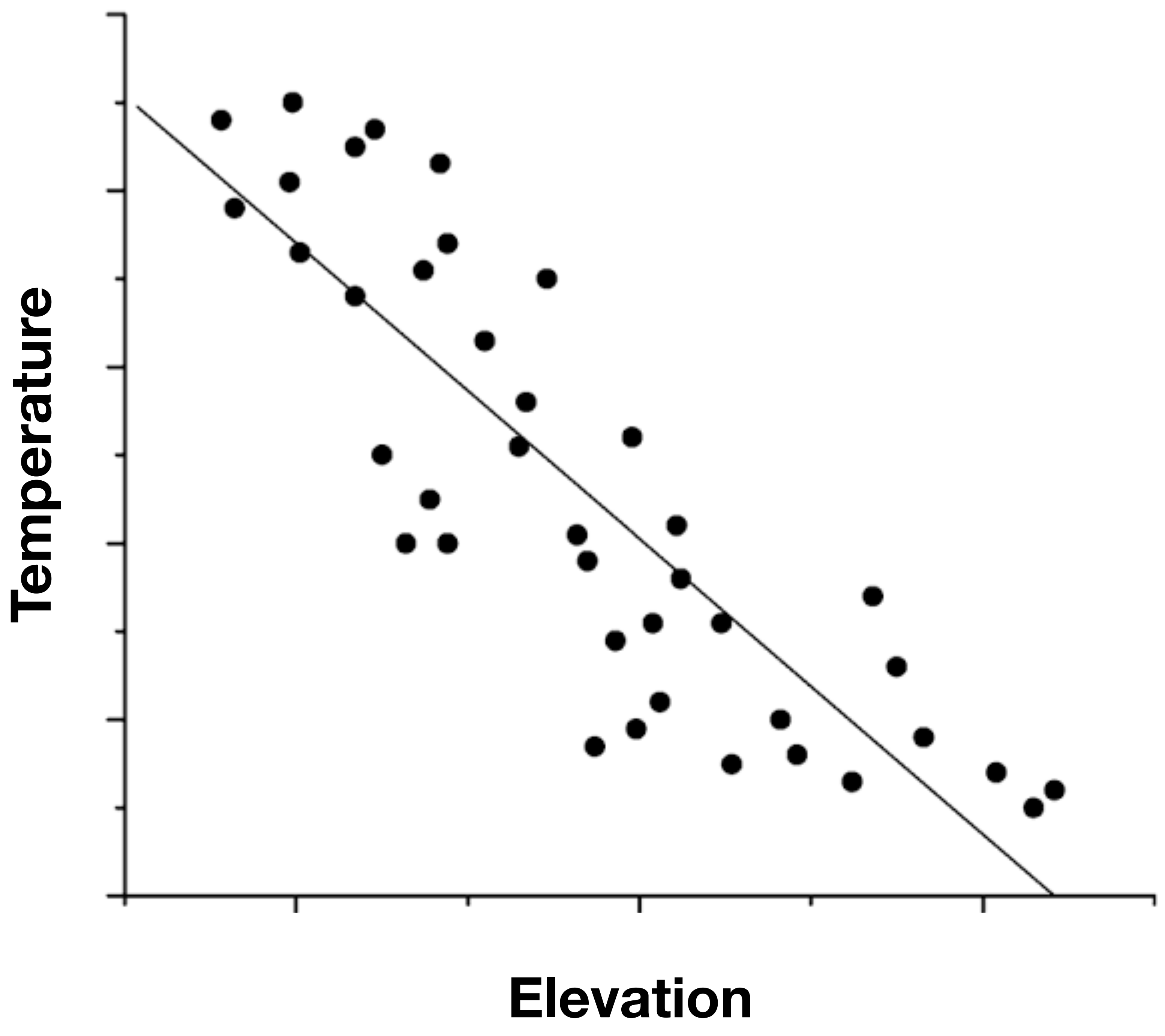
Elevation



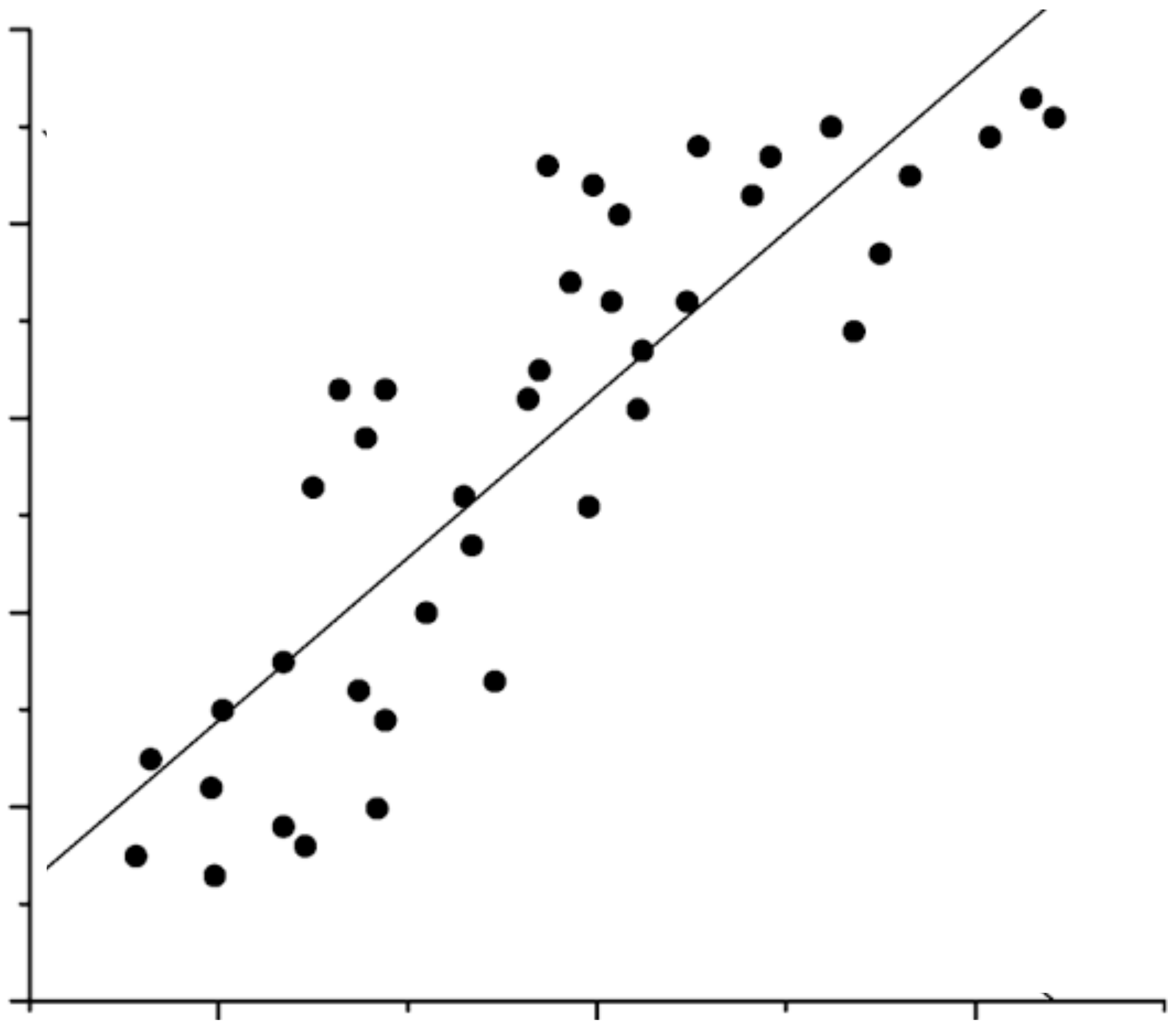
Environmental Data

Variables correlation

Negative correlation

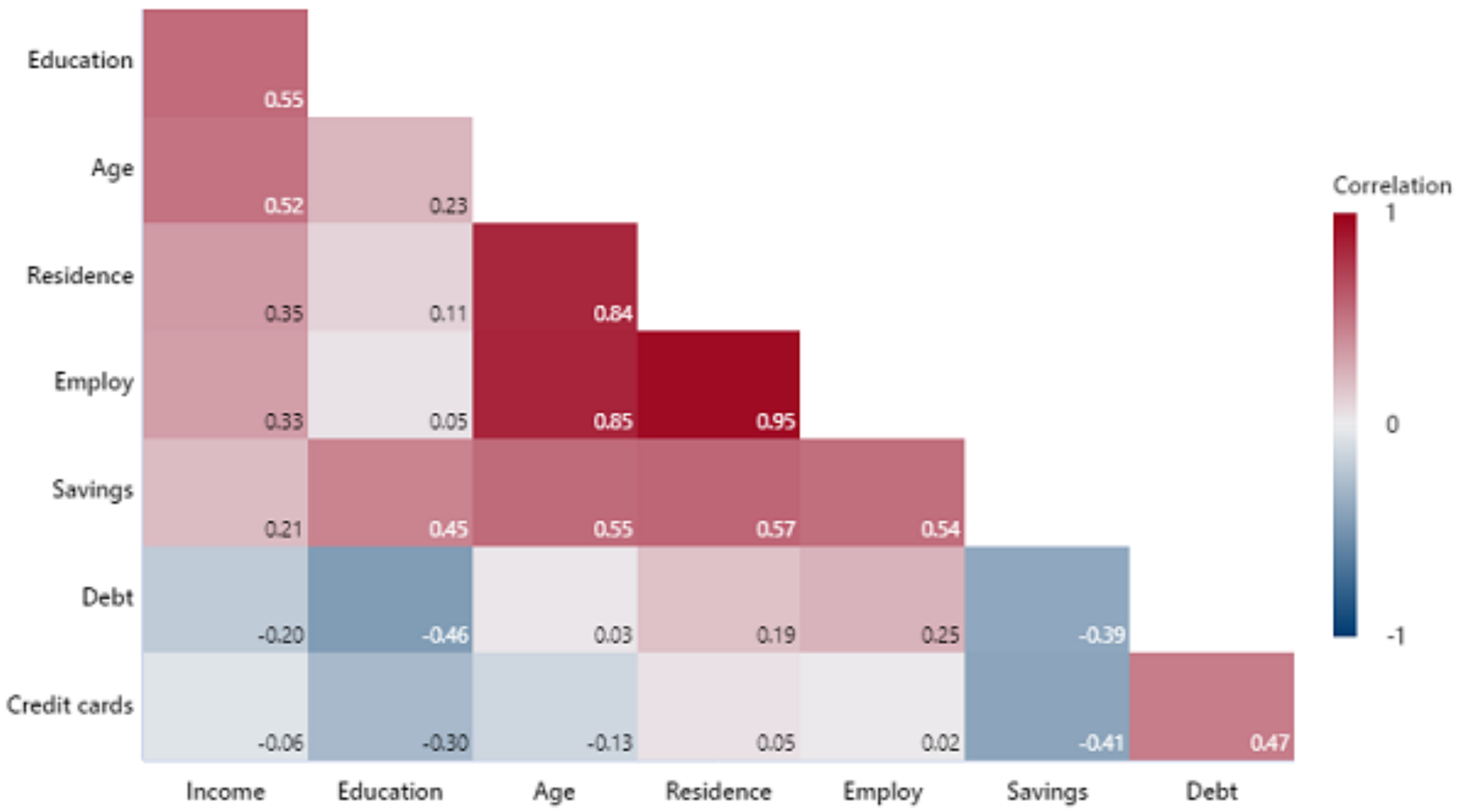


Positive correlation



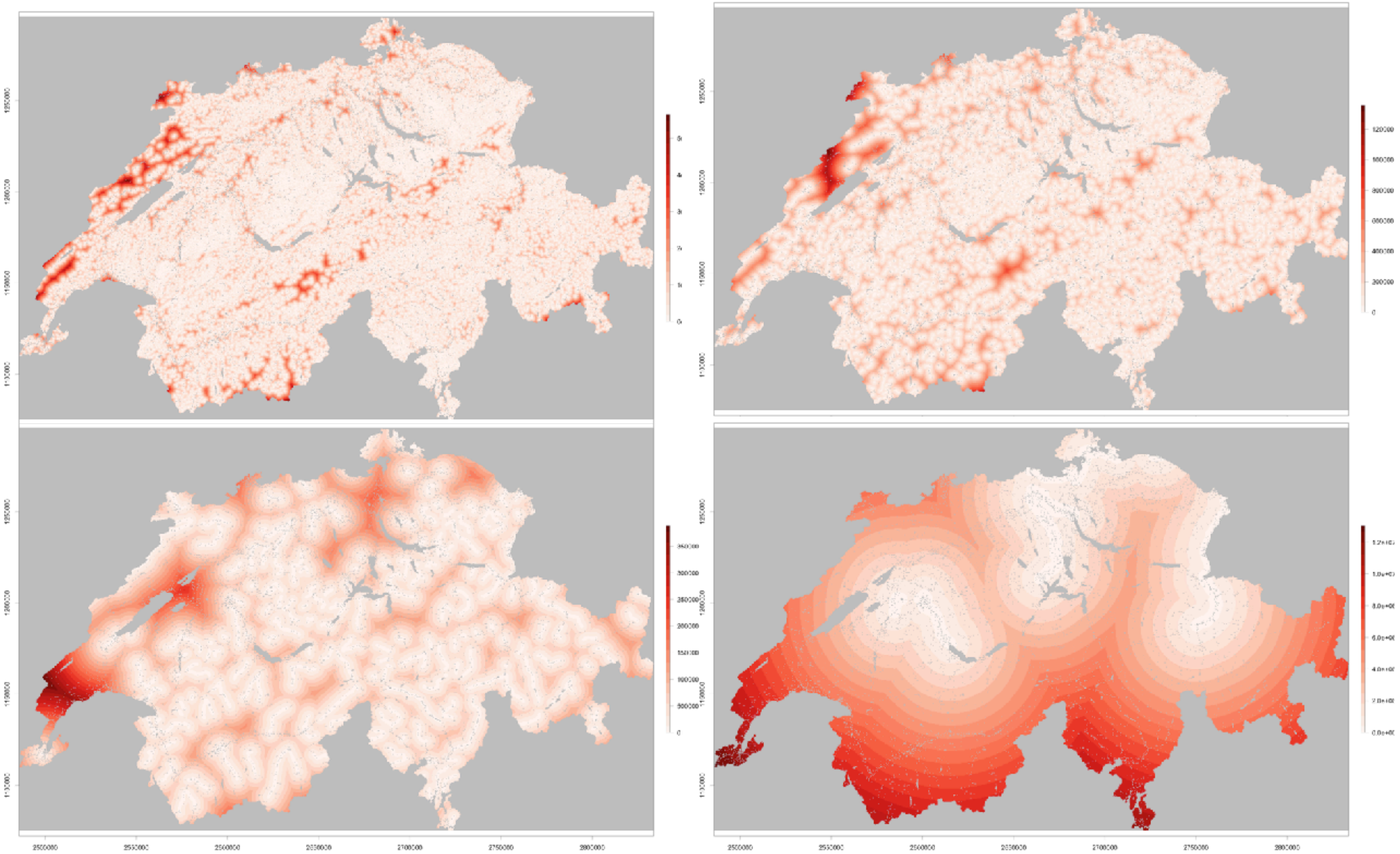
Environmental Data

Variables correlogram



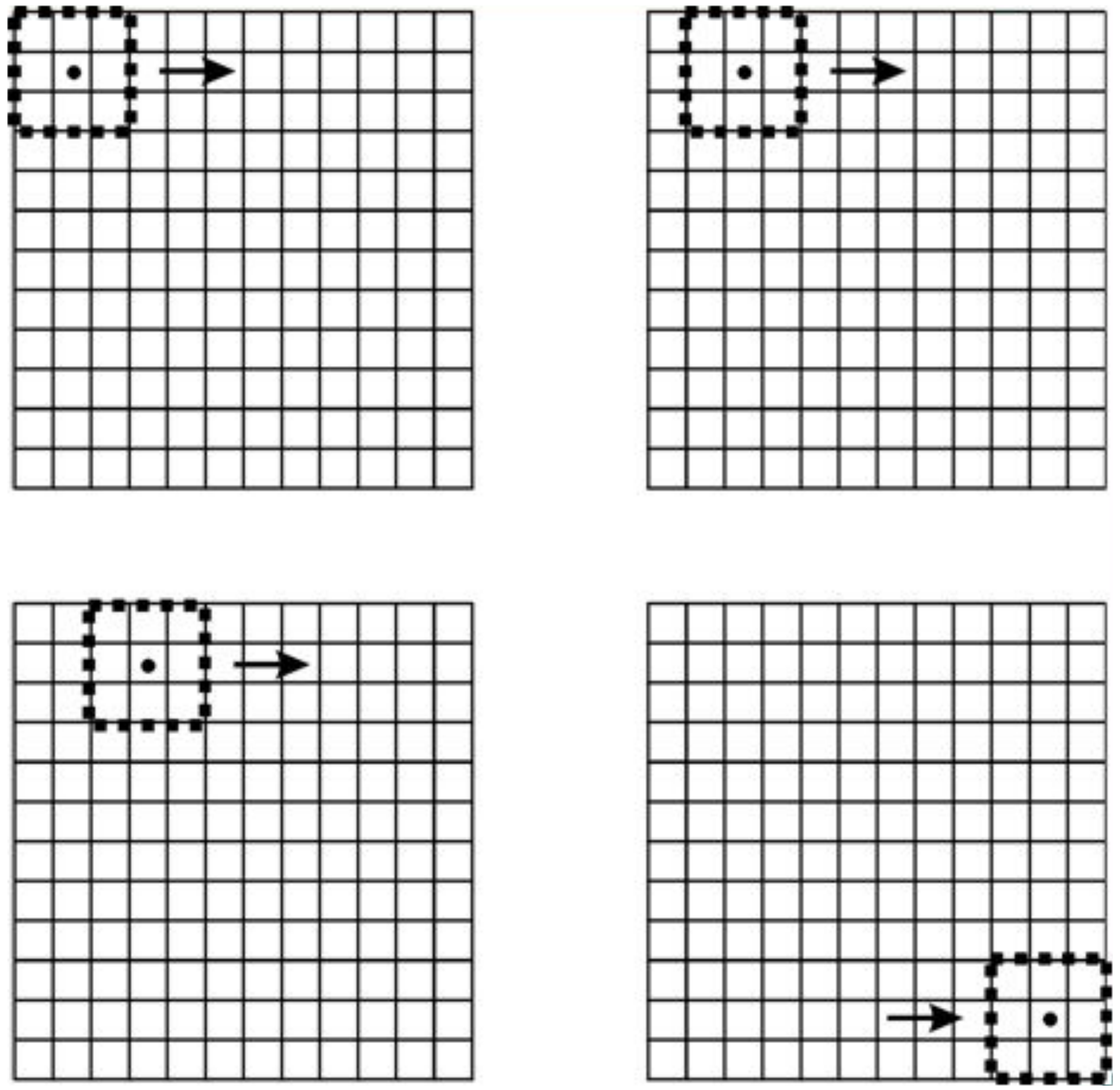
Environmental Data

Distance to… rivers of different sizes

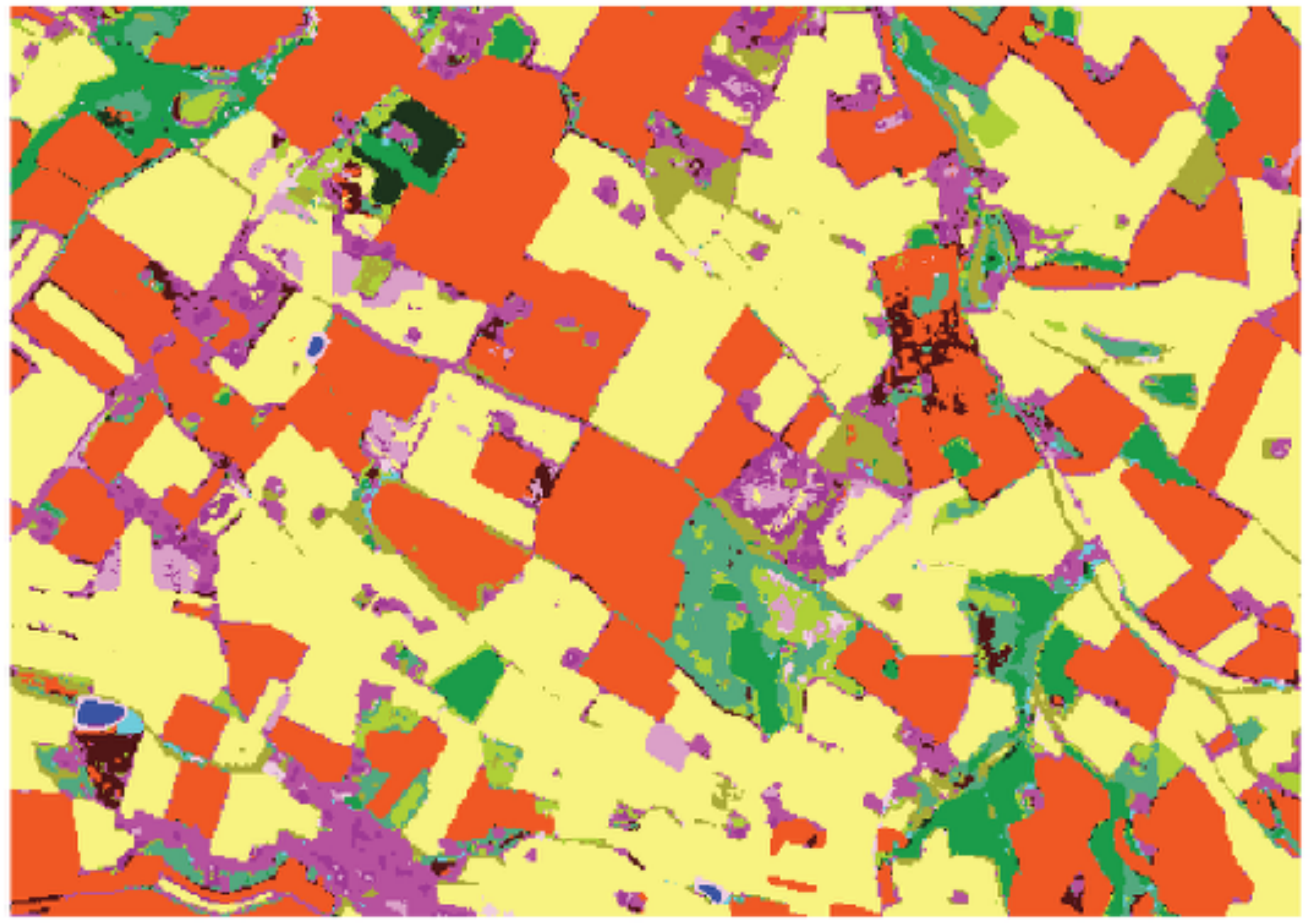


Environmental Data

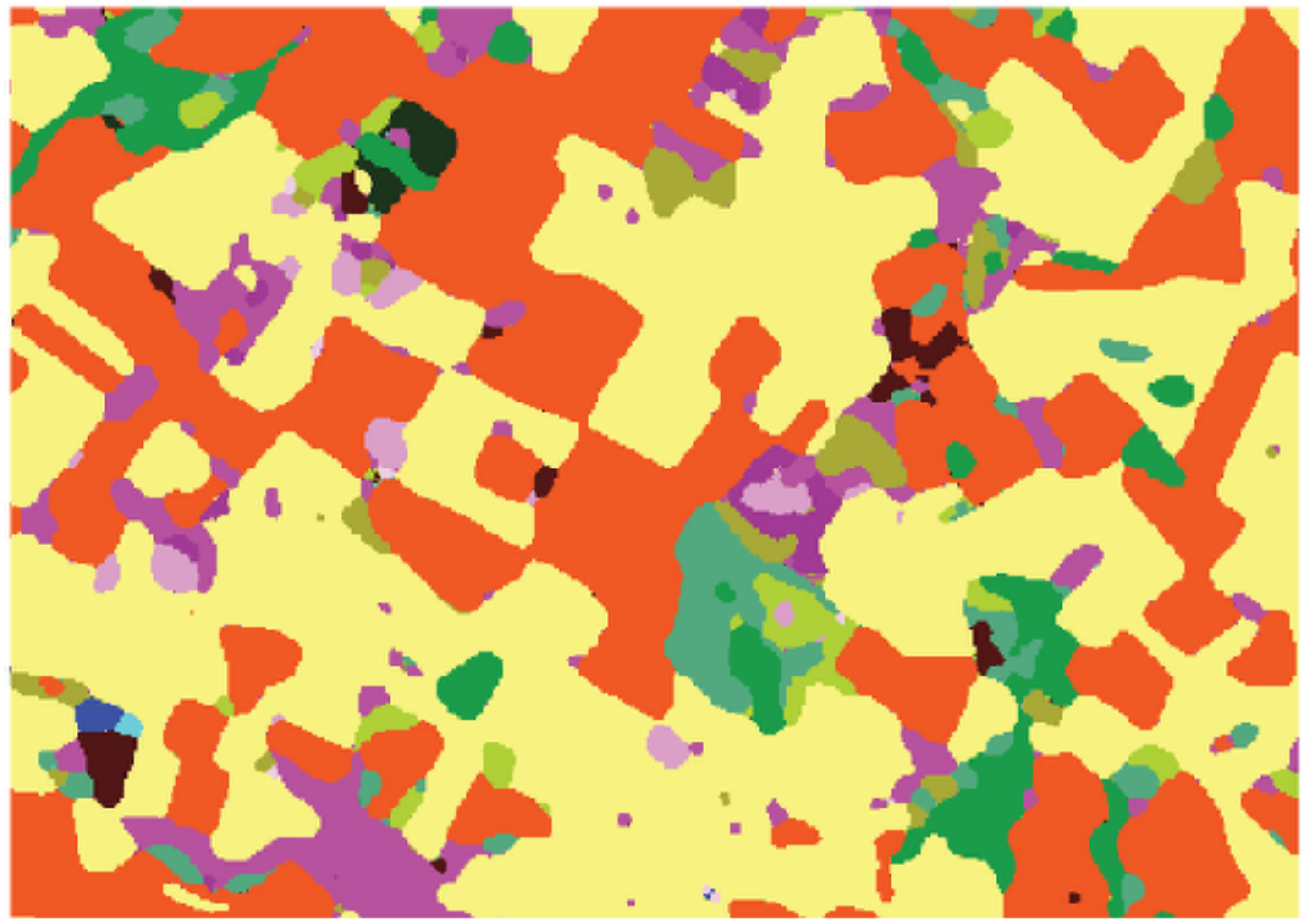
Moving windows



Original



11x11 px.
Moving Window Majority



Open Access Article

A Metric for Evaluating the Geometric Quality of Land Cover Maps Generated with Contextual Features from High-Dimensional Satellite Image Time Series without Dense Reference Data

by Dawa Derksen [1,*], Jordi Inglada [1,2] and Julien Michel [2]

ORCID

1 CESBIO, CNES, CNRS, IRD, UPS, Université de Toulouse, 31400 Toulouse, France
2 Centre National d'Etudes Spatiales, 18 avenue Edouard Belin, 31400 Toulouse, France
* Author to whom correspondence should be addressed.

Processing Environmental Data

Wallace Component “Process Env”

Processing Environmental Data

Presence-background SDMs

Presence-absence

X	Y	Pres_Abs
50.4082	13.2343	1
49.2938	12.1341	1
51.9349	11.1233	0
52.9392	13.2303	0

Presence-only

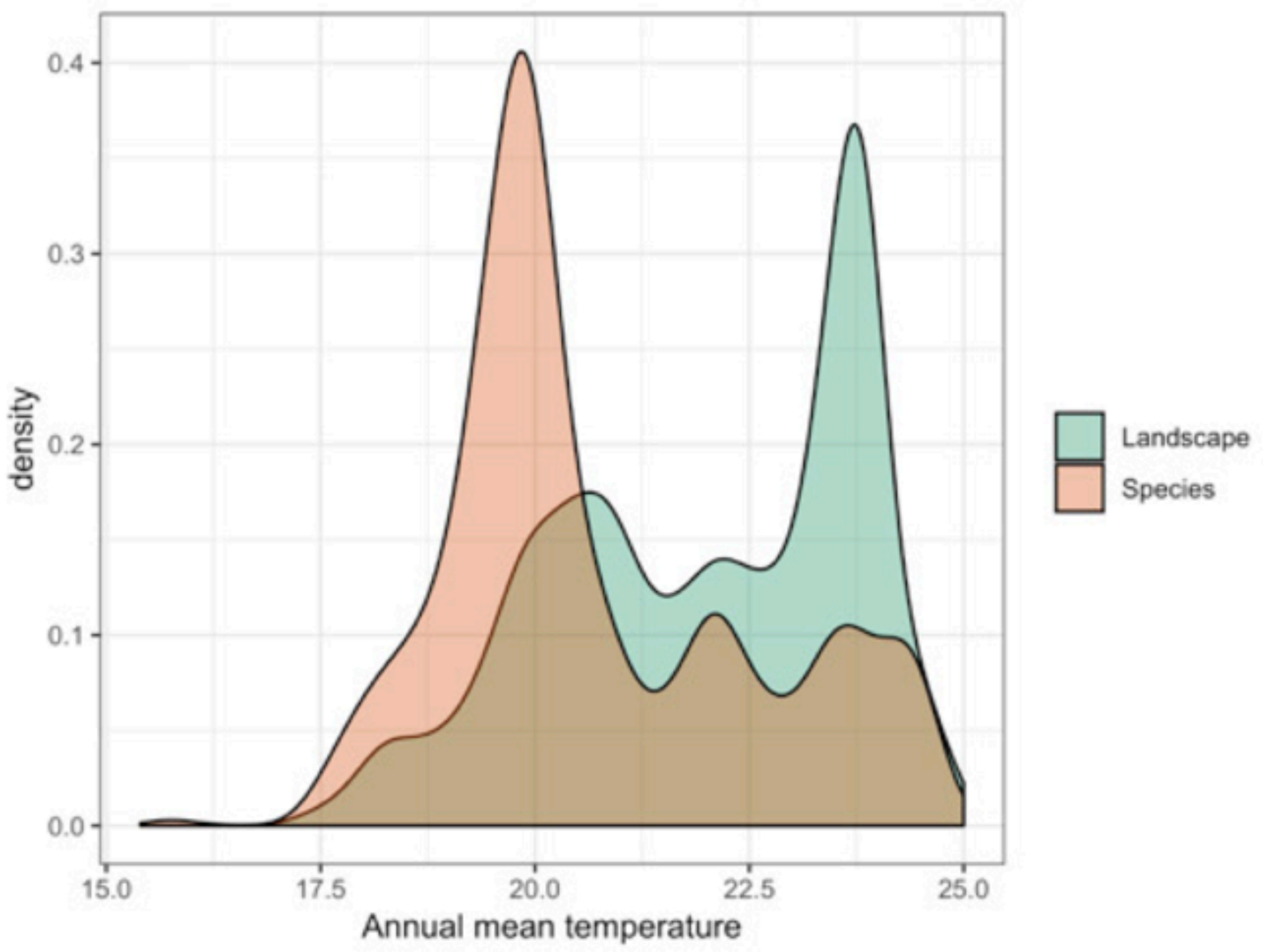
X	Y
50.4082	13.2343
49.2938	12.1341
51.9349	11.1233
52.9392	13.2303

Processing Environmental Data

False absences in presence-absence

Processing Environmental Data

Presence-background SDMs



Biodiversity Informatics, 15, 2020, pp. 69-80

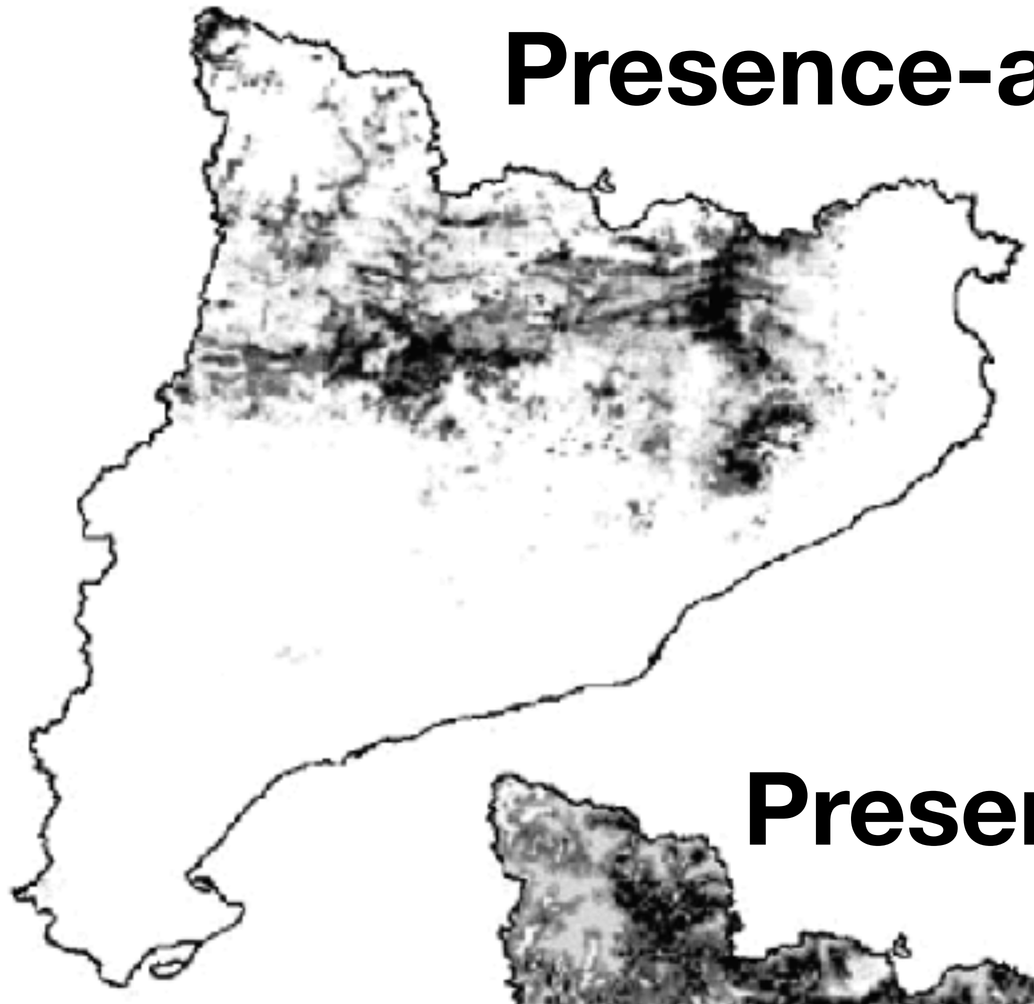
PRESENCE-ONLY AND PRESENCE-ABSENCE DATA FOR COMPARING SPECIES DISTRIBUTION MODELING METHODS

JANE ELITH[1*], CATHERINE H. GRAHAM[2], ROOZBEH VALAVI[1], MEINRAD ABEGG[2], CAROLINE BRUCE[3], ANDREW FORD[4], ANTOINE GUISAN[5], ROBERT J. HIJMANS[6], FALK HUETTMANN[7], LUCIA LOHMANN[8], BETTE LOISELLE[9], CRAIG MORITZ[10], JAKE OVERTON[11], A. TOWNSEND PETERSON[12], STEVEN PHILLIPS[13], KAREN RICHARDSON[14], STEPHEN E. WILLIAMS[15], SUSAN K. WISER[16], THOMAS WOHLGEMUTH[2], NIKLAUS E. ZIMMERMANN[2]

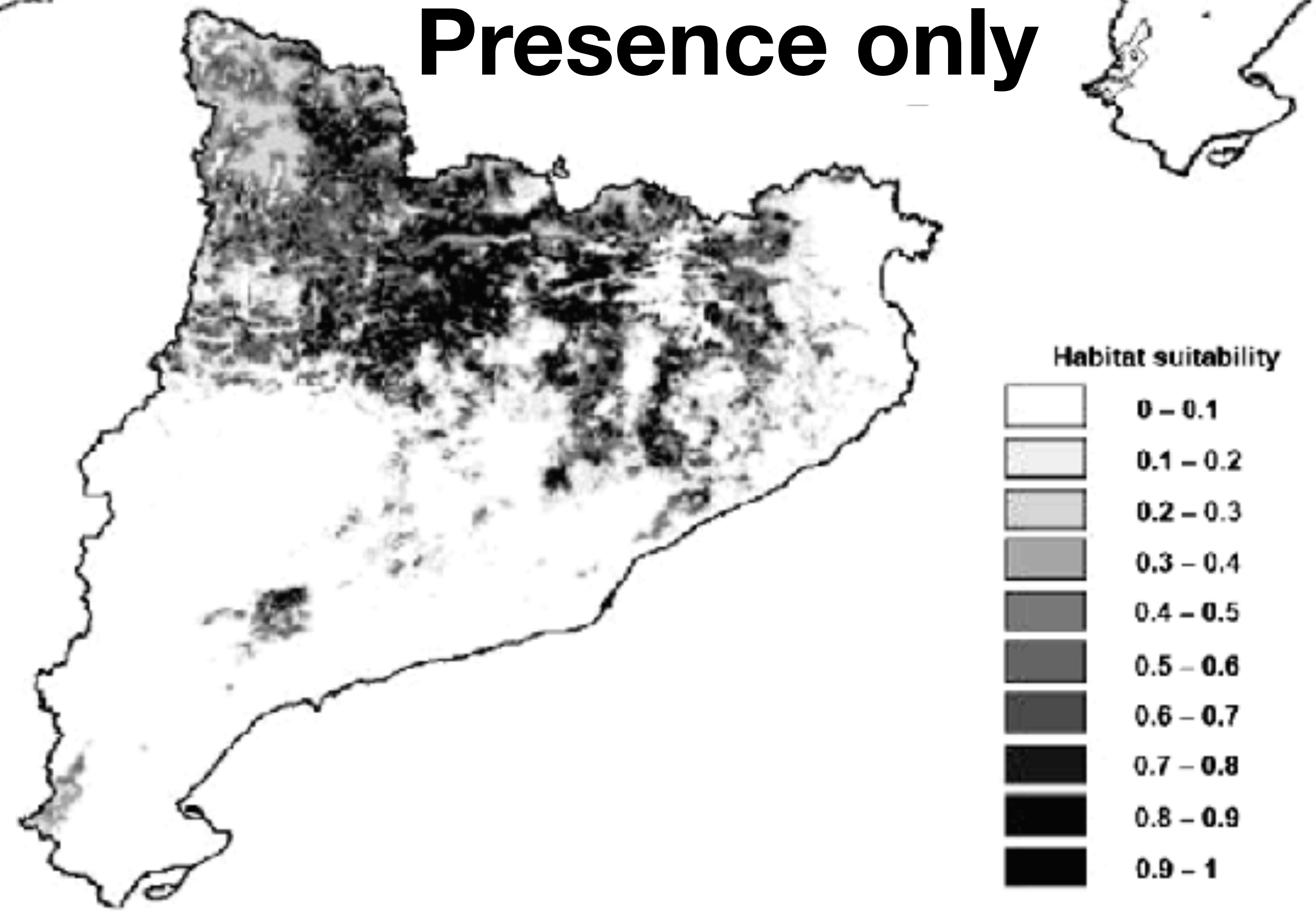
Processing Environmental Data

Presence-background SDMs

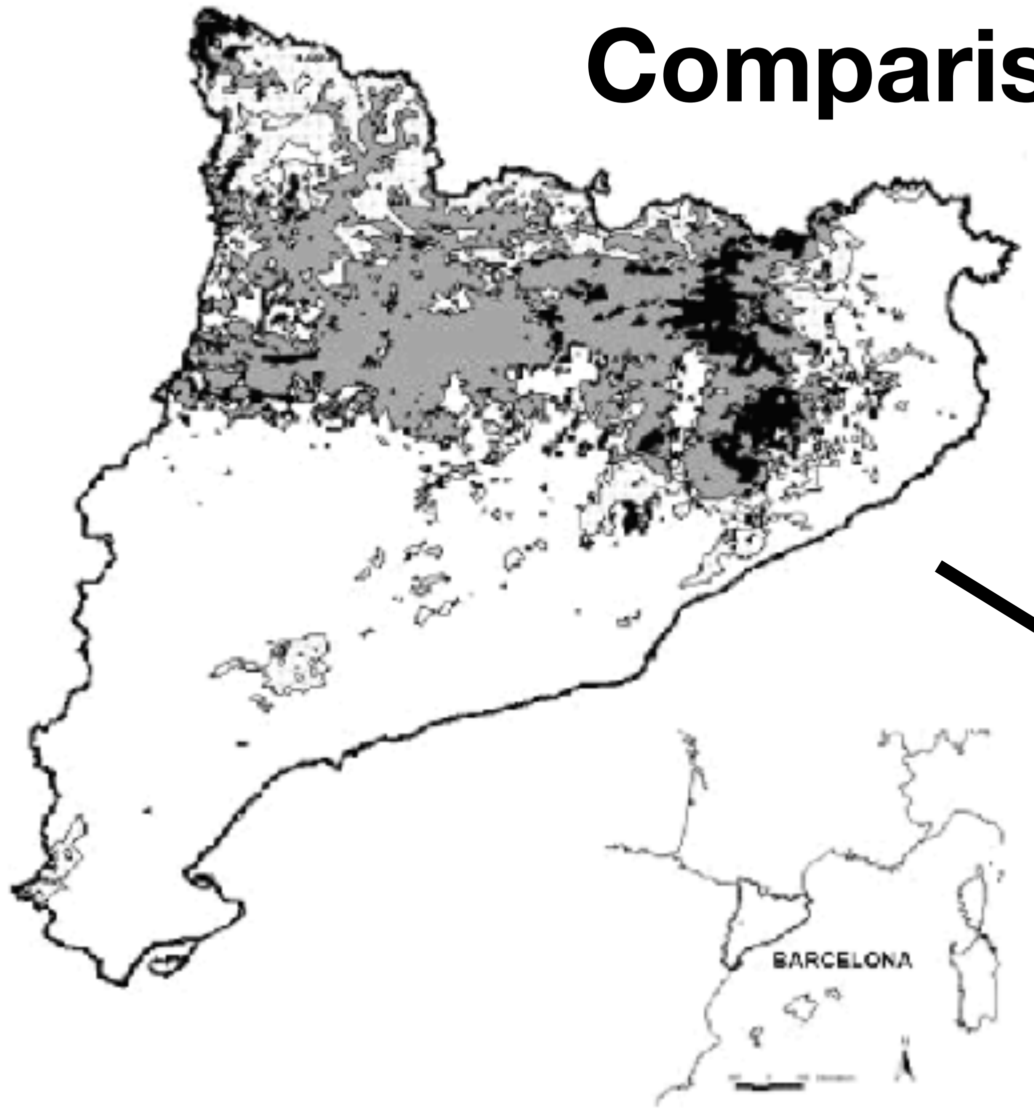
Presence-absence



Presence only



Comparison



ECOGRAPHY 27: 437–448, 2004

Presence-absence versus presence-only modelling methods for predicting bird habitat suitability

Lluís Brotons, Wilfried Thuiller, Miguel B. Araújo and Alexandre H. Hirzel

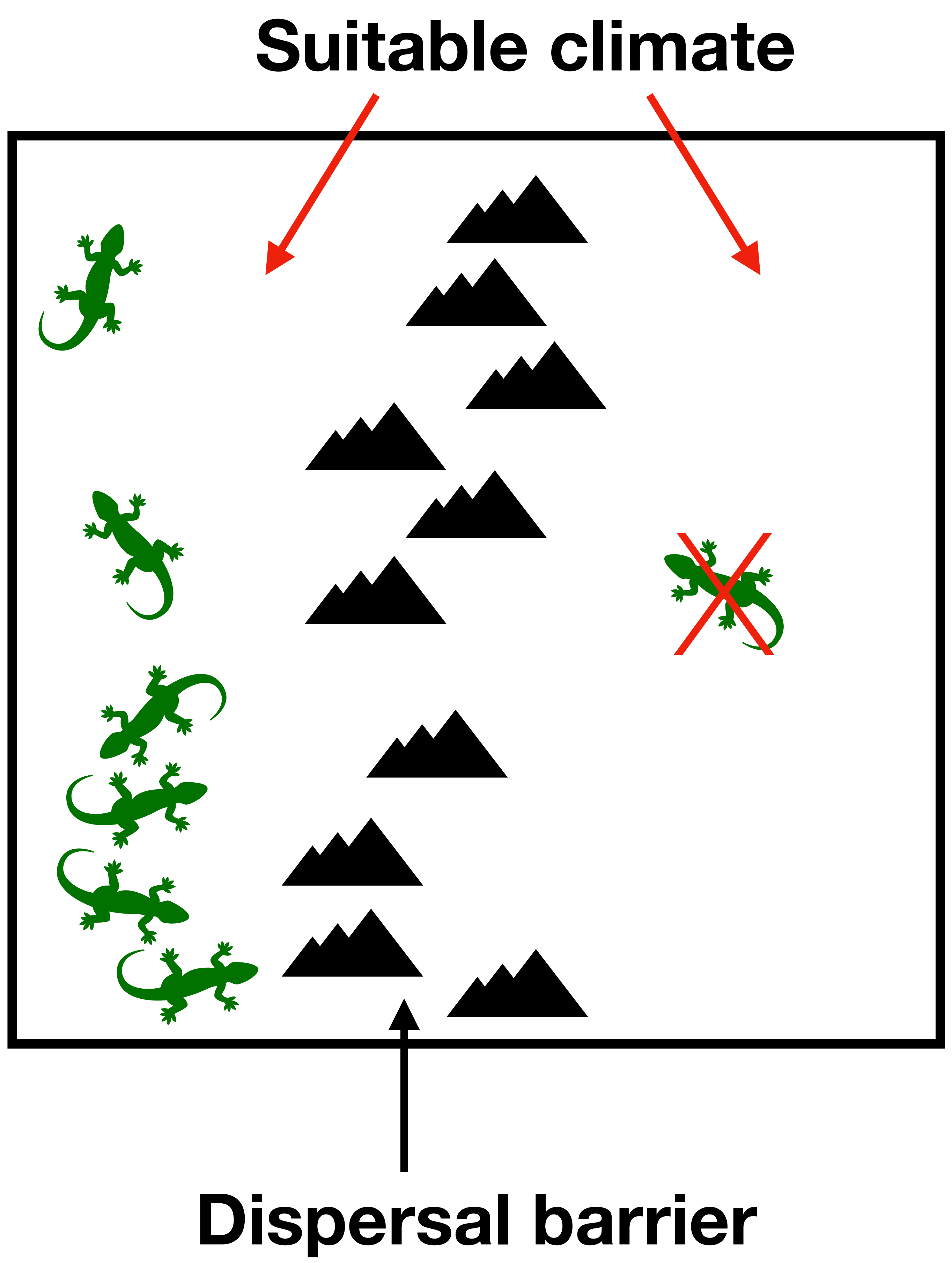
Black: presence-only predicted species absence and presence-absence presence.

Light grey: presence-only predicted presence and presence-absence absence.

Dark grey: coincidence in model predictions.

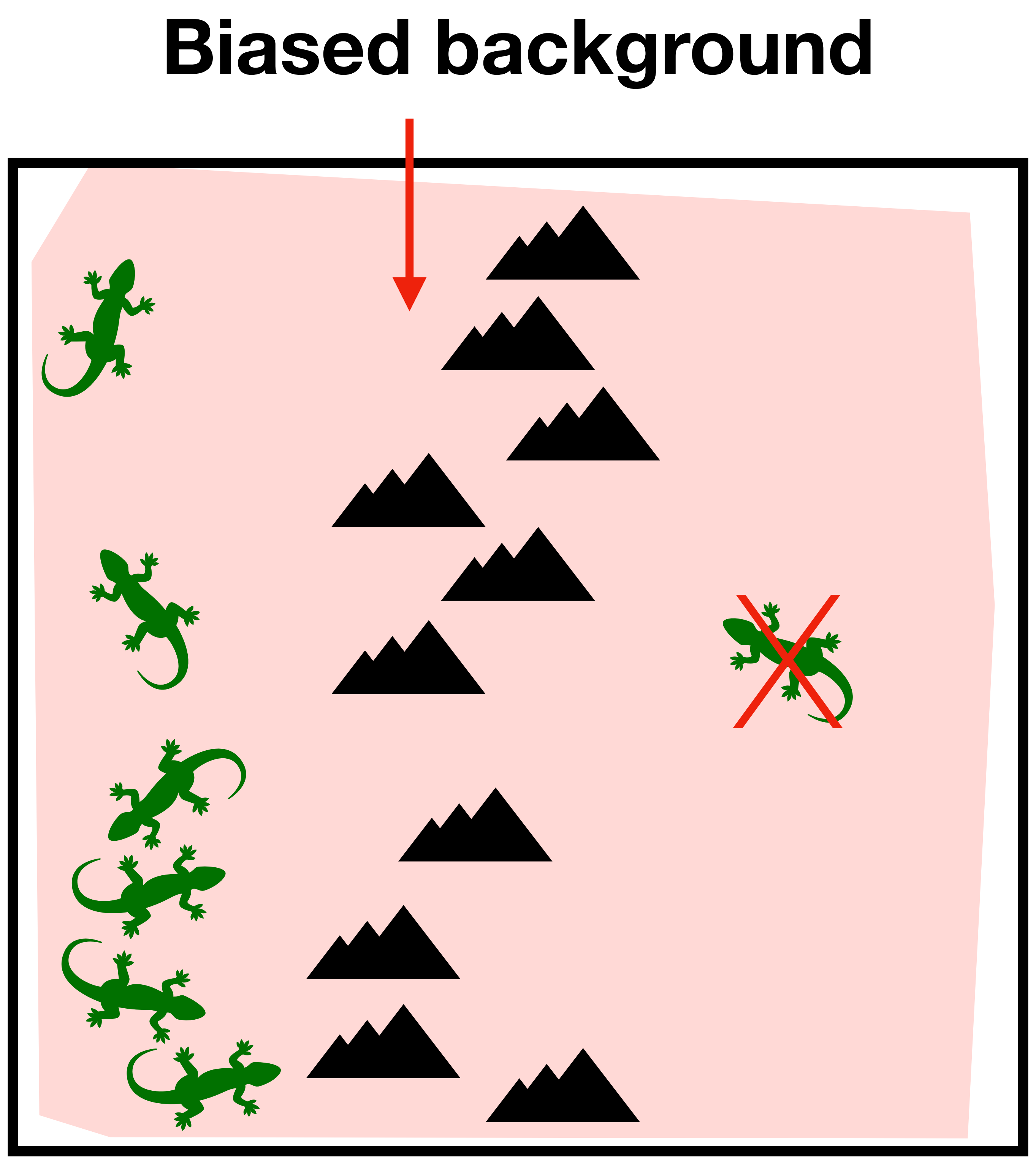
Processing Environmental Data

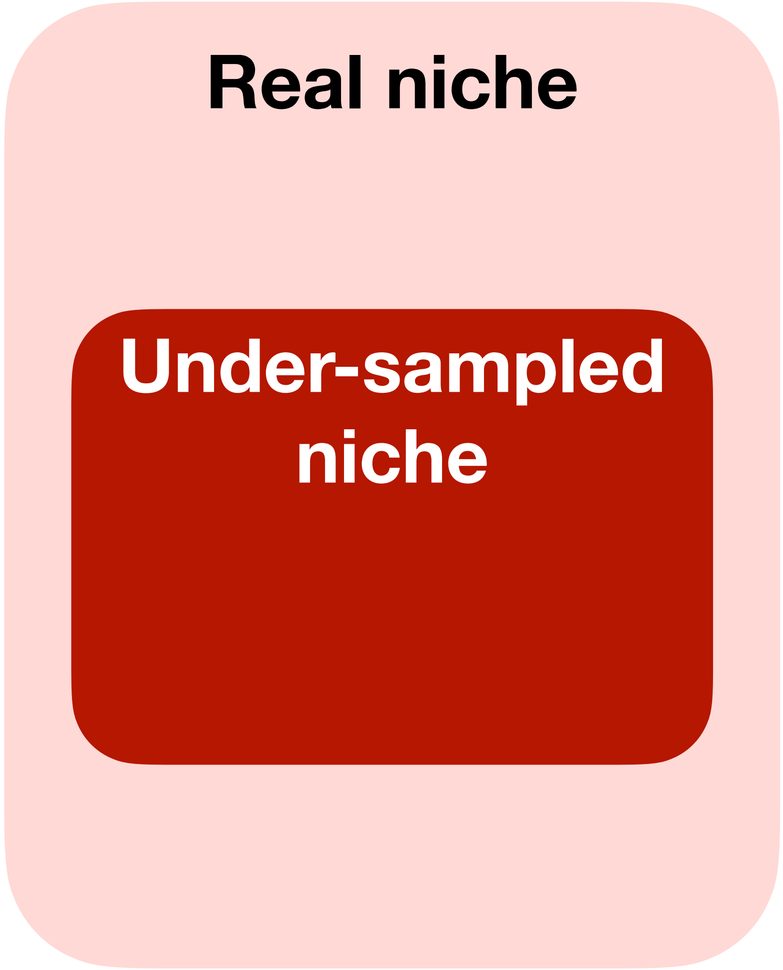
Historical dispersal and background selection



Processing Environmental Data

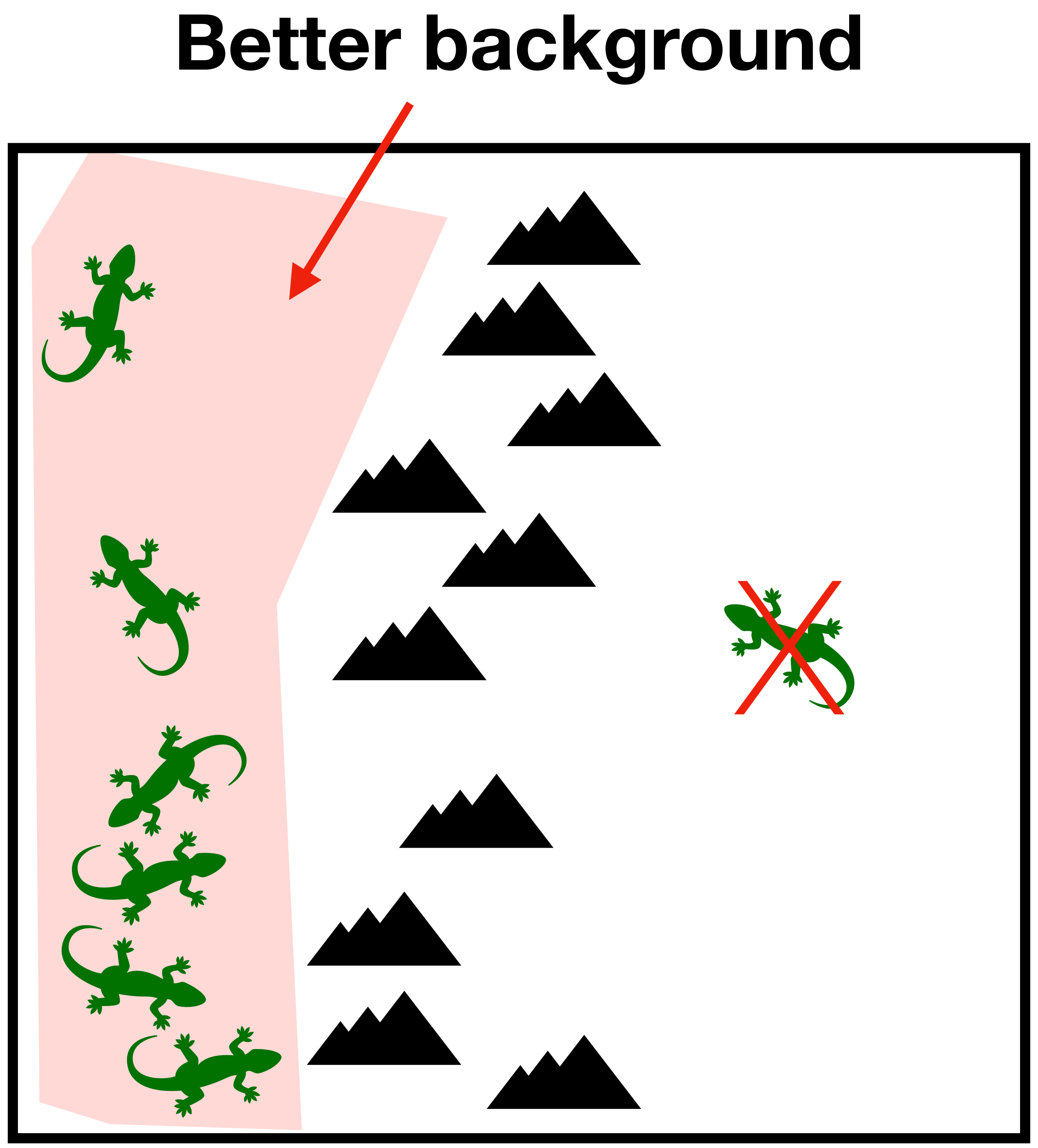
Historical dispersal and background selection





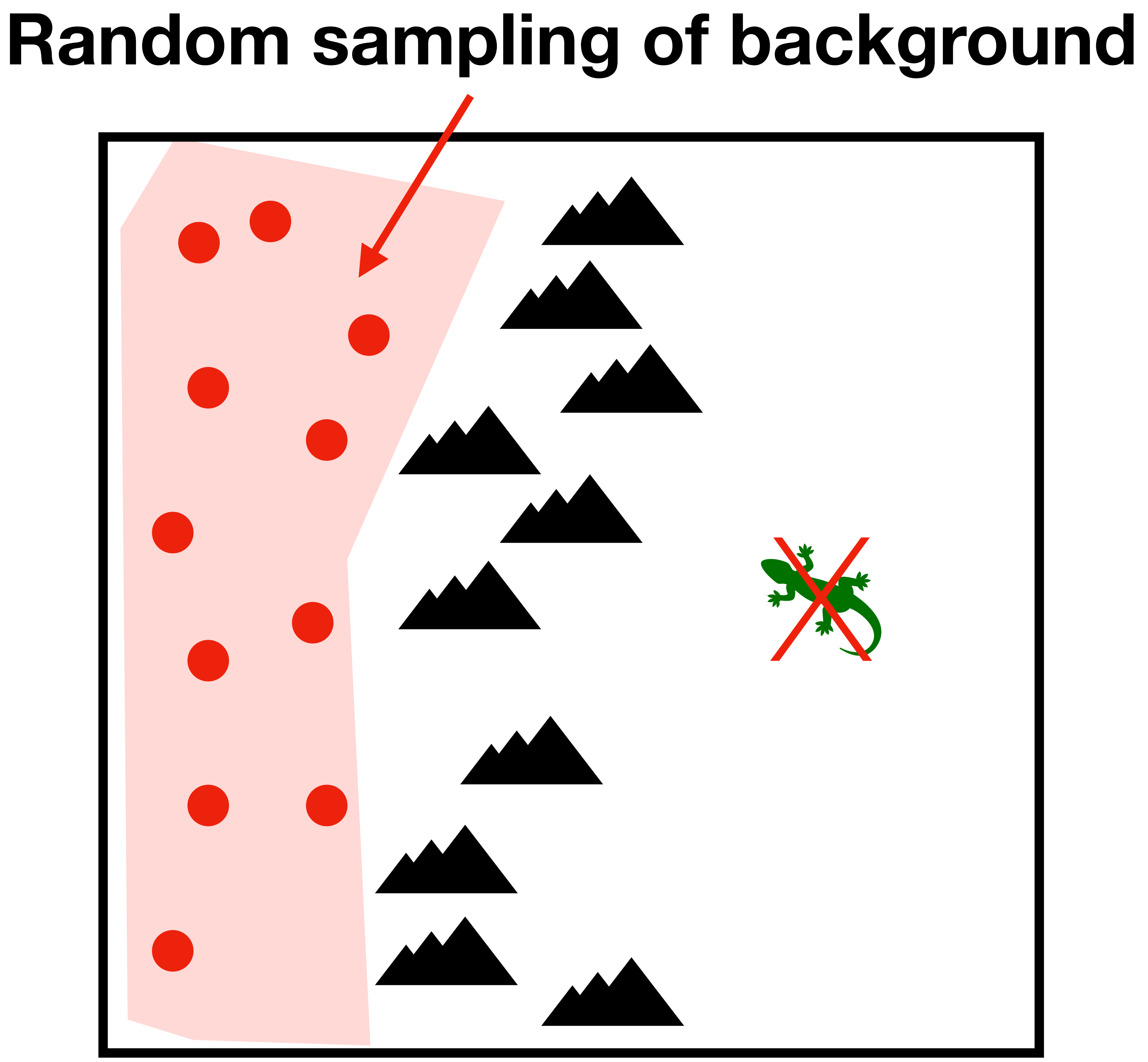
Processing Environmental Data

Historical dispersal and background selection



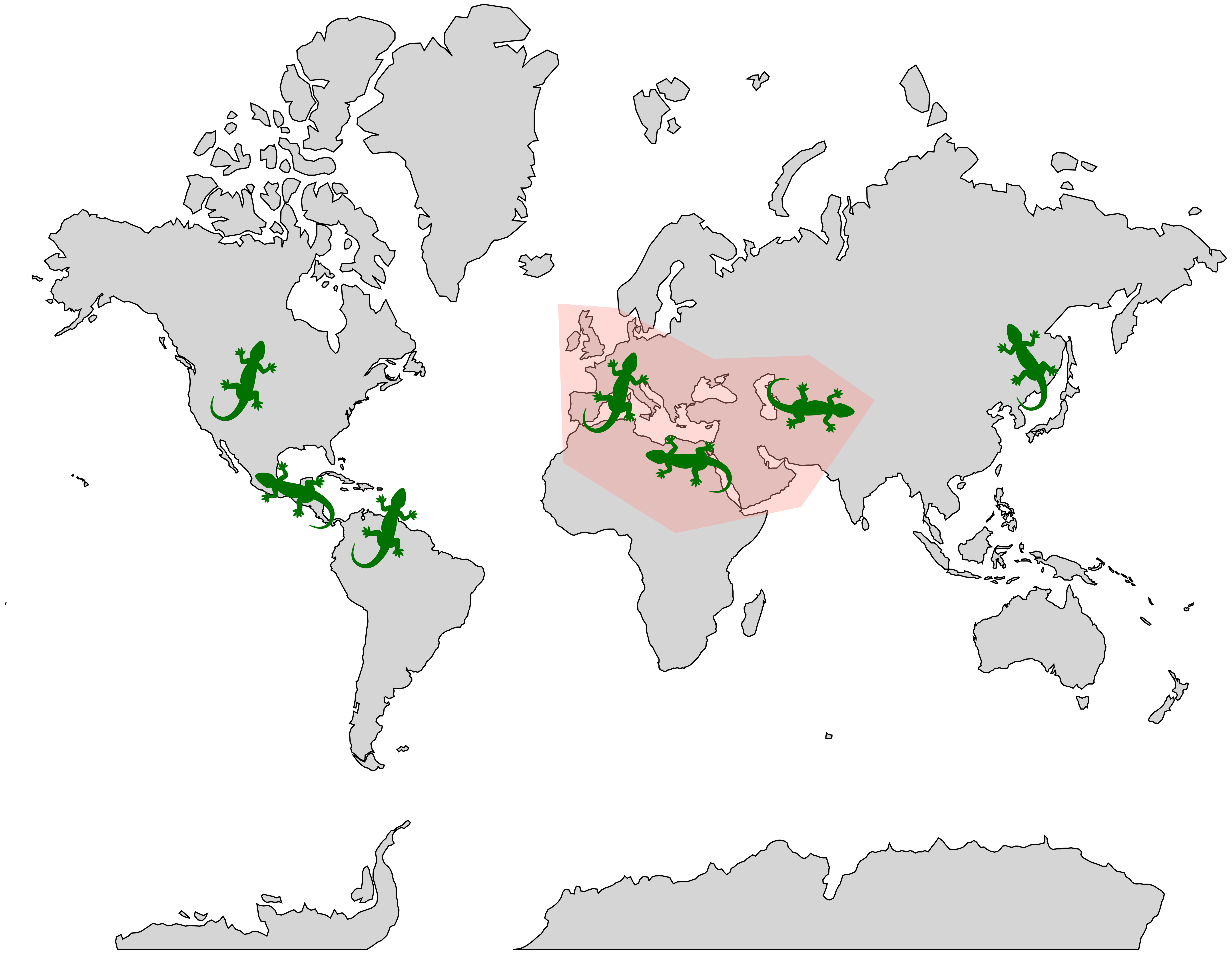
Processing Environmental Data

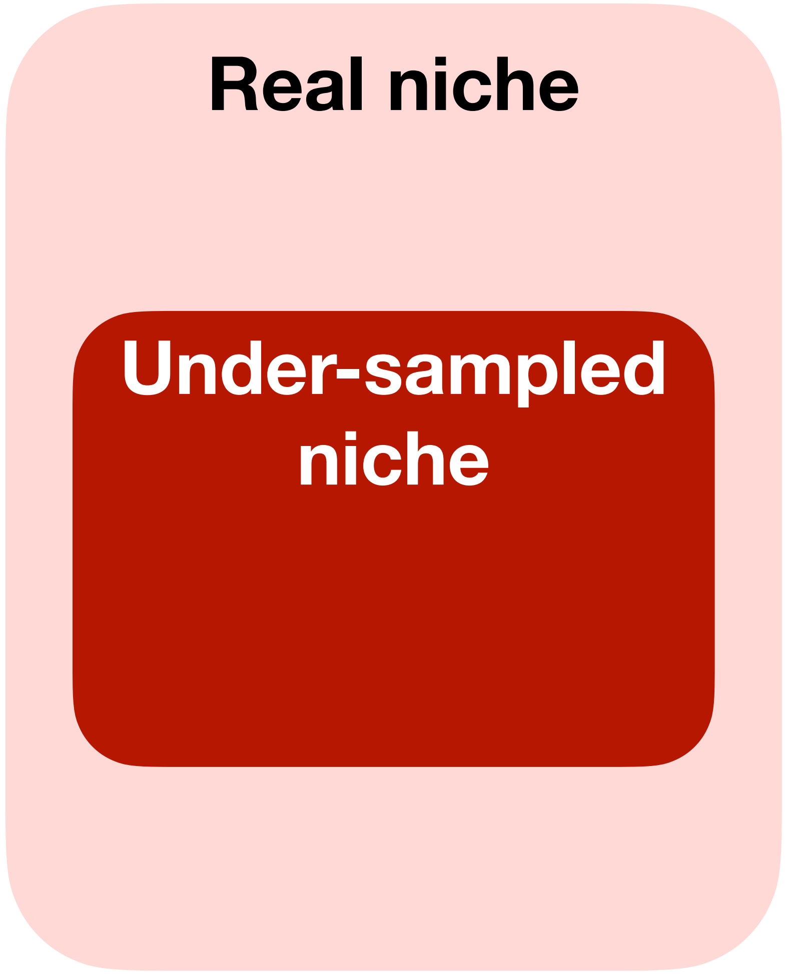
Historical dispersal and background selection



Processing Environmental Data

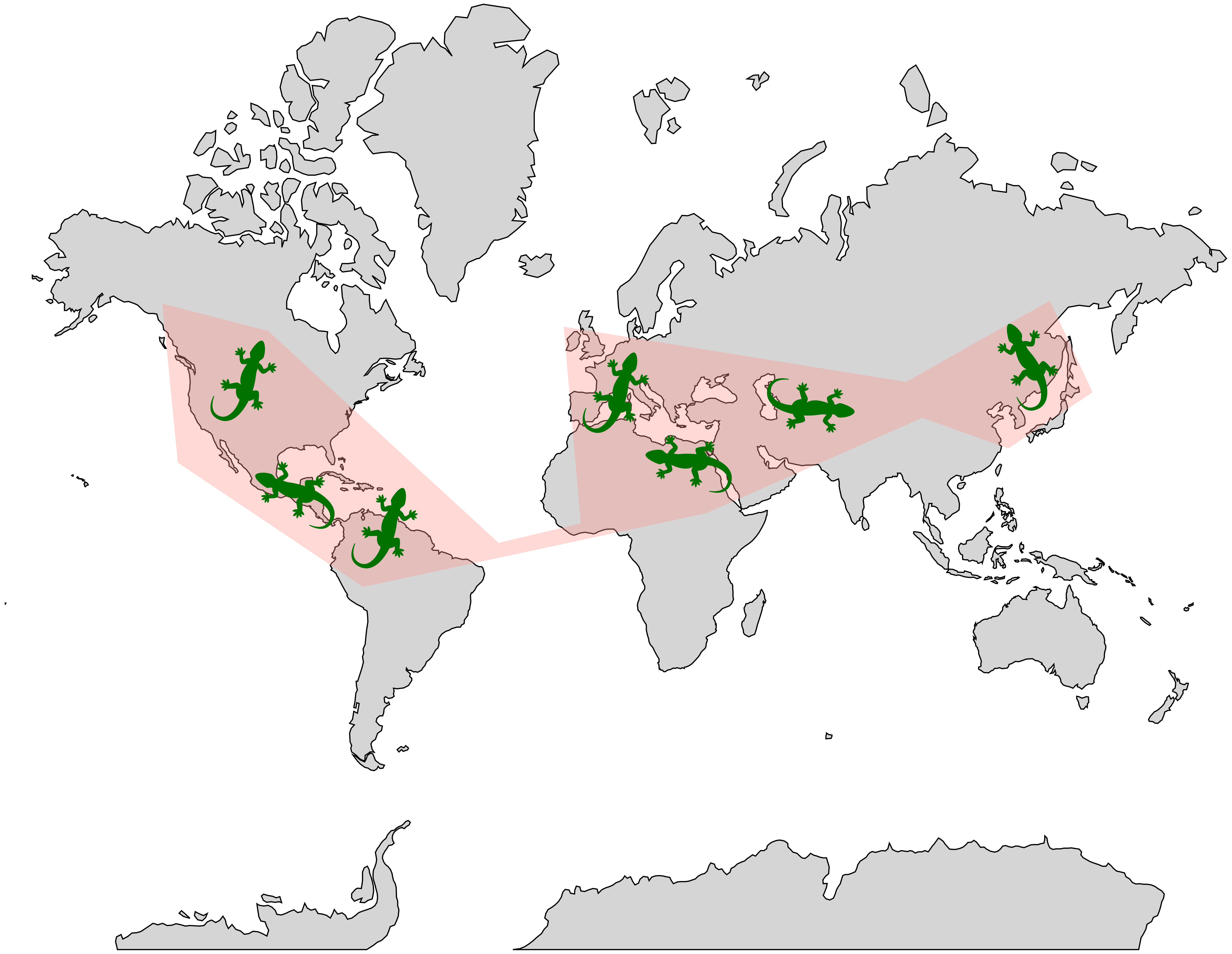
Niche truncation





Processing Environmental Data

Niche truncation



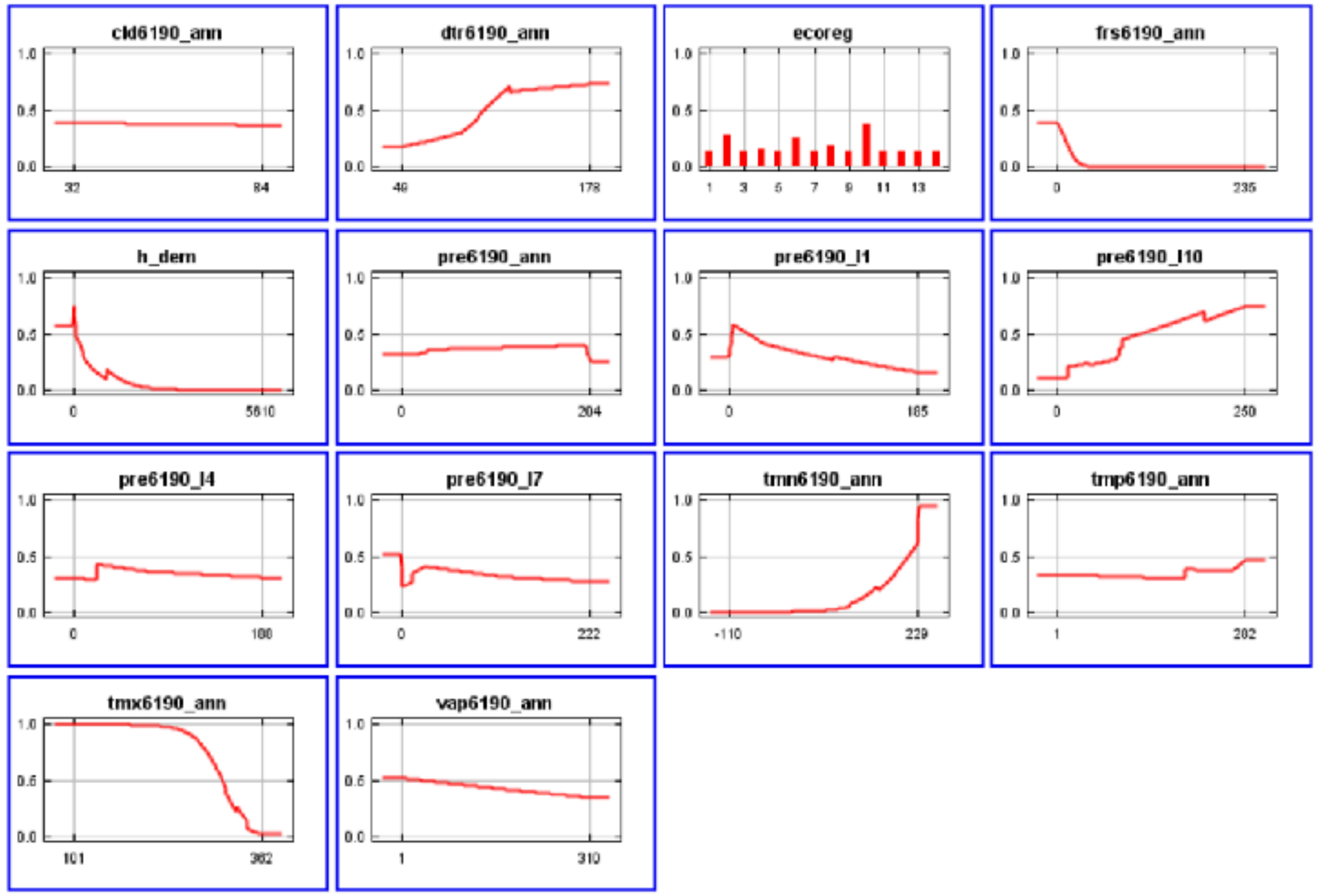
Model Outputs

Wallace Component “7 Visualise”

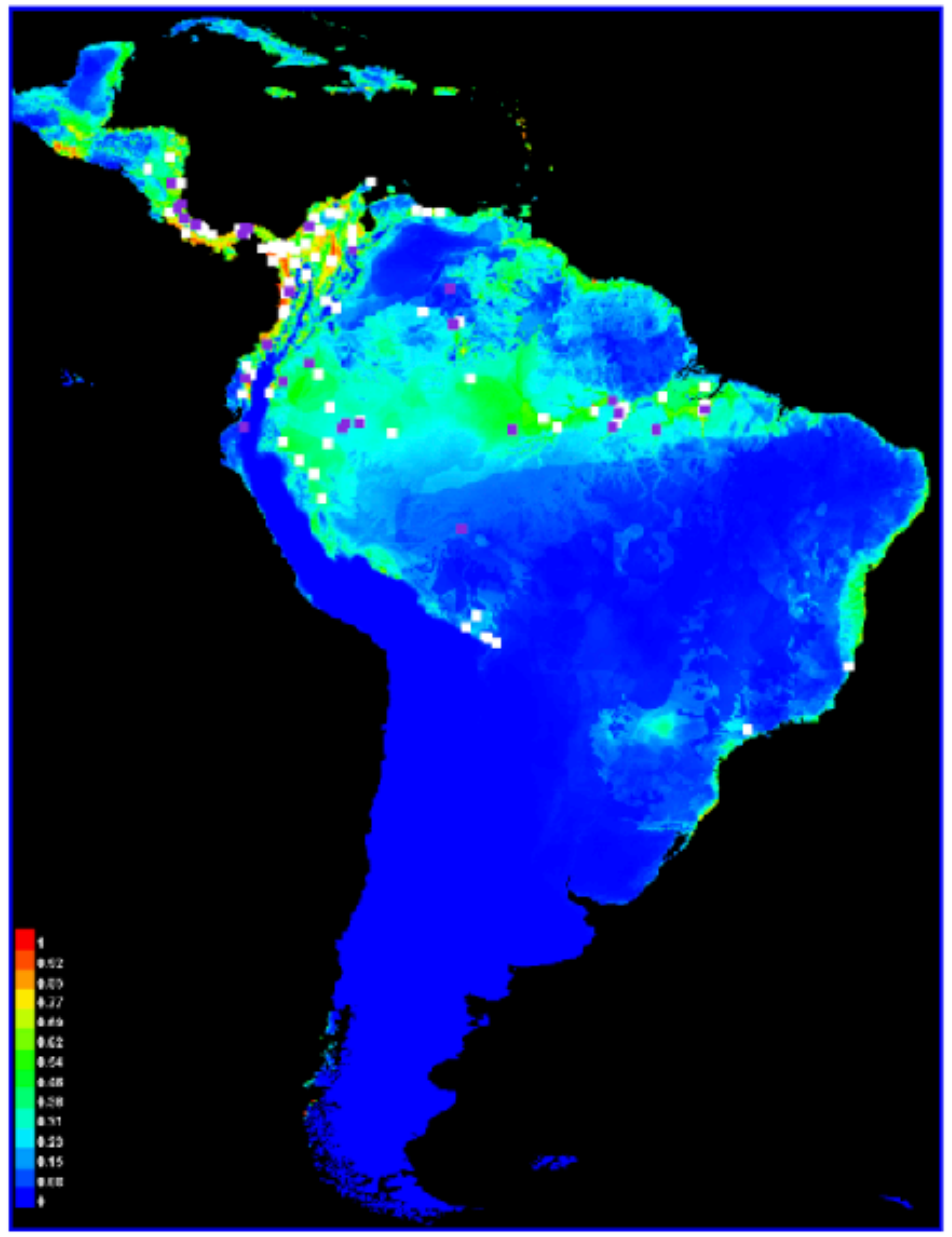
Model Outputs

MaxEnt evaluation plots, 2 kinds of visualisations

Environmental variables space



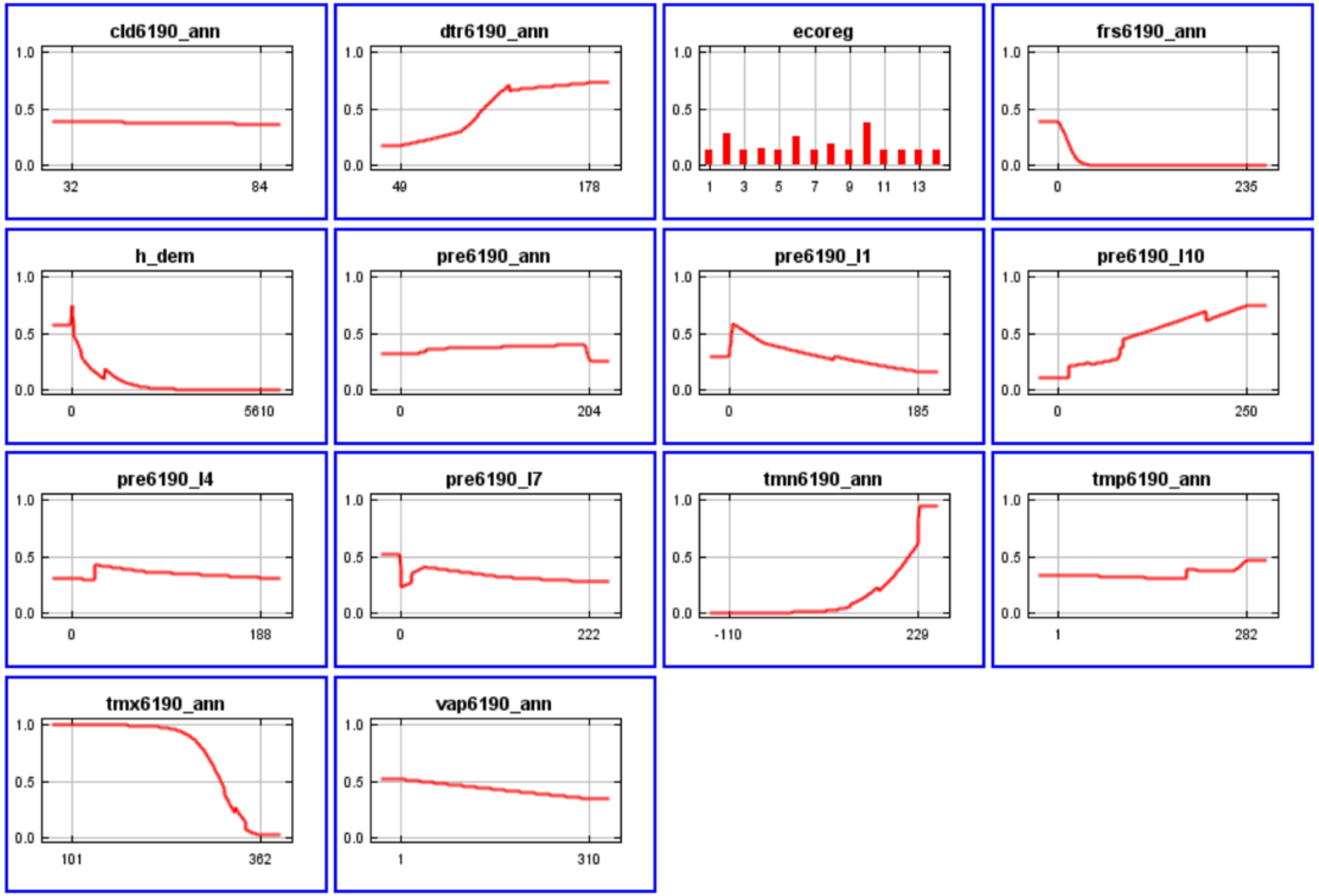
Geographic space



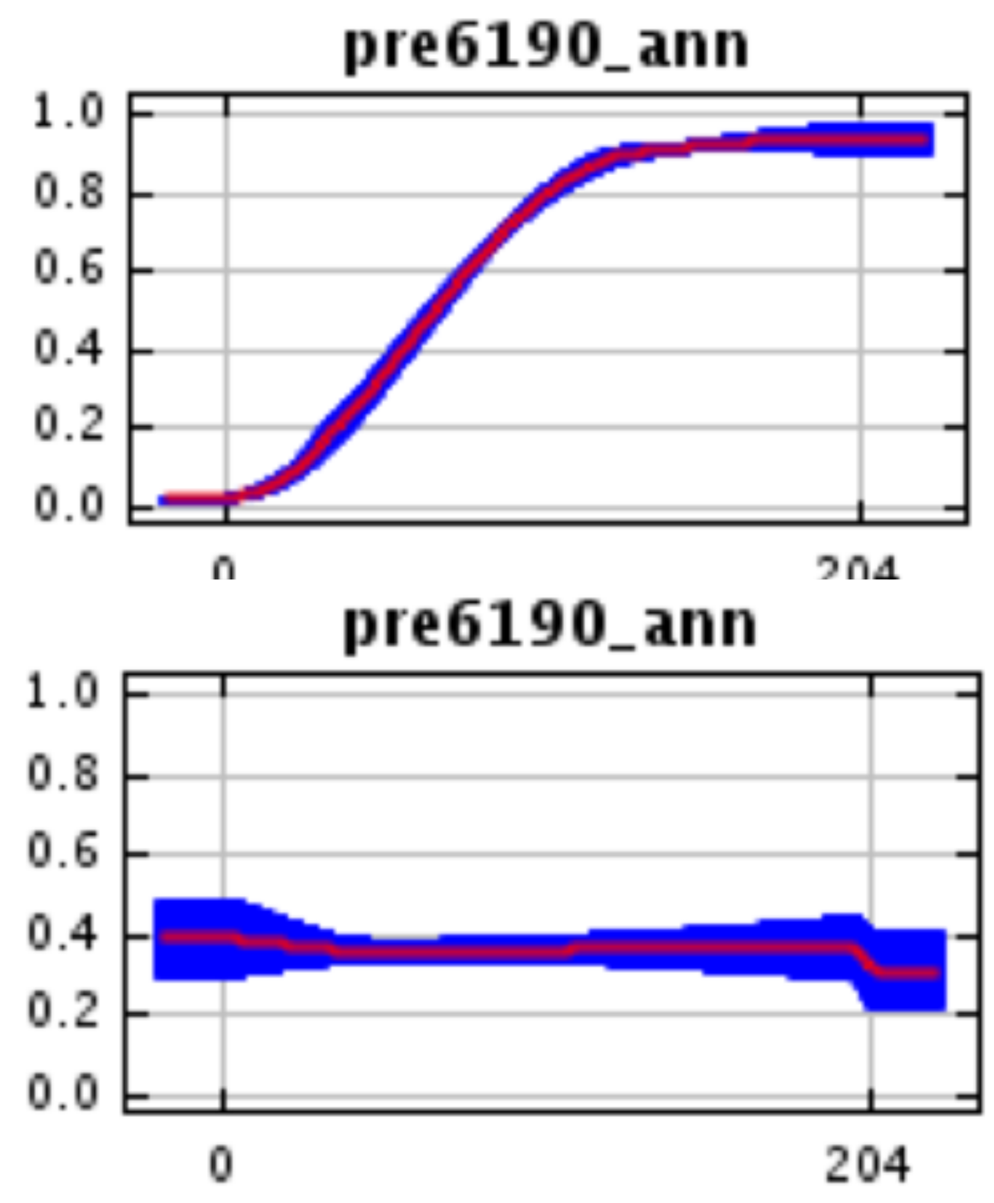
https://biodiversityinformatics.amnh.org/open_source/maxent/Maxent_tutorial_2021.pdf

Model Outputs

Response curves



For replicated runs:

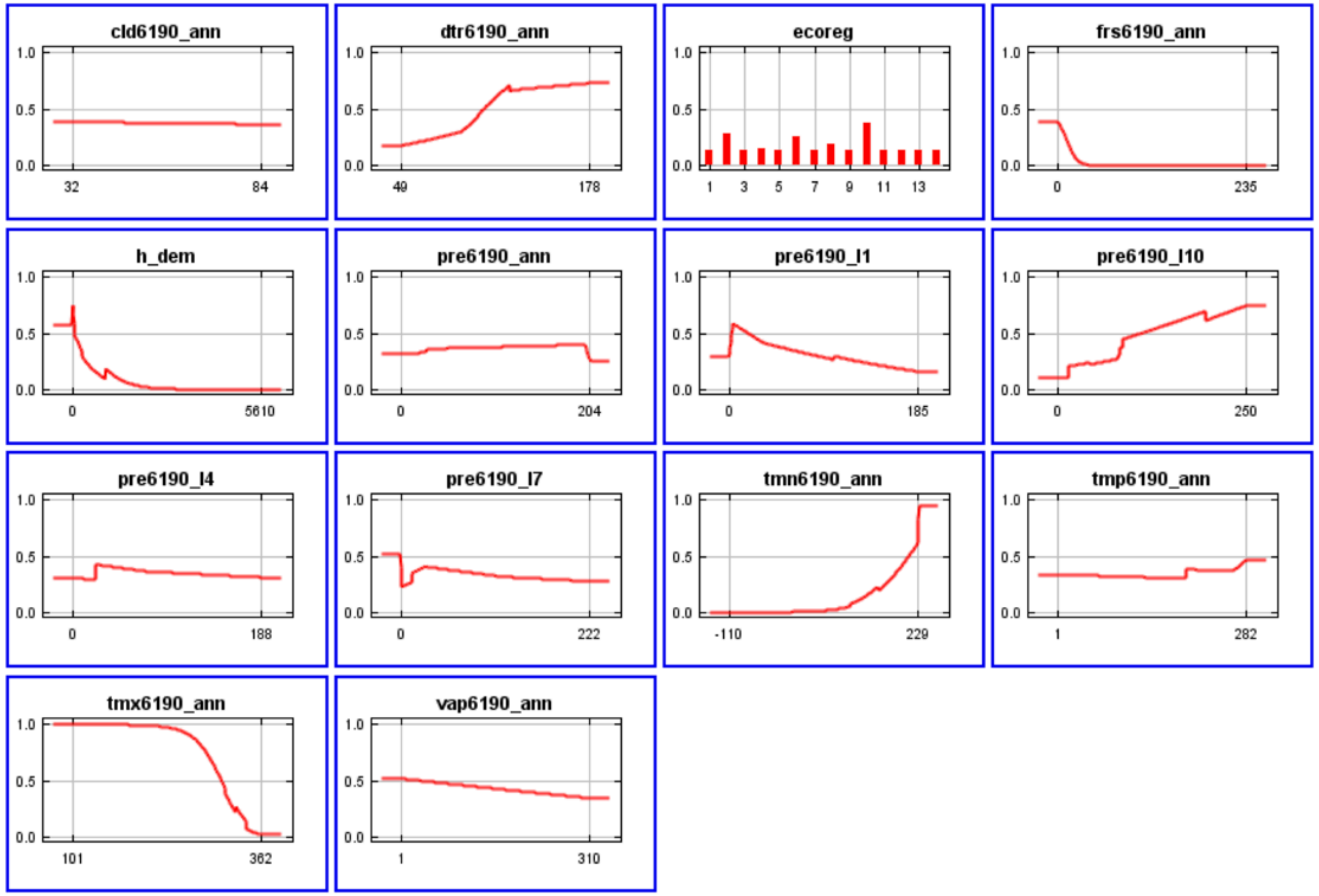


Model Outputs

Response curves

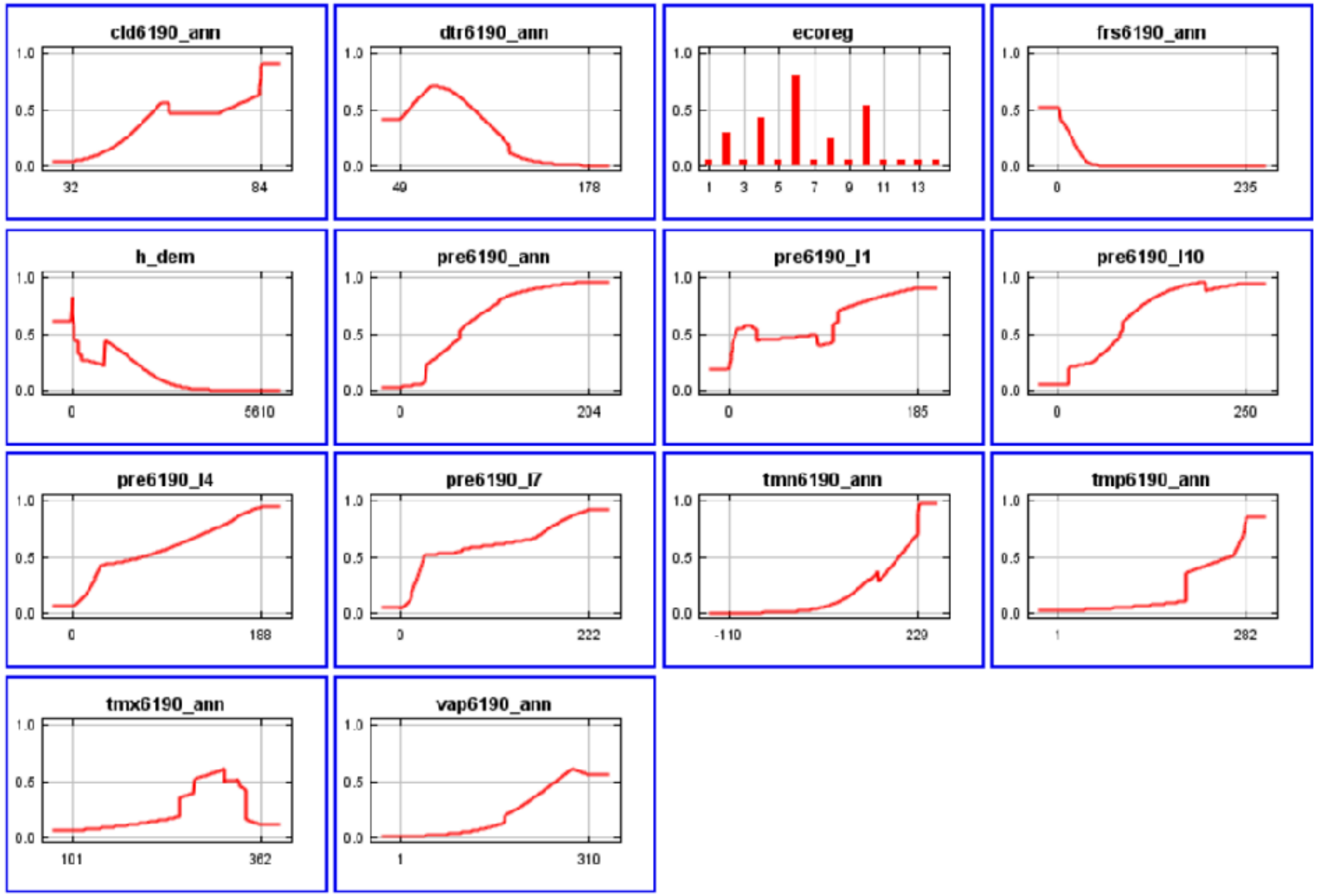
Marginal

Varying one variable while maintaining other ones at their mean value.
Biased by variables correlation



“Individual”

A model is built with only one variable.



Model Outputs

Variables contribution

Which variables matter most?

- Percentage contribution
    - At each iteration of the MaxEnt algorithm, the increase or decrease in gain caused by each variable is summed. >> *Euristic, inconsistent, MaxEnt specific.*
- Permutation importance
    - For each variable, the values of training presence and background are randomly permuted.
- Jackknife test
    - For each variable, the model is iterated without and with only that variable.

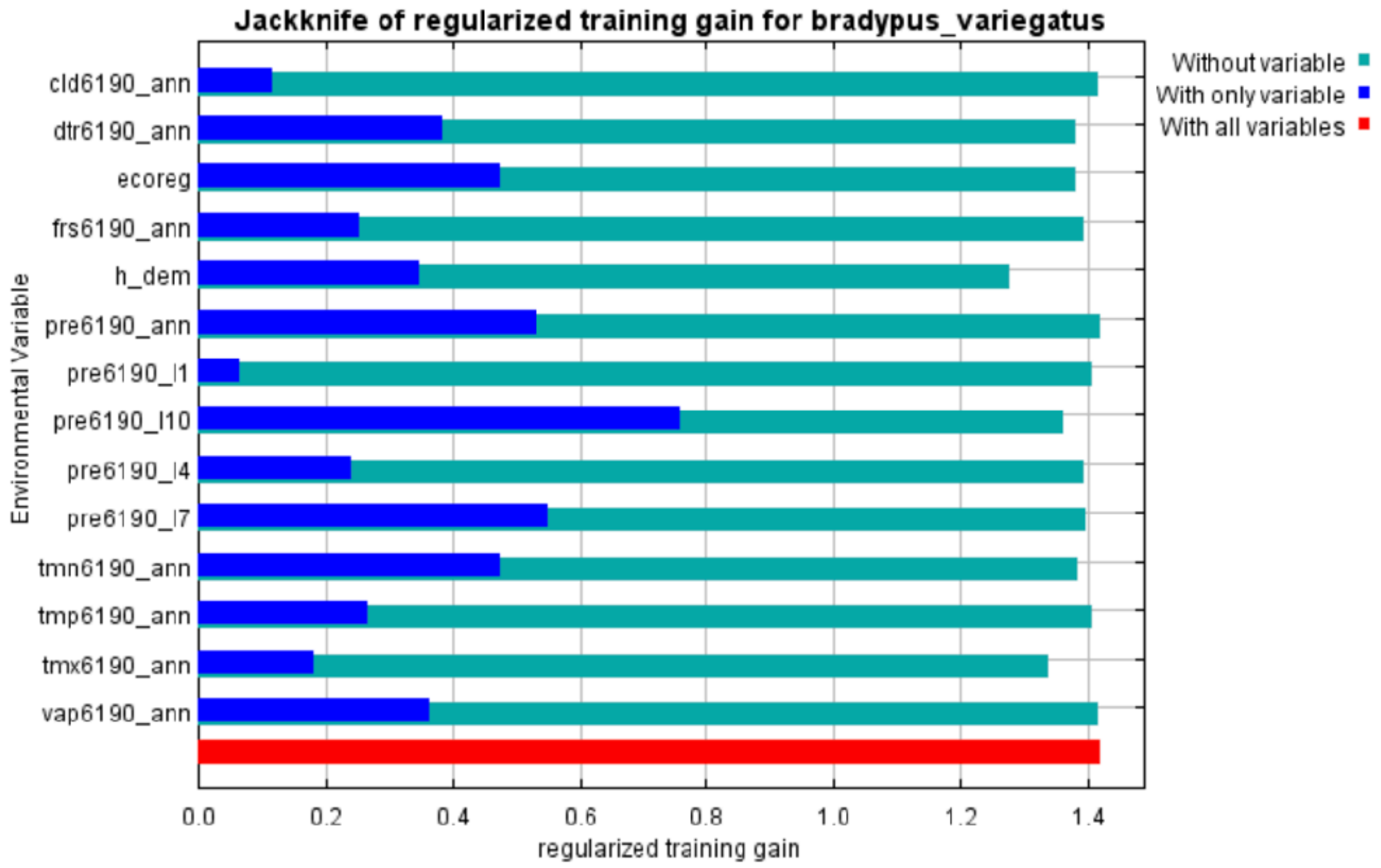
Model Outputs

Variables contribution

Percentage contribution
Permutation importance

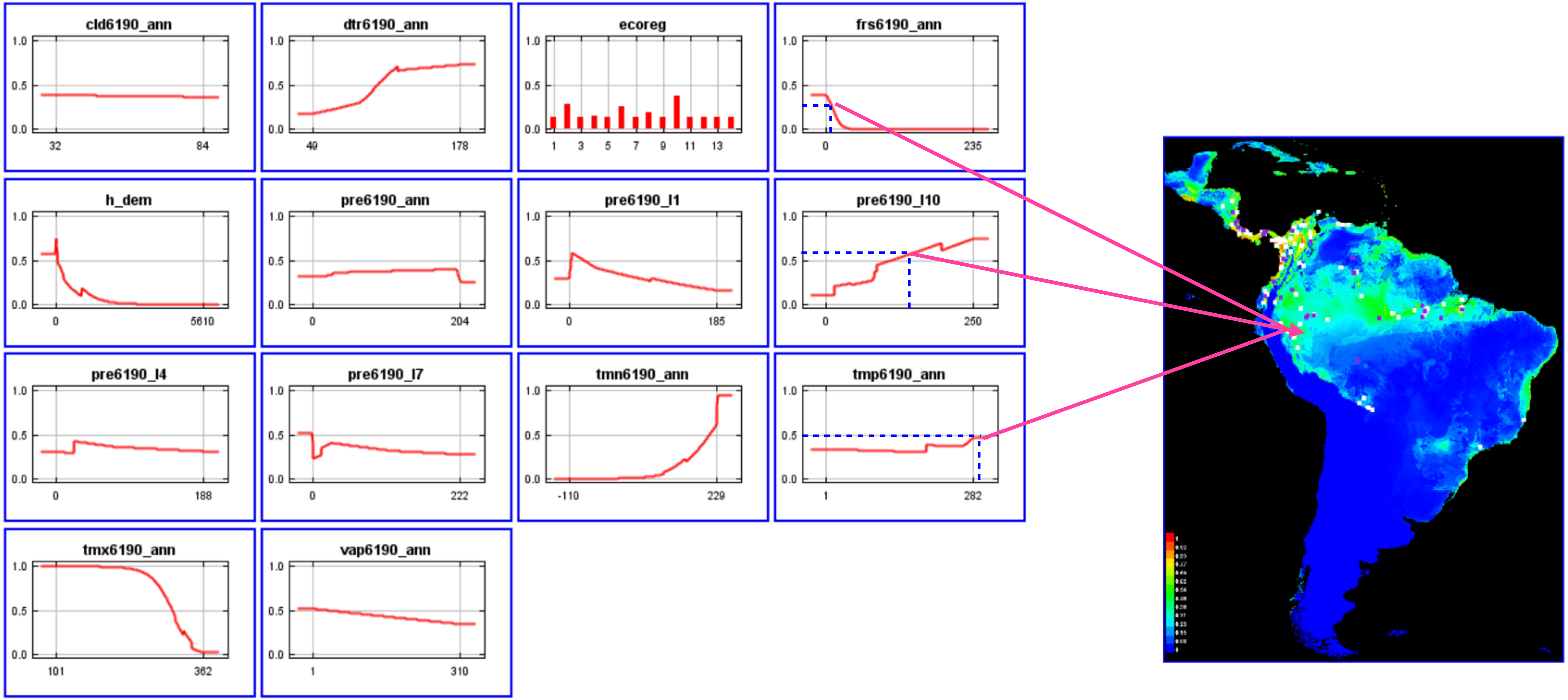
Variable	Percent contribution	Permutation importance
pre6190_l10	31.1	5.4
pre6190_l7	23.6	1.3
tmn6190_ann	14.7	20.6
h_dem	10.3	13.2
ecoreg	6.6	3.7
tmx6190_ann	4.3	19.6
pre6190_l1	2.2	1.8
frs6190_ann	2.1	25.6
pre6190_l4	1.8	3
vap6190_ann	1.6	0.3
tmp6190_ann	1.1	0.7
dtr6190_ann	0.4	4.7
pre6190_ann	0.3	0.1
cld6190_ann	0	0

Jackknife test



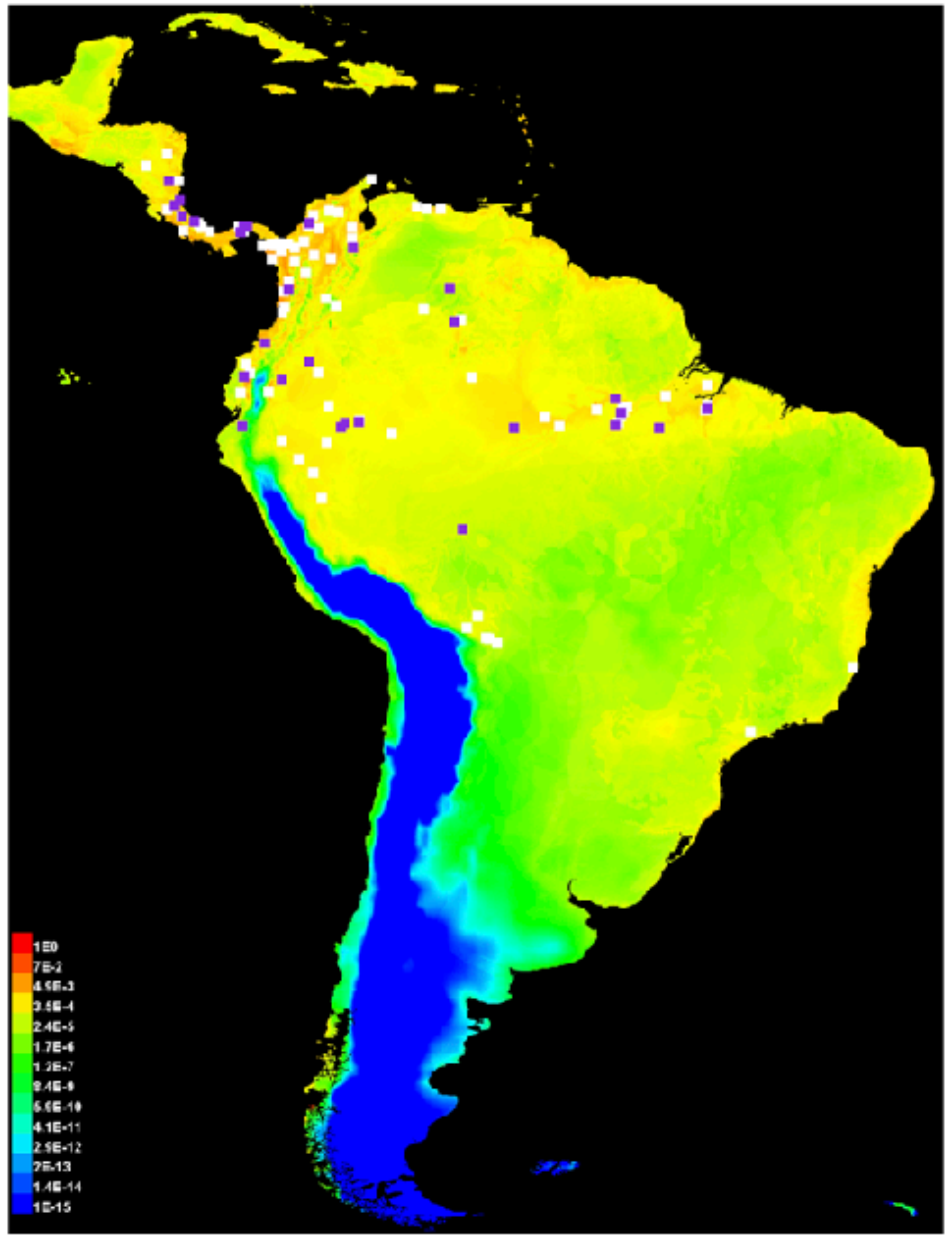
Model Outputs

Relationship between variables and geographic spaces



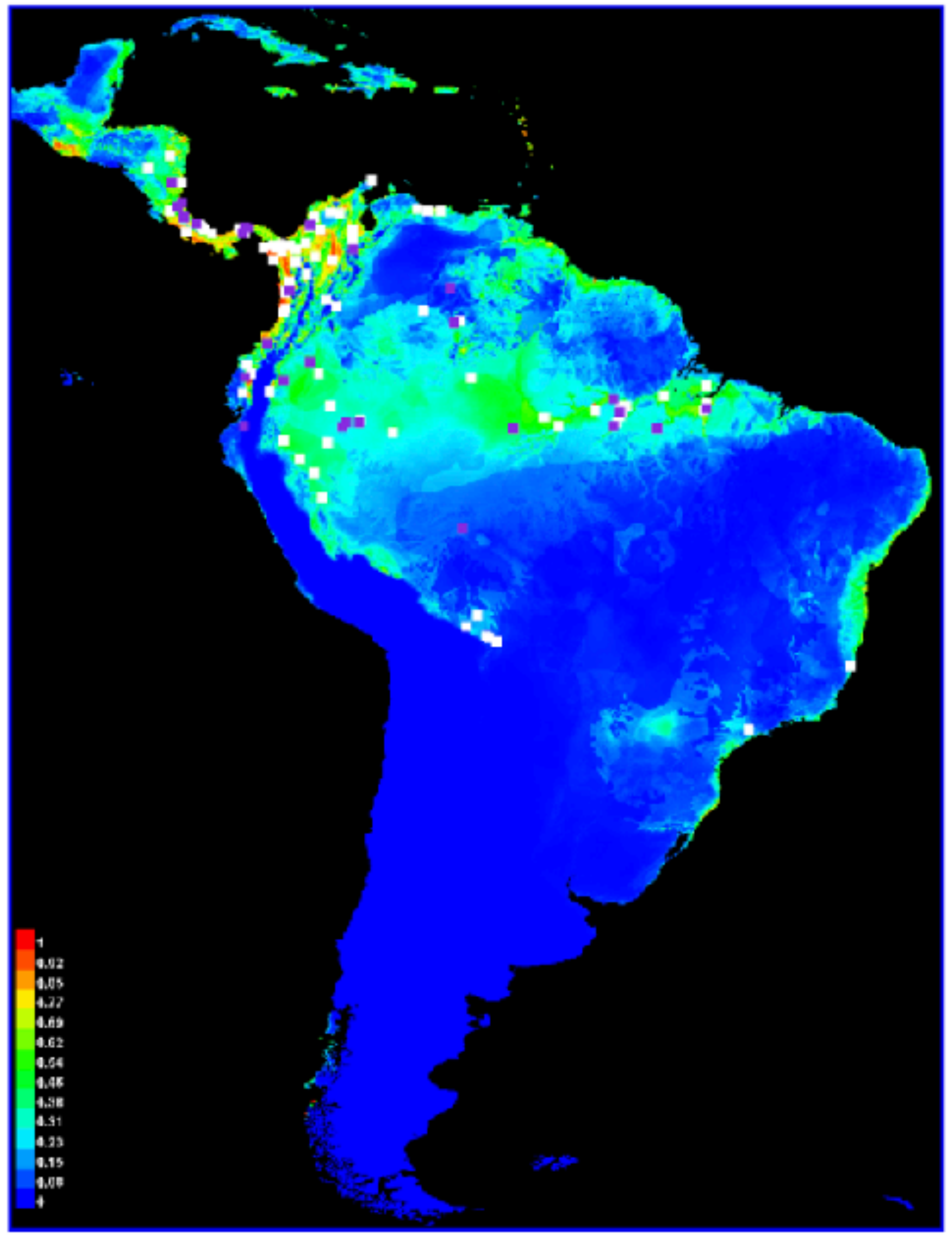
Model Outputs

Output formats



Raw

- Values of background pixels sum to 1 and can represents relative abundance
- Very few high values
- Logarithmic colour scale



Logistic & ClogLog

- Estimate between 0 and 1 of probability of presence
- **Logistic:** assumes that prevalence of the species equals 0.5 (Yackulic et al. 2012; Merow et al. 2013).
- **ClogLog:** assumptions are made regarding spatial dependence and cell size (Phillips et al. 2017).
- Logistic and ClogLog transformed values are generally similar, but cloglog tends to be higher for mid- to high-range values (Phillips et al. 2017).

Model Outputs

Binary outputs

Typical threshold selection:

- Minimum training presence
    - The lowest suitability score for any occurrence localities used to train the model.
- 10th percentile training presence
    - The lowest suitability score for any occurrence localities used to train the model after excluding the lowest 10% of them.
- Maximisation of sensitivity and specificity sum