

# Interpretable ML for biodiversity

An introduction using species distribution models

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## MAIN GOALS

1. How do we produce a model?
2. How do we convey that it works?
3. How do we talk about how it makes predictions?
4. How do we use it to guide actions?



## BUT WHY...

**... think of SDM as ML problems?** Because they are! We want to learn a predictive algorithm from data

**... the focus on explainability?** We cannot ask people to *trust* - we must *convince* and *explain*



## WHAT WE WILL NOT DISCUSS

1. Image recognition
2. Sound recognition
3. Generative AI



## LEARNING/TEACHING GOALS

- ML basics
  - cross-validation
  - hyper-parameters tuning
  - bagging and ensembles
- Pitfalls
  - data leakage
  - overfitting
- Explainable ML
  - partial responses
  - Shapley values
- Counterfactuals

§ 1

## Problem statement

## THE PROBLEM IN ECOLOGICAL TERMS

We have information about a species, taking the form of (lon, lat) for points where the species was observed

Using this information, we can extract a suite of environmental variables for the locations where the species was observed

We can do the same thing for locations where the species was not observed

Where could we observe this species?

## THE PROBLEM IN ML TERMS

We have a series of labels  $\mathbf{y}_n \in \mathbb{B}$ , and features  $\mathbf{X}_{m,n} \in \mathbb{R}$

We want to find an algorithm  $f(\mathbf{x}_m) = \hat{y}$  that results in the distance between  $\hat{y}$  and  $y$  being *small*

An algorithm that does this job well is generalizable (we can apply it on data it has not been trained on) and makes credible predictions



## SETTING UP THE DATA FOR OUR EXAMPLE

We will use data on observations of *Turdus torquatus* in Switzerland, downloaded from the copy of the eBird dataset on GBIF

Two series of environmental layers

1. CHELSA2 BioClim variables (19)
2. EarthEnv land cover variables (12)

Now is *not* the time to make assumptions about which are relevant!



## THE OBSERVATION DATA





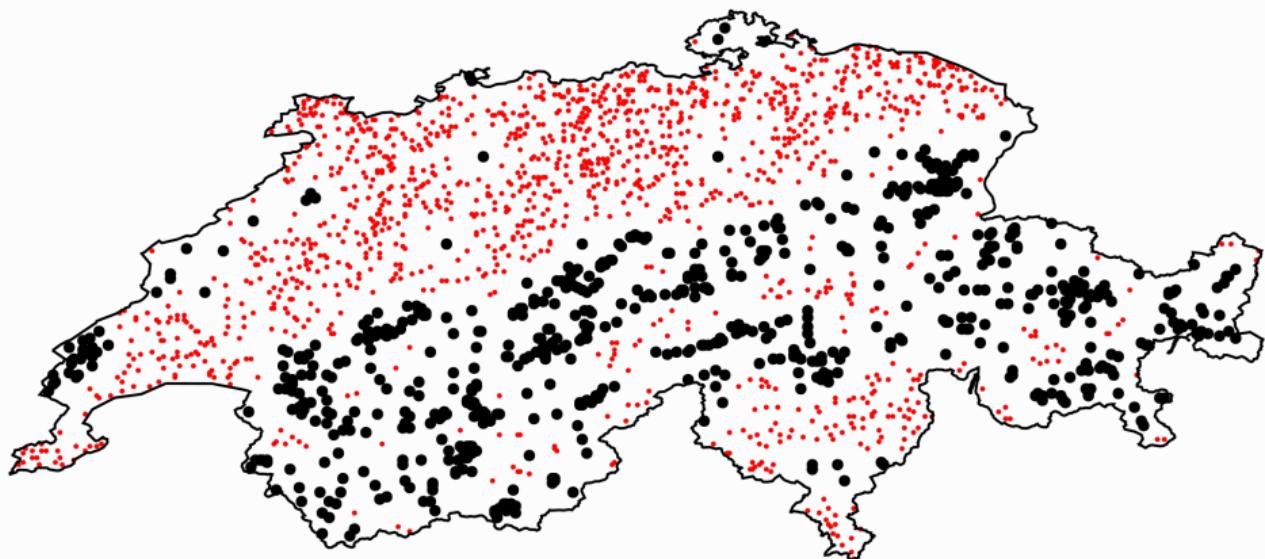
## PROBLEM (AND SOLUTION)

We want  $\mathbf{y} \in \mathbb{B}$ , and so far we are missing **negative values**

We generate **pseudo-absences** with the following rules:

1. Locations further away from a presence are more likely
2. Locations less than 5km away from a presence are ruled out

## THE (INFLATED) OBSERVATION DATA



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## Training the model



## A SIMPLE DECISION TREE

 **SETUP**



## CROSS-VALIDATION

Can we train the model?

More specifically – if we train the model, how well can we expect it to perform?

assumes parallel universes with slightly less data

is the model good?



## NULL CLASSIFIERS

coin flip

no skill

constant

 EXPECTATIONS

The null classifiers tell us what we need to beat in order to perform **better than random**.

<b>Model</b>	<b>MCC</b>	<b>PPV</b>	<b>NPV</b>	<b>DOR</b>	<b>Accuracy</b>
No skill	-0.00	0.34	0.66	1.00	0.55
Coin flip	-0.32	0.34	0.34	0.26	0.34
+	0.00	0.34			0.34
-	0.00		0.66		0.66

In practice, the no-skill classifier is the most informative: what if we **only** know the positive class prevalence?



## CROSS-VALIDATION STRATEGY

k-fold

validation / training / testing



## CROSS-VALIDATION RESULTS

<b>Model</b>	<b>MCC</b>	<b>PPV</b>	<b>NPV</b>	<b>DOR</b>	<b>Accuracy</b>
No skill	-0.00	0.34	0.66	1.00	0.55
Dec. tree (val.)	0.64	0.77	0.87	26.59	0.84
Dec. tree (tr.)	0.66	0.78	0.88	28.70	0.85

## WHAT TO DO IF THE MODEL IS TRAINABLE?

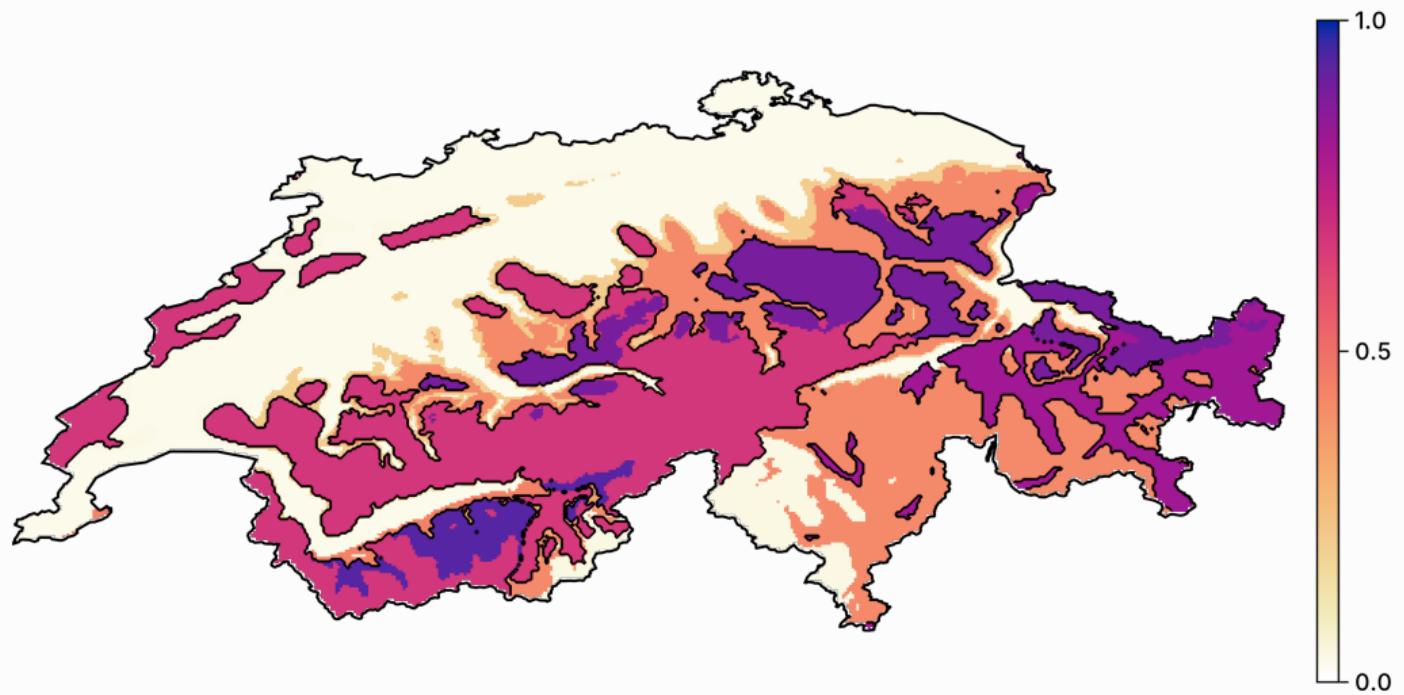
train it!

re-use the full dataset



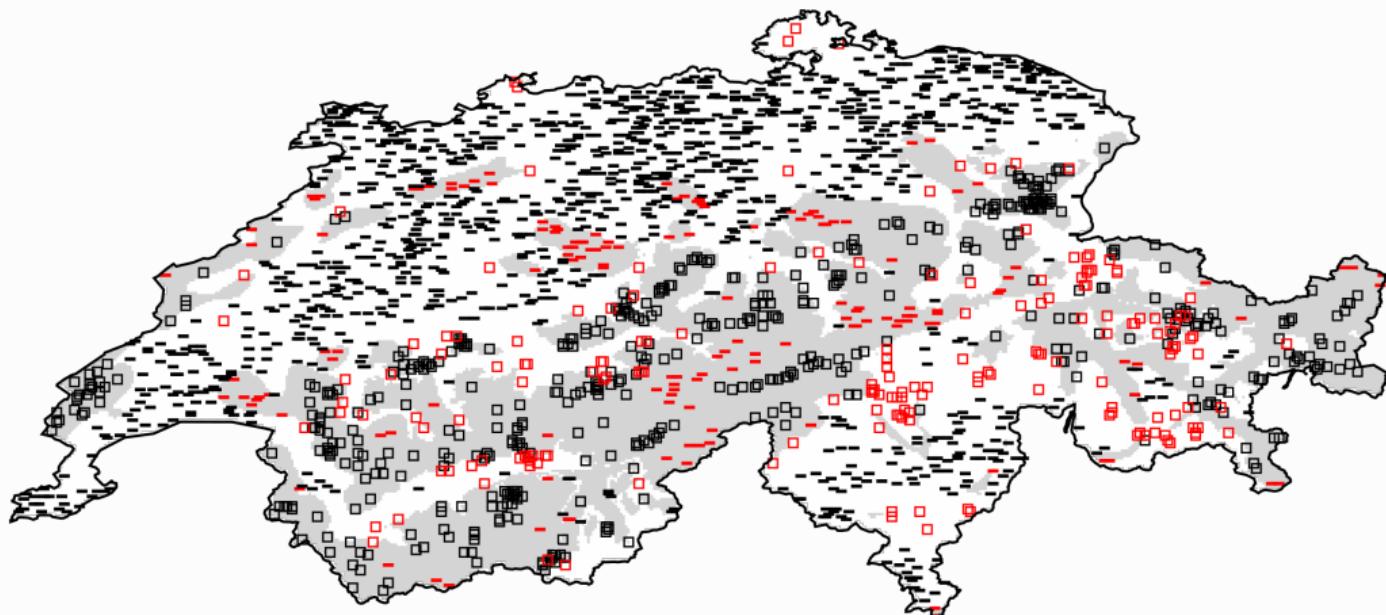
## THE MODEL TRAINING PIPELINE

# INITIAL PREDICTION





## HOW IS THIS MODEL WRONG?





## CAN WE IMPROVE ON THIS MODEL?

variable selection

data transformation

hyper-parameters tuning

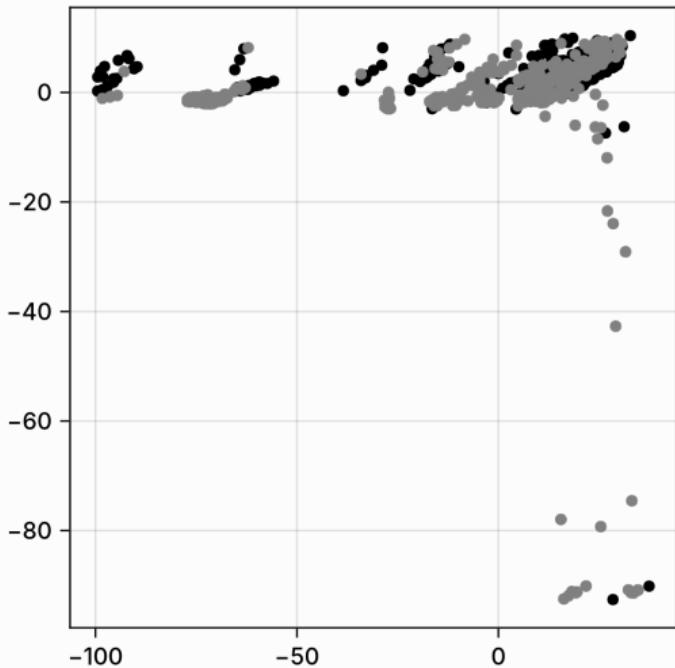
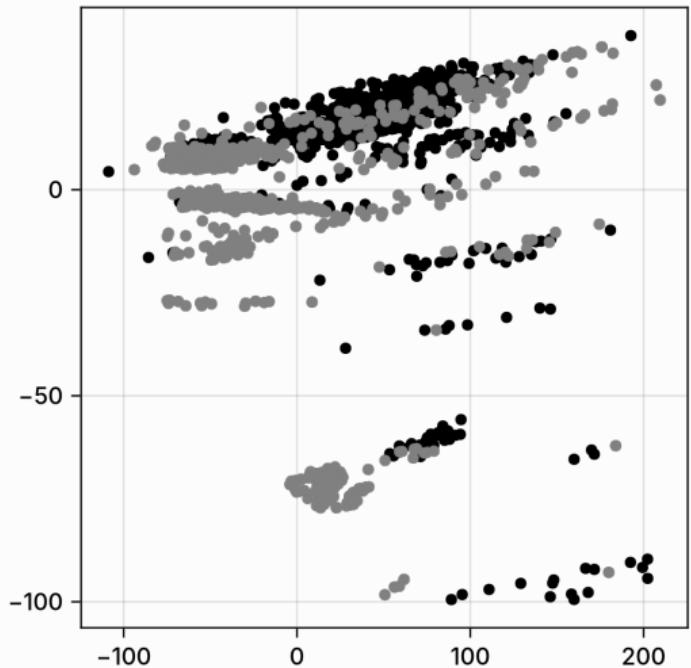
will focus on the later (same process for the two above)



## DATA LEAKAGE



## A NOTE ON PCA



## MOVING THRESHOLD CLASSIFICATION

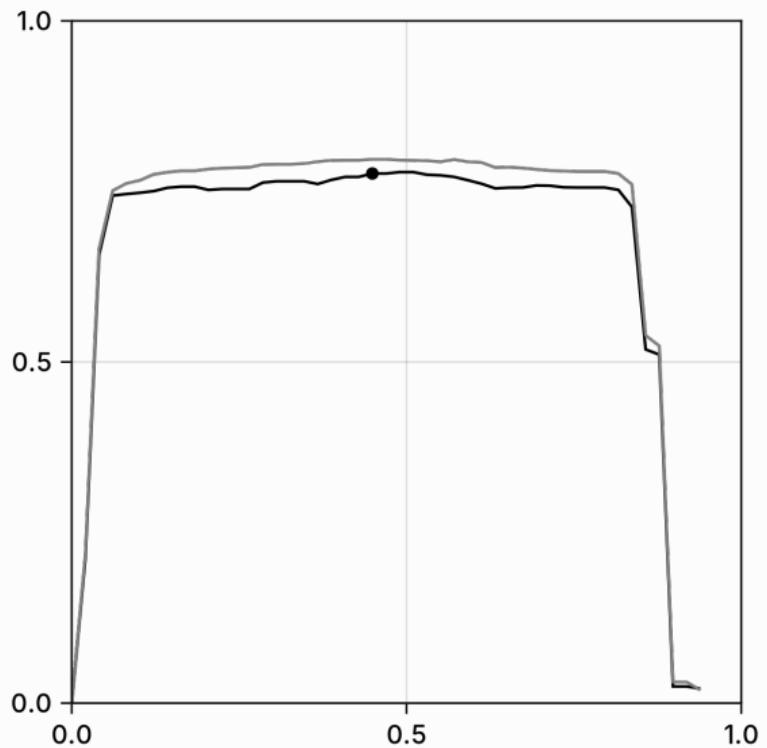
$p_{\text{plus}} > p_{\text{minus}}$  means threshold is 0.5

is it?

how do we check this

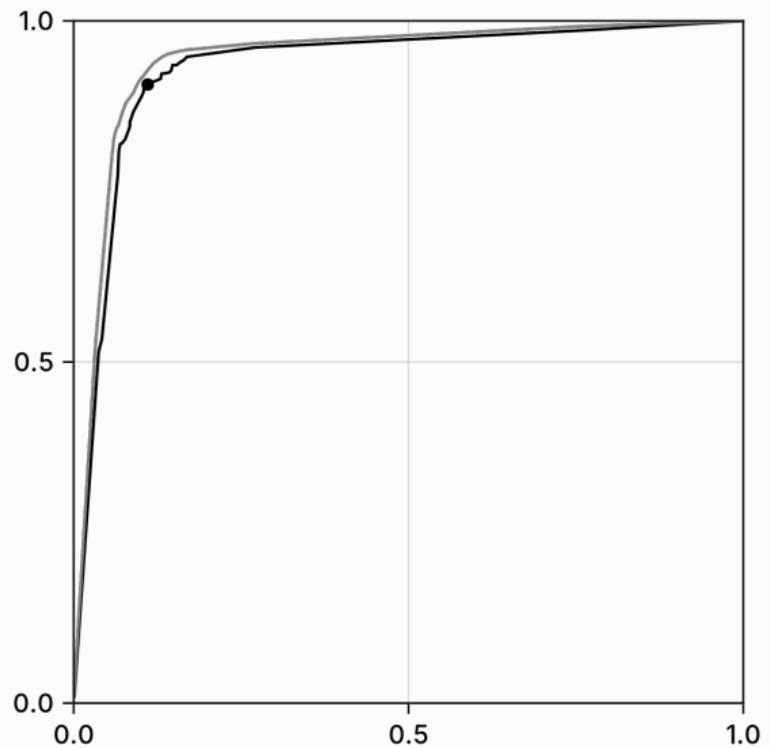


## LEARNING CURVE FOR THE THRESHOLD



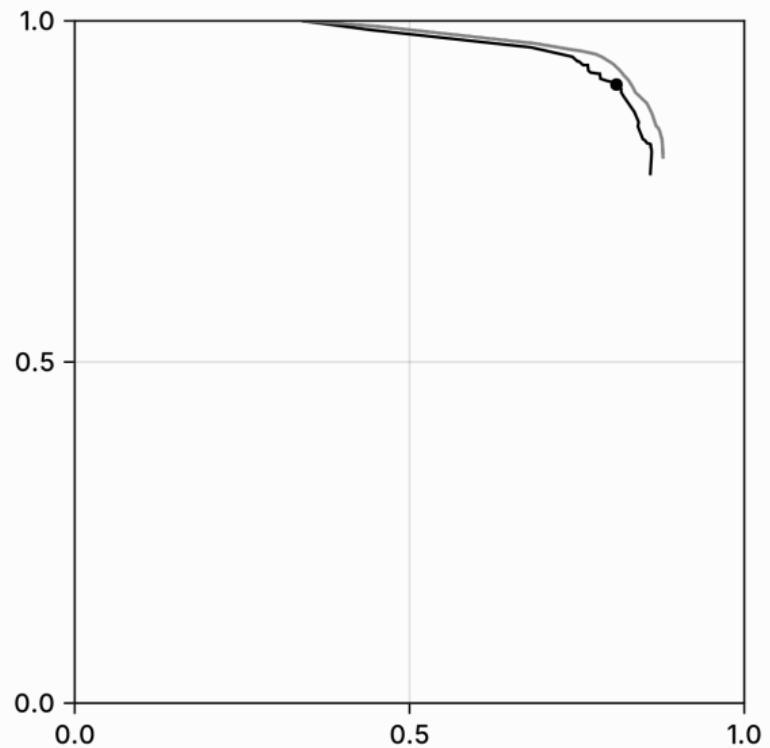


## RECEIVER OPERATING CHARACTERISTIC





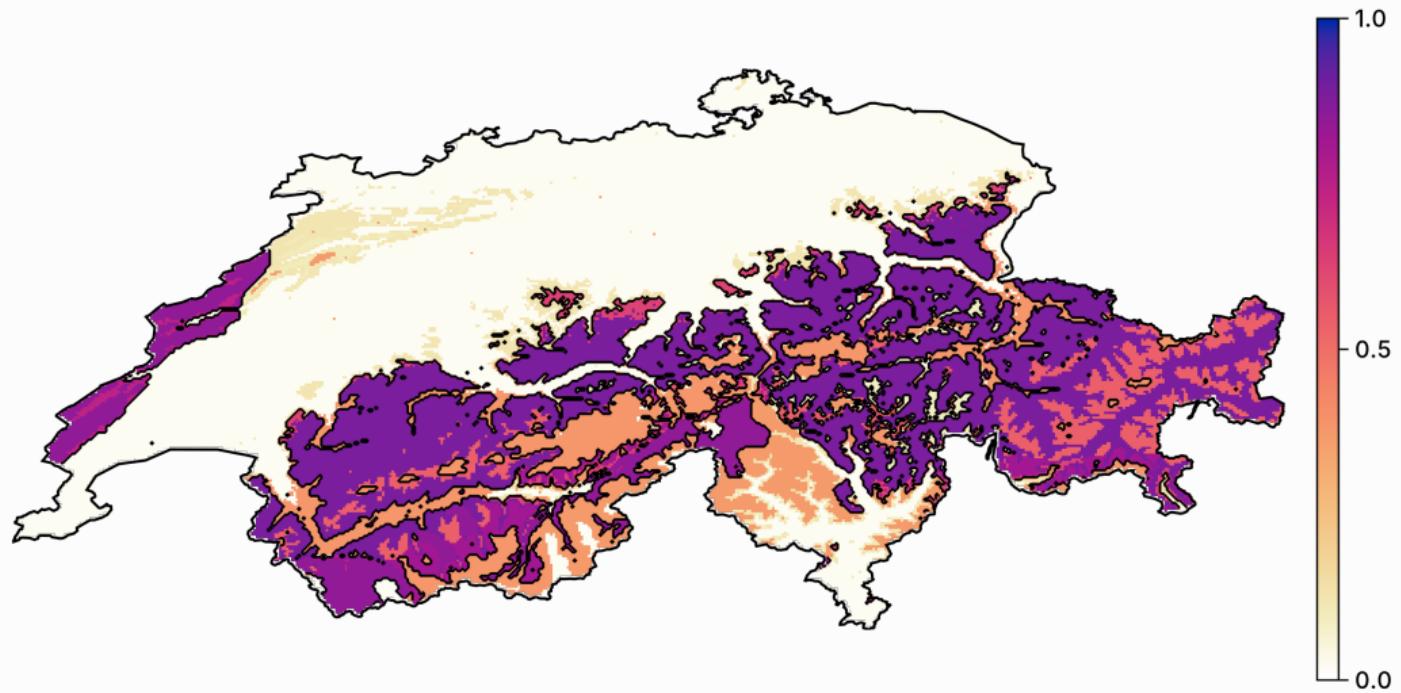
## PRECISION-RECALL CURVE



## REVISITING THE MODEL PERFORMANCE

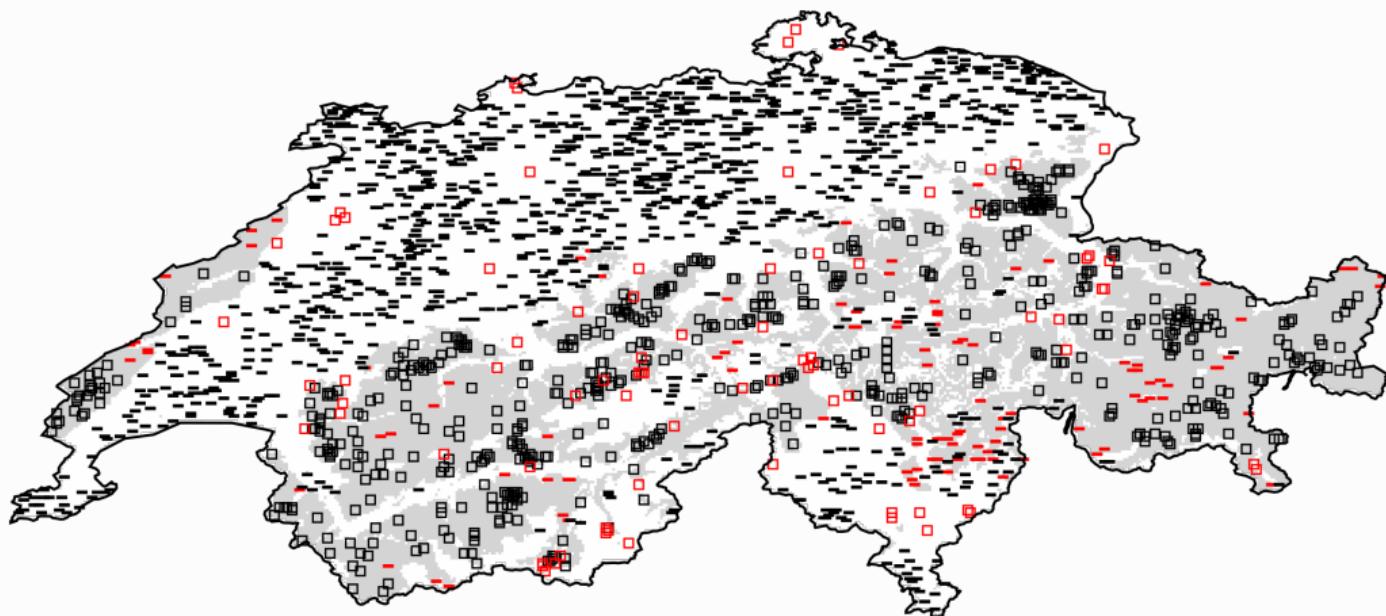
<b>Model</b>	<b>MCC</b>	<b>PPV</b>	<b>NPV</b>	<b>DOR</b>	<b>Accuracy</b>
No skill	-0.00	0.34	0.66	1.00	0.55
Dec. tree (val.)	0.64	0.77	0.87	26.59	0.84
Dec. tree (tr.)	0.66	0.78	0.88	28.70	0.85
Tuned tree (val.)	0.77	0.79	0.95	113.44	0.89
Tuned tree (tr.)	0.80	0.81	0.96	114.37	0.90

 UPDATED PREDICTION





## HOW IS THIS MODEL BETTER?





## BUT WAIT!

slide on overfitting

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## Ensemble models

## LIMITS OF A SINGLE MODEL

- a single model
- different parts of data may have different signal
- do we need all the variables all the time?
- bias v. variance tradeoff
- limit overfitting



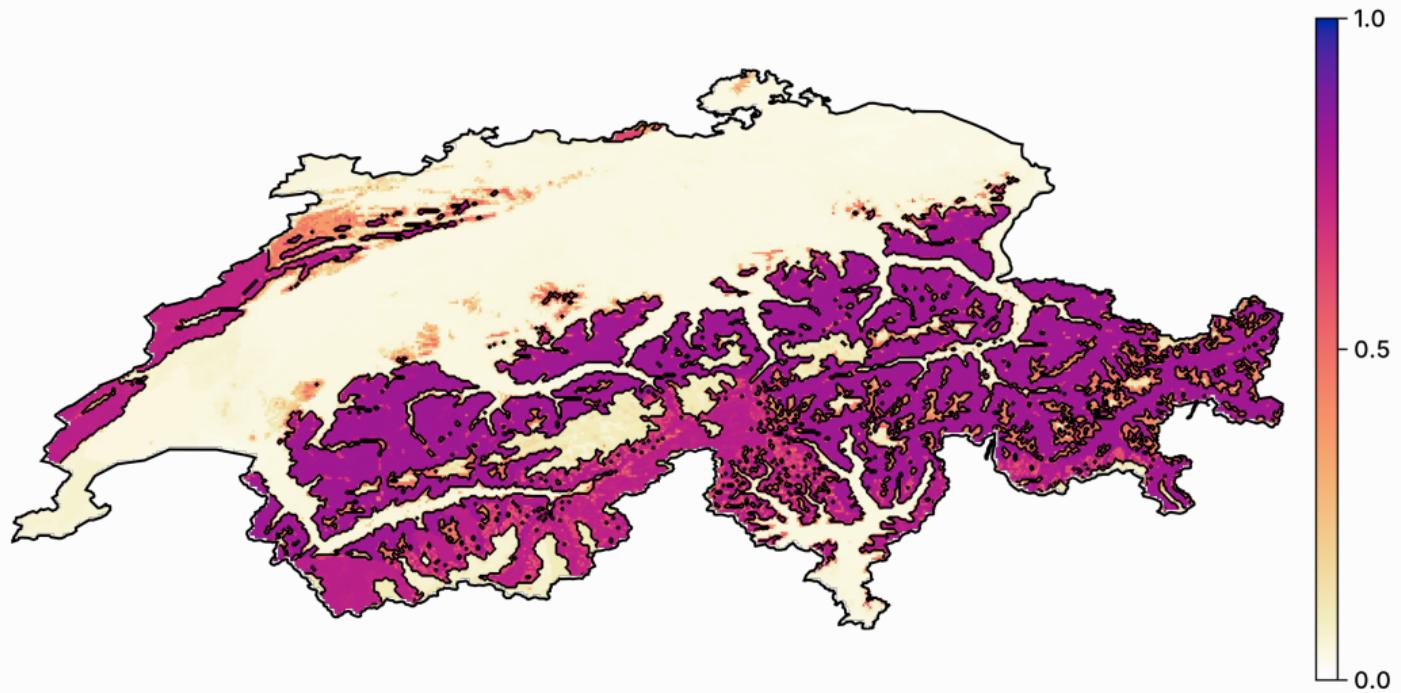
## BOOTSTRAPPING AND AGGREGATION

 IS THIS WORTH IT?

<b>Model</b>	<b>MCC</b>	<b>PPV</b>	<b>NPV</b>	<b>DOR</b>	<b>Accuracy</b>
No skill	-0.00	0.34	0.66	1.00	0.55
Dec. tree (val.)	0.64	0.77	0.87	26.59	0.84
Dec. tree (tr.)	0.66	0.78	0.88	28.70	0.85
Tuned tree (val.)	0.77	0.79	0.95	113.44	0.89
Tuned tree (tr.)	0.80	0.81	0.96	114.37	0.90
Forest (val.)	0.76	0.79	0.95	93.47	0.89
Forest (tr.)	0.76	0.80	0.95	70.60	0.89

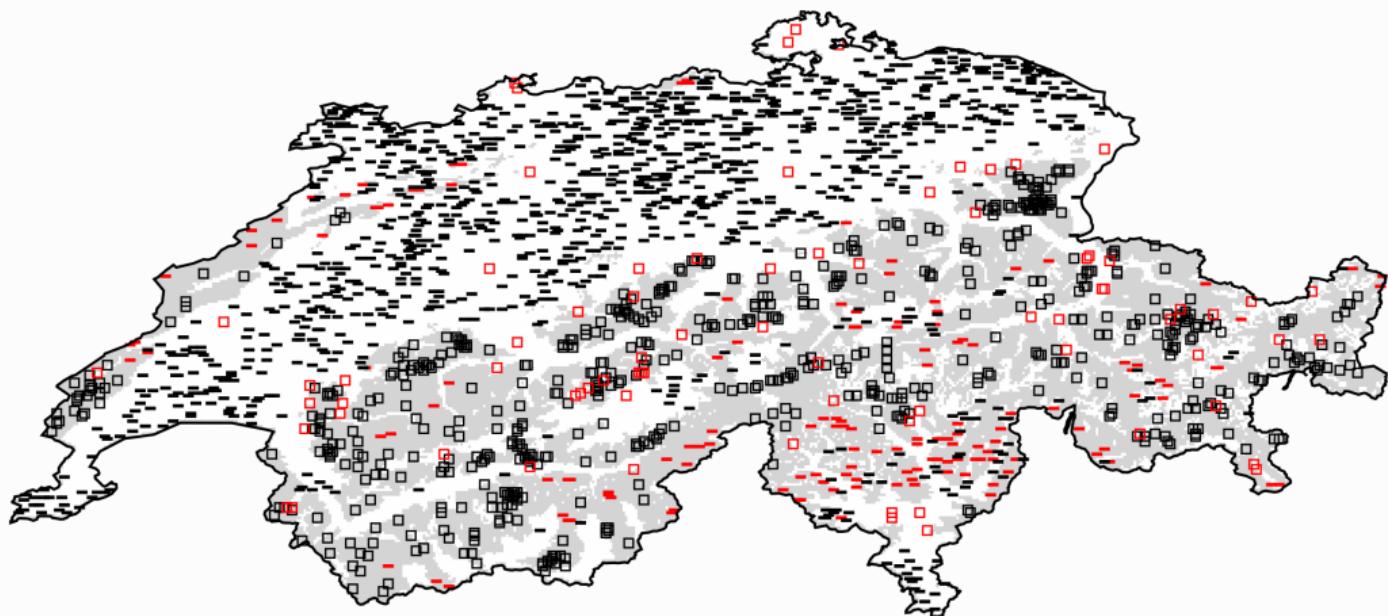


## PREDICTION OF THE ROTATION FOREST

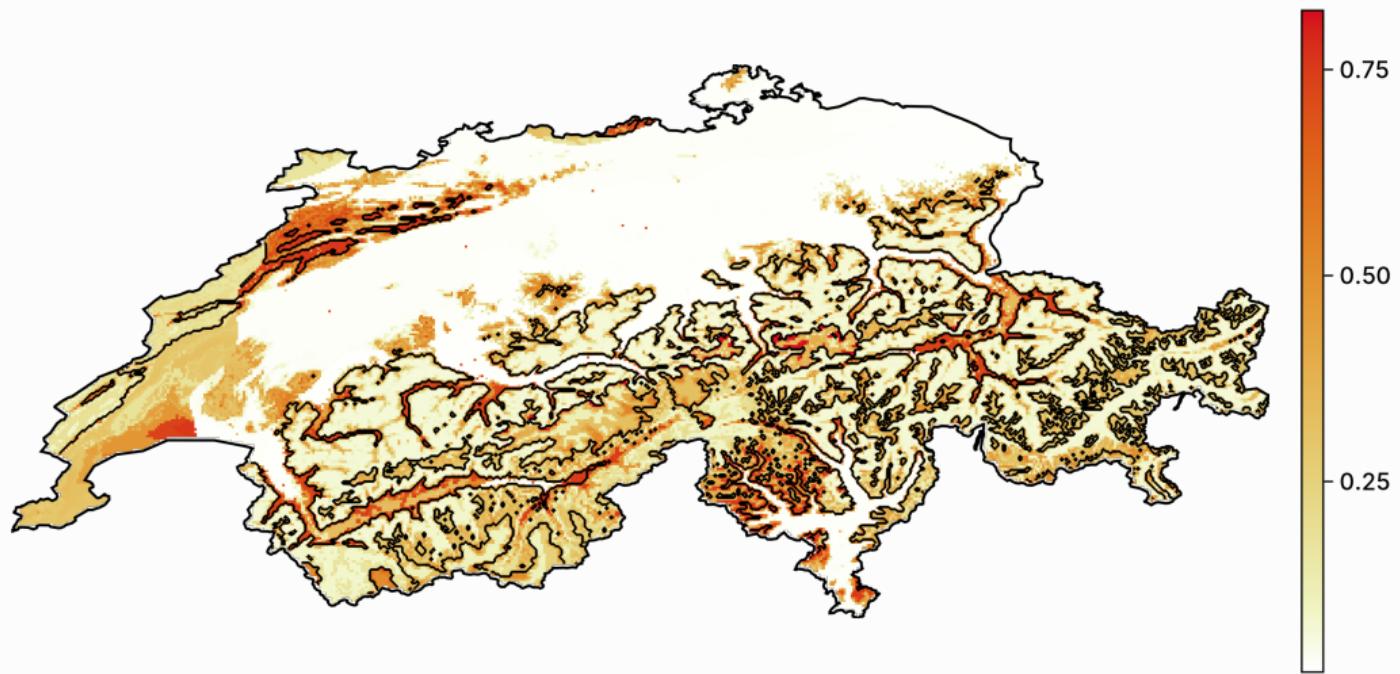




## PREDICTION OF THE ROTATION FOREST



# UNCERTAINTY





## REVISITING ASSUMPTIONS

- pseudo-absences
- not just a statistical exercise



## VARIABLE IMPORTANCE

<b>Layer</b>	<b>Variable</b>	<b>Import.</b>
1	BIO1	0.826496
8	BIO8	0.137103
29	Snow/Ice	0.0209848
24	Shrubs	0.00981907
3	BIO3	0.00559774

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## But why?





## INTRO EXPLAINABLE



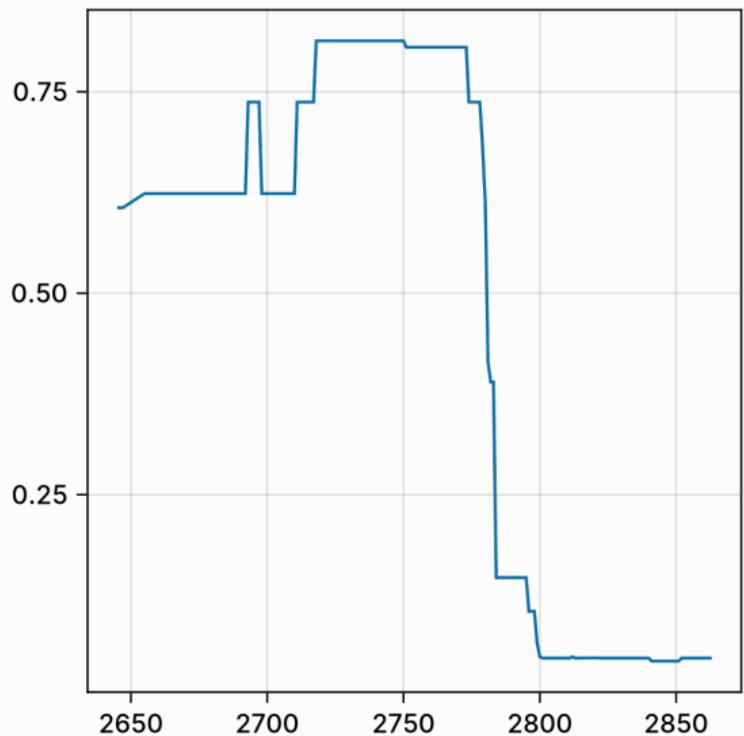
## PARTIAL RESPONSE CURVES

If we assume that all the variables except one take their average value, what is the prediction associated to the value that is unchanged?

Equivalent to a mean-field approximation

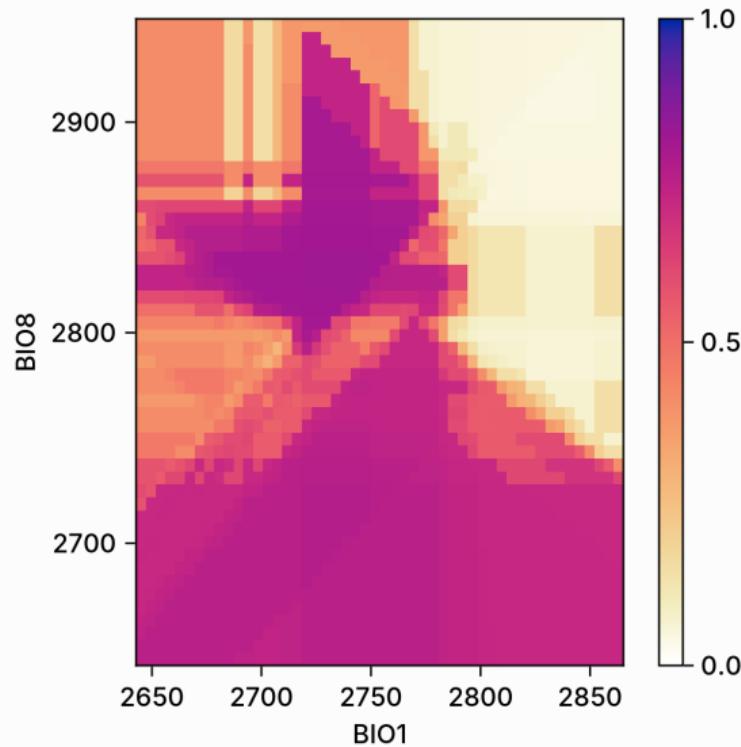


## EXAMPLE WITH TEMPERATURE



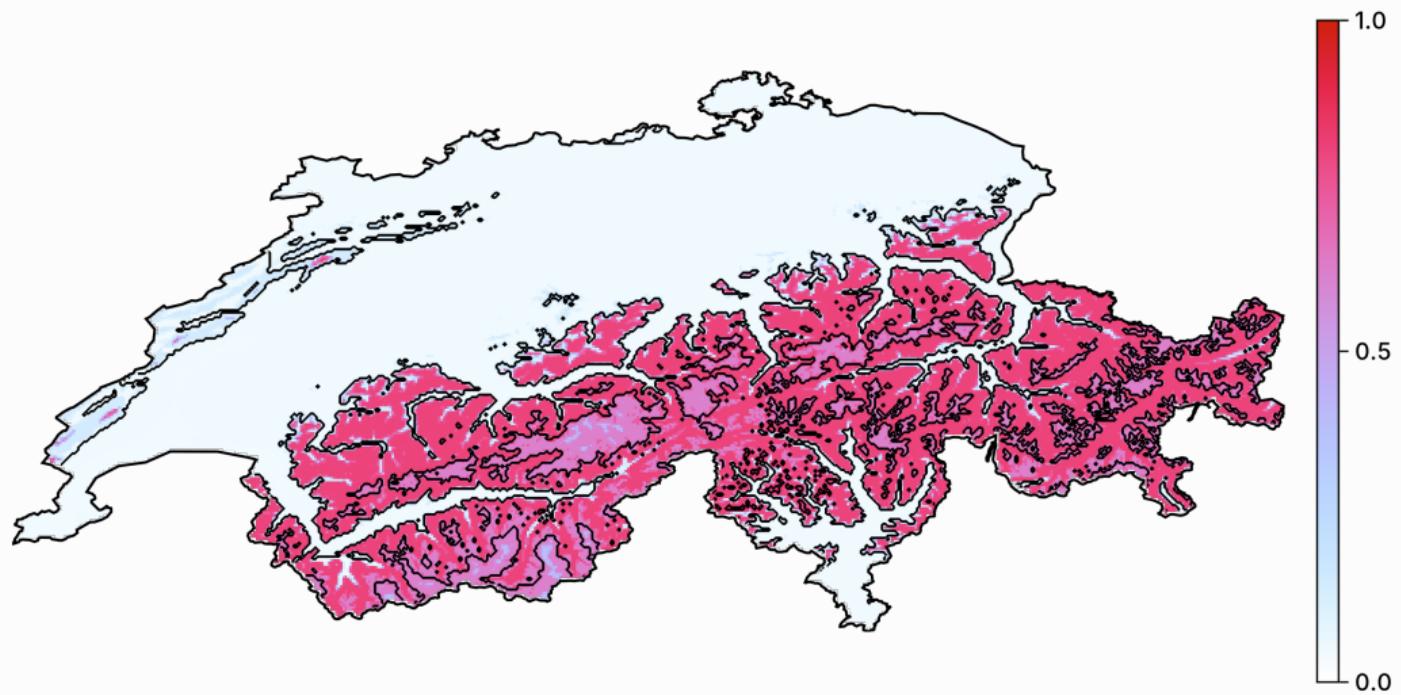


## EXAMPLE WITH TWO VARIABLES



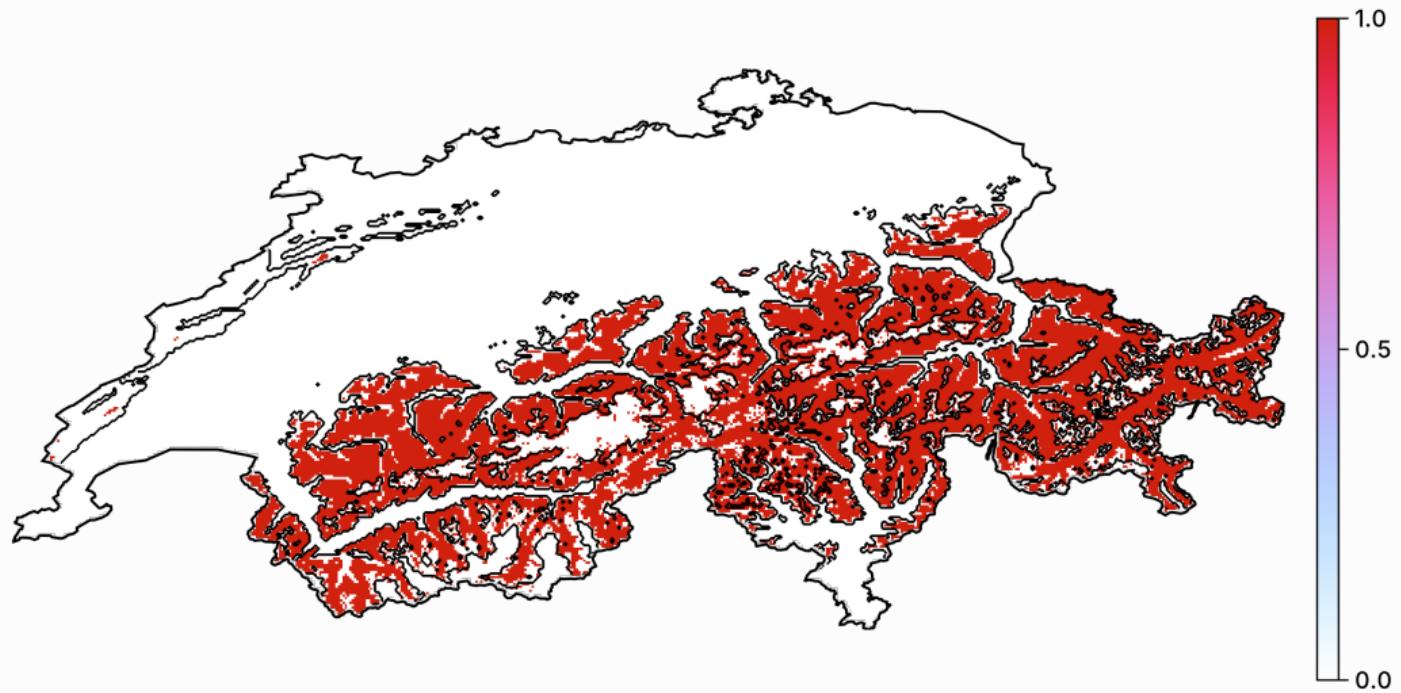


## SPATIALIZED PARTIAL RESPONSE PLOT





## SPATIALIZED PARTIAL RESPONSE (BINARY OUTCOME)



## INFLATED RESPONSE CURVES

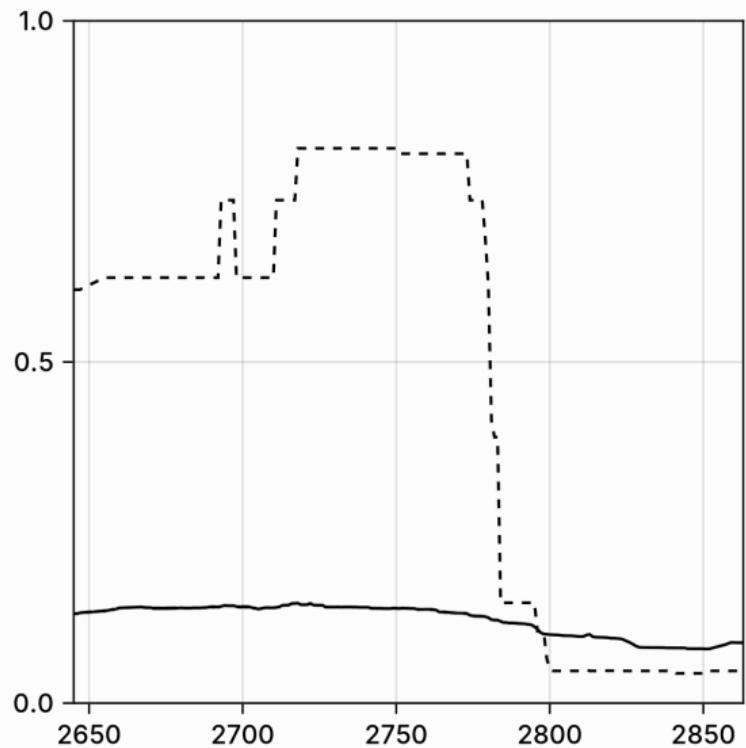
Averaging the variables is **masking a lot of variability!**

Alternative solution:

1. Generate a grid for all the variables
2. For all combinations in this grid, use it as the stand-in for the variables to replace

In practice: Monte-Carlo on a reasonable number of samples.

## EXAMPLE



 LIMITATIONS

- partial responses can only generate model-level information
- they break the structure of values for all predictors at the scale of a single observation
- their interpretation is unclear

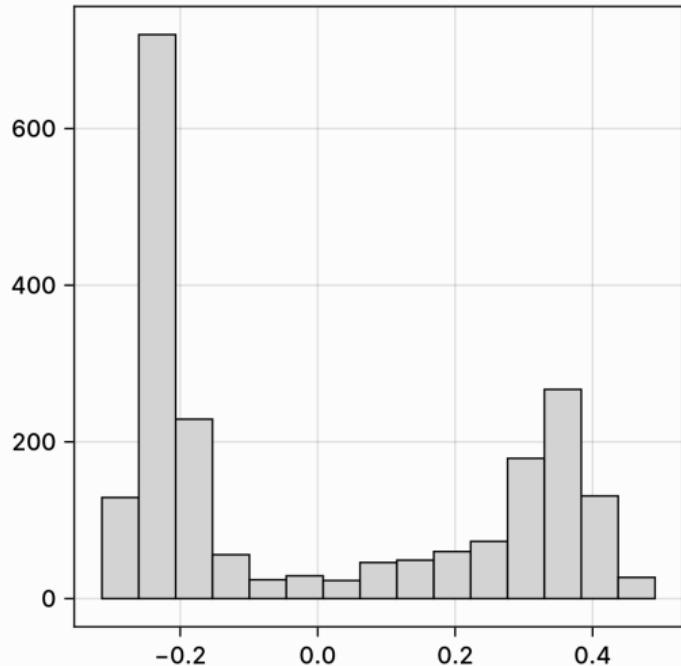
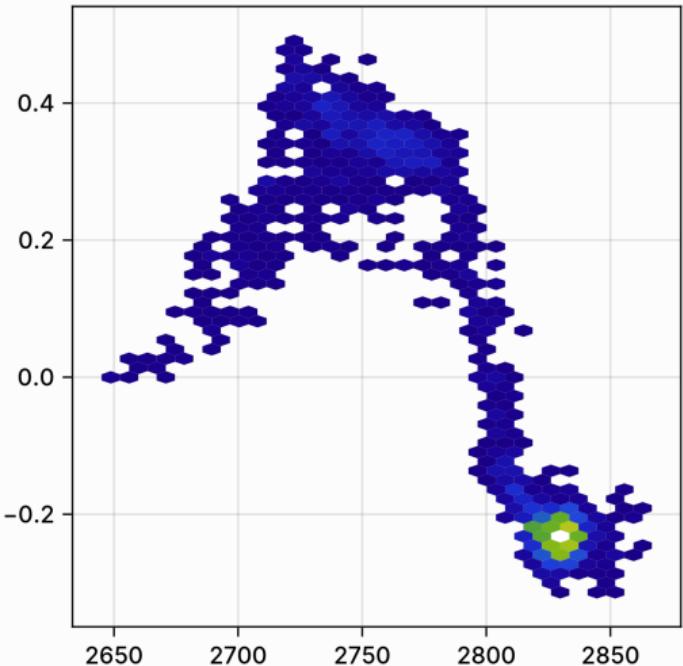




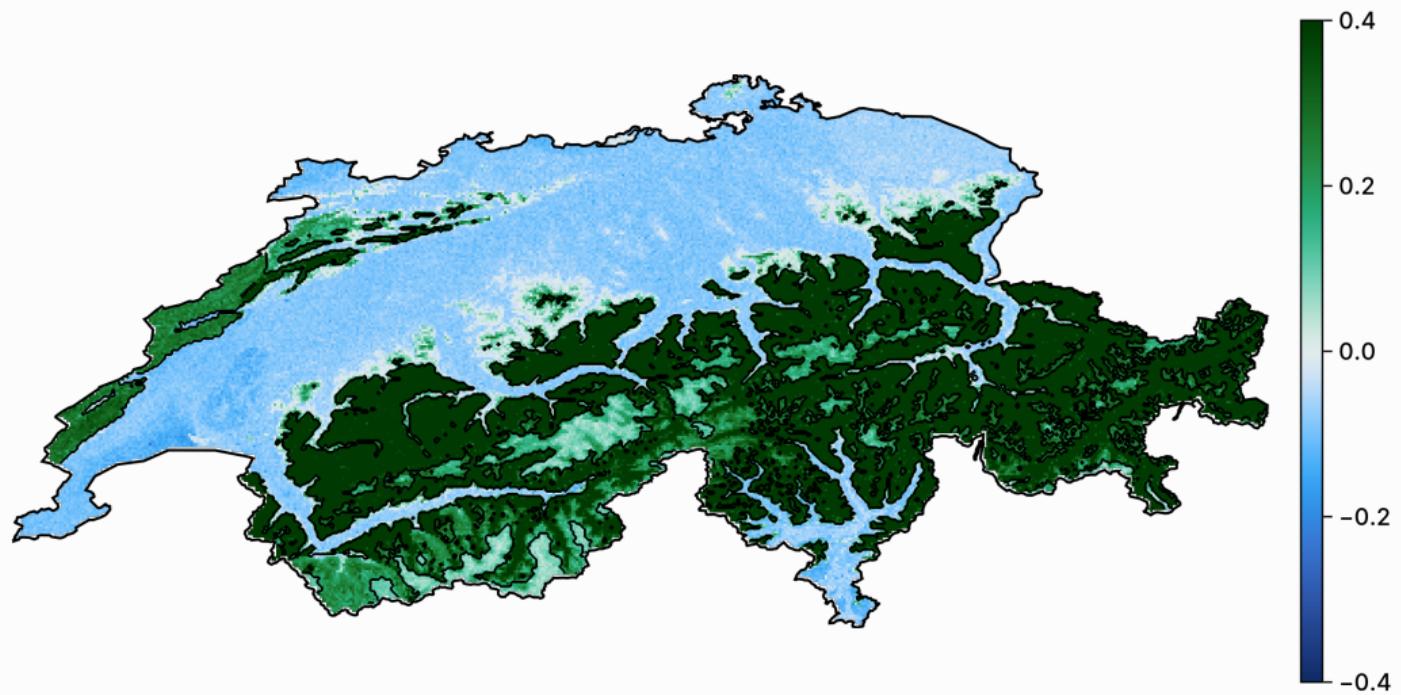
## EXAMPLE



## RESPONSE CURVES REVISITED



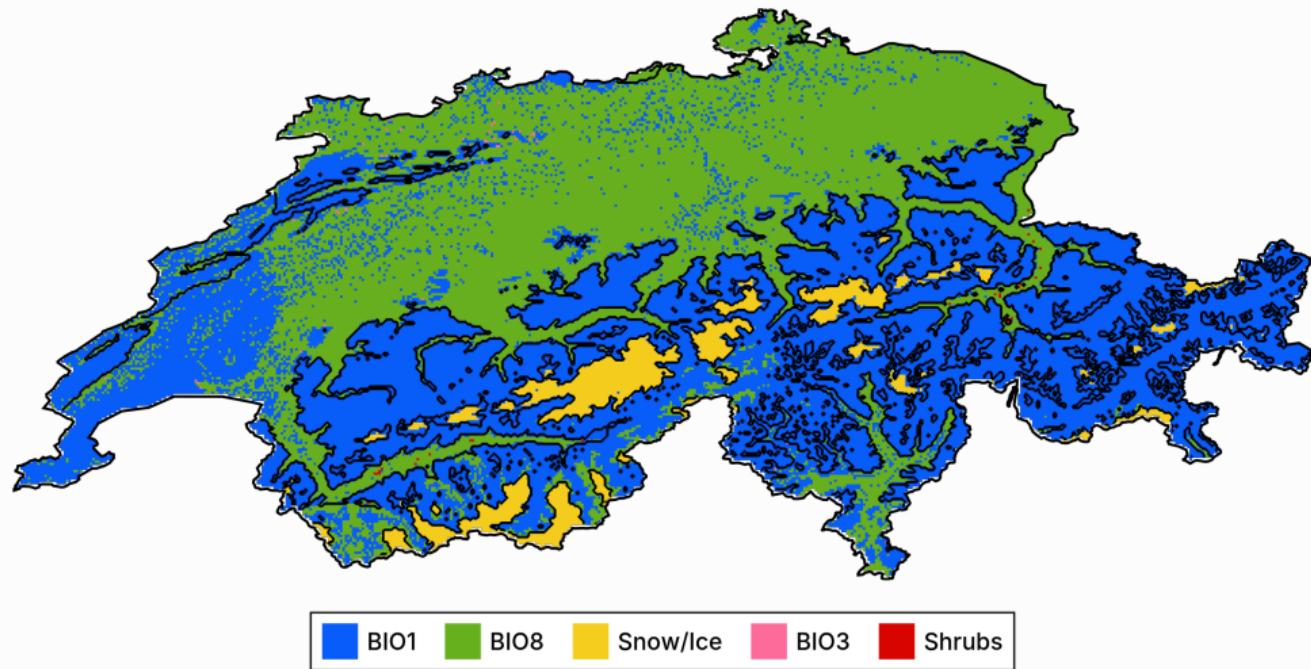
ON A MAP



## VARIABLE IMPORTANCE REVISITED

<b>Layer</b>	<b>Variable</b>	<b>Import.</b>	<b>Shap. imp.</b>
1	BIO1	0.826496	0.588227
8	BIO8	0.137103	0.285221
29	Snow/Ice	0.0209848	0.0528098
24	Shrubs	0.00981907	0.0431225
3	BIO3	0.00559774	0.0306201

## MOST IMPORTANT PREDICTOR



## REVISITING THE DATA TRANSFORMATION

all in a single model so we can ask effect of variable instead of effect of PC1 or whatever

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## What if?



## INTRO TO COUNTERFACTUALS

what they are



## THE RASHOMON EFFECT

- different but equally likely alternatives
- happens at all steps in the process
- variable selected, threshold used, model type



## GENERATING A COUNTERFACTUAL



## EVALUATING THE COUNTERFACTUALS

## WHAT IS A GOOD COUNTERFACTUAL

learning rate and loss function

use on prediction score and not yes/no!



## ALGORITHMIC RE COURSE

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## Conclusions



