MIDTERM TALK

TESTING THE CLIMATE-NICHE PARADIGM FOR SPECIES EXTINCTION RISK

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OUTLINE

UNCERTAINTIES/ ARBITRATY ASSUMPTIONS

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WHICH CONCLUSIONS CAN I DRAW?

1. INTRODUCTION

EXTINCTION RISK MEASURED BY RED LIST

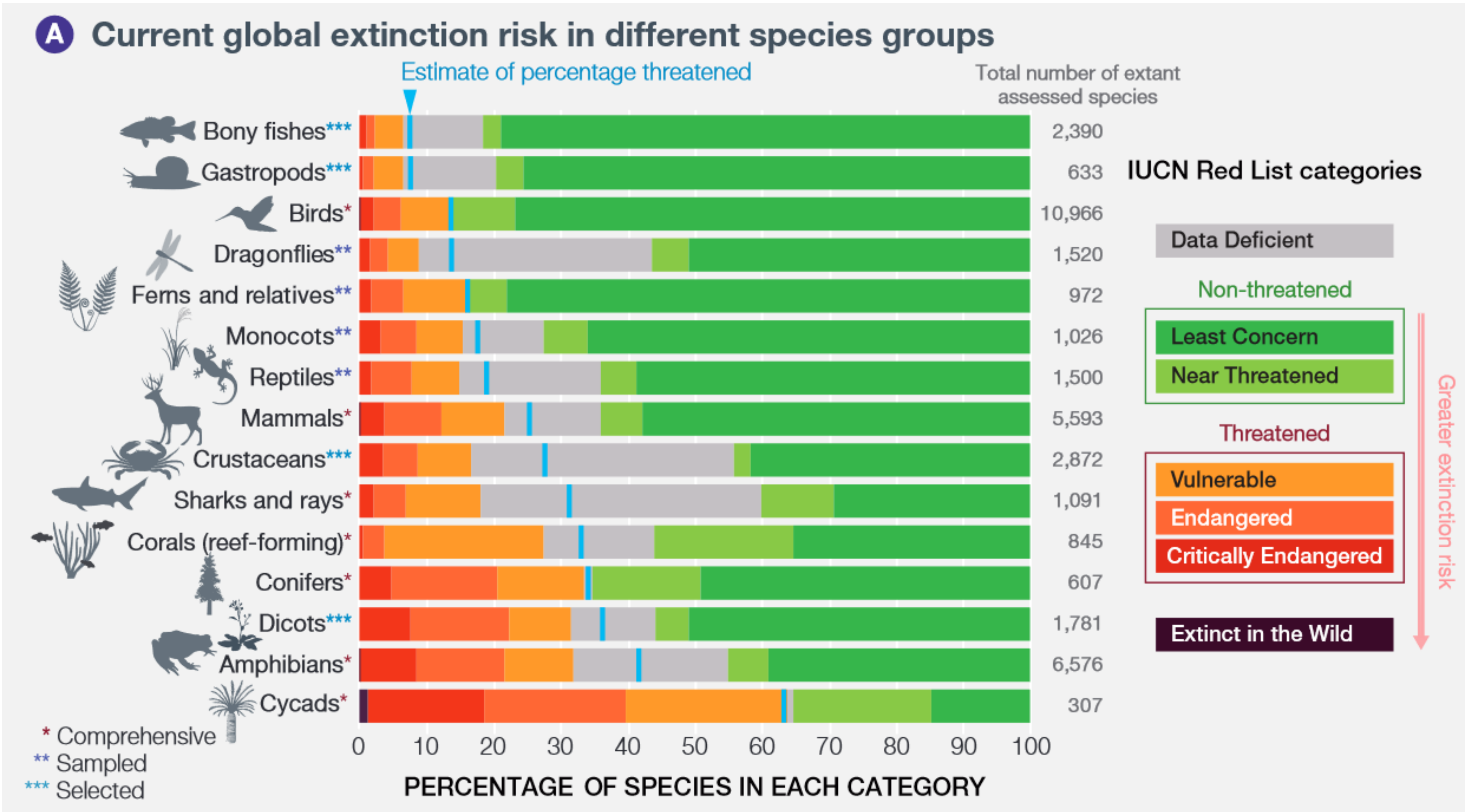
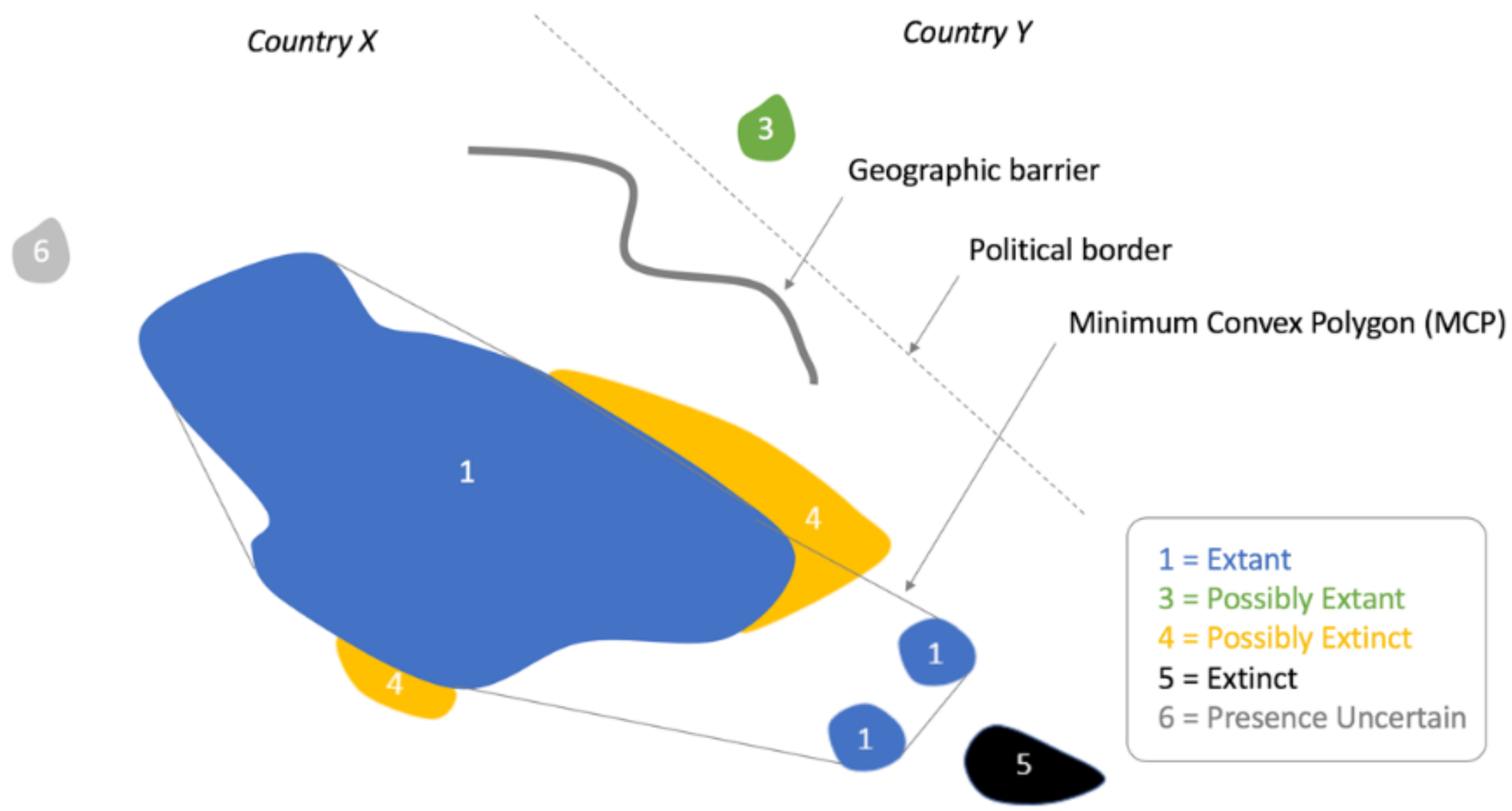


Figure from IPBES (2019) - Fig SPM.3

Provided by the International Union for Conservation of Nature (IUCN)

IUCN RANGE MAPS (POLYGONS)



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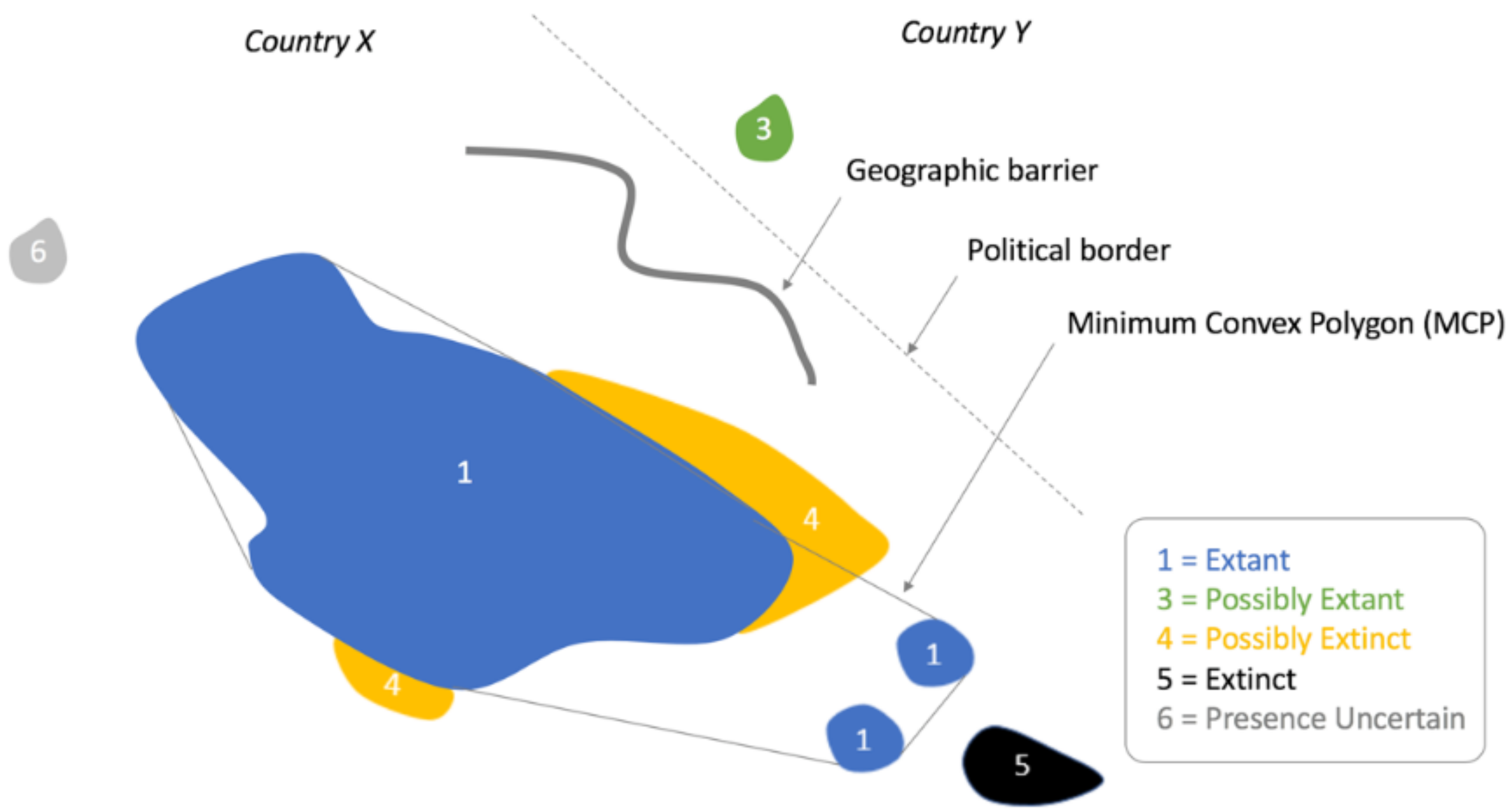

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- Expert-drawn polygons available

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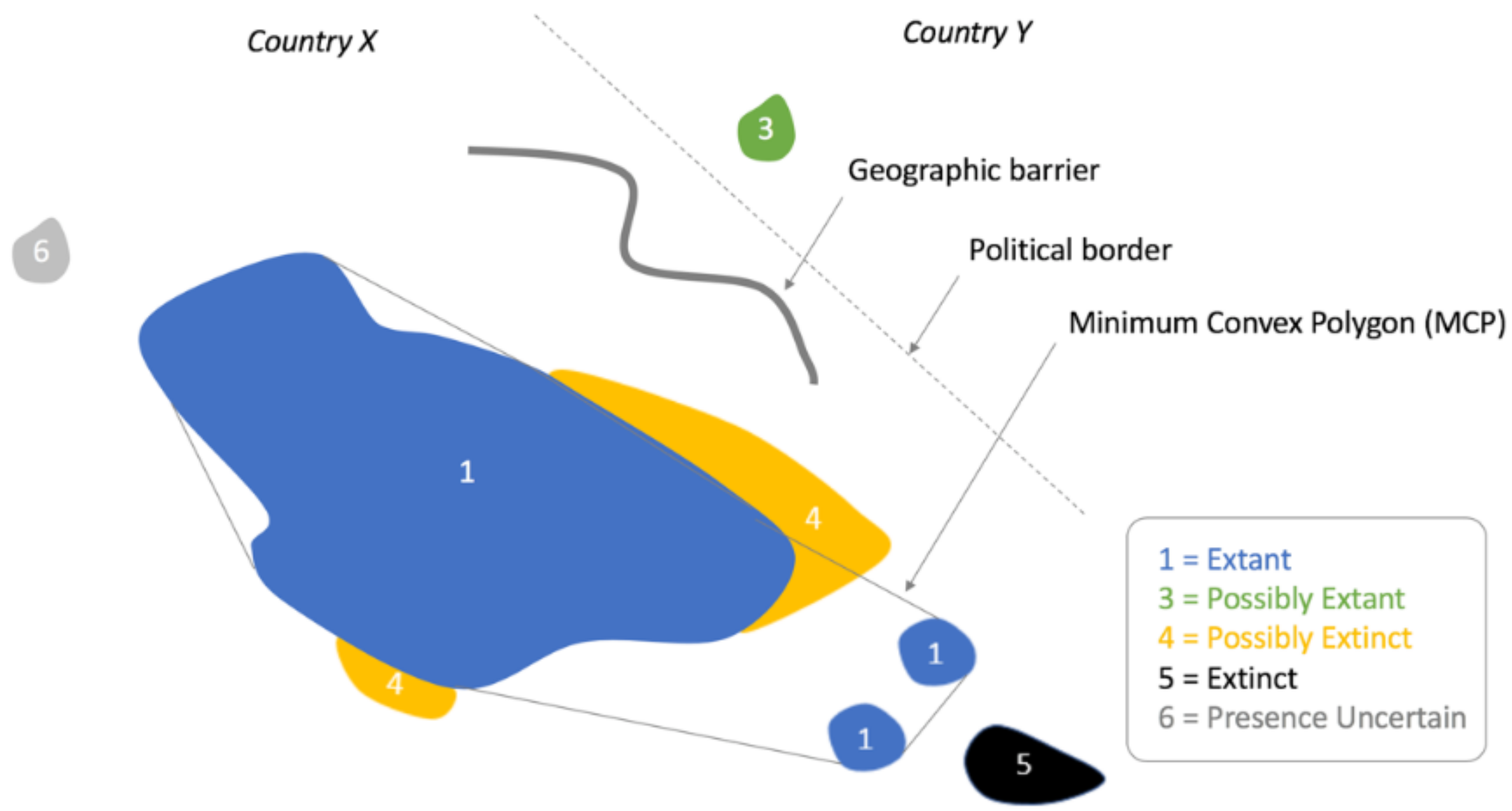

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- Expert-drawn polygons available
- Frequently used data source

SPECIES DISTRIBUTION MODELING (SDM)

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Projection studies:

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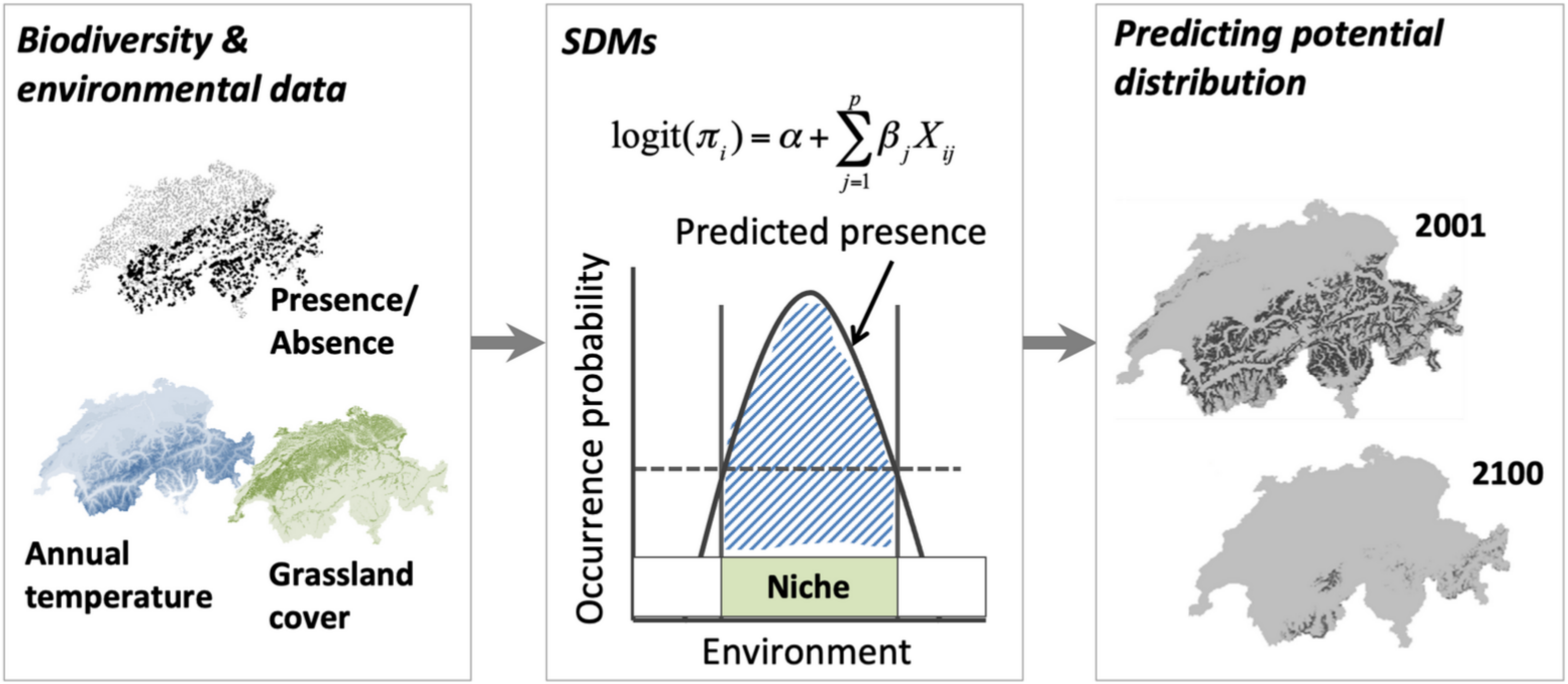

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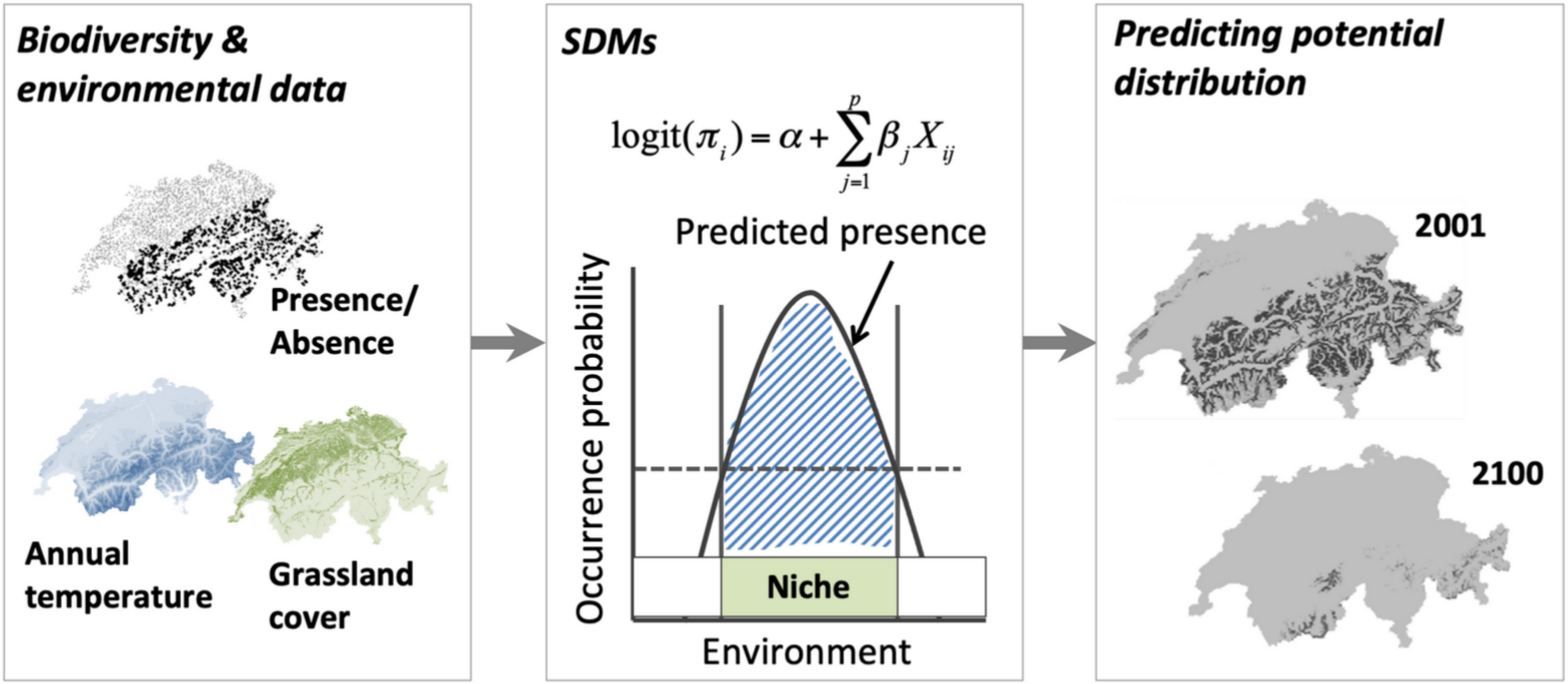

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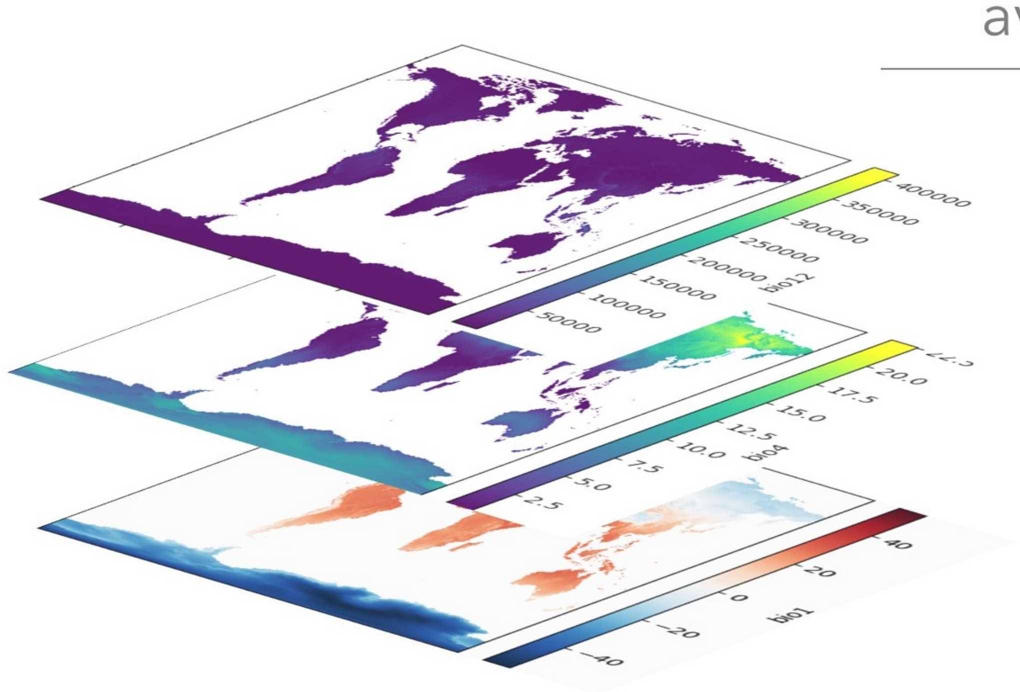
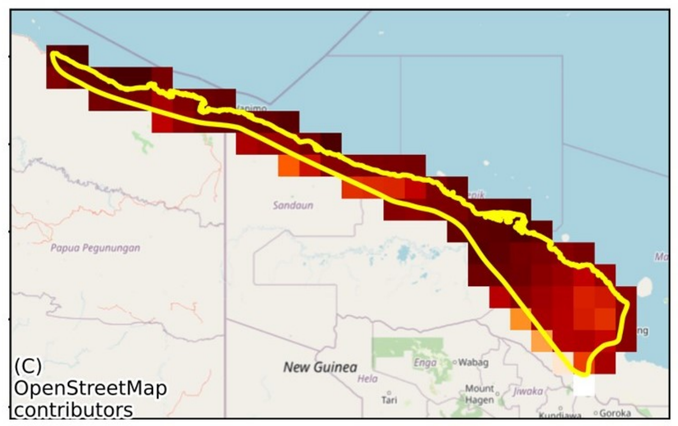
- One of the best performing models is maxent: Choose distribution with maximum entropy, but with same moments as observed (Phillips et al., *Ecological Modelling* (2006))

RED LIST CATEGORY PREDICTION MODELS

Human pressure & environmental data



average



+
Biological traits, range characteristics, Conservation actions

predict

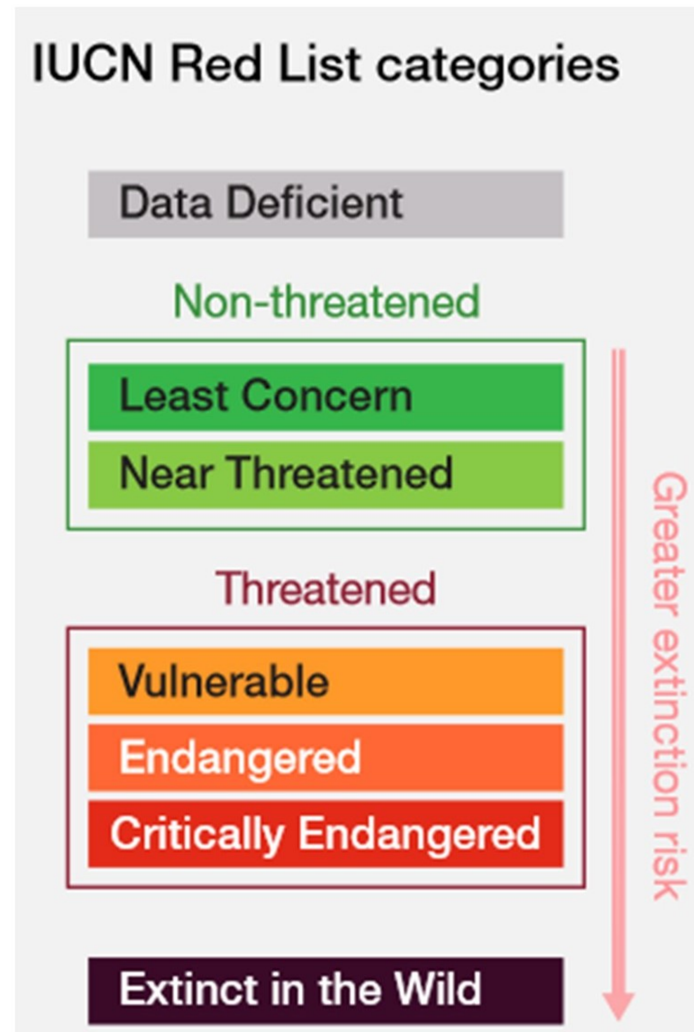


Image: IPBES (2019)

Also see Di Marco, *Nat Commun* (2018) and review article Cazalis et al., *Trends in Ecol. & Evol.* (2022)

CAN SDMS PLAY A ROLE ON CATEGORY PREDICTION?

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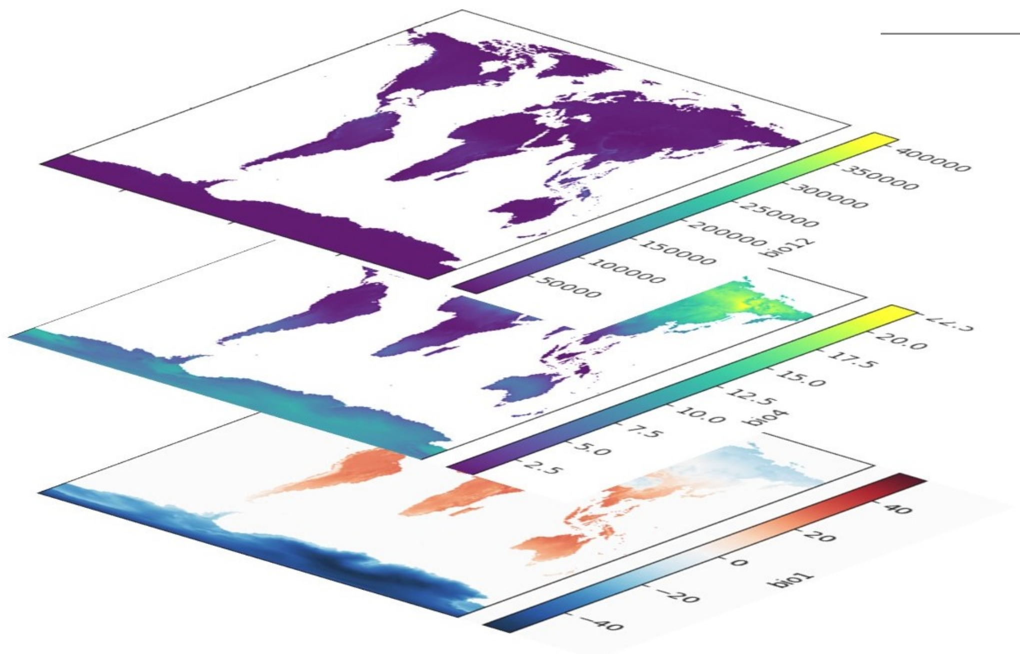

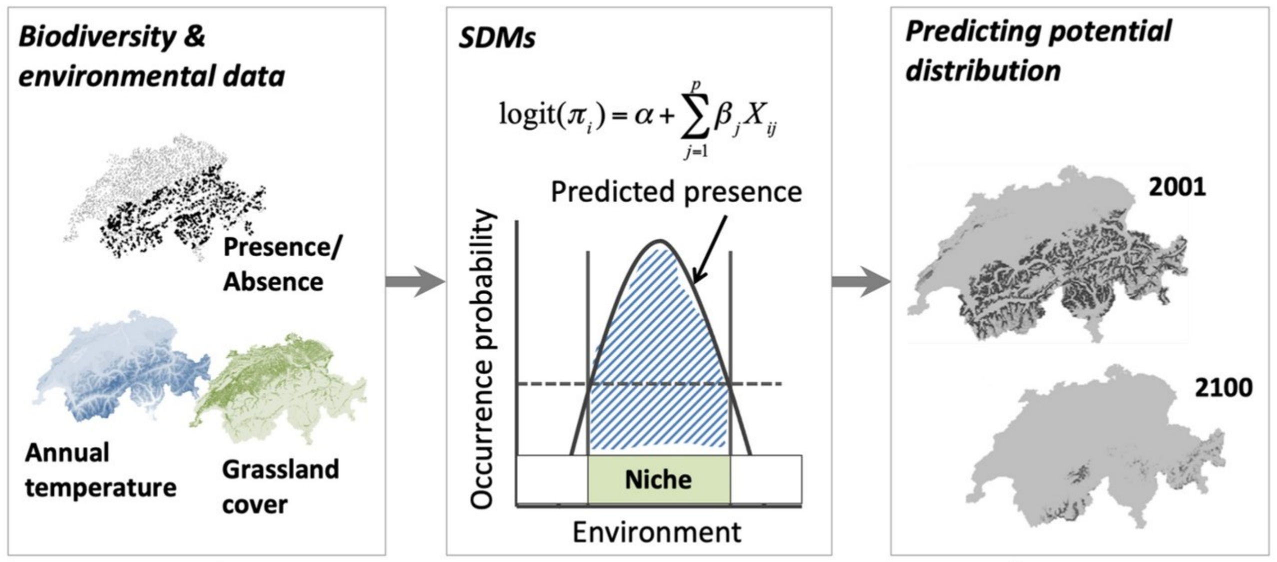

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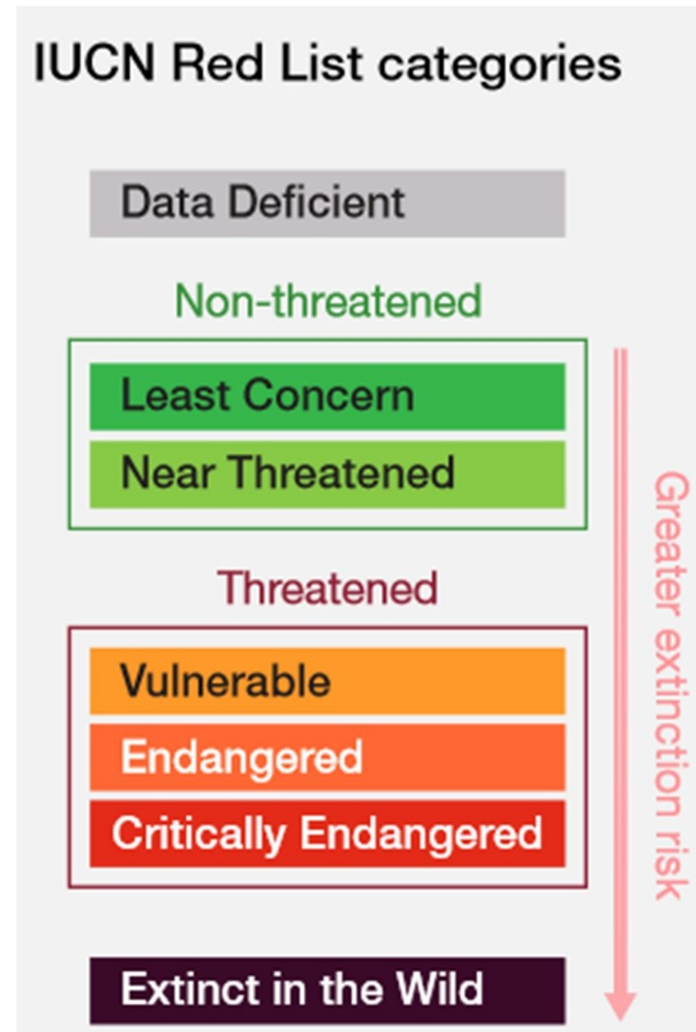

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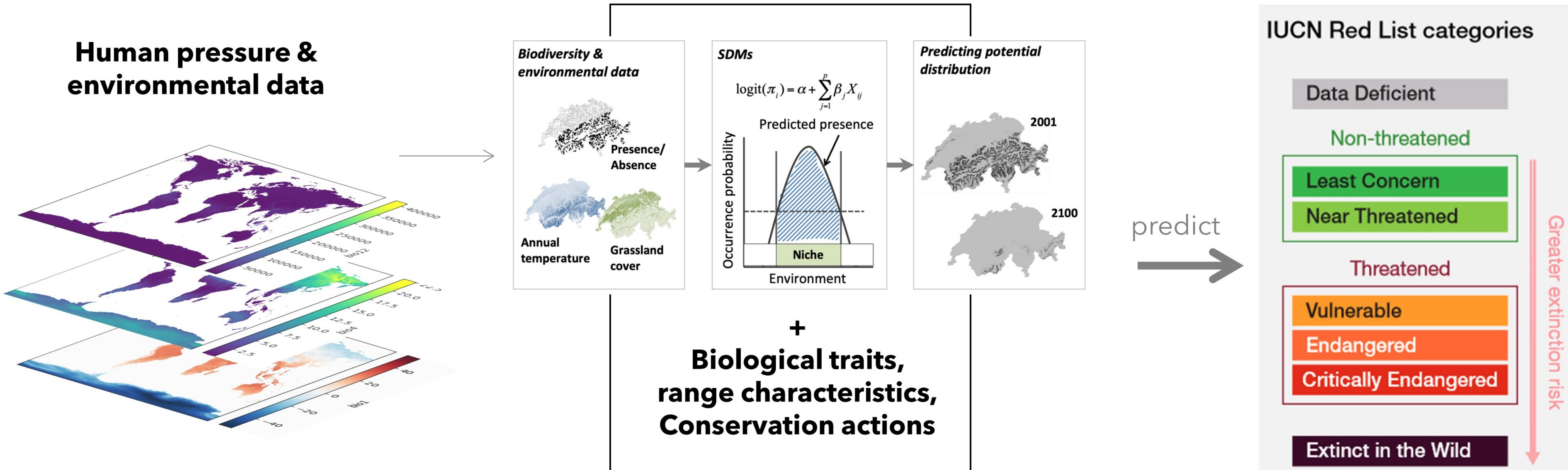

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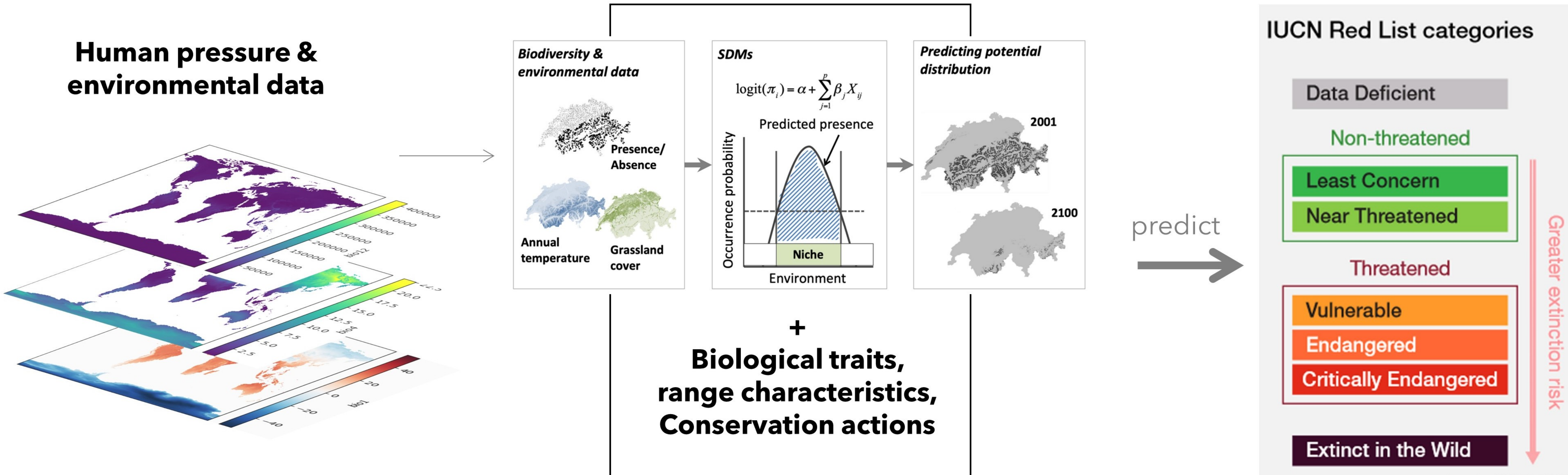

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- identify the most important climate variables.

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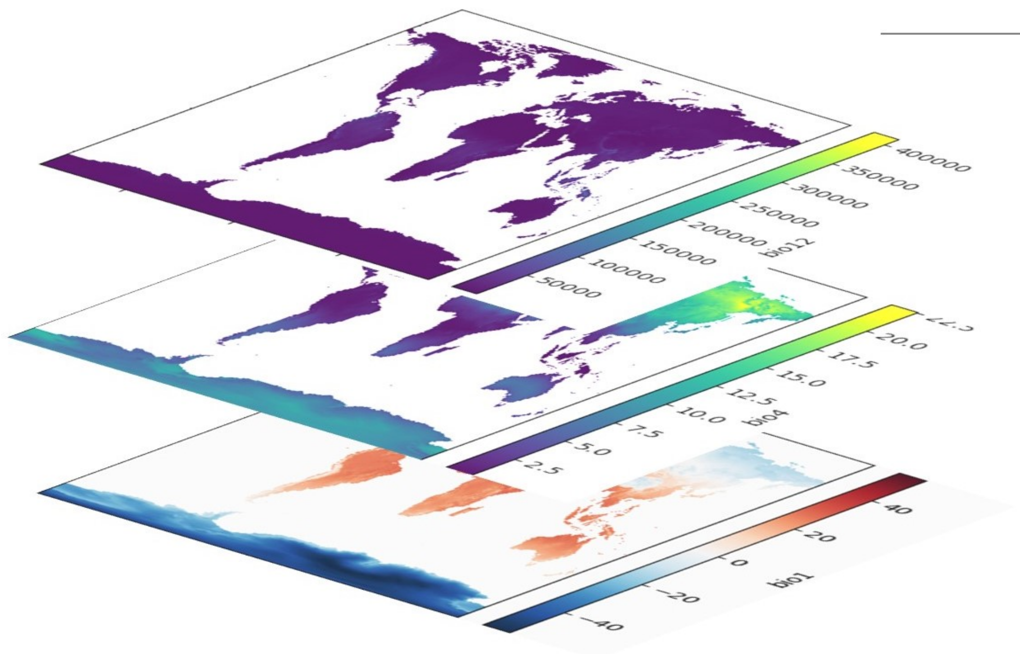

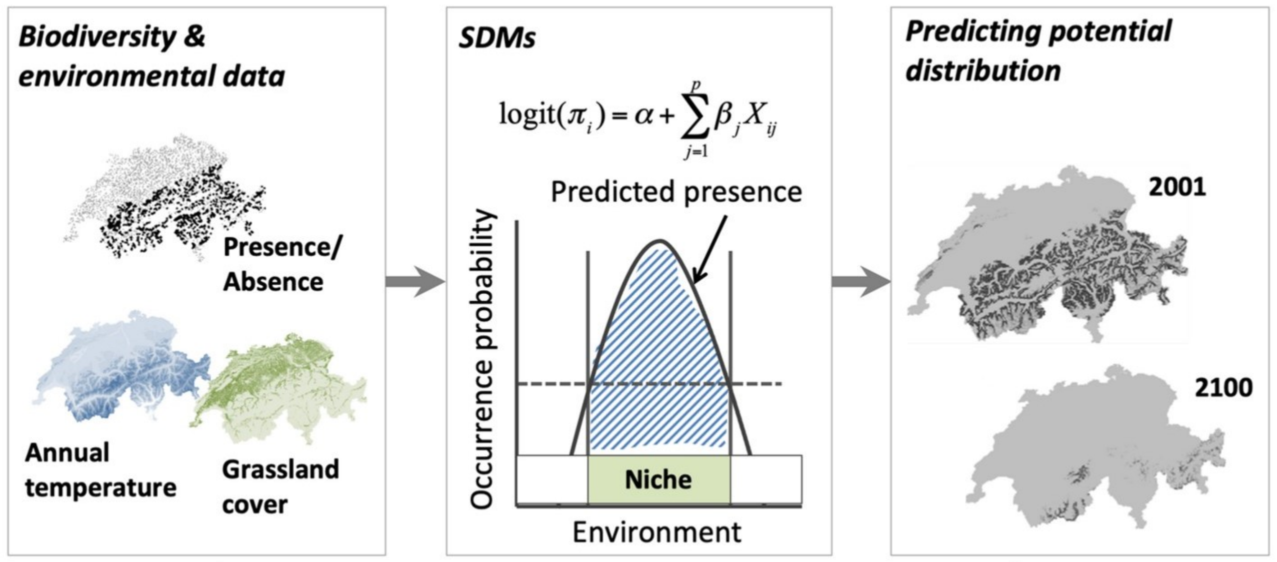

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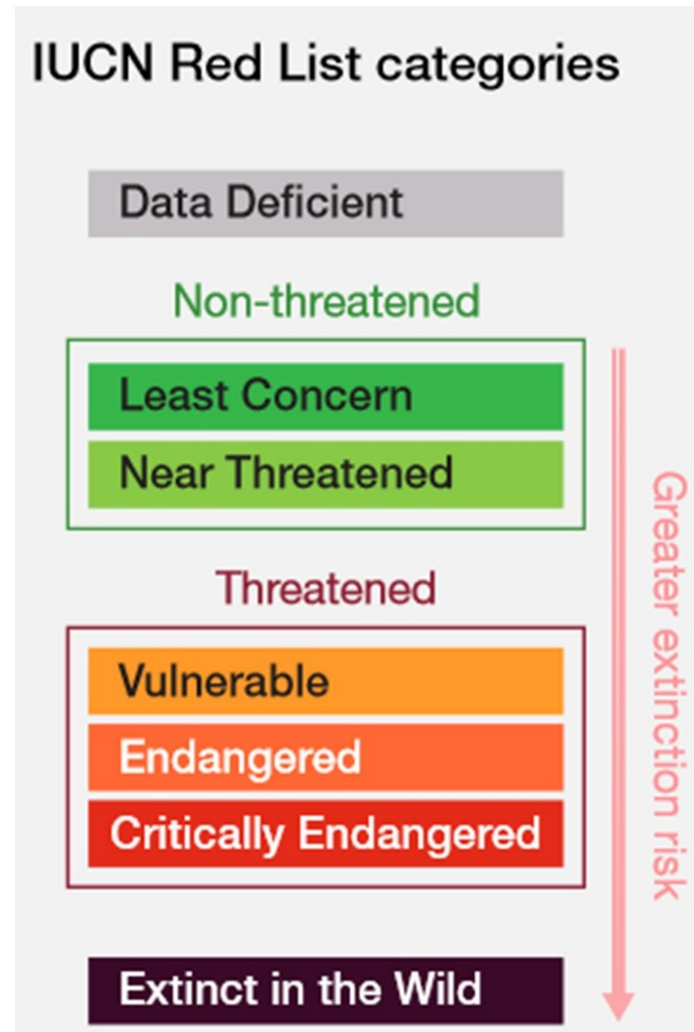

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- identify the most important climate variables.
- **Both comes down to model selection**

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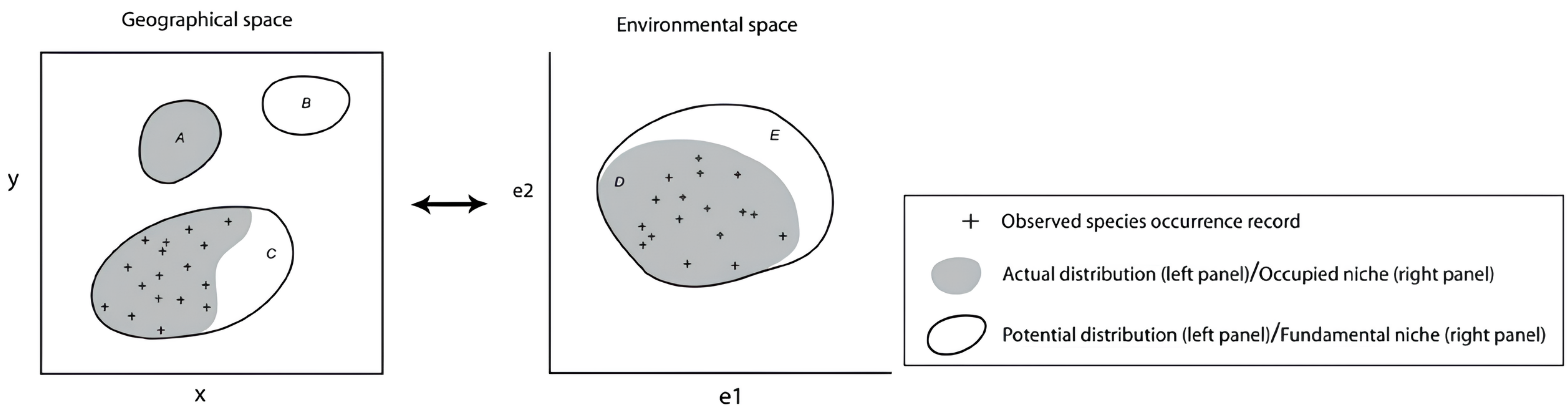

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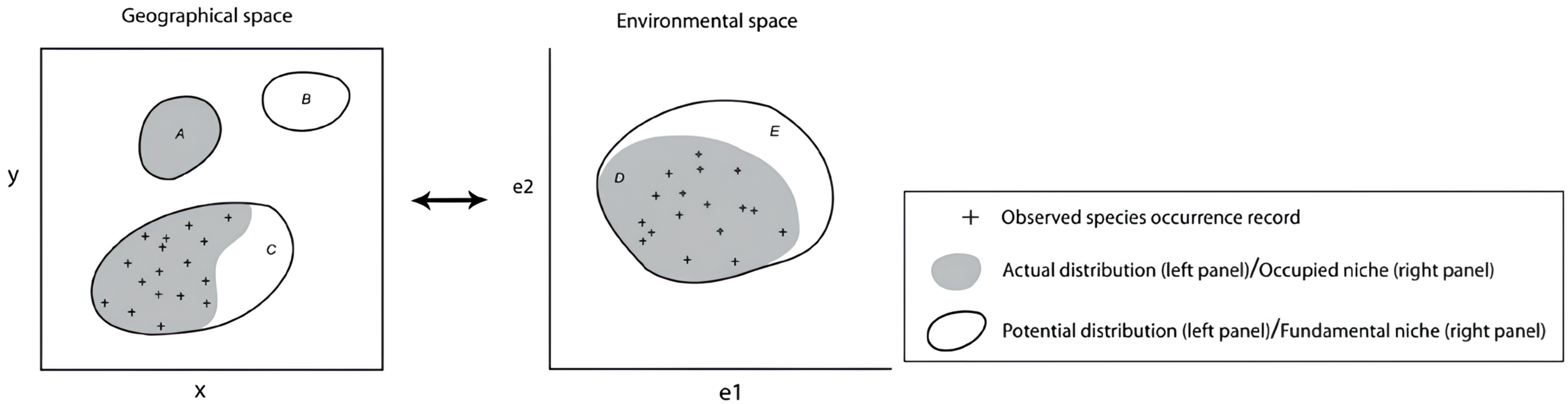

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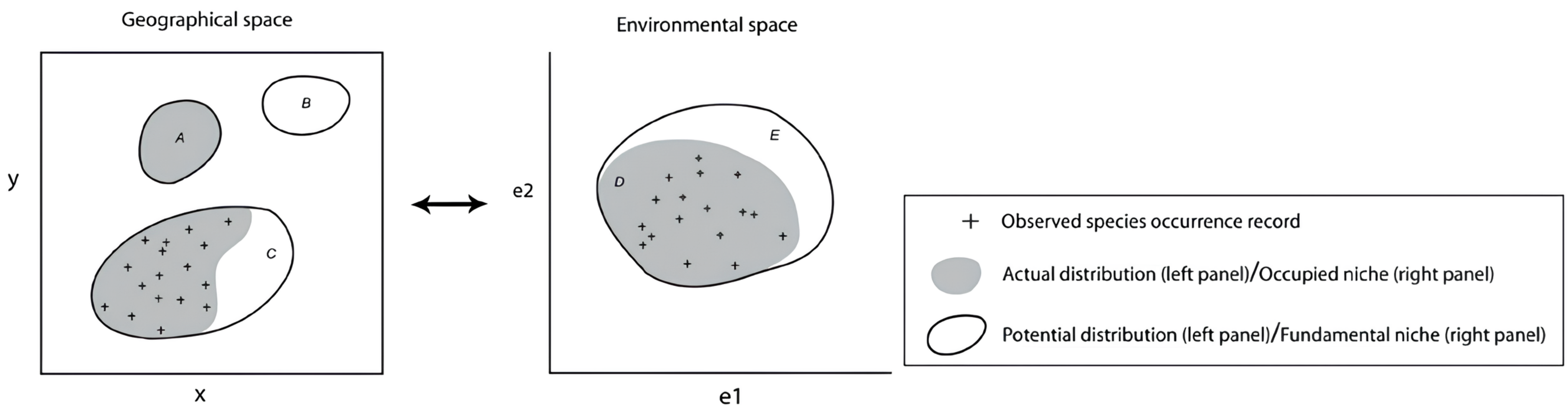

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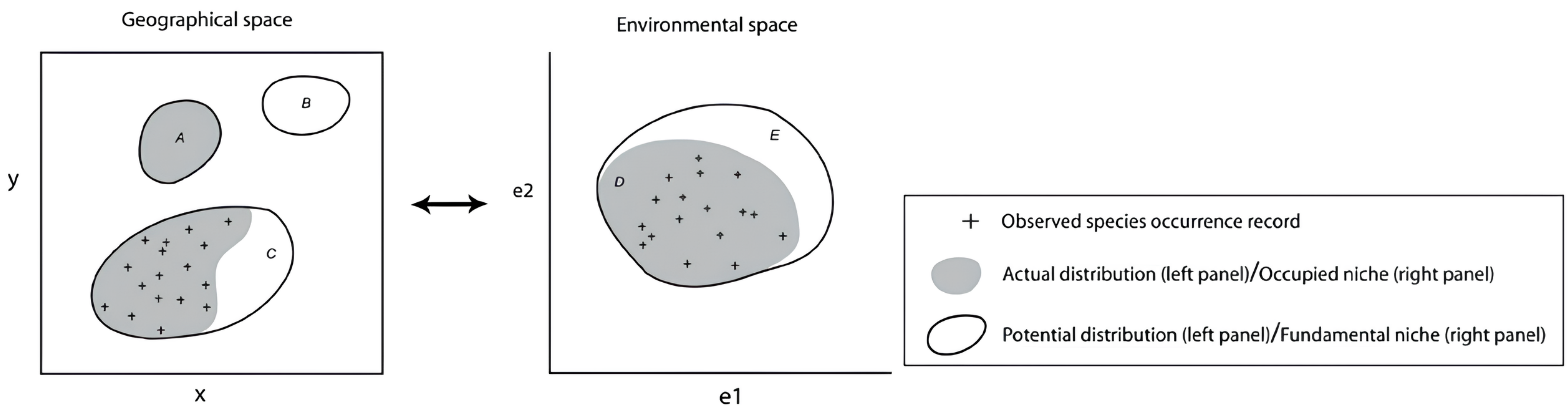

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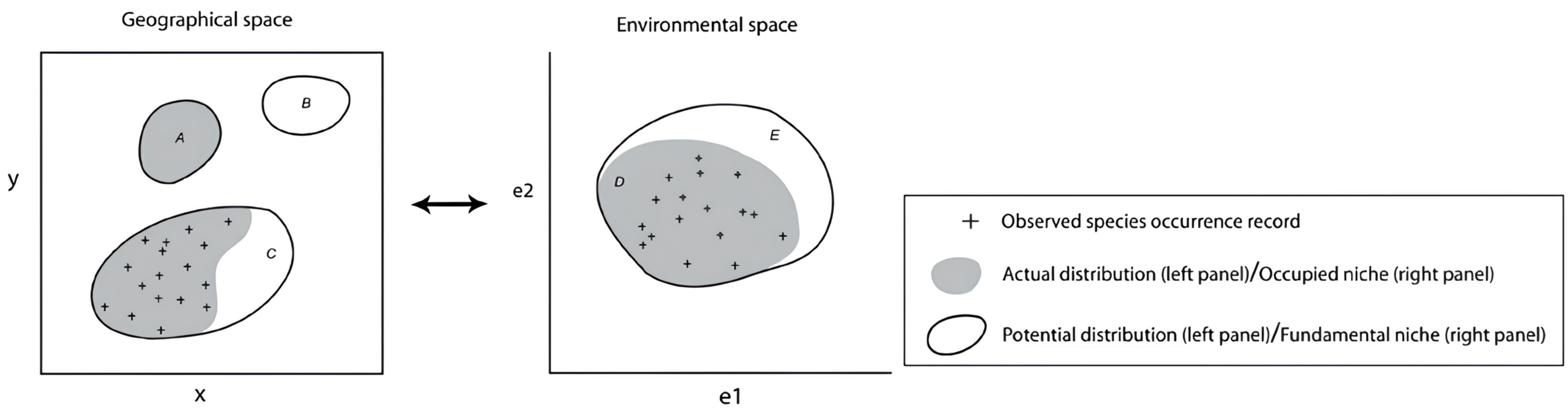

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- Include other species groups with higher dispersal ability

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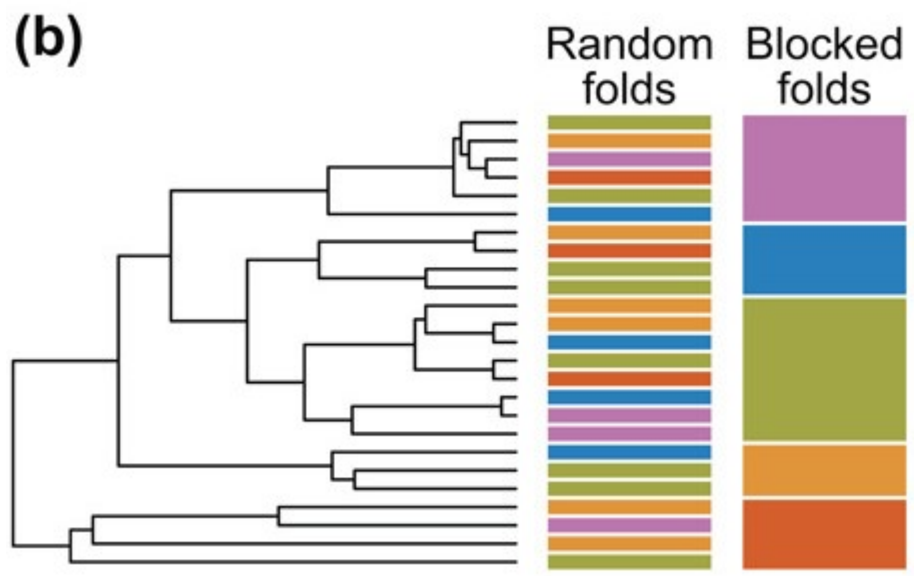

- Figure: Blocks based on phylogenetic tree (Roberts et al., *Ecography* (2016))

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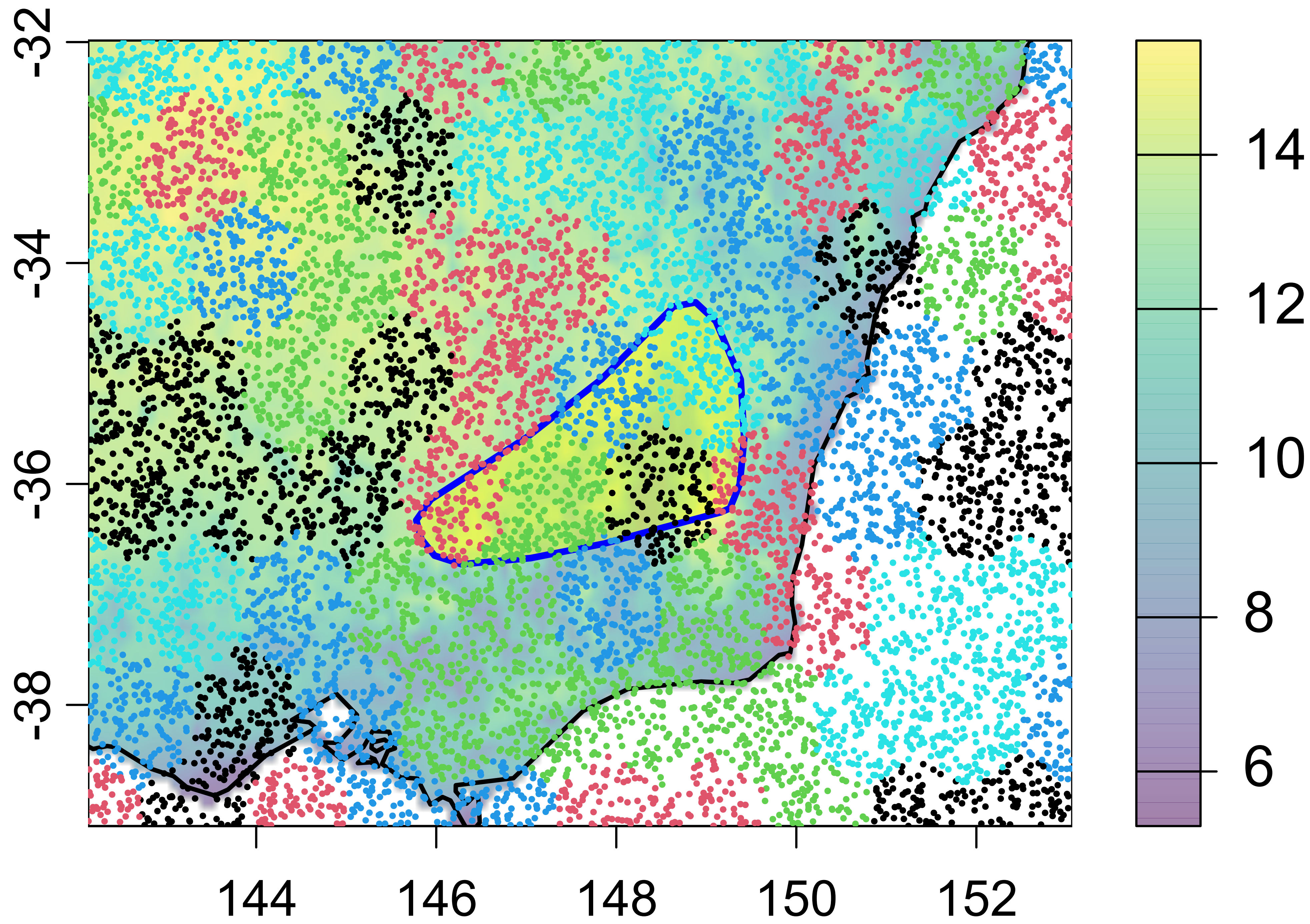
Species distribution modeling

- k-fold spatial block validation (Roberts et al., *Ecography* (2016))



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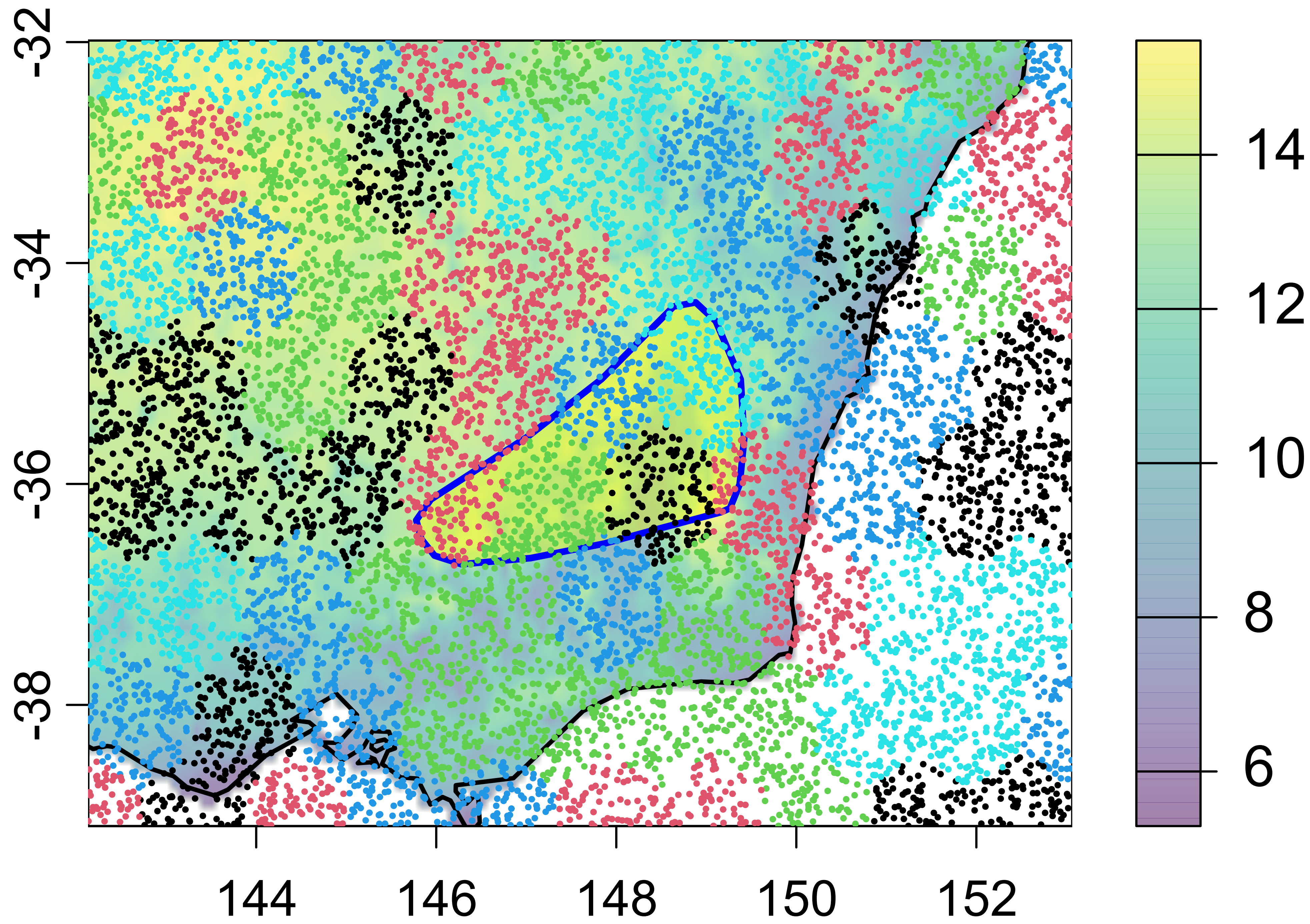

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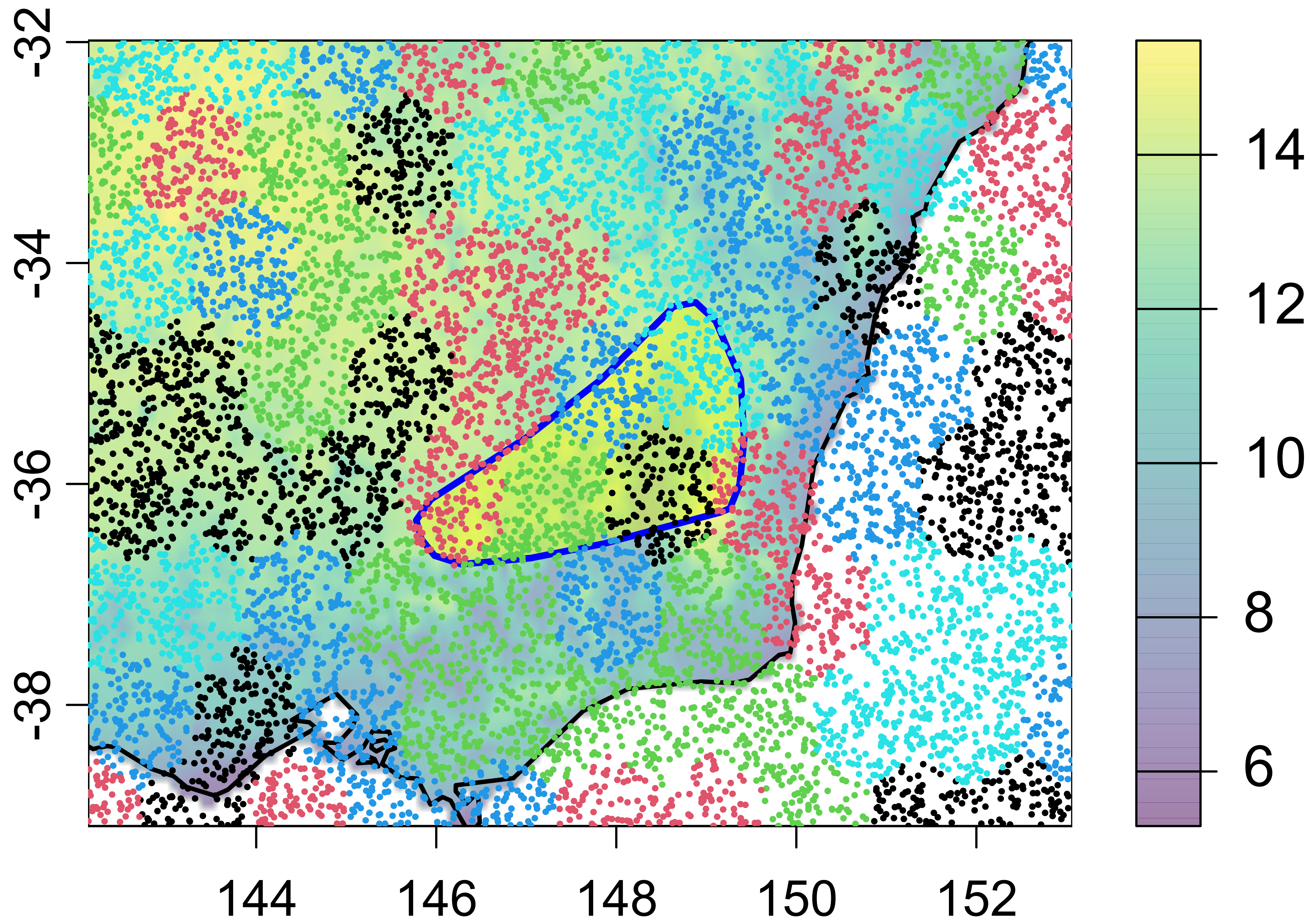
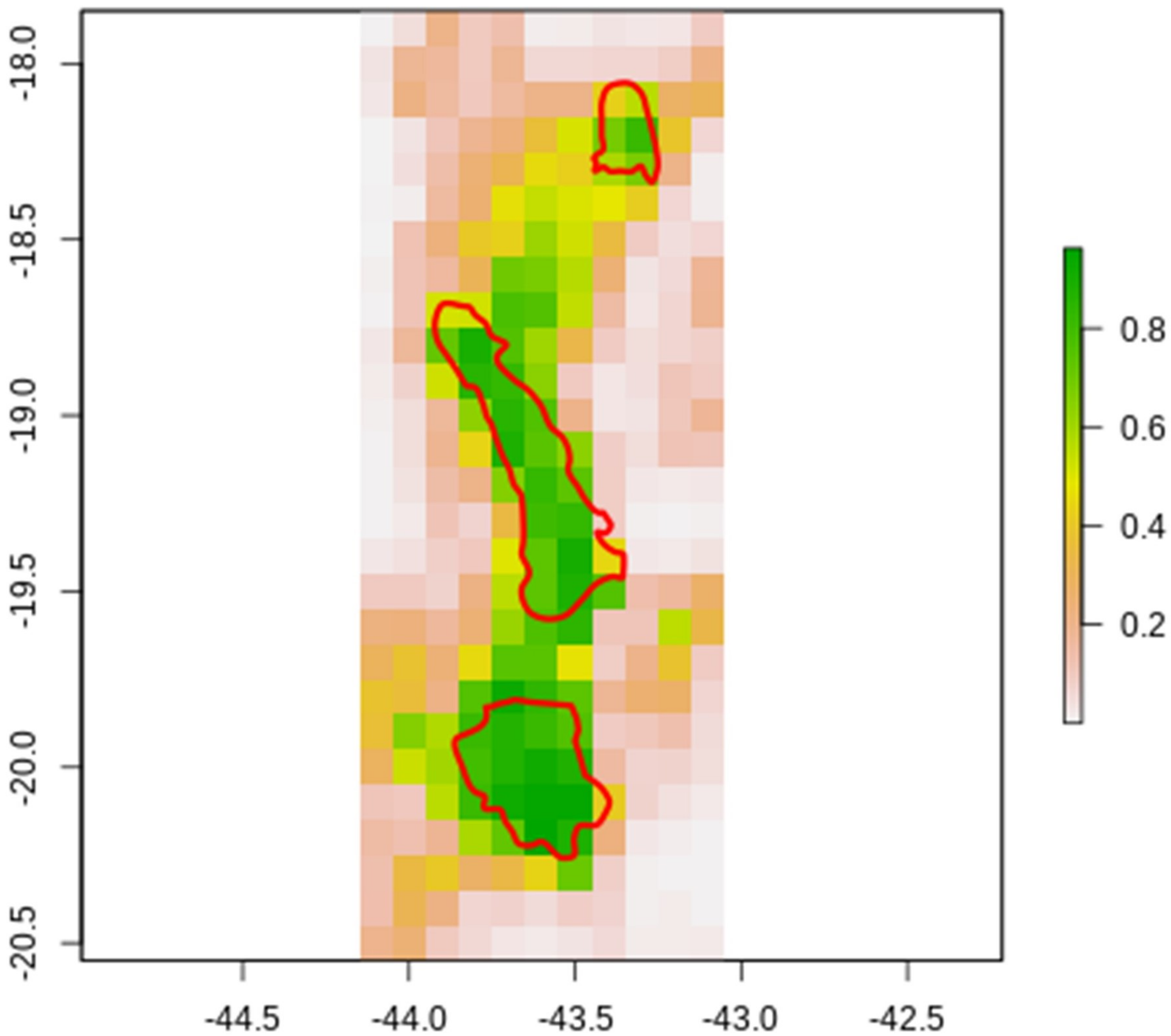


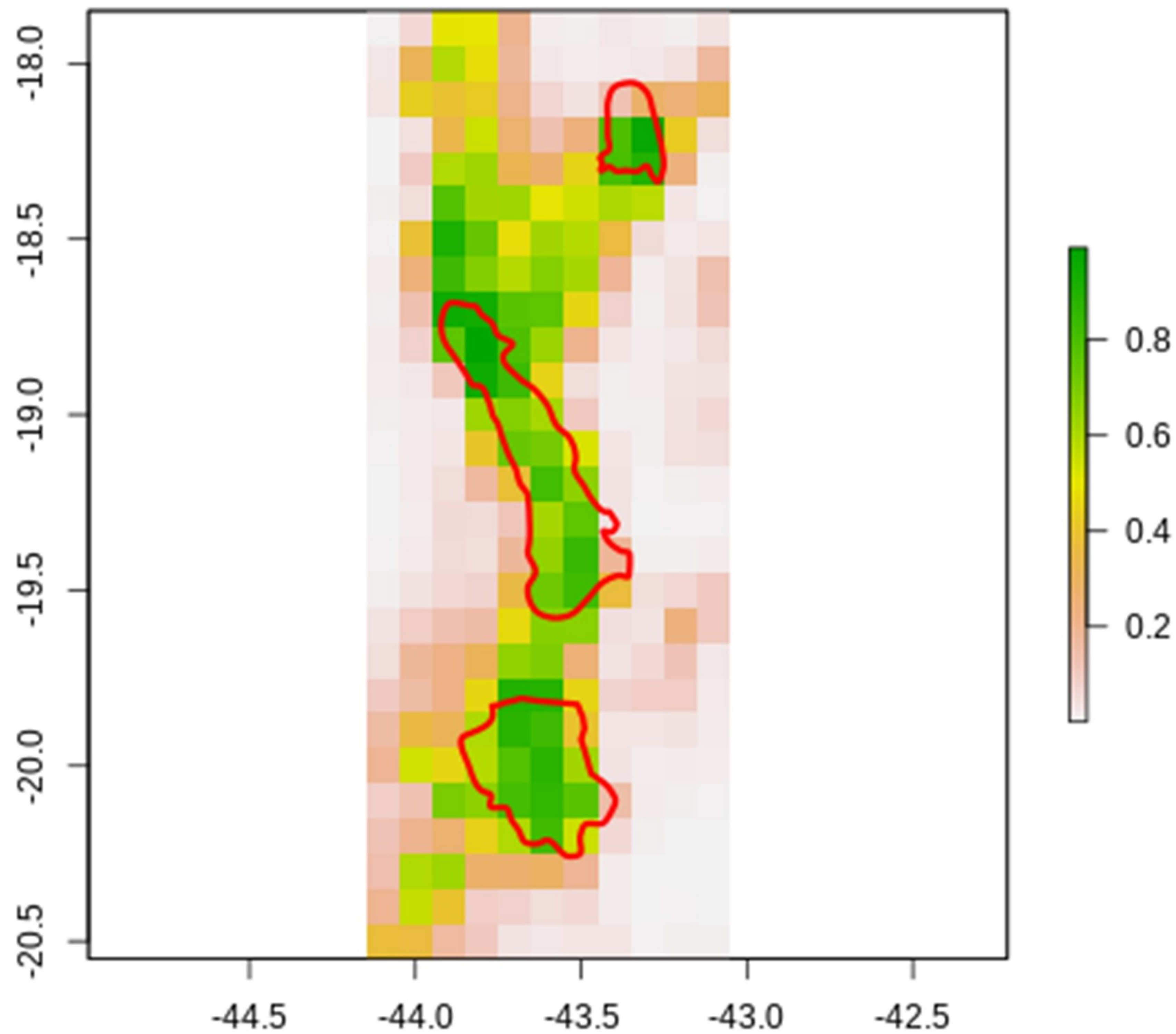
- Deliberately induce extrapolation
- Decrease overestimation in model performance

5. UNCERTAINTIES

SDM training $\langle 1974, \ldots, 2004 \rangle$



SDM prediction $\langle 1991, \ldots, 2021 \rangle$



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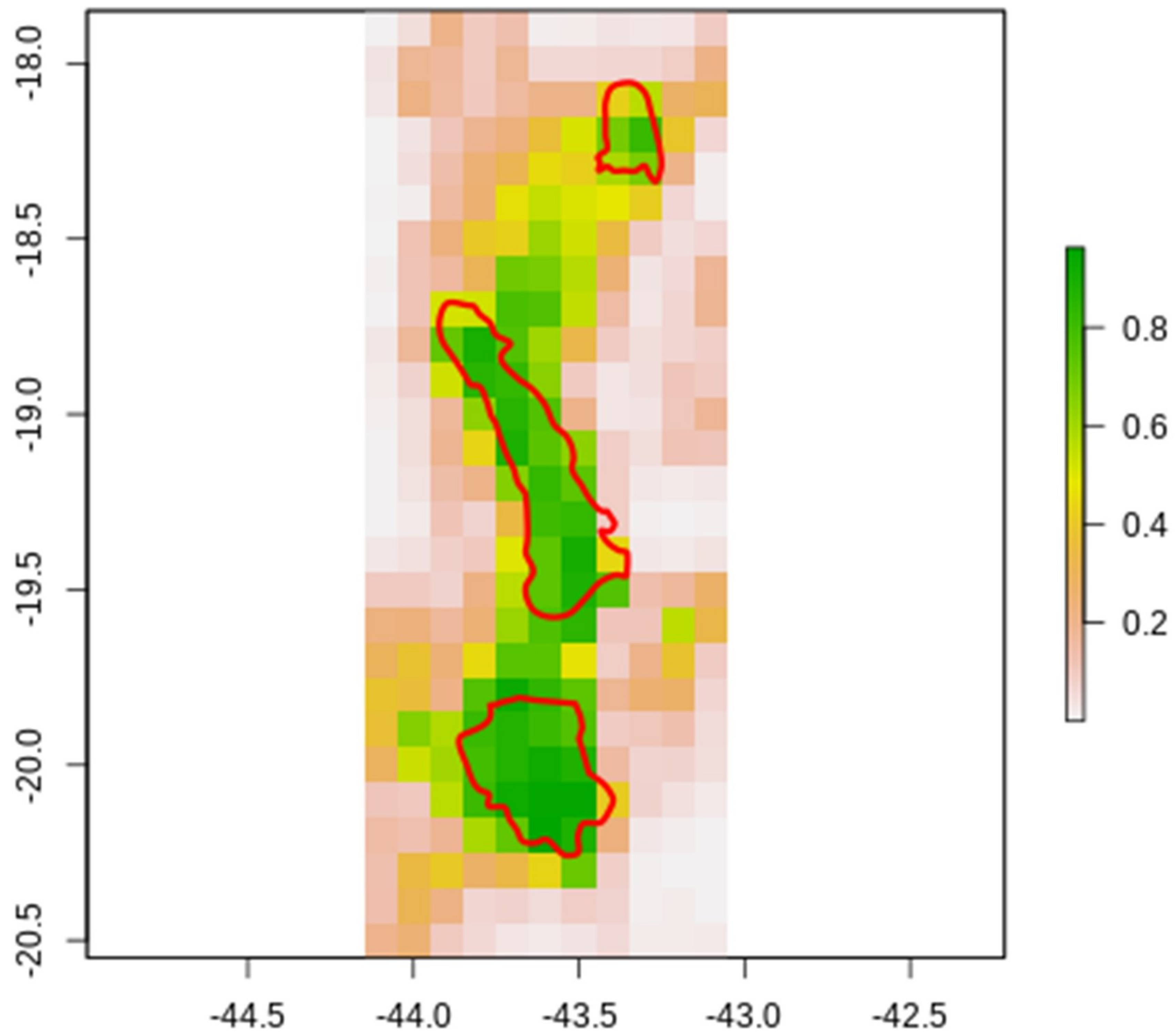

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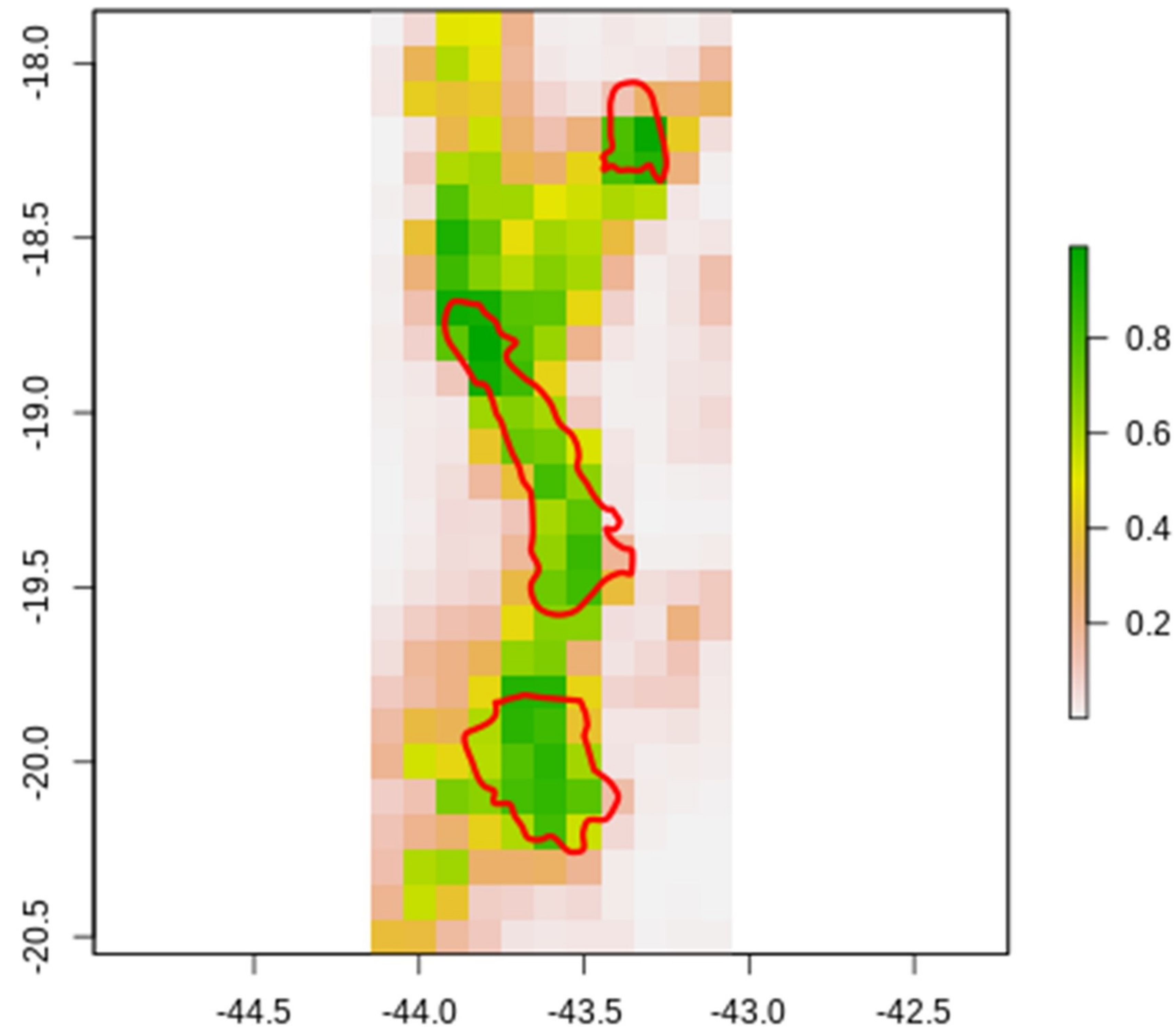

- Uncertainty in climate data

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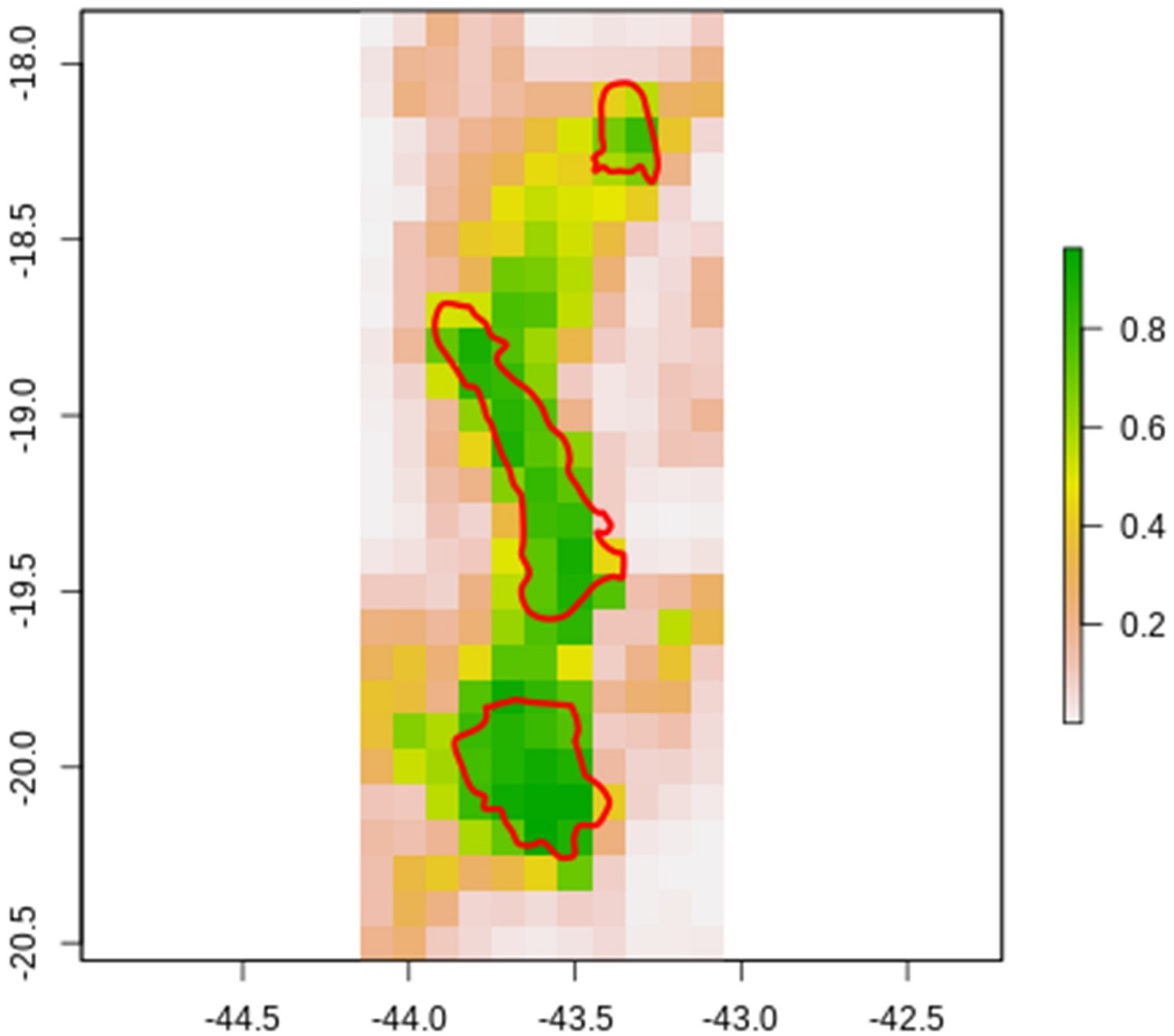

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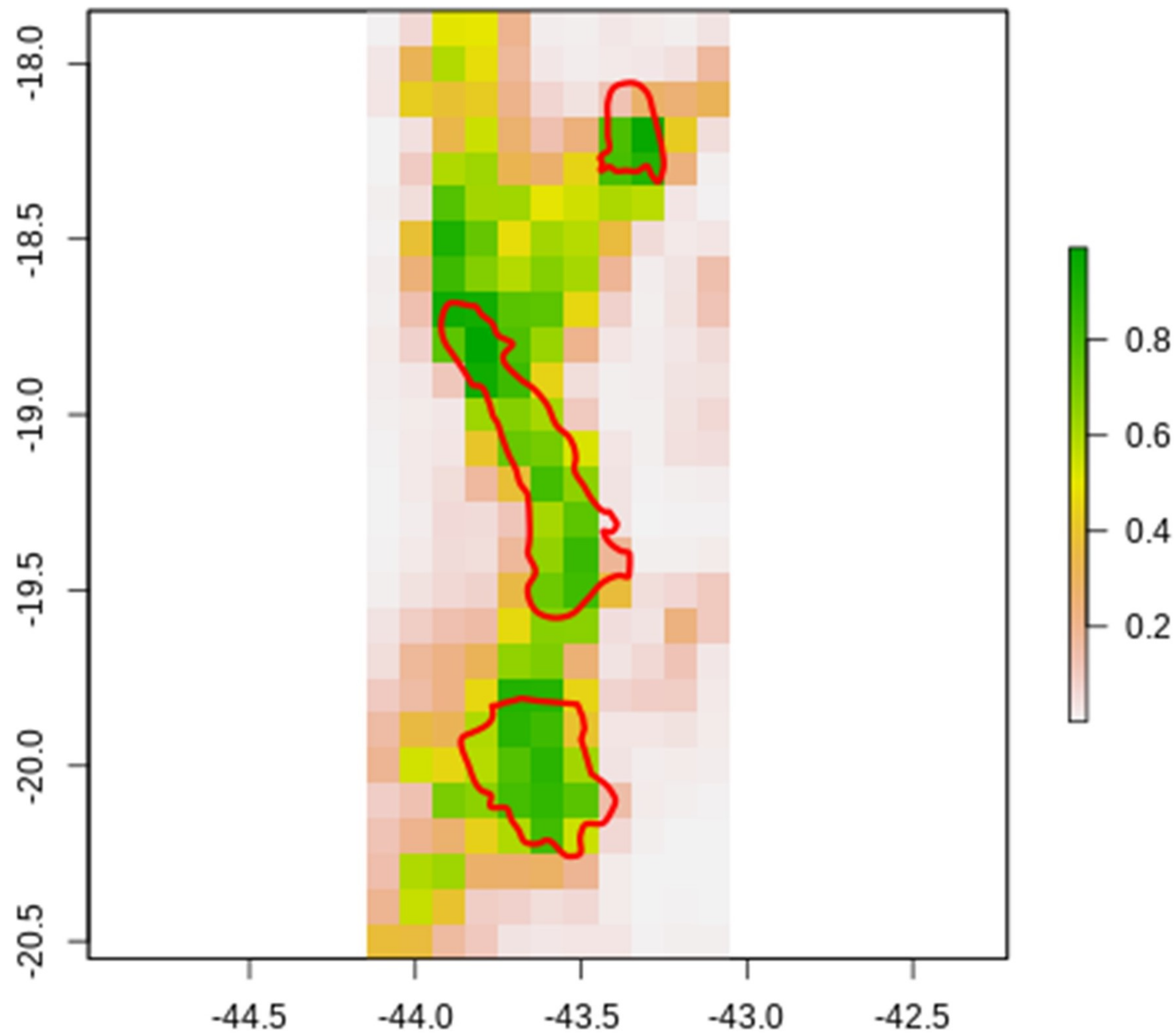

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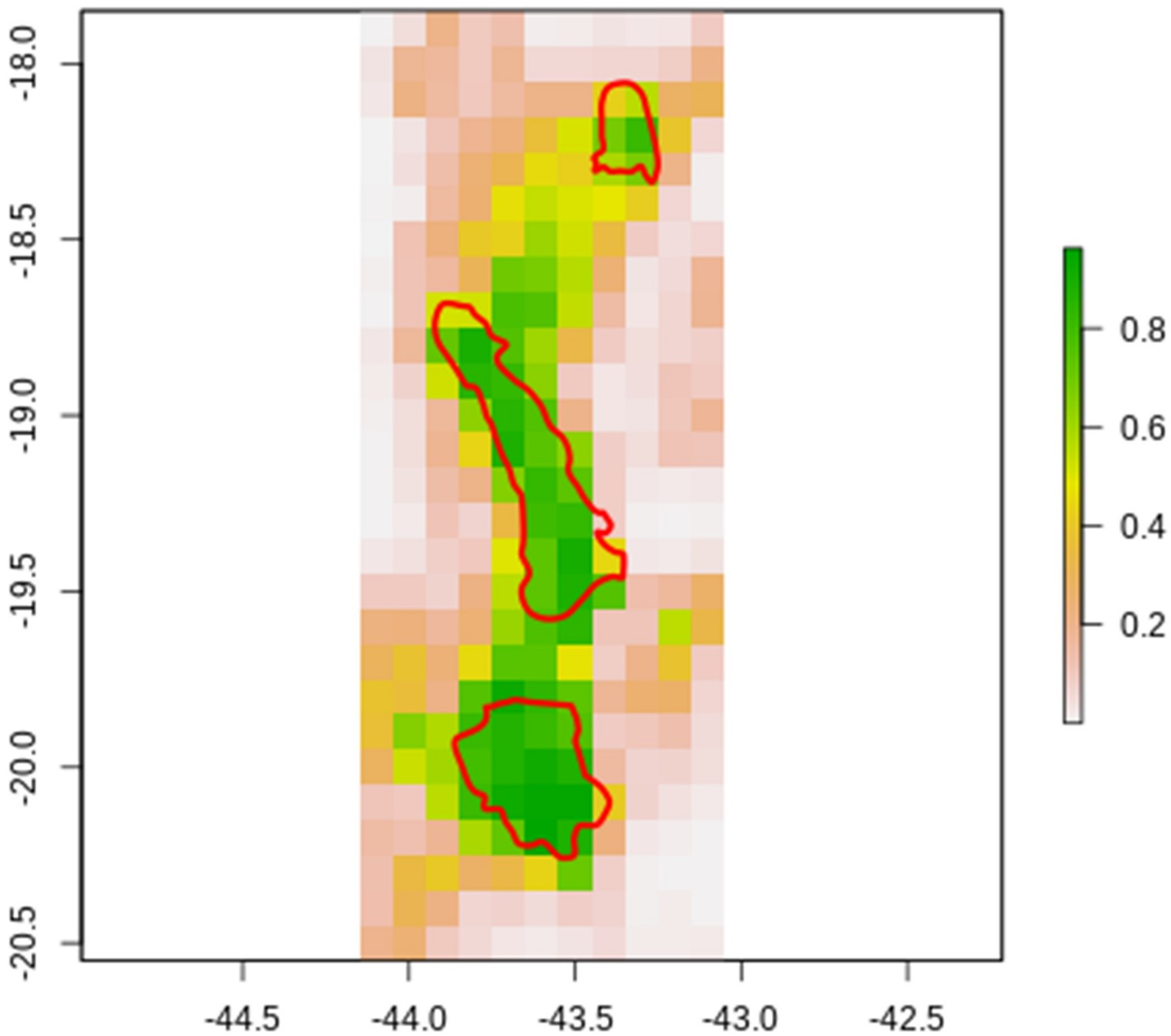

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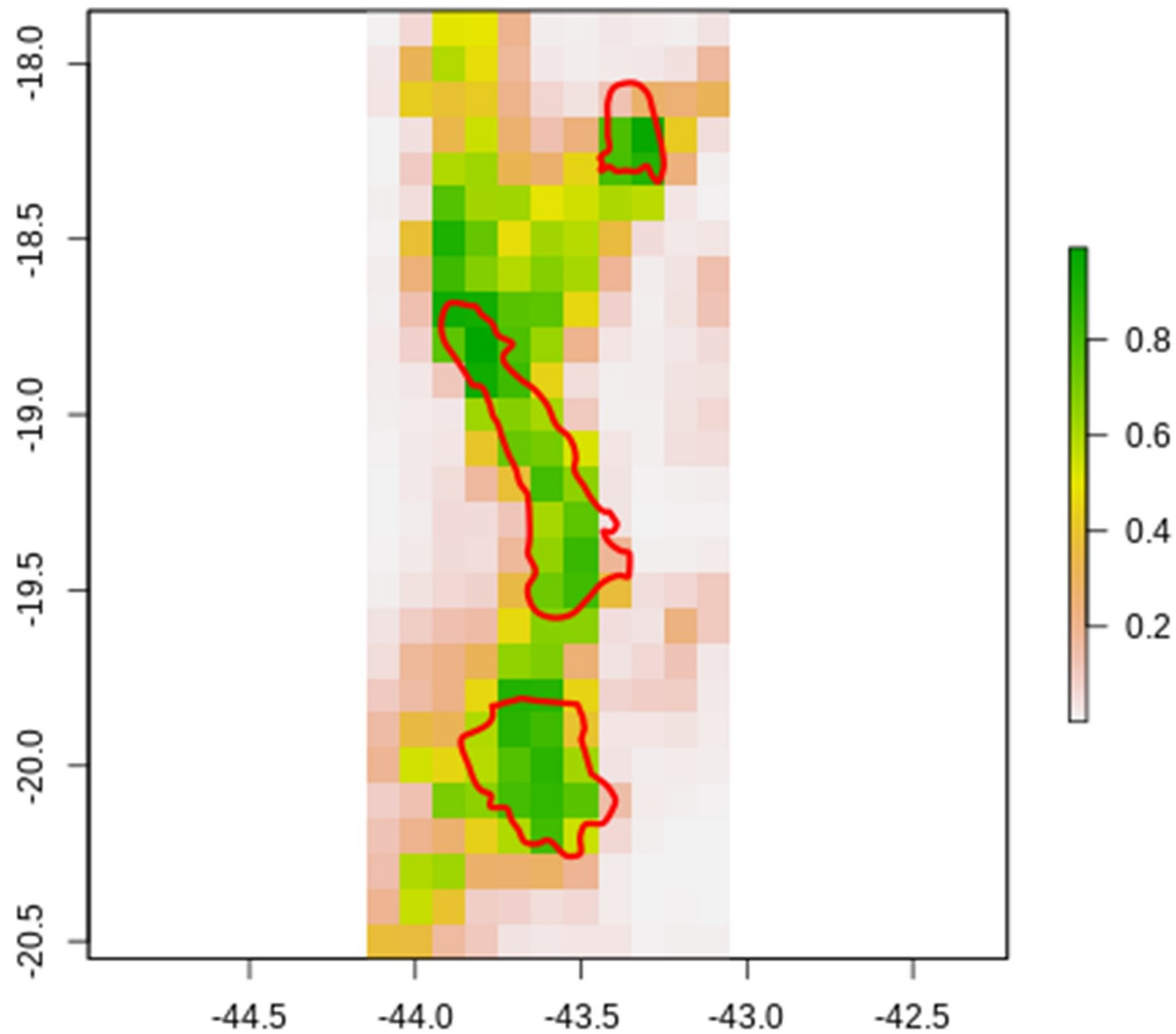

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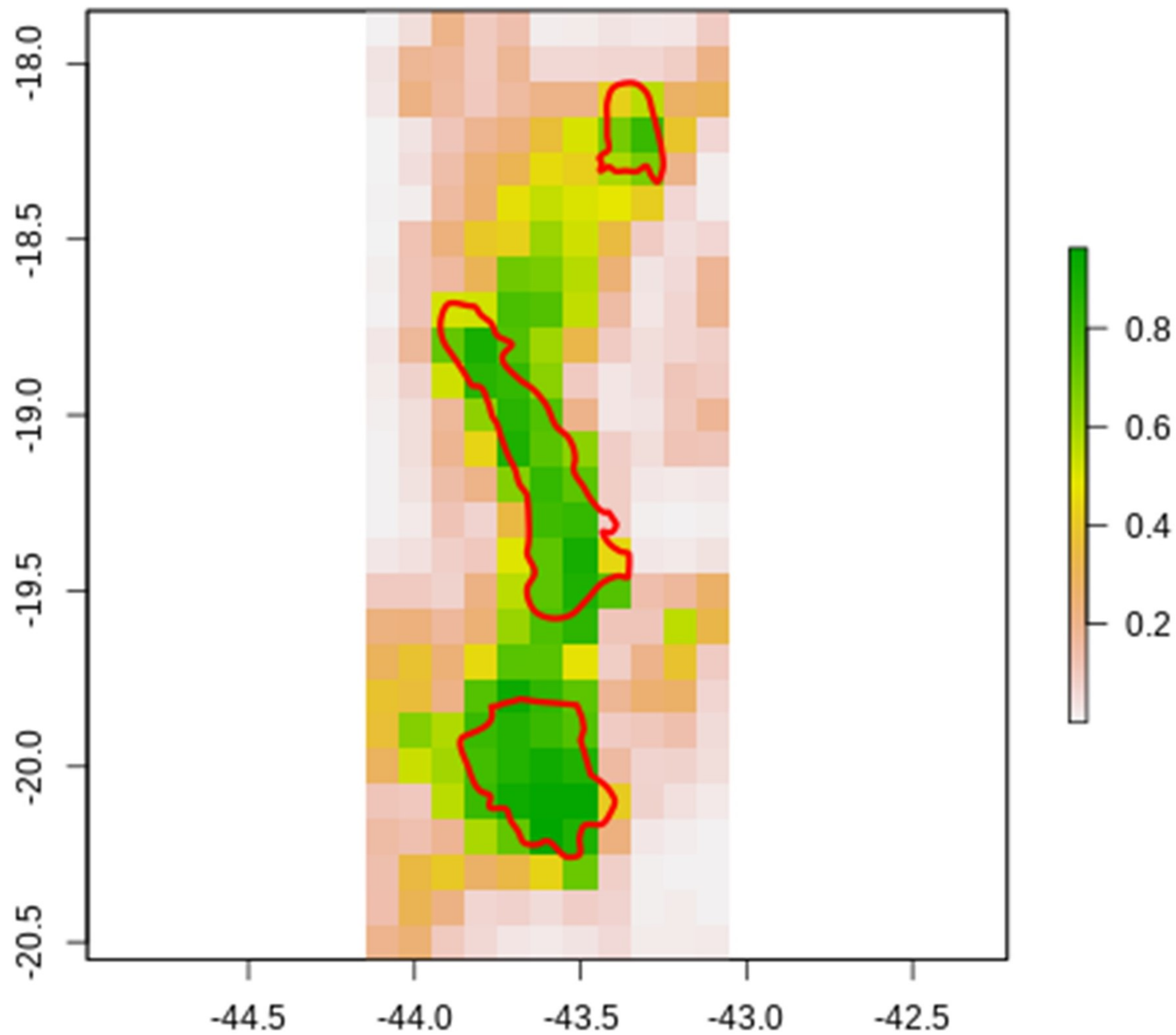

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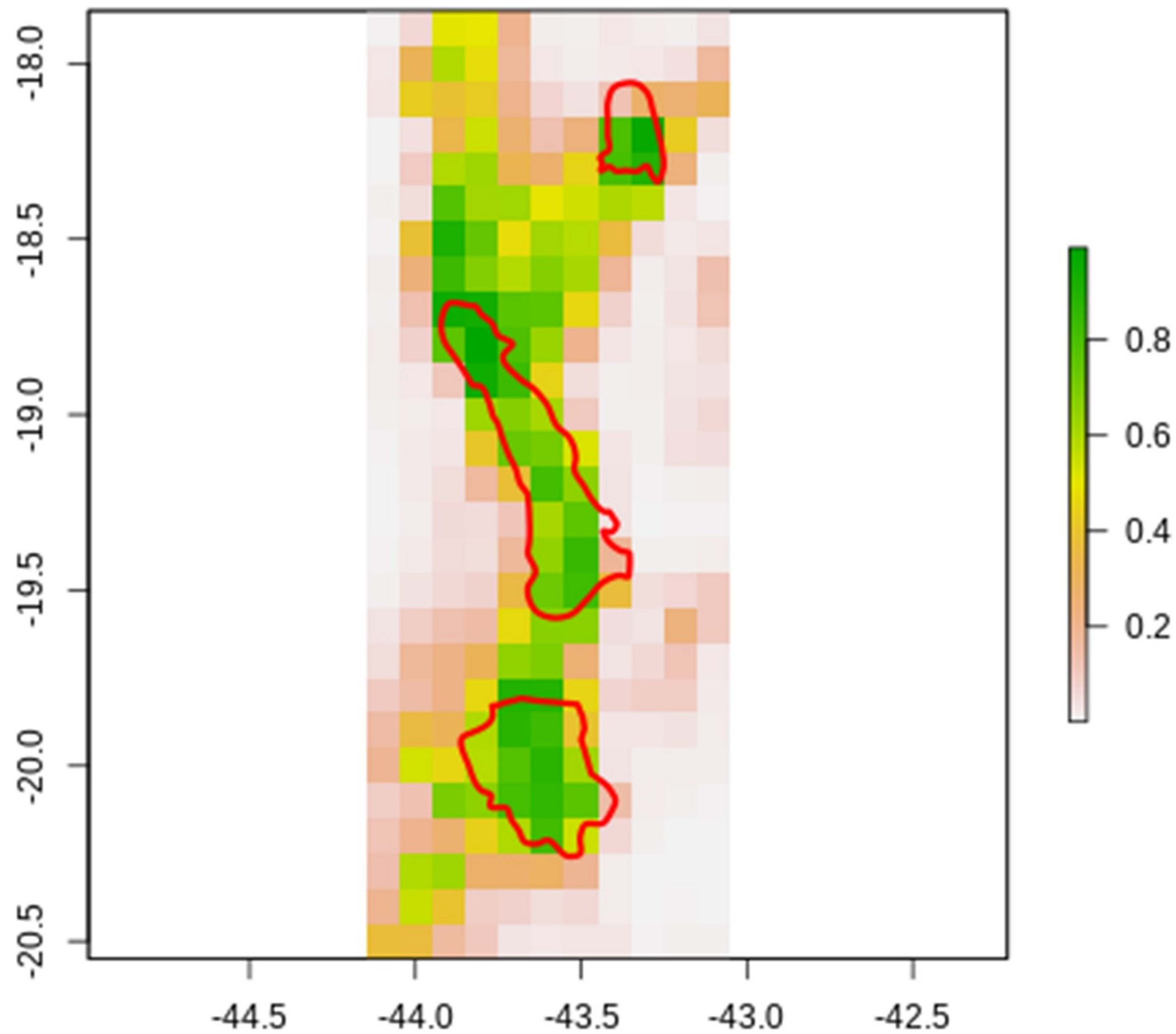

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- **RL prediction**: definition of target variable

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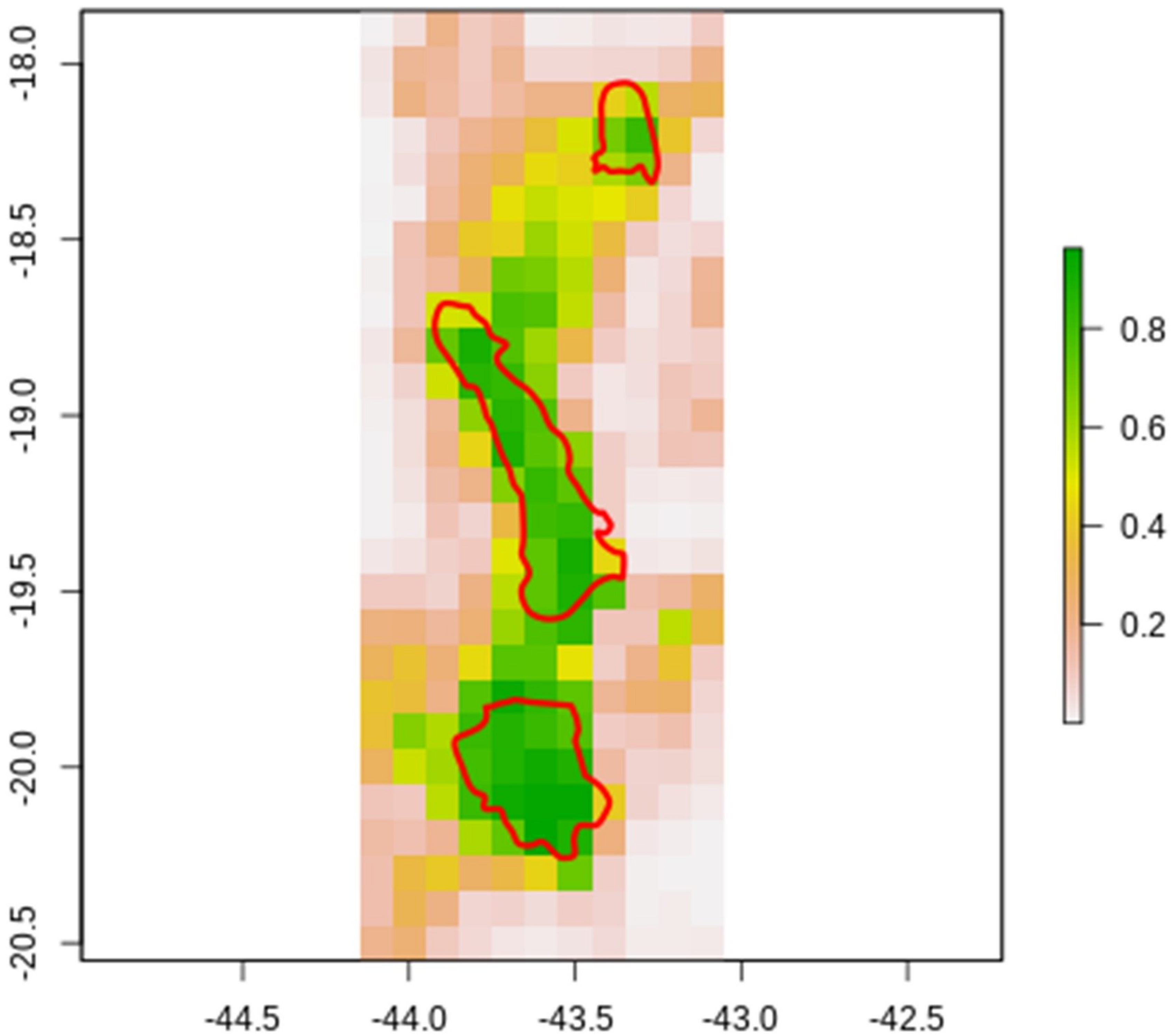

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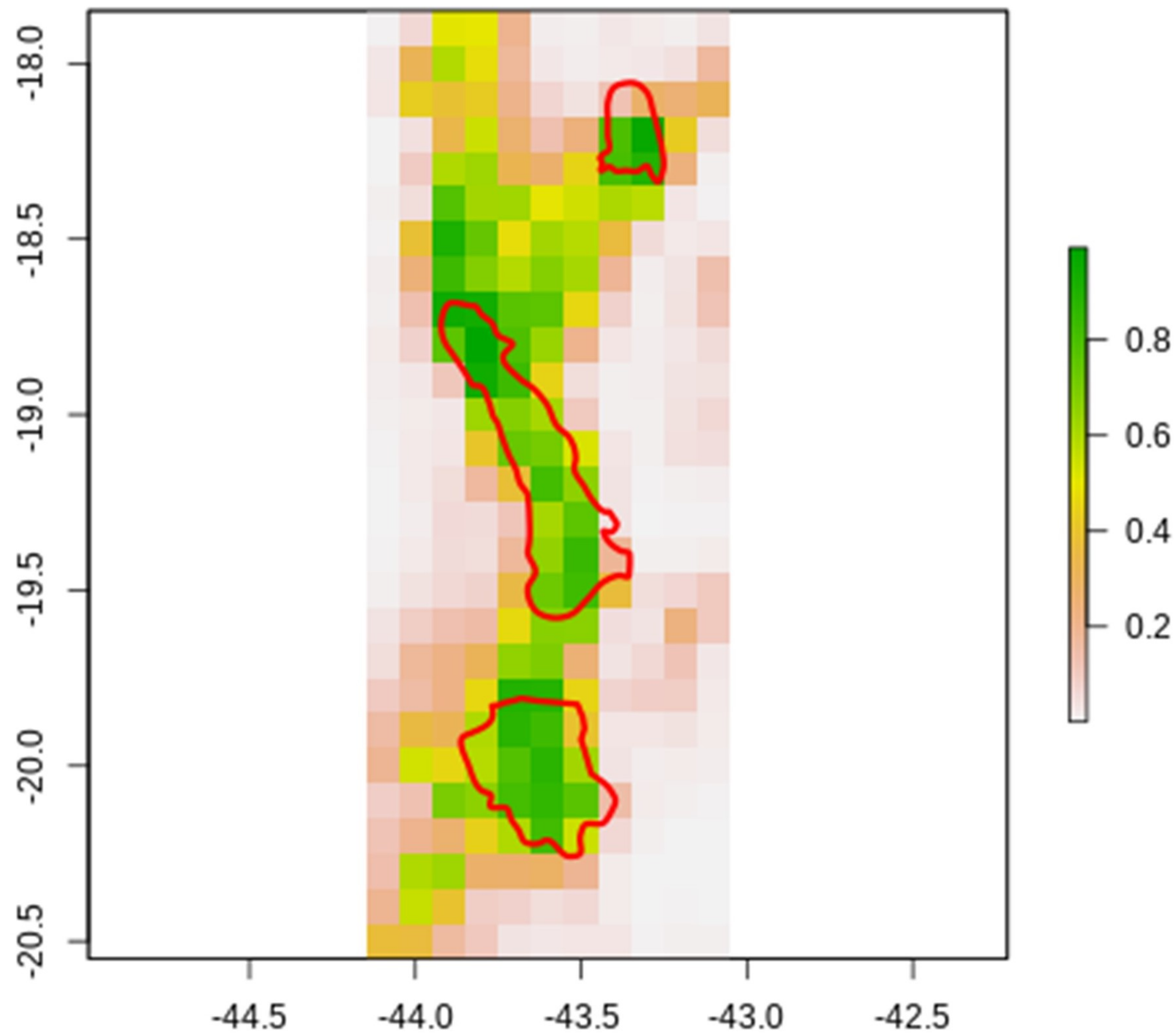
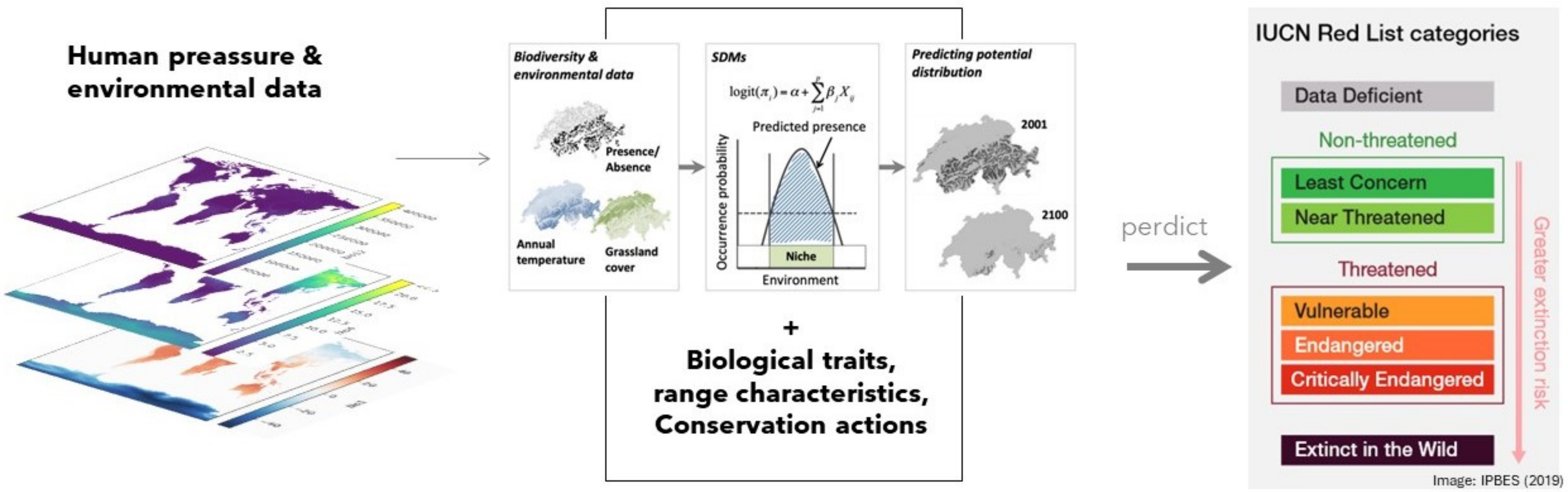


- Uncertainty in climate data
- Uncertainty in sampling
- Different sets of variables
- **RL prediction**: definition of target variable
- ~~Different models~~

6. OUTLOOK

REMINDER:



6. OUTLOOK

- **Next step: get uncertainty for species prediction, based on different climate data resources and sampling strategies**

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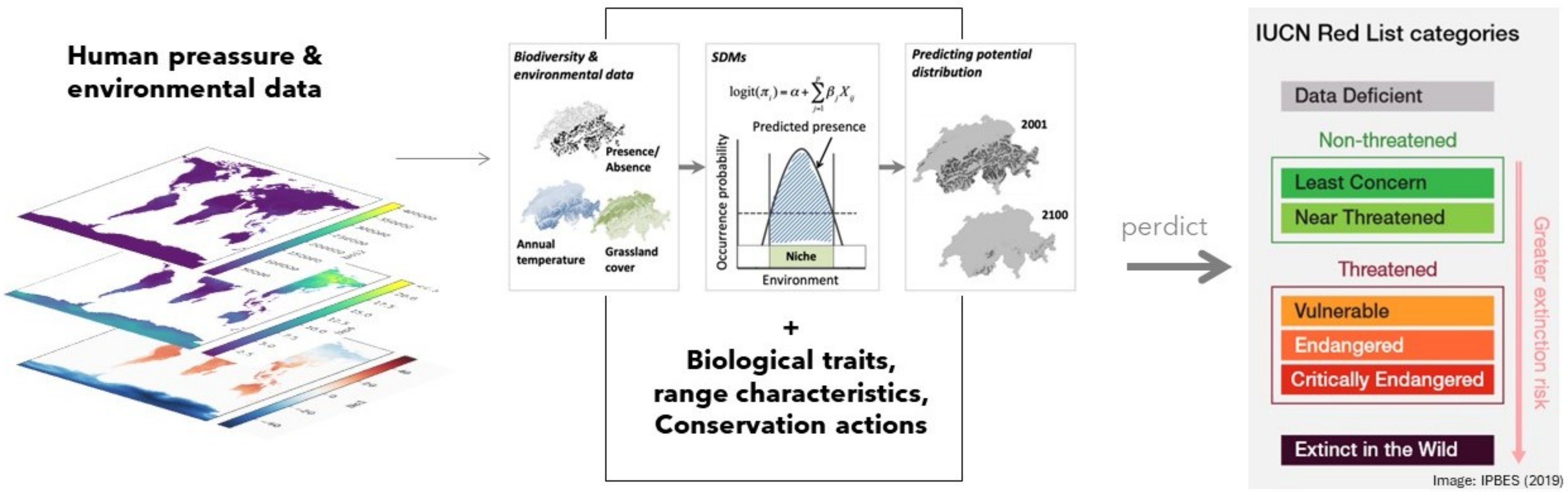

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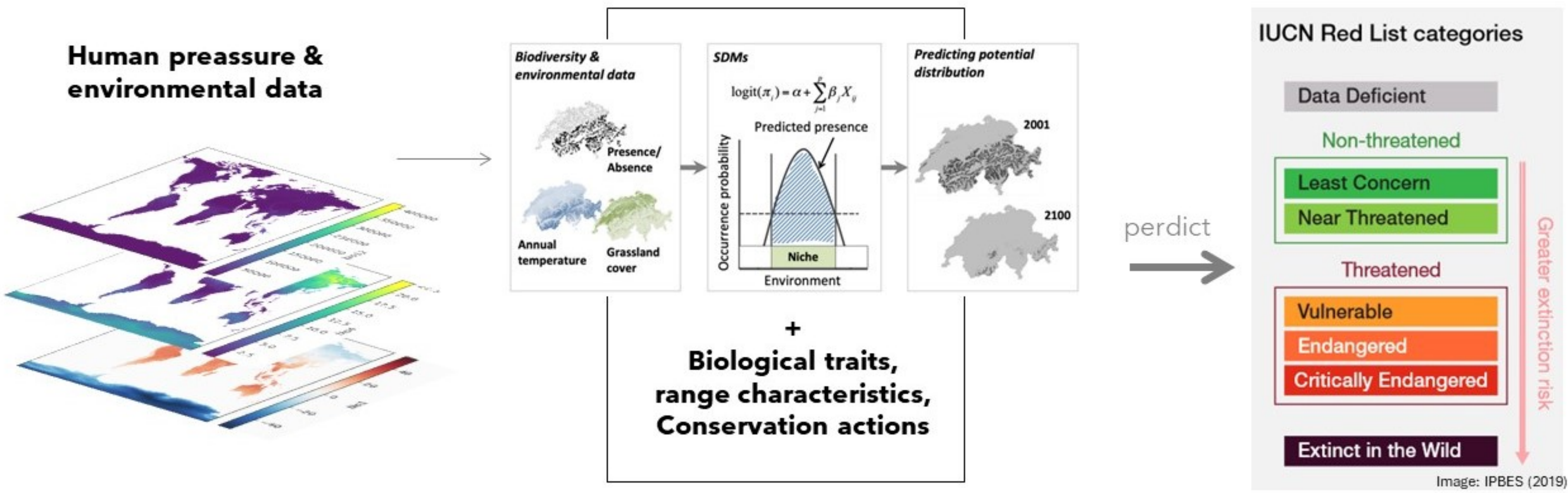

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- Compare models and select variables

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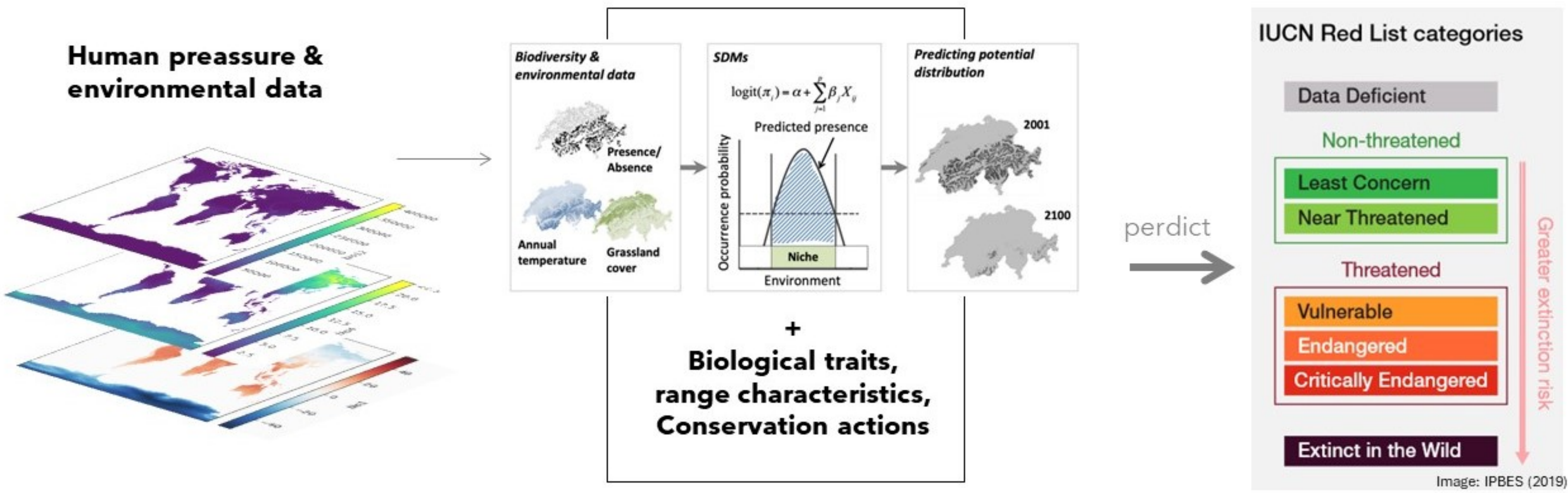

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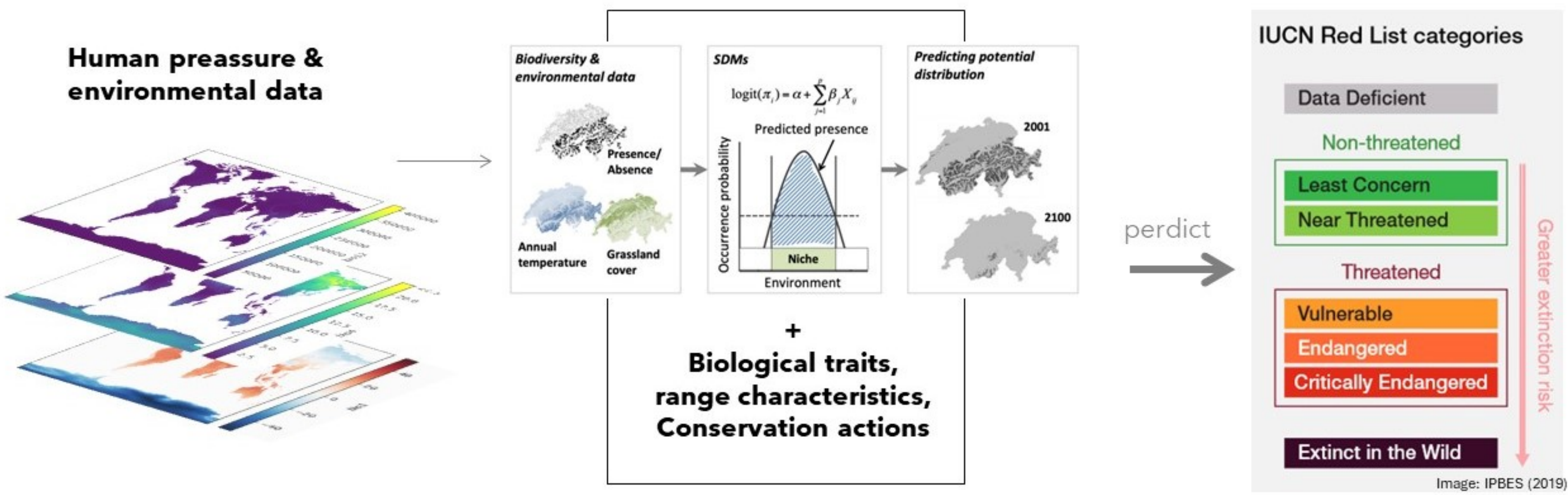
- Compare models and select variables
- Extend to other species groups

REMINDER:



7. LITERATURE

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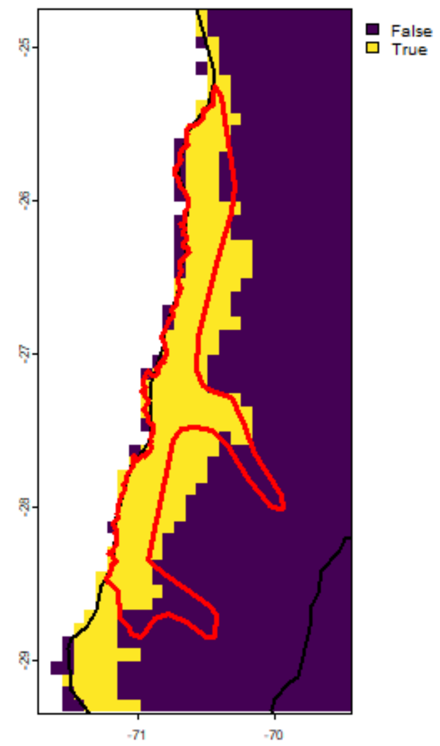
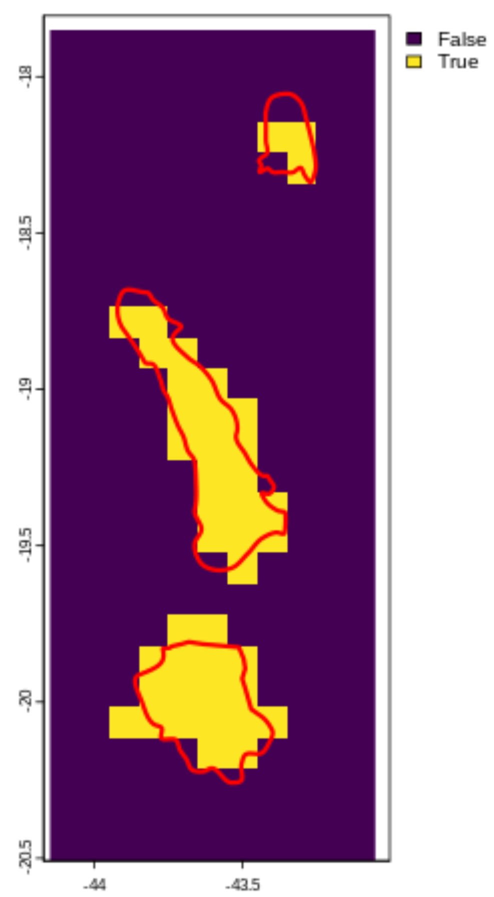
QUESTIONS, SUGGESTIONS, FEEDBACK

BACKUP SLIDES

PLOTS OF MY SDM PREDICTIONS

Bioclimatic variables from ERA5, 5min





RED LIST CRITERIA

A. Population size reduction. Population reduction (measured over the longer of 10 years or 3 generations) based on any of A1 to A4

	Critically Endangered	Endangered	Vulnerable
A1	≥ 90%	≥ 70%	≥ 50%
A2, A3 & A4	≥ 80%	≥ 50%	≥ 30%

A1 Population reduction observed, estimated, inferred, or suspected in the past where the causes of the reduction are clearly reversible AND understood AND have ceased.

A2 Population reduction observed, estimated, inferred, or suspected in the past where the causes of reduction may not have ceased OR may not be understood OR may not be reversible.

A3 Population reduction projected, inferred or suspected to be met in the future (up to a maximum of 100 years) *[(a) cannot be used for A3]*.

A4 An observed, estimated, inferred, projected or suspected population reduction where the time period must include both the past and the future (up to a max. of 100 years in future), and where the causes of reduction may not have ceased OR may not be understood OR may not be reversible.

based on any of the following:

- **(a)** direct observation *[except A3]*
- **(b)** an index of abundance appropriate to the taxon
- **(c)** a decline in area of occupancy (AOO), extent of occurrence (EOO) and/or habitat quality
- **(d)** actual or potential levels of exploitation
- **(e)** effects of introduced taxa, hybridization, pathogens, pollutants, competitors or parasites.

B. Geographic range in the form of either B1 (extent of occurrence) AND/OR B2 (area of occupancy)

	Critically Endangered	Endangered	Vulnerable
B1. Extent of occurrence (EOO)	< 100 km²	< 5,000 km²	< 20,000 km²
B2. Area of occupancy (AOO)	< 10 km²	< 500 km²	< 2,000 km²
AND at least 2 of the following 3 conditions:			
(a) Severely fragmented **OR** Number of locations	= 1	≤ 5	≤ 10

(b) Continuing decline observed, estimated, inferred or projected in any of: **(i)** extent of occurrence; **(ii)** area of occupancy; **(iii)** area, extent and/or quality of habitat; **(iv)** number of locations or subpopulations; **(v)** number of mature individuals

(c) Extreme fluctuations in any of: **(i)** extent of occurrence; **(ii)** area of occupancy; **(iii)** number of locations or subpopulations; **(iv)** number of mature individuals

C. Small population size and decline

	Critically Endangered	Endangered	Vulnerable
Number of mature individuals	< 250	< 2,500	< 10,000
AND at least one of C1 or C2			
C1. An observed, estimated or projected continuing decline of at least (up to a max. of 100 years in future):	25% in 3 years or 1 generation (whichever is longer)	20% in 5 years or 2 generations (whichever is longer)	10% in 10 years or 3 generations (whichever is longer)
C2. An observed, estimated, projected or inferred continuing decline AND at least 1 of the following 3 conditions:			
(a) **(i)** Number of mature individuals in each subpopulation	≤ 50	≤ 250	≤ 1,000
(ii) % of mature individuals in one subpopulation =	90–100%	95–100%	100%
(b) Extreme fluctuations in the number of mature individuals			

D. Very small or restricted population

	Critically Endangered	Endangered	Vulnerable
D. Number of mature individuals	< 50	< 250	**D1.** < 1,000
D2. *Only applies to the VU category* Restricted area of occupancy or number of locations with a plausible future threat that could drive the taxon to CR or EX in a very short time.	-	-	**D2.** typically: AOO < 20 km² or number of locations ≤ 5

E. Quantitative Analysis

	Critically Endangered	Endangered	Vulnerable
Indicating the probability of extinction in the wild to be:	≥ 50% in 10 years or 3 generations, whichever is longer (100 years max.)	≥ 20% in 20 years or 5 generations, whichever is longer (100 years max.)	≥ 10% in 100 years

DRIVERS AND MEASURES FOR BIODIVERSITY LOSS

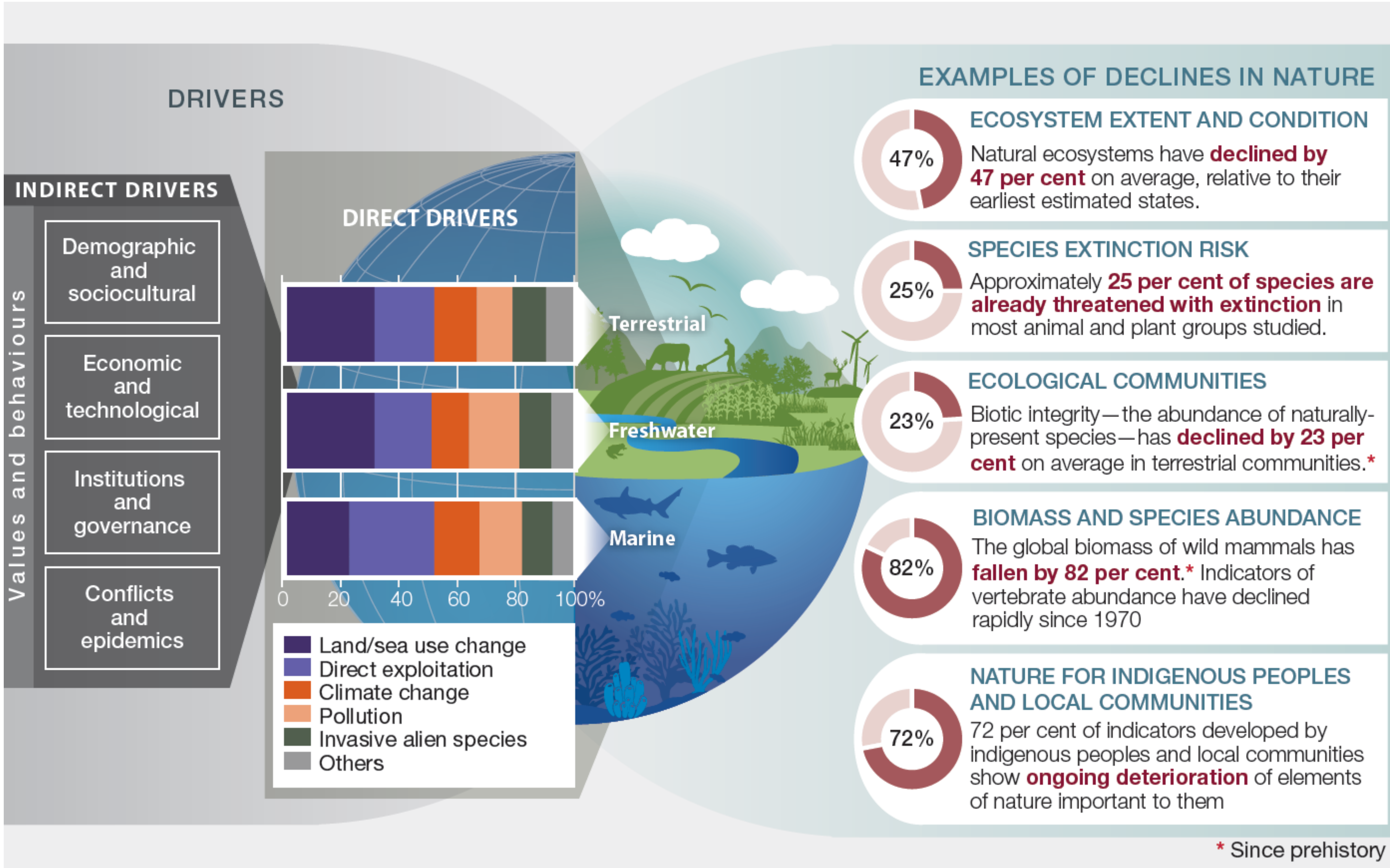


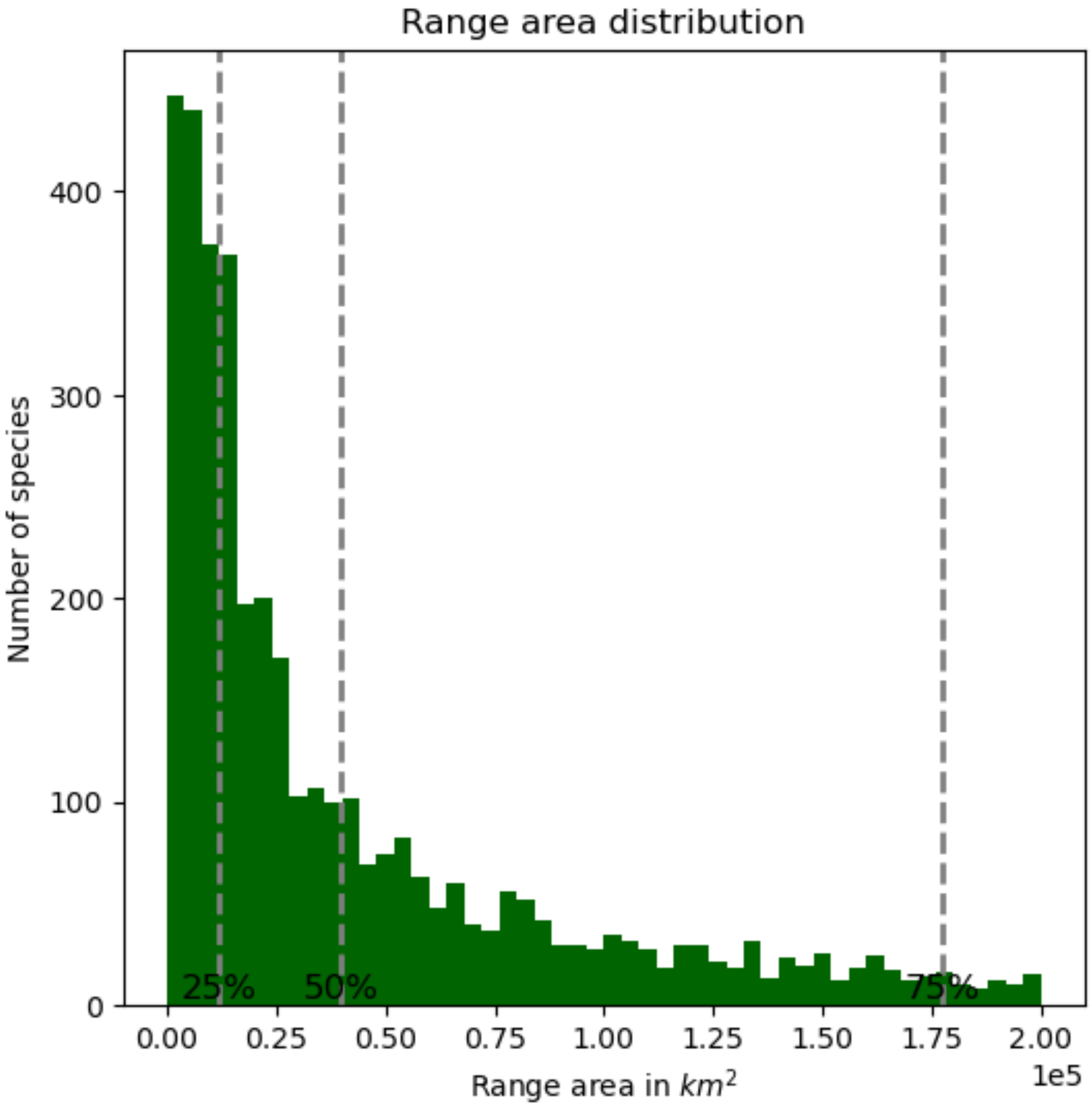
Figure from IPBES (2019) , Fig SPM.2

TRUE SKILL STATISTIC

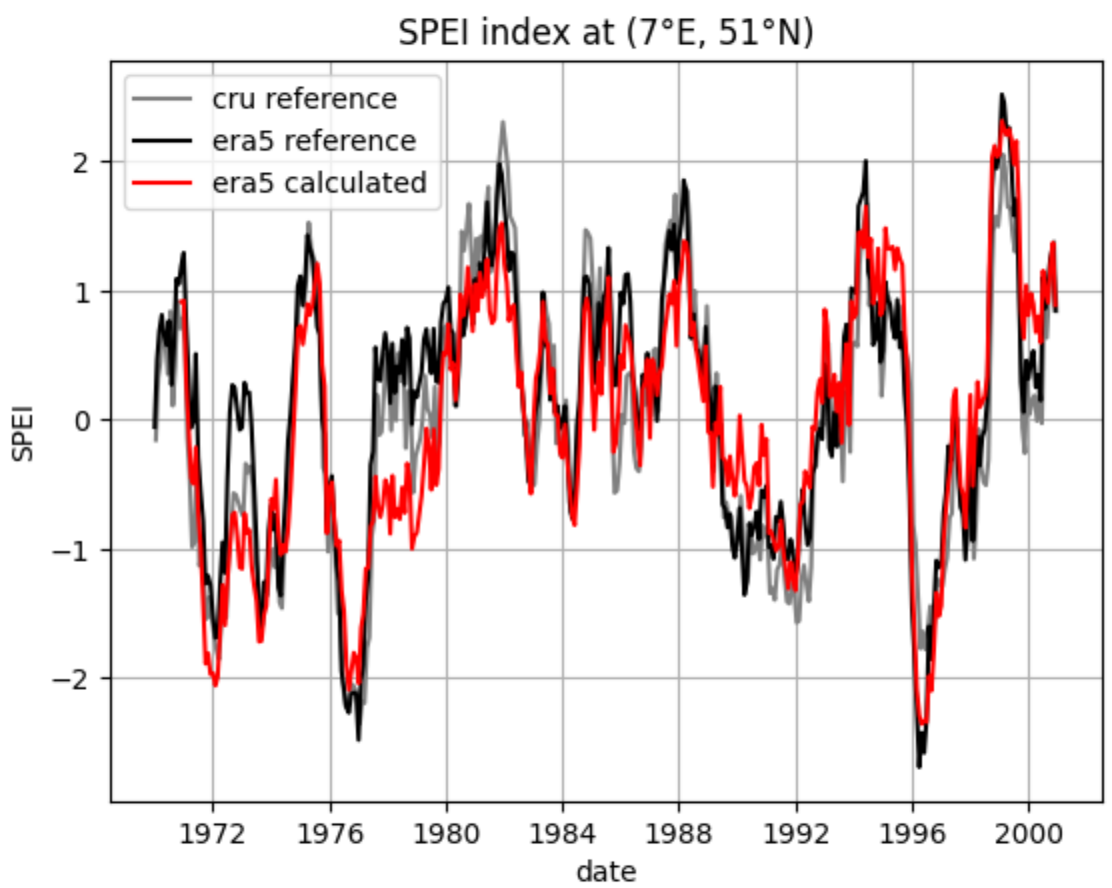
$$\text{TSS} = \underbrace{\frac{\text{true positive}}{\text{true positive}+\text{false negative}}}_{\text{sensitivity}} + \underbrace{\frac{\text{true negative}}{\text{true negative}+\text{false positive}}}_{\text{specificity}} - 1$$

- Between 0 and 1, intuitive
- corrects for class imbalance
- presumes threshold

GAA2 RANGE AREA DISTRIBUTION



SPEI


SPEI index at (7°E, 51°N)
cru reference
era5 reference
era5 calculated
SPEI
2
1
0
−1
−2
1972
1976
1980
1984
1988
1992
1996
2000
date