Machine learning-based maps of the environment: challenges of extrapolation and overfitting

Part 1: Introduction to the topic
Part 2: Predictive mapping and dealing with the challenges in practice

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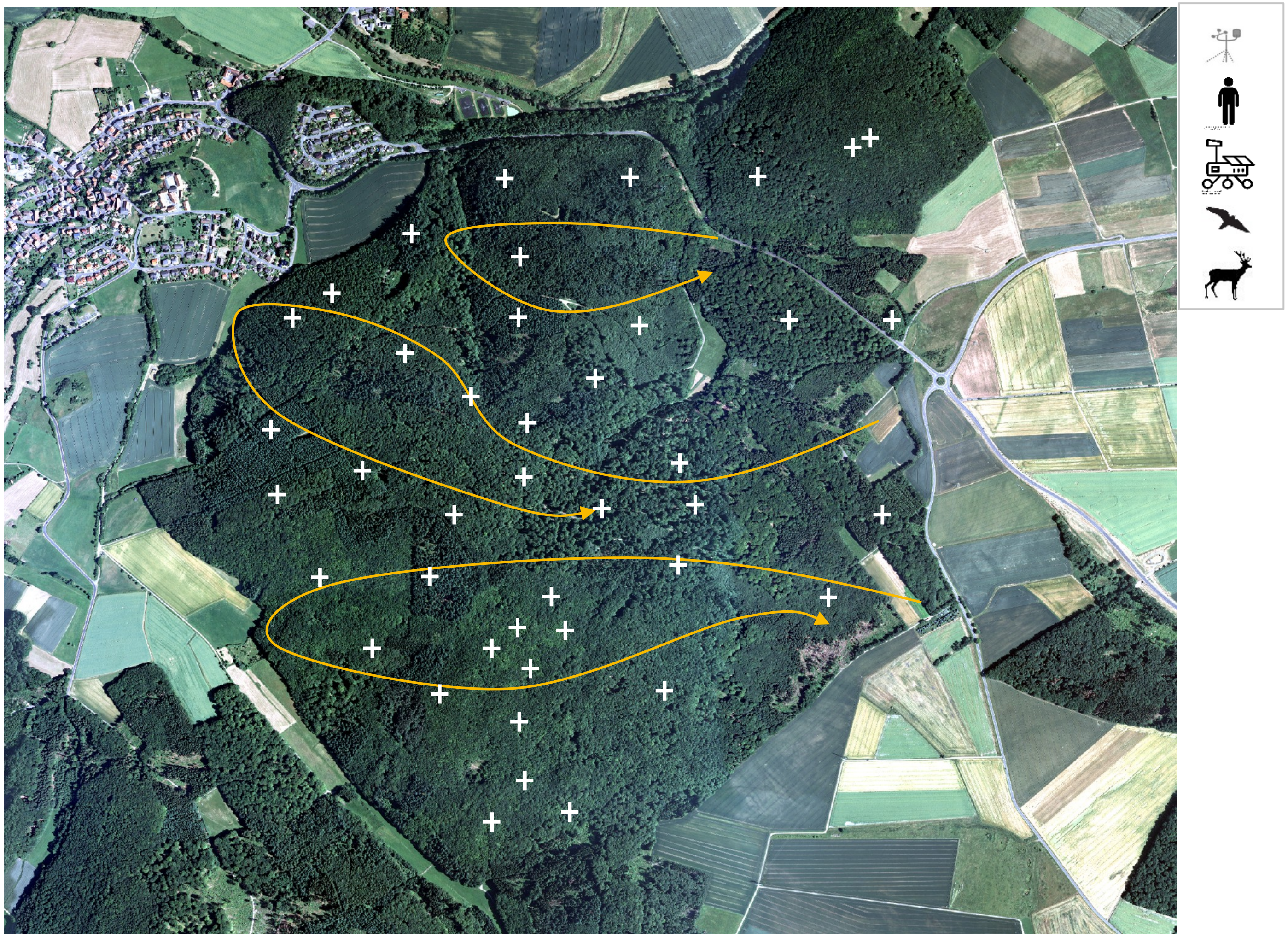
Remote Sensing & Spatial Modelling,
Institute of Landscape Ecology, WWU Münster

Aim of this workshop

- Lecture
  - Learn the general concepts of machine learning for predictive mapping
  - Get to know about potential pitfalls and solutions
- Practice:
  - Use R for model training and prediction
  - Two examples
    - Land cover classification
    - Regression model: Leaf area index

Problem: From field observations to maps of ecosystem variables

Nature 4.0 | Sensing Biodiversity



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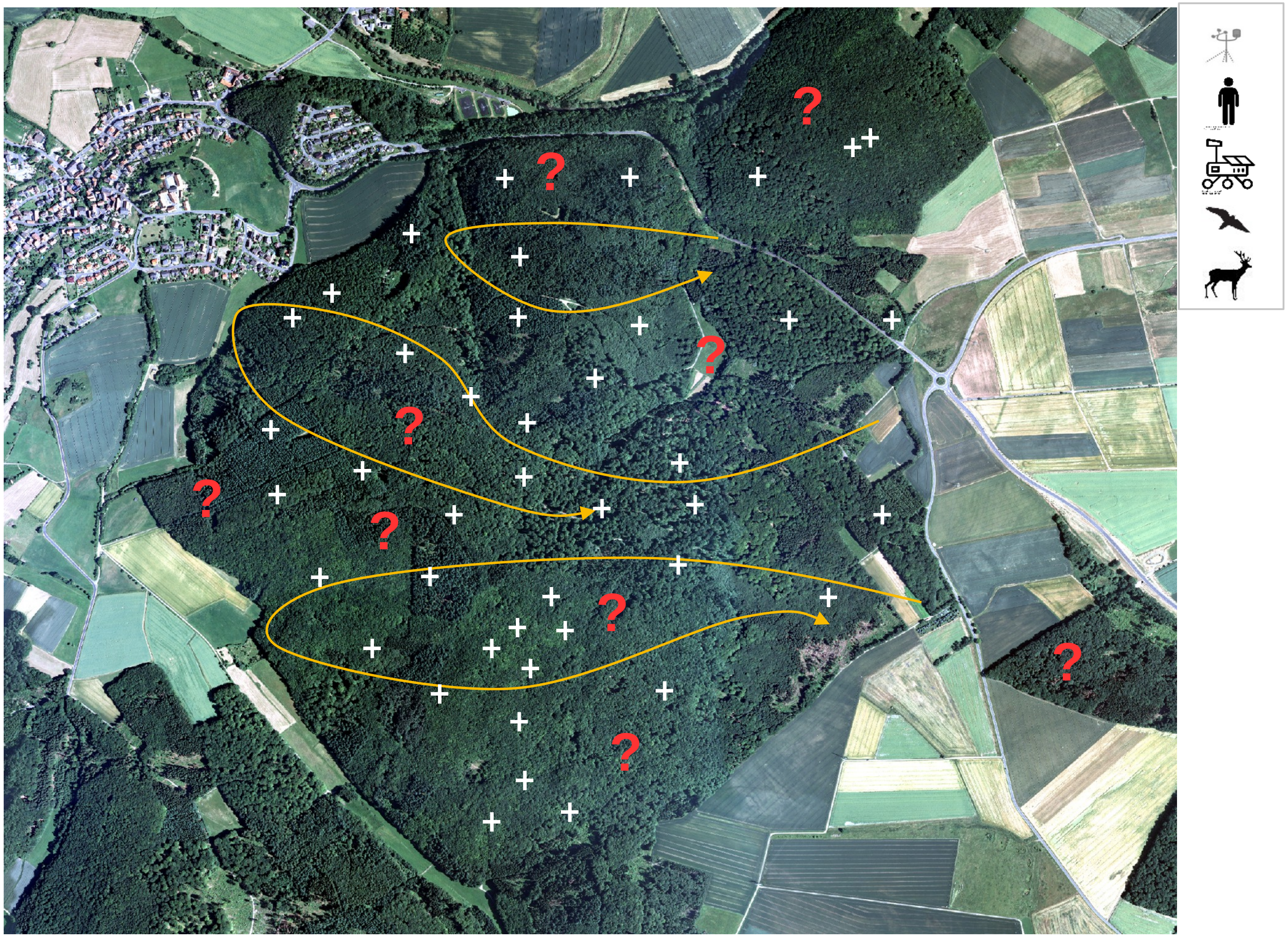

Remote Sensing to derive continuous information

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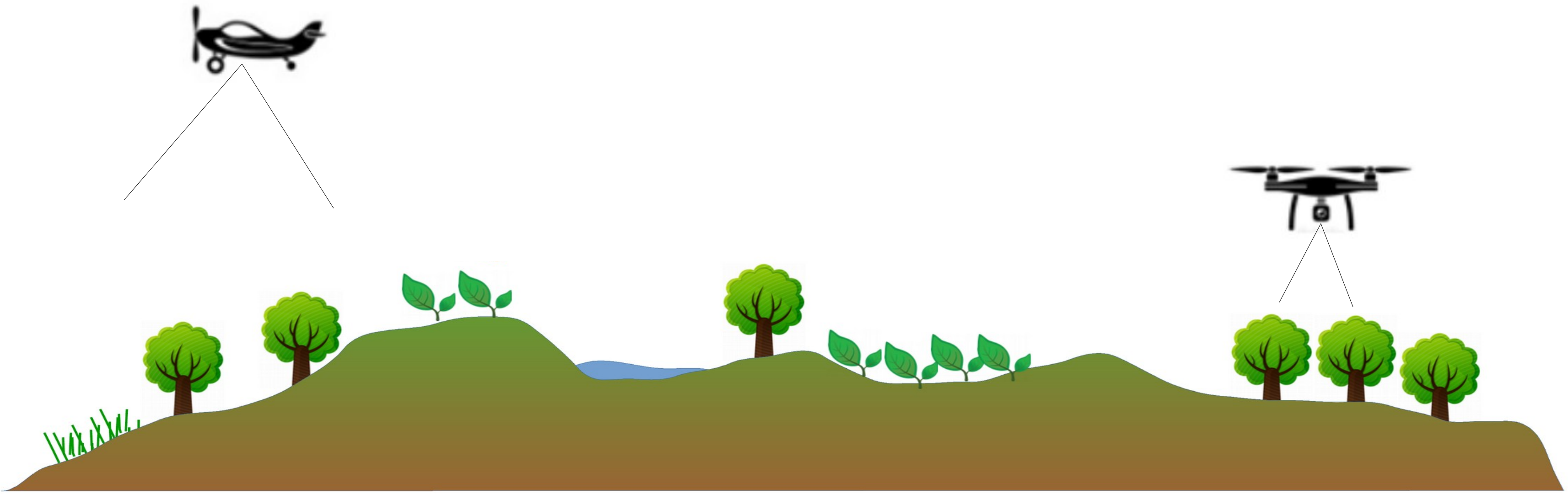

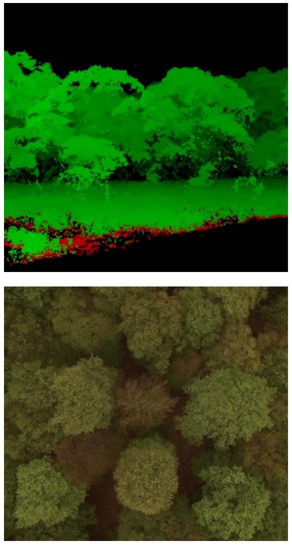

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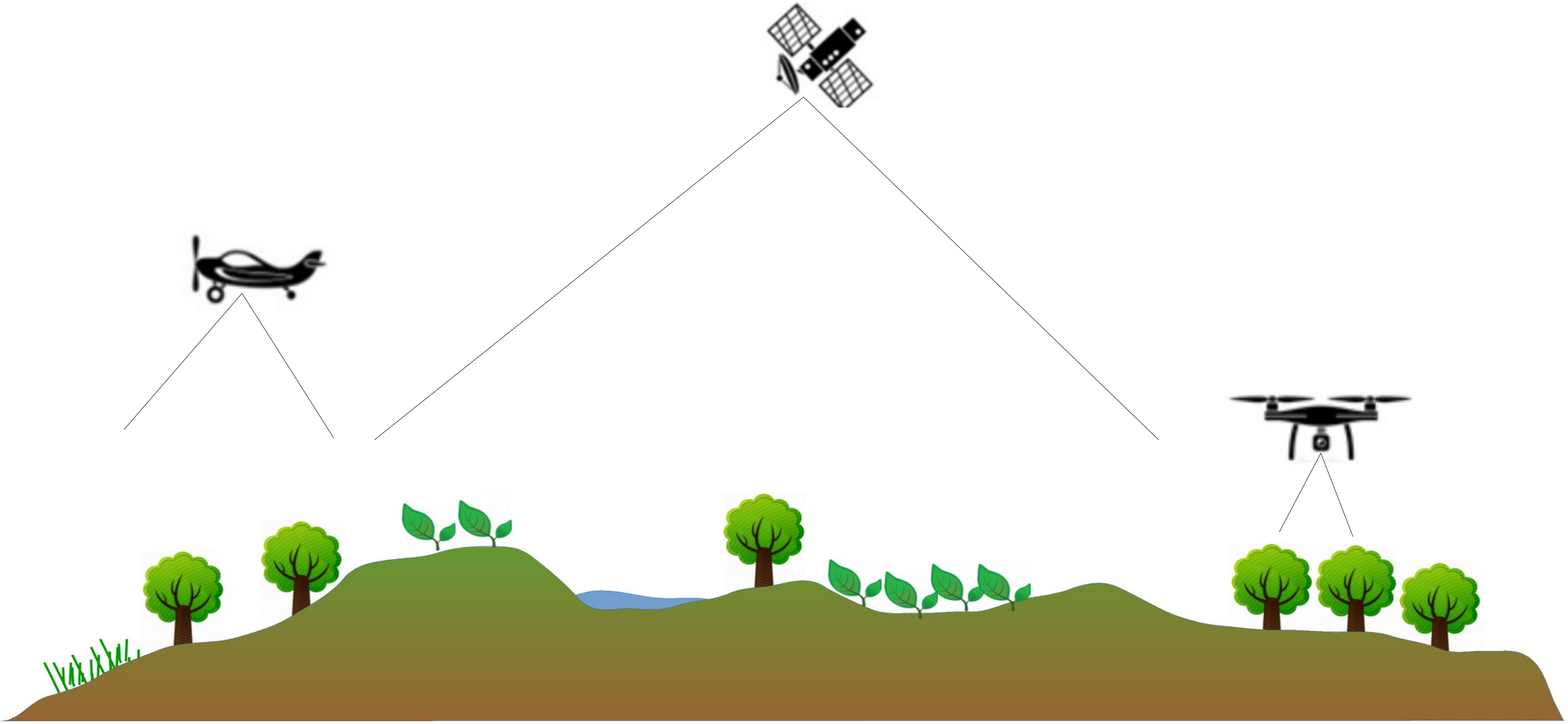

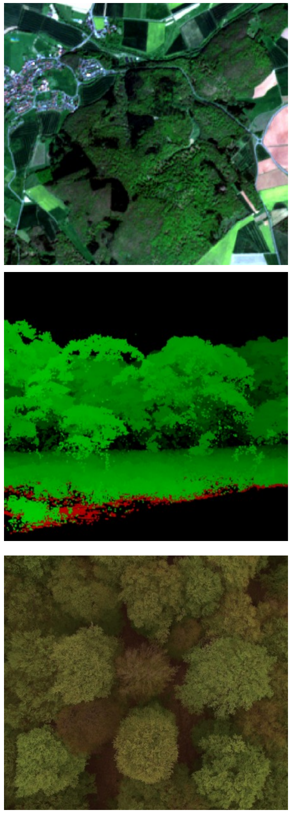

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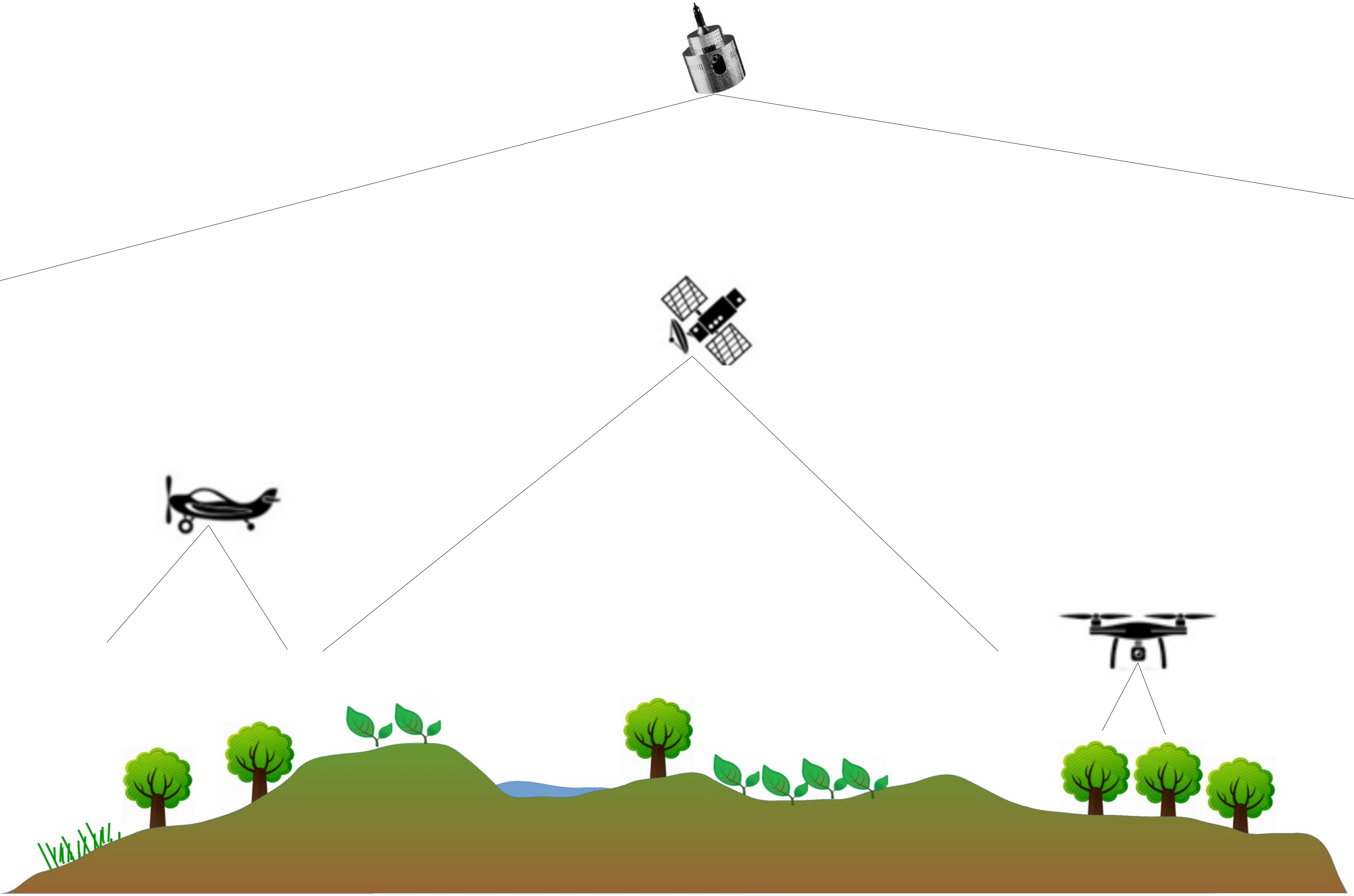

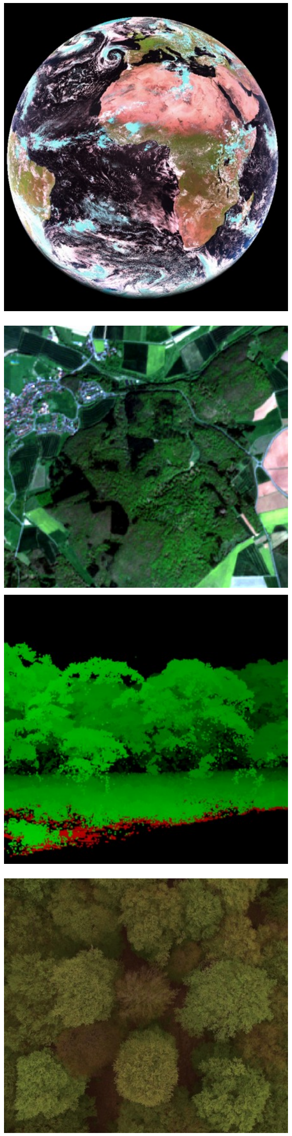

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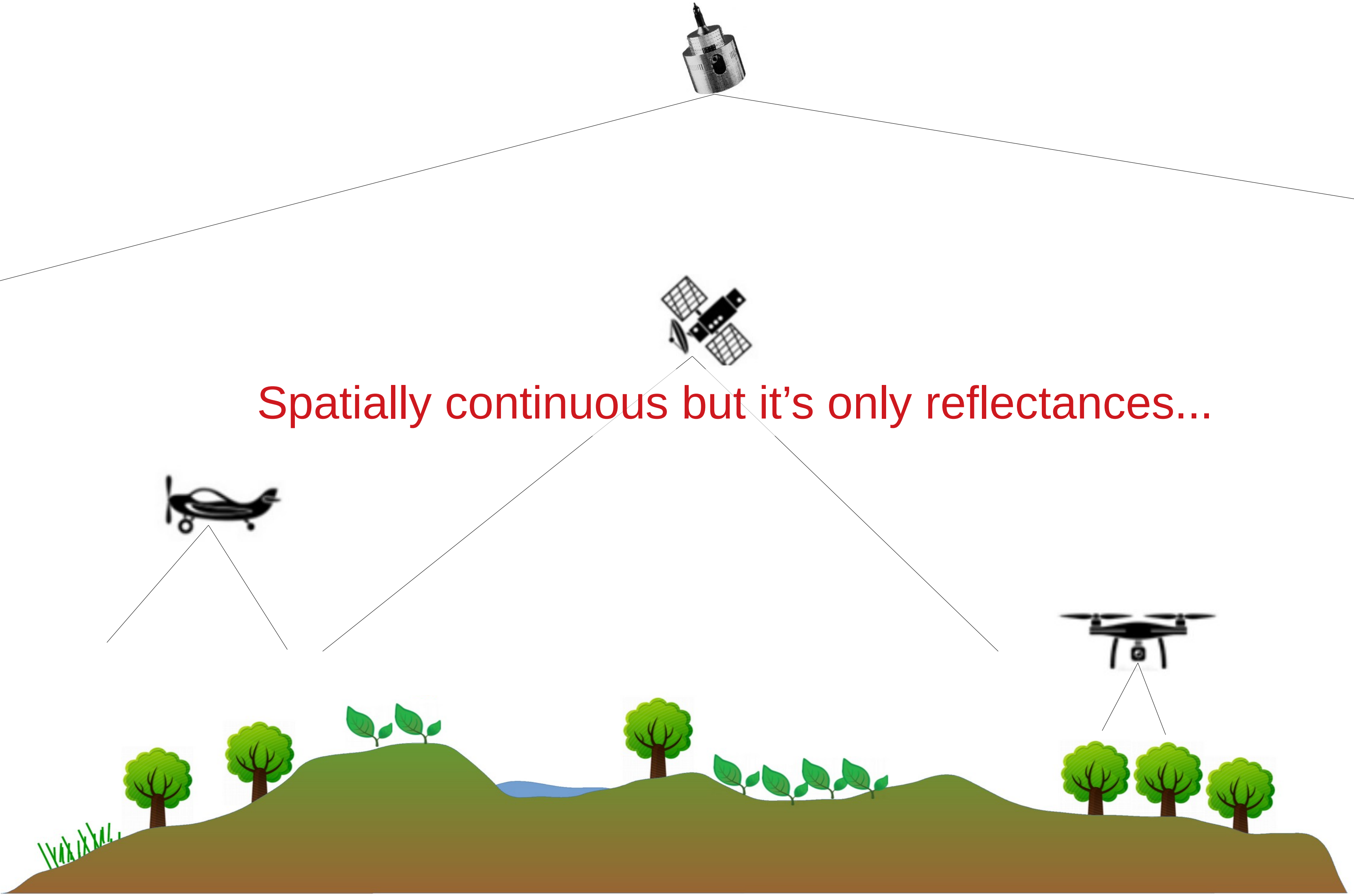
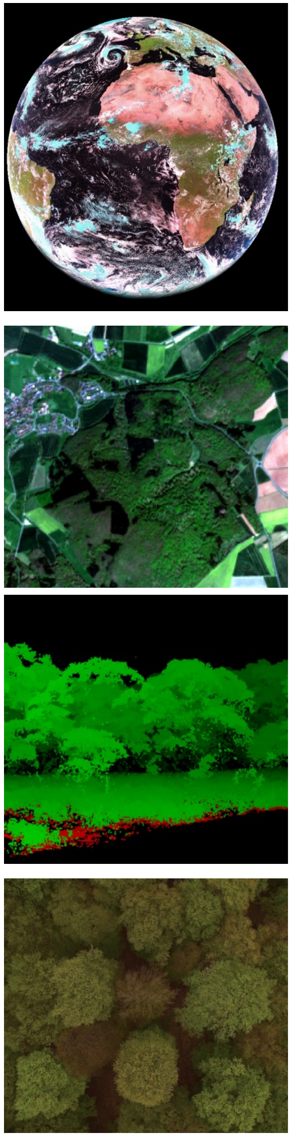


Spatially continuous but it's only reflectances...



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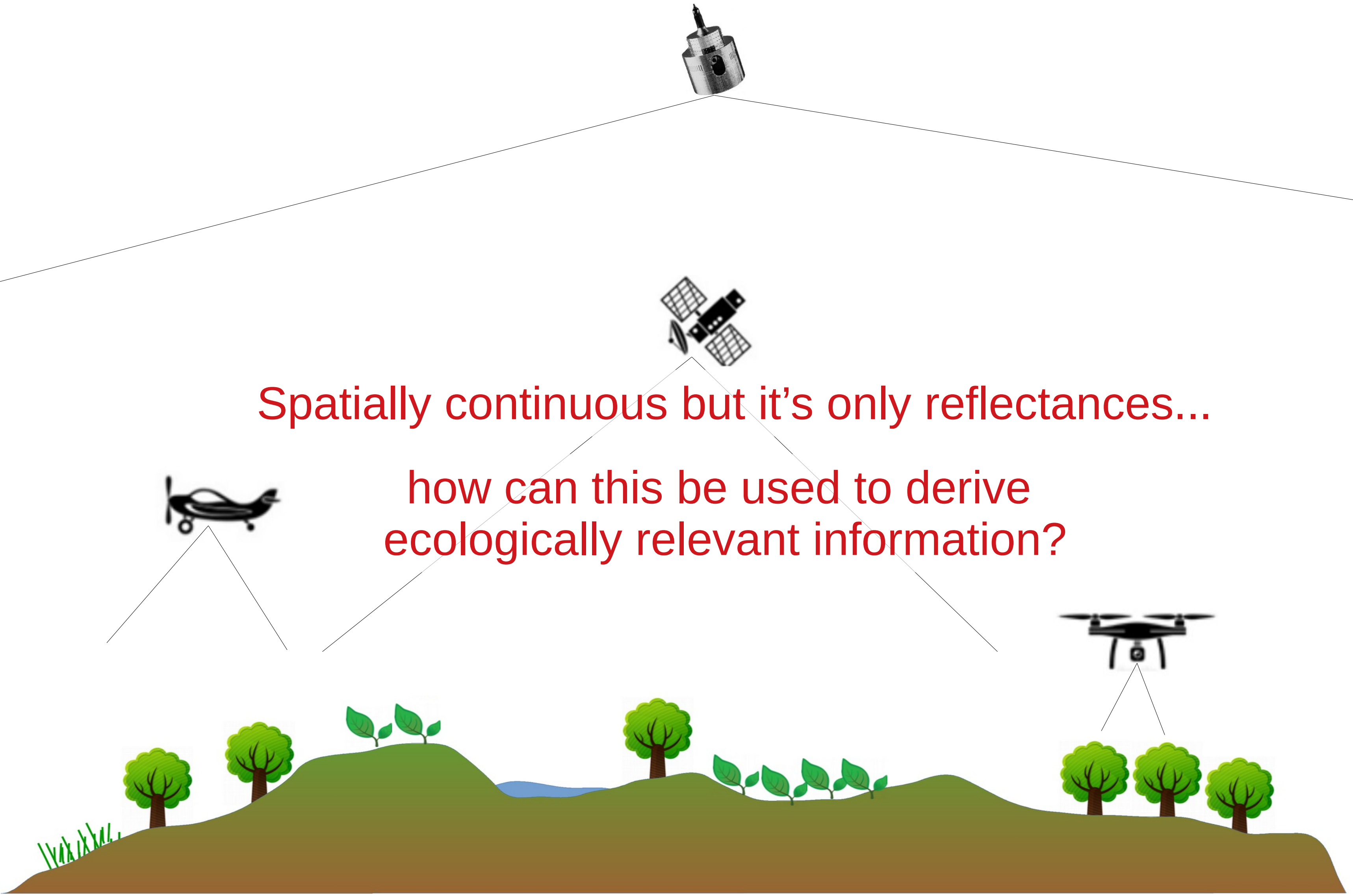
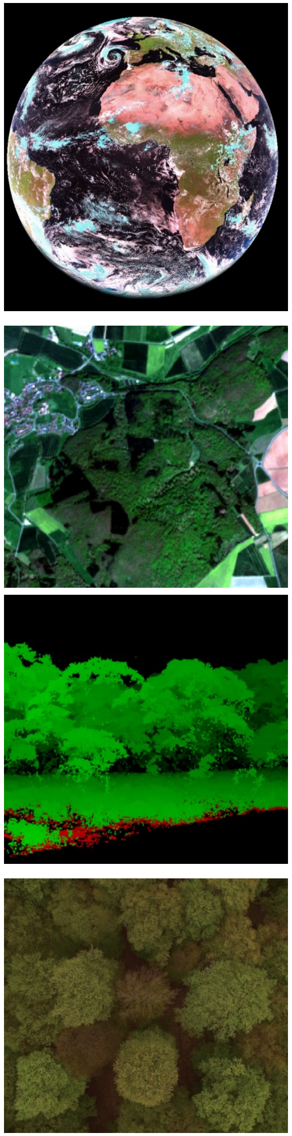


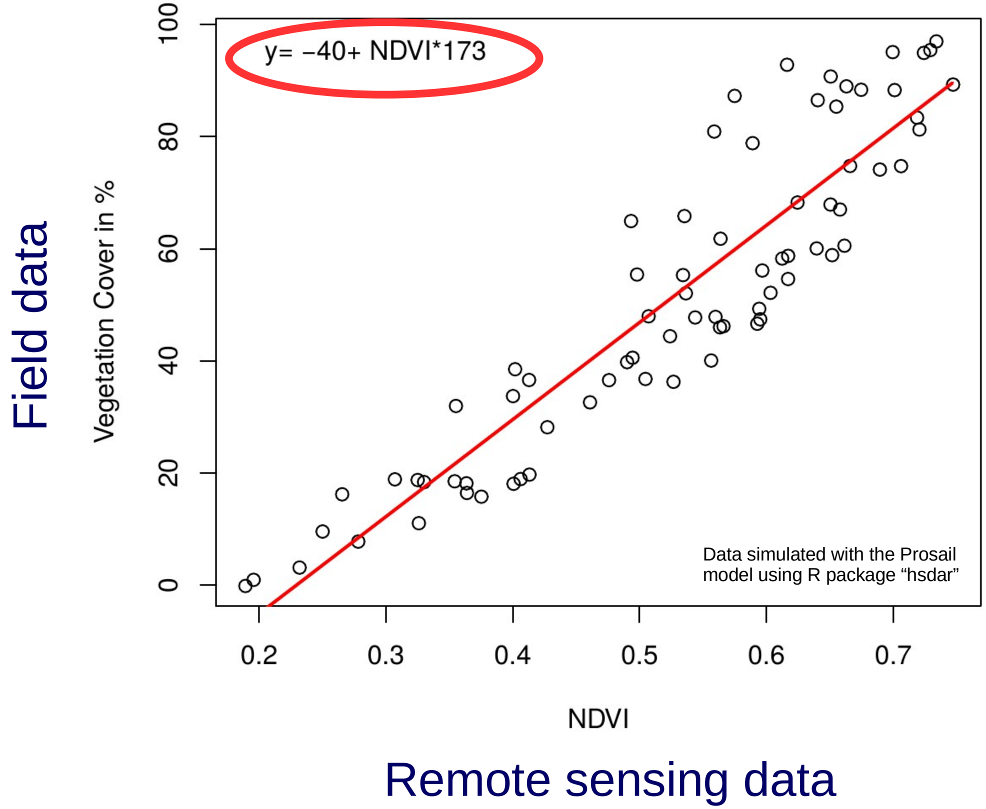
Spatially continuous but it’s only reflectances...

how can this be used to derive ecologically relevant information?



How can we translate the remote sensing information to the ecological variable?

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



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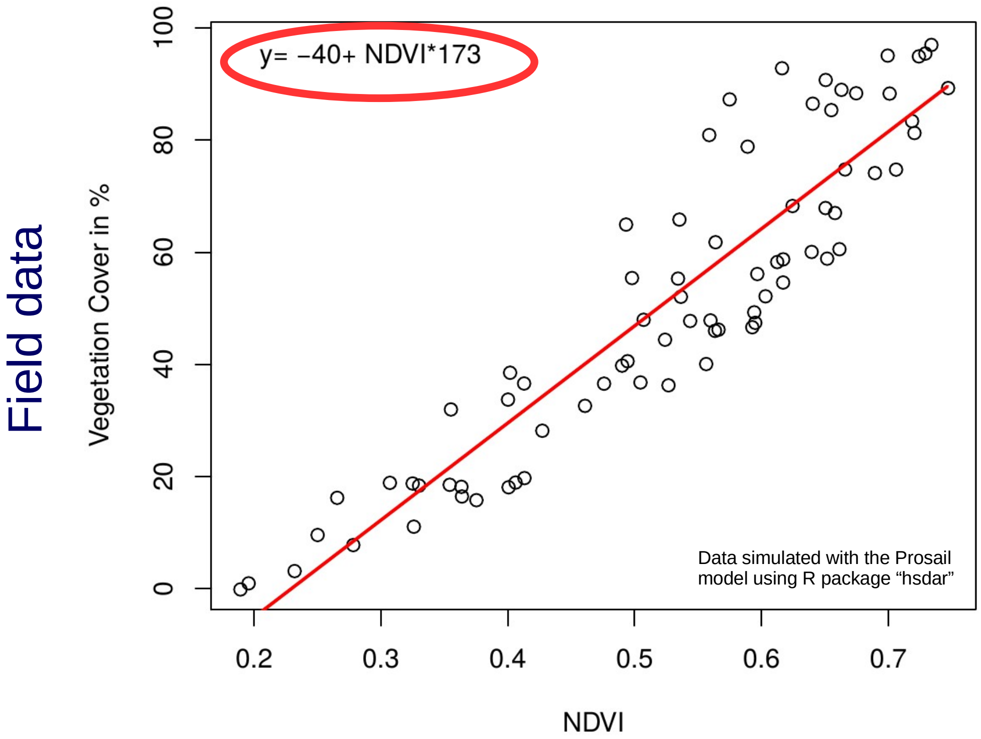
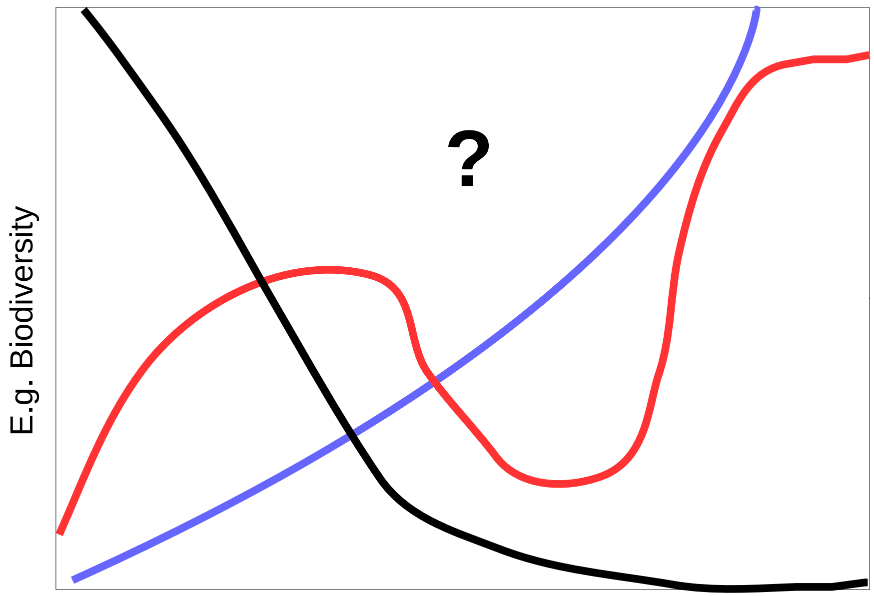
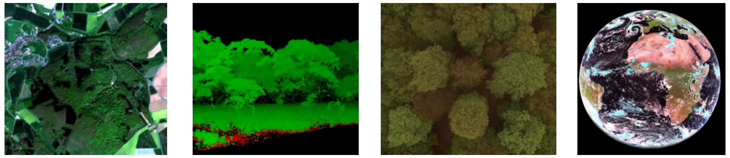


Remote sensing data

Typical ecological variables from satellite?





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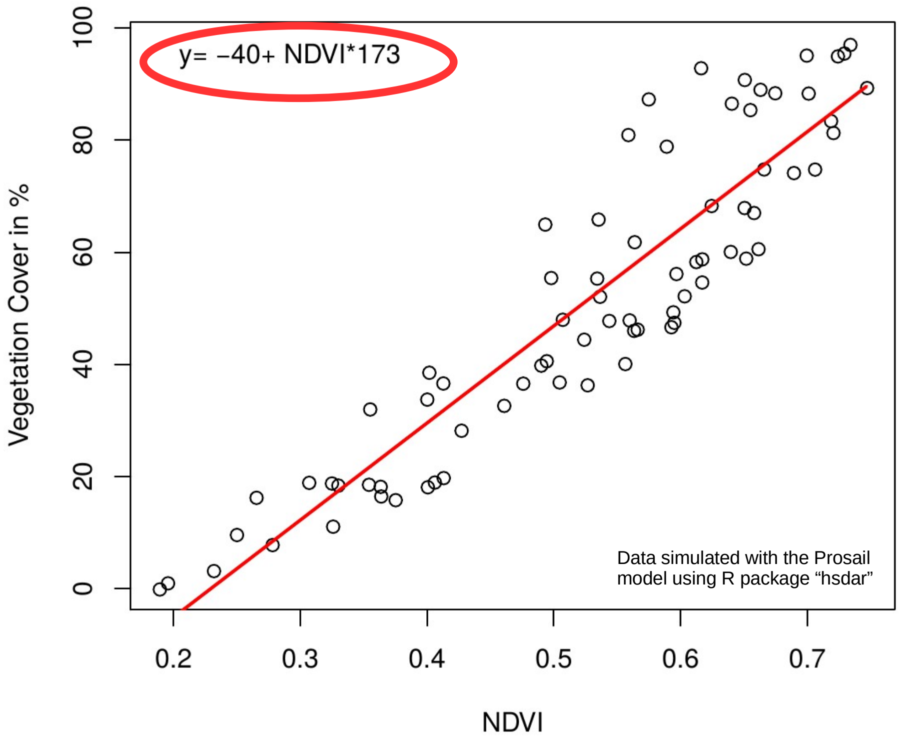
Field data



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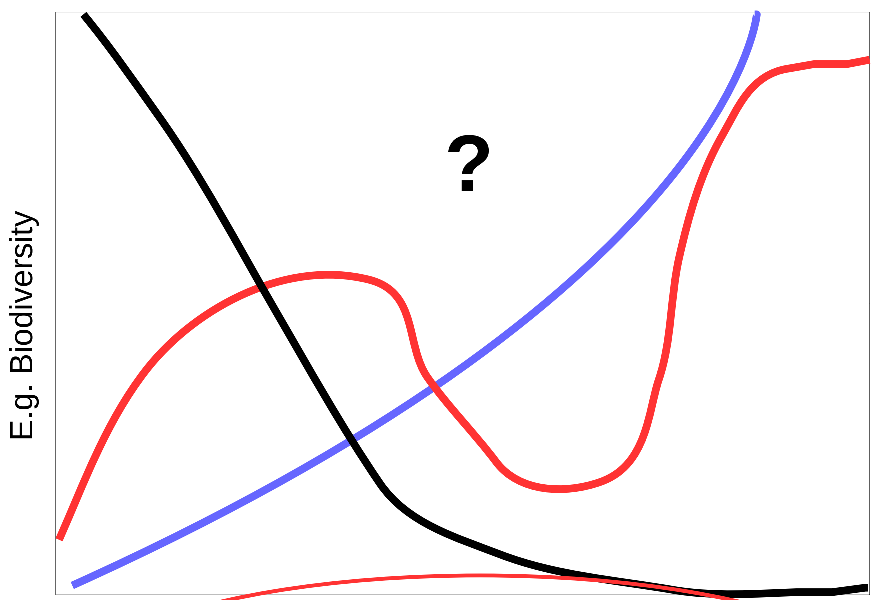
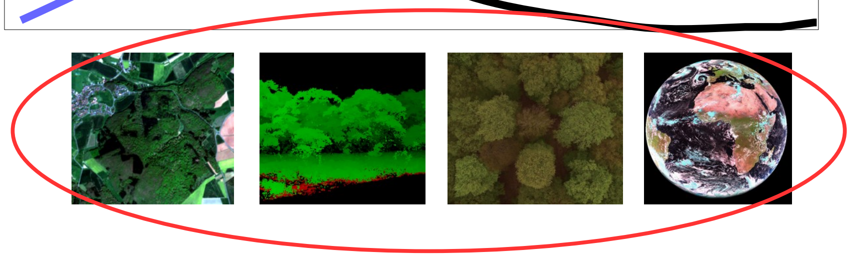
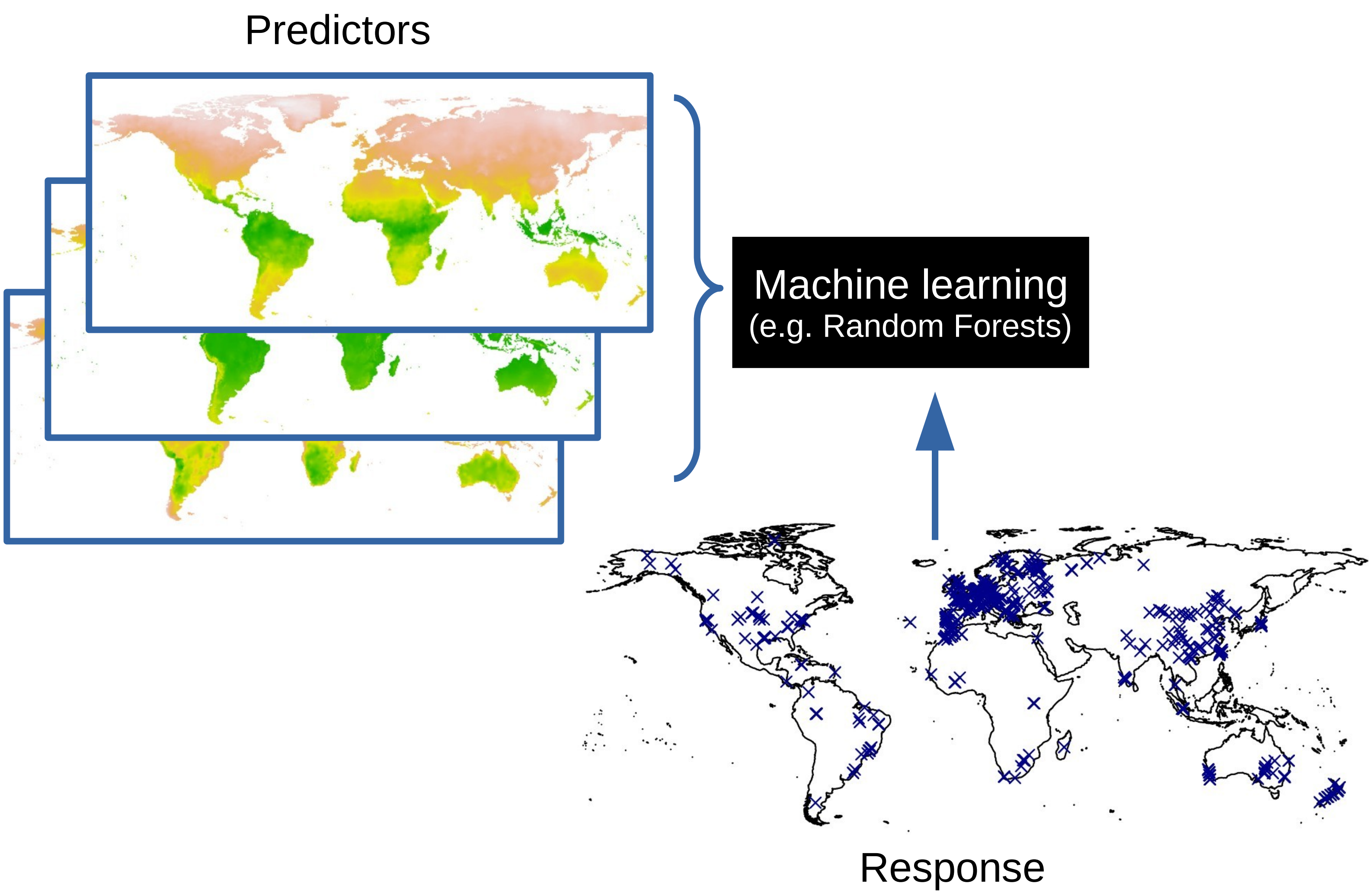




Models that can deal with complex nonlinear relationships are required!

How do we get “maps” of ecosystem variables ?



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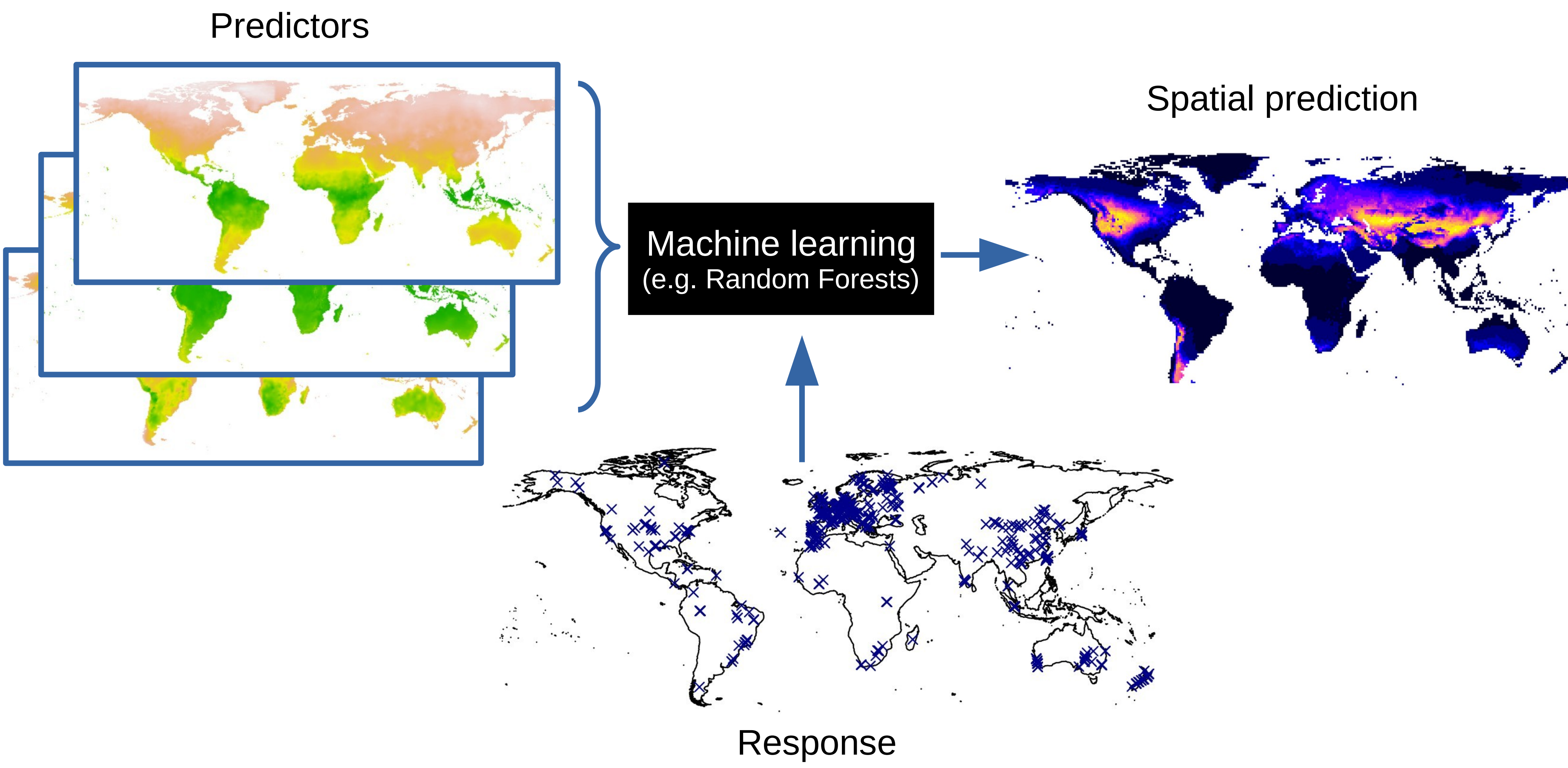
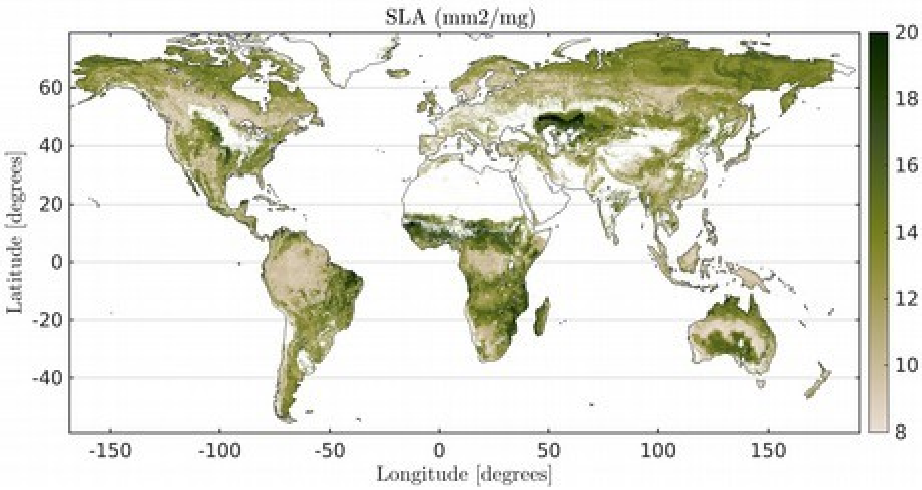
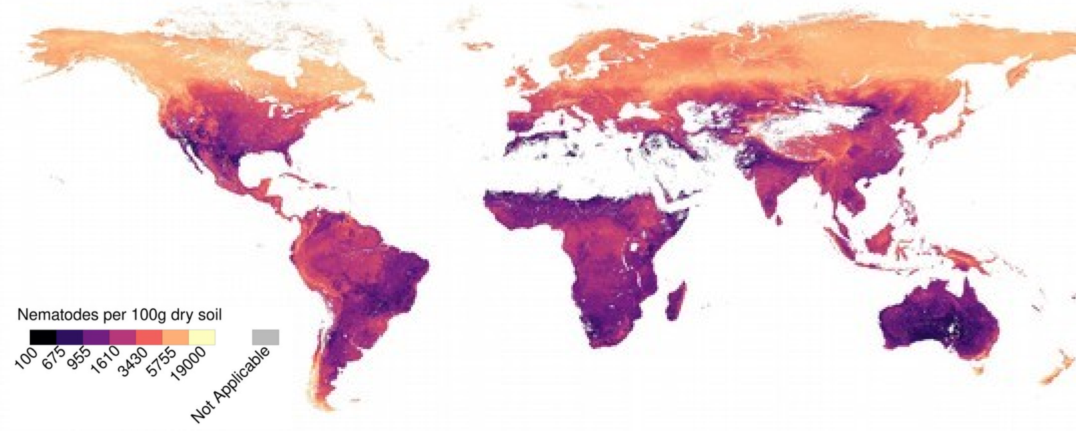


Global maps of ecosystem variables based on machine learning (a few examples)



Moreno-Martínez et al., 2018



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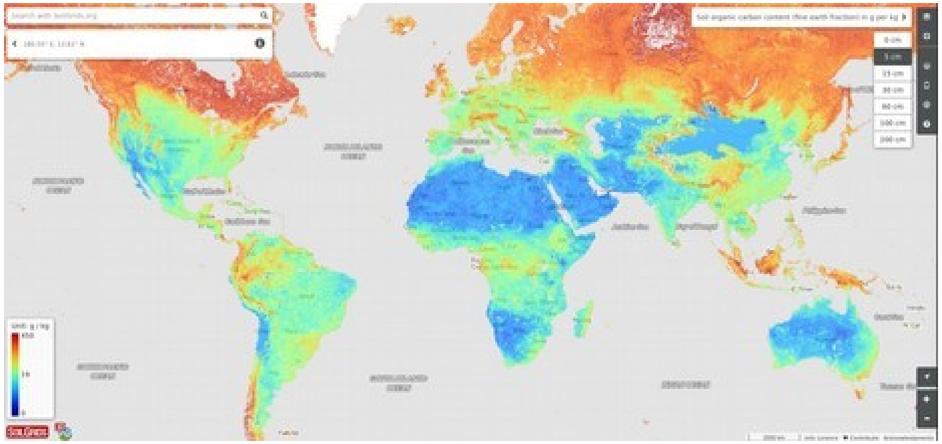
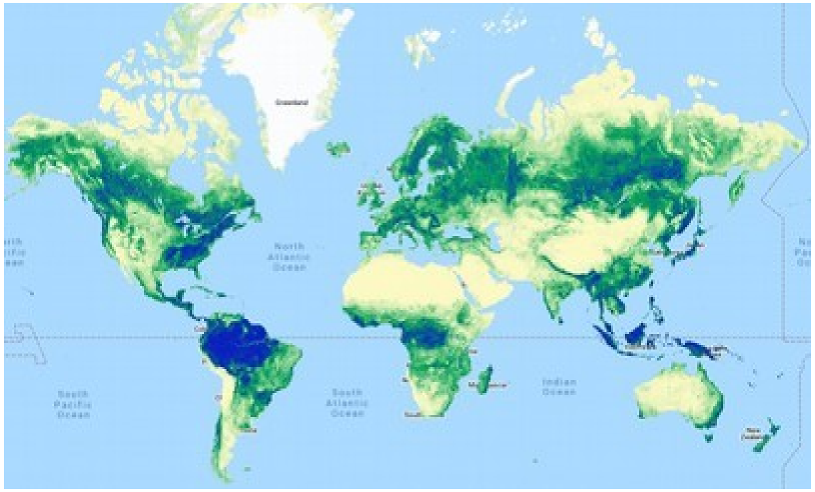


Hengl et al., 2017



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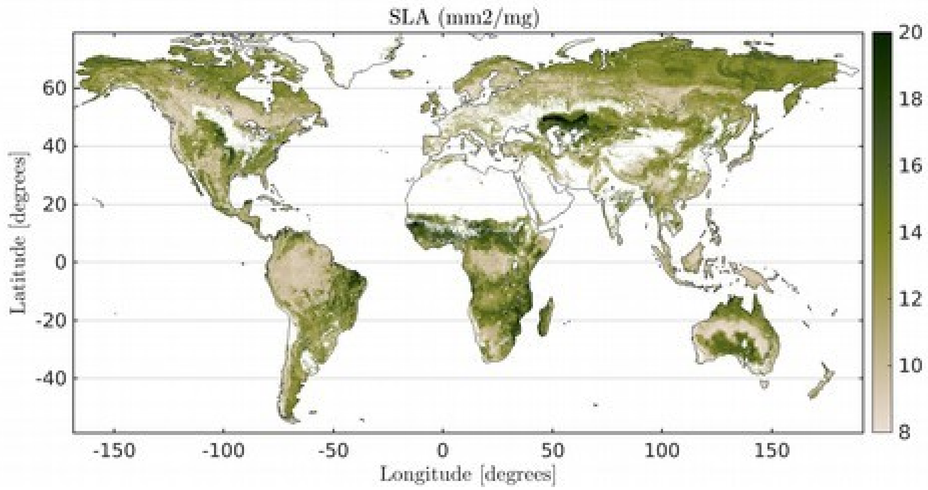

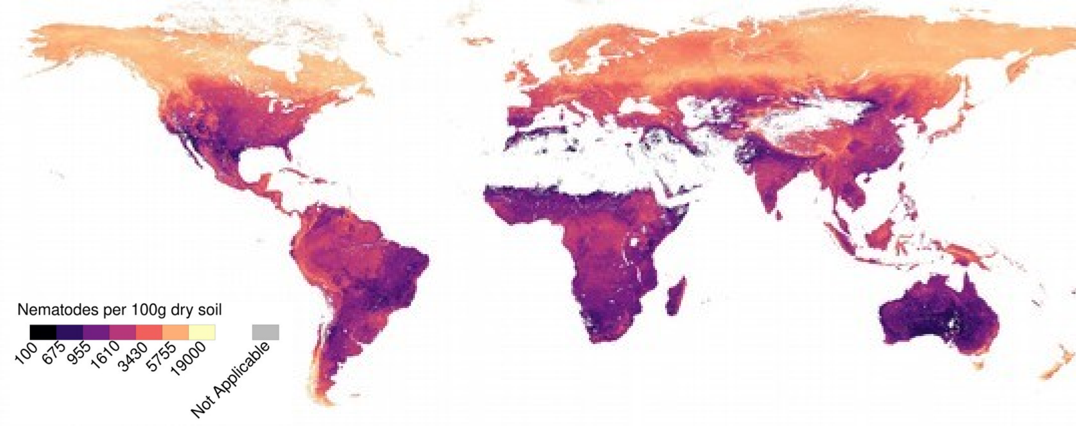

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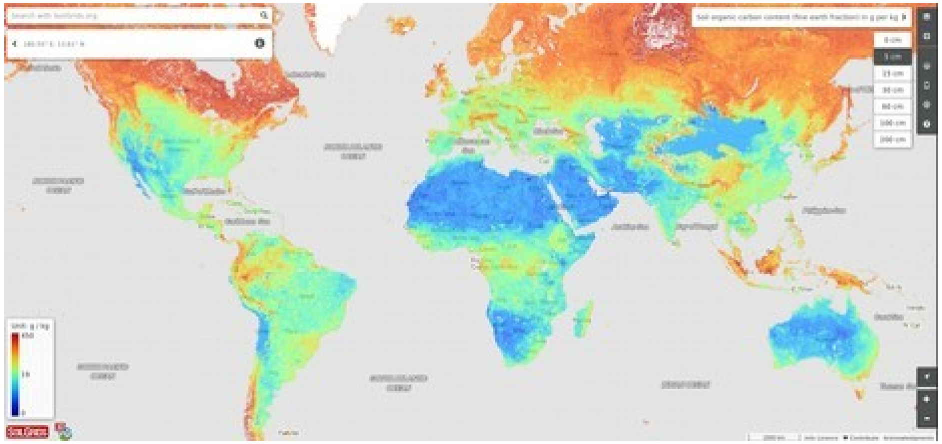

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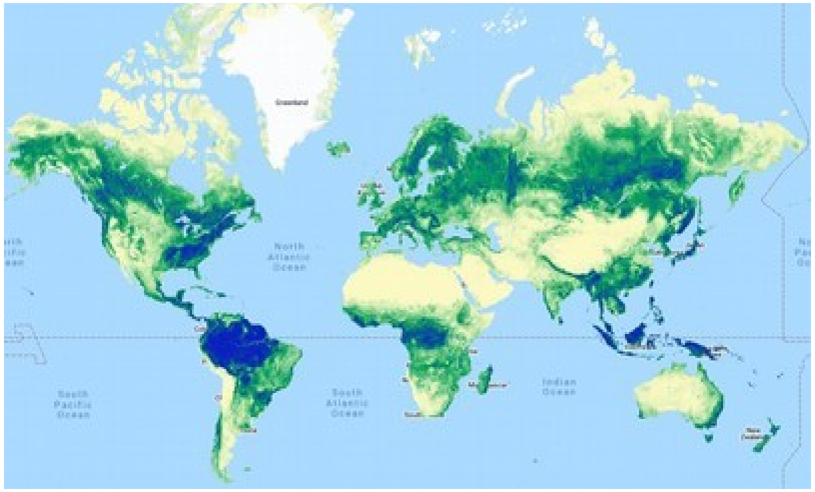

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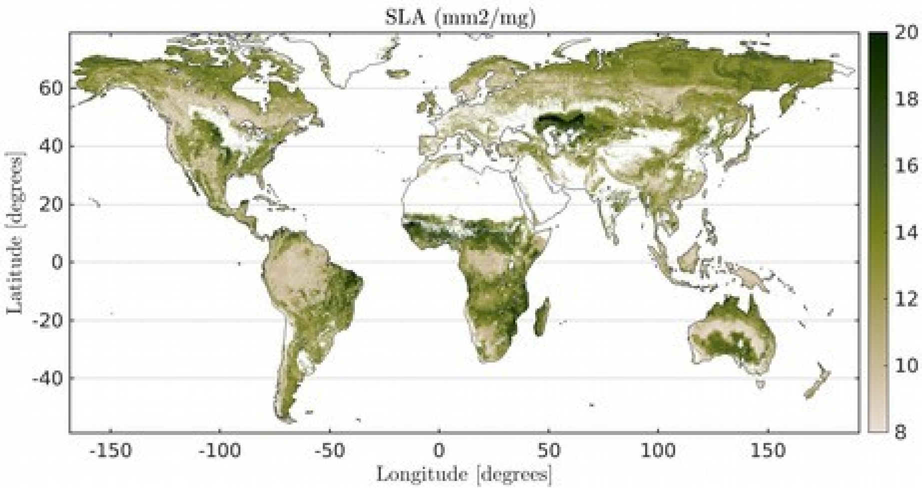

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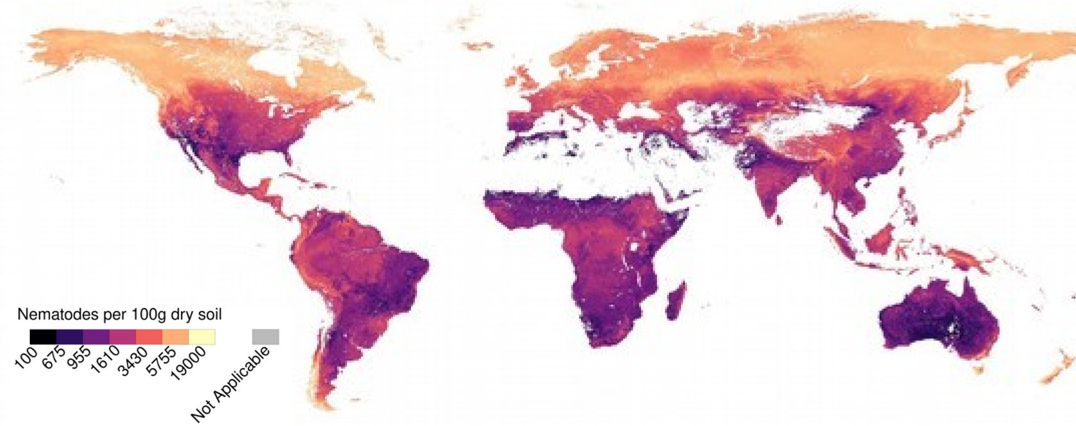

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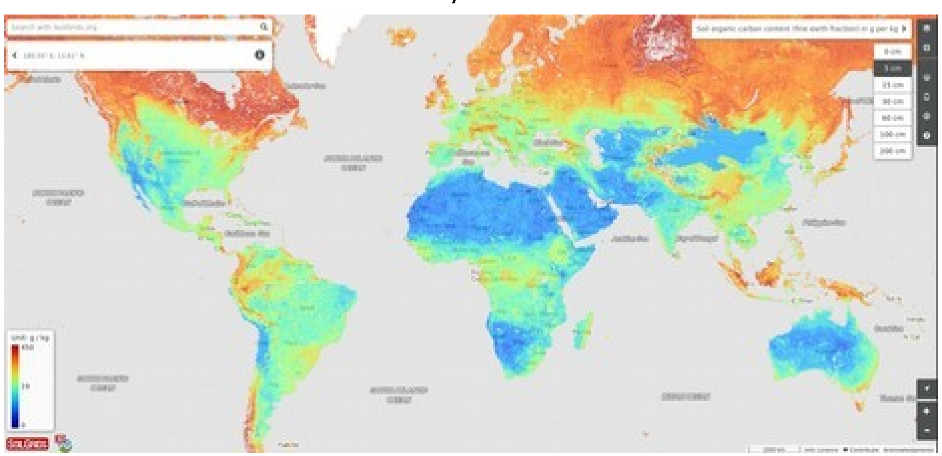

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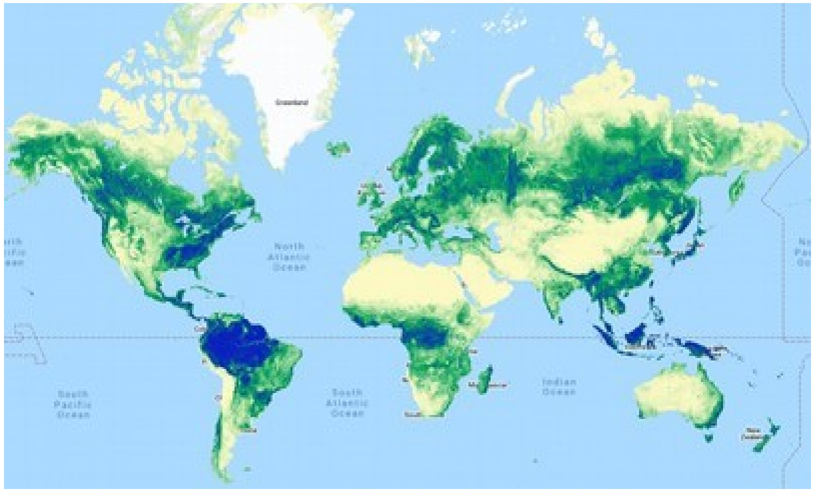

Bastin et al. 2019

Machine learning as a magic tool to map everything ?

...but there are increasingly doubts about the quality of these results

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
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BY DOUGLAS HEAVEN

Nature 574, 163-166 (2019)

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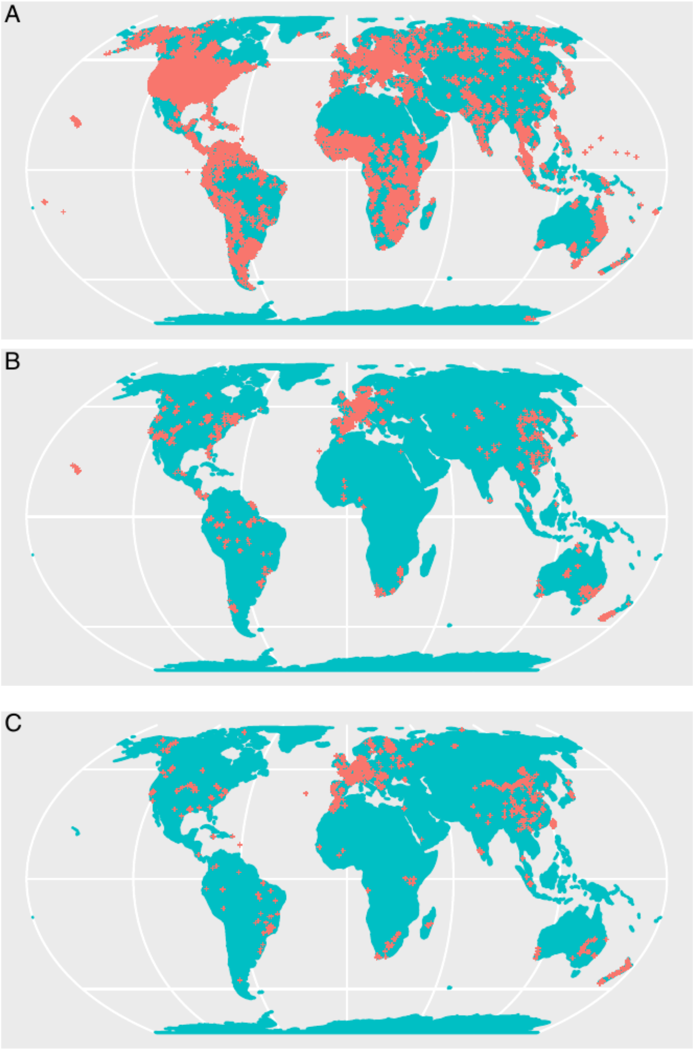
Have we been too ambitious? When and why might the models fail?

What do these applications have in common?

Soil maps

Plant traits

Nematodes



Meyer & Pebesma (2022)

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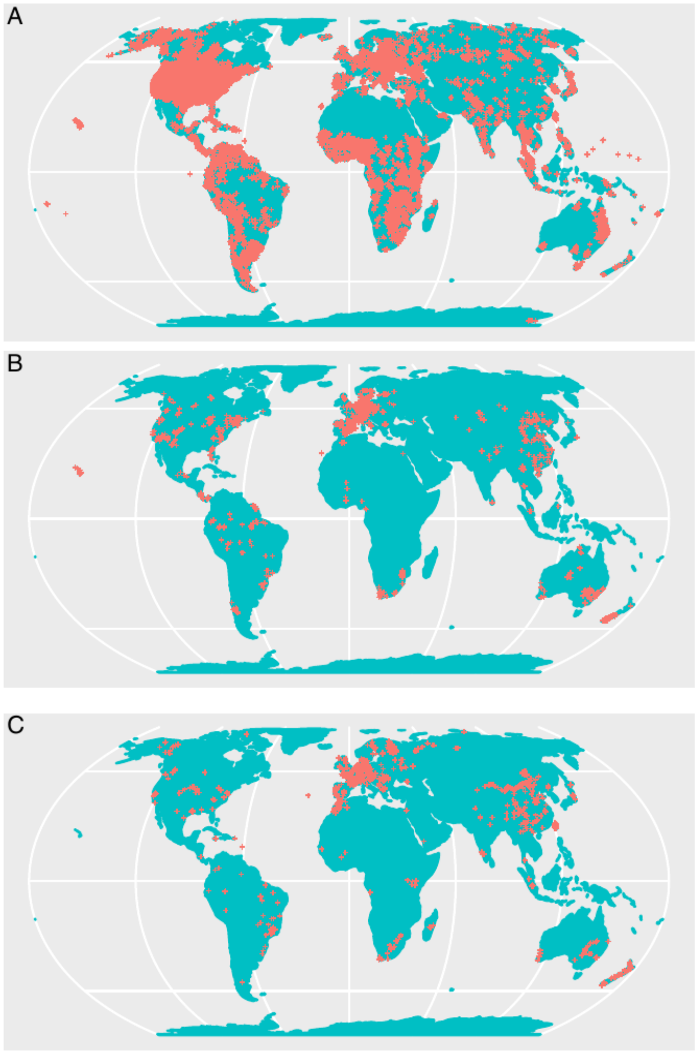

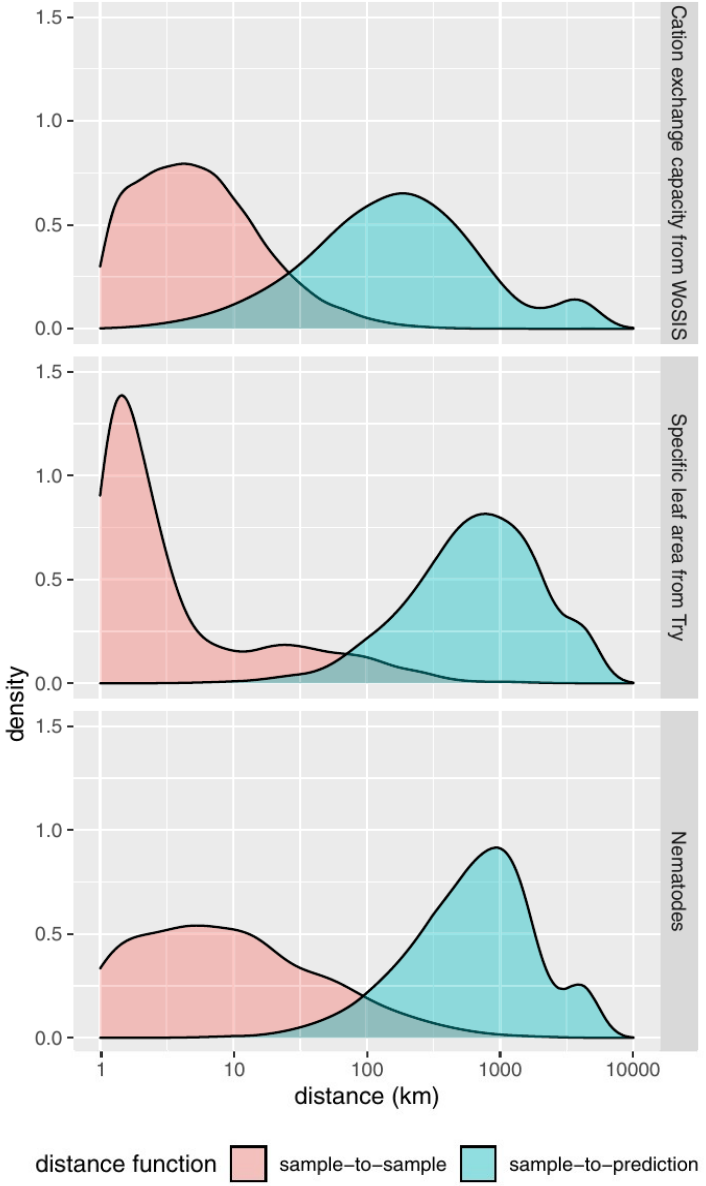

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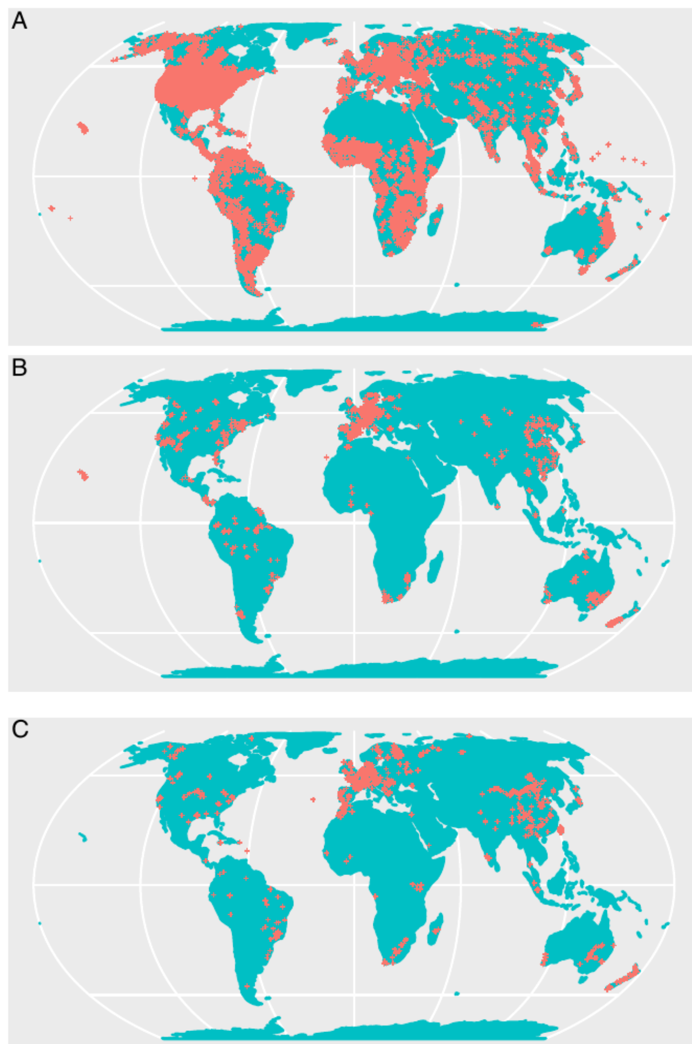
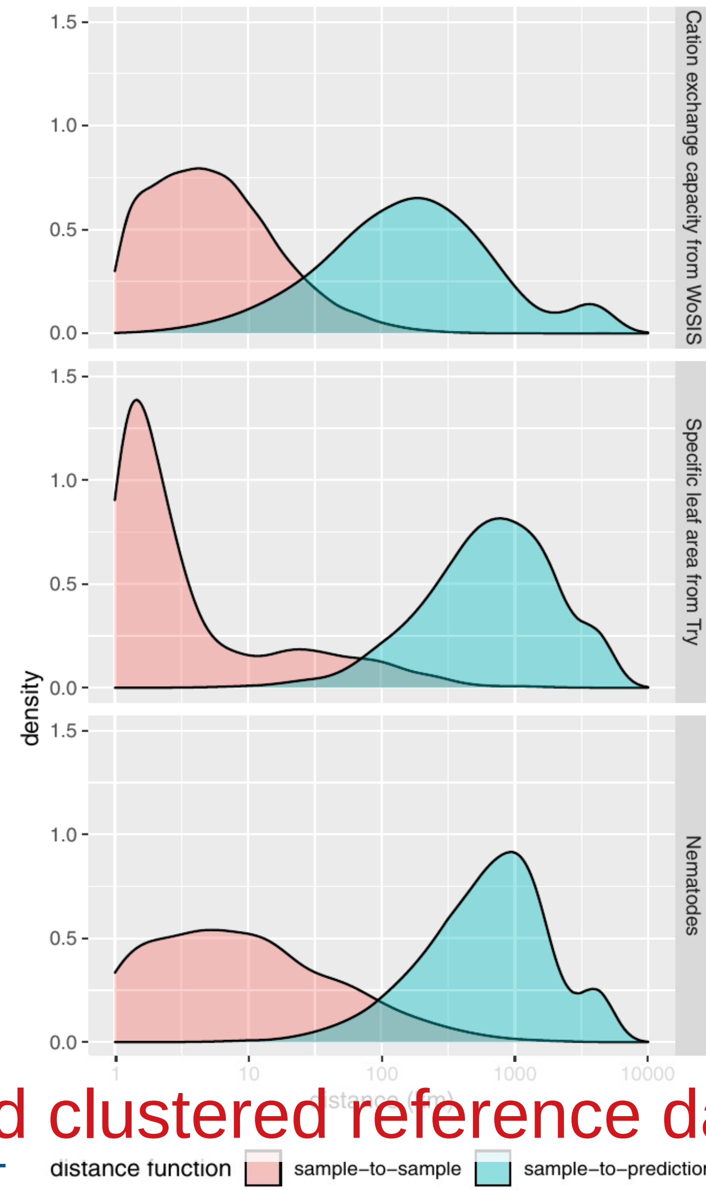
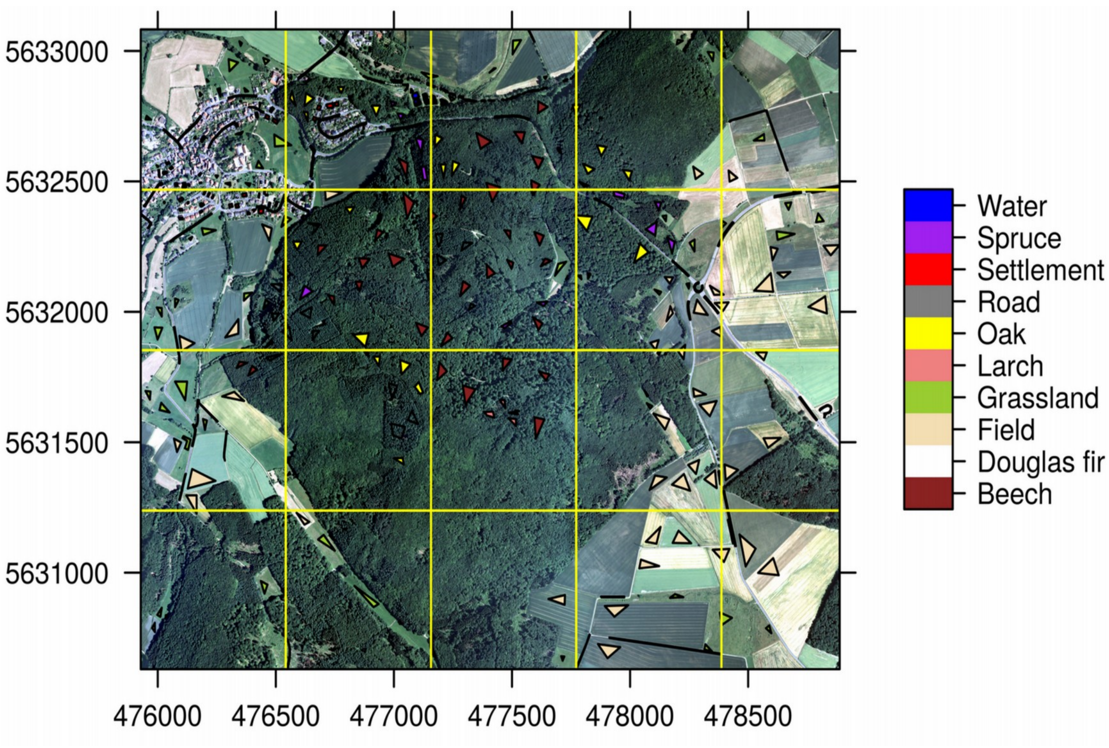




Meyer & Pebesma (2022)

Mapping requires prediction far beyond clustered reference data!

This is not just an issue for global applications



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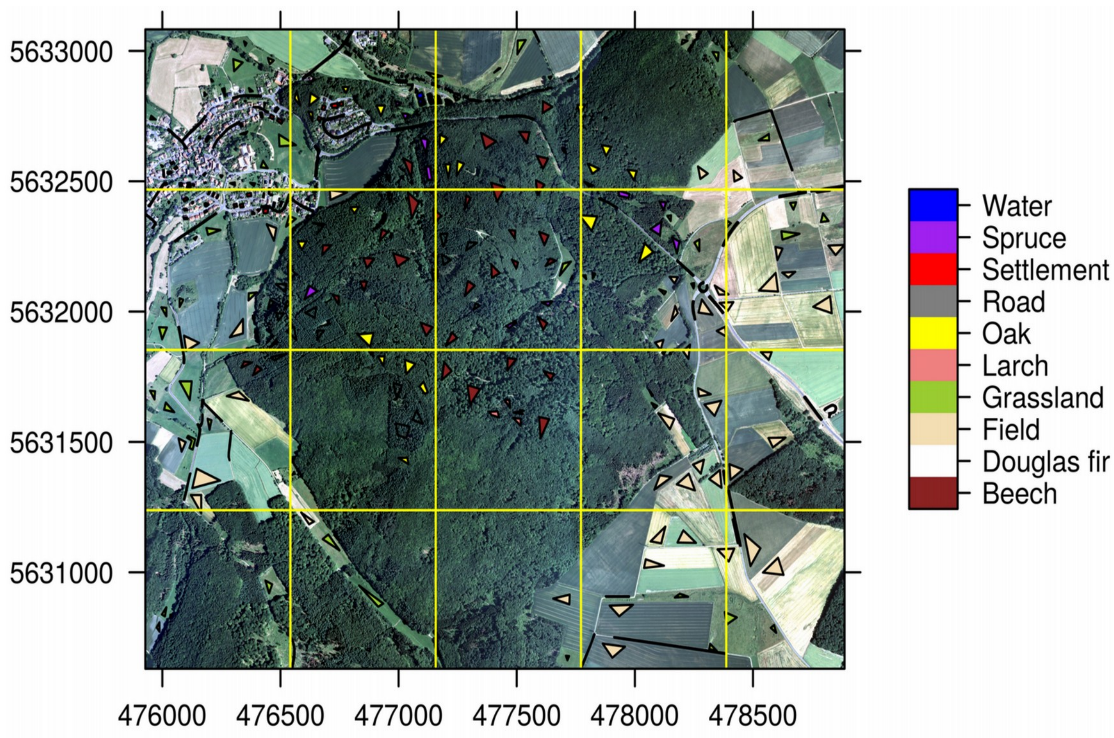

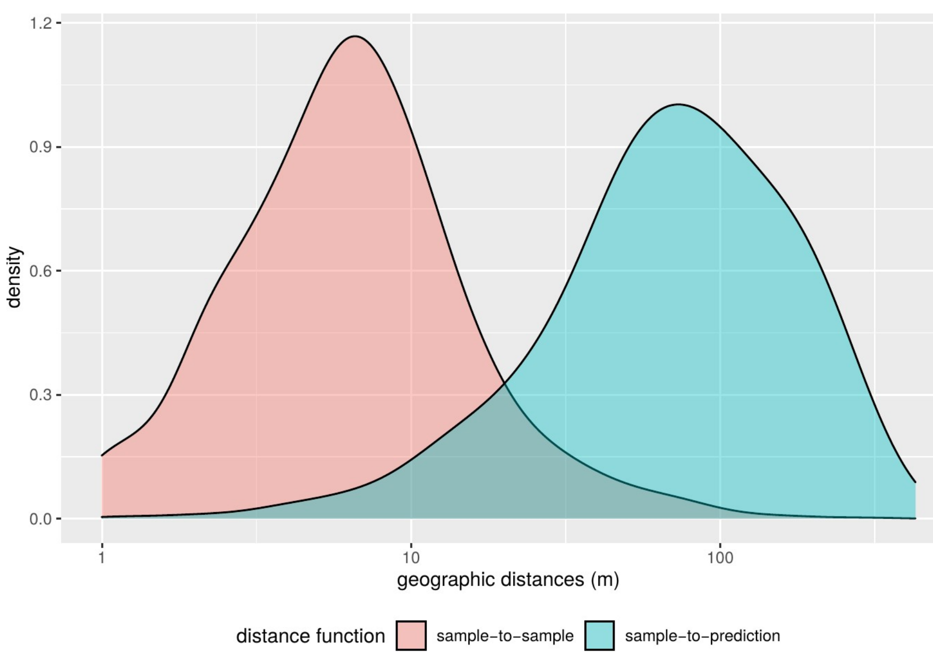

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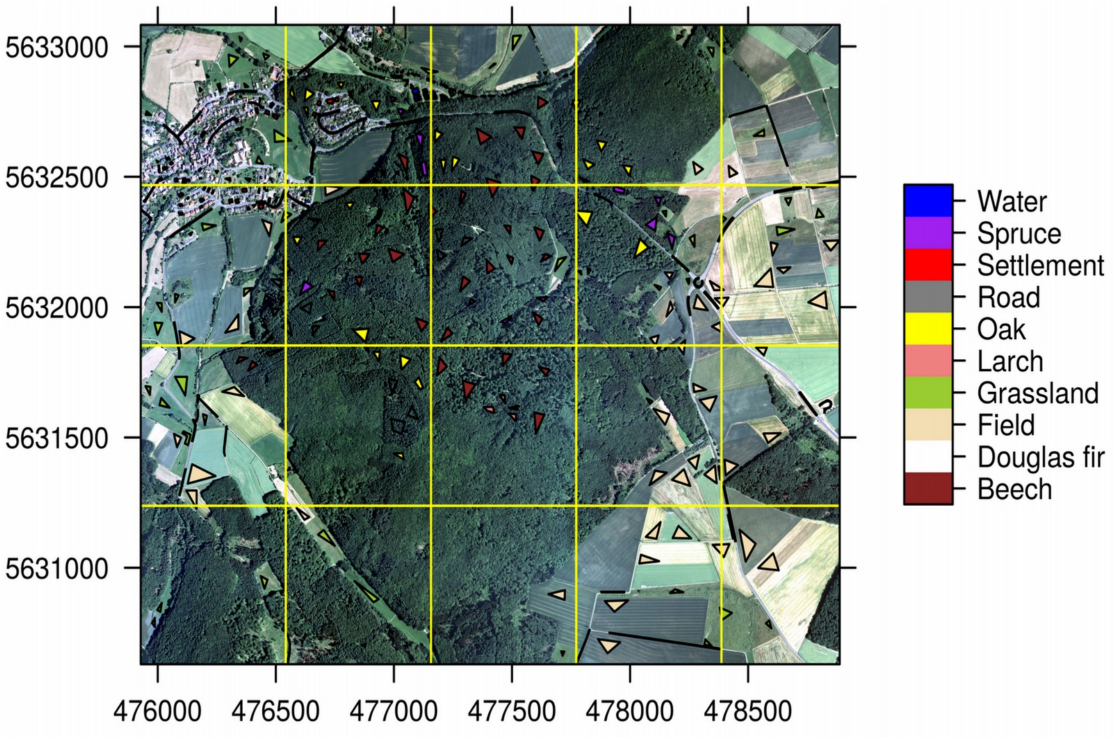
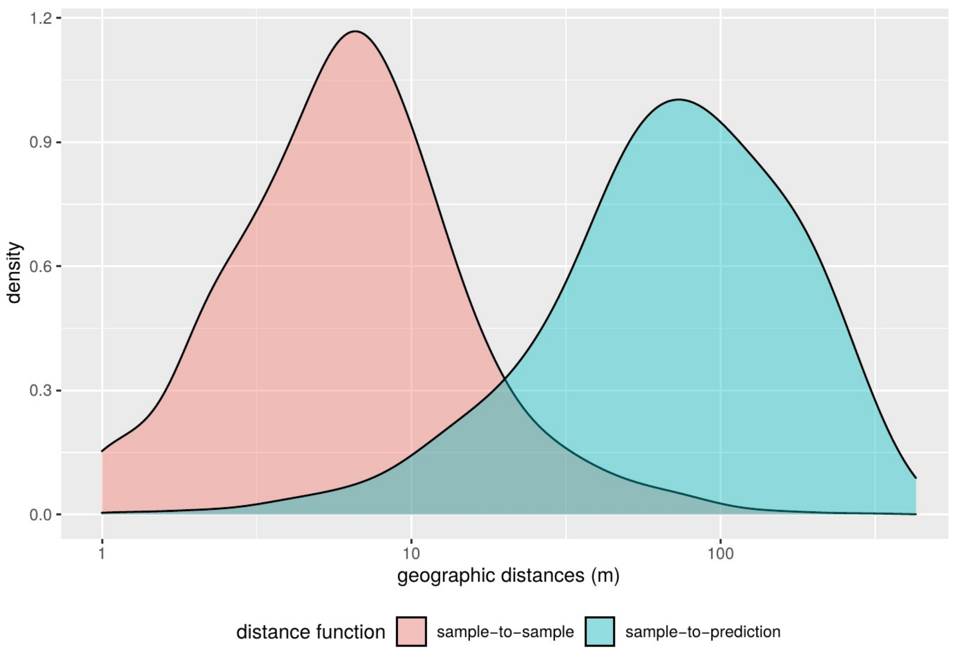
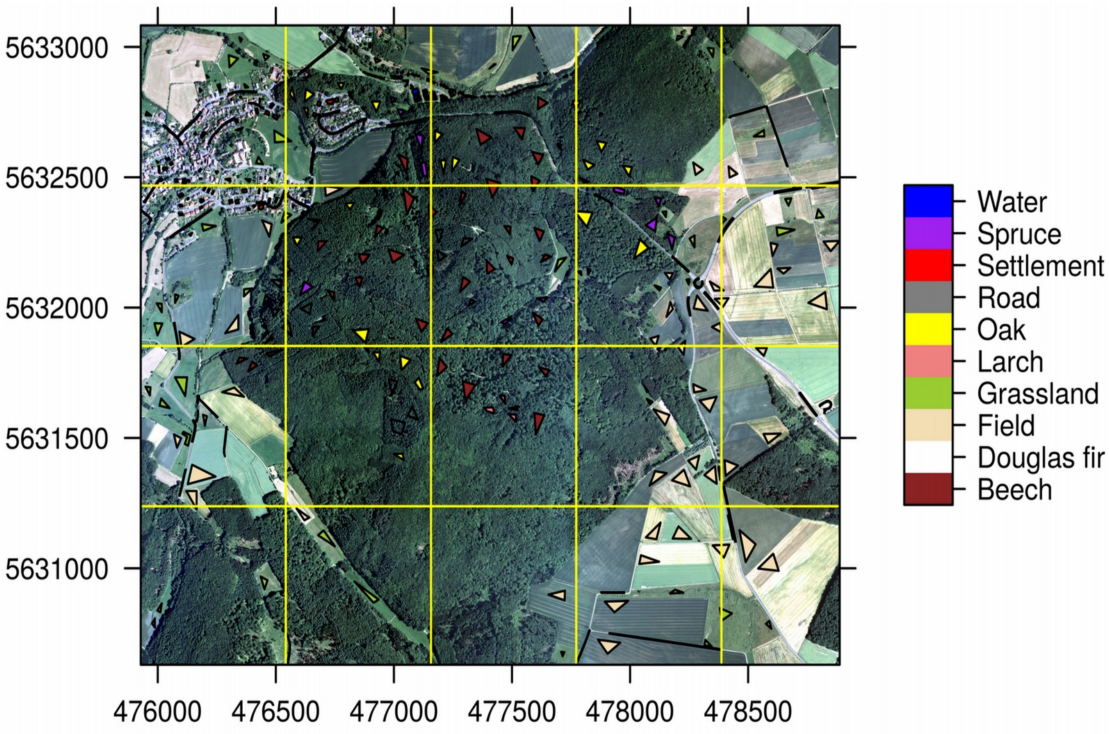




Does the clustered pattern cause problems?
Let’s explore with this case study...

Is this a problem? Example of a “classic” land cover classification

Aerial image overlayed by training sites



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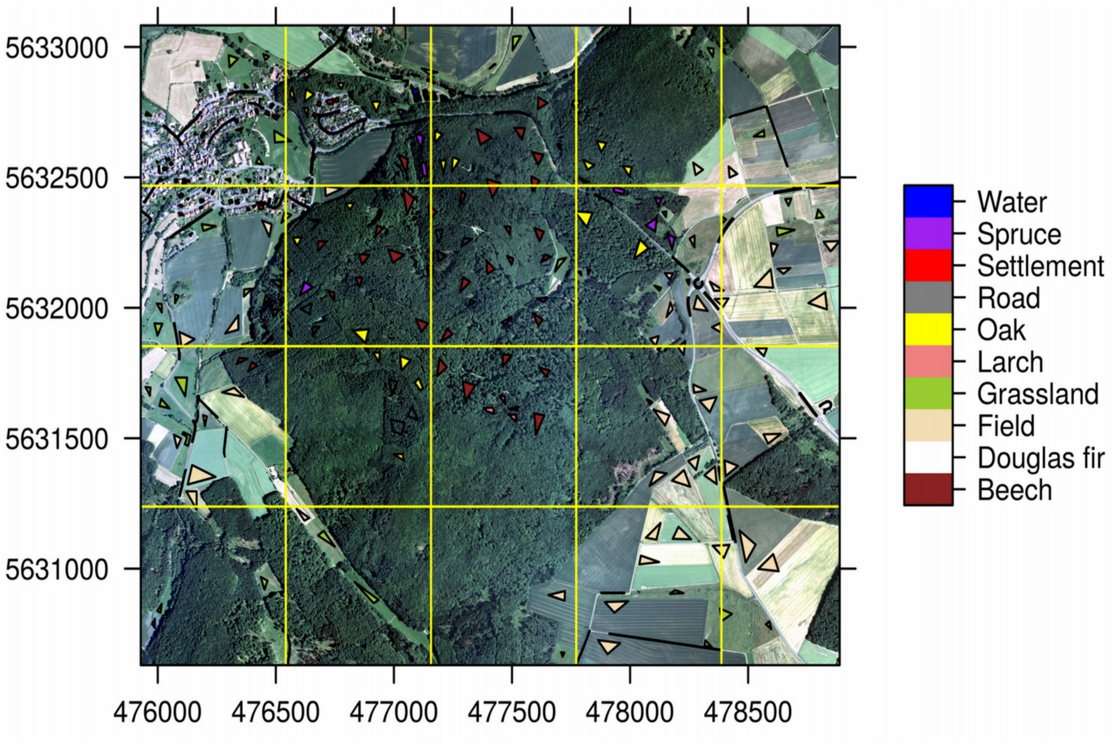

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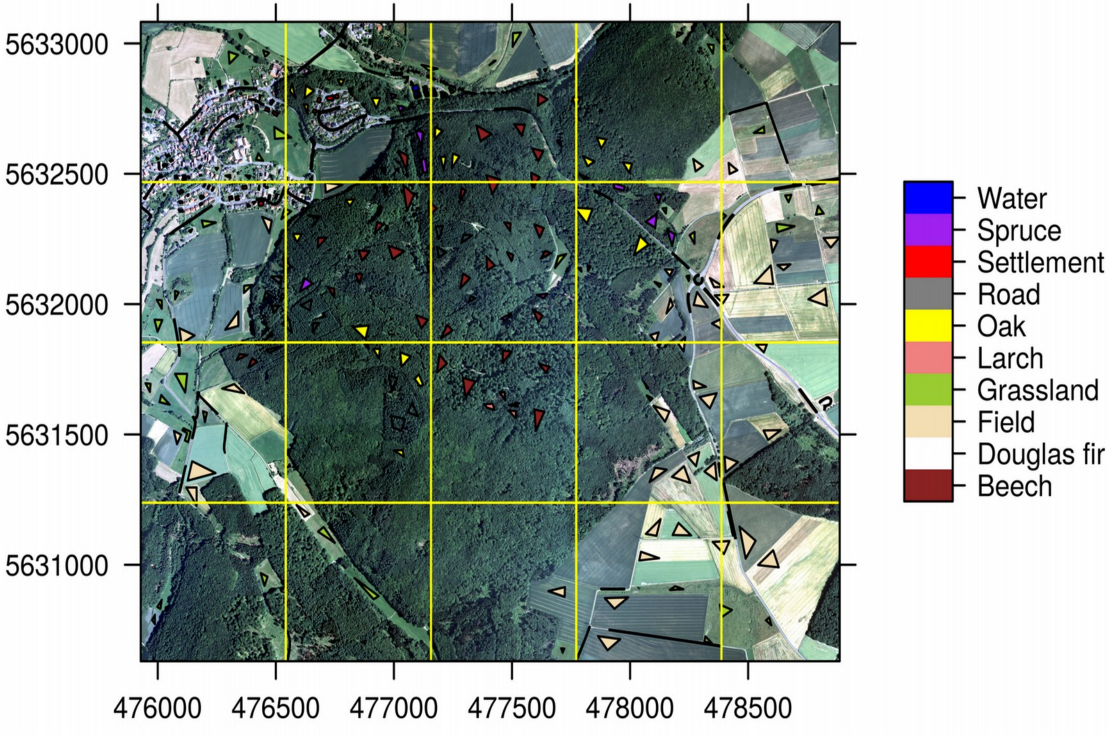
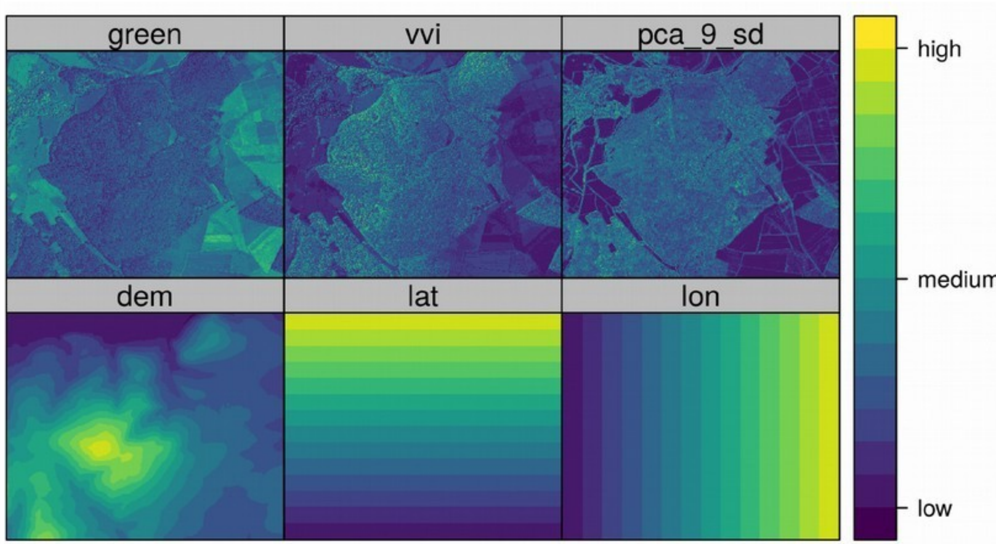


Example of predictors



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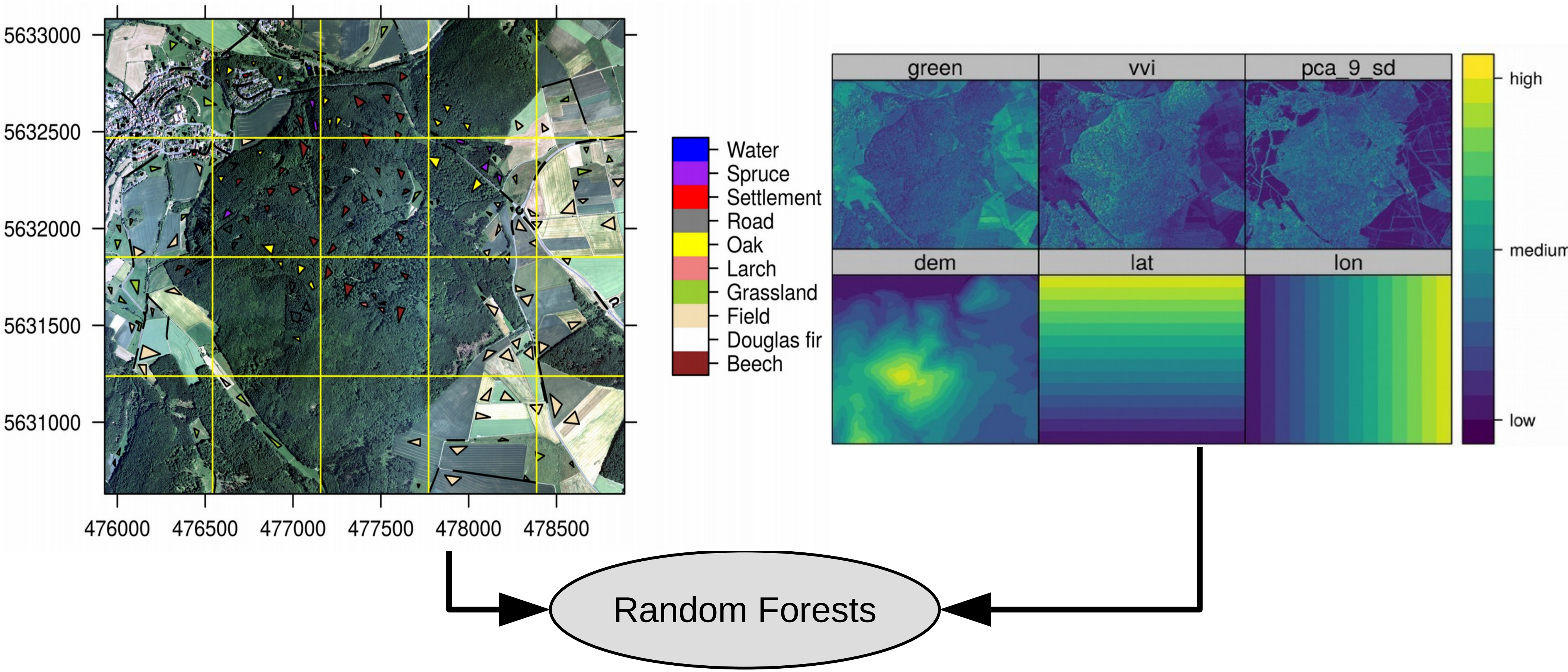

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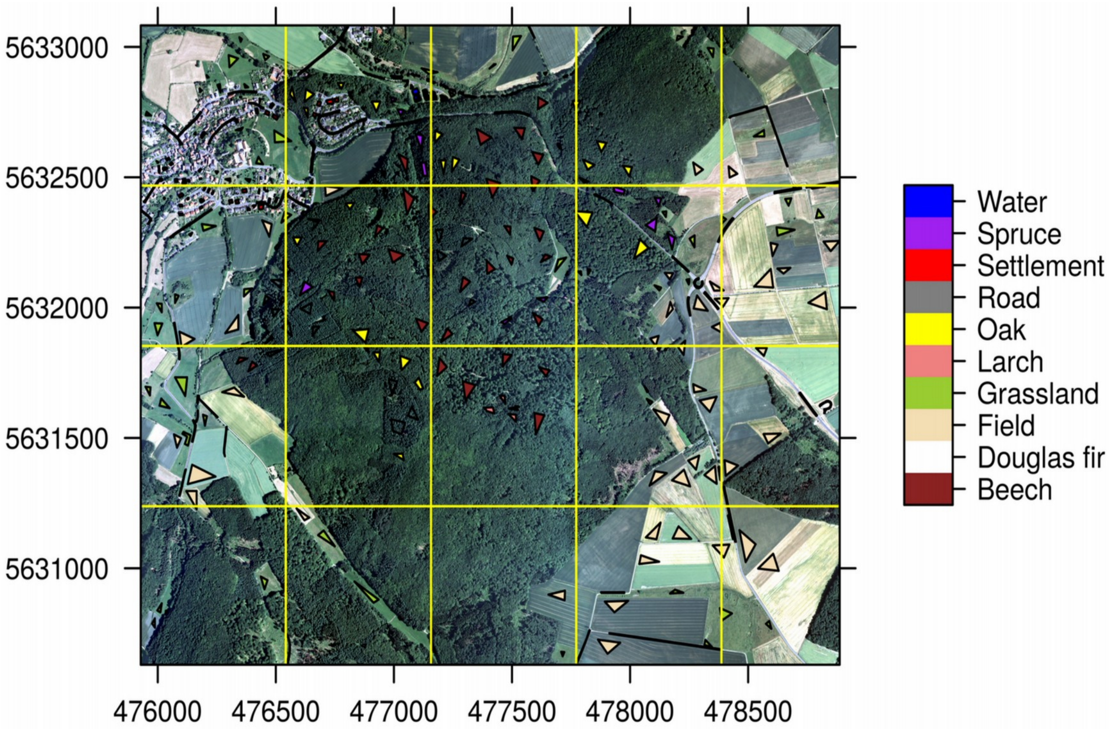

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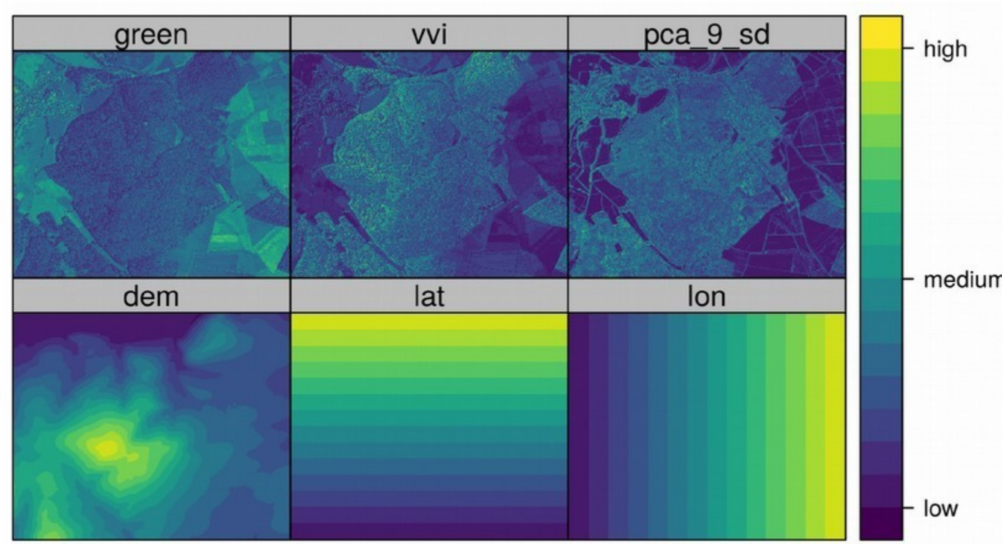

How well can we model land cover with this approach?

Performance assessment by the default validation strategy

Variables	Validation	Accuracy	Kappa
all	random	>0.99	>0.99
all	spatial	**0.68**	**0.61**

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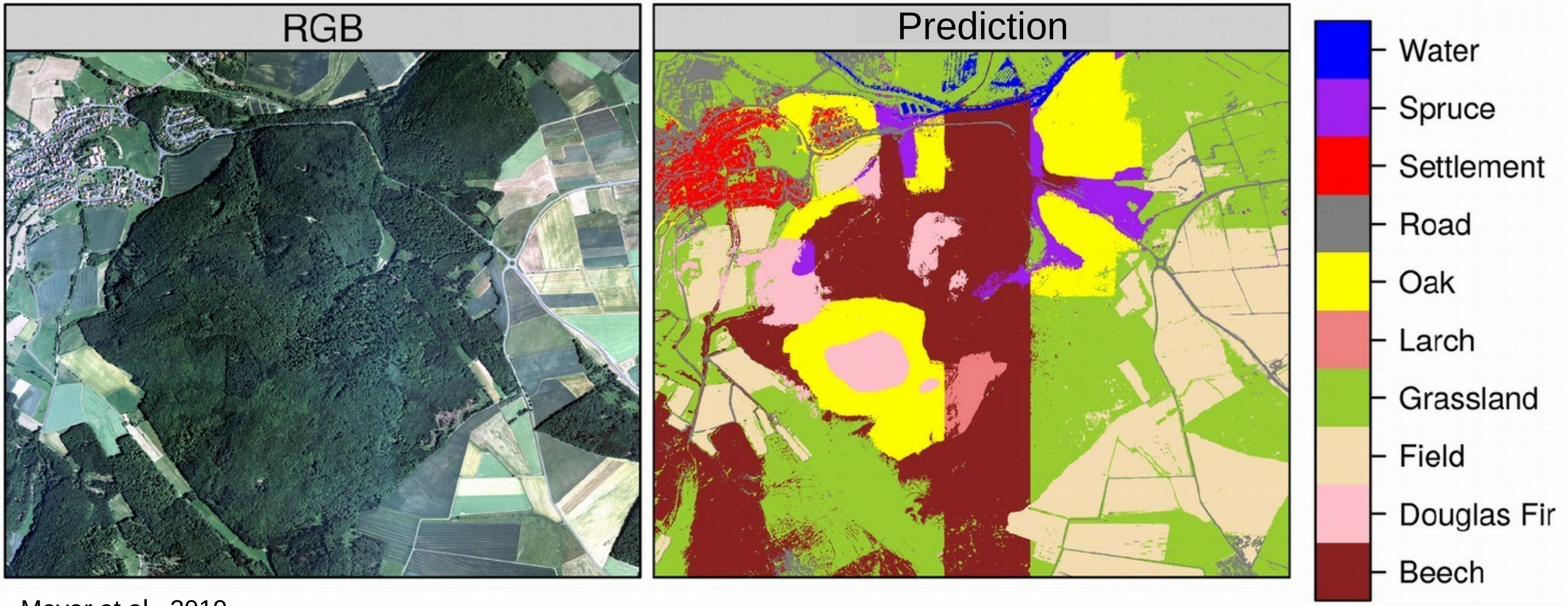
Perfect prediction?

...but it doesn't look like a perfect prediction



Meyer et al., 2019

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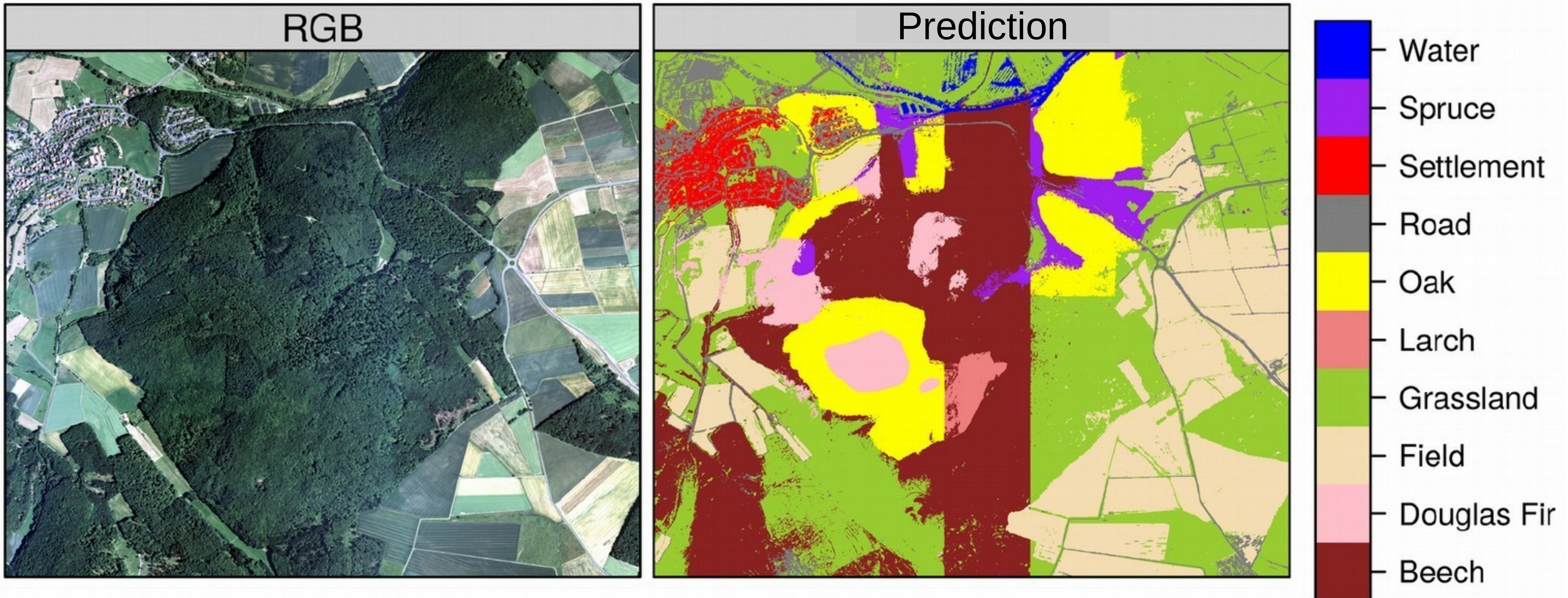

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But statistically it's a perfect model.
How is this possible?

Assessment of performance by default random cross-validation

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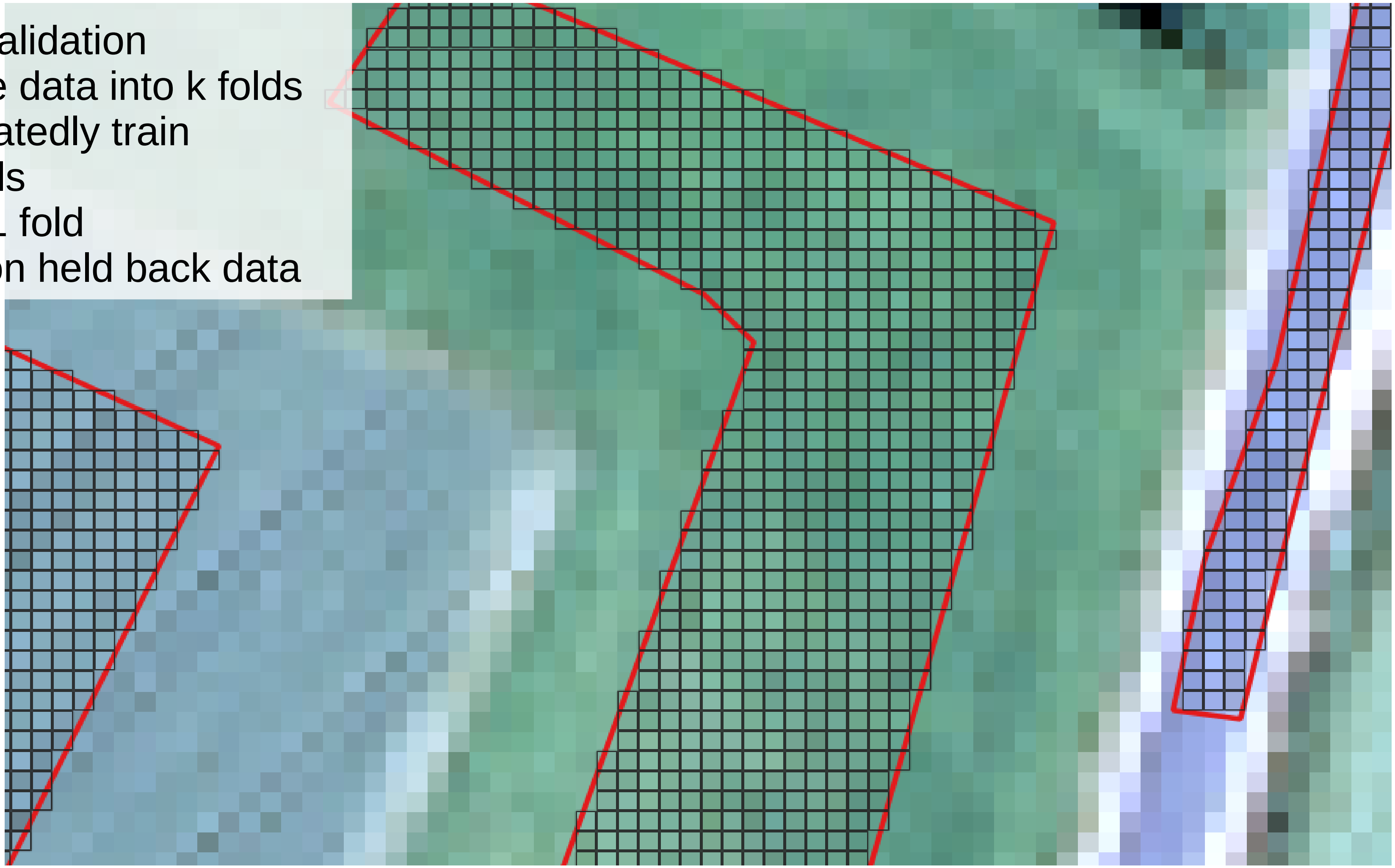

Cross-validation
- Divide data into k folds
- Repeatedly train models
  on k-1 fold
- Test on held back data

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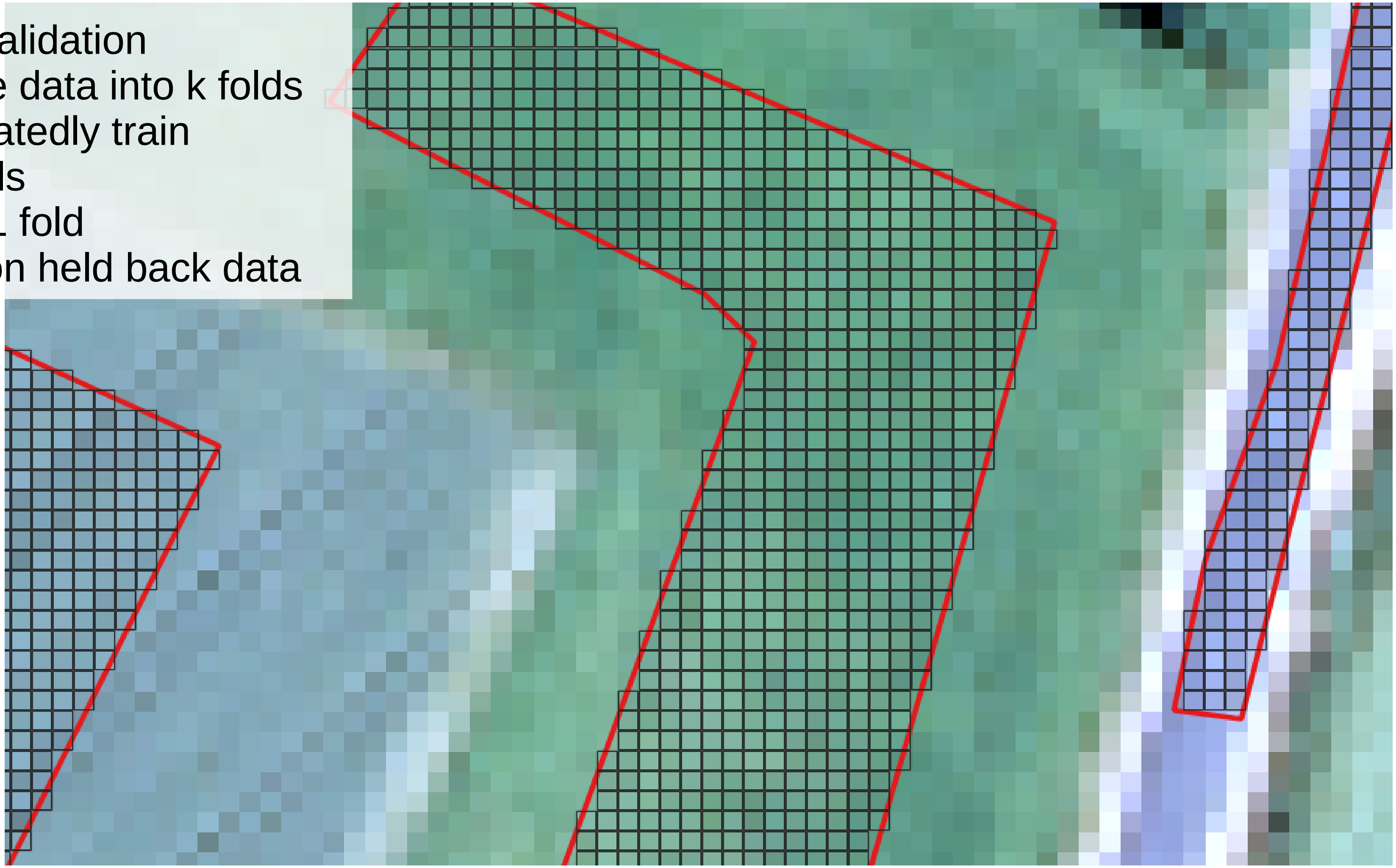

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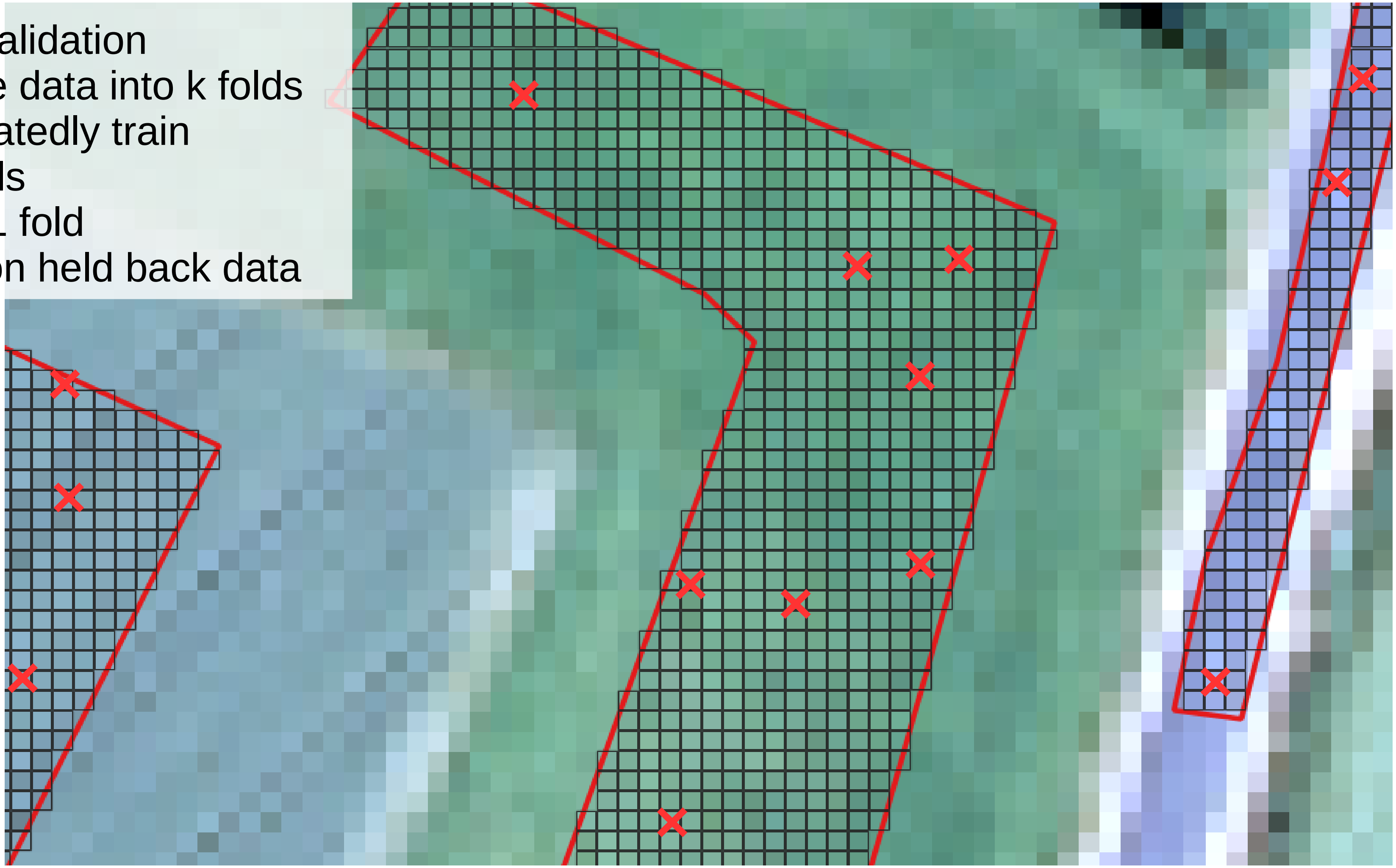

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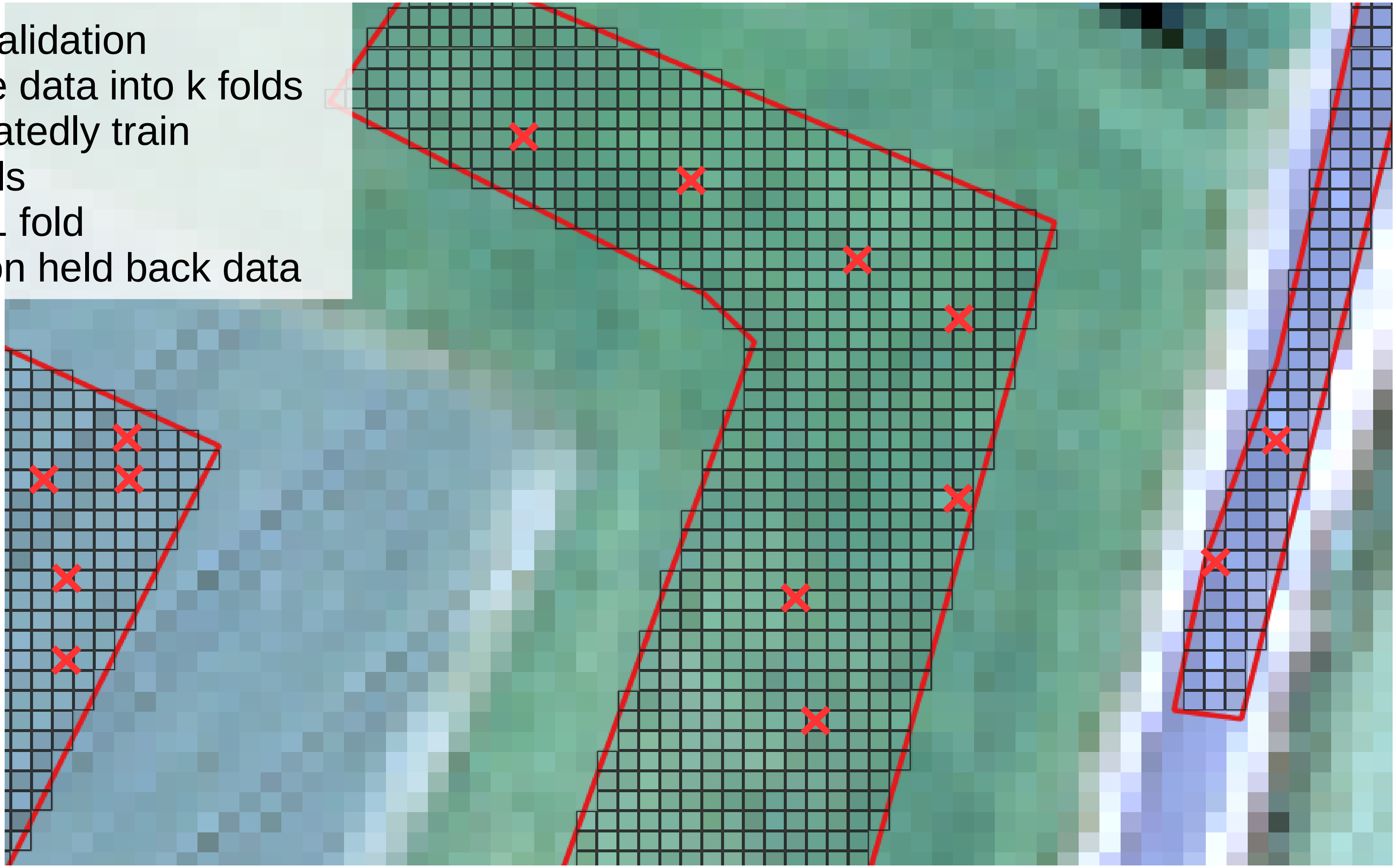

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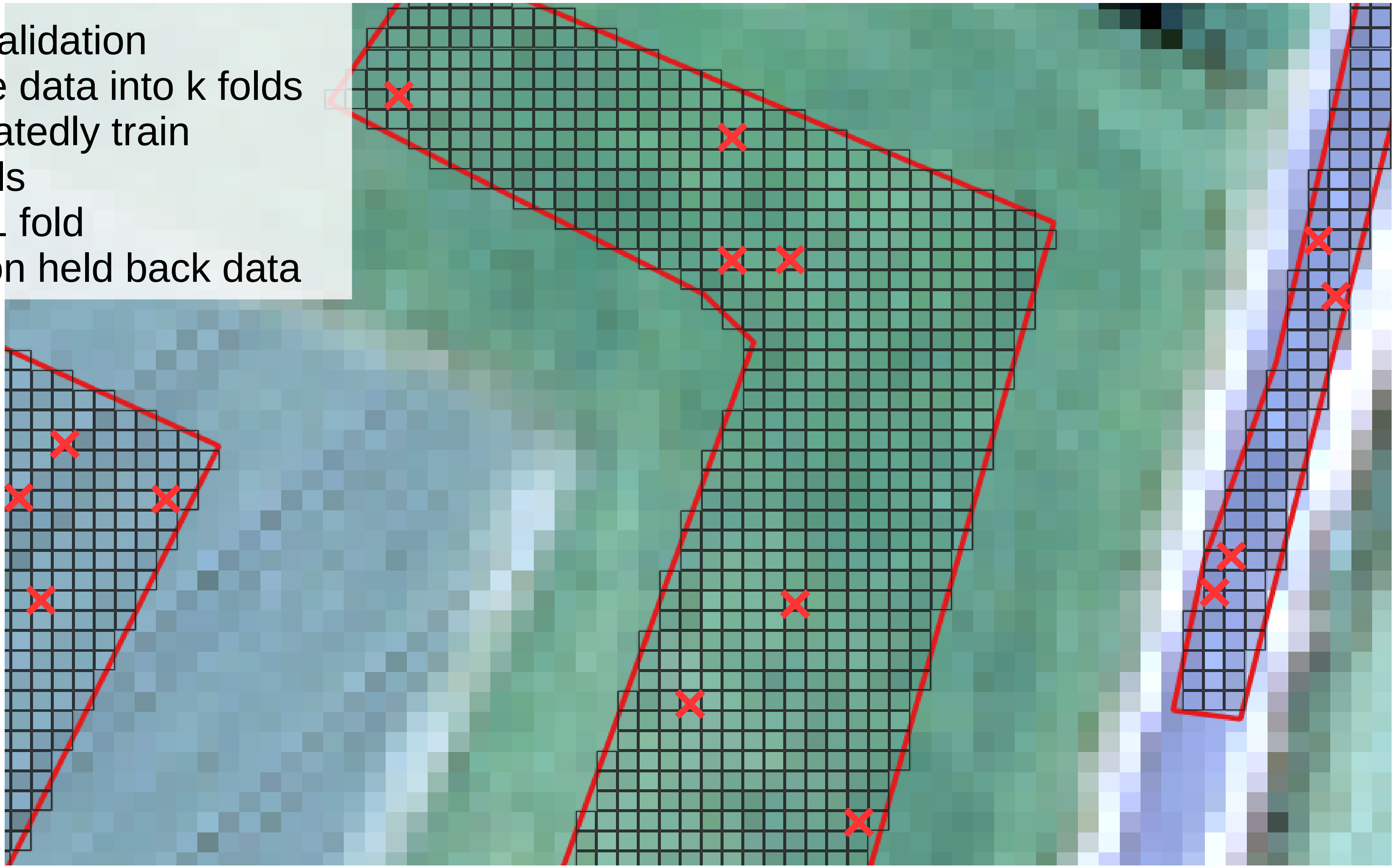

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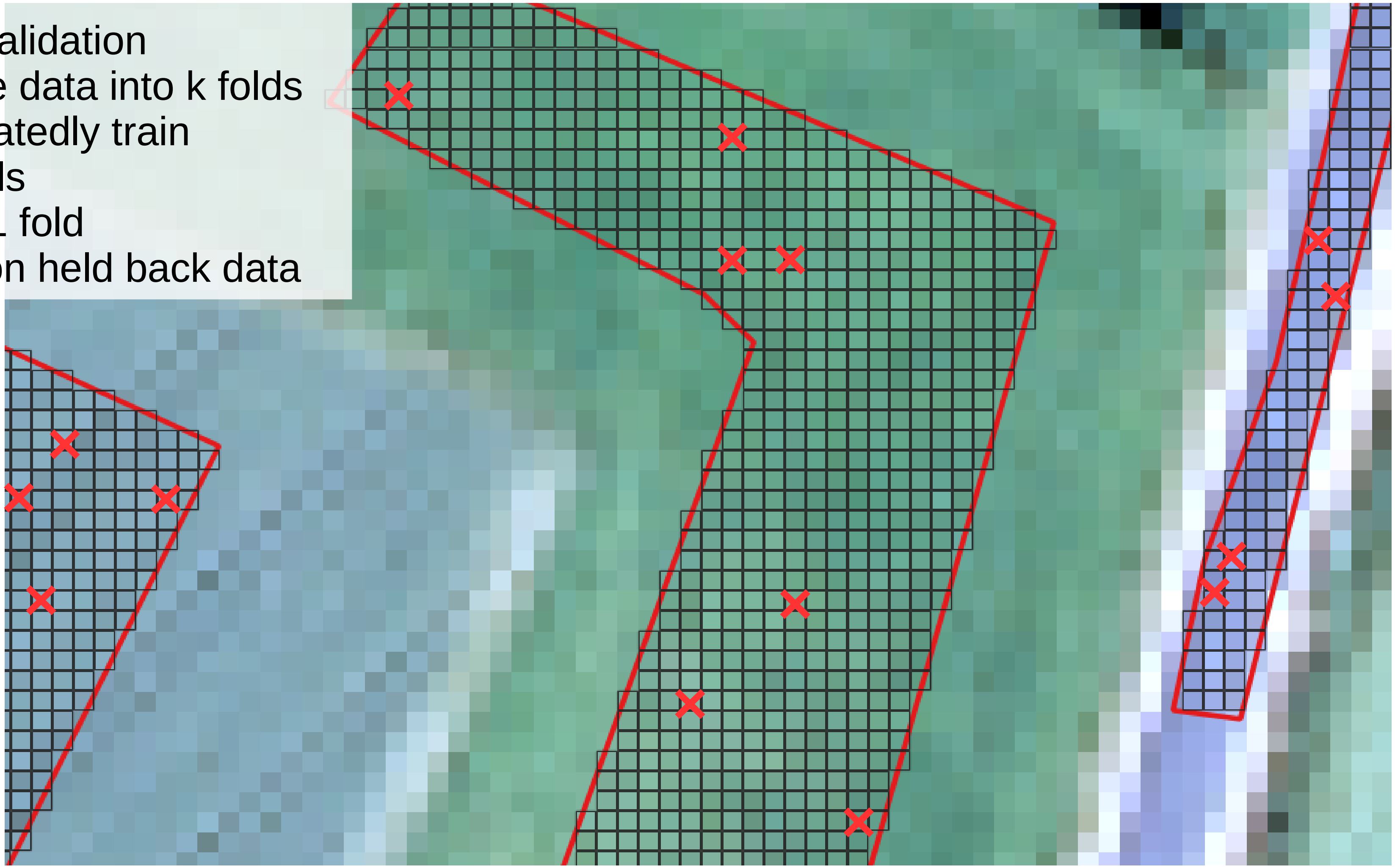

Answers question how well model performs on very similar locations

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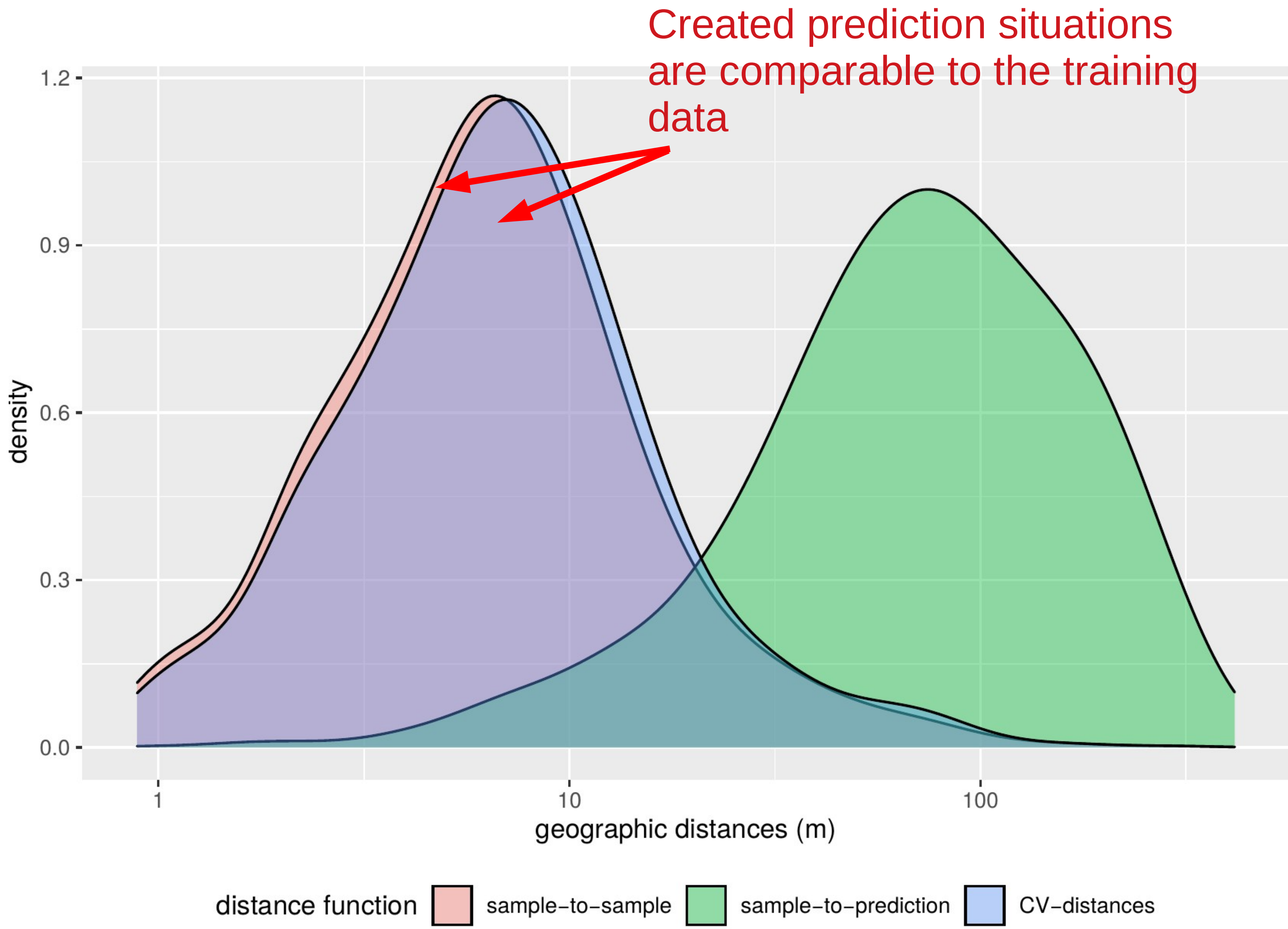

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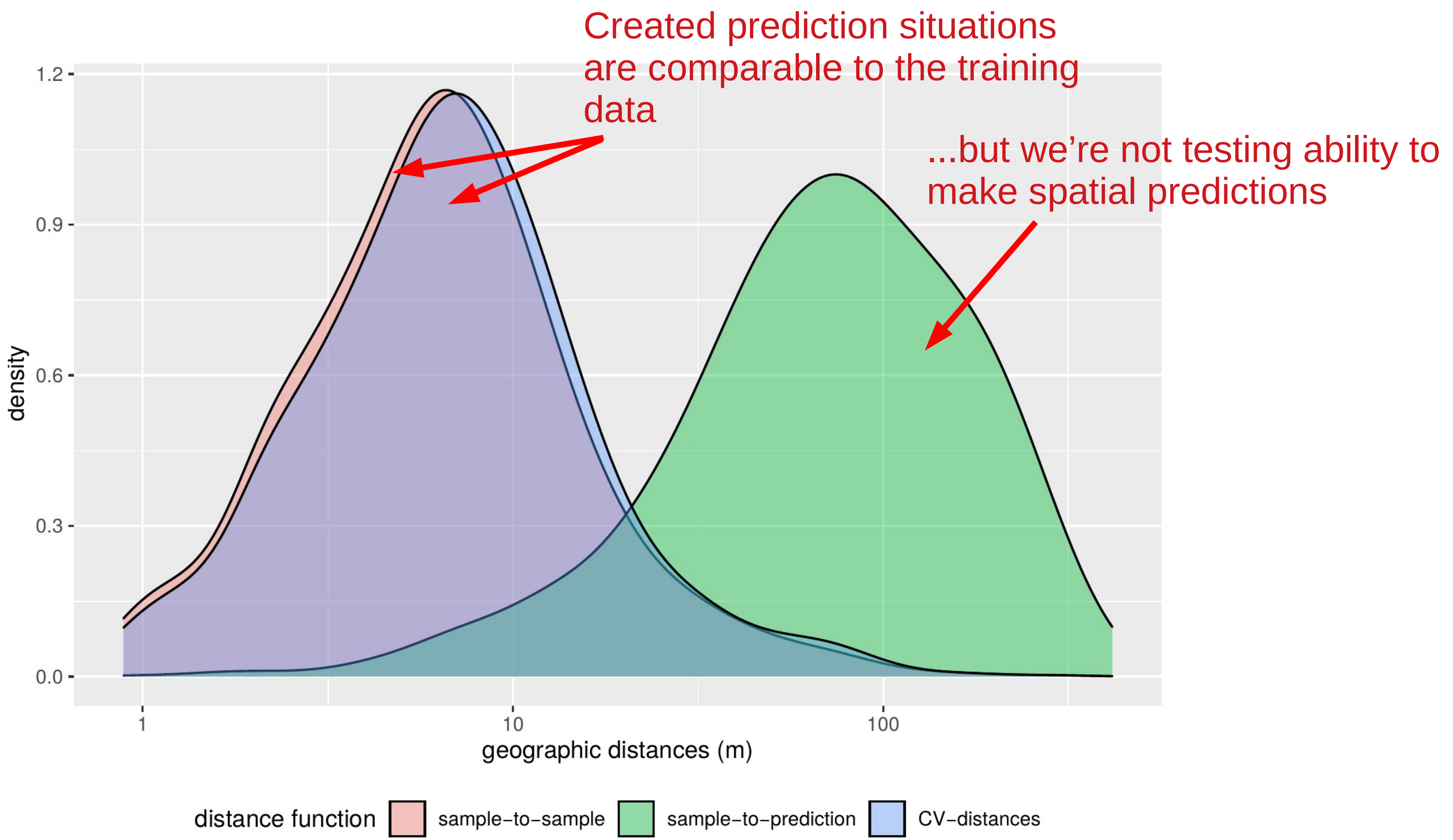

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...But the aim is to fill the gaps between sampling locations!
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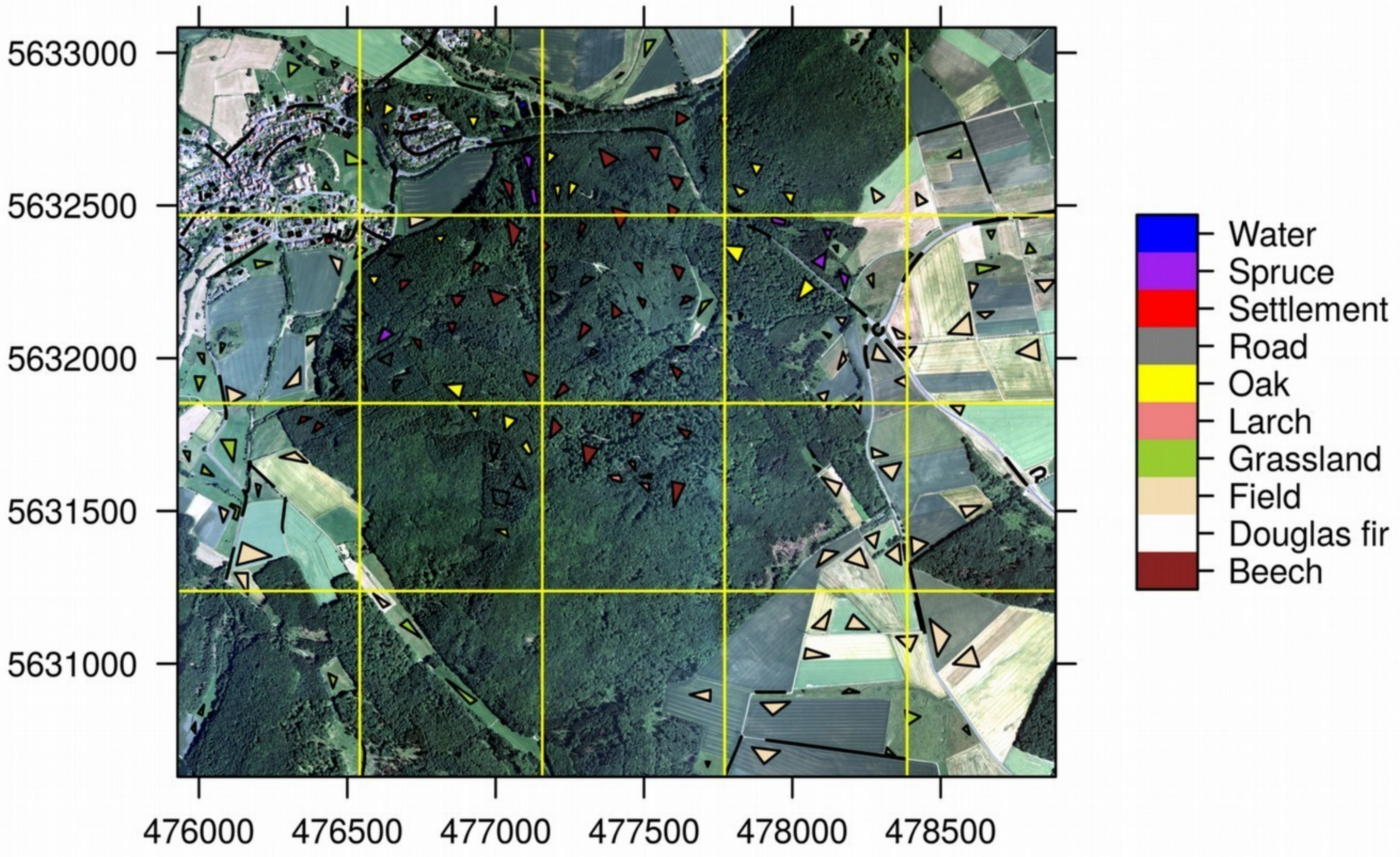

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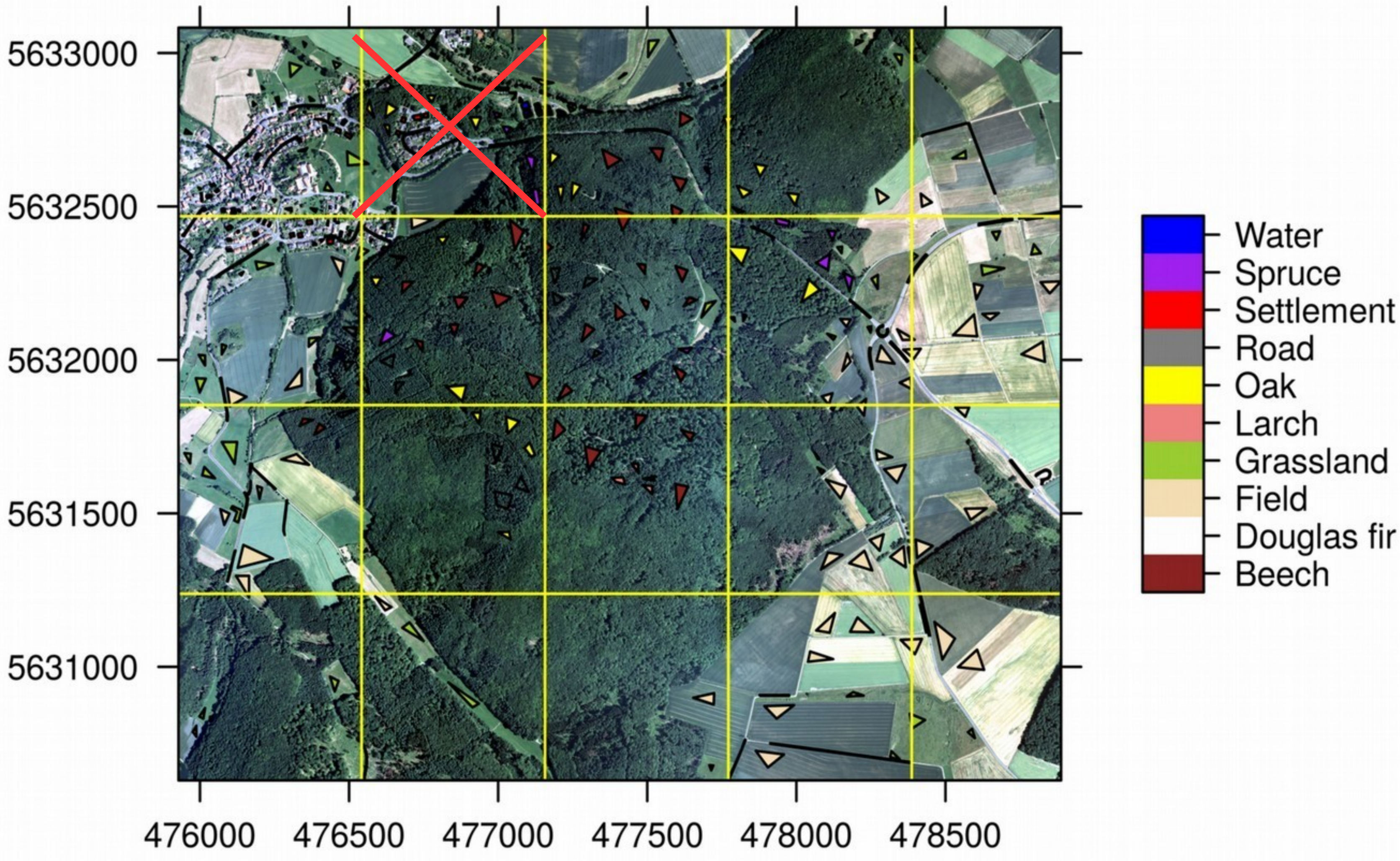

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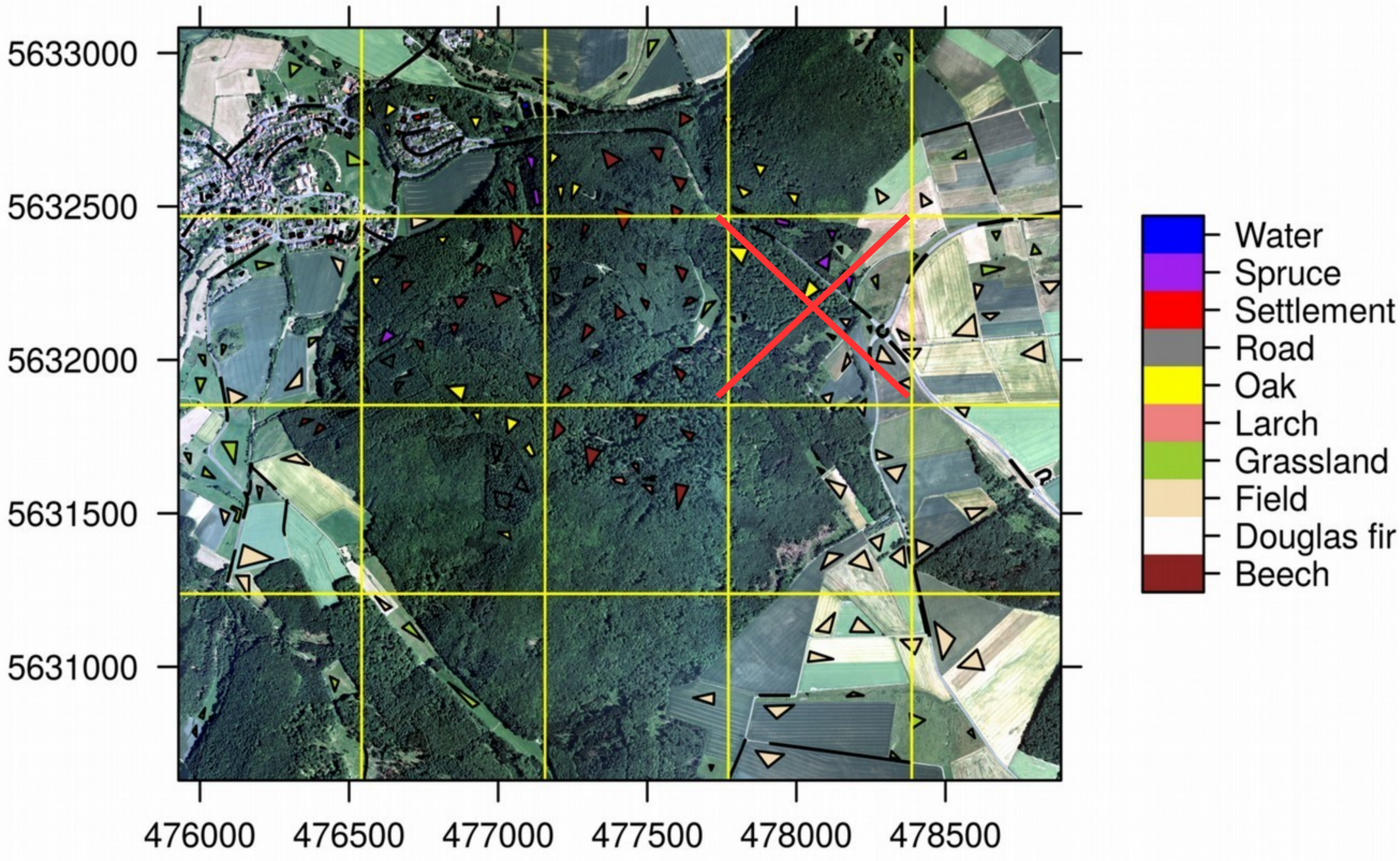

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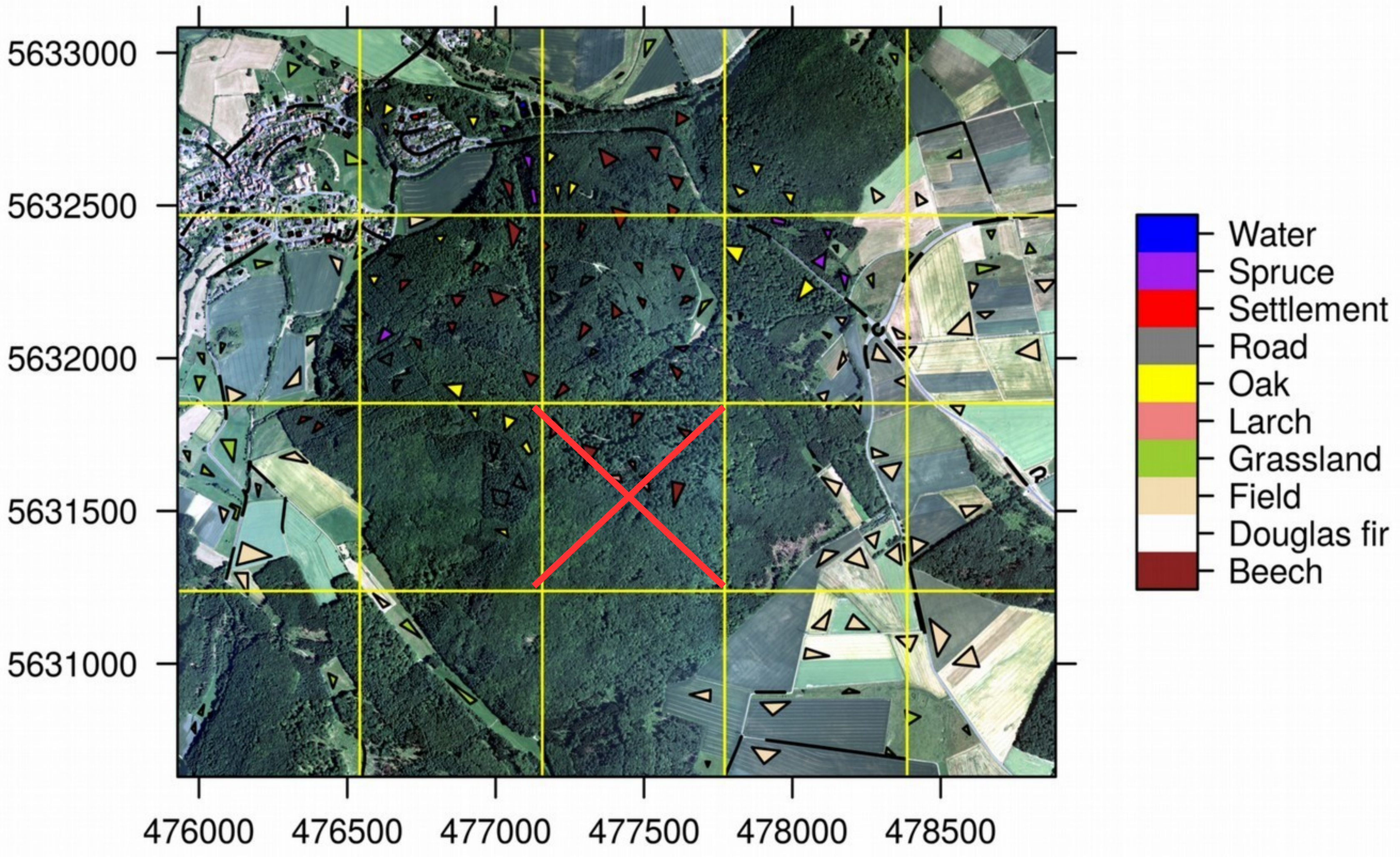

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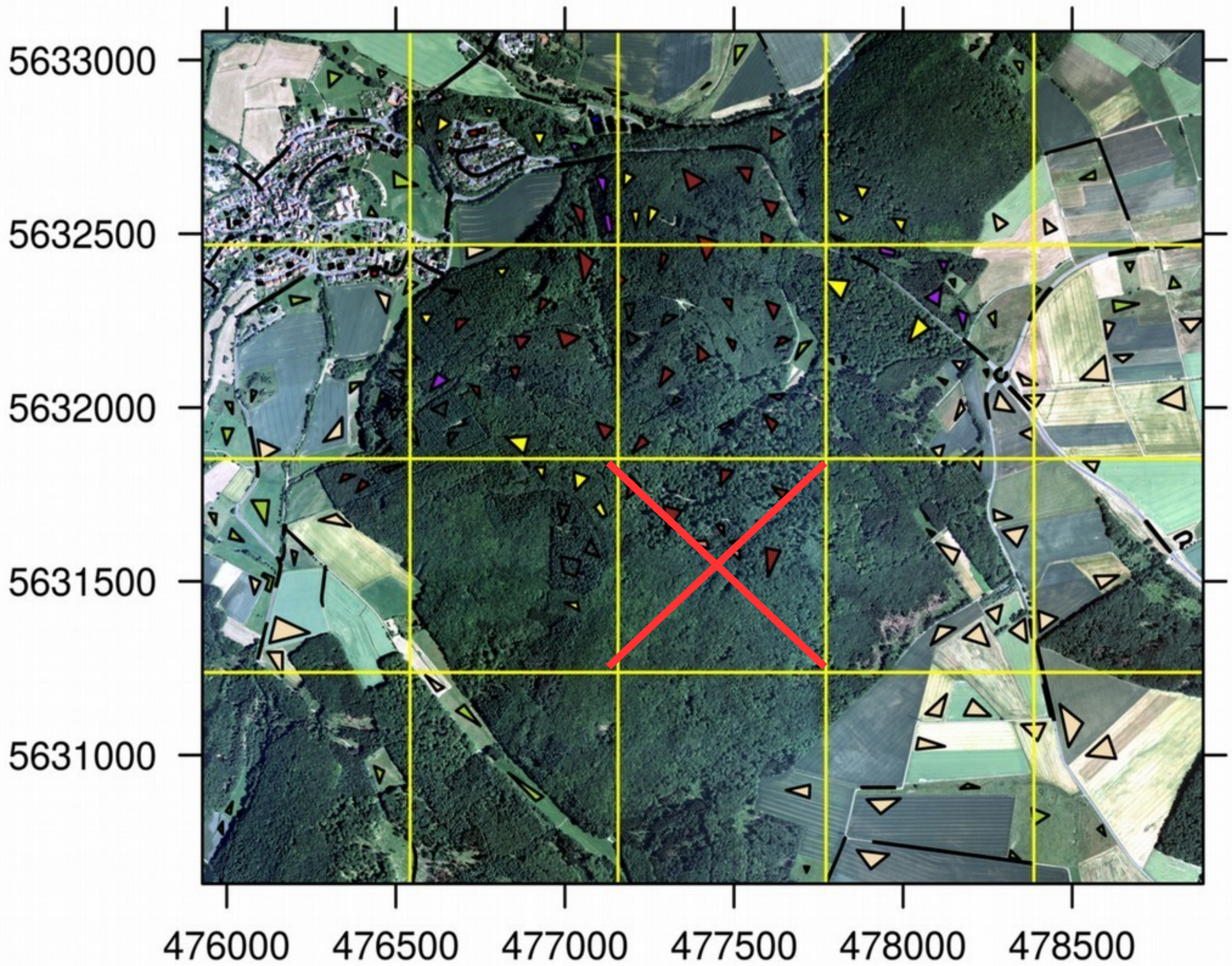

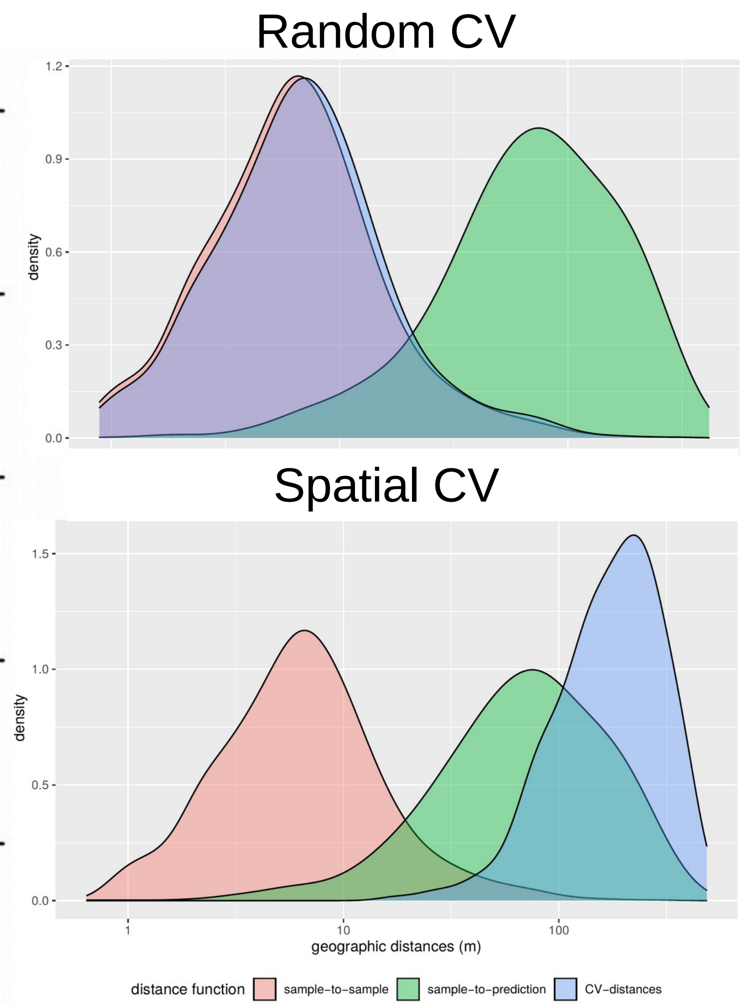

Convinced? So why is the value of spatial CV then still discussed?

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Ecological Modelling
Volume 457, 1 October 2021, 109692

Short communication

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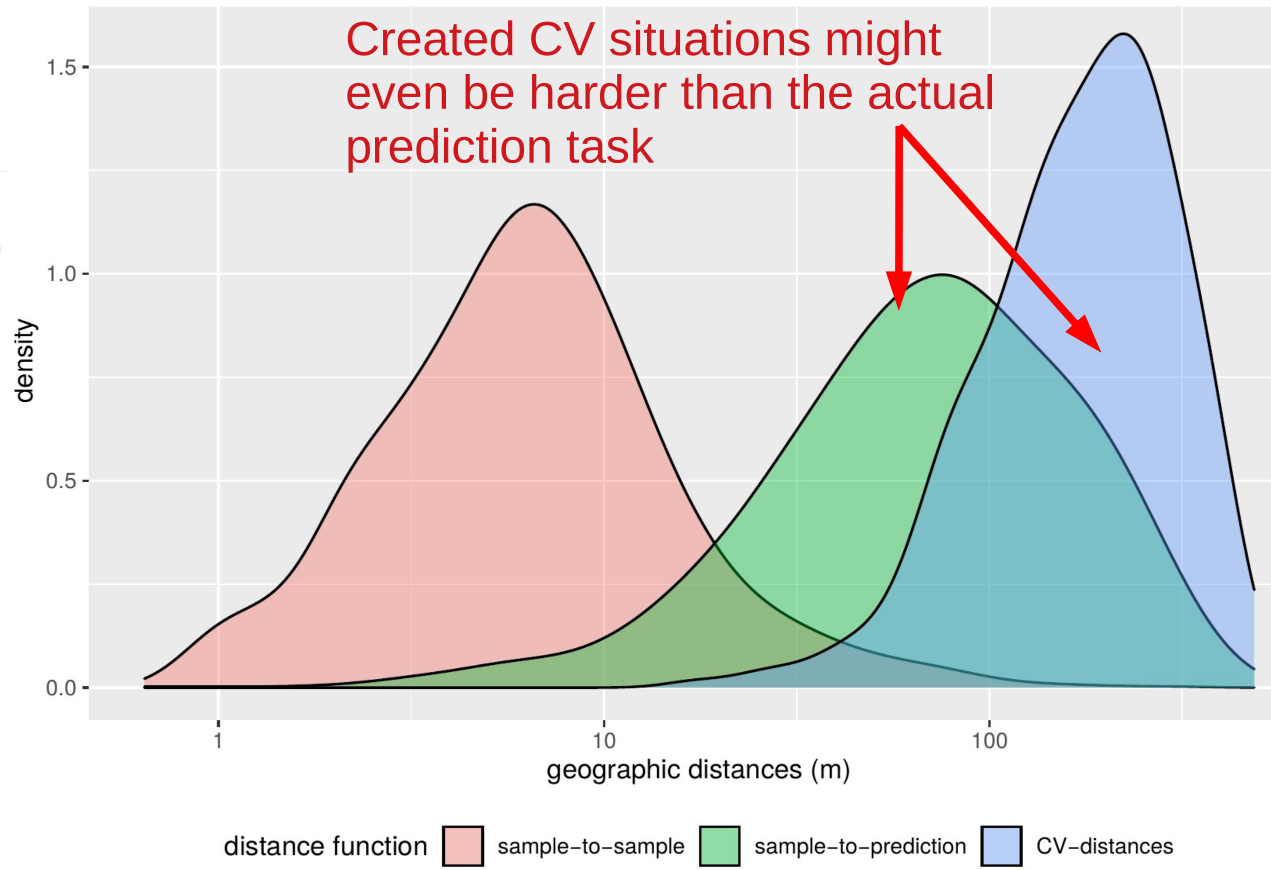

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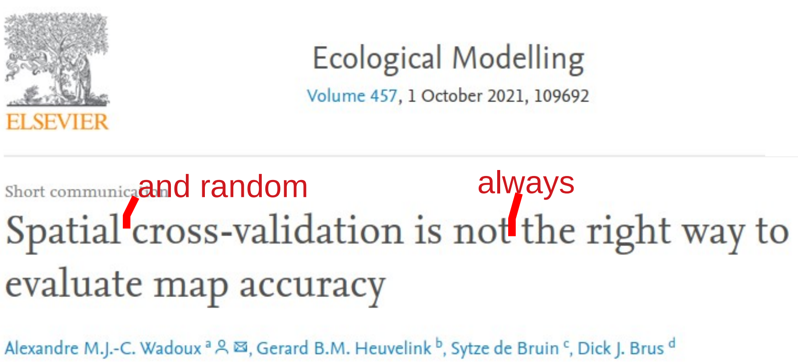
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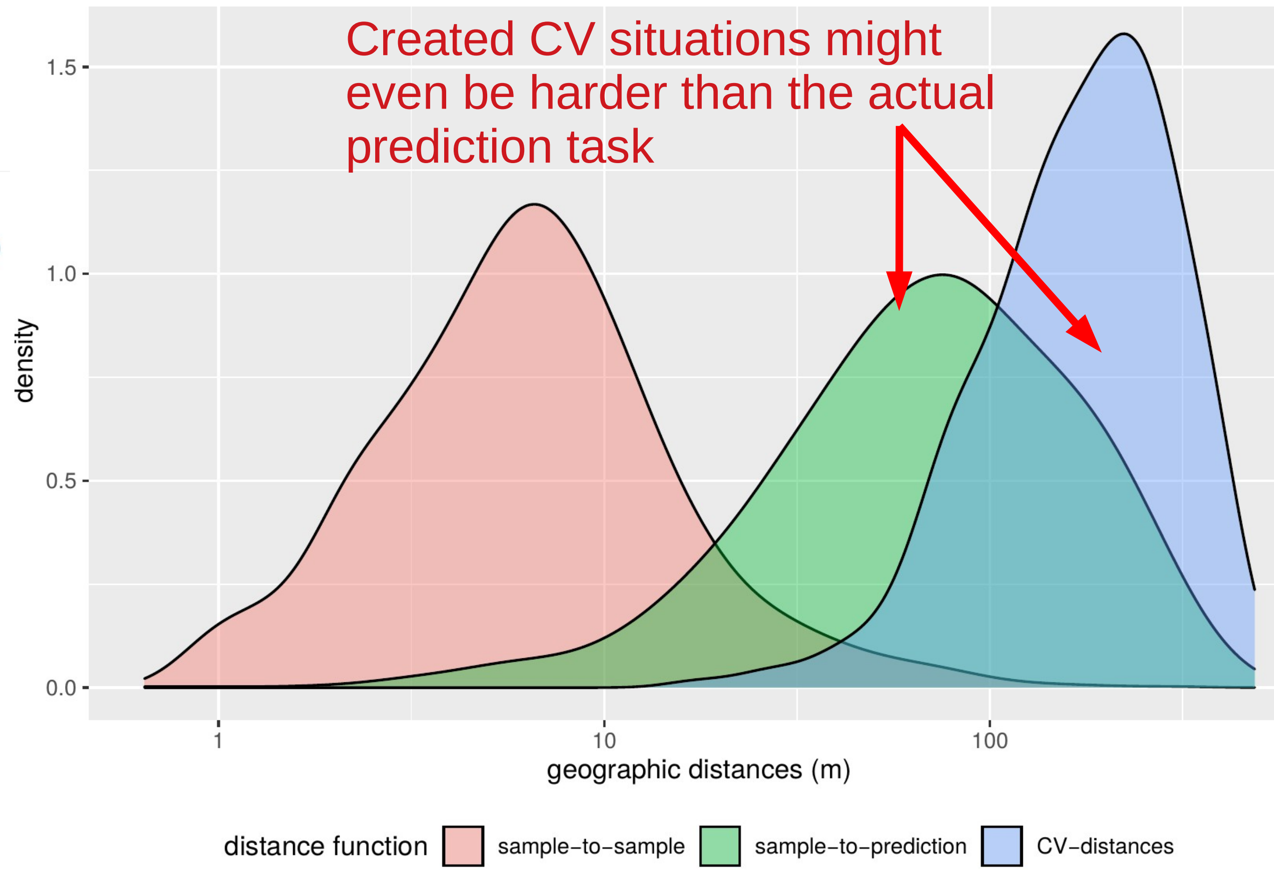

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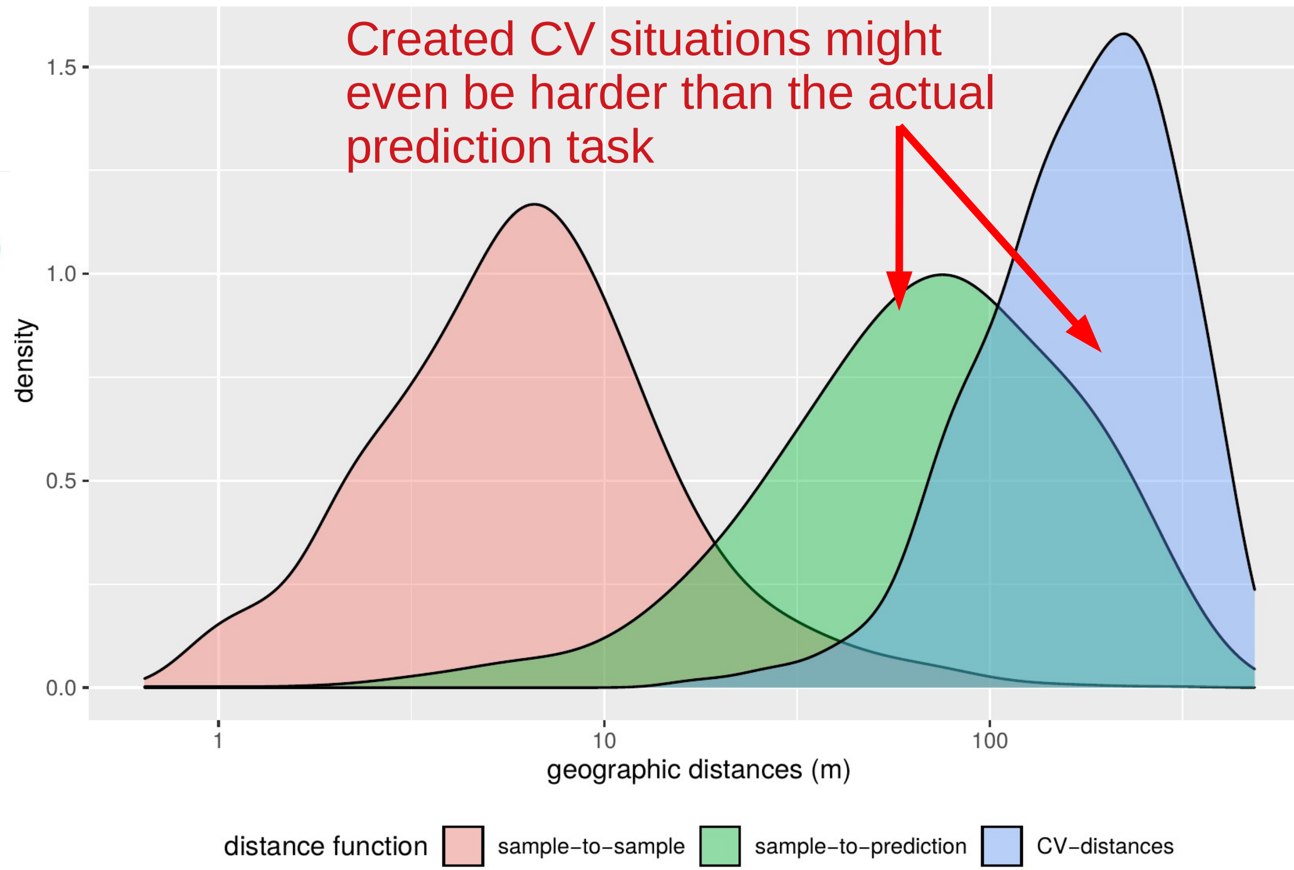

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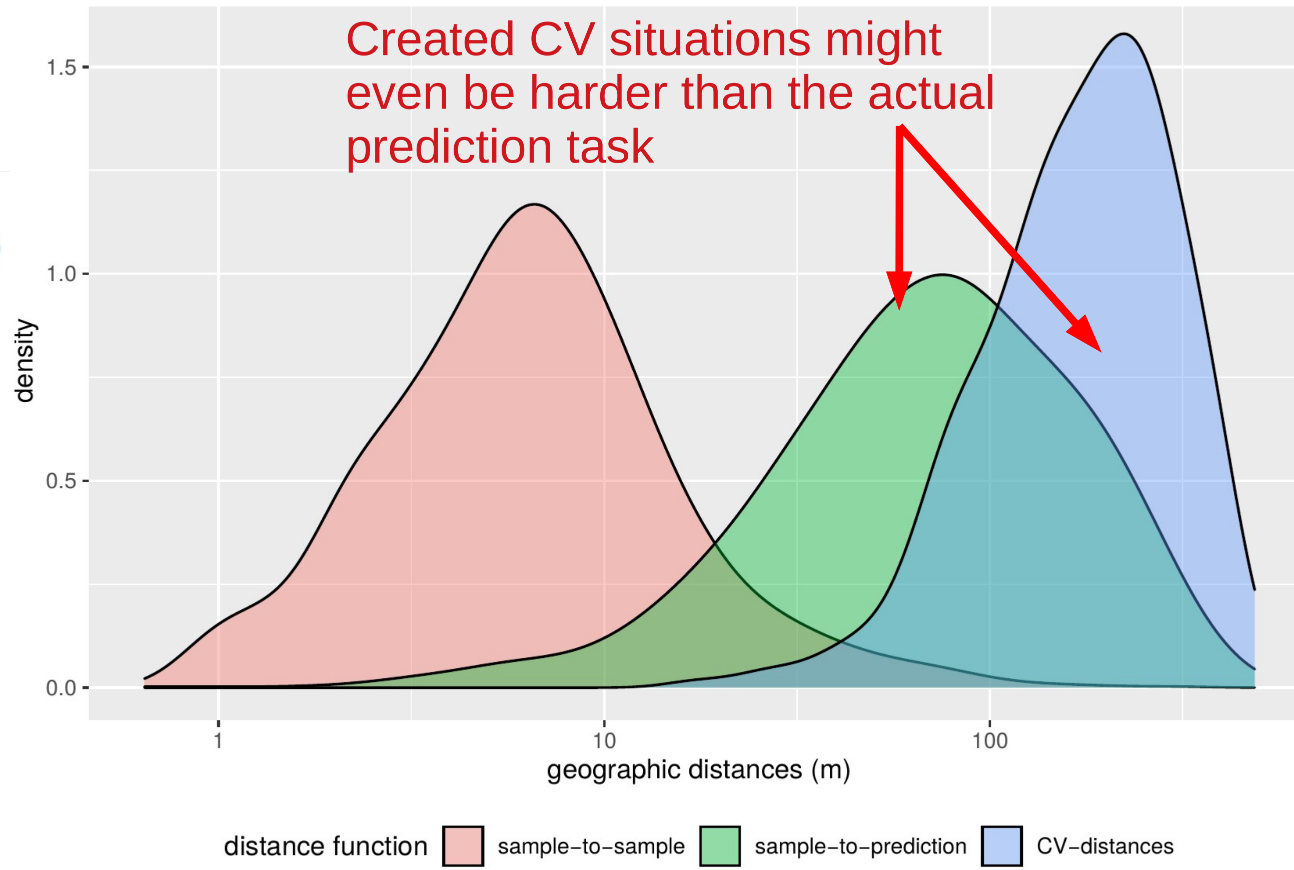

We can do that the trial-and-error-way or….

Suggestion of a nearest neighbor distance matching LOO CV

Received: 20 September 2021 | Accepted: 8 March 2022
DOI: 10.1111/2041-210X.13851

Methods in Ecology and Evolution BRITISH ECOLOGICAL SOCIETY

RESEARCH ARTICLE

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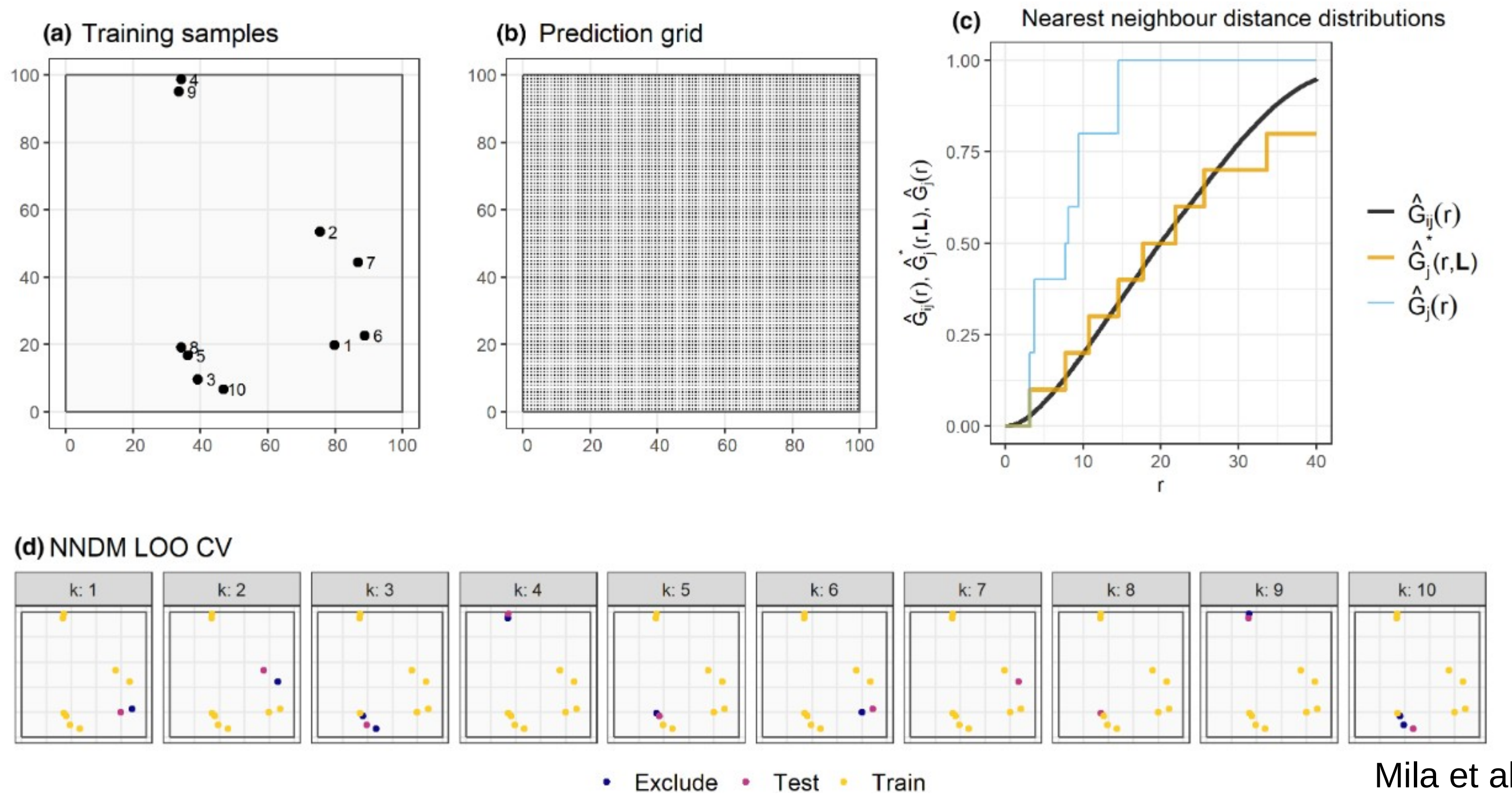

Mila et al., 2022

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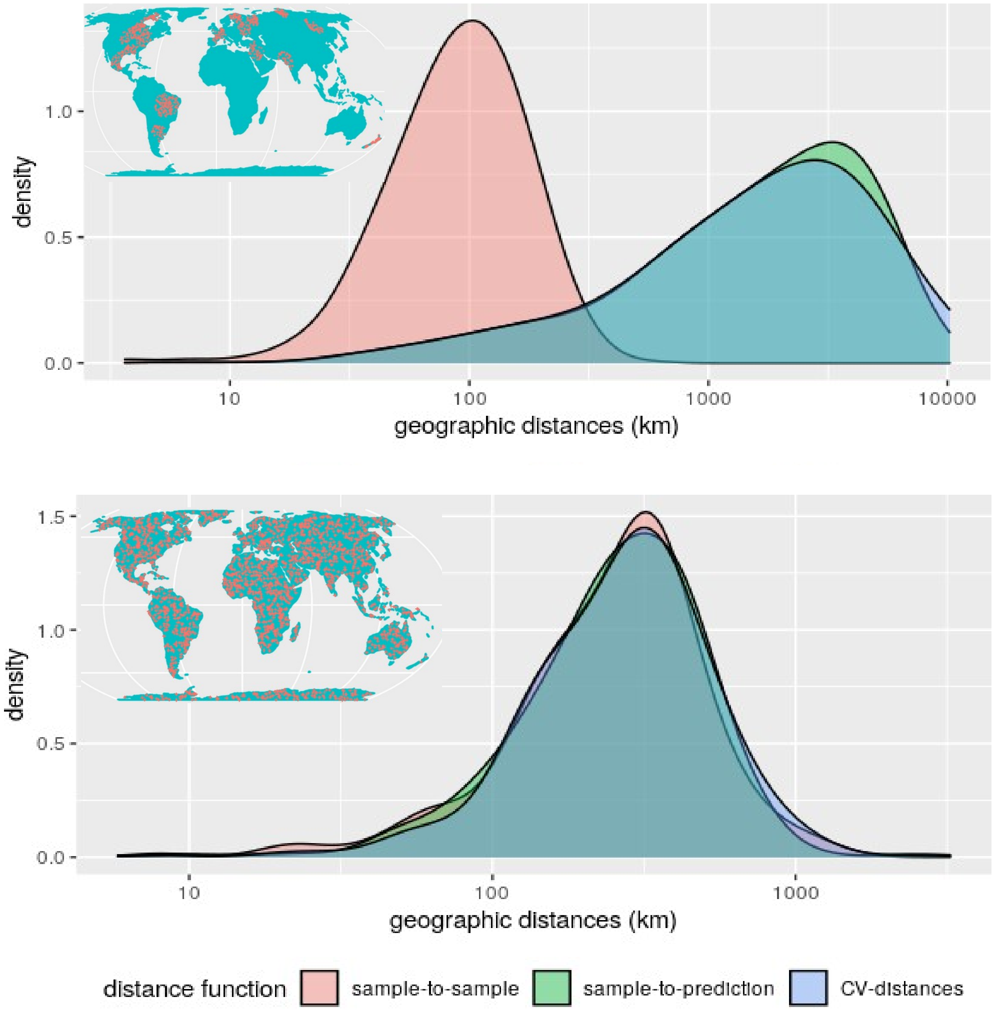

Reproduce figures: hannameyer.github.io/CAST/articles/cast04-plotgeodist.html

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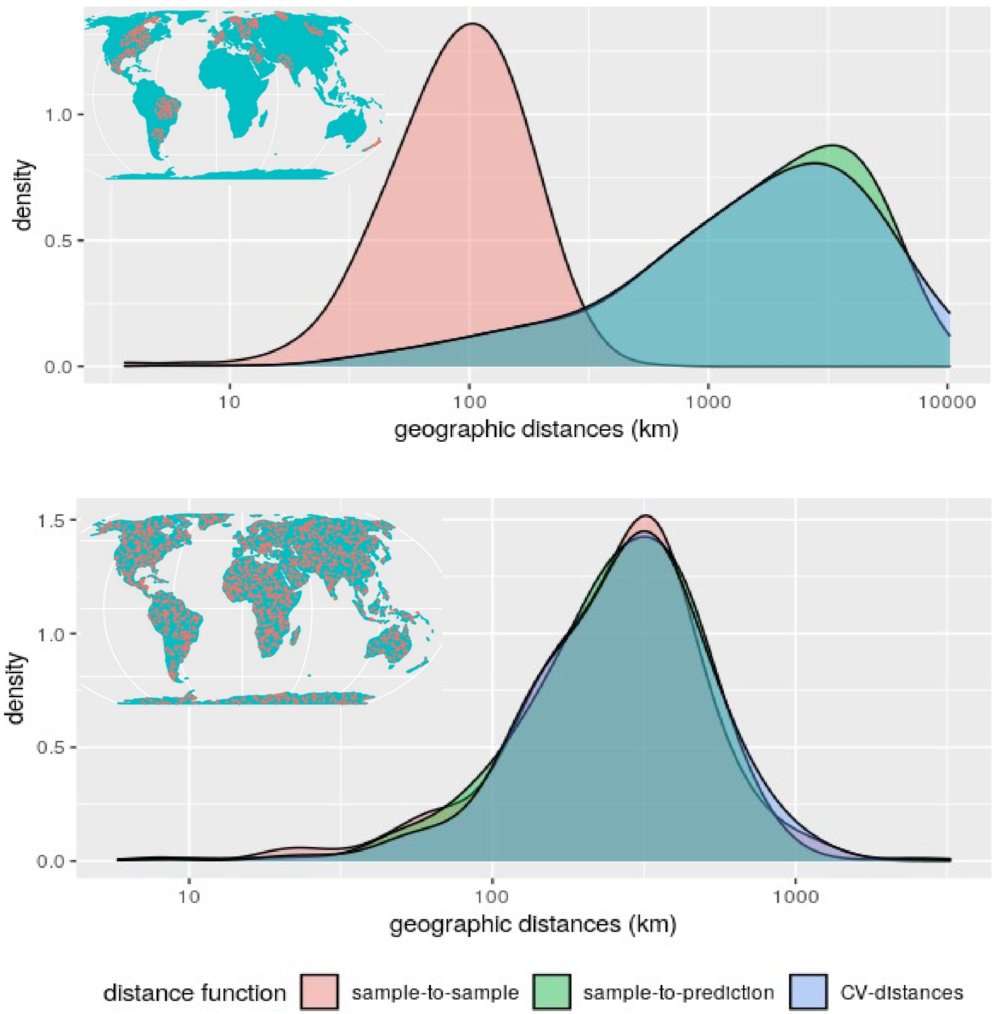

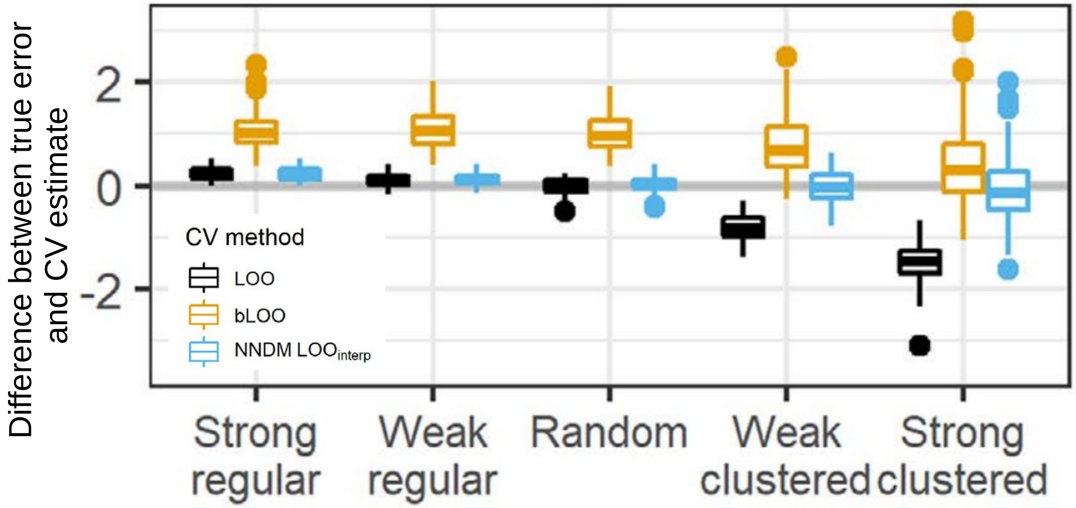

Mila et al., 2022

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Coming back to our case study...

Variables	Validation	Accuracy	Kappa
all	random	>0.99	>0.99
all	spatial	**0.68**	**0.61**

Perfect prediction?
We need to assess this by a suitable CV strategy!

Assessment of spatial performance

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- Prediction situations created during CV need to resemble those encountered while predicting the map from the reference data

...but the relevance of spatial validation is still highly underestimated

"*I am actually surprised to see the poor performance of your NN approach[...]. Typically with sufficient training data a NN approach can often reproduce the predicted variable very well even if the underlying reasons are unknown*"
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Data reproduction is not the same as data prediction!

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Spatial
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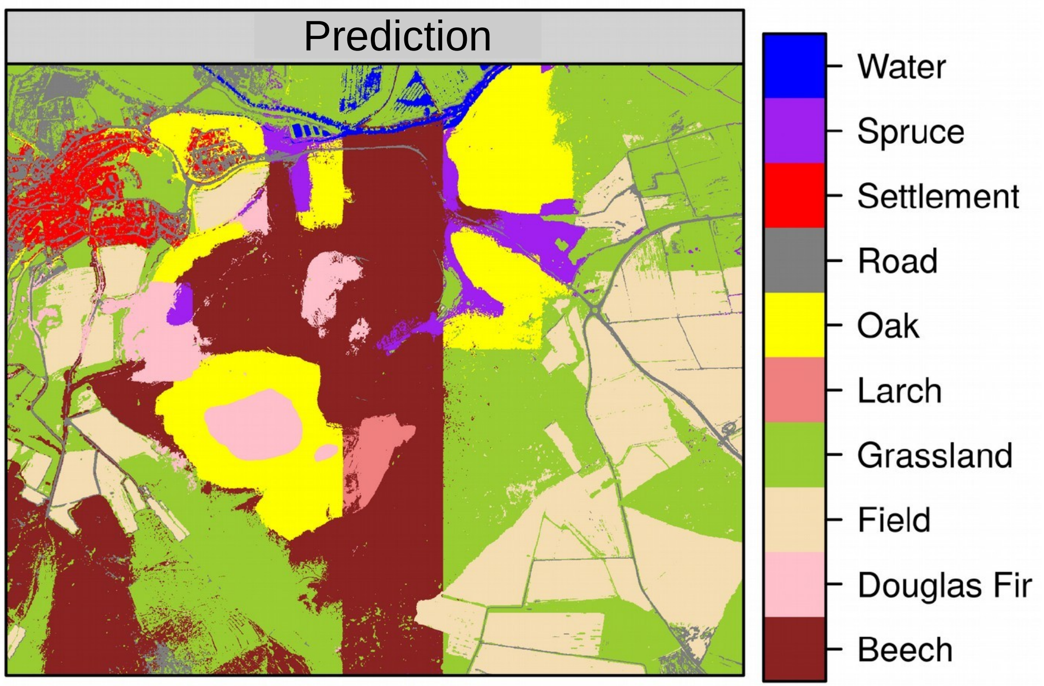
Spatial performance of models needs to be improved!



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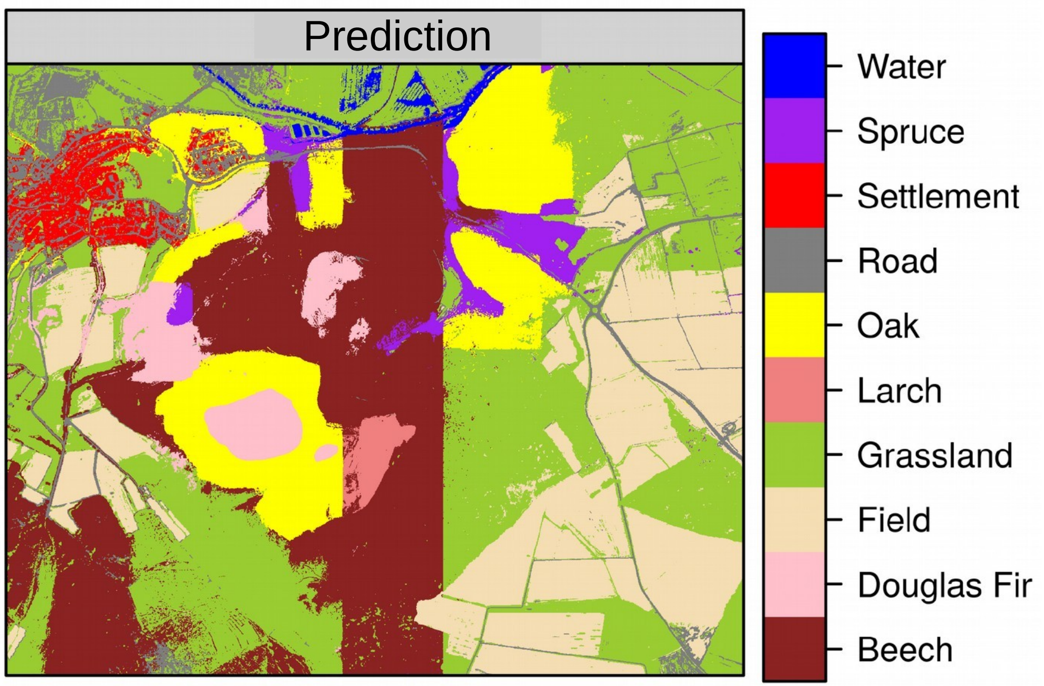

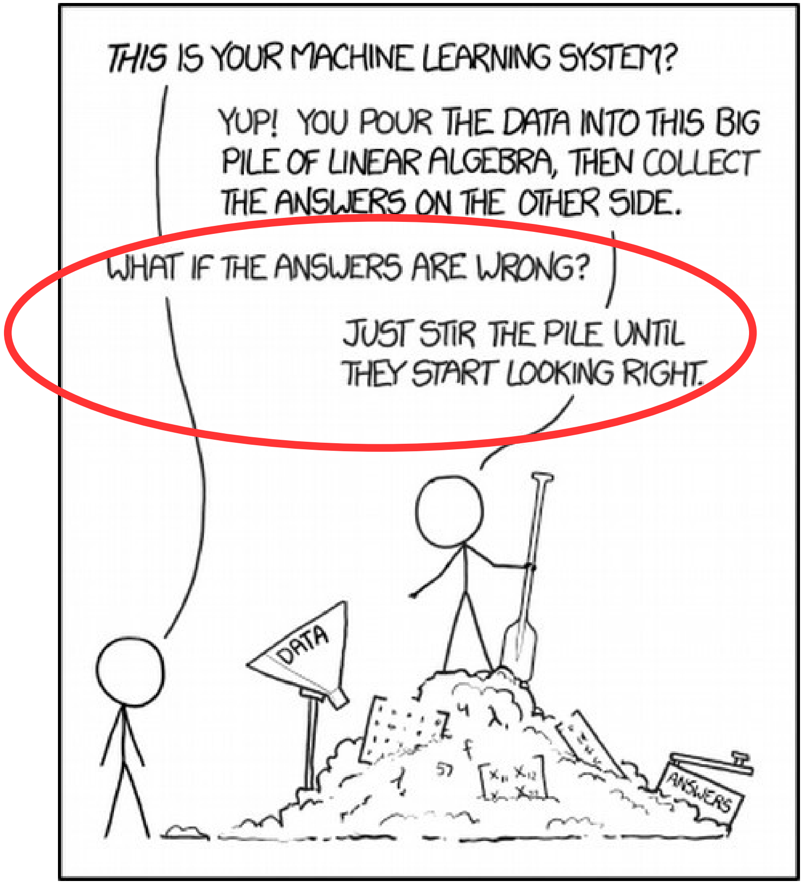

https://xkcd.com/1838/

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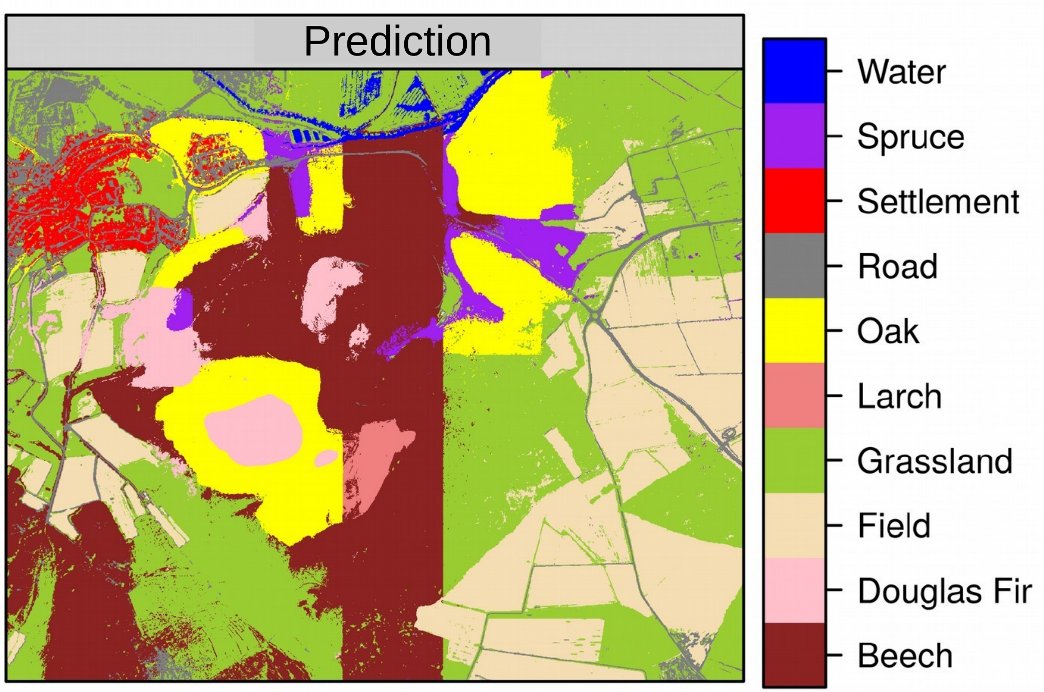
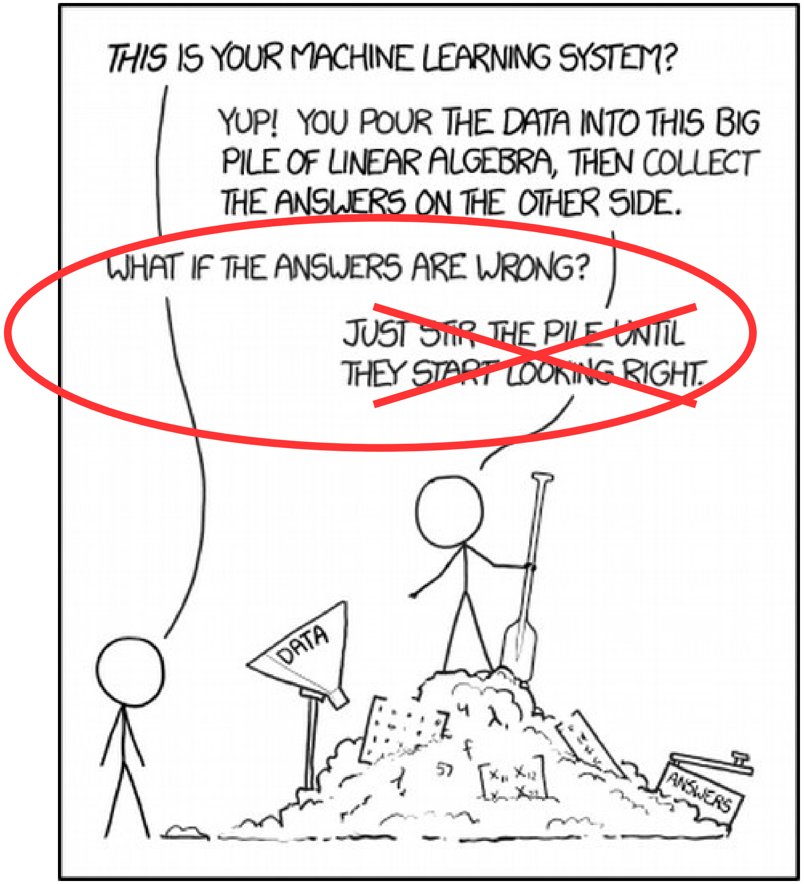
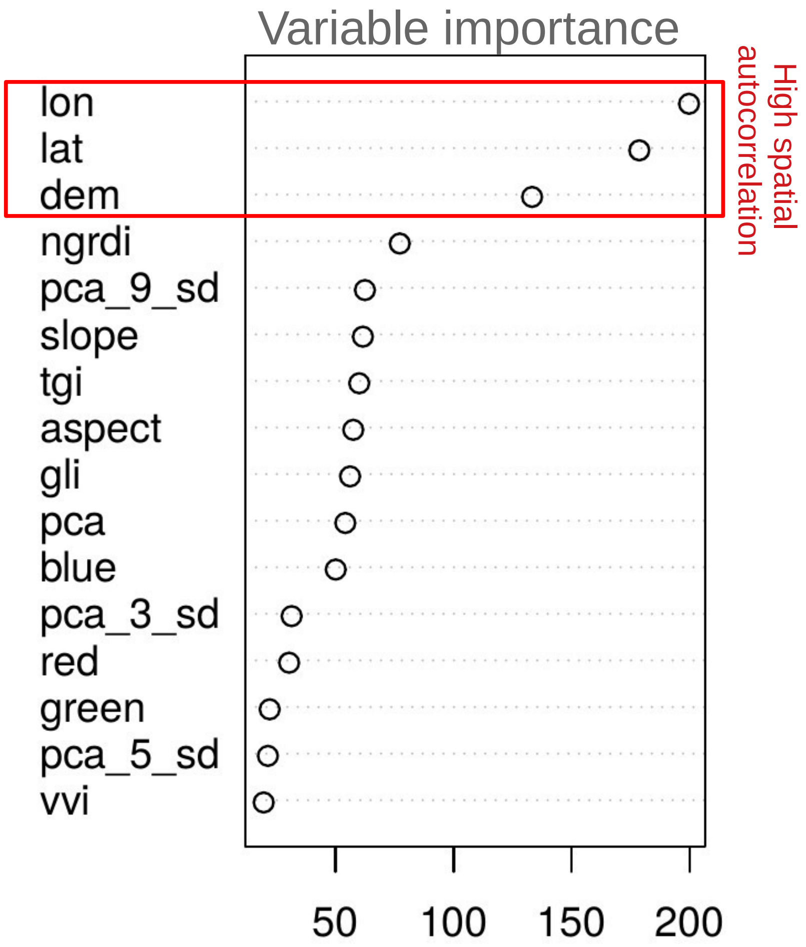




Where do these prediction patterns come from?

https://xkcd.com/1838/

An example of the “clever Hans effect” ?



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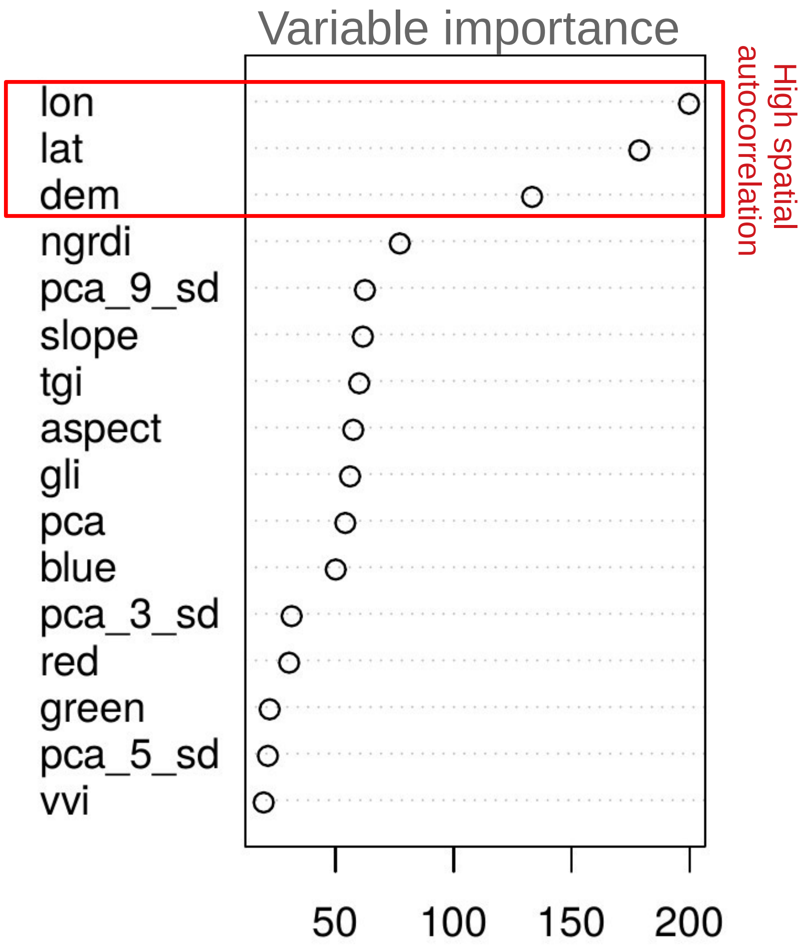
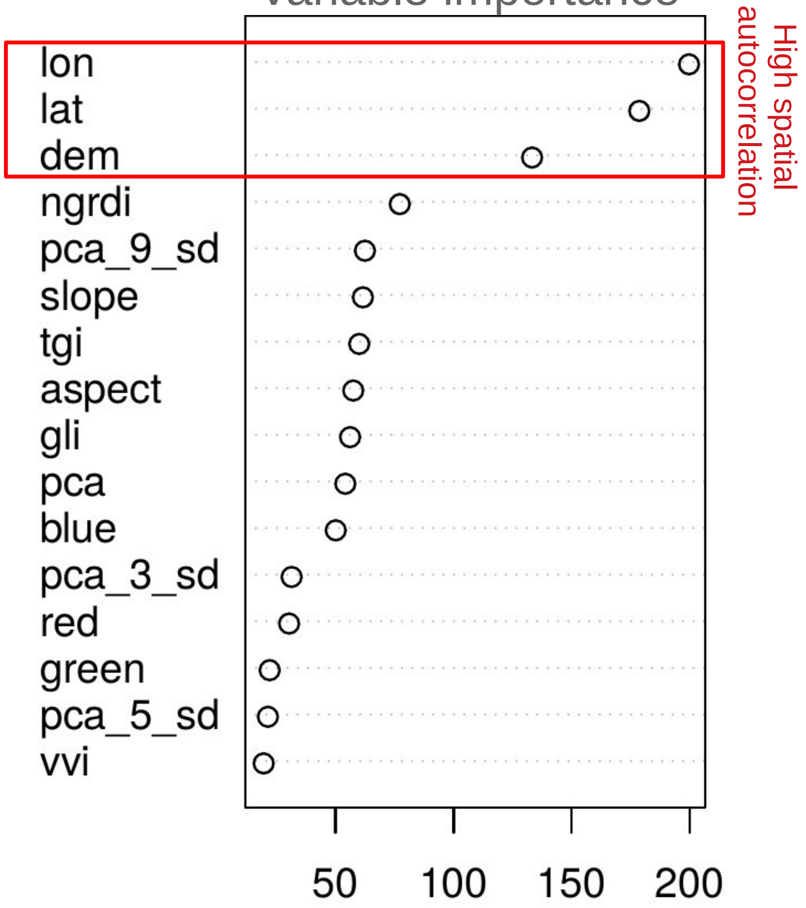


Suspicion: spatial dependencies lead to confounding variables.

→ True relationships not recognized, causing the model to fail in making predictions?

An example of the “clever Hans effect” ?

Variable importance



Is the model behaving like the “clever Hans” ?

https://commons.wikimedia.org/wiki/File:Osten_und_Hans.jpg#/media/Datei:Osten_und_Hans.jpg

Suspicion: spatial dependencies lead to confounding variables.

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“Unmasking Clever Hans predictors and assessing what machines really learn”
(Lapuschkin et al., 2019, Nature communications)

Horse-picture from Pascal VOC data set

What is the information the algorithm uses to detect the horse?

Lapuschkin et al., 2019

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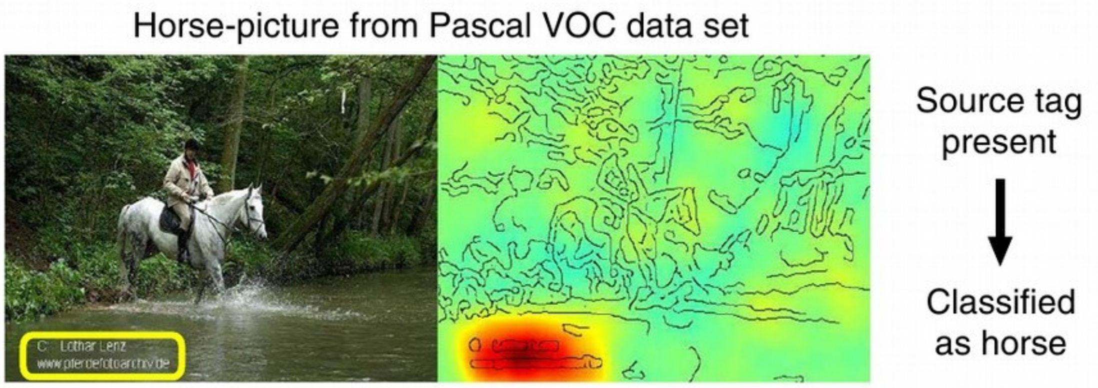

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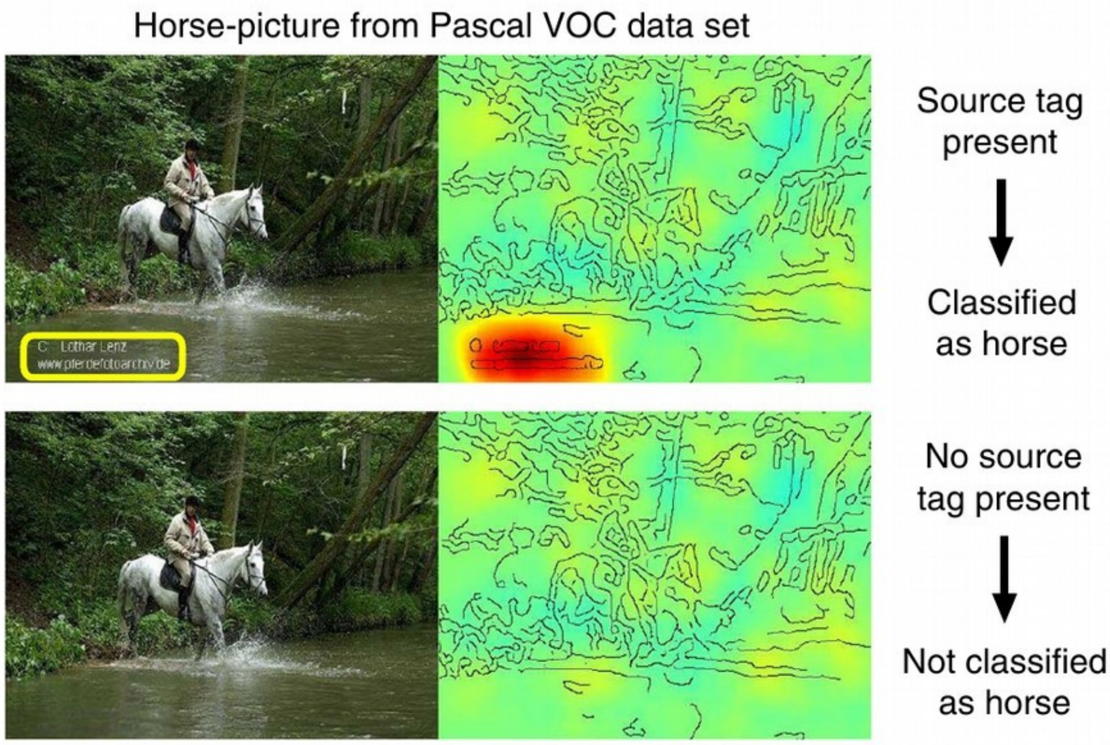

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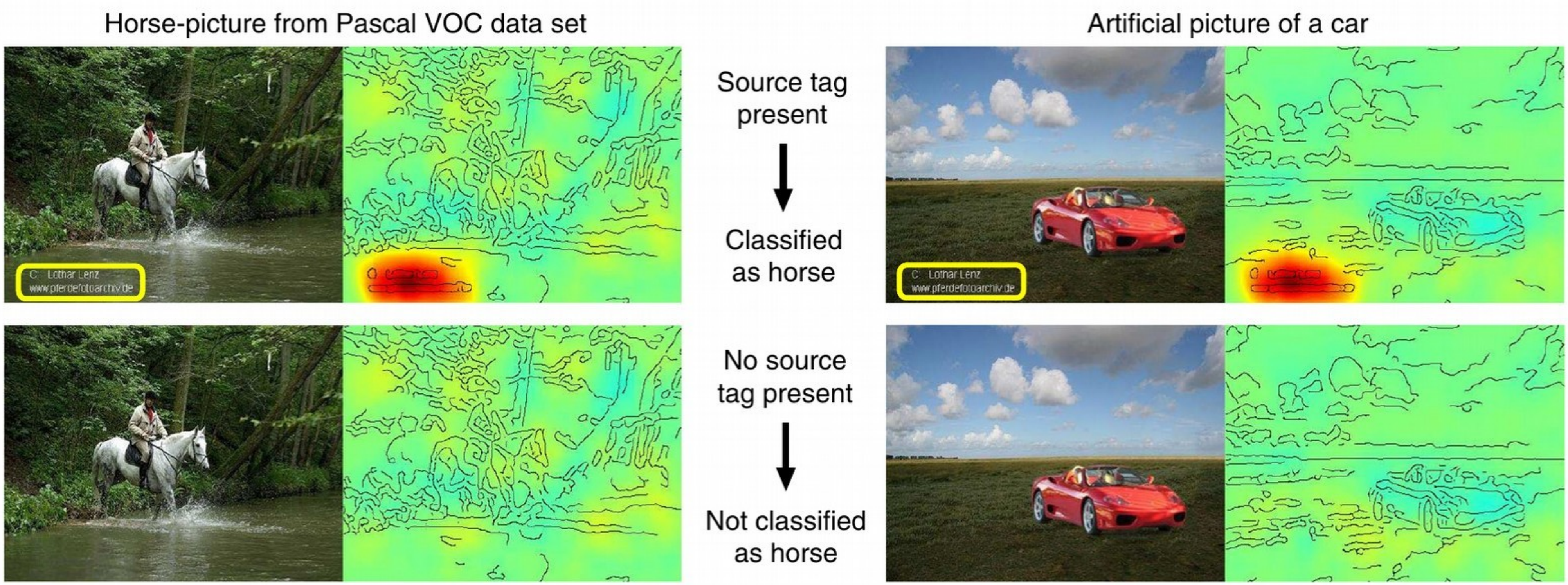

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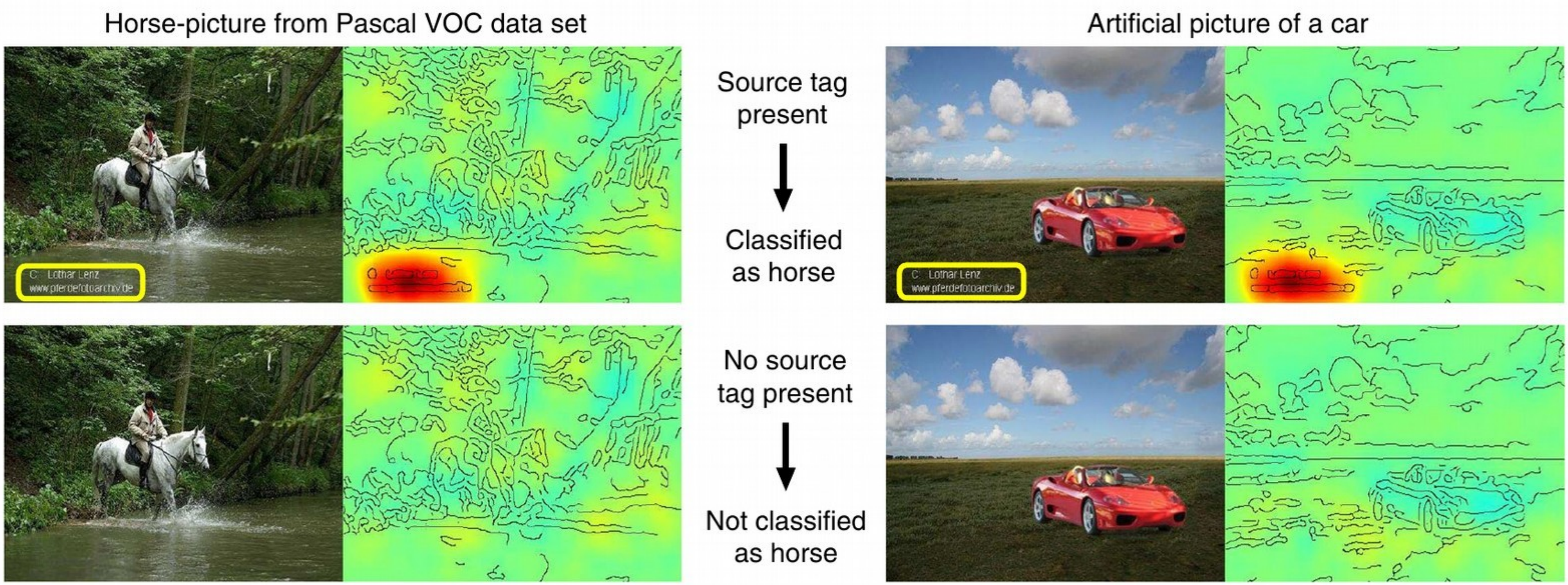

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“Right for the wrong scientific reasons” (Schramowski et al., 2020)?
If scientific reason is not right, the model won’t be able to make reliable predictions for new samples!

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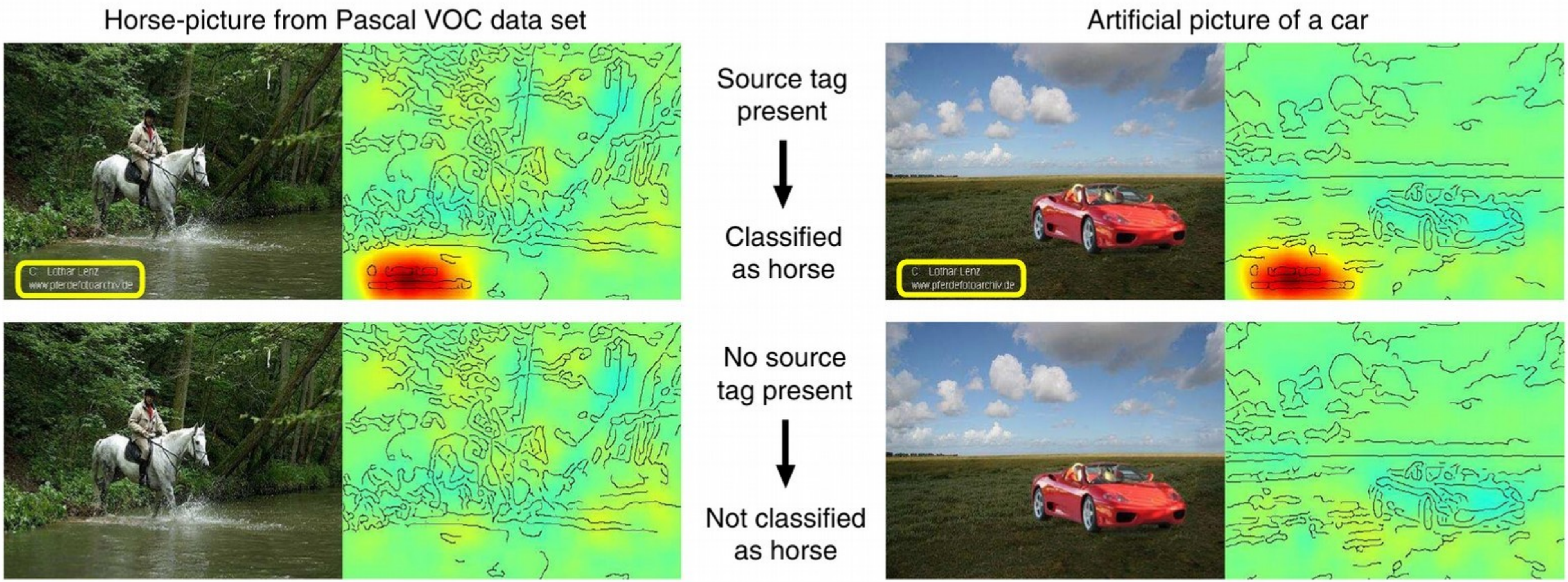
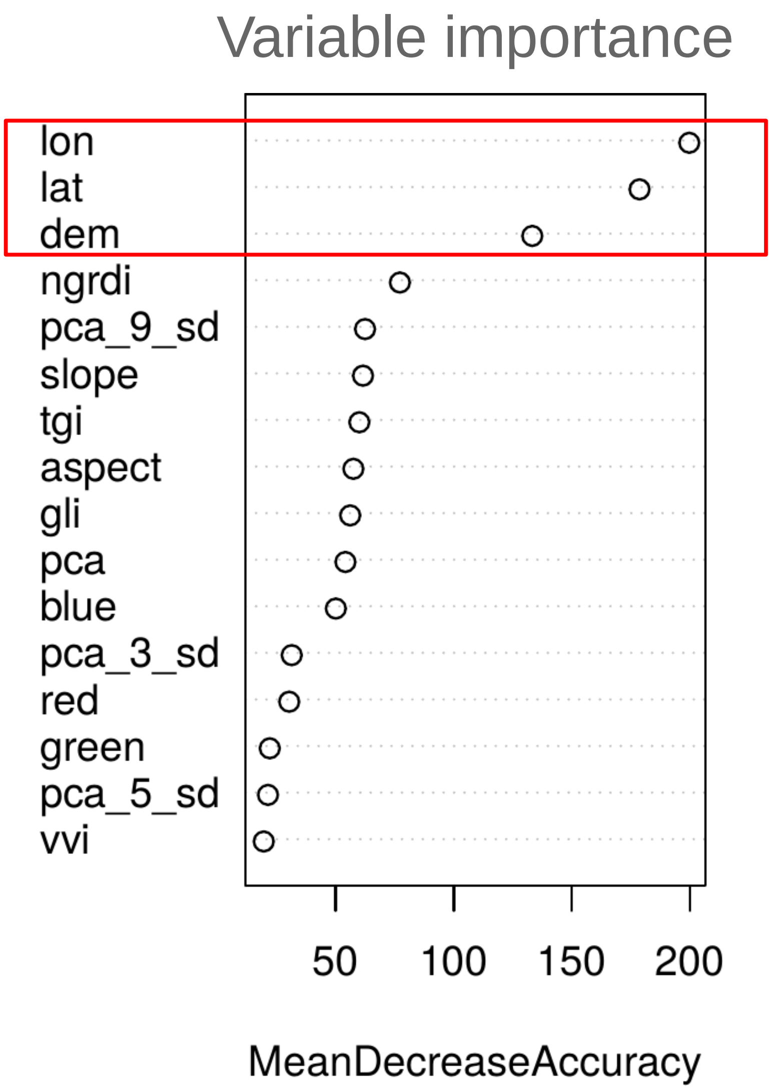


Lapuschkin et al., 2019

"Right for the wrong scientific reasons" (Schramowski et al., 2020)?
If scientific reason is not right, the model won't be able to make reliable predictions for new samples!
→ We already revealed by spatial validation that our case study model is not right…
But how to get it right?

Unmasking “clever Hans predictors” to improve the model?



- Assumption: spatial autocorrelation leads to “clever Hans predictors”

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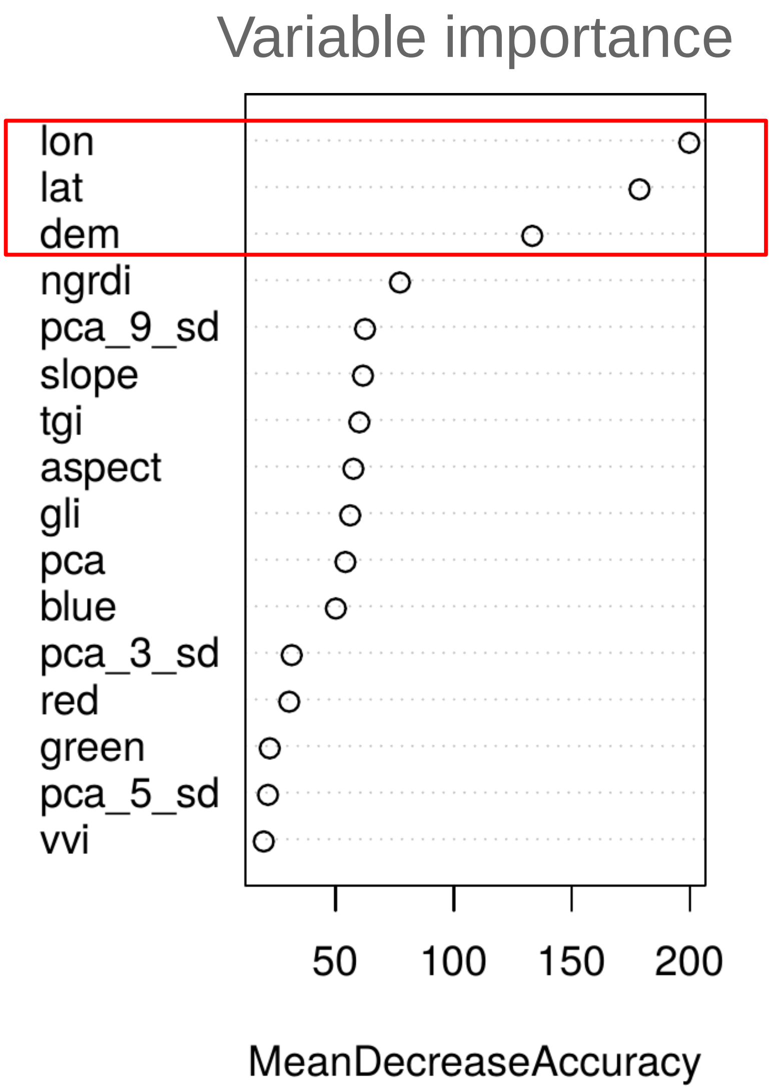

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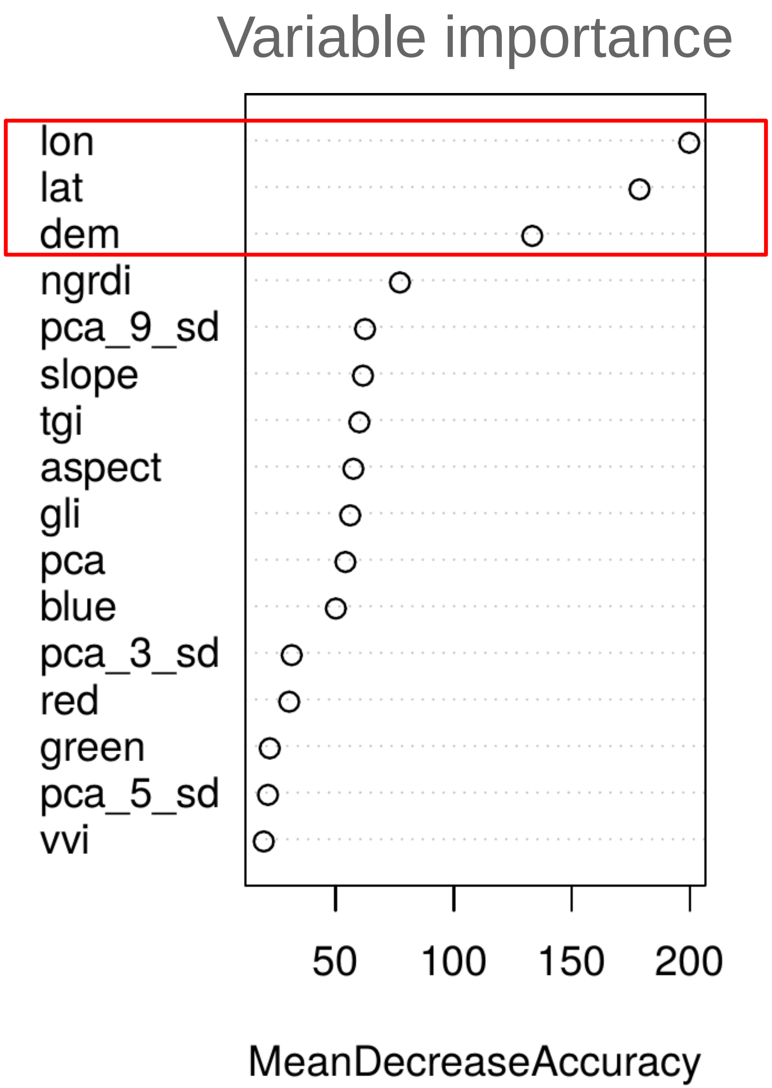

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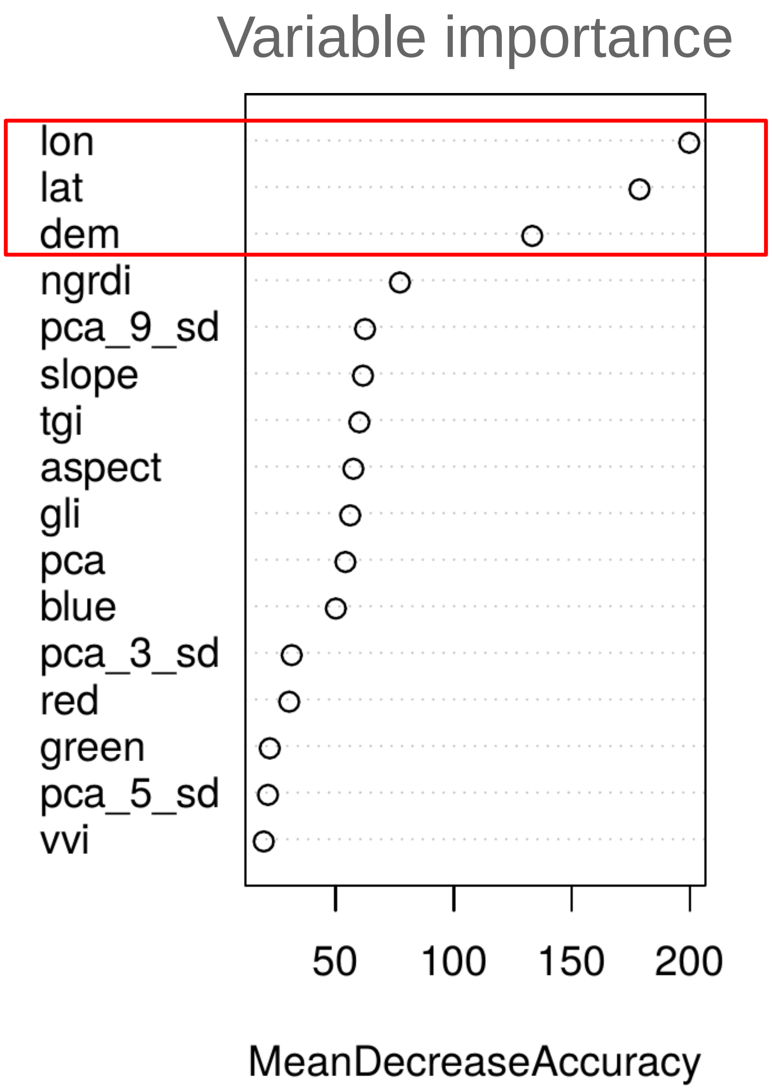

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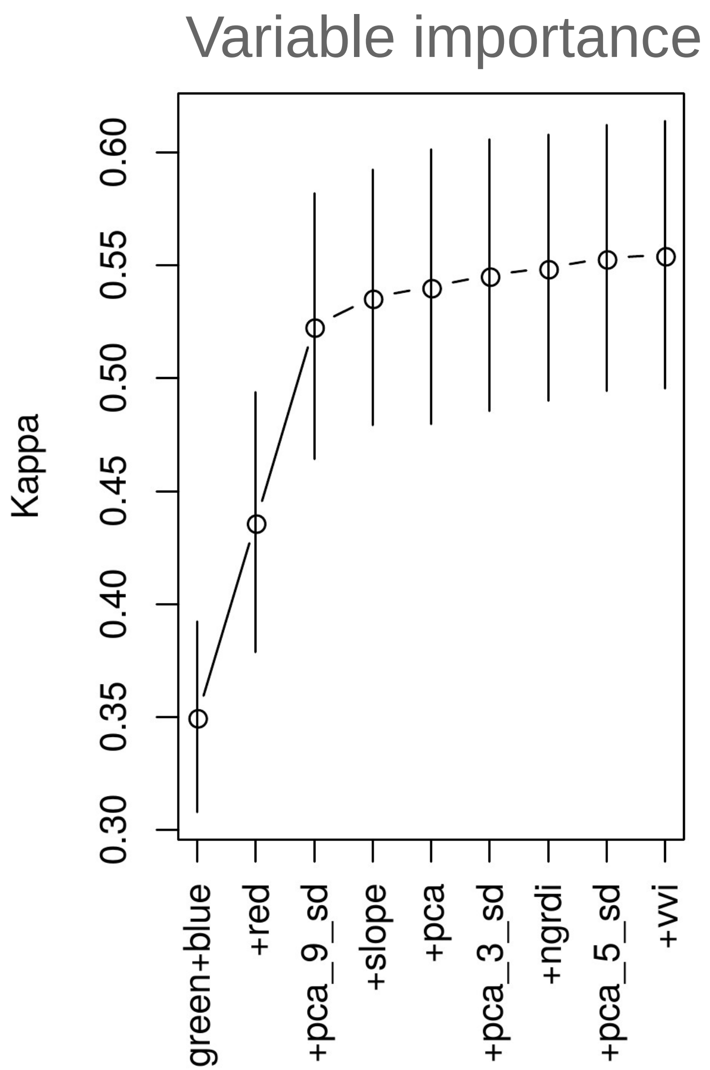

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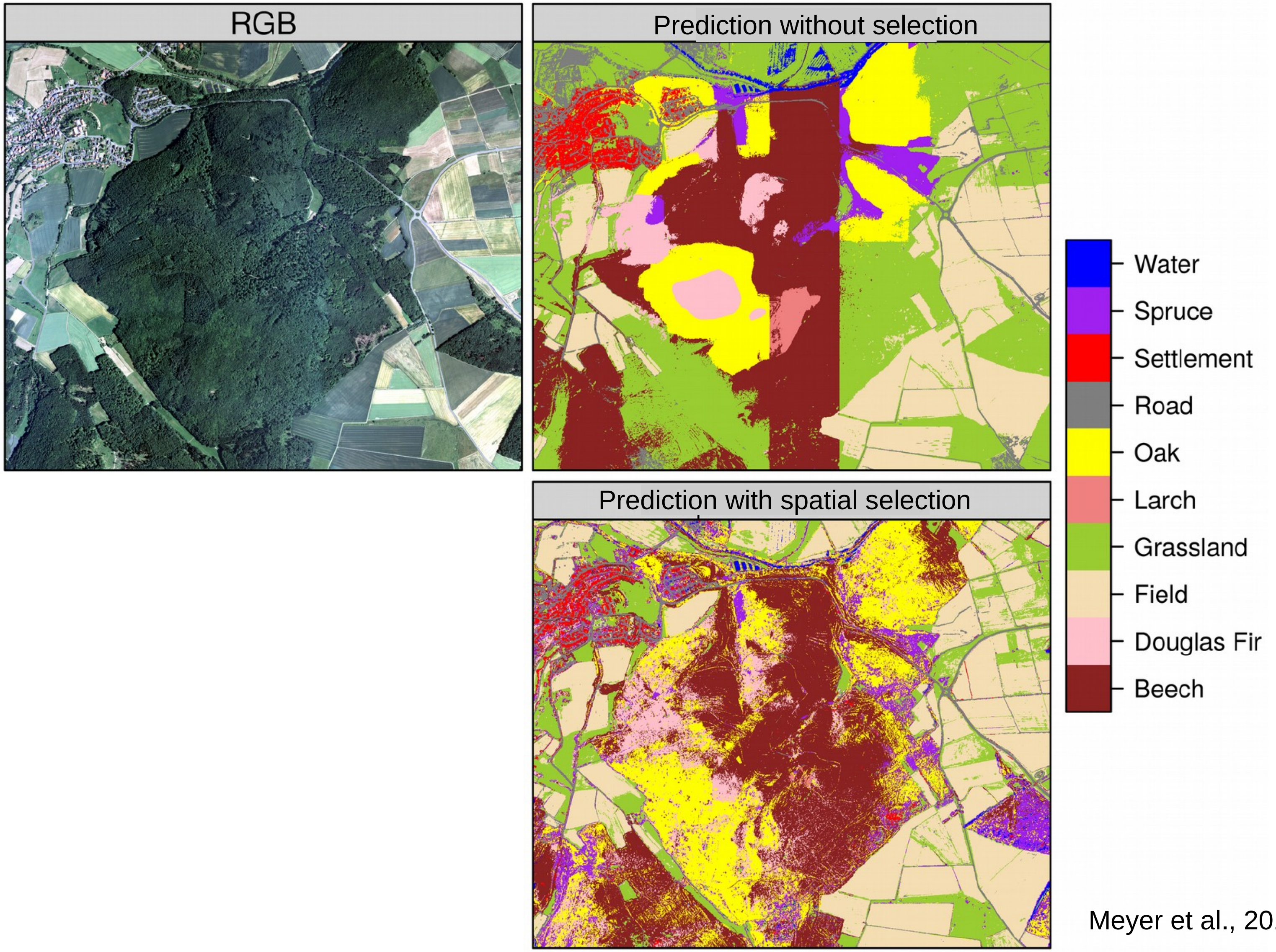

Meyer et al., 2019

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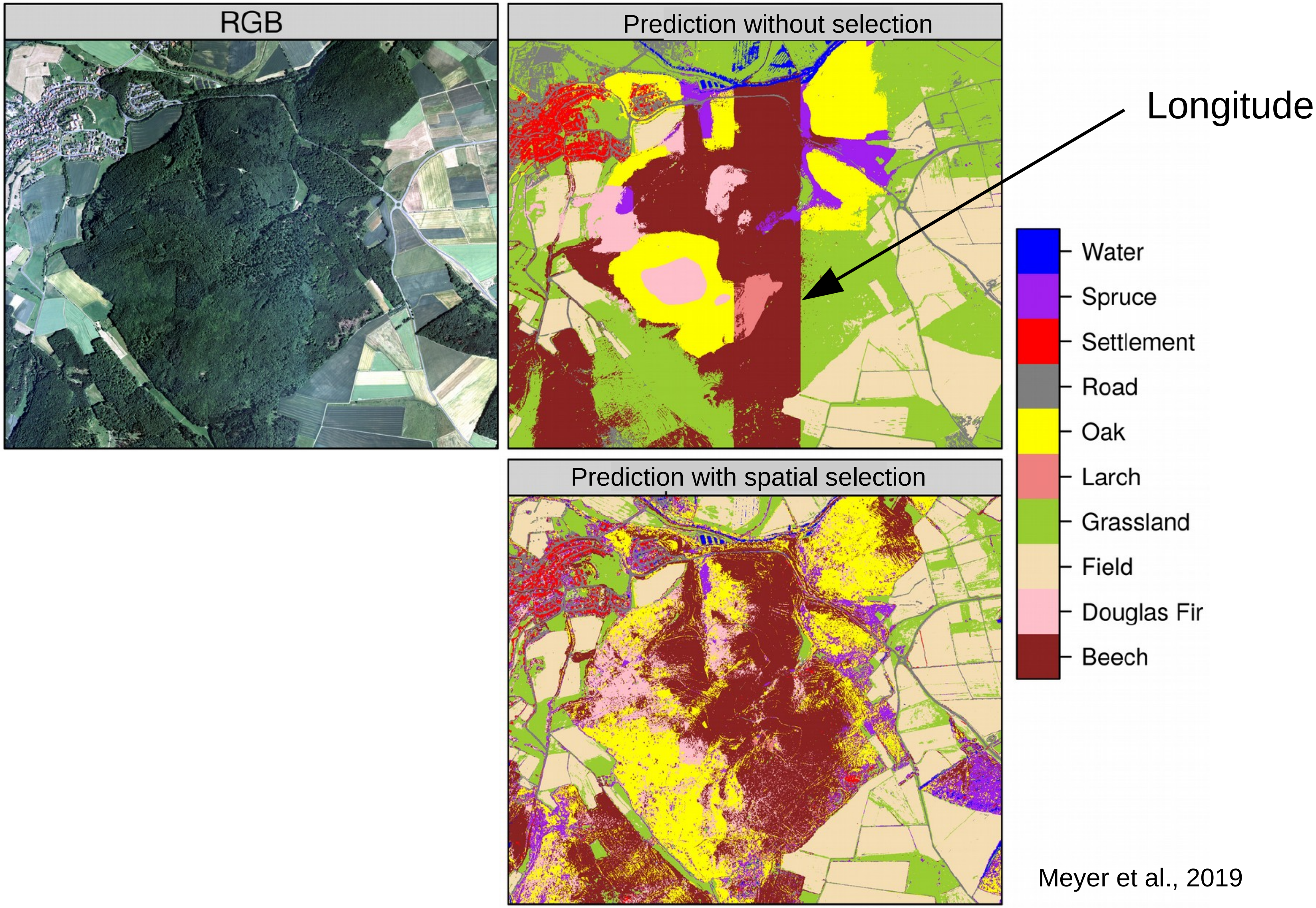

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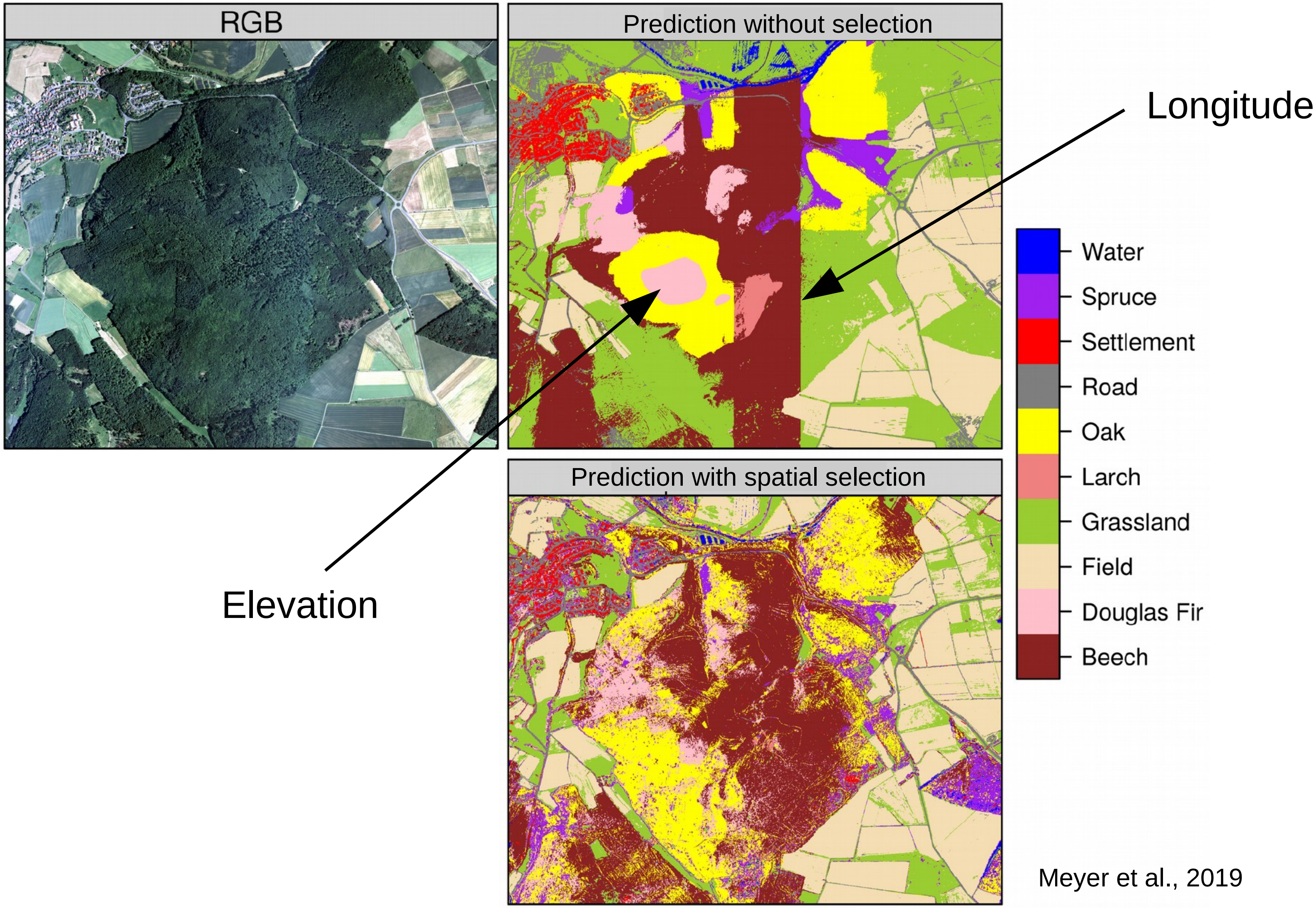

Meyer et al., 2019

What we have learned so far...

- Cross-validation strategy affect:
  - Performance estimate
  - Selected hyperparameters
  - Variable selection
- Consequences of using an unsuitable CV:
  - Unreliable performance estimates
  - Models that can well reproduce but not necessarily predict ("clever Hans effect")
- Hence, CV strategies that fit the prediction task are required during model selection and validation!

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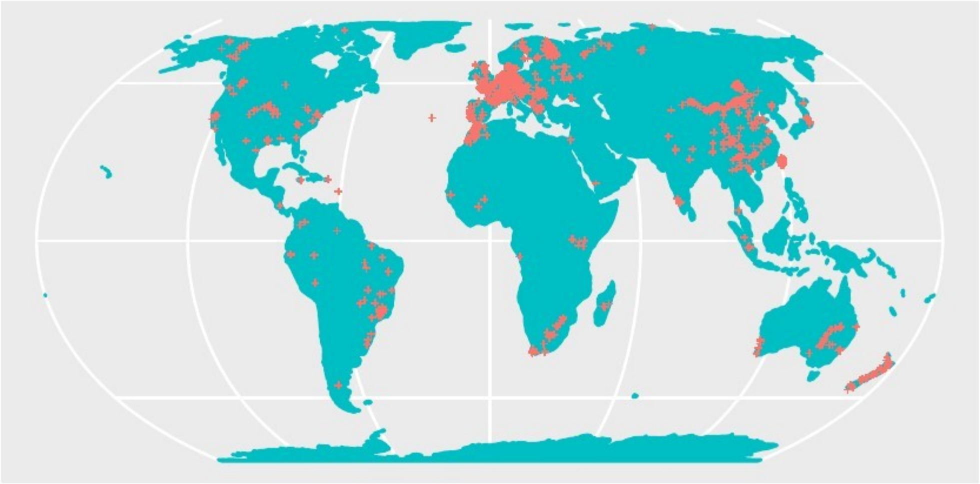
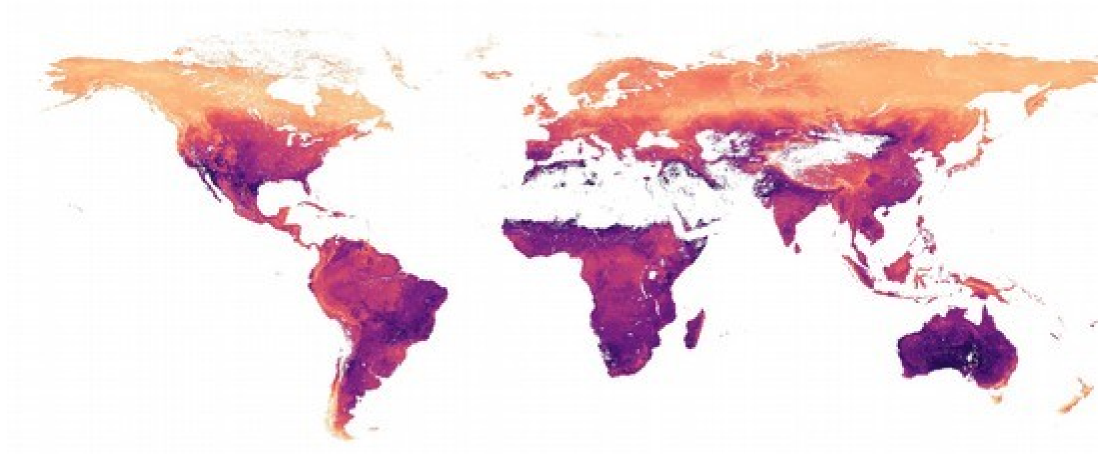
But is this sufficient for reliable (global) mapping ?

Limits to accuracy assessment



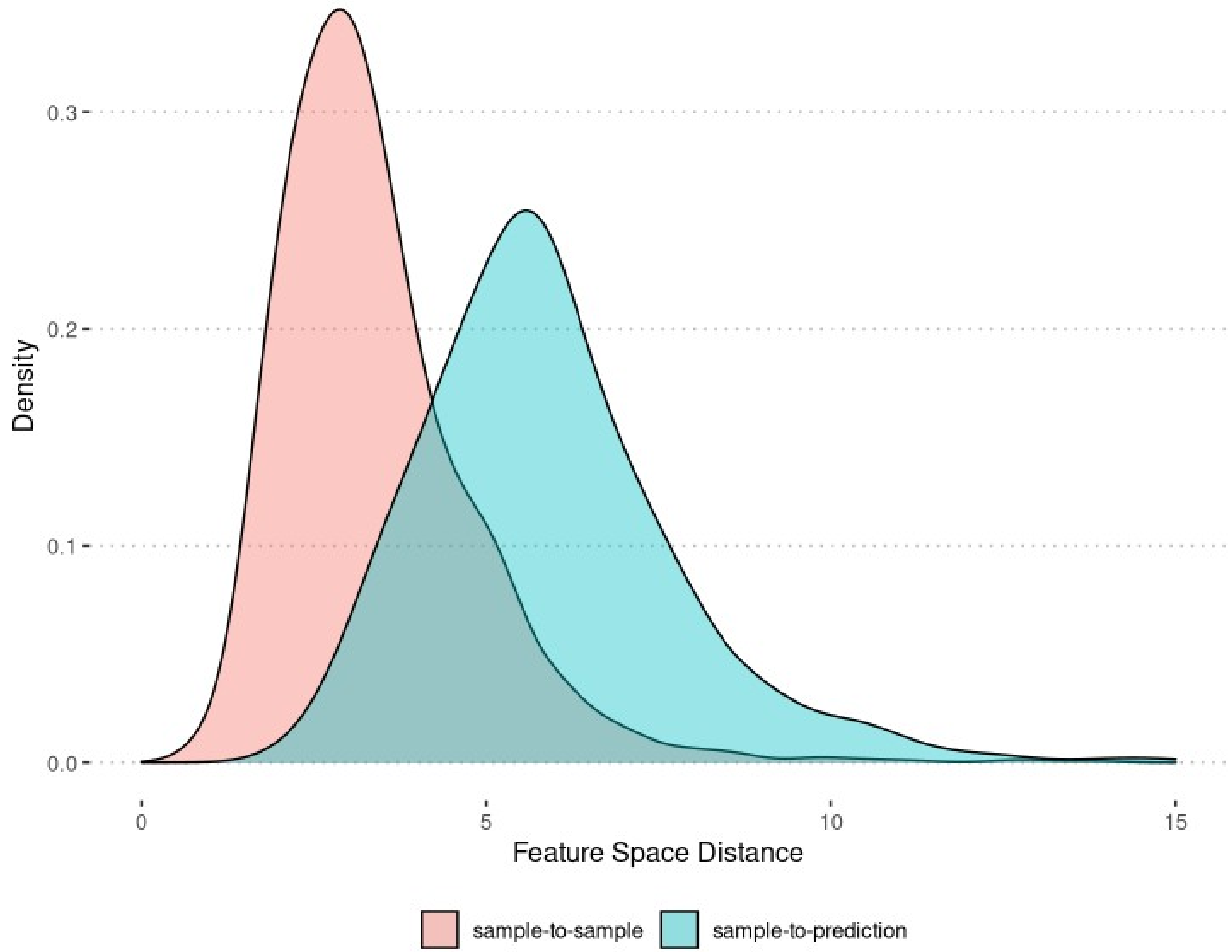


Based on van den Hoogen et al., 2019

- Mapping requires prediction far beyond clustered reference data
- Transfer to new space required
- New space might differ in environmental properties

New geographic space often goes along with new predictor properties

Example of the Nematodes model by van den Hoogen et al., 2019.
Nearest neighbor distance in the predictor space:

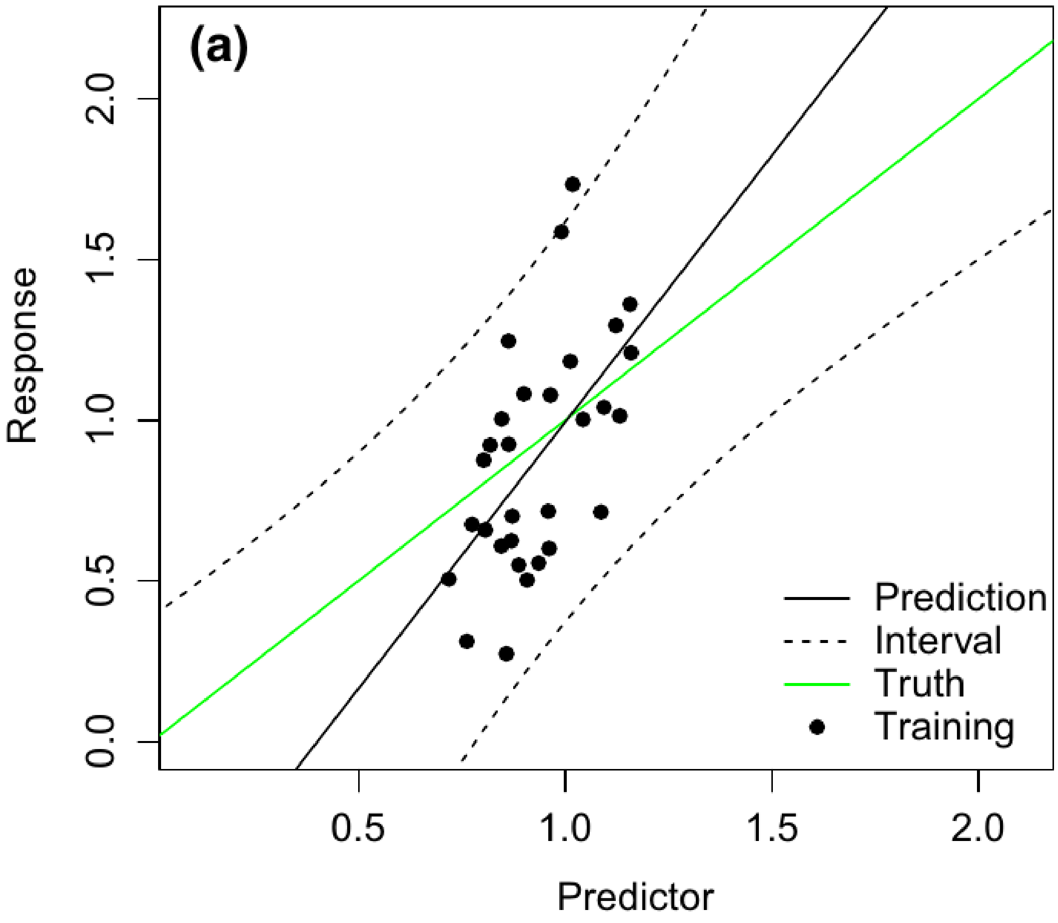


New geographic space often goes along with new predictor properties

Example of the Nematodes model by van den Hoogen et al., 2019.
Nearest neighbor distance in the predictor space:

...but what happens if the model has never “seen” such new predictor properties?

Predictions and common uncertainty measures are unreliable beyond training data



Meyer & Pebesma 2021

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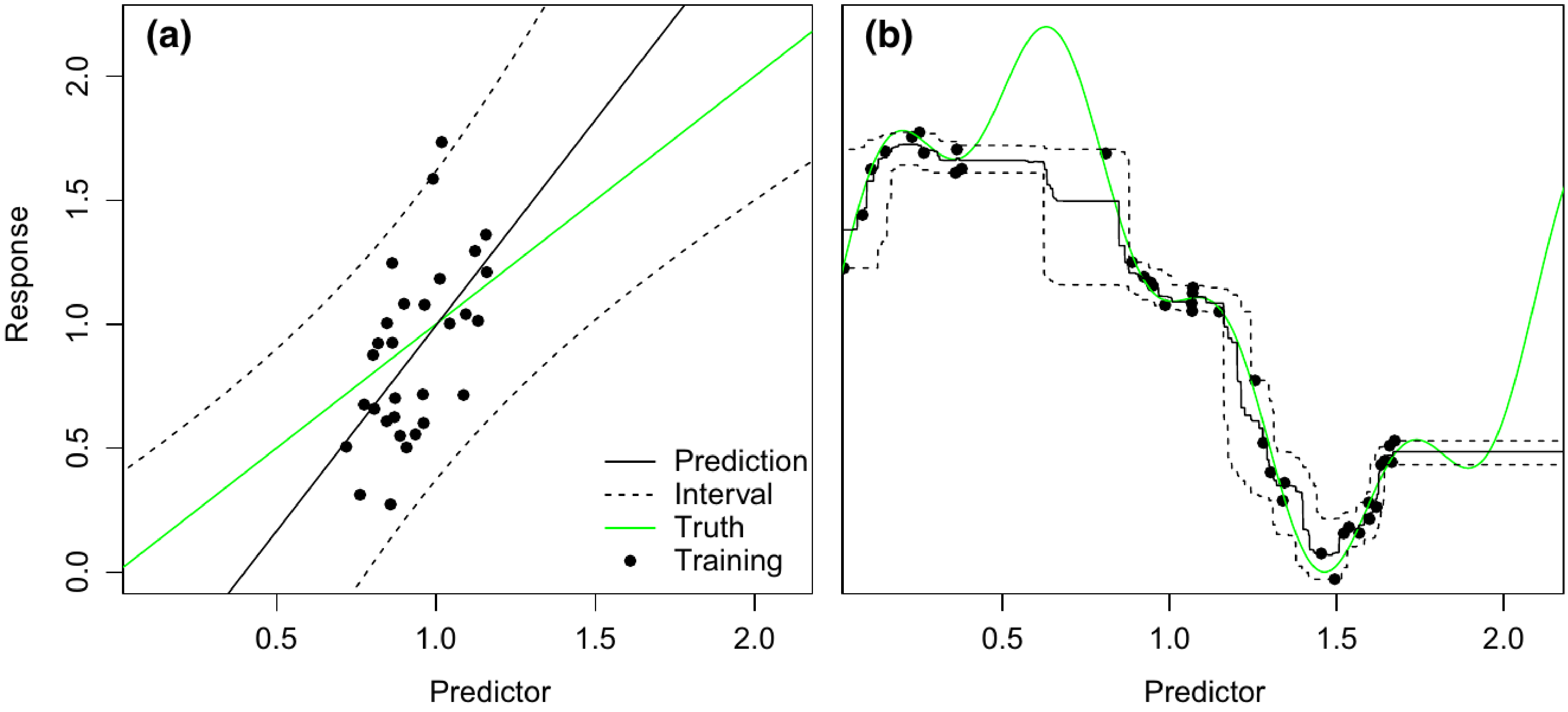

Meyer & Pebesma 2021

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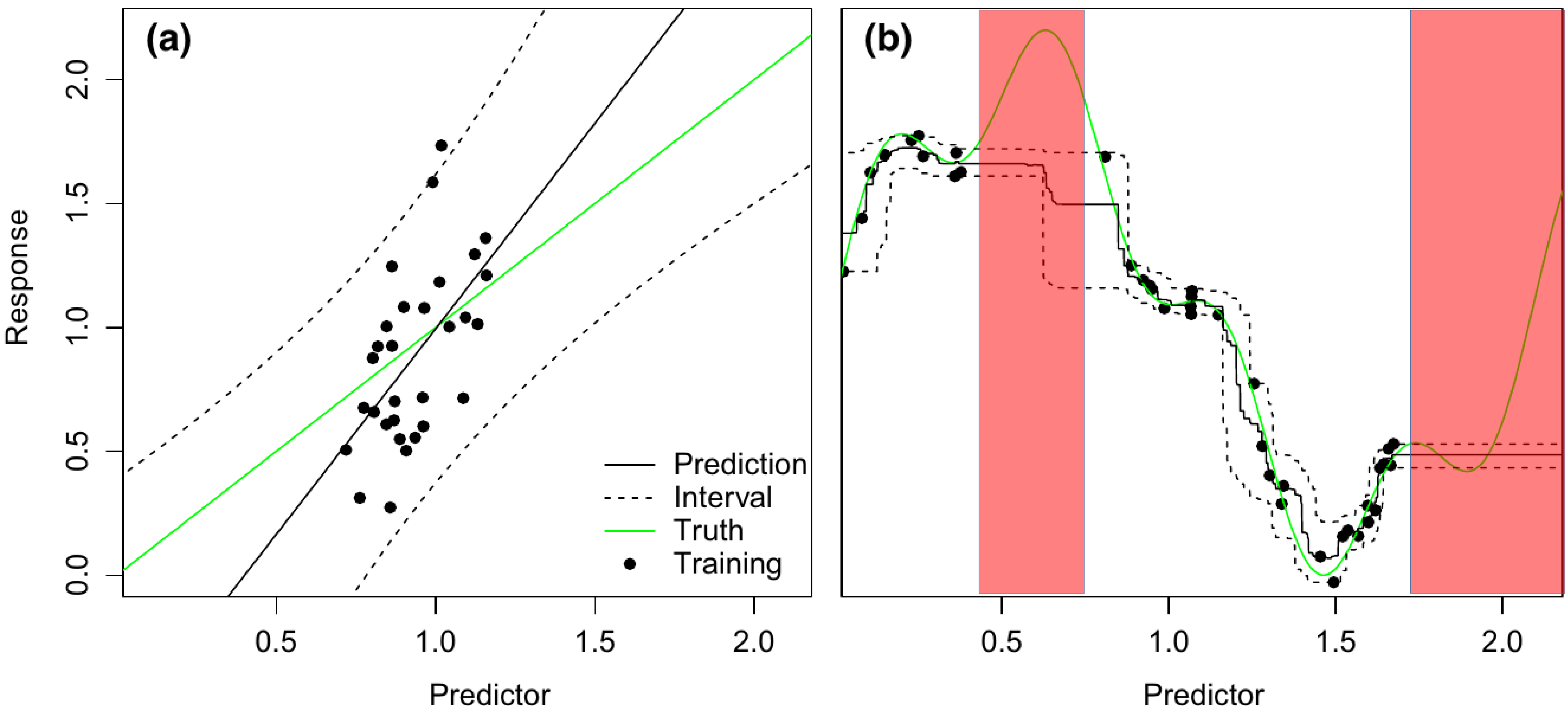

Meyer & Pebesma 2021

Shouldn't we avoid predictions into "unknown space"?

Suggestion: Area of Applicability (AOA)

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

Hanna Meyer, Edzer Pebesma

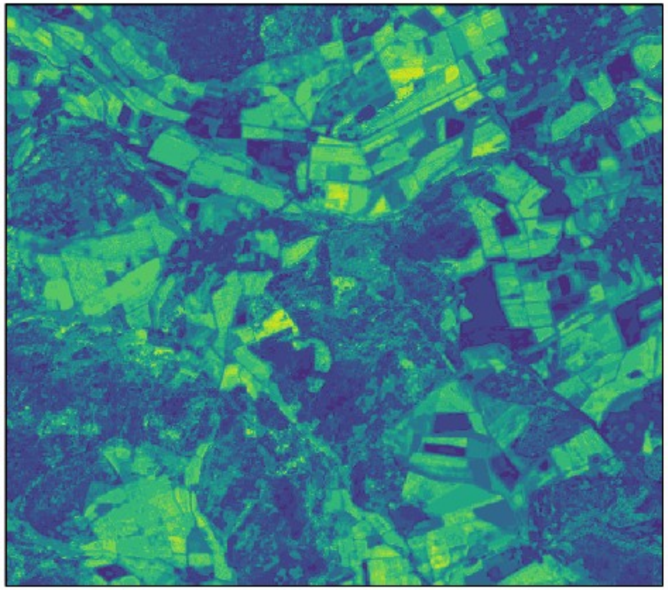
We try to derive the area...

- to which the model can be applied because it has been enabled to learn about relationships
- where the estimated performance holds

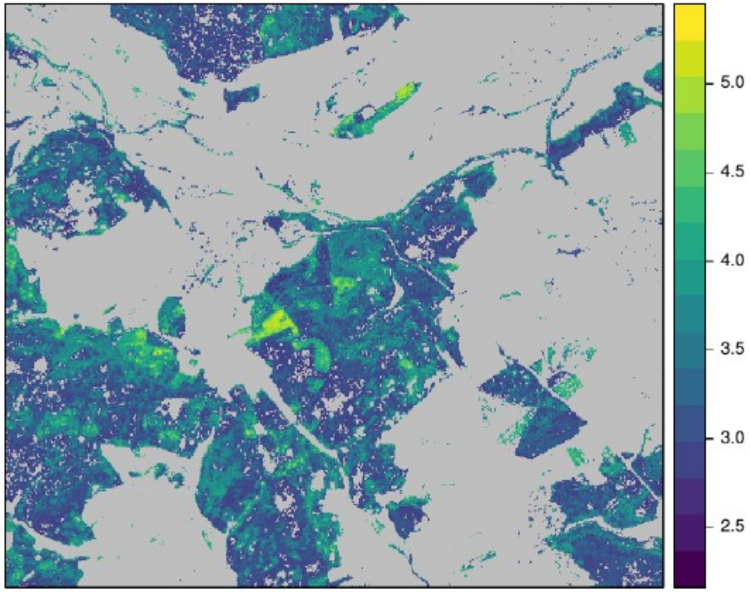
A very obvious and simple example

Sentinel-2 scene and training data points of leaf area index

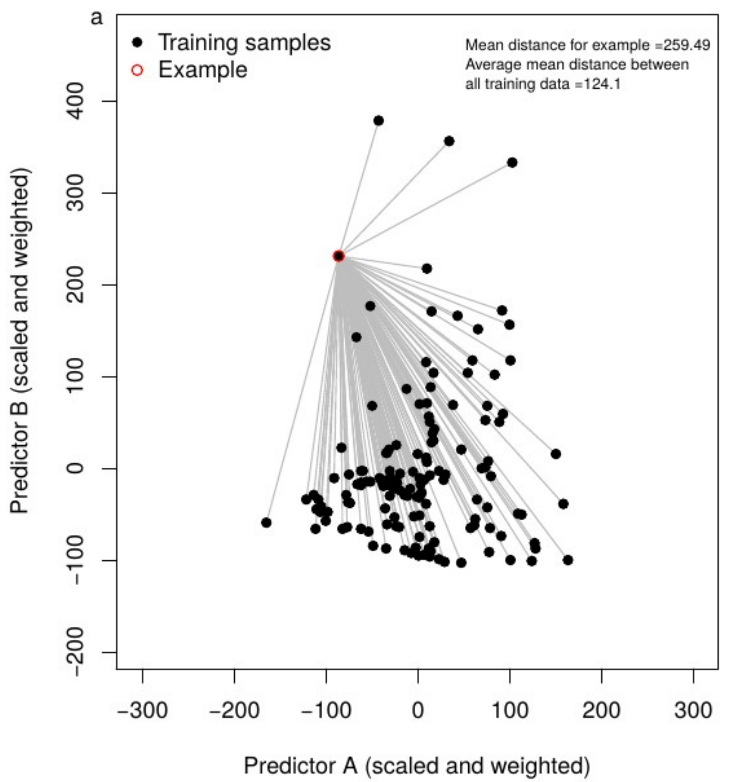
Predictions



Predictions limited to the AOA



How do we derive the AOA ?



Meyer & Pebesma (2021)

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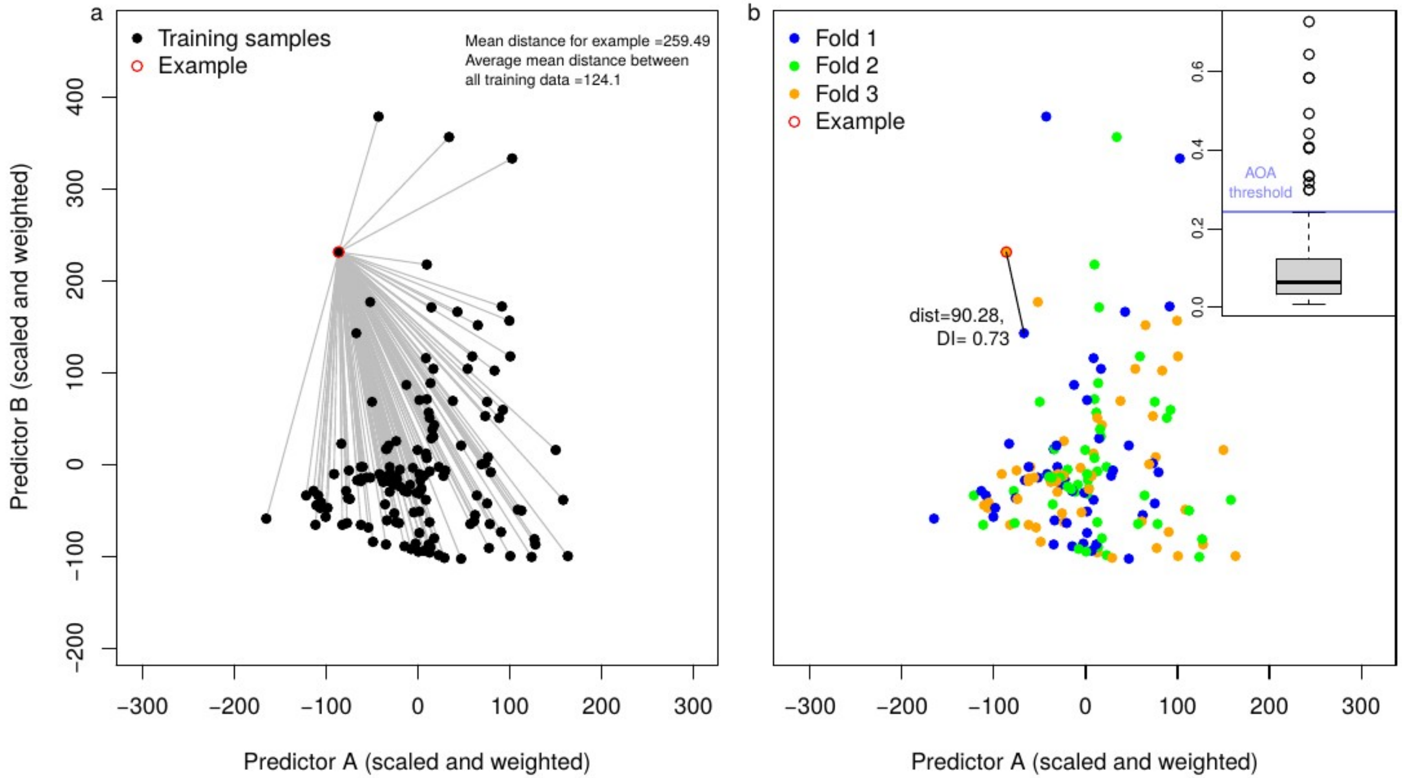
Calculation of a
Dissimilarity Index (DI)



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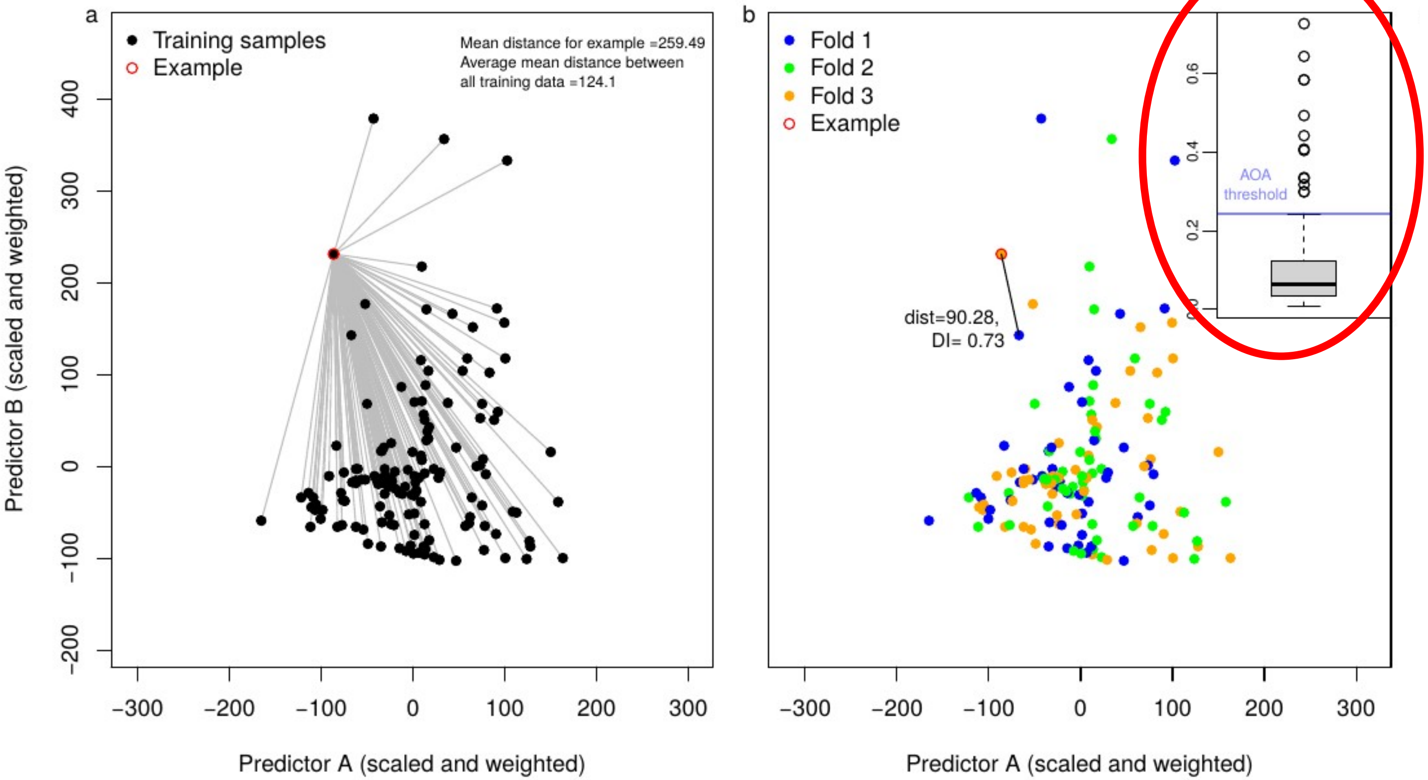

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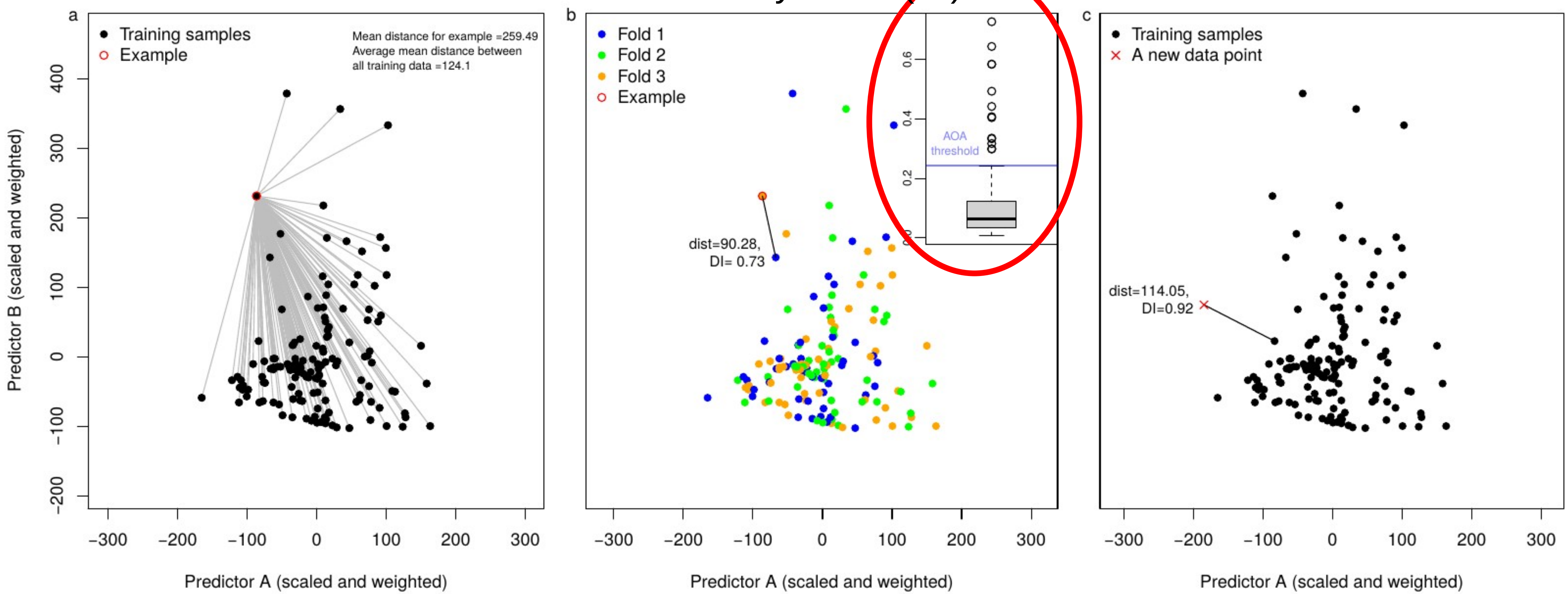
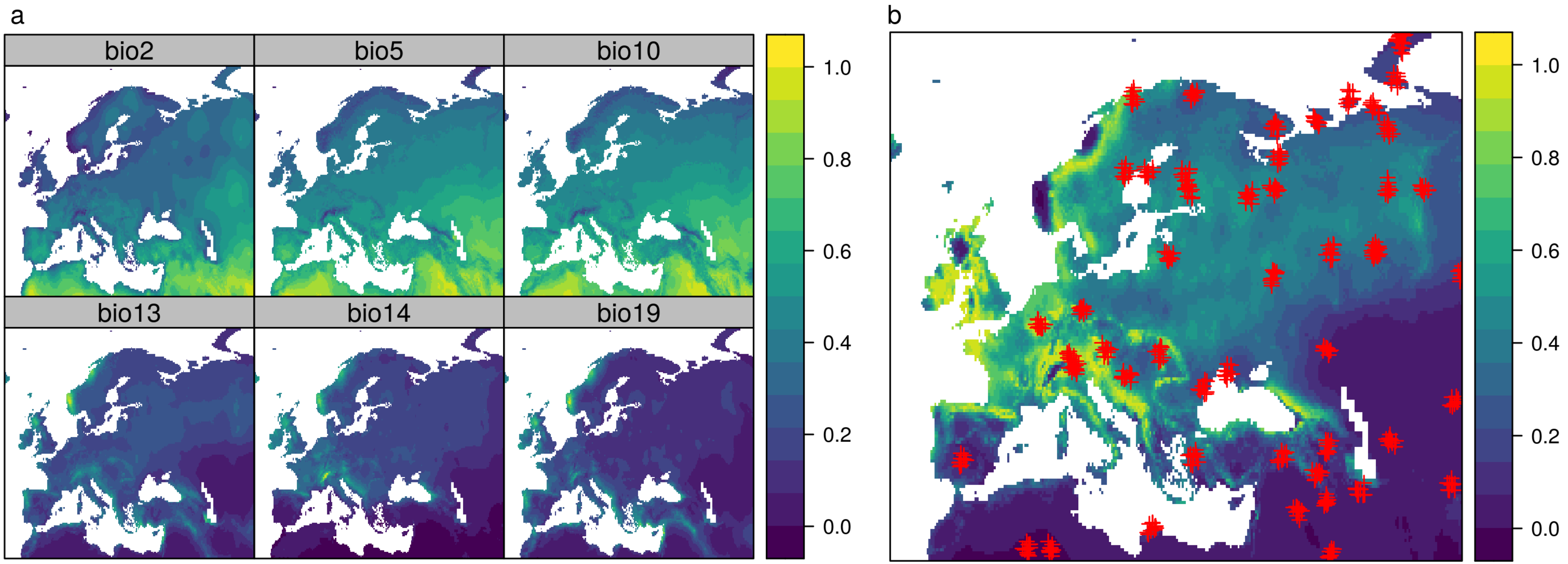


Meyer & Pebesma (2021)

Simulated example: Predictors and response



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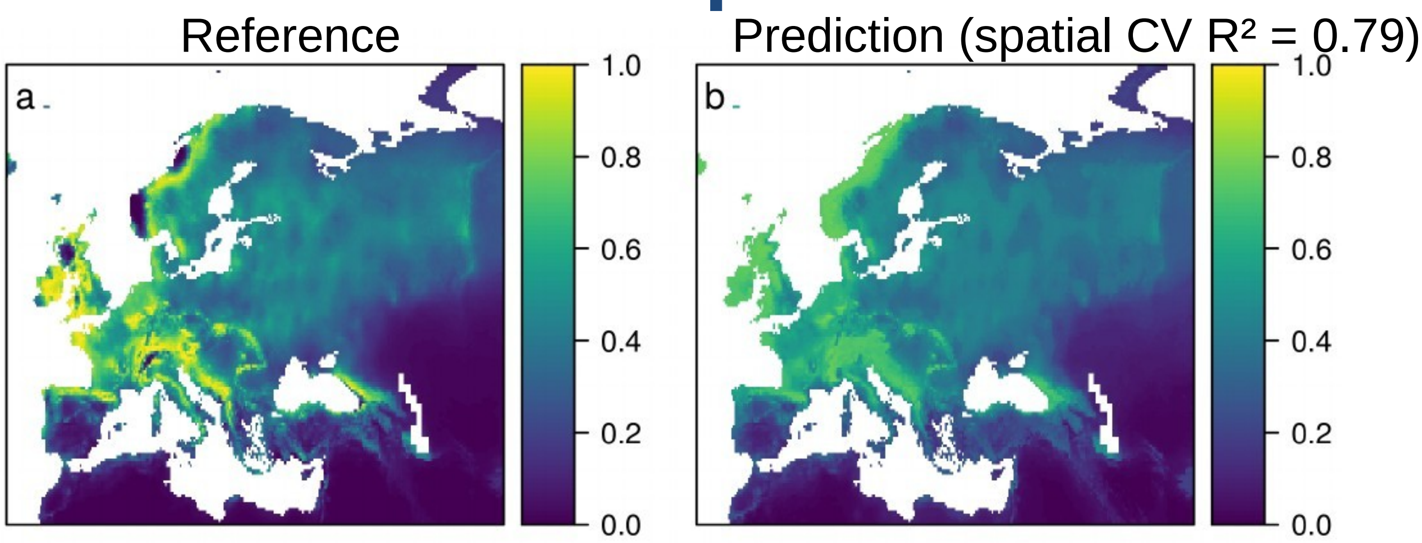
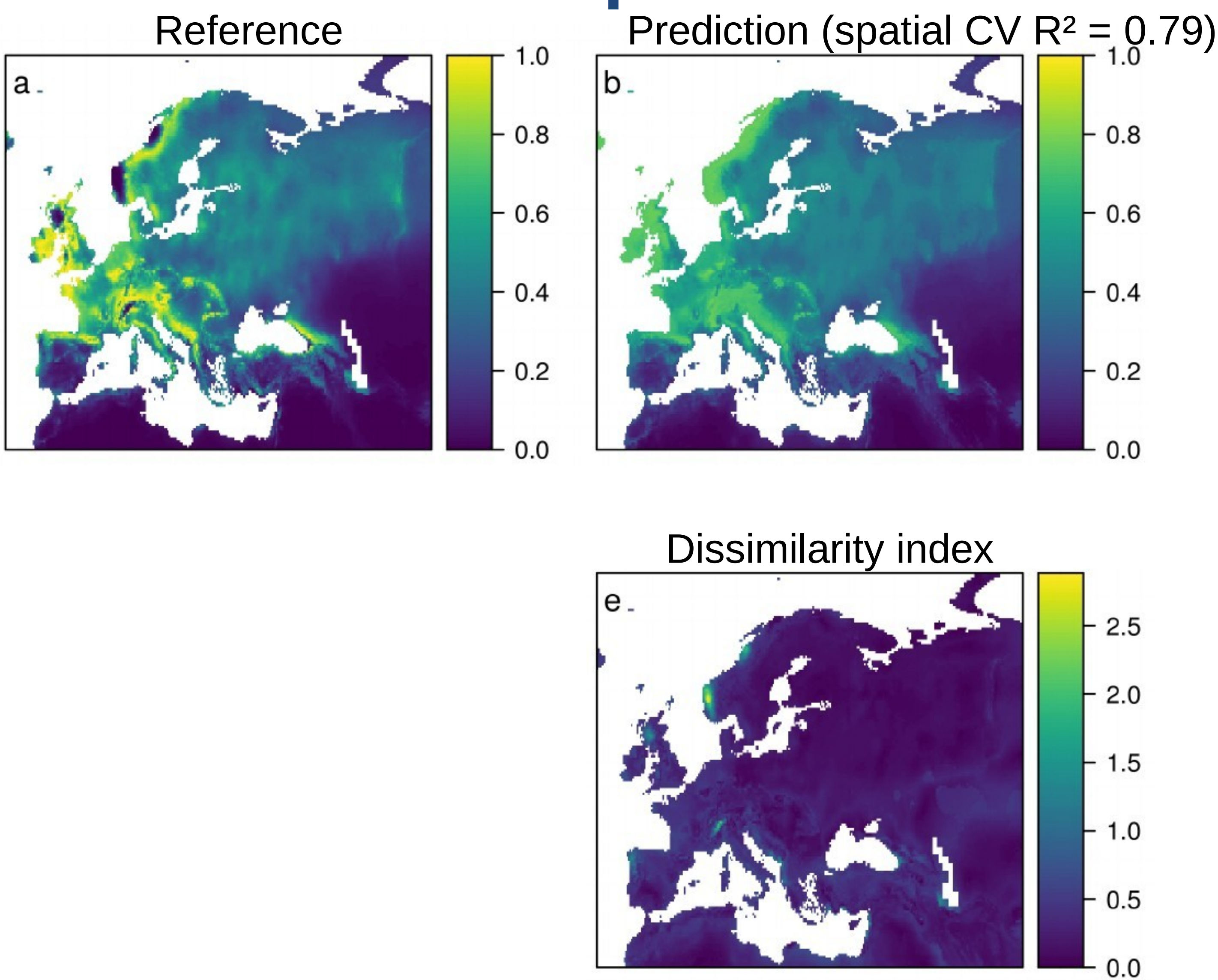
Simulated example: Results



Reproduce example:
github.com/HannaMeyer/MEE_AOA

Meyer & Pebesma (2021)

Simulated example: Results



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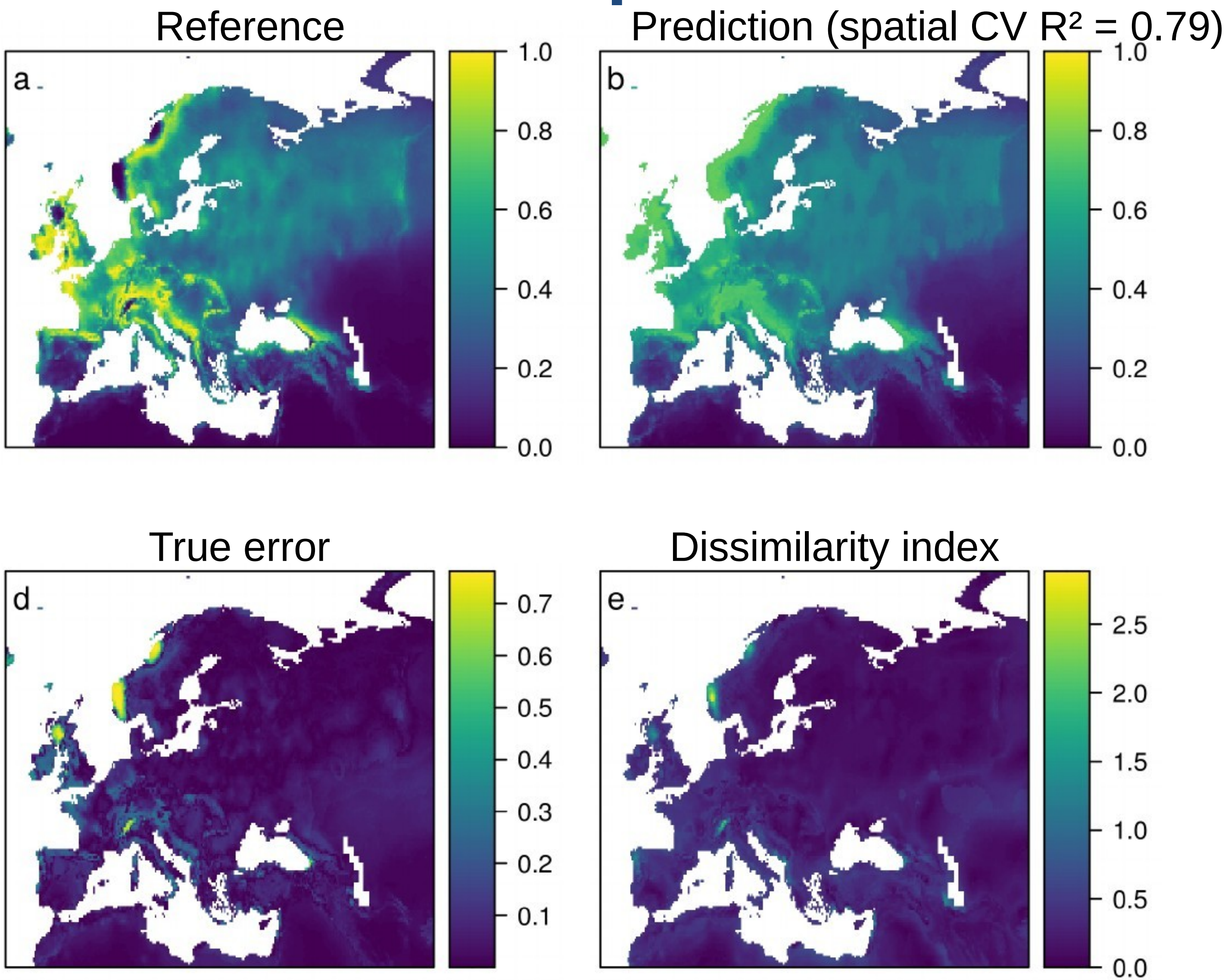

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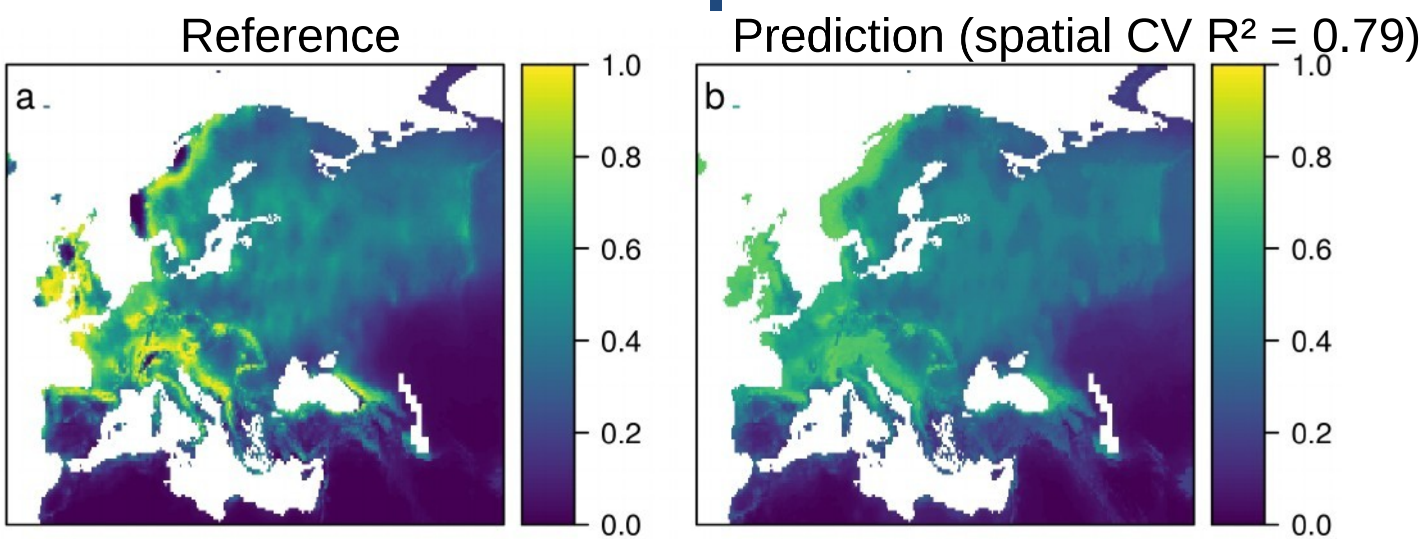

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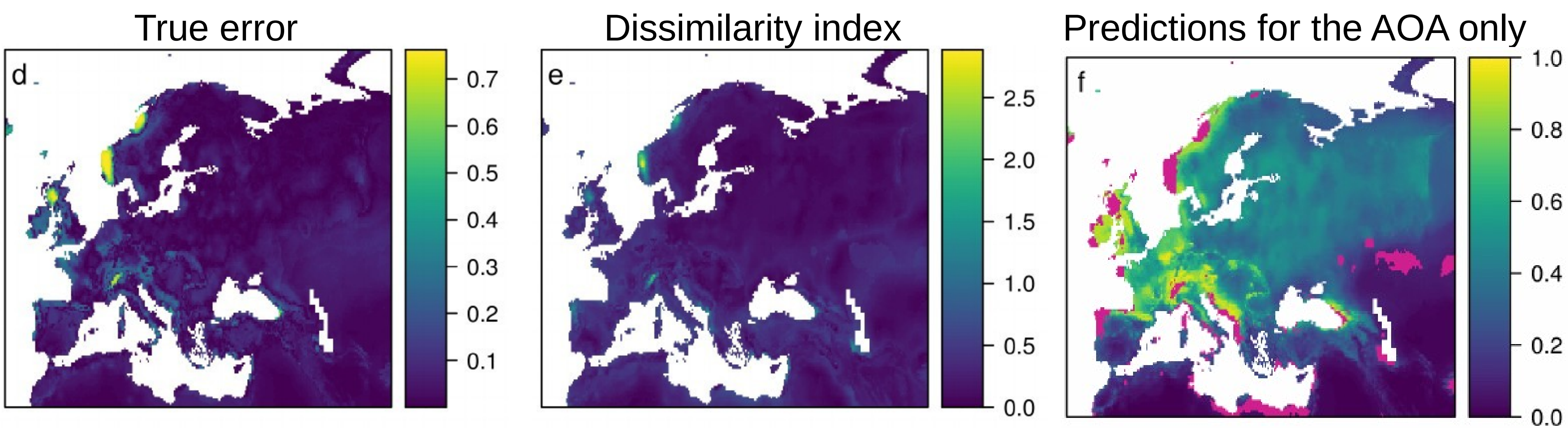

Meyer & Pebesma (2021)

Why is it relevant to map “unknown space”?

Results are not just nice maps but used for...

- subsequent modeling
- nature conservation
- risk assessment
- …

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nature COMMUNICATIONS

COMMENT

https://doi.org/10.1038/s41467-022-29838-9 OPEN

Machine learning-based global maps of ecological variables and the challenge of assessing them

Hanna Meyer [1] & Edzer Pebesma [2]

Our opinion: predictions should only be presented for the area of applicability to avoid error propagation or misplanning

Conclusions

This is not an argument against machine learning but an appeal to keep in mind that applying models to map the entire world based on limited field samples is challenging

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- Predictions should only be made for the AOA (accept gaps!?)
- We (= producers of the maps) are responsible for clearly indicating usage of maps, don’t leave it to the user.
- There is still a lot to do...

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