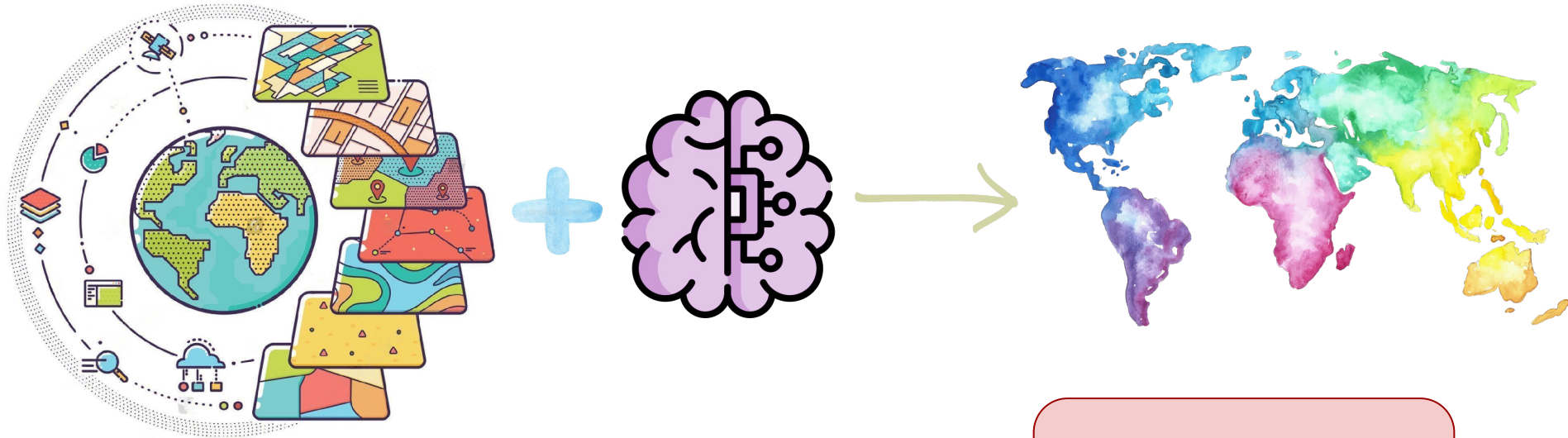

Area of applicability

Laura Martínez-Ferrer
(UV)



Intro/Motivation



Spatial distribution of measurements remains sparse.

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

Hanna Meyer¹  | Edzer Pebesma² 

1: Standardization of predictor variables

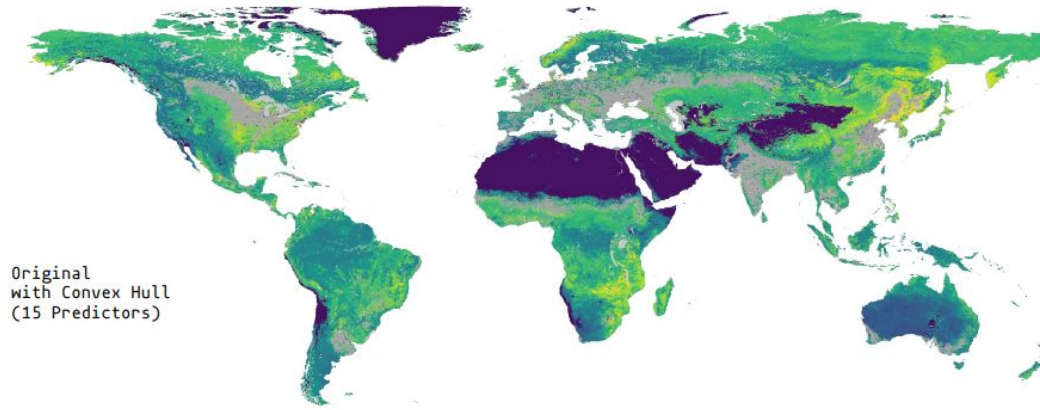
2: Weighting of variables $X_j^{sw} = w_j * X_j^s$

3: Distance from new prediction location k and training dataset $d(k, i) = \sqrt{\sum_{j=1}^p (X_{k,j}^{sw} - X_{i,j}^{sw})^2}$

4: Nearest training point $d_k = \arg_i \min d(k, i)$

5: Dissimilarity index $DI_k = d_k / \bar{d}$

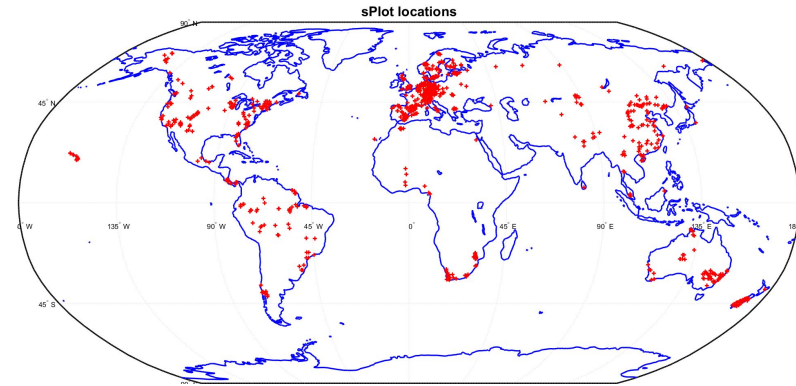
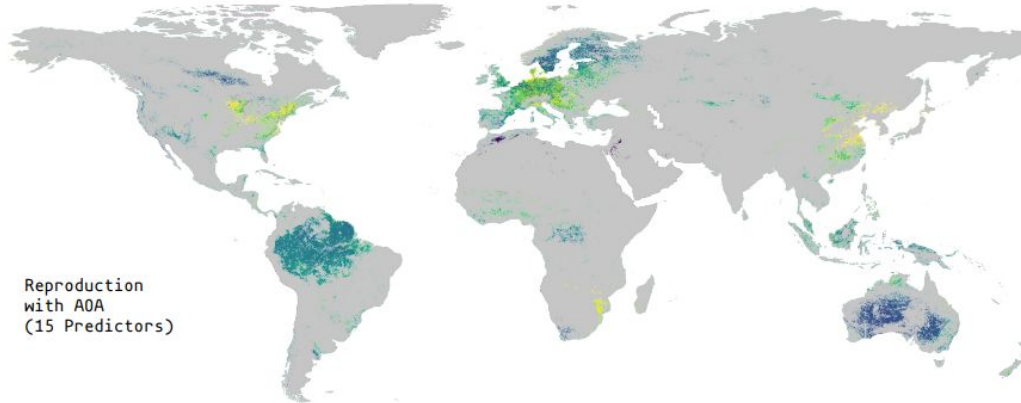
AOA



Specific Leaf Area (SLA)

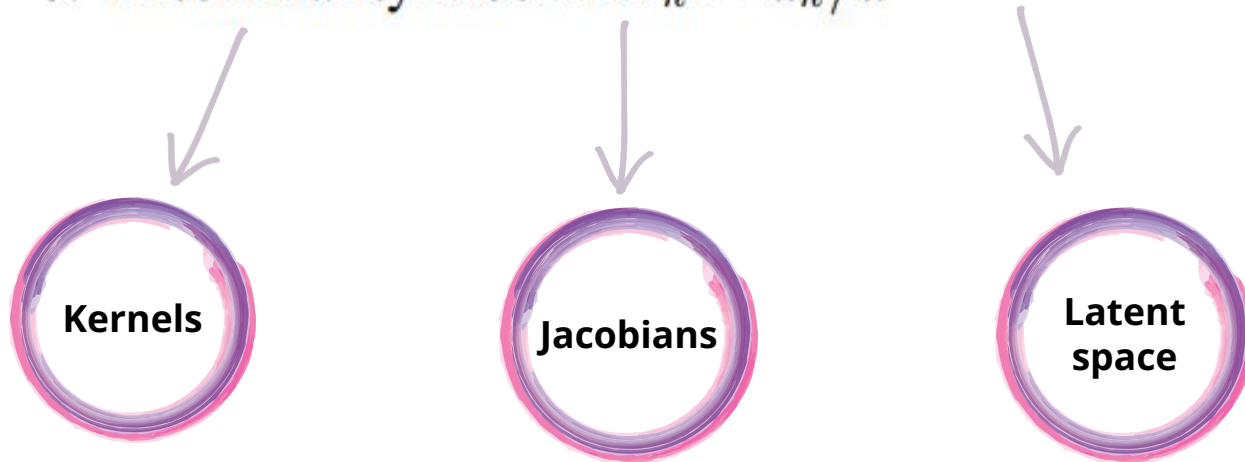


Not Applicable

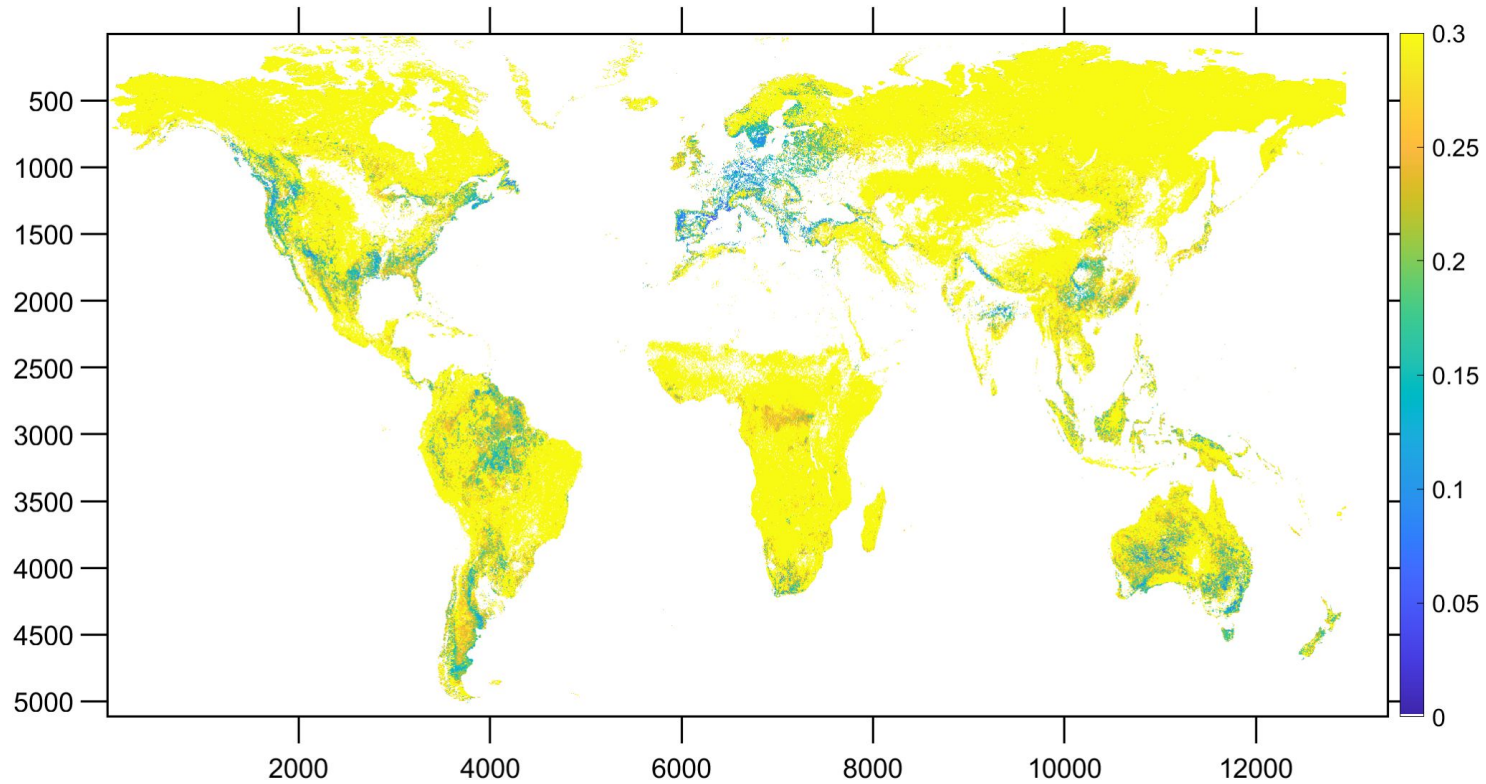
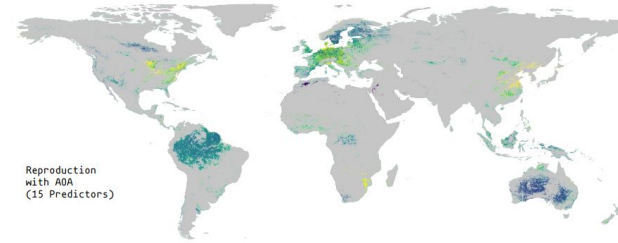


AOA

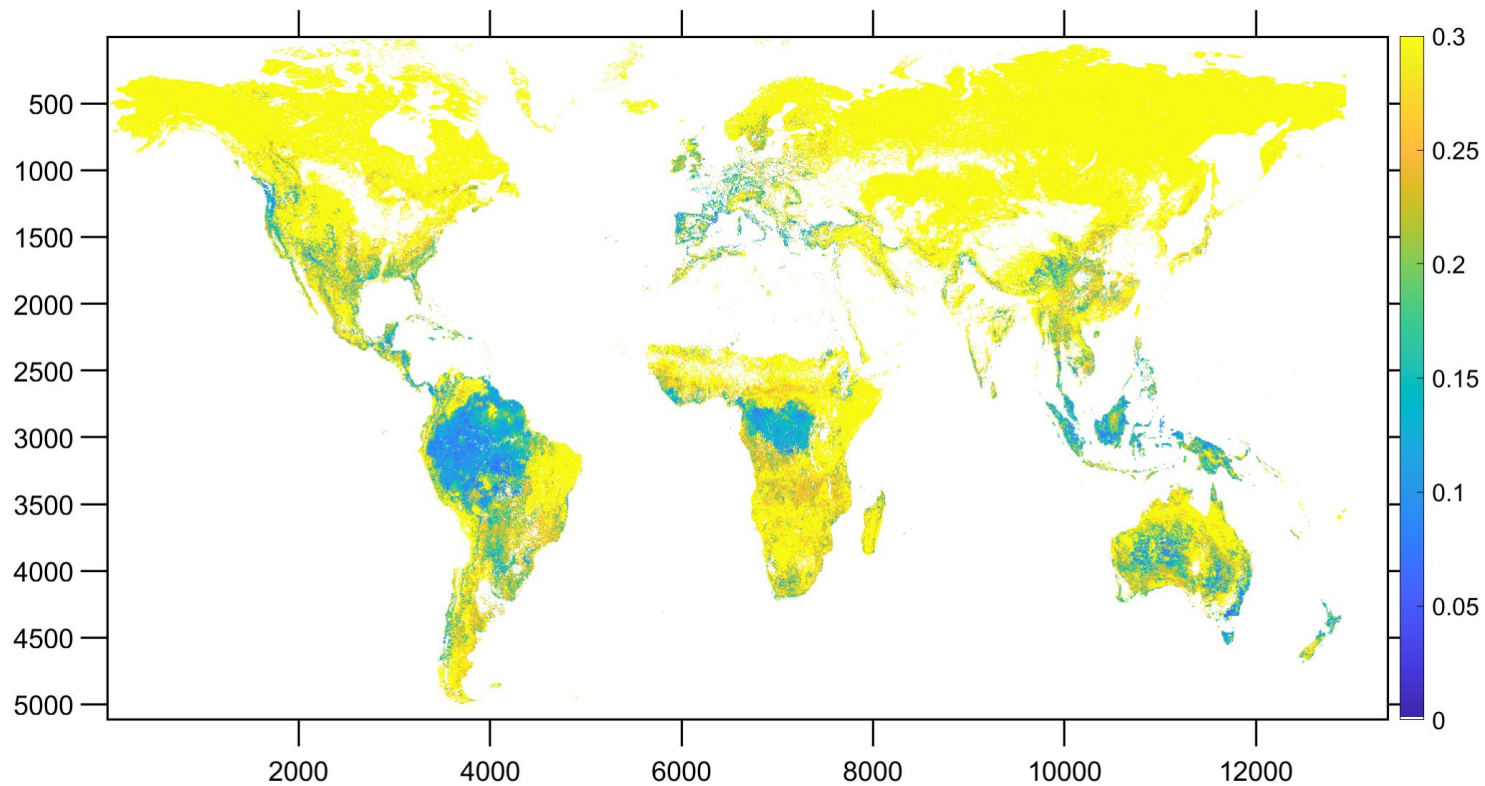
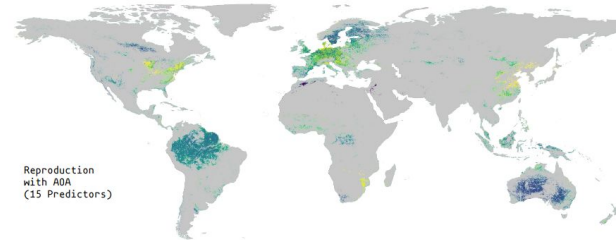
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NN Jacobian

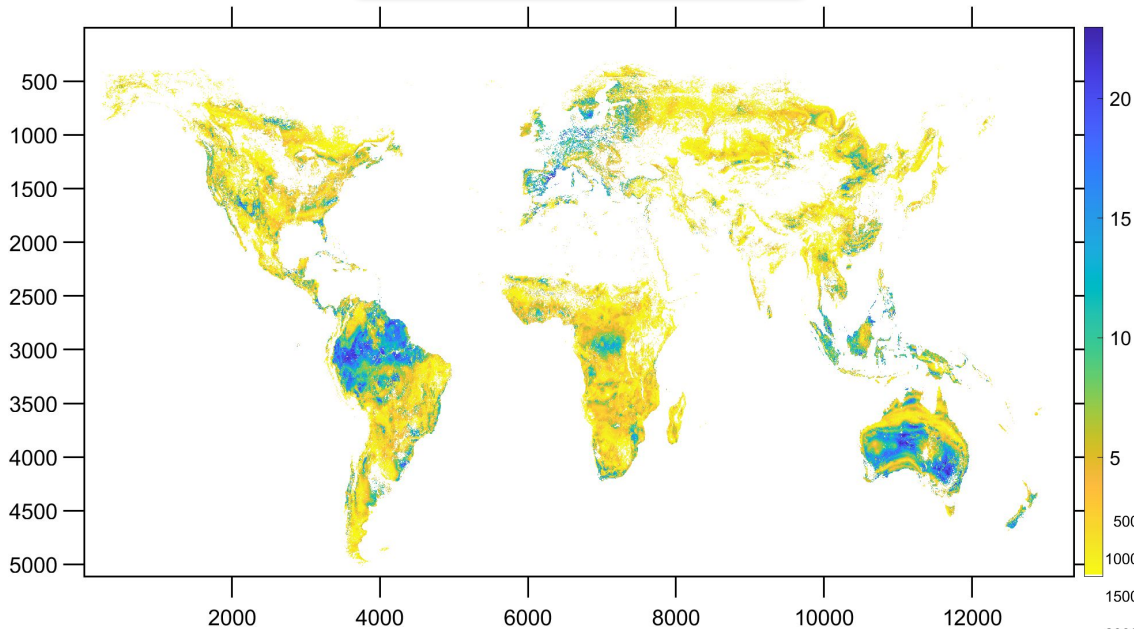


NN Latent Space

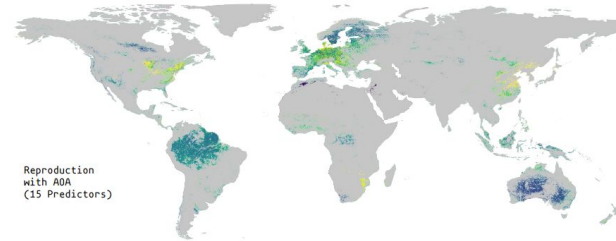


GPs

GP-Dissimilarity Index

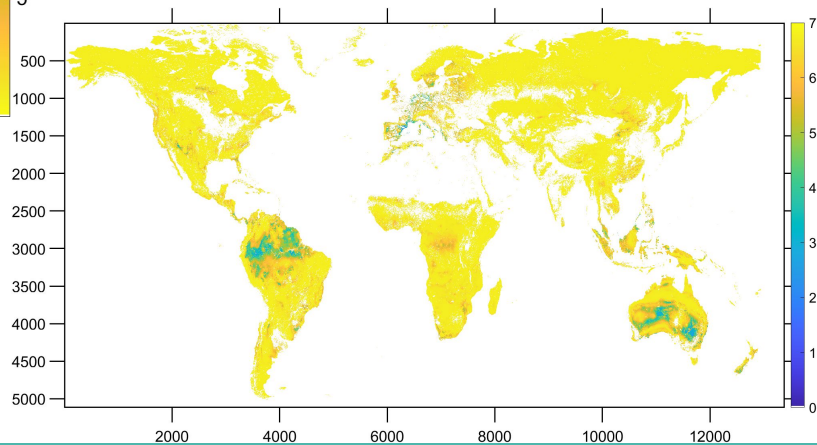


GP variance



ARD Kernel

$$k(x_i, x_j | \theta) = \sigma_f^2 \exp \left[-\frac{1}{2} \sum_{m=1}^d \frac{(x_{im} - x_{jm})^2}{\sigma_m^2} \right]$$



Conclusions/open questions

- ★ Where is the advantage if the AOA coincides with the locations of the training data?
- ★ Meyer proposed to find the predictors combination that maximizes the AOA
- ★ Different ML methods/approaches lead to similar results