

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



§ 2

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?



NUL CLASSIFIERS

coin flip

no skill

constant

 EXPECTATIONS

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

Model	MCC	PPV	NPV	DOR	Accuracy
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



CROSS-VALIDATION STRATEGY

k-fold

validation / training / testing



CROSS-VALIDATION RESULTS

Model	MCC	PPV	NPV	DOR	Accuracy
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
Validation	0.62	0.76	0.87	23.25	0.83
Training	0.65	0.77	0.88	24.87	0.84

WHAT TO DO IF THE MODEL IS TRAINABLE?

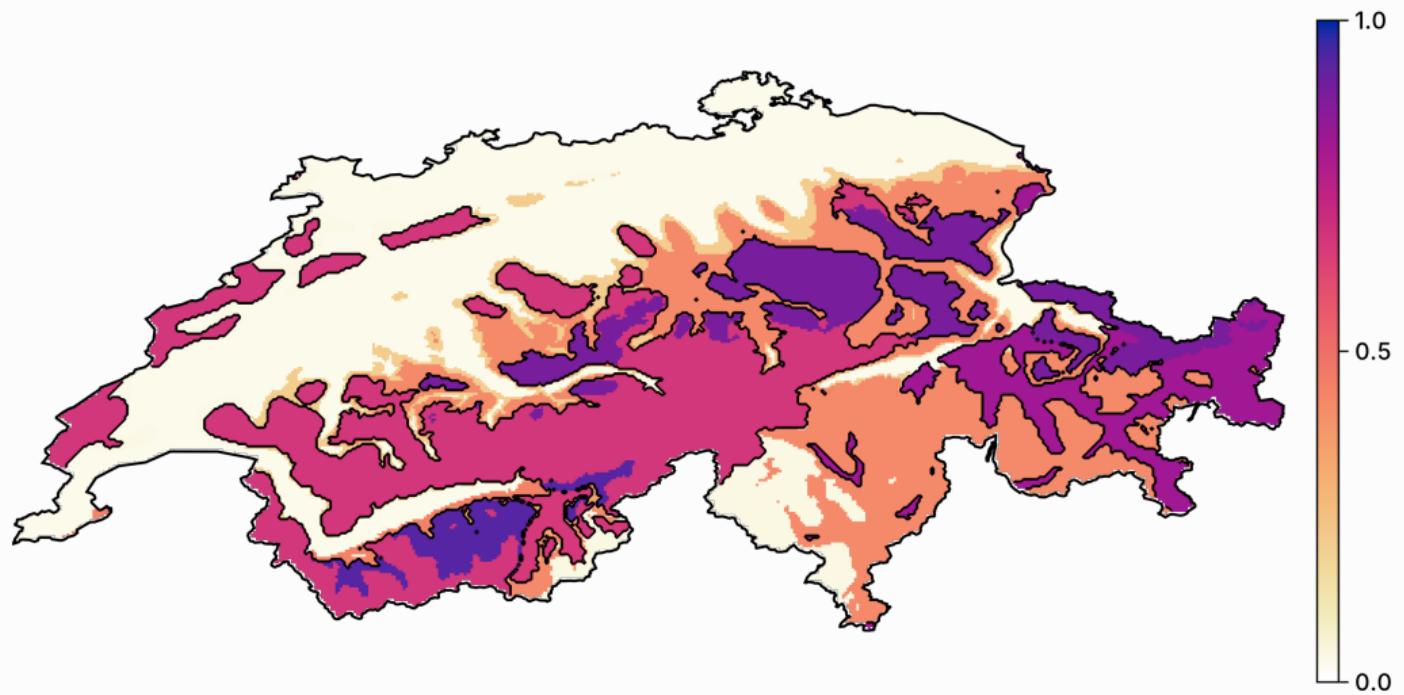
train it!

re-use the full dataset



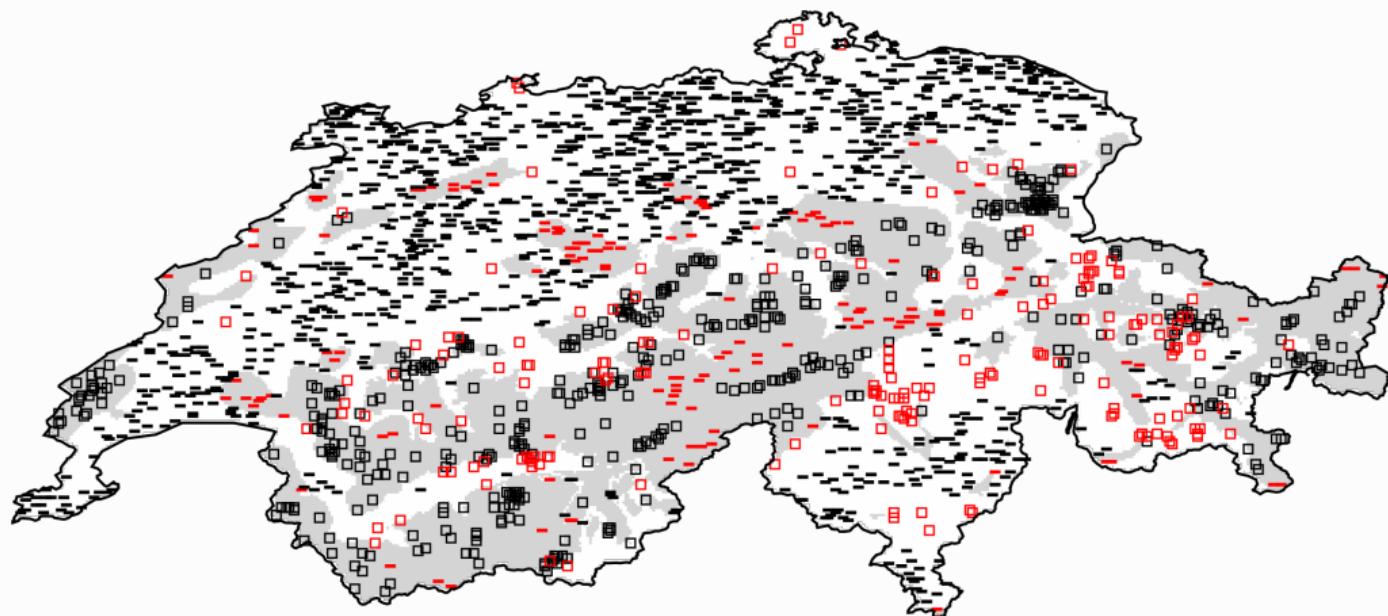
THE MODEL TRAINING PIPELINE

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

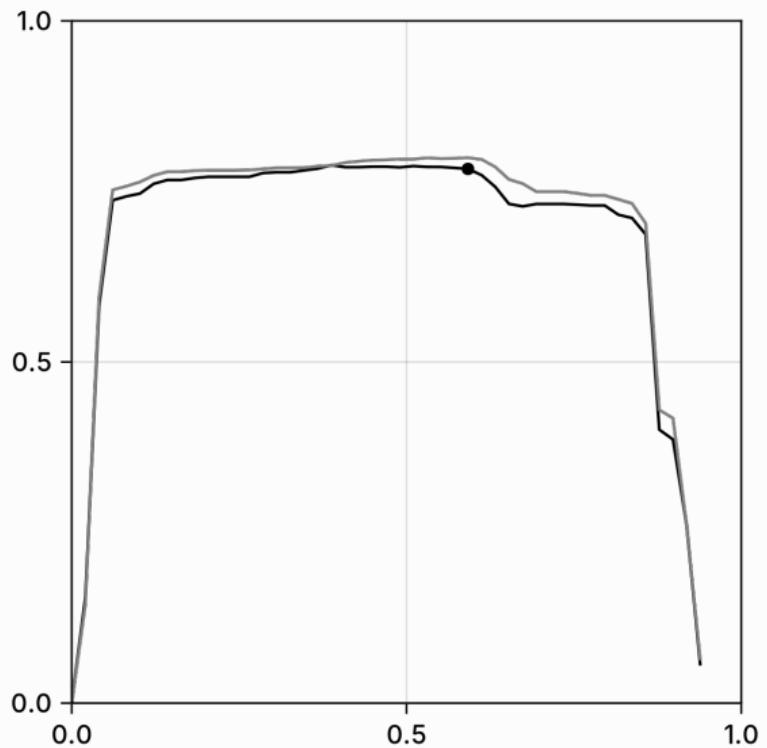
$p_{\text{plus}} > p_{\text{minus}}$ means threshold is 0.5

is it?

how do we check this

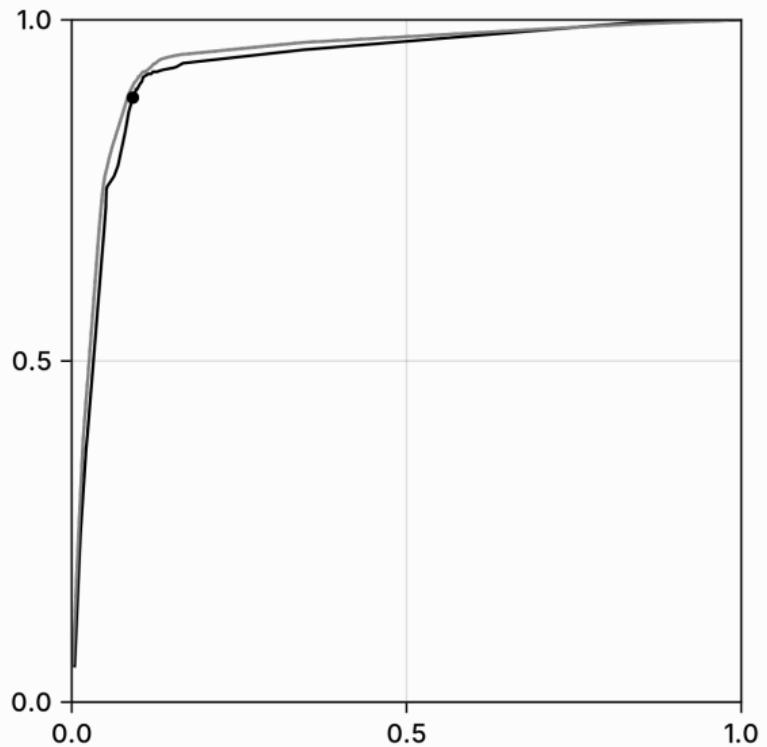


LEARNING CURVE FOR THE THRESHOLD



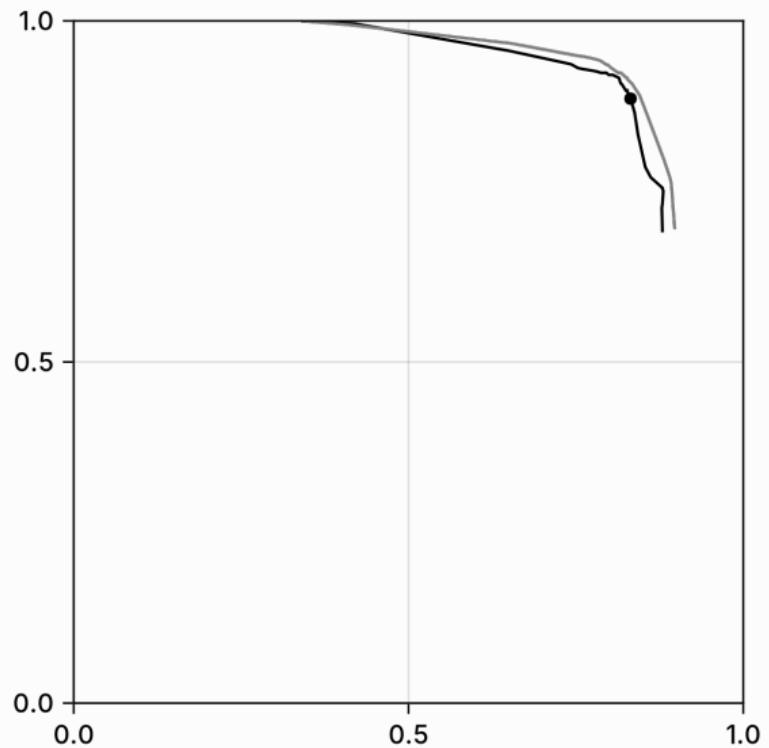


RECEIVER OPERATING CHARACTERISTIC





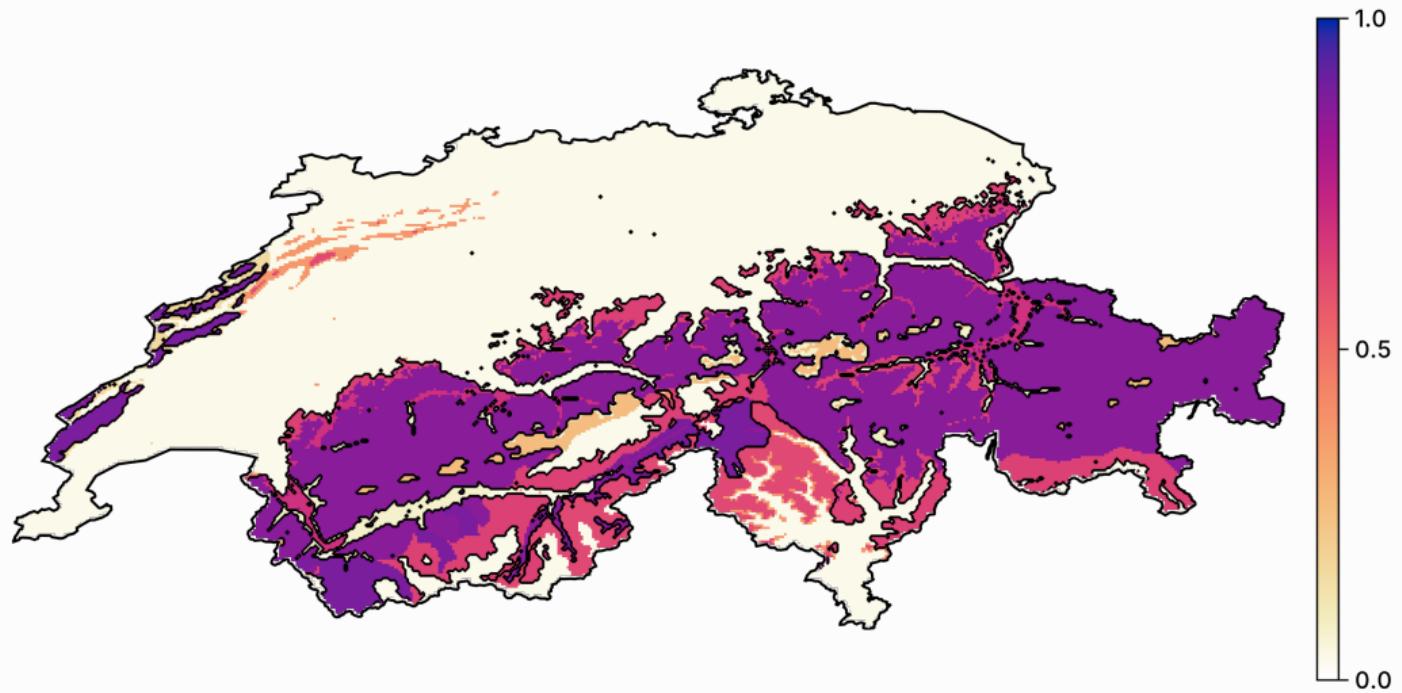
PRECISION-RECALL CURVE



REVISITING THE MODEL PERFORMANCE

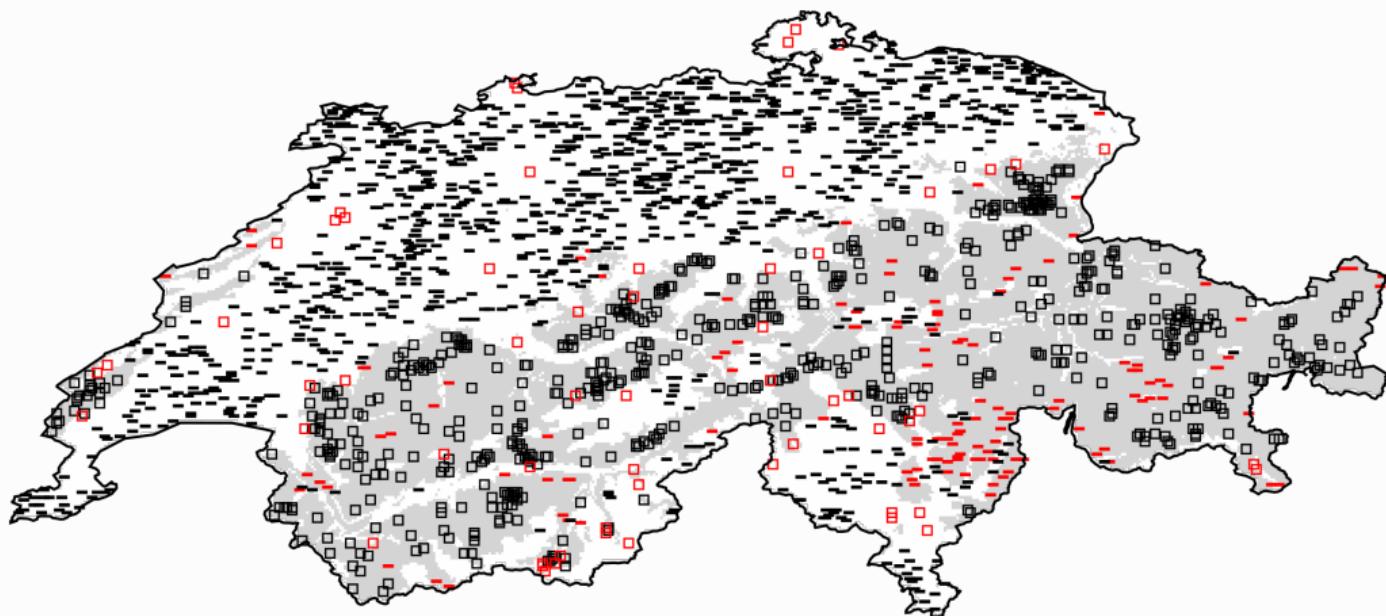
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Coin flip	-0.32	0.34	0.34	0.26	0.34
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-	0.00		0.66		0.66
Validation	0.62	0.76	0.87	23.25	0.83
Training	0.65	0.77	0.88	24.87	0.84
Validation	0.77	0.84	0.93	116.05	0.90
Training	0.79	0.85	0.94	95.70	0.91

 UPDATED PREDICTION





HOW IS THIS MODEL BETTER?





BUT WAIT!

slide on overfitting

§ 3

Ensemble models

LIMITS OF A SINGLE MODEL

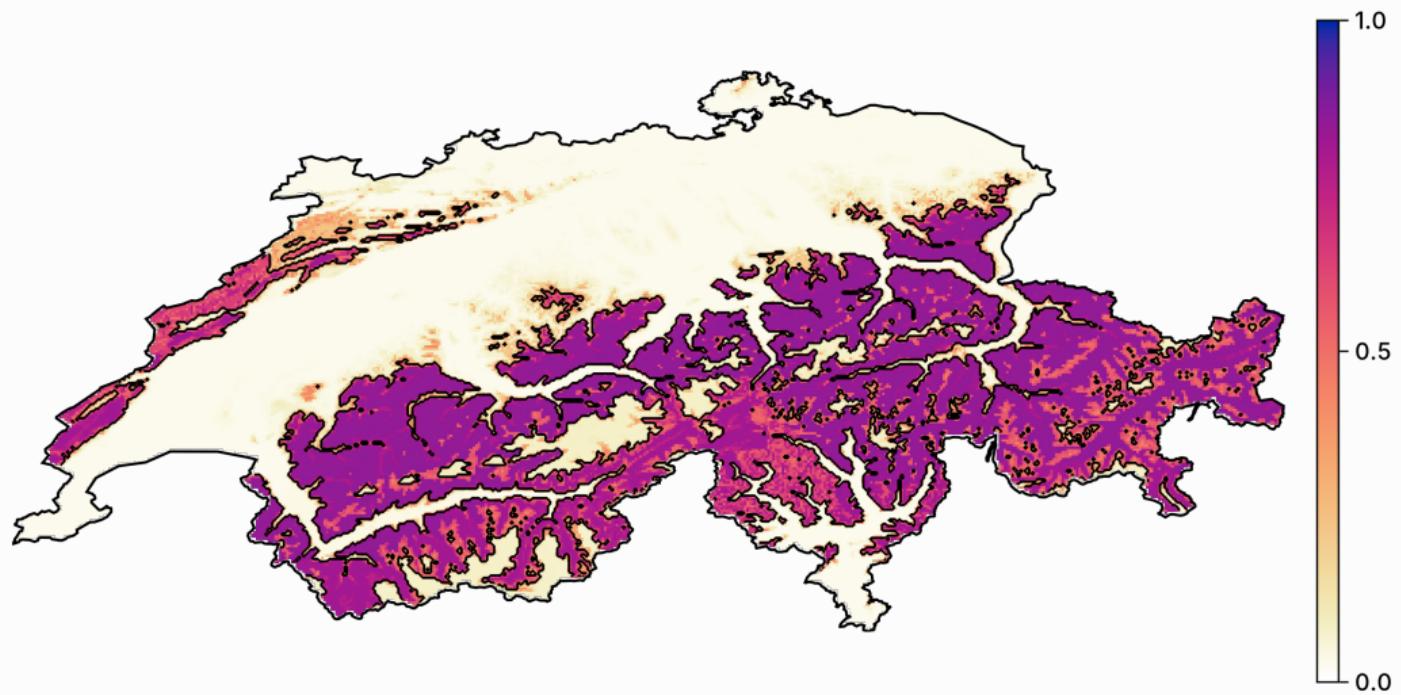
- a single model
- different parts of data may have different signal
- do we need all the variables all the time?
- bias v. variance tradeoff
- limit overfitting



BOOTSTRAPPING AND AGGREGATION



PREDICTION OF THE ROTATION FOREST

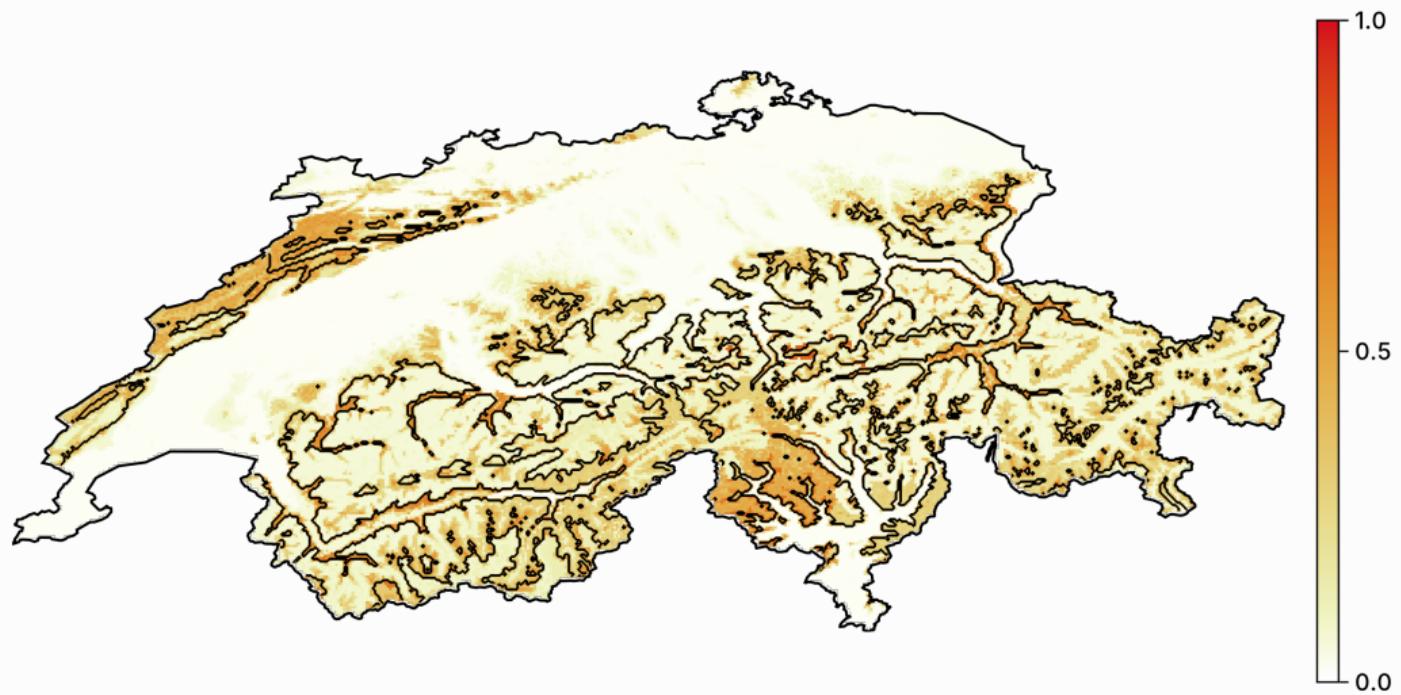




PREDICTION OF THE ROTATION FOREST



UNCERTAINTY





REVISITING ASSUMPTIONS

- pseudo-absences
- not just a statistical exercise



VARIABLE IMPORTANCE

Layer	Variable	Import.
1	BIO1	0.790935
10	BIO10	0.138616
8	BIO8	0.0557785
29	Snow/Ice	0.00755729
24	Shrubs	0.00616345
27	Regularly Flooded Vegetation	0.000949339

§ 4

But why?



INTRO EXPLAINABLE



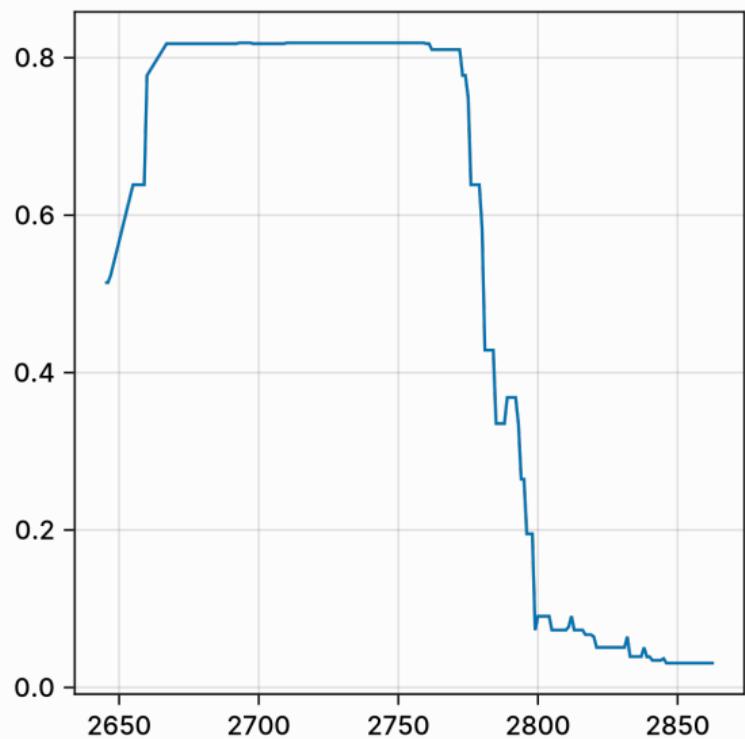
PARTIAL RESPONSE CURVES

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

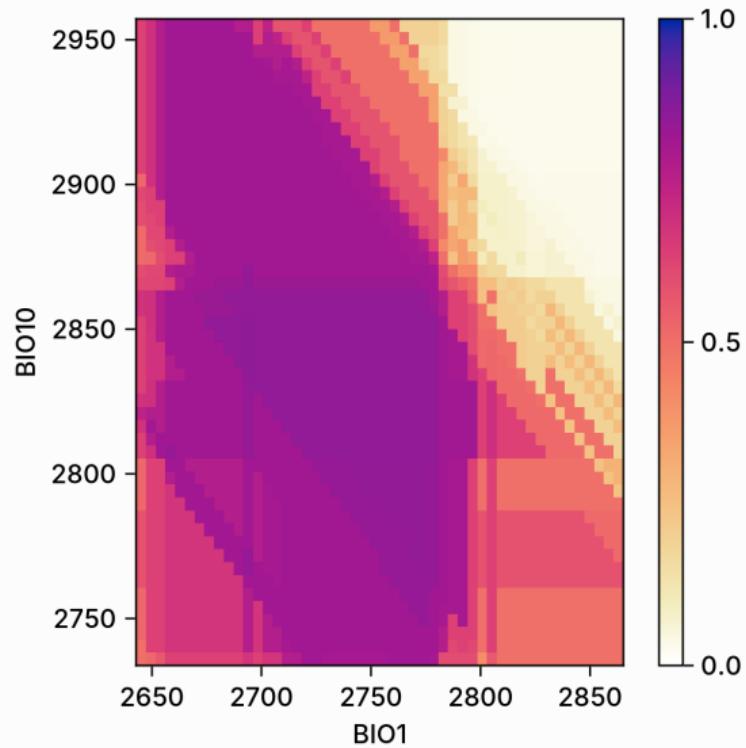


EXAMPLE WITH TEMPERATURE



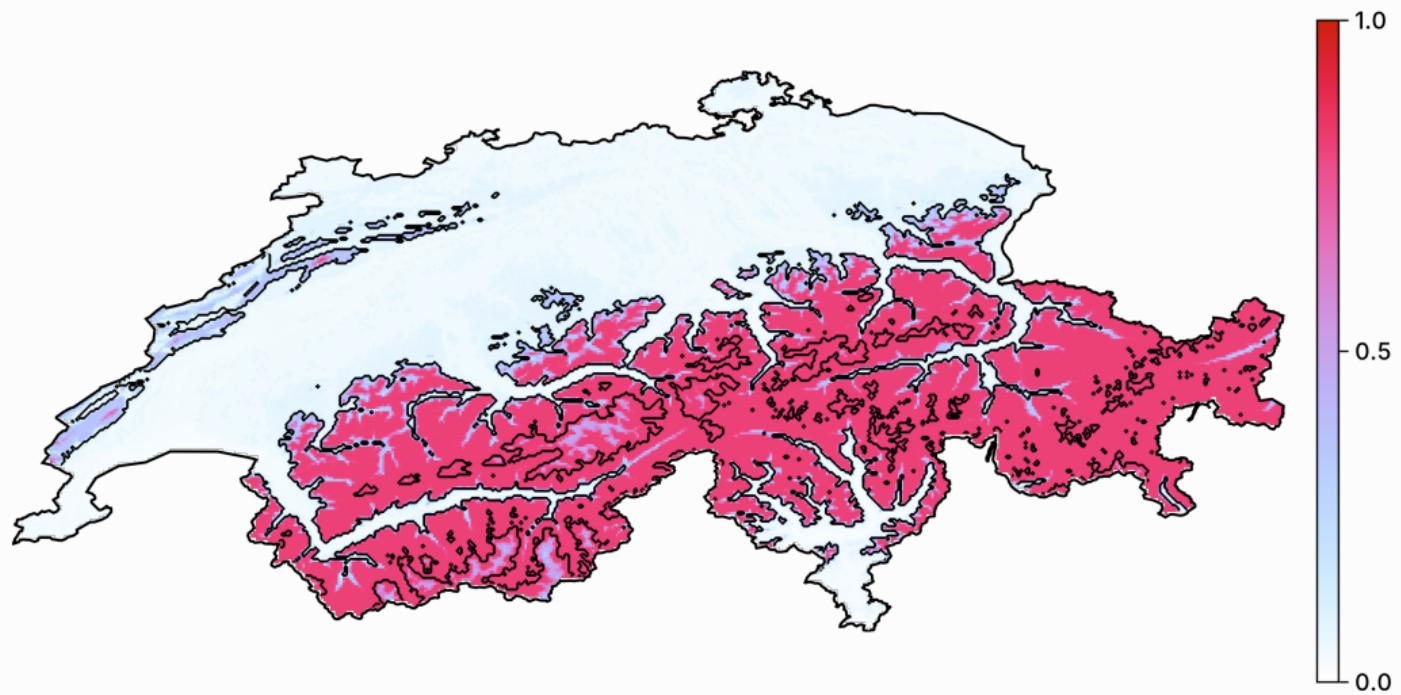


EXAMPLE WITH TWO VARIABLES



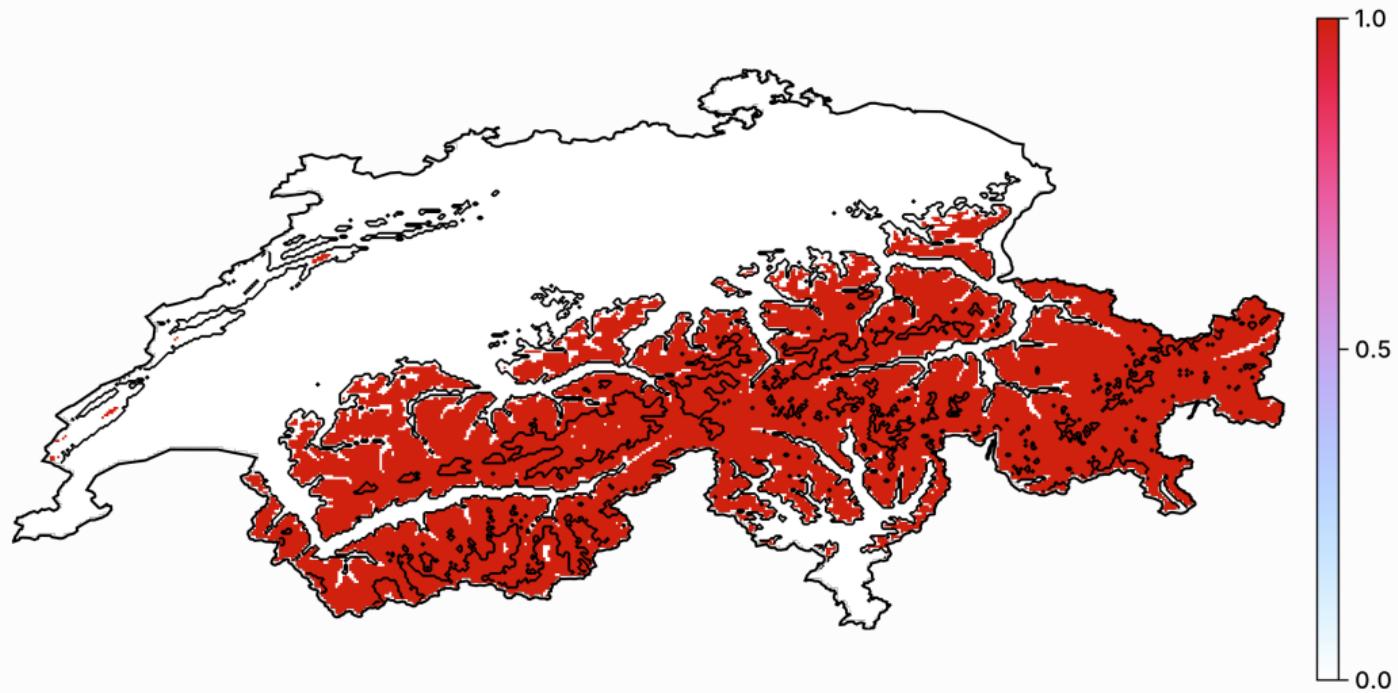


SPATIALIZED PARTIAL RESPONSE PLOT





SPATIALIZED PARTIAL RESPONSE (BINARY OUTCOME)



INFLATED RESPONSE CURVES

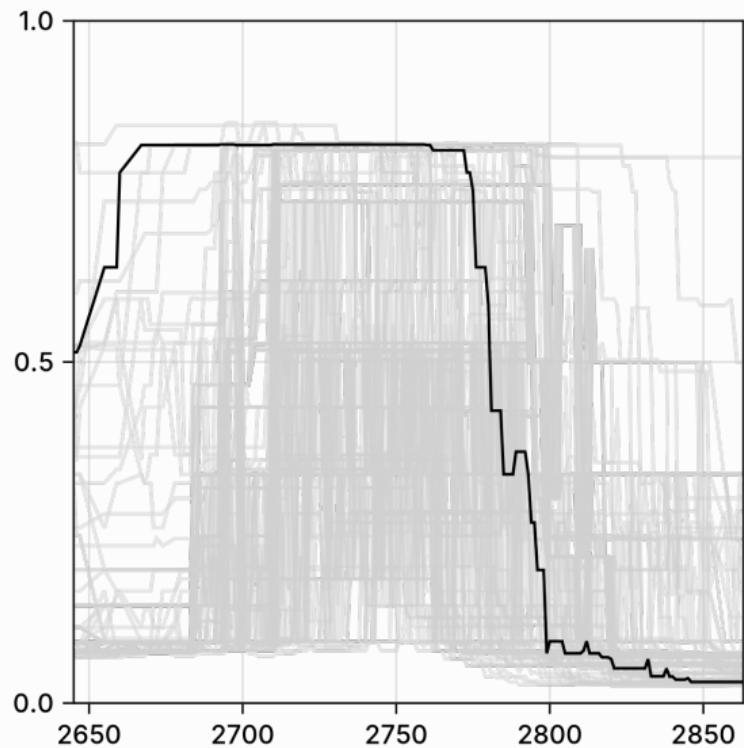
Averaging the variables is **masking a lot of variability!**

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

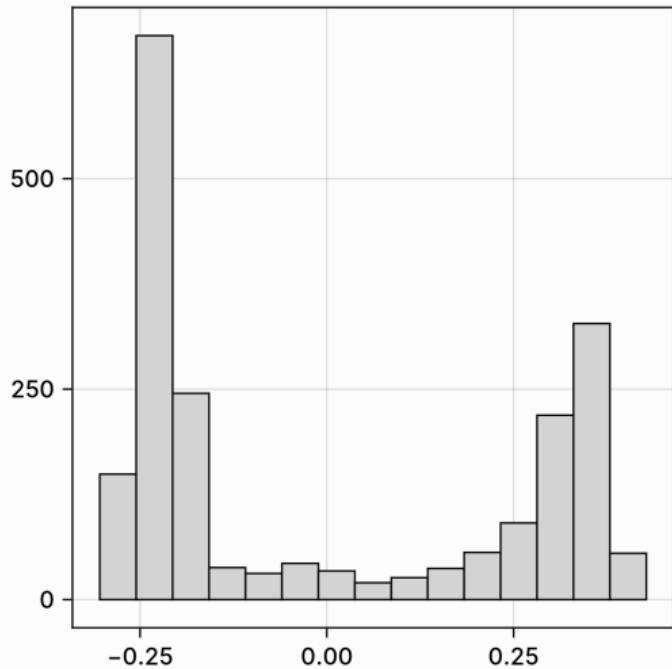
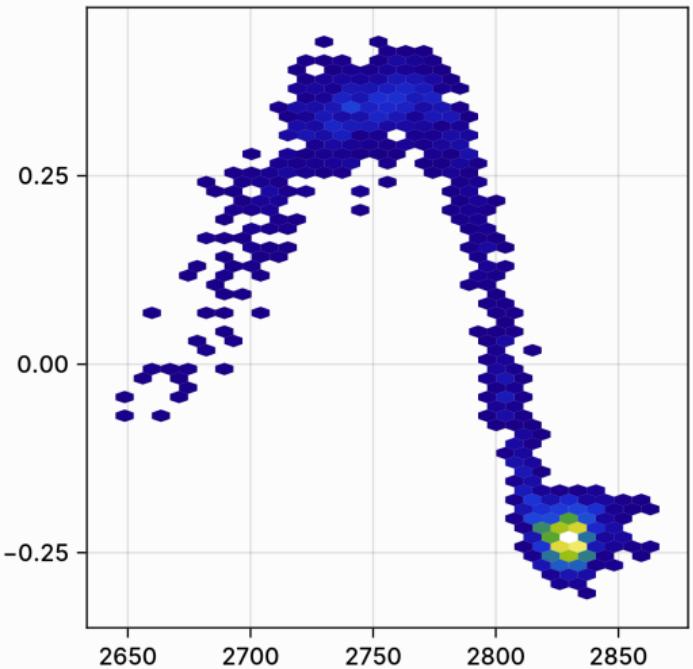




EXAMPLE



RESPONSE CURVES REVISITED



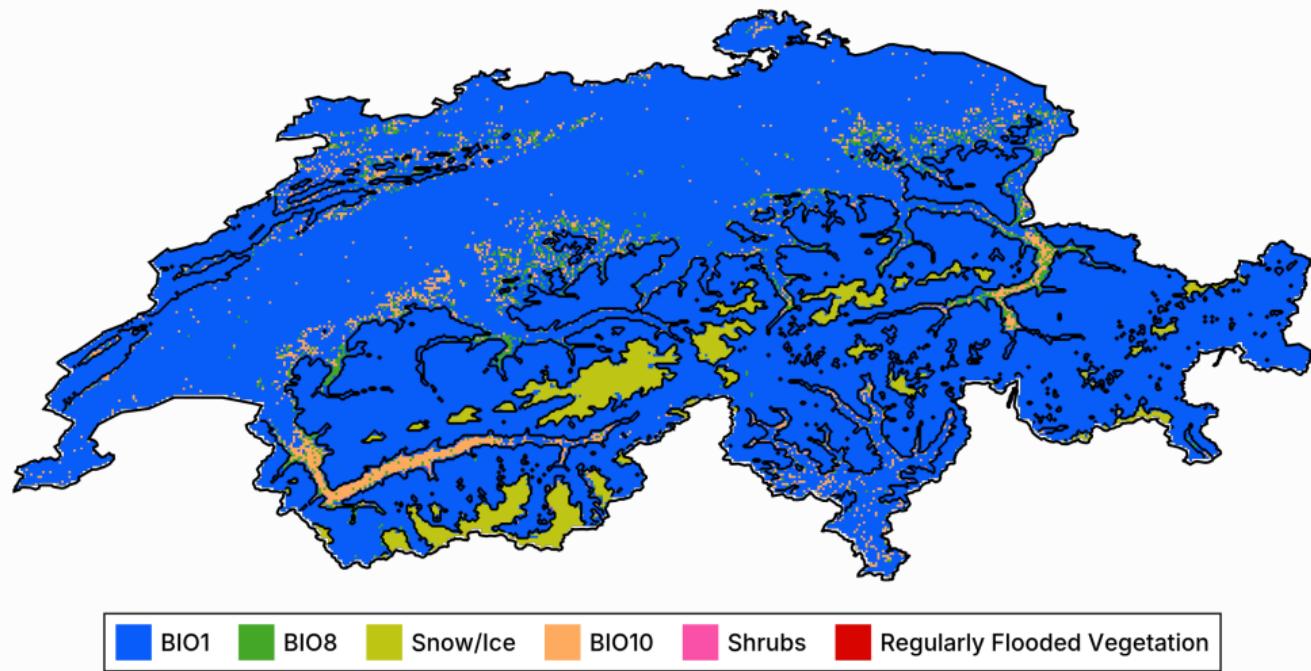
ON A MAP



VARIABLE IMPORTANCE REVISITED

Layer	Variable	Import.	Shap. imp.
1	BIO1	0.790935	0.576689
10	BIO10	0.138616	0.253547
8	BIO8	0.0557785	0.104797
29	Snow/Ice	0.00755729	0.0460891
24	Shrubs	0.00616345	0.017193
27	Regularly Flooded Vegetation	0.000949339	0.00168559

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

§ 5

What if?



INTRO TO COUNTERFACTUALS

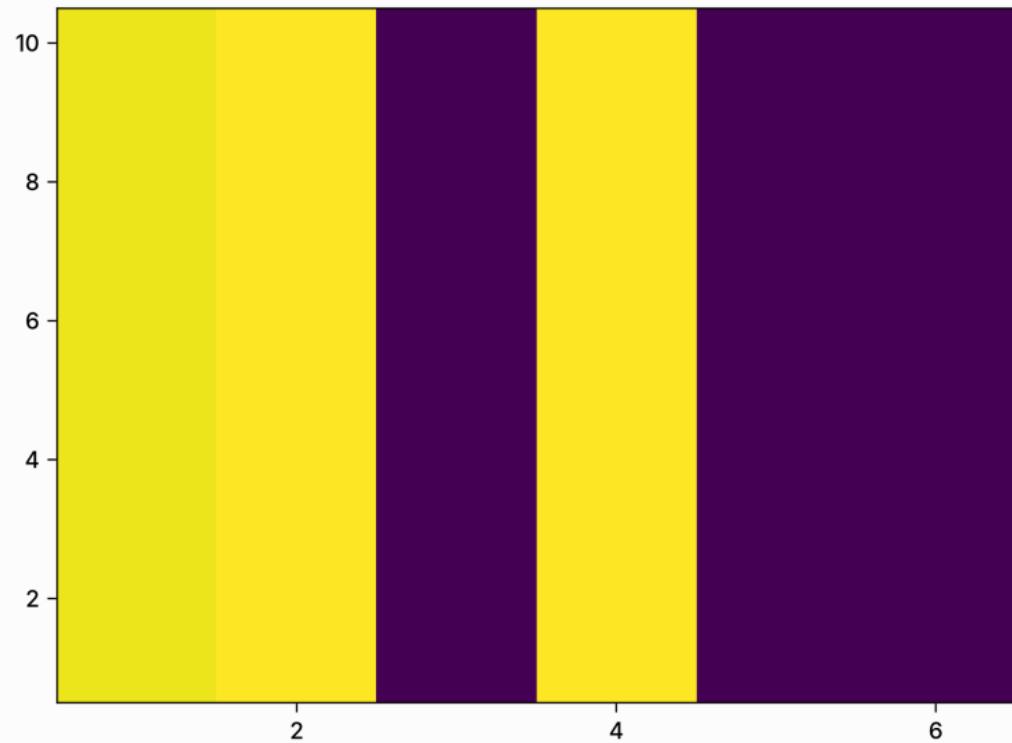
what they are



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

§ 6

Conclusions



