Transdisciplinary Nature Conservation:

The IUCN Red List of Threatened Species from evaluation to practice

Luca Bütikofer, 15.09.2022

Luca Bütikofer

Spatial- Agro- Macro- Ecologist

Studies:

- BSc & MSc University of Pavia (Italy)
- PhD Massey University (New Zealand)
- PostDoc University of Exeter (UK)
- PostDoc Rothamsted Research (UK)

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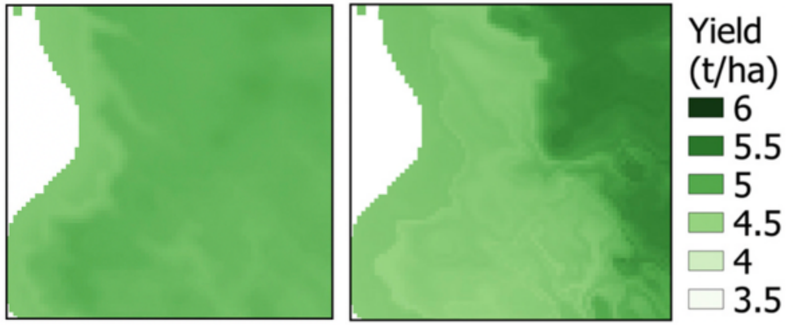
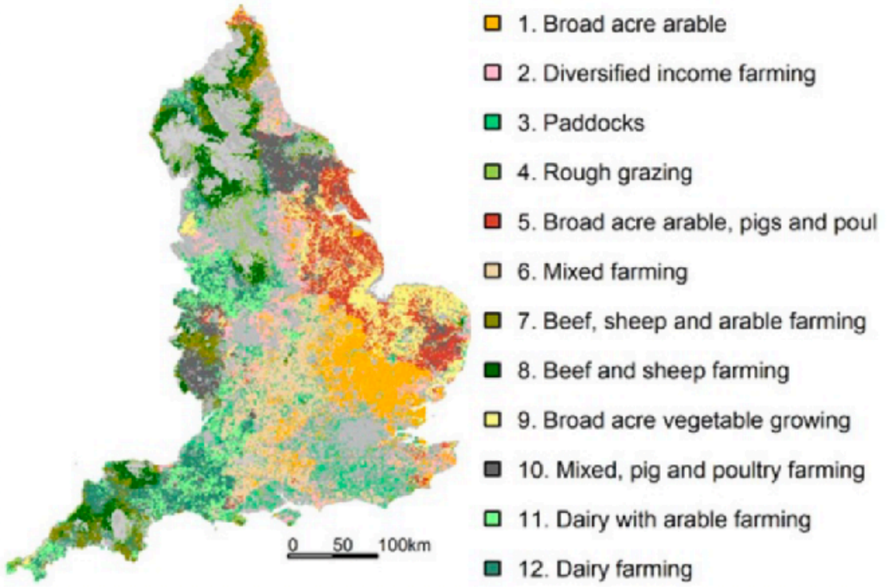
Luca Bütikofer

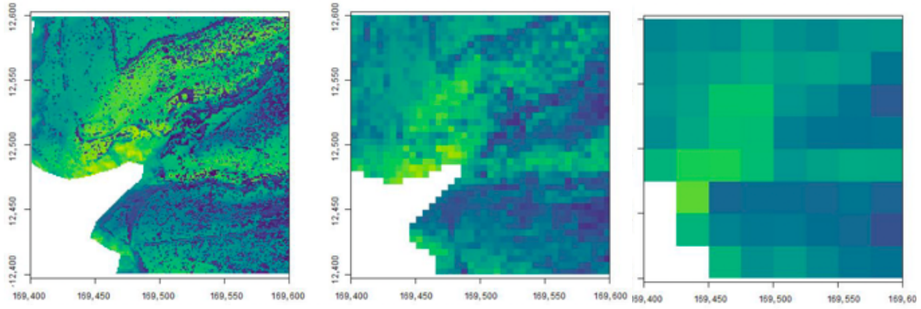
Spatial- Agro- Macro- Ecologist



PostDoctoral research:

- Scale in biological systems
- Microclimate and agriculture
- Farming system's sustainability and ecosystem services
- Land-use change





Environmental Data

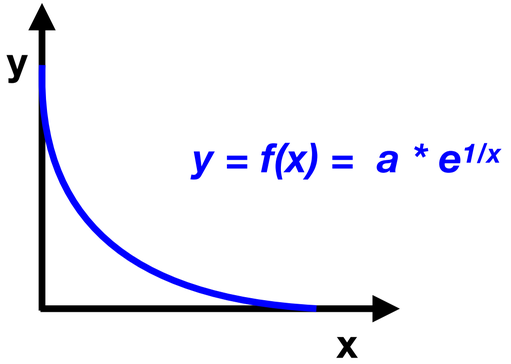
Wallace Component “3 Env Data”

Environmental Data

These are the model's explanatory variables

What explains the distribution of the species?

- y: number of mice observations
- x, *explanatory variable:* 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?

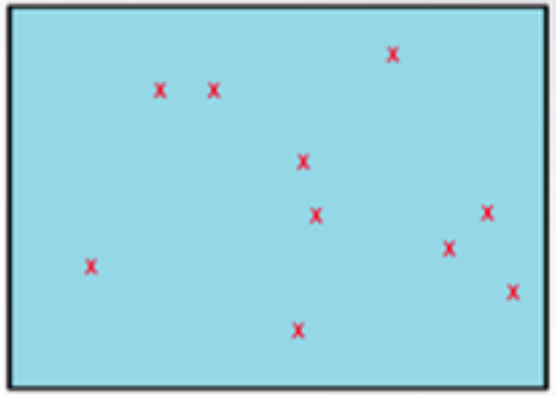
- Typical examples:
  - Climate
  - Geology
  - Soil
  - Hydrology
- Land-use / land-cover
- Distance to…
- Moving windows

Environmental Data

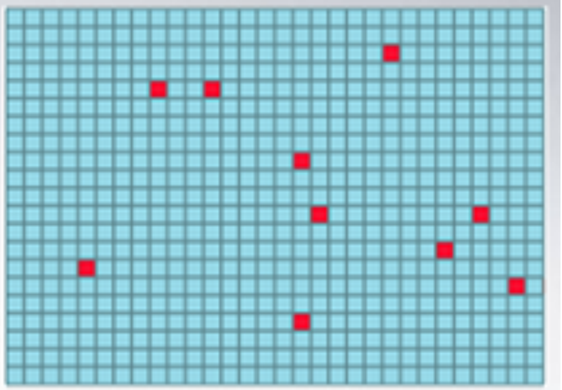
The raster format

Two main geographic data formats:

- Vectorial
  - Point
  - Line
  - Polygon
- Raster

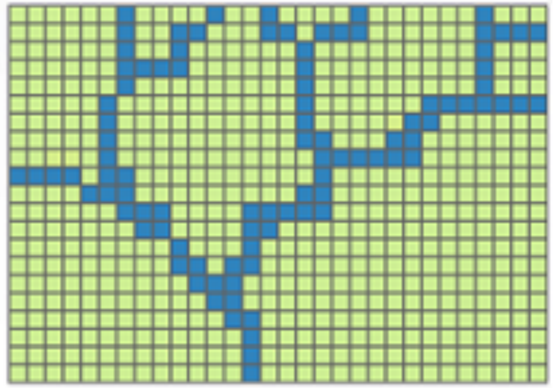


Point features



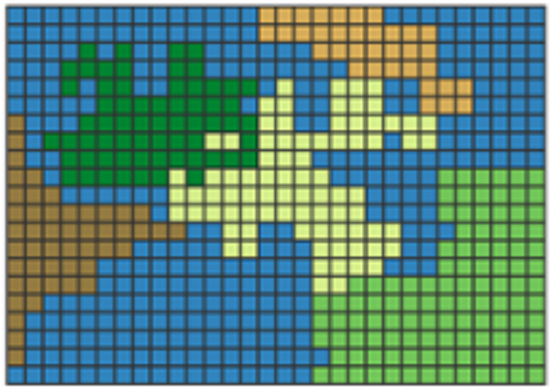
Raster point features

Line features



Raster line features

Polygon features

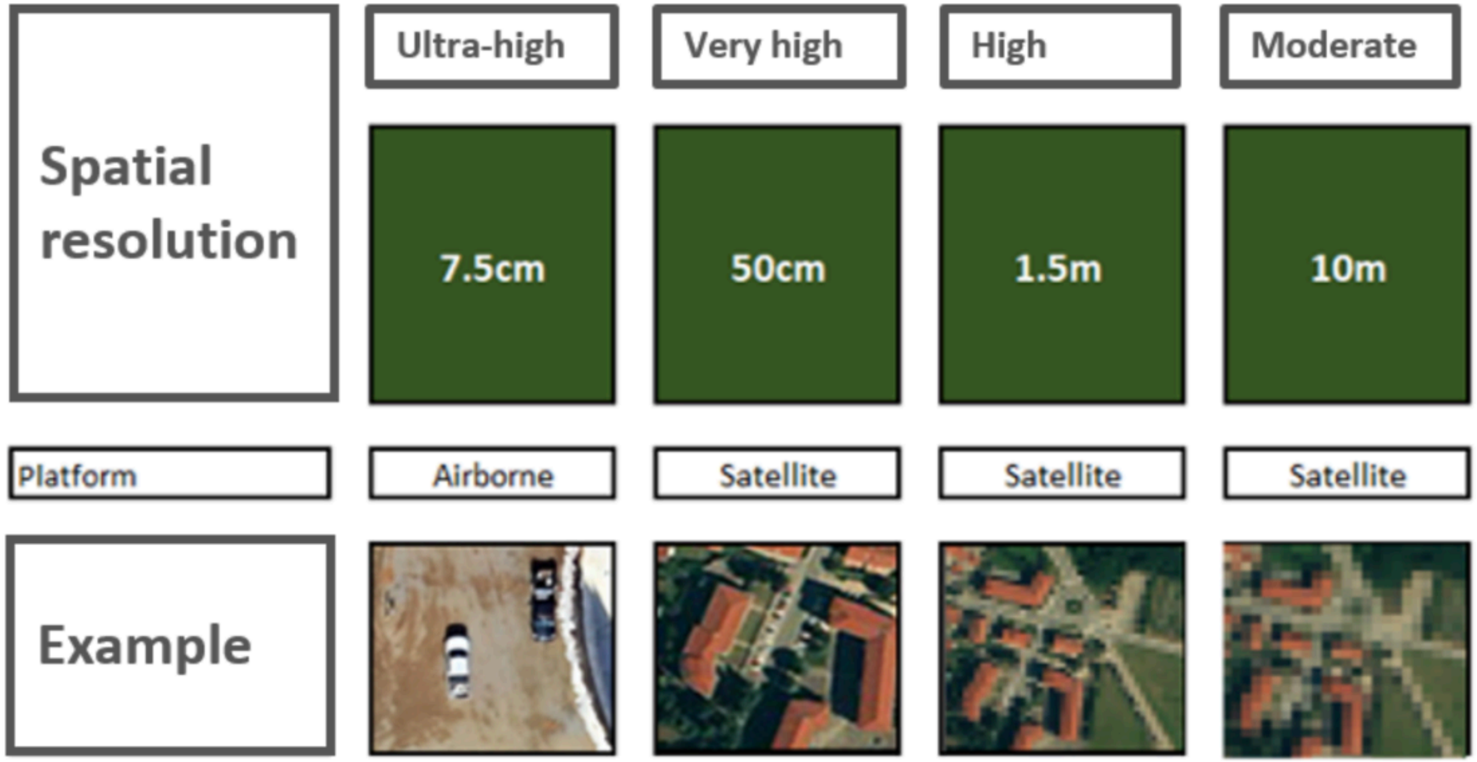


Raster polygon features

Environmental Data

Scale

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



Environmental Data

Scale

Don’t know the resolution?

- Multiple scales
- Scale-based decomposition of landscape features into different variables

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

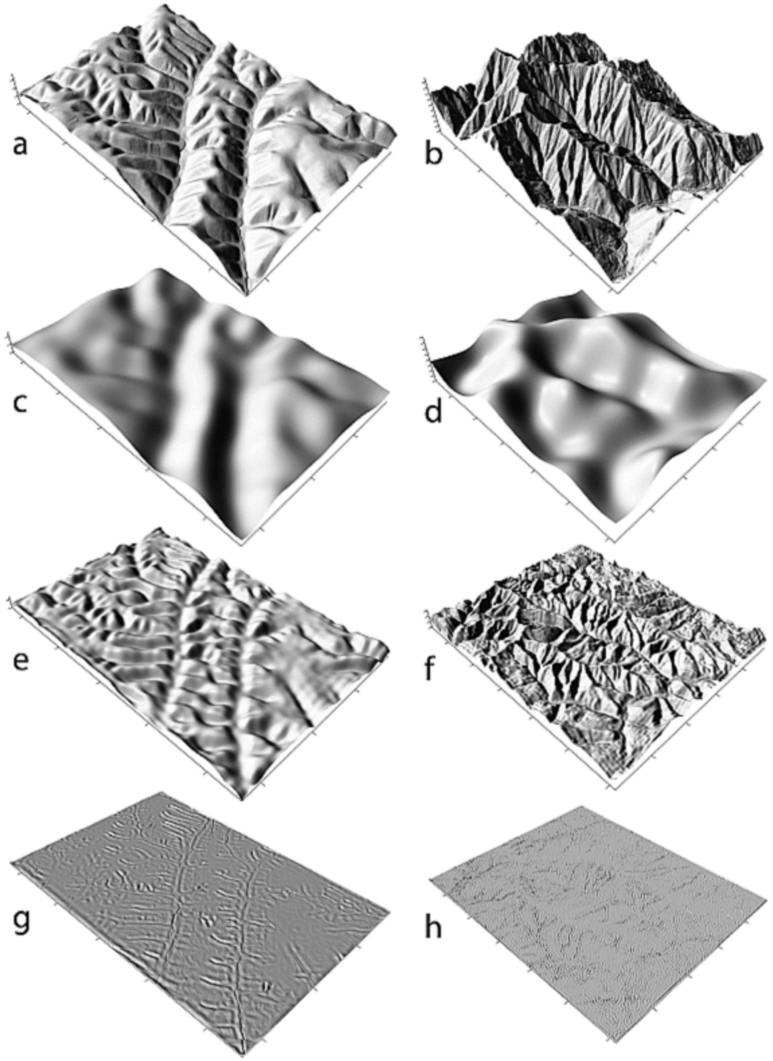
First published: 07 October 2008 | https://doi.org/10.1029/2007JF000866 | Citations: 111

Example landscapes:

Large valleys:

Smaller valleys:

Terrain roughness:



Environmental Data

Climatic variables

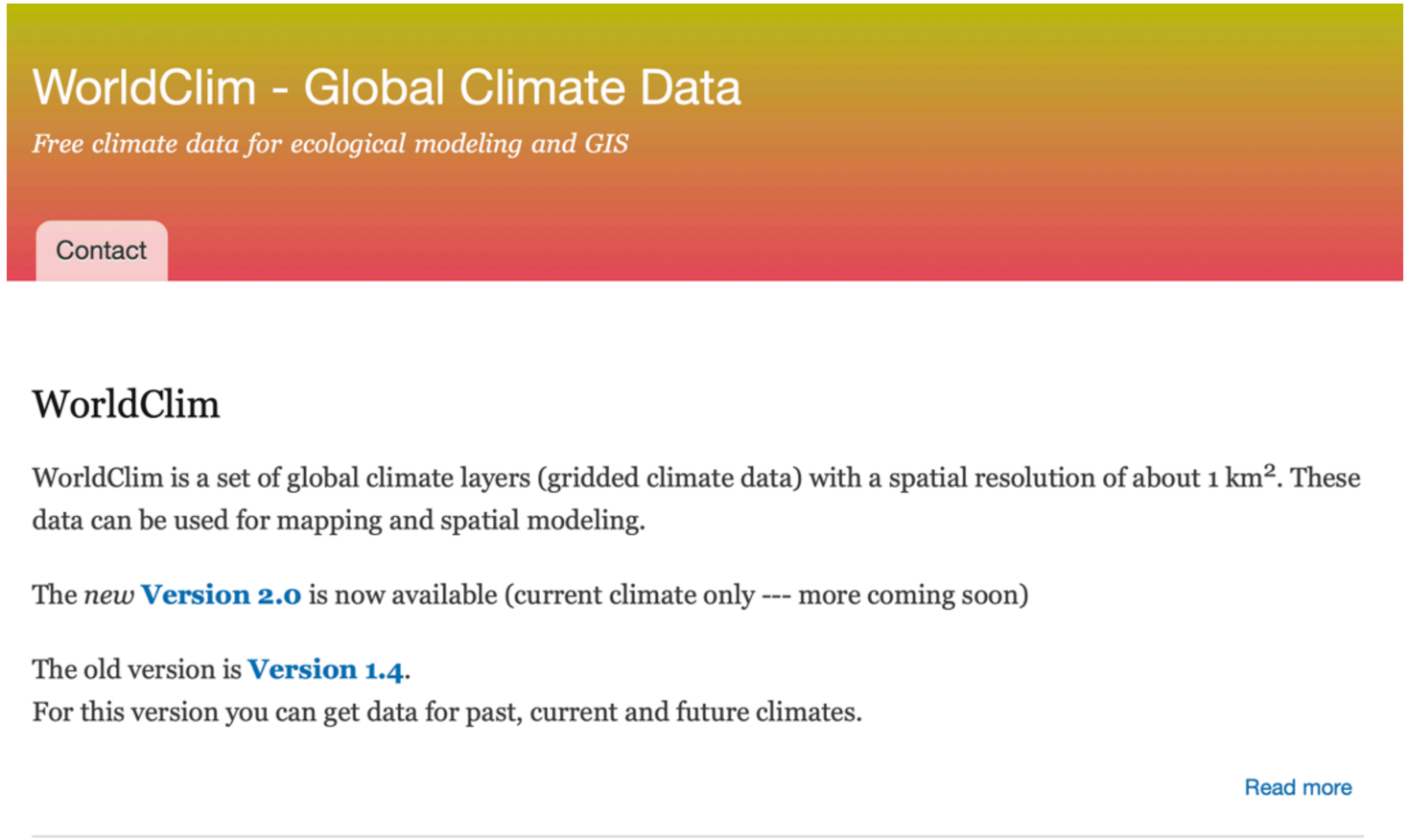
WorldClim Bioclims:

- 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

Climatic variables



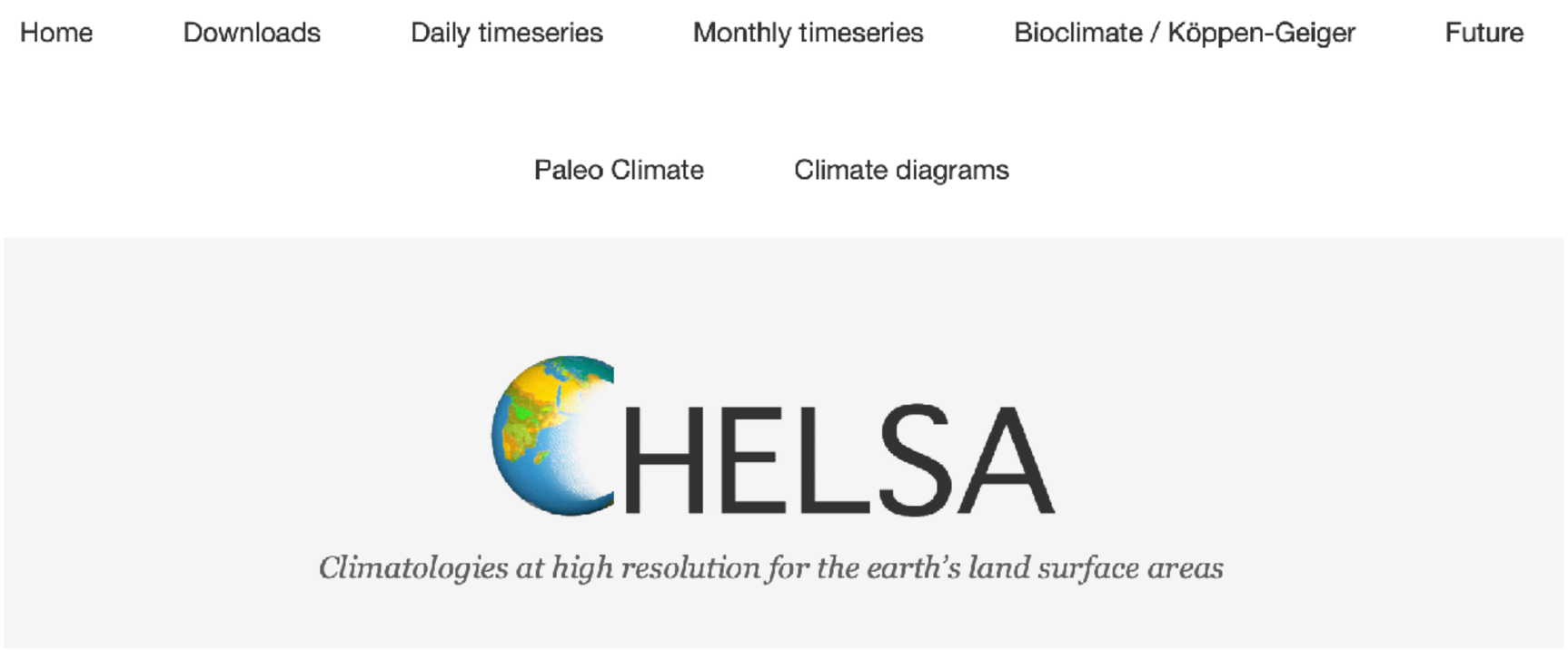
https://www.worldclim.com

Environmental Data

Climatic variables

Alternatives to Bioclims

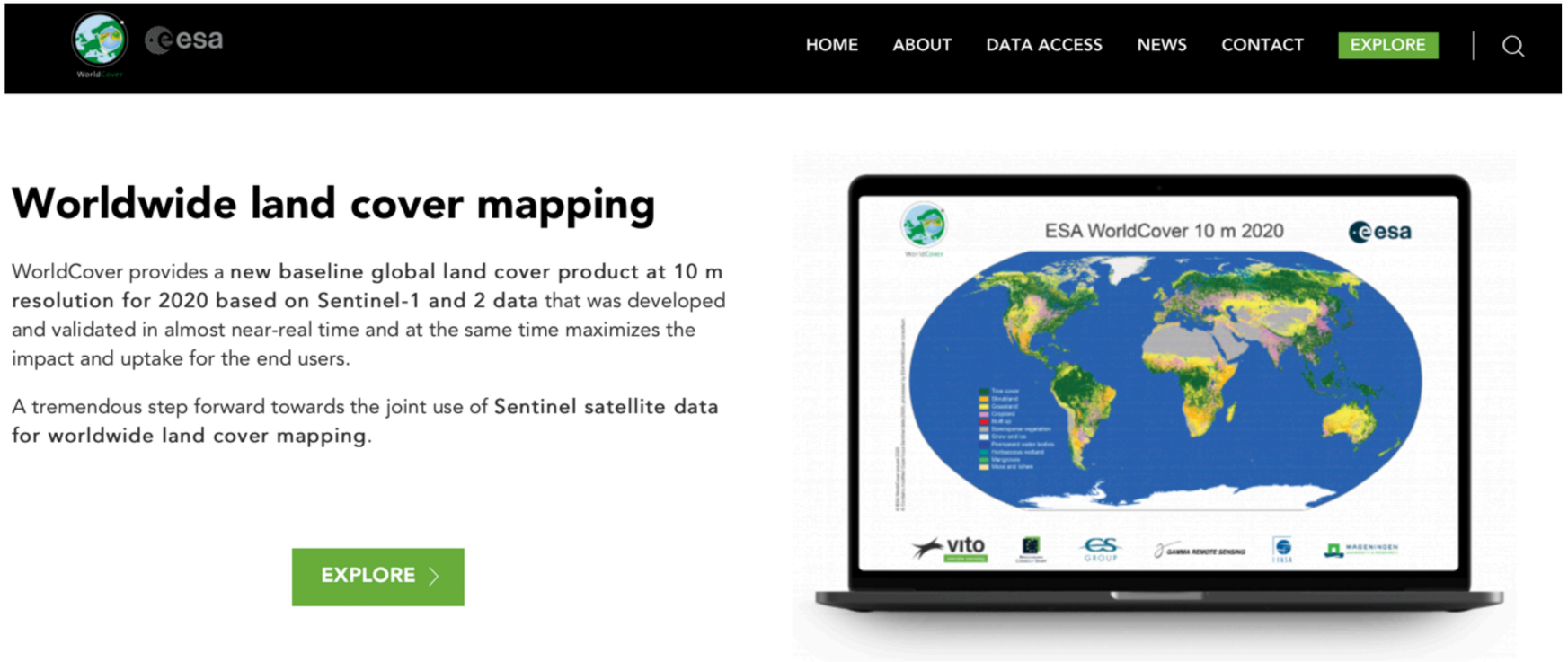
- CHELSA, https://chelsa-climate.org



Environmental Data

Land-use / land-cover

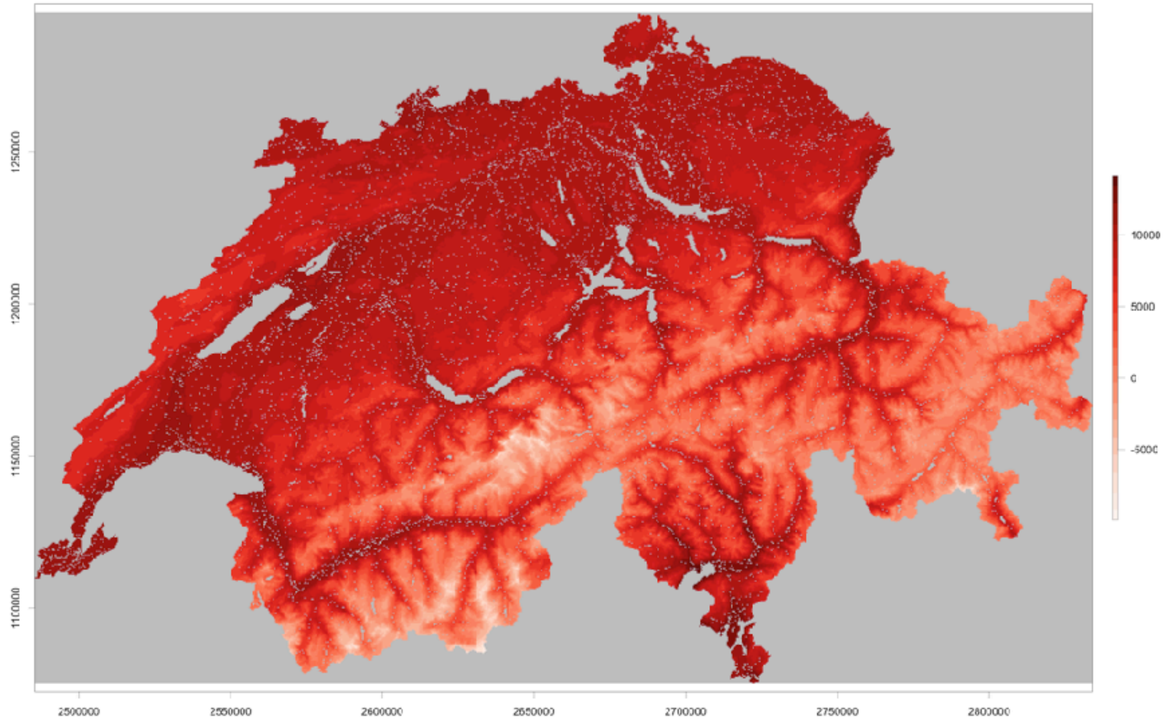
ESA WorldCover data set at 0.3-seconds resolution (https://esa-worldcover.org/en)



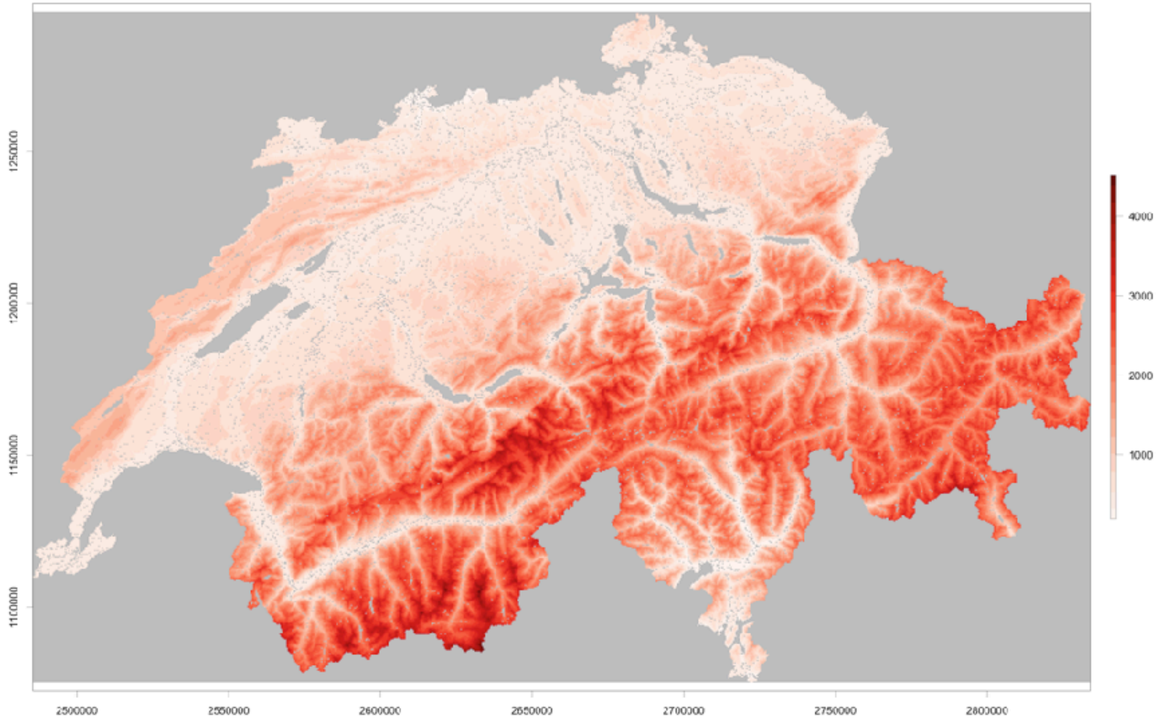
Environmental Data

Notice anything suspicious about these two variables?

Temperature



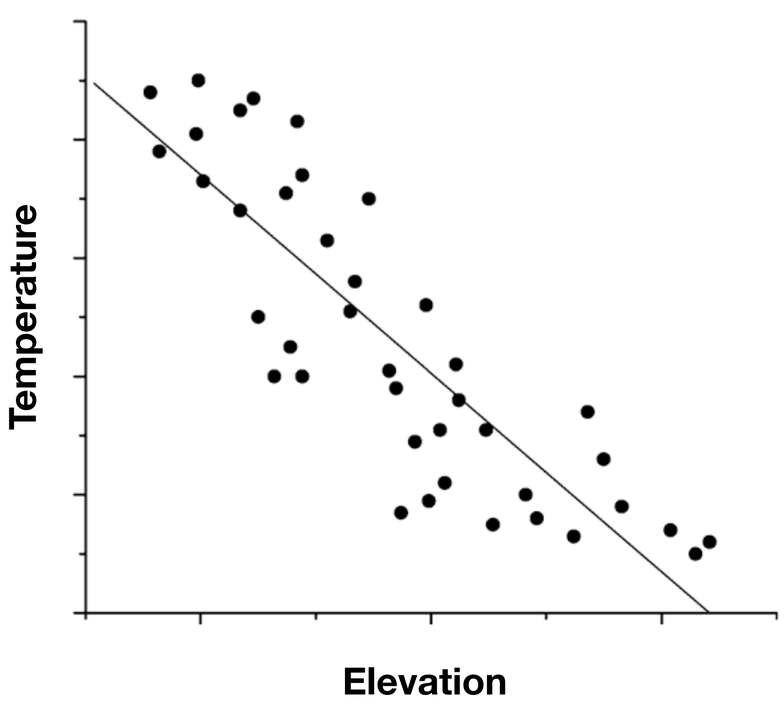
Elevation



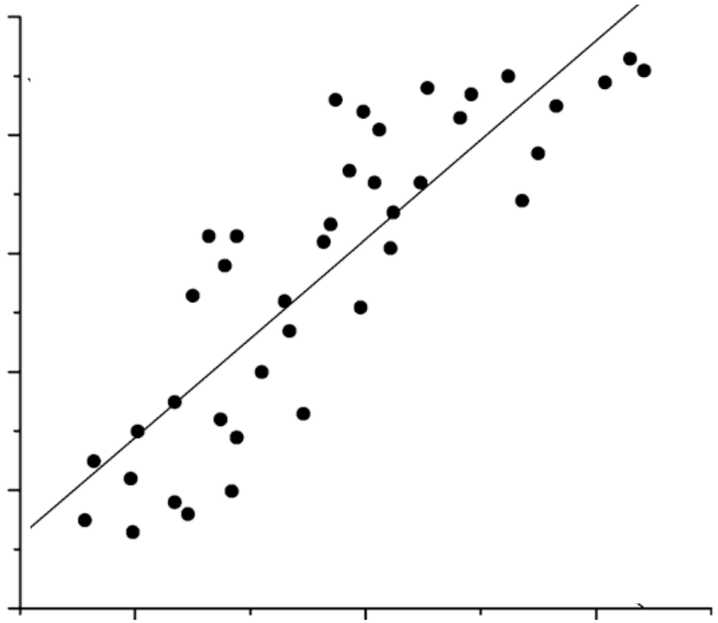
Environmental Data

Variables correlation

Negative correlation

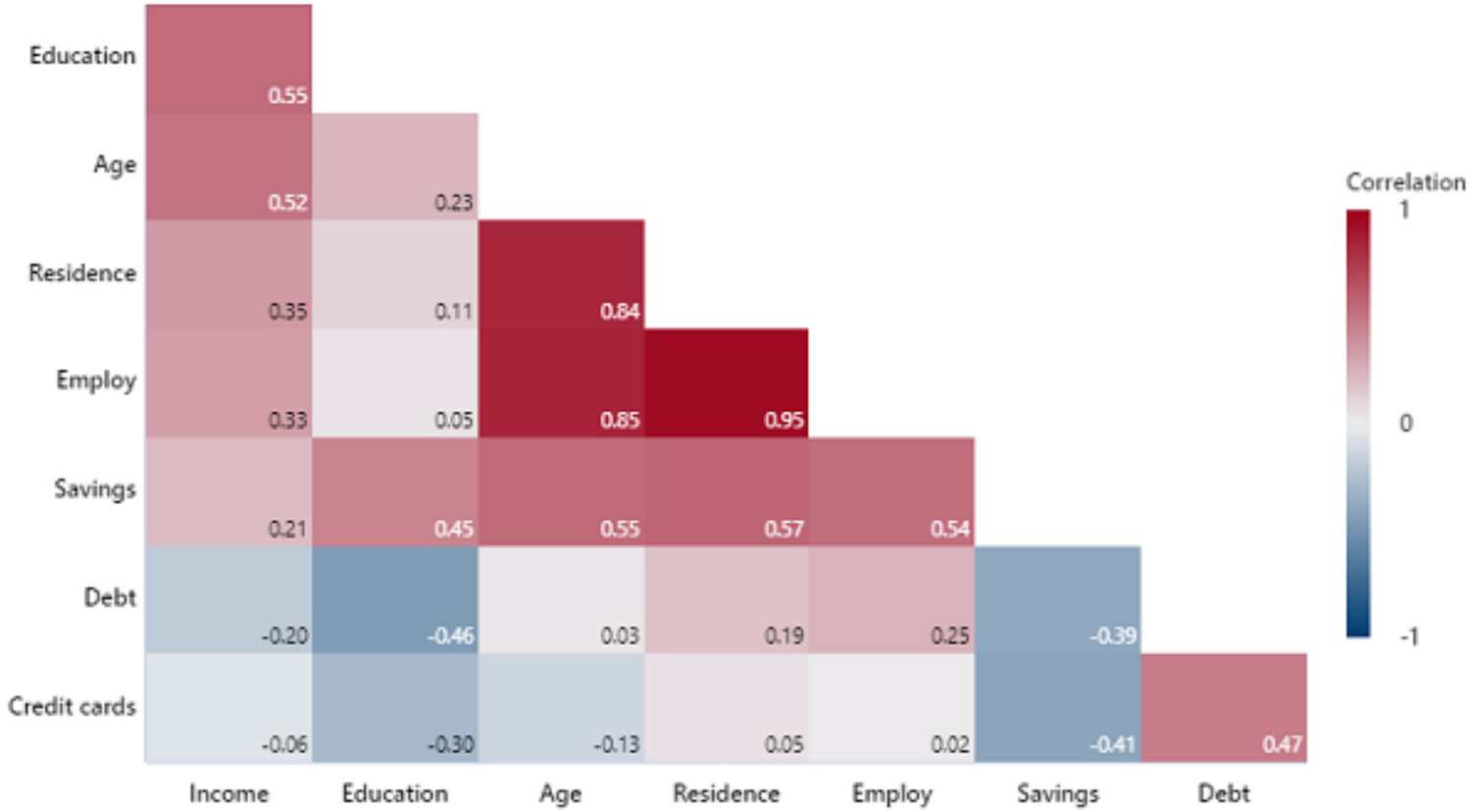


Positive correlation



Environmental Data

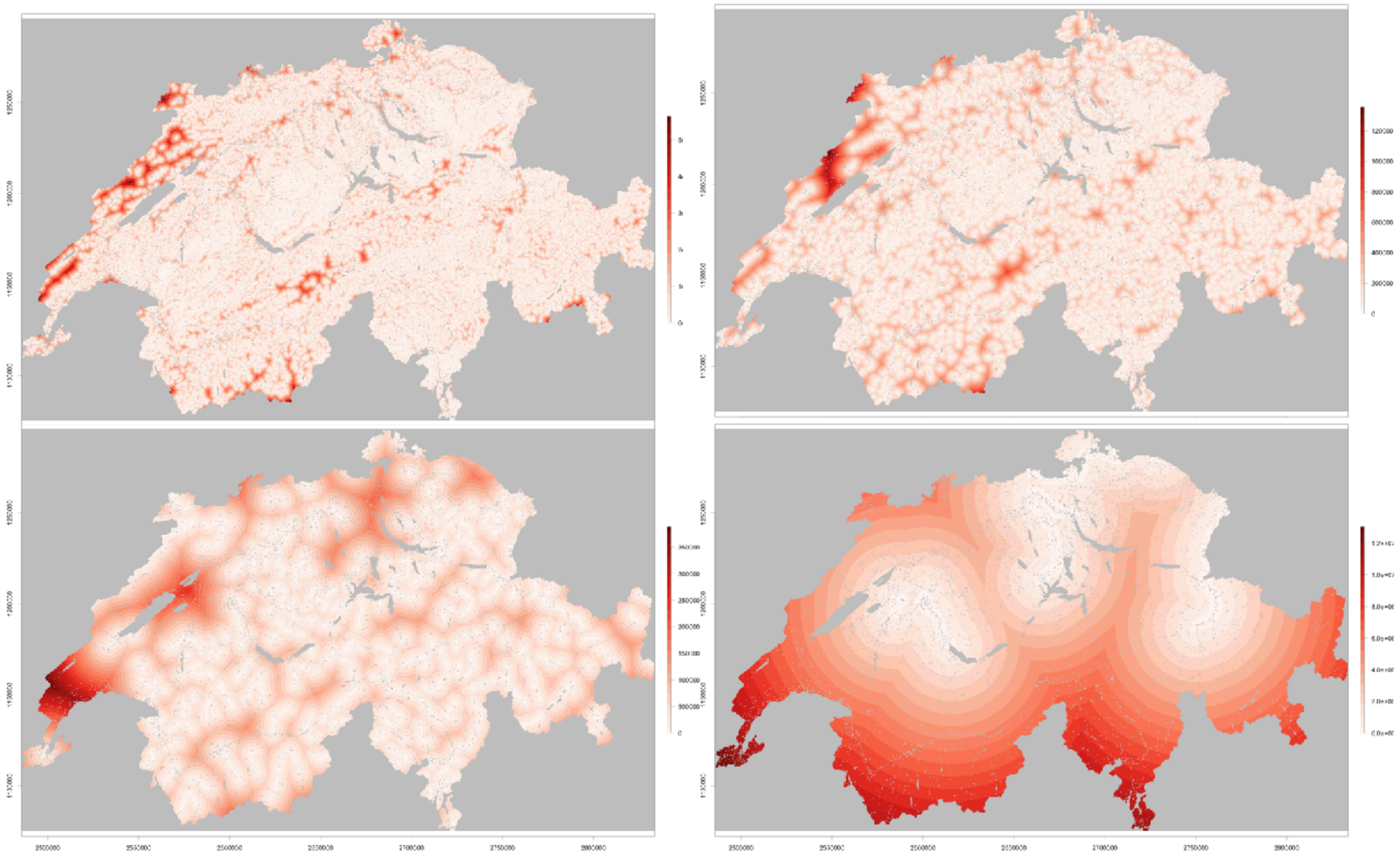
Variables correlogram



Environmental Data

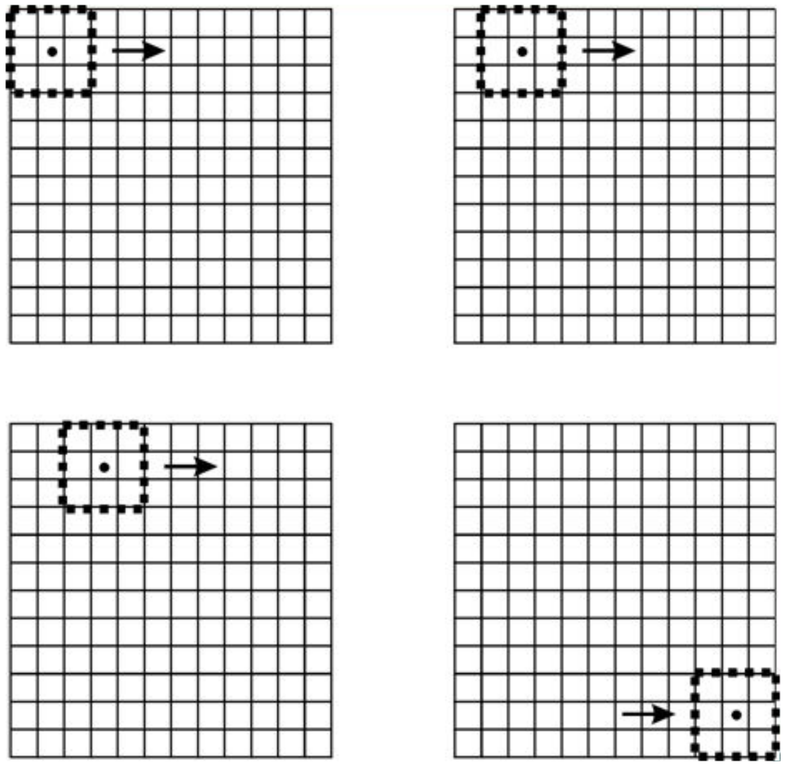
Distance to…

Rivers of different sizes



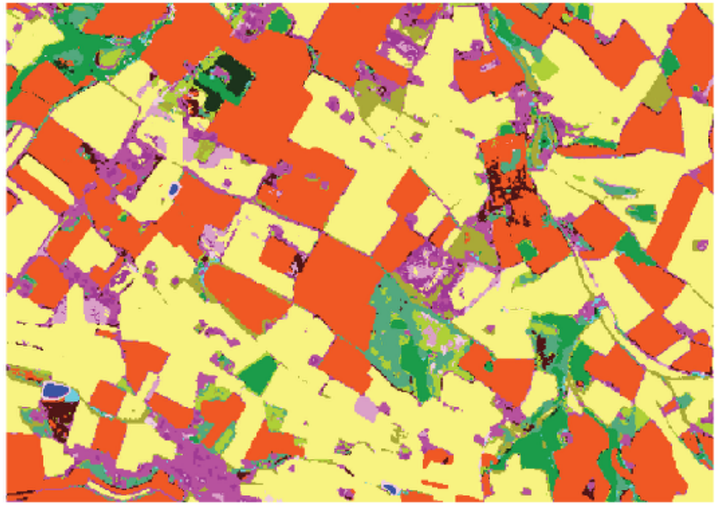
Environmental Data

Moving windows

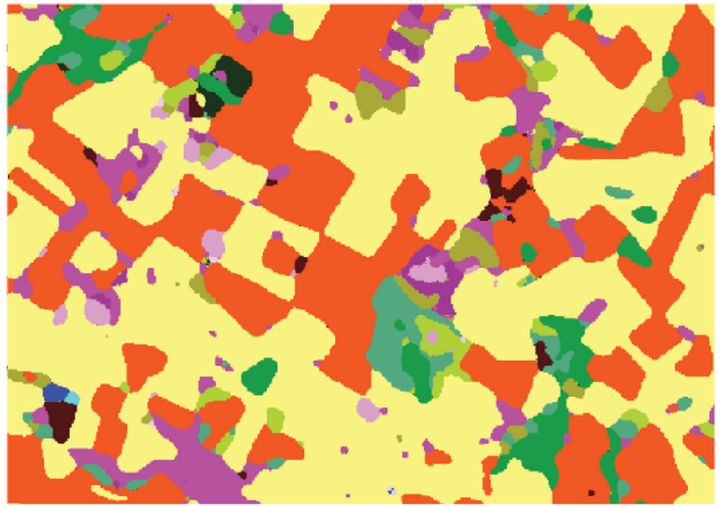


Noise reduction →

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] CESBIC, 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.

- Annual Summer Crops
- Annual Winter Crops
- Orchards
- Vineyards
- Intensive Grasslands
- Natural Grasslands
- Water Bodies
- Continuous Urban Fabric
- Discontinuous Urban Fabric
- Industrial or Commercial Units
- Road Surfaces
- Woody Moorlands
- Coniferous Forests
- Broad-Leaved Forests

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 or presence-background

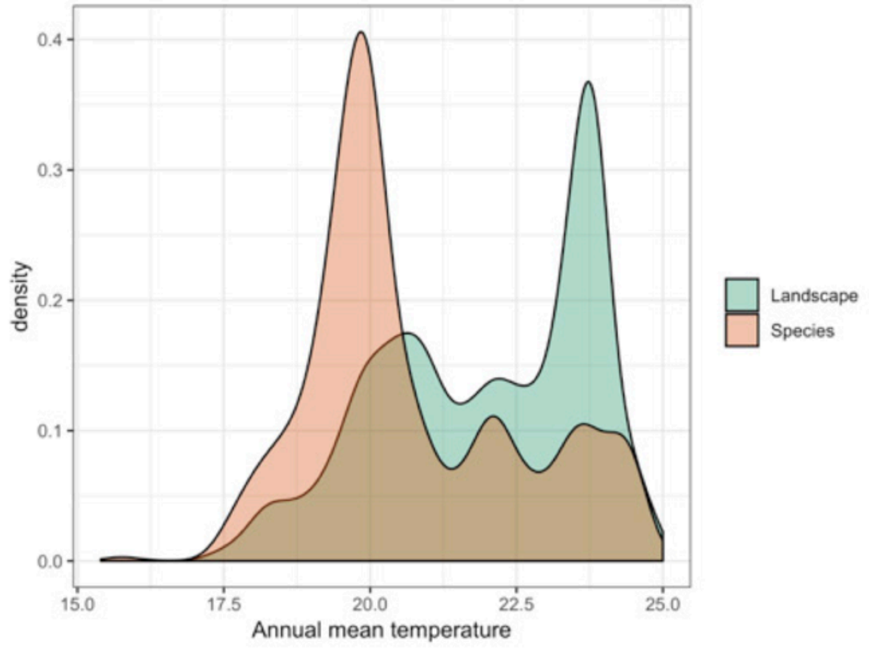
X	Y
50.4082	13.2343
49.2938	12.1341
51.9349	11.1233
52.9392	13.2303

Processing Environmental Data

False negatives (false absences) in presence-absence

Processing Environmental Data

Presence-background SDMs



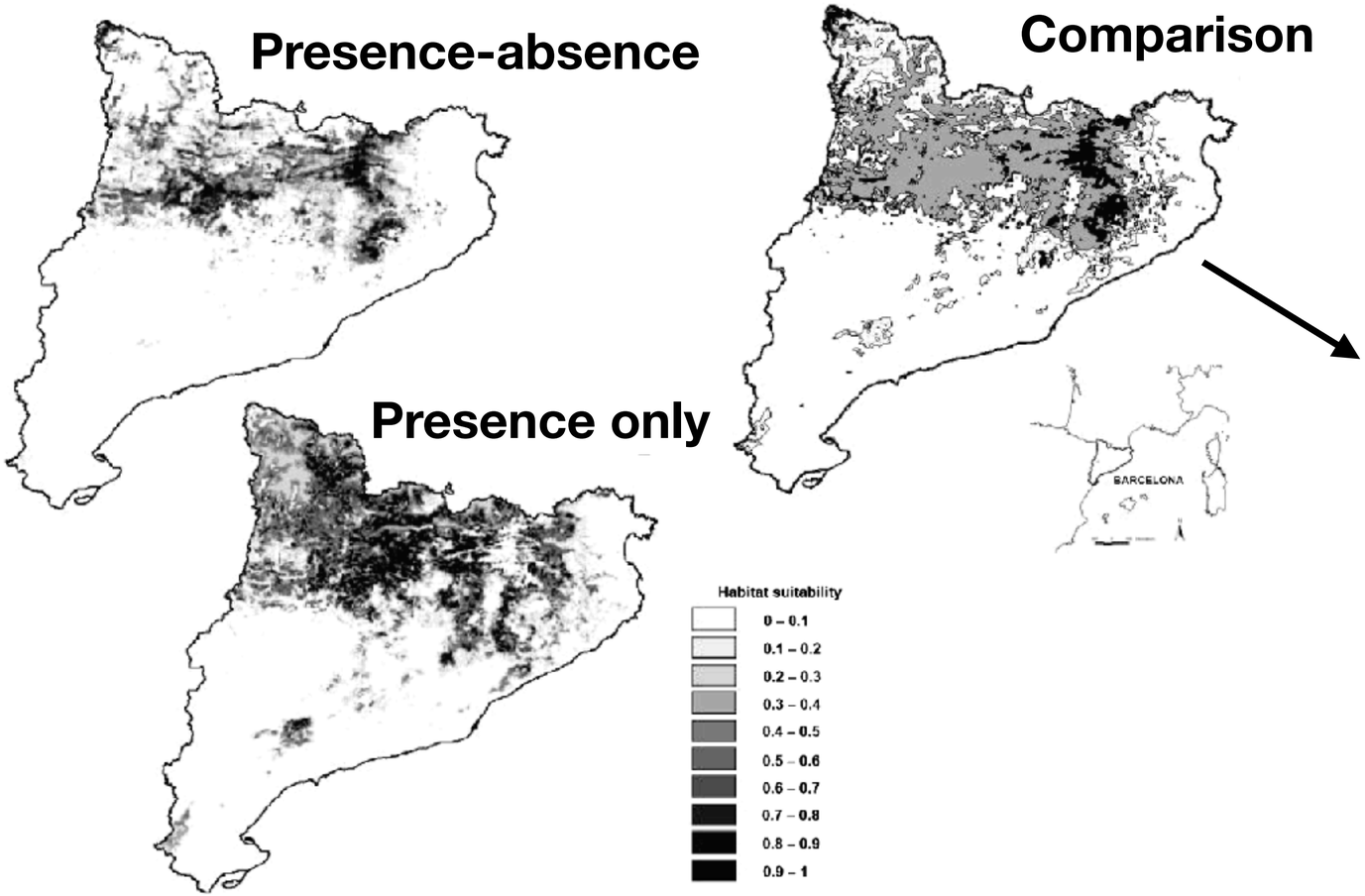
Biodiversity Informatics, 15, 2020, pp. 69-80

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 VS. Presence-absence



ECOGRAPHY 27: 437–448, 2004

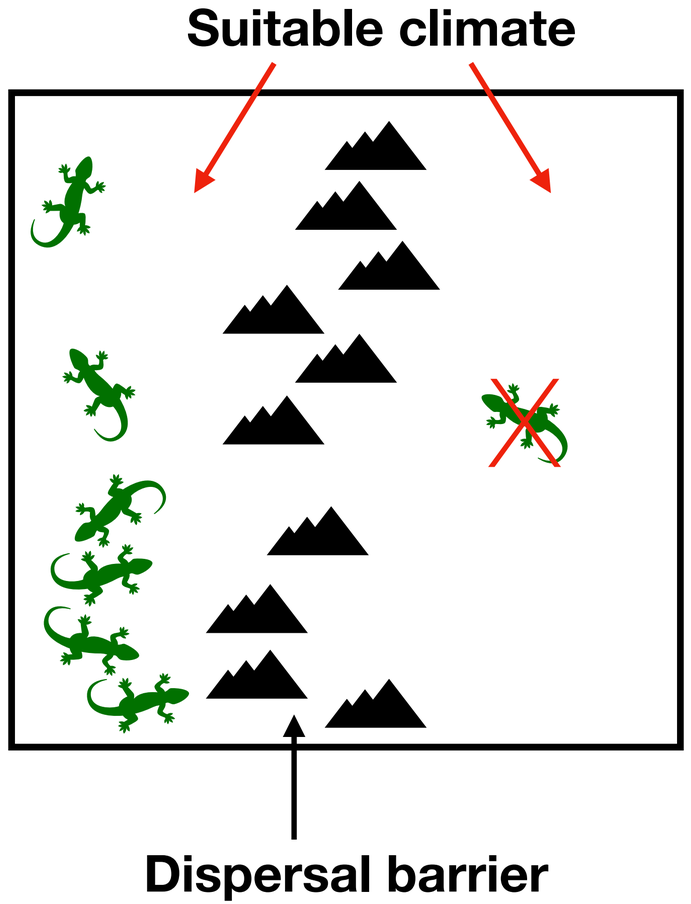
Presence-absence versus presence-only modelling methods for predicting bird habitat suitability

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

- Black: presence-only predicted species absence and presence-absence presence.
- Light grey (difficult to see): presence-only predicted presence and presence-absence absence.
- Dark grey: coincidence in model predictions.

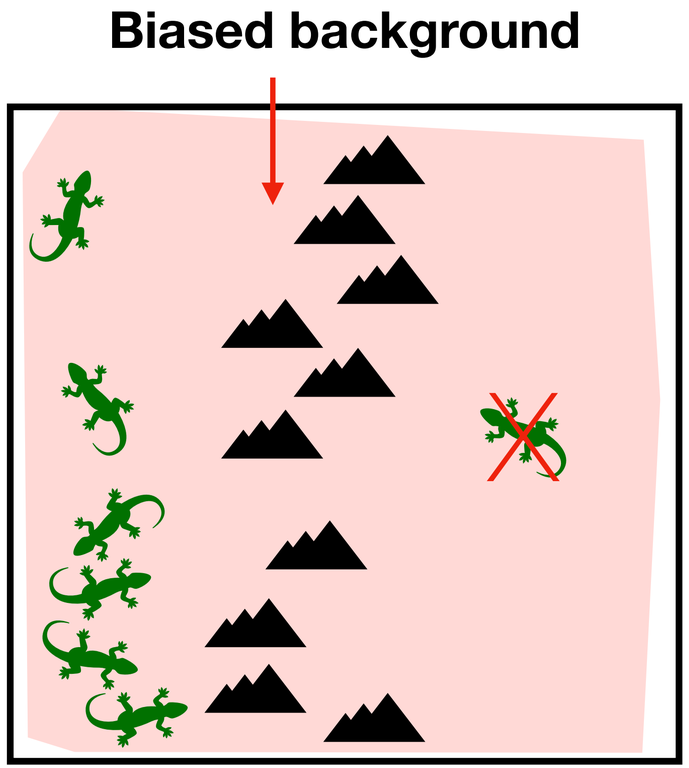
Processing Environmental Data

Historical dispersal and background selection

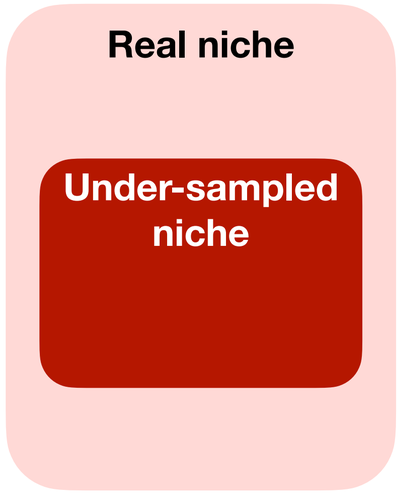


Processing Environmental Data

Historical dispersal and background selection

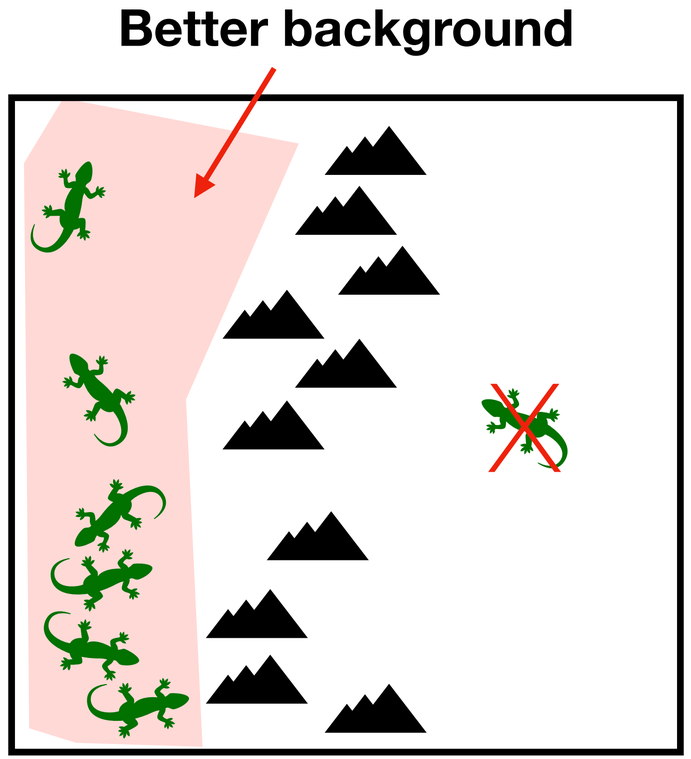


Absent just because cannot cross barrier



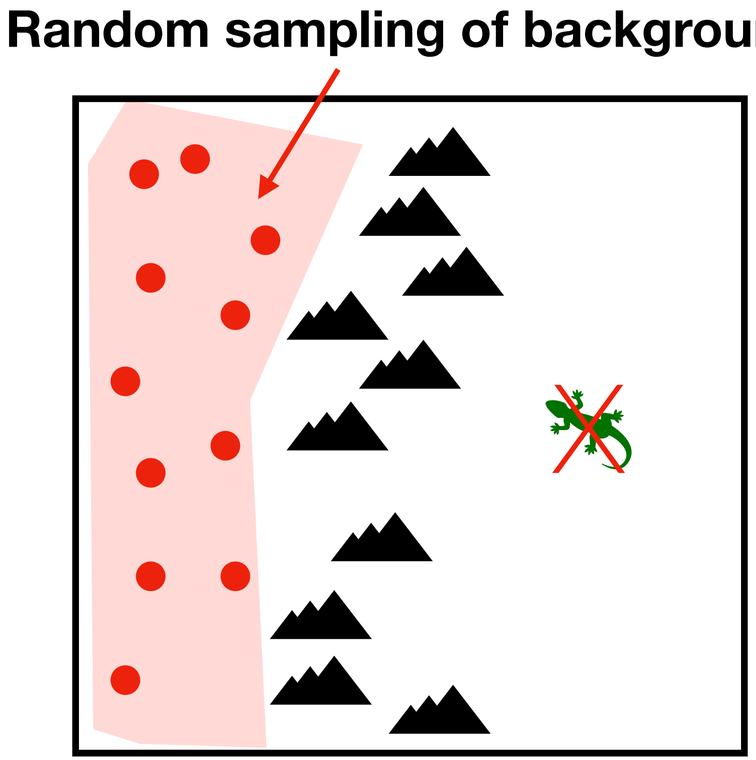
Processing Environmental Data

Historical dispersal and background selection



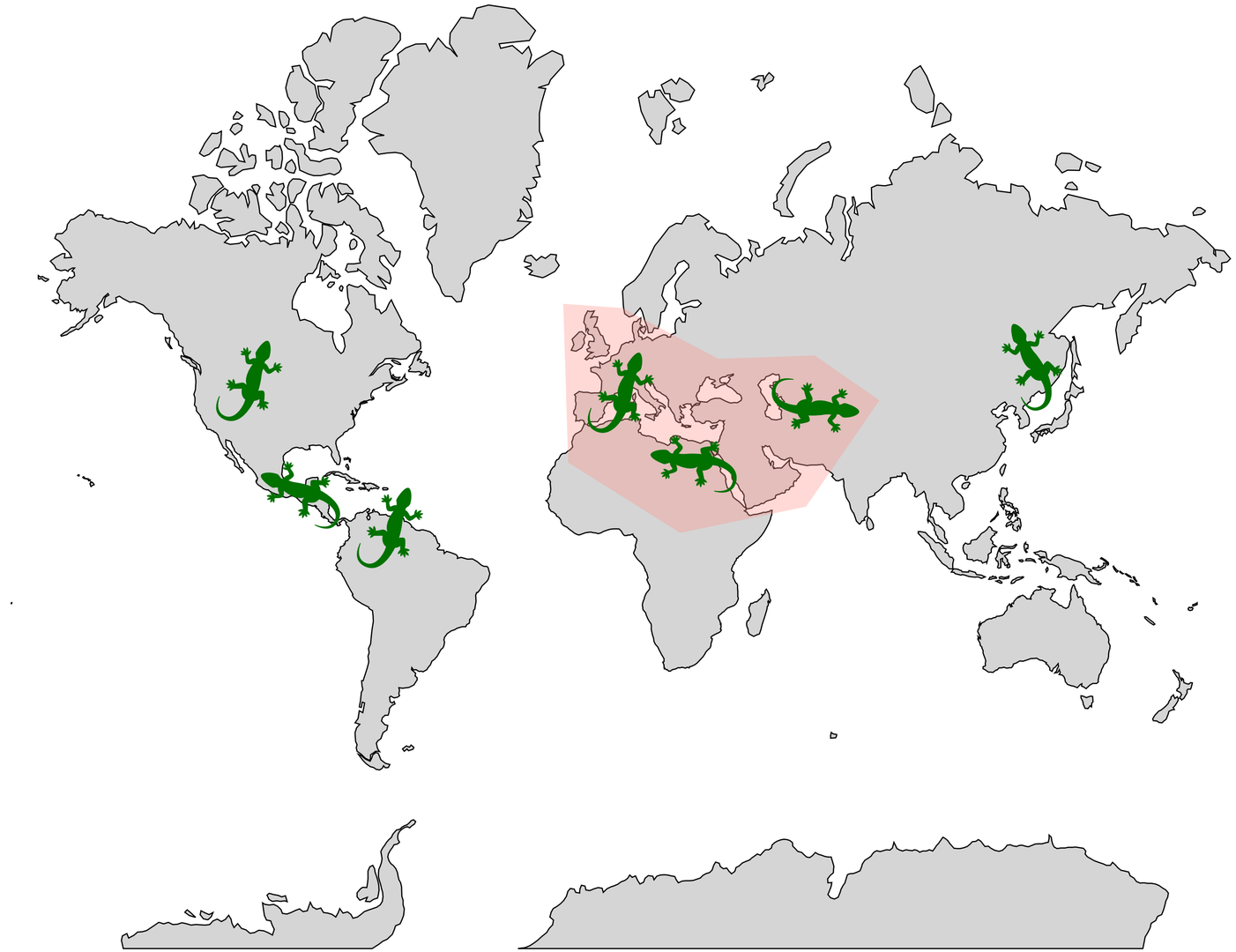
Processing Environmental Data

Historical dispersal and background selection



Processing Environmental Data

Niche truncation

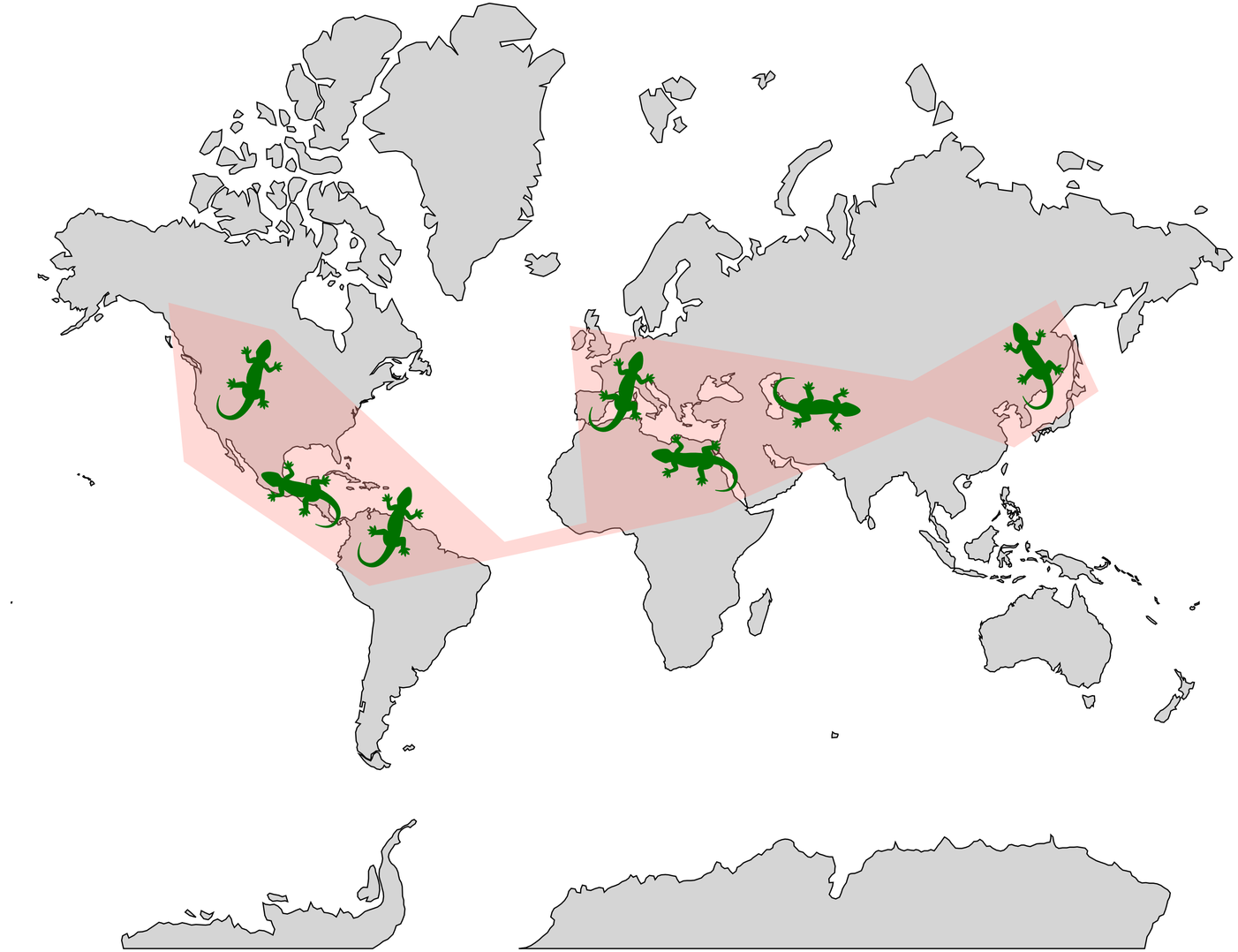


Real niche

Under-sampled niche

Processing Environmental Data

Better background selection



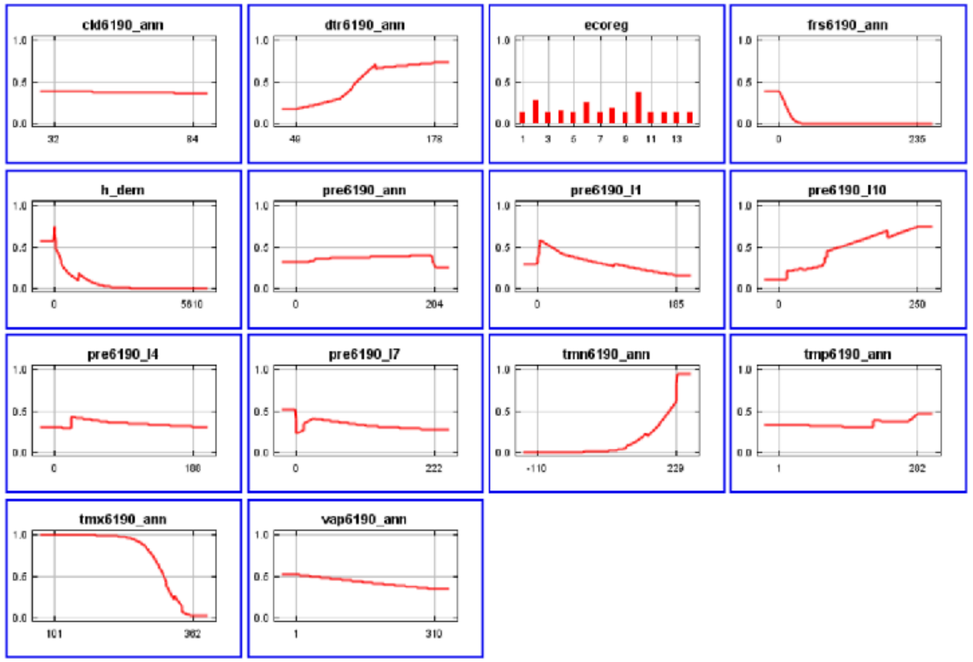
Model Outputs

Wallace Component “7 Visualise”

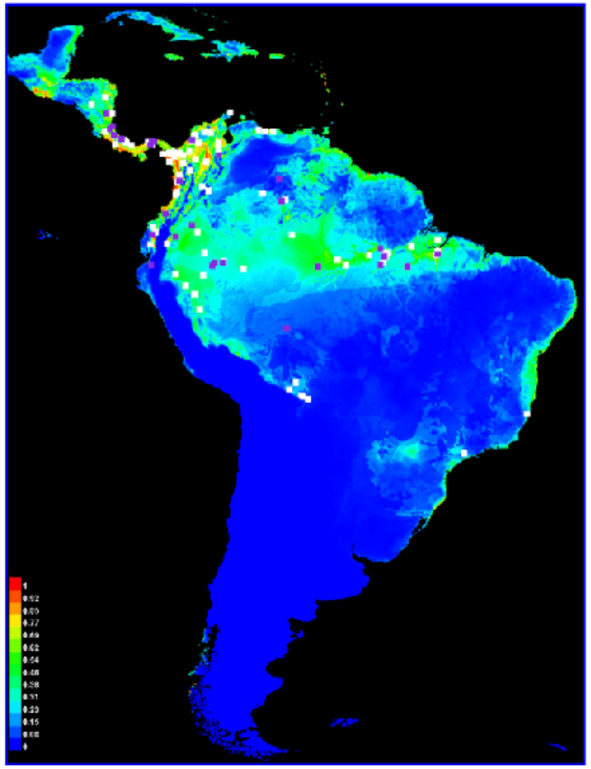
Model Outputs

MaxEnt evaluation plots, 2 kinds of visualisations

Environmental variables space



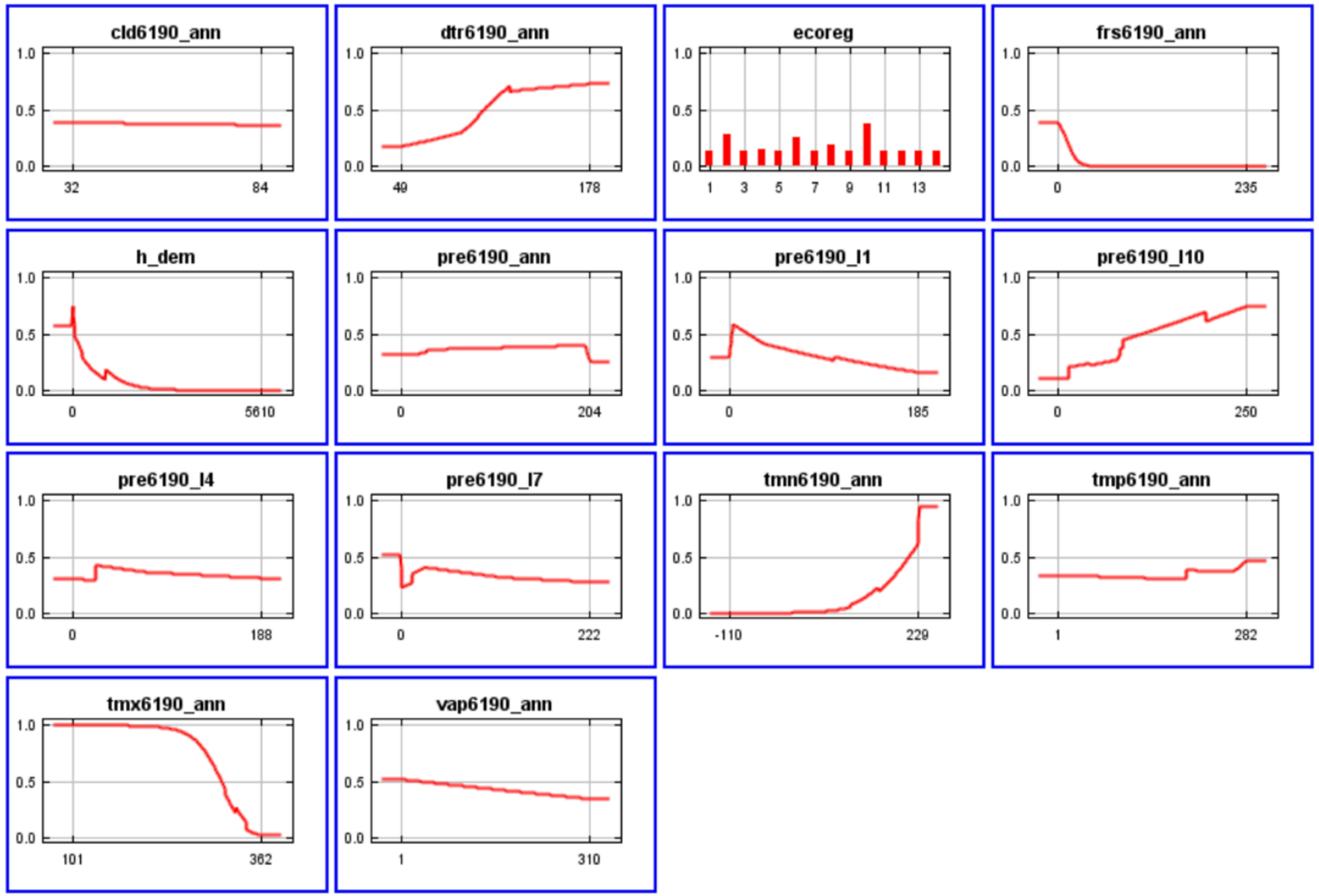
Geographic space



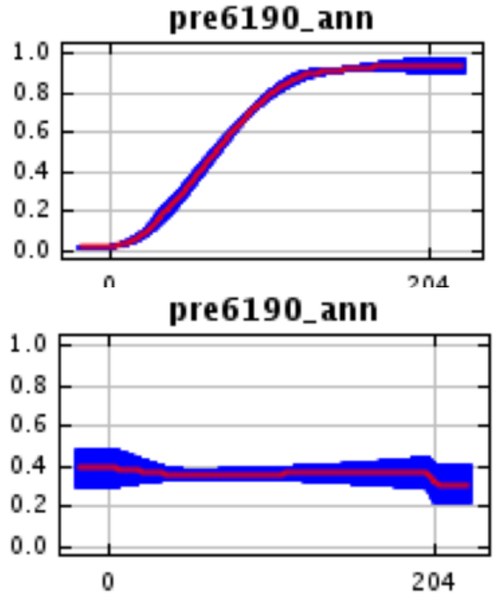
https://biodiversityinformatics.amnh.org/open_source/maxent/Maxent_tutorial_2021.pdf

Model Outputs

Response curves



For replicated runs:

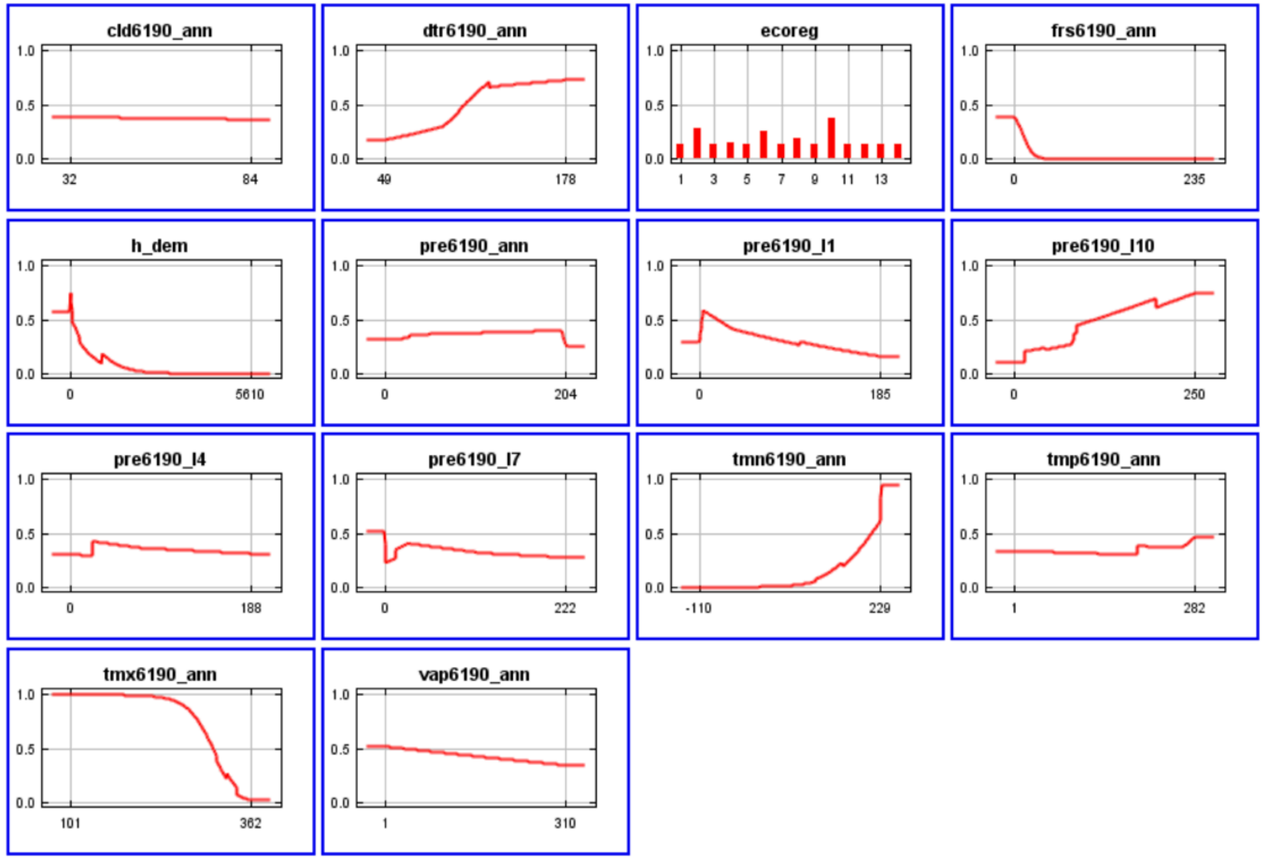


Model Outputs

Response curves in the presence of variables correlation

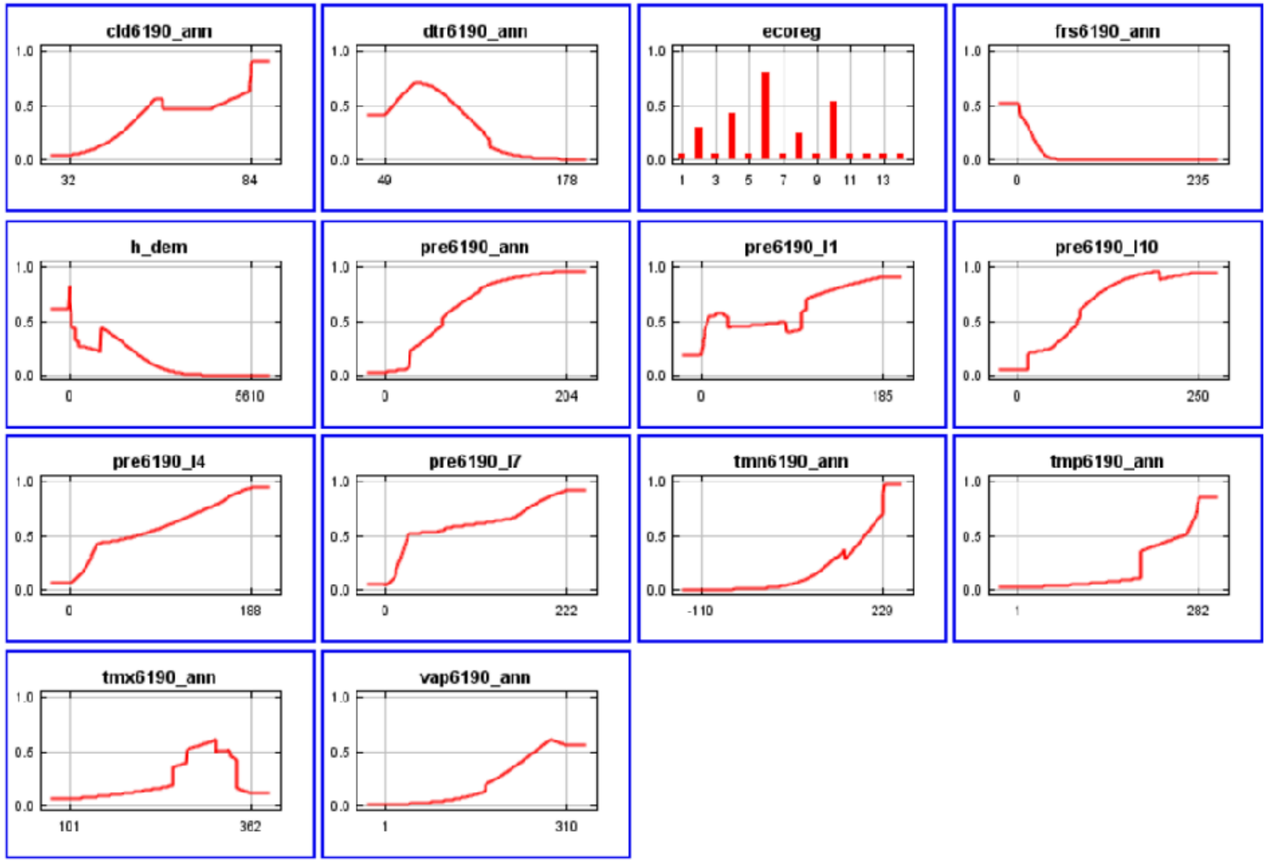
Marginal

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.

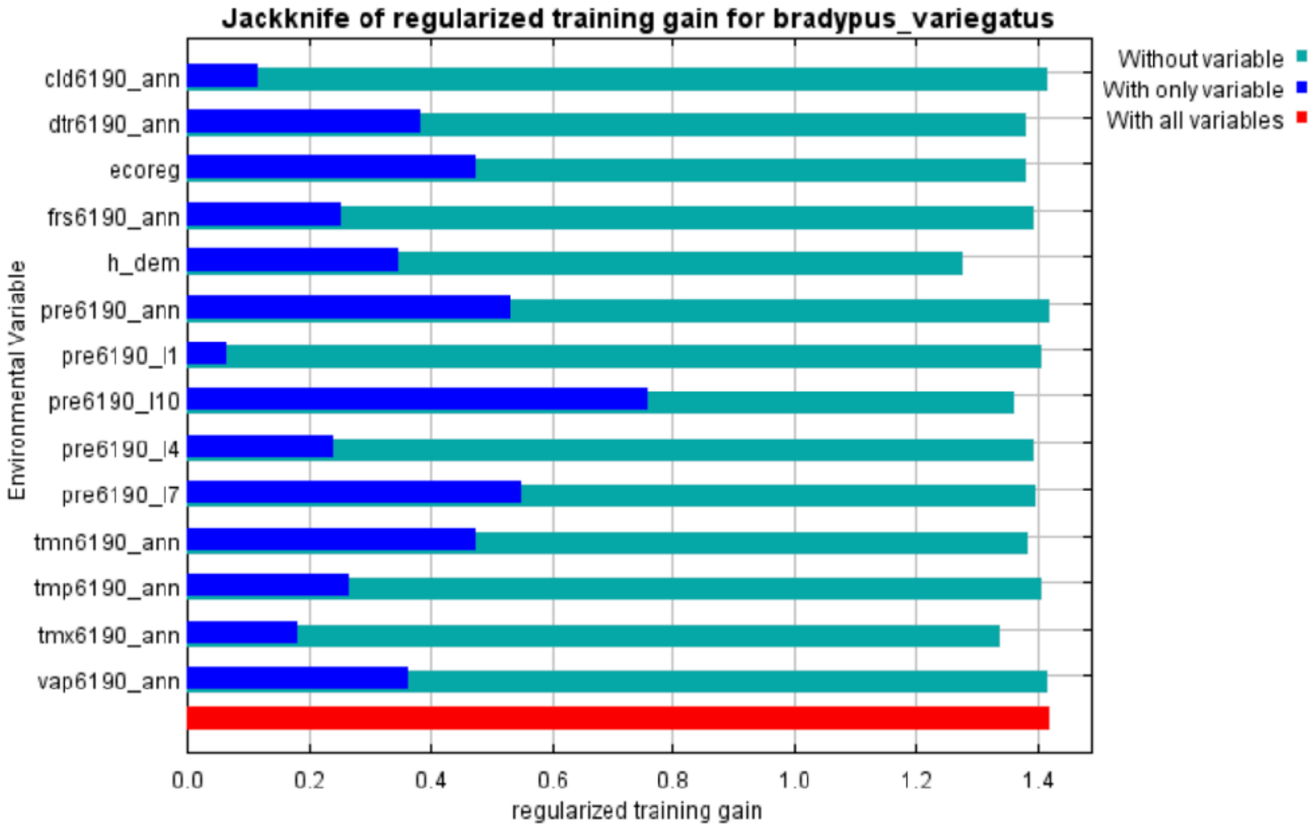
Model Outputs

Variables contribution

Percentage contribution
Permutation importance

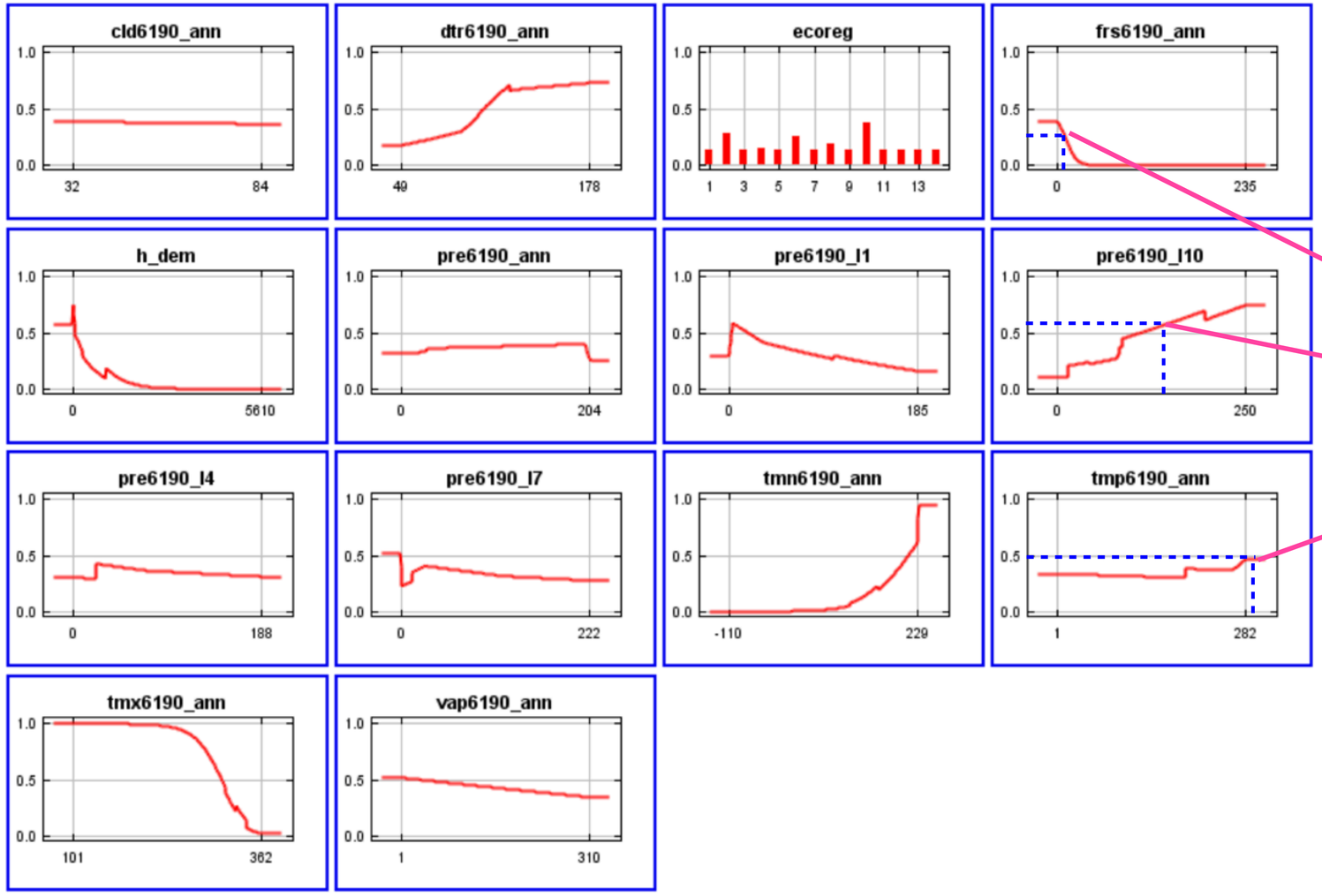
Variable	Percent contribution	Permutation importance
pre6190_l10	31.1	5.4
pre6190_l7	23.6	1.3
tmn6190_ann	14.7	20.6
h_dem	10.3	13.2
ecoreg	6.6	3.7
tmx6190_ann	4.3	19.6
pre6190_l1	2.2	1.8
frs6190_ann	2.1	25.6
pre6190_l4	1.8	3
vap6190_ann	1.6	0.3
tmp6190_ann	1.1	0.7
dtr6190_ann	0.4	4.7
pre6190_ann	0.3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

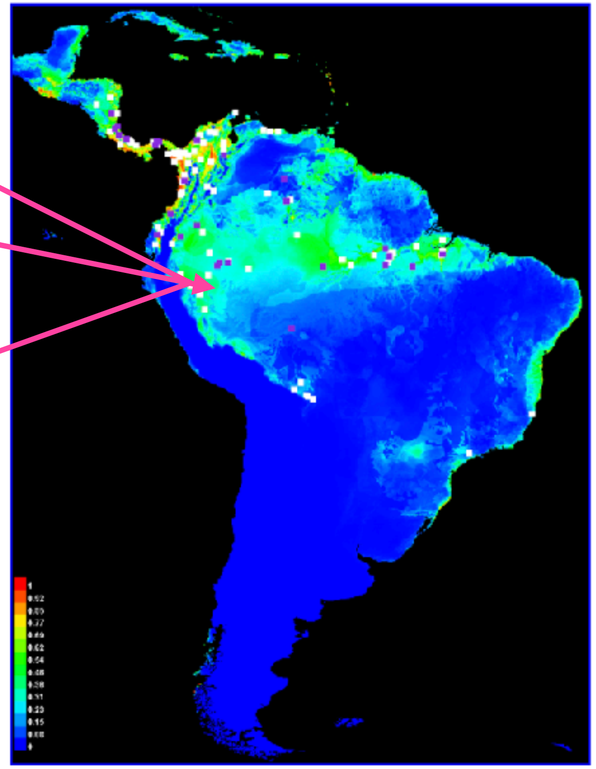
Jackknife test



Model Outputs

Projecting between variables and geographic spaces





Model Outputs

Output formats

Ecography 40: 887–893, 2017
doi: 10.1111/ecog.03049

Subject Editor: Michael Borregaard. Editor-in-Chief: Miguel Araújo. Accepted 9 March 2017

Opening the black box: an open-source release of Maxent

Steven J. Phillips, Robert P. Anderson, Miroslav Dudík, Robert E. Schapire and Mary E. Blair

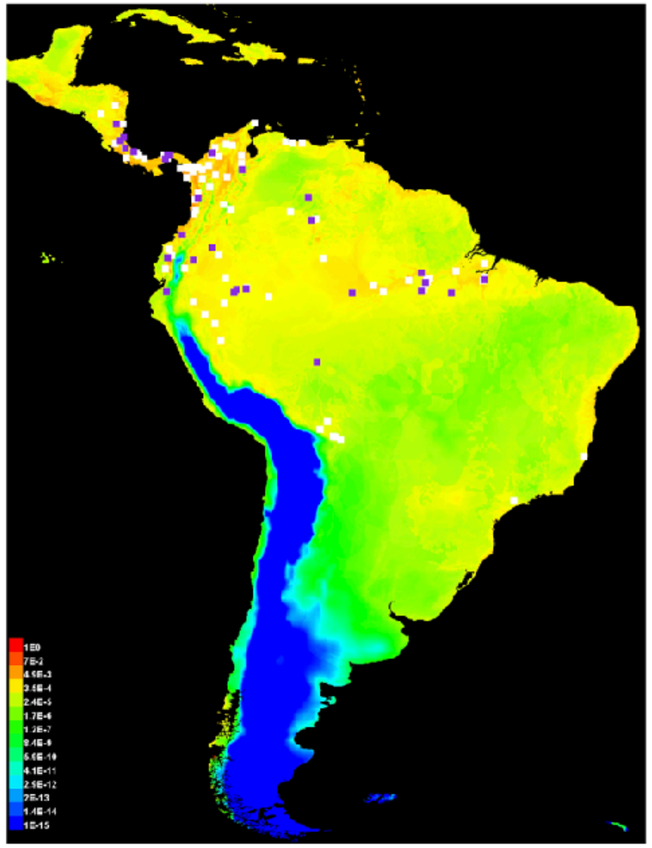
Diversity and Distributions, (Diversity Distrib.) (2011) 17, 43–57

BIODIVERSITY RESEARCH

A statistical explanation of MaxEnt for ecologists

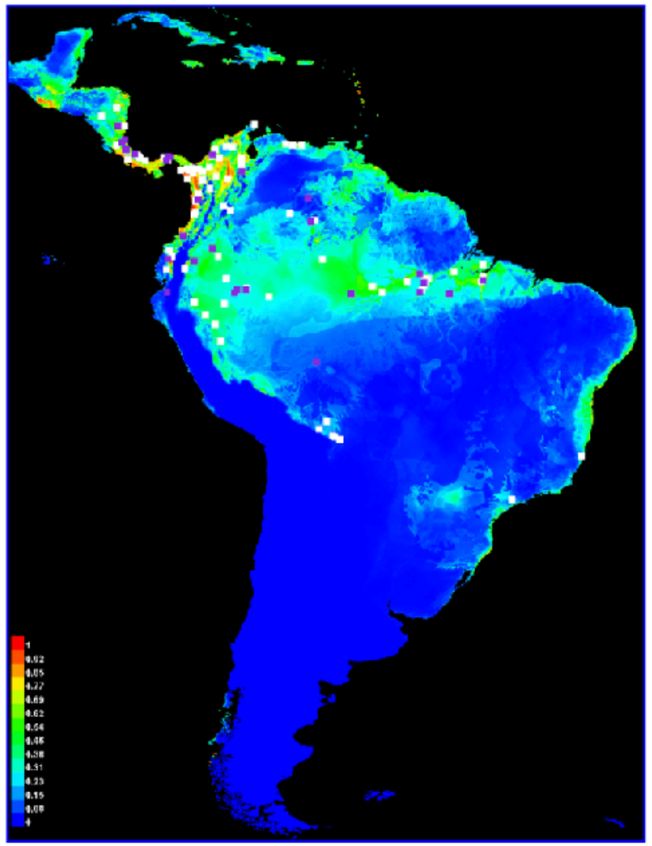
Jane Elith[1]*, Steven J. Phillips[2], Trevor Hastie[3], Miroslav Dudík[4], Yung En Chee[1] and Colin J. Yates[5]

MASSIVE ASSUMPTIONS!



Raw

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

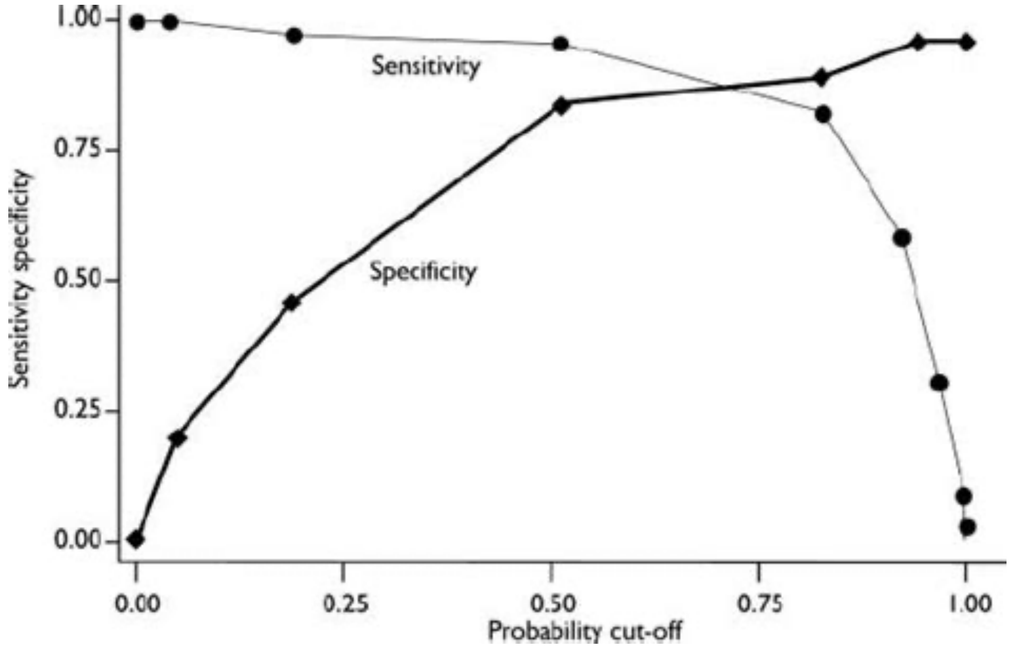


Logistic & ClogLog

- Estimate between 0 and 1 of probability of presence
- **Logistic:** assumes that prevalence of the species equals 0.5 in locations of average suitability.
- **ClogLog:** Stronger theoretical justification. Assumptions are made regarding spatial dependence and cell size.
- Logistic and ClogLog are very similar, but cloglog tends to be higher for mid- to high-range values.

Model Outputs

Binary outputs



Typical threshold selection:

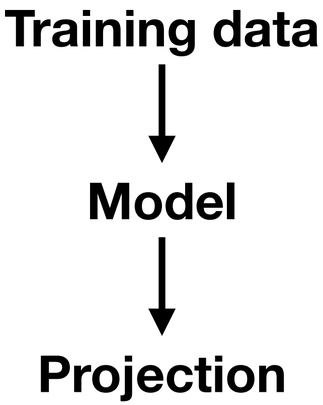
- Minimum training presence
  - The lowest suitability score for any occurrence localities used to train the model.
- 10th percentile training presence
  - The lowest suitability score for any occurrence localities used to train the model after excluding the lowest 10% of them.
- Maximisation of sensitivity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

Model Projection

Wallace Component “8 Project”

Model Projection

Making predictions

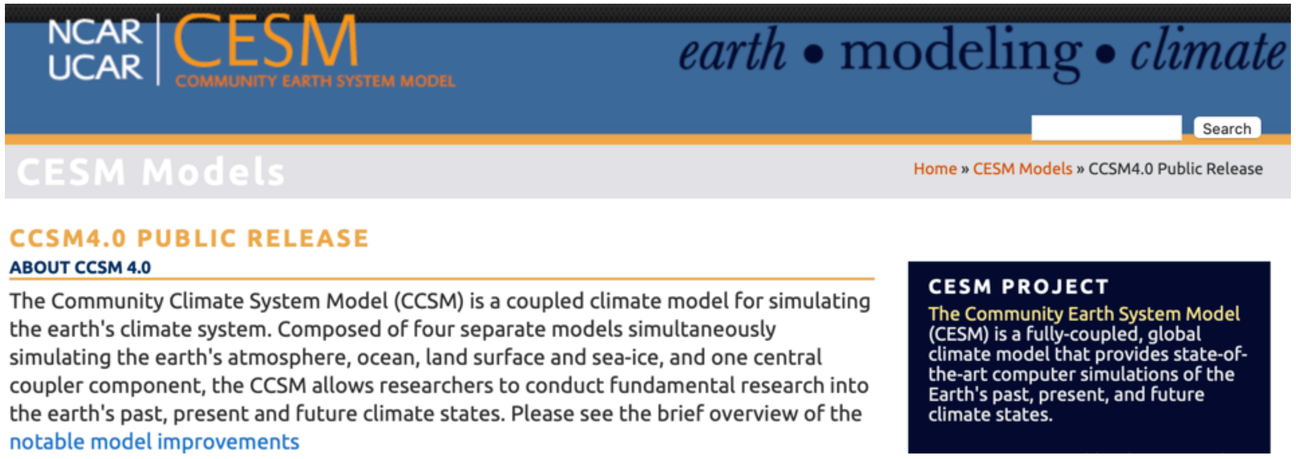


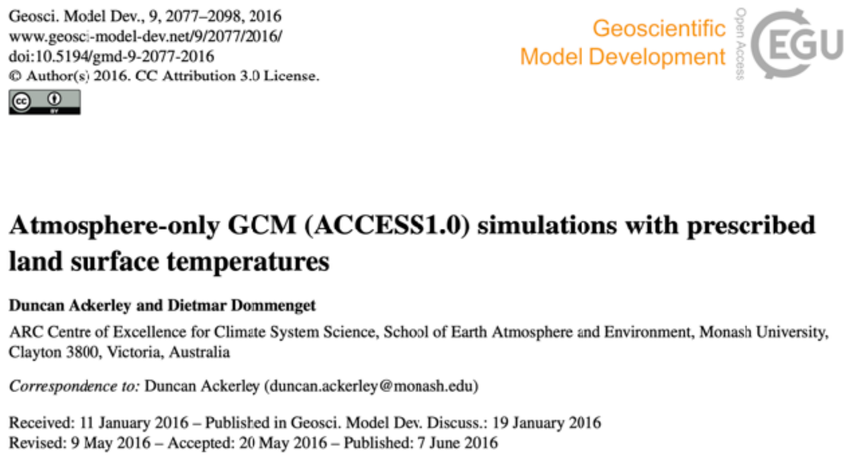
- New locations (e.g. for biological innovations)
- New climate scenarios (e.g. future under climate change)
- New land-use scenarios (e.g. deforestation or urbanisation)

Model Projection

New climate scenarios: General Circulation Models (-> Global Climate Models)

General Circulation Models and Global Climate Models are used for weather forecasting, understanding the climate, and forecasting climate change.

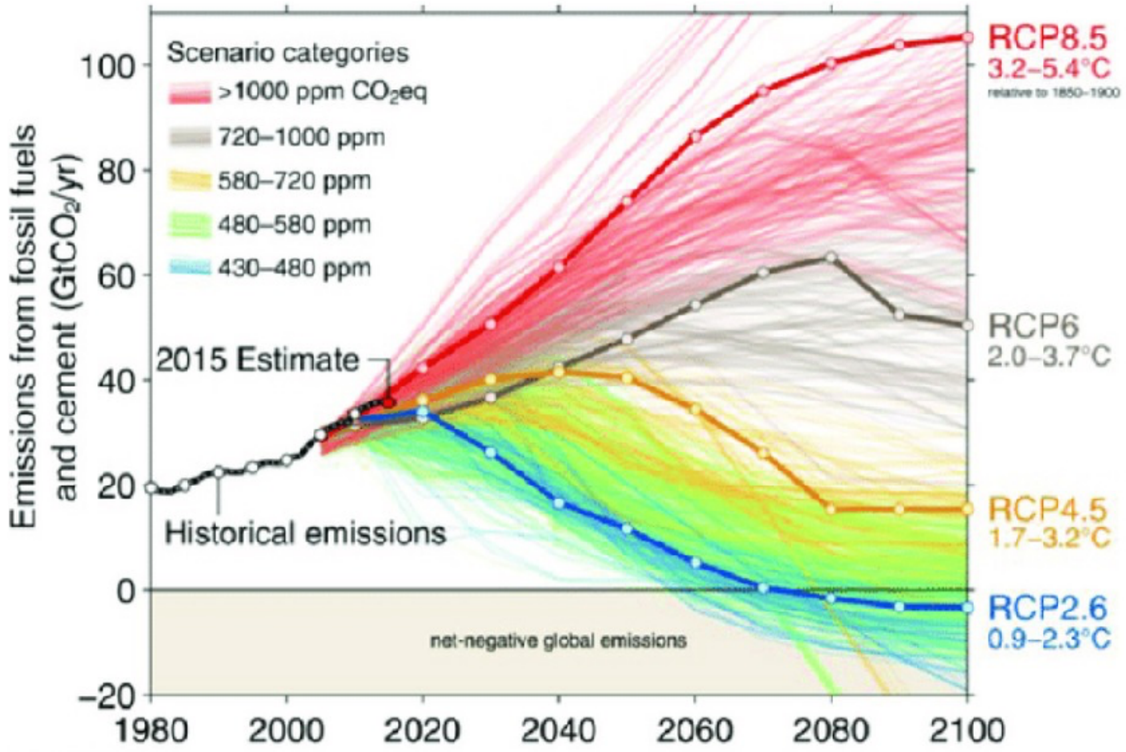




Model Projection

New climate scenarios: Representative Concentration Pathways (RCPs)

Greenhouse gas concentration (not emissions) trajectory adopted by the Intergovernmental Panel on Climate Change (IPCC).



Model Projection

Multivariate Environmental Similarity Surface (MESS)

Measures the similarity of any given point to a reference set of points, with respect to the chosen predictor variables.

Methods in Ecology and Evolution

British Ecological Society

Methods in Ecology and Evolution 2010, **1**, 330–342 doi: 10.1111/j.2041-210X.2010.00036.x

The art of modelling range-shifting species

Jane Elith[1]*, Michael Kearney[2] and Steven Phillips[3]

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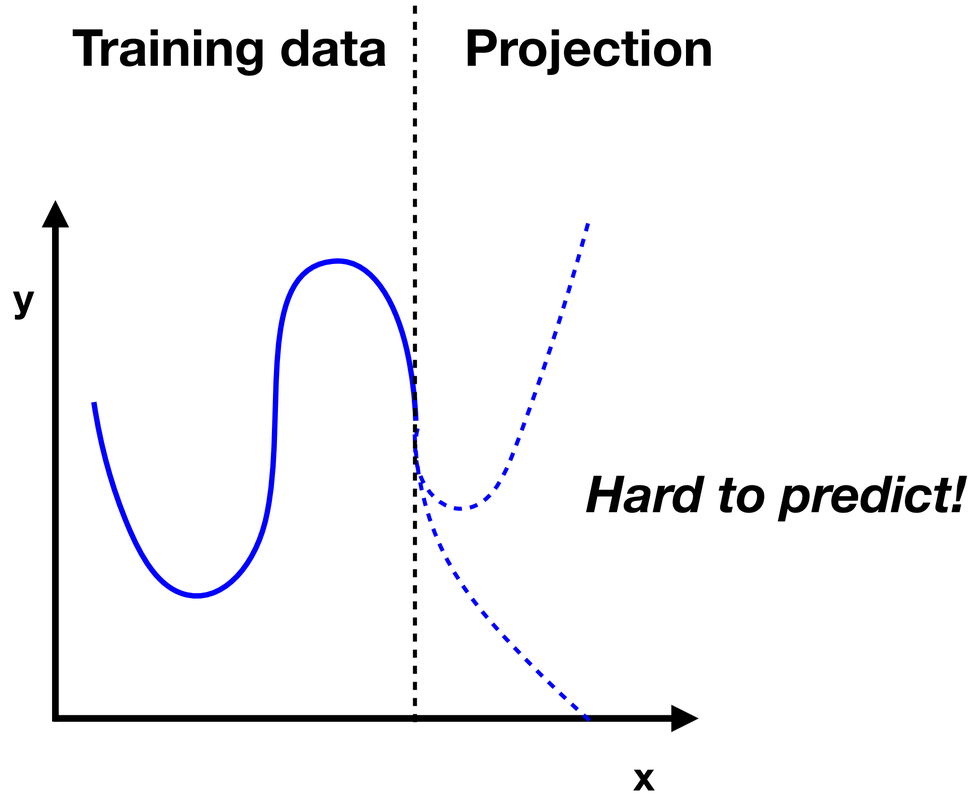
Model Projection

Uncharted land



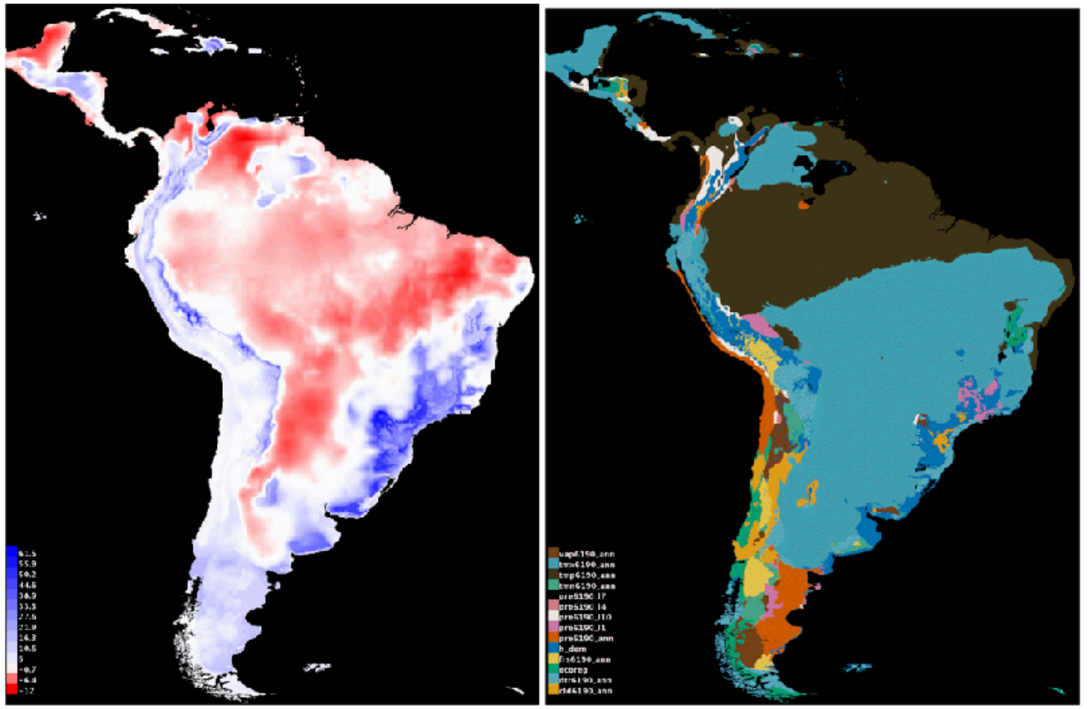
Model Projection

Environmental similarity

Measures the similarity of any given point to a reference set of points, with respect to the chosen predictor variables.

- Left: how different each pixel is in the new climate conditions.
  (the minimum over all predictor variables of how far out of range the point is, expressed as a fraction of the range of that variable's values.)

- Right: environmental variable that is the most different from the training range at each pixel.



Extract R Code

Wallace Component “Session Code”

Extract R Code

R Markdown