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Institut für Landschaftsökologie ILÖK

Remote Sensing & Spatial Modelling

Machine learning for earth observation:
Mapping the „Area of Applicability“ of spatial prediction models

Hanna Meyer
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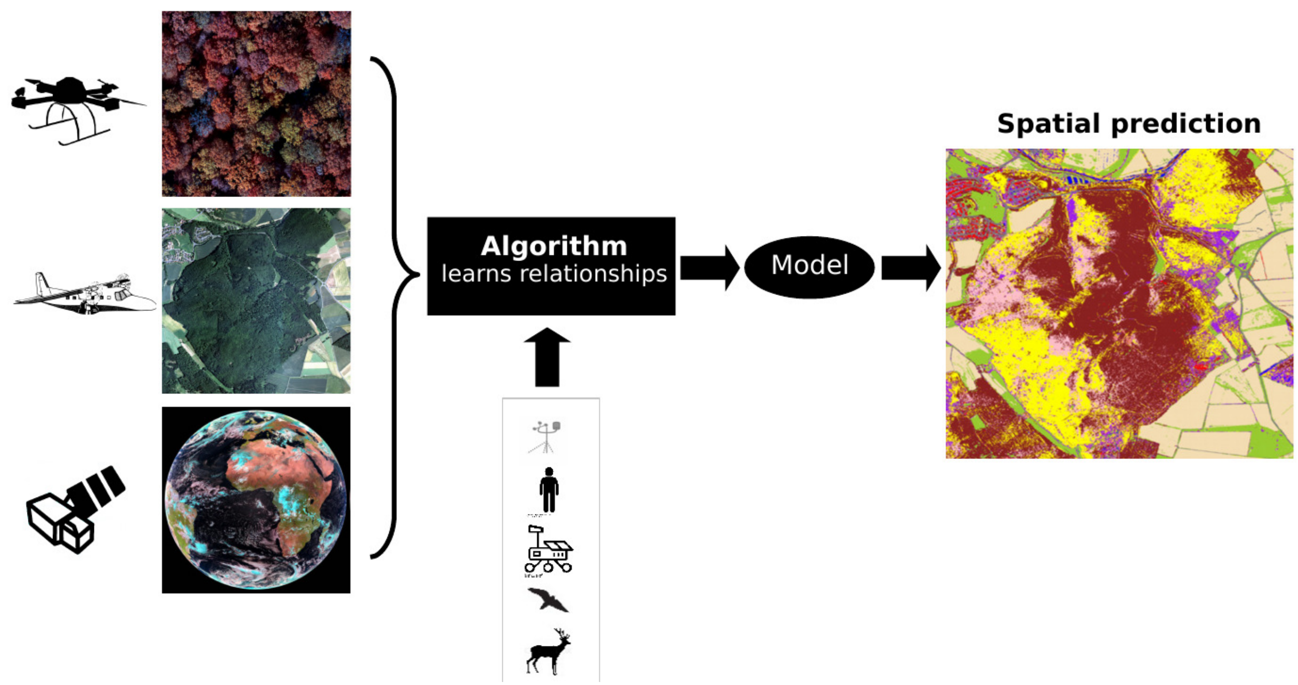
Institute of Landscape Ecology, WWU Münster



Problem: Moving from field observations to maps of ecosystem variables

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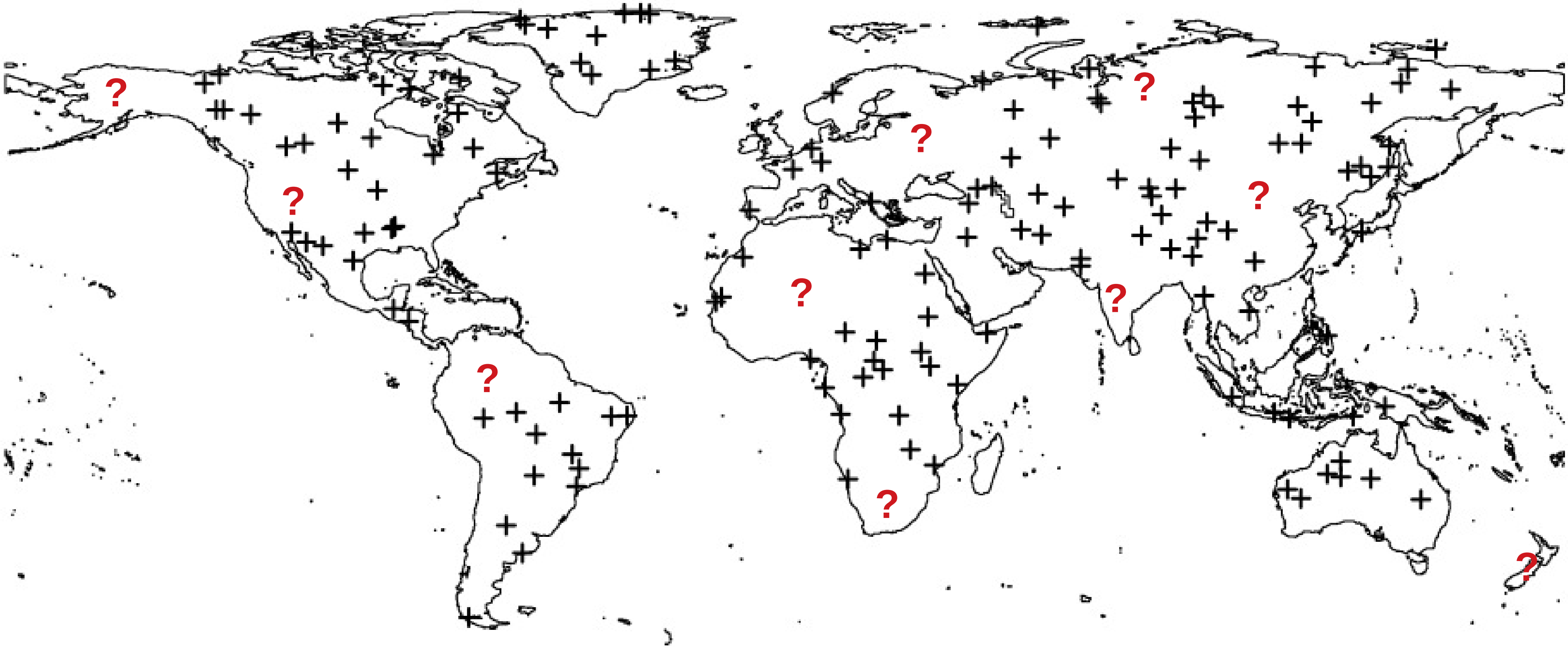
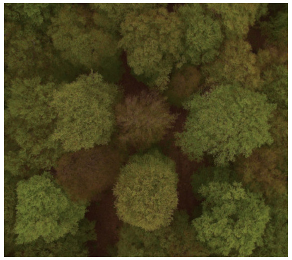


How do we fill the gaps between sampling locations?

Remote Sensing of landscapes



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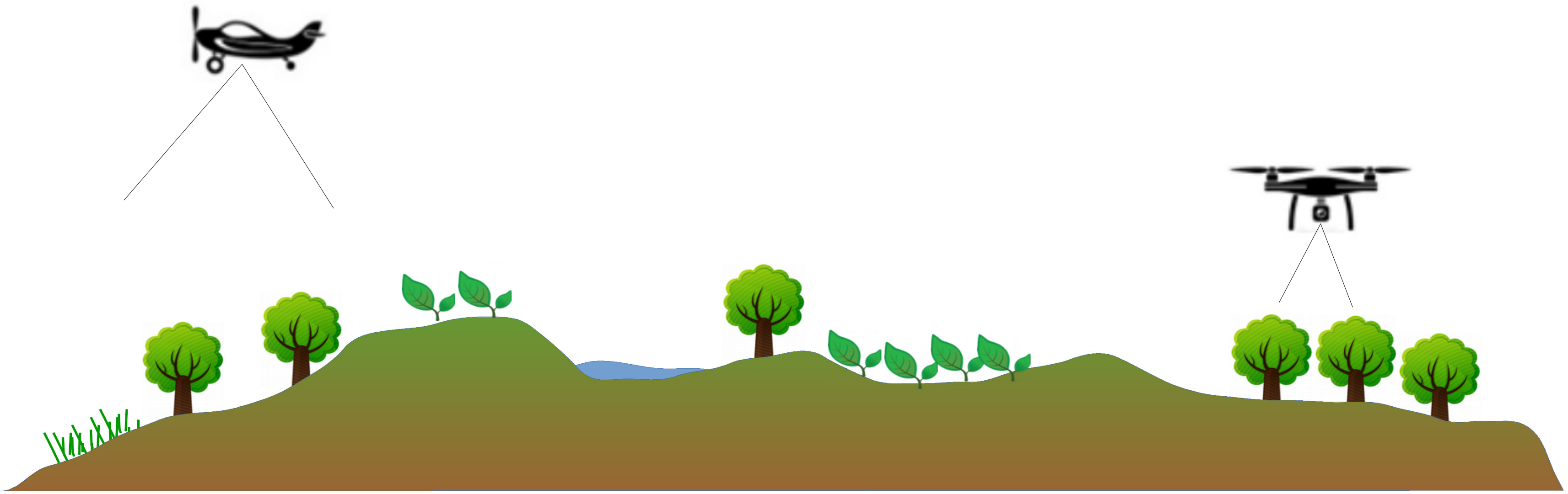

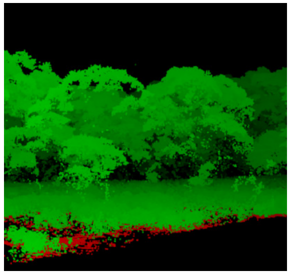

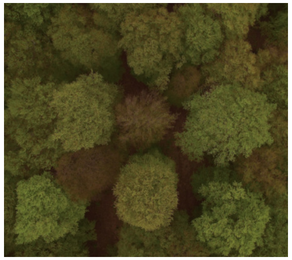

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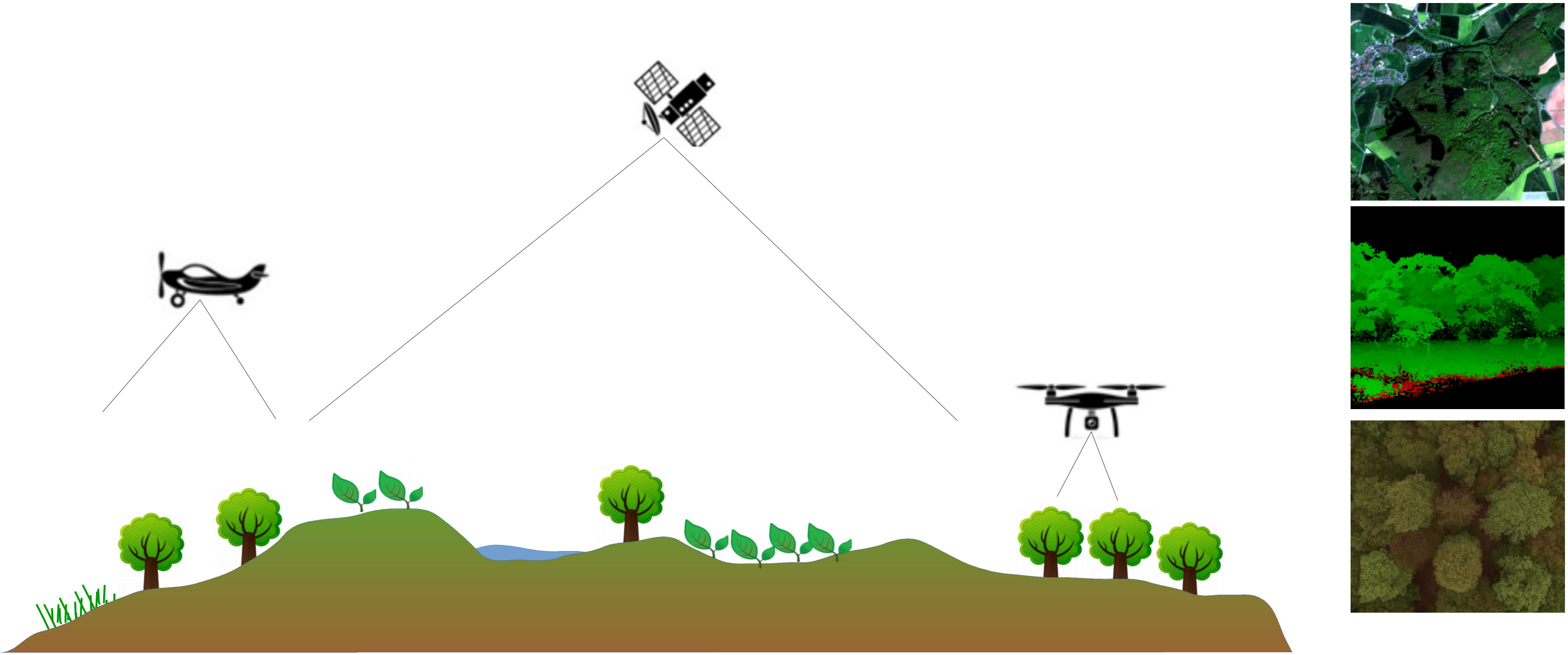

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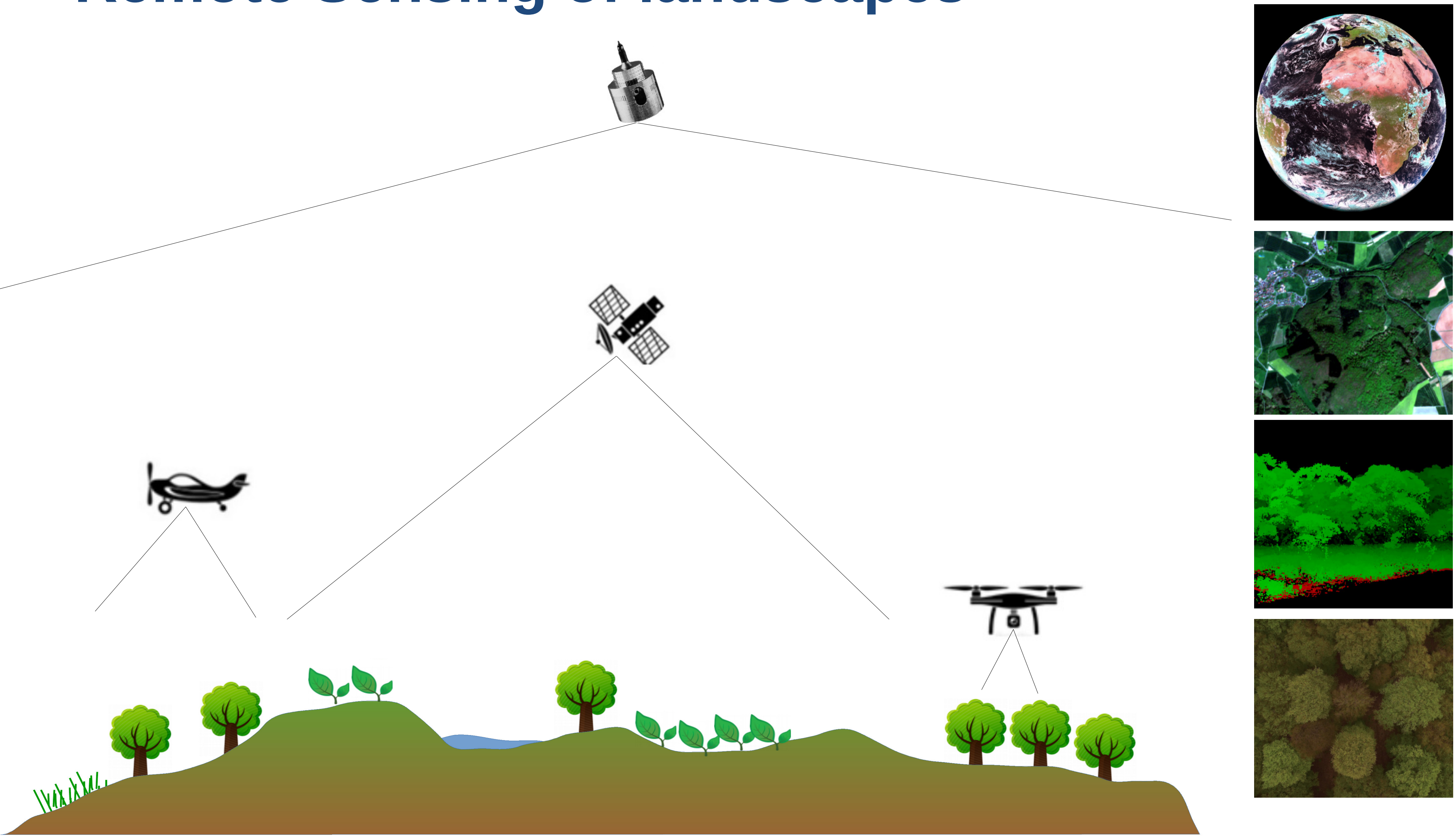

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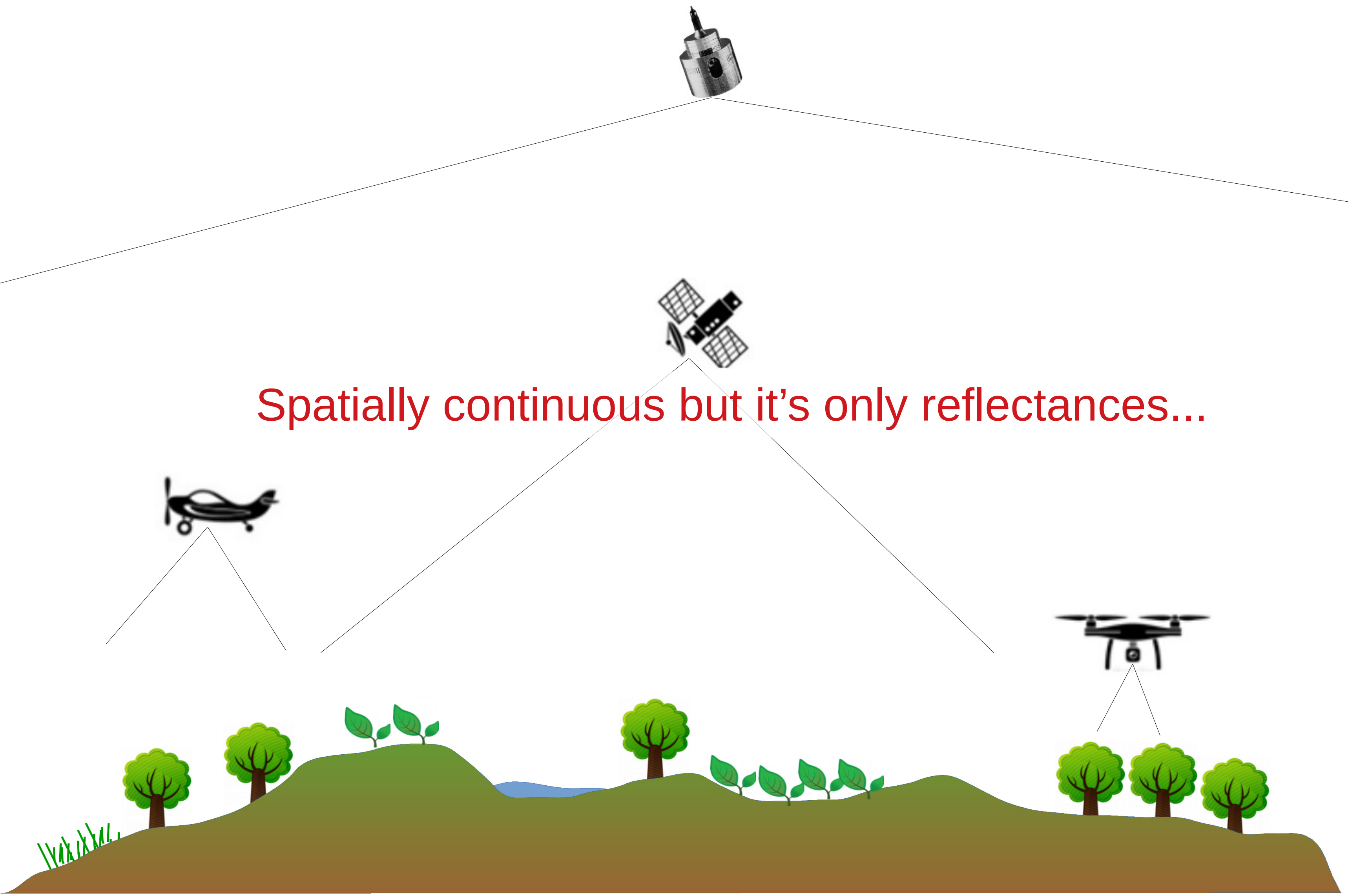
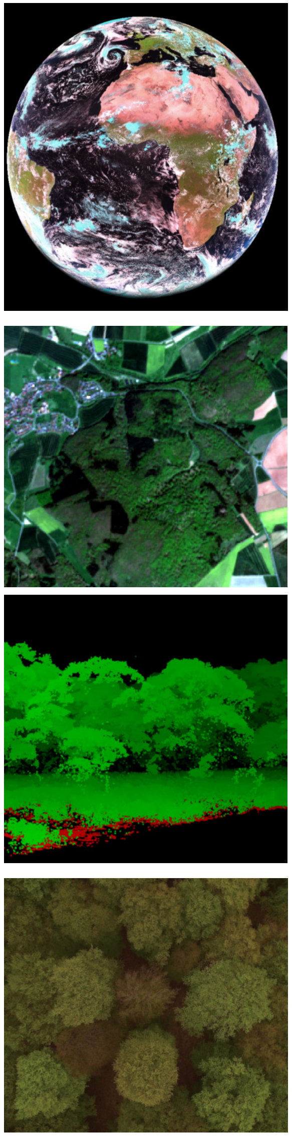


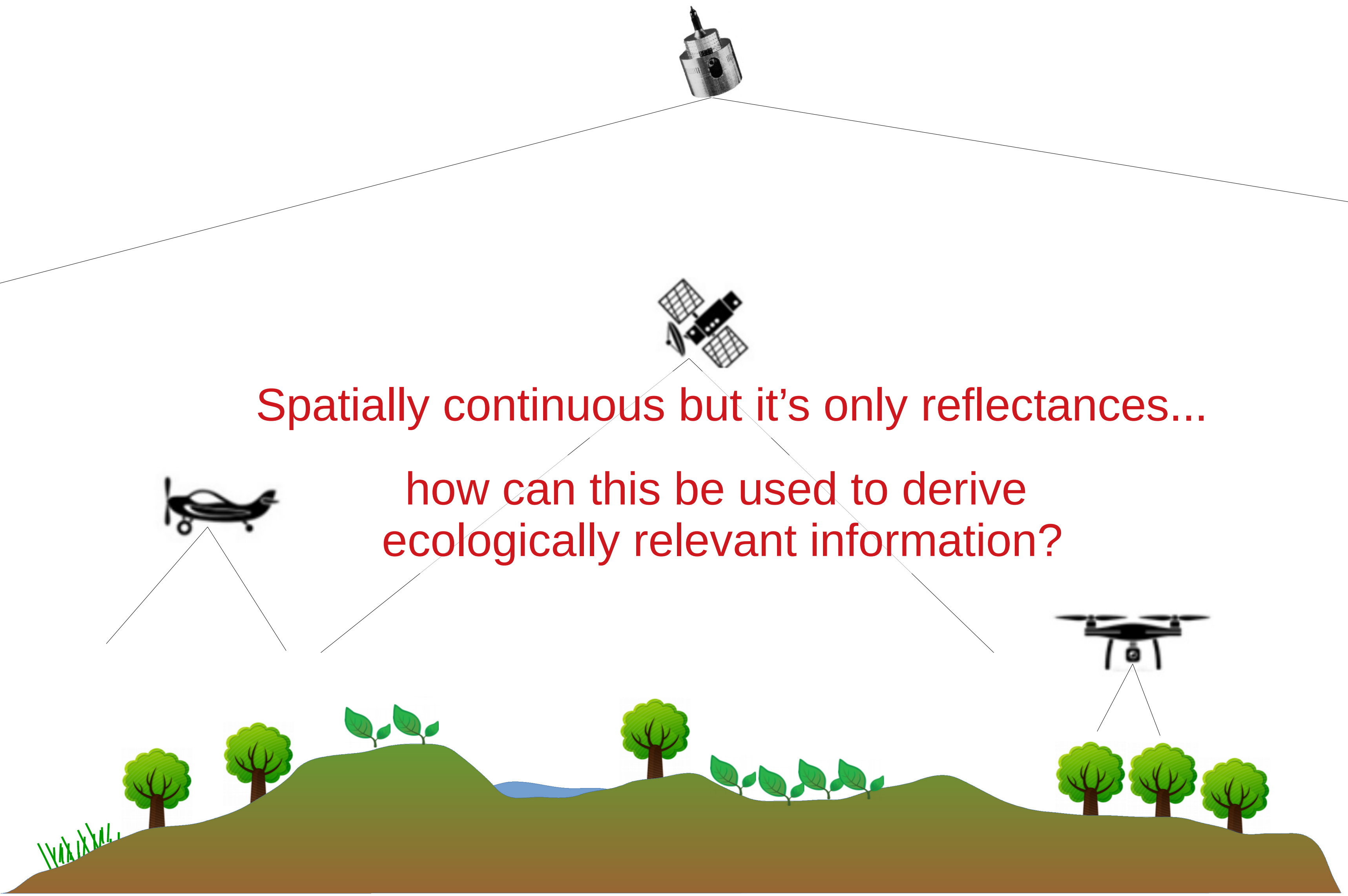


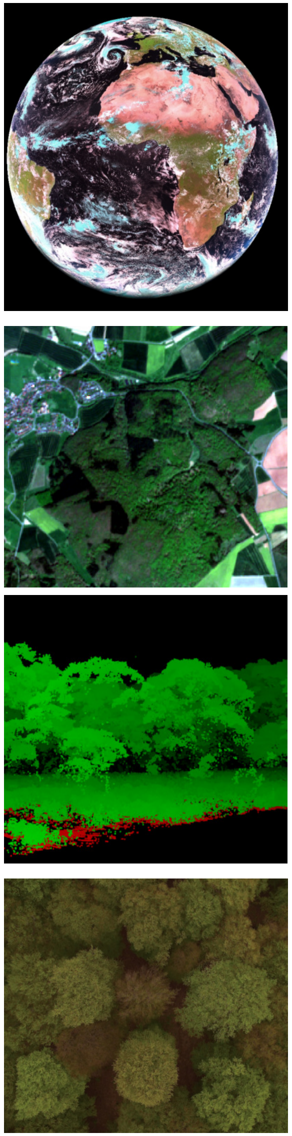
Spatially continuous but it’s only reflectances...

Remote Sensing of landscapes

Spatially continuous but it’s only reflectances...

how can this be used to derive
ecologically relevant information?

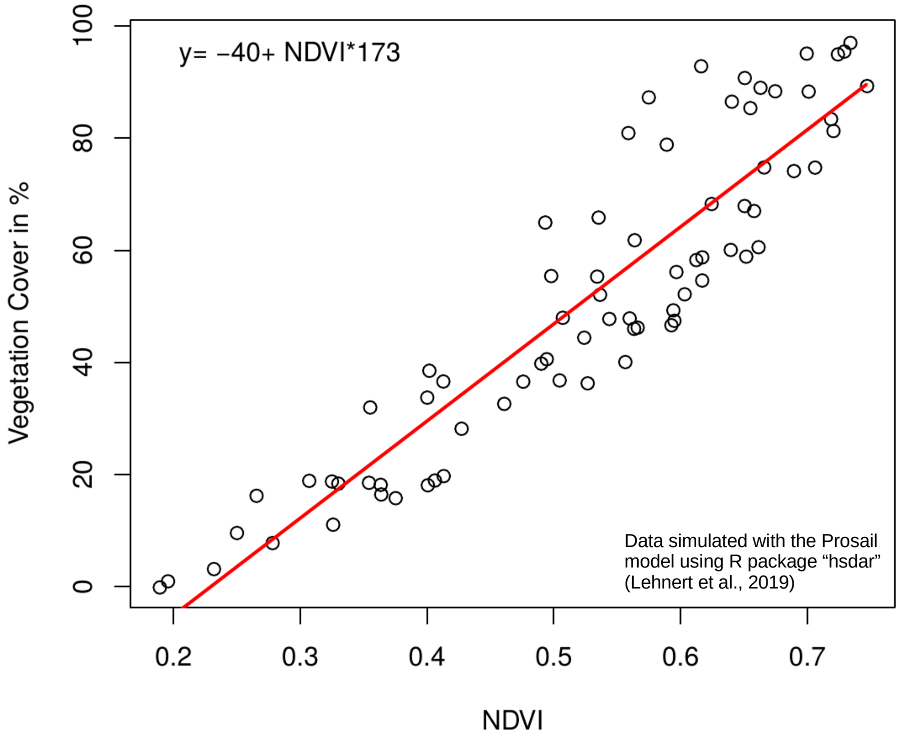




Predictive modelling of the environment

e.g. vegetation cover from satellite (VIS/NIR)

Field data



Remote sensing data

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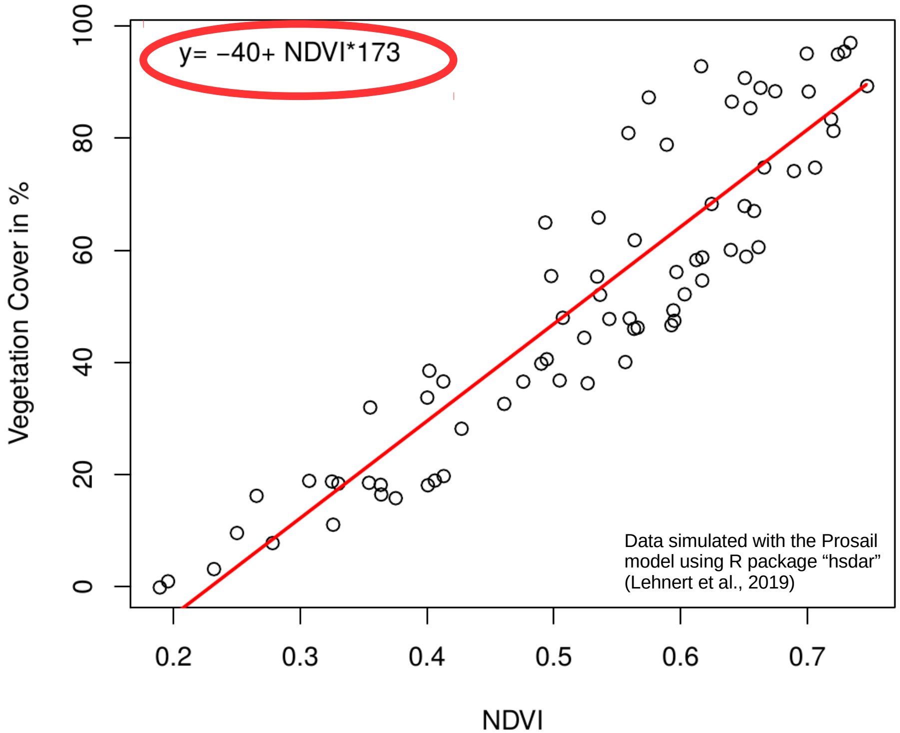

Remote sensing data

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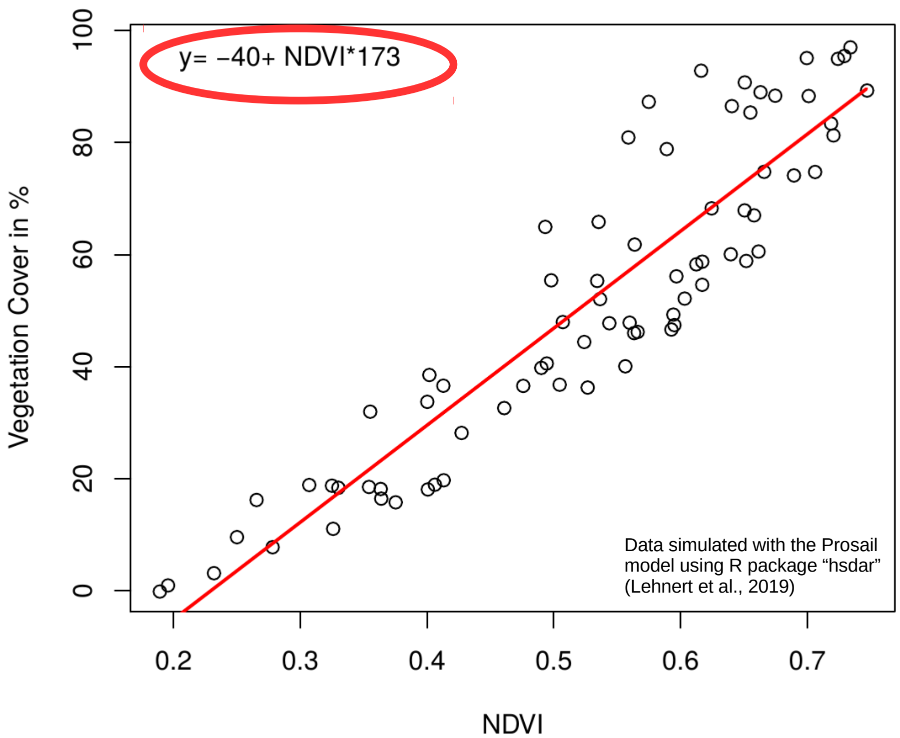
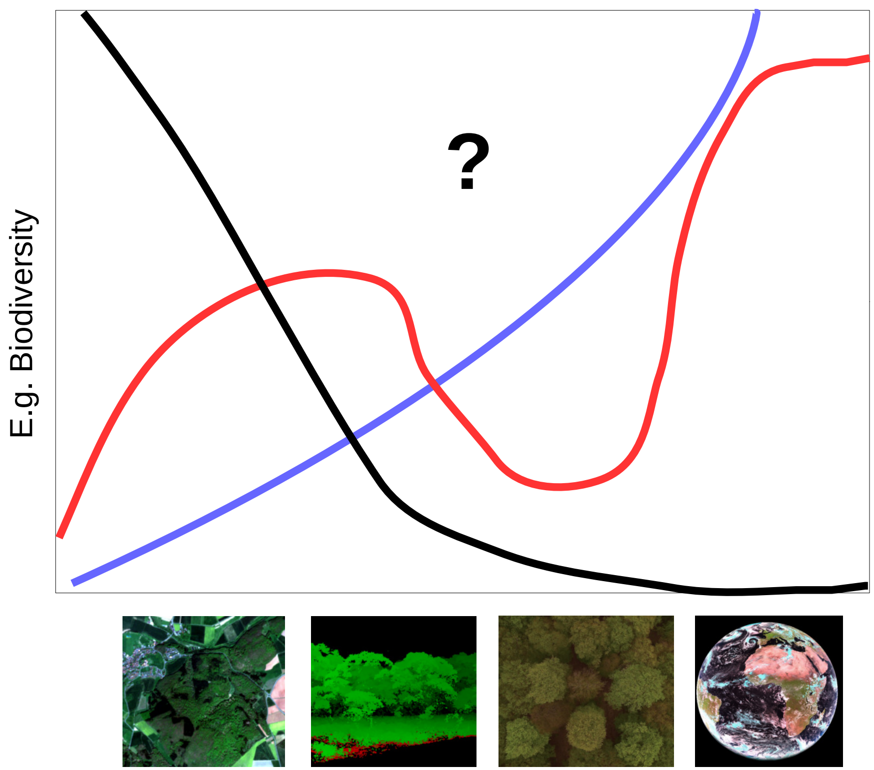


Remote sensing data

Typical ecological variables from satellite?



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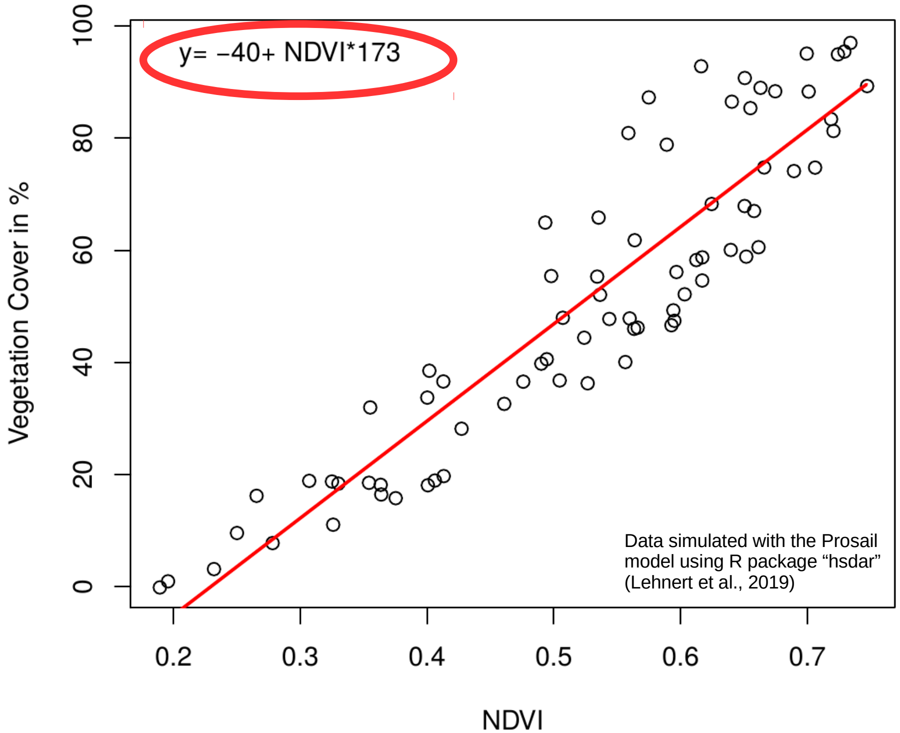

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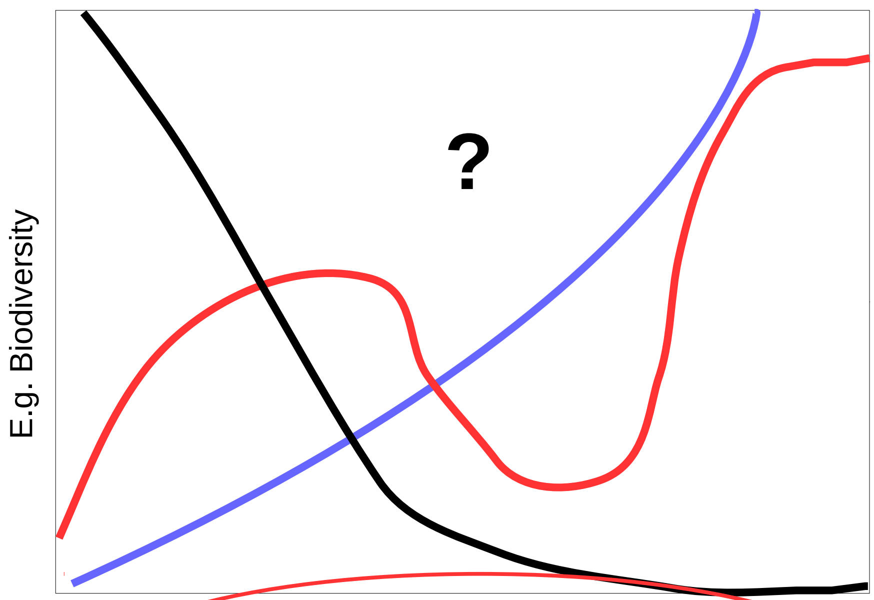
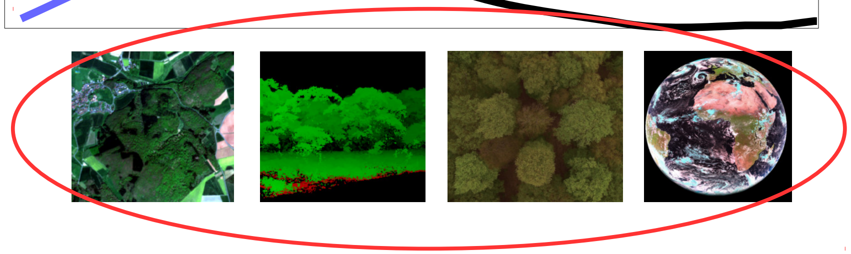
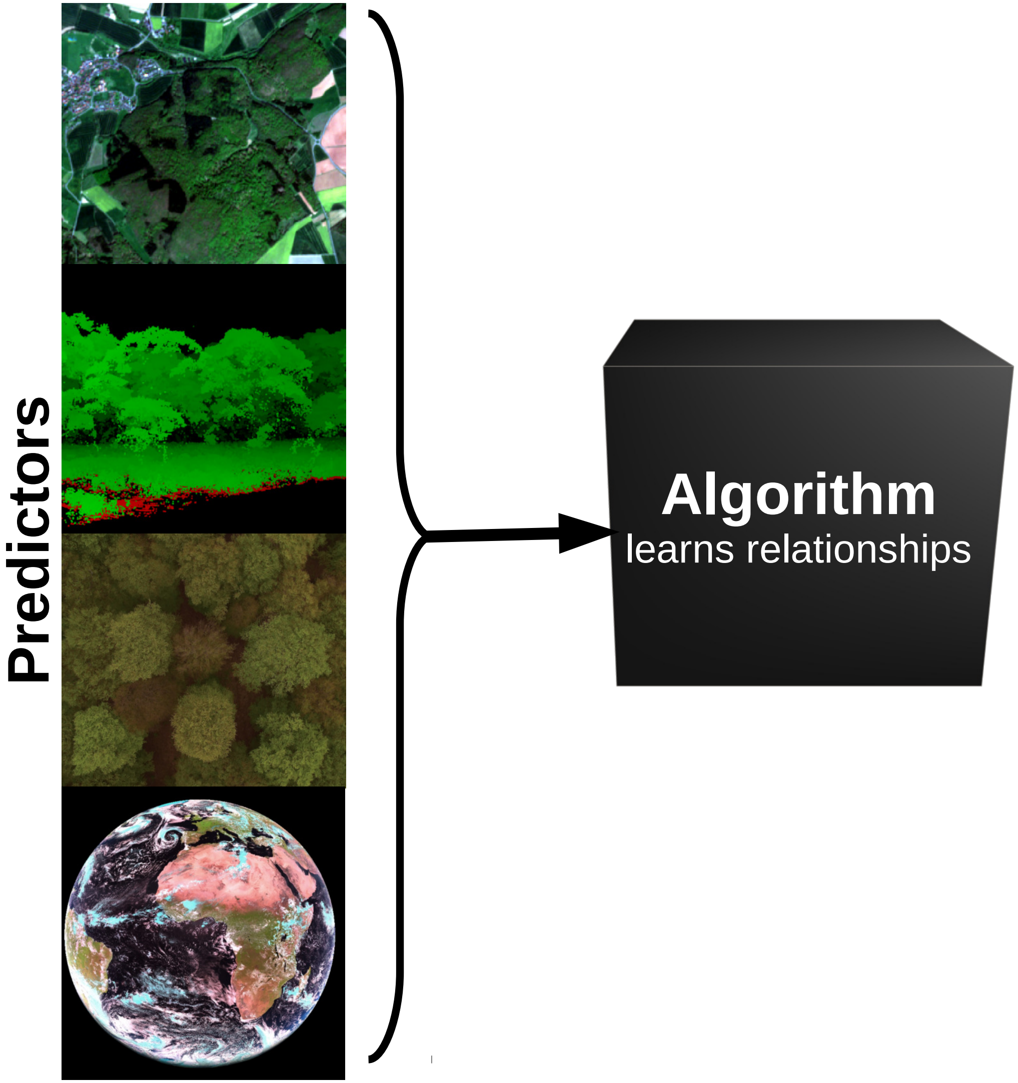




Models that can deal with complex nonlinear relationships are required!

Predictive modelling of the environment: The machine learning way



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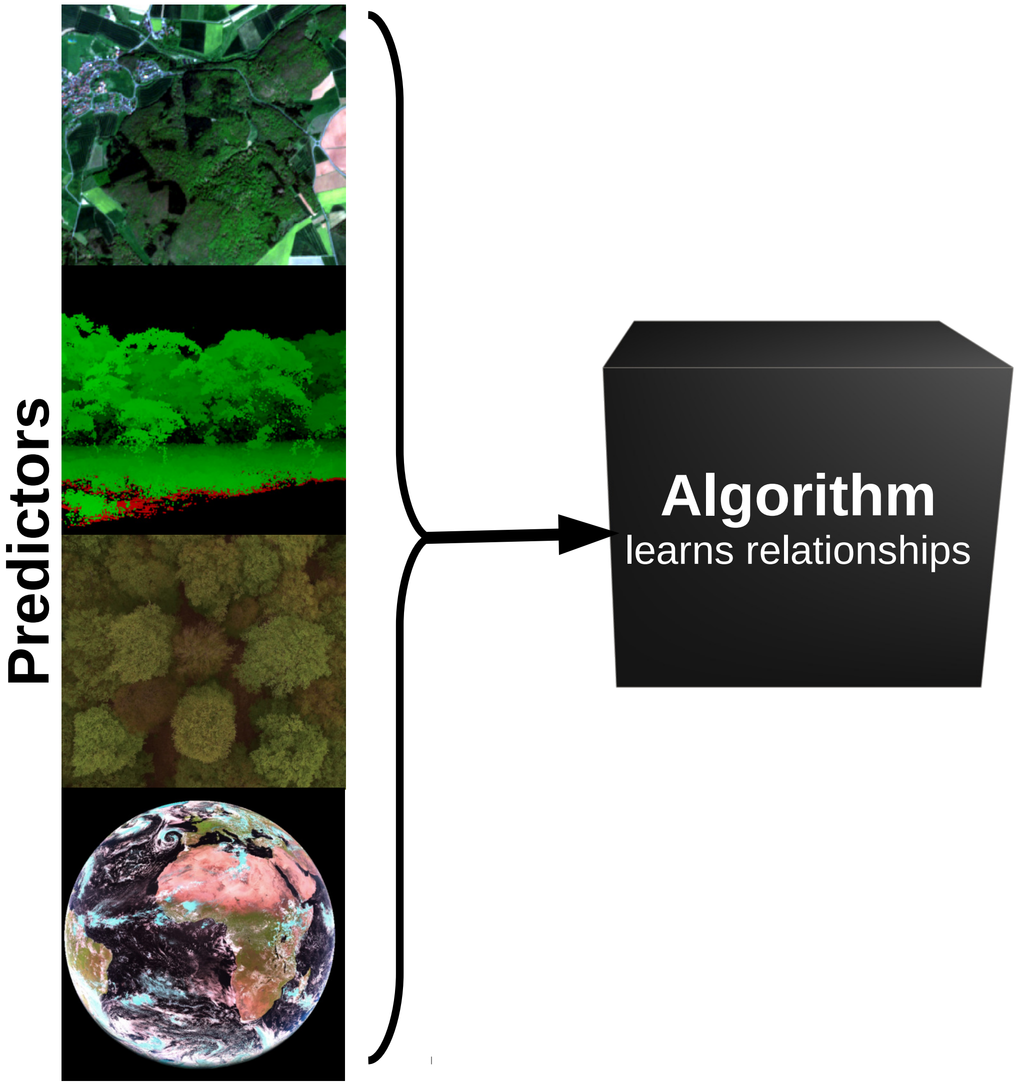

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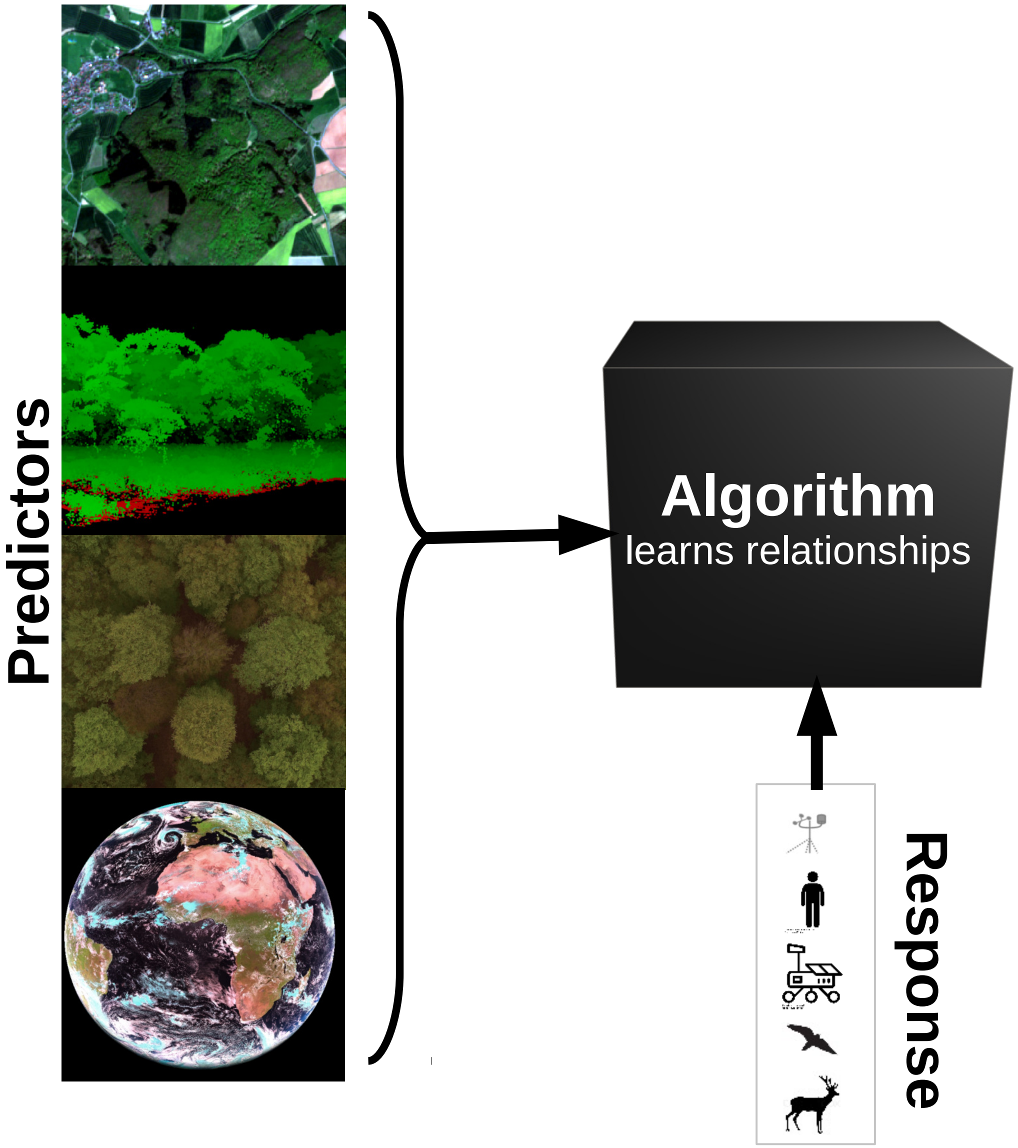

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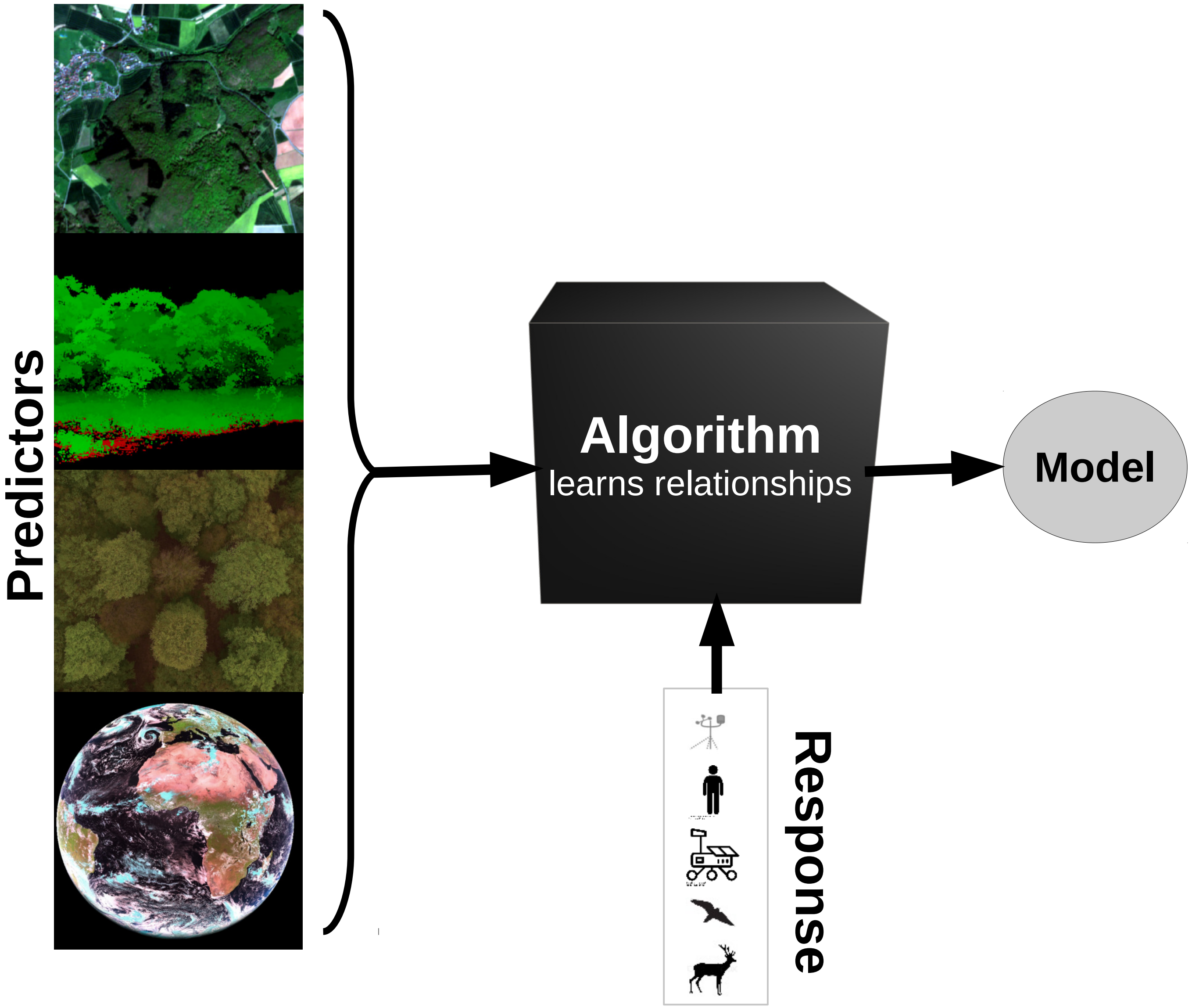

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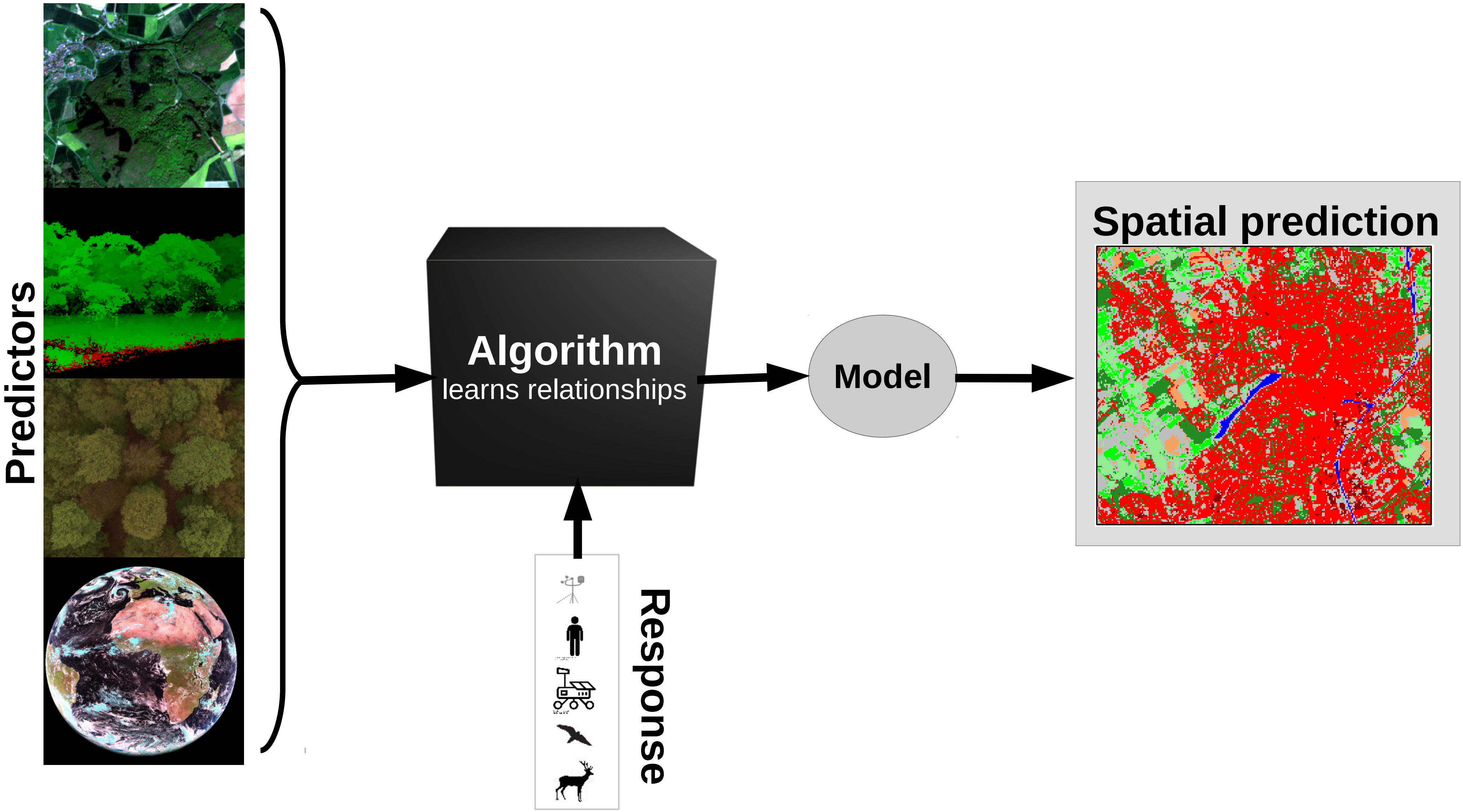
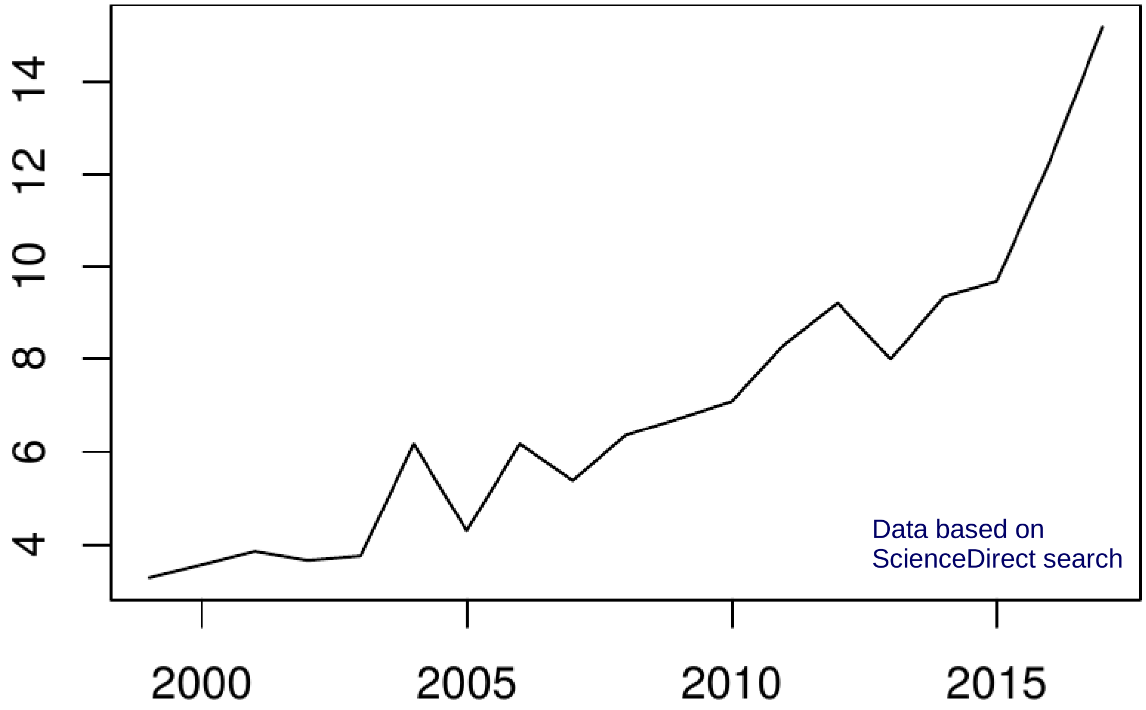


Global maps of ecosystem variables based on machine learning

Proportion of publications that use machine learning in environmental remote sensing



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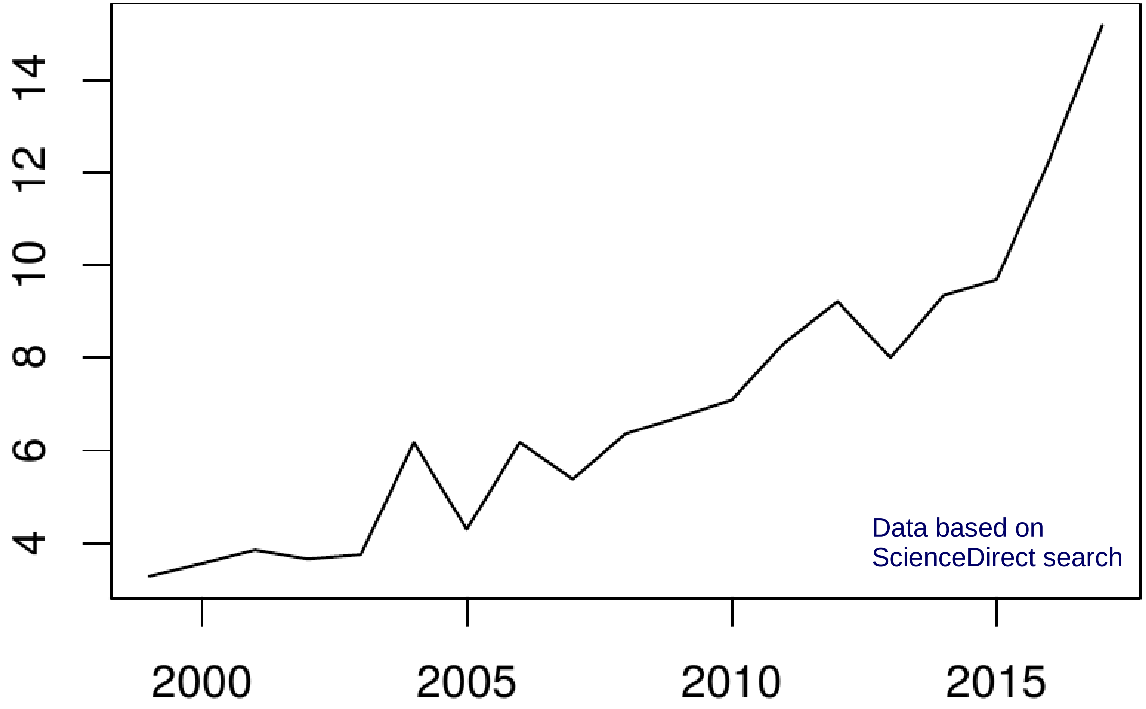

Including **global** datasets on

- soil properties
- abundances of microorganisms
- Biodiversity
- tree restoration potential
- ...and many more

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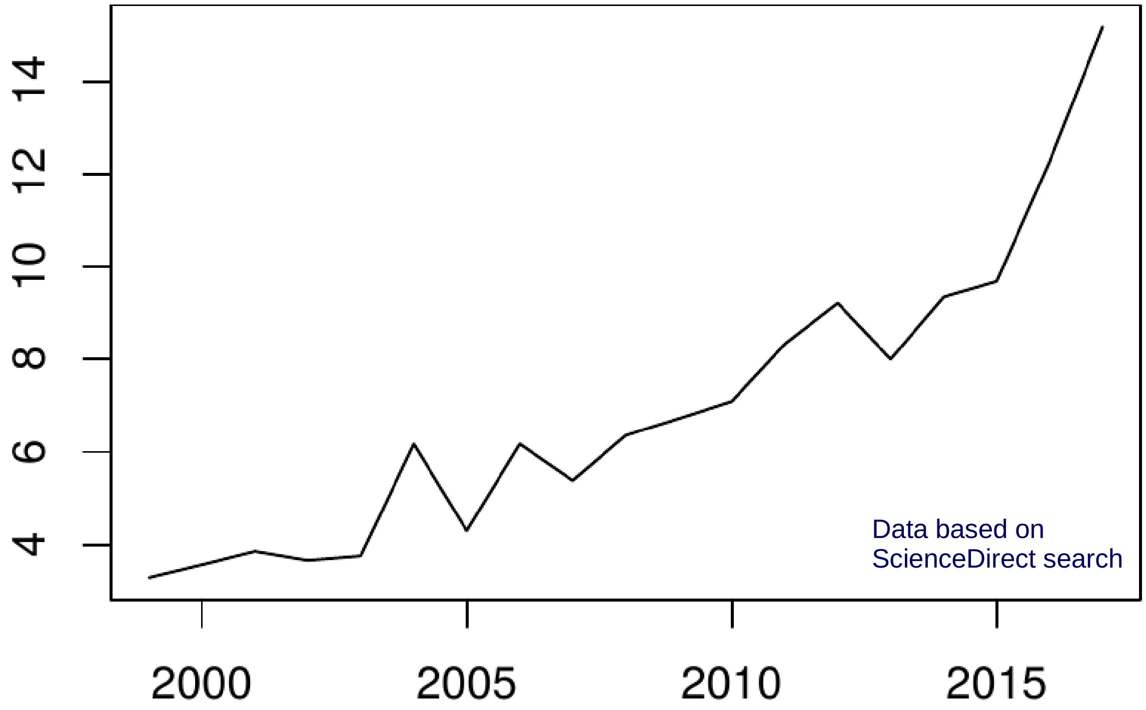

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Machine learning as a „magic tool“ to map basically everything ?

...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

Nature 574, 163-166 (2019)

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KATARINA ZIMMER

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

What we have learned so far…

See e.g. workshop at previous OpenGeoHub Summer School

Spatial dependencies need to be taken into account for machine learning applications!

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- Standard validation procedures lead to an overoptimistic view on prediction performance
  → Spatial validation is essential

What we have learned so far…

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Spatial dependencies need to be taken into account for machine learning applications!

- Standard validation procedures lead to an overoptimistic view on prediction performance
  → Spatial validation is essential
- Spatial dependencies can lead to misinterpretation of predictor variables
  → Spatial variable selection is required

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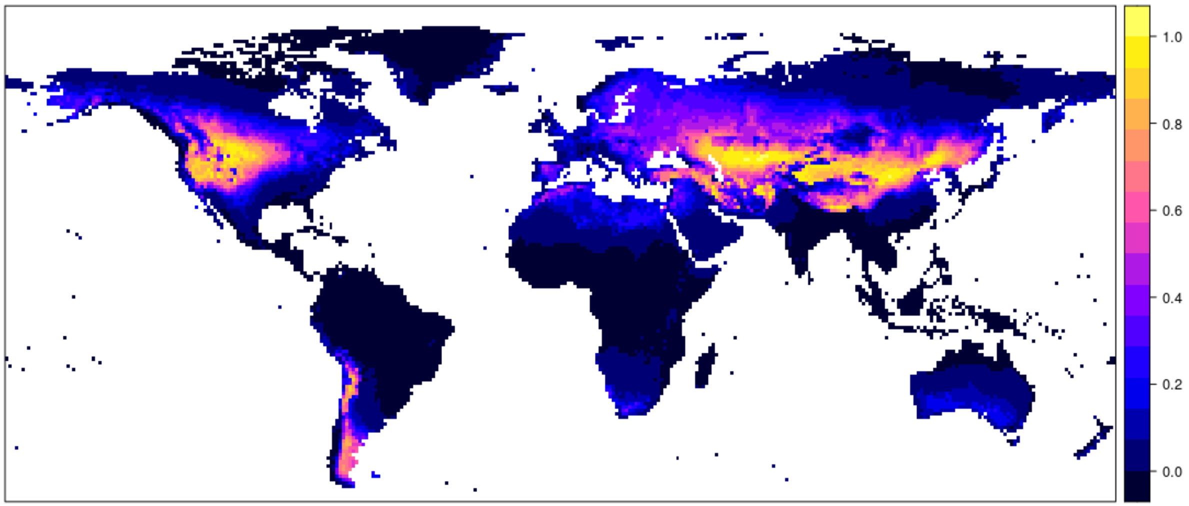
...but is this sufficient for reliable (global) mapping?

Largest challenge: predictions far beyond training samples



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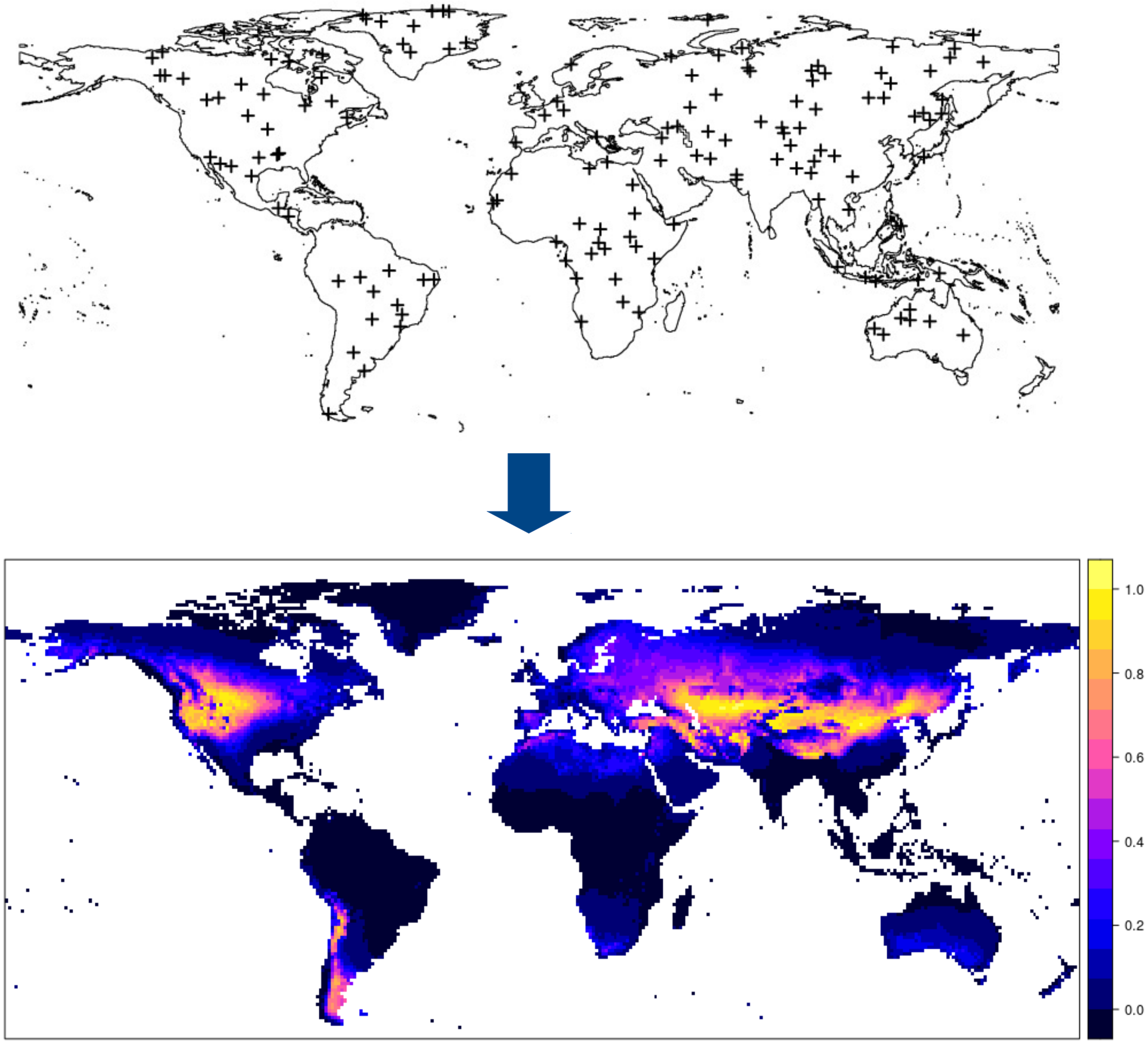

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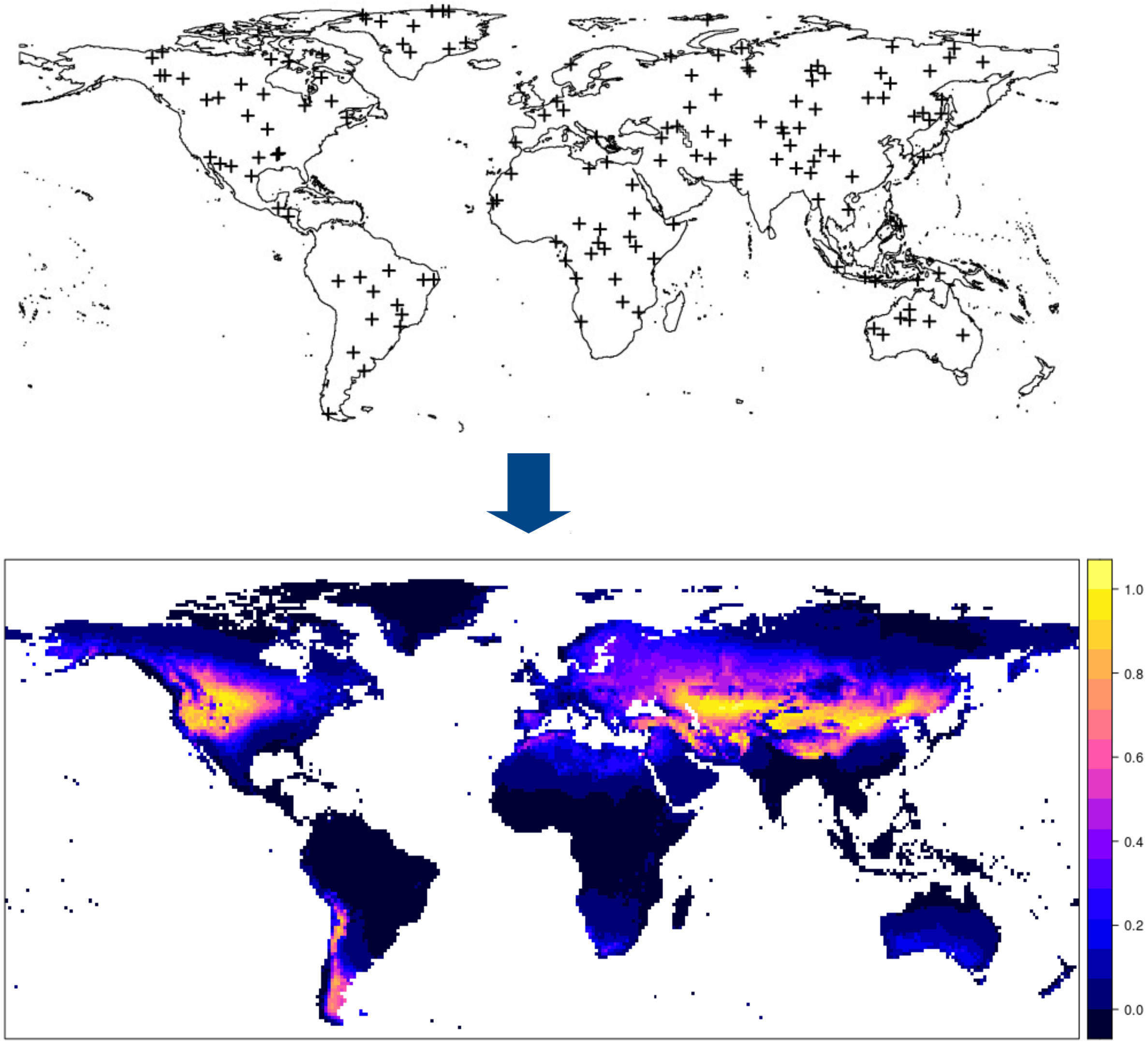
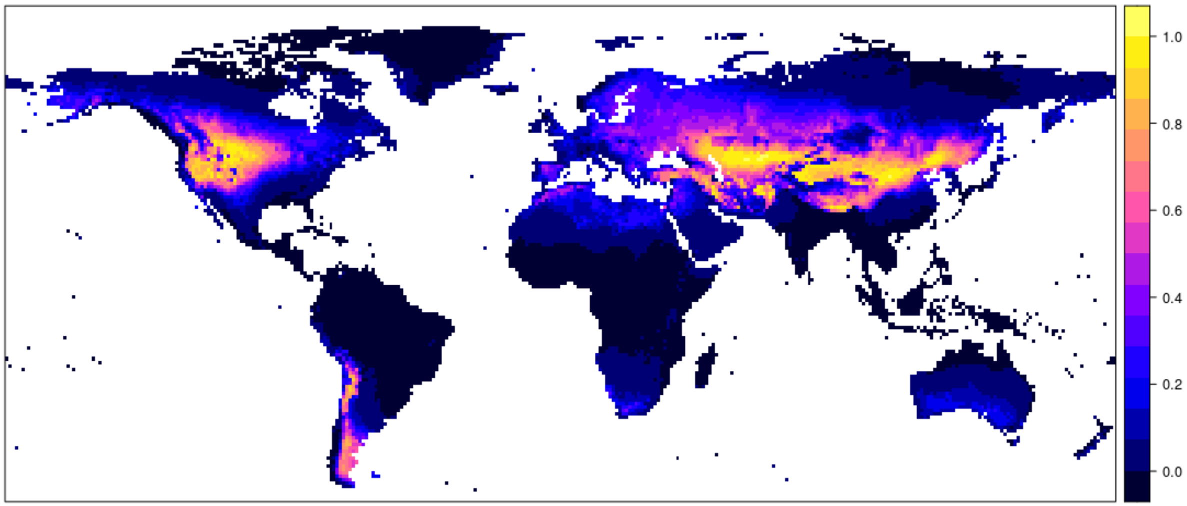


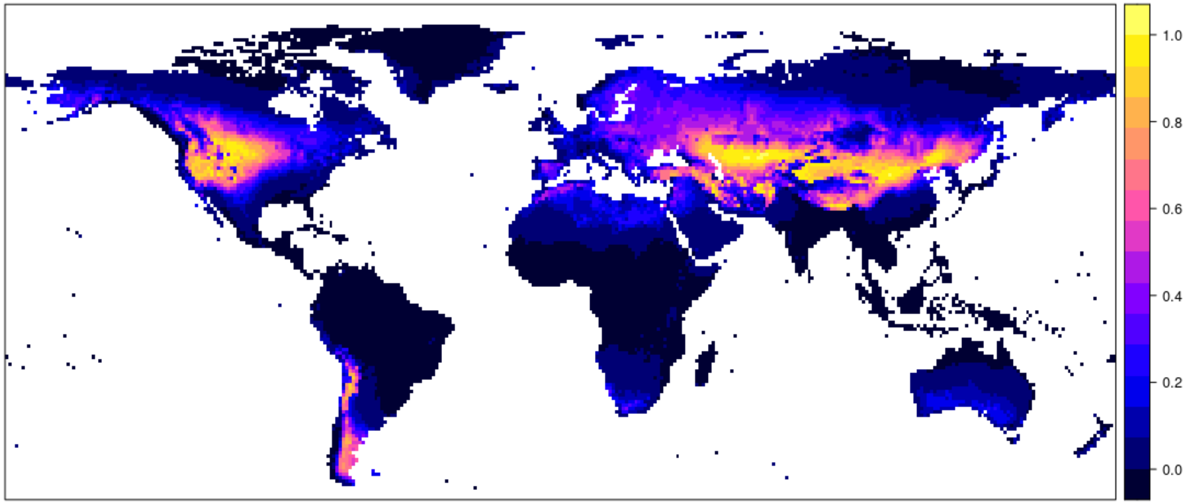
- Transfer to new space required

Largest challenge: predictions far beyond training samples



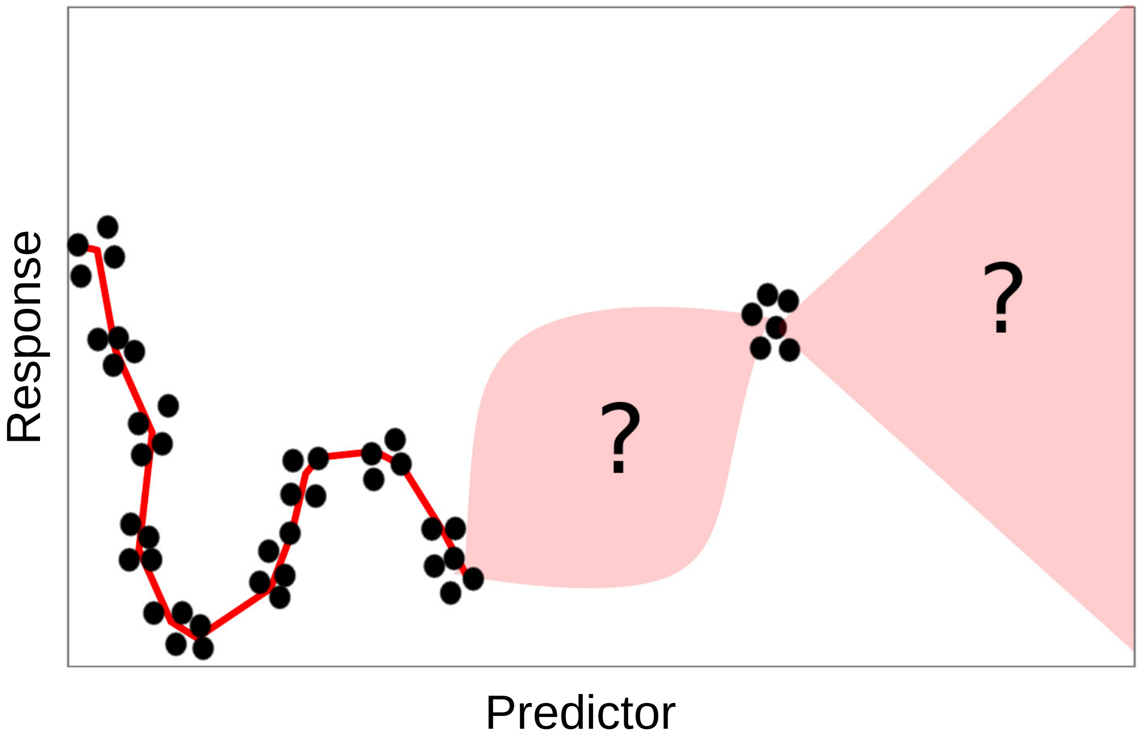
- Transfer to new space required
- New space might differ in environmental properties

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



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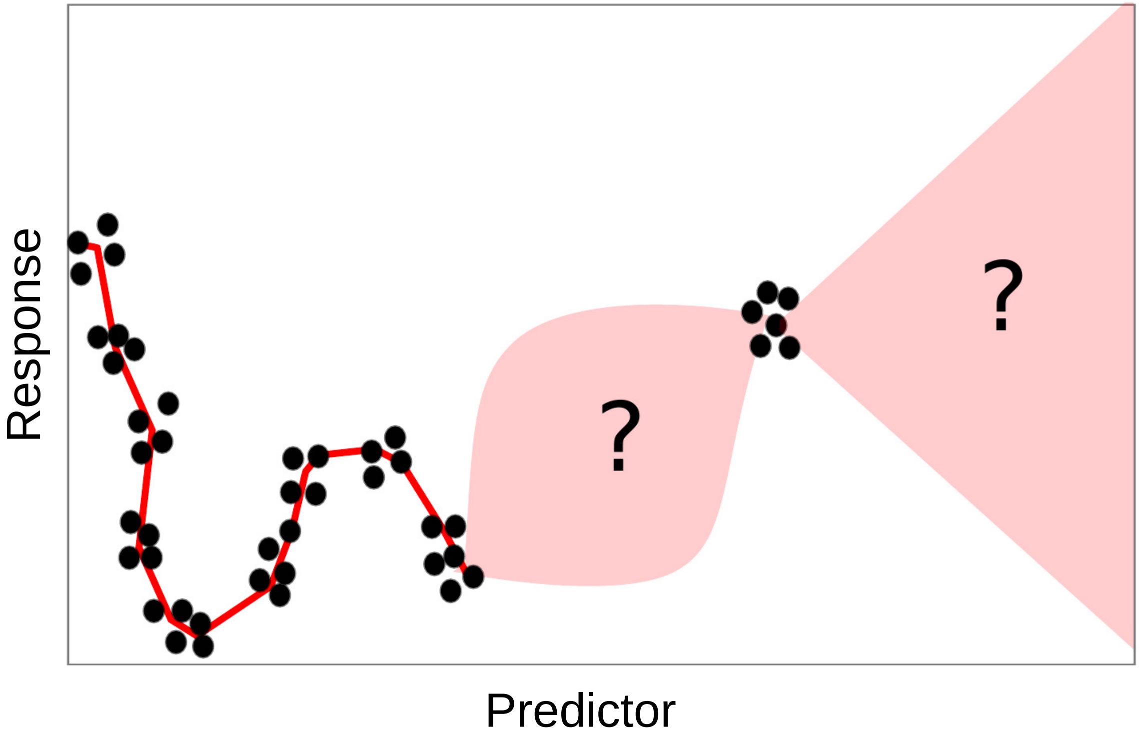

- Machine learning can fit very complex relationships.
- But gaps in predictor space are problematic (the model has no knowledge about these areas!)

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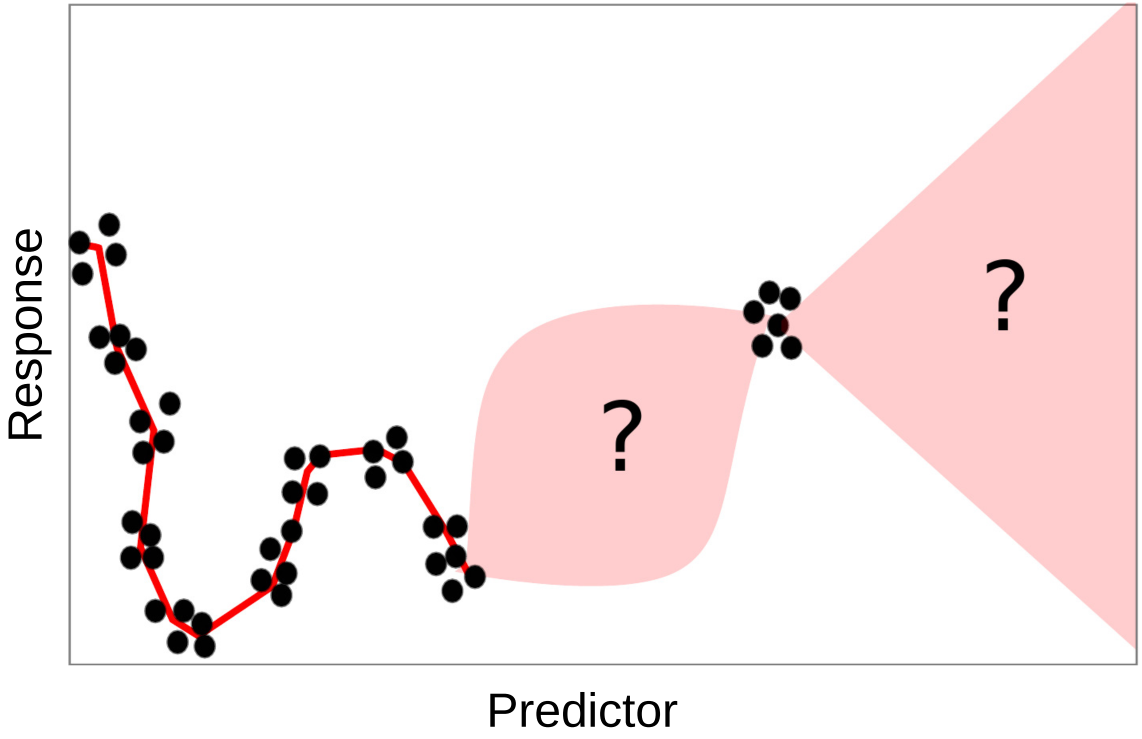
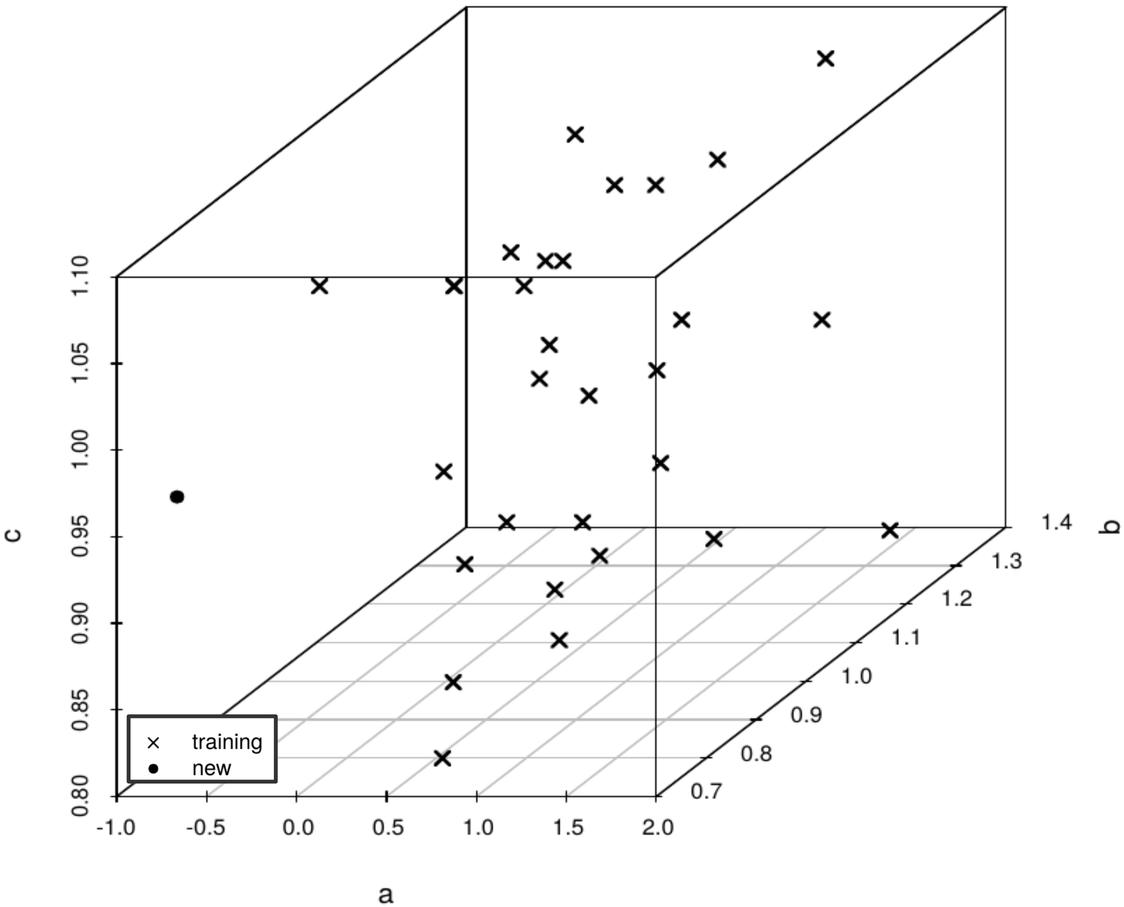


- Machine learning can fit very complex relationships.
- But gaps in predictor space are problematic (the model has no knowledge about these areas!)
- A measure for “unknown space” is needed

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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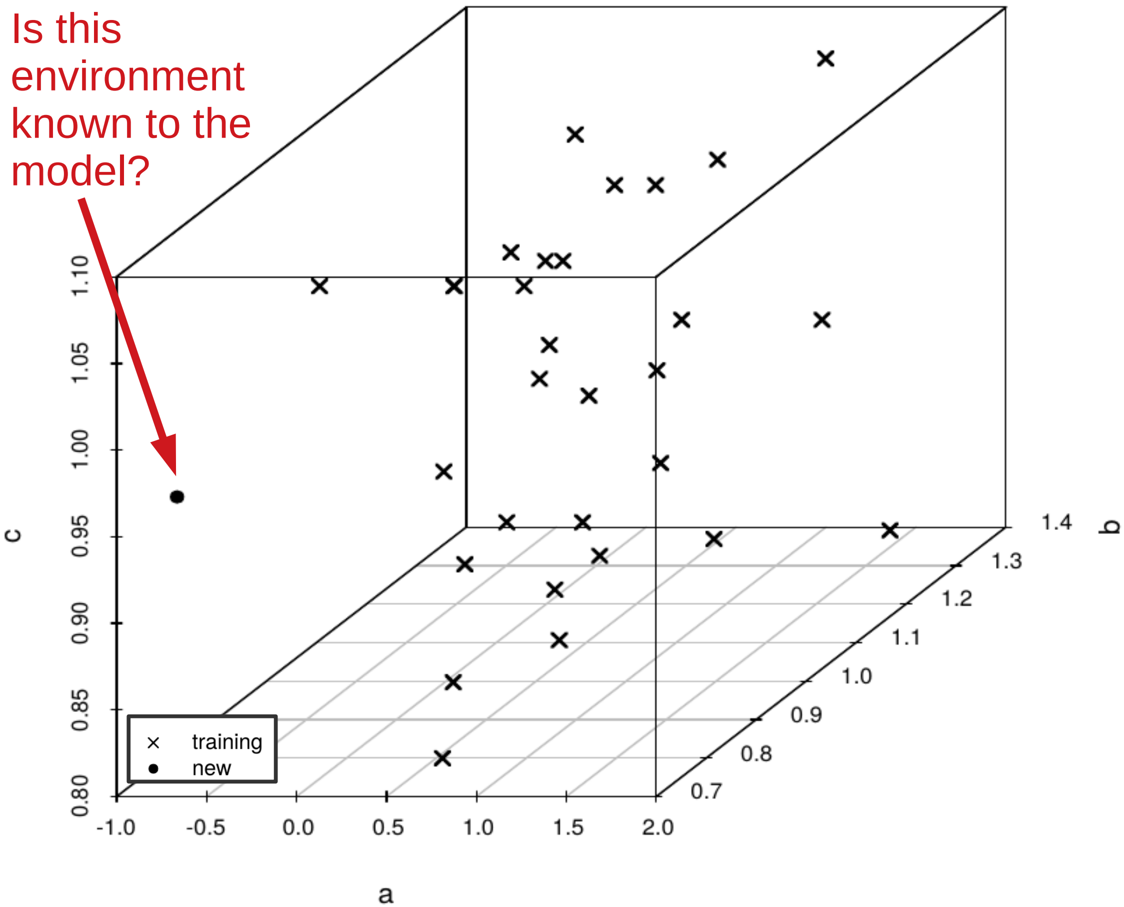

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Distances in feature space as a measure for "unknown space"

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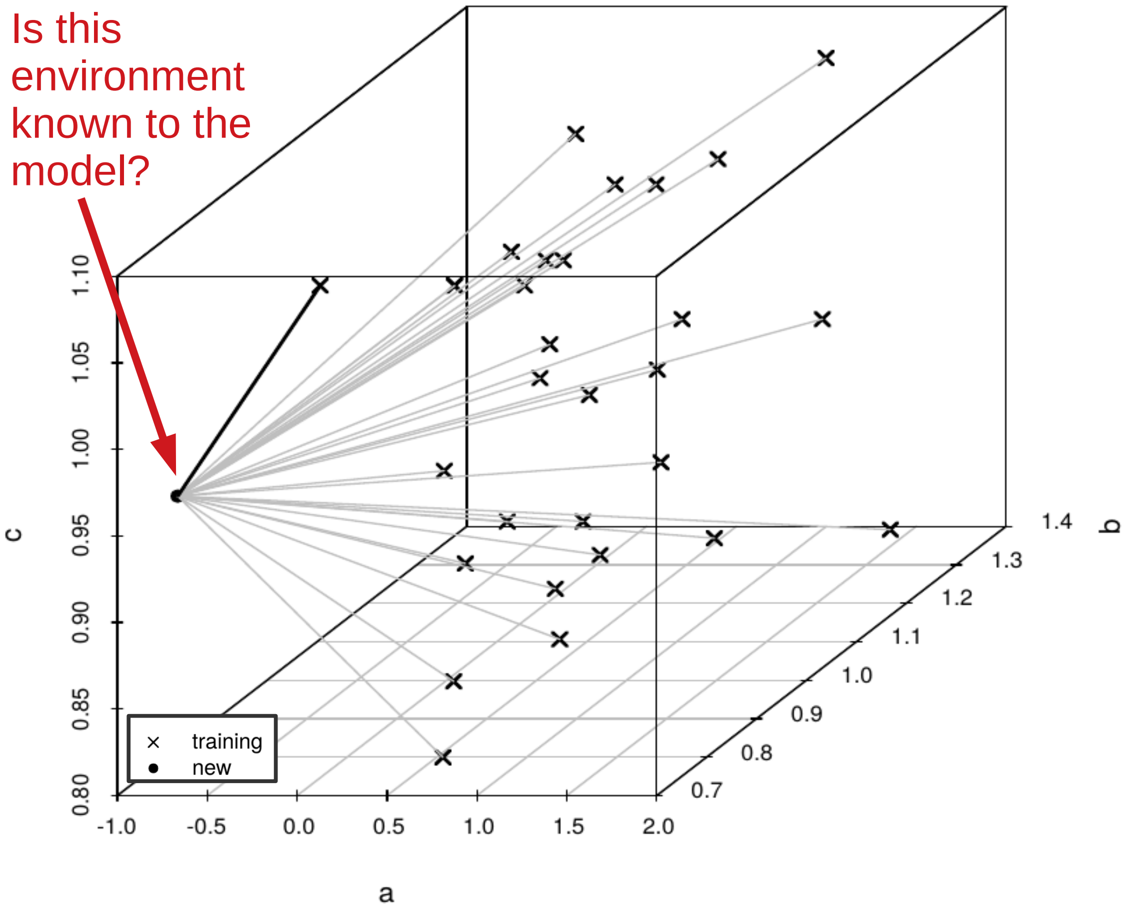

- Unknown space: Environmental conditions that are very different from the training locations
- Suggestion: Dissimilarity Index based on distances in the (weighted) predictor space*

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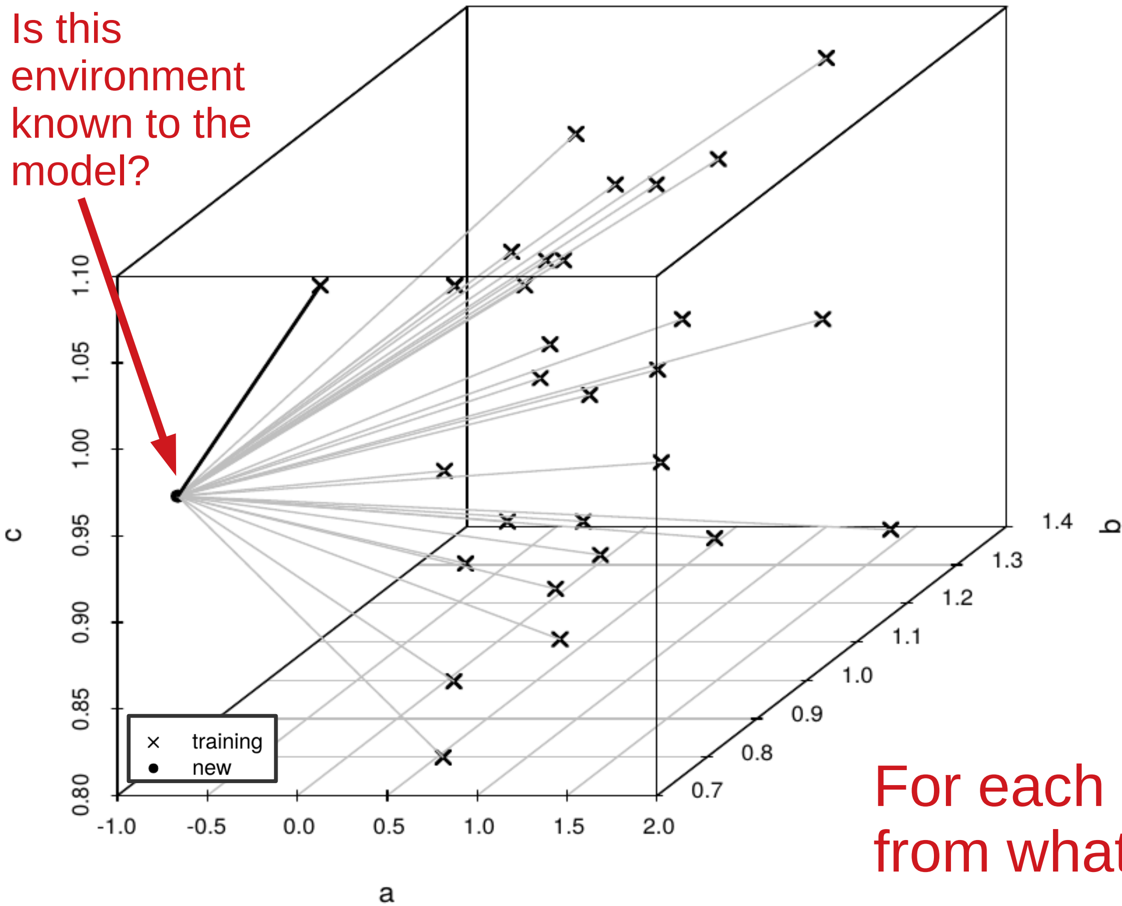

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For each new location/pixel: how distant is it from what the algorithm has seen?

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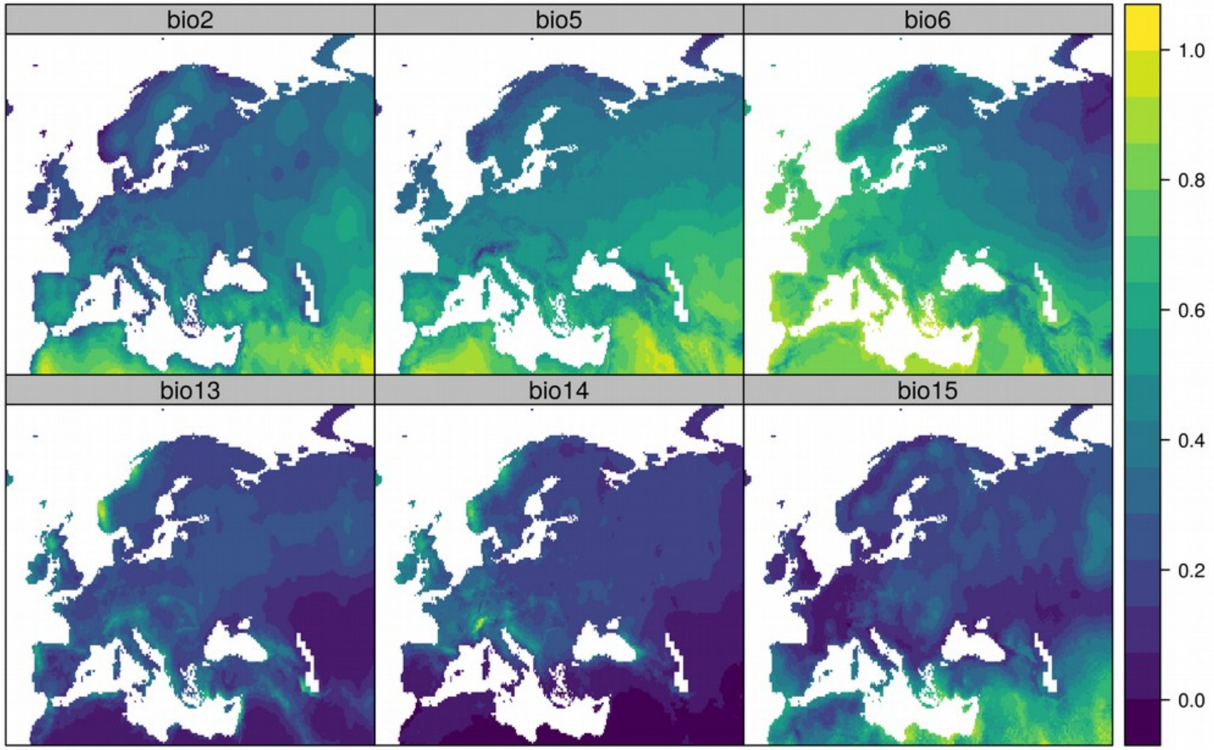
Mapping the area of applicability - Example

Predictors



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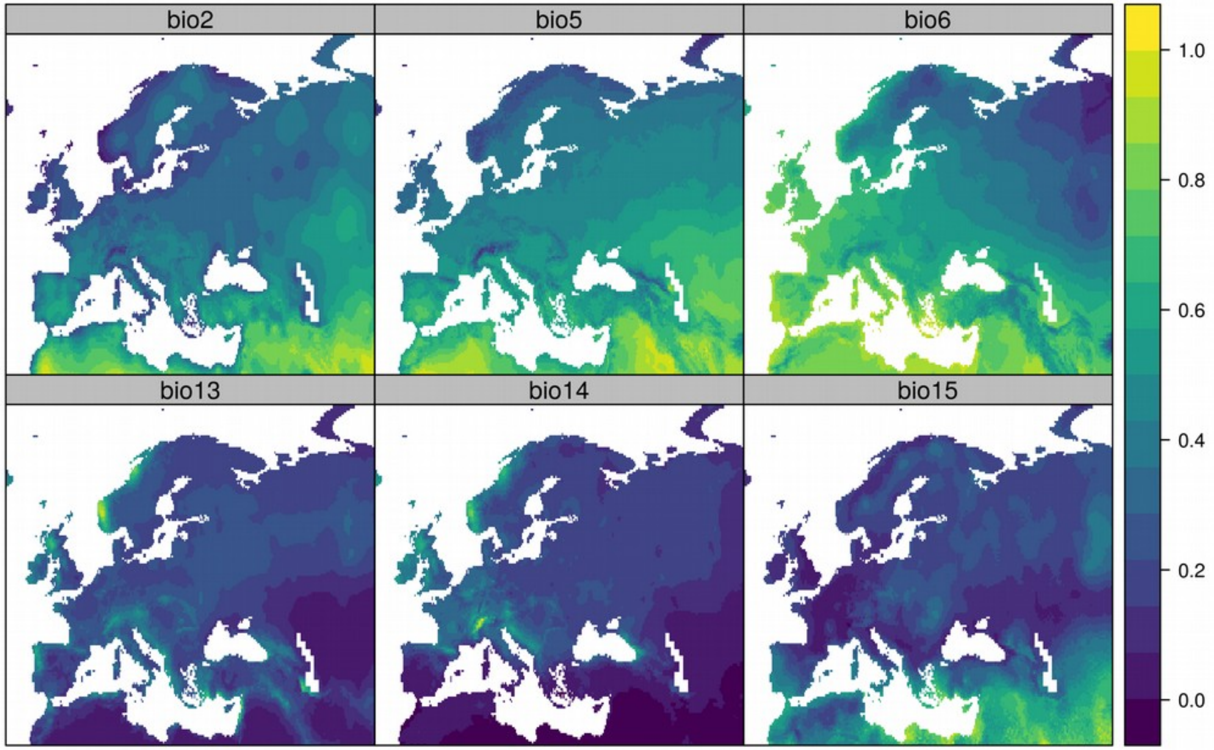
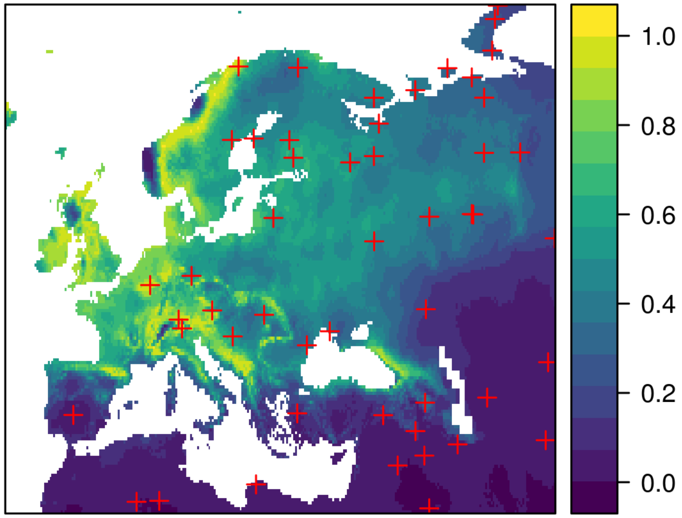


Virtual Response and simulated samples



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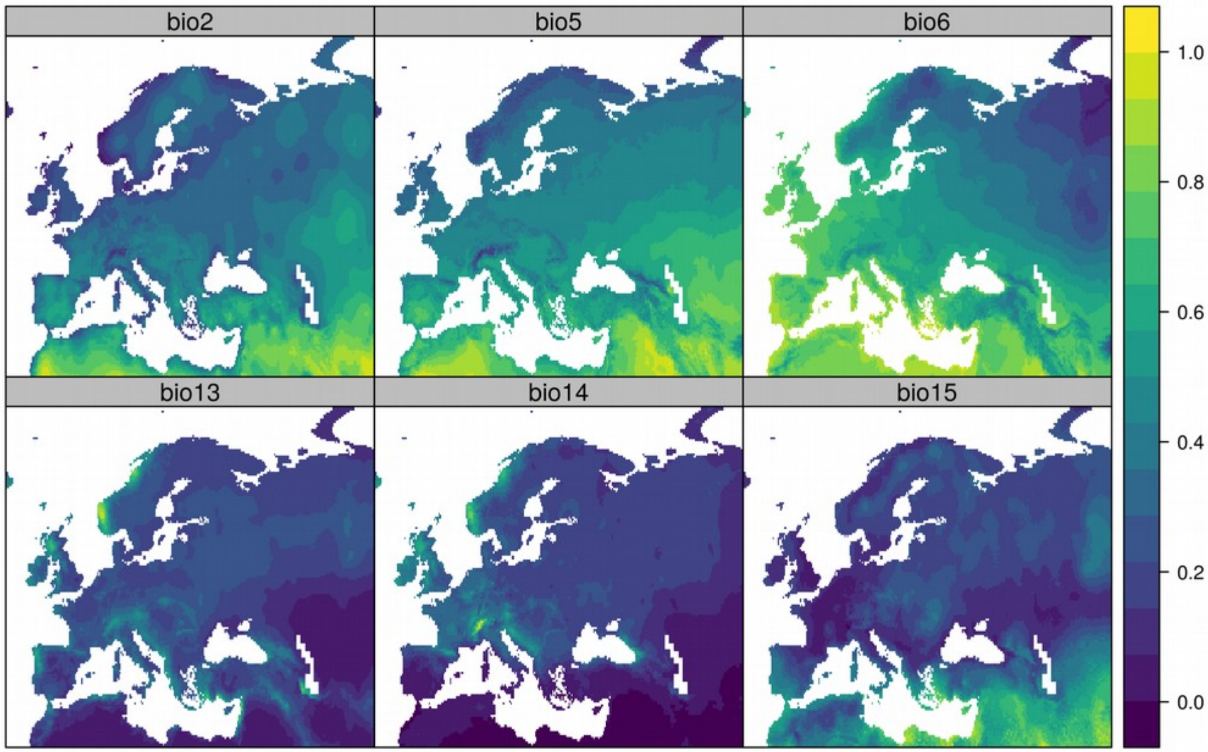

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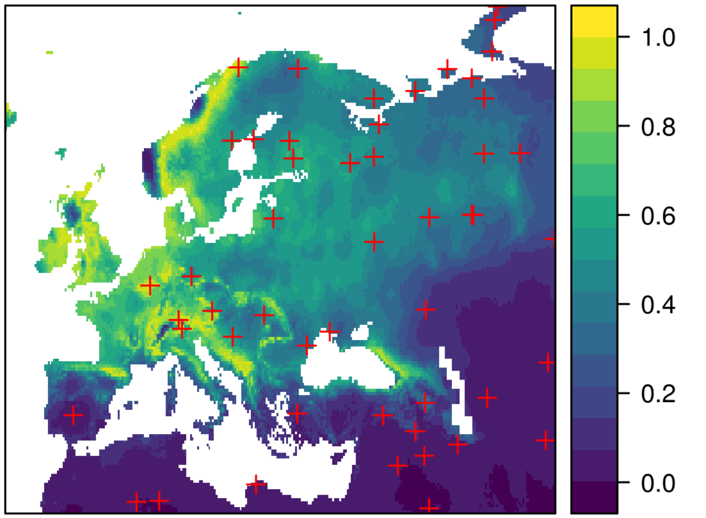

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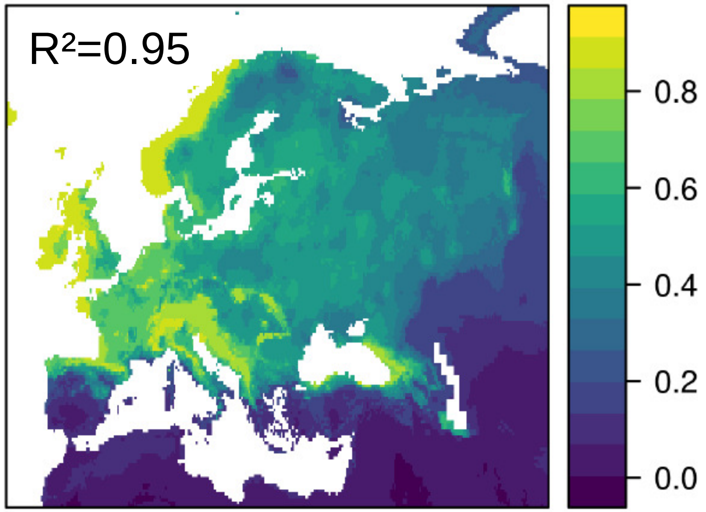

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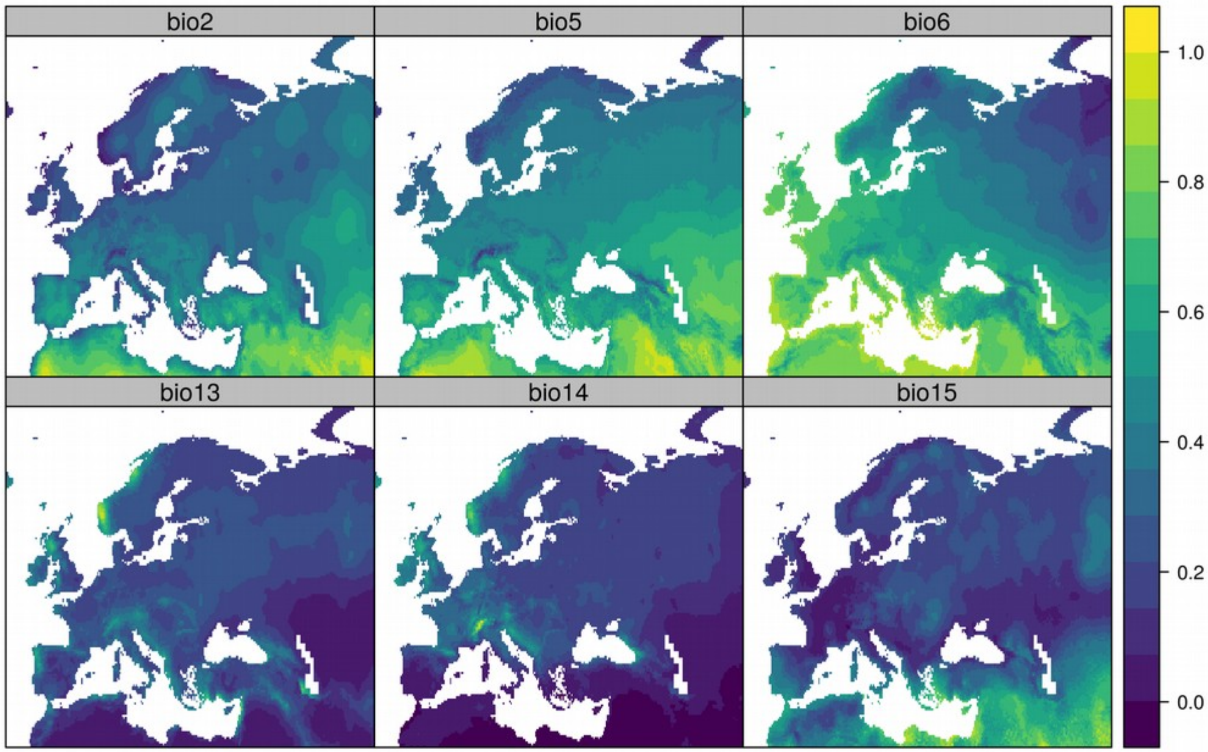

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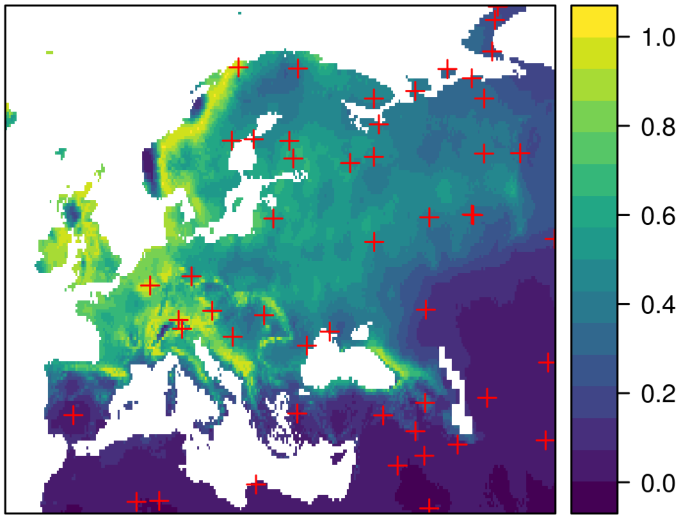

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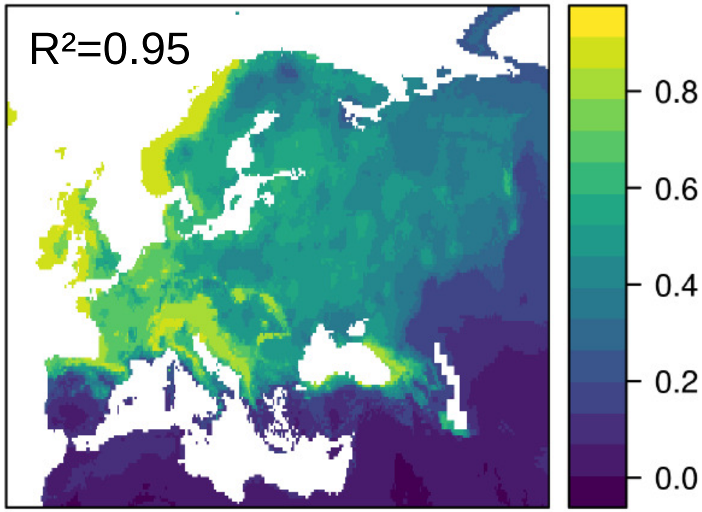
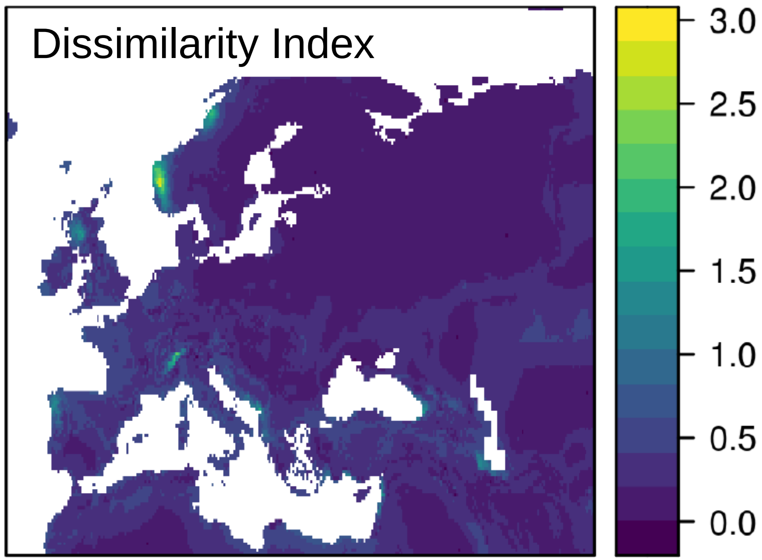


Where can we trust the predictions
and where should we better not?

Mapping the area of applicability - Example



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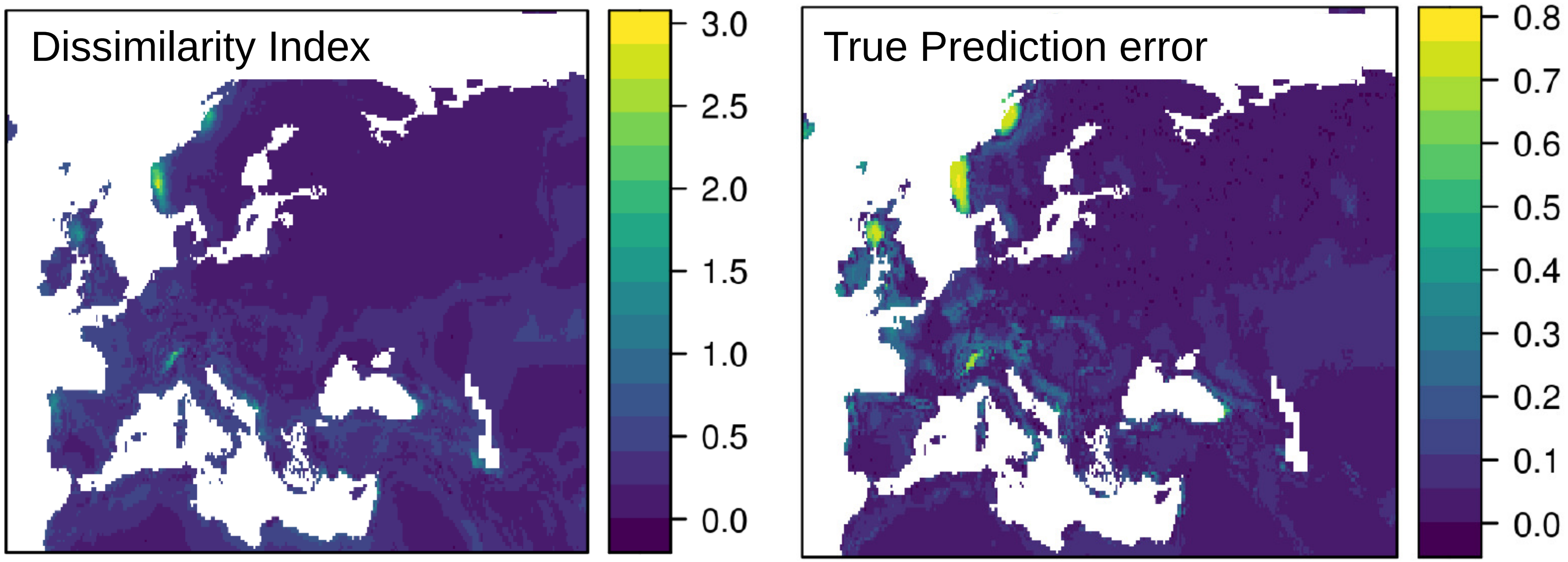

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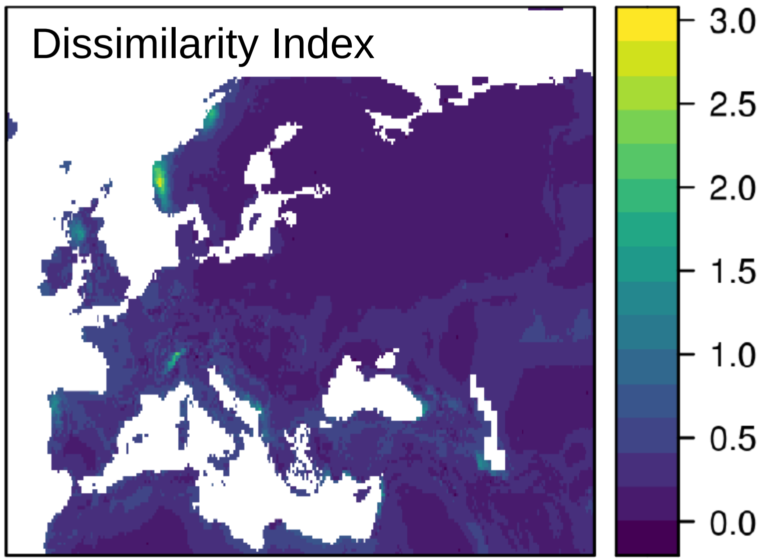
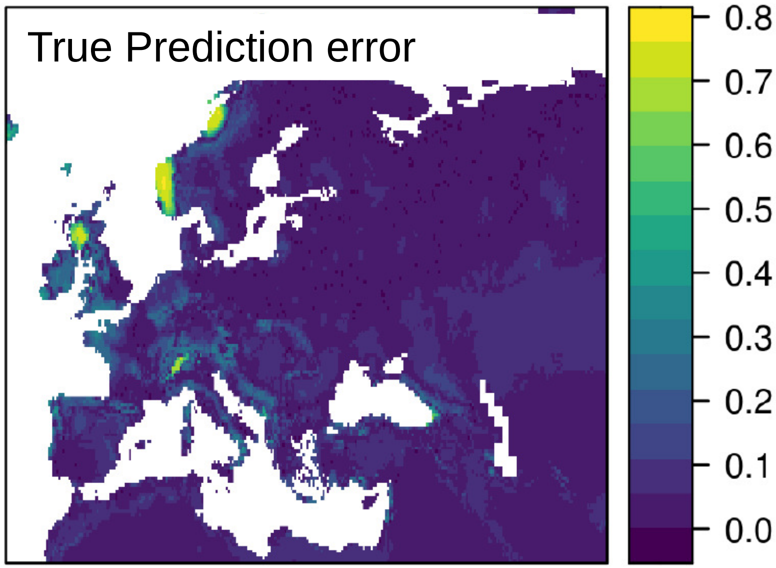
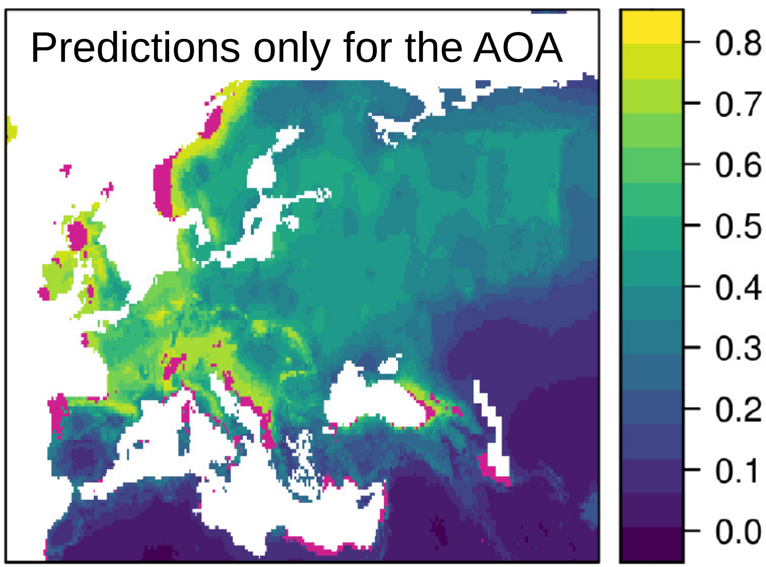






Threshold = DI of cross-validated training data

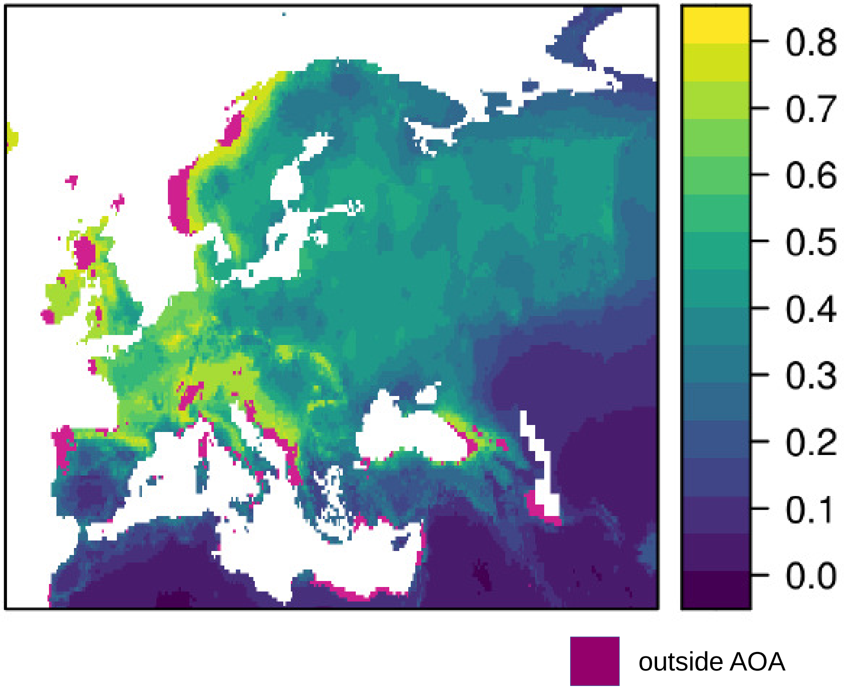
DI < threshold = inside AOA
DI > threshold = outside AOA

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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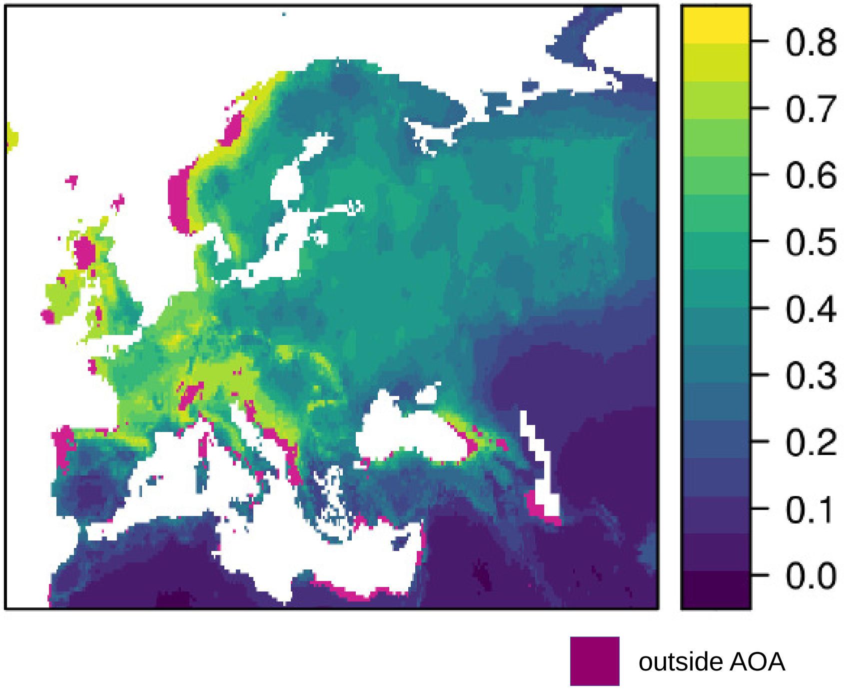
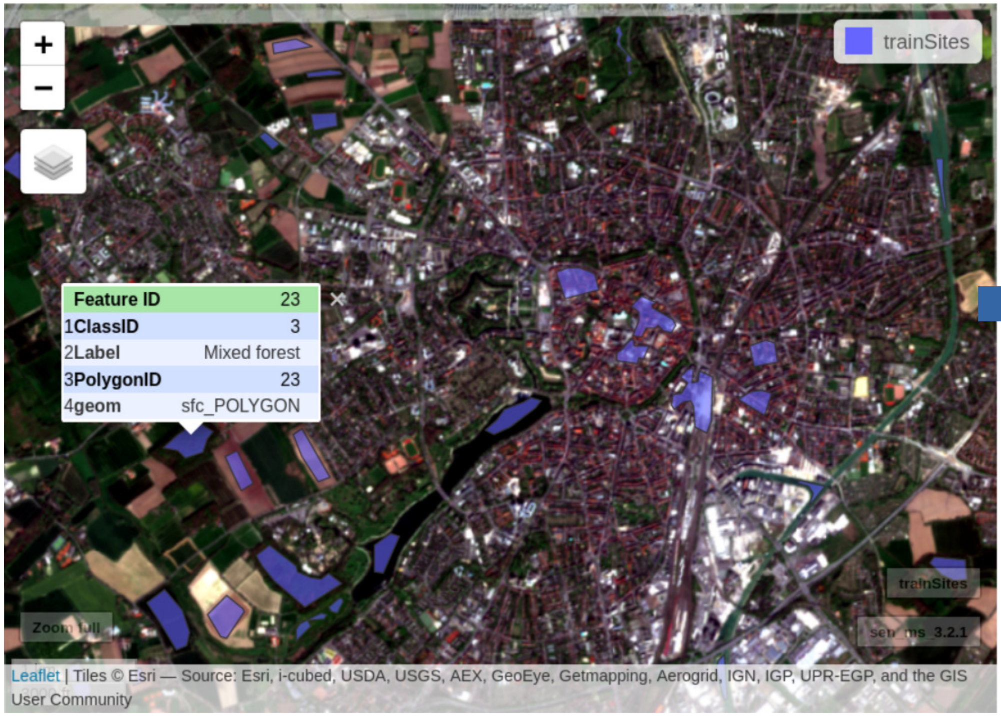
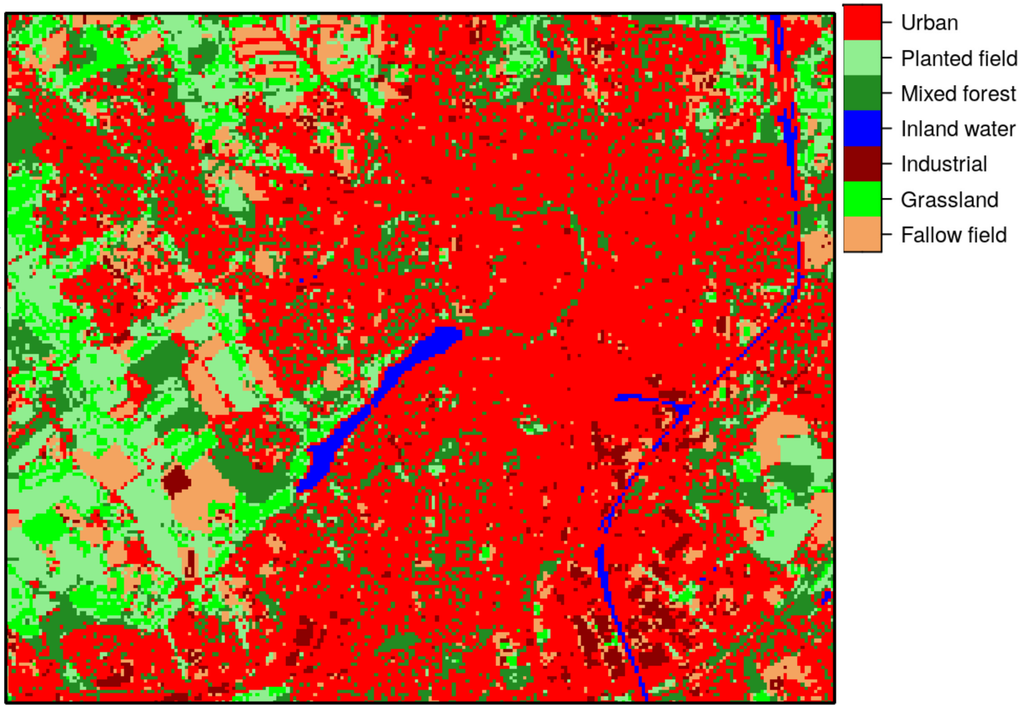


Predictions should only be presented for the area of applicability to avoid error propagation or misplanning (and to keep trust in the methods)!

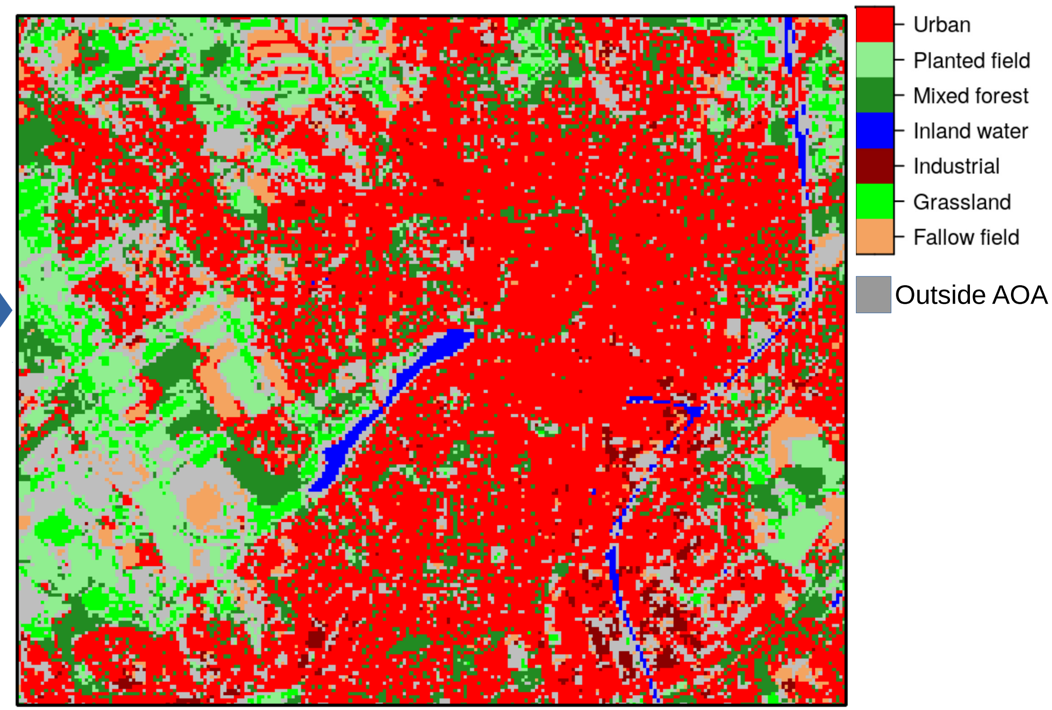
Today’s hands-on exercise





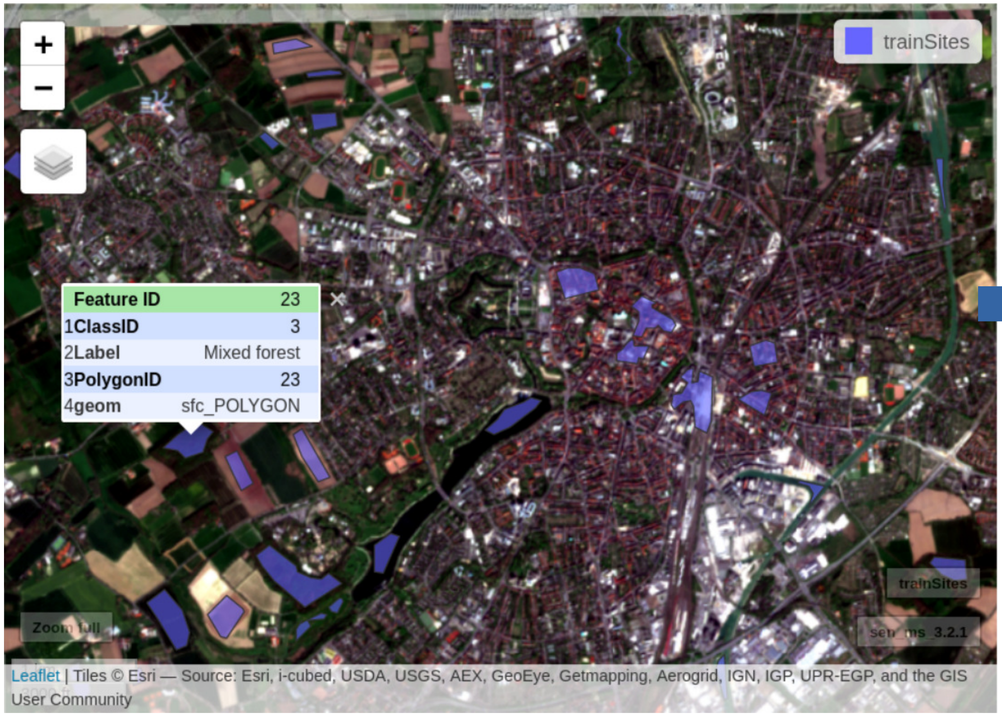
- Machine learning for remote sensing based land cover classification

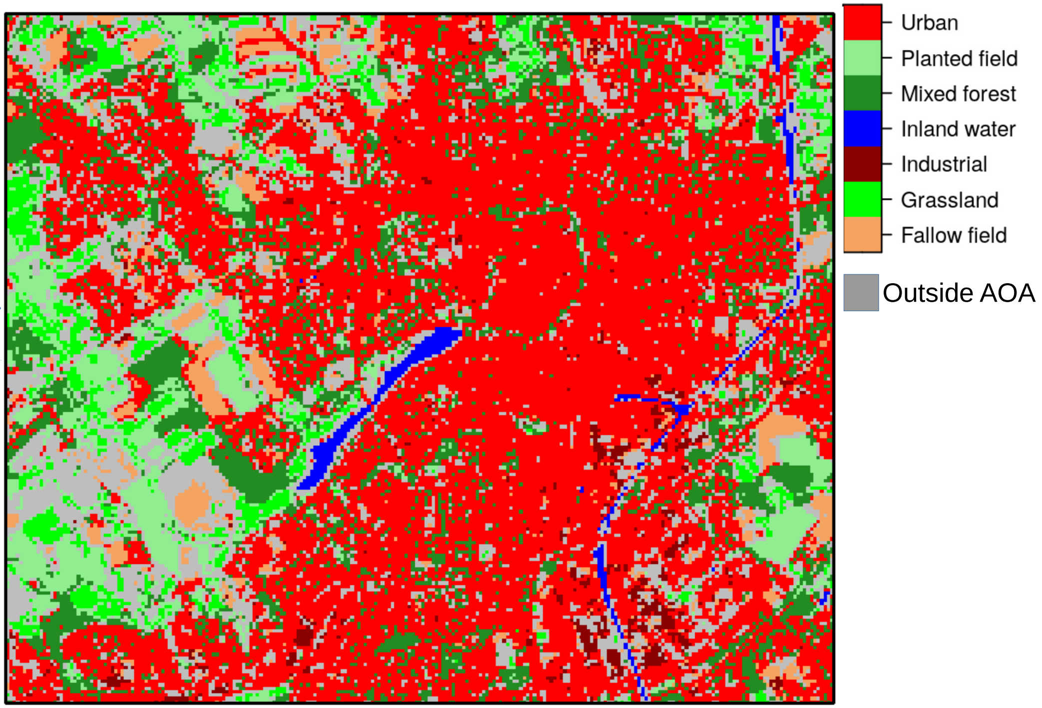
Today's hands-on exercise



- Machine learning for remote sensing based land cover classification
- Analysing the area of applicability

Today’s hands-on exercise





- Machine learning for remote sensing based land cover classification
- Analysing the area of applicability
- Assessing the transferability of a model