Predicting into unknown space?
Estimating the area of applicability of spatial prediction models

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Problem: Moving from field observations to maps of ecosystem variables

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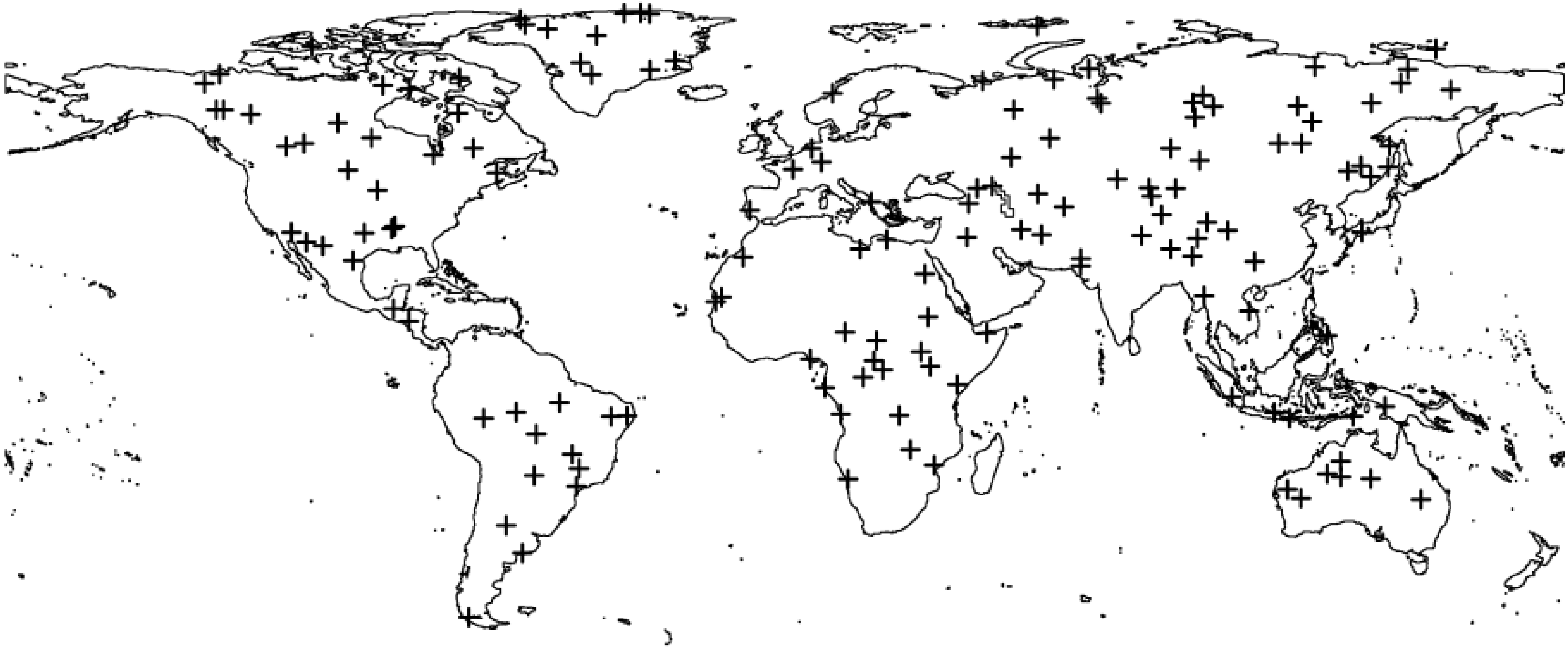

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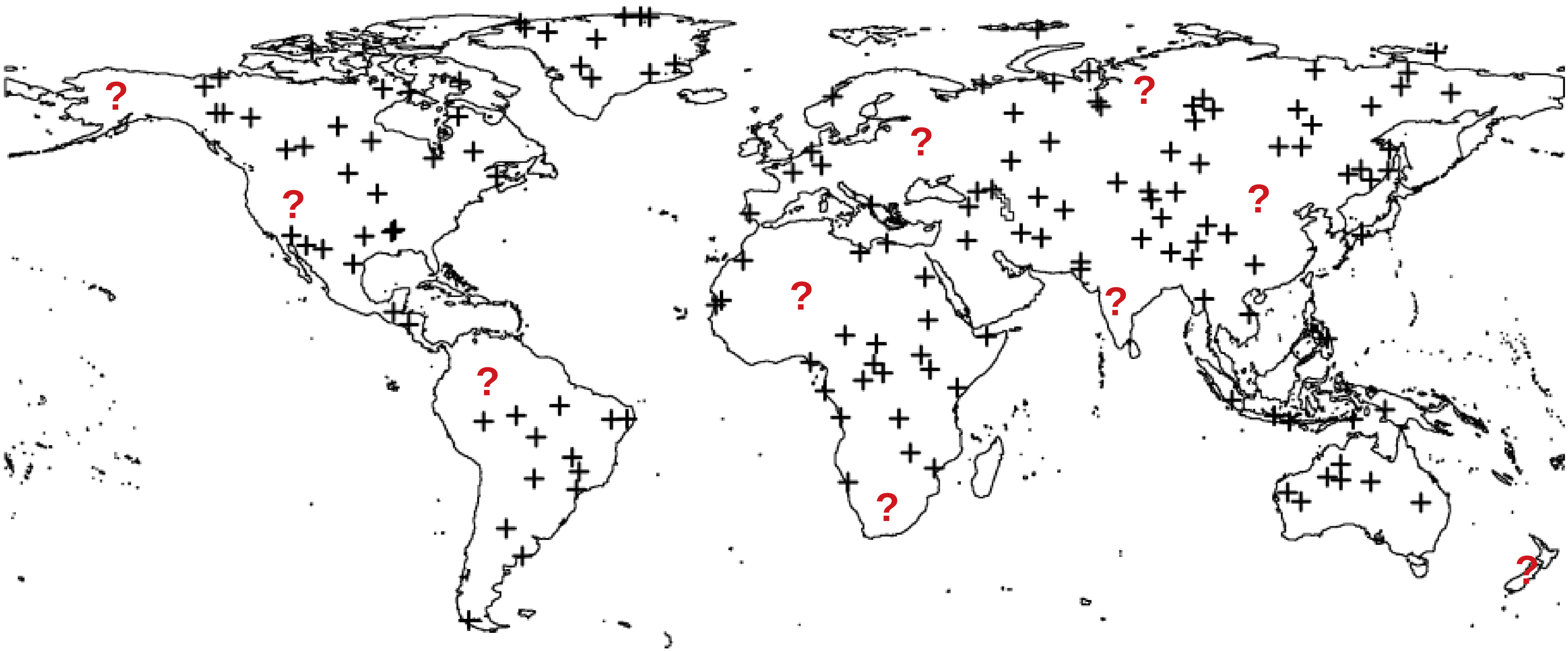
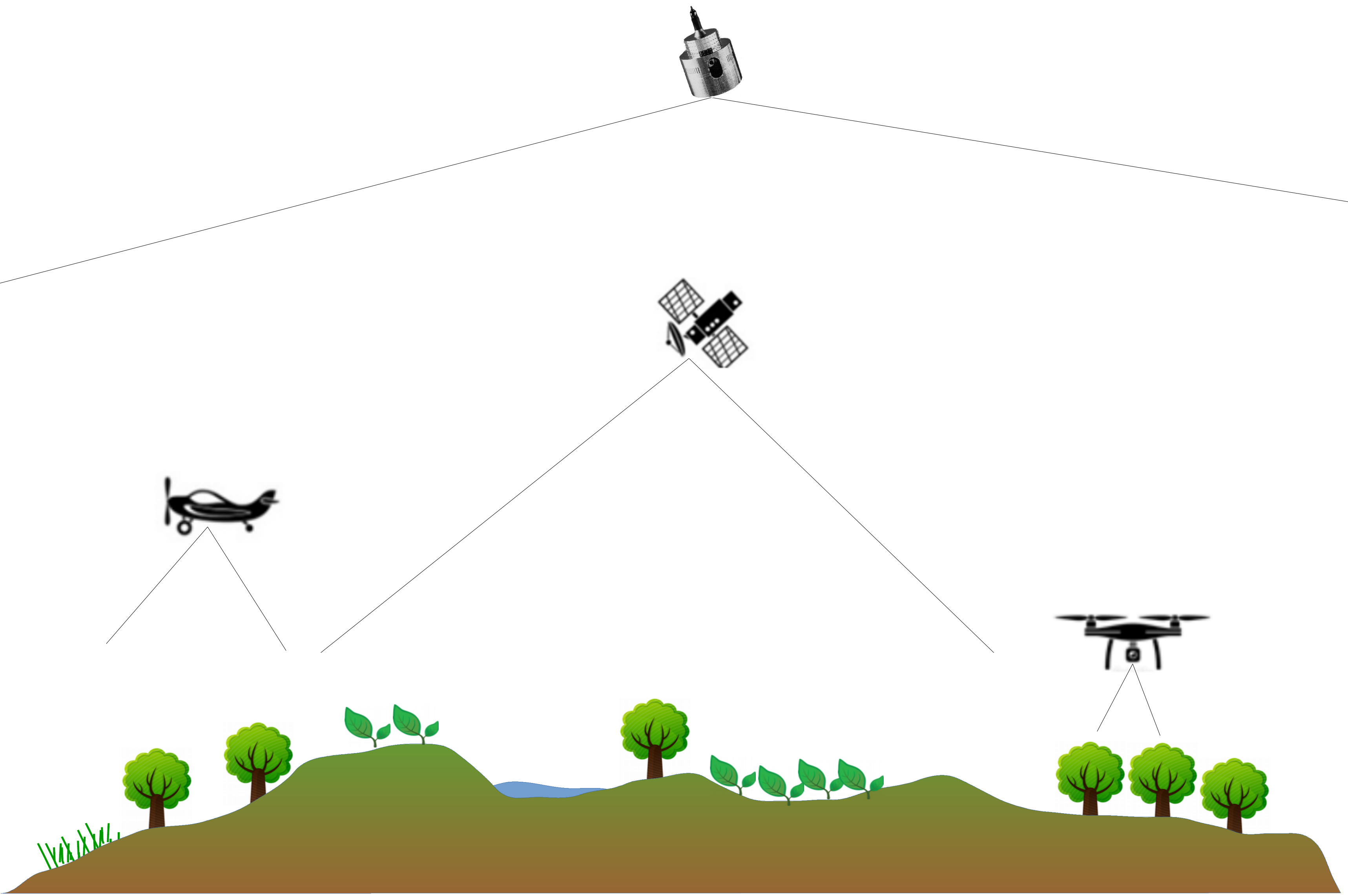
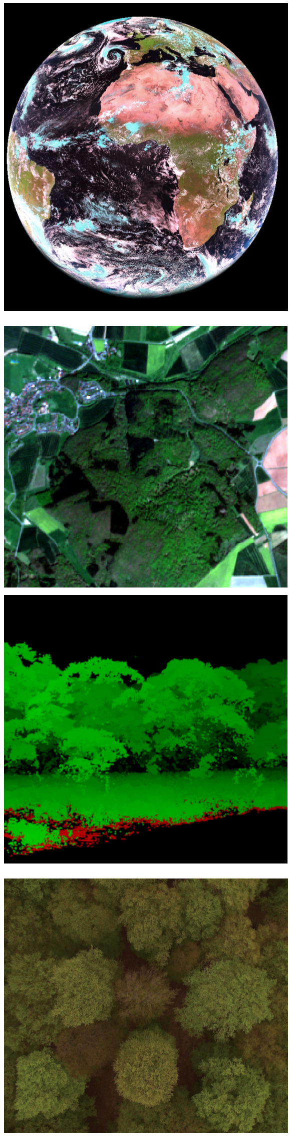


How do we fill the gaps between sampling locations?

Remote Sensing of landscapes





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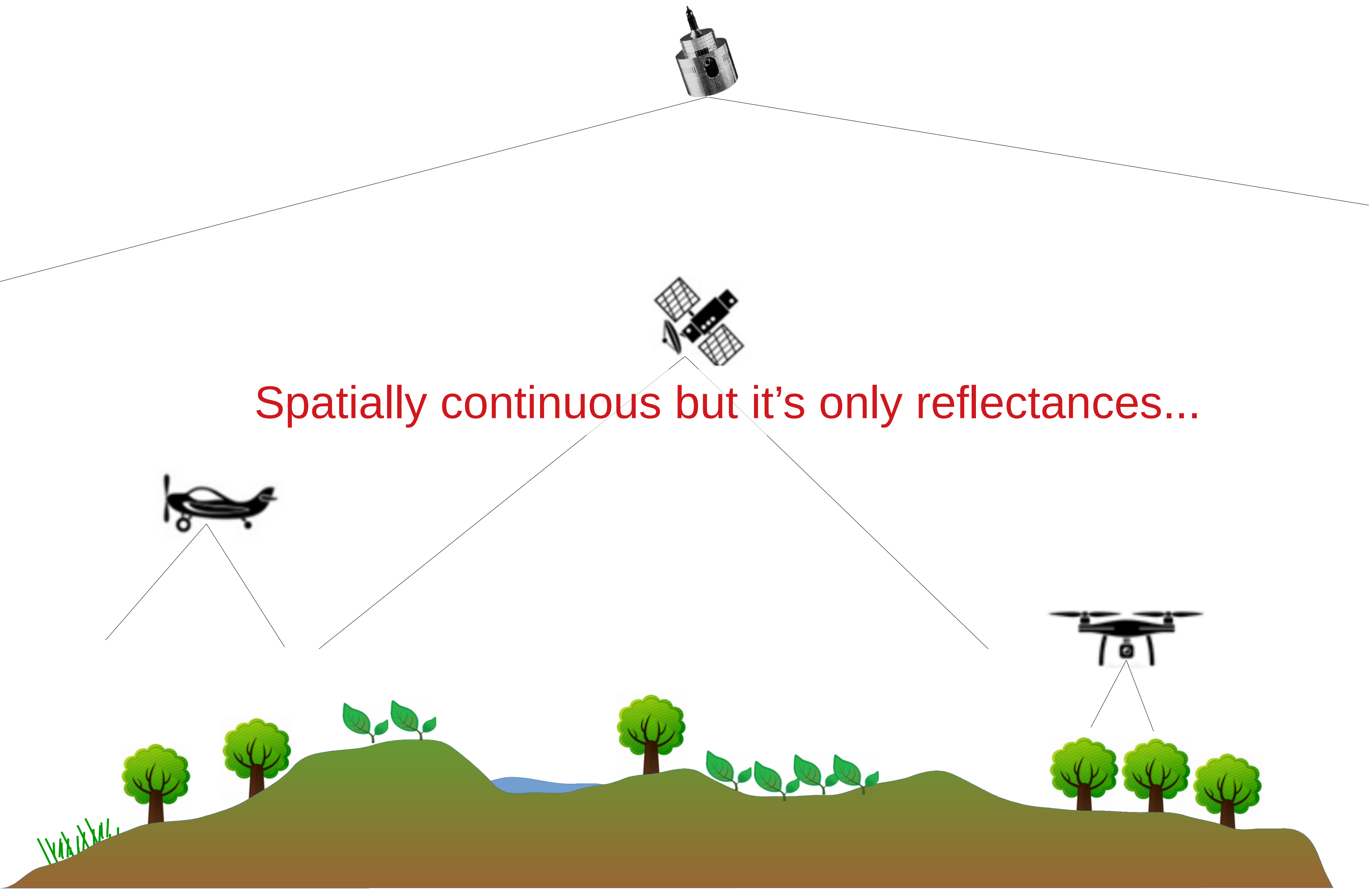
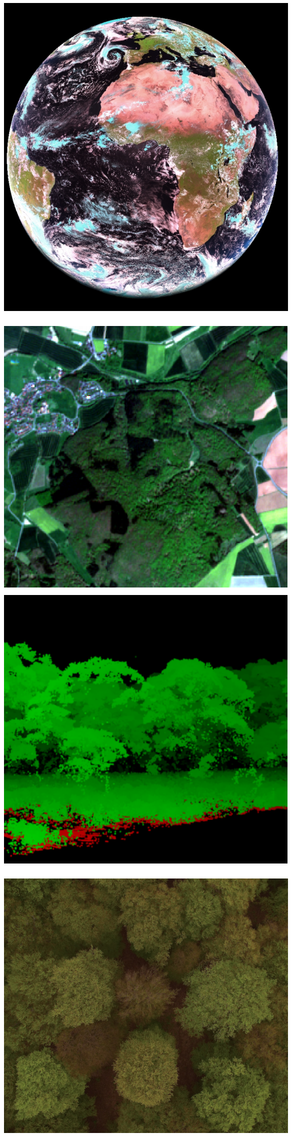


Spatially continuous but it's only reflectances...



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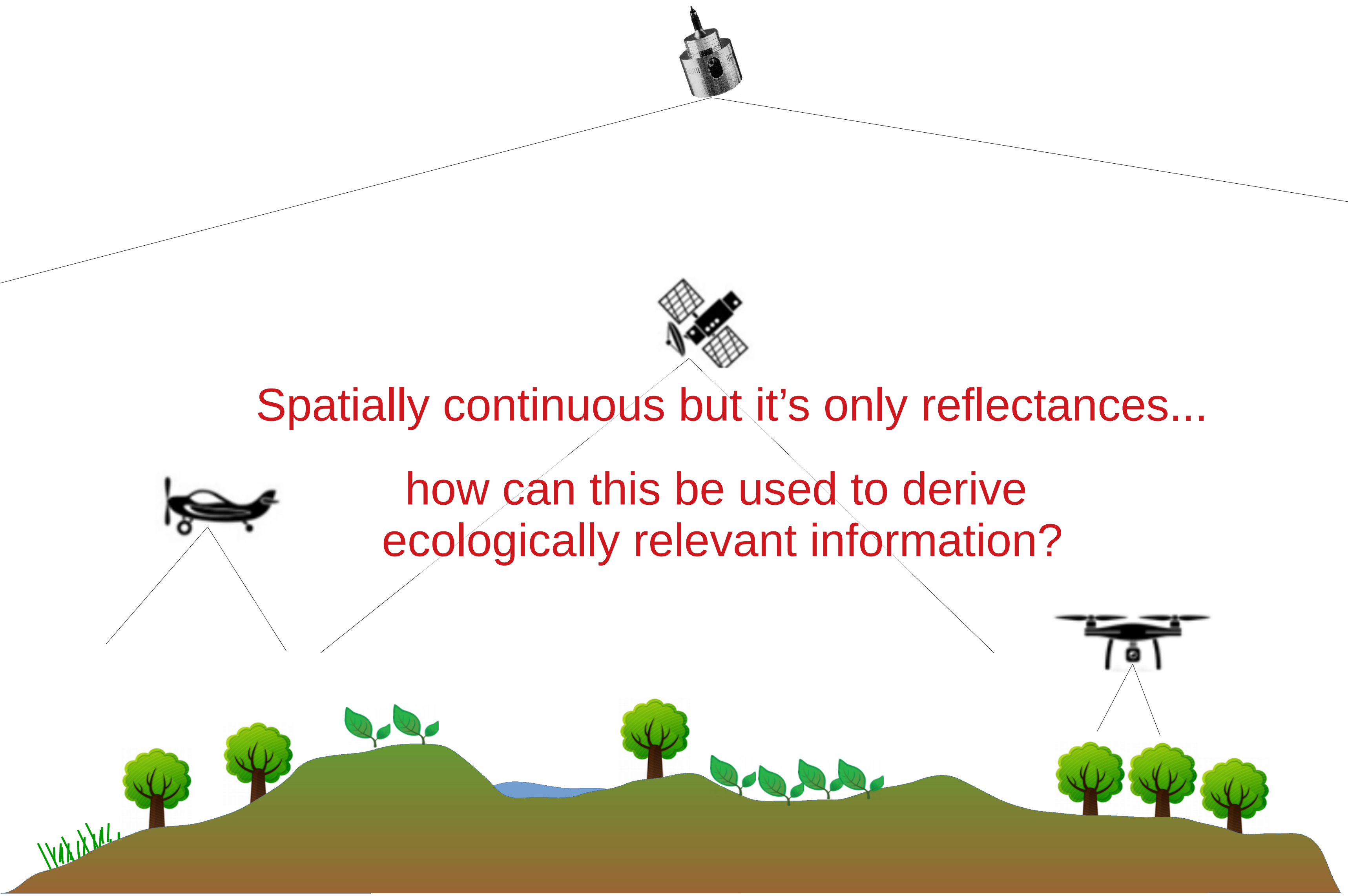
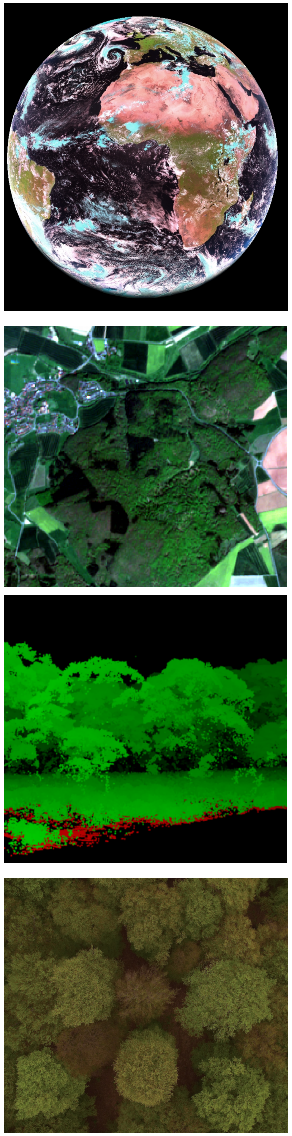
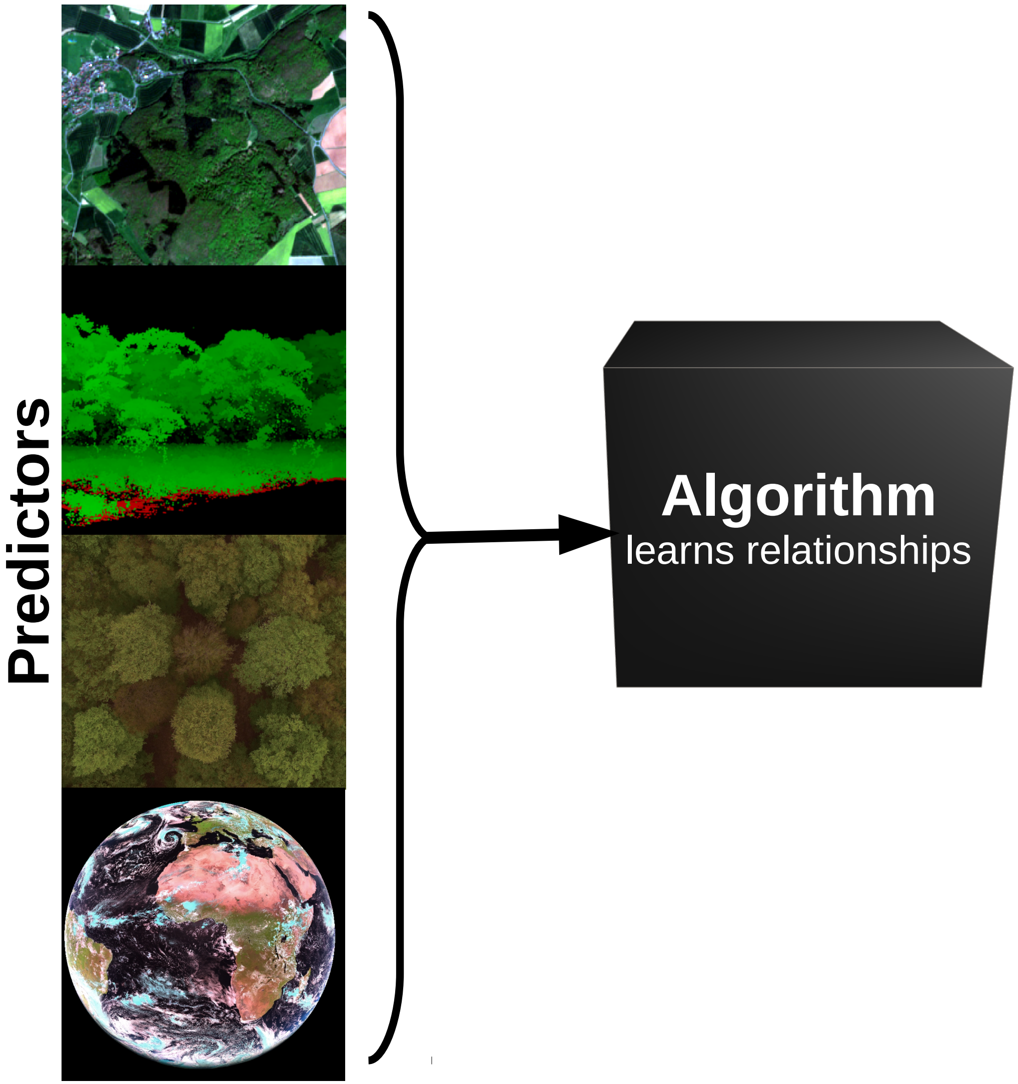


Spatially continuous but it’s only reflectances...

how can this be used to derive
ecologically relevant information?



Predictive modelling of the environment: The machine learning way



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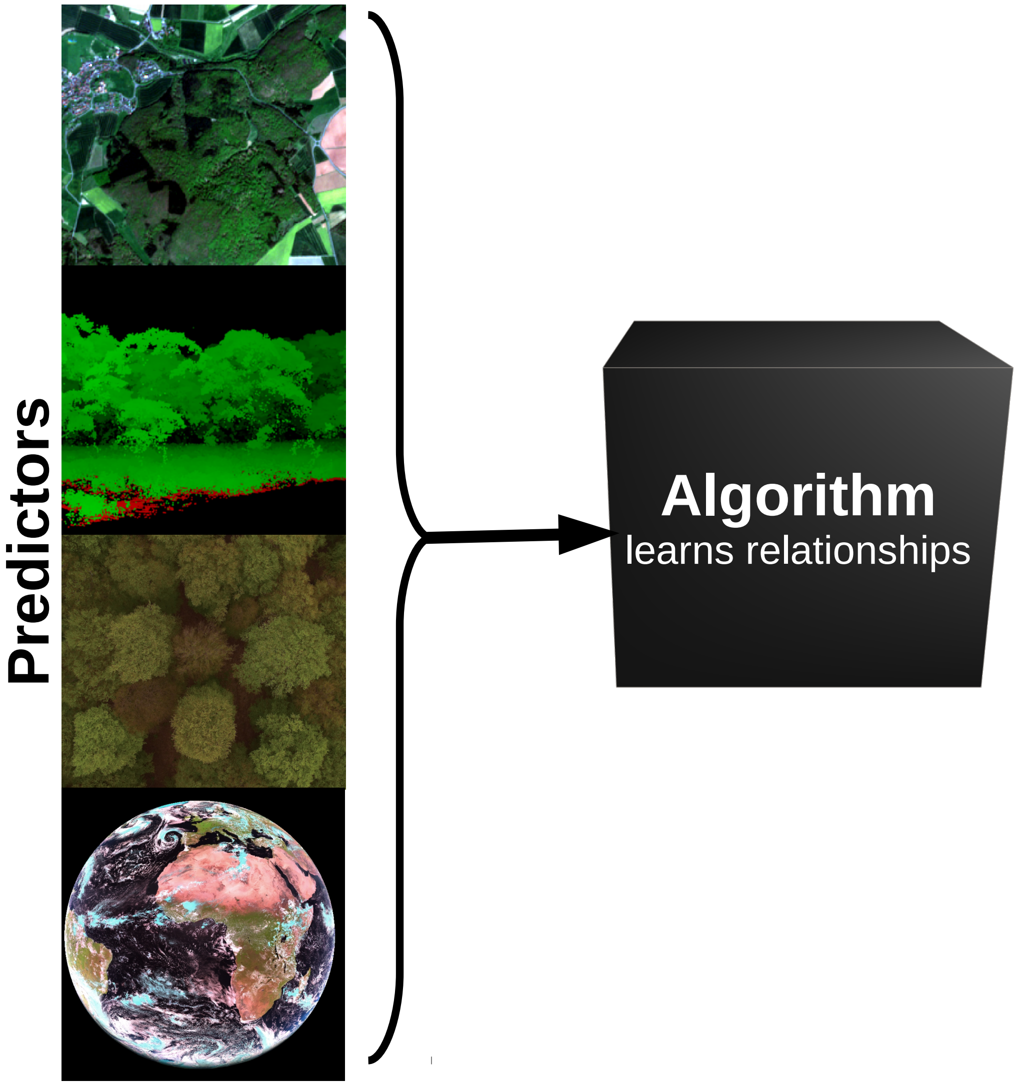

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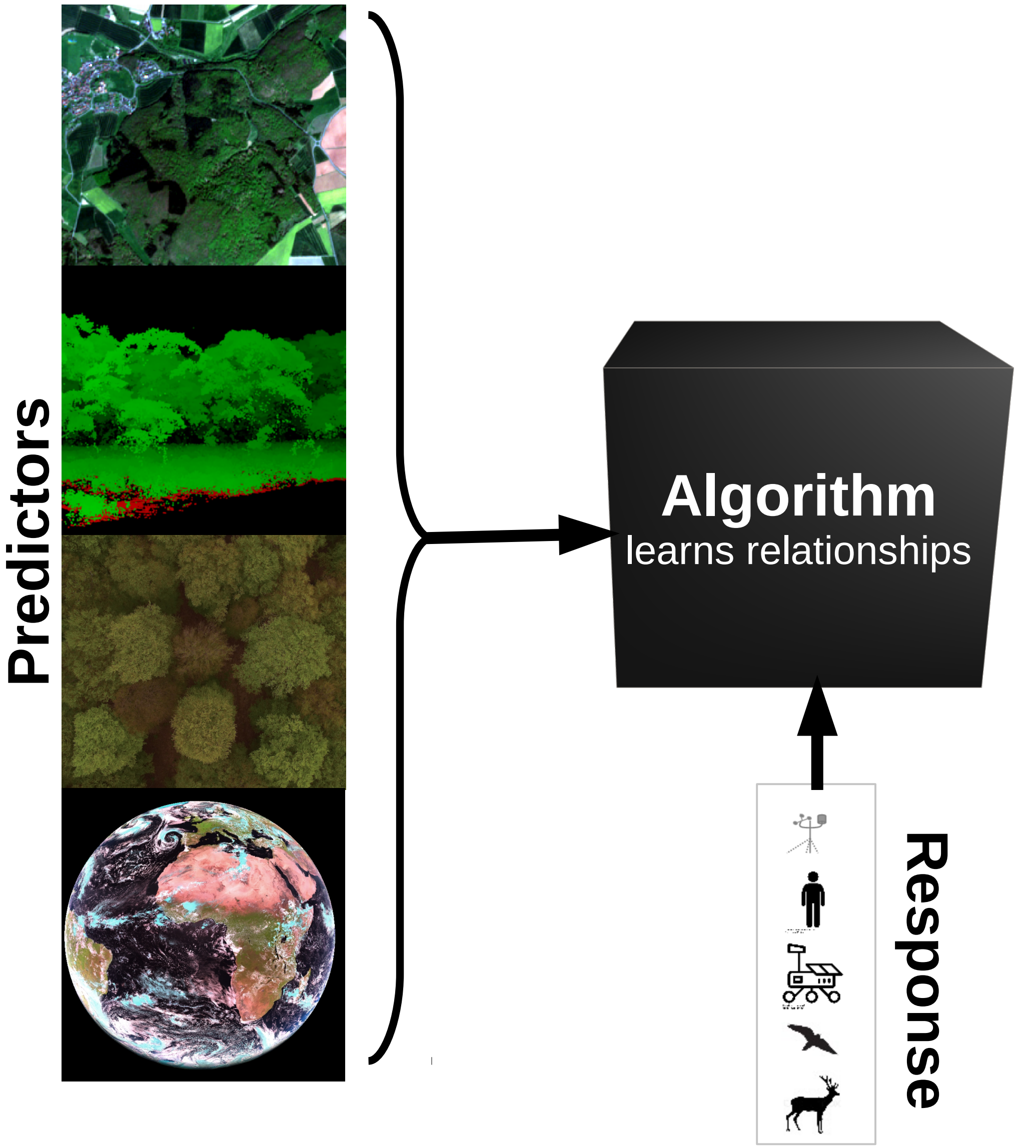

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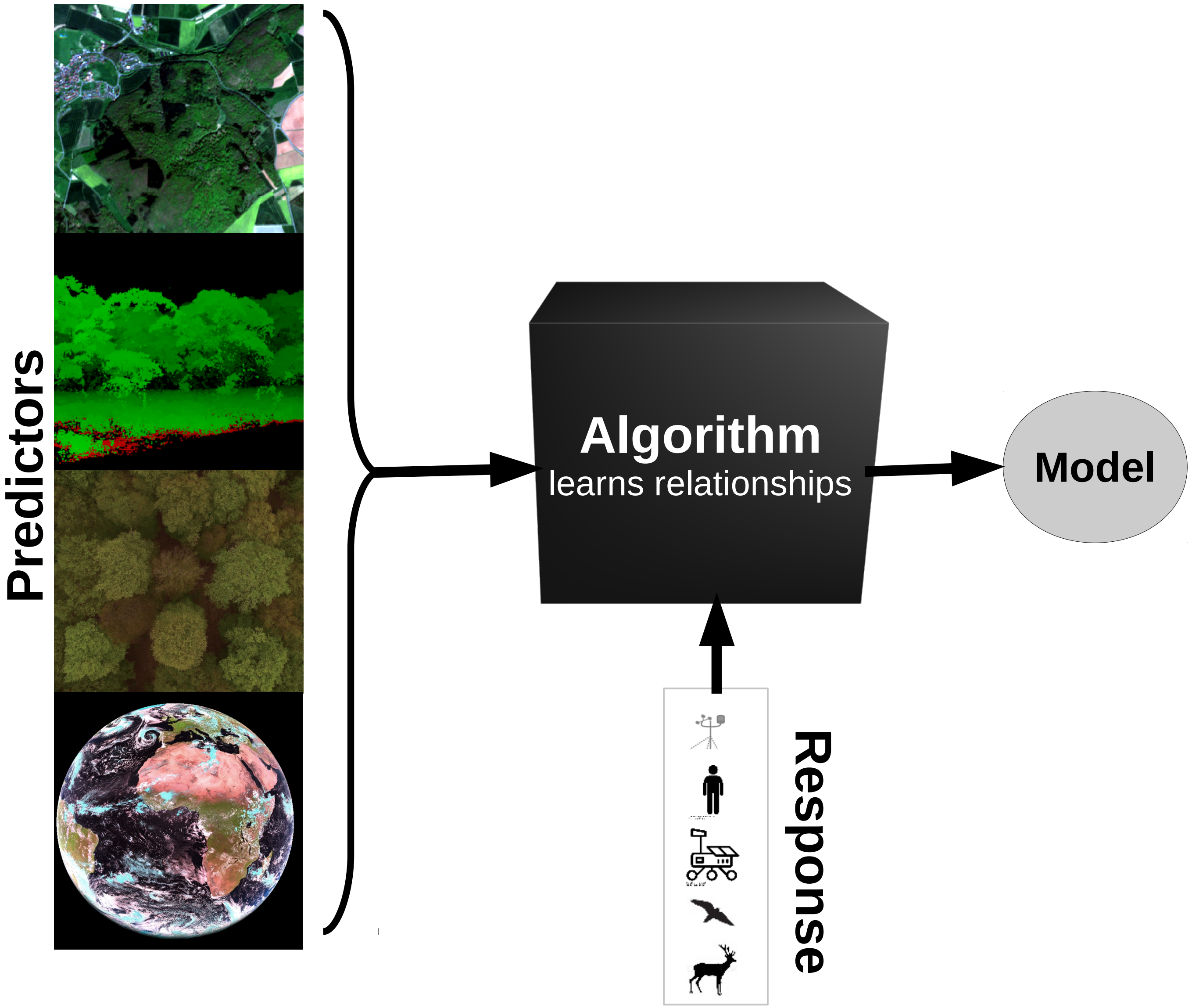

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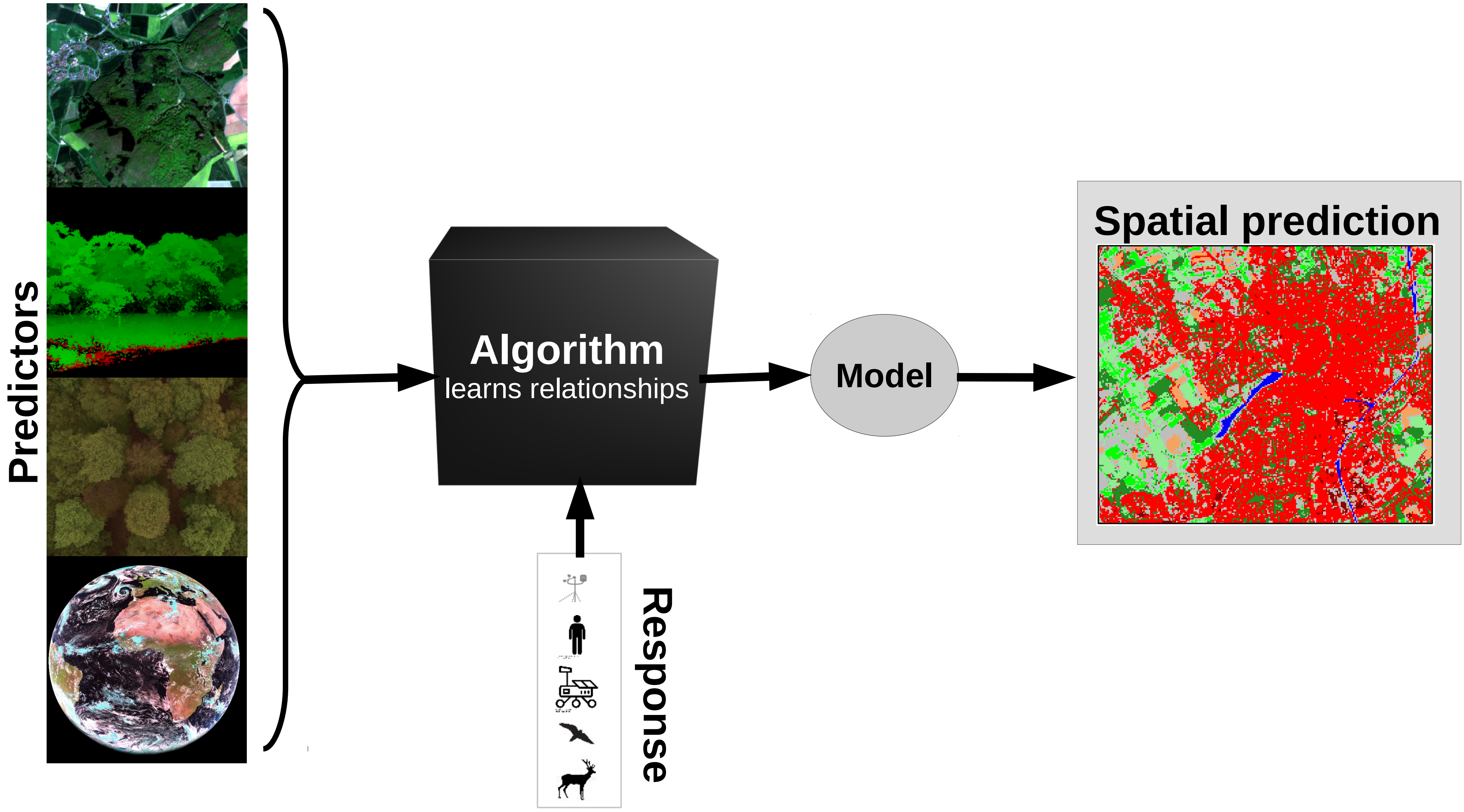
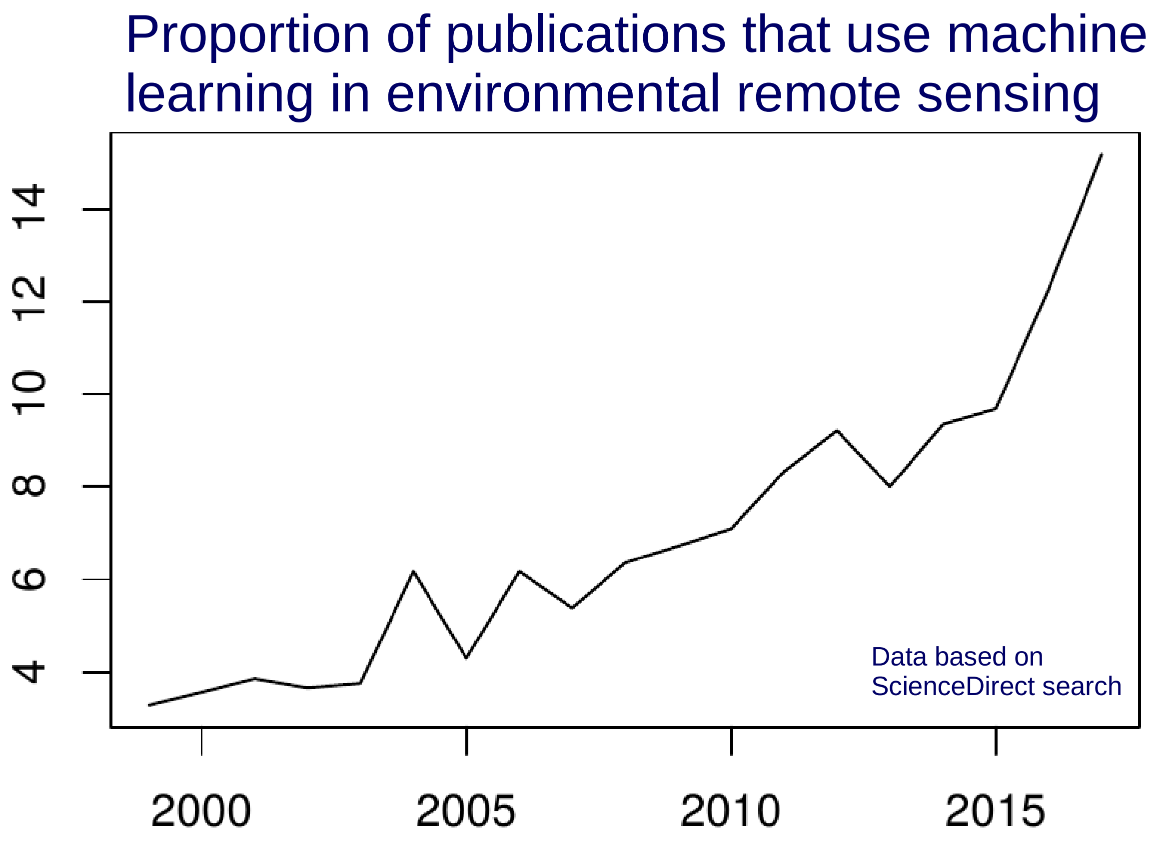
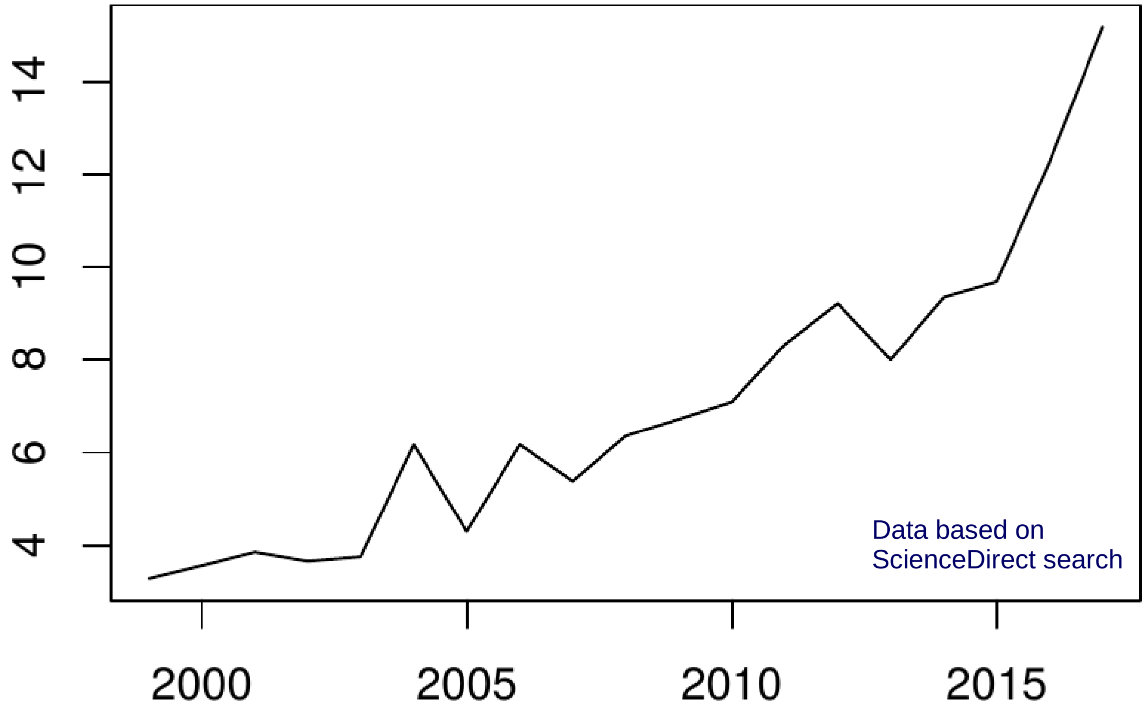


Global maps of ecosystem variables based on machine learning



Global maps of ecosystem variables based on machine learning

Proportion of publications that use machine learning in environmental remote sensing



Including **global** datasets on
- soil properties
- abundances of microorganisms
- Biodiversity
- tree restoration potential
- ...and many more

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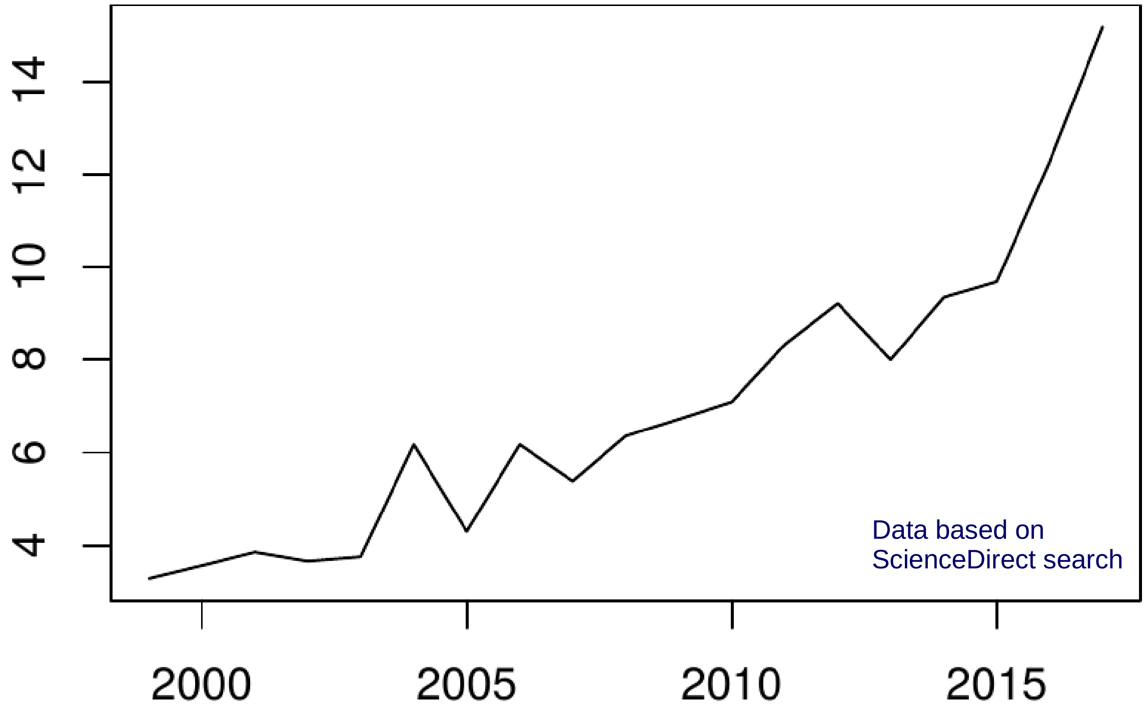

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Machine learning as a „magic tool“ to map basically everything ?

...but there are increasingly doubts about the methods

Wissenschaft

Wenn die KI daneben liegt

Welche Fehler drohen, wenn Forscher Wissenslücken per Computer schließen wollen, zeigen zwei aktuelle Klimastudien.

Von **Tin Fischer**

6. November 2019, 16:44 Uhr / Editiert am 9. November 2019, 17:42 Uhr / DIE ZEIT Nr. 46/2019, 7. November 2019 / 9 Kommentare

AUS DER ZEIT NR. 46/2019

DEEP TROUBLE FOR DEEP LEARNING

BY DOUGLAS HEAVEN

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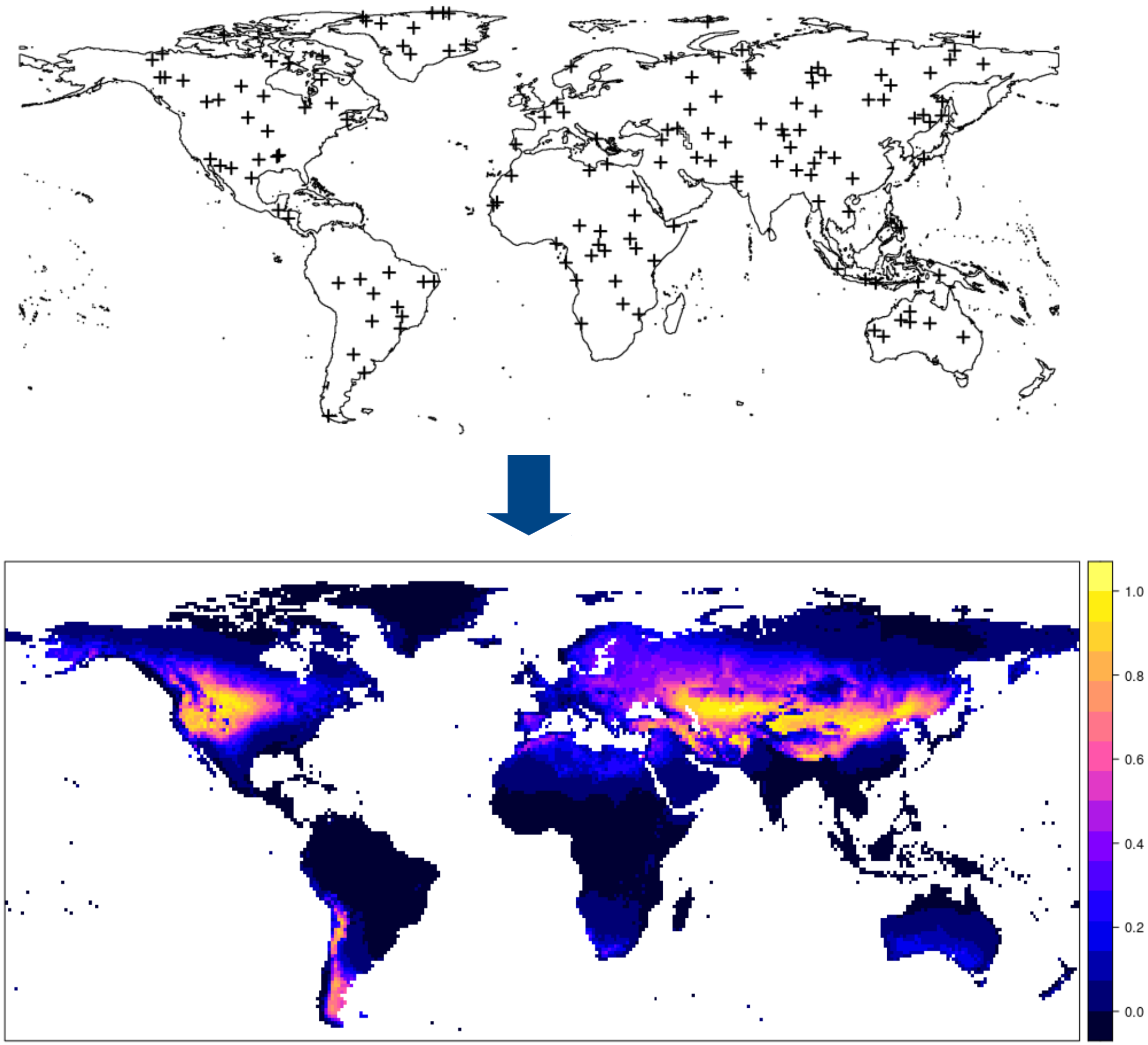
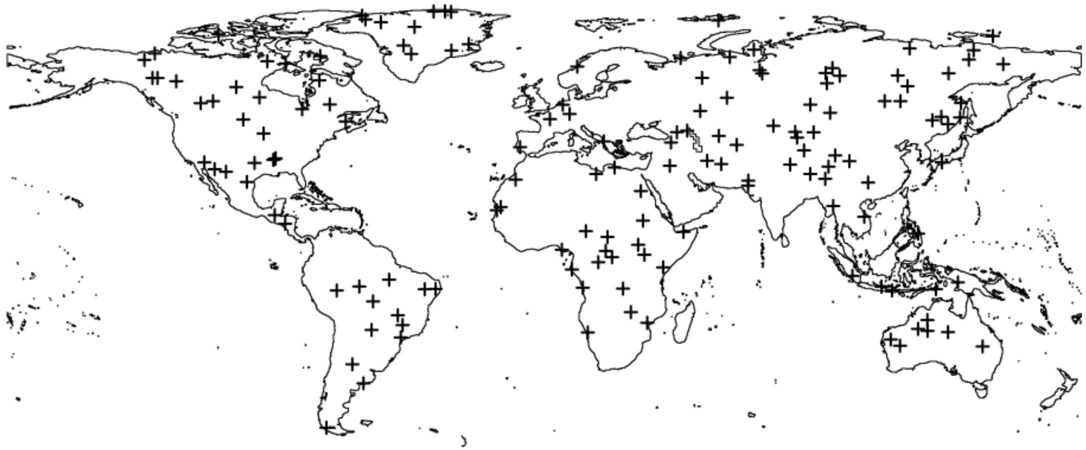
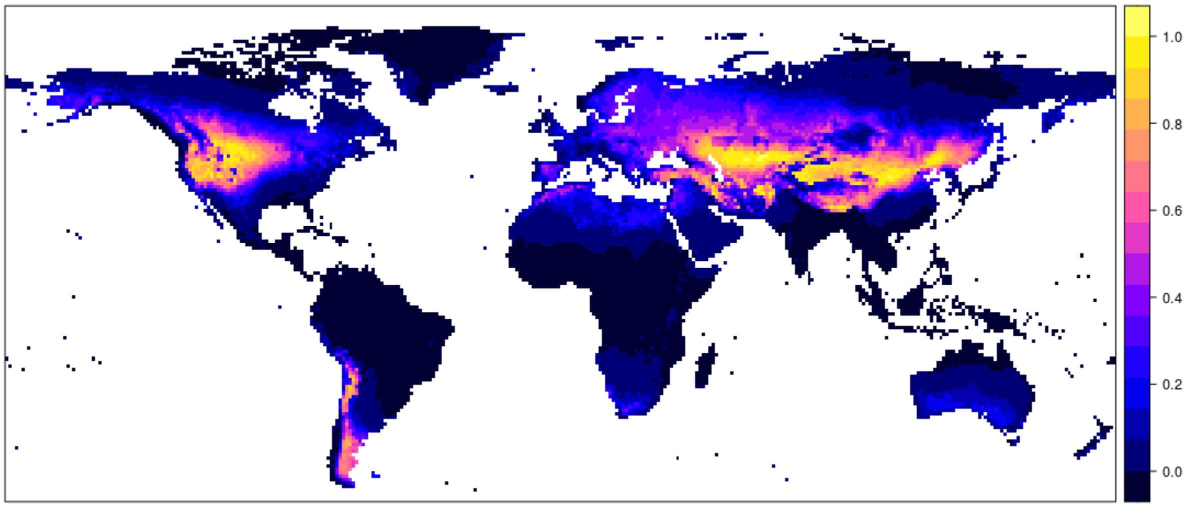
Have we been too ambitious? Why might the models fail?

Largest challenge: predictions far beyond training samples



Largest challenge: predictions far beyond training samples





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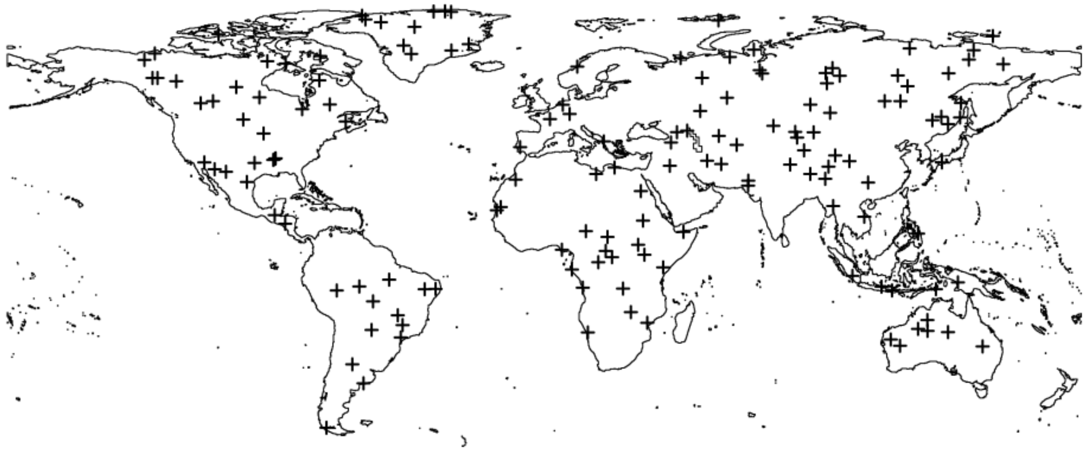

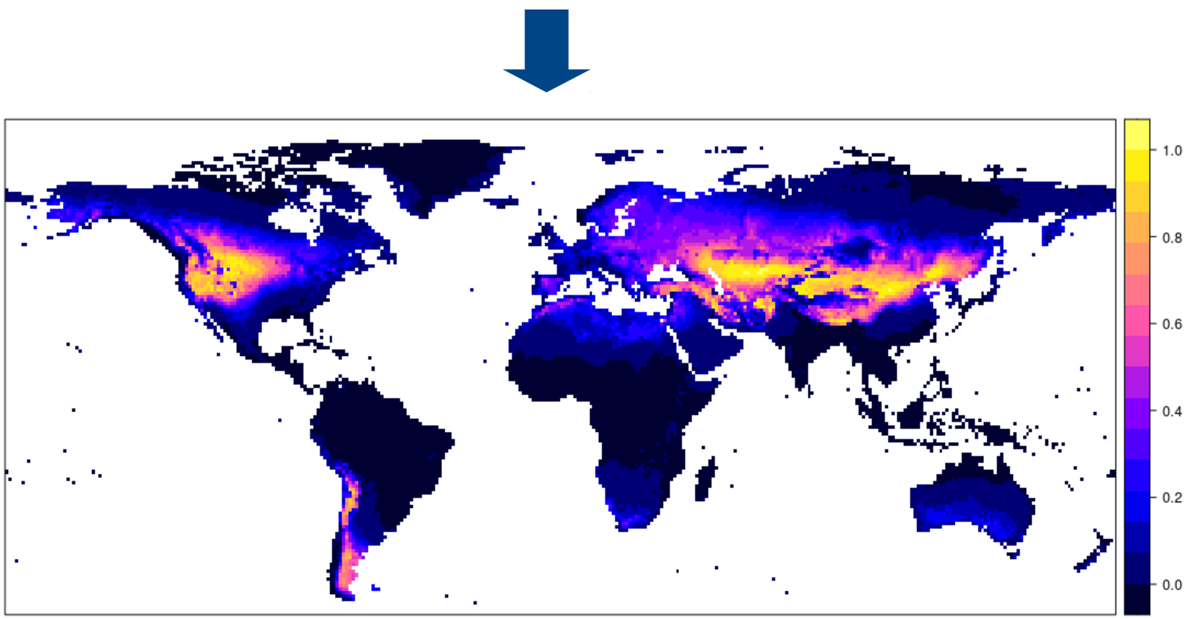

- Transfer to new space required

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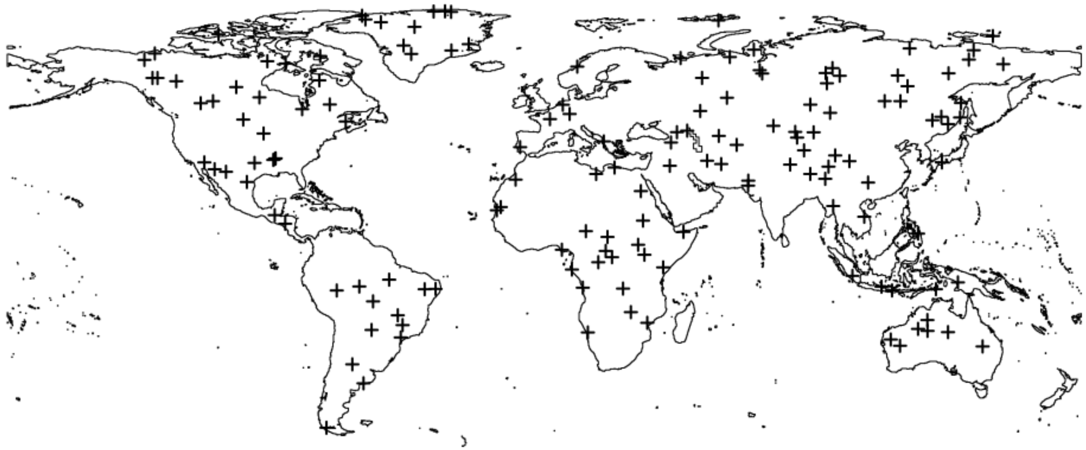
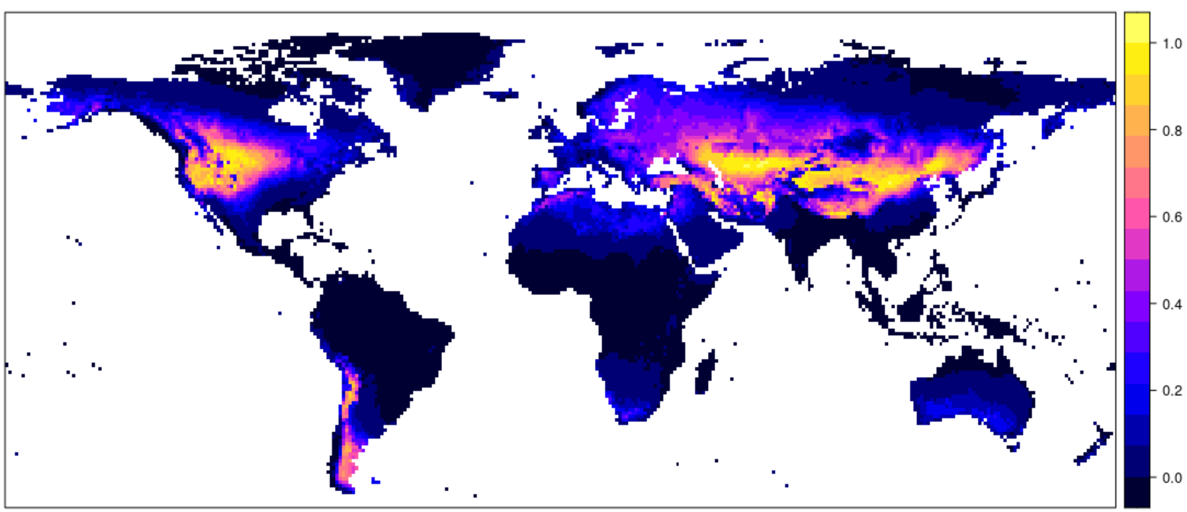
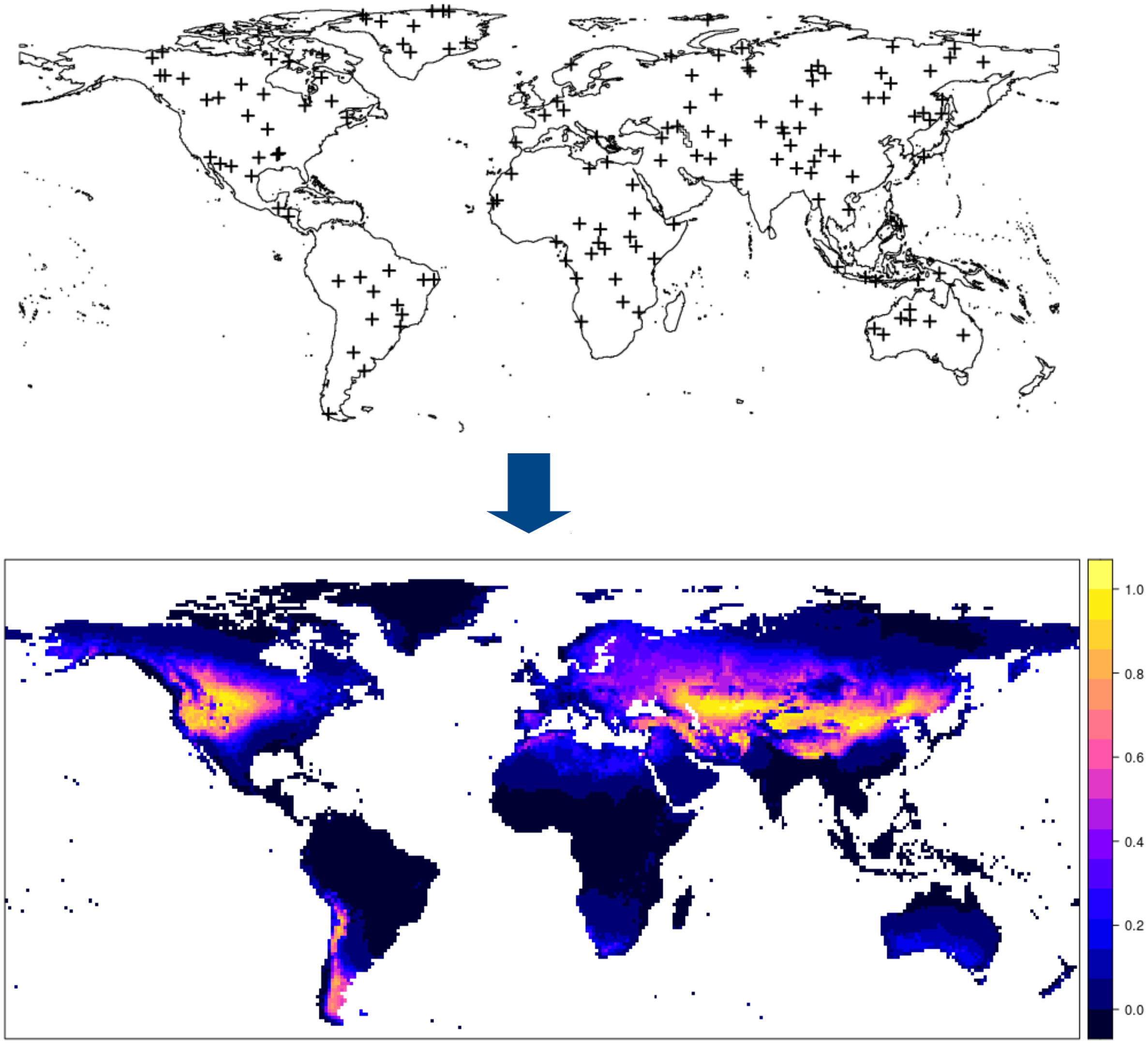




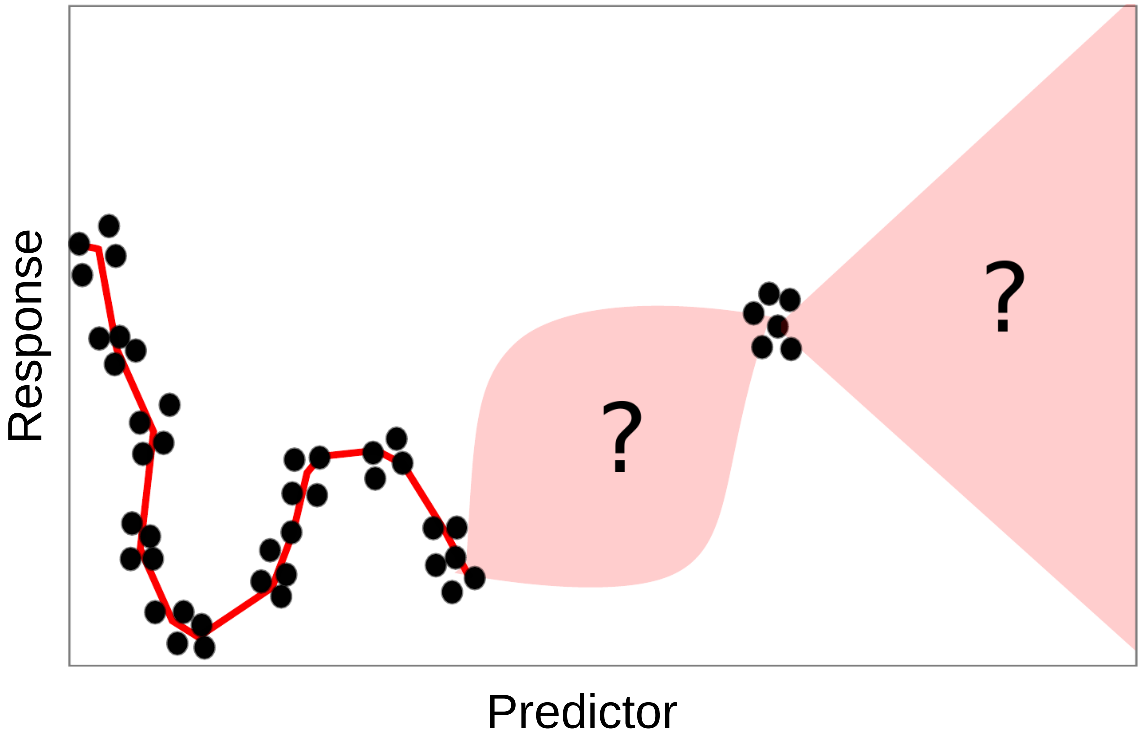
- Transfer to new space required
- New space might differ in environmental properties

Largest challenge: predictions far beyond training samples



- Transfer to new space required
- New space might differ in environmental properties
- But what if the algorithm has never seen such properties?

Machine learning models are weak in extrapolations



- Machine learning can fit very complex relationships.

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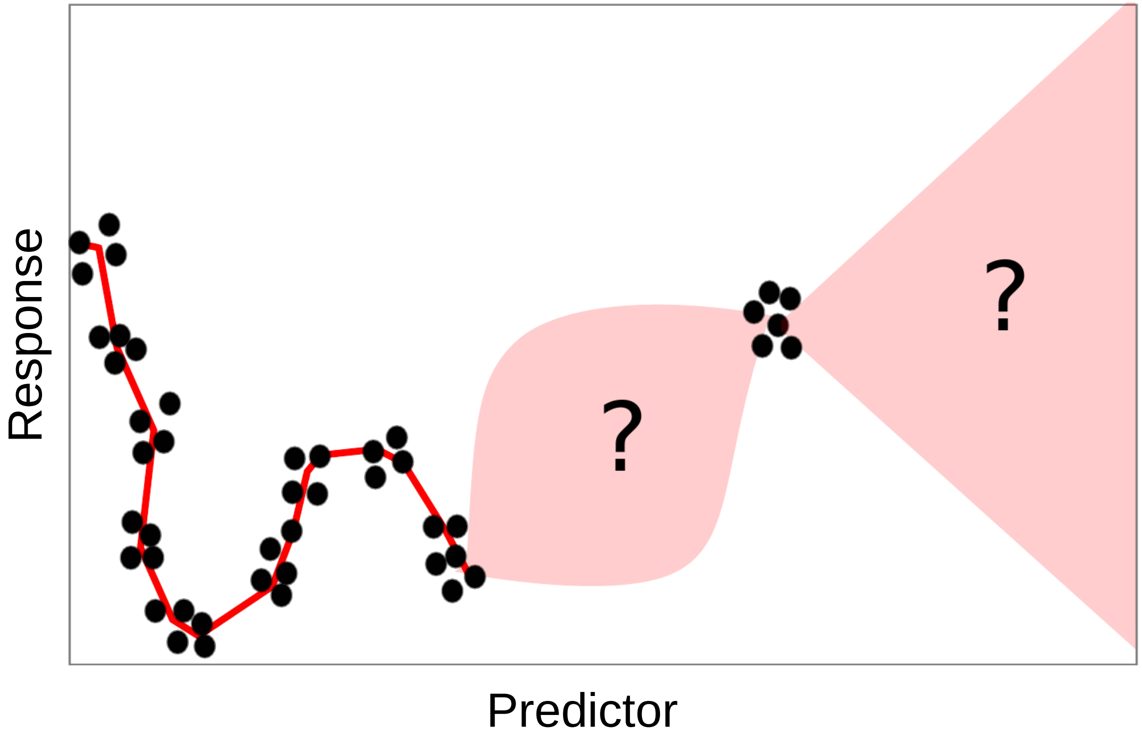

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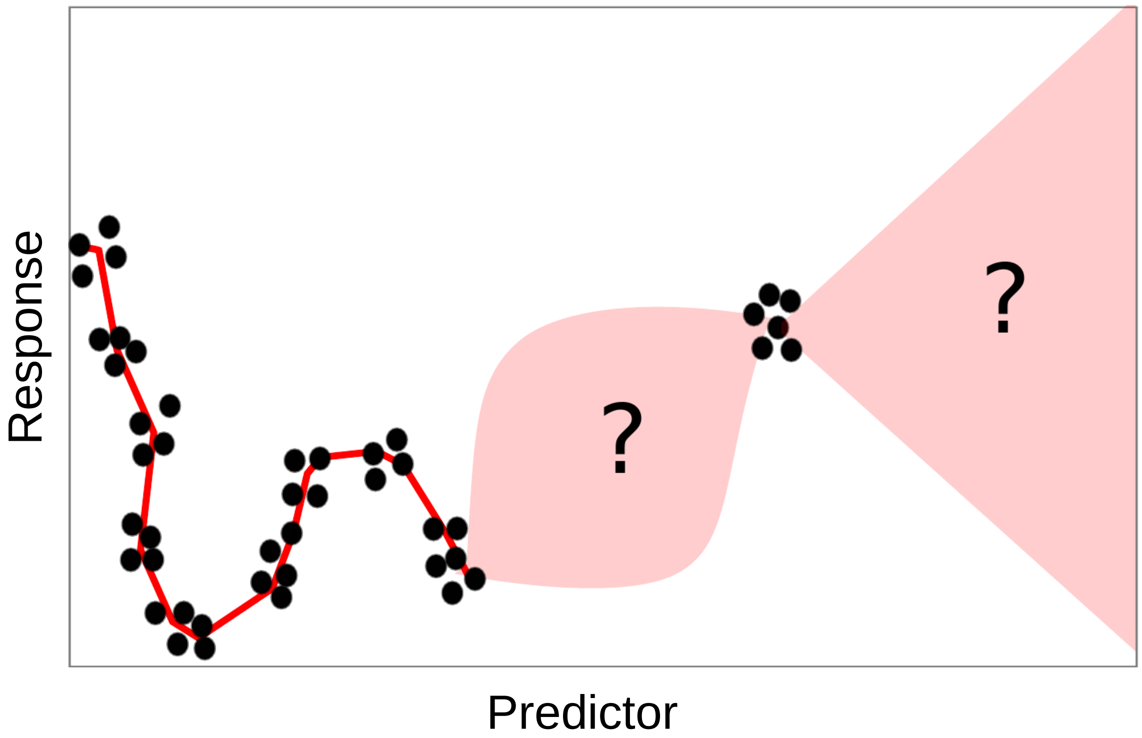

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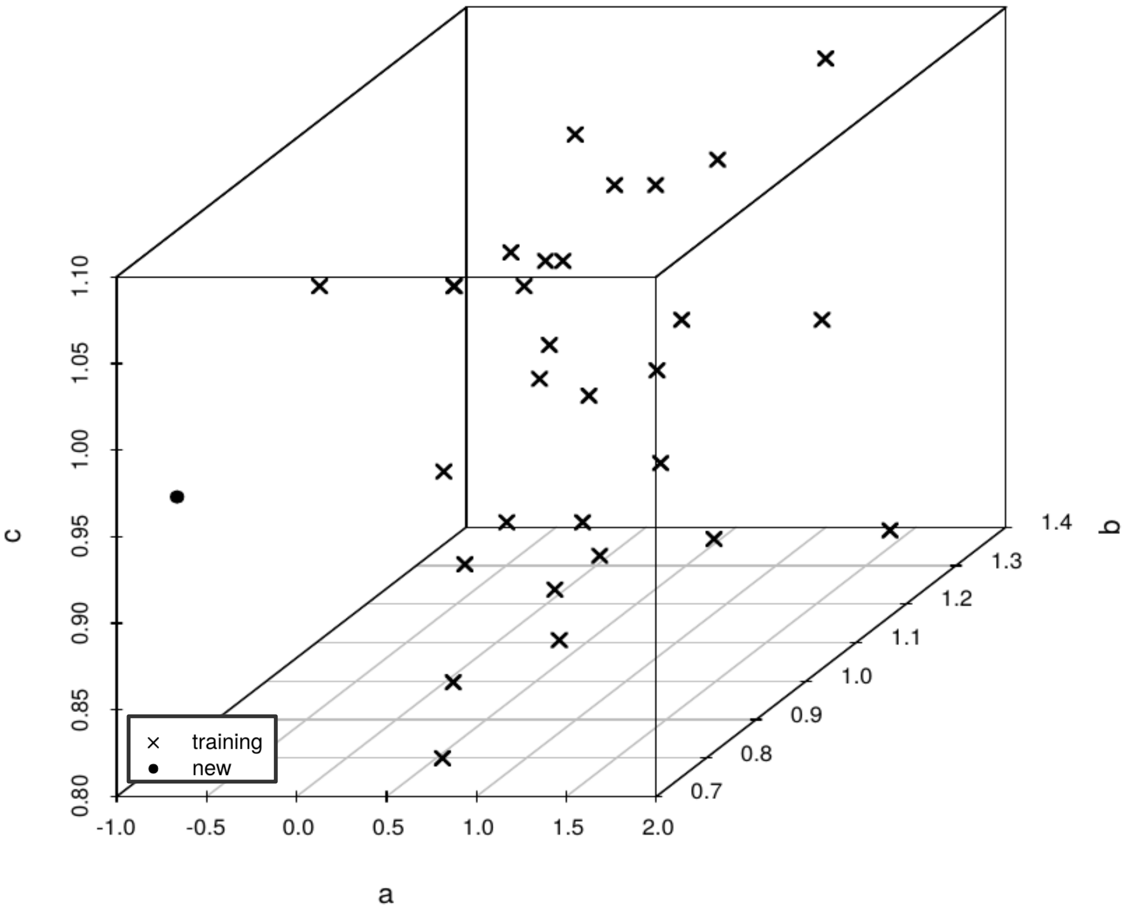
- But gaps in predictor space are problematic (the model has no knowledge about these areas!)
- A measure for “unknown space” is needed

Distances in feature space as a measure for "unknown space"



- Unknown space: Environmental conditions that are very different from the training locations

*More details: https://arxiv.org/abs/2005.07939

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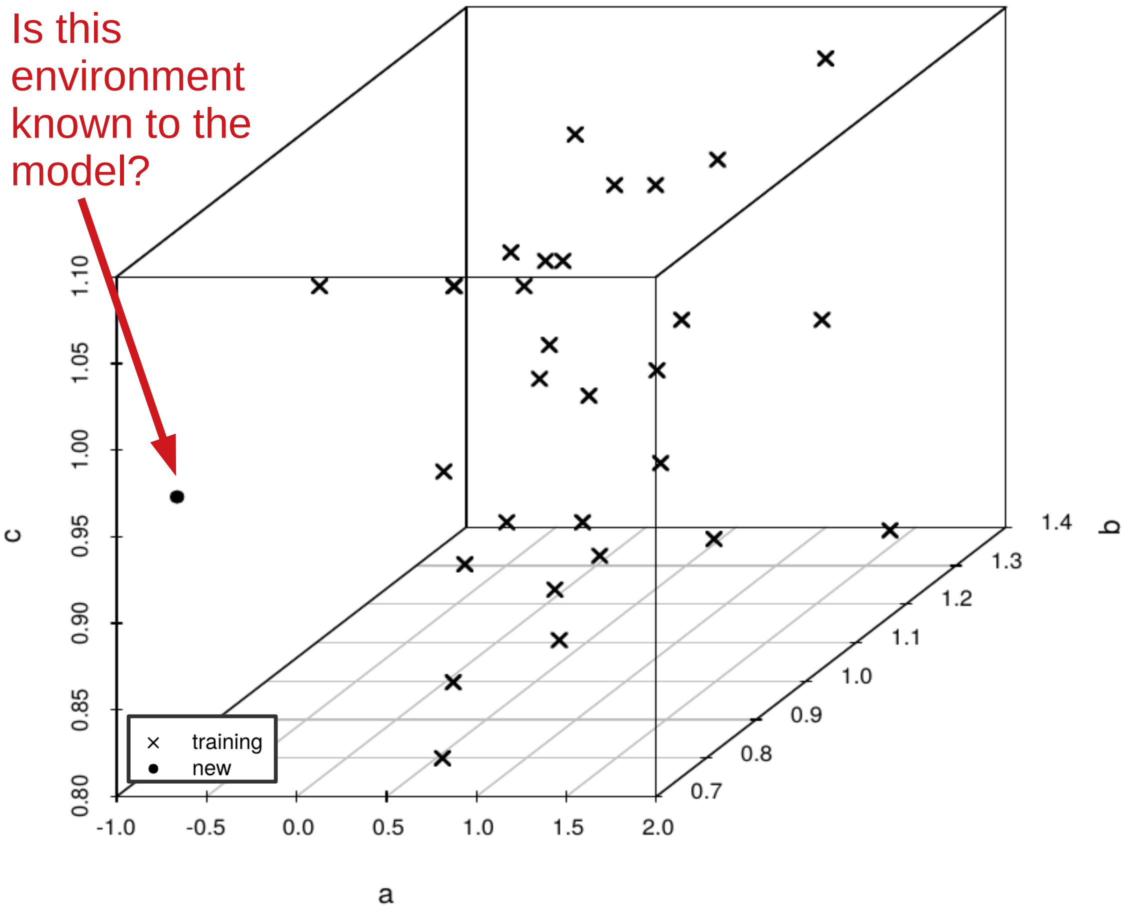

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Distances in feature space as a measure for “unknown space”

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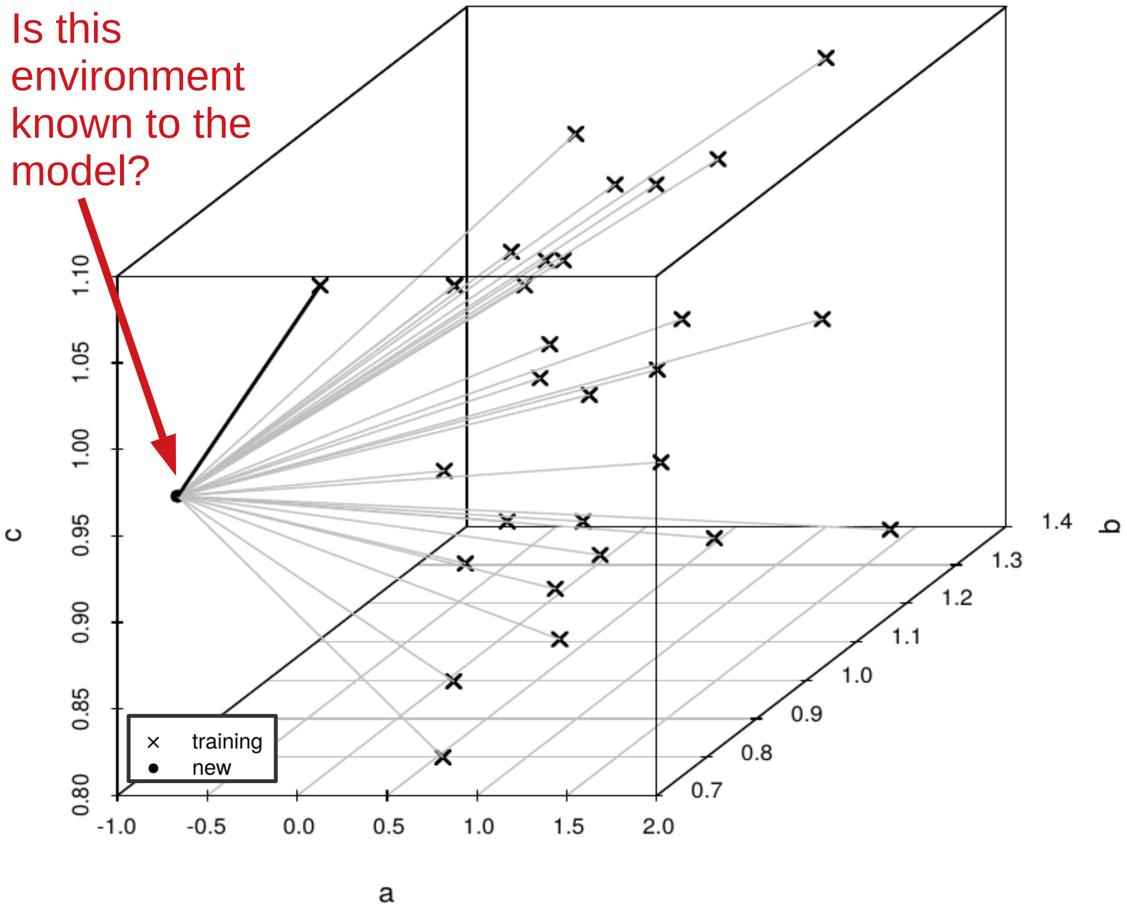

- Unknown space: Environmental conditions that are very different from the training locations
- Suggestion: Dissimilarity Index based on distances in the (weighted) predictor space*

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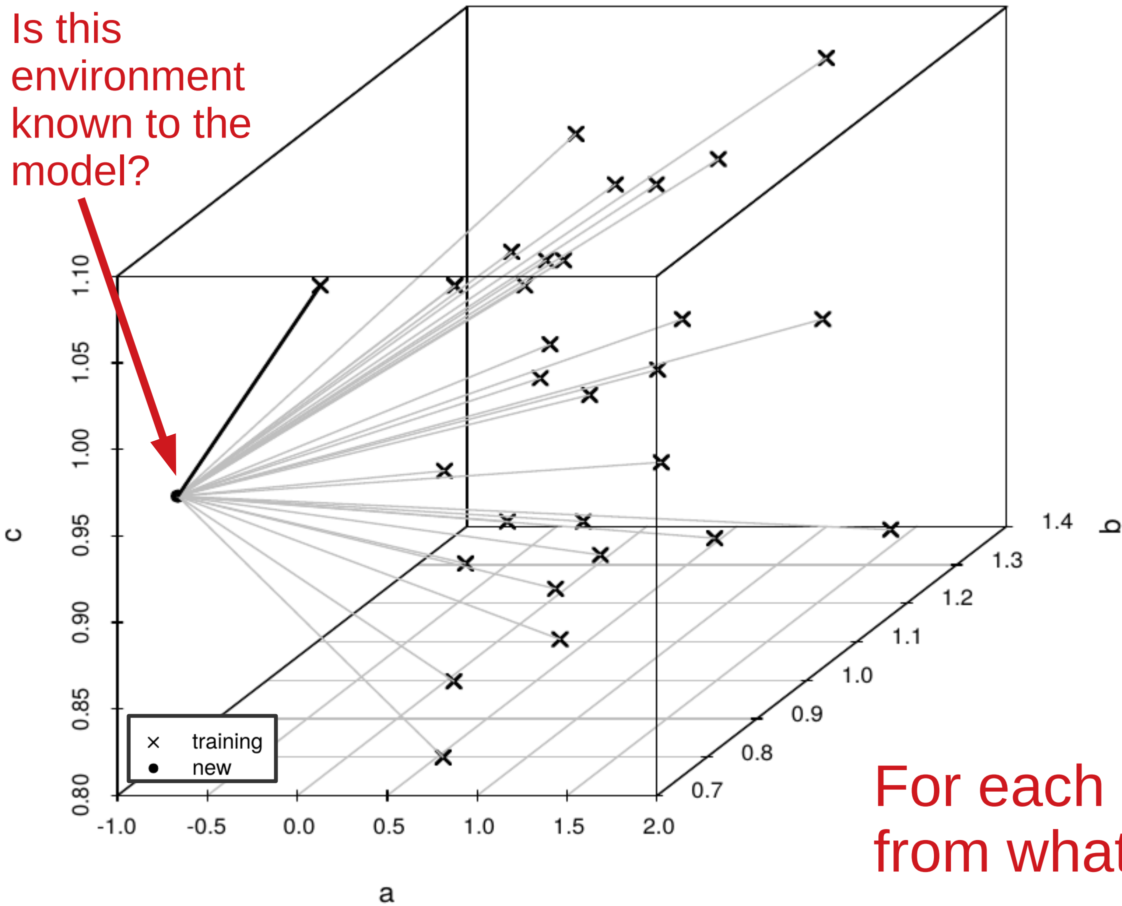

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- Suggestion: Dissimilarity Index based on distances in the (weighted) predictor space*

For each new location/pixel: how distant is it from what the algorithm has seen?

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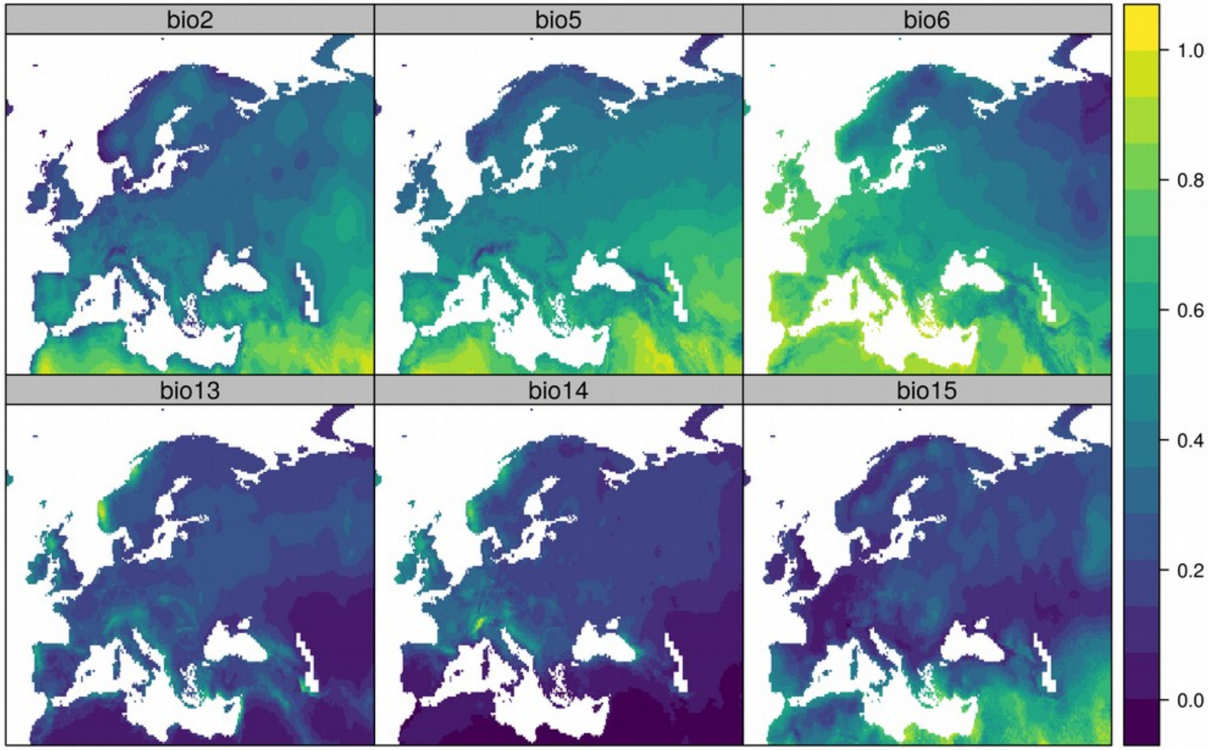
Mapping the area of applicability - Example

Predictors



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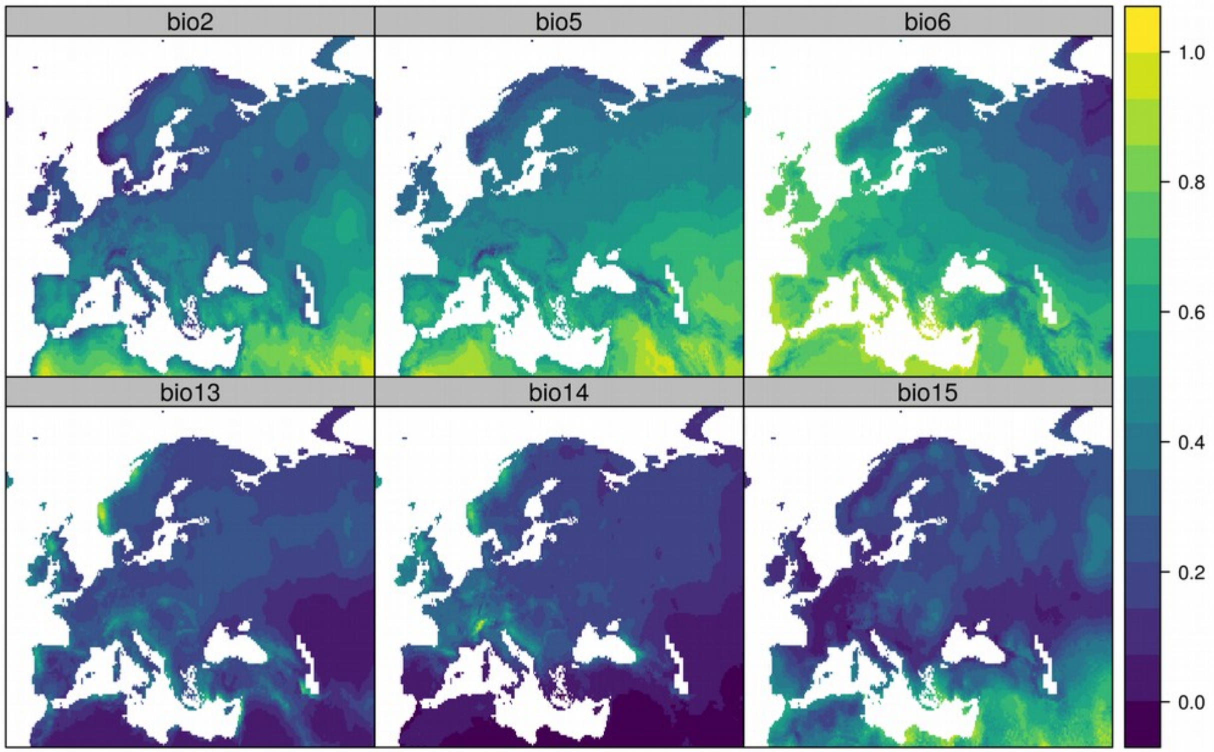
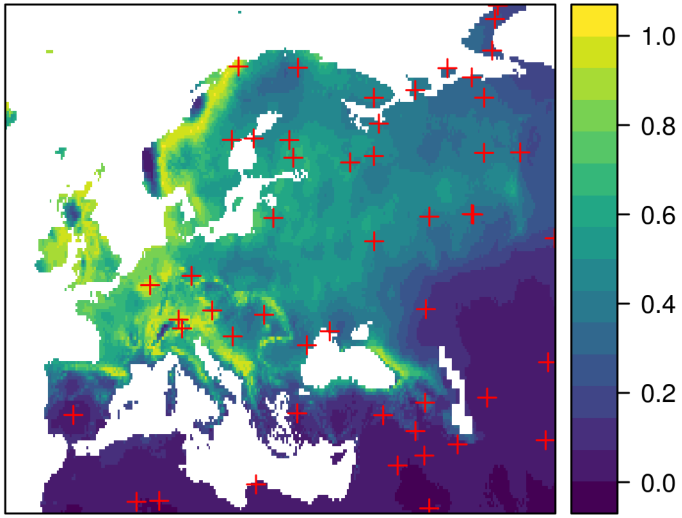


Virtual Response and simulated samples



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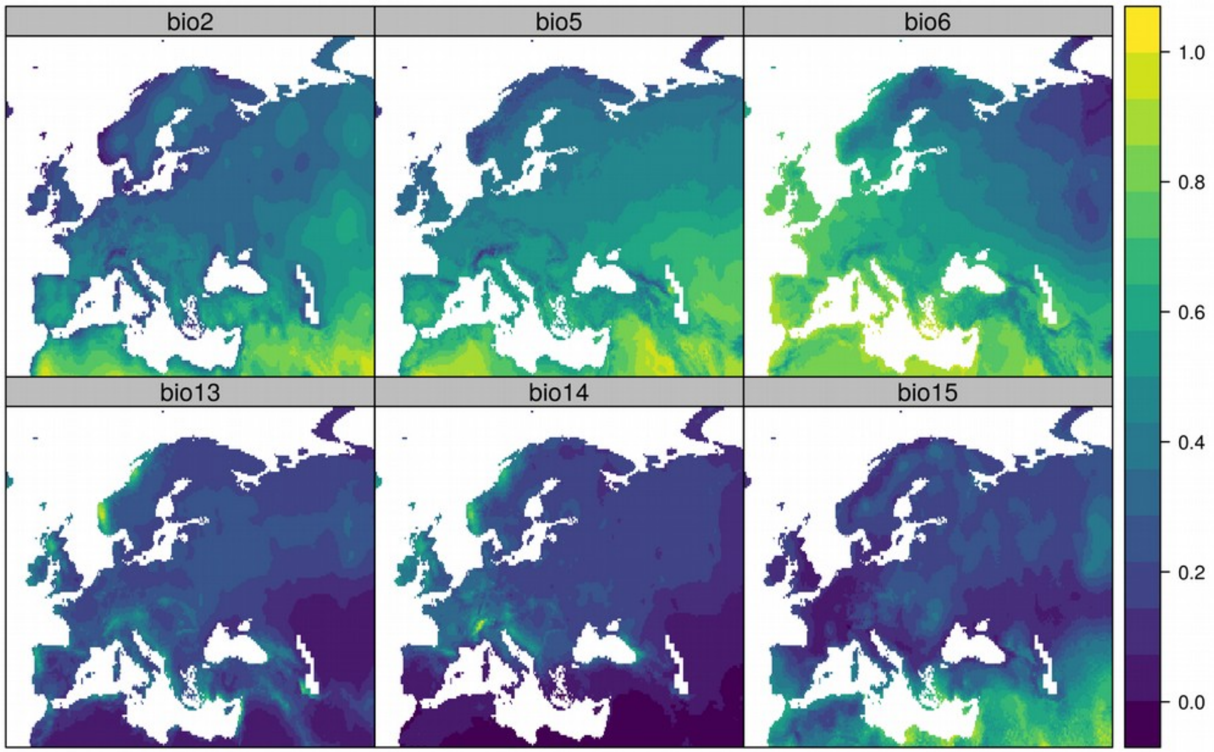

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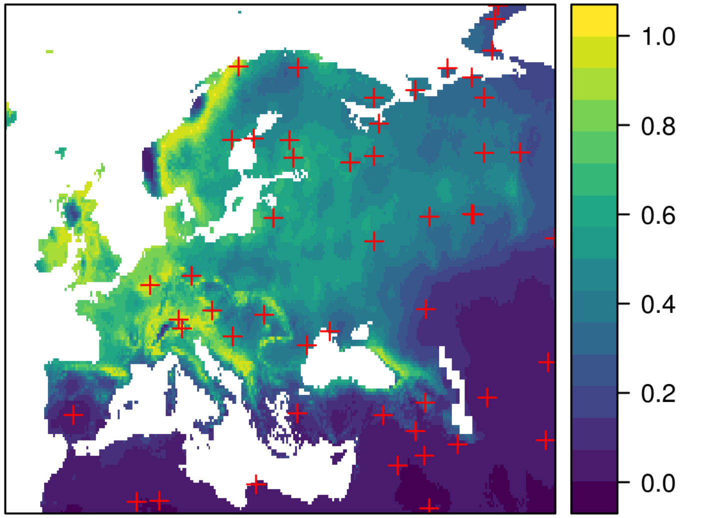

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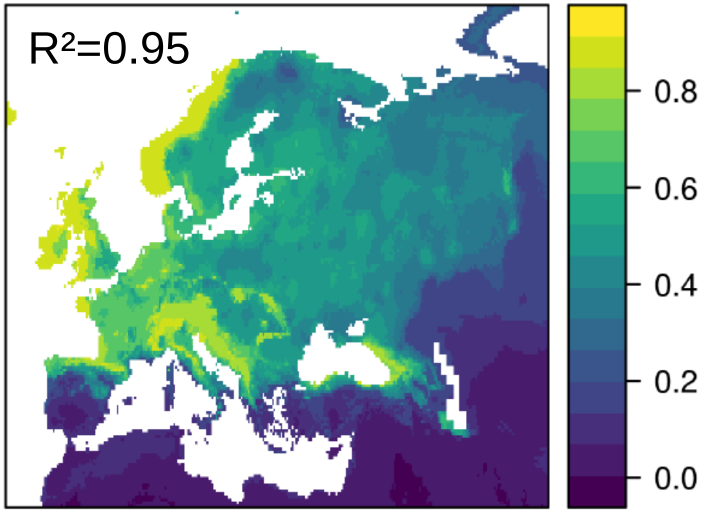

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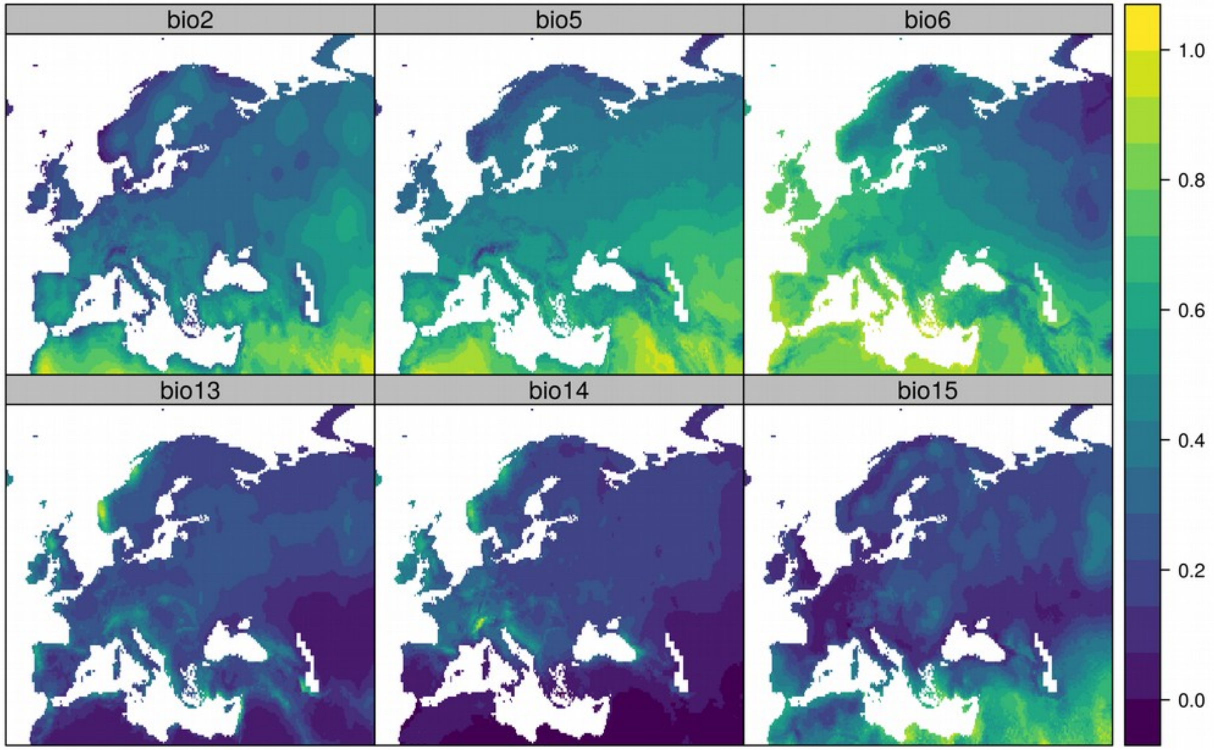

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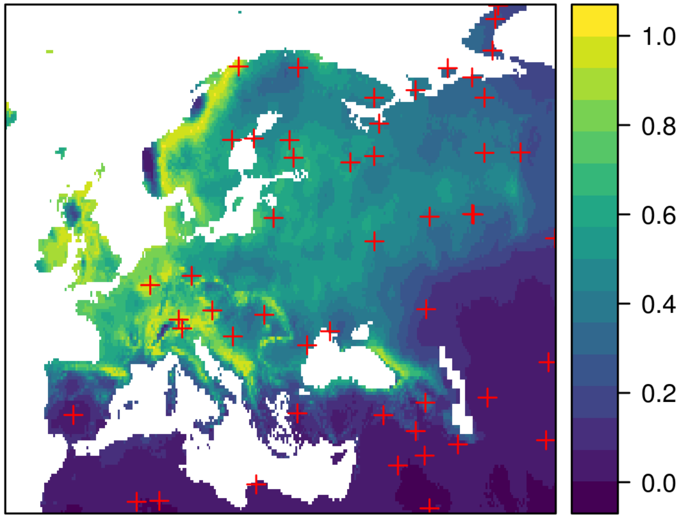

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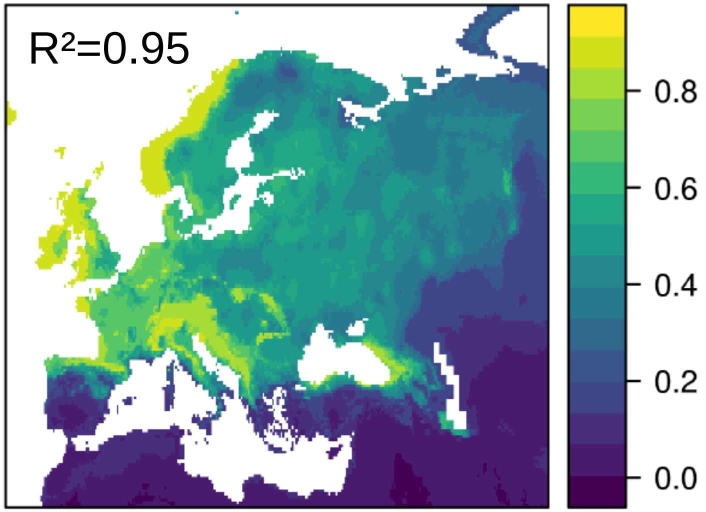

Where can we trust the predictions
and where should we better not?

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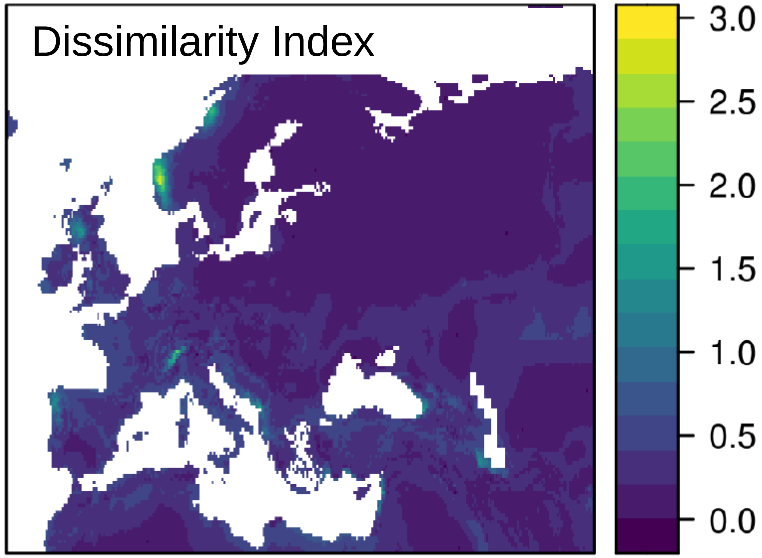

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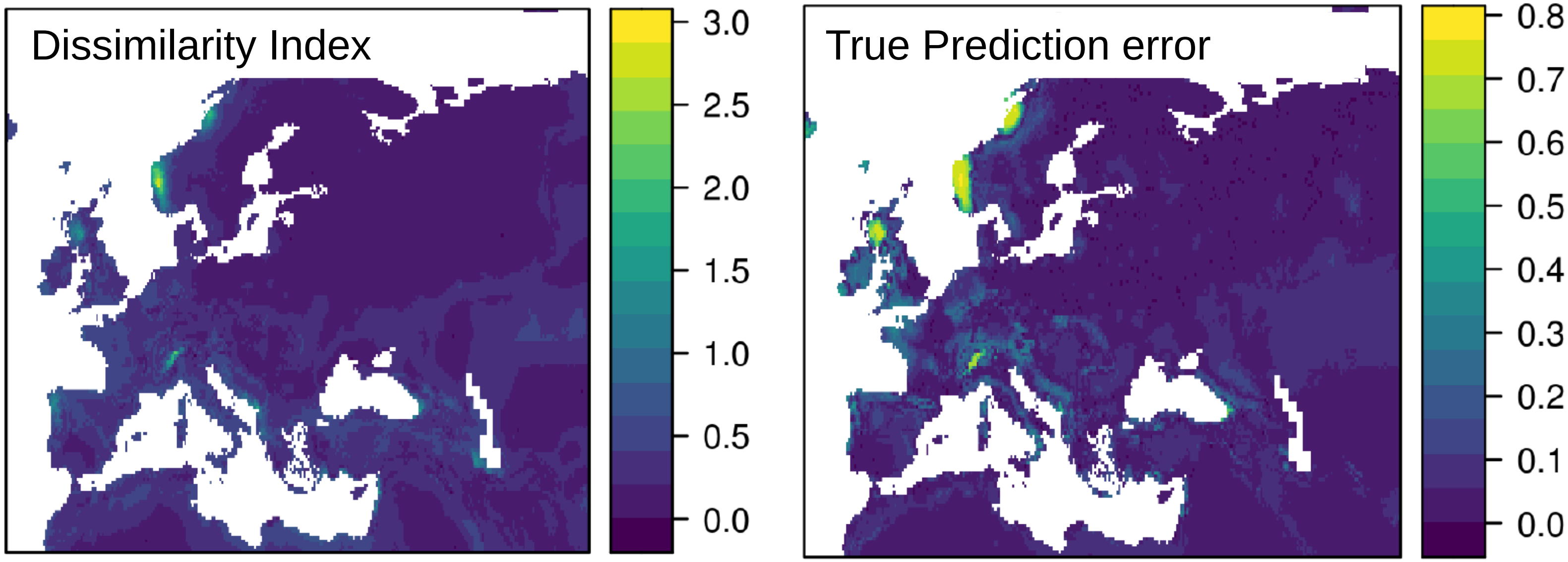

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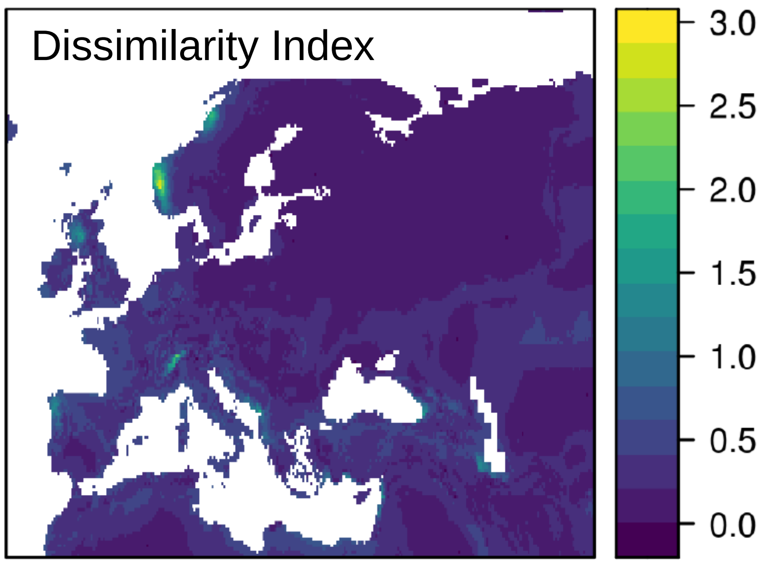
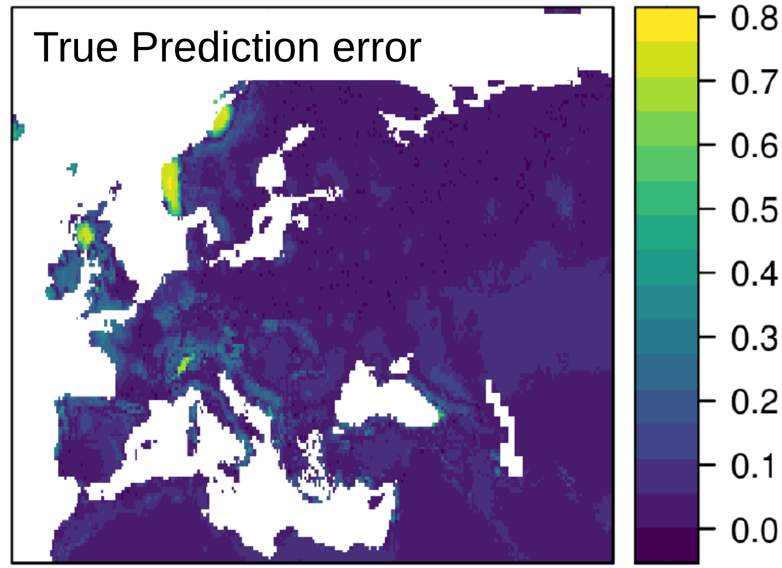
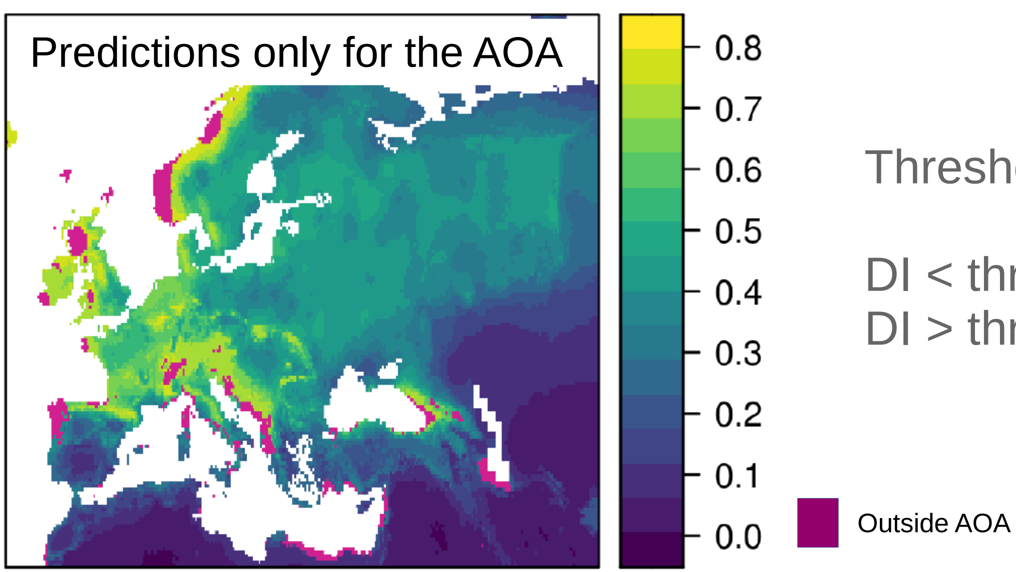






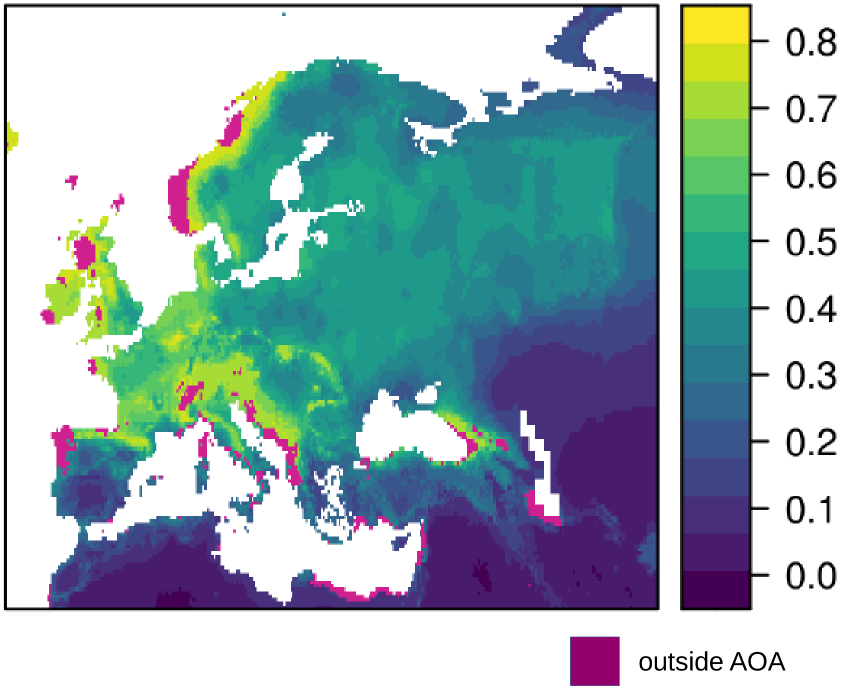
Threshold = DI of cross-validated training data

DI < threshold = inside AOA
DI > threshold = outside AOA

Why is it relevant to map the area of applicability?

Results are not just nice maps but used for…

- subsequent modeling
- nature conservation
- risk assessment
- ...



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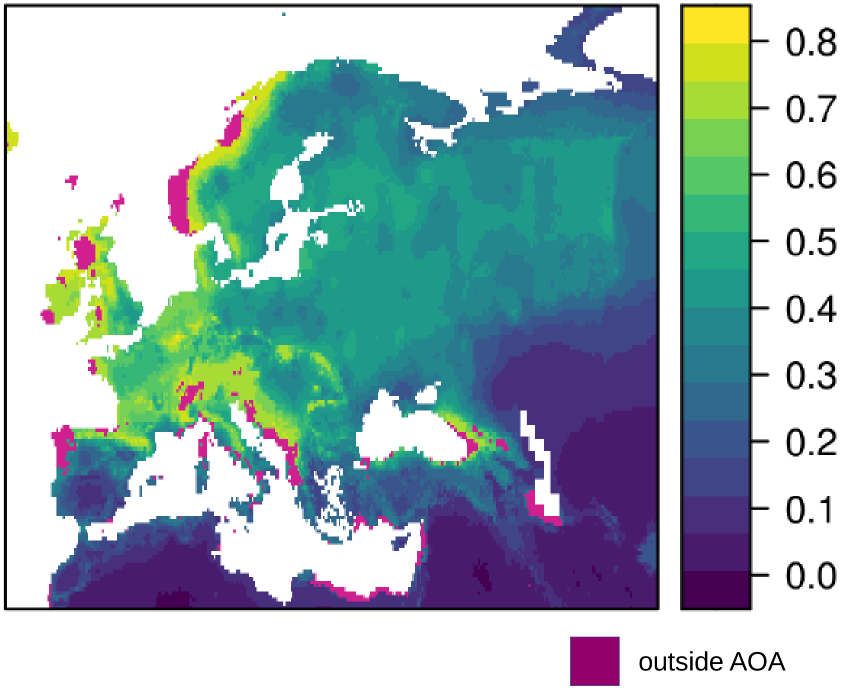

Predictions should only be presented for the area of applicability to avoid error propagation or misplanning (and to keep trust in the methods)!

More information

- Meyer H, Pebesma E: Predicting into unknown space? Estimating the area of applicability of spatial prediction models. https://arxiv.org/abs/2005.07939
- Method implemented in the R Package “CAST”: https://CRAN.R-project.org/package=CAST
- Tutorial: https://github.com/HannaMeyer/OpenGeoHub_2020