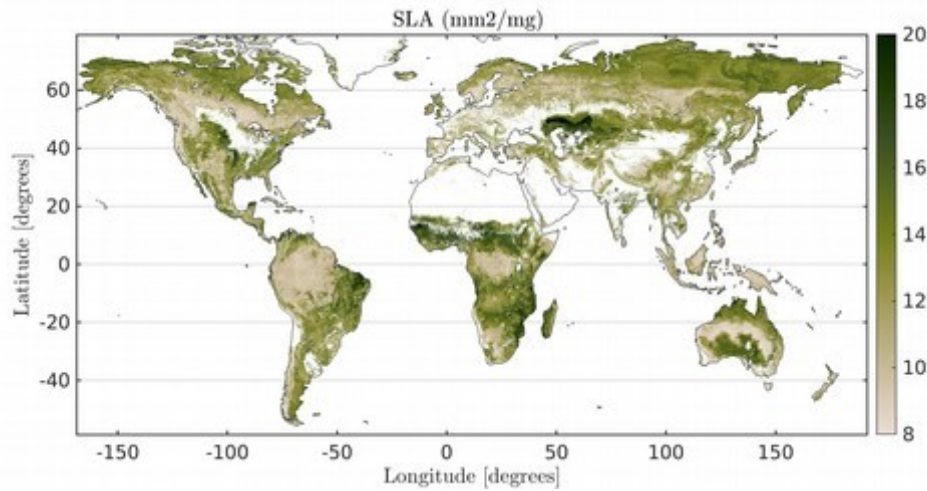


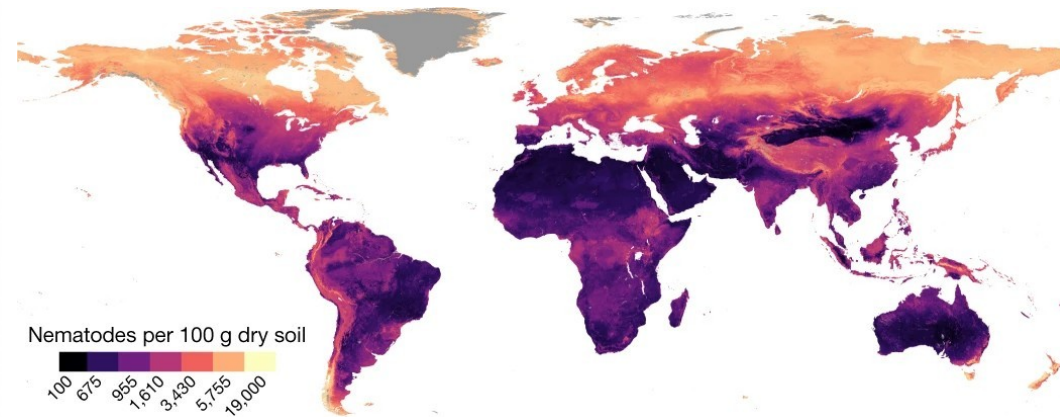
# ML and EO for (global) mapping of the environment: Discussing challenges of model extrapolation and accuracy assessment

Hanna Meyer & Edzer Pebesma

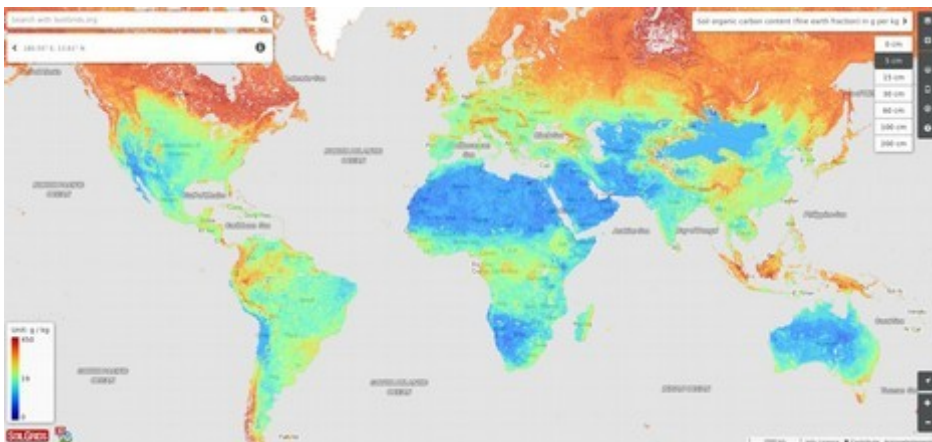
# Global maps of ecological variables based on machine learning (a few of many examples)



Moreno-Martínez et al., 2018



van den Hoogen et al., 2019



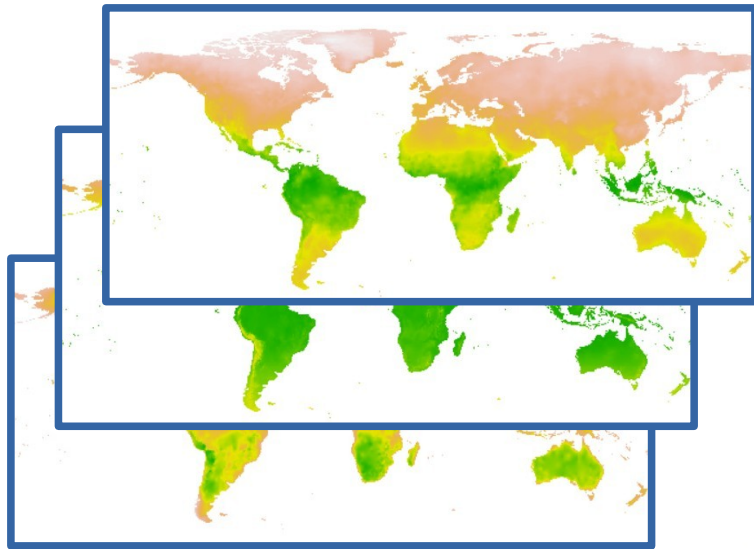
Hengl et al., 2017



Bastin et al. 2019

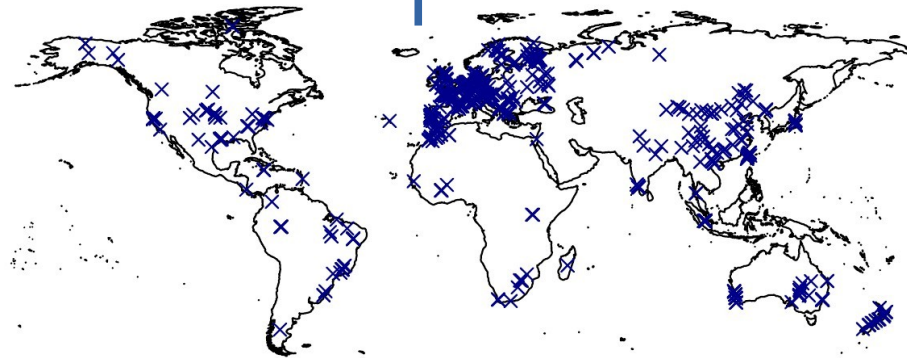
# How do we get “maps” of ecosystem variables ?

Predictors

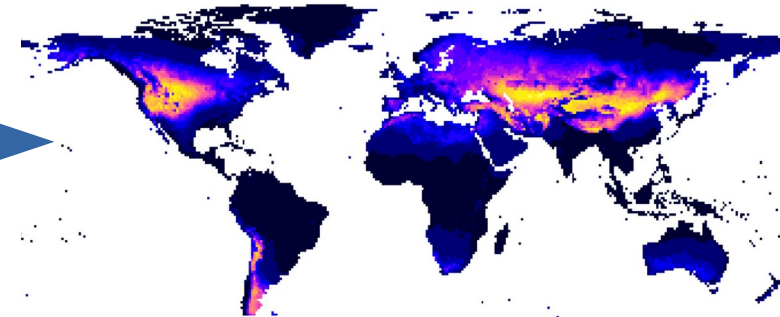


Machine learning  
(e.g. Random Forests)

Spatial prediction



Response



Machine learning as a magic tool to map everything ?

# Reported performance measures are impressive but there are increasingly doubts

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



# DEEP TROUBLE FOR DEEP LEARNING

Nature 574, 163-166 (2019) BY DOUGLAS HEAVEN

Home / News & Opinion

## Researchers Find Flaws in High-Profile Study on Trees and Climate

Comment | Published: 23 August 2021

### Conservation needs to break free from global priority mapping

Carina Wyborn & Megan C. Evans

Nature Ecology & Evolution (2021) | Cite this article

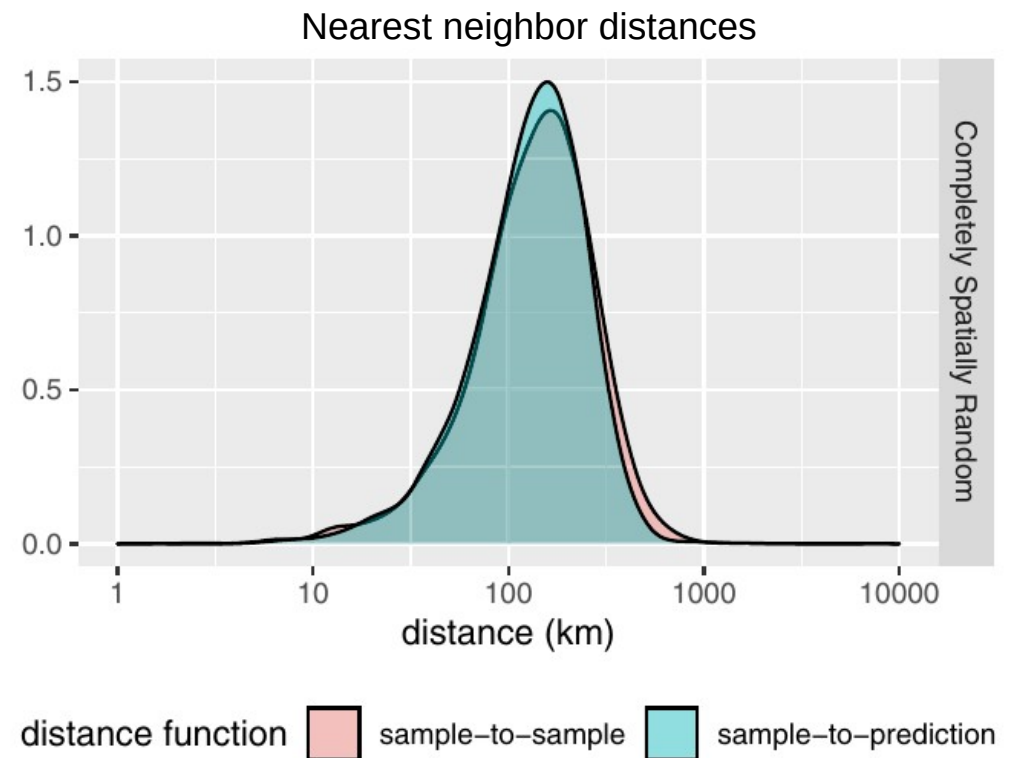
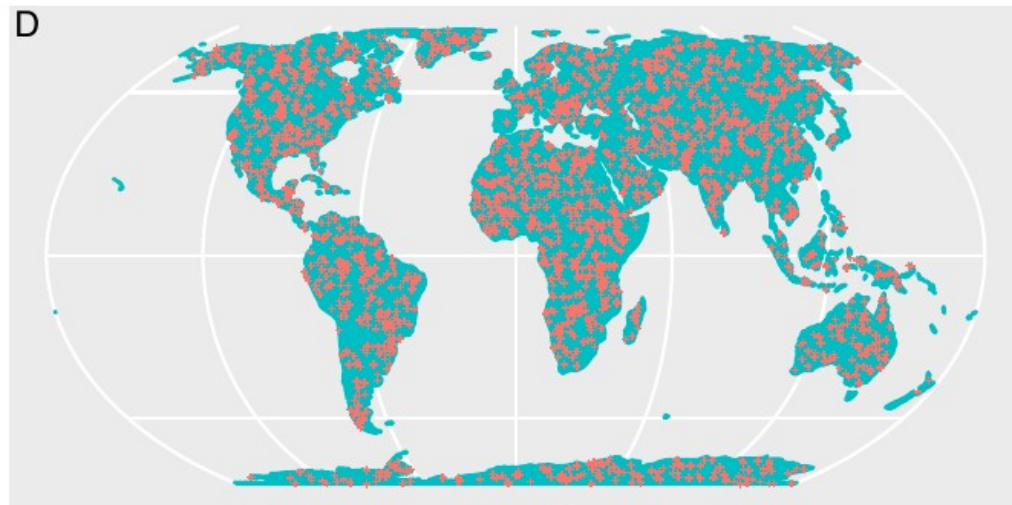
Four independent groups say the work overestimates the global forest restoration, but the authors insist their original

Oct 17, 2019  
KATARINA ZIMMER

## Have we been too ambitious? Do our models fail ?

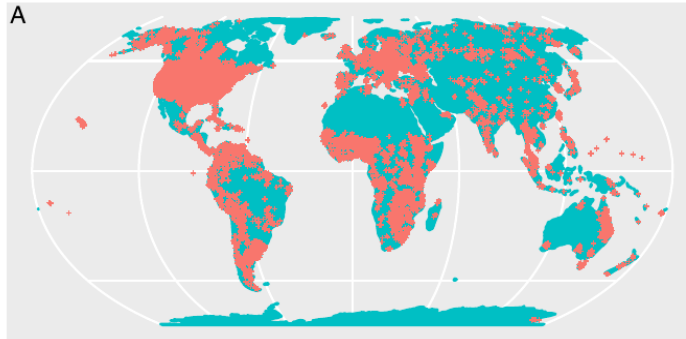
# How do we assess the accuracy of global maps?

Ideal: Design-based inference using a probability sample

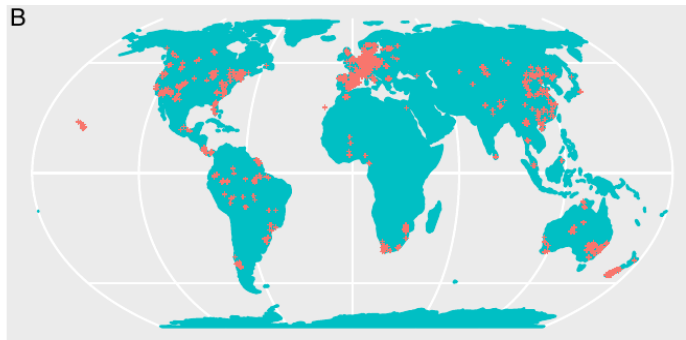


# Global reference data used in machine learning applications

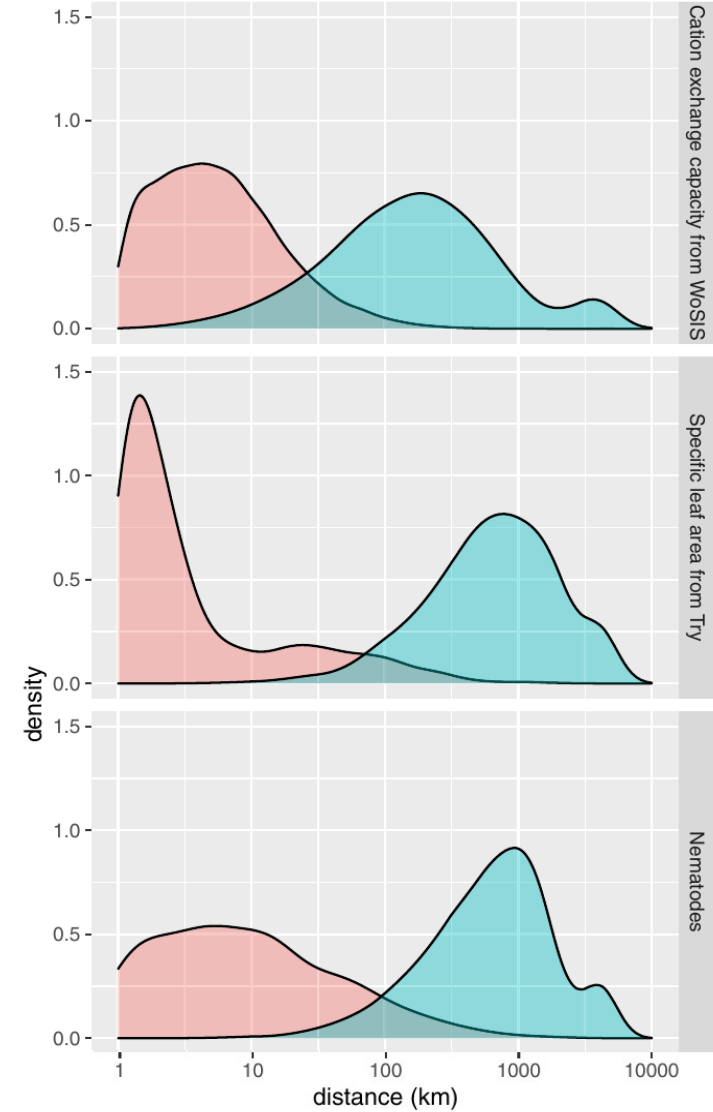
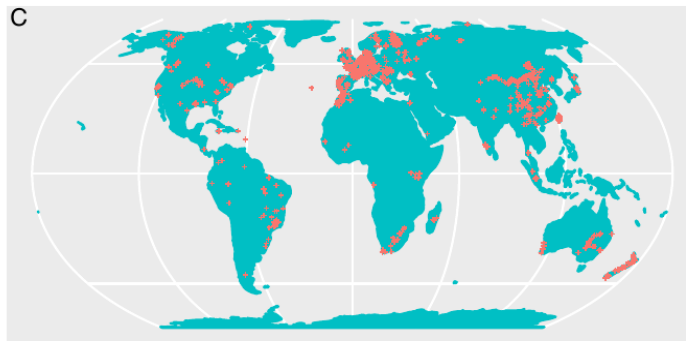
Soil maps



Plant traits



Nematodes



Meyer & Pebesma (2022)

Design based approaches not possible!

distance function ■ sample-to-sample ■ sample-to-prediction

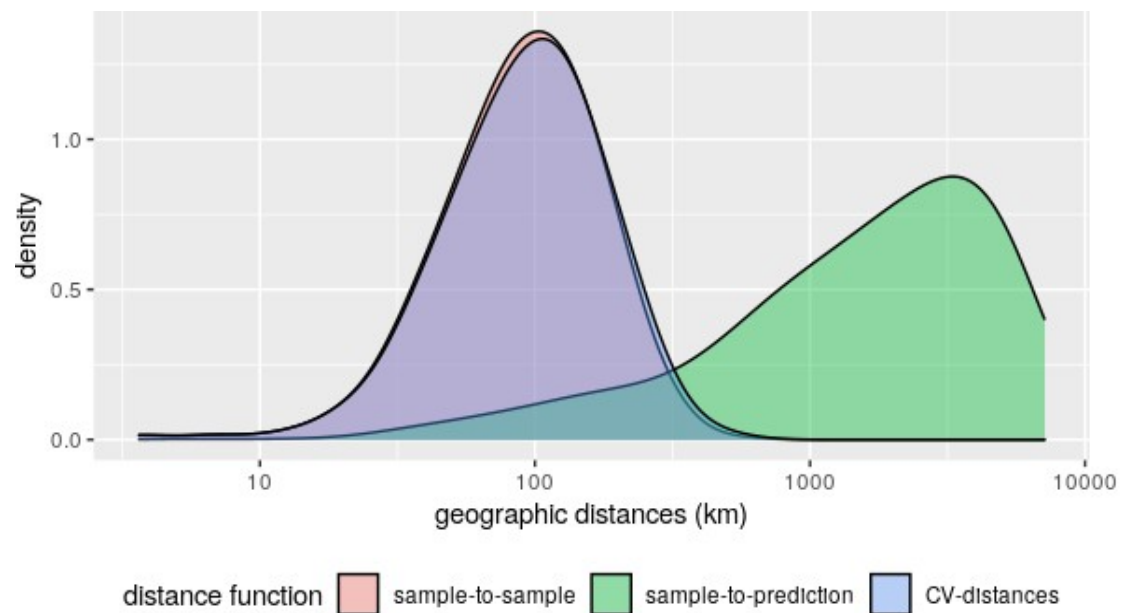
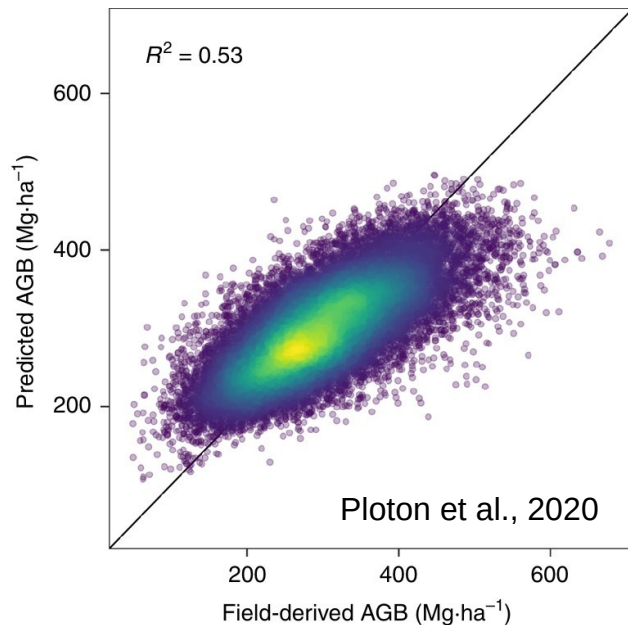
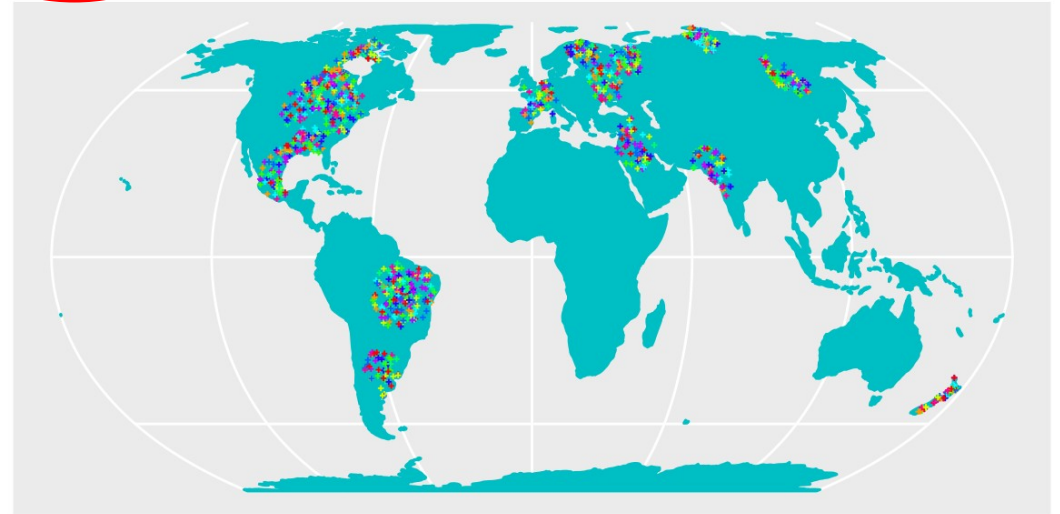
# Performance assessment by default random cross-validation

## Cross-validation in general:

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

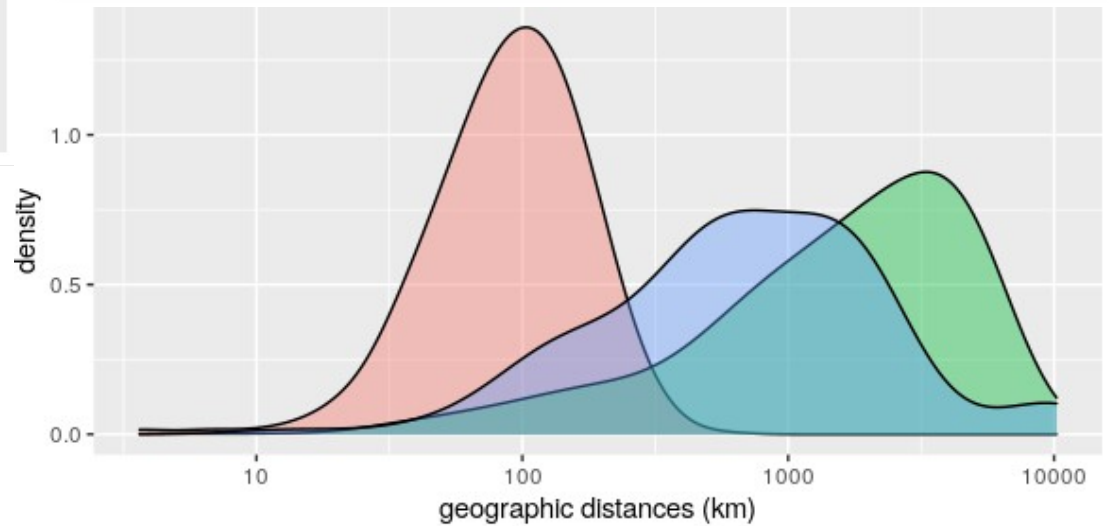
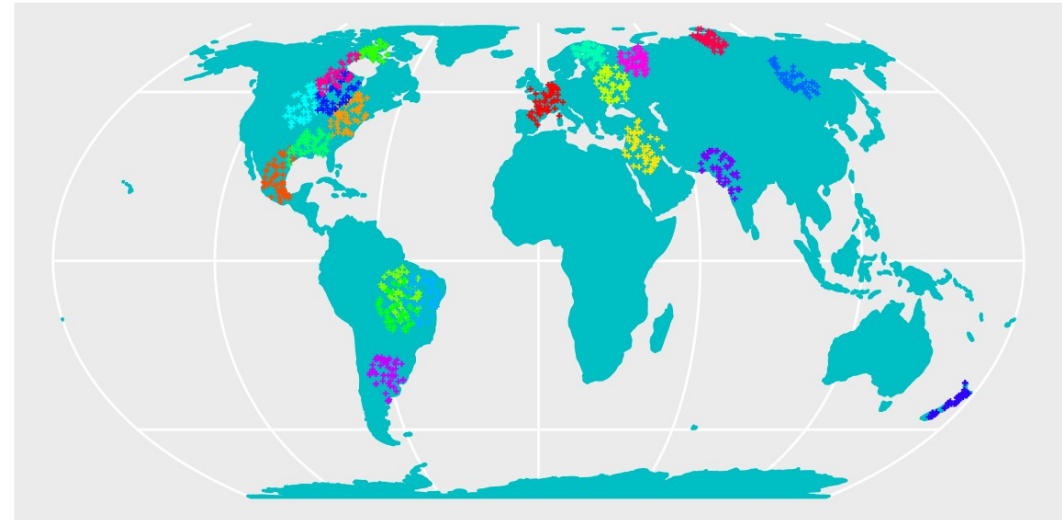
Random CV indicates here how well we can **reproduce** the training data

random fold membership shown by color



# Performance assessment by a simple spatial cross-validation

spatial fold membership by color



Indicates how well we can make spatial predictions !

distance function ■ sample-to-sample ■ sample-to-prediction ■ CV-distances

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

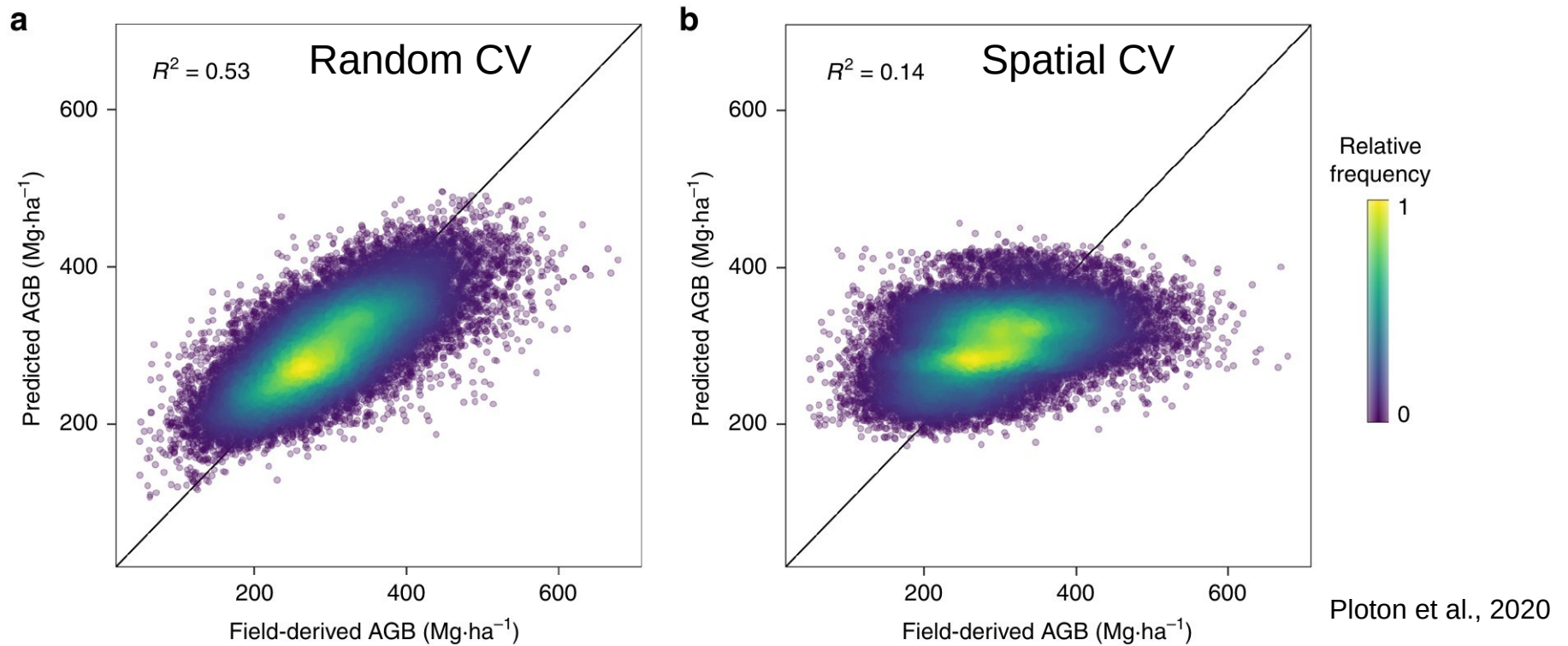


# Performance assessment using different CV strategies

## Spatial validation reveals poor predictive performance of large-scale ecological mapping models

[Pierre Ploton](#) ✉, [Frédéric Mortier](#), [Maxime Réjou-Méchain](#), [Nicolas Barbier](#), [Nicolas Picard](#), [Vivien Rossi](#), [Carsten Dormann](#), [Guillaume Cornu](#), [Gaëlle Viennois](#), [Nicolas Bayol](#), [Alexei Lyapustin](#), [Sylvie Gourlet-Fleury](#) & [Raphaël Pélissier](#)

*Nature Communications* 11, Article number: 4540 (2020) | [Cite this article](#)



...but spatial CV methods are still under discussion...

# ...but spatial CV has also been blamed to be too pessimistic. Why ?

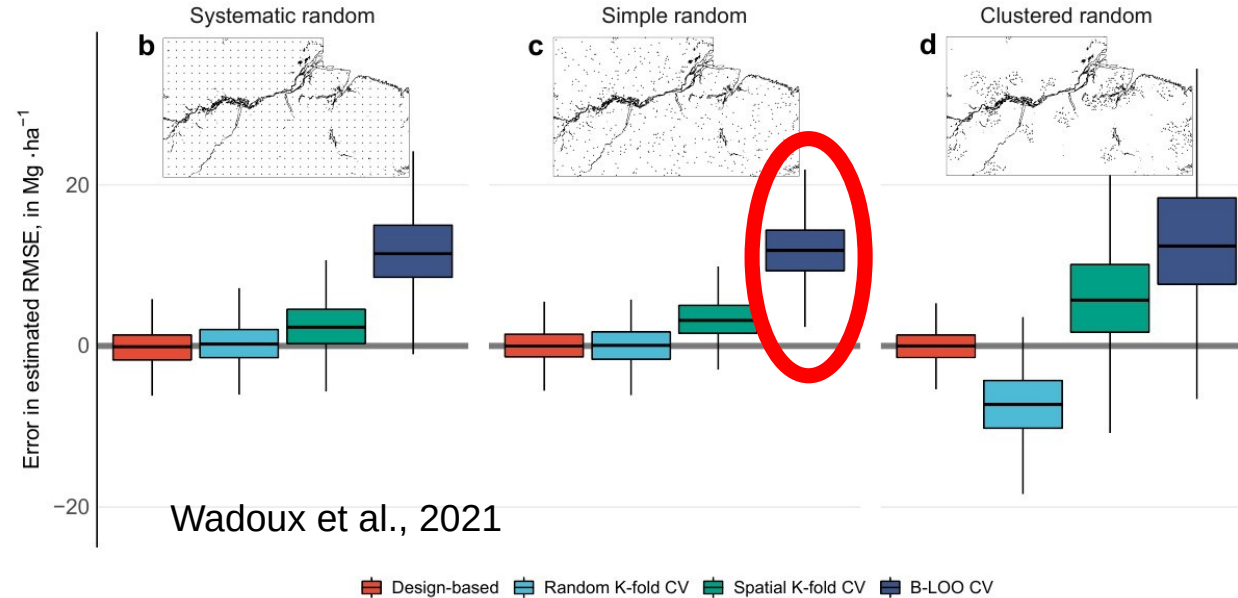
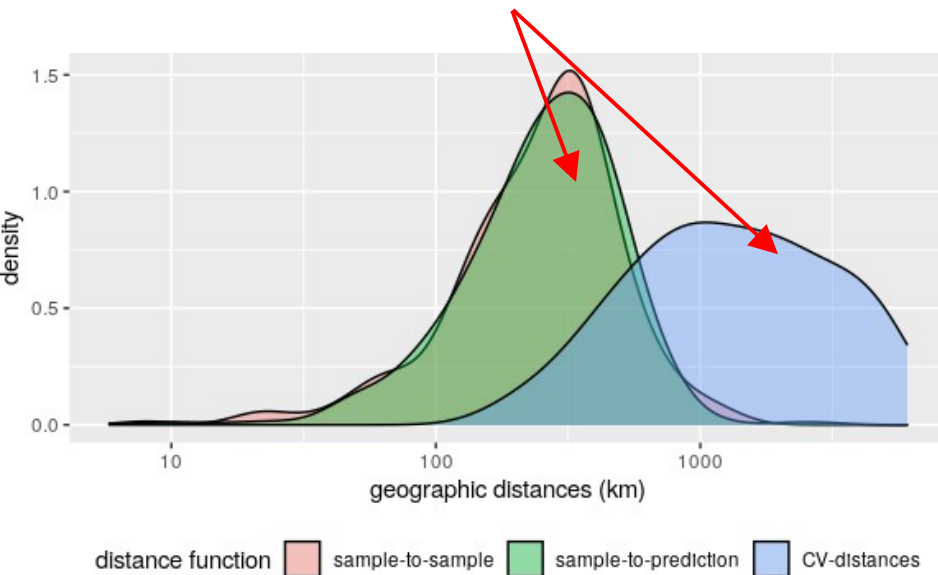


Ecological Modelling  
Volume 457, 1 October 2021, 109692

Short communication  
Spatial cross-validation is not the right way to evaluate map accuracy

Alexandre M.J.-C. Wadoux<sup>a</sup>, Gerard B.M. Heuvelink<sup>b</sup>, Sytze de Bruin<sup>c</sup>, Dick J. Brus<sup>d</sup>

CV predictions are harder than the actual prediction task



It's obviously NOT the right way here. Why?

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

# Suggestion of a nearest neighbor distance matching LOO CV

Received: 20 September 2021 | Accepted: 8 March 2022

DOI: 10.1111/2041-210X.13851

RESEARCH ARTICLE

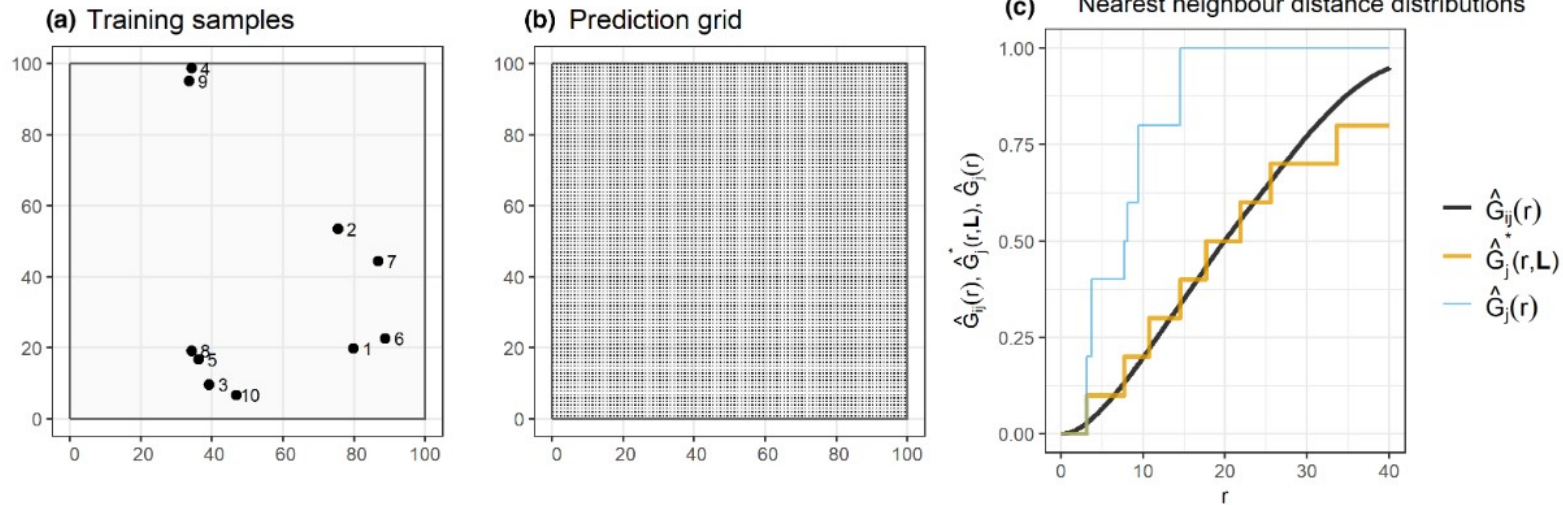
Methods in Ecology and Evolution



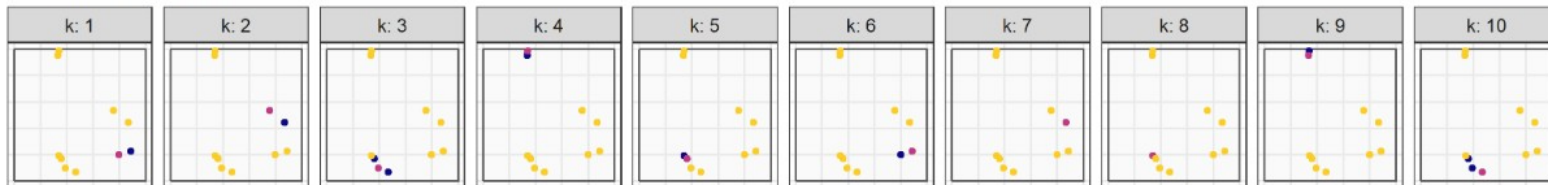
**Aim:** Prediction situations created during CV resemble those encountered while predicting the map

## Nearest neighbour distance matching Leave-One-Out Cross-Validation for map validation

Carles Milà<sup>1</sup> | Jorge Mateu<sup>2</sup> | Edzer Pebesma<sup>3</sup> | Hanna Meyer<sup>4</sup>



### (d) NNDM LOO CV



• Exclude • Test • Train

Milà et al., 2022

# Suggestion of a nearest neighbor distance matching

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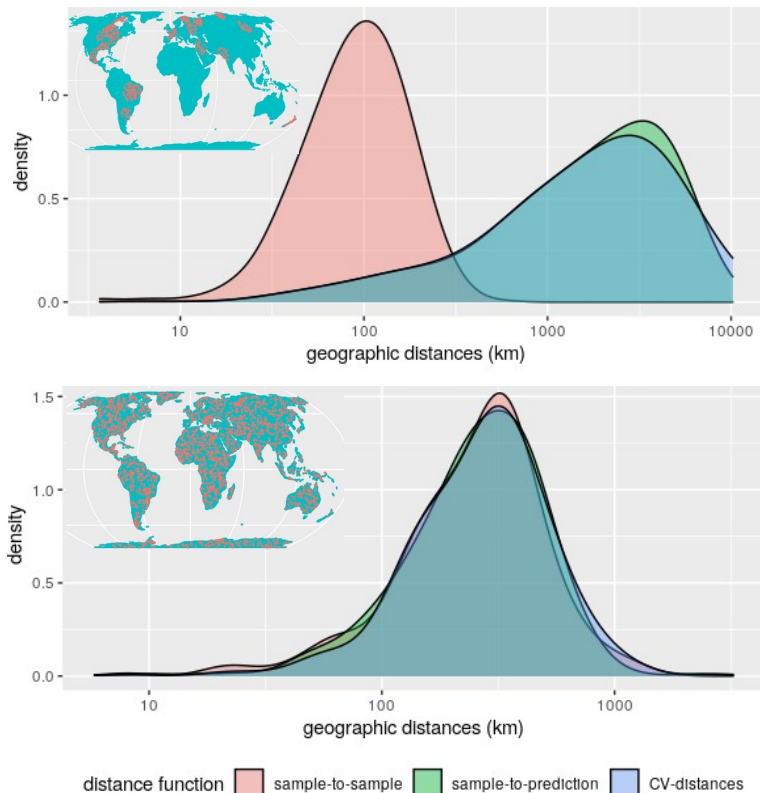
RESEARCH ARTICLE

Methods in Ecology and Evolution 

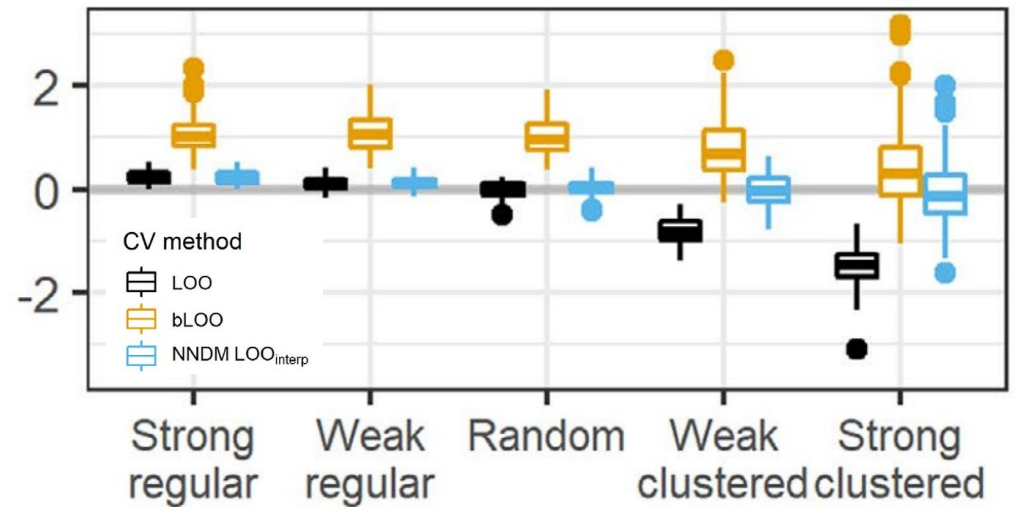
## Nearest neighbour distance matching Leave-One-Out Cross-Validation for map validation

Carles Milà<sup>1</sup> | Jorge Mateu<sup>2</sup> | Edzer Pebesma<sup>3</sup> | Hanna Meyer<sup>4</sup>

**Aim:** Prediction situations created during CV resemble those encountered while predicting the global map



Difference between true error and CV estimate



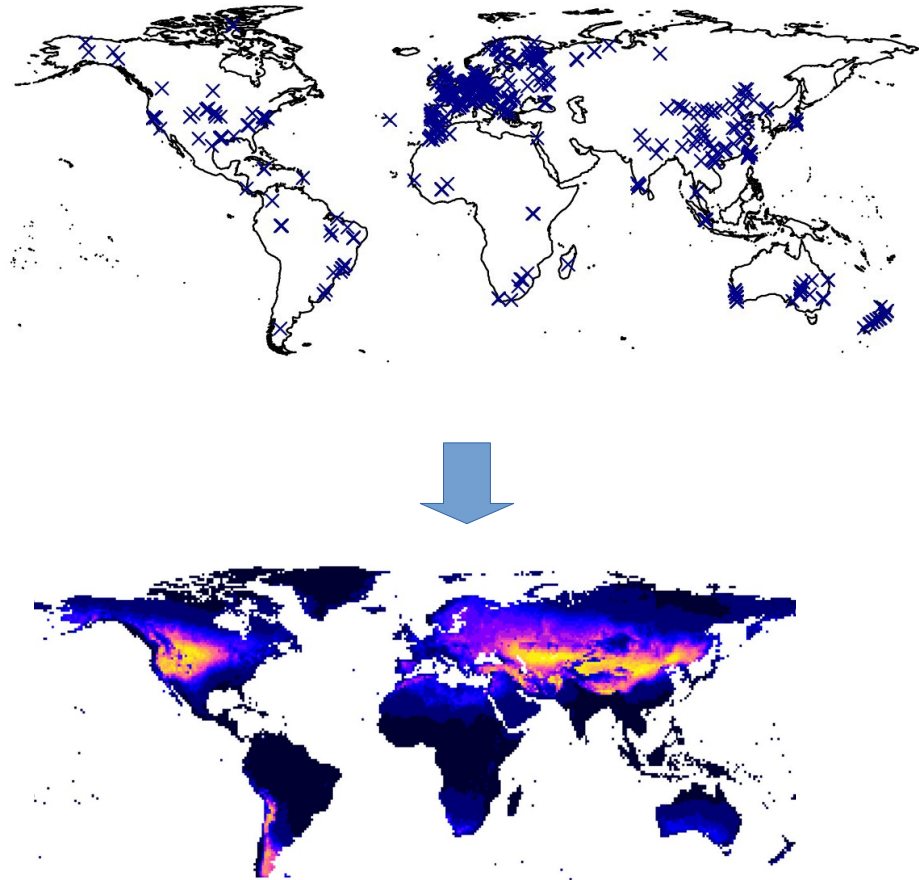
Mila et al., 2022

# Relevance of choosing a suitable CV strategy

- Cross-validation strategy affect:
  - Performance estimate
  - Selected hyperparameters
  - Variable selection
- Consequences of using a unsuitable CV:
  - Unreliable performance estimates
  - Models that can well reproduce but not necessarily predict
- Hence, CV strategies that fit the prediction task are required!

**But is this sufficient for reliable global mapping ?**

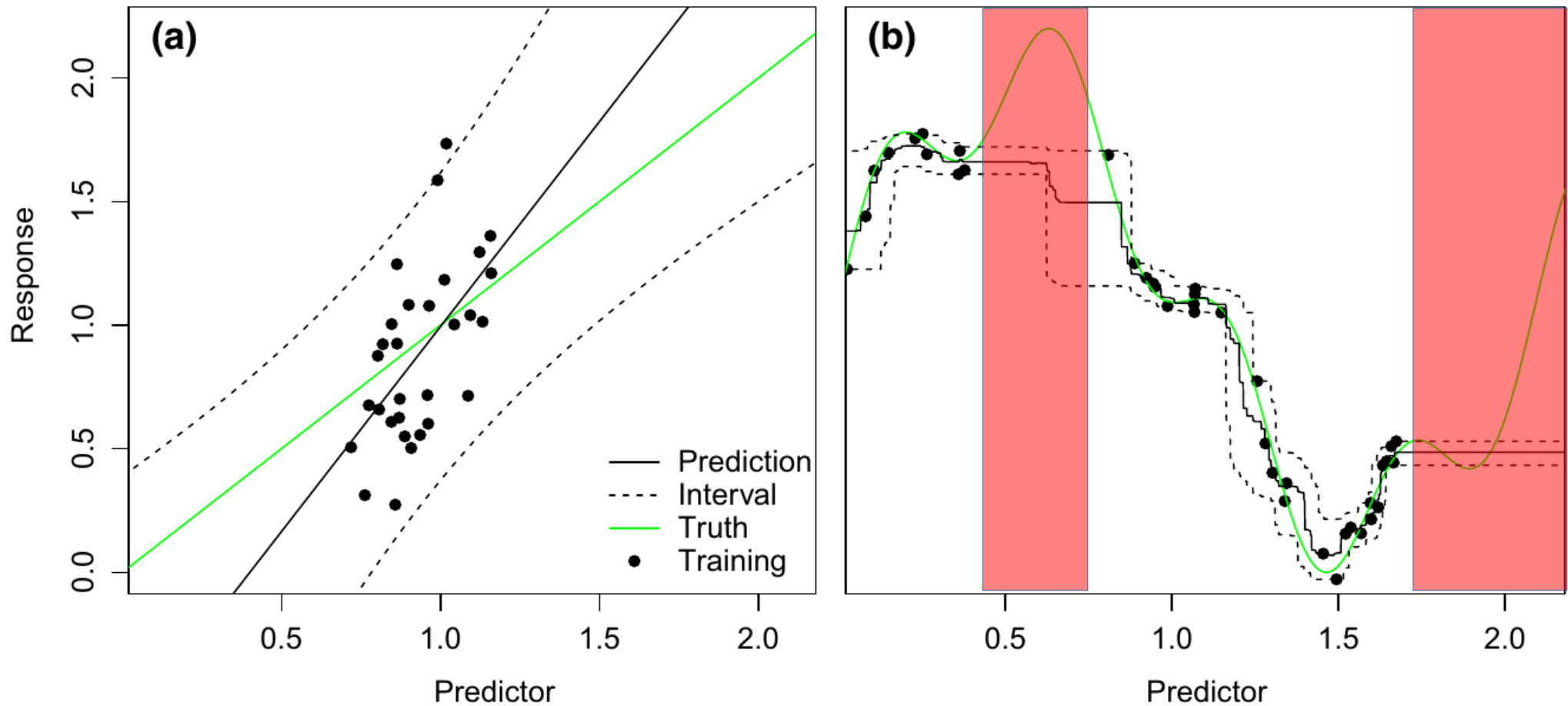
# Limits to accuracy assessment



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

...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

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

# Suggestion: Area of Applicability (AOA)

Methods in Ecology and Evolution



RESEARCH ARTICLE | Open Access |

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

Hanna Meyer Edzer Pebesma

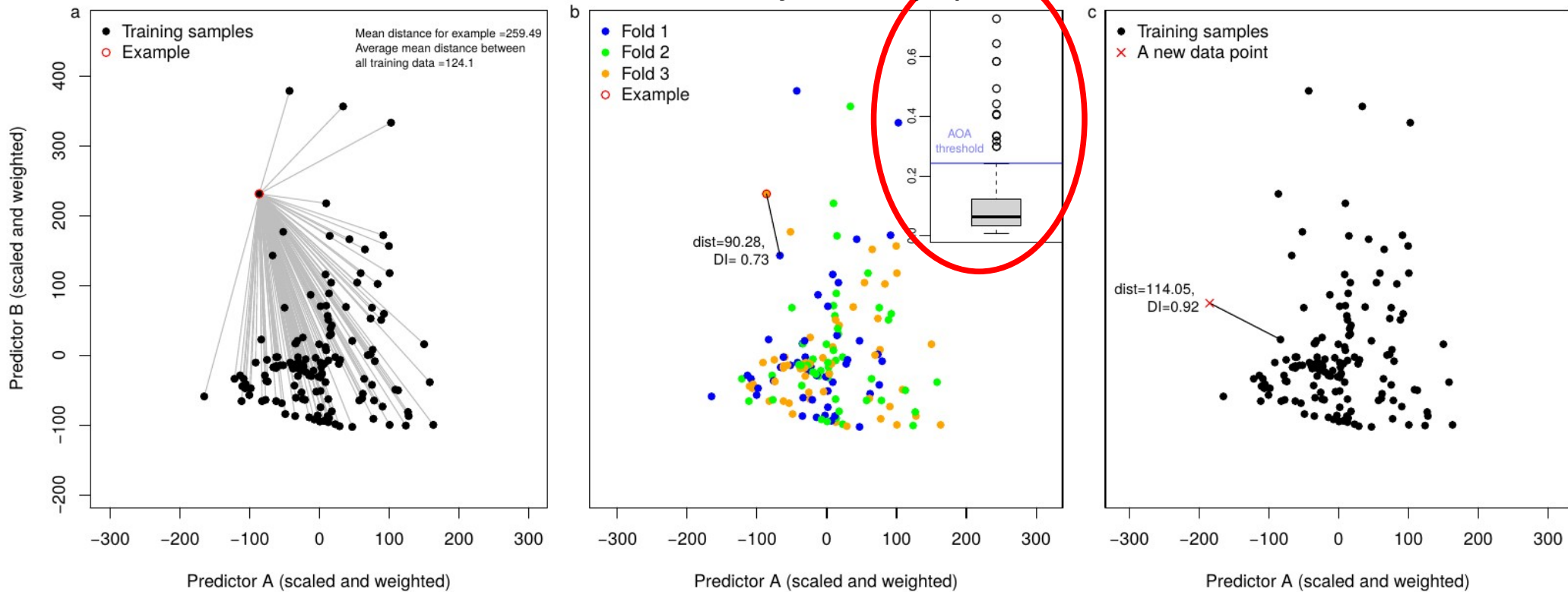
**We try to derive the area...**

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



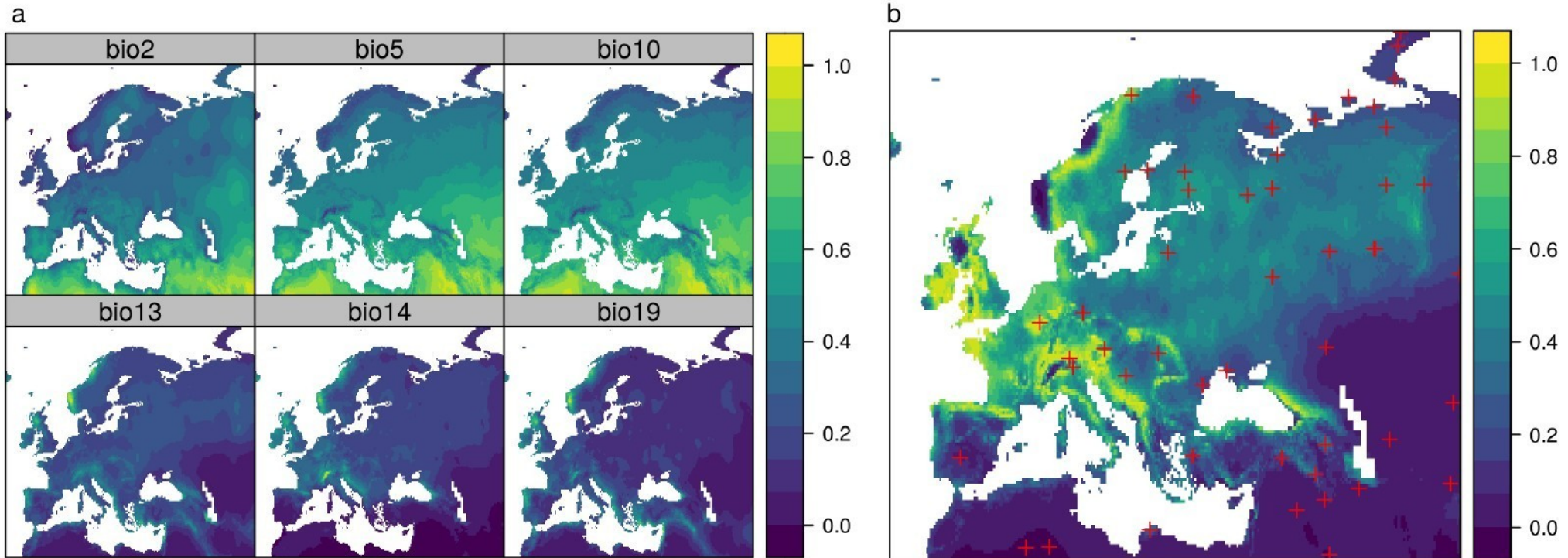
# Suggestion of a method to derive the AOA

## Calculation of a Dissimilarity Index (DI)



Meyer & Pebesma (2021)

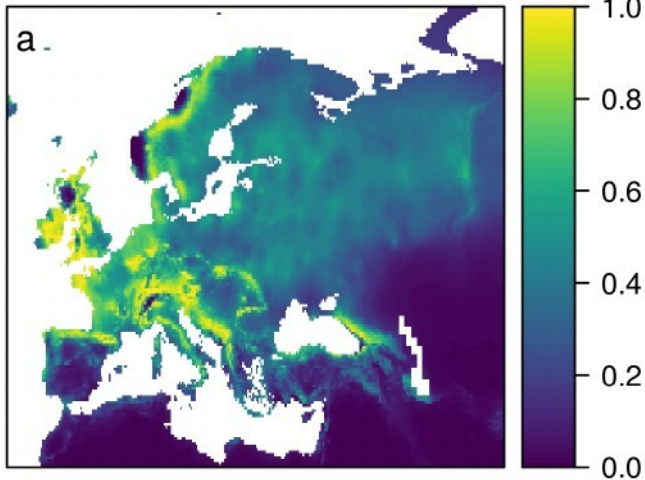
# Simulated example: Predictors and response



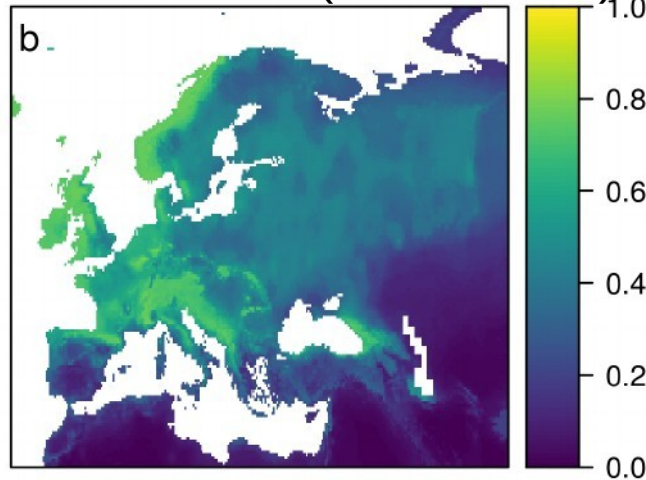
Meyer & Pebesma (2021)

# Simulated example: Results

Reference

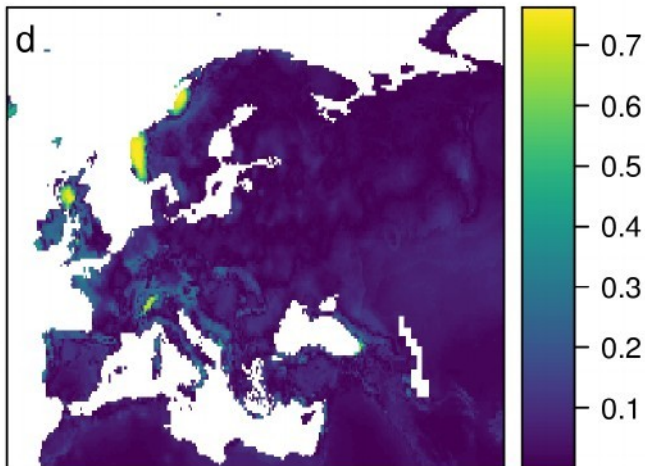


Prediction (CV  $R^2 = 0.95$ )

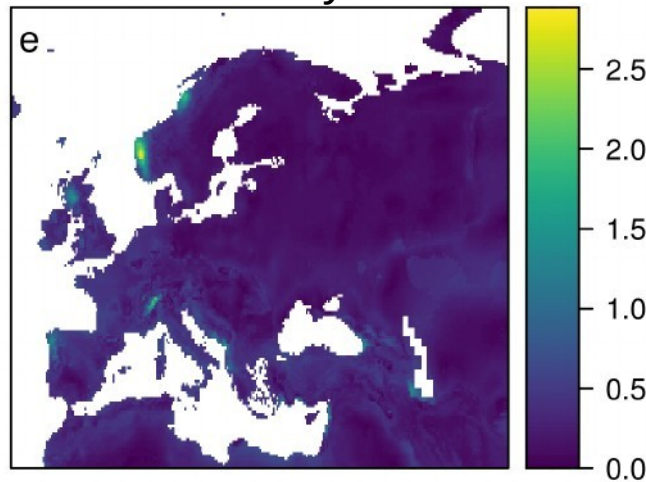


Reproduce example:  
[github.com/HannaMeyer/MEE\\_AOA](https://github.com/HannaMeyer/MEE_AOA)

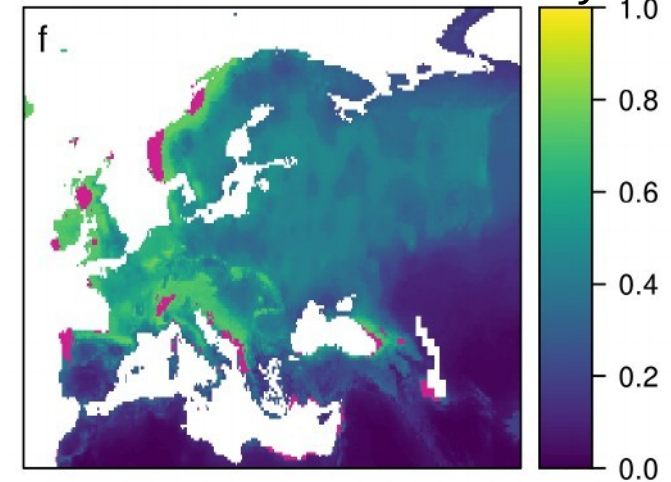
True error



Dissimilarity index



Predictions for the AOA only



Meyer & Pebesma (2021)

# Conclusions & Discussions

- Results are not just nice maps but used for subsequent modeling, nature conservation, risk assessment,...
- We think that 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
- Methods suggested here are implemented in the R package CAST
- We have to work on methods to better assess the prediction performance and uncertainties, especially local performance estimates

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