



BIODIVERSITY
Data Lab

**NATUR
VÅRDS
VERKET**



SWEDISH
ENVIRONMENTAL
PROTECTION
AGENCY

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www.biodiversity.se

Remote sensing applications for biodiversity monitoring



Model performance evaluation is crucial for informing appropriate use cases



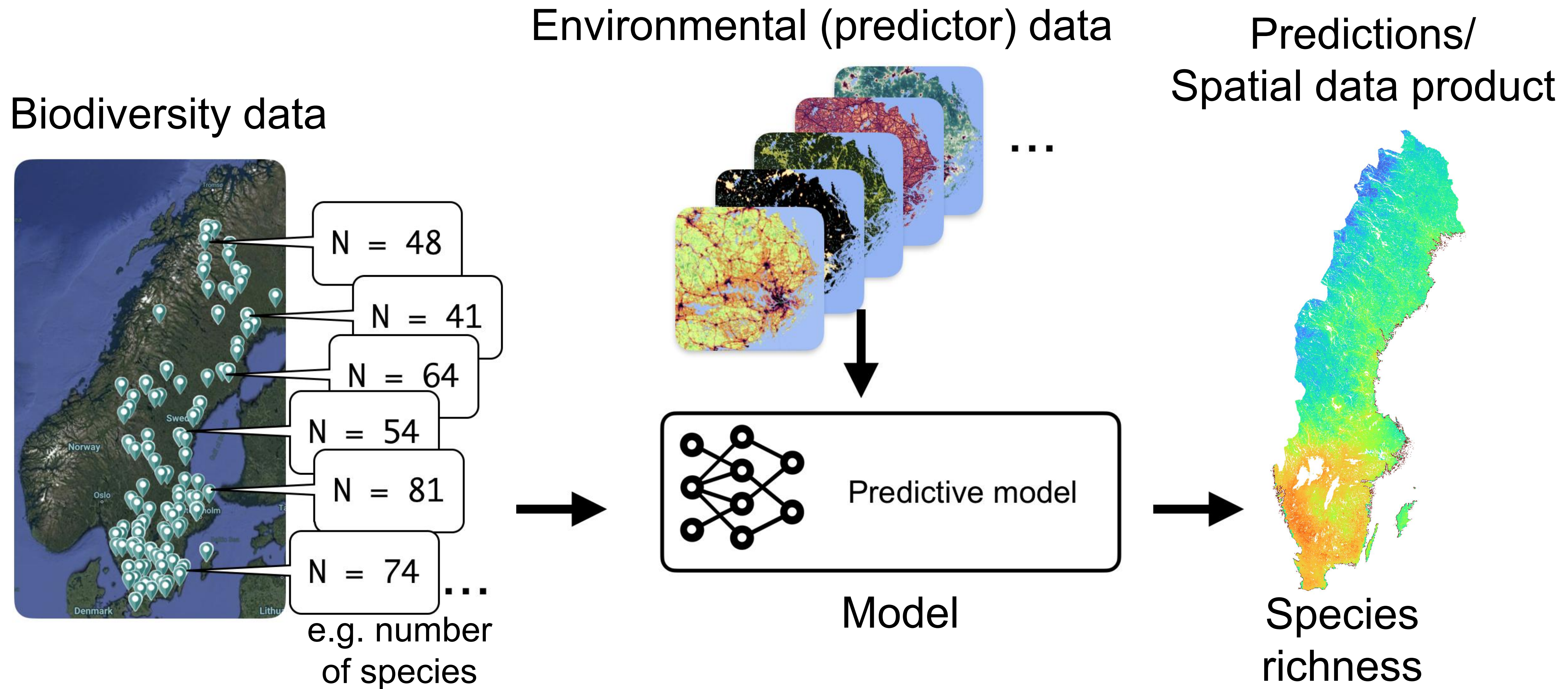
UPPSALA
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 SciLifeLab



Vetenskapsrådet

How to build a predictive biodiversity model

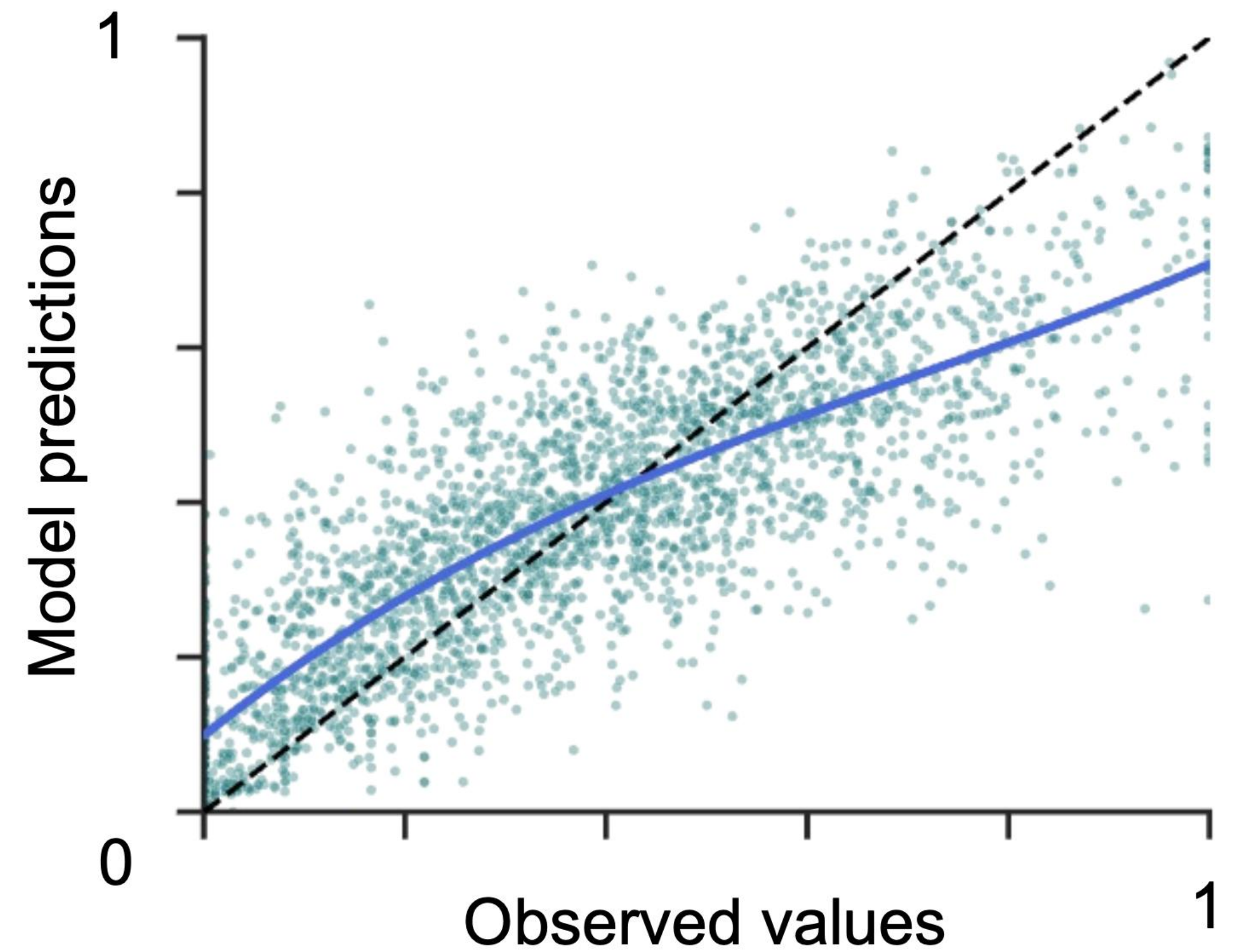


Any model can produce a map,
but to what degree can we trust it?

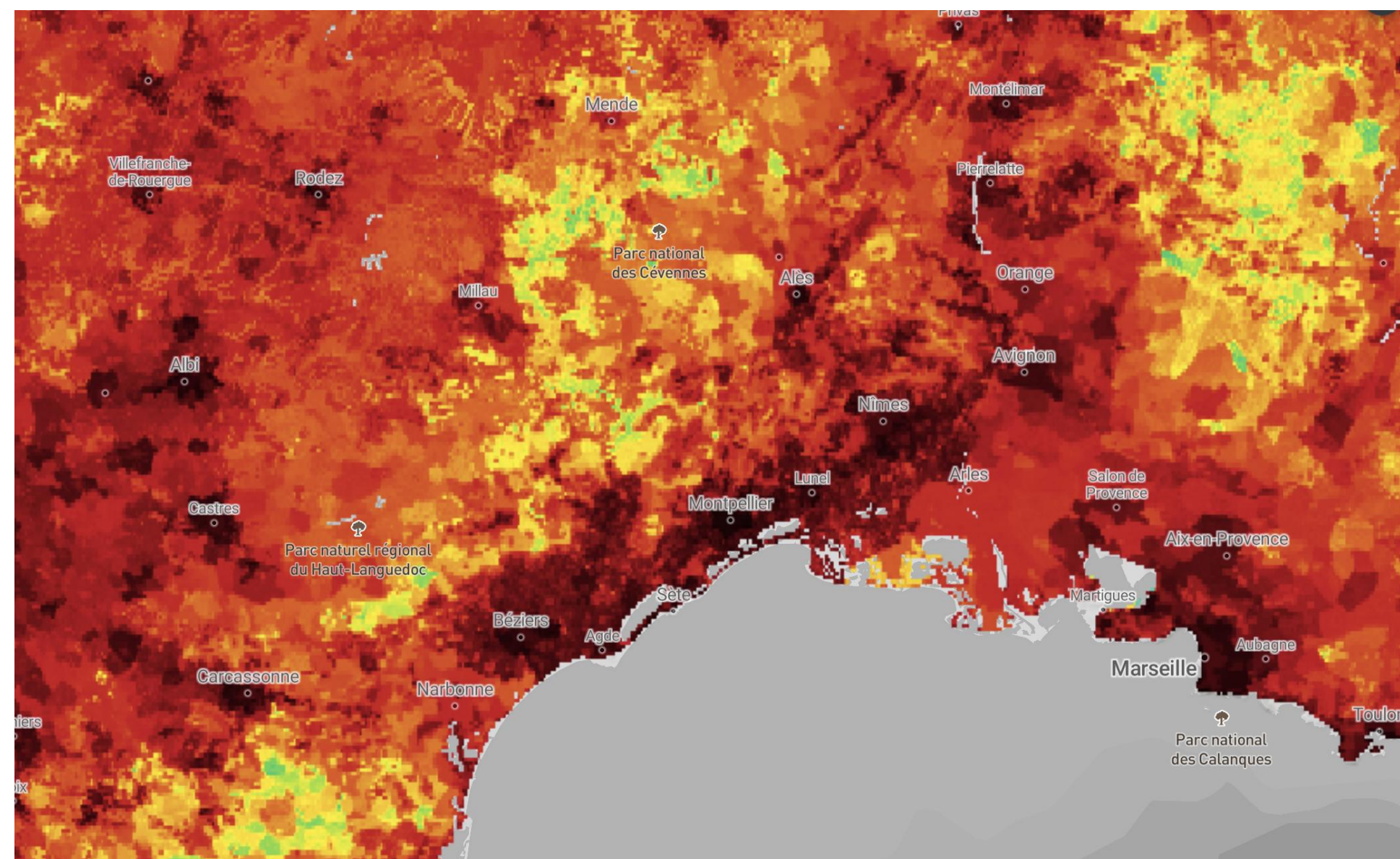
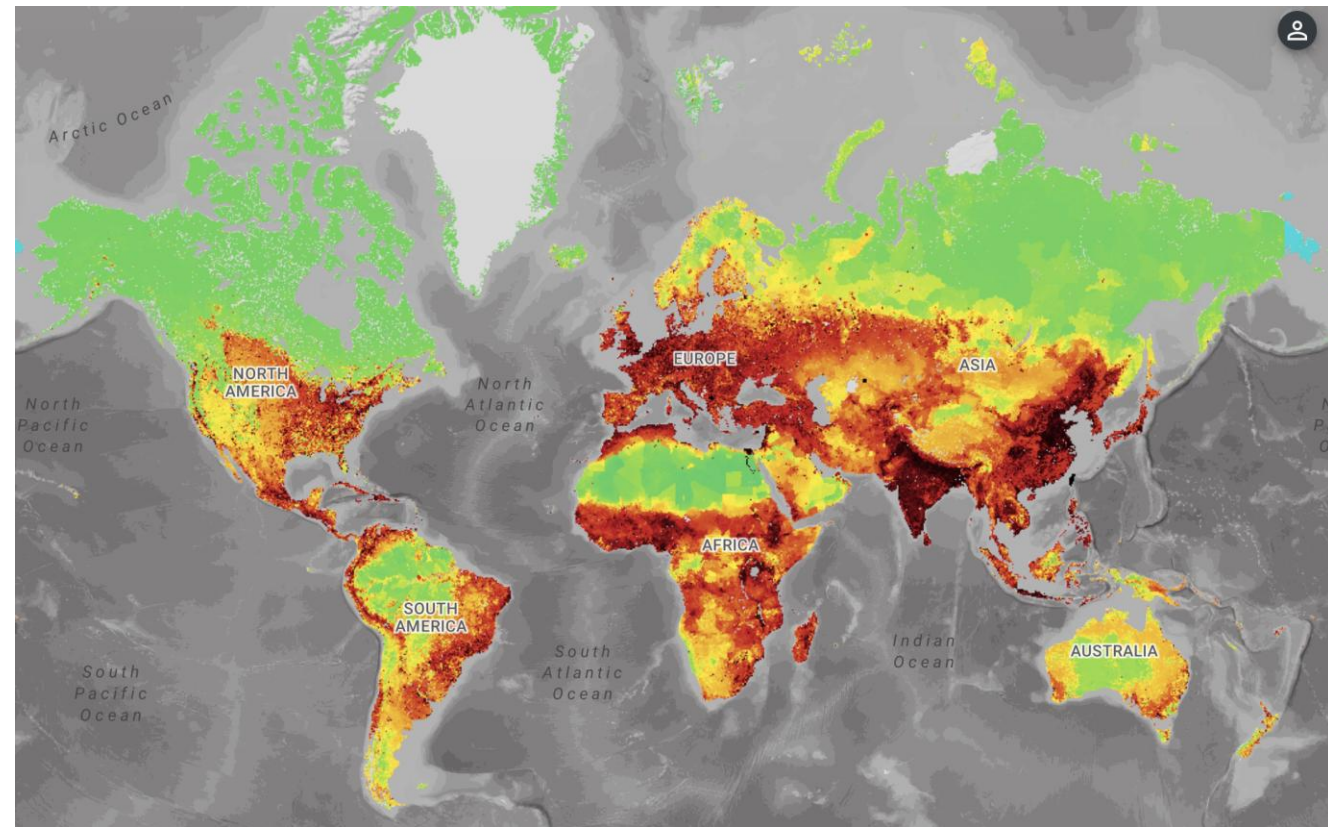
Predictive performance metrics

- Pearson correlation coefficient (r)
 - Linear association between predicted and observed values
- Spearman rank correlation (ρ)
 - Rank-based
- Mean Absolute Error (**MAE**)
 - Absolute differences
- Mean Absolute Percentage Error (**MAPE**)
 - Relative differences

Should be based on independent test data



Predictive performance evaluation is essential when using model for predictions



The **Biodiversity Intactness Index (BII)**, predicted globally at 1km resolution (Newbold et al., 2015, *Nature*)

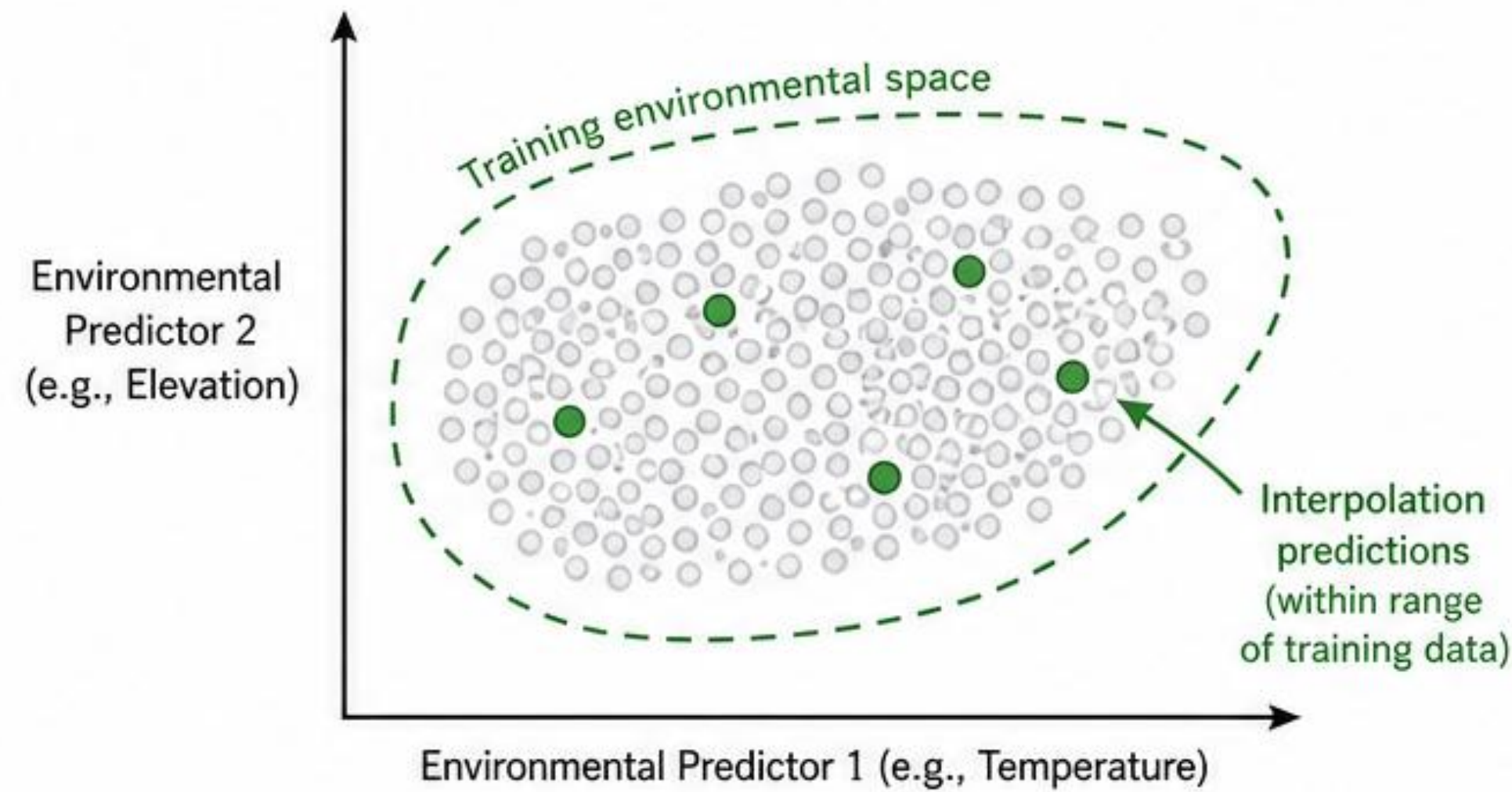
- Model has not been tested for predictive performance, but is often used to produce spatially explicit maps
 - Recommended as model-based indicator for reporting/monitoring by CBD and IPBES



PREDICTS: Training data, 817 studies comprising 35,736 sampling sites in 101 countries (meta-database)

INTERPOLATION (within the training space)

Predicting for conditions similar to those in the training data (environmental space is **represented**).



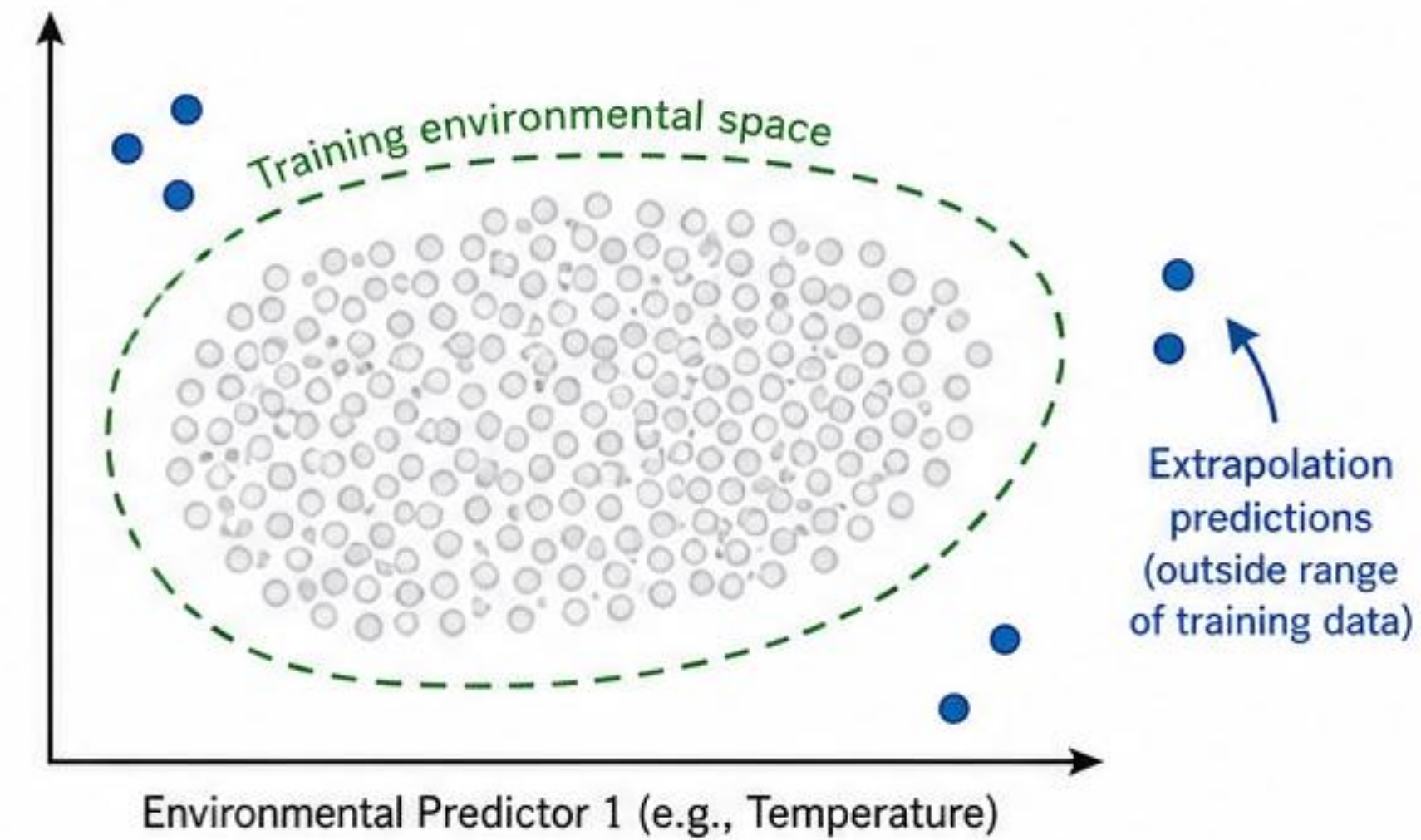
Example on a map



Predictions in areas with environmental conditions similar to the training data.
More reliable.

EXTRAPOLATION (outside the training space)

Predicting for conditions different from those in the training data (environmental space is **not represented**).



Example on a map



Predictions in areas with environmental conditions different from the training data.
Less reliable.

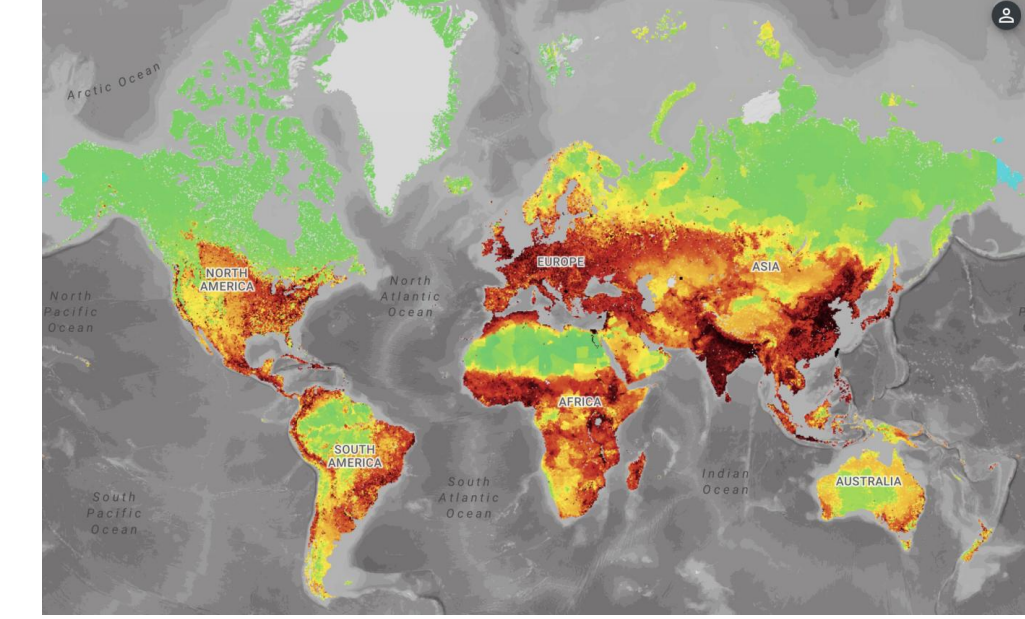
Legend

- Training data (observed biodiversity & environments)
- Interpolation prediction (within training space)
- Extrapolation prediction (outside training space)
- - Training environmental space (represented by the data)



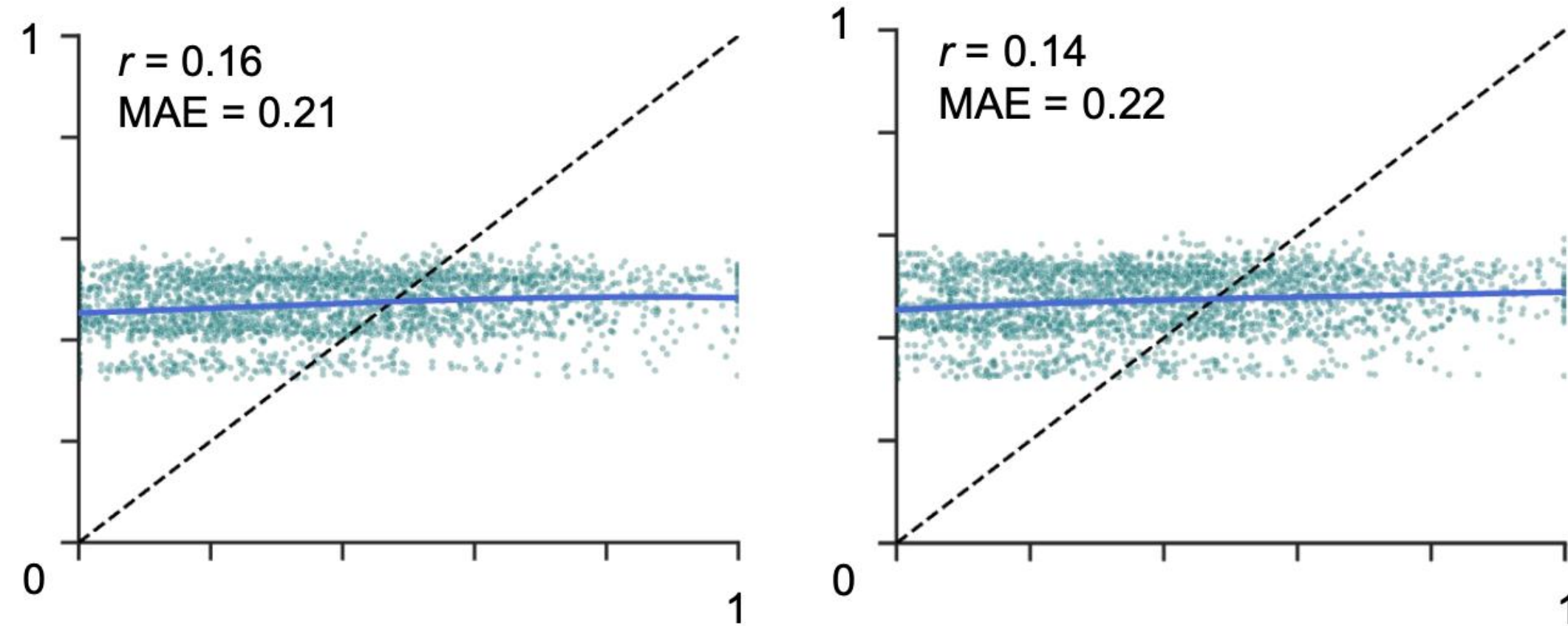
Key takeaway: **Interpolation** is prediction within the range of the training data (safer). **Extrapolation** is prediction beyond that range (riskier) because the model is asked to make inferences for environmental conditions it has not seen.

Models need to be fit for purpose

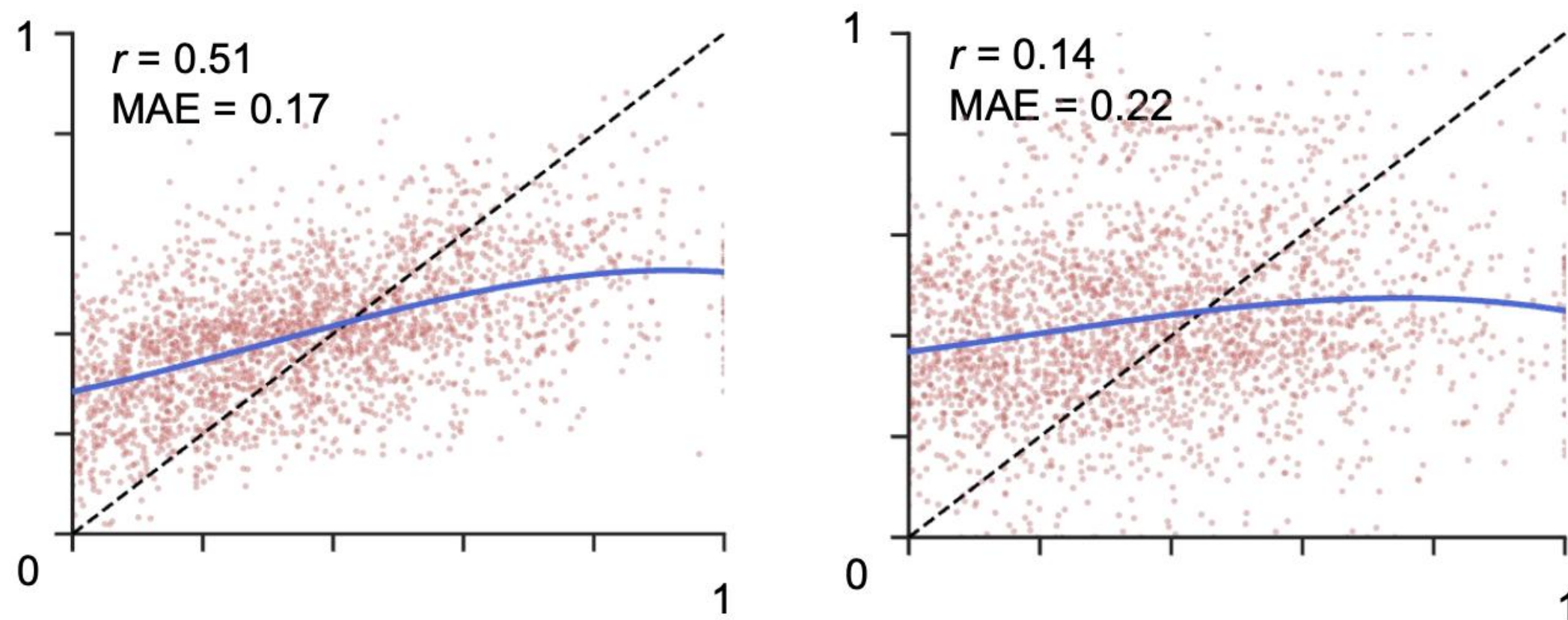


Biodiversity Intactness Index (BII)

BII-inspired model-structure



Model-structure improved for predictive capability



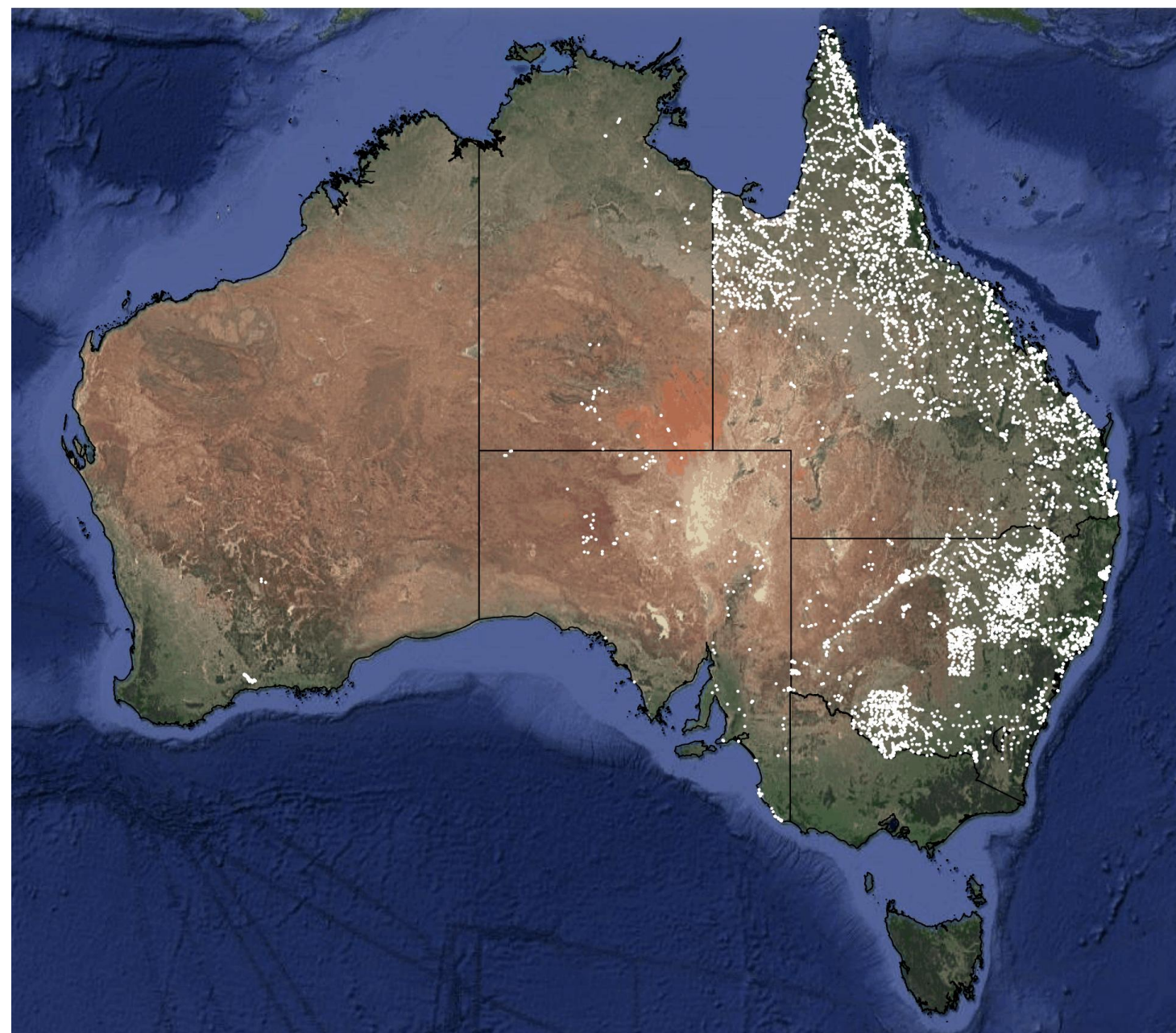
- Structured cross-validation approaches can simulate interpolation/extrapolation
- Not every model structure is optimal for predictive tasks (explanatory vs. predictive)
- Data gaps and heterogeneity of datasets remains challenge for modeling (metadatasets)
- We need more organized and standardized data collection to model most biodiversity metrics globally

Nyström et al. 2025, preprint, <https://doi.org/10.32942/X2507T>

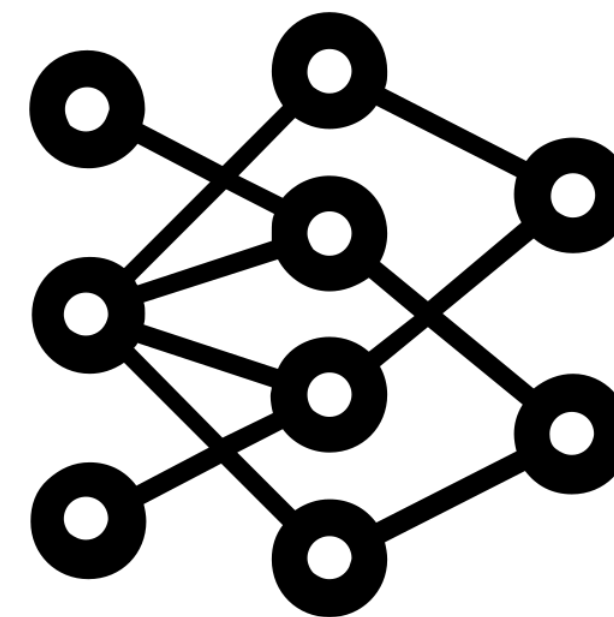
Where can we trust the model to make predictions?

Predicting species richness of vascular plants

Spatially biased training data

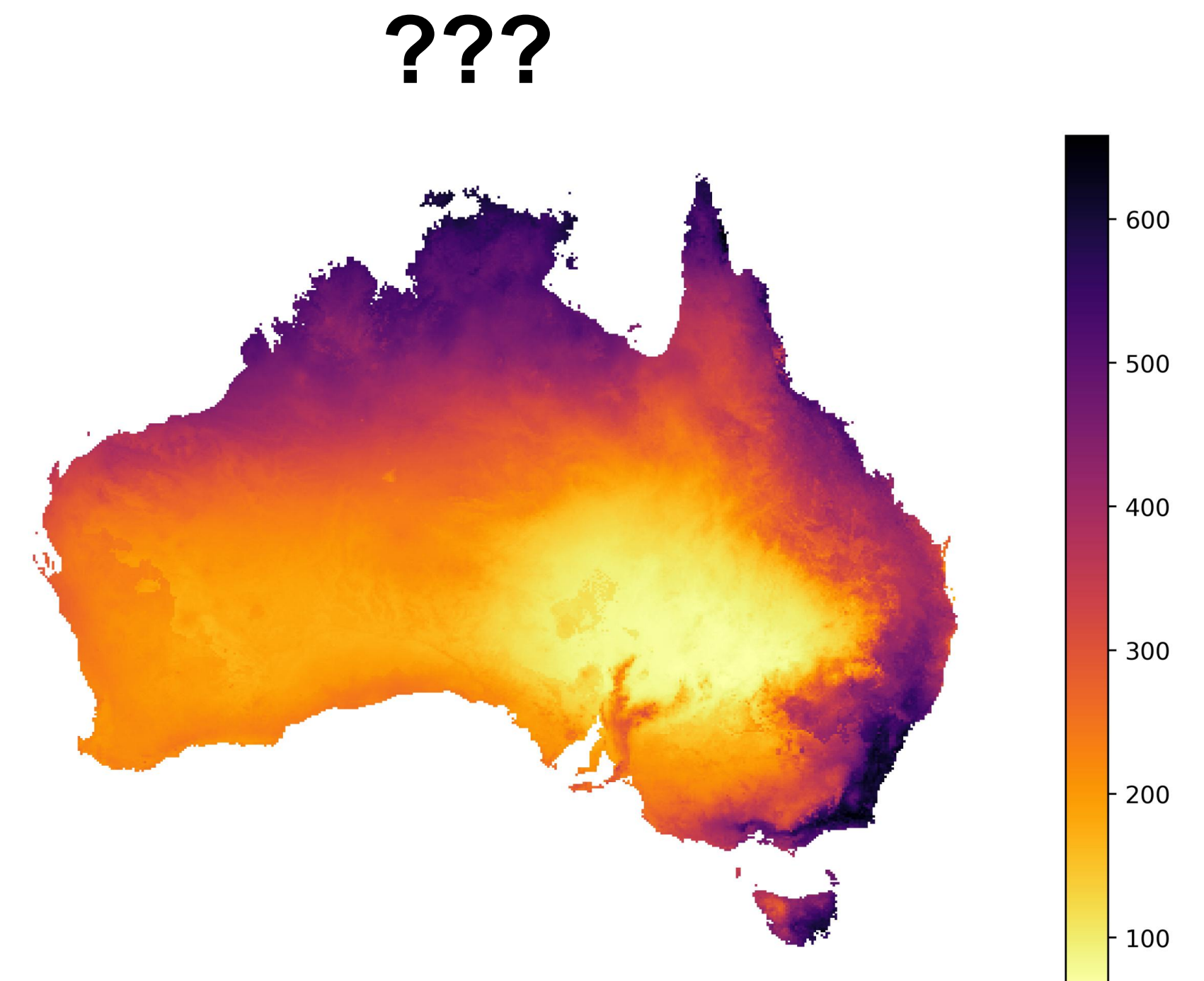


Train



Model

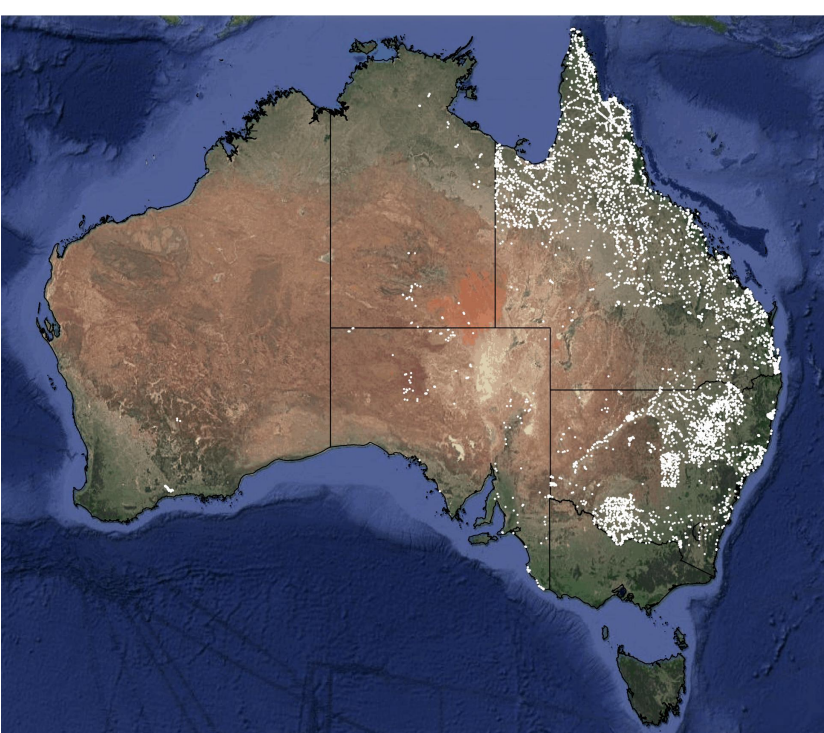
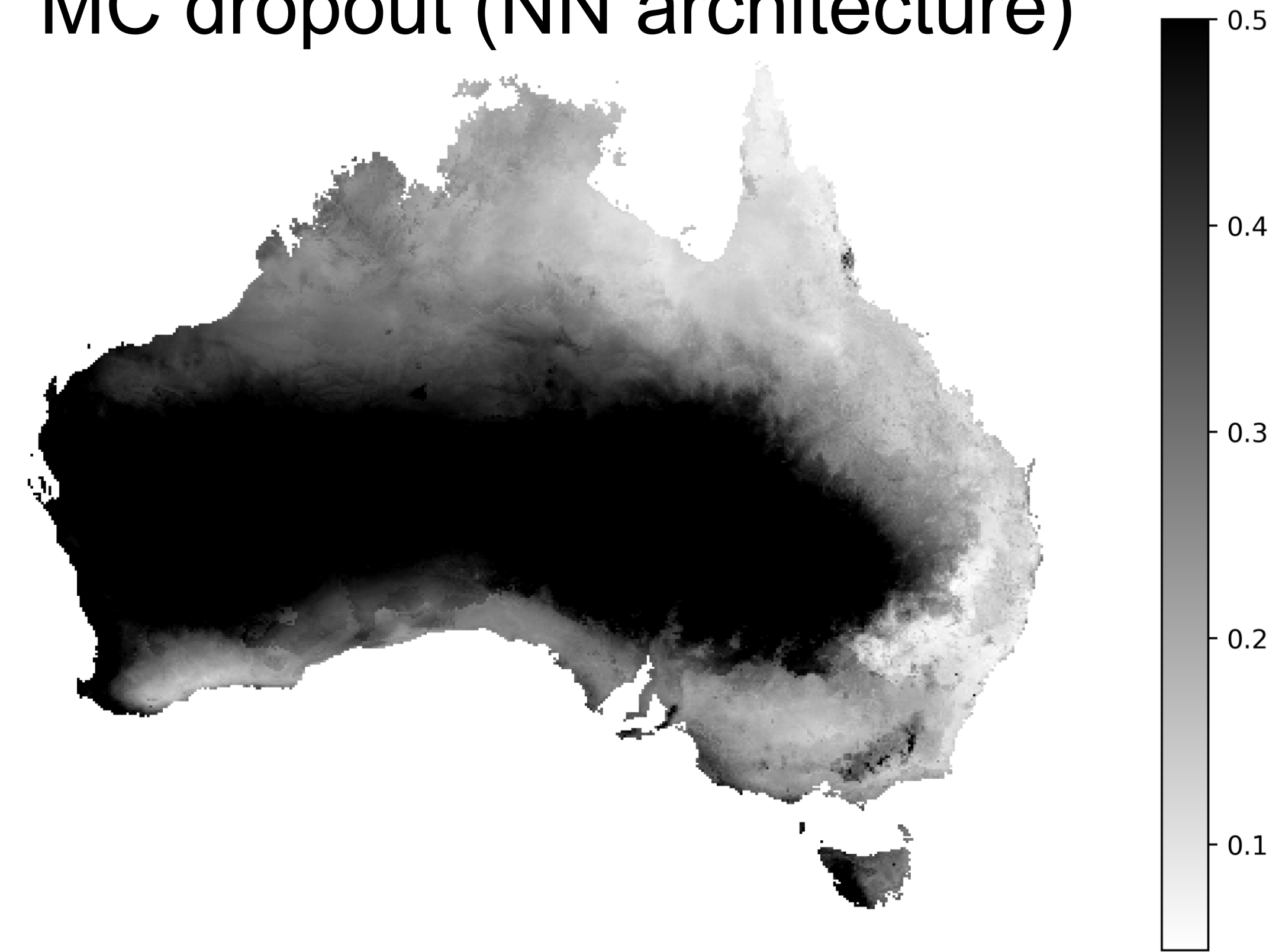
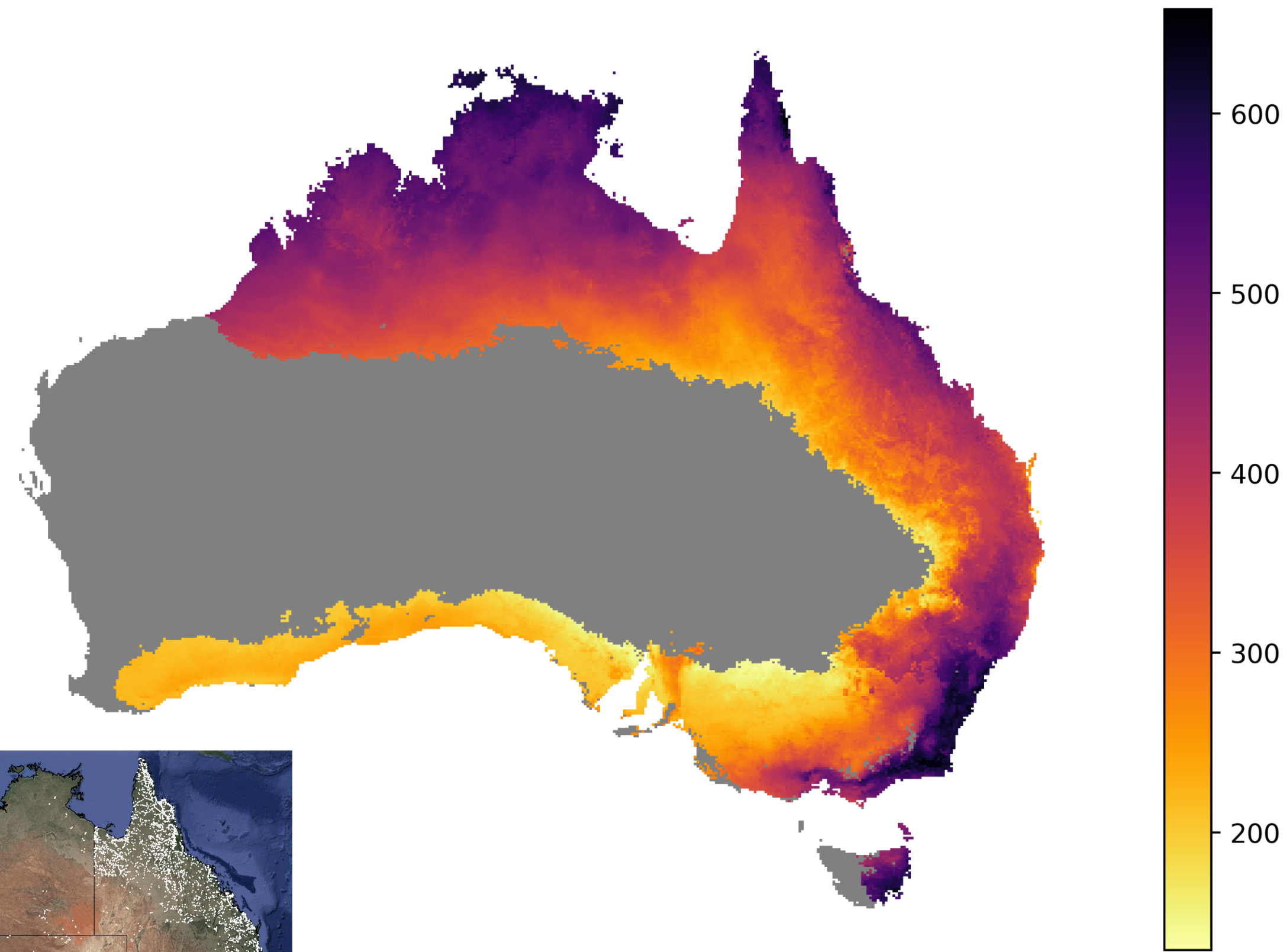
Predict



Andermann et al., 2022, <https://doi.org/10.3389/fpls.2022.839407>

Predicting species richness of vascular plants

Uncertainty determined with
MC dropout (NN architecture)



Andermann et al., 2022, <https://doi.org/10.3389/fpls.2022.839407>

What are we able to model?
Classification of ecosystem integrity/naturalness

National/regional scale models

Training data:

Low conservation value forests (forestry registry):

- forest parcels that have been clearcut within last 80 years
- ~ 593,000 annotated polygons in Sweden

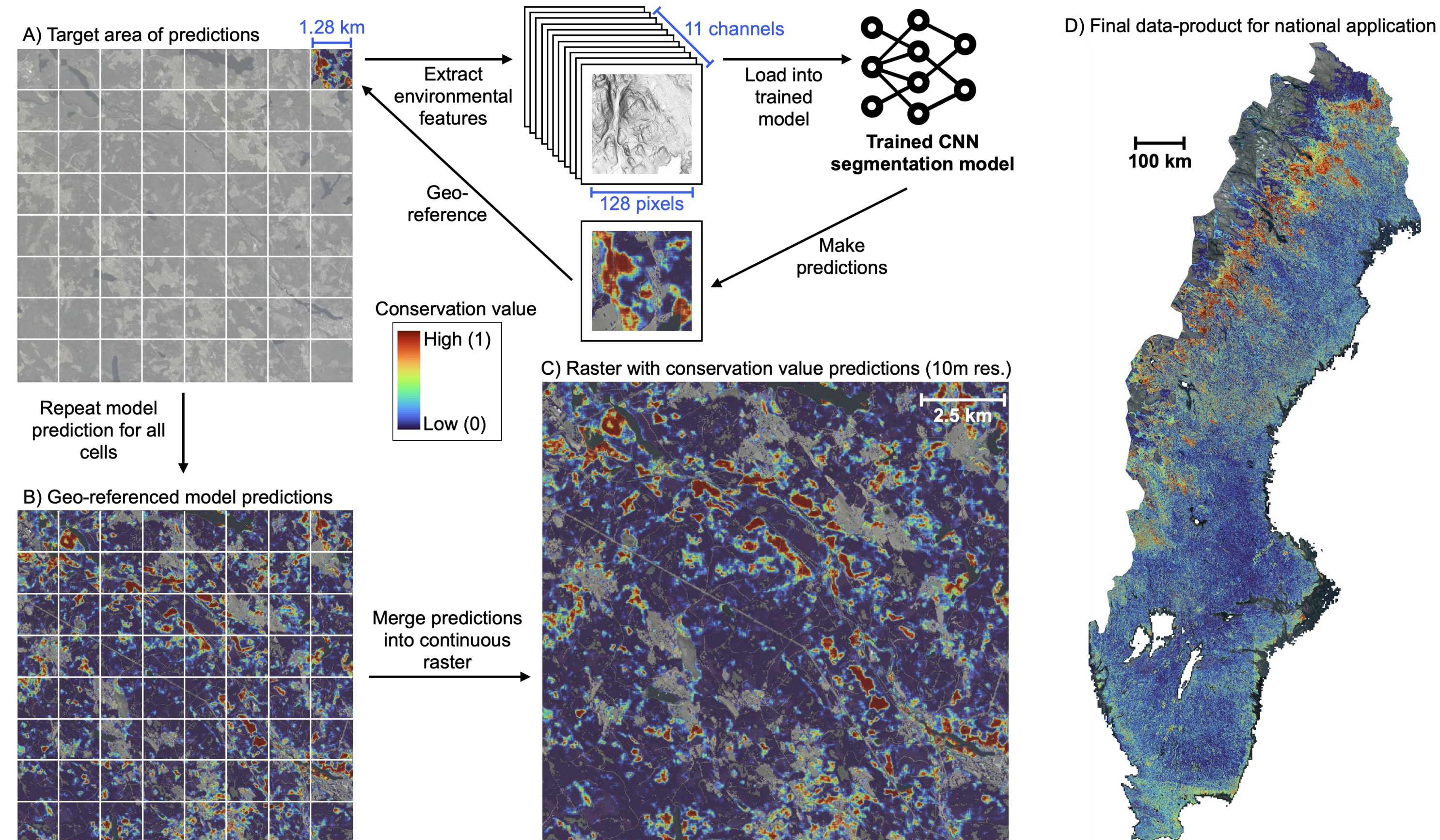


High conservation value forests (manual inventories):

- high naturalness (according to Swedish Forest Agency)
- ~67,000 annotated polygons in Sweden



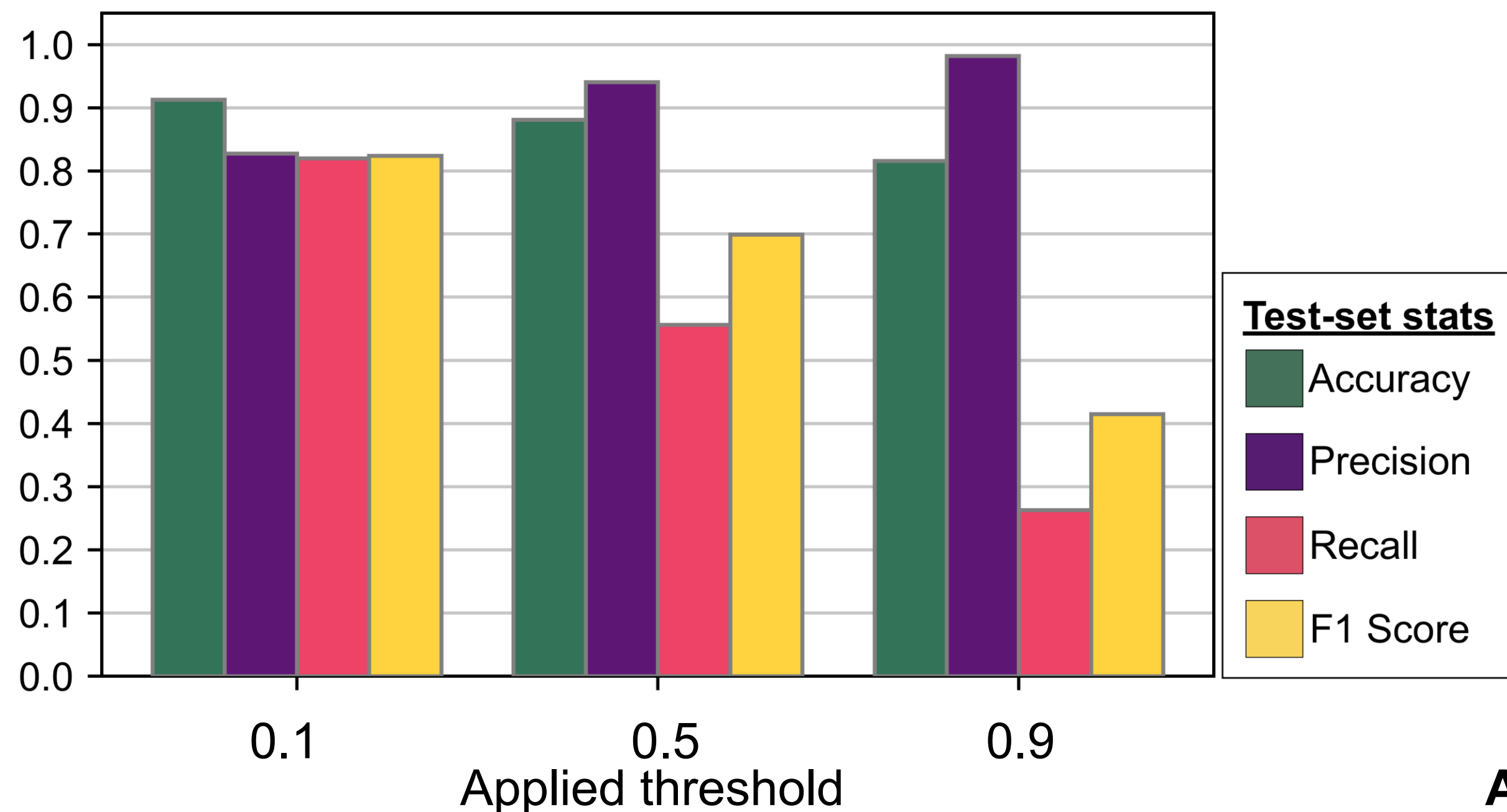
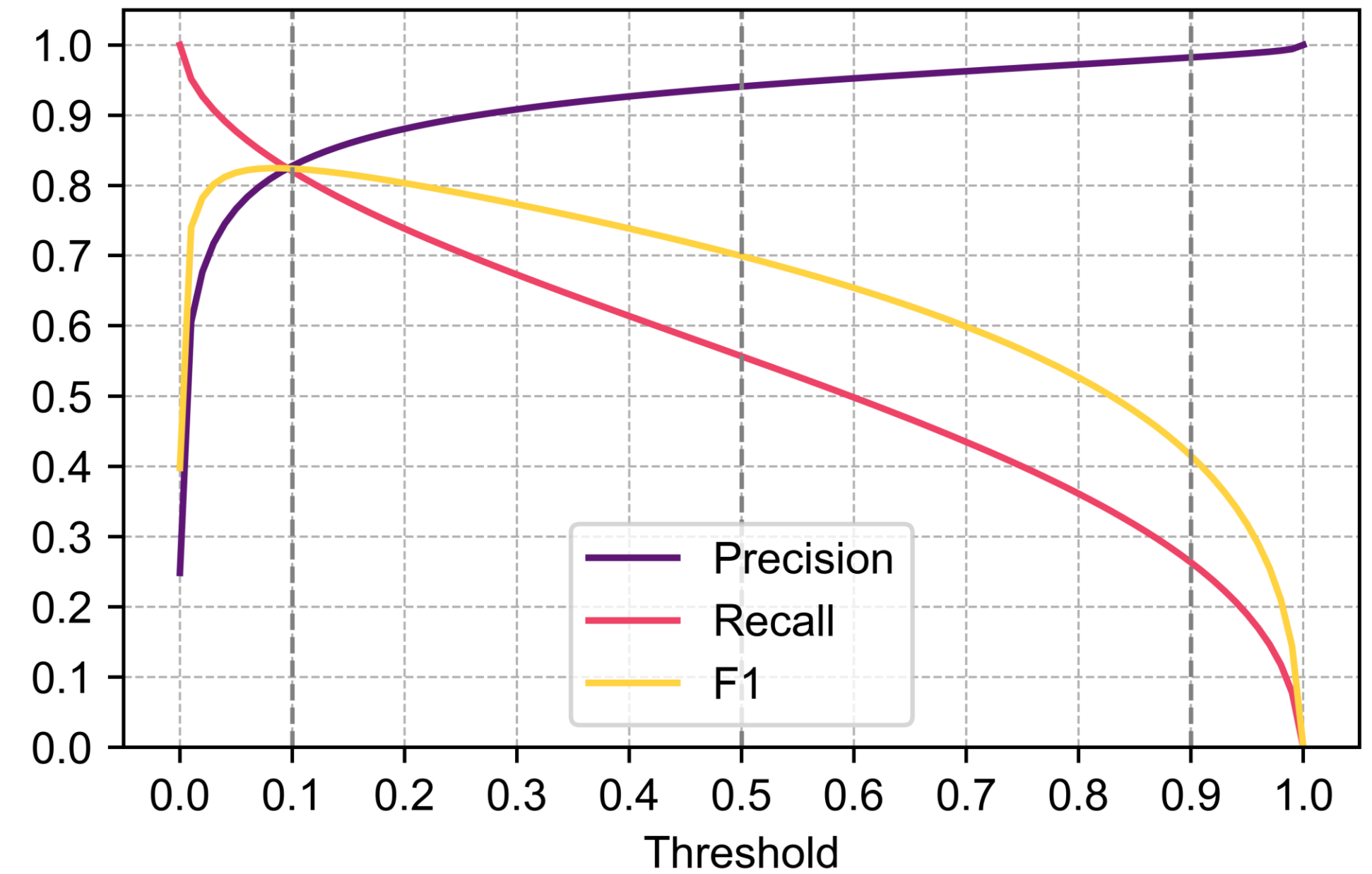
Mapping high-conservation-value forests



Andermann et al., preprint, <https://doi.org/10.21203/rs.3.rs-4734879/v1>

Model performance

- **Precision:** Proportion of pixels inferred as target class, which are correctly predicted
- **Recall:** Proportion of existing target class pixels that were correctly identified



$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Discussion topics

- How to strike a good compromise between recognizing limitations and promoting use cases?
 - What is good enough?
- Are we ready to use model-based indicators for biodiversity monitoring?
- Which biodiversity metrics are most important for global monitoring?
 - Ecosystem integrity?
 - Species composition/richness?

From habitat type field inventory to a wall-to-wall habitat type map?

Building a habitat type monitoring system for Finland



Motivation

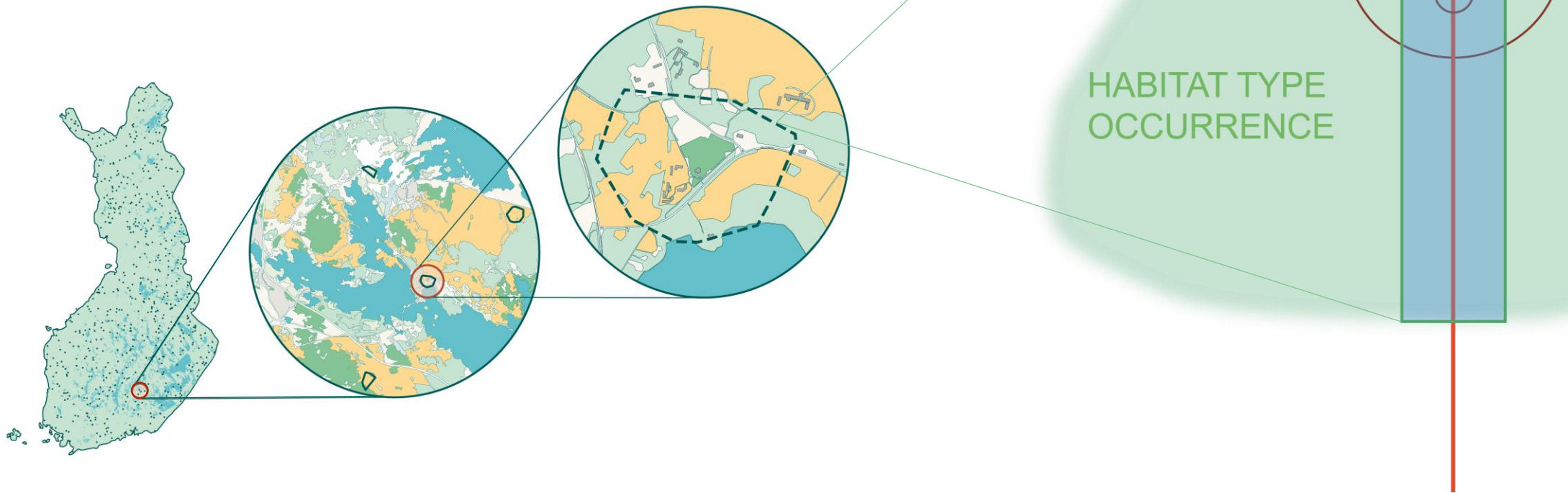
- Reporting for Nature restoration regulation
 - Occurrence
 - Quality
 - **90% should be known by 2030**
- Many European countries already have extensive habitat type monitoring schemes

Motivation

- Reporting for Nature restoration regulation
 - Occurrence
 - Quality
 - **90% should be known by 2030**
- Many European countries already have extensive habitat type monitoring schemes
- Finland does **not**

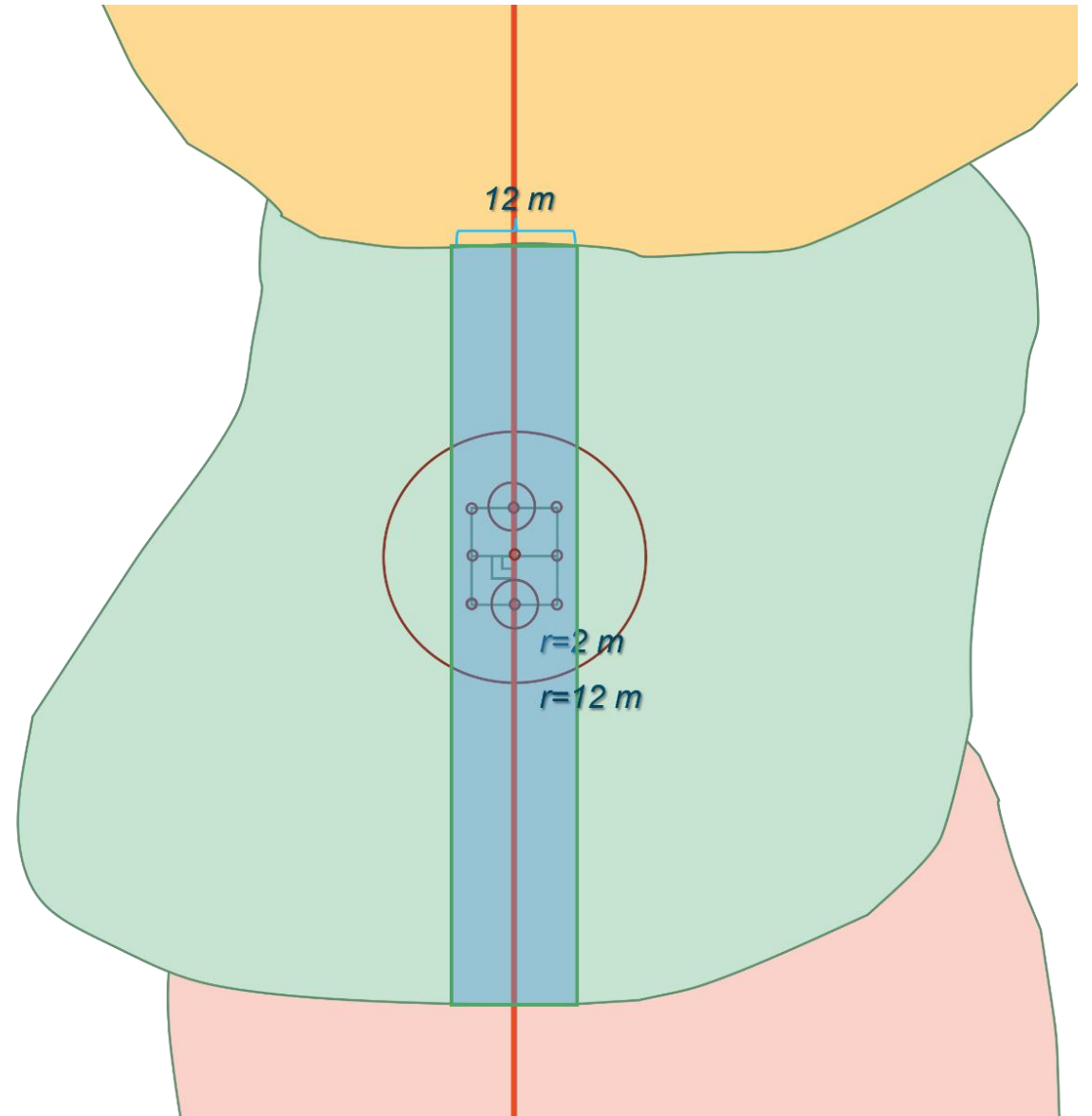
National habitat type monitoring starting in 2027

- Nationwide habitat type monitoring
 - Stratified random sampling using preliminary geoinformation
 - Field transects + plots
- Focus on terrestrial habitat types
 - Marine habitat types have their own monitoring scheme
- Precision positioning of plots
 - Enables linkage with RS/EO datasets



Measurement units

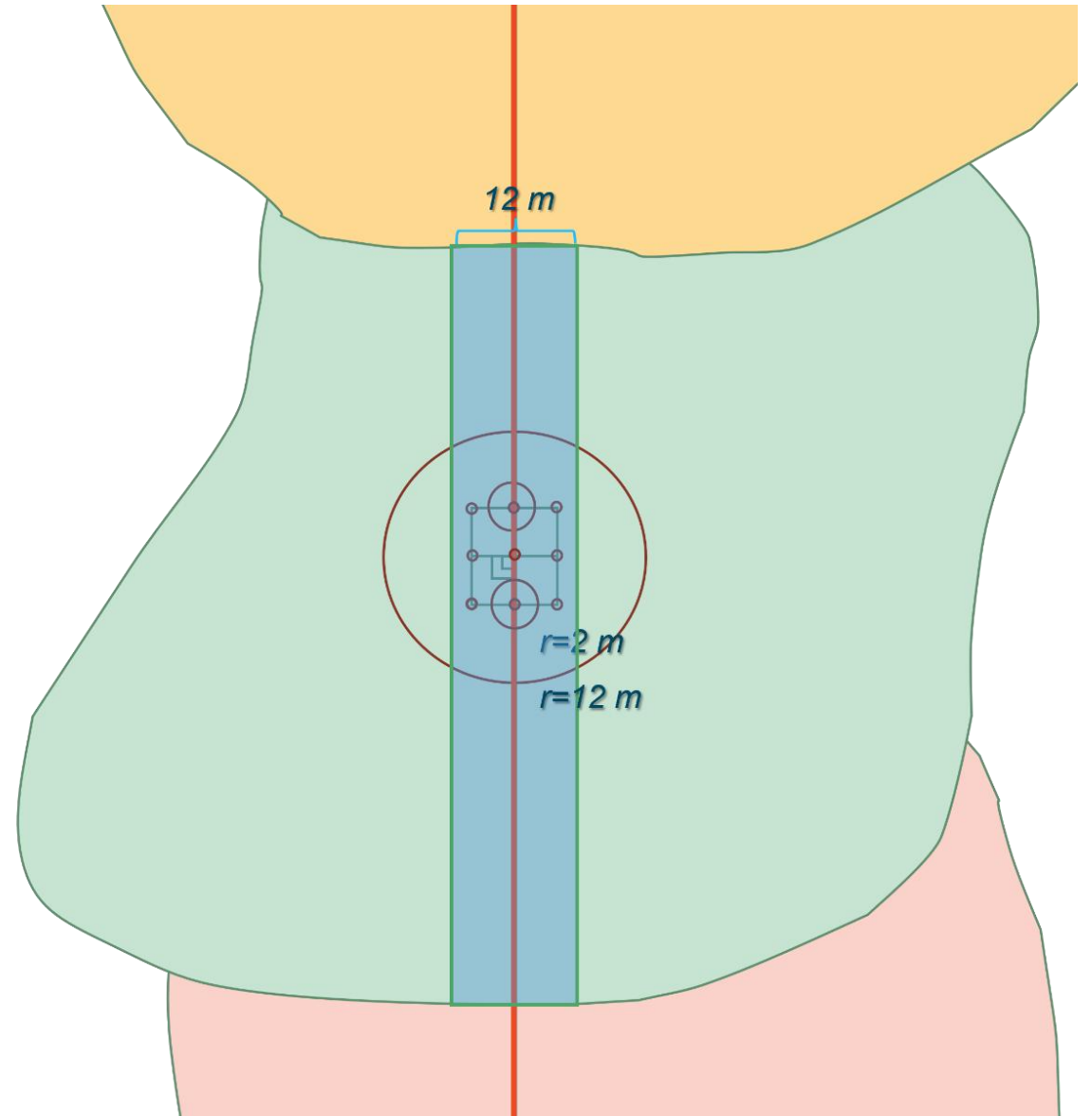
- Transect
 - *Habitat type (Annex I and Finnish system)*
 - ...
- Lane (width = 12 m)
 - *Deadwood*
 - *Human influence and natural disturbances*
 - ...
- Vegetation plots
 - *Presence/absence/frequency information on plant species*
 - *Water table level on peatland*
 - ...
- Circular plots ($r = 2\text{--}12\text{ m}$)
 - *Living trees, seedlings, and shrubs*
 - *Other indicators of ecological quality of living trees (cavity trees etc.)*
 - ...



Measurement units

Extent

- Transect
 - *Habitat type (Annex I and Finnish system)*
 - ...
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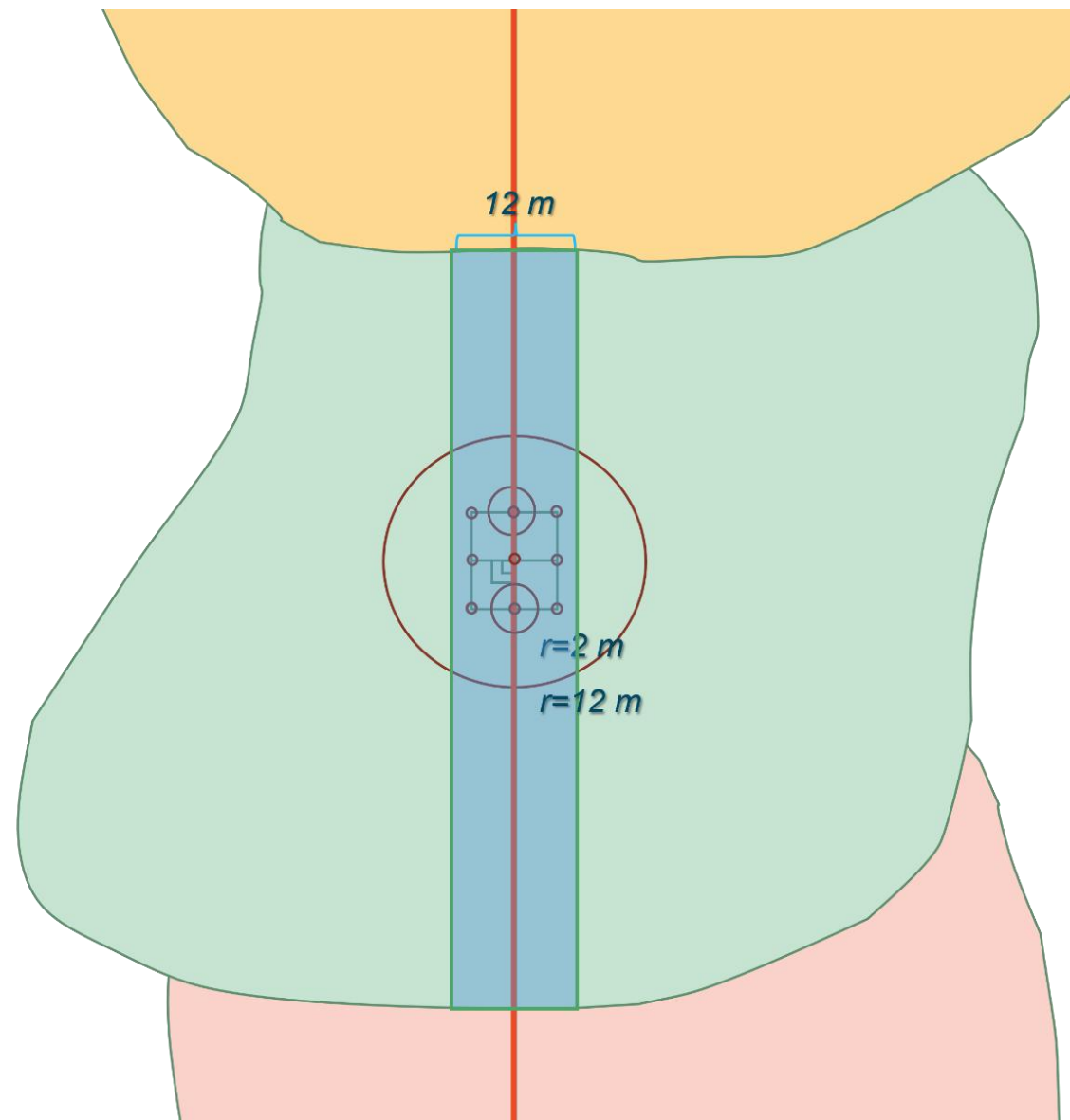
Measurement units

Extent

- Transect
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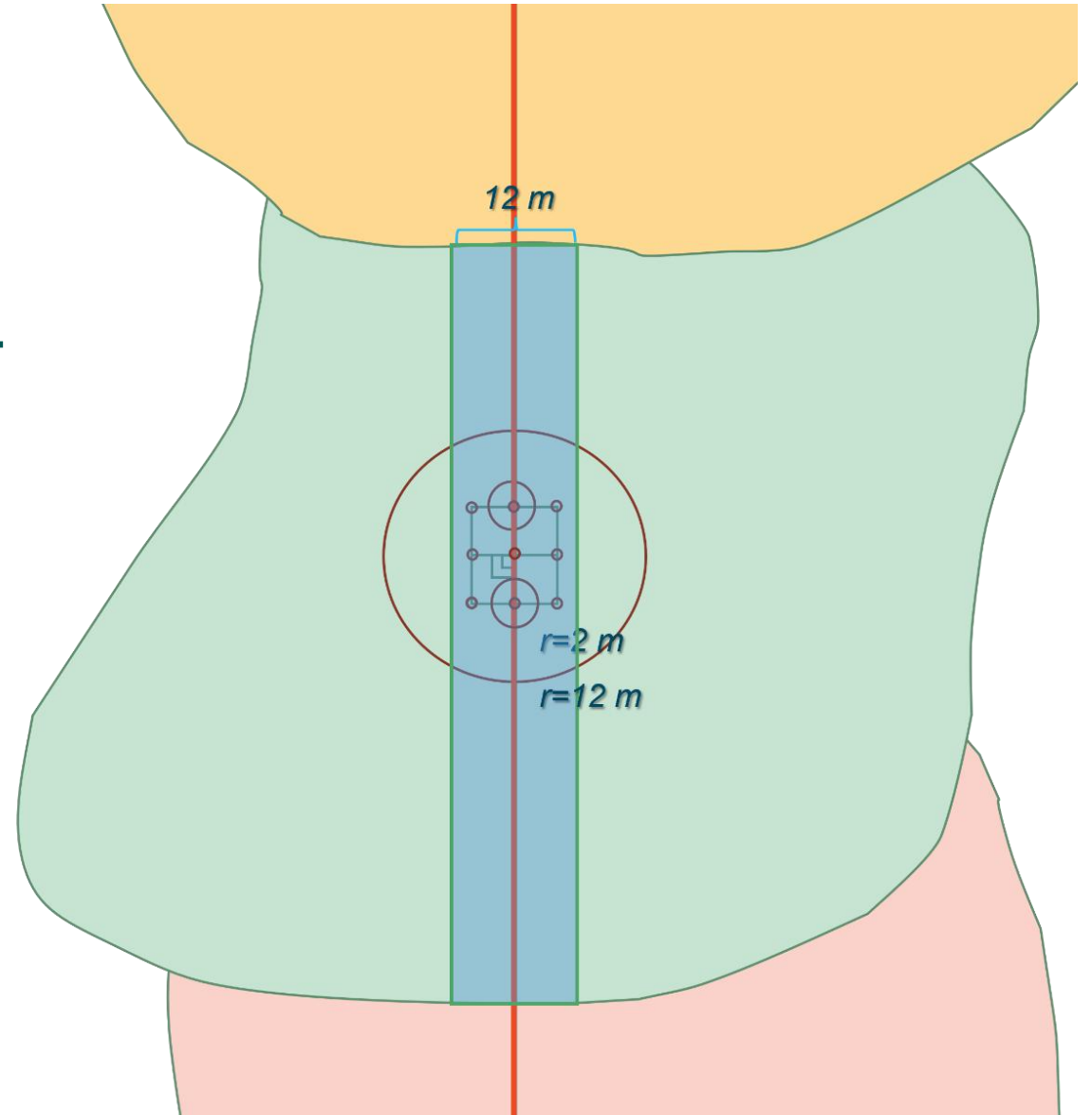
Quality

- Lane (width = 12 m)
 - *Deadwood*
 - *Human influence and natural disturbances*
 - ...
- Vegetation plots
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Estimates for habitat types

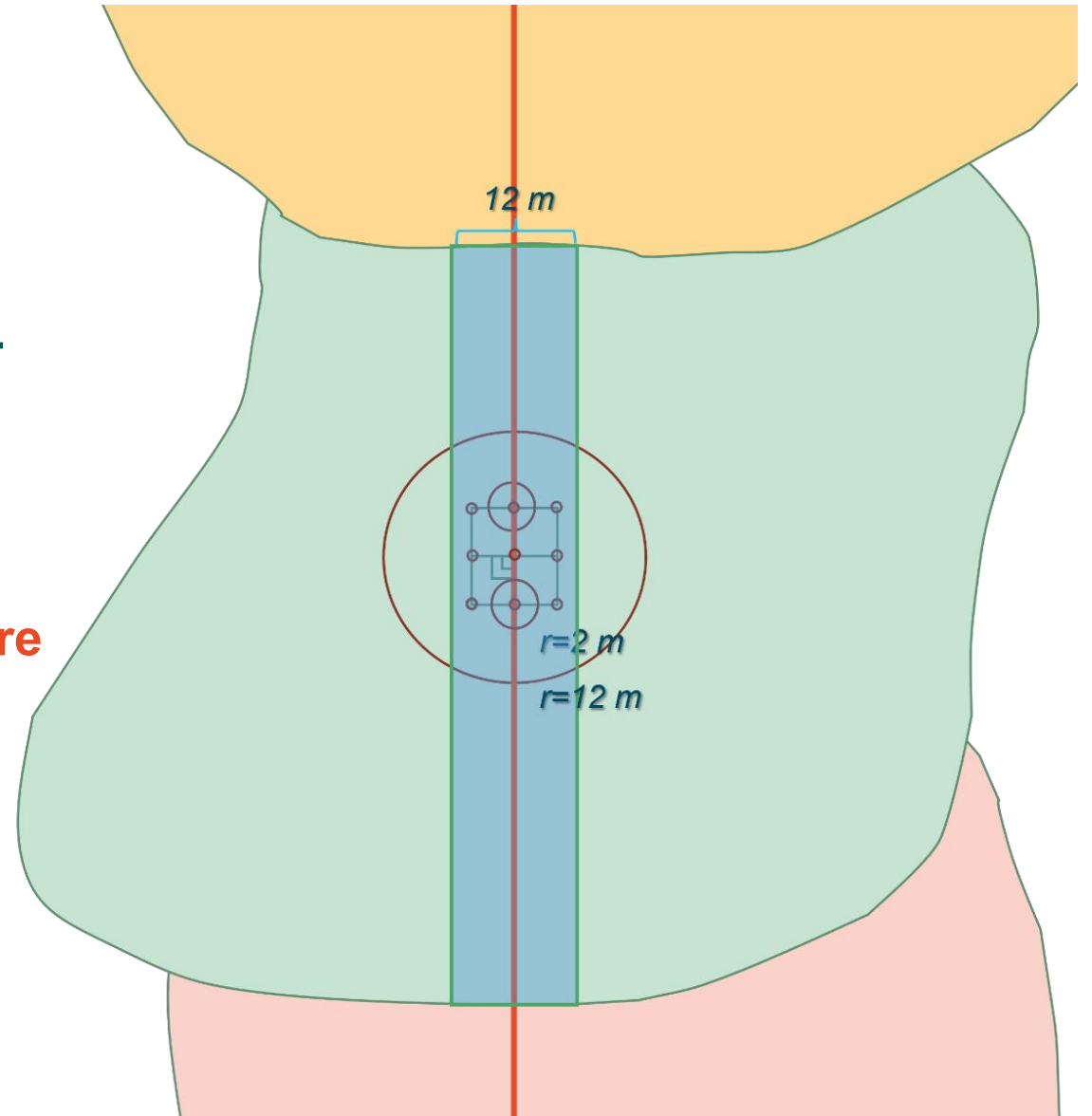
- The system enables estimates of habitat type coverage and quality at the national level



Estimates for habitat types

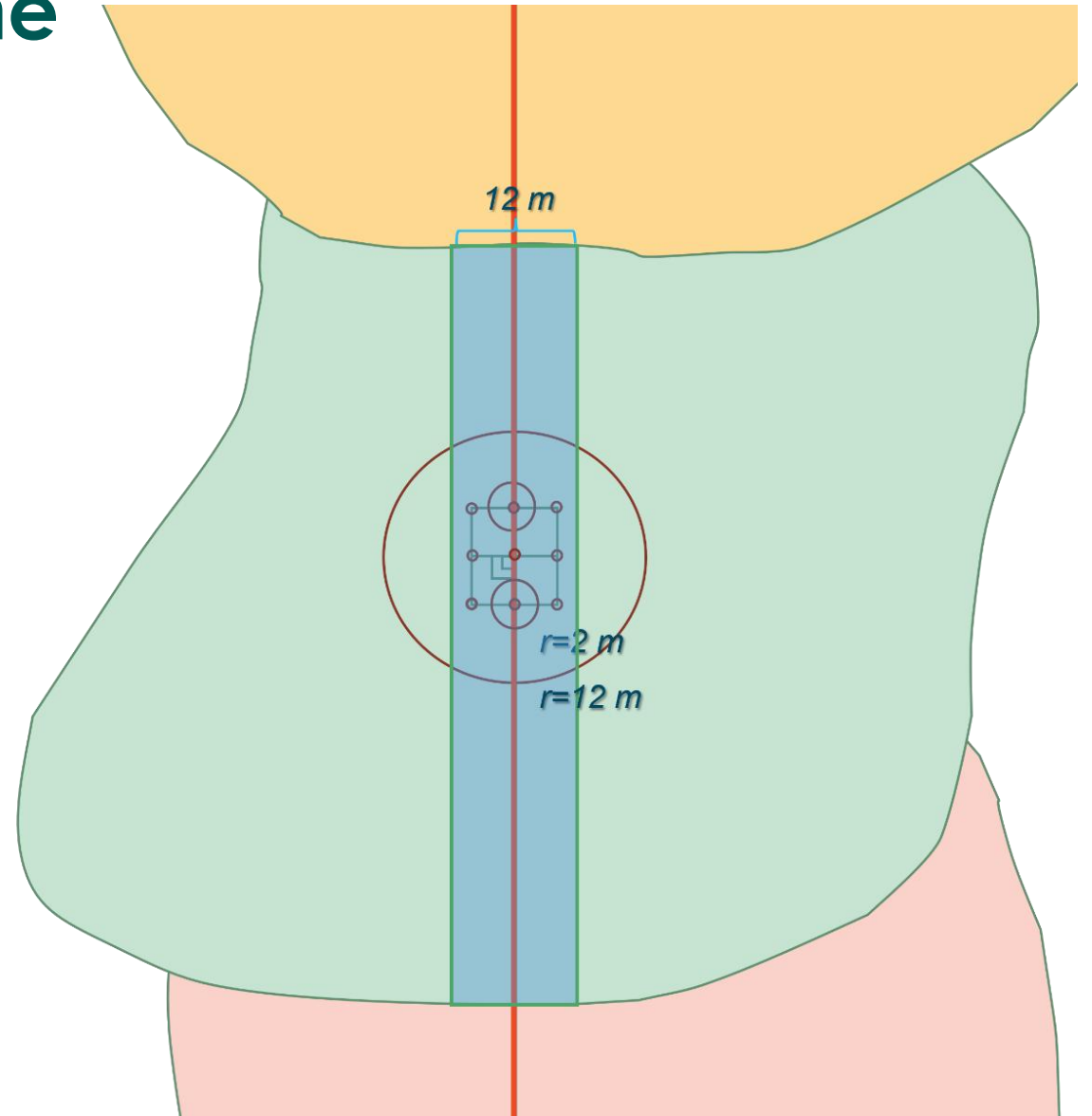
- The system enables estimates of habitat type coverage and quality at the national level

But how to estimate where the habitat patches are and what is the ecological condition?



A simple plan for upscaling the data

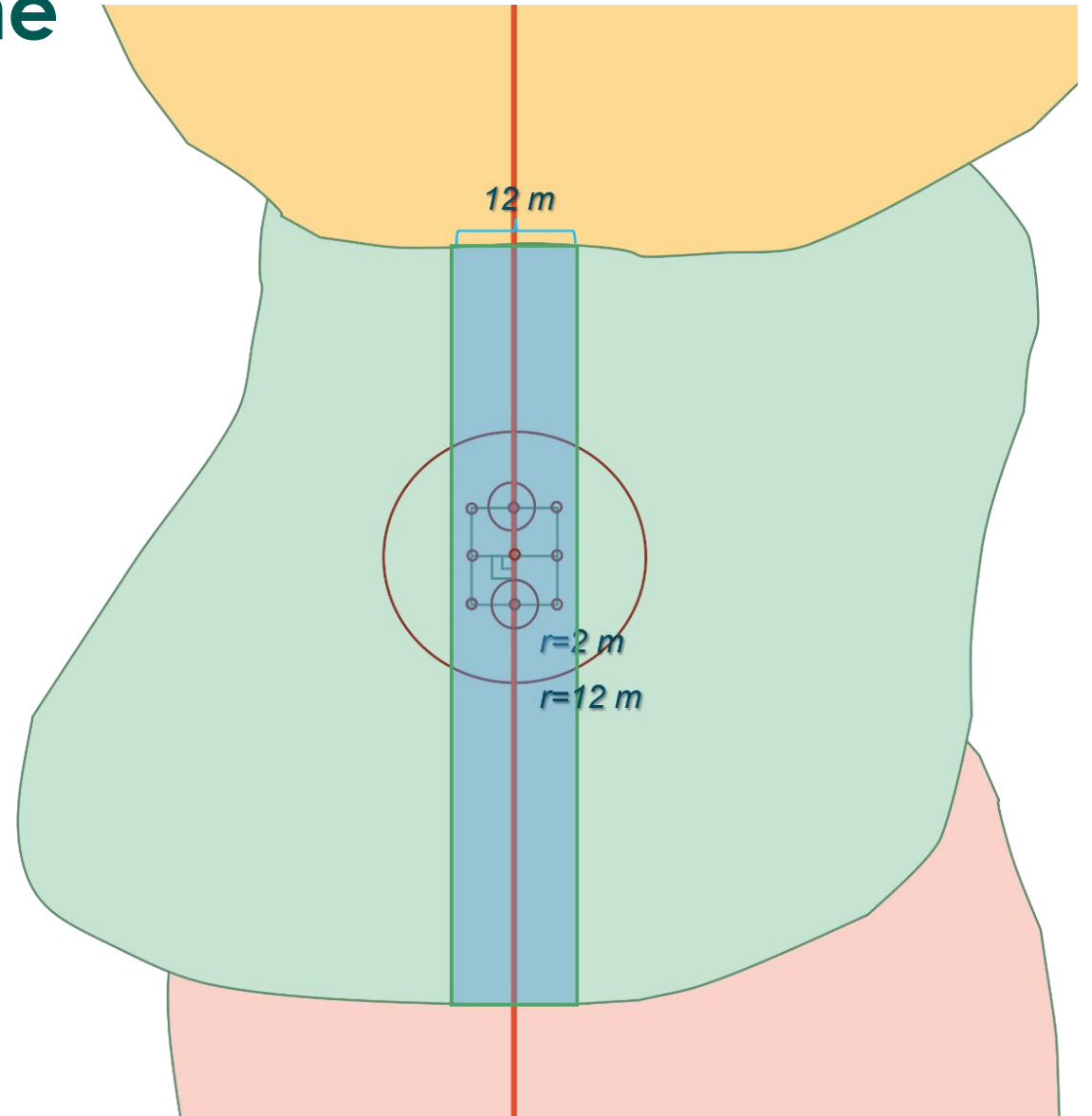
- Plenty of RS/EO-datasets available
 - Aerial images (GSD 0.25 m)
 - Airborne LiDAR (20 points/m²)
 - Different satellite sensors
- Machine and deep learning methods
 - Efficient in combining diverse field data with multidimensional RS data
 - Crave loads of training data
 - Need to be verified with field data to ensure the quality



A simple plan for upscaling the data

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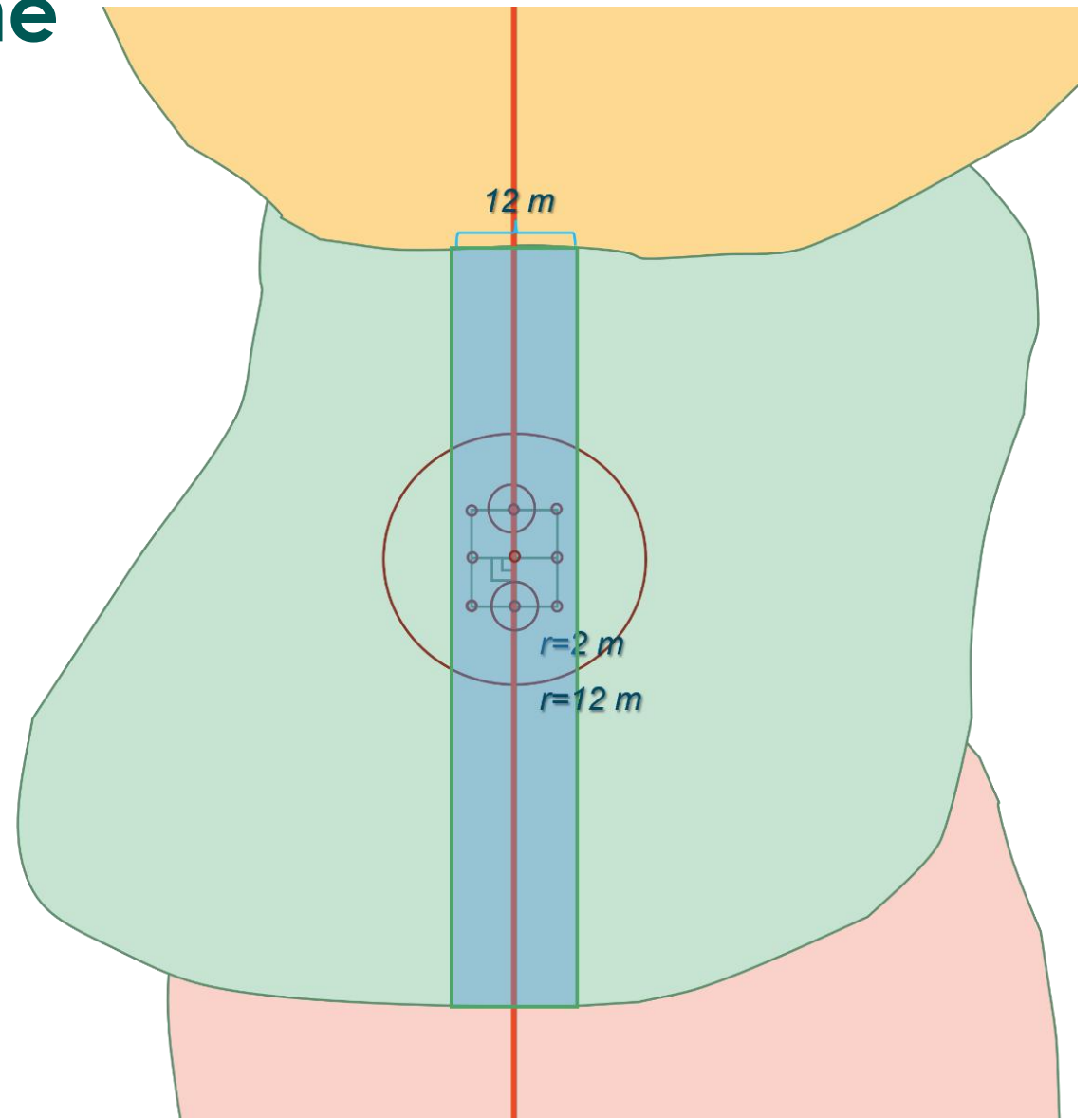
But is the field data enough for all this?



A simple plan for upscaling the data

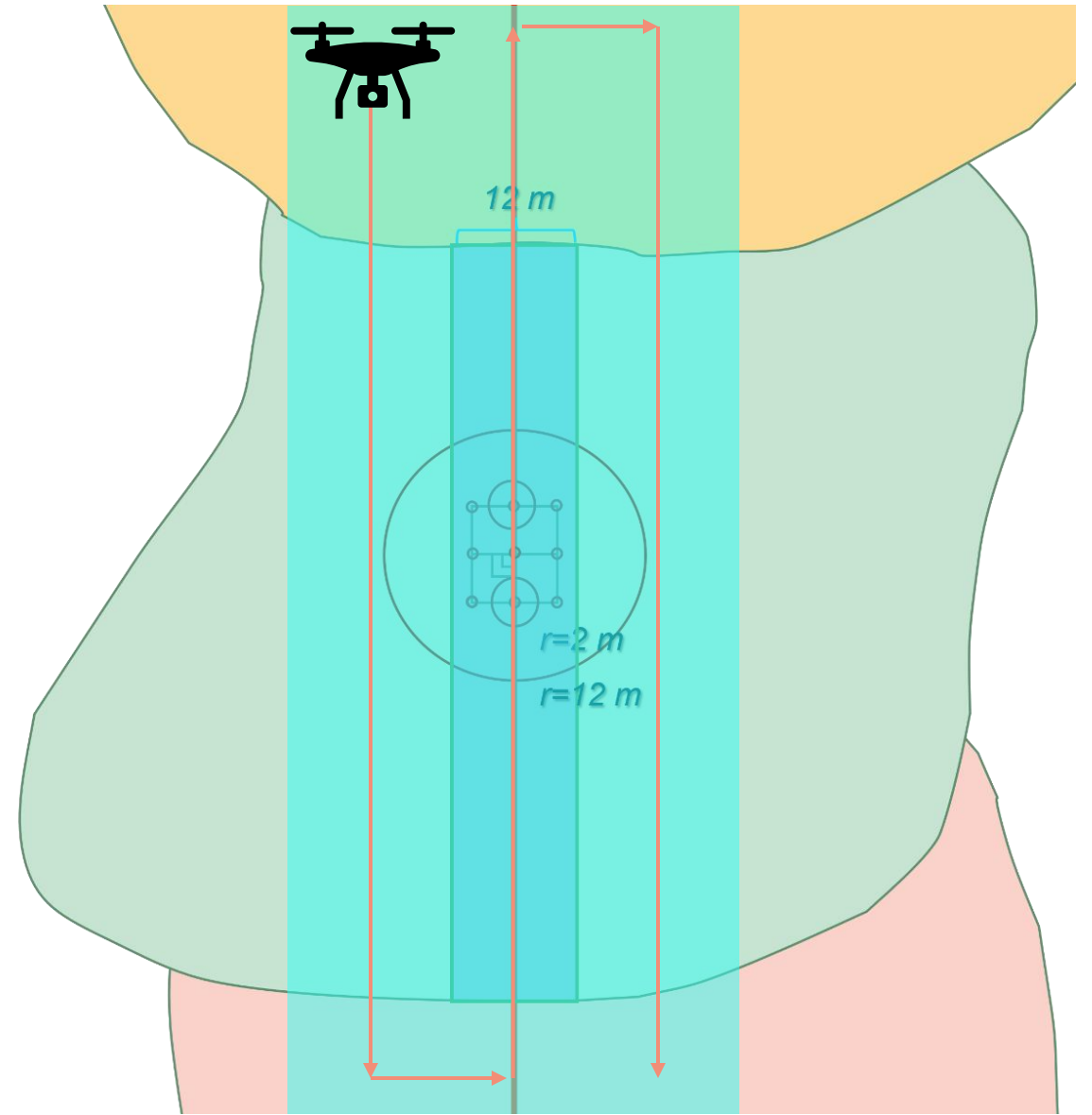
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**But is the field data enough for all this?
Probably not.**



How about first upscaling the field data?

- Using drones for capturing training data from wider areas
 - Multiple sensor options
 - Very high spatial resolution
 - Ideally would be collected simultaneously with the field data

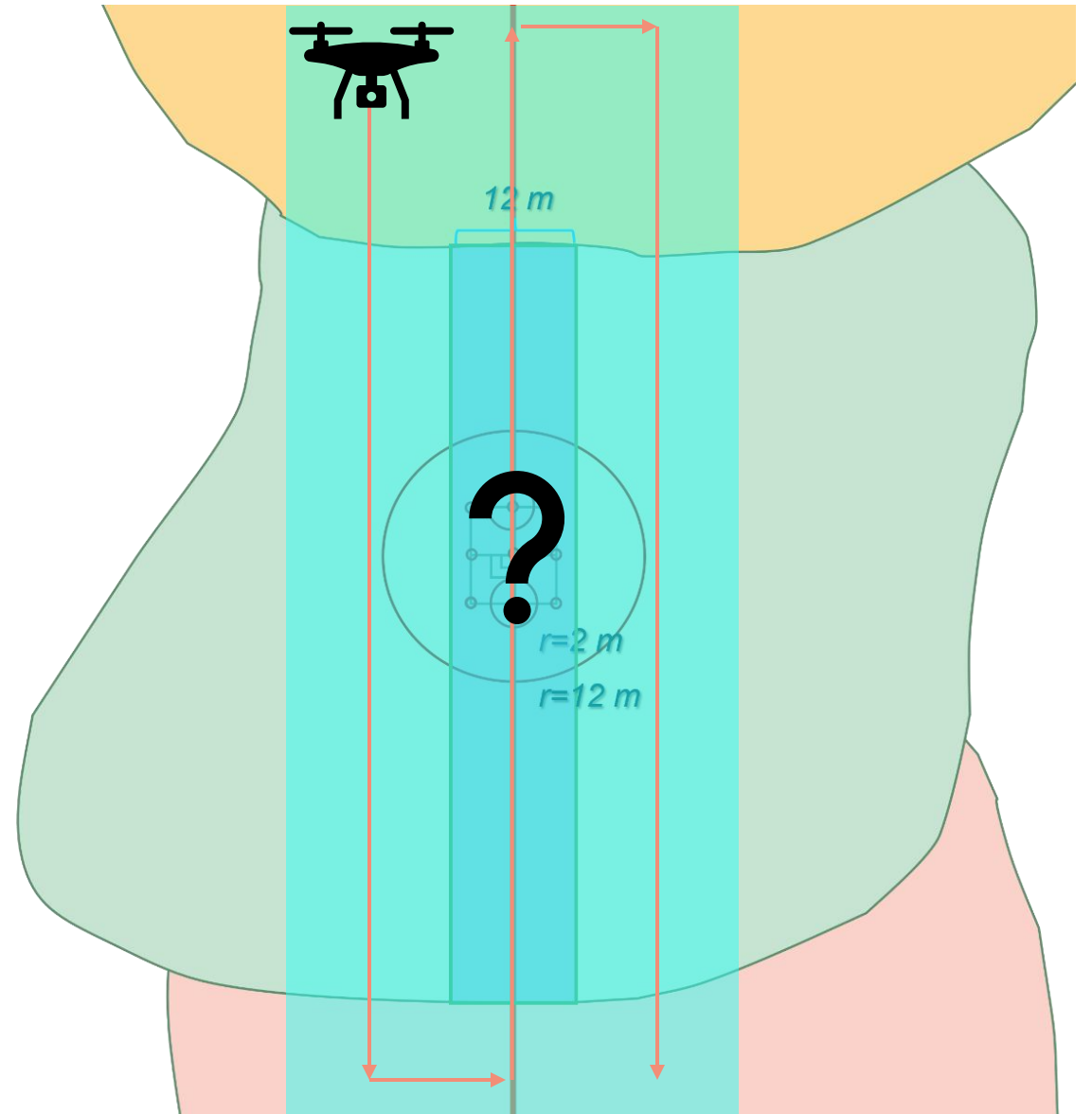


How about first upscaling the field data?

- Using drones for capturing training data from wider areas
 - Multiple sensor options
 - Very high spatial resolution
 - Ideally would be collected simultaneously with the field data

• But how to do this meaningfully and efficiently?

- Sensors
- Flight patterns and automatization
- Data processing
- What else?



Linking spatial scales:

Boosting vegetation monitoring performance with
drone- and satellite data

Hans Gardfjell, Arvid Sjöberg

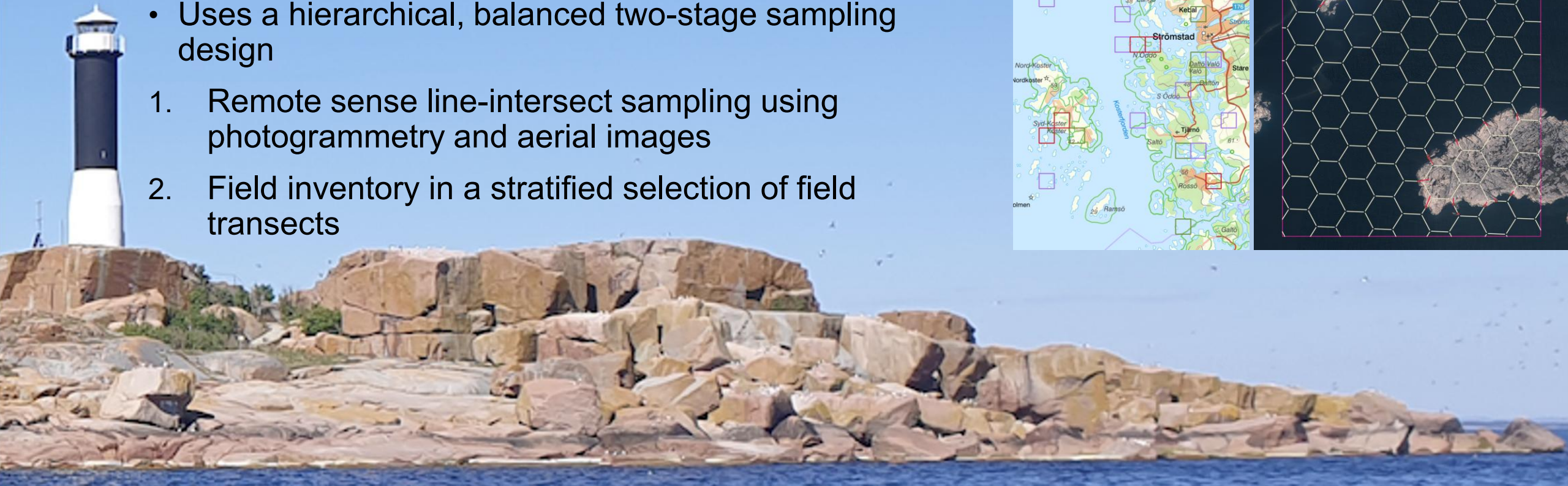
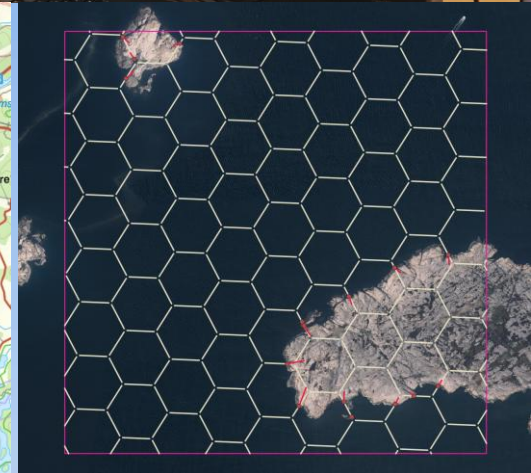
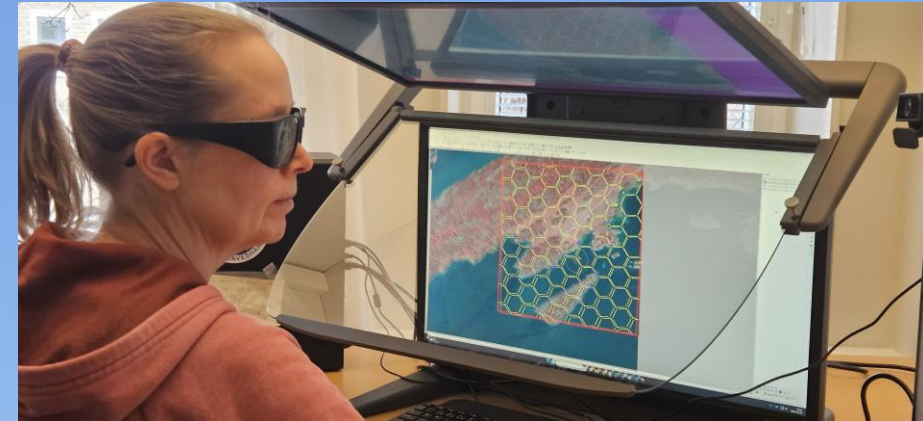


BioMonWeek

2026

Swedish seashore inventory

- Started as a LIFE+ Nature project in 2012
- Coastline 45 000 km, shore area 600 km²
- Surveys 10 coastal Annex I habitats plus 7 coastal dune habitats
- Uses a hierarchical, balanced two-stage sampling design
 1. Remote sense line-intersect sampling using photogrammetry and aerial images
 2. Field inventory in a stratified selection of field transects

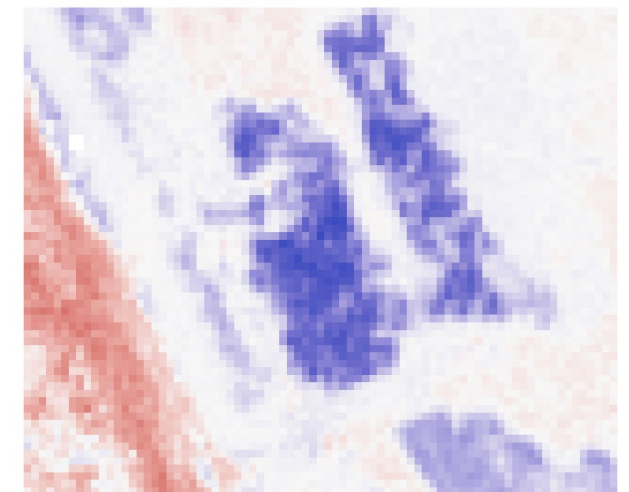


Sentinel 2 monitoring of coastal dunes

- Building data pipe-lines for monitoring of all coastal dunes using openEO and Sentinel 2 sensor data
- Using a 'complete' data set of known coastal dunes polygons (both inside and outside Natura 2000 areas)
- Building monthly time series for detecting changes
- Restoration activities shows up clearly
- Hopefully also more gradually diffuse changes, like increase in shrubs, and vegetation cover
- Next step, coastal meadows and salt marshes



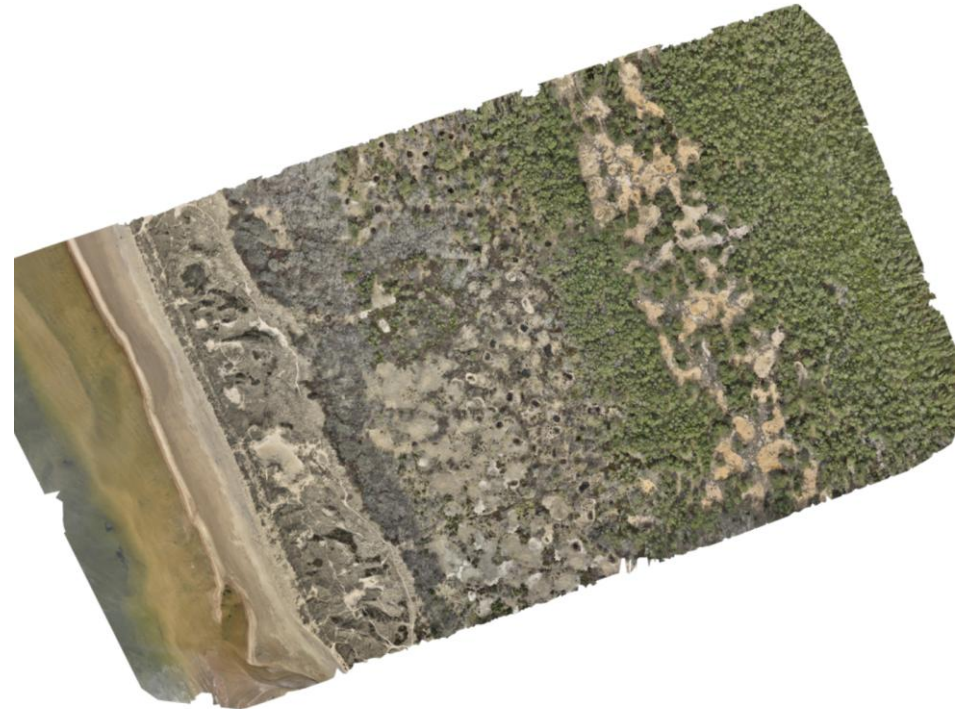
NDVI change analysis April 2017 - April 2016
2017 - 2016



NDVI diff
-0.6 -0.3 0.0 0.3 0.6

Drones improving spatial resolution

- In our field sampling programs, species and vegetation data are collected in sampling plots of the sizes from 0.25 – 1000 m²
- A larger spatial coverage could improve the understanding of the vegetation structure and we are currently starting to build a collection of drone imagery from coastal dunes.
- Drone images from different years allows for detailed change analysis of shrubs, dwarf-shrubs, and other functional plant groups
- Better ground truth calibration data for satellite sensor-based vegetation models



ELEVATE

Implementing new technologies into the Swedish alpine vegetation monitoring program NILS

Focusing on drones/UAS and deep neural networks

Project financed by Naturvårdsverket (Swedish EPA)



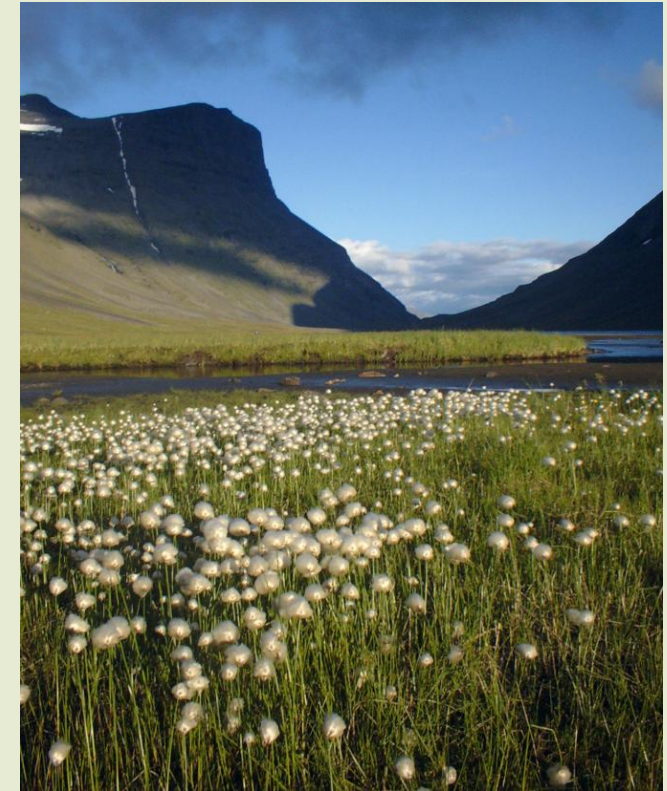
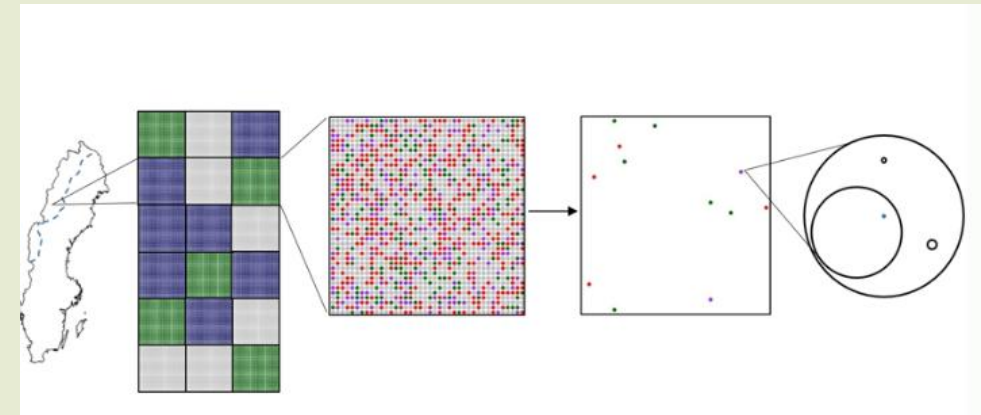
NILS Alpine Inventory

Two stage inventory design:

1. Model based identification of interesting habitats
2. Field inventory by personnel

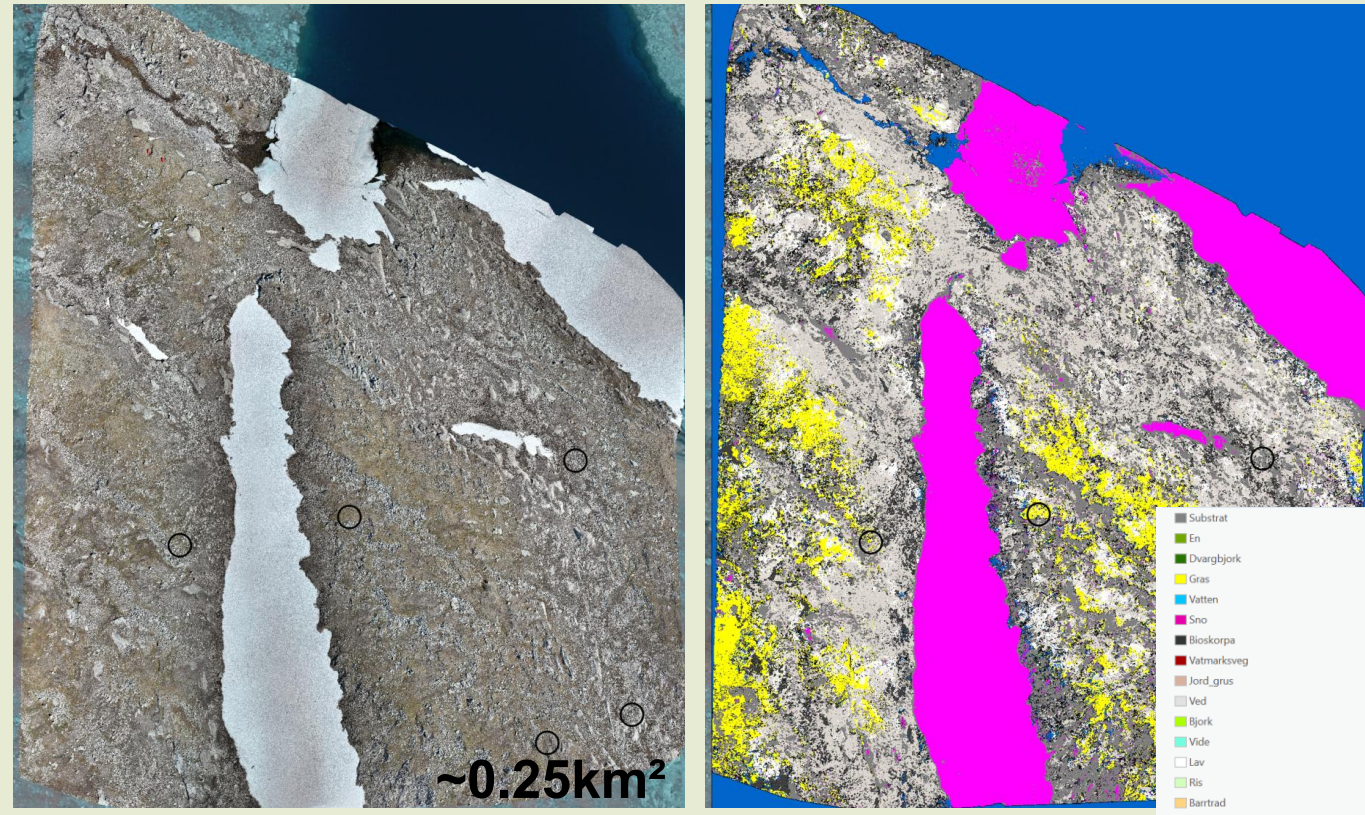
The design is tested and reliable, however limited in spatial resolution.

Drones since 2021: ca 200 flights.



Drones and deep neural networks

1. Compiling orthomosaics from drone images
2. Annotating class training polygons (15 classes)
3. DNN training and inference pipeline
4. Highly detailed segmented vegetation map



Drones and deep neural networks

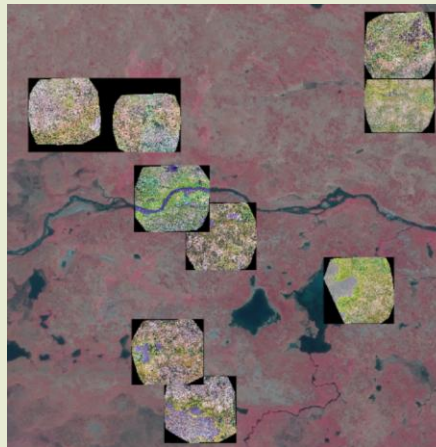
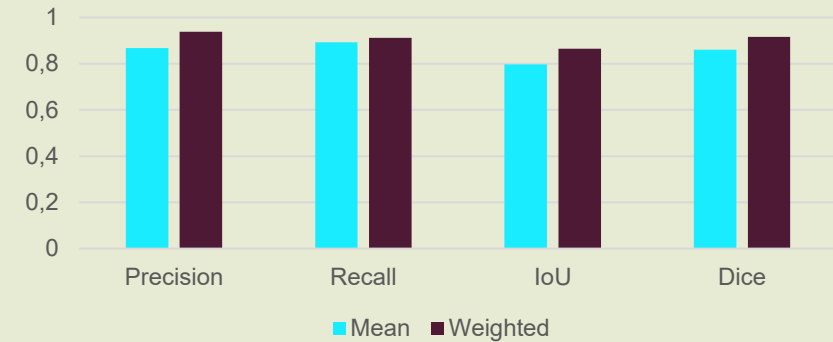
High metric scores on local data.

Lower on “regional” data.

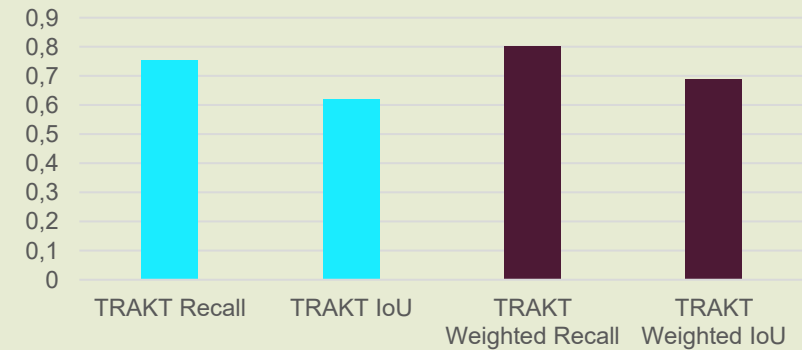
Transferability of models is a weak-point



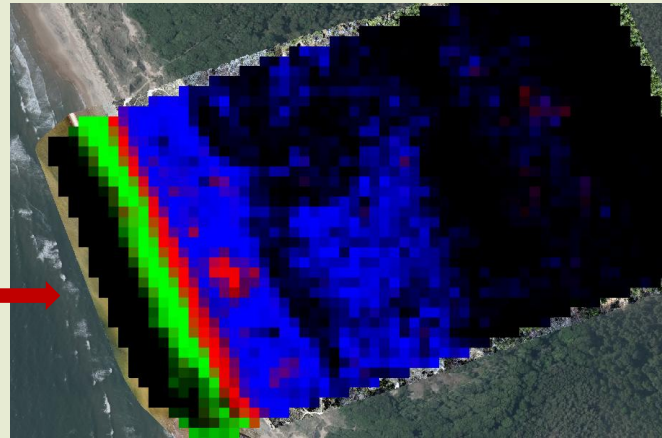
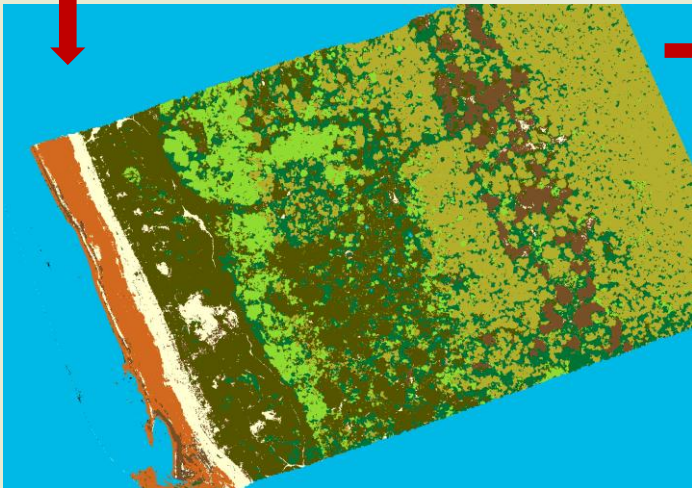
Local mean performance (15 classes)



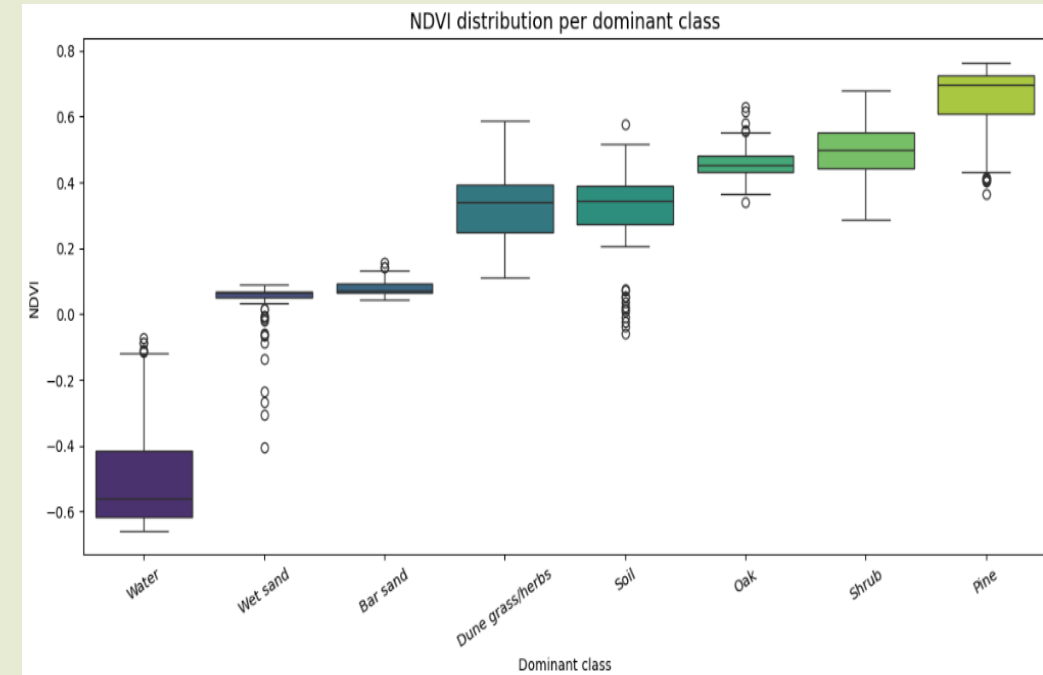
Tract (1x1km) cross-val performance



Segmenting dune vegetation: A mini-case study



Class fractions within S2 pixels (10x10m NDVI)



Using drone segmentation models we can differentiate dune vegetation using Sentinel-2 NDVI data.

Thank you!



SCIENCE AND
EDUCATION
**SUSTAINABLE
LIFE**