



BIODIVERSITY.AQ



# CALIBRATION:

All you should think about and check before running a model !

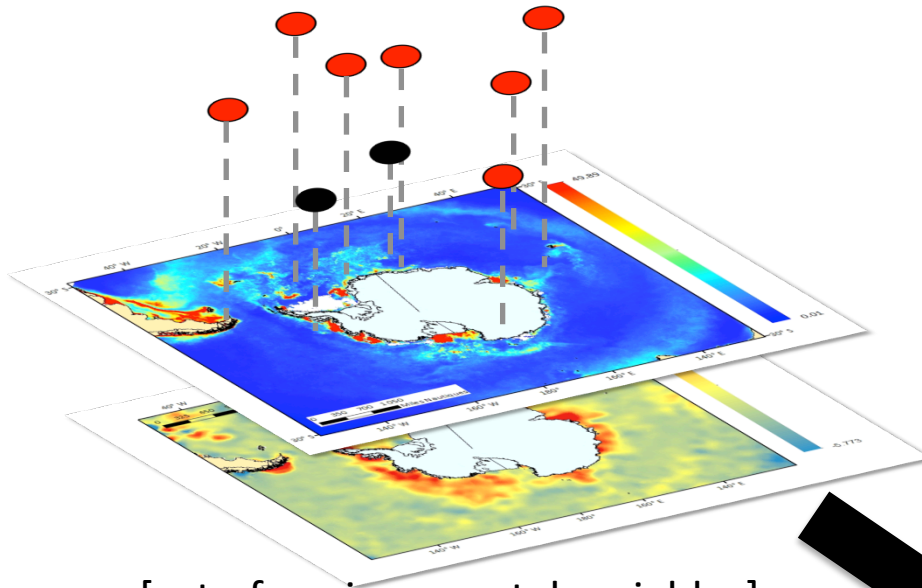


Tuesday 3rd, September  
Guillaumot Charlène  
charleneguillaumot21@gmail.com



# SPECIES DISTRIBUTION MODELS principle

[presence + absence records]

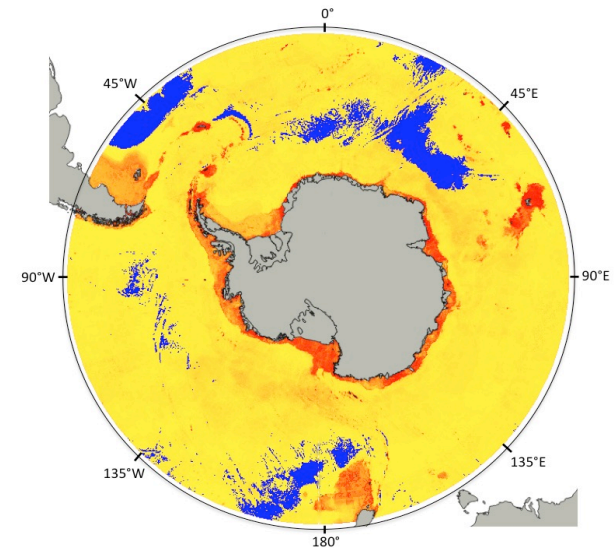


[set of environmental variables]

Presence / absence?	Layer 1 e.g. Depth	Layer 2 e.g. T°	Layer 3 e.g. Salinity
1	-351	0.2	32.4
1	-150	-1.4	32.1
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1	-3042	0.3	31.9
...	...	...	...

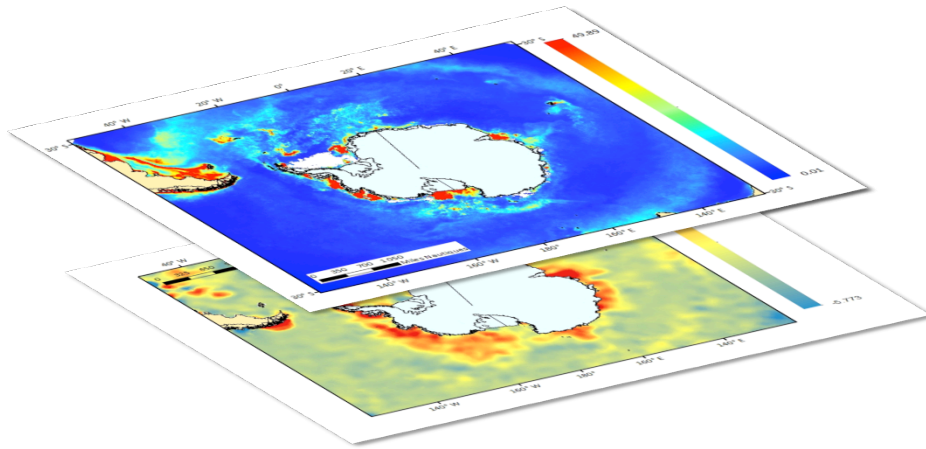
**SDM**

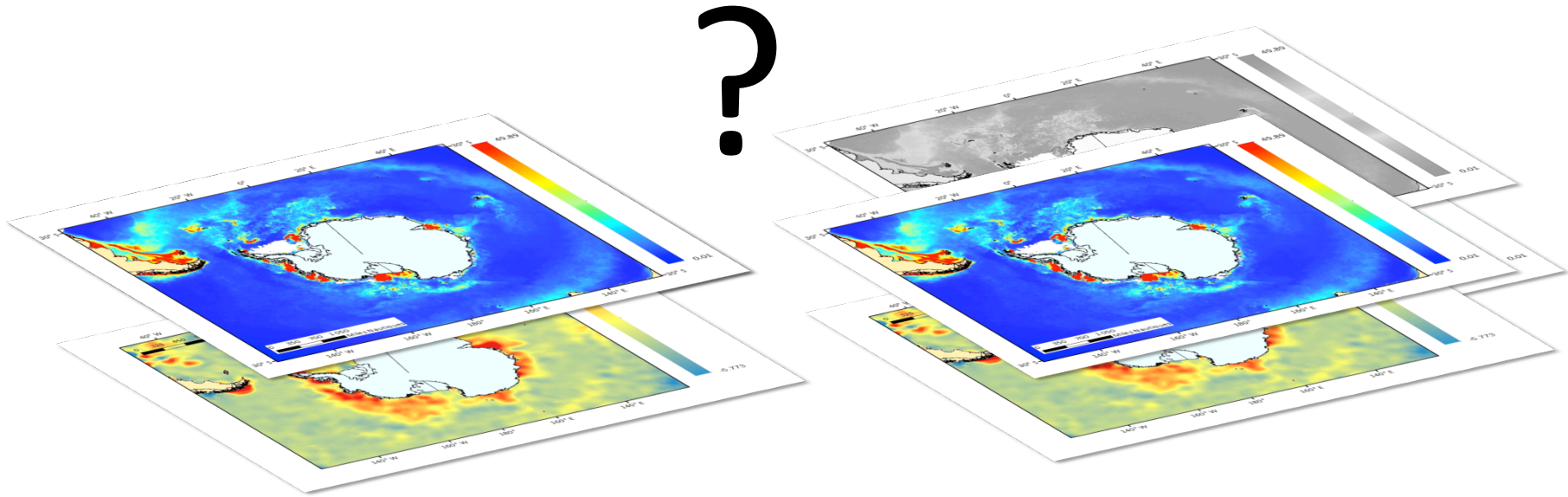
[Predicted distribution]



0 1

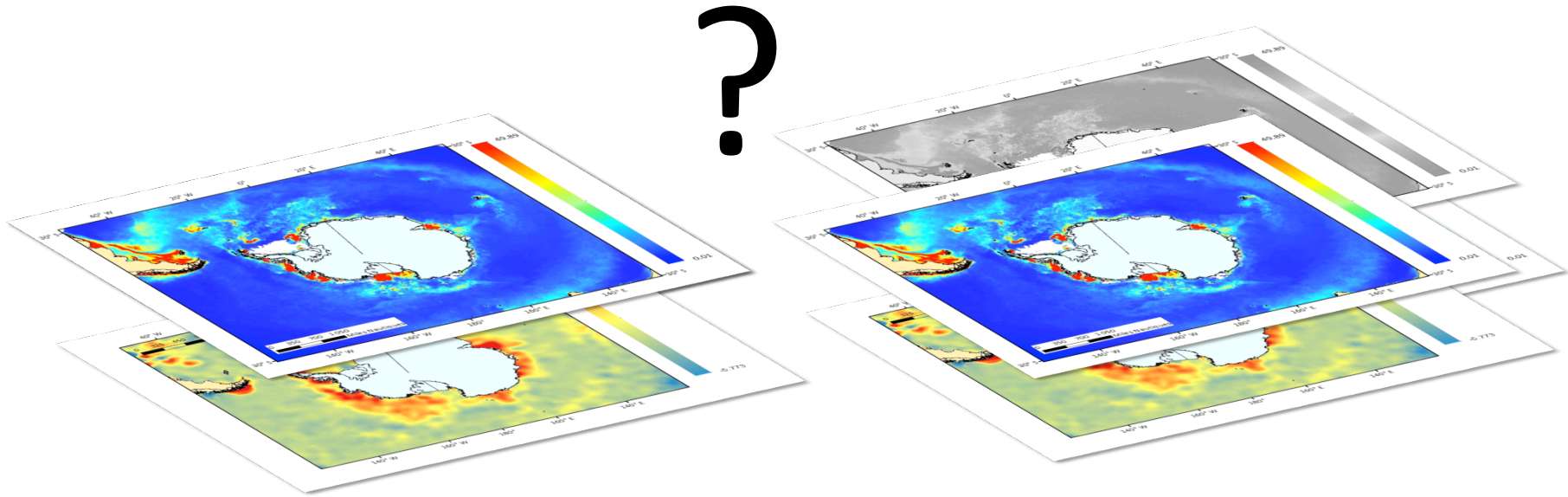
# CALIBRATION: Environmental variables





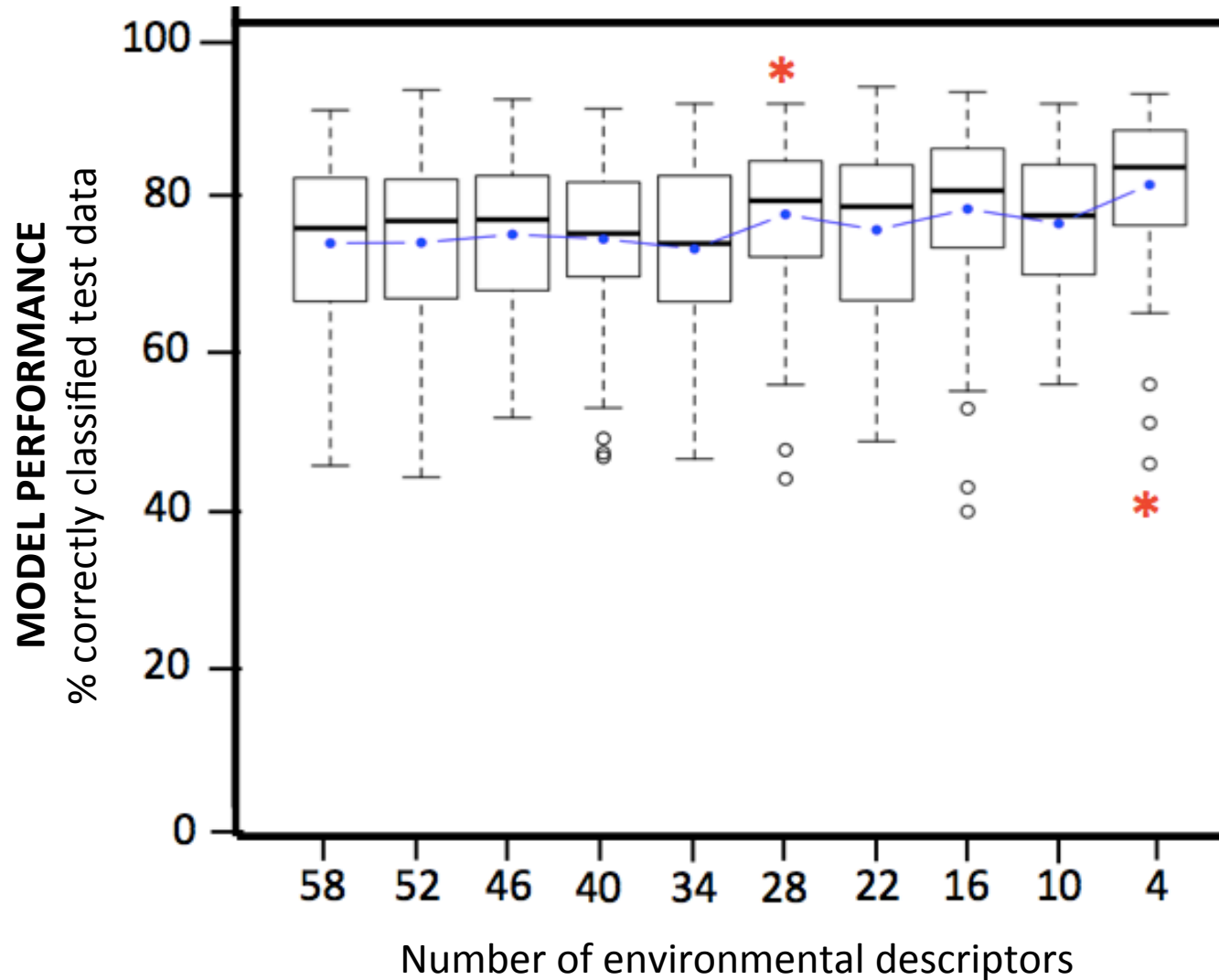
- Number of environmental variables?

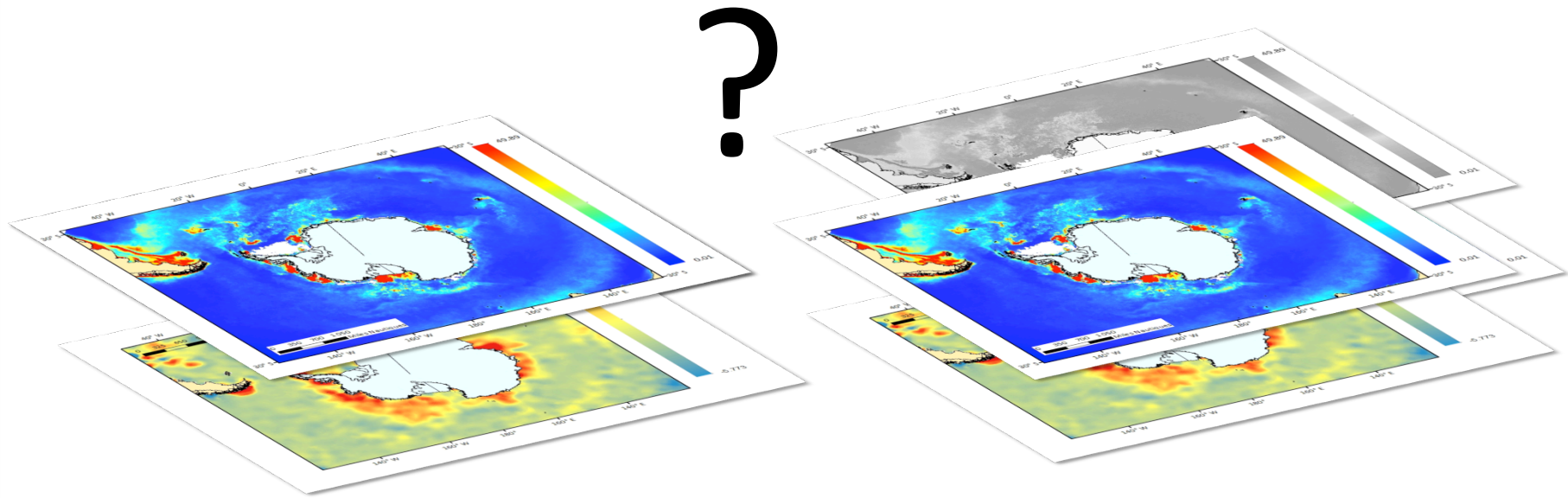




- Number of environmental variables?
  - ➔ Ecological relevance vs. parcimony
  - ➔ New algorithms can deal with redondant/useless information

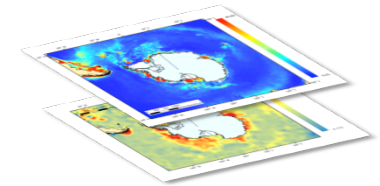
BRT



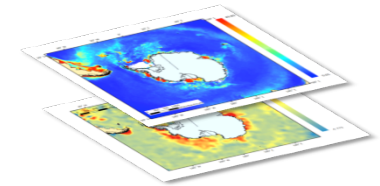


- Number of environmental variables?
  - ➔ Ecological relevance vs. parcimony
  - ➔ New algorithms can deal with redondant/useless information
- Be careful with average information
  - ➔ (relevance of average environment ? vs. amplitude/min/max?)

## CORRELATION BETWEEN ENVIR. VARIABLES

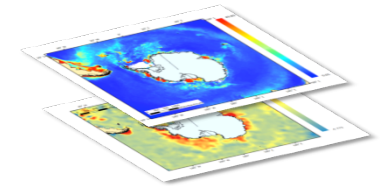


## CORRELATION BETWEEN ENVIR. VARIABLES



-> situation where at least two variables are related in a statistical model

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-> situation where at least two variables are related in a statistical model



- Can bias modelling outputs
- Can inflate errors
- Generally removed before generating the models

## STATISTICS TO DEAL WITH COLLINEARITY

- Spearman correlation/ correlation matrix
- Variance Inflation Factor (VIF) (threshold : 10 or 5 according to studies)

$$VIF = \frac{1}{1 - R^2}$$

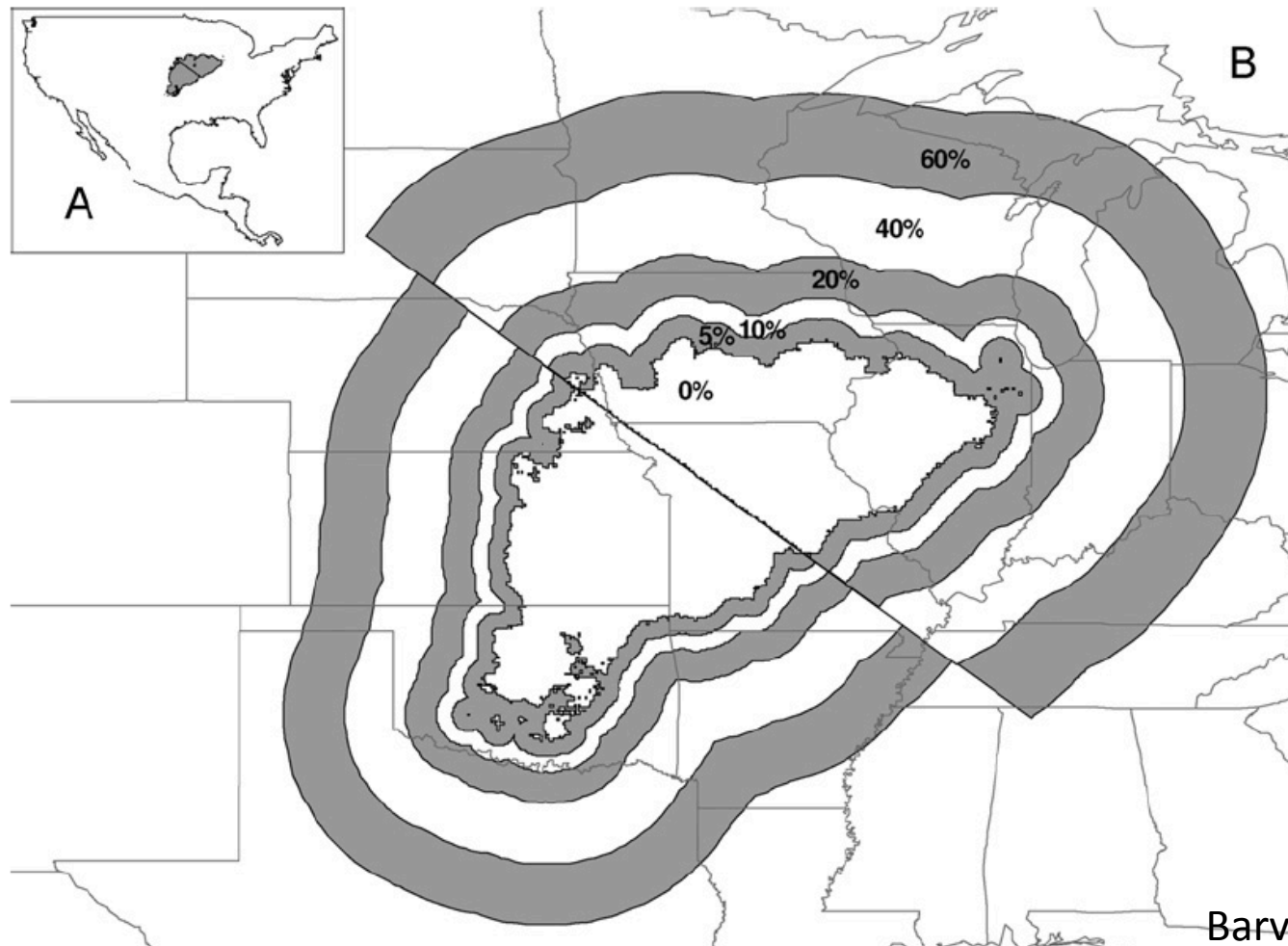
(more details in <https://www.statisticshowto.datasciencecentral.com/variance-inflation-factor/>)

- Automatic removal by most machine learning approaches



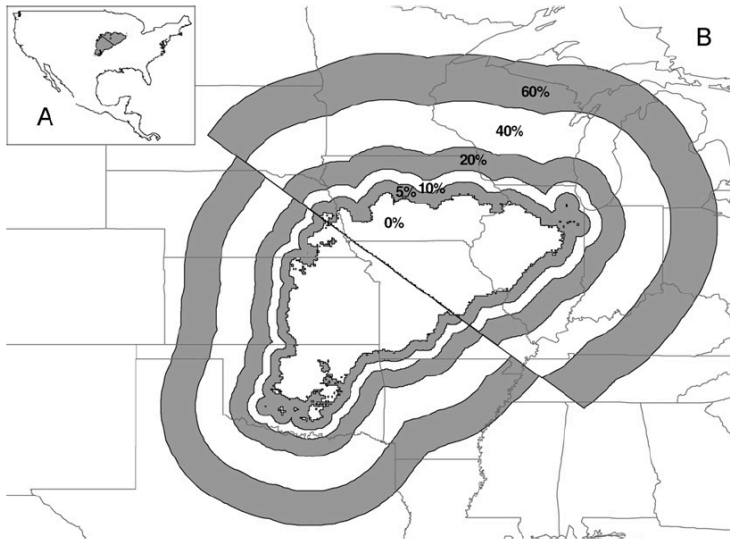
## **INFLUENCE OF SPATIAL RESOLUTION AND SCALE**

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Barve et al. 2011

## INFLUENCE OF SPATIAL RESOLUTION AND SCALE



**Narrower niches  
-> better predictive performances**

Barve et al. 2011

## INFLUENCE OF MISSING DATA



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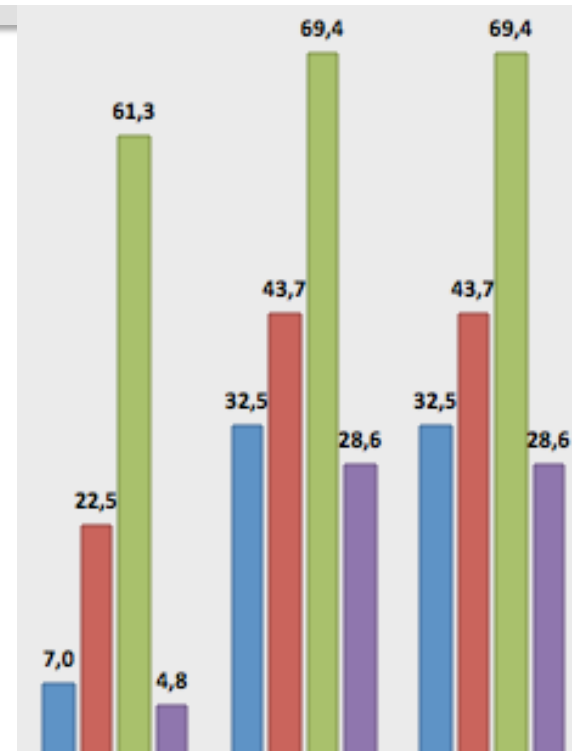
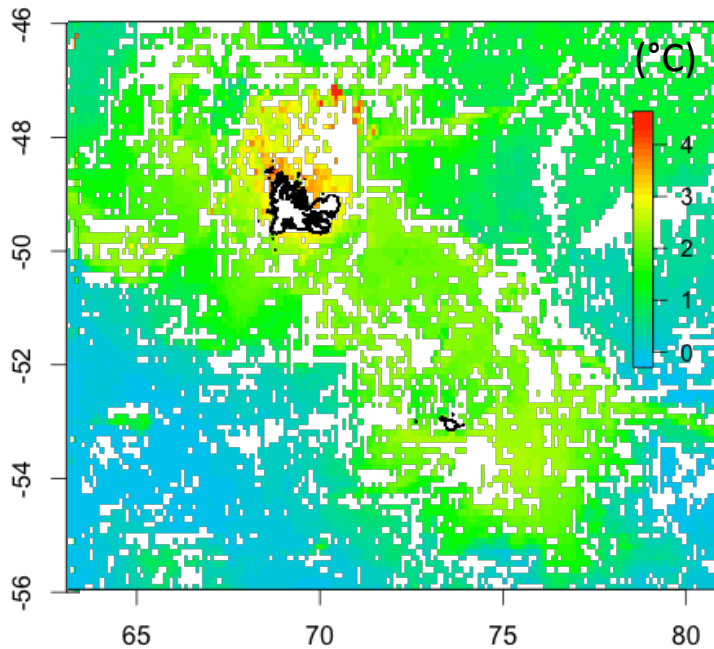


- Partial coverage of the information -> interpolation or not / missing values

Presence data falling on missing values

■ Ctenocidaris ■ Sterechinus ■ Abatus ■ Brisaster

Seafloor T° on the Kerguelen Plateau



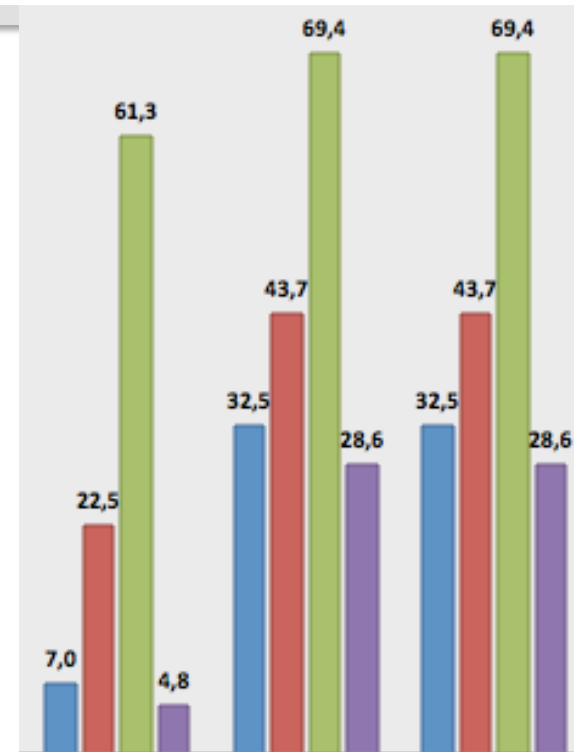
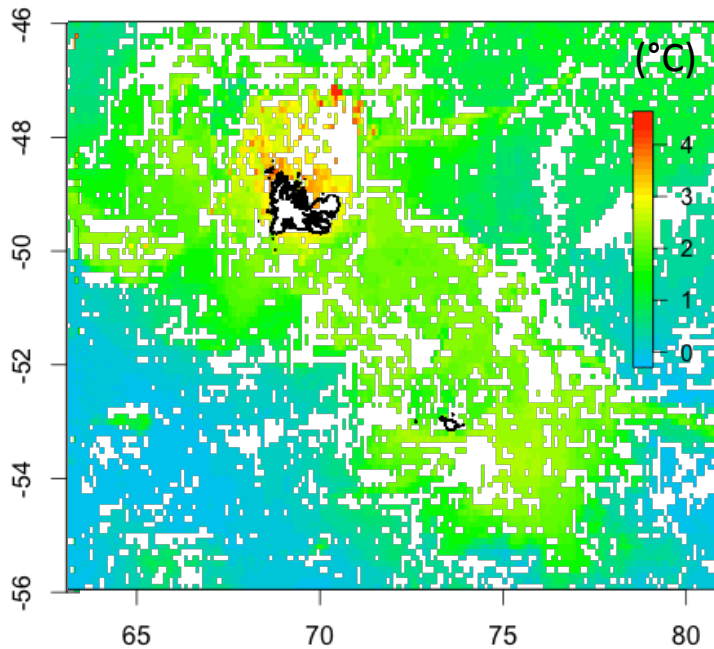
## INFLUENCE OF MISSING DATA

- Partial coverage of the information -> interpolation or not / missing values
- Full night in winter -> no satellite data

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## INFLUENCE OF MISSING DATA



- Partial coverage of the information -> interpolation or not / missing values
- Full night in winter -> no satellite data
- **Some algorithms cannot handle missing data !**
  - ➔ See tomorrow's course
  - ➔ Need to interpolate the data
  - ➔ Be careful with the interpretation of your results

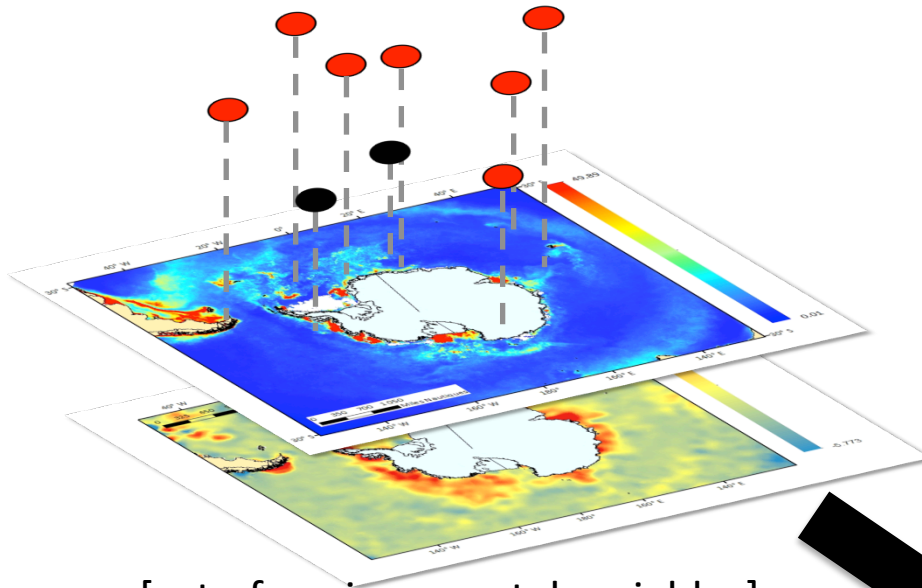


Questions on this  
part ???



# SPECIES DISTRIBUTION MODELS principle

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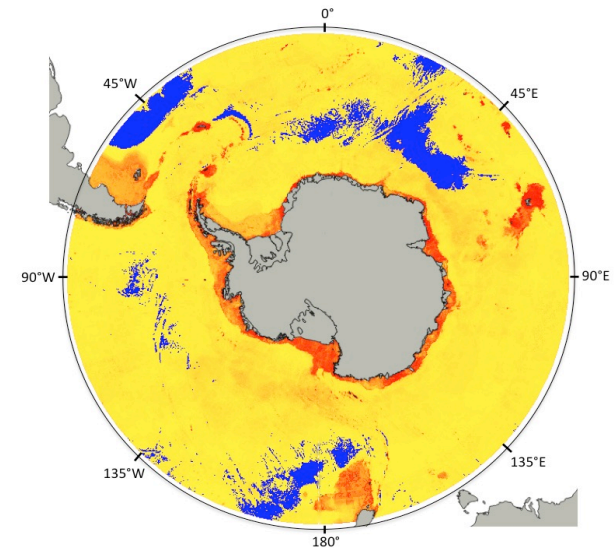


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**SDM**

[Predicted distribution]







SDM can be run with

- Abundance data (some algorithms)
- Presence- absence data
- Presence-only data

RK: Occurrence and environmental variables selection is the most difficult task for running SDMs !



Generate absence data



## Generate absence data

- Experts dires
- Absences surveys (trawls)

In broad-scale areas

- > difficult to rely on absence records
- > above all if historical compilation of several datasets



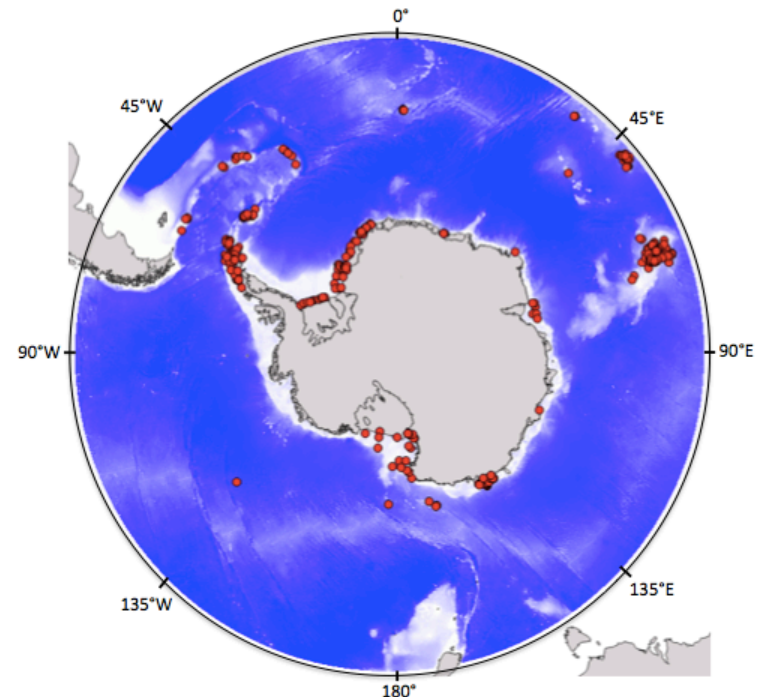
In the case of presence-only data, it is necessary to define the environment around which they are located

➔ Sampling of background data in the area to calibrate the model



In broad scale areas, difficult to rely on absence data

Presence-only/background SDMs are less reliable and powerful than presence-absence models (Brotons et al. 2004, Wisz & Guisan 2009)

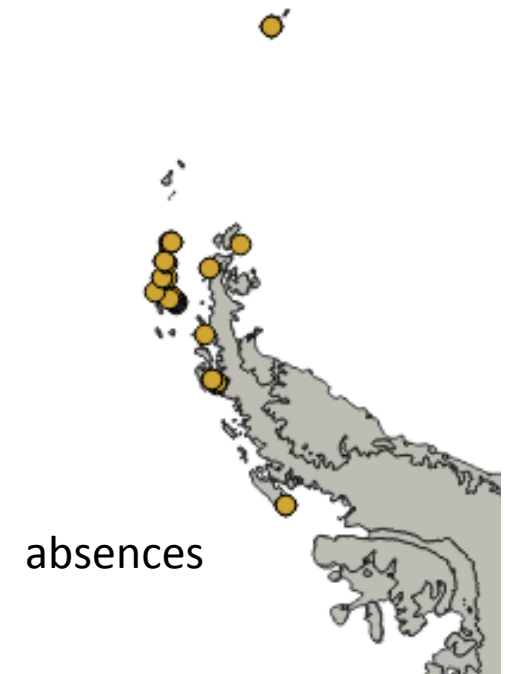


Occurrences of a sea star species in the SO

Presence records *Halicarcinus platanus*

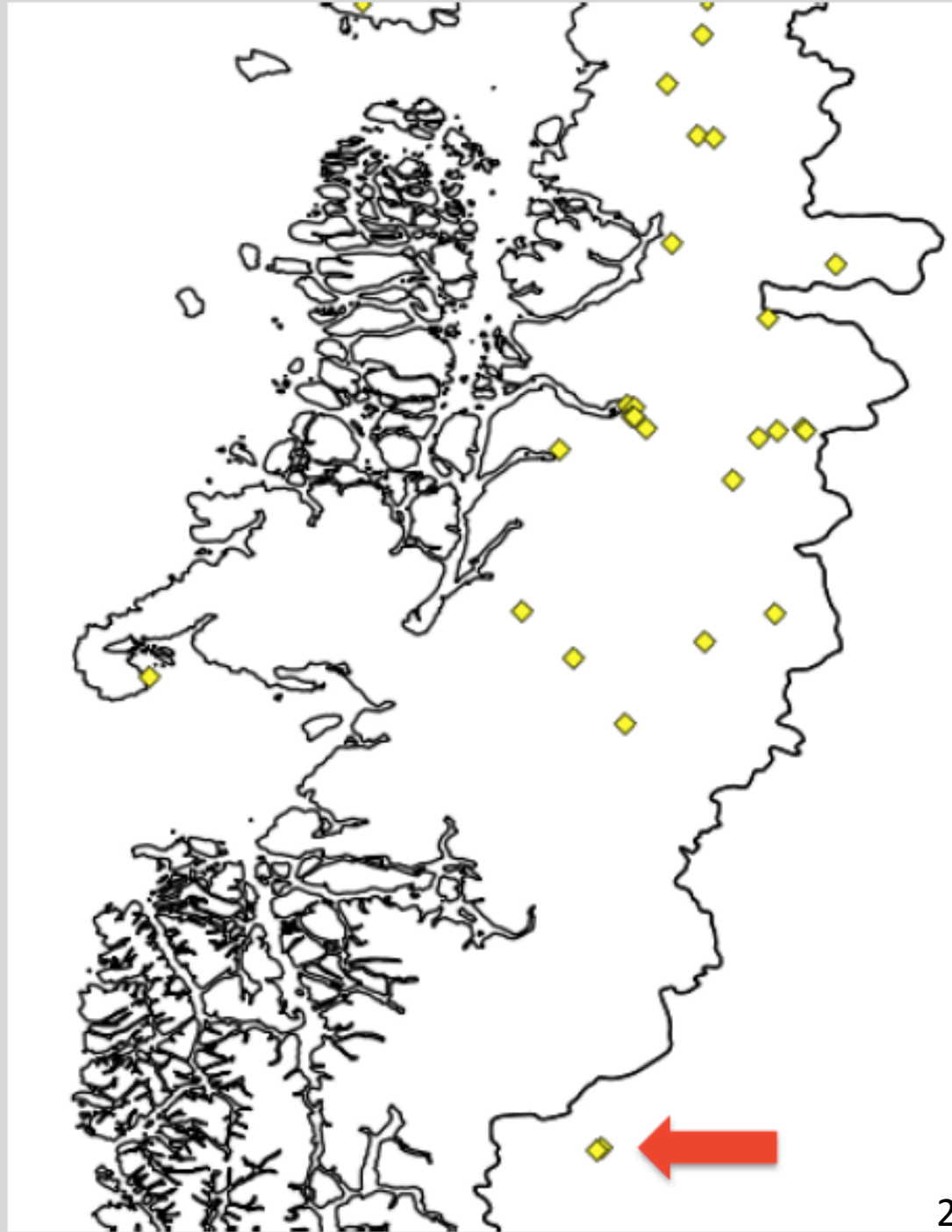
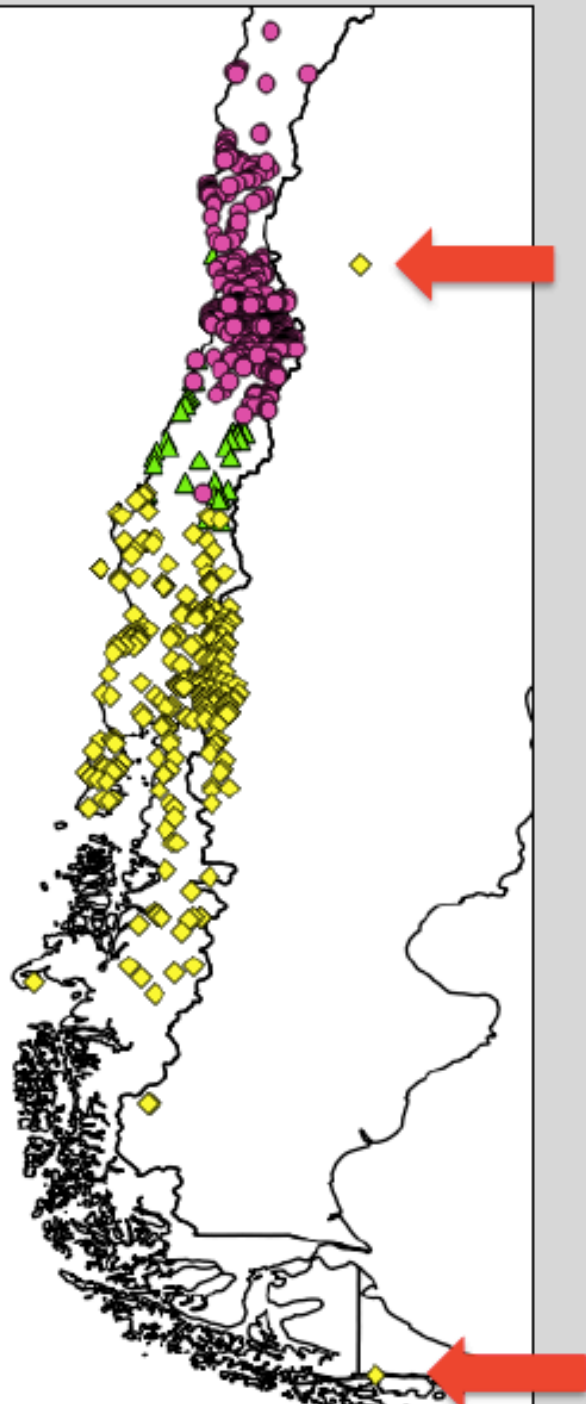


Presence records *Halicarcinus platanus*



### CRUCIAL TO EXPLORE YOUR DATASET

- Plot it, study each occurrence -> reliable or not ?
  - Georeferencing errors ?
- ➔ Essential because it is responsible for strong bias in your SDM (you wrongly calibrate the initial conditions of your model, which conditions your species tolerates...)



### **PRACTICE !**

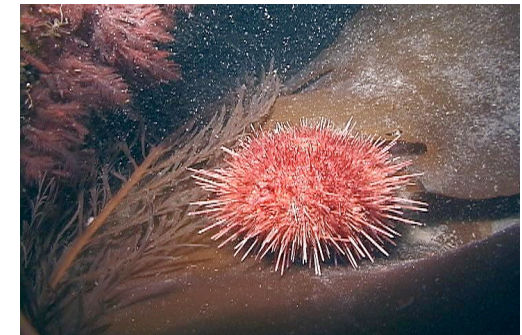
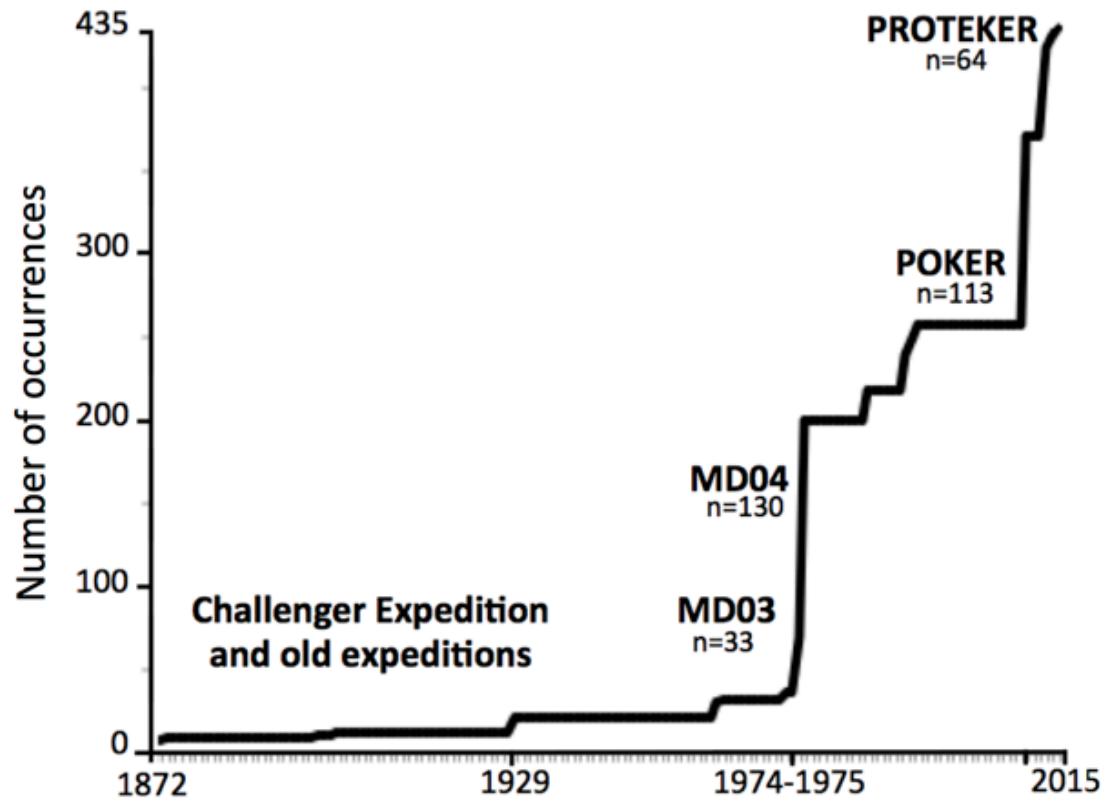
- Plot the occurrence records on the bathymetry layer
- In the provided example, do you have presence-absence data or presence-only data ? Where is it defined in the code?

## **SPATIAL AGGREGATION IN OCCURRENCE DATASETS**



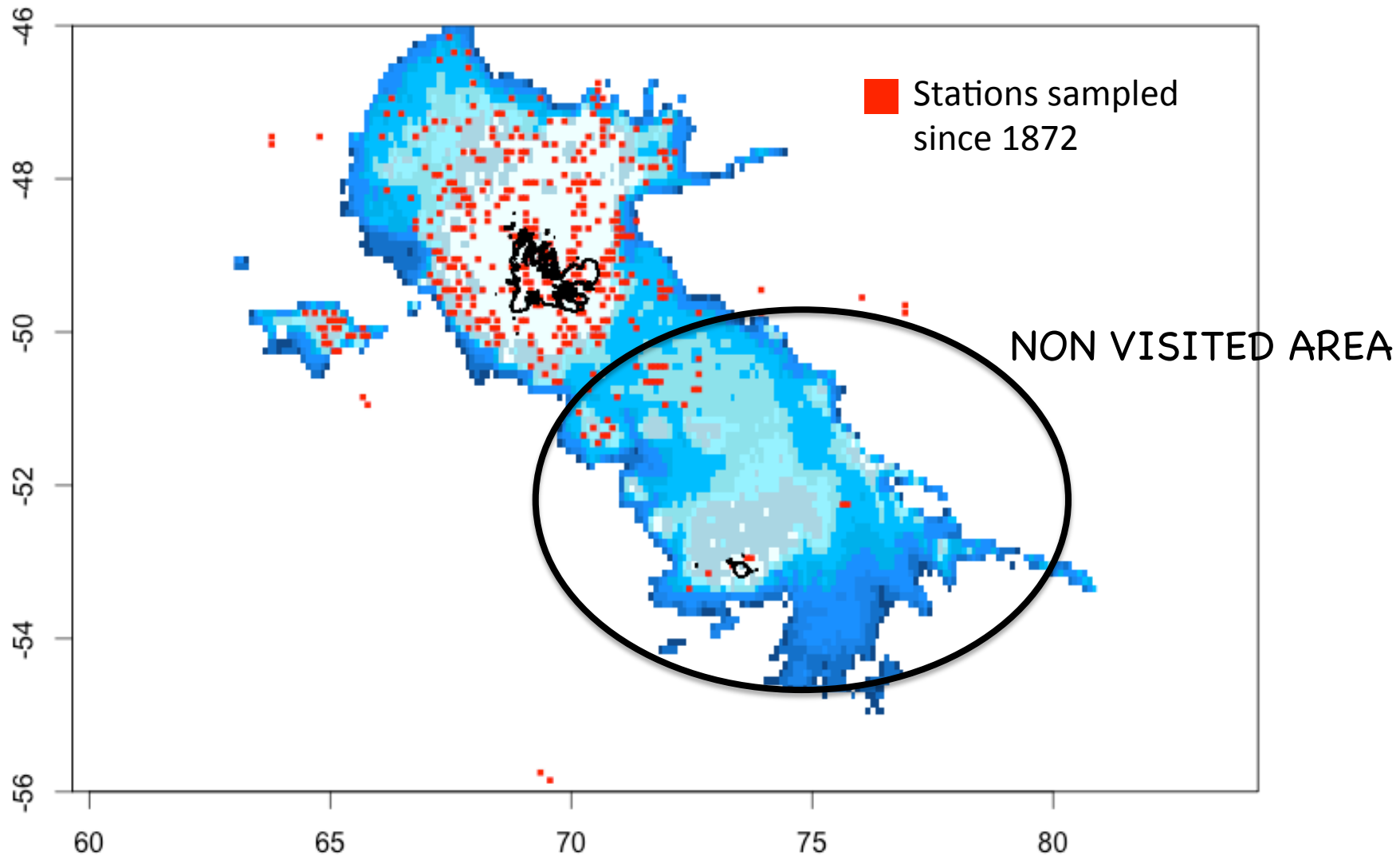
## SPATIAL AGGREGATION IN OCCURRENCE DATASETS

Historical collection  
Compilation of datasets



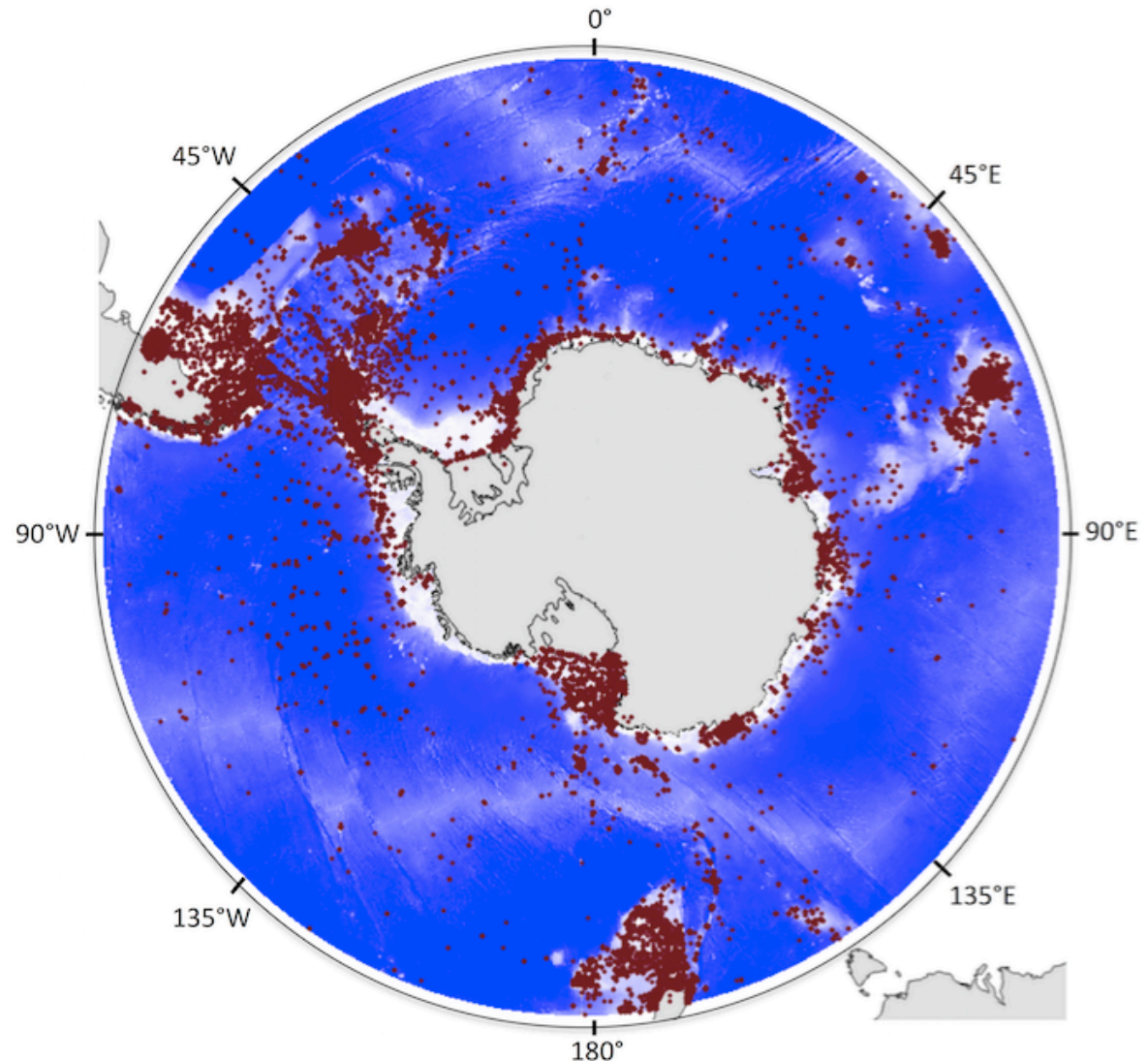
Sea urchins in Kerguelen  
(Guillaumot et al. 2018)

## SPATIAL AGGREGATION IN OCCURRENCE DATASETS

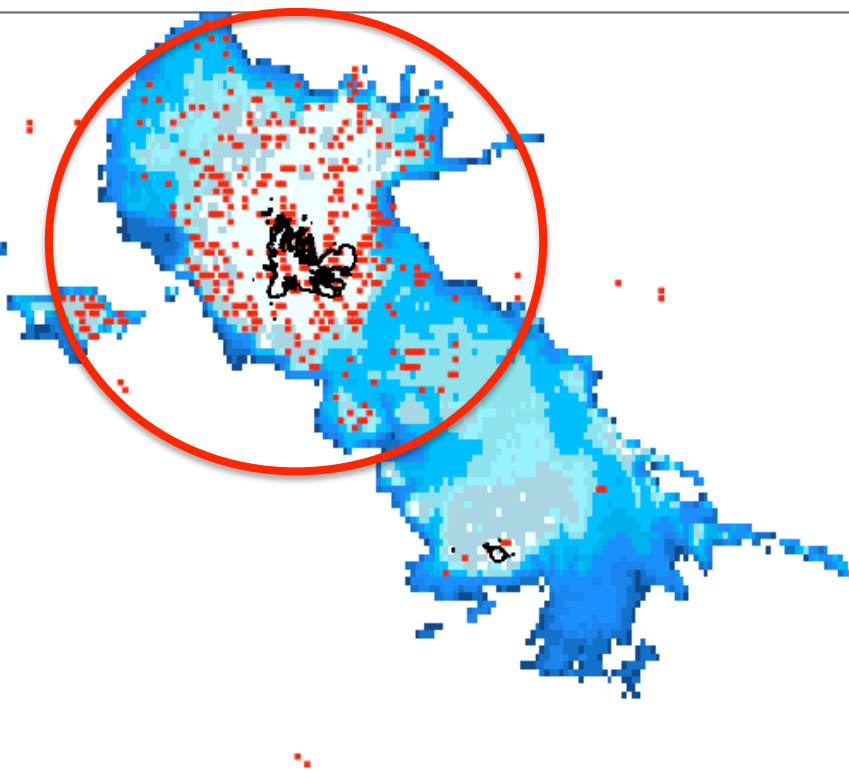


## SPATIAL AGGREGATION IN OCCURRENCE DATASETS

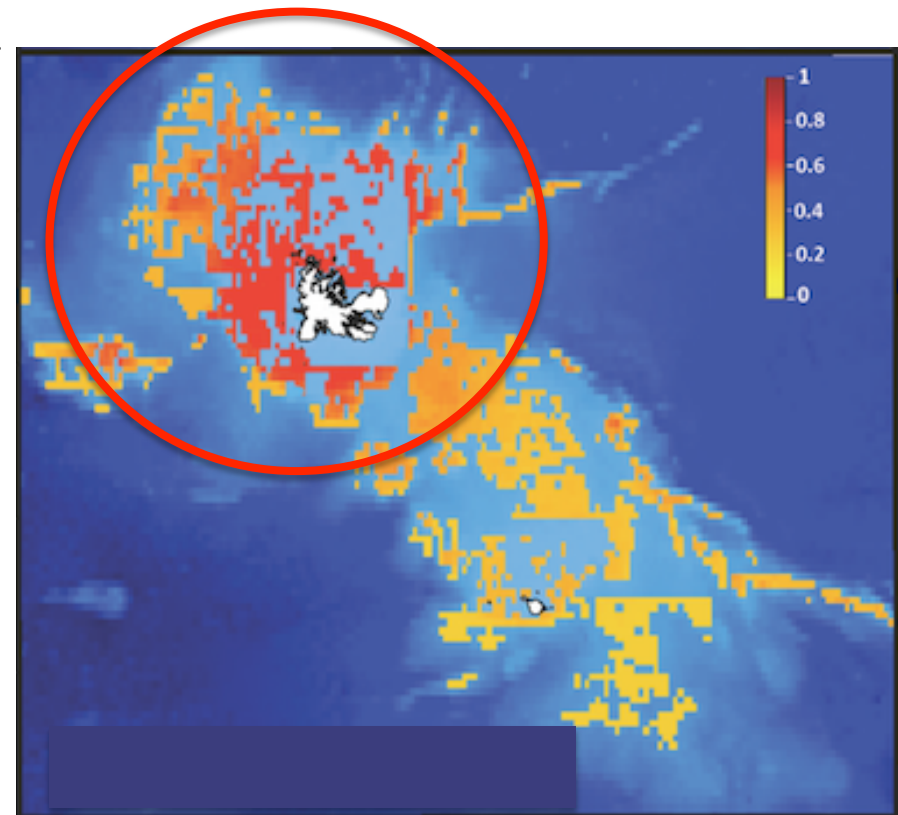
All visited pixels for  
benthic sampling



## SPATIAL AGGREGATION IN OCCURRENCE DATASETS



Aggregated occurrence data



SDM predictions

# SPATIAL AGGREGATION IN OCCURRENCE DATASETS

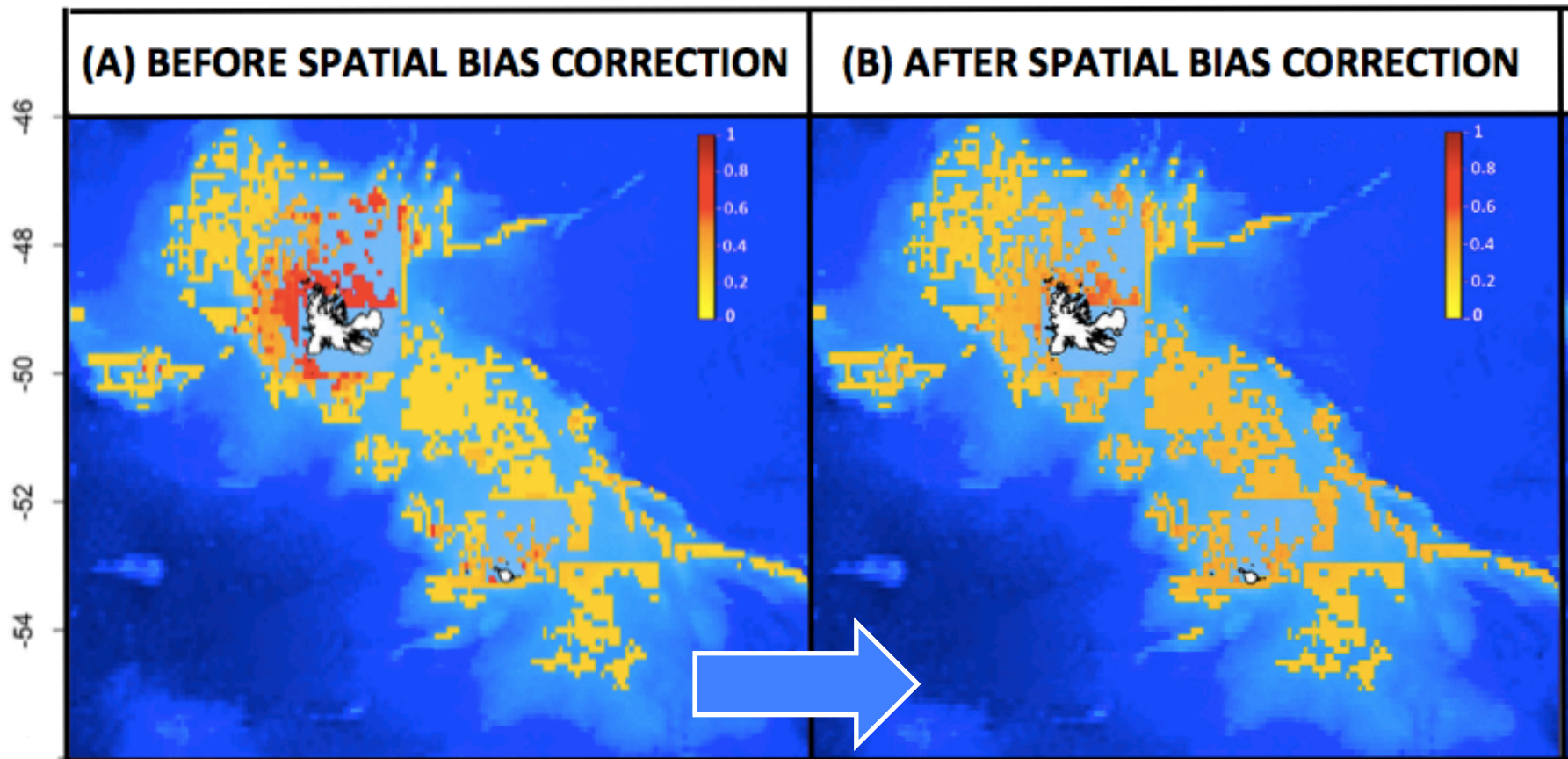


## SPATIAL AGGREGATION CAN BE MEASURED WITH

- Moran I index
- Variogram

-> both study the relationship between the value (predictions, variance in the result and the distance between points/pixels)

## SPATIAL AGGREGATION IN OCCURRENCE DATASETS



**APPLY CORRECTIONS !**

Guillaumot et al. (2018)

## CORRECTION FOR SPATIAL BIAS

- (1) Filter and sample just one occurrence per pixel  
(‘pseudo-replication’, Boria et al. 2014)

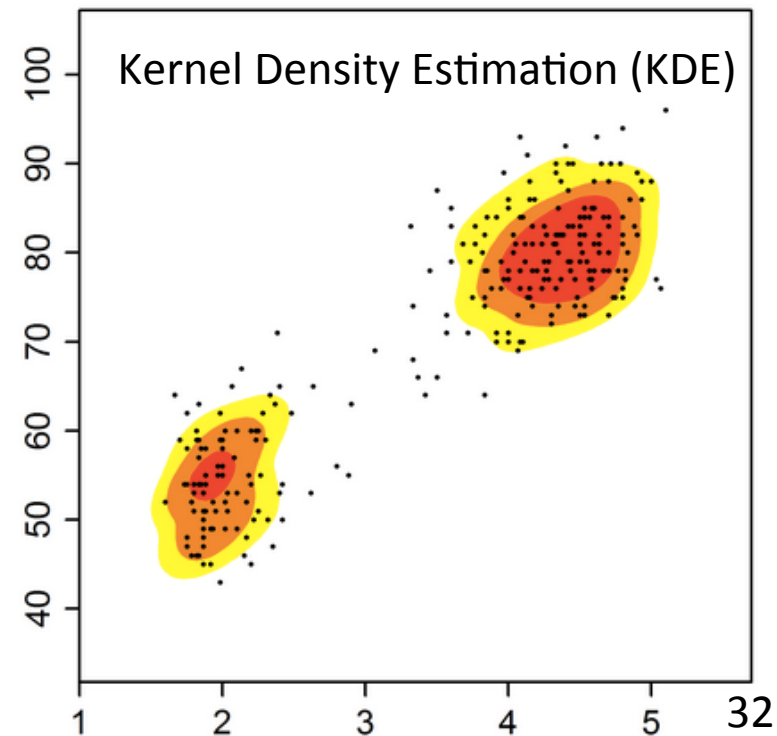
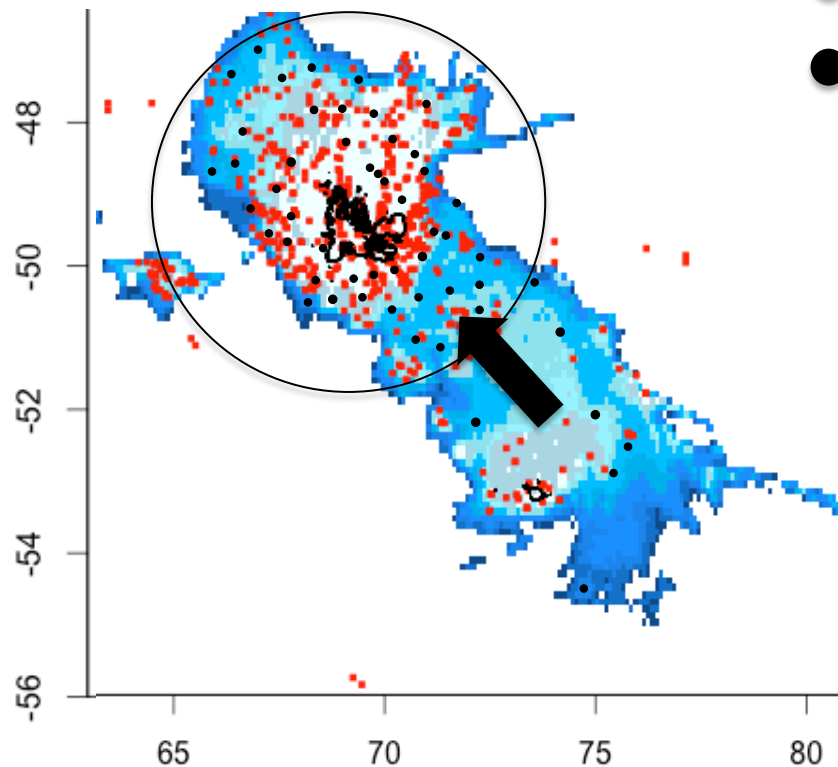


## CORRECTION FOR SPATIAL BIAS

(2) Target-background approach: sample background data following the spatial pattern (Phillips et al. 2009)

● Presence-only records

● Background records





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(2) Target-background approach: sample background data following the spatial pattern (Phillips et al. 2009)

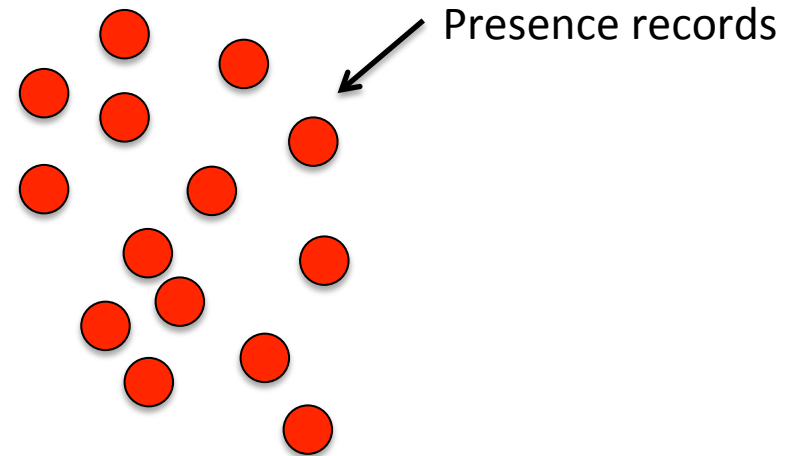
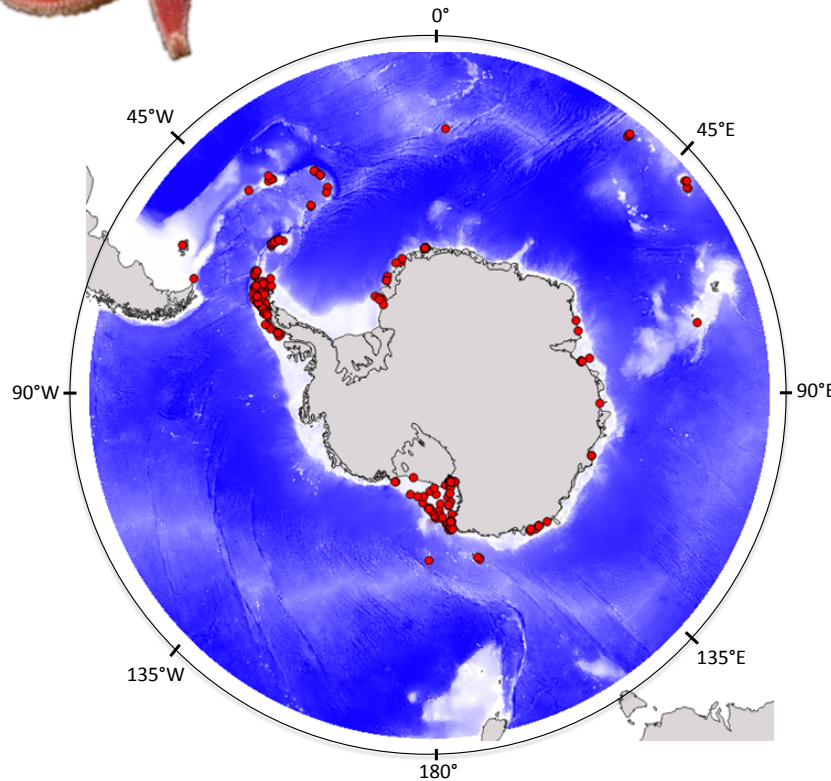
You can also :

- Generate disks around the presences and sample the background data inside these disks
- Sample background data in areas where an associated species is present

More options in Phillips et al. (2009) and in the biomod2 R package

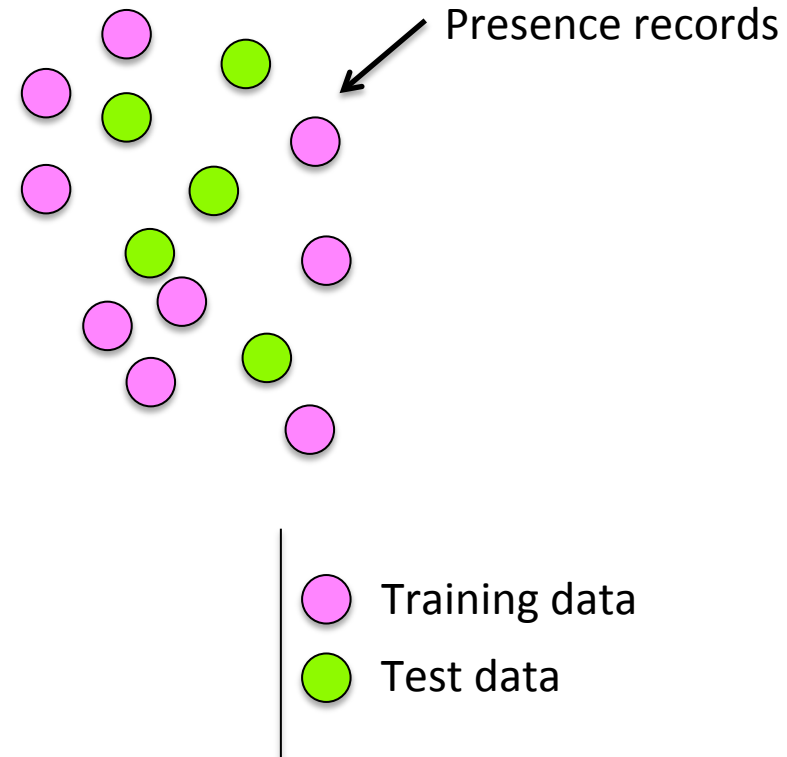
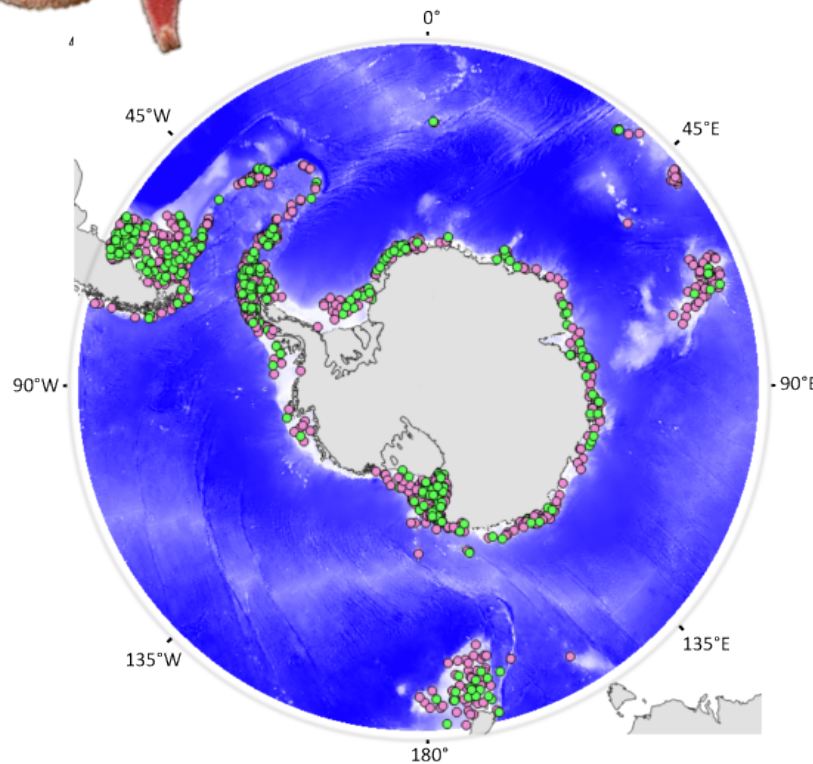
# **CONSEQUENCES OF DATA AGGREGATION ON MODEL VALIDATION**

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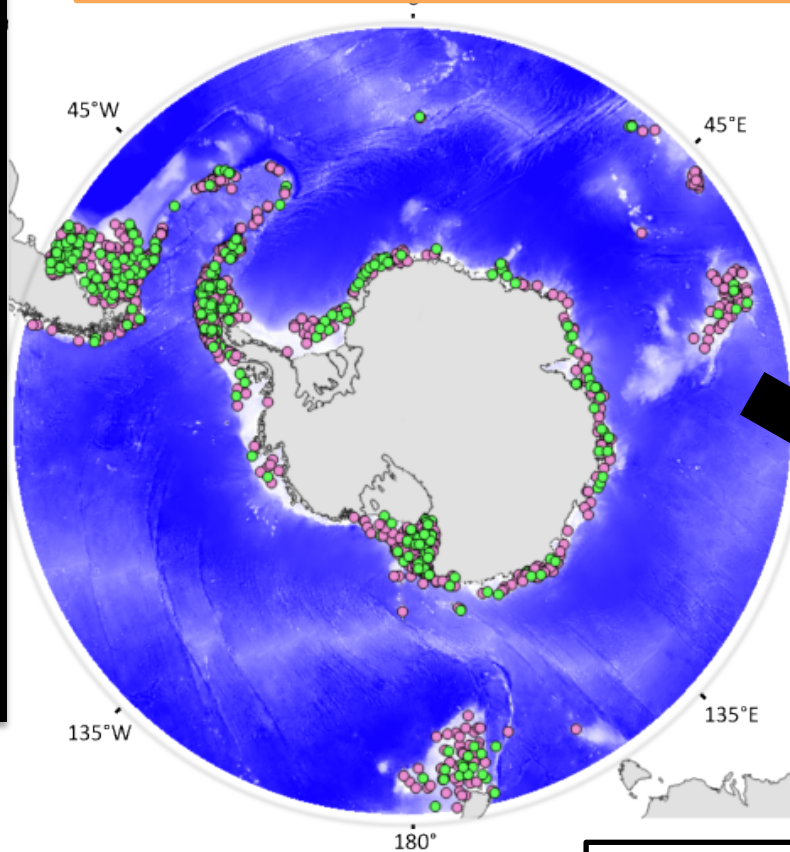
Guillaumot *et al.* (2019)

## CONSEQUENCES OF DATA AGGREGATION ON MODEL VALIDATION



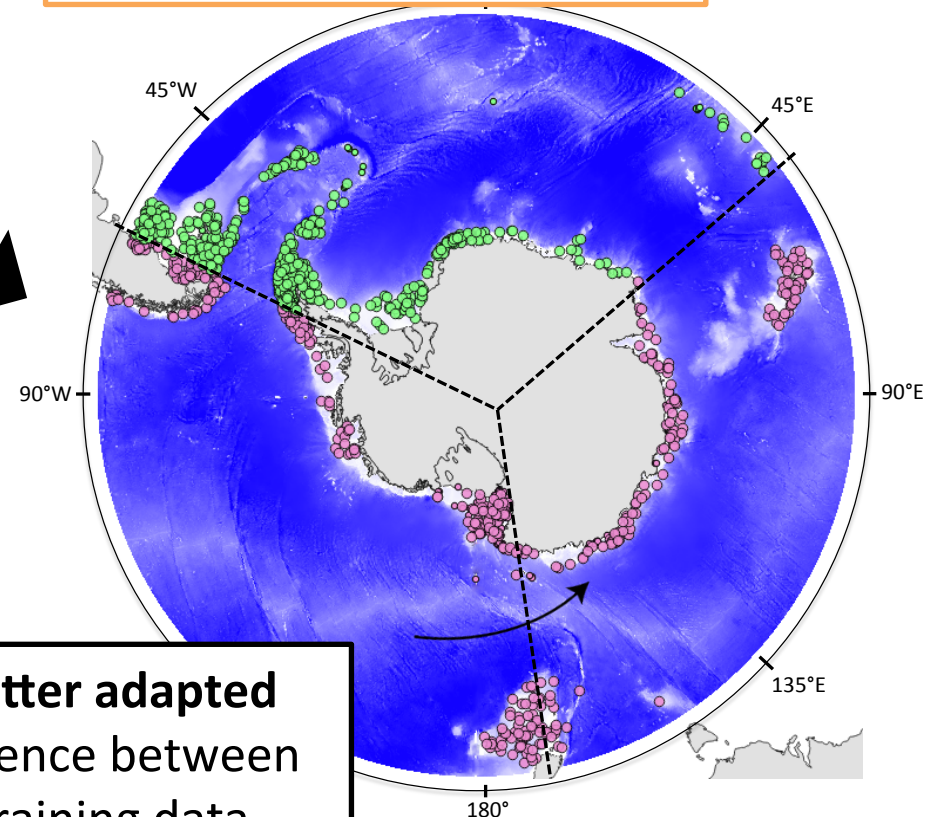
Guillaumot *et al.* (2019)

## Standard cross-validation



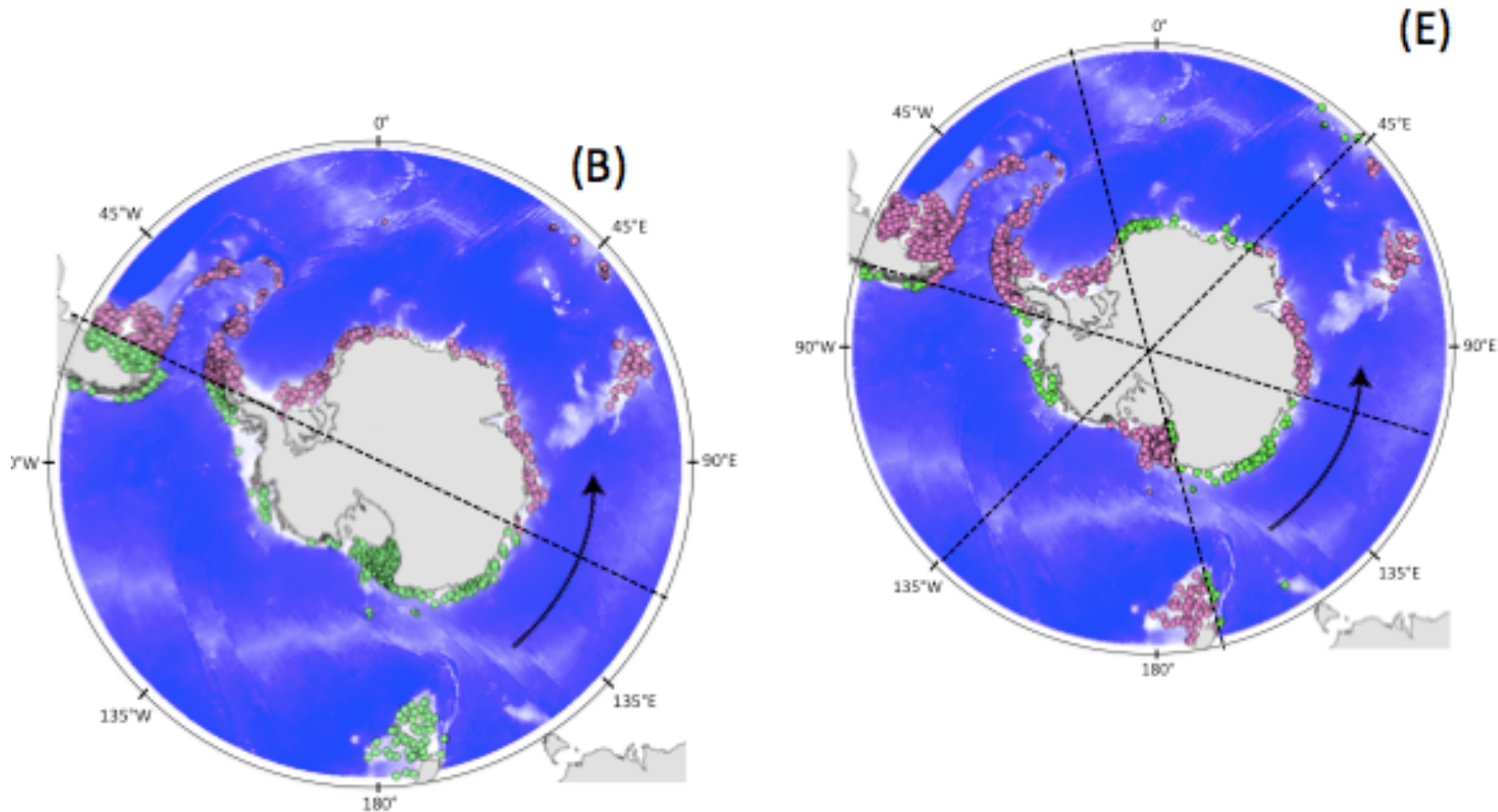
- Training data
- Test data

## Spatial cross-validation



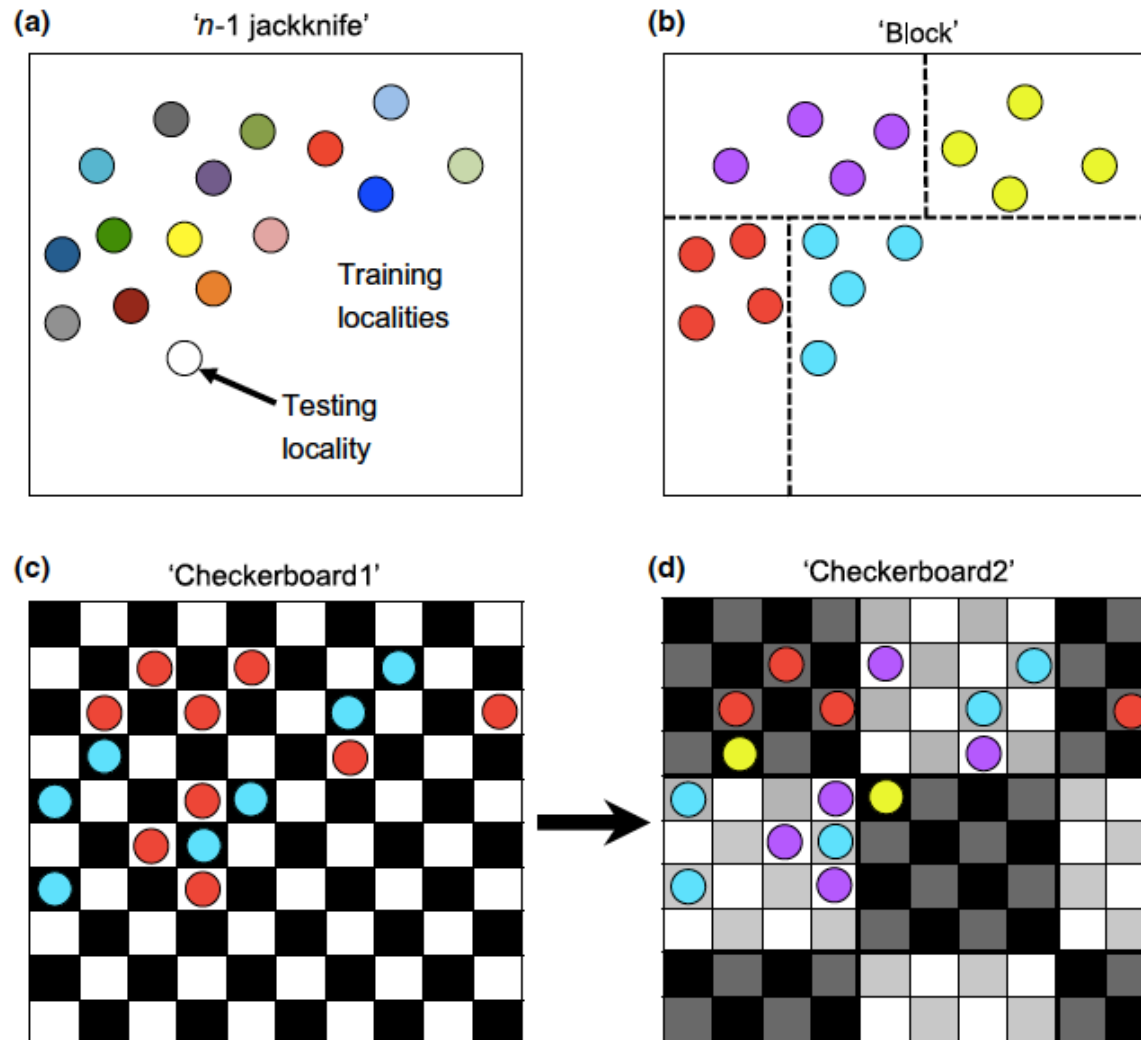
**Method better adapted**  
-> independence between  
test and training data

More cross-validation designs & comparisons in Guillaumot et al. (2019)





And generalised to all areas in Muscarella et al. (2014)



Little outline of this part ! =)

- > occurrence dataset used to calibrate the models
- > introduction of the use of background data
- > datasets spatially aggregated

=> why?

⇒ How to measure it ?

⇒ Consequences on SDM predictions

⇒ Methods to correct it

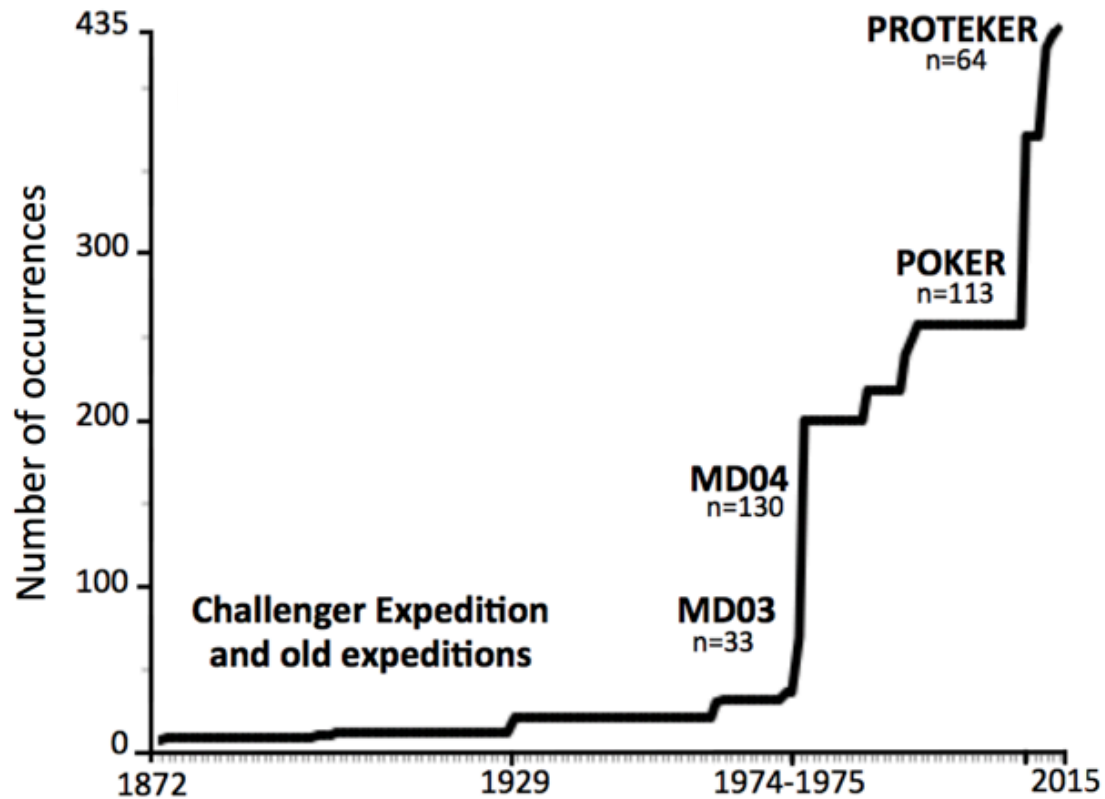
⇒ Consequences on model validation & corrections

-> temporal biases

-> extrapolation

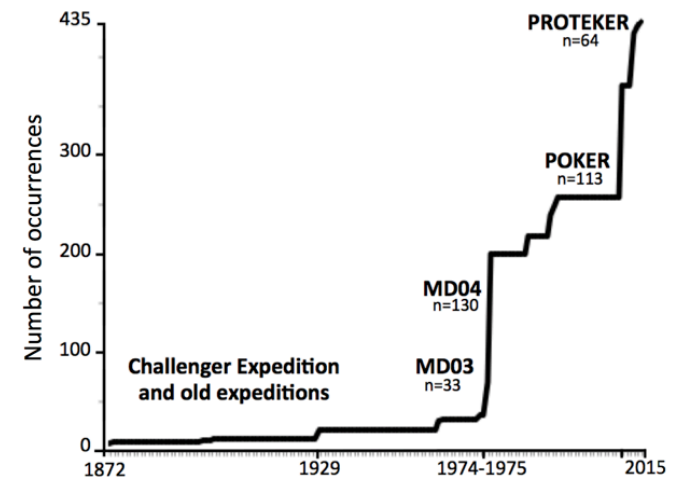


# TEMPORAL BIASES



## TEMPORAL BIASES

- Old & recent datasets mixed together...

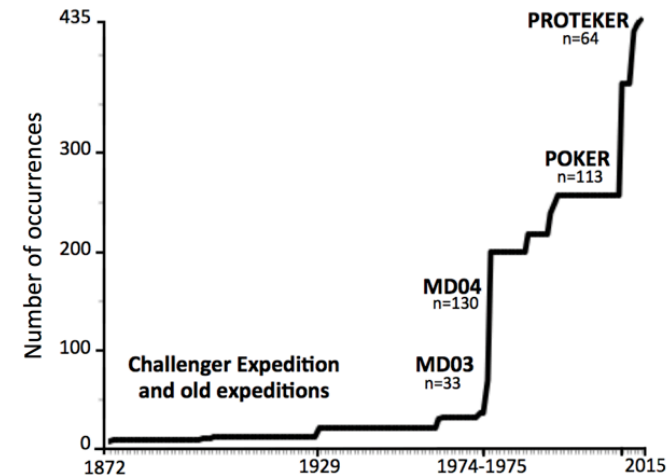


- Changes in species preferences to environmental conditions ?
- Population migrations ?
- Past environmental conditions have changed ? => species niche has changed??

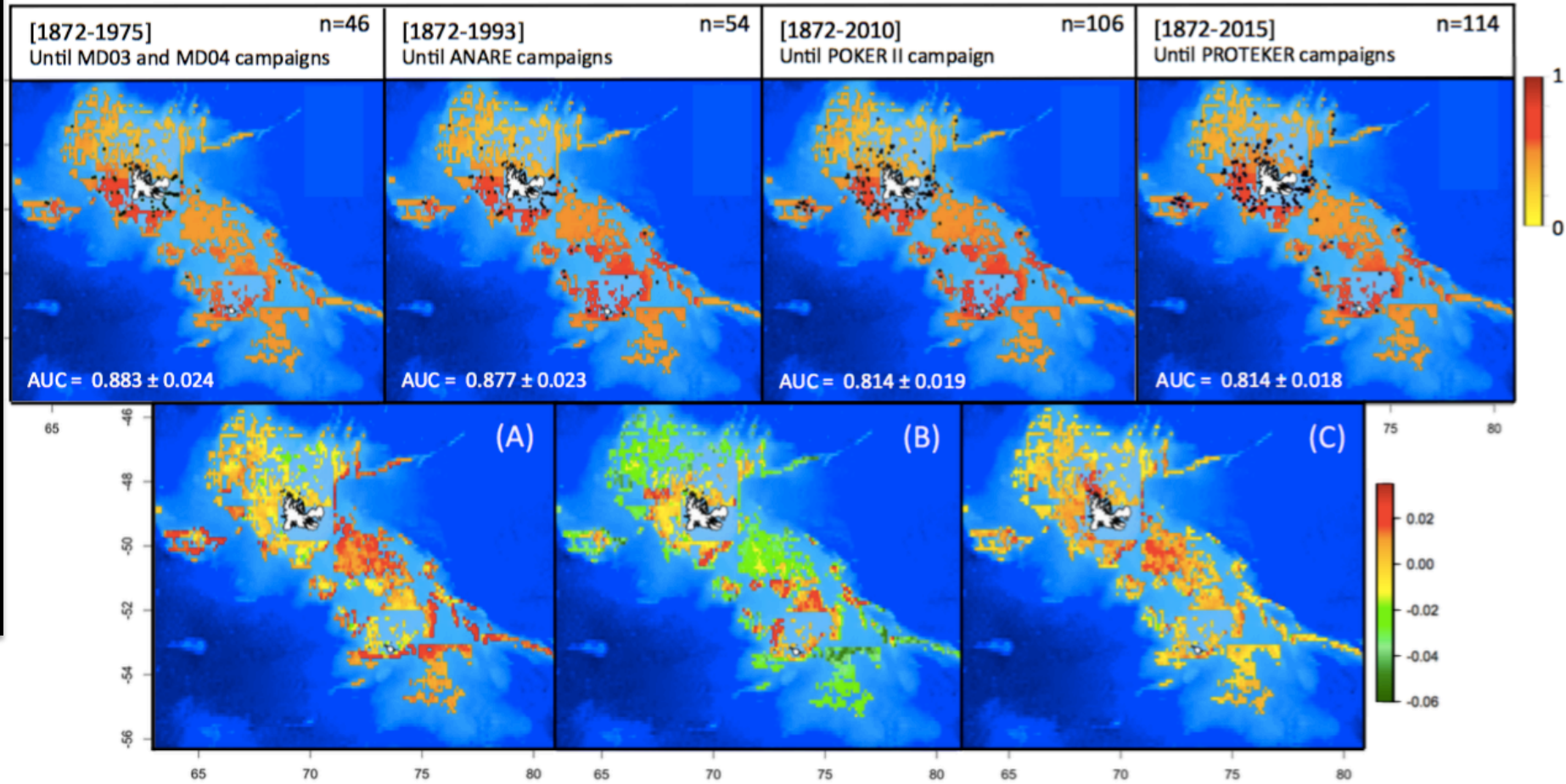
**STRONG ASSUMPTIONS...BE CAREFUL WITH INTERPRETATION**

## TEMPORAL BIASES

- Old & recent datasets mixed together...
- Biases linked to the number of occurrences and addition of new data



# CALIBRATION: Occurrence dataset

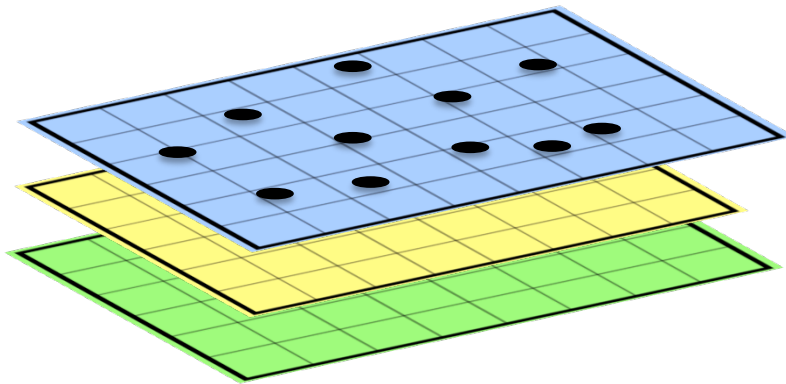


Guillaumot et al. (2018)

EXTRAPOLATION...

## EXTRAPOLATION...

Presence records



Descriptor A interval  $[a1, a2]$



Descriptor B interval  $[b1, b2]$

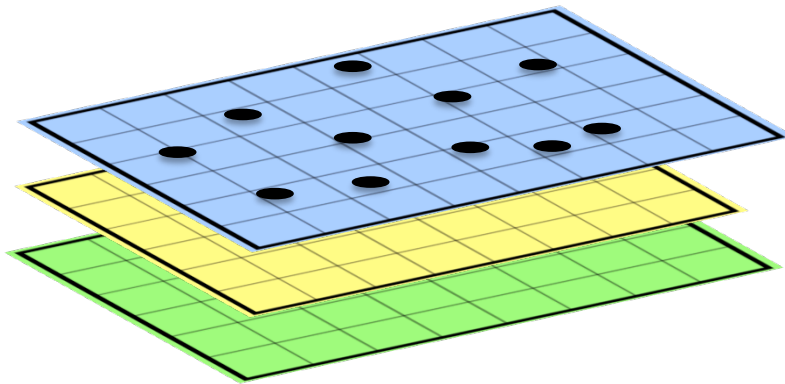


Descriptor C interval  $[c1, c2]$

...

## EXTRAPOLATION...

Presence records



Descriptor A interval  $[a1, a2]$



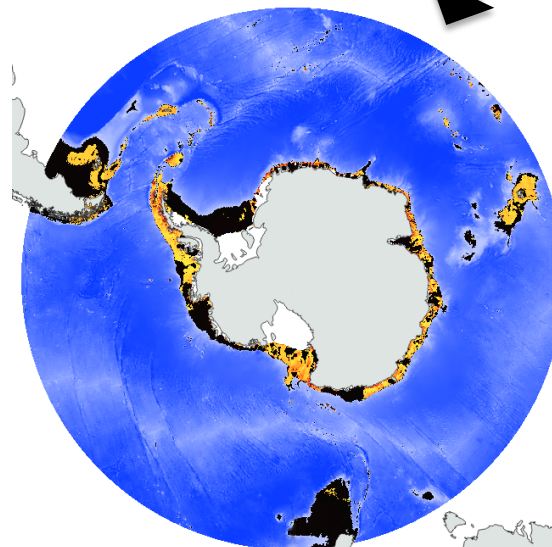
Descriptor B interval  $[b1, b2]$



Descriptor C interval  $[c1, c2]$

...

MESS: Multivariate  
Environmental Similarity  
Surface  
(Elith et al. 2010)



More than 60% of the  
area: extrapolation !  
➔ To take into  
consideration

# Questions ???





## EXTRA PRACTICE

Have you spotted in your code where you can change the layer of environmental variables on which you will project your model ? If you want for example to make a future projection ?