biodiversa+
European Biodiversity Partnership

Webinar “Discovering remote sensing techniques for biodiversity monitoring”

Task 2.3.1 “Novel technologies and approaches”

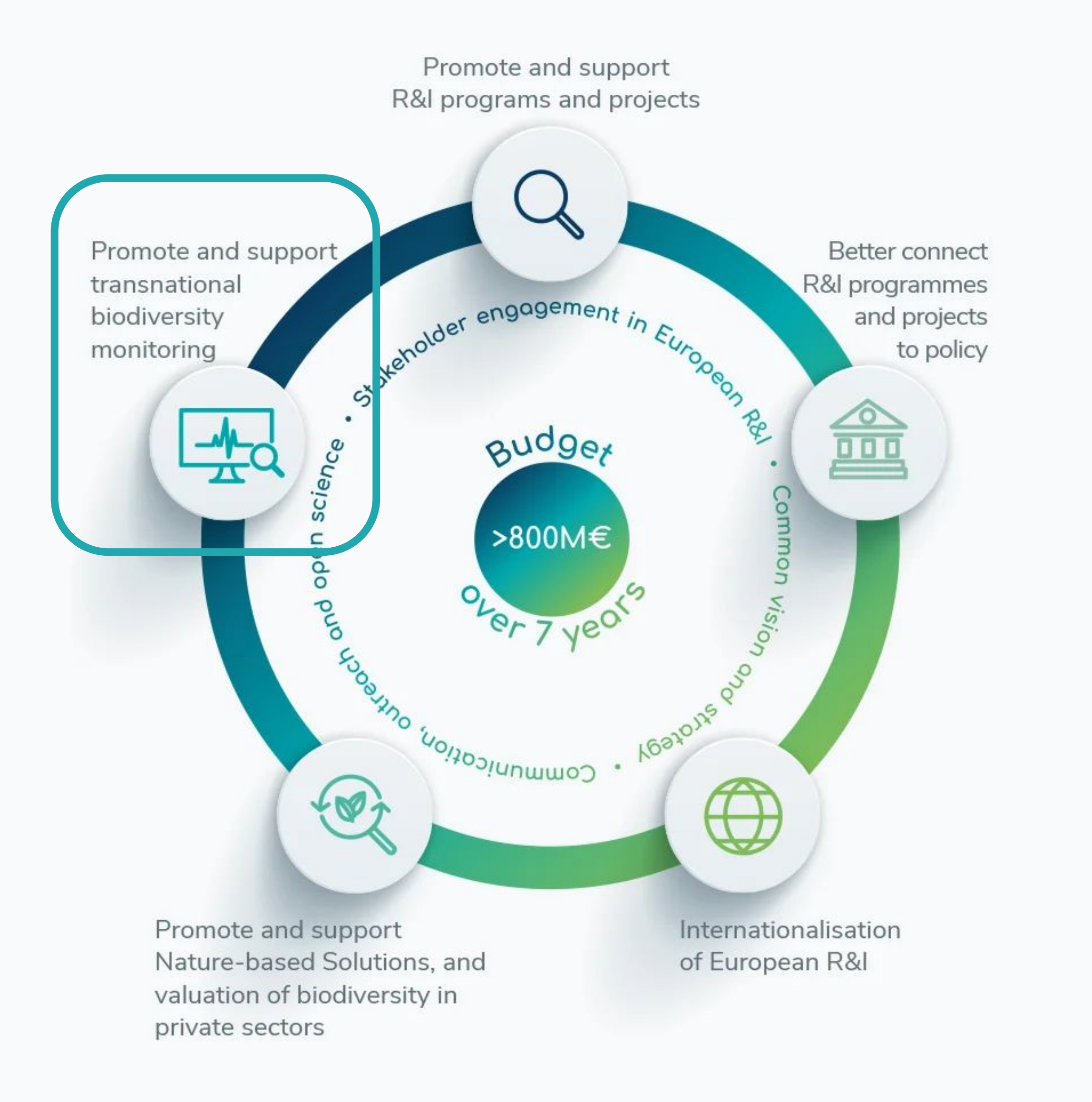
Organized by DTER (Catalonia) and Marlies Laethem (OT Biodiversa+)

October 30th, 2025

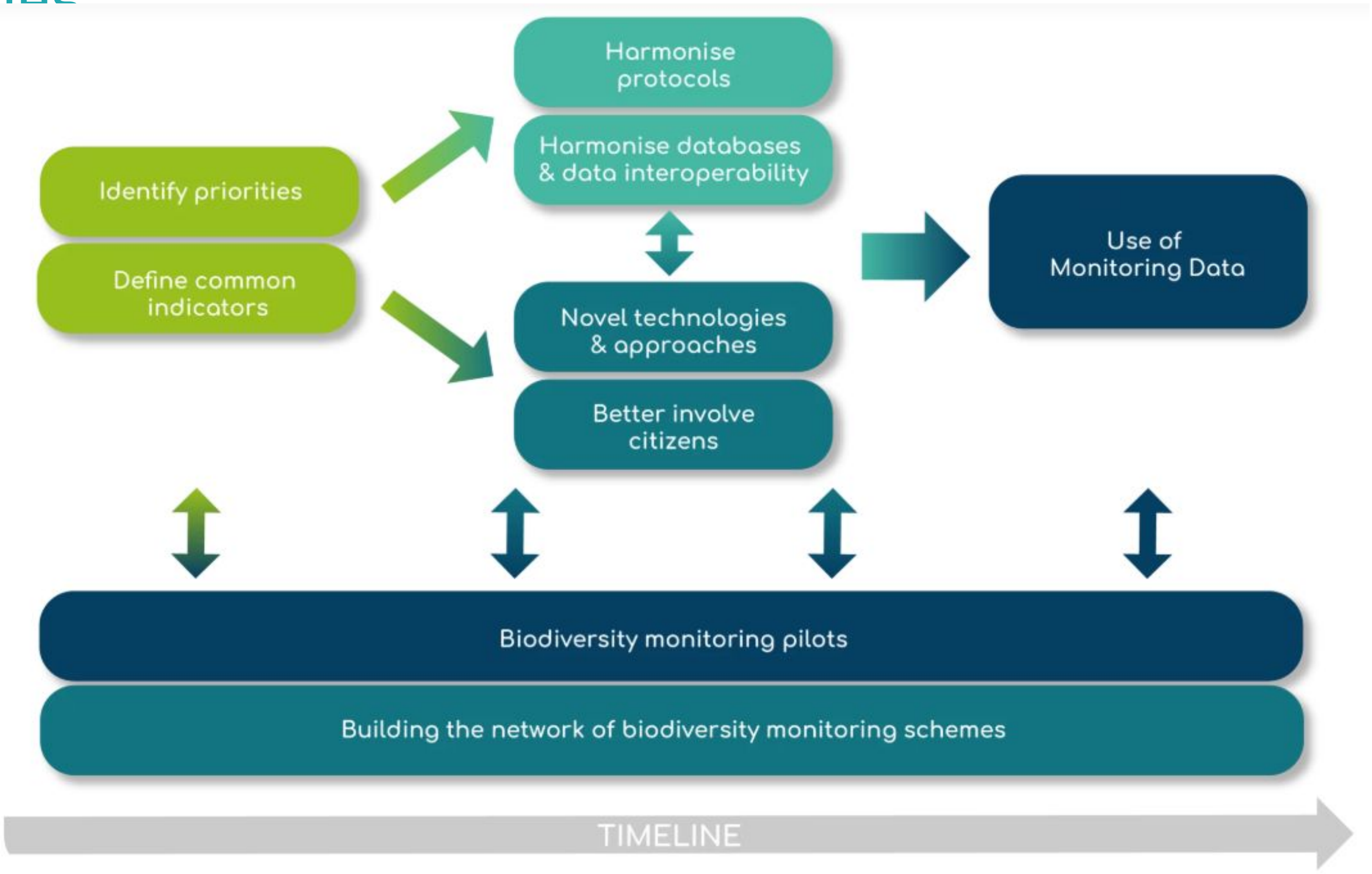
About Biodiversa+

Biodiversa+ is the European Biodiversity Partnership supporting excellent research on biodiversity with an impact on policy and society.

Workpackge 2: Set up a network of harmonised schemes to improve monitoring of biodiversity and ecosystem services across Europe



Biodiversa+ Workpackage 2, Task 2.3.1"Novel technologies and approaches"



Biodiversa+ Workpackage 2, Task 2.3.1"Novel technologies and approaches"

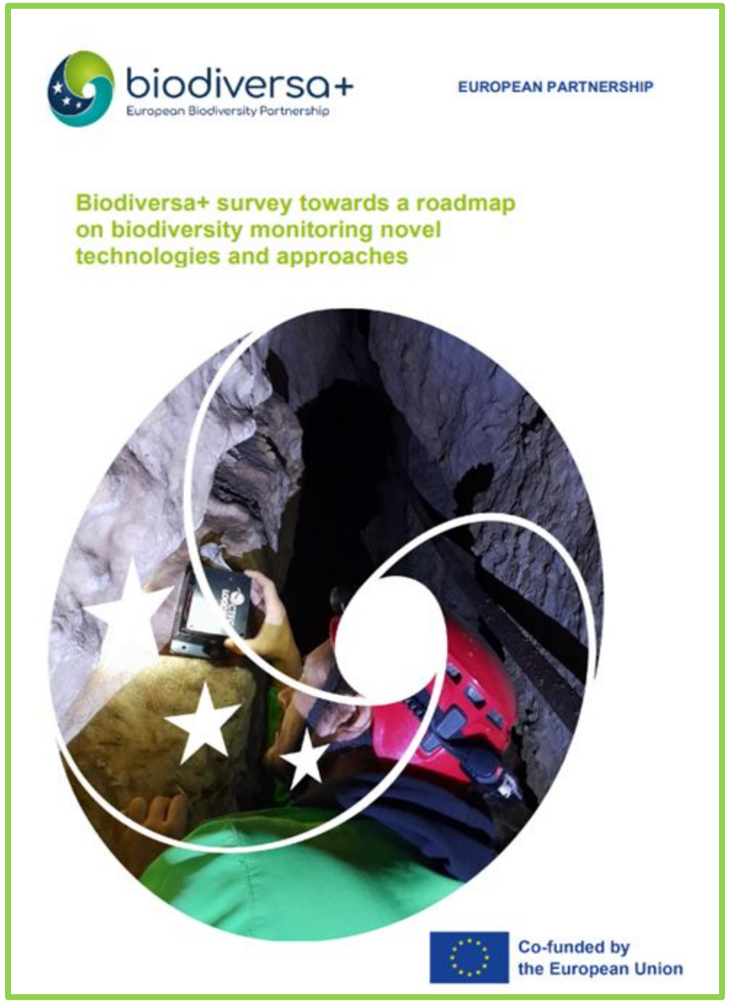
Survey of novel technologies monitoring across partners

- Deployment state / interest
- Targeted taxa and EBVs
- Challenges and constrains

Series of webinars on novel technologies for biodiversity monitoring

- Image-based approaches
- Environmental DNA
- Bioacoustics
- Sensor networks

✔ More webinars to come, stay tuned!

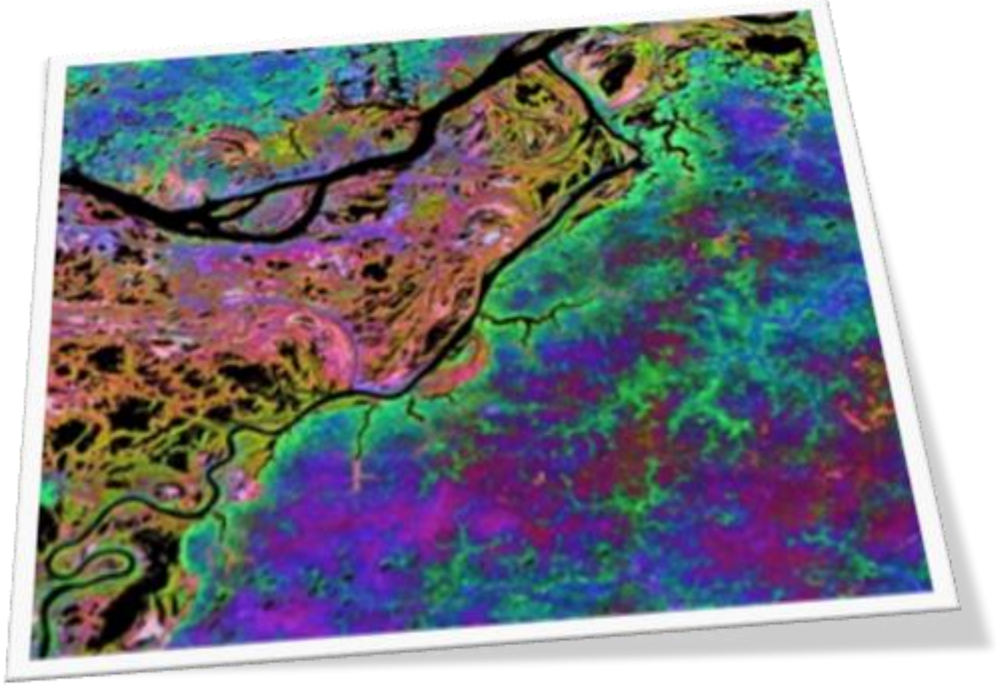


Webinar agenda

1. Introduction of the webinar and speakers.
2. Presentation by María J. Santos (University of Zurich & OBSGESSION).
3. Presentation by Sara Wiman (Biodiversa+ Habitat pilot coordinator, SEPA, Government of Sweden).
4. Questions / debate.

Remote Sensing of Biodiversity

Prof. Dr. Maria J. Santos



Webinar “Discovering remote sensing techniques for biodiversity monitoring”

Task 2.3.1 “Novel technologies and approaches”

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where we started…

Red and Photographic Infrared Linear Combinations for Monitoring Vegetation

Compton J. Tucker

(NASA-TM-79620) RED AND PHOTOGRAPHIC INFRARED LINEAR COMBINATIONS FOR MONITORING VEGETATION (NASA) 37 p HC A03/MF A01 CSCL 08F

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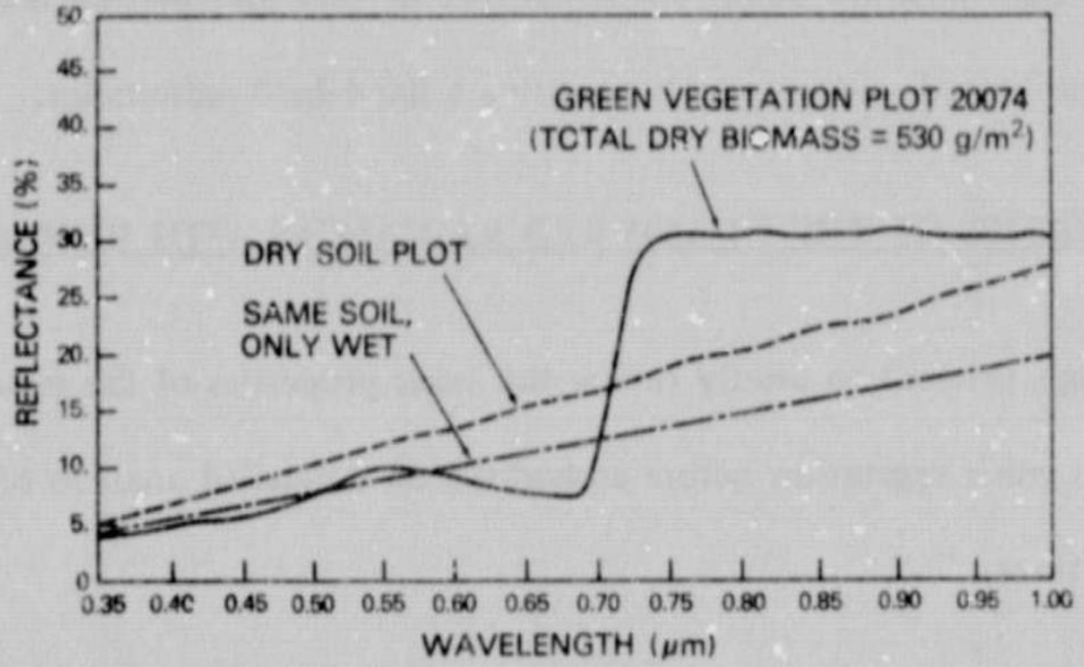
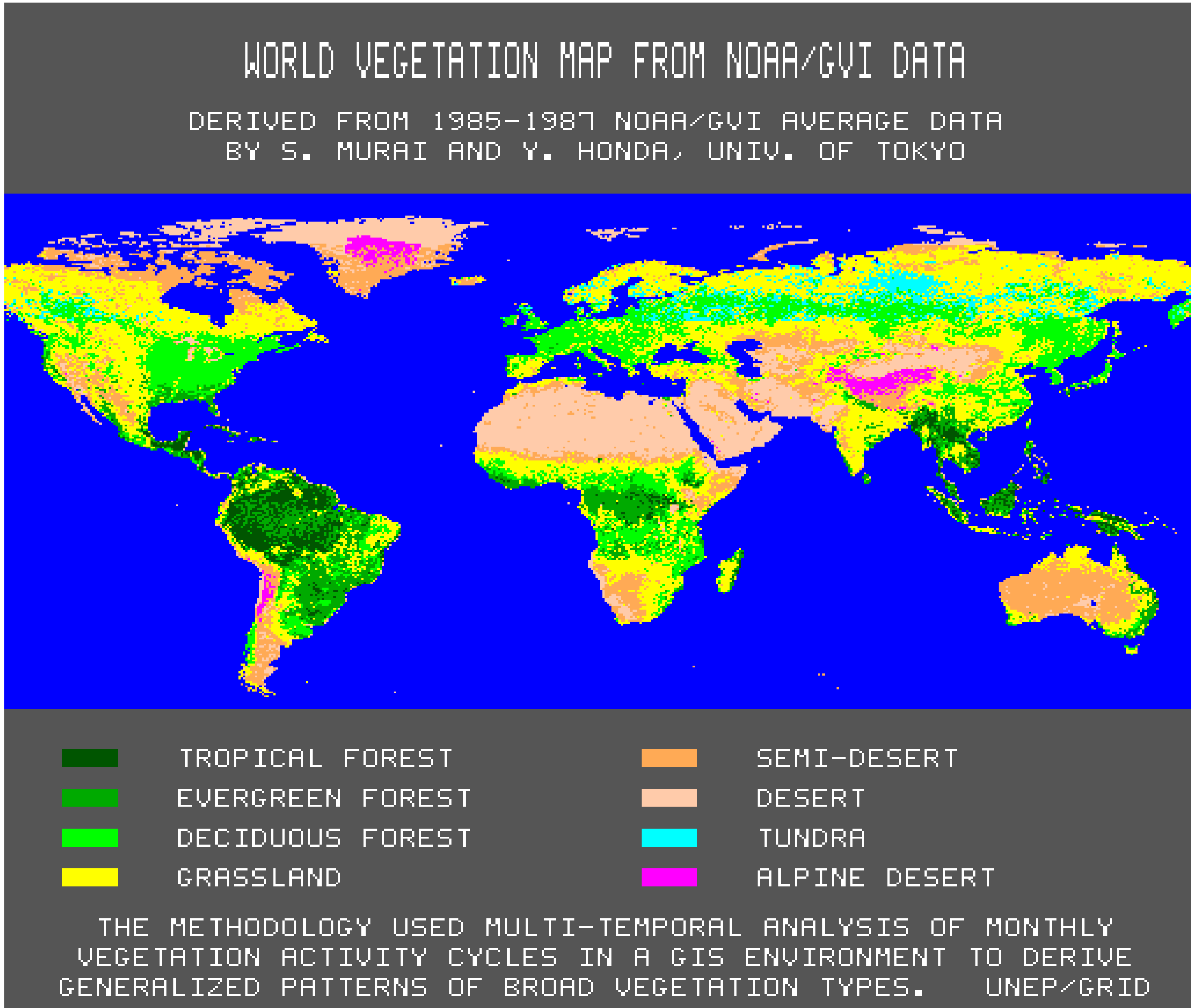
MAY 1978



Early Global Vegetation Map

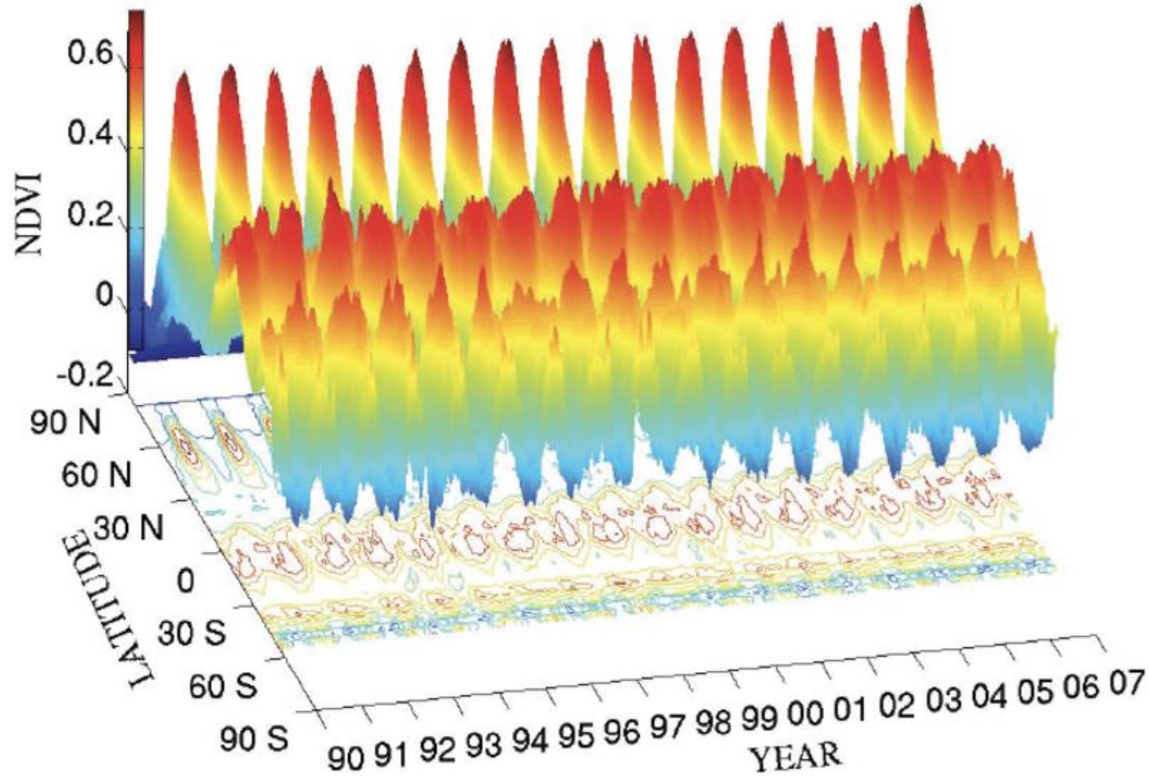
(NDVI from NOAA weather satellite)

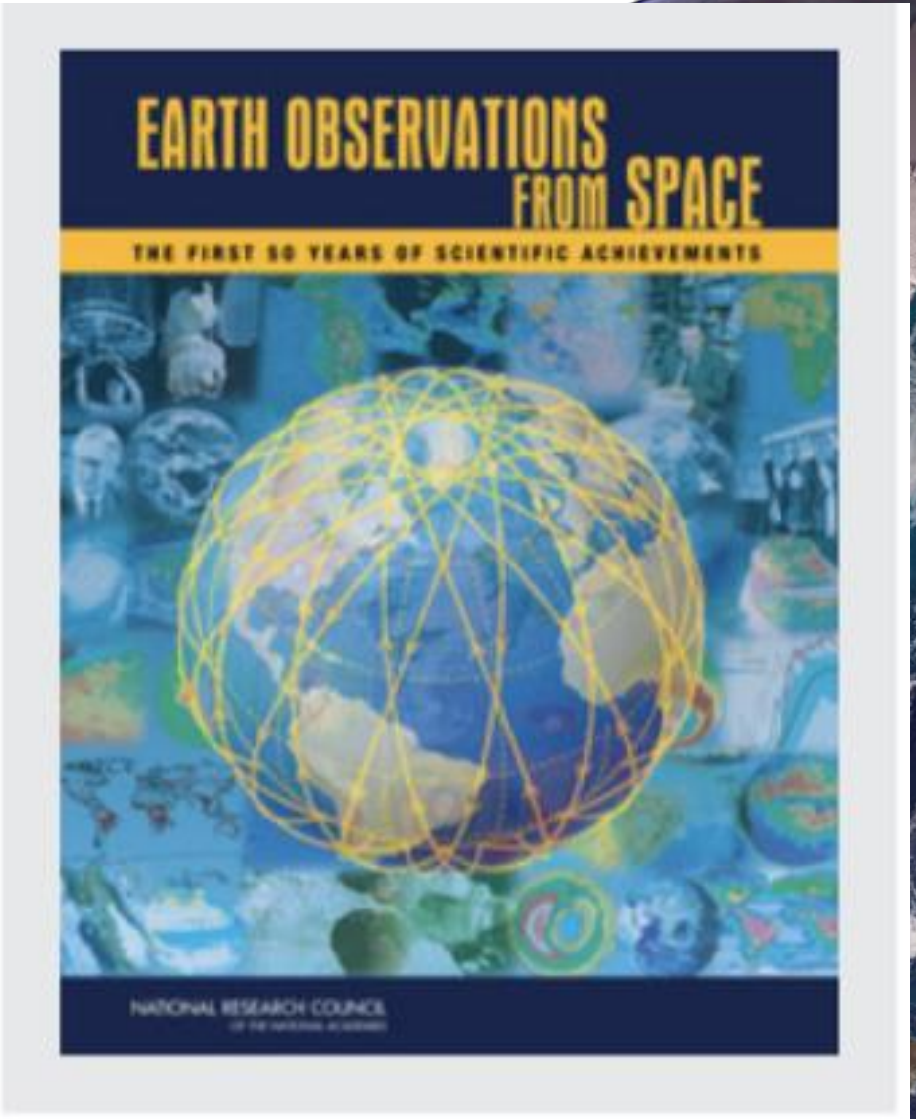


BOX 9.2
Converting Radiance to Plant Productivity

Jordan (1969) was the first to use a ratio of near-infrared and red radiation to estimate biomass and leaf area index (leaf area/ground surface area) in a forest understory. This study was quickly followed by application of near-infrared/red ratios to estimate biomass in rangelands (e.g., Pearson and Miller 1972; Rouse et al. 1973, 1974; Maxwell 1976) and was extended by Carneggie et al. (1974) to the Earth Resources Technology Satellite (ERTS-1) observations of seasonal growth, which showed that the seasonal peak in the near-infrared/red ratio coincided with maximum foliage production, thus effectively tracking the phenological cycle.

Rouse et al. (1974) introduced a spectral index, a normalized ratio that reduced illumination differences and other extrinsic effects by dividing the difference of the two bands by their sum, a ratio adopted as the normalized difference vegetation index (NDVI). A landmark paper by Tucker (1979) established linear relationships between vegetation spectral indices (ratios of visible and near-infrared bands) to leaf area and biomass. Following this paper, vegetation indices rapidly became an established method for analysis of plant biophysical properties using laboratory, field, airborne, and Landsat data. Today, nearly 2,000 papers have been published using the NDVI, and nearly 6,000 have used some type of vegetation index to study vegetation. These early studies established that red and near-infrared satellite bands could track changes in plant growth and development.





Earth Observation

1 a wealth of Earth Observation platforms

2 detailed **monitoring** of ecosystems, plant communities, and even some species

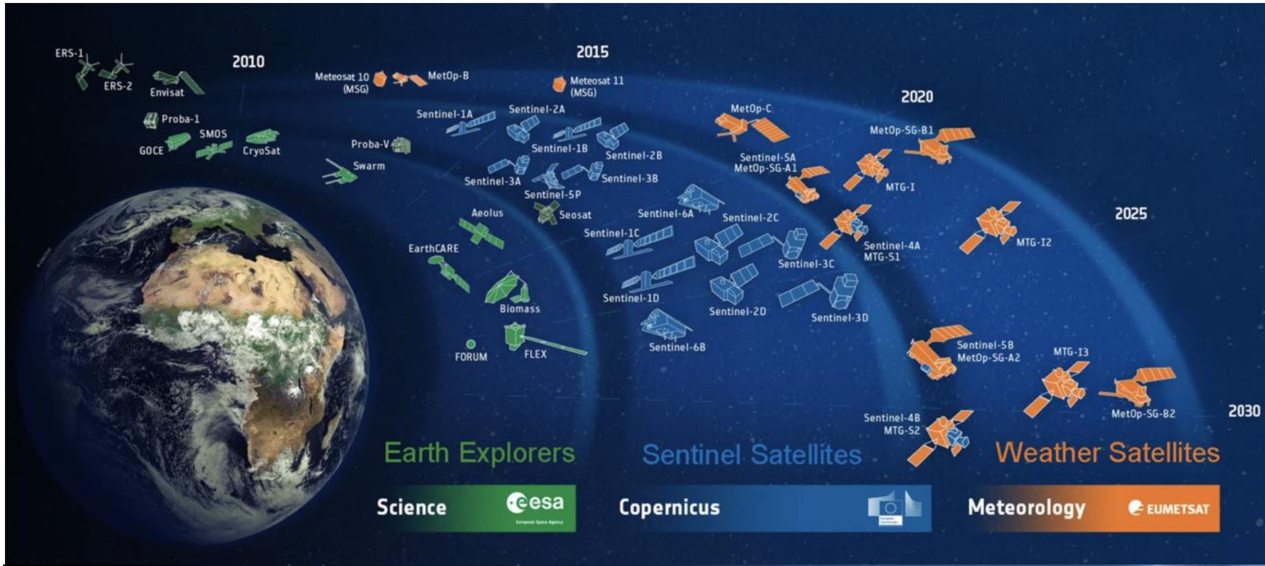
3 **ecosystem functional relationships among plant traits:** e.g. leaf mass area (LMA), total nitrogen content, and leaf area index (LAI)

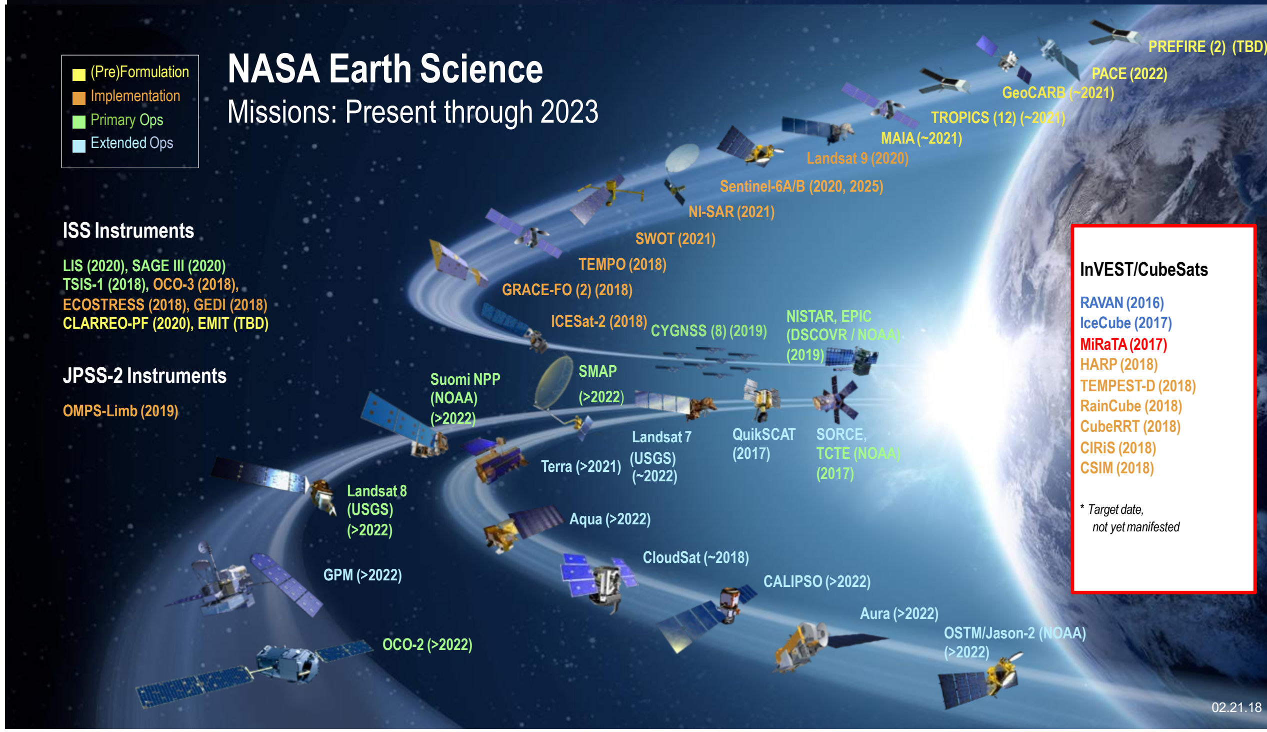
4 **physiological processes:** photosynthesis, transpiration and respiration and stress detection

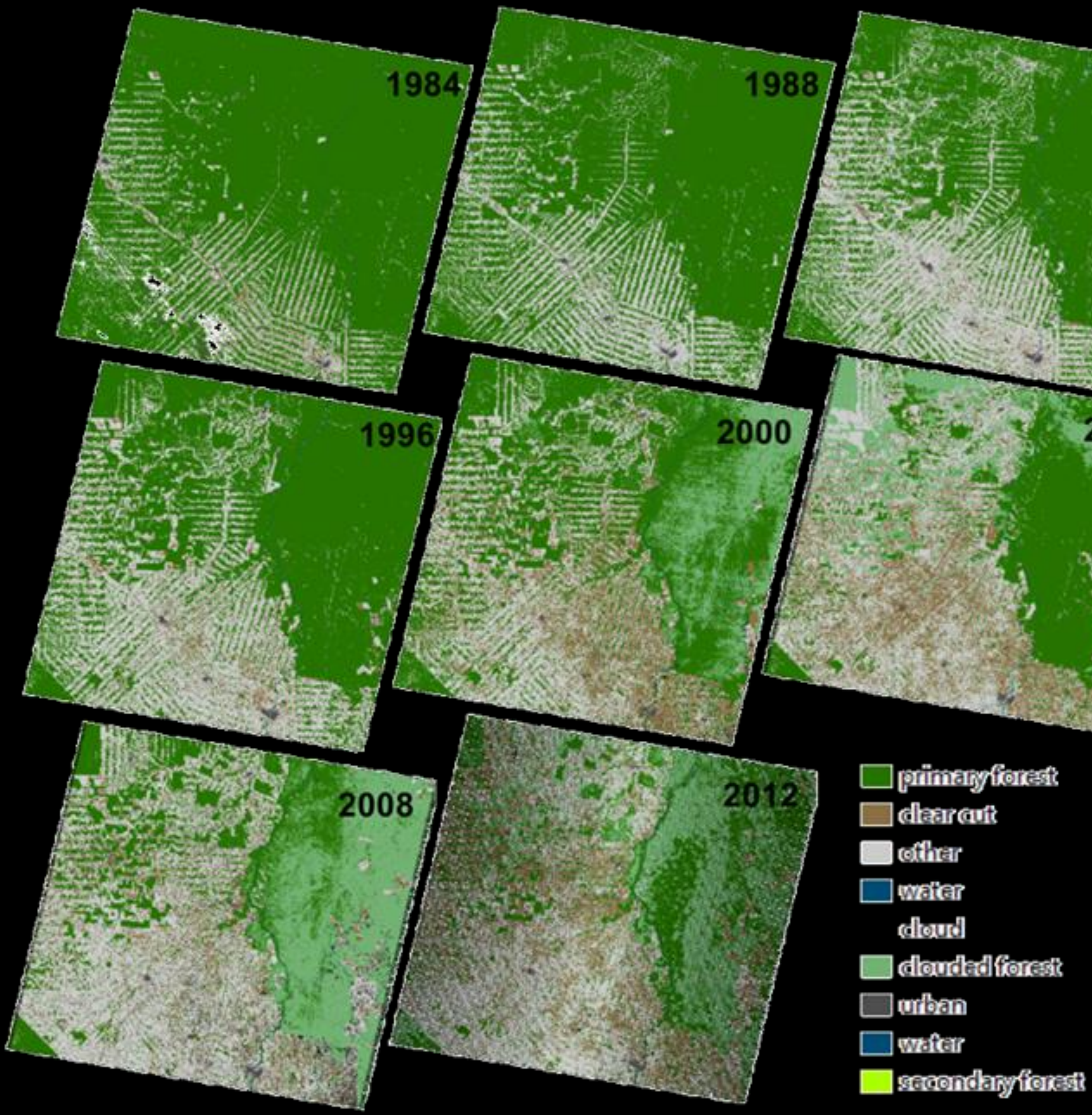
5 **plant and soil biophysical properties**:
- canopy and soil temperature and emissivity,
- chlorophyll fluorescence
- biogeochemical contents like photosynthetic pigments (e.g., chlorophylls, carotenoids, and phycobiliproteins from cyanobacteria),
- water, cellulose, lignin, and nitrogen in foliar proteins

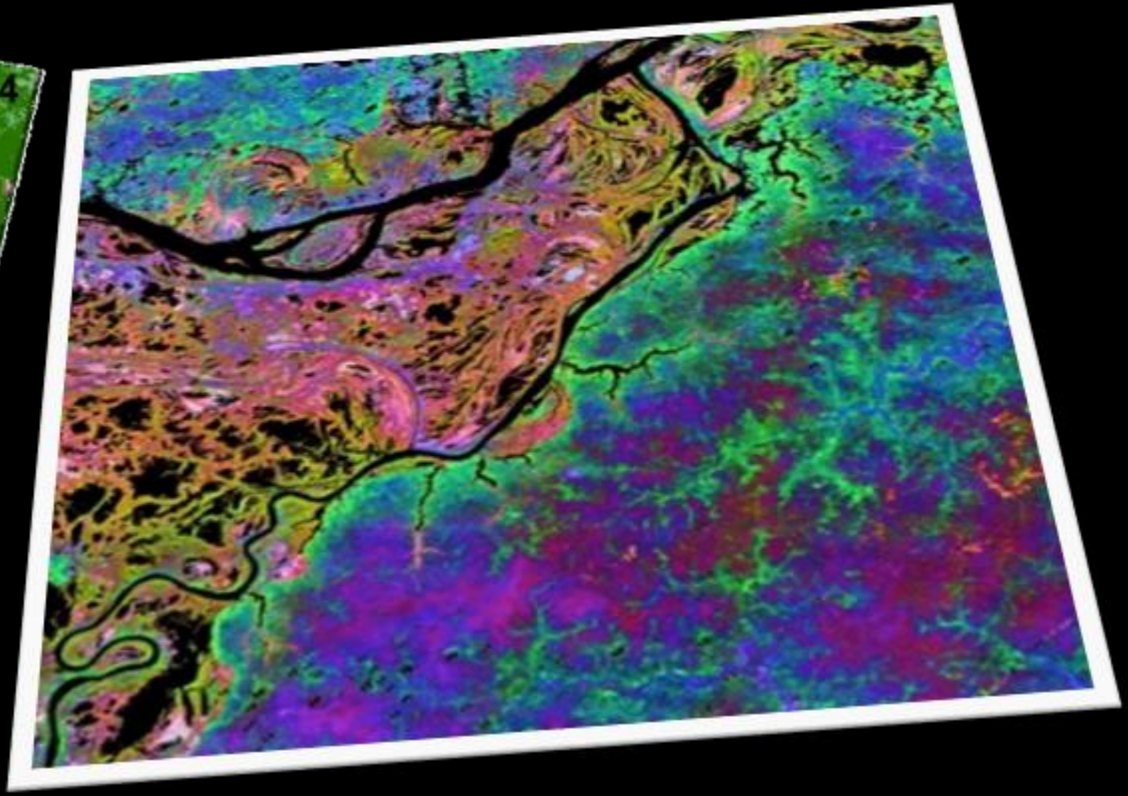
6 surface topography and structure, and **3-dimensional canopy properties**: height, area, vertical profiles, and gap structure

[Ustin and Middleton et al. 2021, 2024]

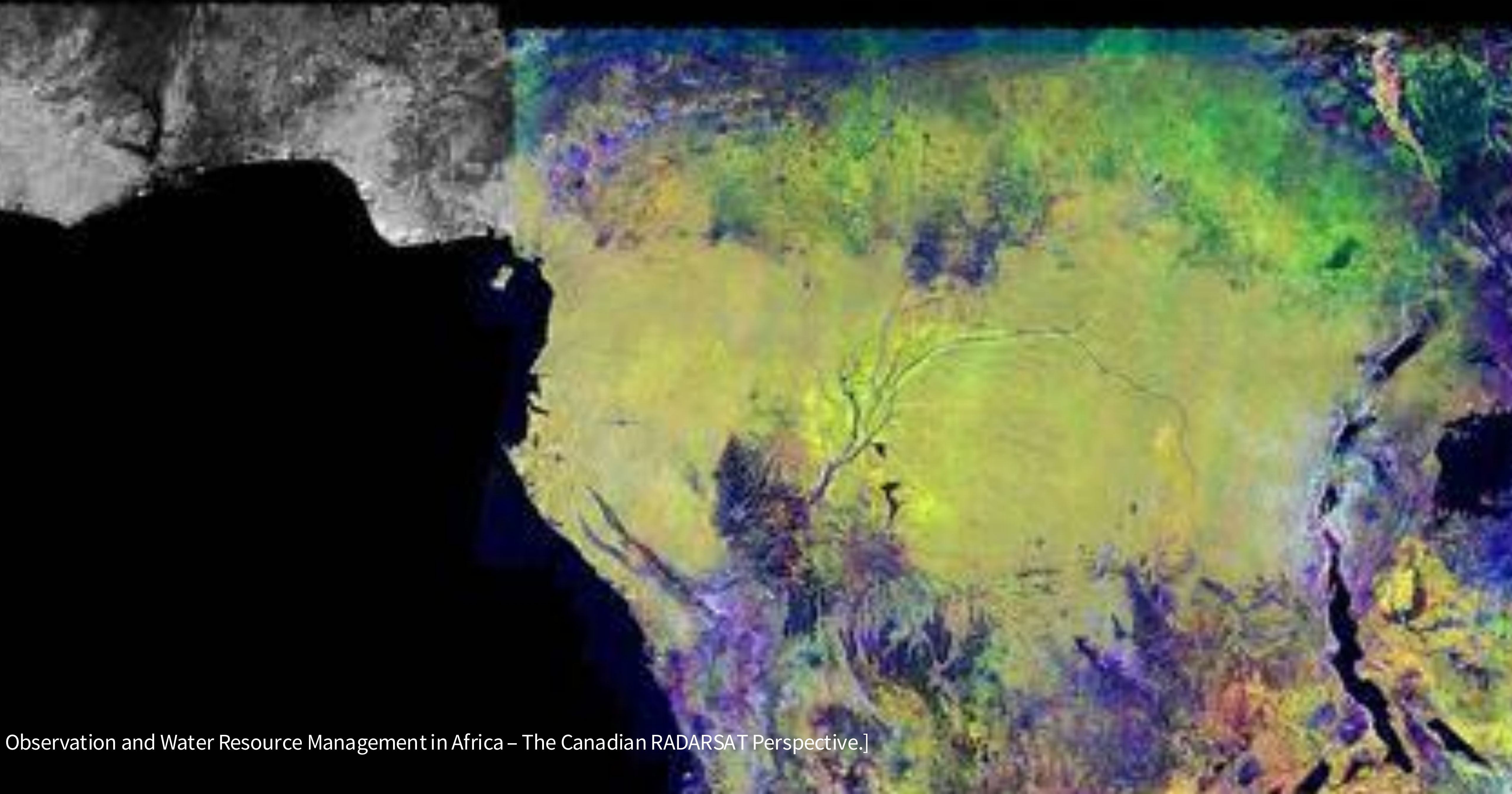








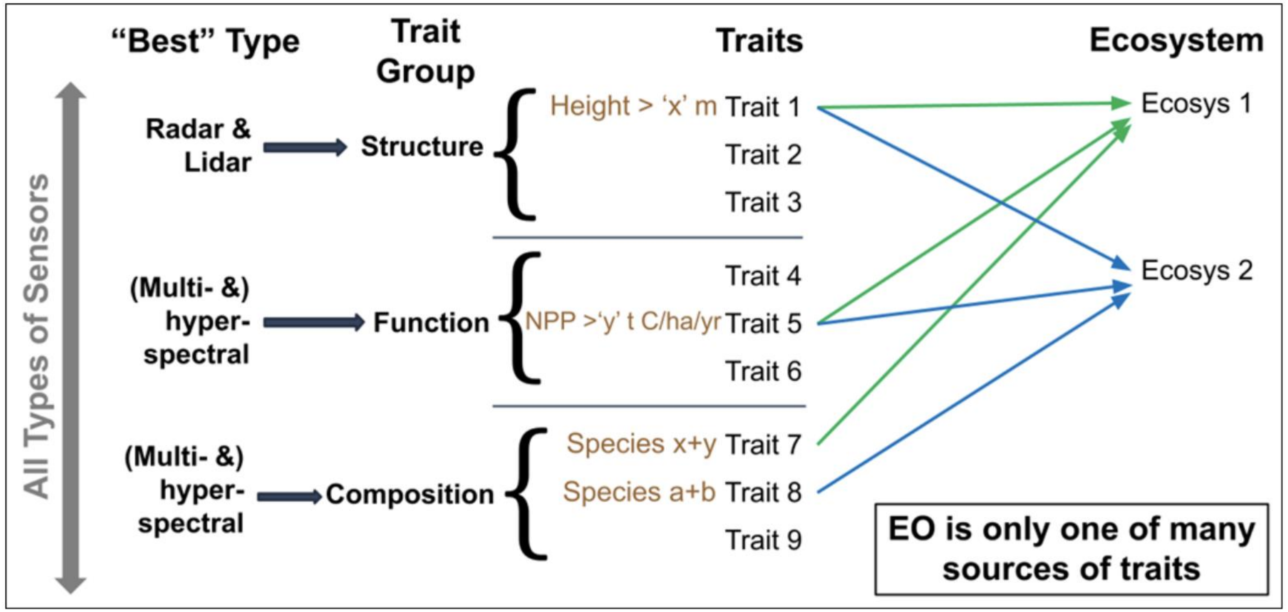
[Santos et al. 2018.]



Observation and Water Resource Management in Africa – The Canadian RADARSAT Perspective.]

Land Cover and Ecosystem Extent

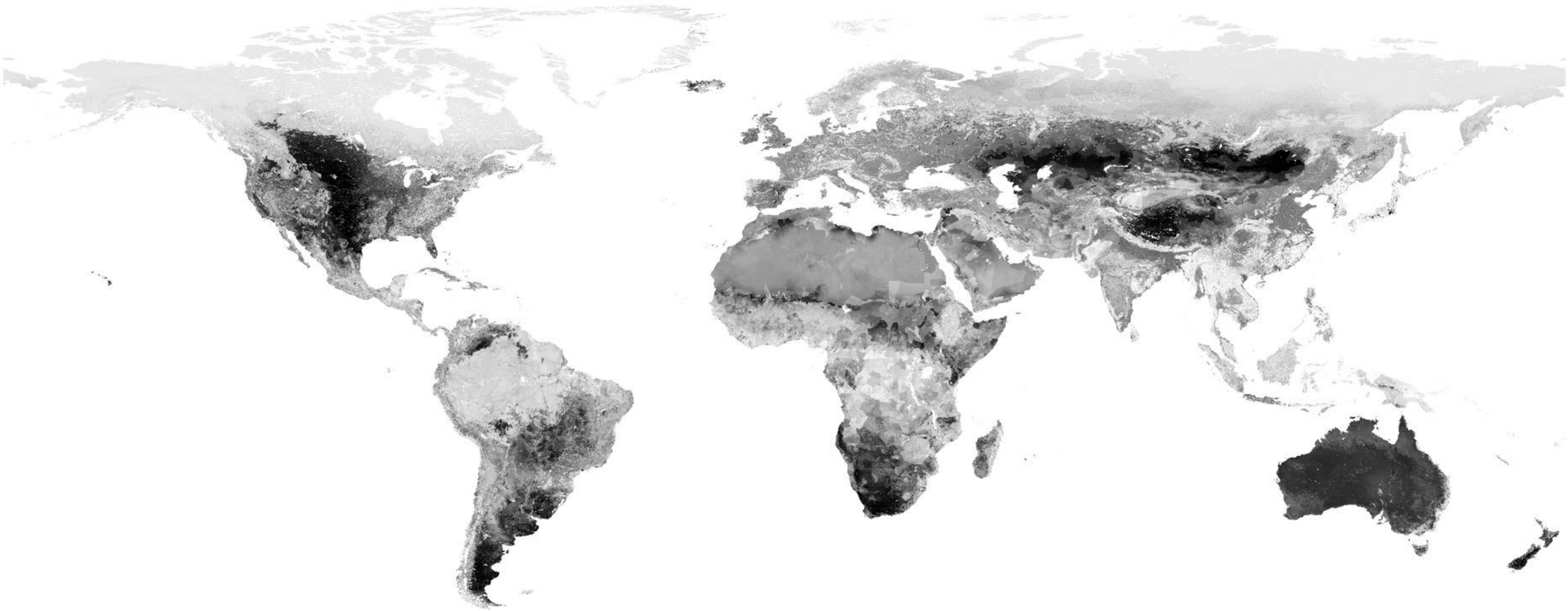
Summary of Challenges
Limited availability of value-added products. These include Essential Biodiversity Variables and other derived products that would advance ecosystem mapping and monitoring.
Combining data from different types of sensors. Although sensors of different types have complementary characteristics needed to discriminate ecosystems, availability of such “fused” products is very limited.
EO data accessibility, usability and technical capacity of users. Technical capabilities (both knowledge & infrastructure) to process and utilize EO data is often limited.
Ecosystem condition. Condition can affect the ecosystem characteristics used to discriminate ecosystems and thus complicates mapping.
Reference data for training and validation. Insufficient reference data is often the biggest limiting factor to mapping ecosystems.
Scale. The characteristics of ecosystems vary depending on the scale being observed, some being found at a local scale while others are at the landscape scale.



[Geller et al. 2023. USGS Report, White Paper to CEOS]

CEOS Committee on Earth Observation Satellites

biodiversity intactness

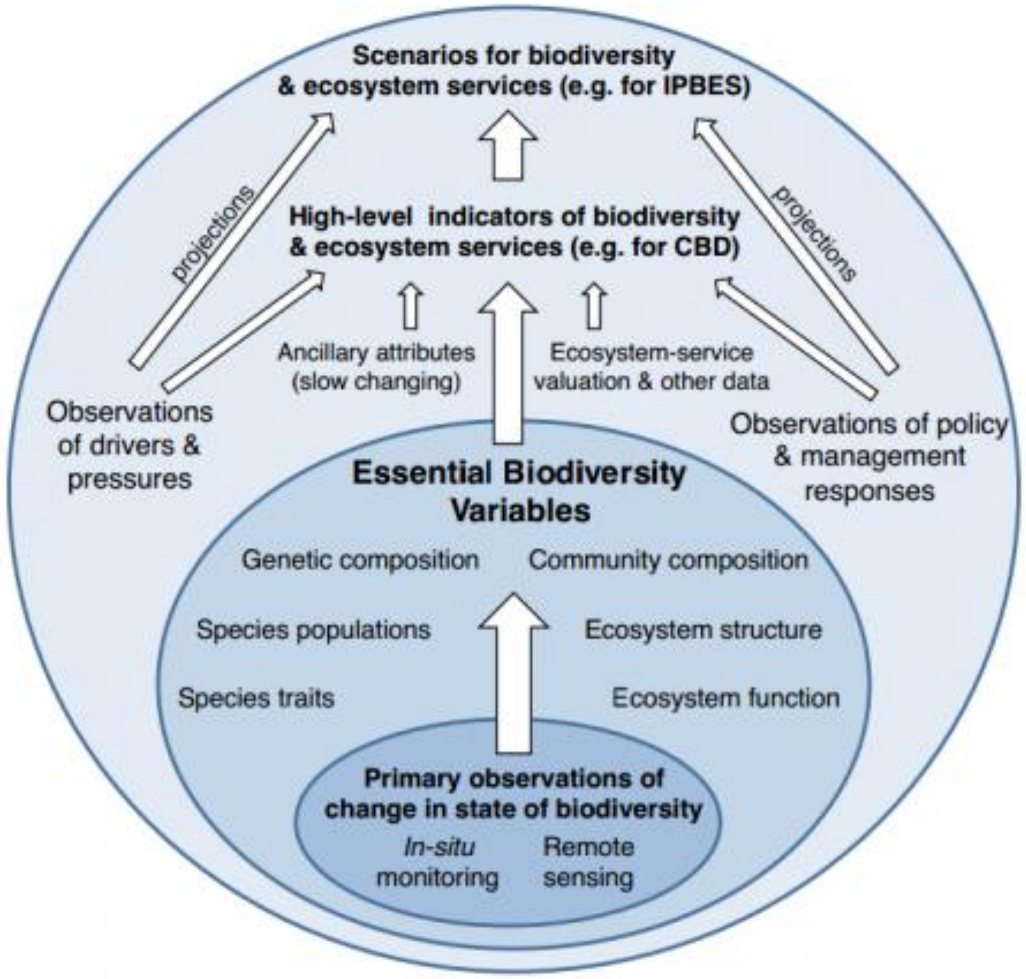


[Newbold et al. 2018]

Essential Biodiversity Variables

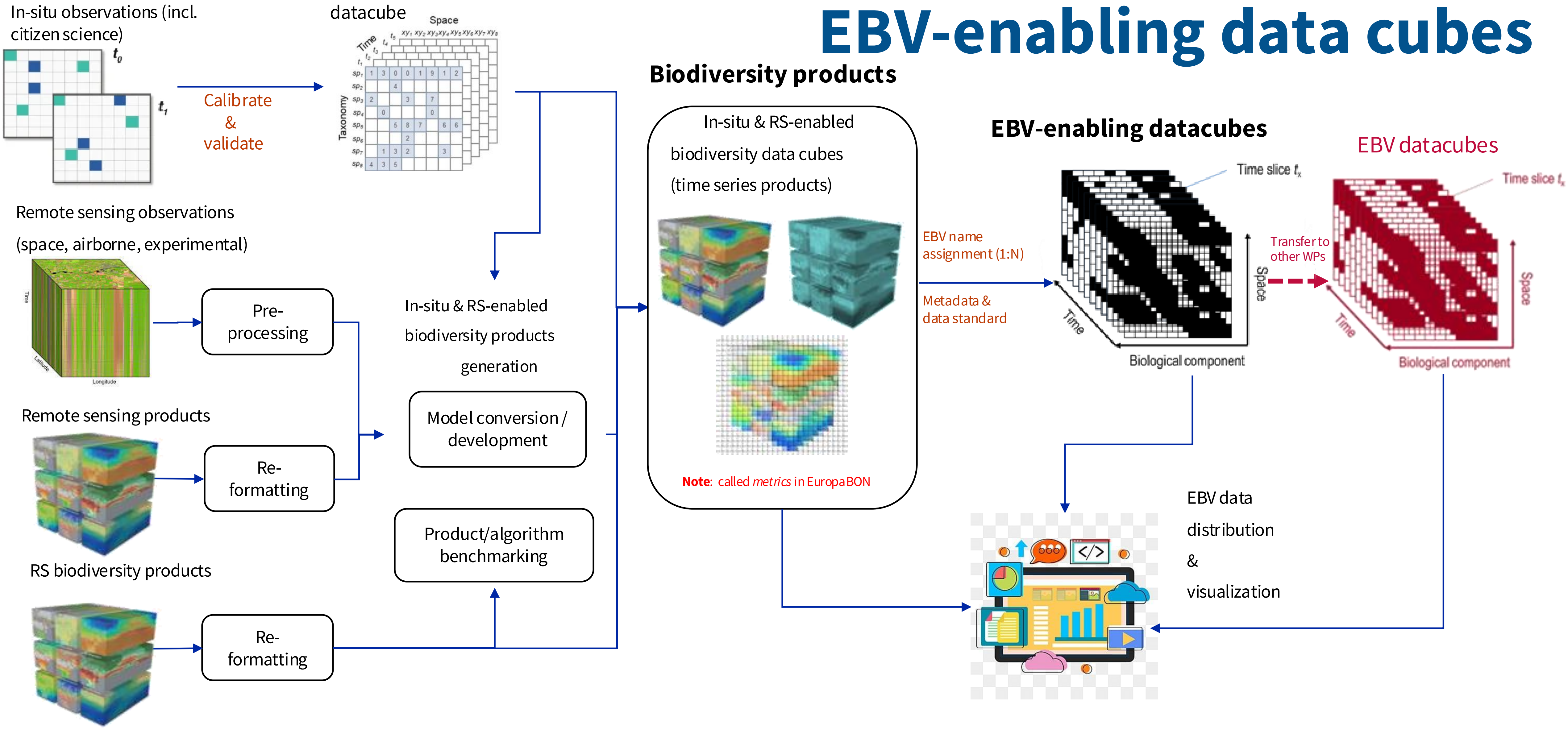
An organizing framework
Some can be directly measured, calculated or modelled using EO

1	Genetic Composition
2	Species Populations
3	Species Traits
4	Community Composition
5	Ecosystem Structure
6	Ecosystem Function

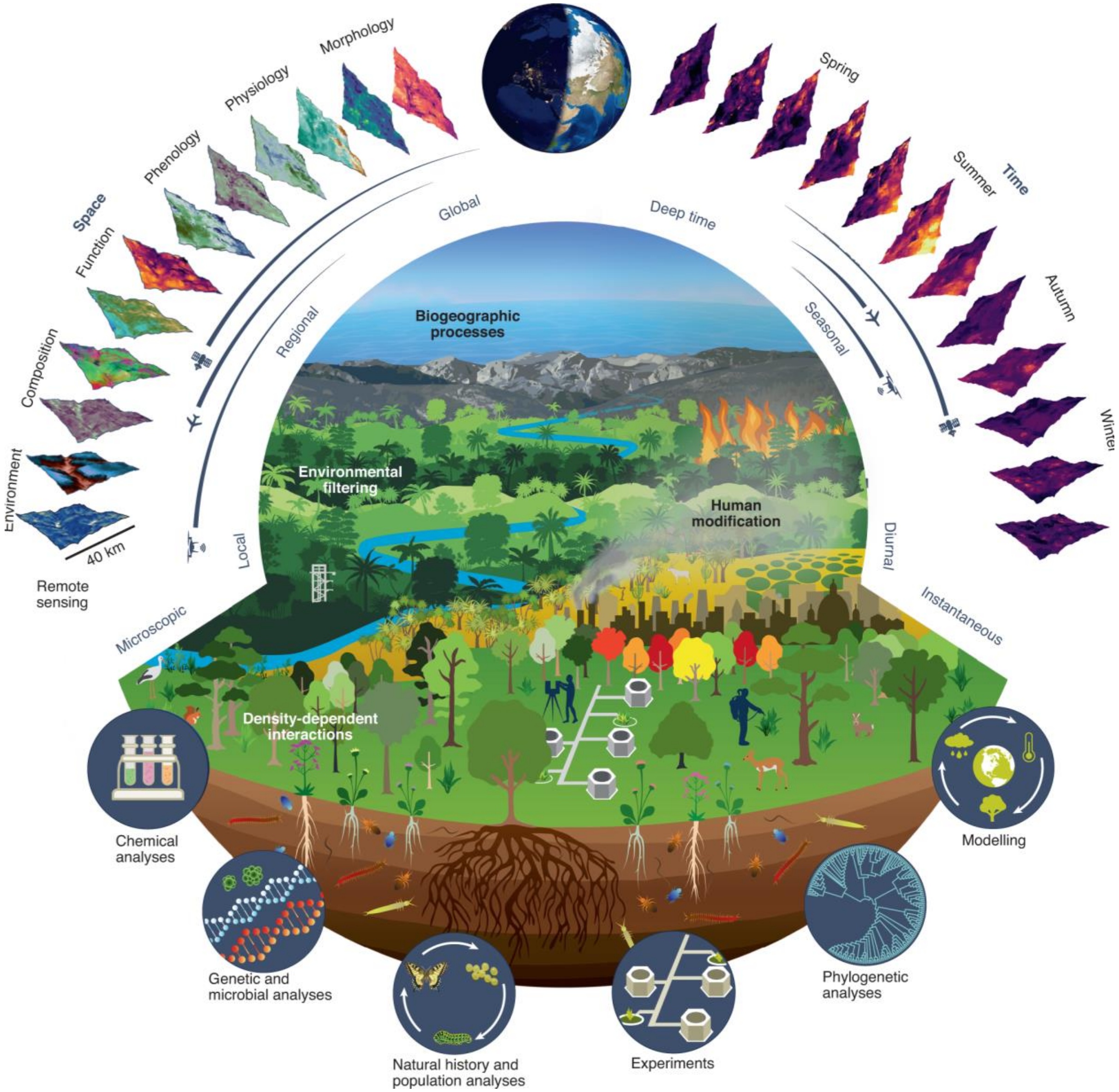


[Pereira et al. 2013, Skidmore et al. 2021]

EBV-enabling data cubes



OBSGESSION



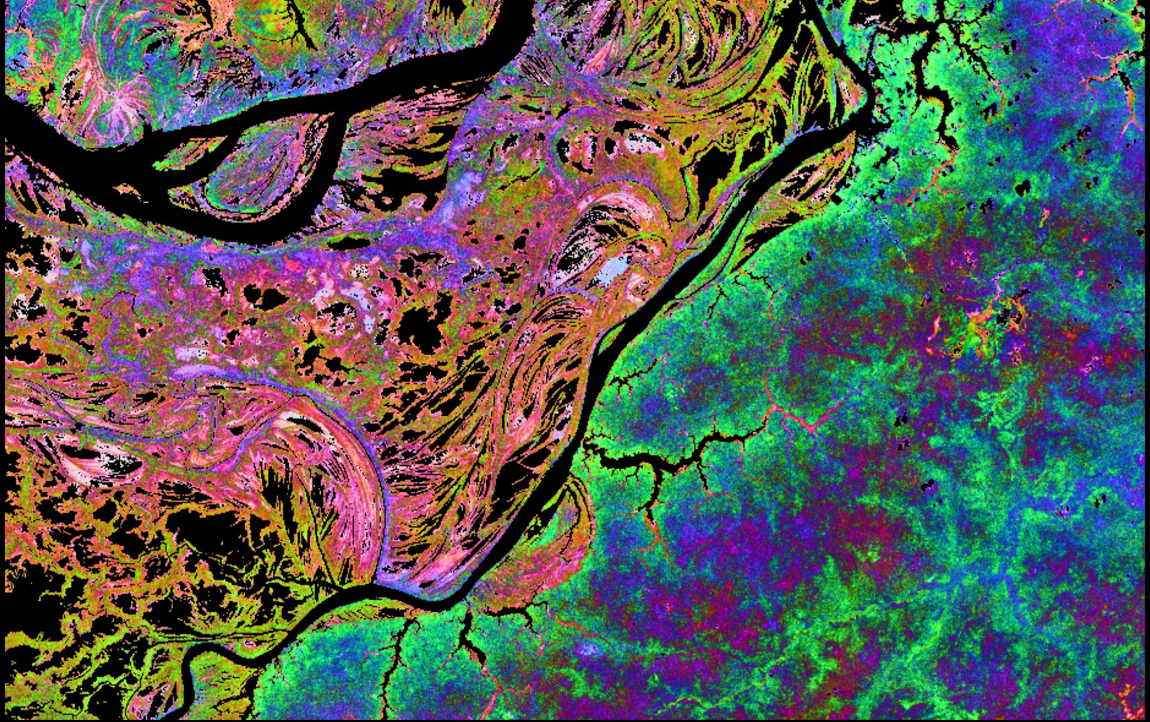
Framework to integrate *in situ* and remote sensing to monitor and understand biodiversity

biodiversity process understanding

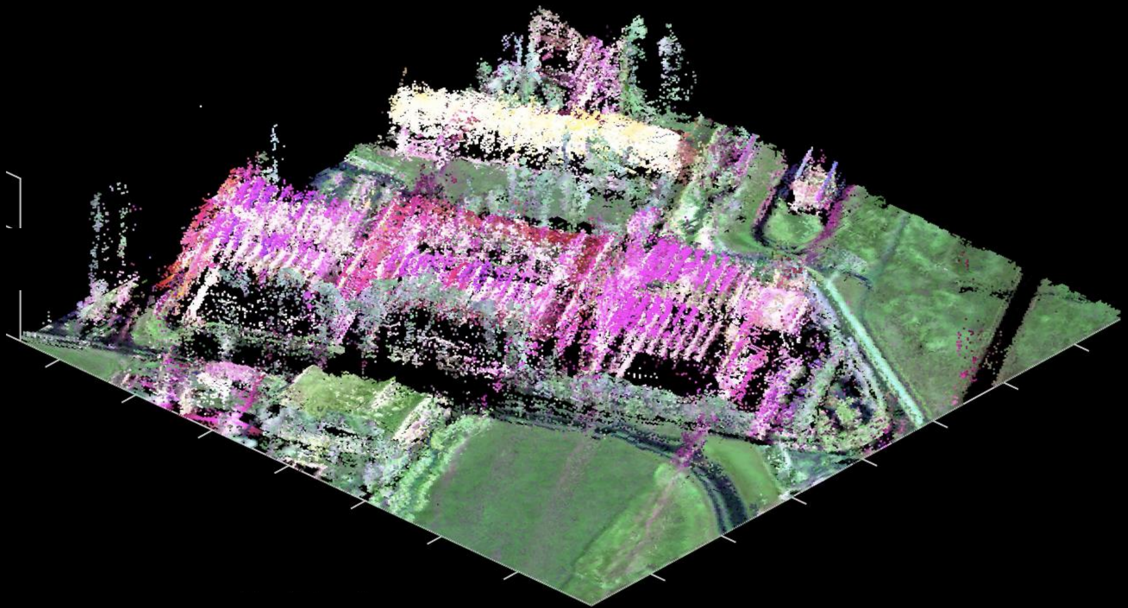
1. Influences of evolutionary and biogeographic legacies on ecosystem functioning
2. Changing global distributions of plant functional traits and trait diversity
3. Ecosystem resilience to global change
4. Past and present human modifications of the land and their consequences
5. Inferring below-ground processes from above-ground information

[Cavendar-Bares, Schneider, Santos et al. 2022]

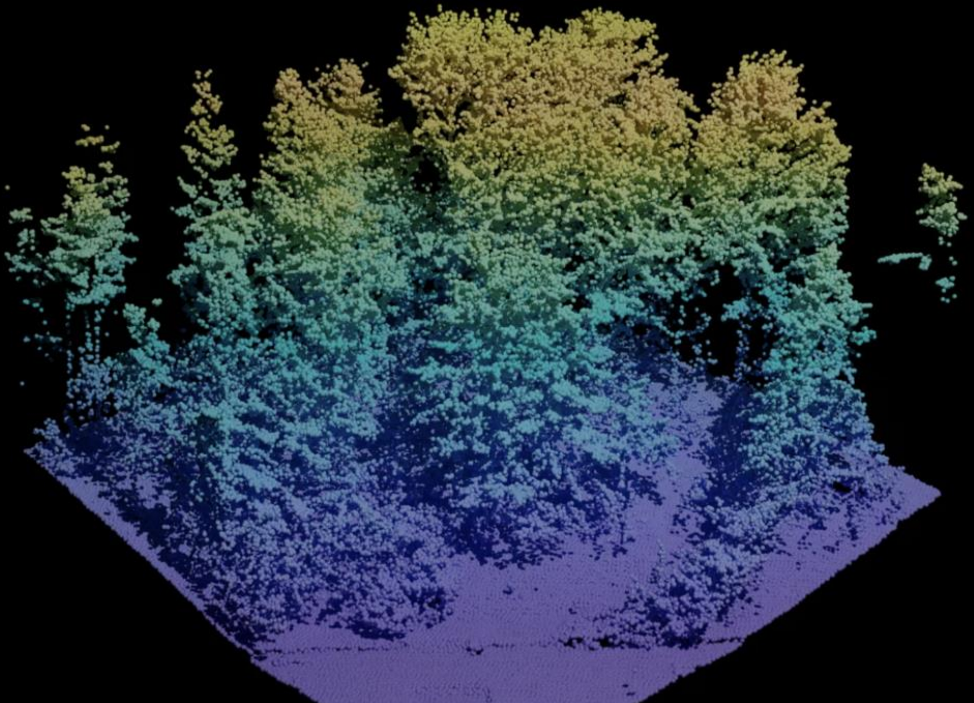
OPTICAL



SAR

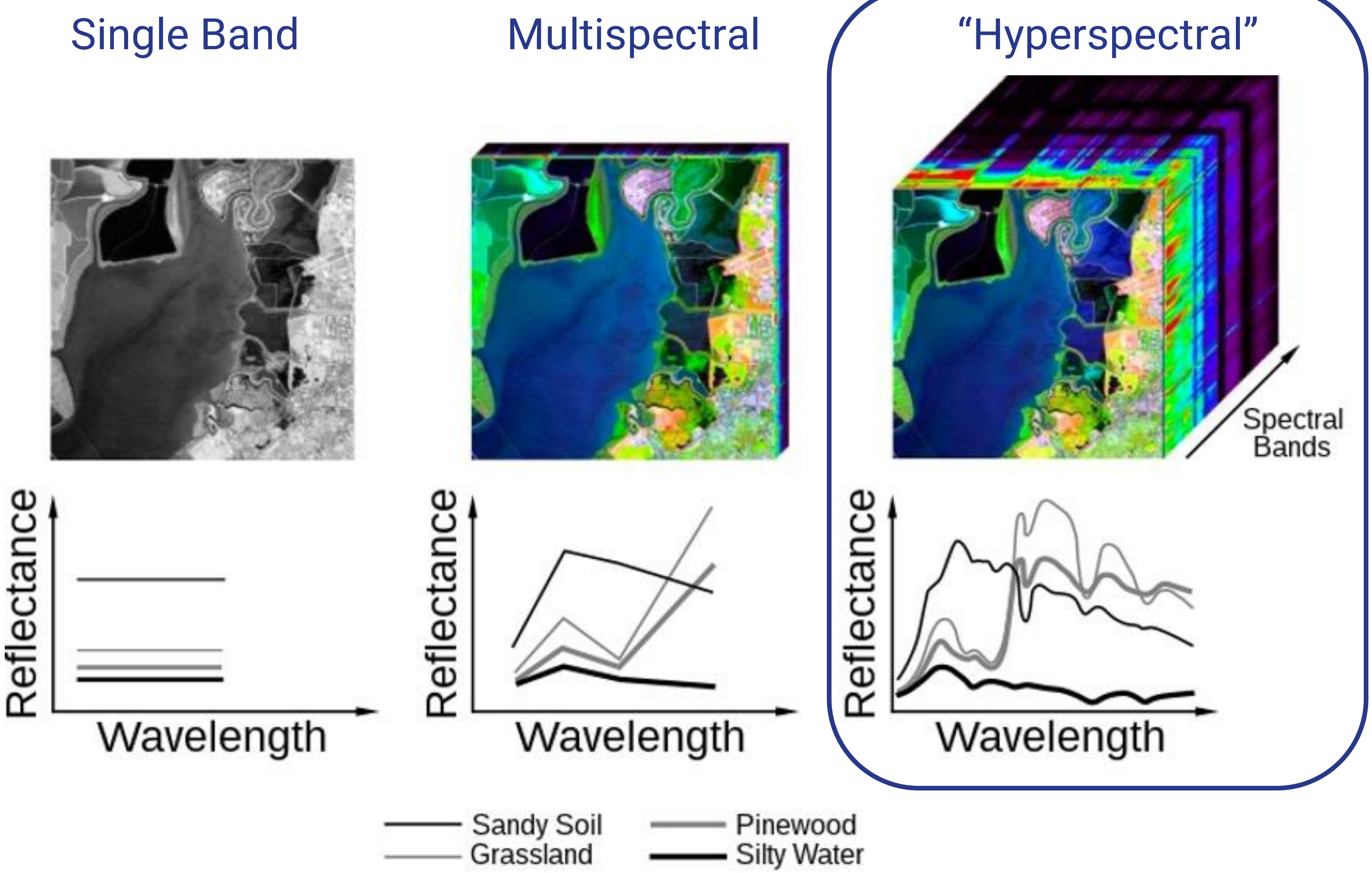


LIDAR



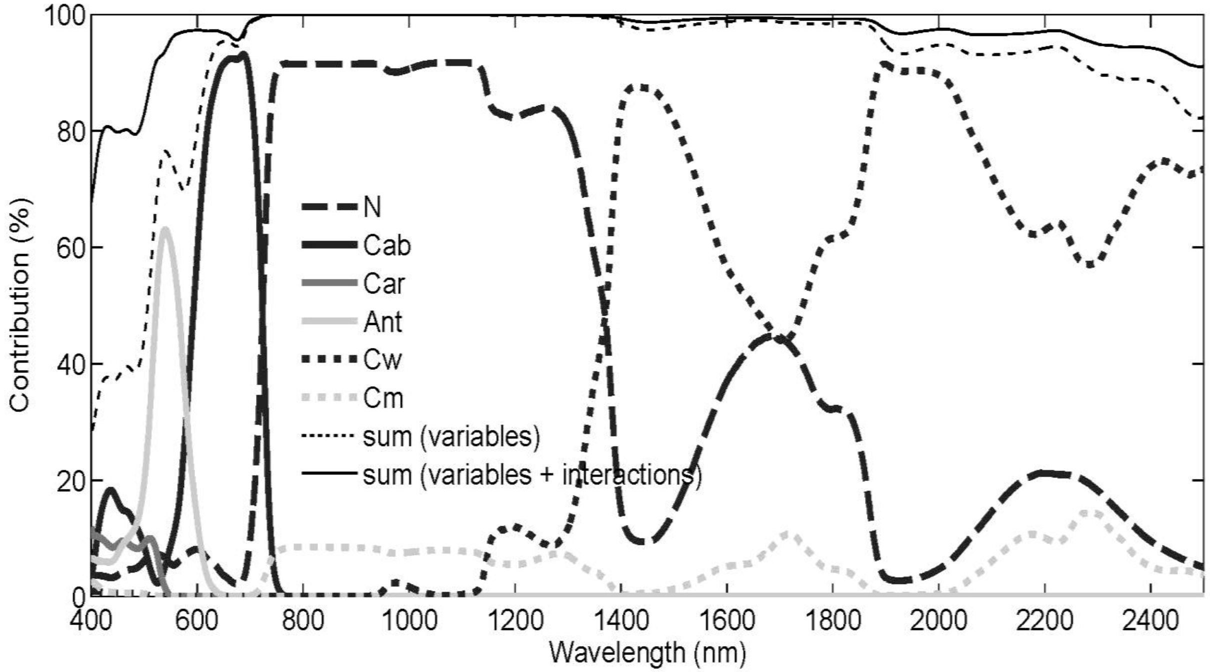
THERMAL

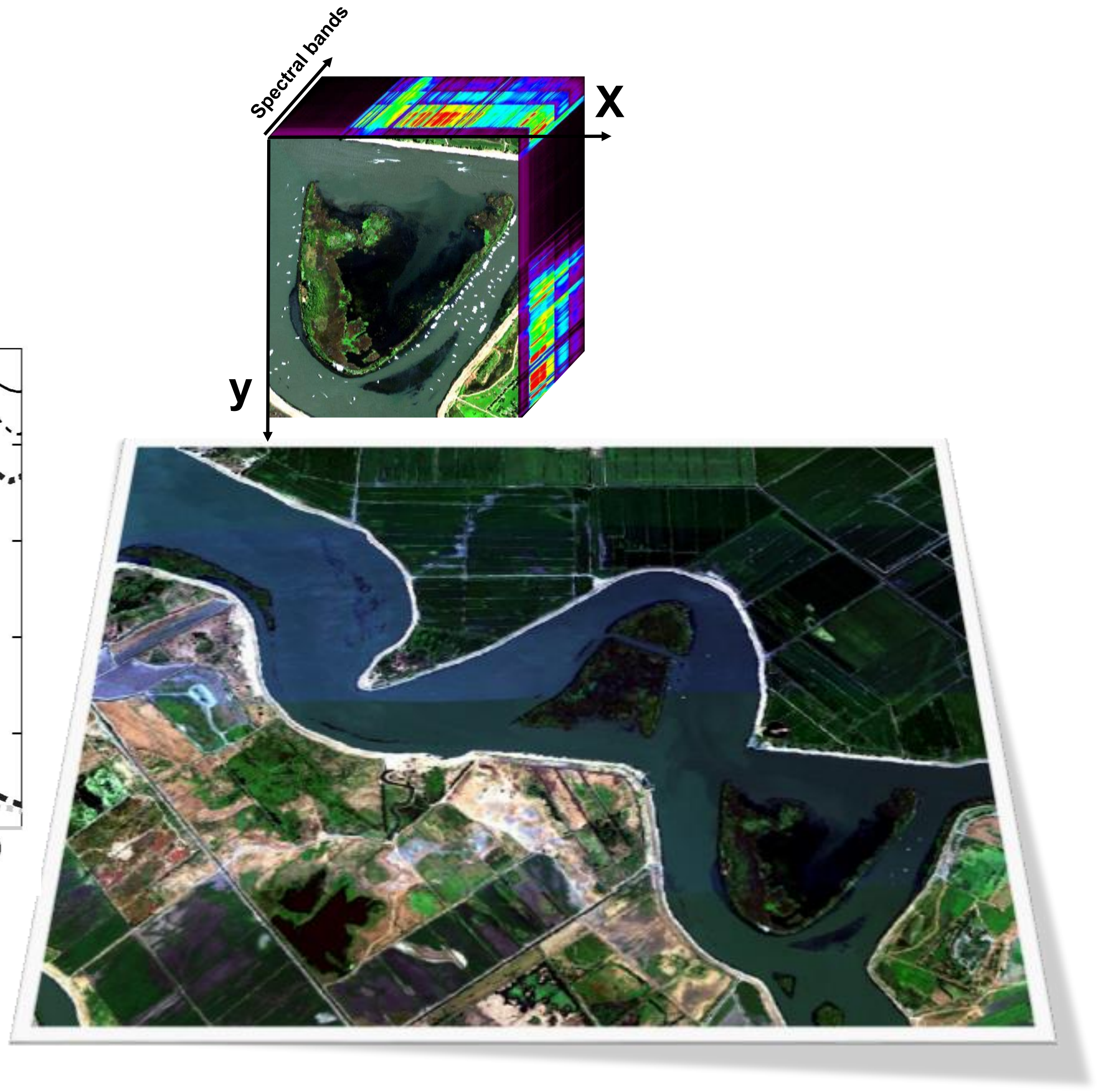
Imaging Spectroscopy



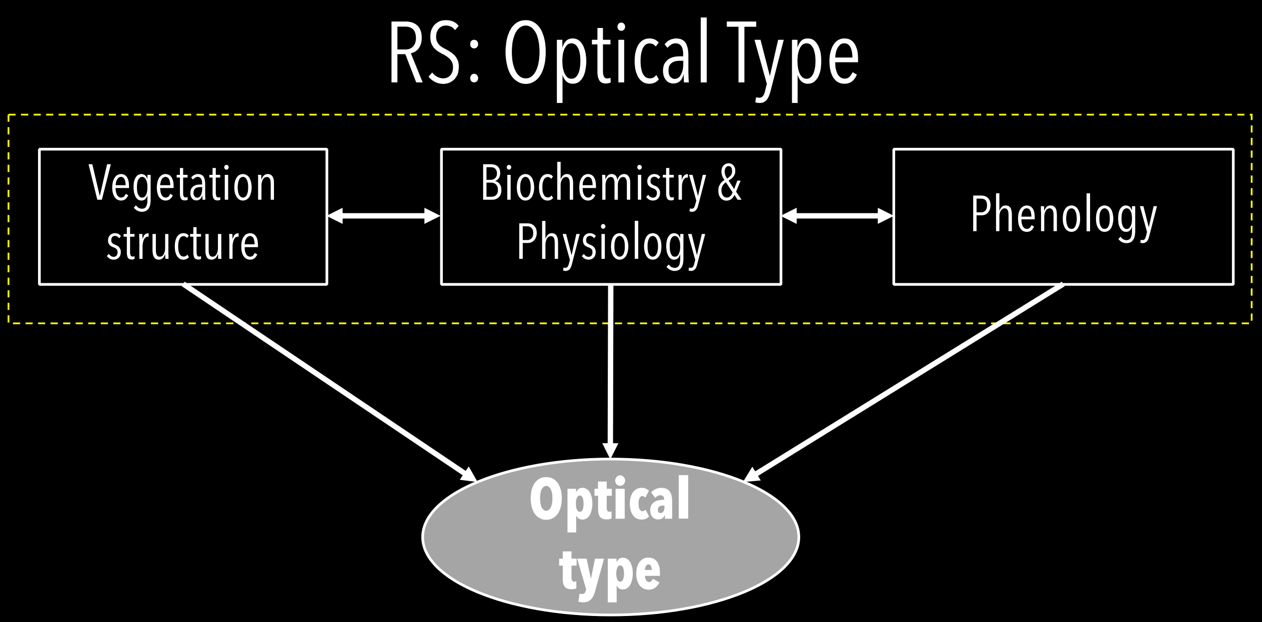
Source: Lucas van den Bosch, https://commons.wikimedia.org/wiki/File:Mono,_Multi_and_Hyperspectral_Cube_and_corresponding_Spectral_Signatures_modified.svg, CC BY-SA 4.0

Imaging spectroscopy



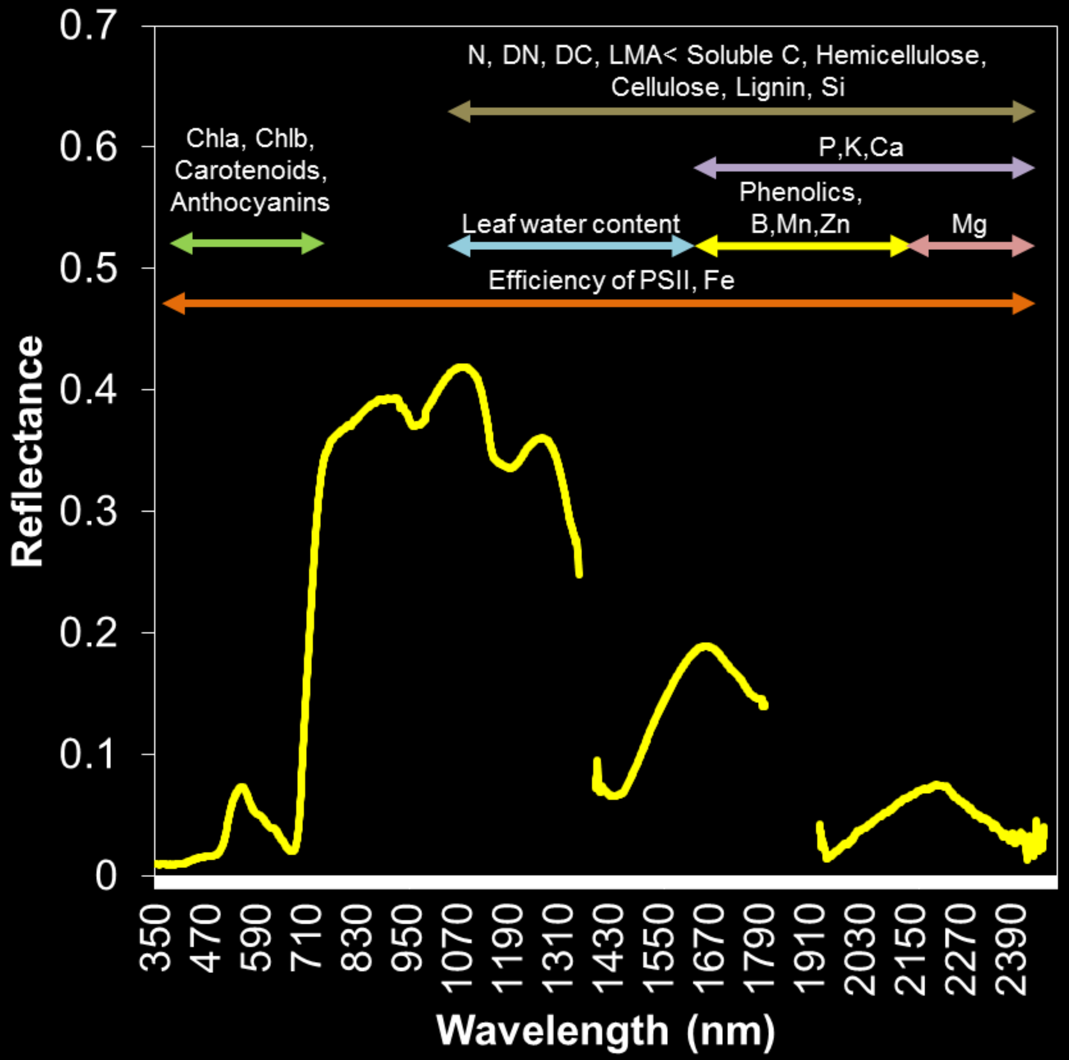


Optical properties of plants are captured in the measured signal

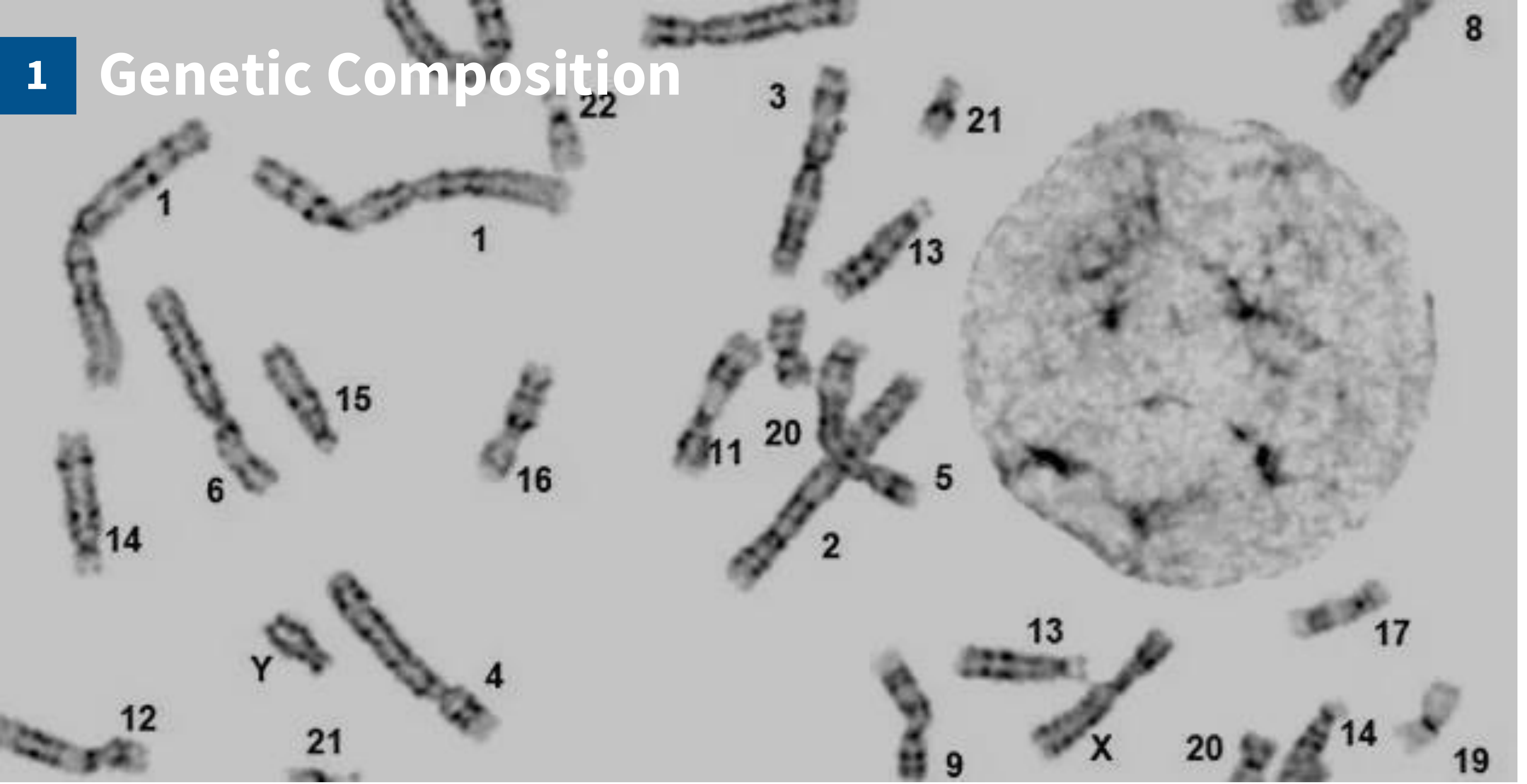


Optical Type:
functional categories accessible from remote sensing

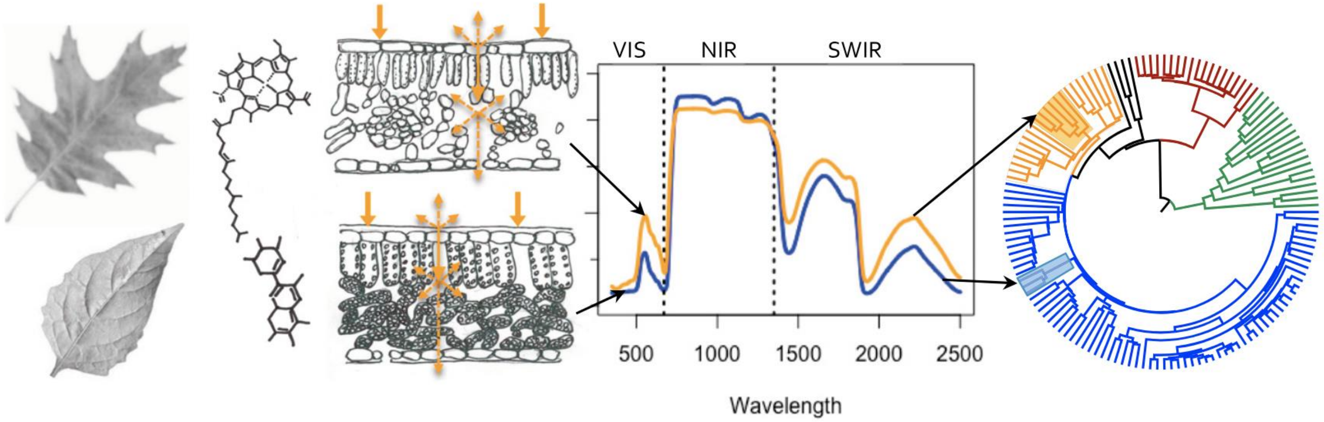
[Ustin and Gamon. 2010. New Phytologist]



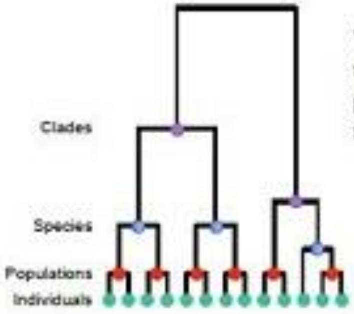
1 Genetic Composition



1 Genetic Composition



Oaks
Aspen
Beech
…

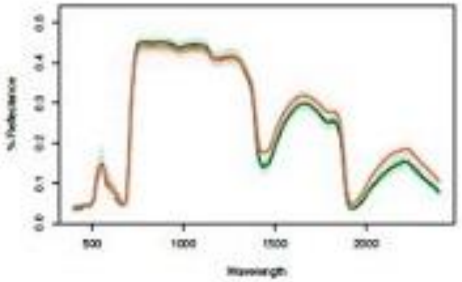


The hierarchical organization of plant diversity that results from their evolutionary history provides a framework for predicting spectral similarity of organisms.

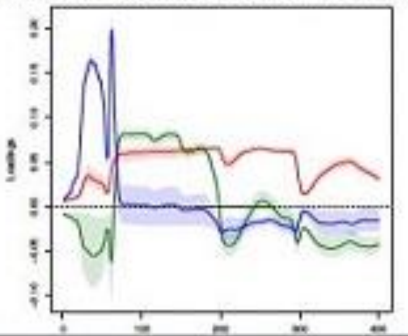
Experiment 1: Multiple genotypes and populations within a single oak species grown in a common garden.

Experiment 2: Many species within the oak genus grown in a common greenhouse environment.

Spectral properties of leaves differ among taxa.



Partial least squares discriminant analysis (PLS-DA) reveals that all parts of the spectra contribute to accurate classification of taxa.

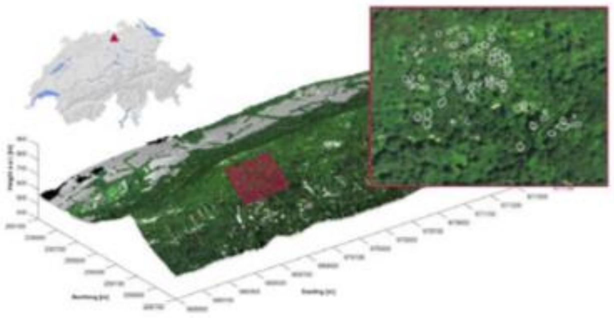


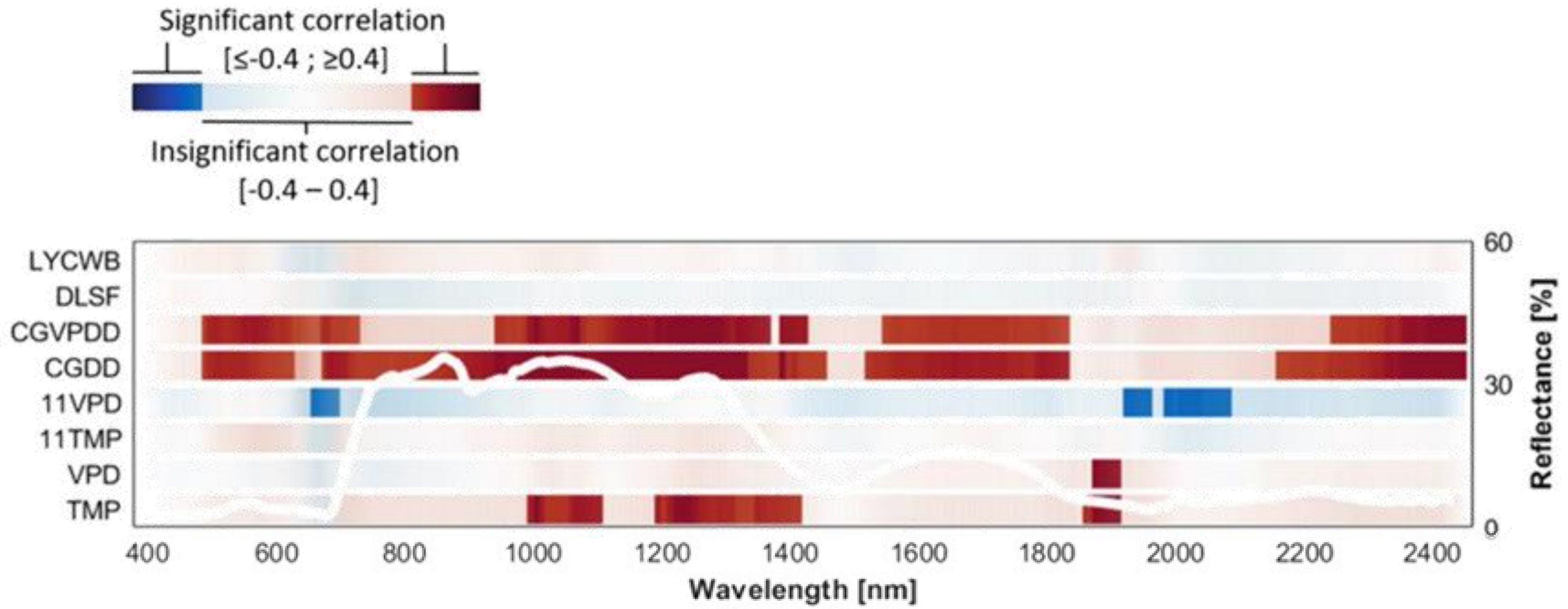
1 Genetic Composition

Different beech genotypes "look" different under stress

Decadal time series

Laegern temperate forest, Switzerland.





Pearson correlation between

Spectral-Genetic Similarity = partial Mantel correlation coefficient between genetic (Nei's) distance and spectral (Euclidean) distance of trees

and

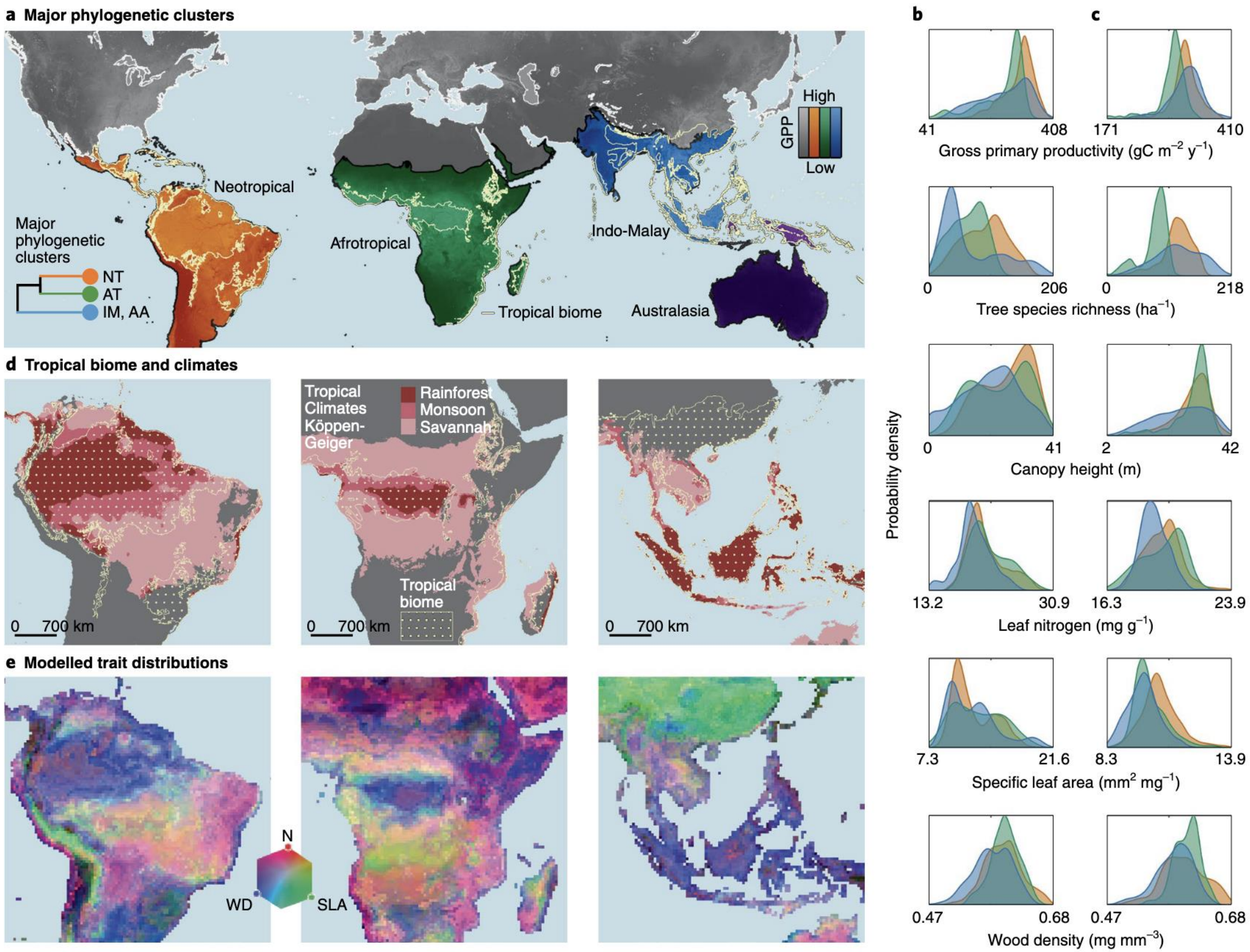
values of environmental variables

Dry conditions, late in the season, are most interesting:

CGVPDD = Cumulative Growing Vapor Pressure Deficit Days
CGDD = Cumulative Growing Degree Days
11VPD = Vapor Pressure Deficit previous 11 Days
VPD = Vapor Pressure Deficit at time of acquisition
TMP = Temperature at time of acquisition

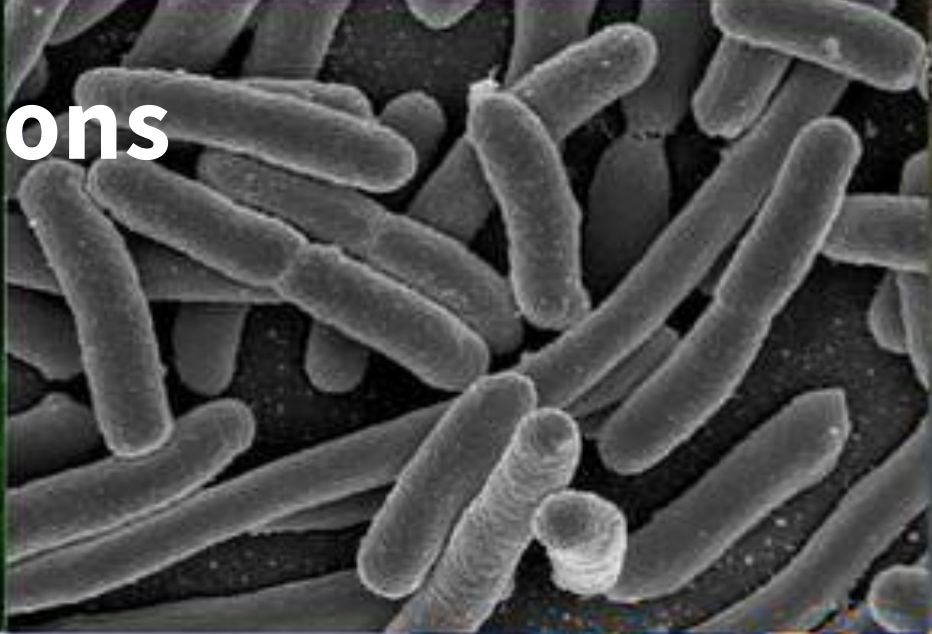
[Czyż *et al*. (2023) doi: 10.1016/j.rse.2022.113338]

1 Evolutionary and biogeographic legacies



2

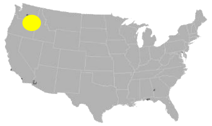
Species Populations

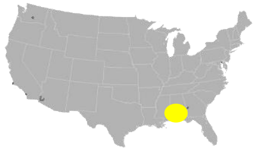


2 Species Populations tracking invasion with imaging spectroscopy















- HyMap
- ASD
- 8 species
- 4 natives
- 4 IAS

- HyMap
- ASD
- 6 species
- 4 natives
- 2 IAS

- HyMap
- ASD
- 15 species
- 13 natives
- 2 IAS

- AVIRIS
- ASD
- 32 species
- 30 natives
- 2 IAS

- AVIRIS
- ASD
- 28 species
- 24 natives
- 4 IAS

- AVIRIS
- ASD
- 12 species
- 11 natives
- 1 IAS

- AVIRIS
- ASD
- 28 species
- 27 natives
- 1 IAS







[Hestir et al. 2008, RSE; Santos et al. 2012. New Phytologist, Santos and Ustin 2018, IGARSS]

2 Species Populations tracking invasion with imaging spectroscopy

Timing of phenologic cycles

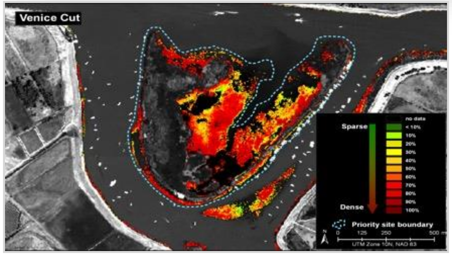
- Timing of data acquisition: after the peak of the growing season → greater separation of the invasive plant species and native species.
- Time series: enhanced using multiple-date data, particularly by combining data from different seasons

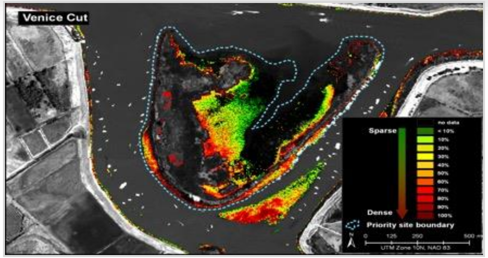
Growth forms

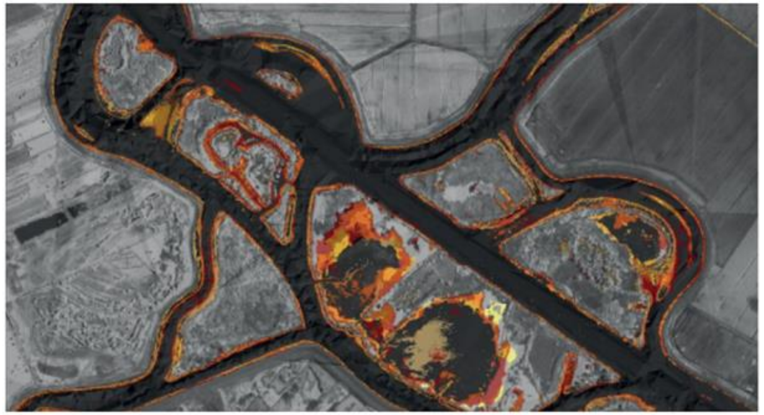
- Detection is best when invasive and native species have different growth forms.
- In cases where the growth forms of invasive and native species are similar, differences in size and density of invasive species vs. native contribute to detection.

Imaging spectroscopy

- IS in the only imagery that can capture differences in concentrations of plant pigments, canopy water, and canopy dry material and differences in soil properties

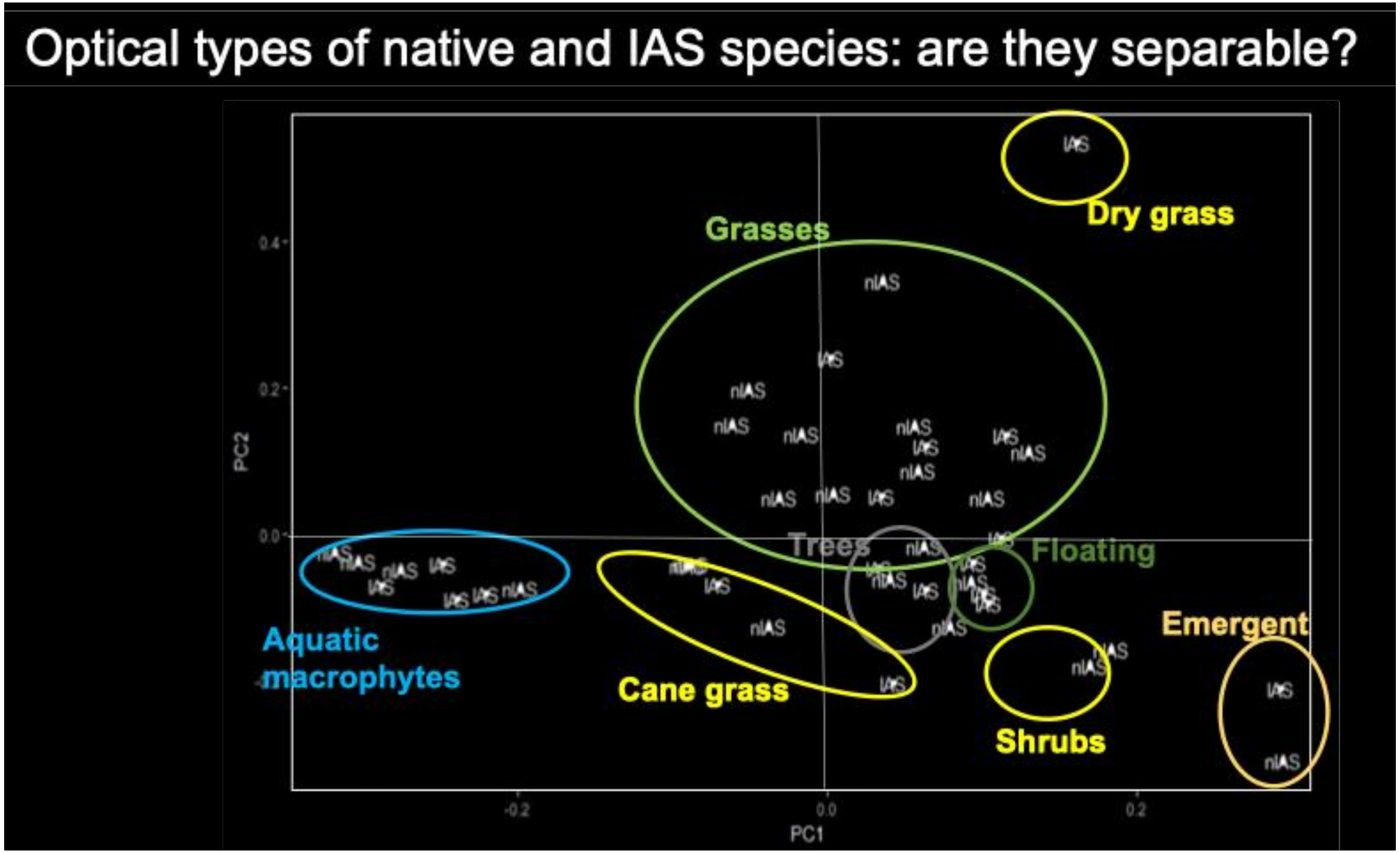


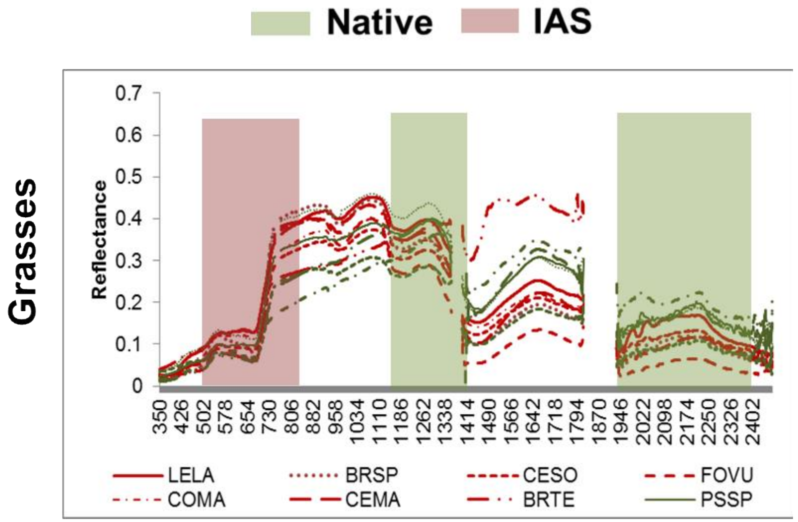


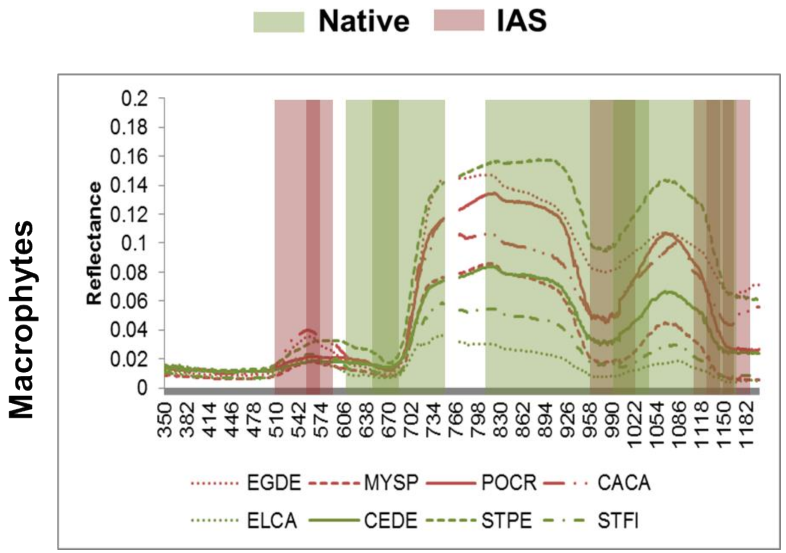


2 Species Populations

tracking invasion with imaging spectroscopy



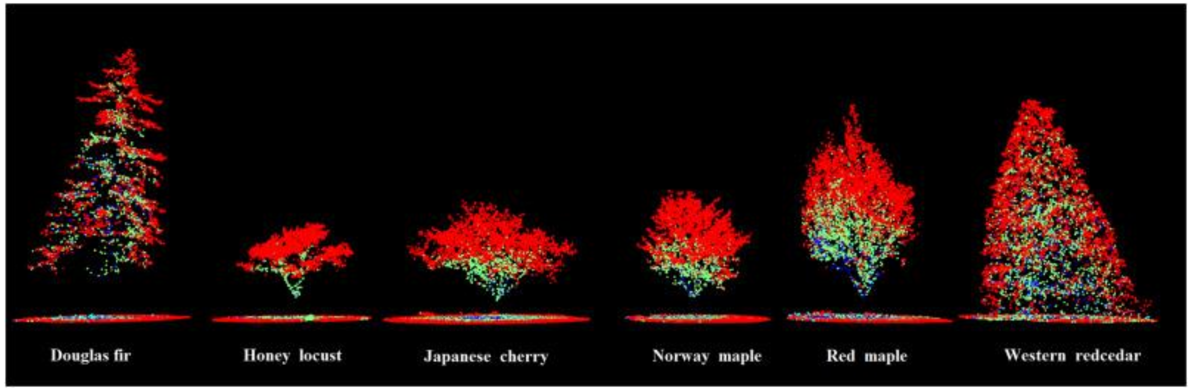




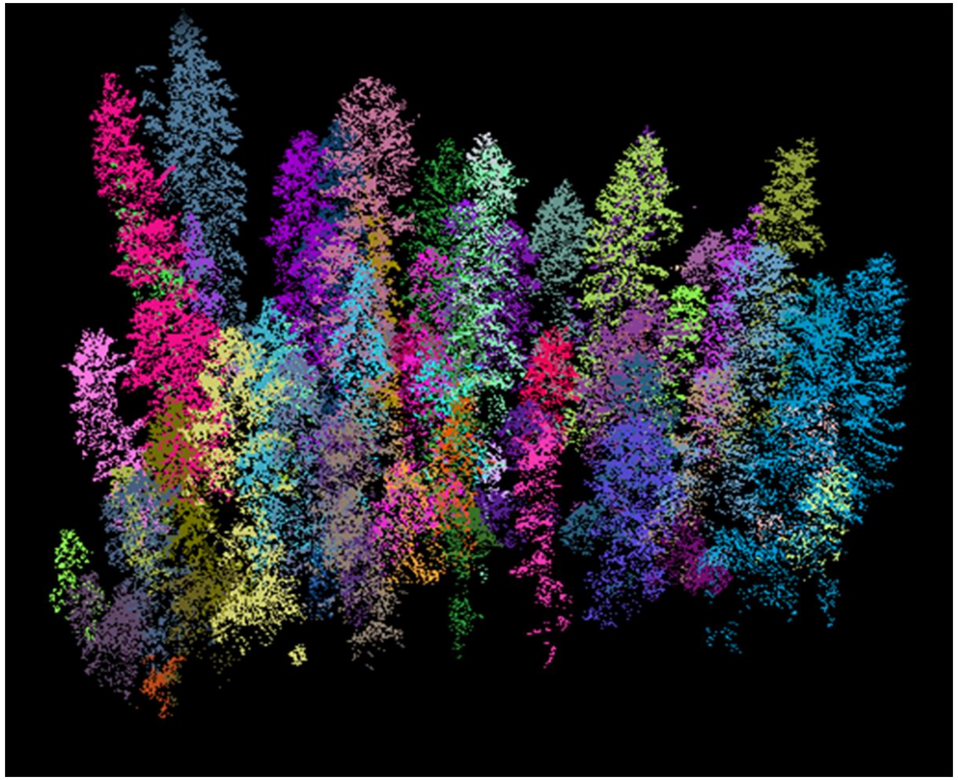
 | [Santos et al. in prep]

2 Species Populations

[Hell et al. 2022]



[Liu et al. 2017]



2 Species Populations

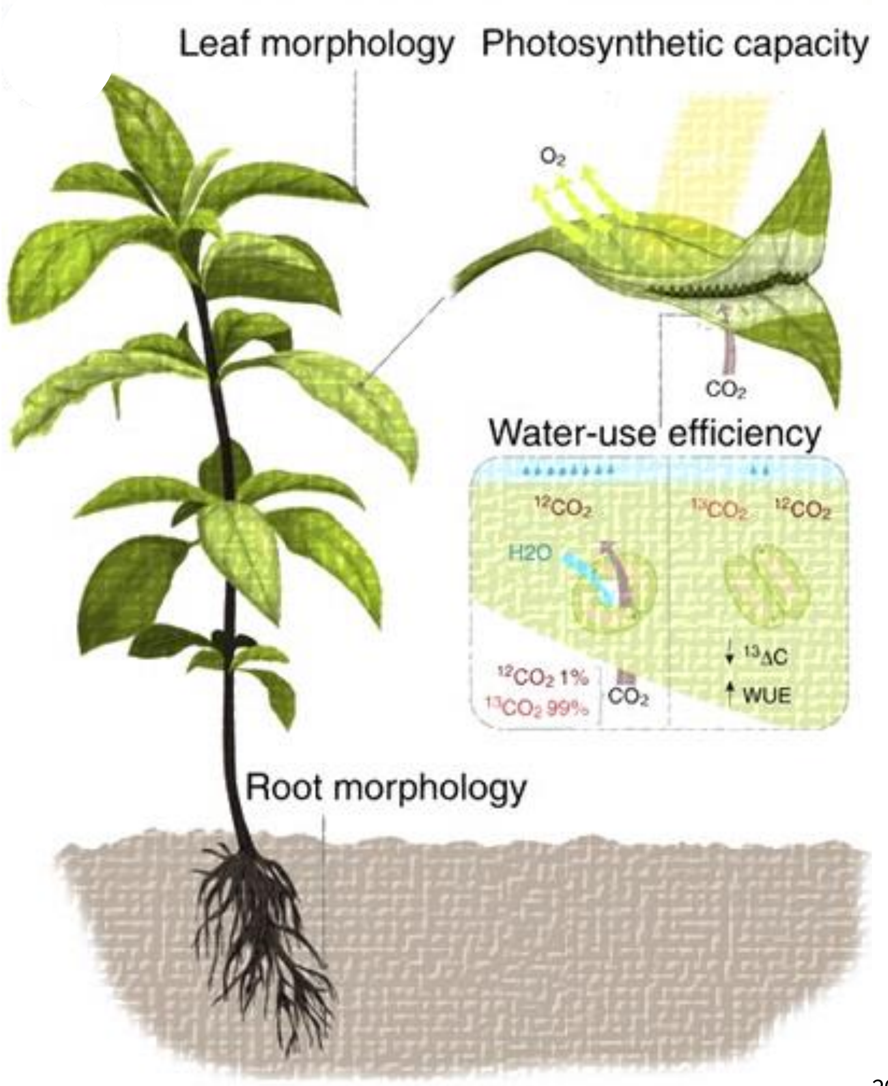
[Kwon et al. 2025]

3 Species Traits

Functional diversity

…the value and distribution of traits among organisms that simultaneously influence their individual fitness and ecosystem functioning…

plant floristic and functional composition can track one another in space and time

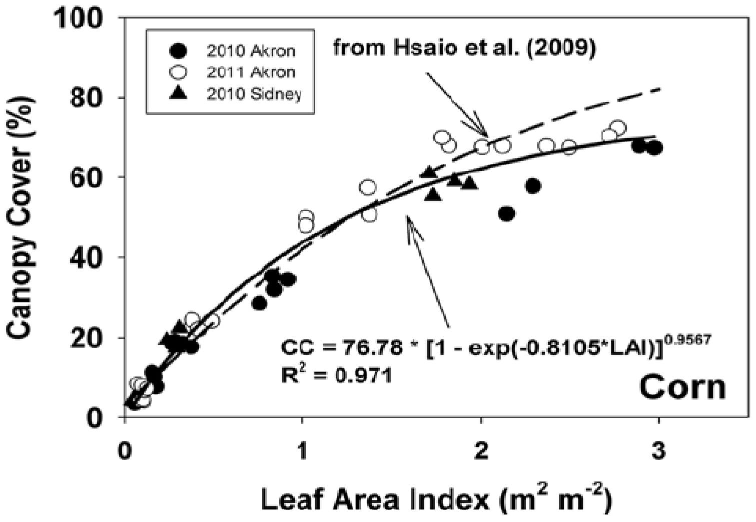


Species Traits

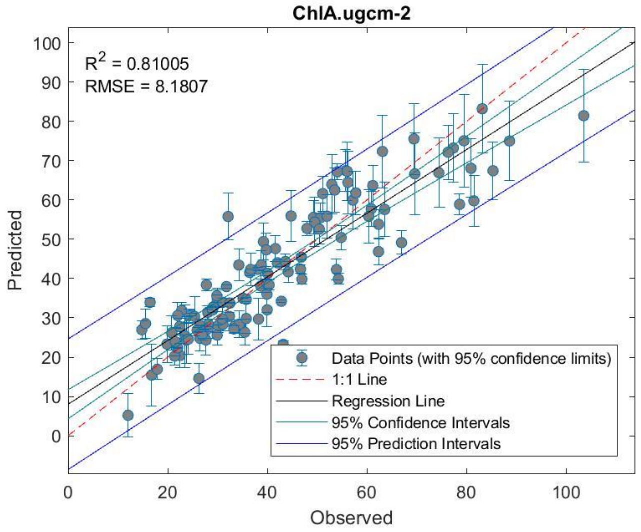
Approaches to detect and quantify foliar traits

1. Statistical

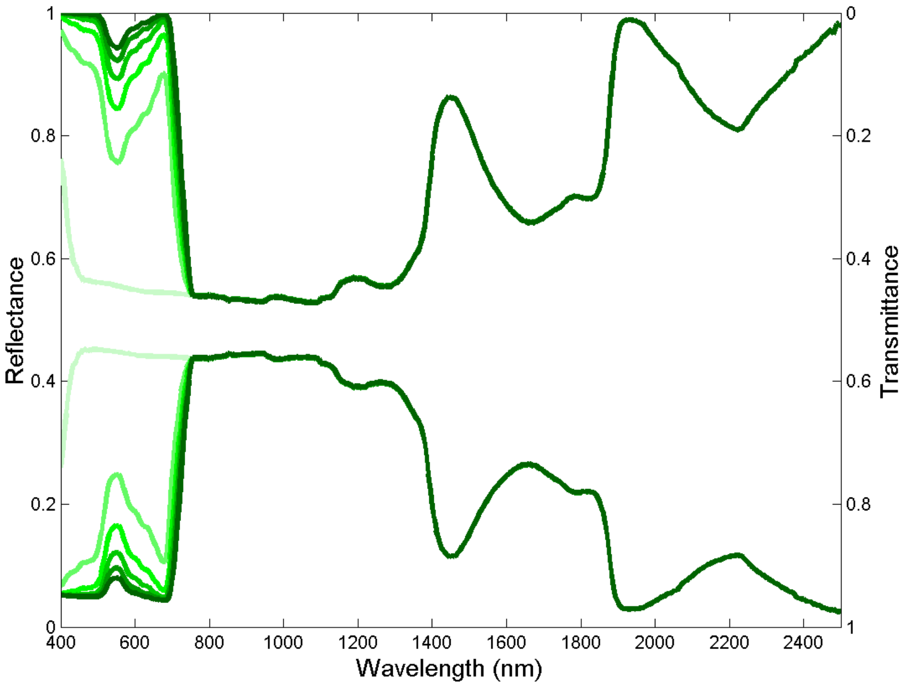
Indices



Multivariate (PLSR)



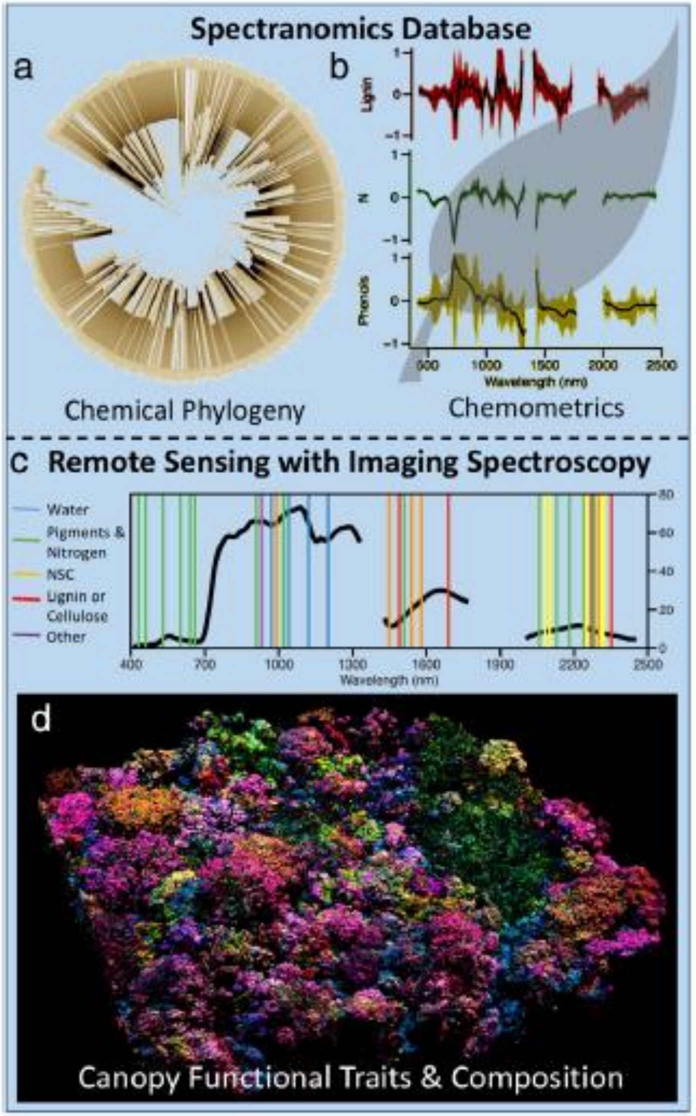
2. Radiative Transfer Modeling



Cab = 0, 16, 32, 48, 64, 80 µg cm^{-2}

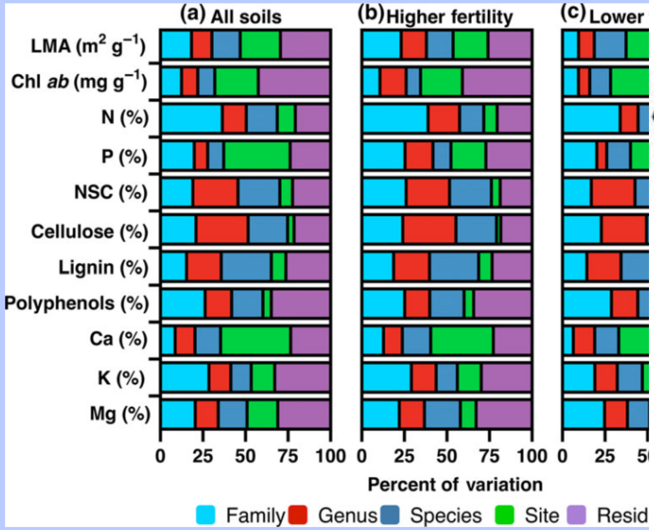
3 Species Traits

Spectranomics

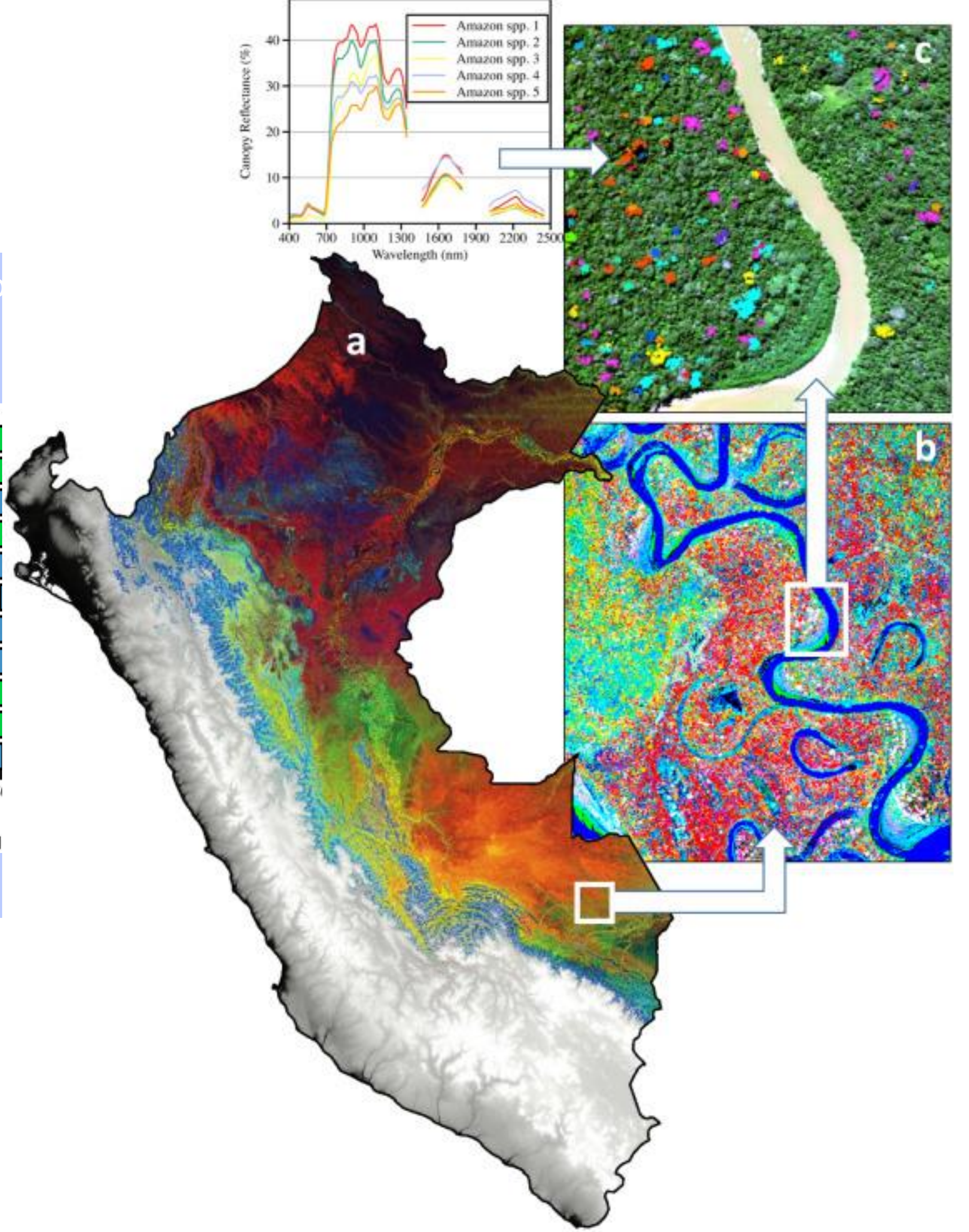


[Asner et al. 2016]

Foliar traits determined from spectra o
tree canopies at 75 sites Using PLSR



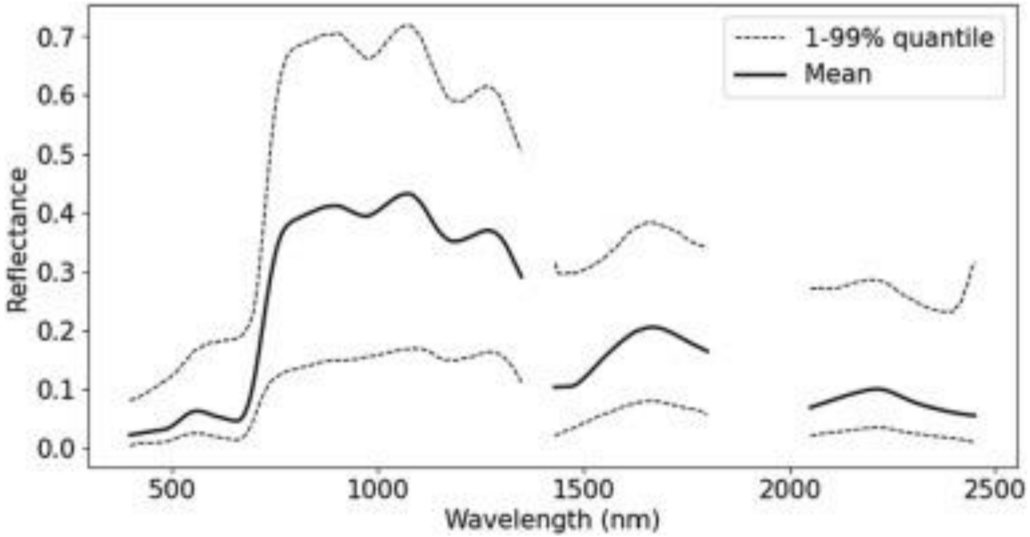
[Martin and Asner 2016]



3 Species Traits

Highlights

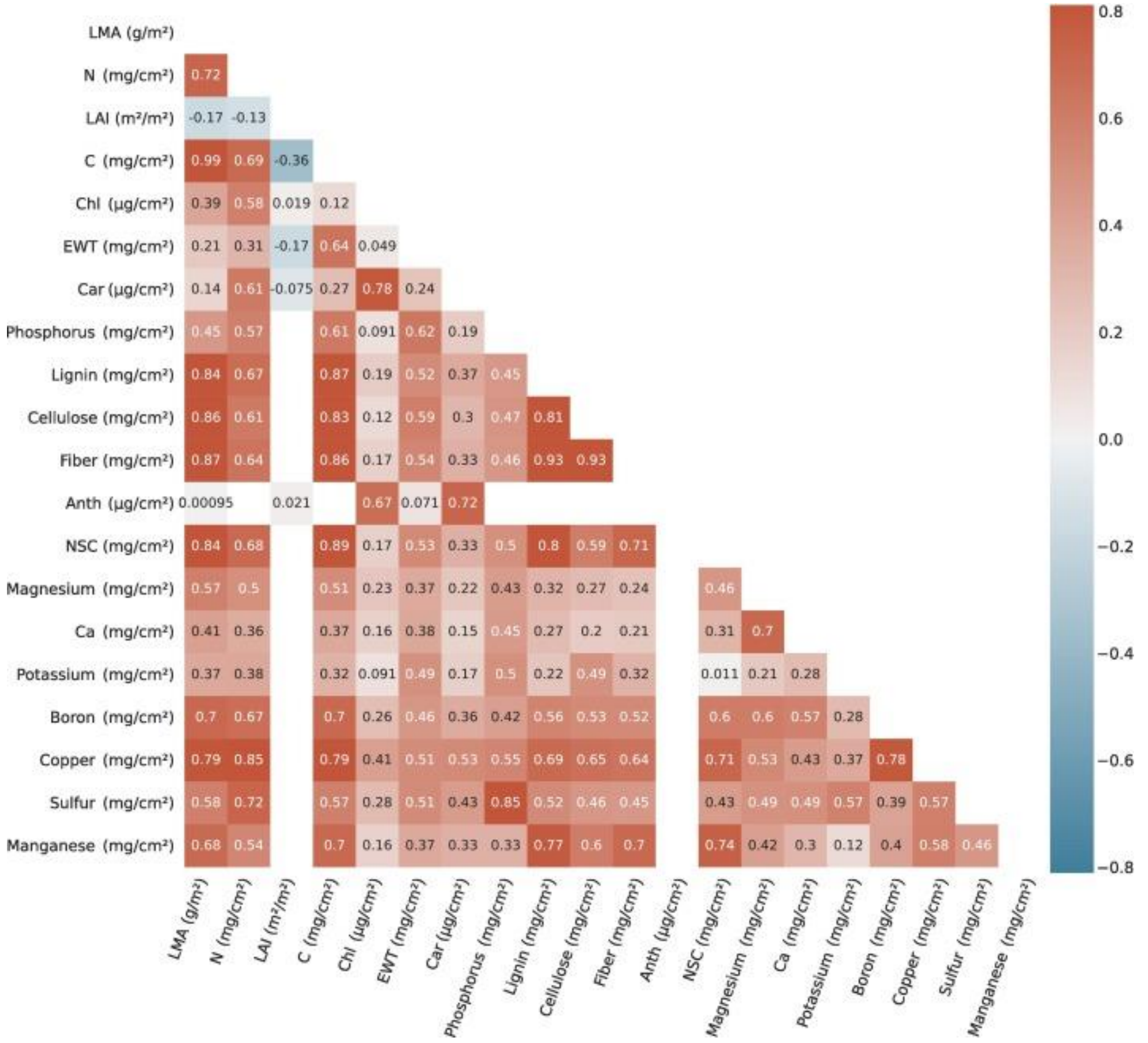
- We retrieve a set of 20 plant traits with a CNN model from canopy spectra.
- The multi-trait model covers various ecosystems, vegetation types and sensors.
- The multi-trait model outperforms partial least squares regression approaches.
- Despite sparsity, data heterogeneity facilitated high retrieval performance.
- Data sharing and collaboration advances the development of transferable models.

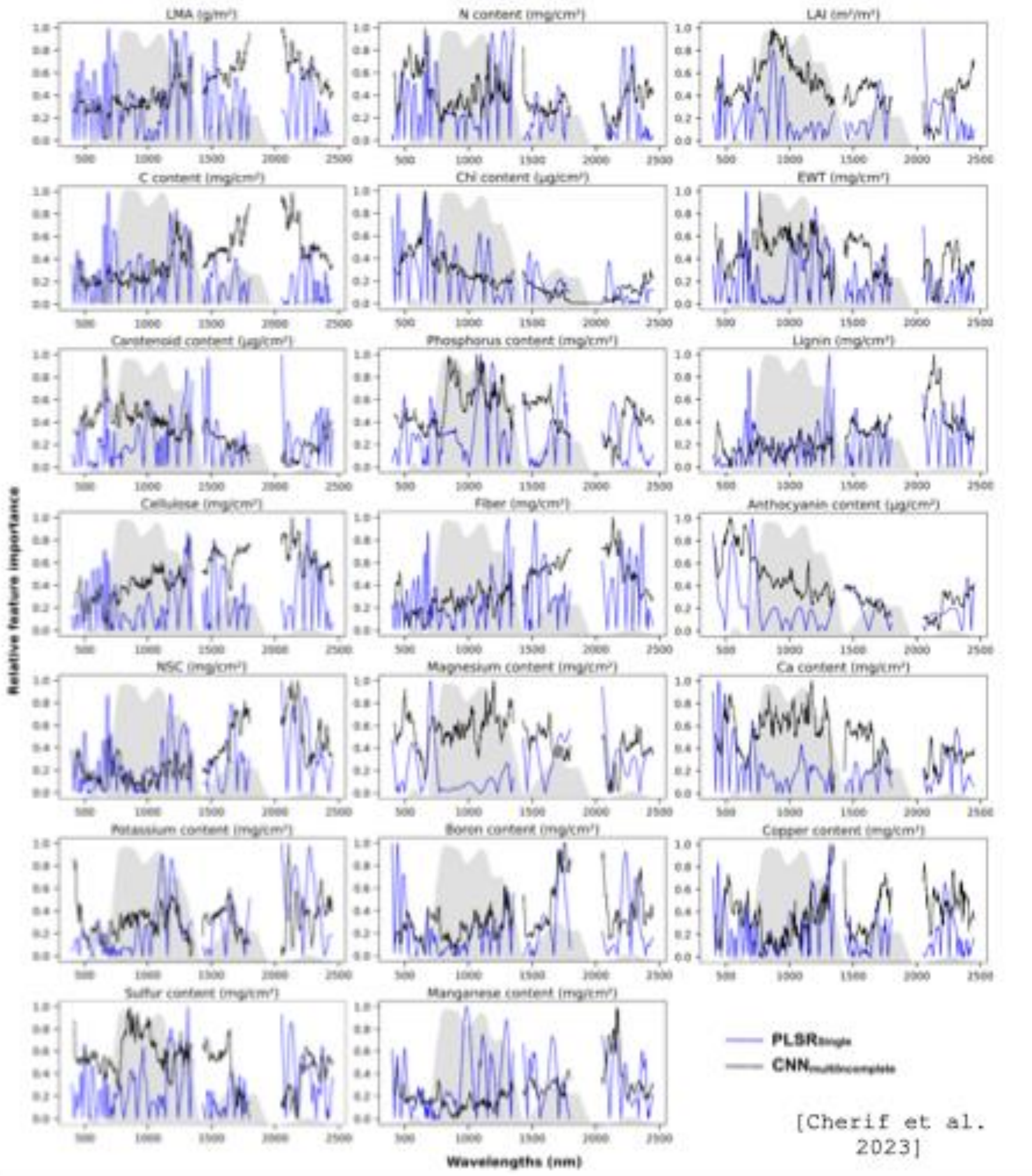


3

Species Traits

Area based trait correlation





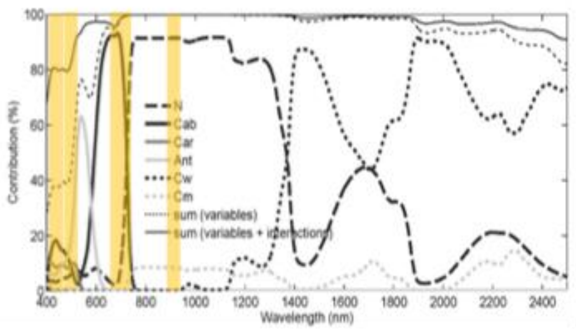
3 Species Traits

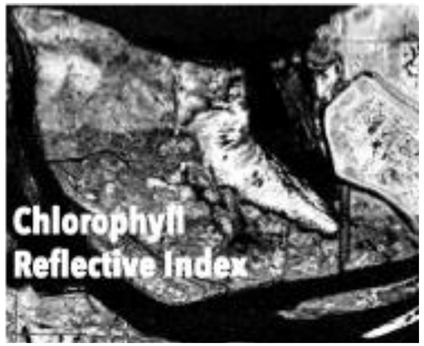
Traits measured with vegetation indices:

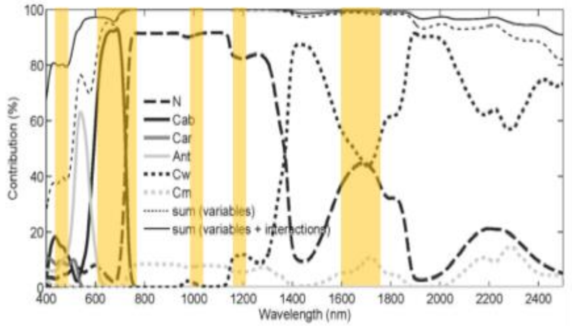
- 30 indices for chlorophyll and other pigments
- 20 indices for leaf area
- 9 indices leaf water content
- 29 indices lignin, cellulose and salinity

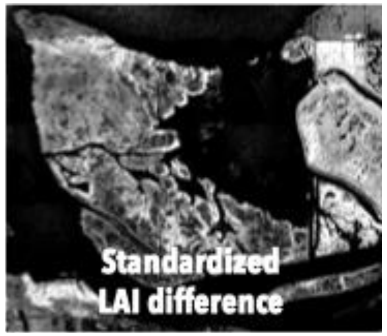
2004-2008
2014-2019

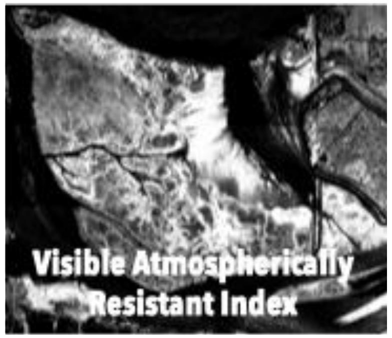
Emergent and riparian vegetation

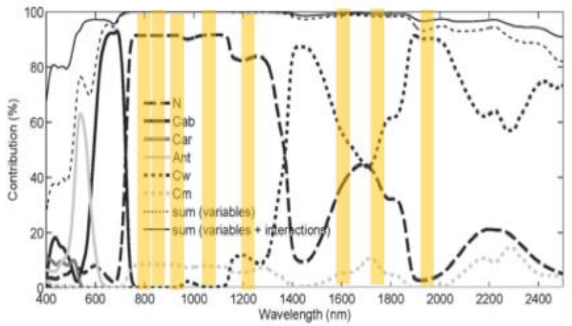


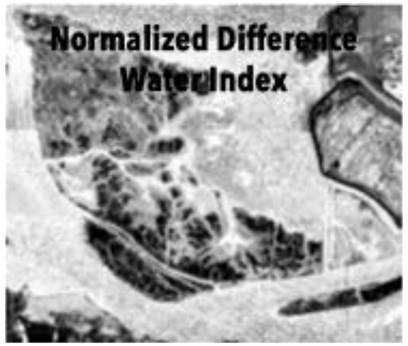


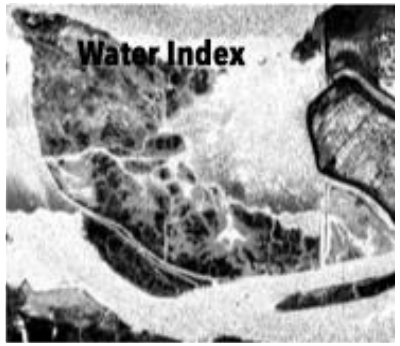


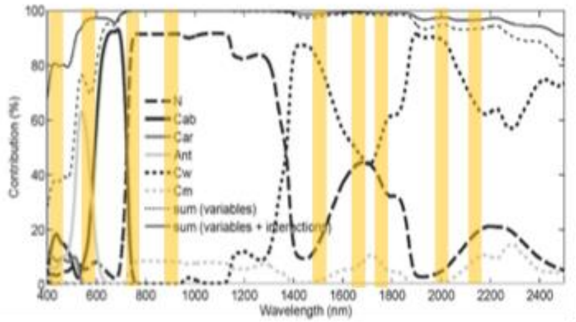




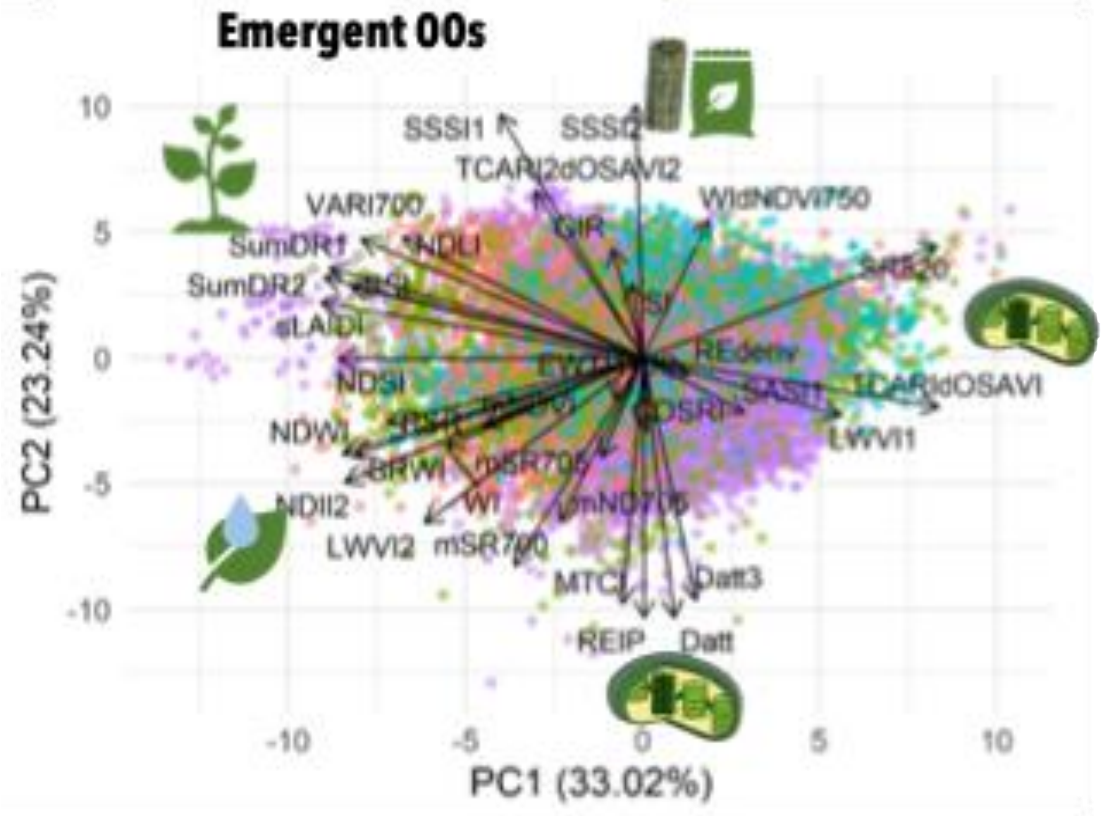


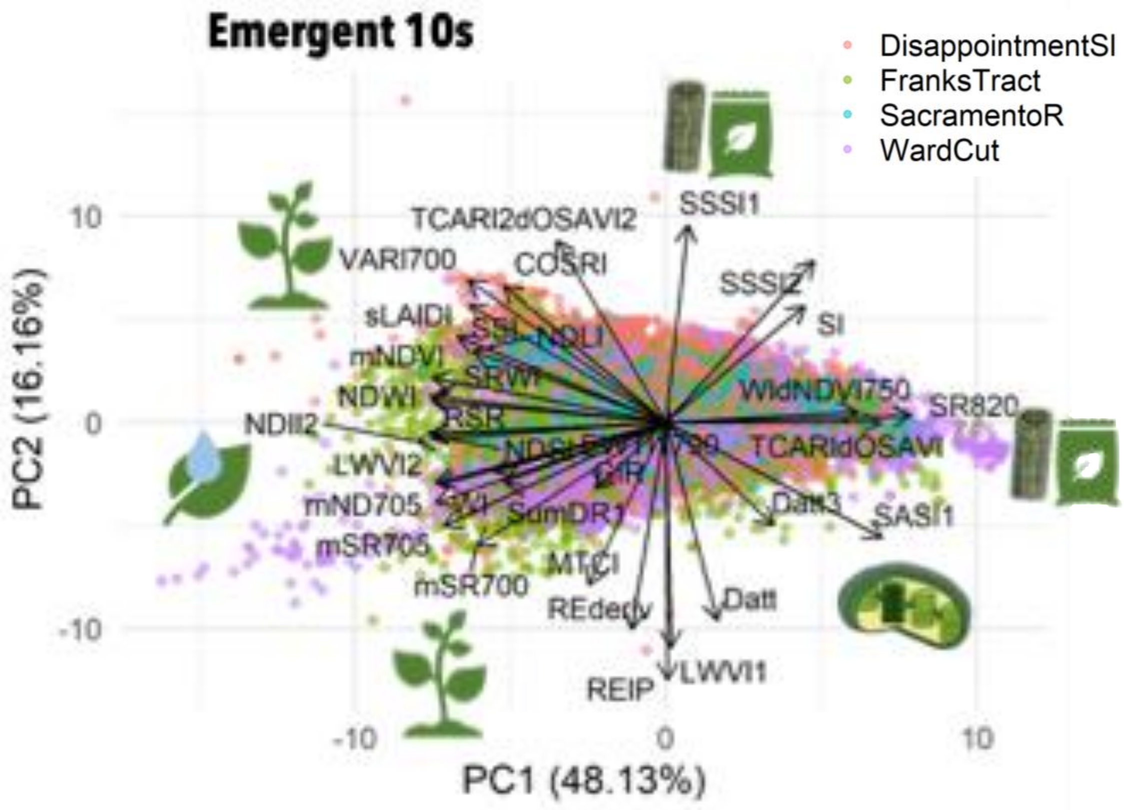




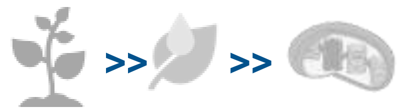


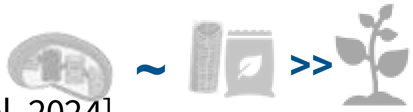
3 Species Traits





Loadings

PC1 

PC2 

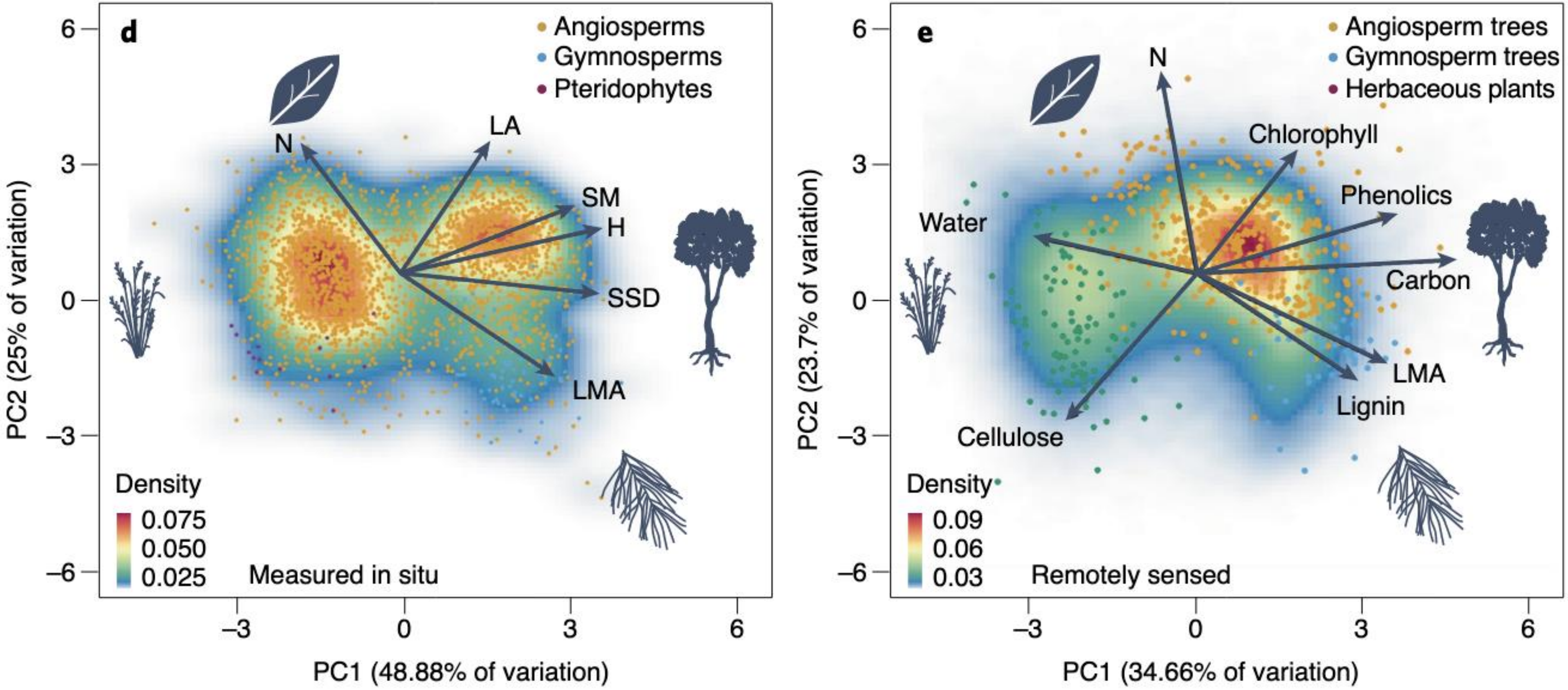
Loadings

PC1 

PC2 

[Santos et al. 2024]

3 Changing global distributions of plant functional traits and trait diversity



4 Community Composition

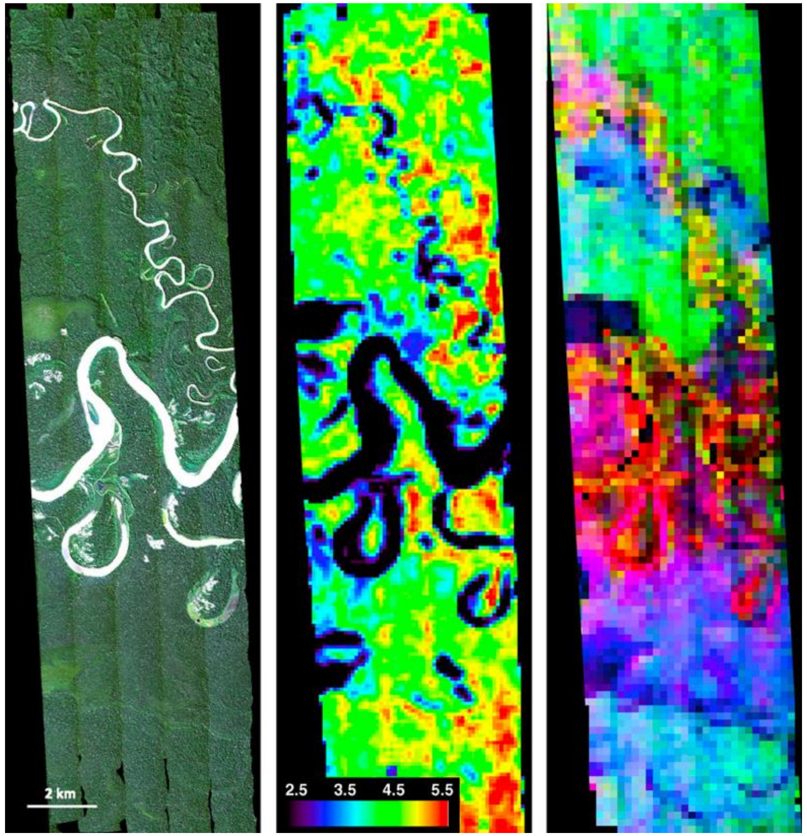
4 Community Composition

Spectral Variability Hypothesis

variability in reflectance or “spectral variability” of an area is an expression of spatial ecosystem heterogeneity and therefore related to plant diversity

Diversity metrics

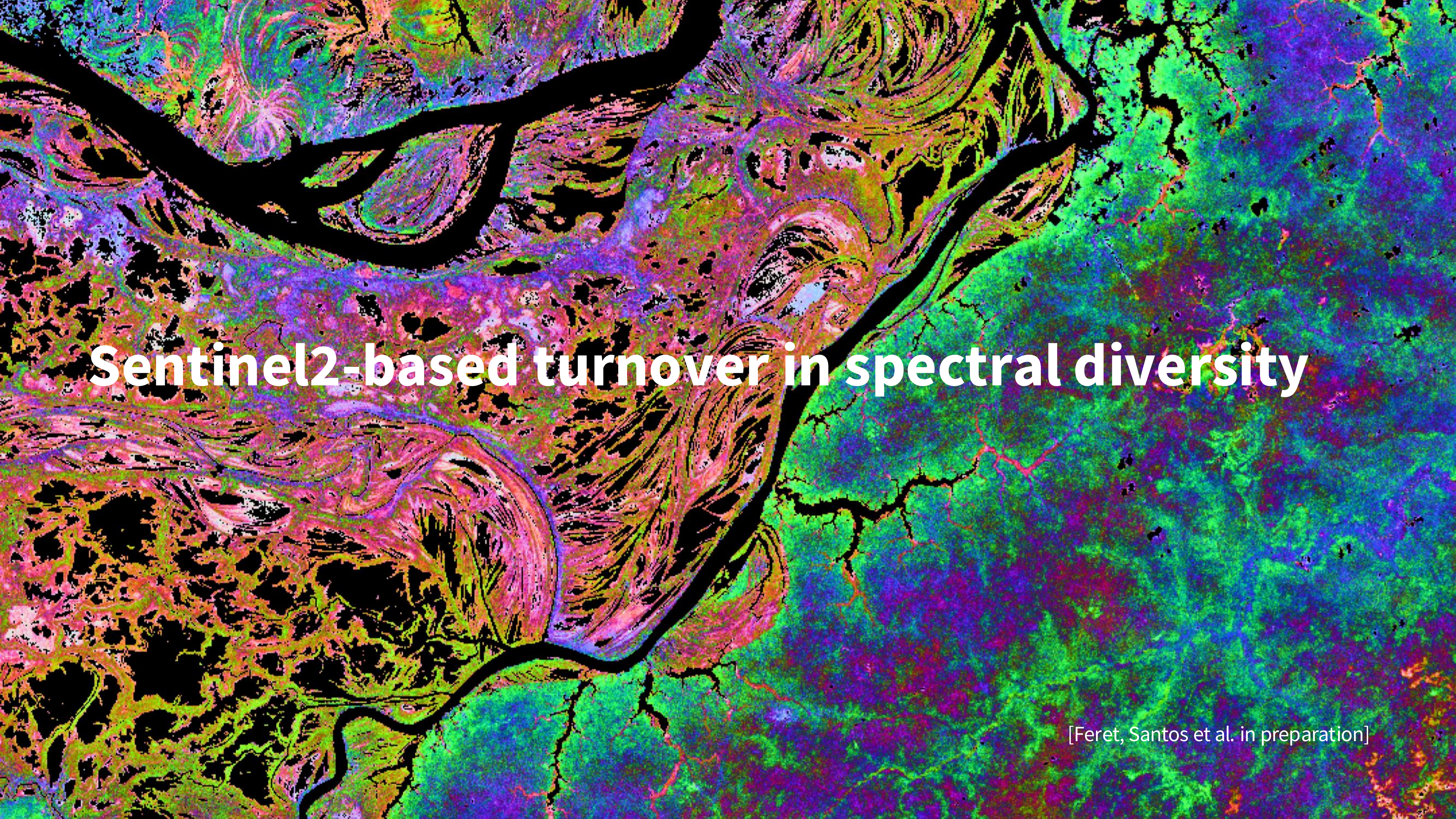
Alpha diversity – local richness
Beta diversity – turnover in species composition



biodivMapR

An R package for α- and β-diversity mapping using remotely-sensed images

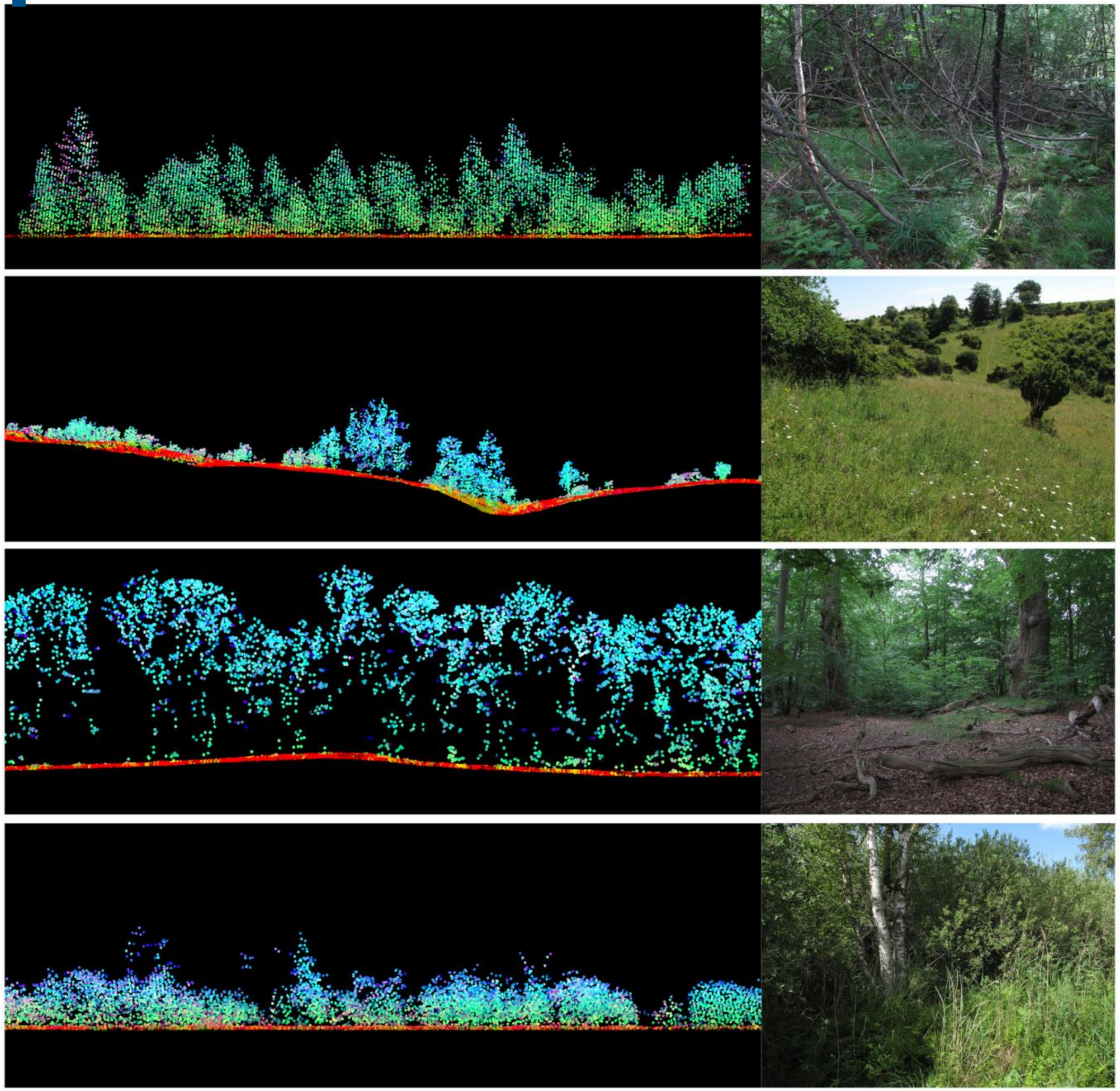
Sentinel2-based turnover in spectral diversity



[Feret, Santos et al. in preparation]

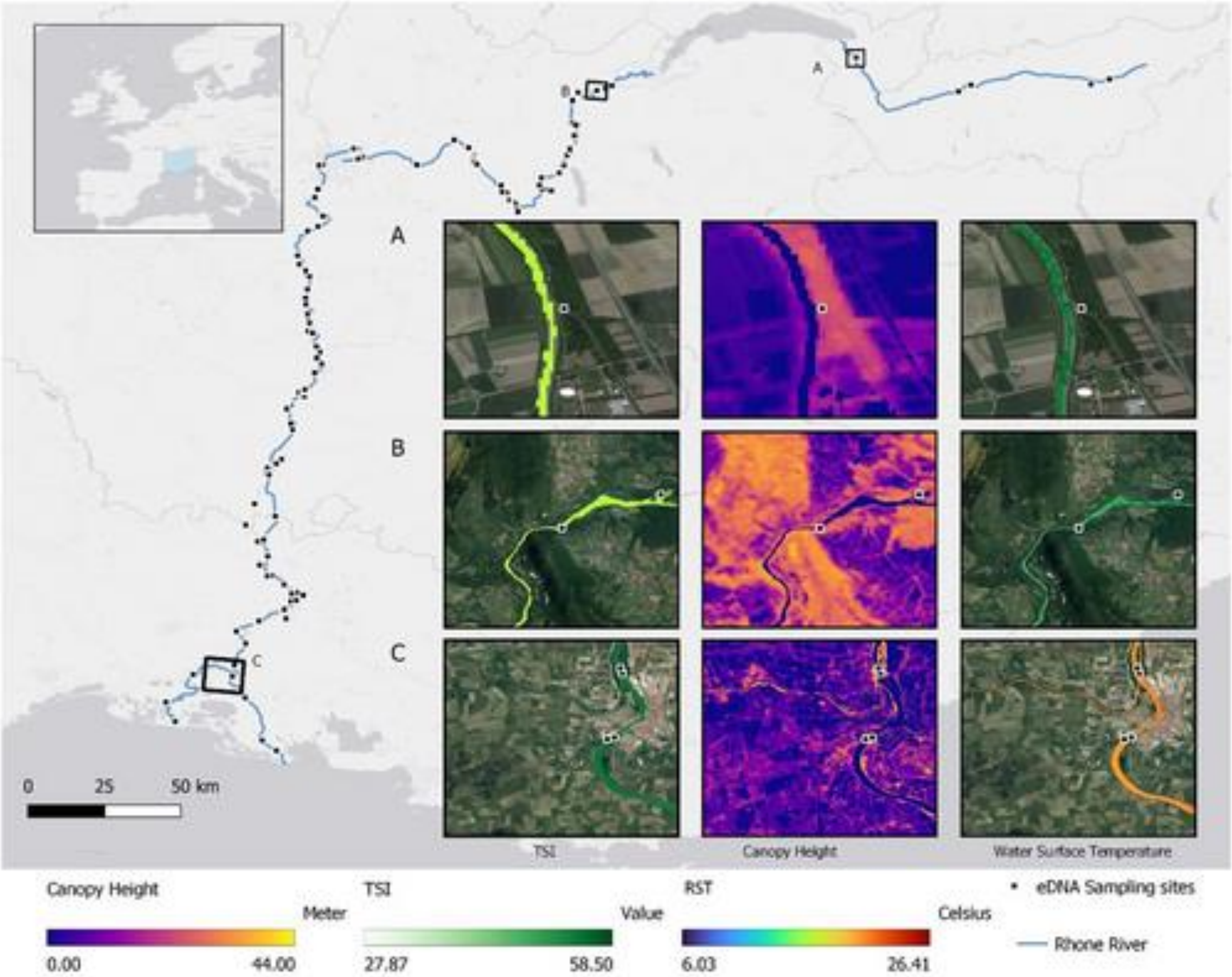
4 Community Composition

- shrub layer density
- medium-tree layer density
- point amplitude
- relative biomass

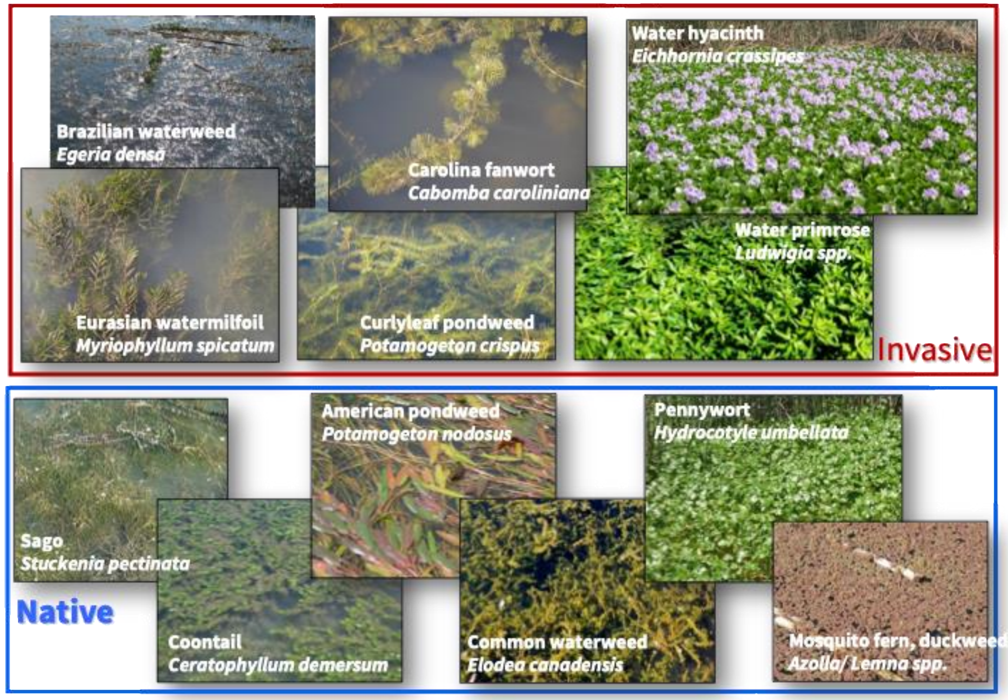


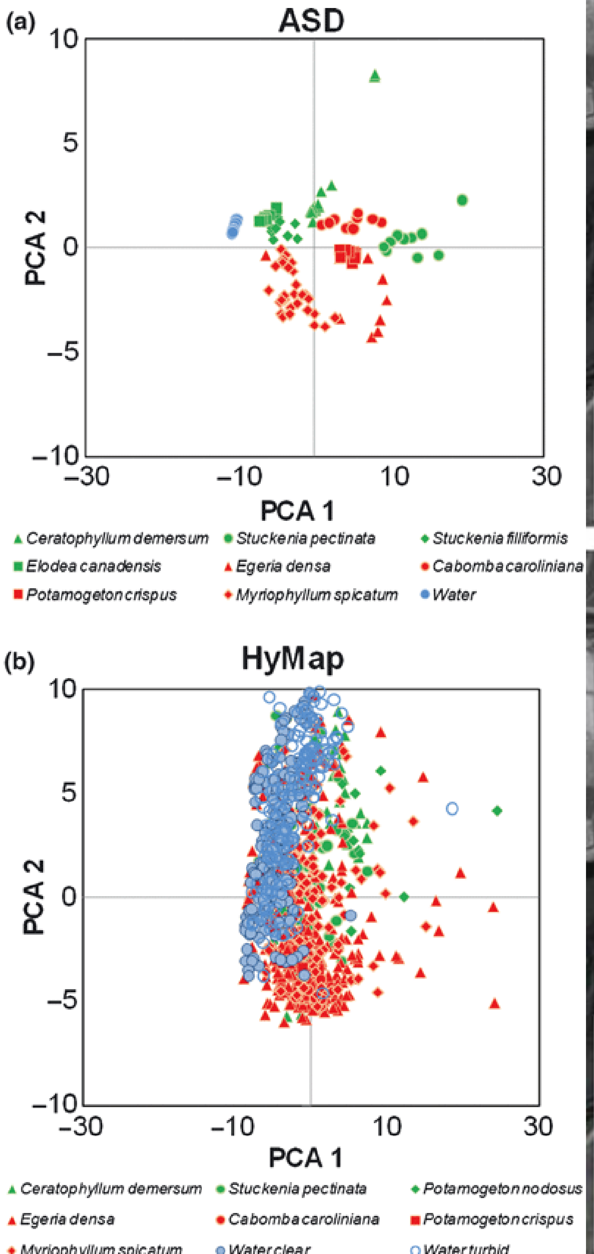
4 Community Composition

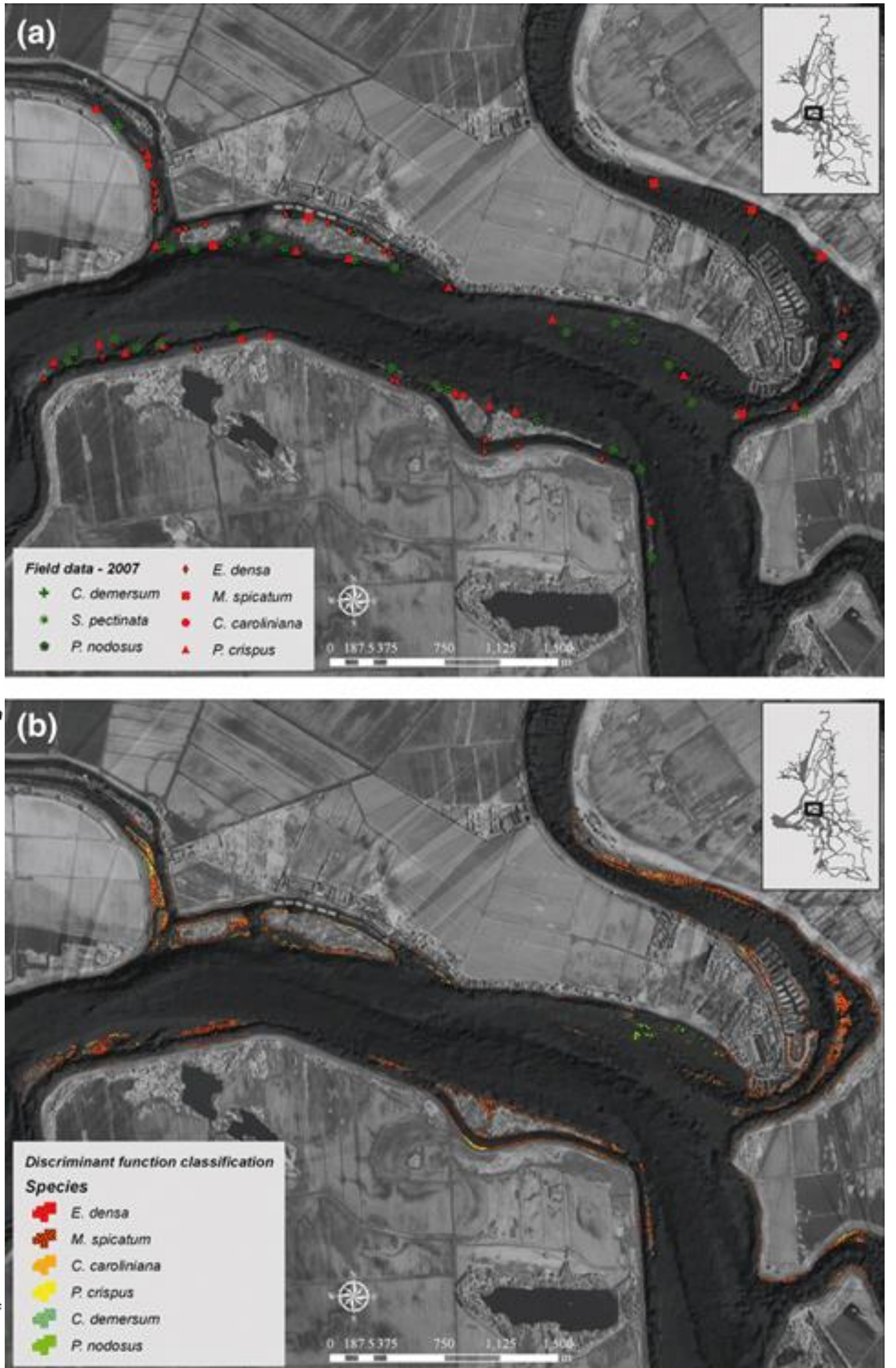
Freshwater systems



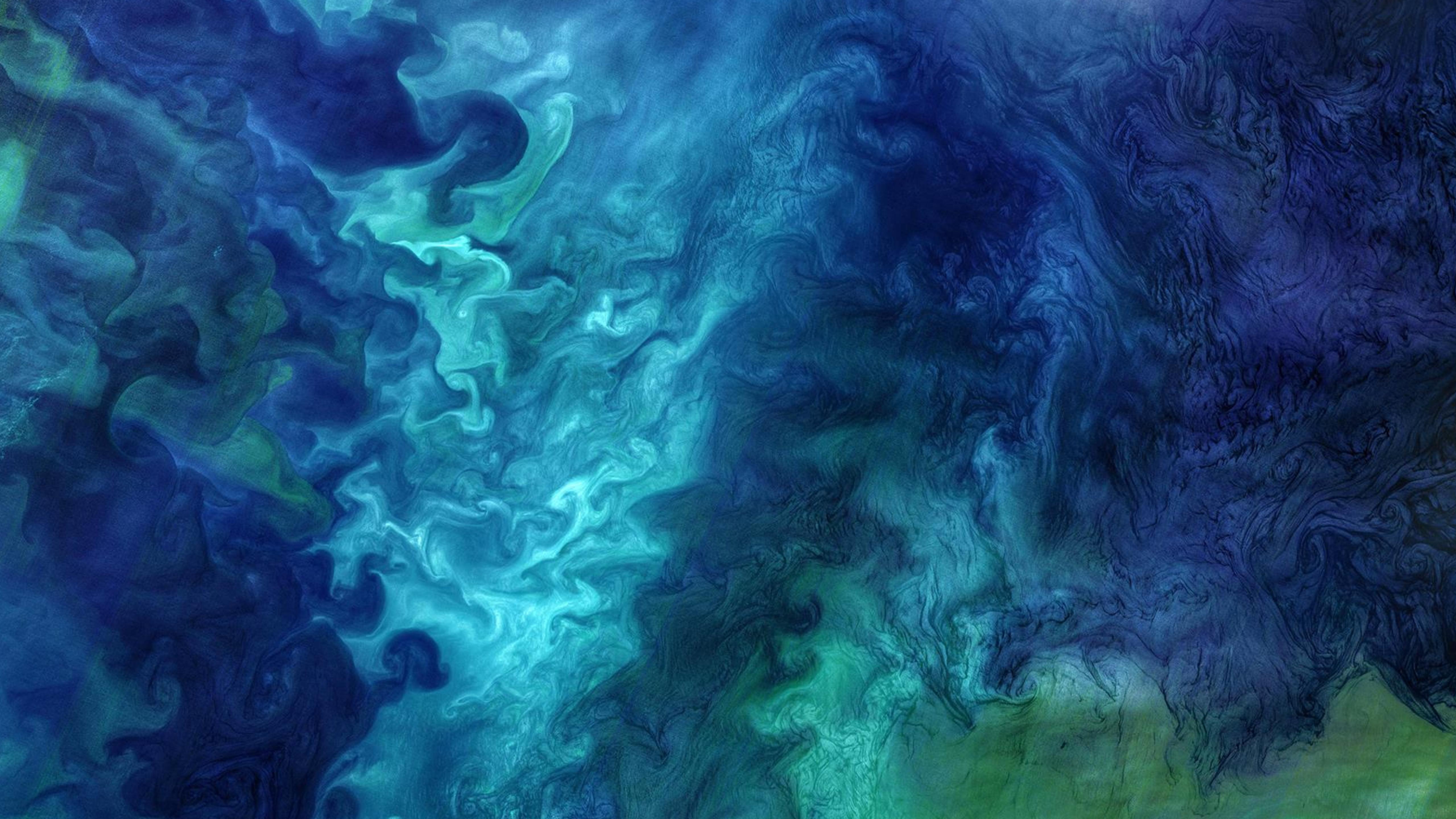
4 Community Composition





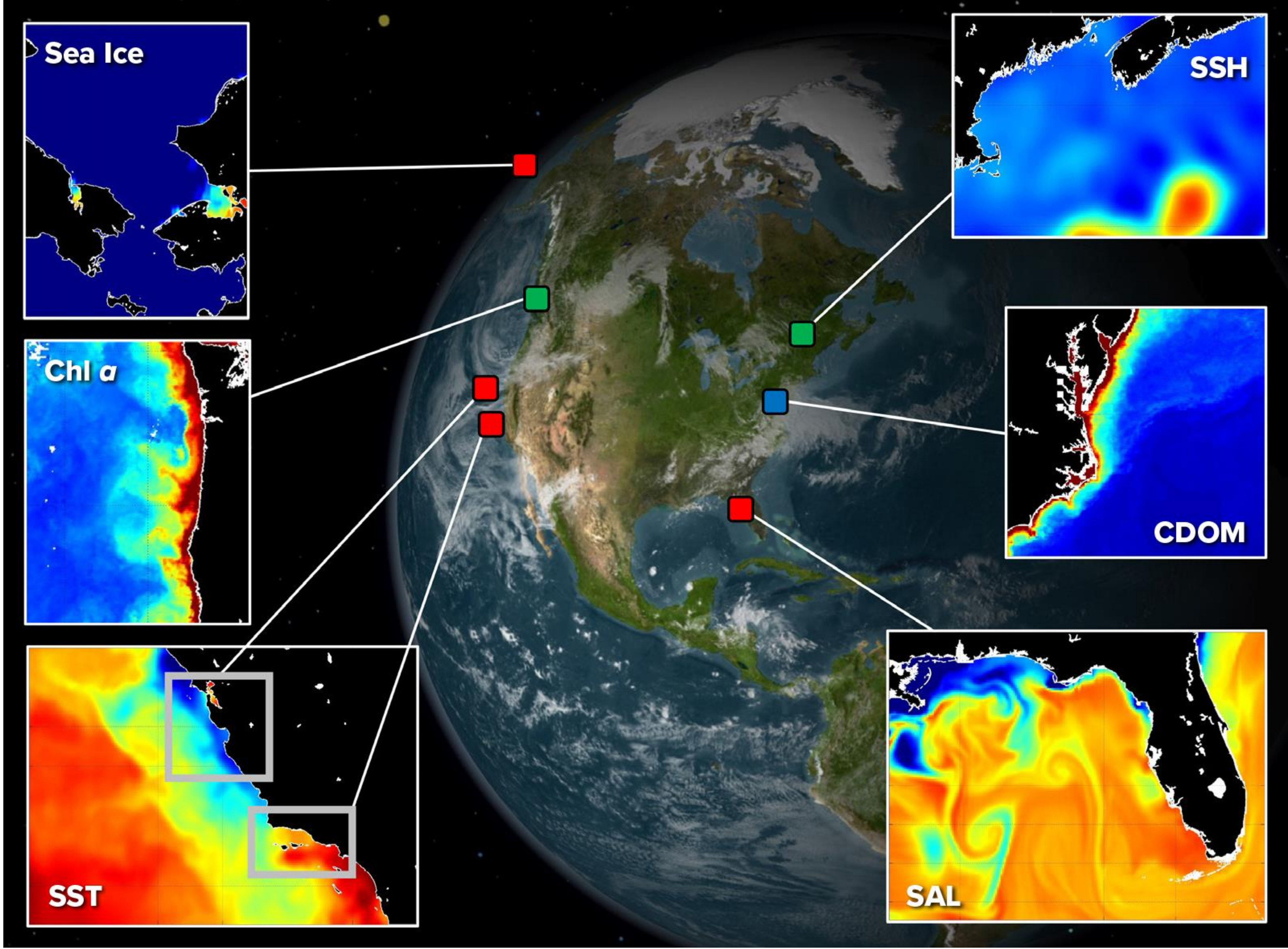


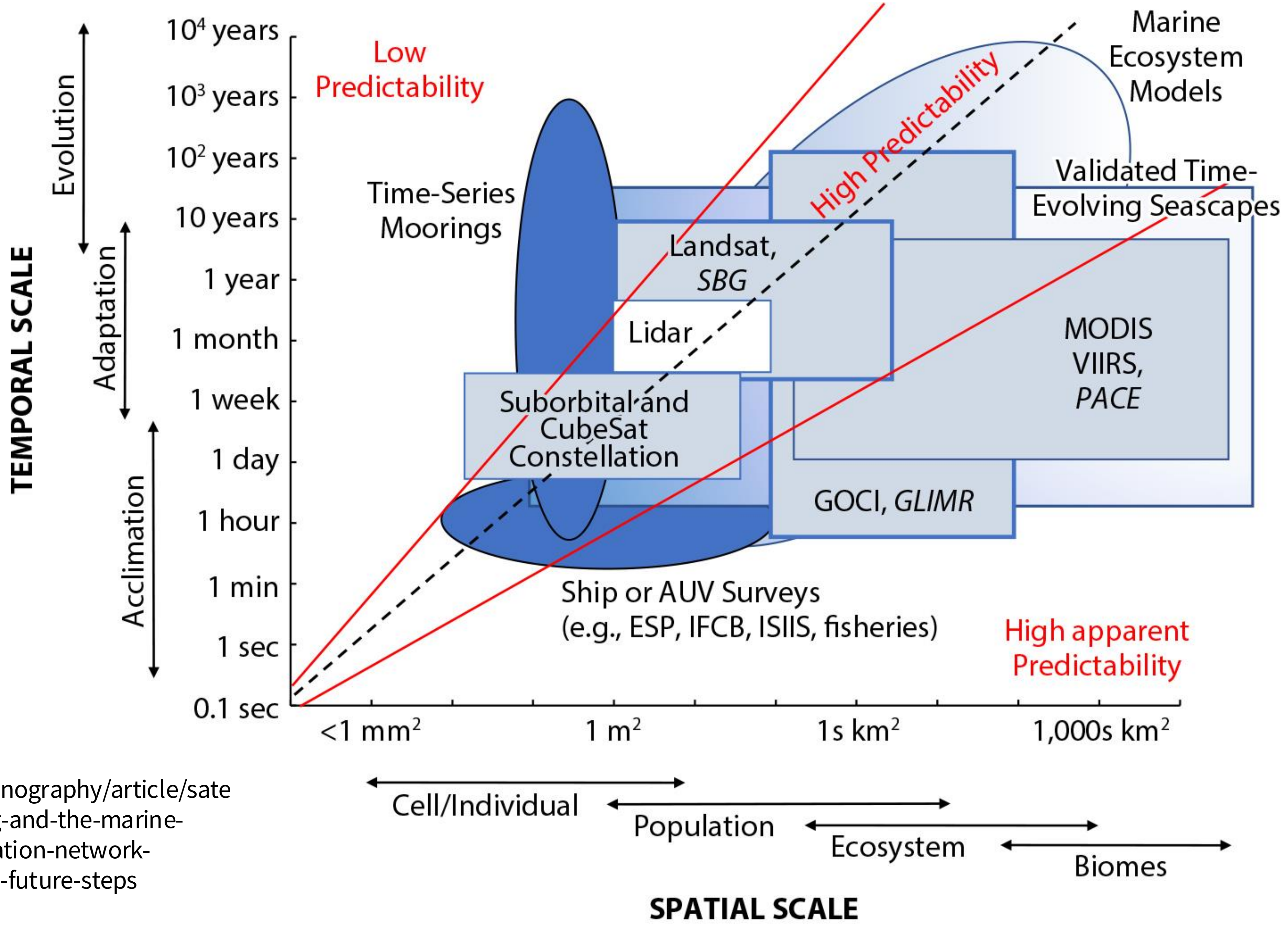
 | Santos et al. 2012



Ocean Color

- sea ice
- sea surface temperature (SST)
- sea surface height (SSH)
salinity (SAL)
- chlorophyll *a* (Chl-*a*)
- chromophoric dissolved organic matter (CDOM)

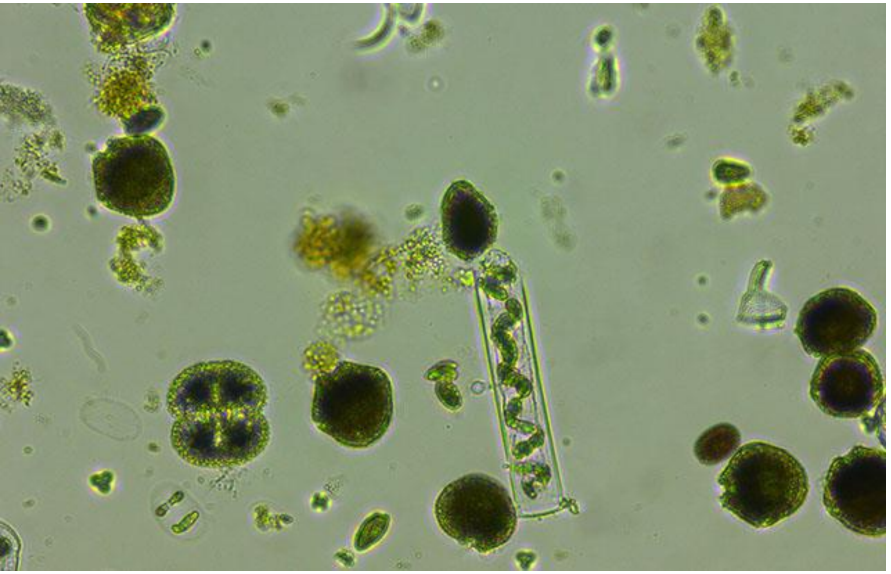


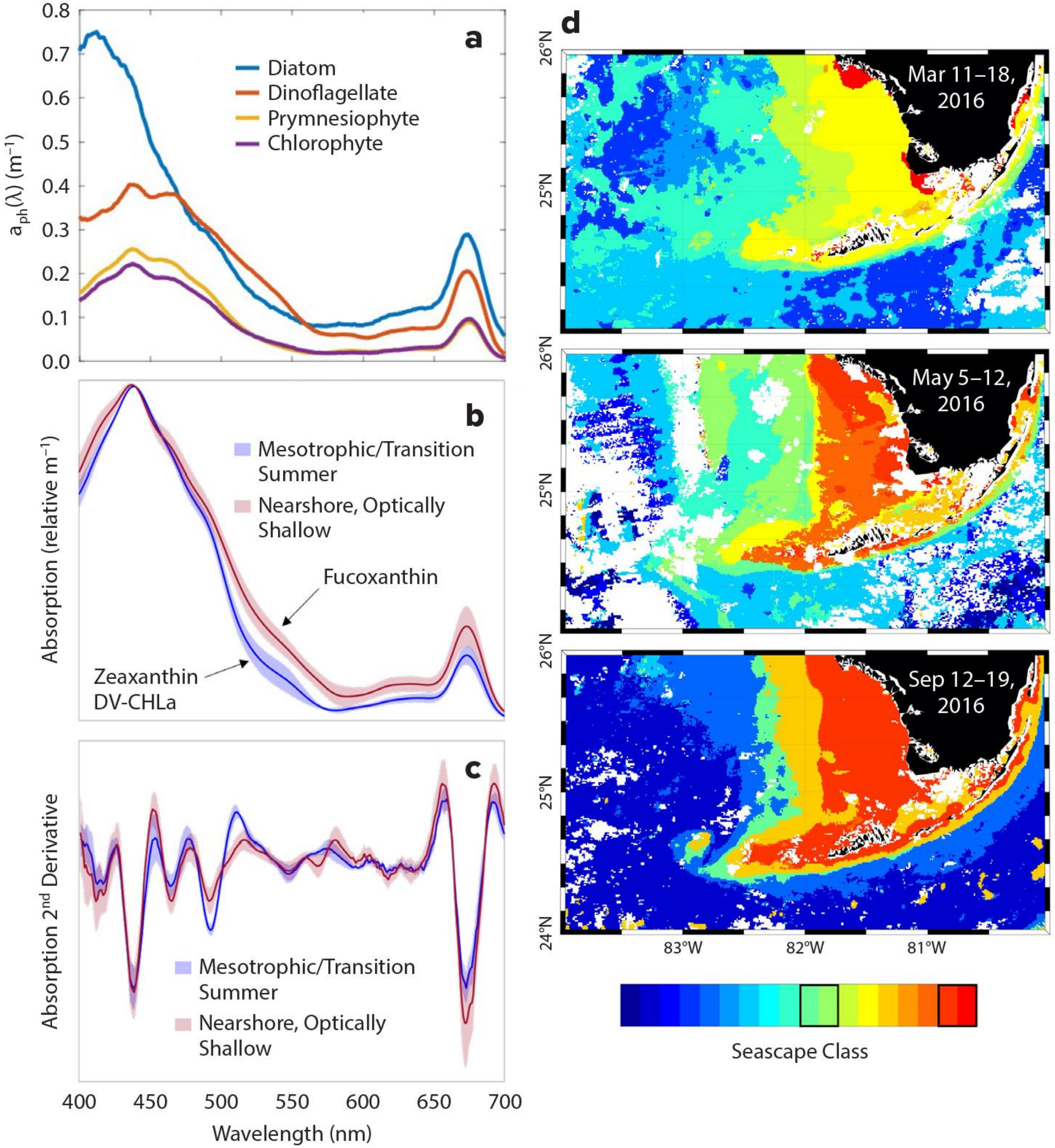


https://tos.org/oceanography/article/satellite-remote-sensing-and-the-marine-biodiversity-observation-network-current-science-and-future-steps

4 Community Composition

Phytoplankton

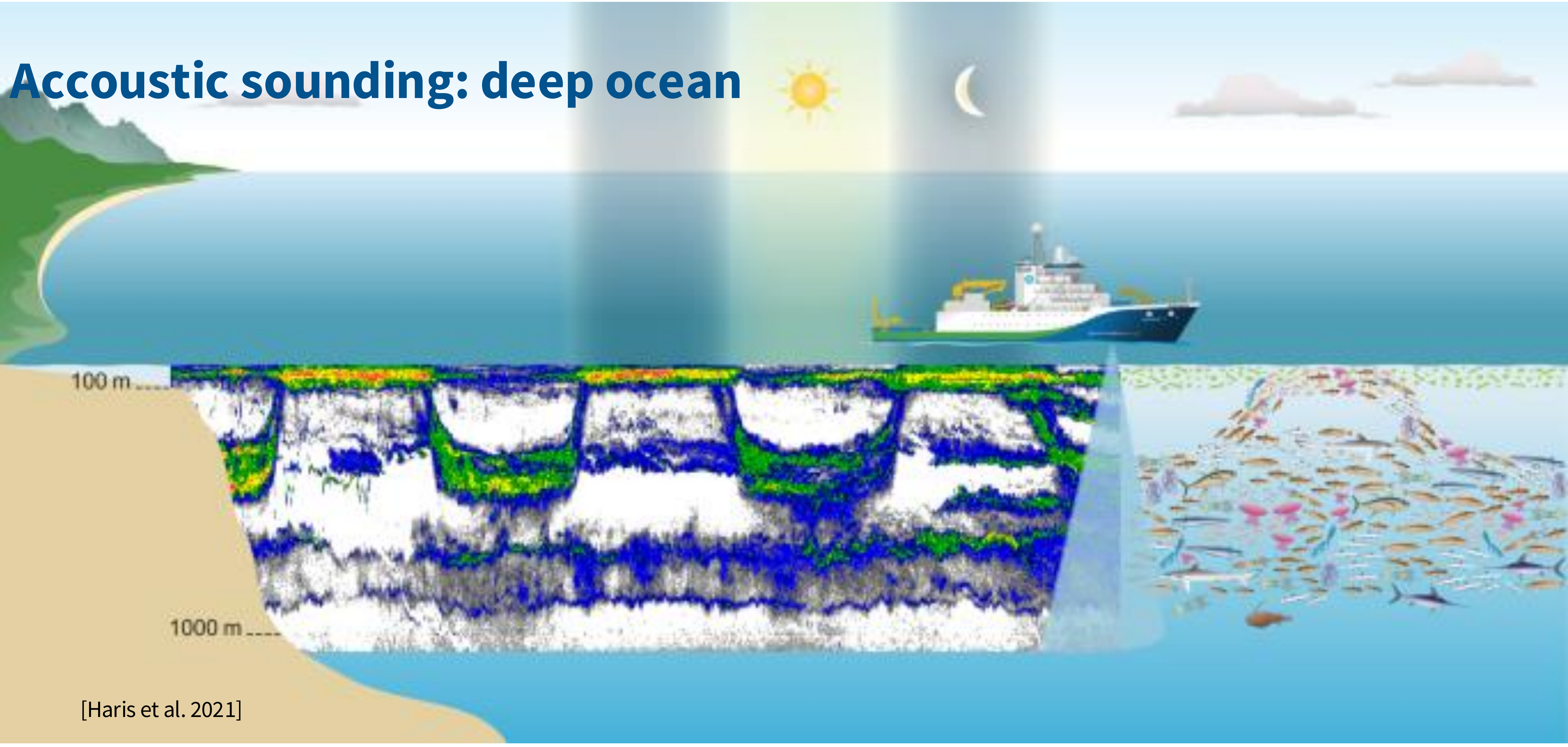




https://tos.org/oceanography/article/satellite-remote-sensing-and-the-marine-biodiversity-observation-network-current-science-and-future-steps

4 Community Composition

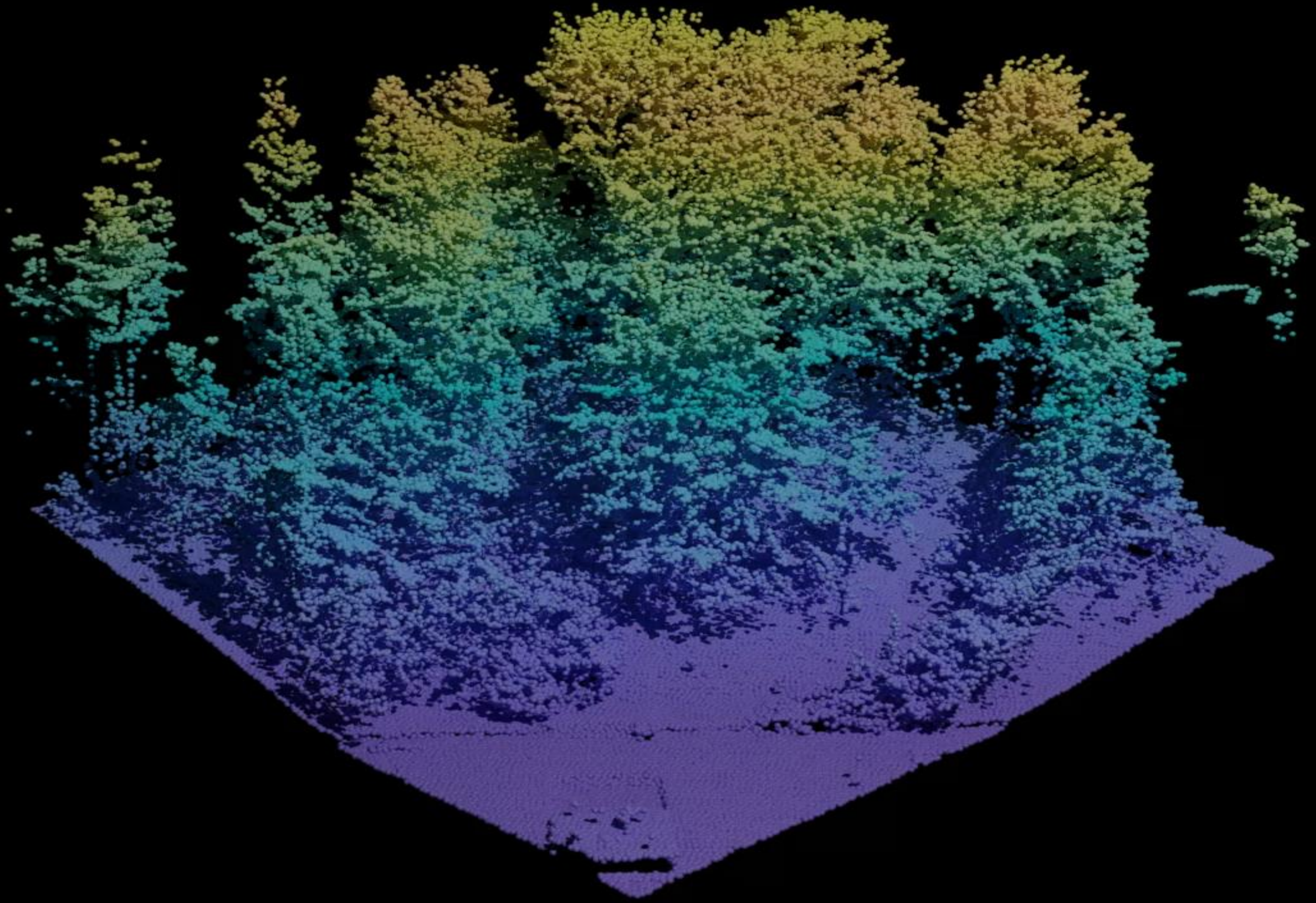
Accoustic sounding: deep ocean

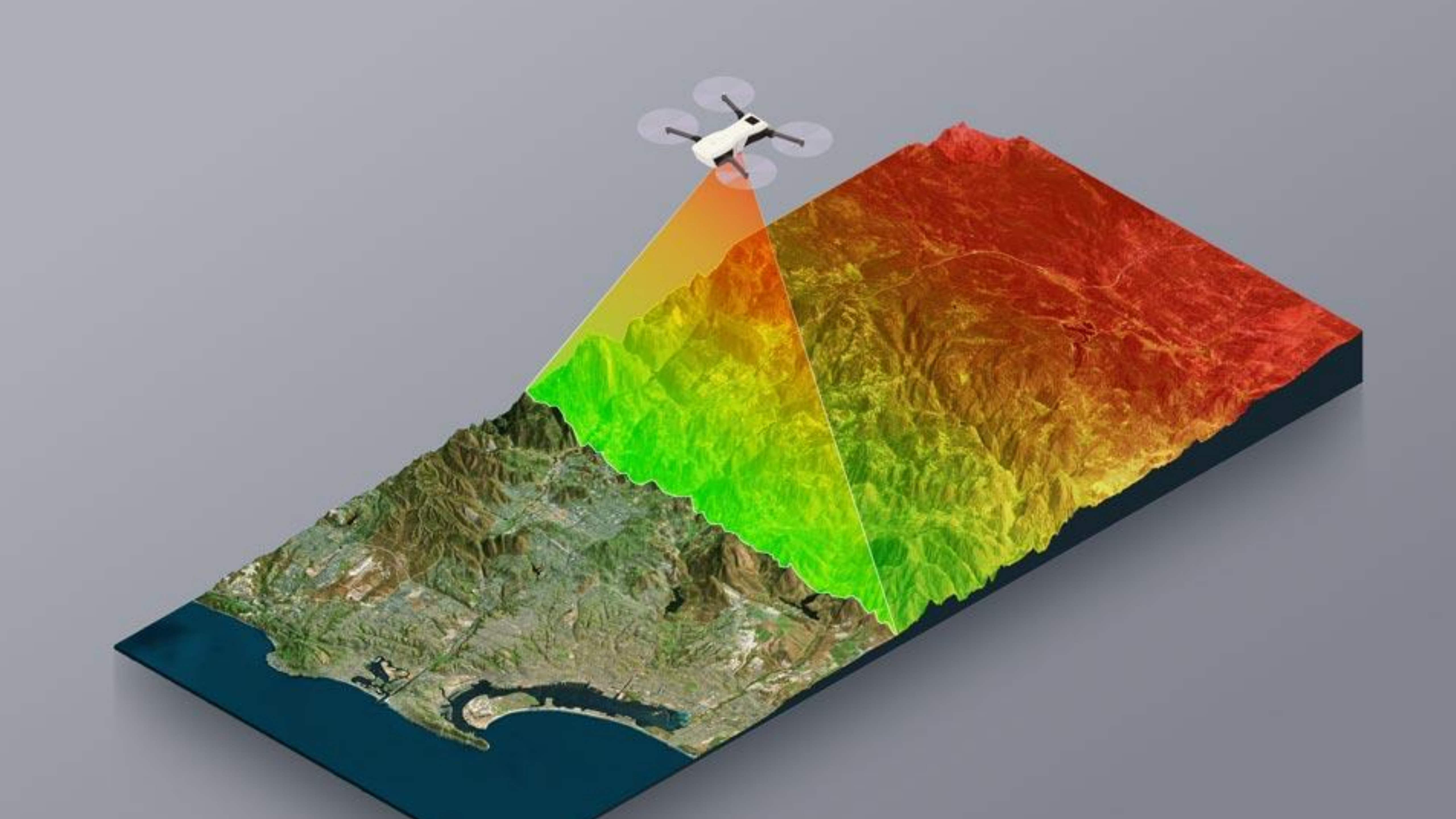


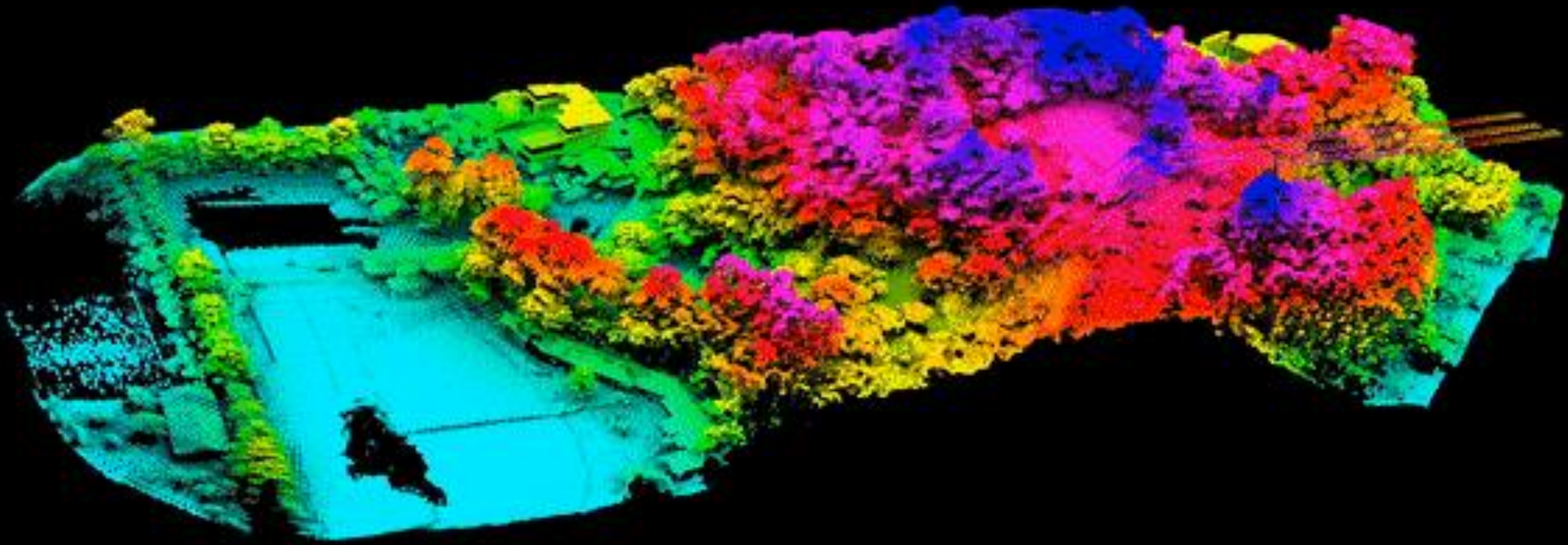
[Haris et al. 2021]

5 Ecosystem structure

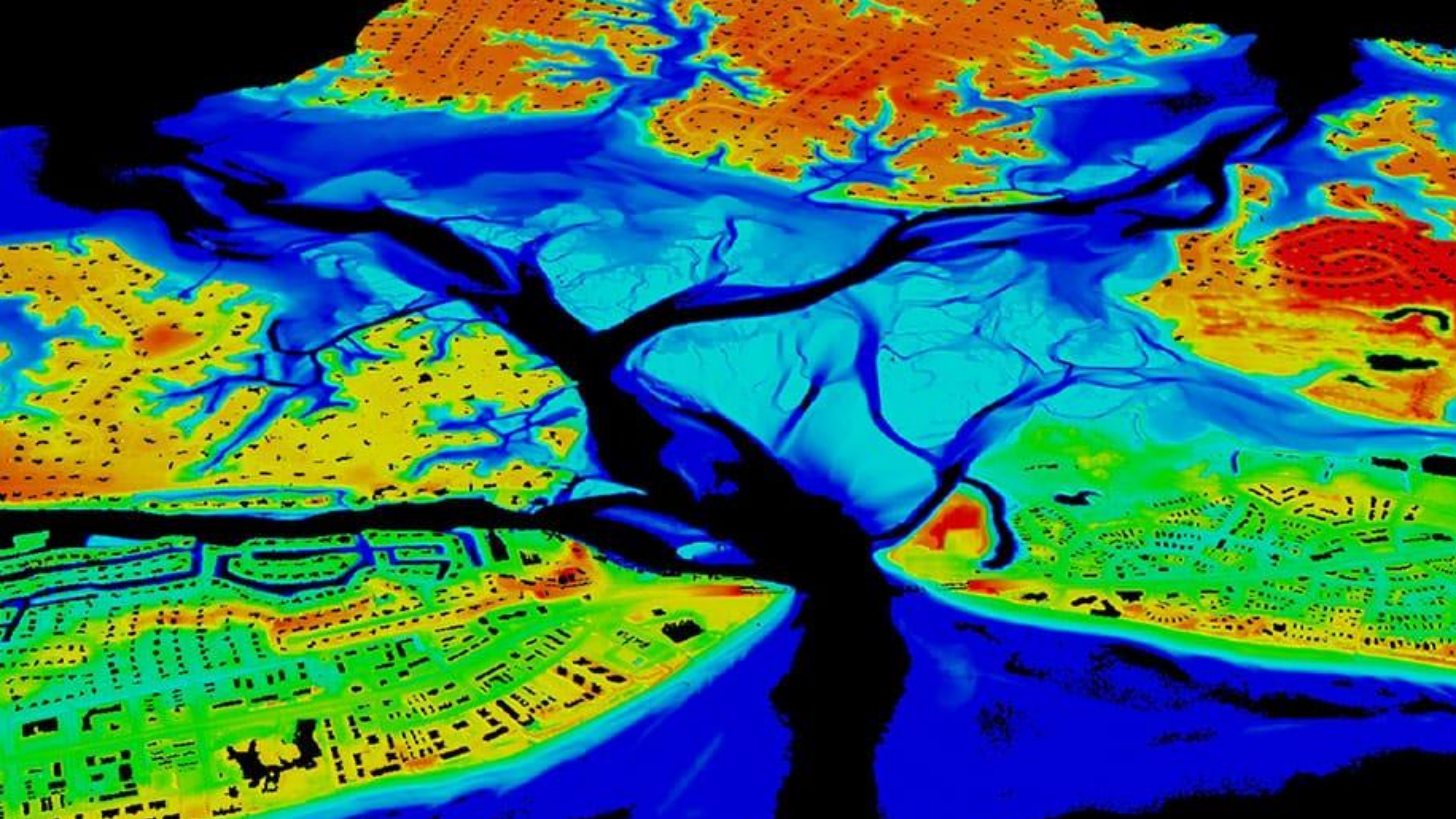
LIDAR







https://enterprise-insights.dji.com/blog/lidar-equipped-uavs



5 Ecosystem structure

WHAT IS ECOSYSTEM STRUCTURE?

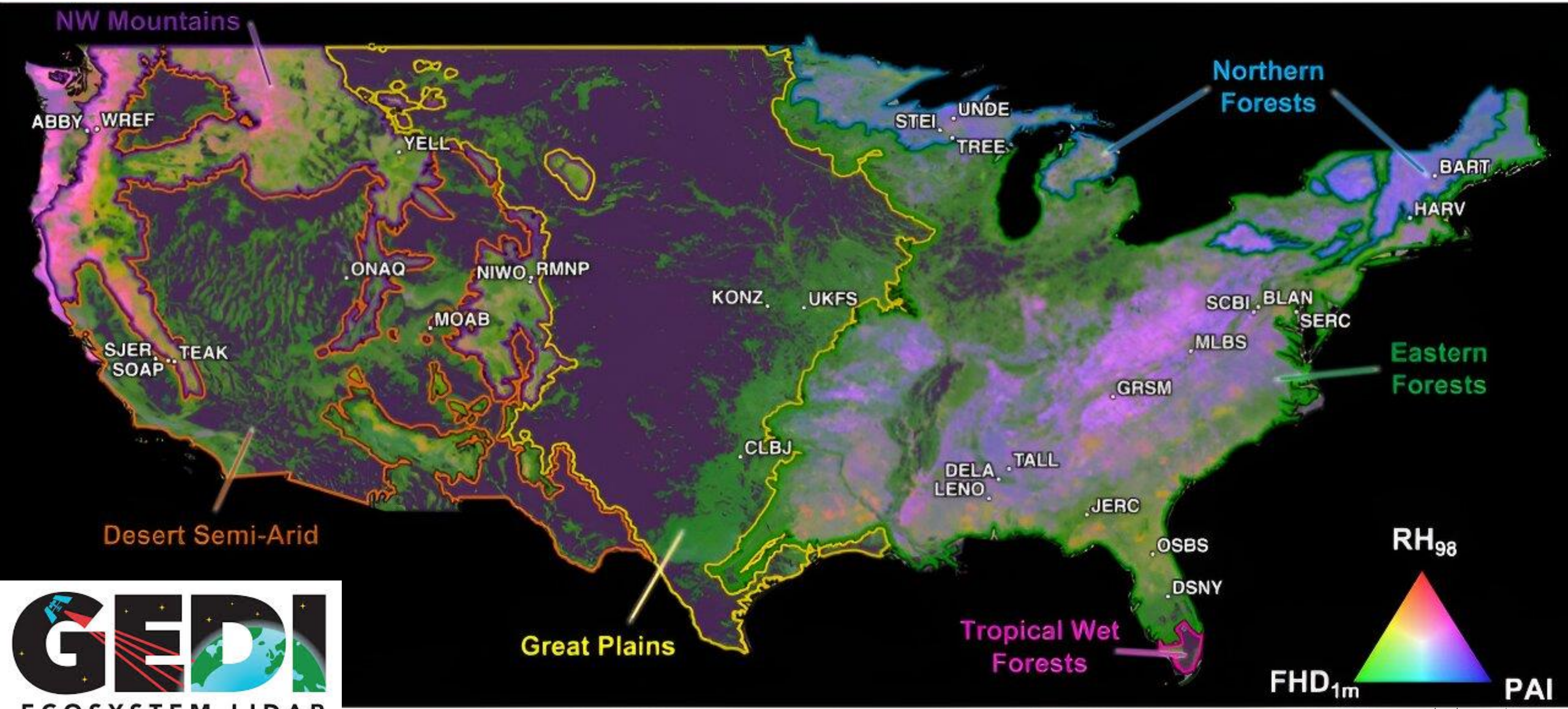
Ecosystems can be characterized by their structure, function and composition. Together, these aspects influence processes such as biogeochemical fluxes and properties such as productivity, habitat quality, and biodiversity. Ecosystem structure refers to the horizontal and vertical distribution of ecosystem elements and their interactions. For example, landscape structure can be characterized by the horizontal distribution of canopy gaps within a forest. On a more local scale, vegetation structure can be characterized by the vertical distribution of stems, branches and leaves. GEDI provides high spatial and vertical resolution measurements of ecosystem structure.

GEDI HAS THREE SCIENCE QUESTIONS:

1. What is the current state of Earth's forest structure?
2. What will forest dynamics look like in the future?
3. How does forest structure affect habitat quality and biodiversity?

5 Ecosystem structure

maximum height (H_{max}), foliage height diversity (FHD), and total plant area index (tPAI)



ECOSYSTEM LIDAR

https://gedi.umd.edu/mission/mission-overview/

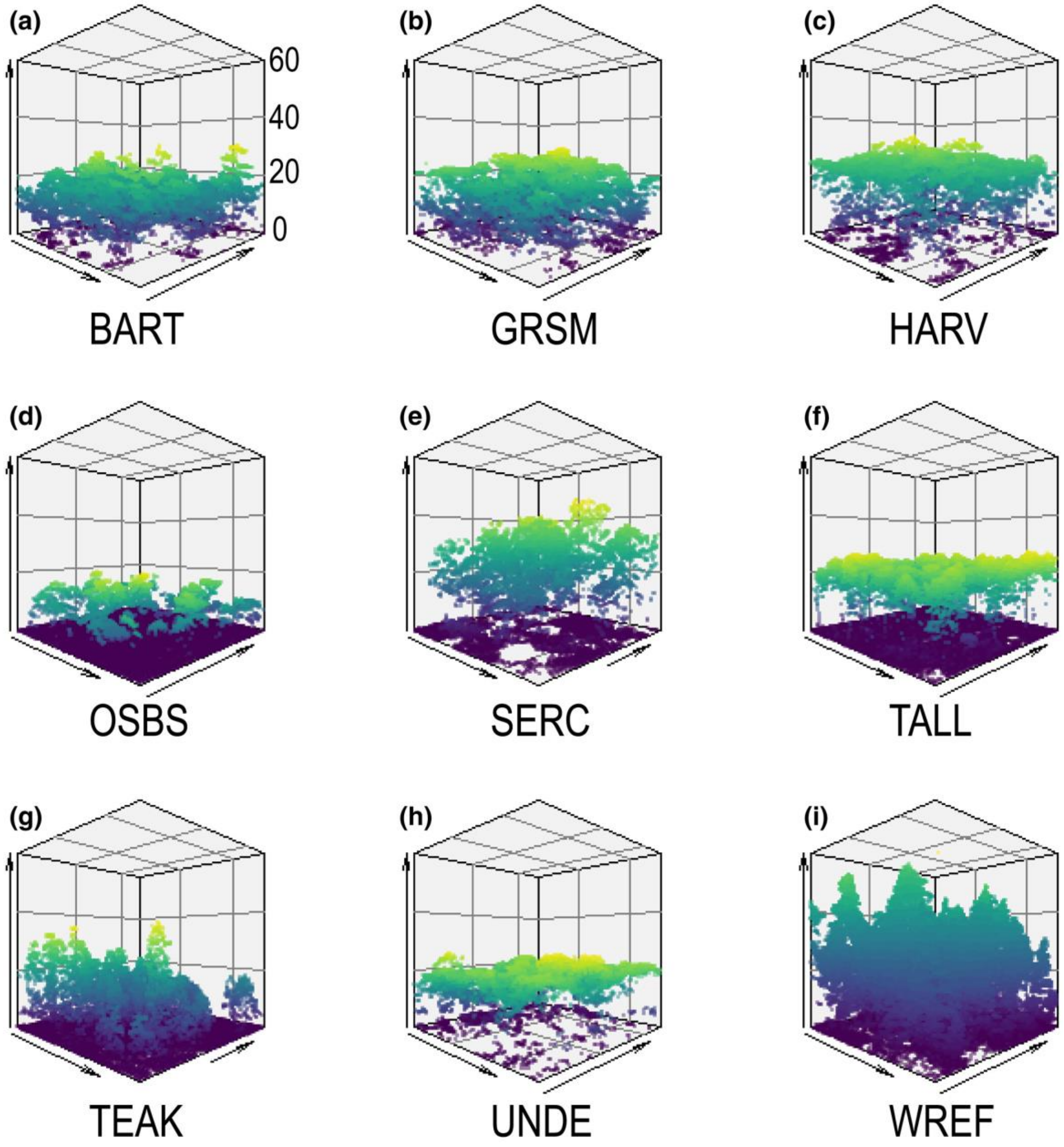
5 Ecosystem structure

Grain size of 25-75 m:

- representative elementary area
- canopy arrangement
- canopy leaf area
- canopy complexity metrics

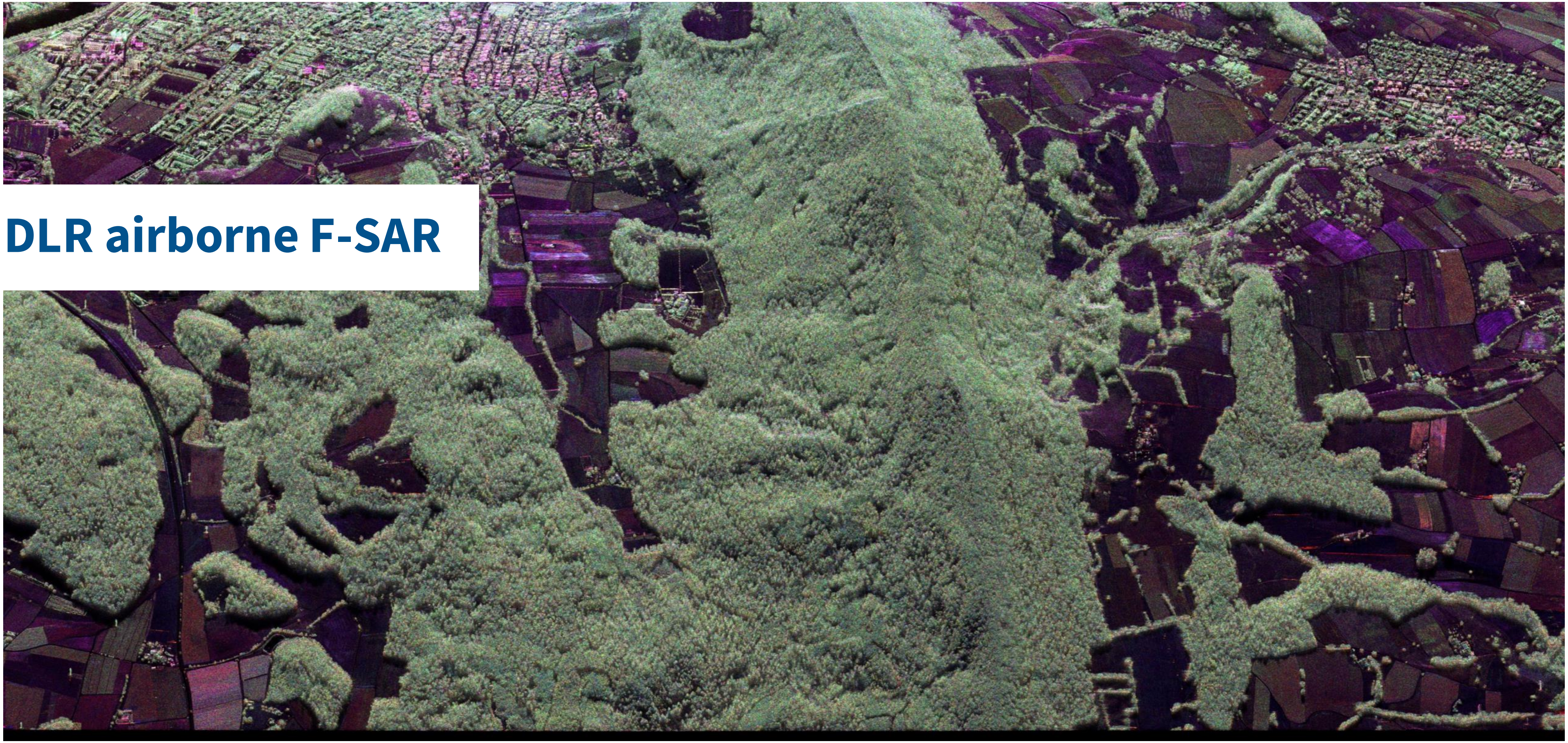
Grain size of 30–150 m:

- representative elementary area captures the REA of canopy height metrics, but differences by type of forest



SAR

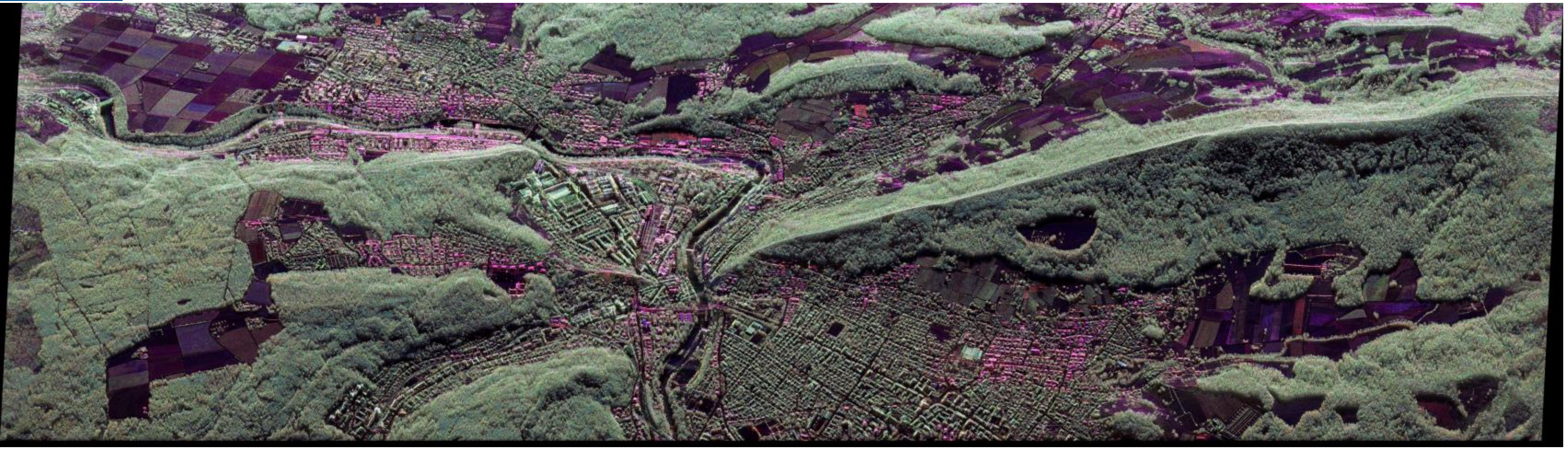
Universität Zürich[UZH]

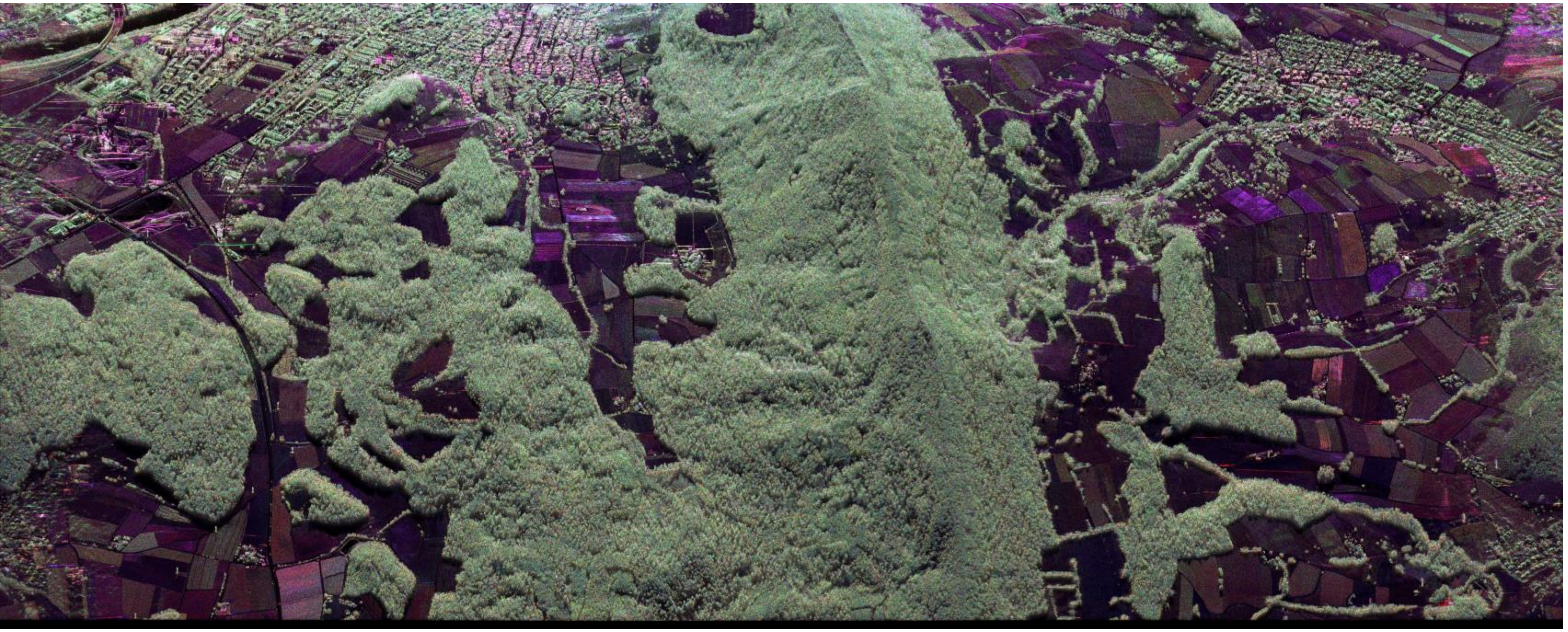


DLR airborne F-SAR

5 Ecosystem structure

L-band (1 GHz to 2 GHz = 15 cm to 30 cm wavelength)





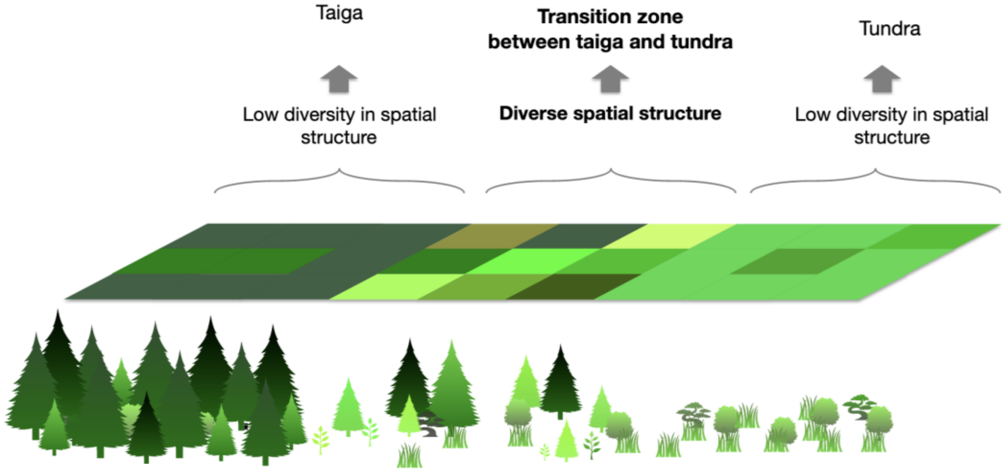
Blue-Dark violet: bare soils or flat surfaces/grasslands whose vegetation is smaller than 15 to 30 cm

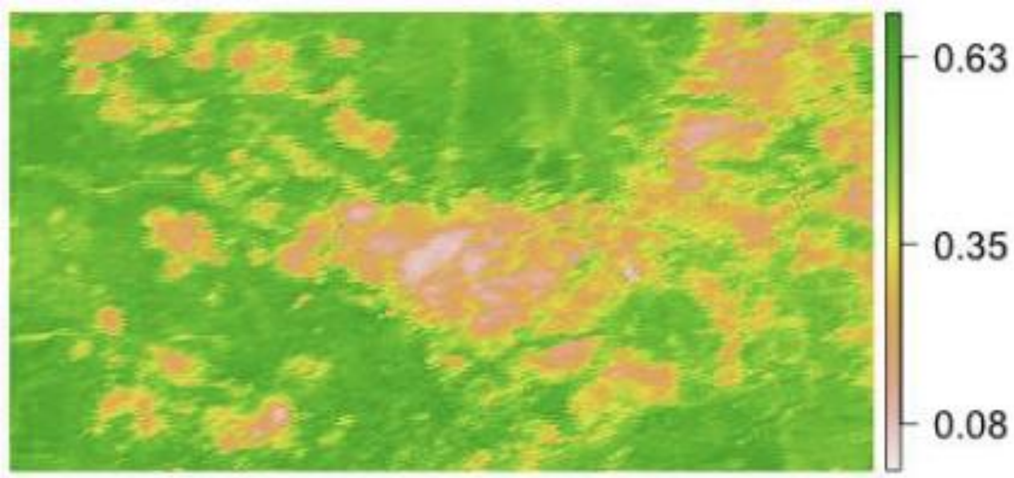
Green: Vegetation (leaves or branches) larger than 15 cm to 30 cm

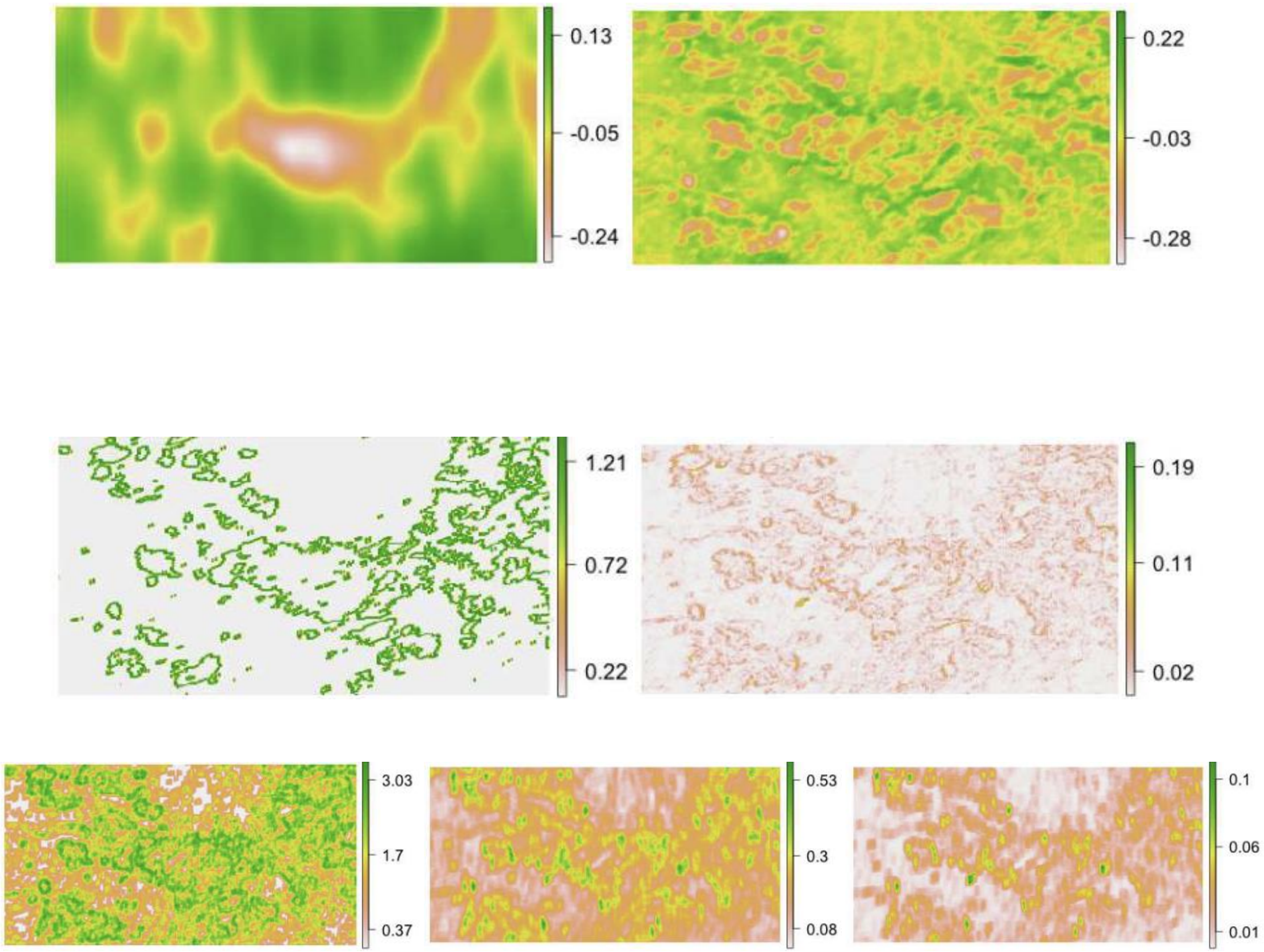
Other colors: artificial objects (houses, power lines, fences, street furniture, signs, traffic lights…)

5 Ecosystem structure

Hidden features in the landscape

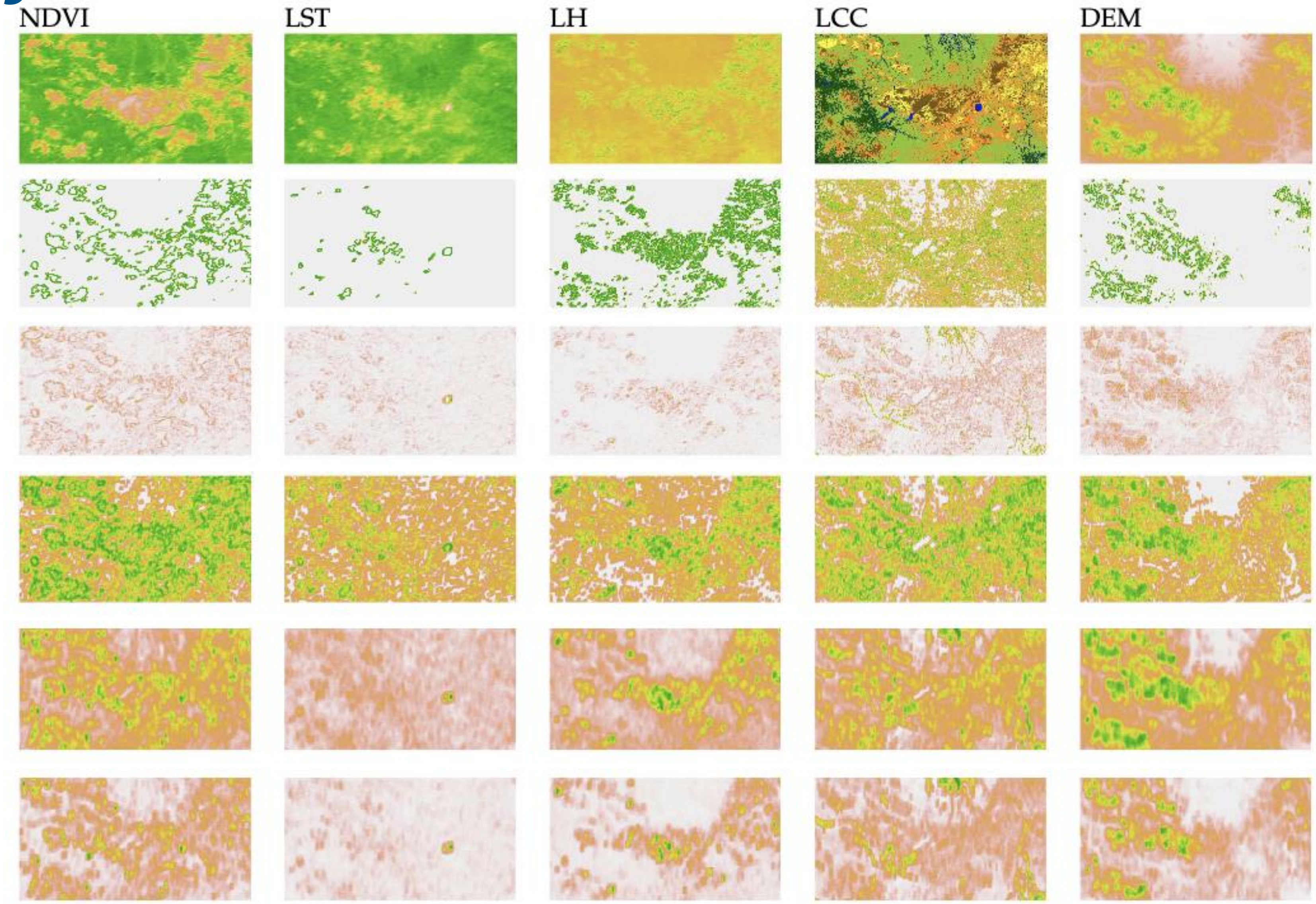




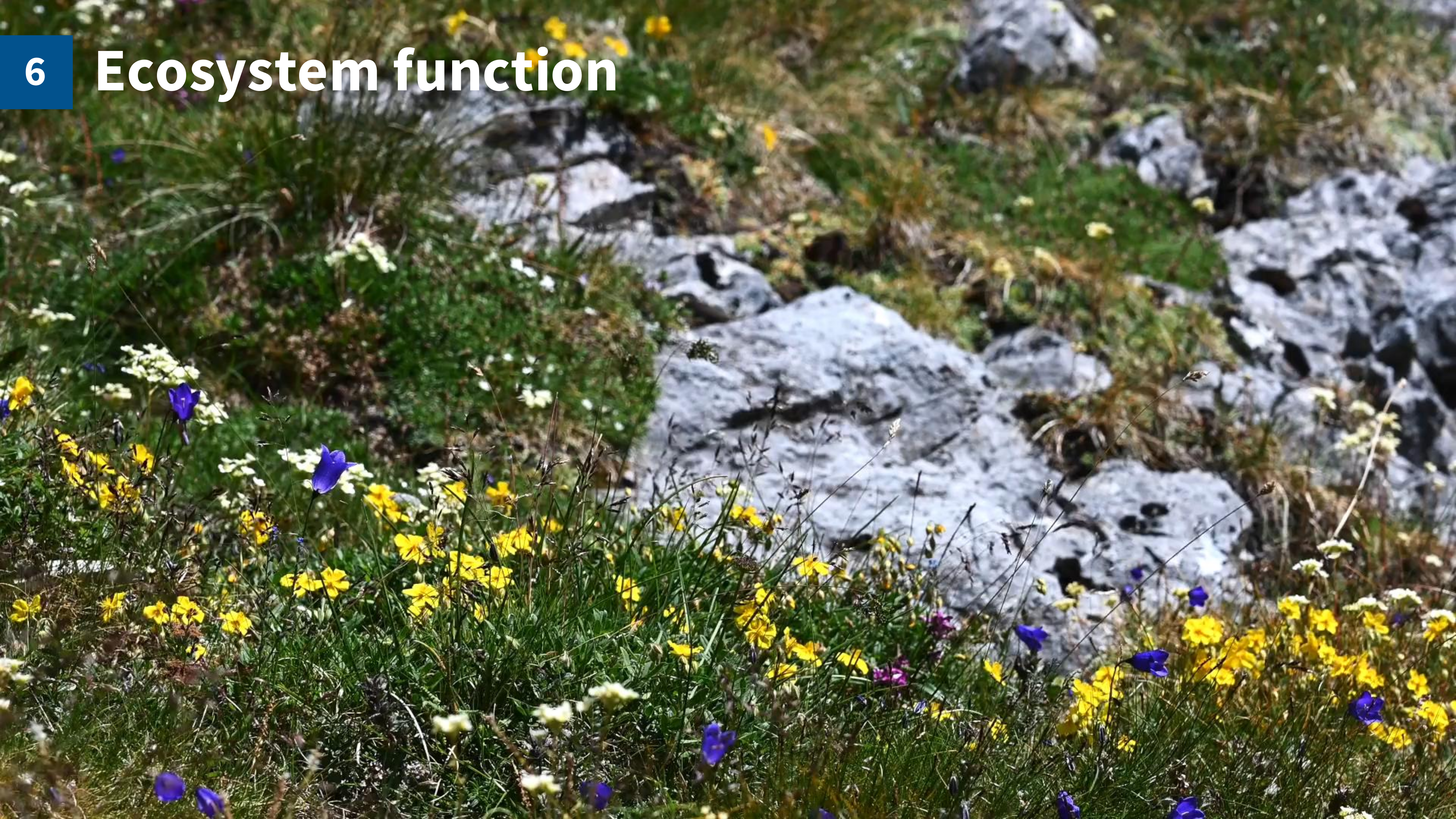


5 Ecosystem structure

Hidden features in the landscape

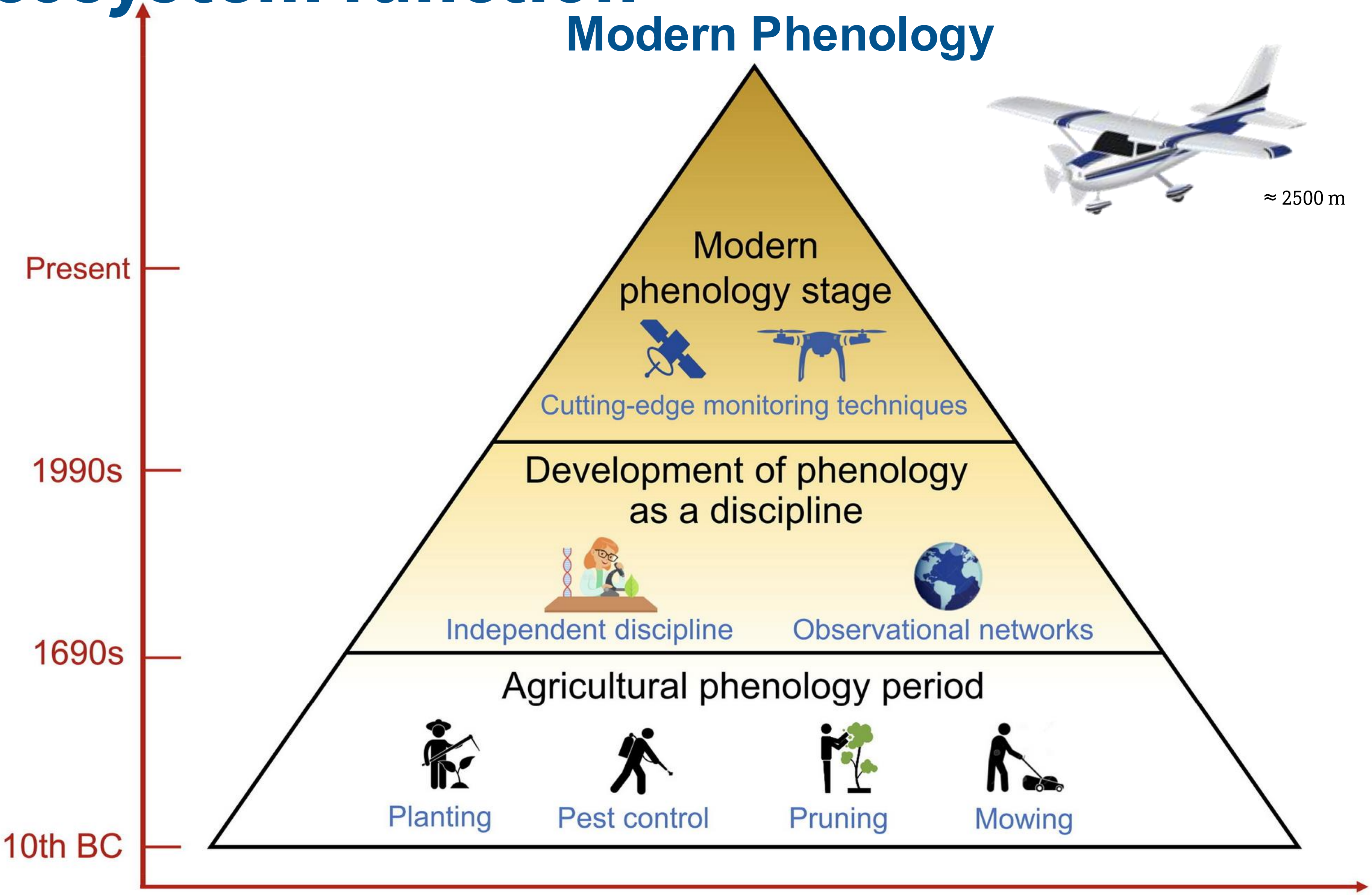


6 Ecosystem function



6 Ecosystem function

Modern Phenology



Lü et al. 2023 https://doi.org/10.1080/07352689.2023.2210922

6 Ecosystem function

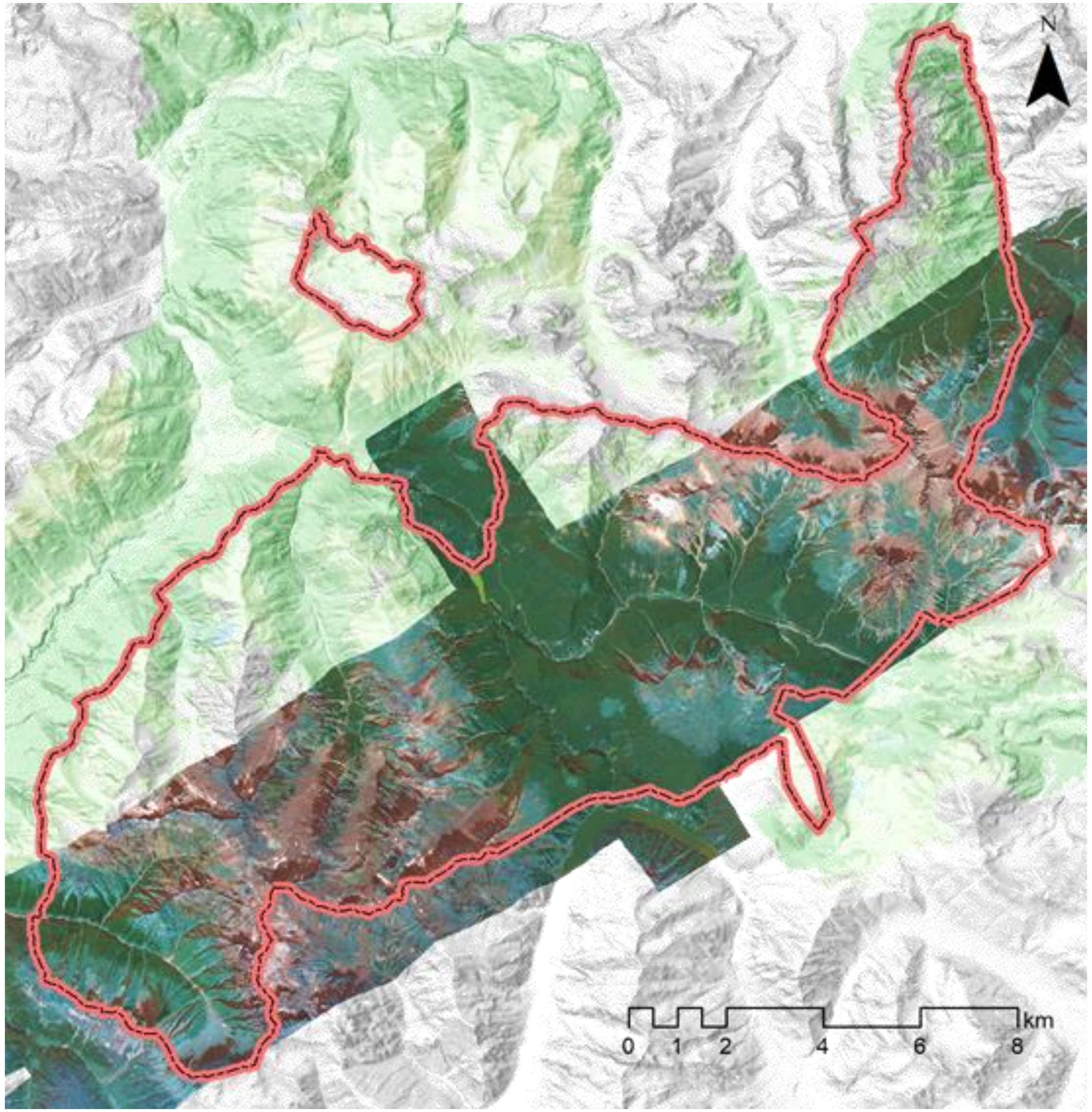
Airborne IS Data

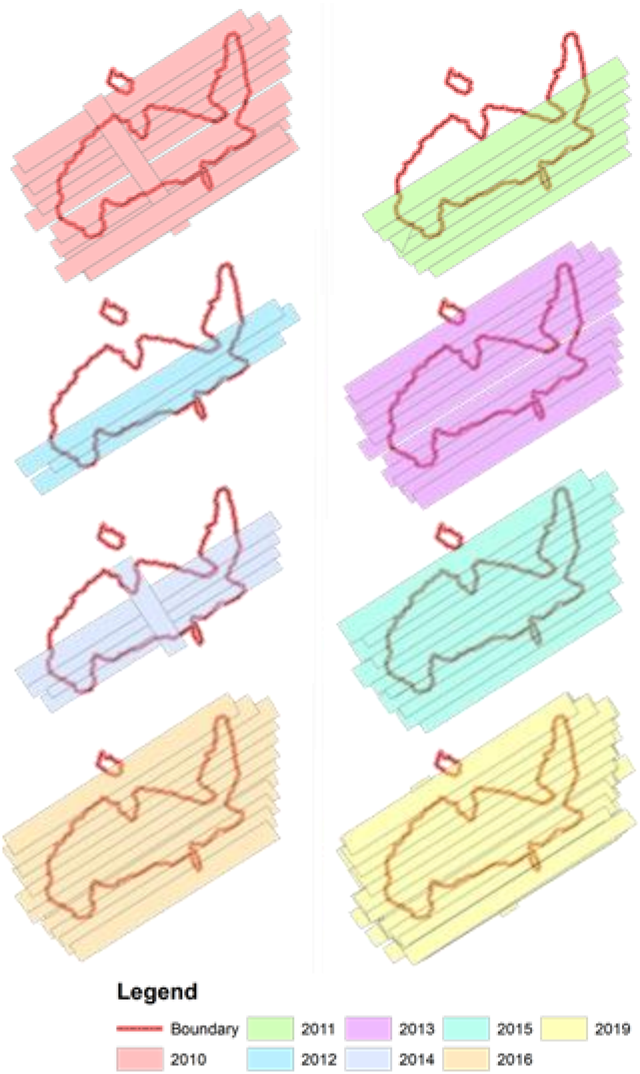
- 2 m spatial resolution
- 400 – 2400 nm spectral resolution

- 2010 – 2016 & 2019 time series
- **Used: 2010, 2012 and 2013**

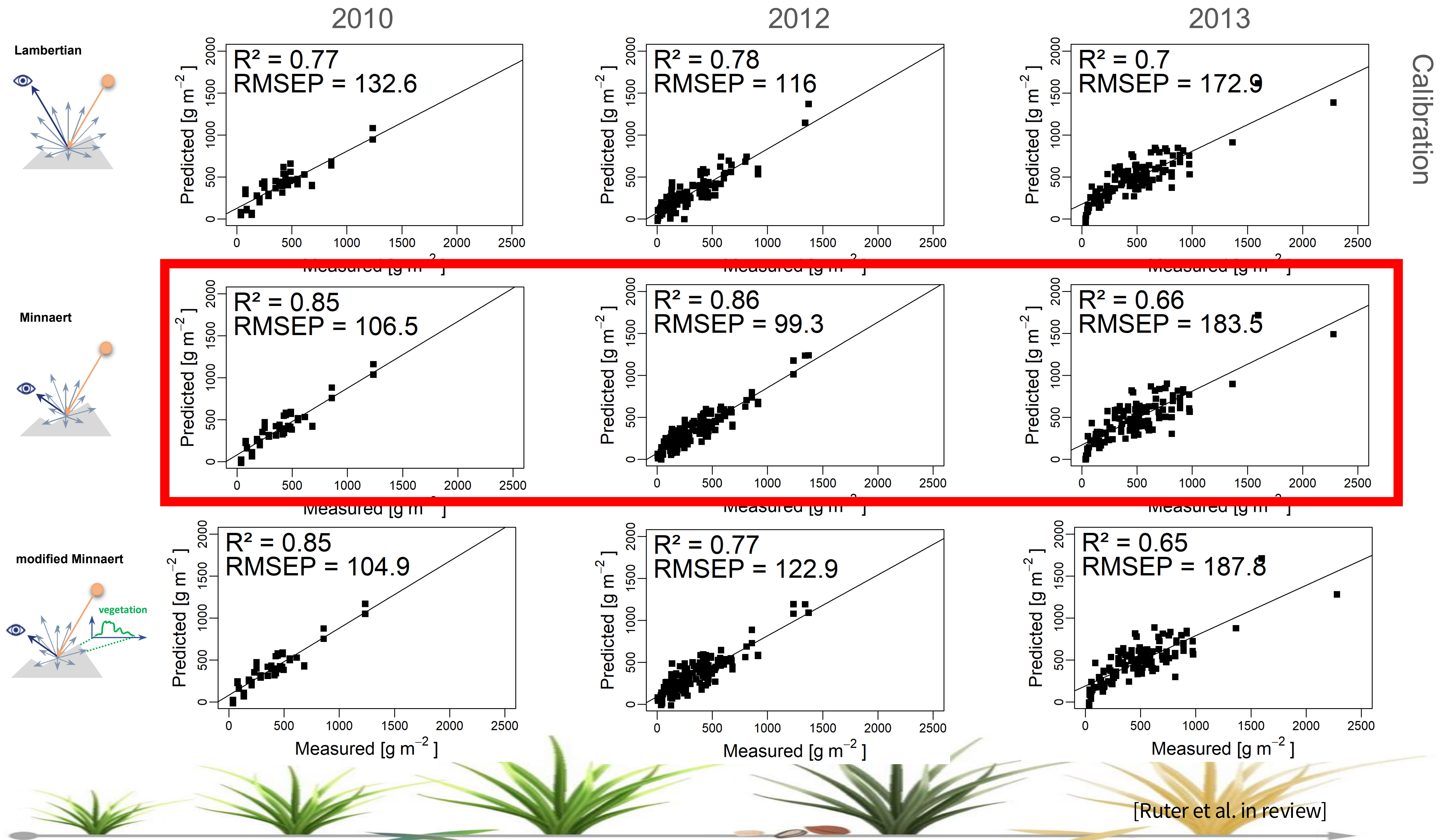
- 2010: 8:34 – 11:12
- 2012: 7:54 – 9:57
- 2013: 9:11 – 10:56

Airborne Prism EXperiment (APEX) sensor





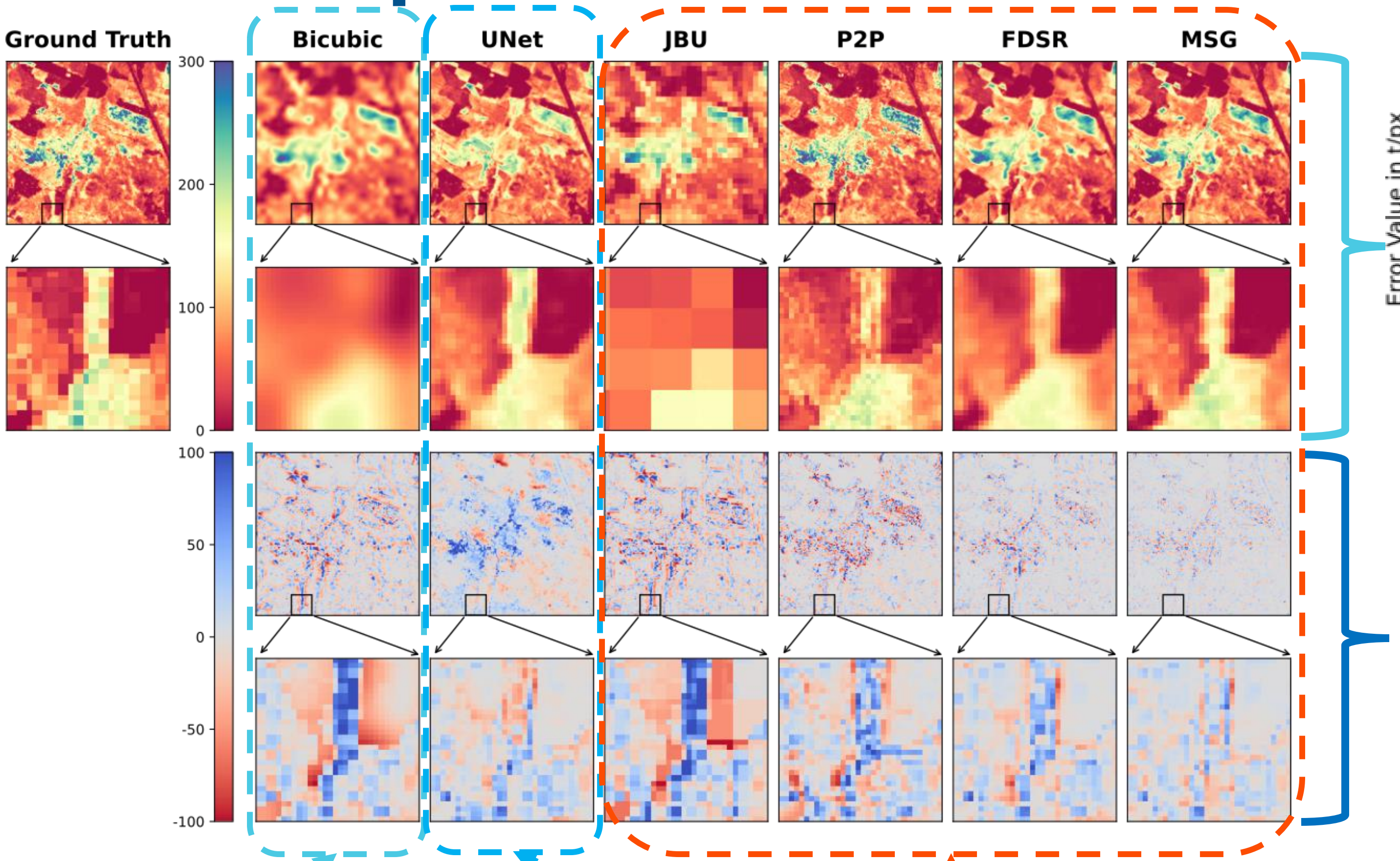
[Ruter et al. in review]

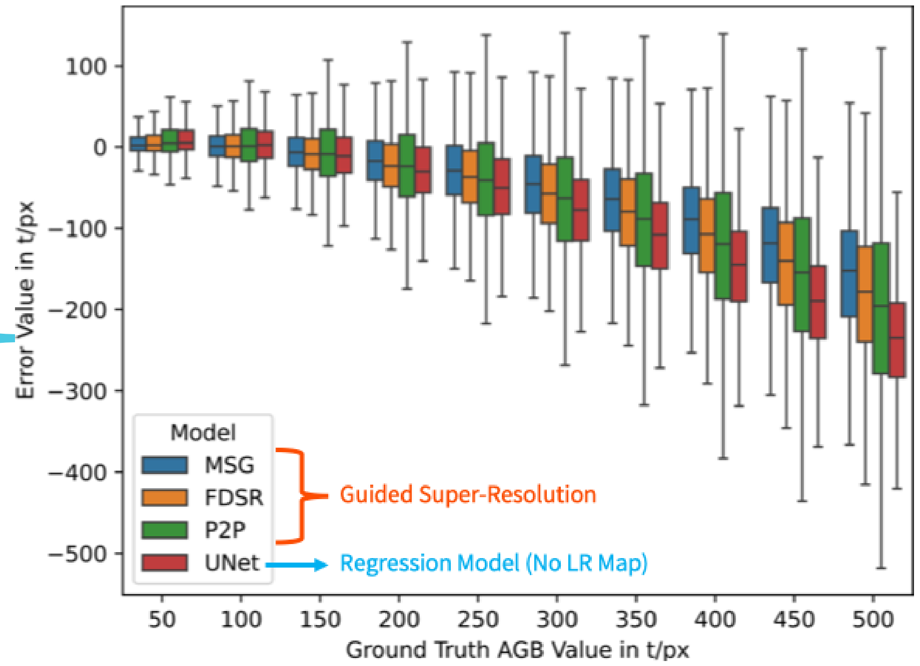


[Ruter et al. in review]

6 Ecosystem function

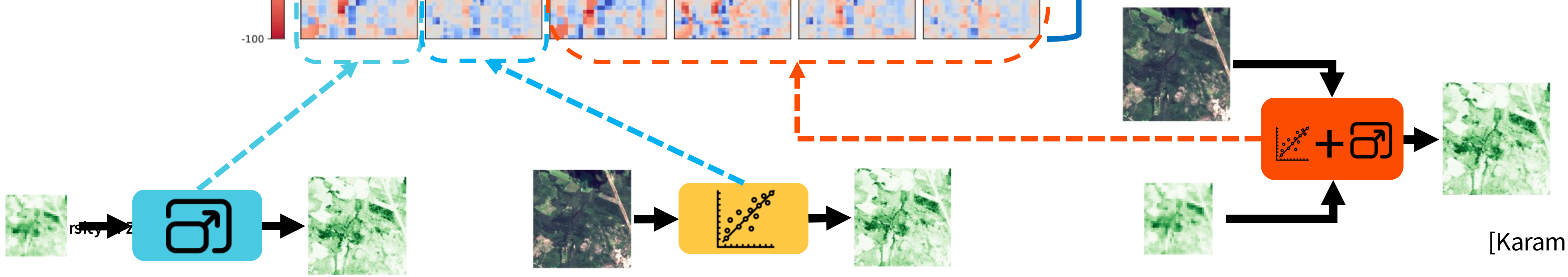
Guided super-resolution





Difference Map
(Target – Pred)

[Karaman et al. 2025]



[Karaman et al. 2025]

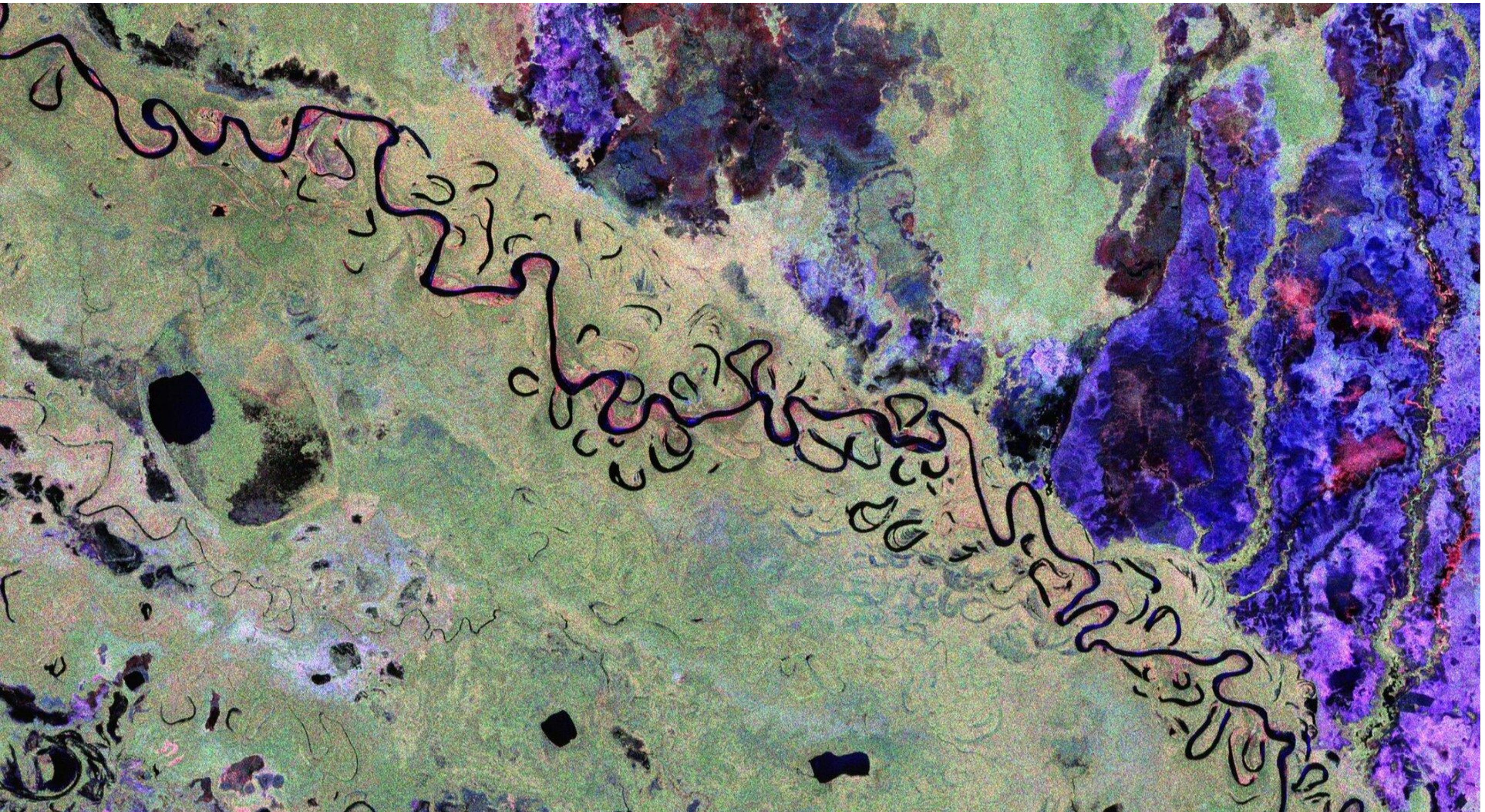
6 Ecosystem function

1st P-band radar in space

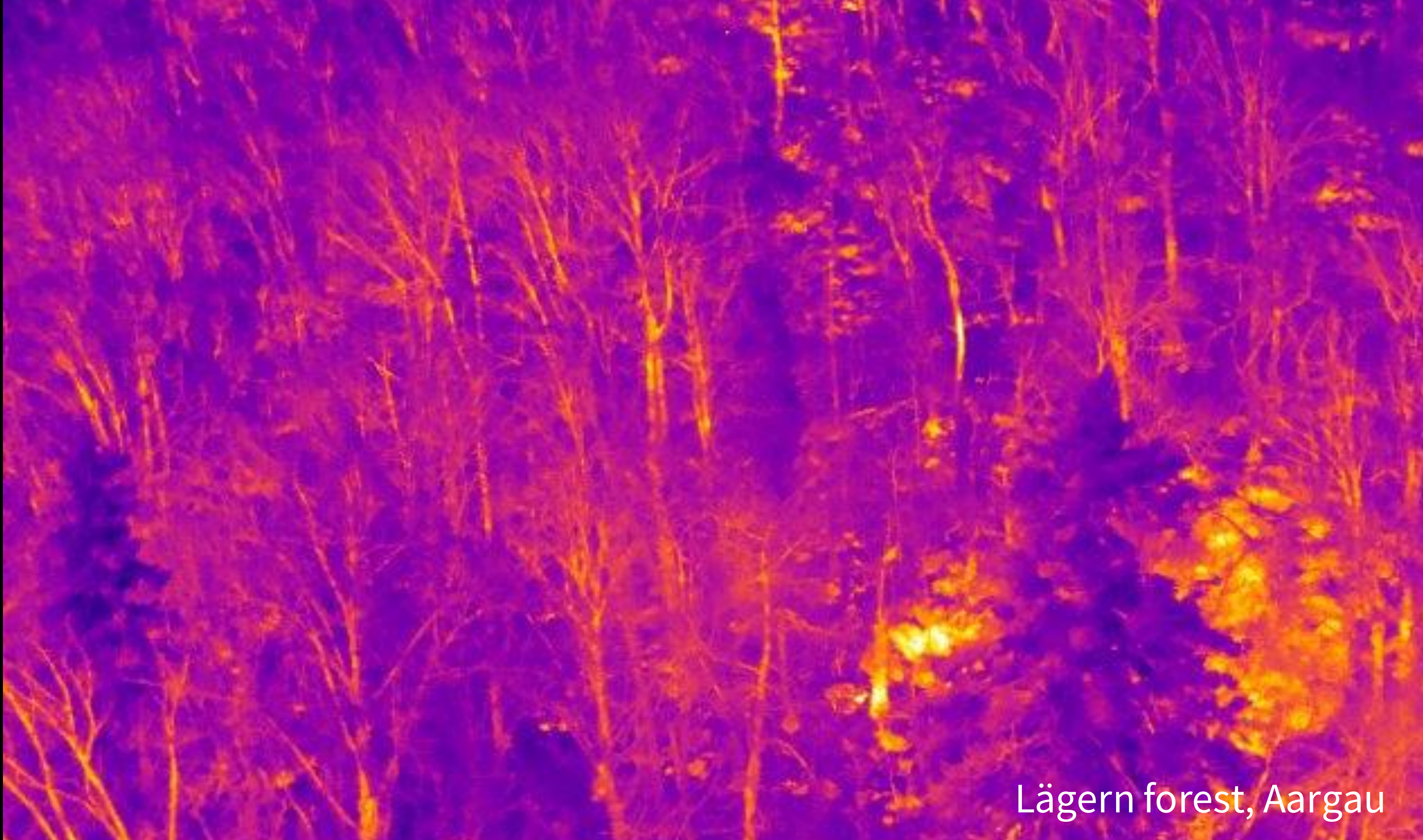
666 km altitude

1250 kg mass

12 m diameter antenna

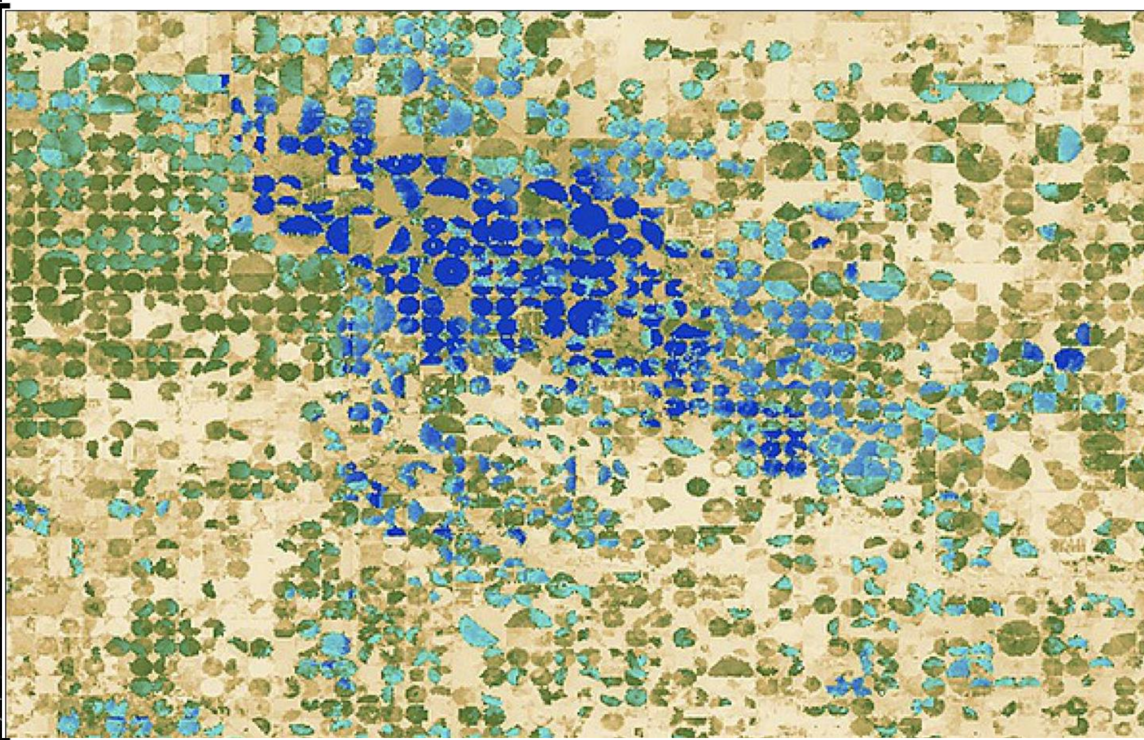


THERMAL

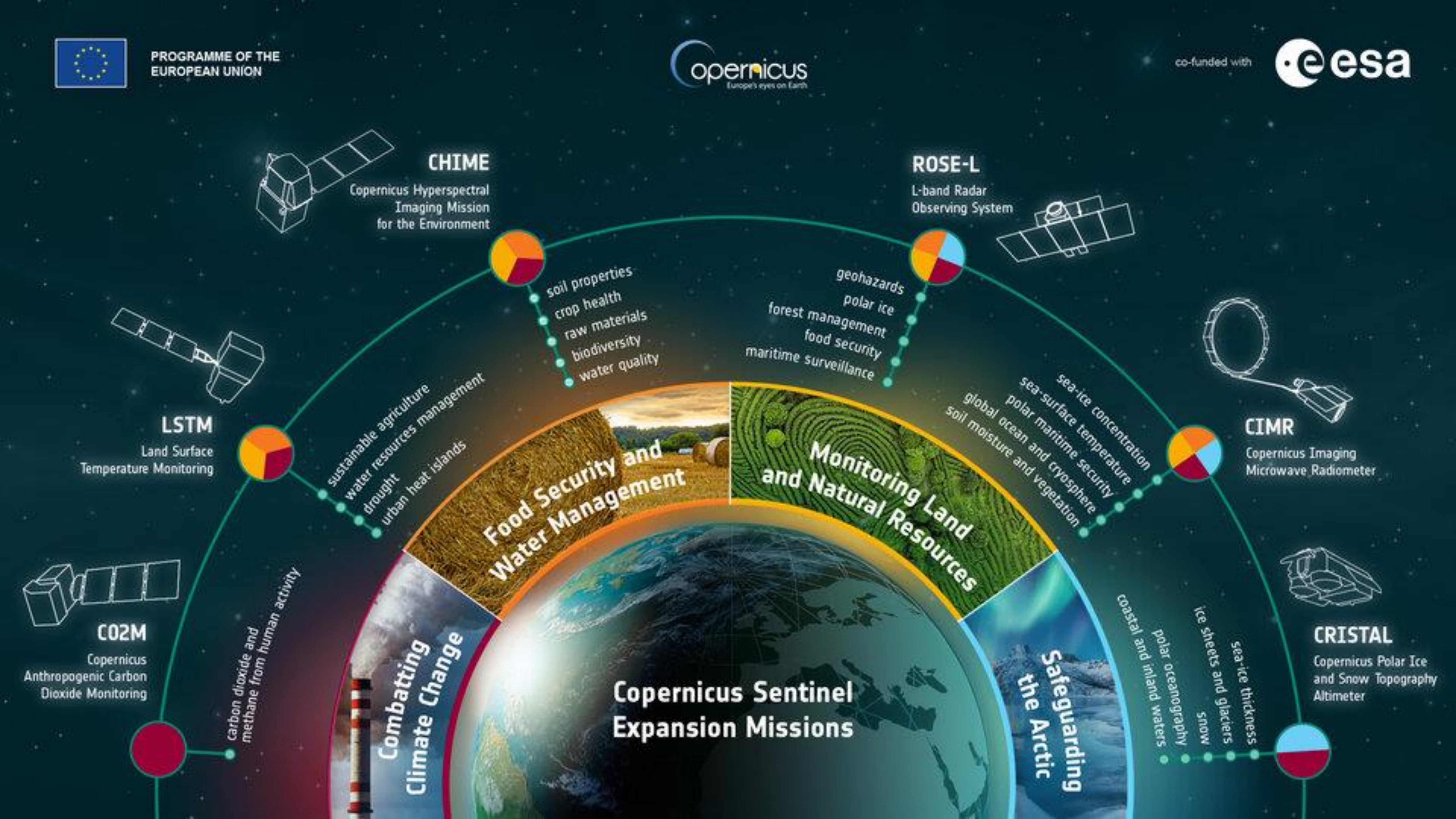


6 Ecosystem function

ECOSTRESS



where are we going…



PROGRAMME OF THE EUROPEAN UNION
Copernicus
Europe's eyes on Earth
co-funded with
esa
CHIME
Copernicus Hyperspectral Imaging Mission for the Environment
soil properties
crop health
raw materials
biodiversity
water quality
ROSE-L
L-band Radar Observing System
geohazards
polar ice
forest management
food security
maritime surveillance
LSTM
Land Surface Temperature Monitoring
sustainable agriculture
water resources management
drought
urban heat islands
CIMR
Copernicus Imaging Microwave Radiometer
sea-ice concentration
sea-surface temperature
polar maritime security
global ocean and cryosphere
soil moisture and vegetation
CO2M
Copernicus Anthropogenic Carbon Dioxide Monitoring
carbon dioxide and methane from human activity
CRISTAL
Copernicus Polar Ice and Snow Topography Altimeter
coastal and inland waters
polar oceanography
ice sheets and glaciers
snow
sea-ice thickness
Food Security and Water Management
Monitoring Land and Natural Resources
Combatting Climate Change
Safeguarding the Arctic
Copernicus Sentinel Expansion Missions

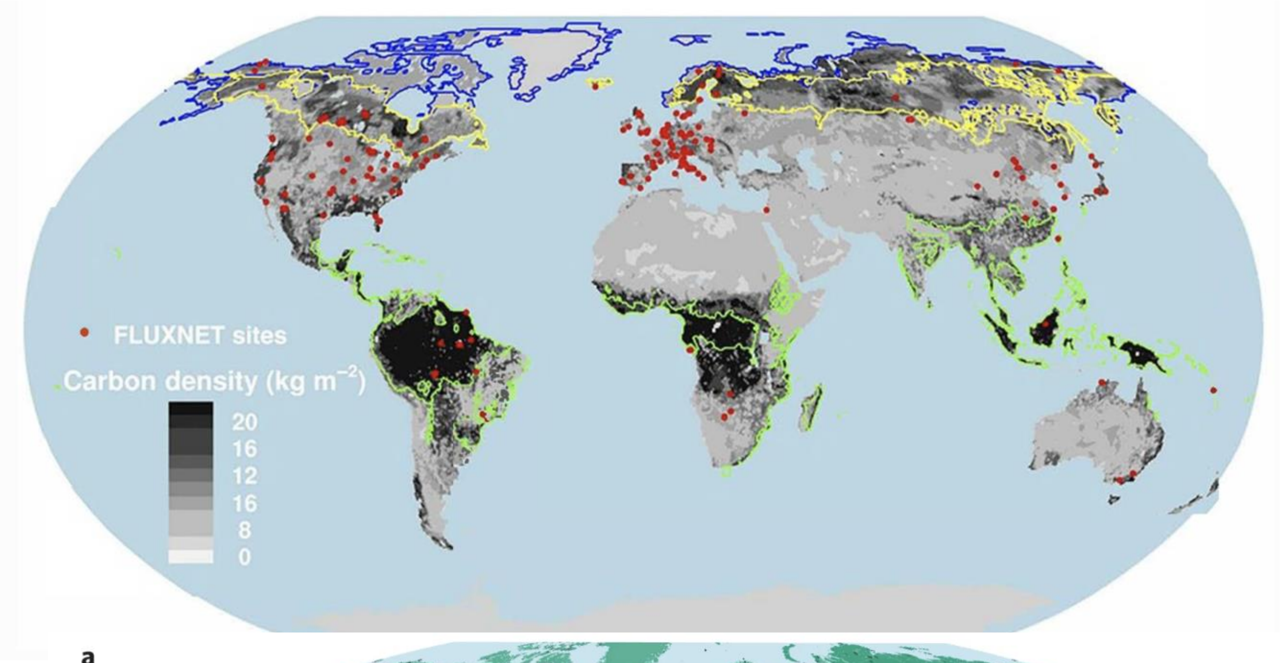
...we need

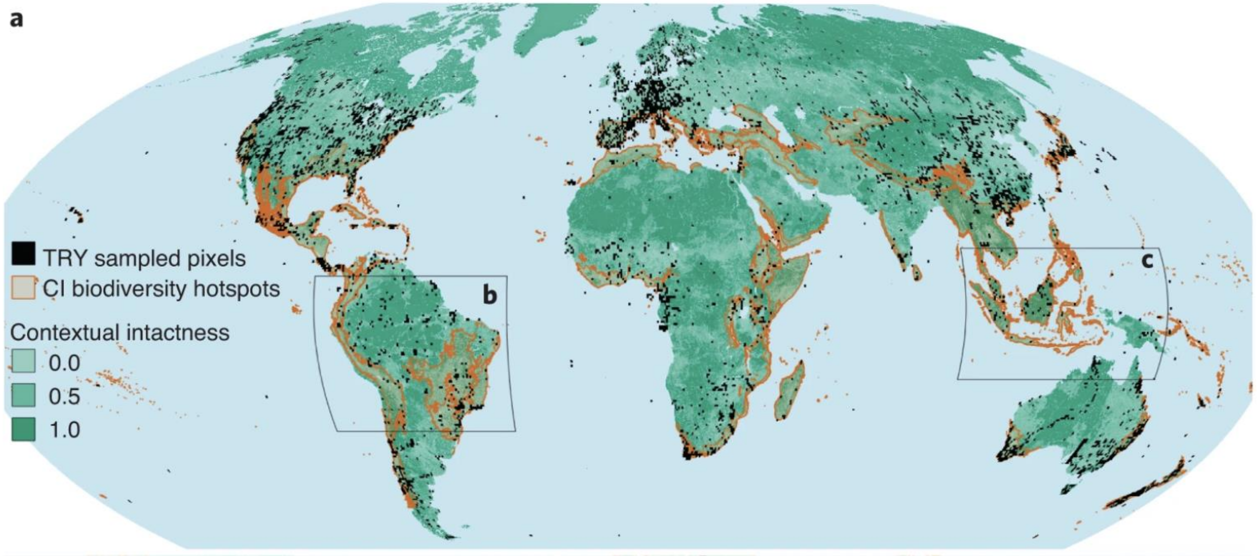
1. In situ and in silico data
2. Uncertainty budgets
3. Super resolution and multimodal integration
4. Central tendency methods:
   missing out on the fundamentals of biodiversity – rarity and uniqueness
5. Full spectrum contributions to measures of biodiversity:
   dimensionality identification
6. Causal mechanisms need to be better specified and drivers of change attributed

1 in situ data

… limited geographical coverage

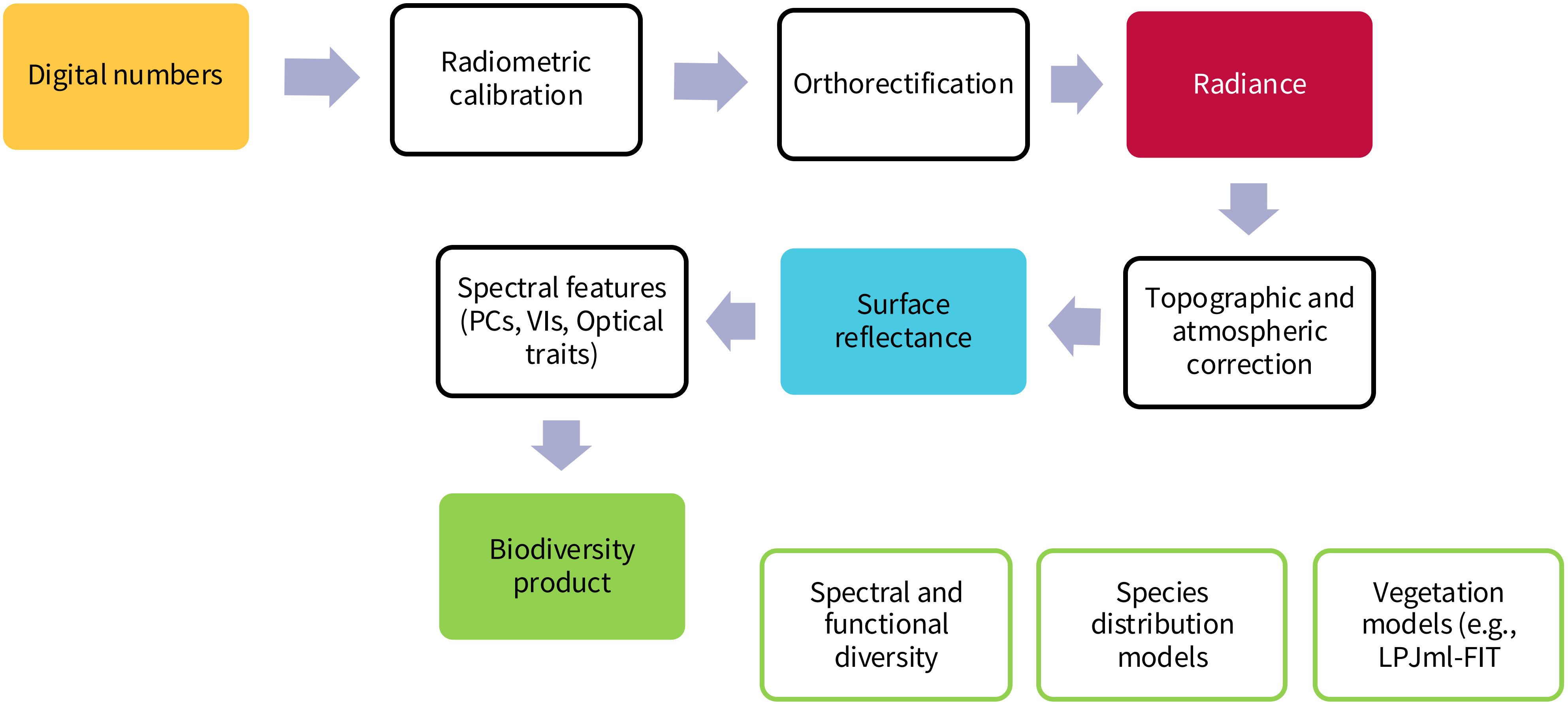
… missing in the areas holding most biodiversity





[Cavendar-Bares, Schneider, Santos et al. 2022]

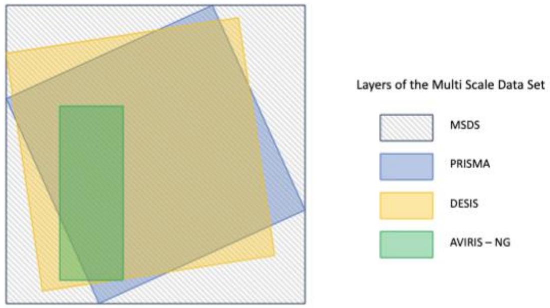
2 uncertainty budgets



[Rossi et al. in prep]

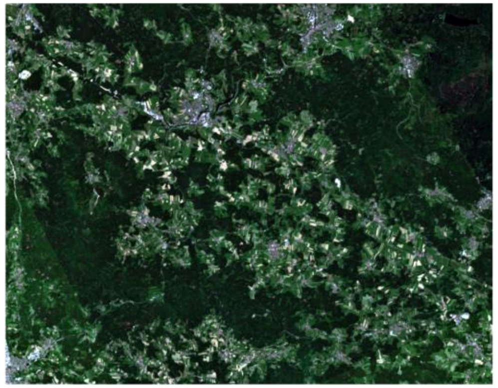
OBSGESSION

Funded by the European Union
UK Research and Innovation
Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

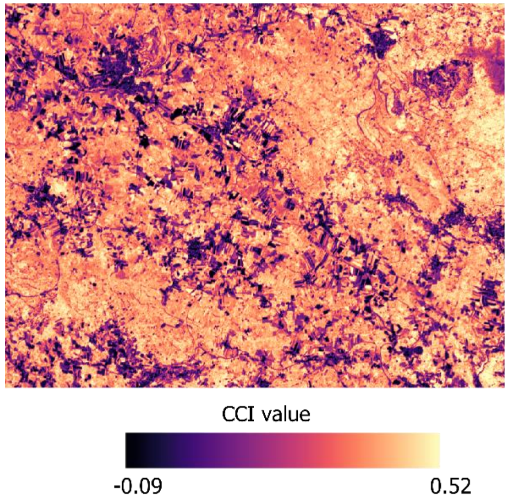


[Werfeli, et al. in prep., Rossi et al. in prep]

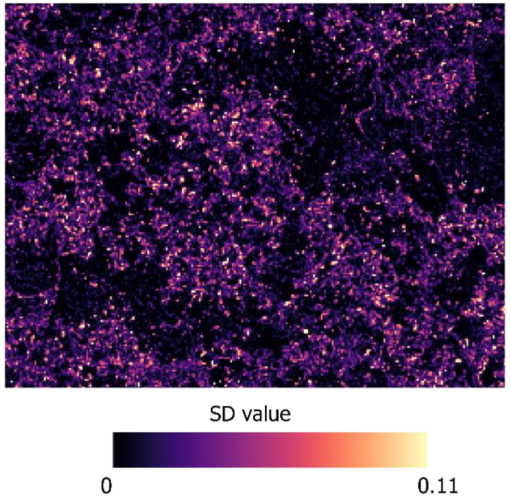
RGB DESIS

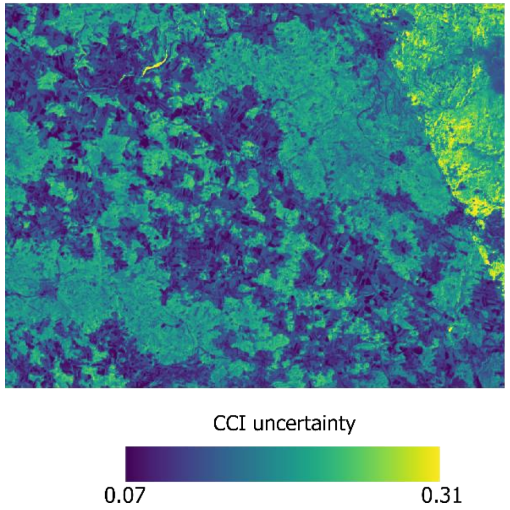


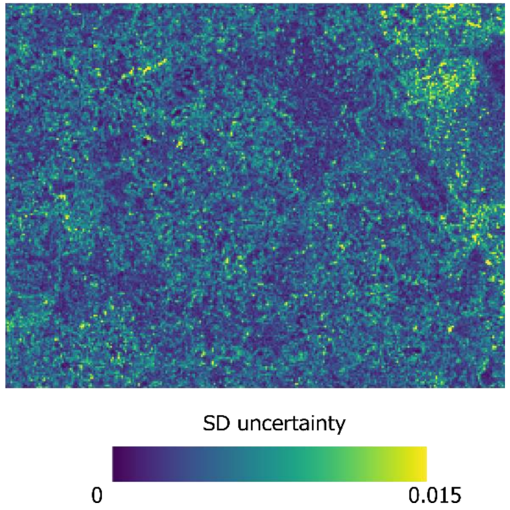
DESIS Chlorophyll/carotenoid index (CCI)



Spectral diversity(SD)







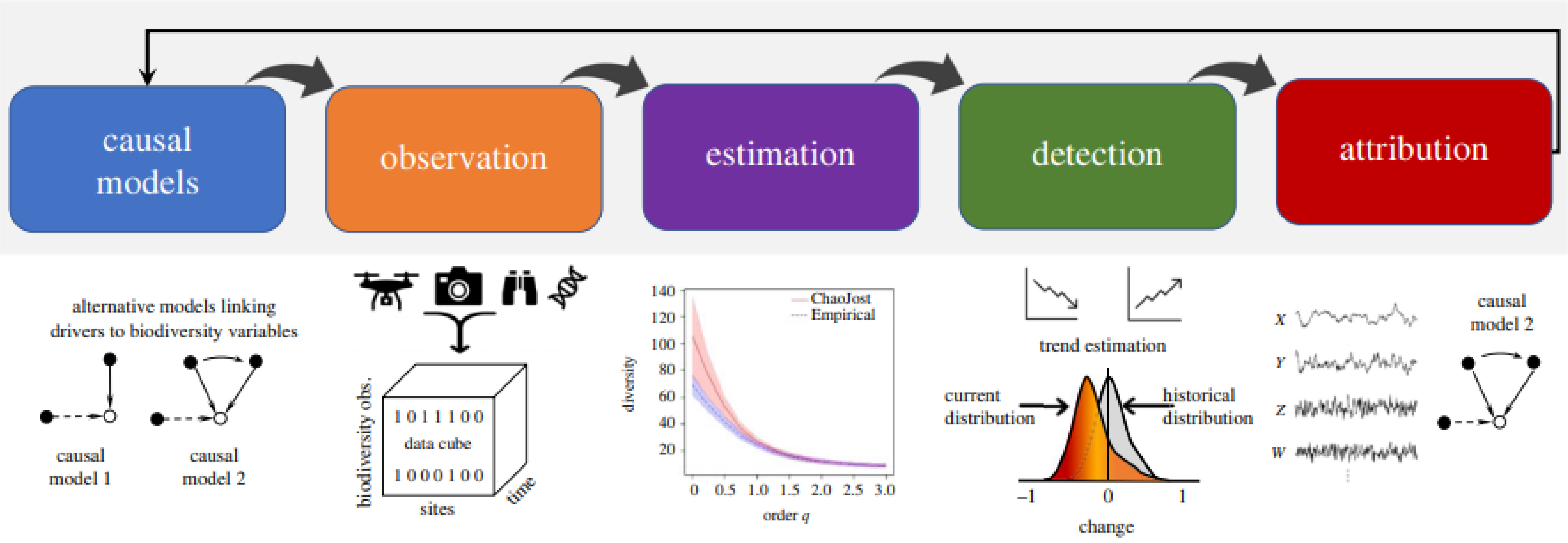
Functional diversity

Spectral diversity

OBSGESSION

Funded by the European Union
UK Research and Innovation
Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

6 Detection and attribution of biodiversity change



Hypothesized models as causal (directed) graphs identifying the direct and indirect effects of driver variables (black) on the biodiversity response variable (white). The dotted arrow indicates dependency owing to an unobserved variable.

The process of collecting data informed by hypothesized causal models. The observations fill a data cube composed of biodiversity observations (e.g. occurrences, abundances) along dimensions of space (e.g. sites) and time (e.g. years). The cube may be *n*-dimensional to include multiple variables.

The process of estimating the biodiversity variable to be analysed for measures of change in the next step. Estimates are typically biased so clear measures of error and uncertainty are required. Studies should report the effort and coverage used.

The statistical detection trends in measures of biodiversity change. Detection may be undertaken at a single site, or across multiple sites. A hierarchical model can estimate the distribution of trends and provide an overall estimate of change across a region.

The attribution step is conditional on the initial causal graphs. Estimate the causal contribution of different variables via structural causal modelling. We can attribute a causal factor if it is consistent with a causal model that includes this factor and is inconsistent with a model that is otherwise identical but excludes the factor.

Gonzalez A, Chase JM, O’Connor MI. 2023 https://doi.org/10.1098/rstb.2022.0182

Biodiversity: generating innovations

- Understanding biodiversity is challenging

- It requires creative and novel ways to use EO beyond measures of ecosystem properties

- New data and technologies are emerging and starting to enable this goal

Thank you for your attention!

maria.j.santos@geo.uzh.ch

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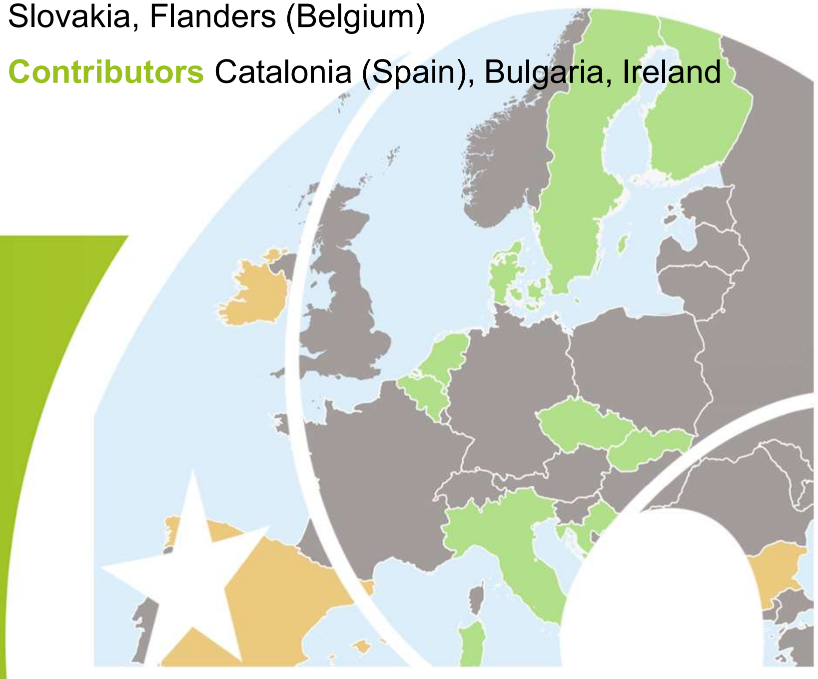
Active partners Autonomous province of Bolzano (Italy), Croatia, Denmark, Finland, Czech republic, Sweden, Slovakia, Flanders (Belgium)

Contributors Catalonia (Spain), Bulgaria, Ireland



Biodiversa+ Habitat pilot: Habitat Mapping and monitoring of condition indicators in grasslands and wetlands

Habitat pilot Aims

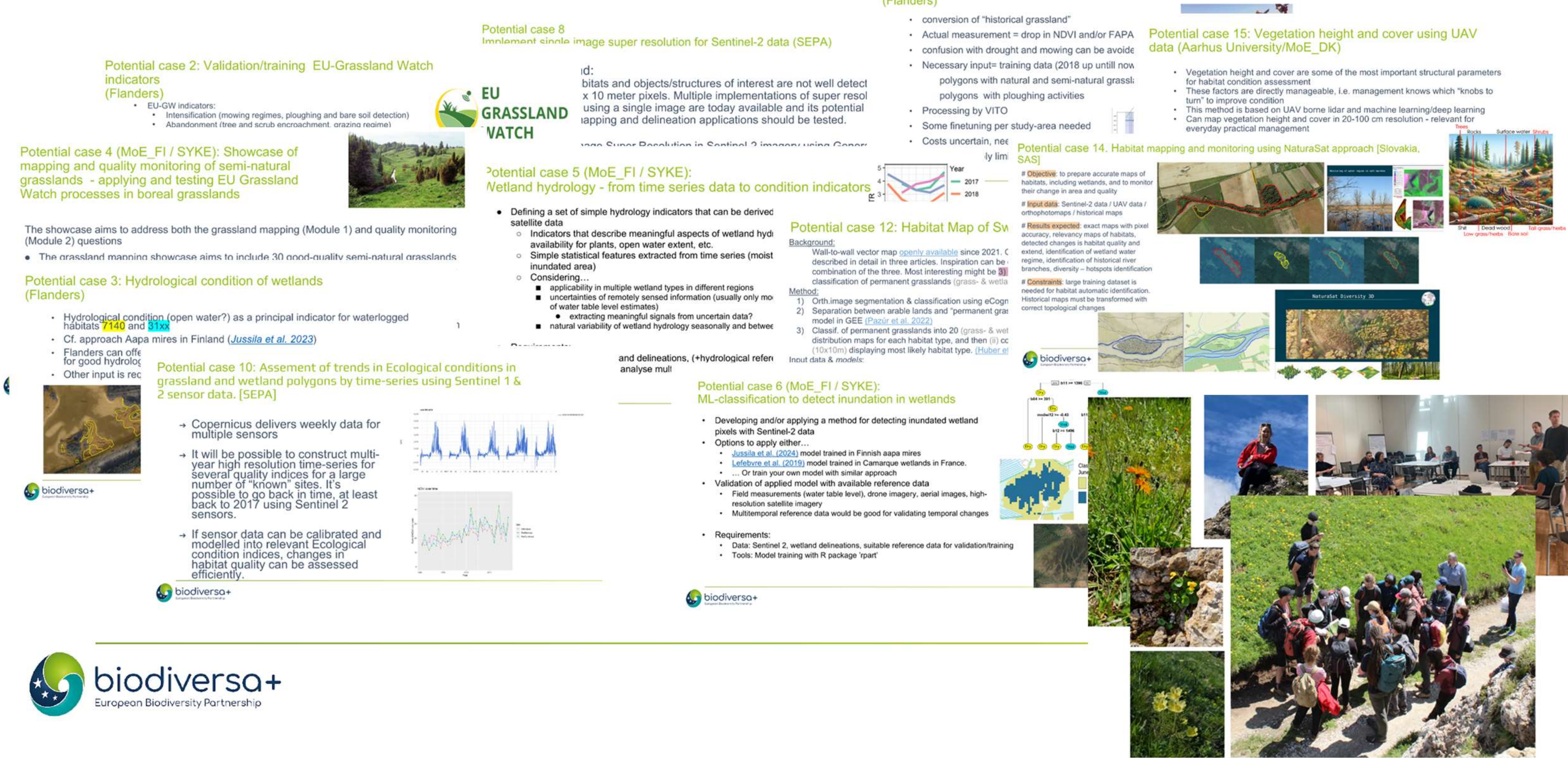
- Evaluating capacity of RS (Copernicus and UAV) and GIS data -based methods to map and monitor grassland and wetland habitats
- Supporting development of harmonised monitoring protocols and systems for the EU

Habitat pilot - Review

Assessed the current remote sensing (RS) methods for mapping and monitoring grassland and wetland habitats across Europe.

- Analysis of >40 habitat mapping & monitoring RS methods
- Assessed strengths, weaknesses, and potential applicability in creating a continent-wide standard for habitat monitoring.
- Significant variability in the approaches and technological integration levels among the participating countries.
- Collected information:
    - Methods used in different countries
    - Detailed description of some methods
    - Input data – accessibility, quality and coverage
- Workshops and field trips for capacity building

Module 1 Review outcome: Proposed methods for testing
Report will be shared



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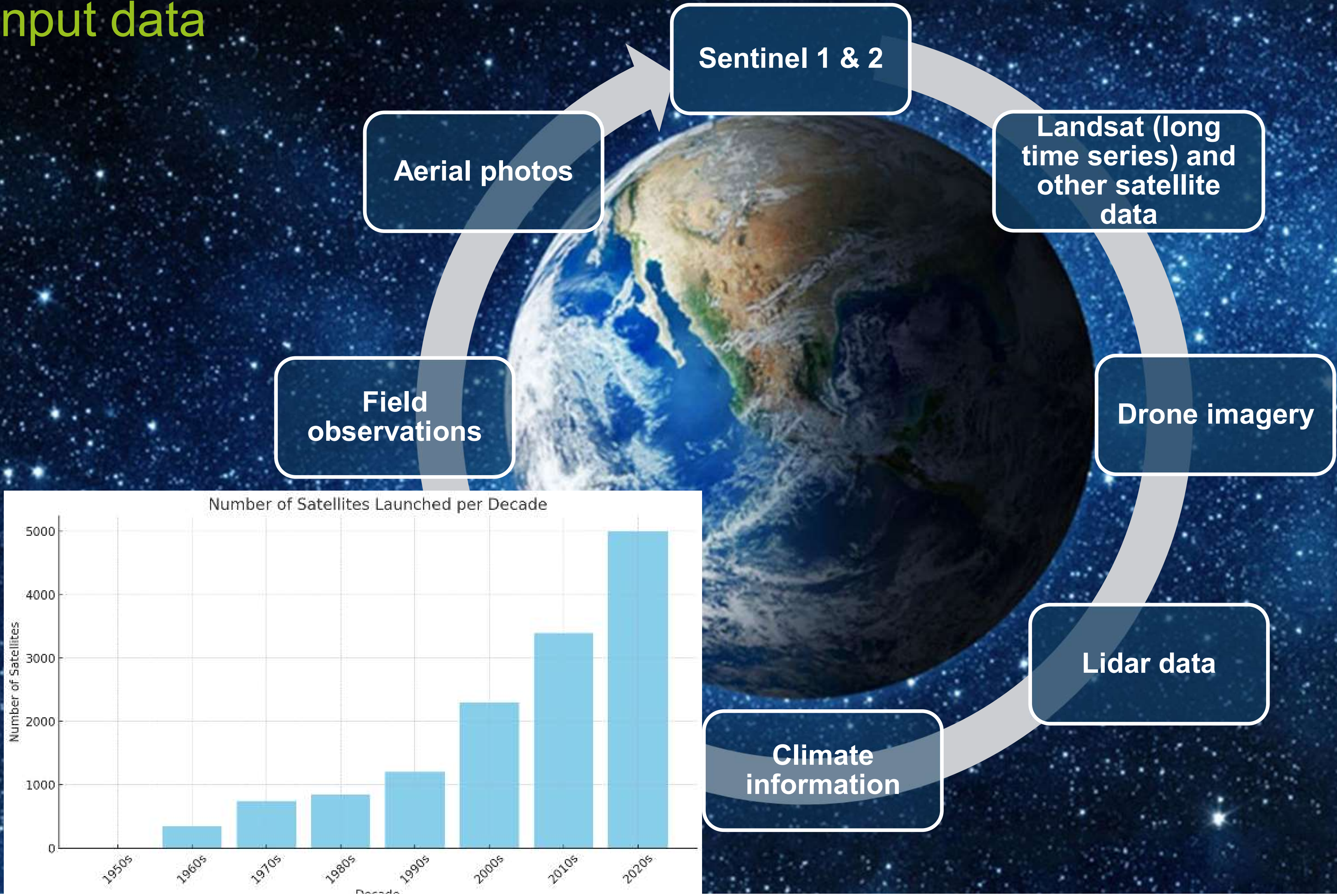
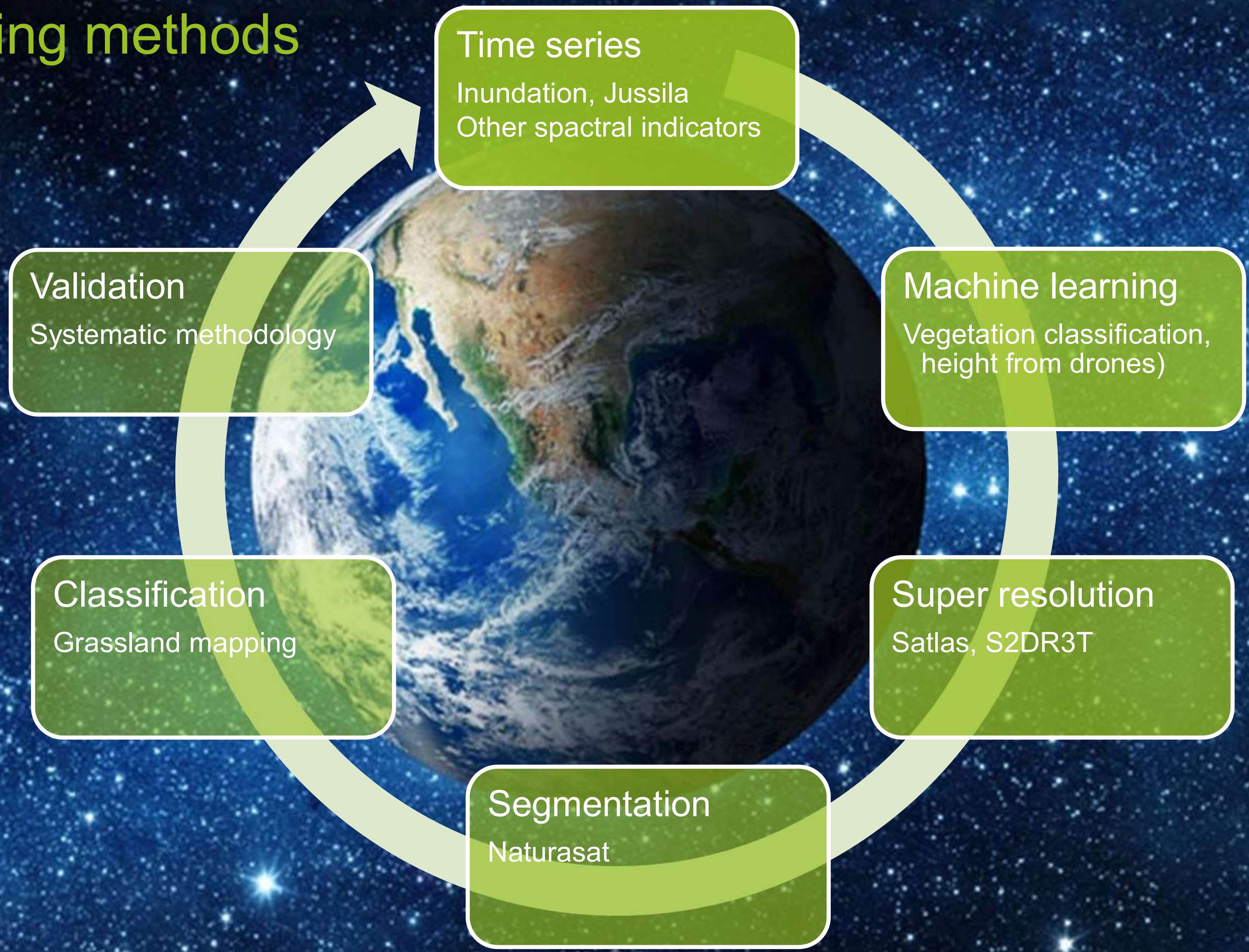
Input data


Sentinel 1 & 2
Landsat (long time series) and other satellite data
Drone imagery
Lidar data
Climate information
Field observations
Aerial photos
Number of Satellites Launched per Decade
Number of Satellites
0
1000
2000
3000
4000
5000
1950s
1960s
1970s
1980s
1990s
2000s
2010s
2020s

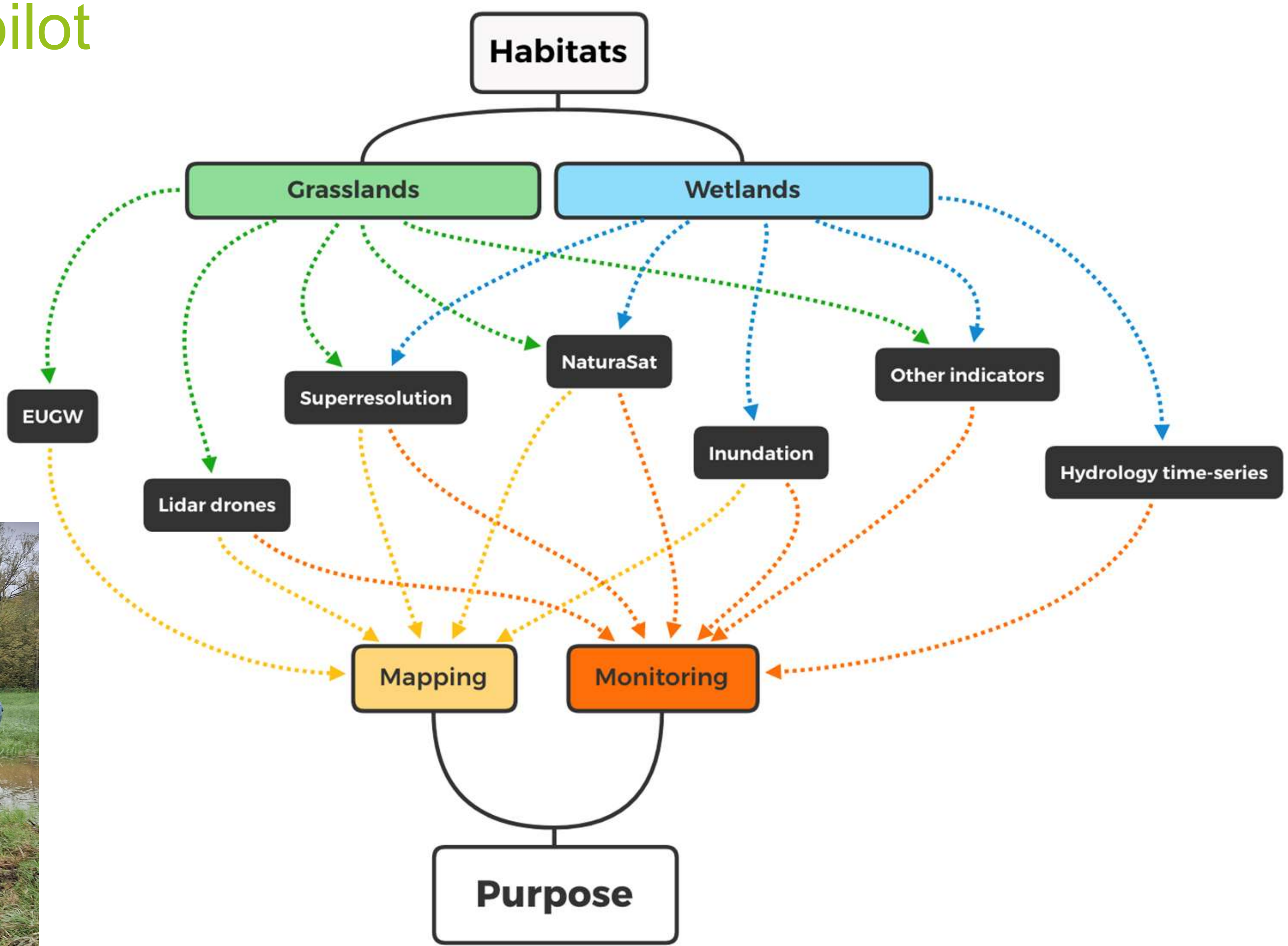
Remote sensing methods



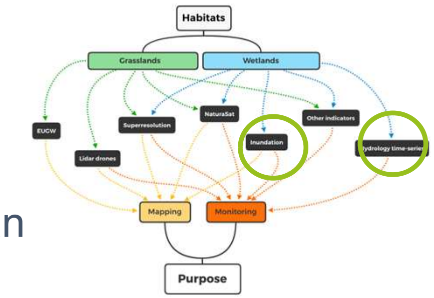
Sub tasks within the Habitat pilot

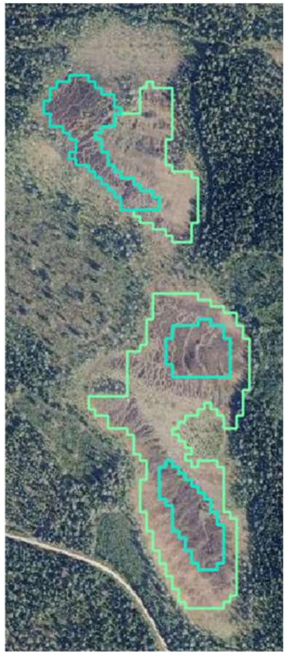
…each tested by several partners

Workshop Oct-25, field visit in Diest, Flanders

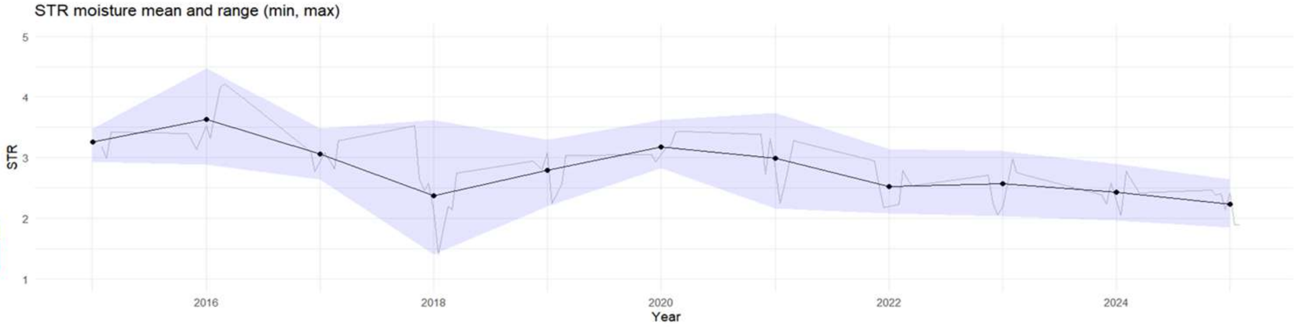


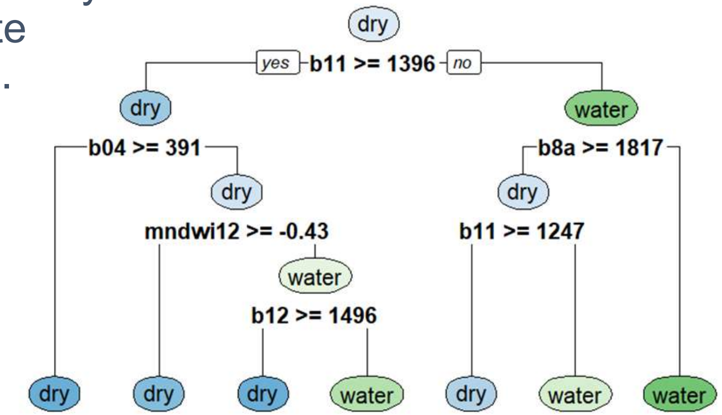
Indicator time series, hydrology



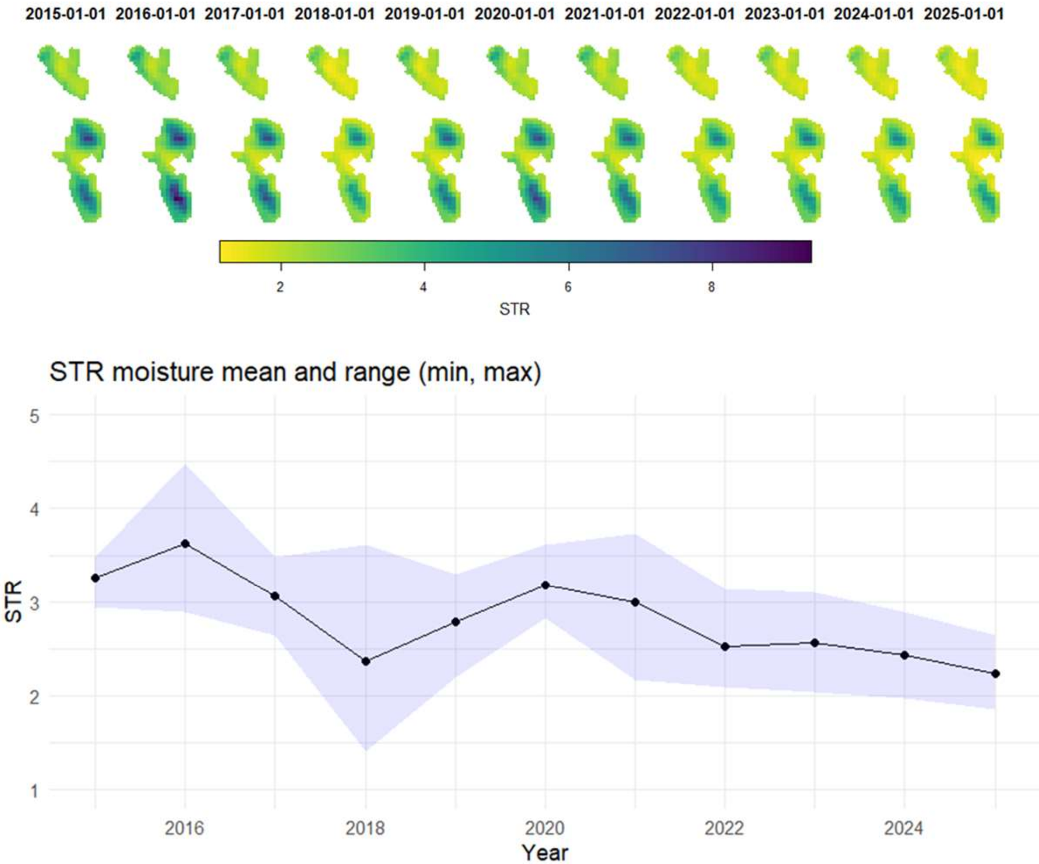


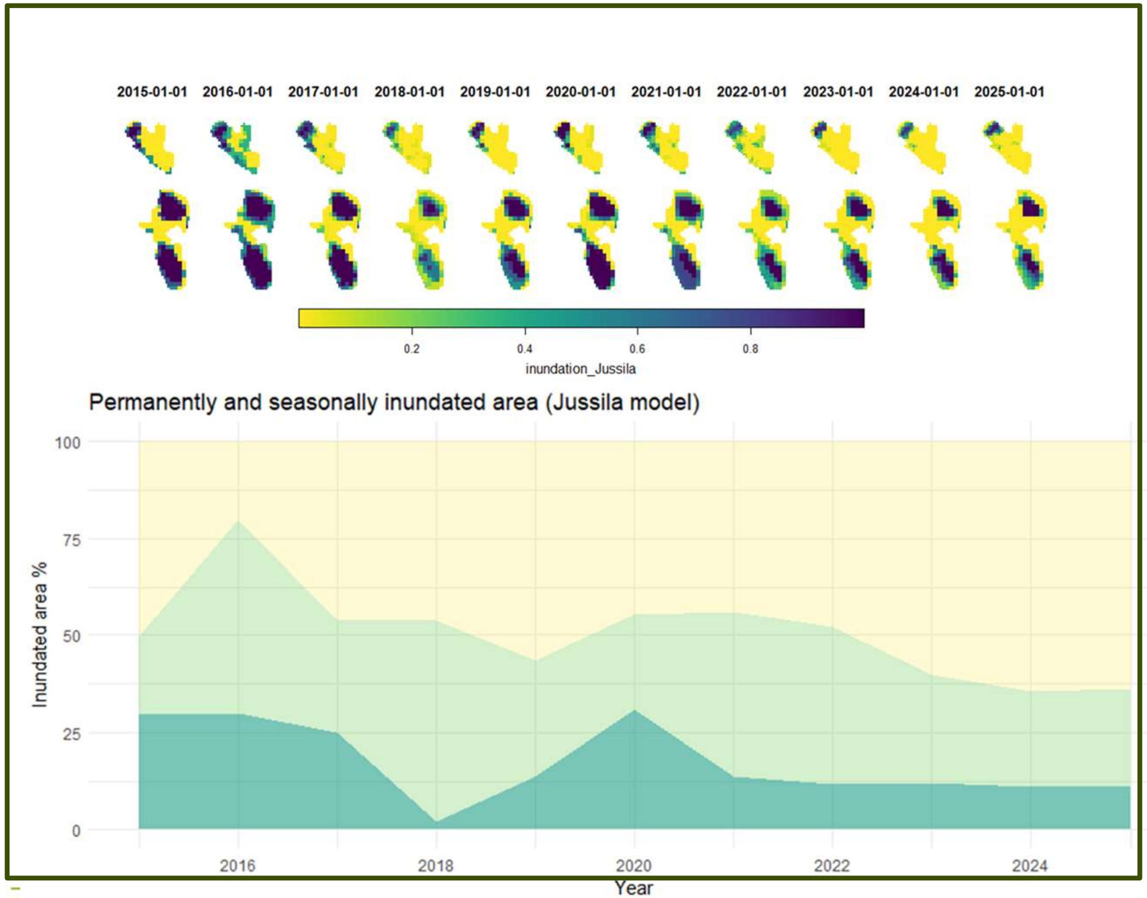
- **Aim:** produce robust indicator time series that describe relevan habitat hydrology
- **Input:** All Sentinel-2 observations for site(s) over multiple years
- **Method:** moisture and water indices, singleband moisture indicators, inundation detection
- **Output:**
  - Time series graphs to show full seasonal variation
  - information aggregated to relevant yearly statistics and corresponding maps to show multi-year trends and localise changes
- **Required steps:** Build datacube. Mask away tree-covered areas. Quality filter observations. Smooth errors in time series by aggregation. Interpolate observations for missing time periods to calculate balanced statistics.





Moisture and Inundation indicators (STR vs Jussila)





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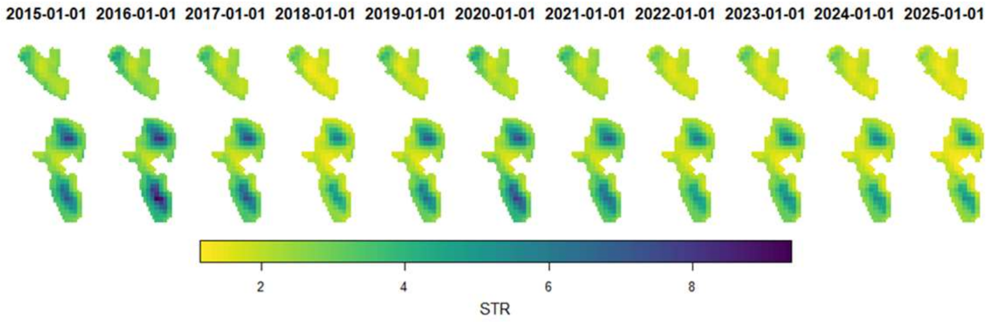
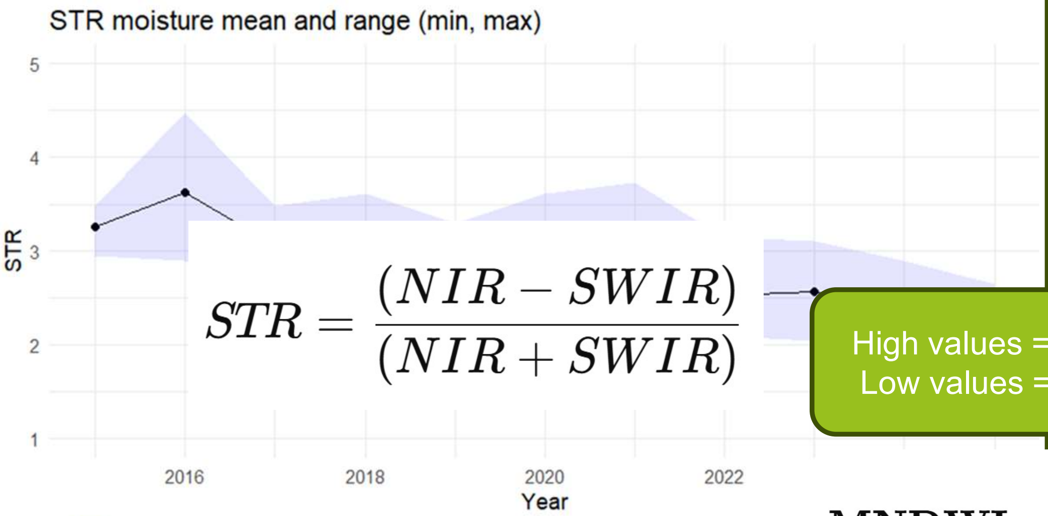
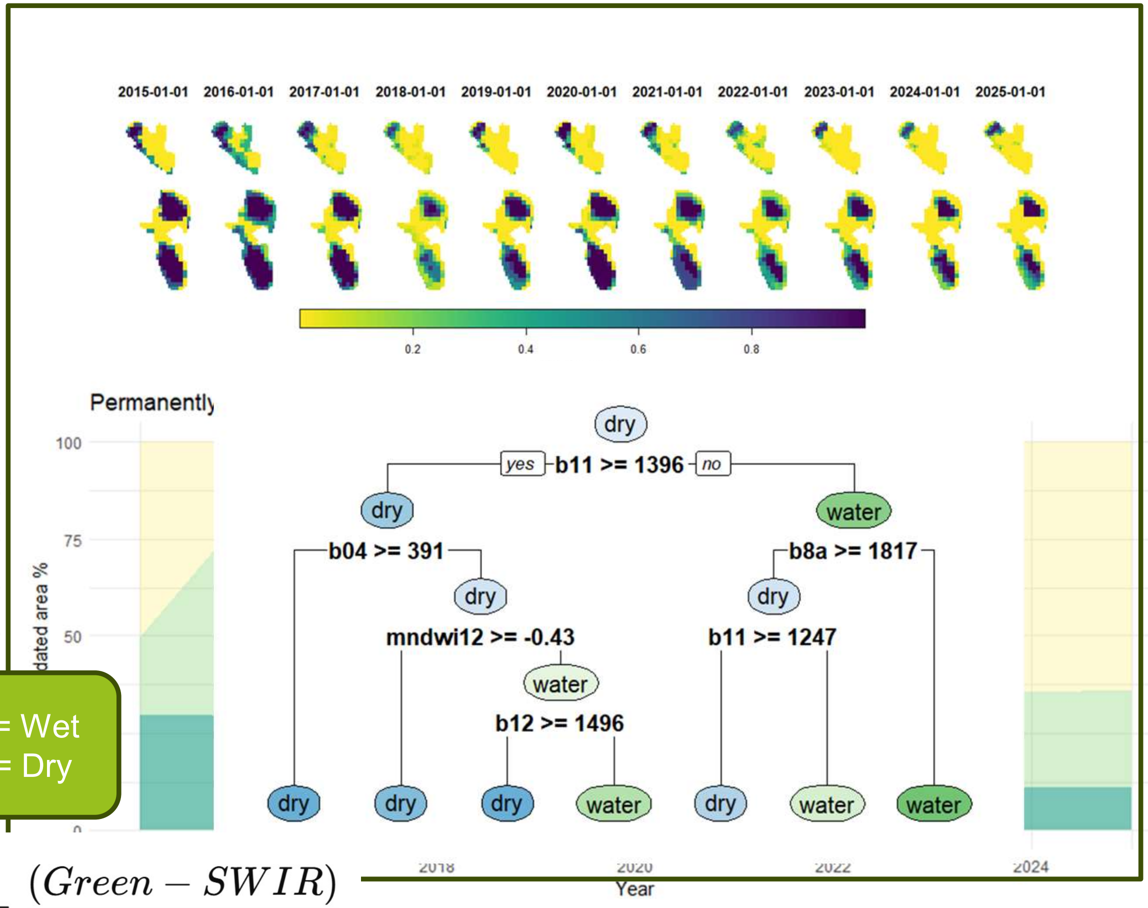
Moisture and Inundation indicators (STR vs Jussila)





$$STR = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

High values = Wet
Low values = Dry



$$\mathbf{MNDWI} = \frac{(Green - SWIR)}{(Green + SWIR)}$$

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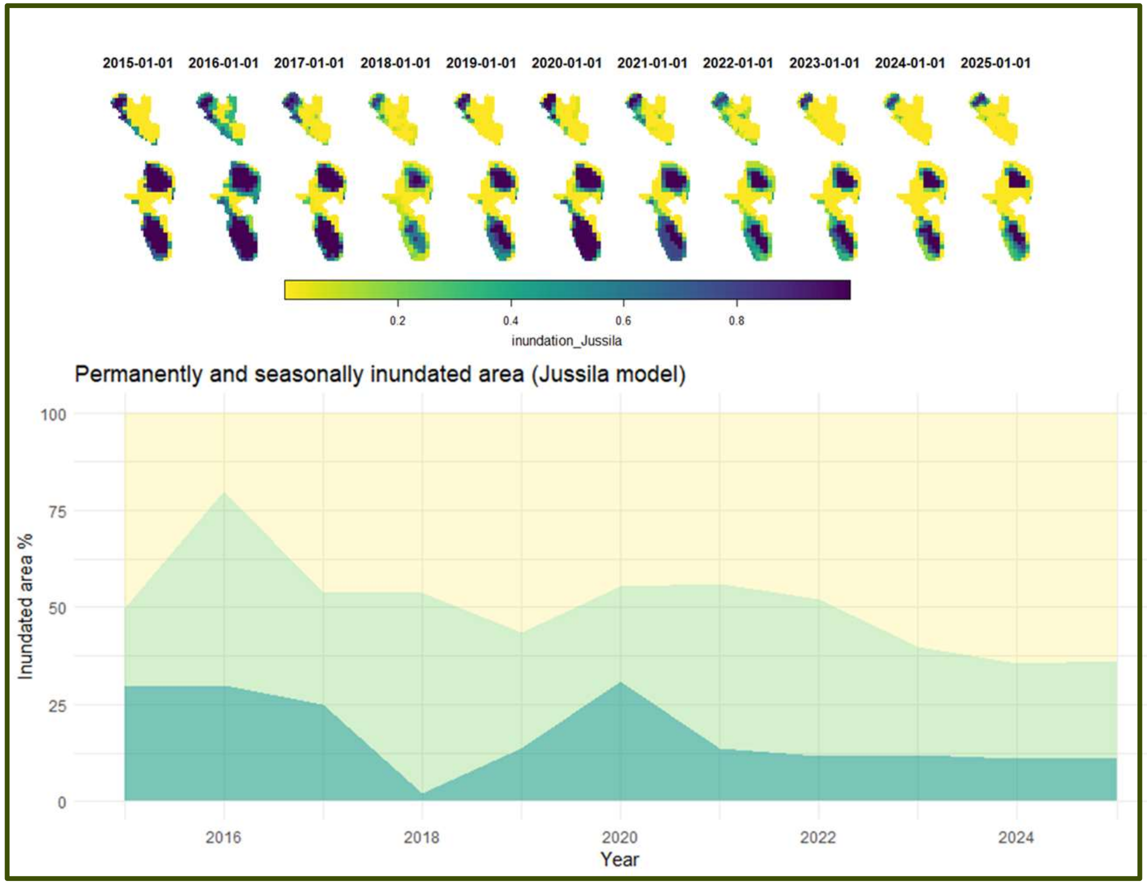
Time series for inundation – Jussila method

In our area we have:

- Permanent water bodies
- Seasonally inundated grasslands

When the grassland are inundate too frequently or too long
→ grassland degradation (loss in biodiversity)



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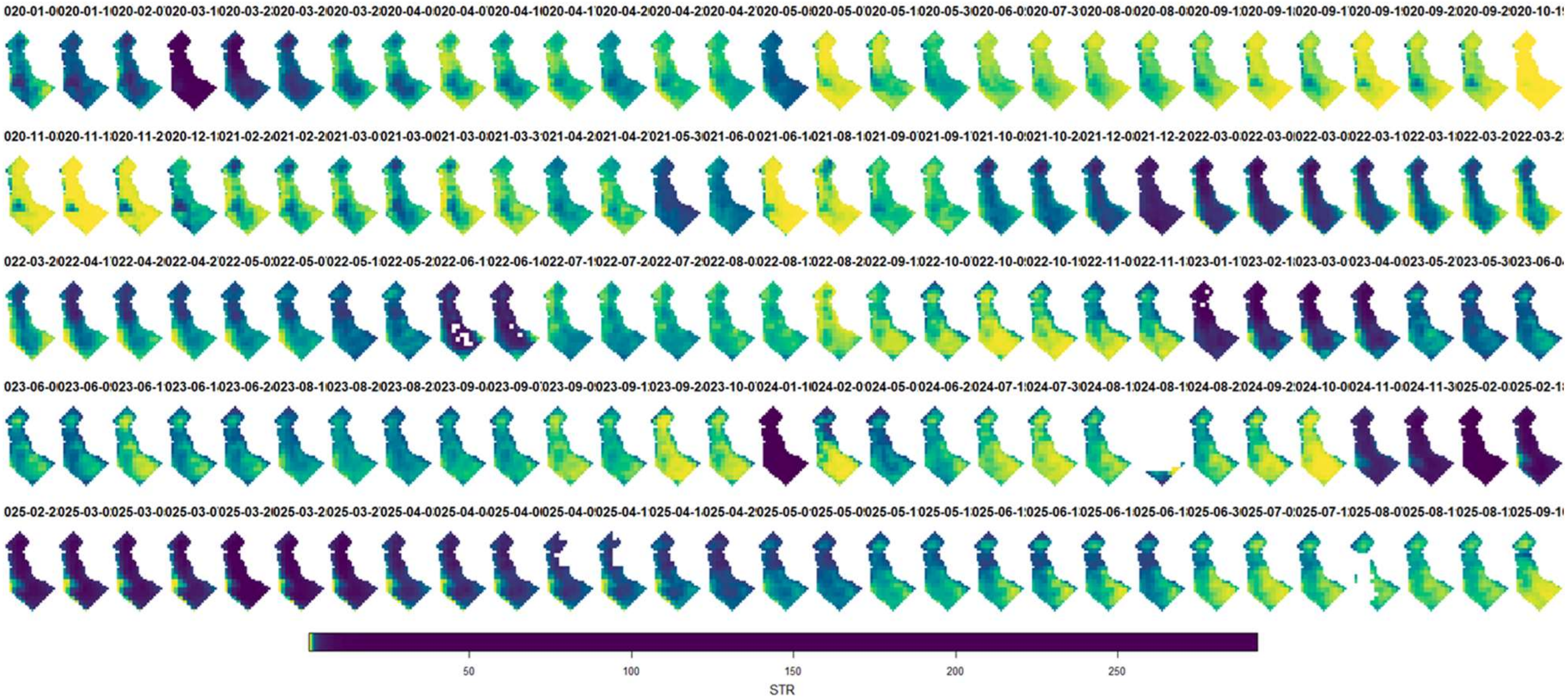
Time series - Inundation

STR – shortwave-infrared transformed reflectance index.

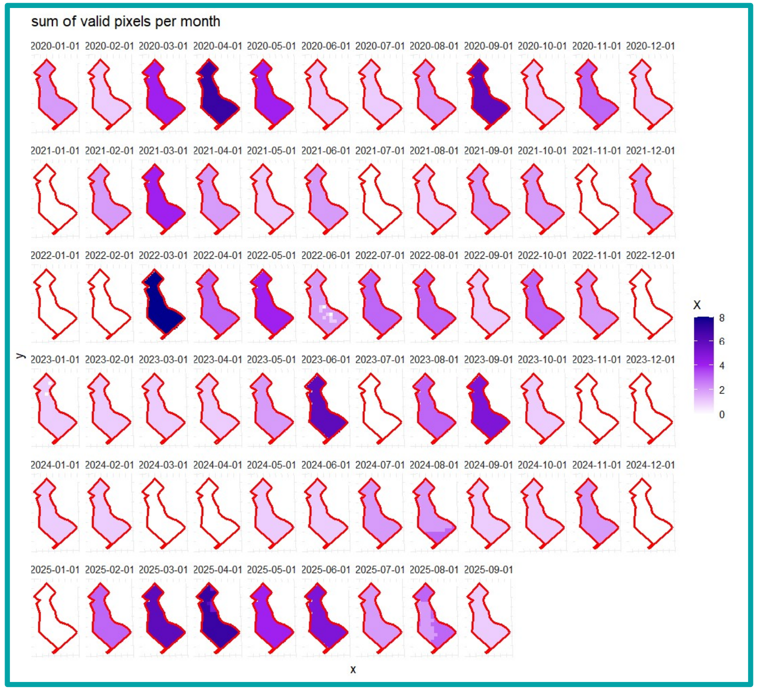
$$\mathbf{STR} = \frac{(SWIR - NIR)}{(SWIR + NIR)}$$



Data completeness

+ uncertainty visualization:

- Spatial completeness per month: number of valid pixels
- Temporal completeness: % of valid months



- In white: the missing months
- Legend: sum of valid pixels

→ expected sum is between 5 and 6 (5 day revisit time), 9-10 (3 day revisit time)

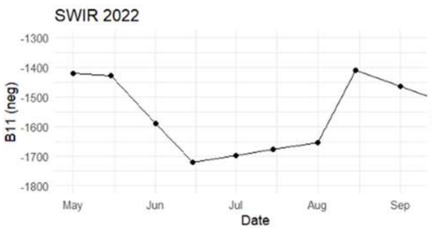
→ Clear under-representation of winter months.

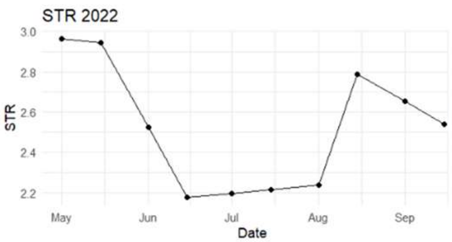
$$\mathbf{MNDWI} = \frac{(Green - SWIR)}{(Green + SWIR)}$$

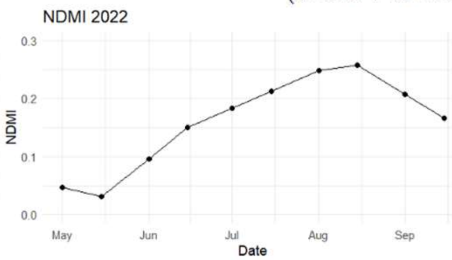
Totally differing seasonal story depending on index:

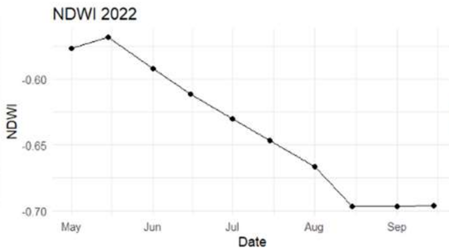
$$\mathbf{NDPI} = \frac{(NIR - Green)}{(NIR + Green)}$$

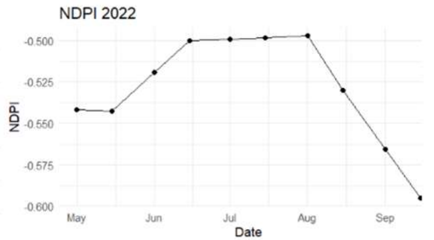
$$\mathbf{NDMI} = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$











$$STR = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

SWIR, STR
Plausible seasonal curve
wet spring, drying in summer, wet autumn

NDMI
Vegetation index?
Opposite pattern. “Low moisture” in spring and increase in summer. Reflects health of vegetation rather than moisture.

NDWI
Decreasing pattern?
Negative values throughout season. This is a water index with water body treshold in about 0.2-0.5. Might not be sensitive to moisture in other than open water surfaces?

NDPI
Opposite pattern?
Negative values throughout season. This is a pond index with water pond treshold in about 0.75. Might not be sensitive to moisture in other than open water surfaces?

- Referring to the spectral curves Maria showed
- SWIR band absorbed in water – the more humid the lower the reflection. Same for NIR, but not as much
- Experimenting with different Indeces

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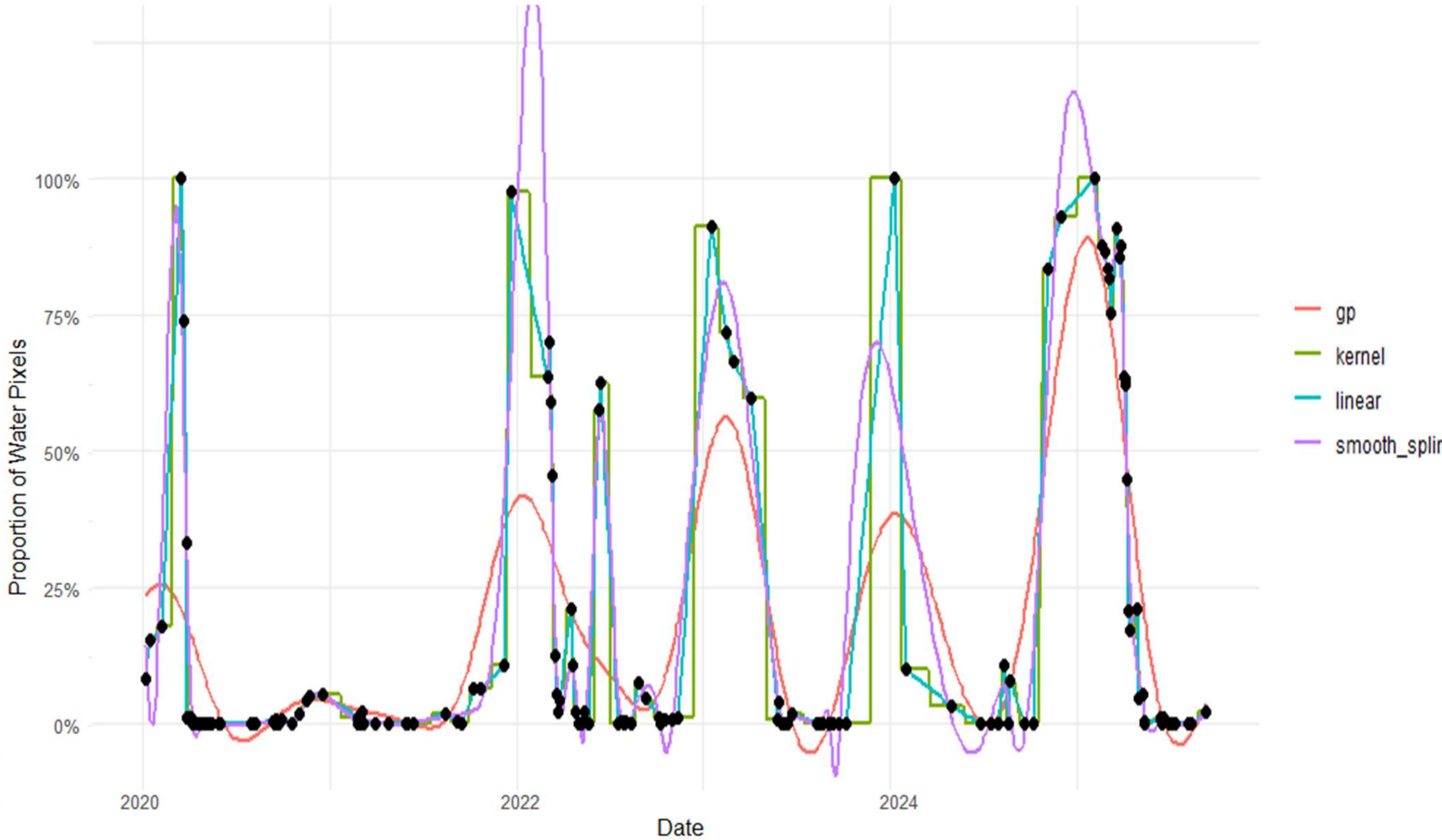
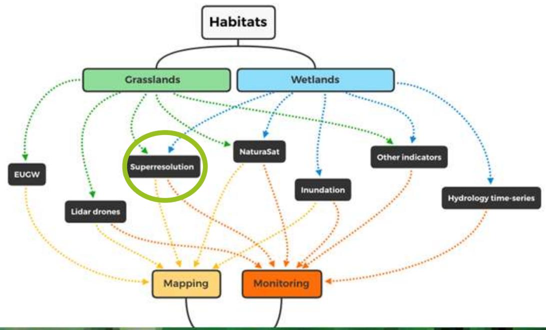
Time series – interpolation of missing observations



Main outcomes of inundation task

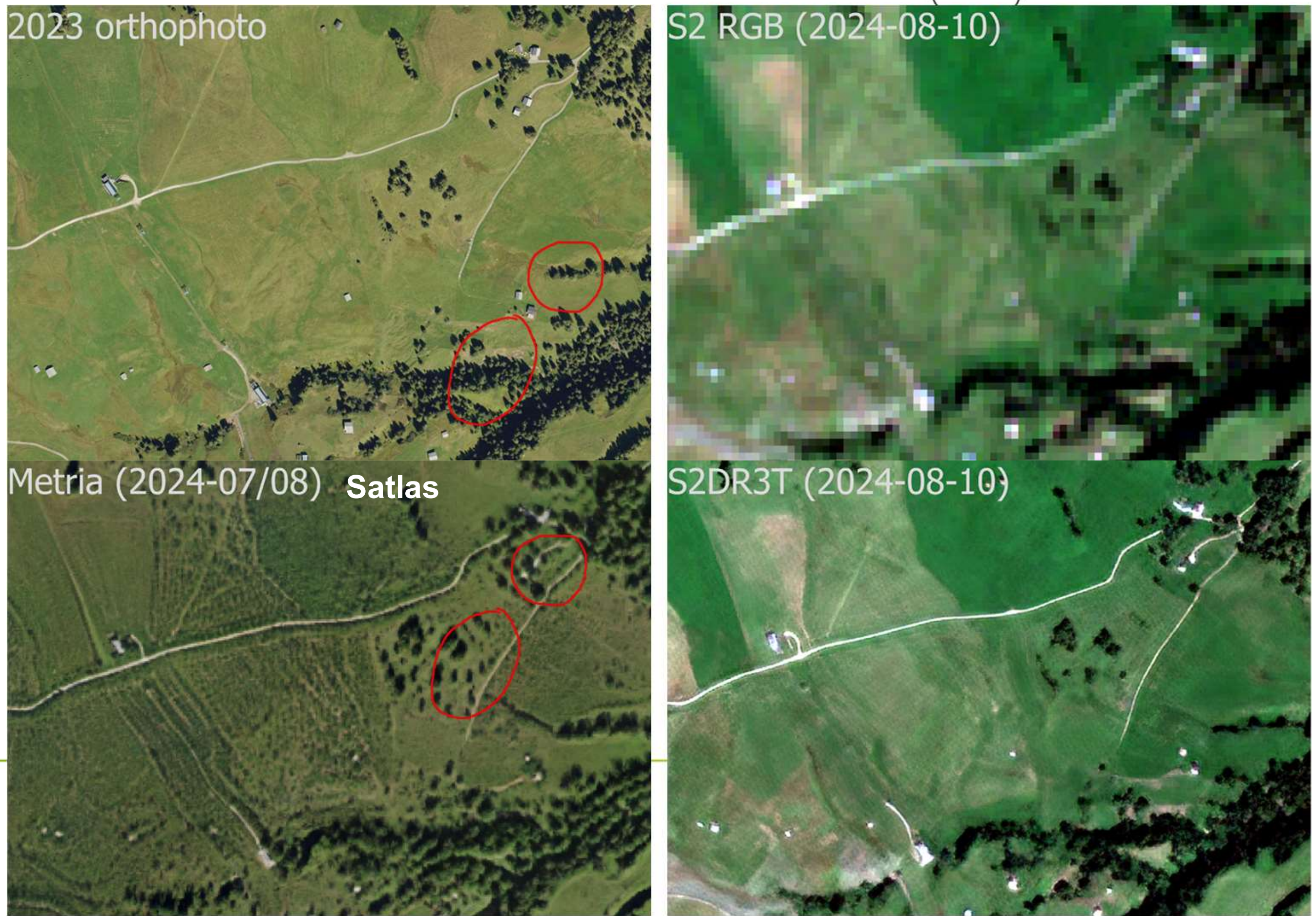
1. Evaluating **model performance** for water detection in wetlands
   1. Good performance in separating open water from drier surfaces
   2. Limitations: small water bodies, trees, shadows, vegetation cover
   3. Regional perspective: Varying realitites and challenges in different habitats/regions (such as reeds and size of wet areas), but generally models behave similarly across regions
   4. Readiness for monitoring? Further validation/calibration for higher confidence in various conditions
2. Testing various **validation approaches**
   1. Uncertainties in validation
   2. Good practices, recommendations
3. Application for inundation time series in hydrology task

Super resolution – two methods tested



Super resolution: using a **model** trained on VHR satellite data/aerial imagery to transform a 10m satellite image into 1m resolution

- S2DR3
- Satlas



Super resolution – two methods tested

Super resolution: using a **model** trained on VHR satellite data or aerial imagery to transform a 10m satellite image to 1m resolution.

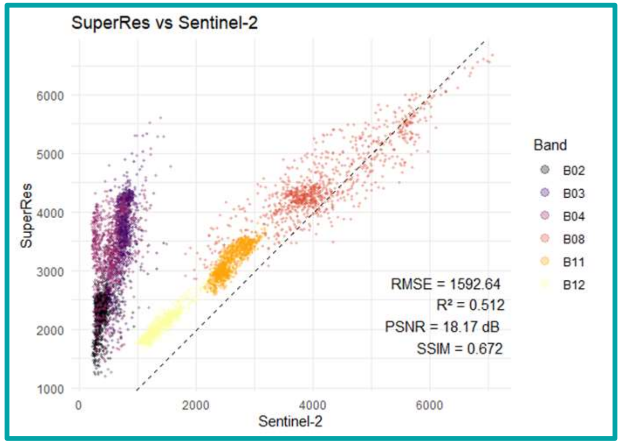
- S2DR3
  - 1 input Sentinel-2
- Satlas
  - 8 input Sentinel-2

Quantative evaluation of Super Resolution images

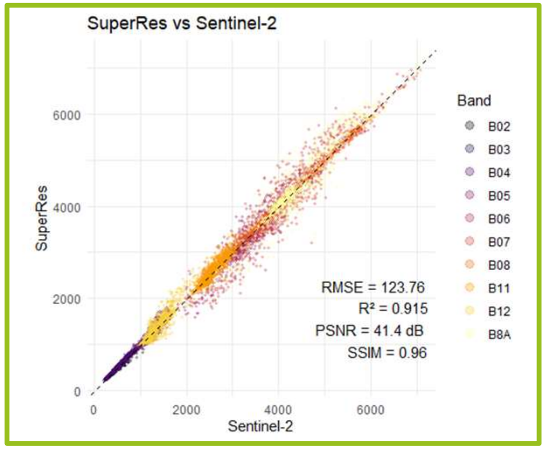
Method by S2DR3 team:

- Downscale SR image to S2 resolution
- Scatterplot pixel vals
- RMSE & R2
- PSNR (Peak Signal-to-Noise Ratio):
  Measures fidelity of e.g., compressed image/audio compared to original
- SSIM (Structural Similarity Index):
  Similarity in terms of luminance, contrast, and structure
- Histogram matching

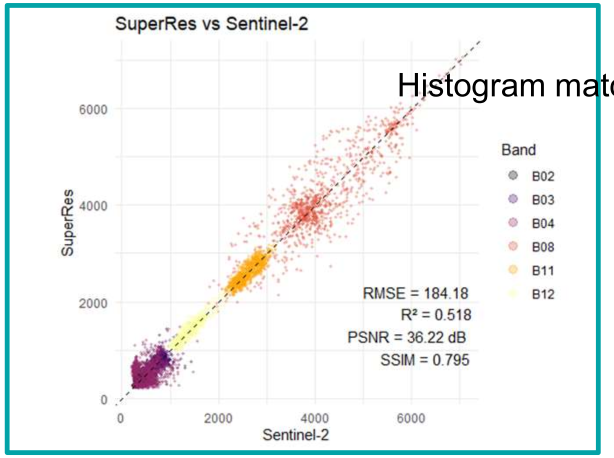
Satlas method

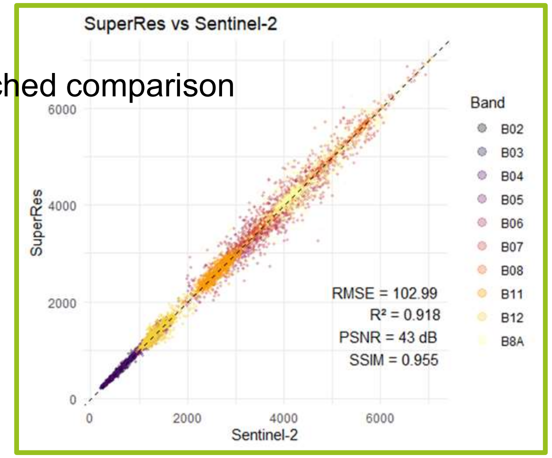


S2DR3 method



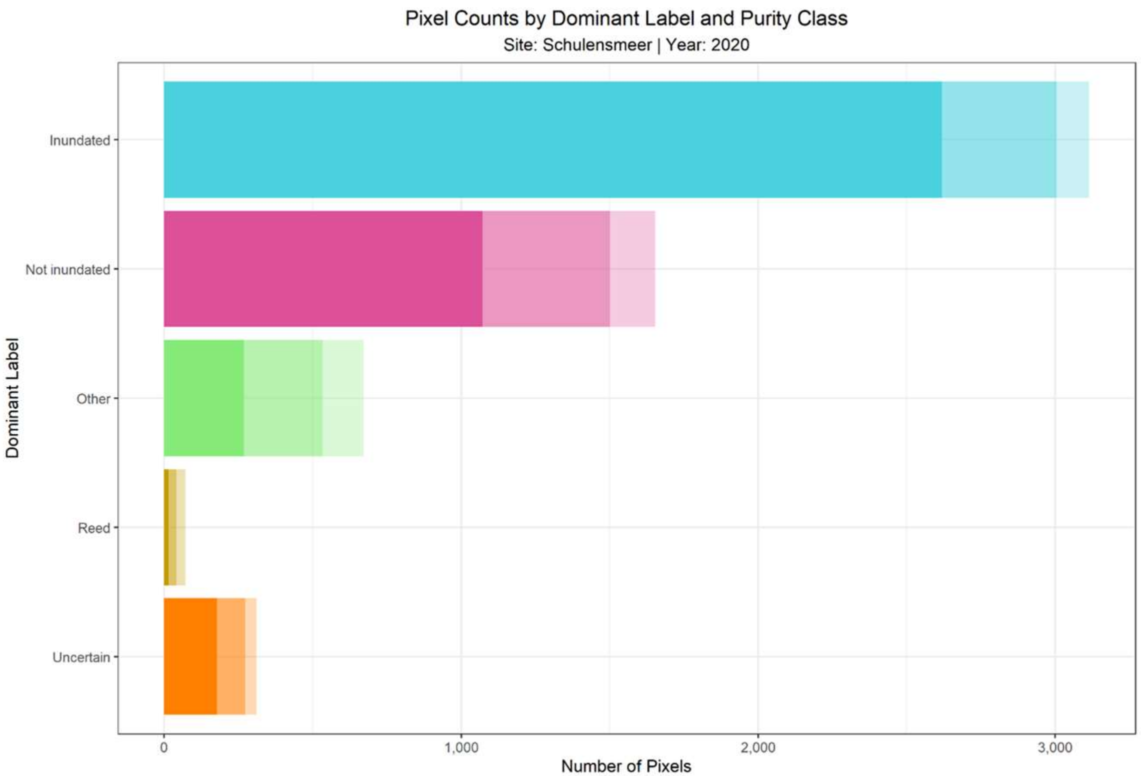
Histogram matched comparison

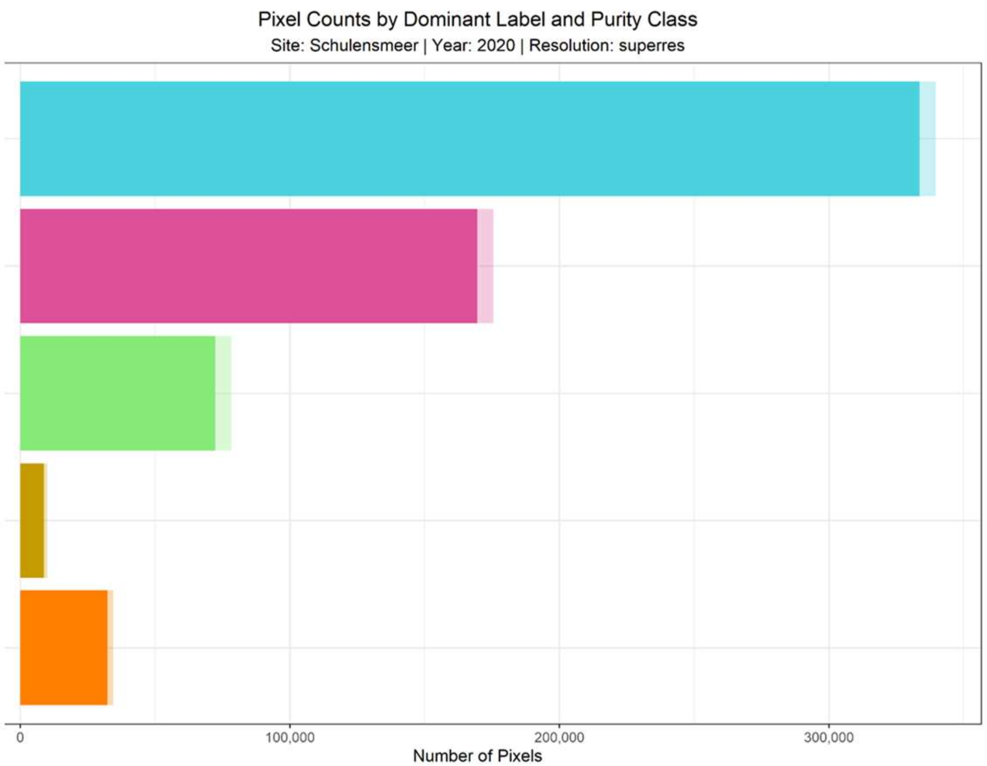




Super resolution (S2DR3T) for inundation

Reduces amount of ”mixels”.





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Super-resolution for inundation (Flanders example)

Sentinel-2 10m Macro F1 = 0.9425

Confusion Matrix

Site: Schulensmeer | Year: 2020

	dry	water
Inundated	134	2,981
Not inundated	1,538	115
Other	389	283
Reed	20	52
Uncertain	190	121

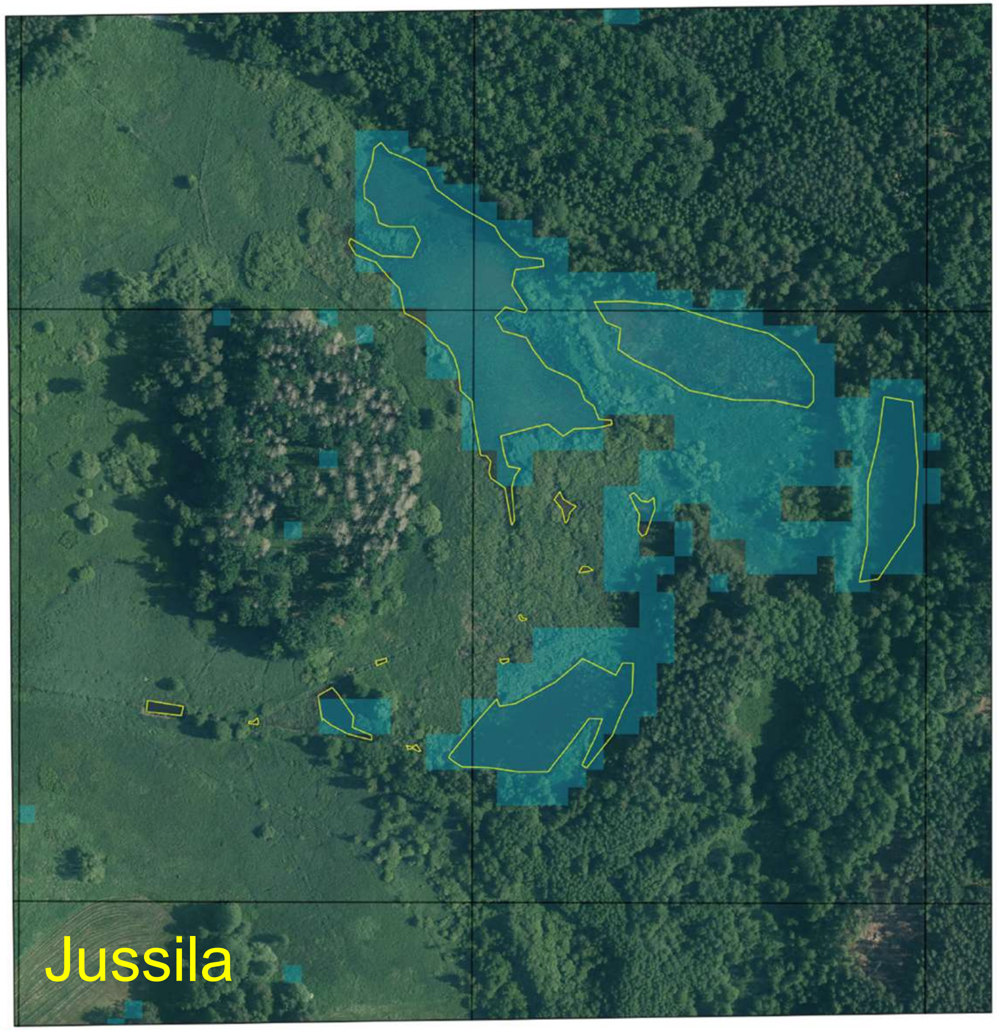
S2DR3T 1m Macro F1 = 0.9605

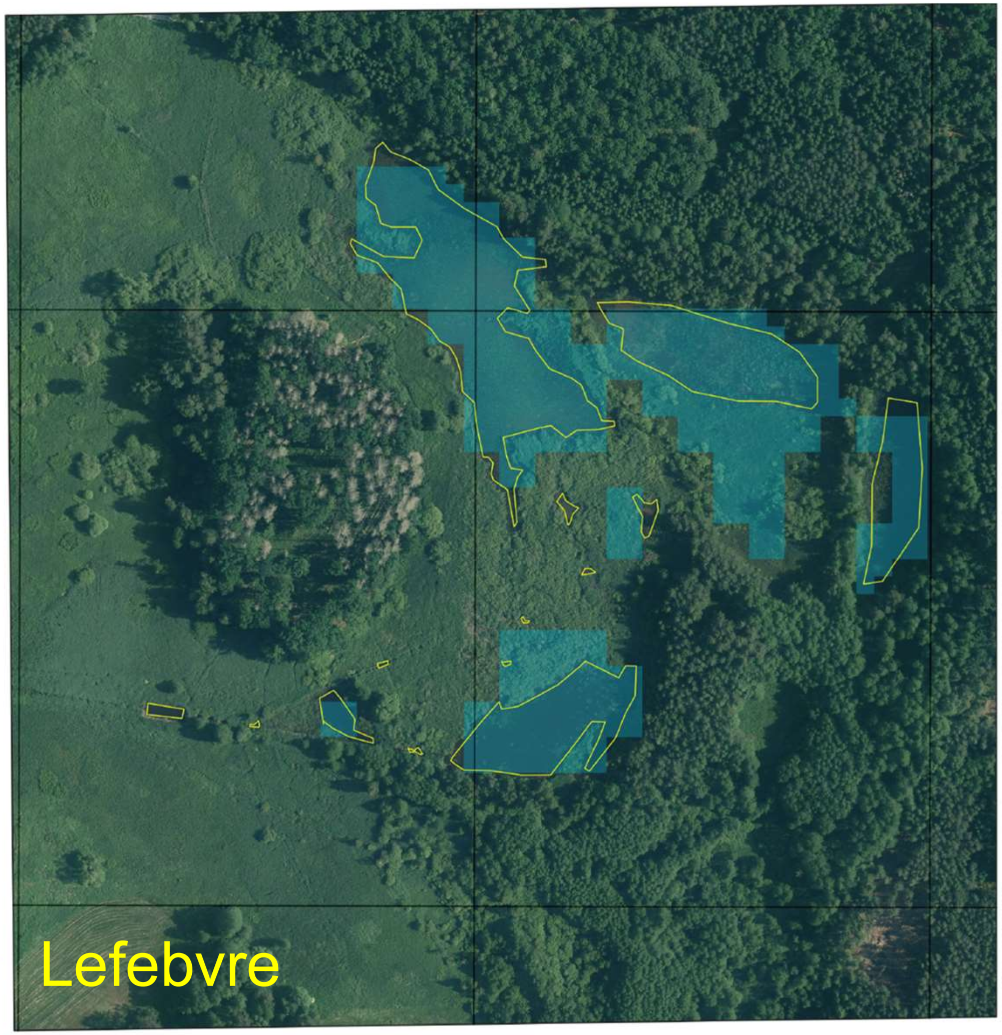
Confusion Matrix

Site: Schulensmeer | Year: 2020 | Resolution: superres

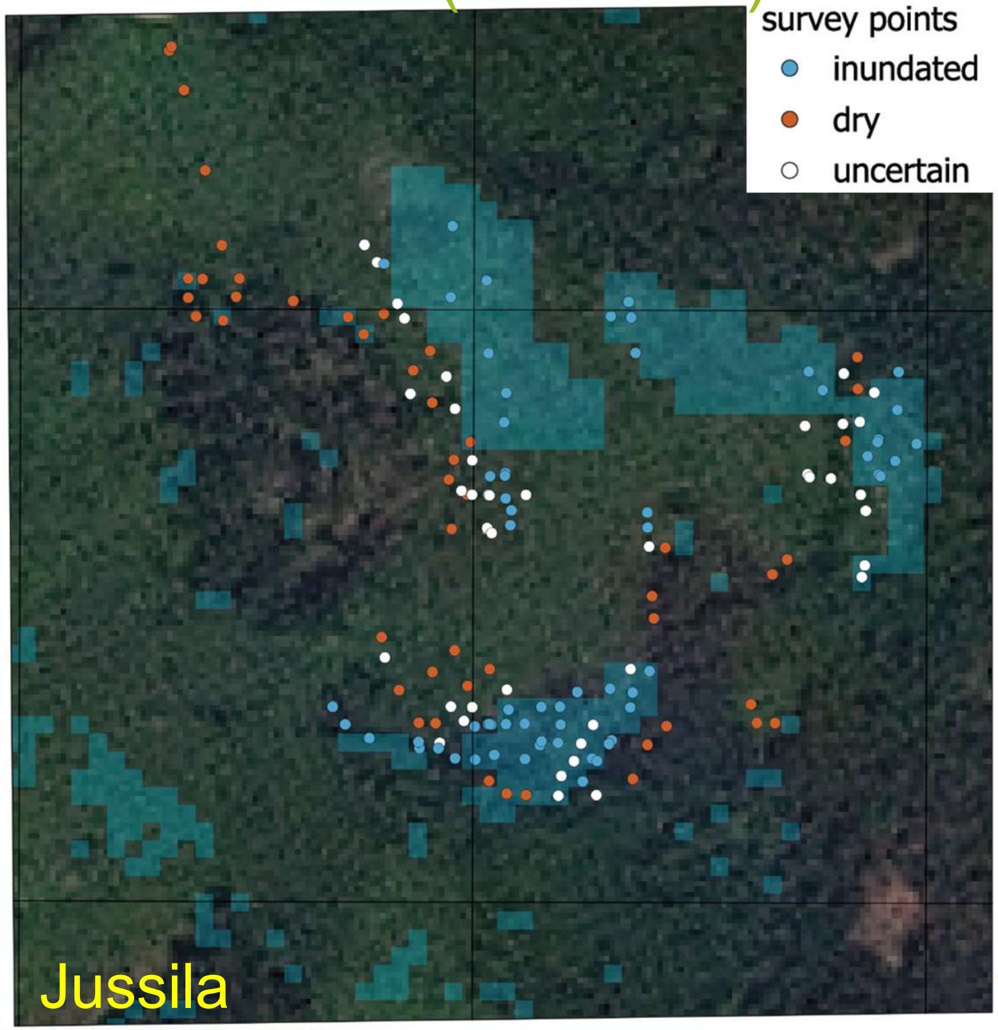
	dry	water
Inundated	9,060	330,542
Not inundated	166,342	9,187
Other	45,277	32,866
Reed	3,793	6,114
Uncertain	22,013	12,413

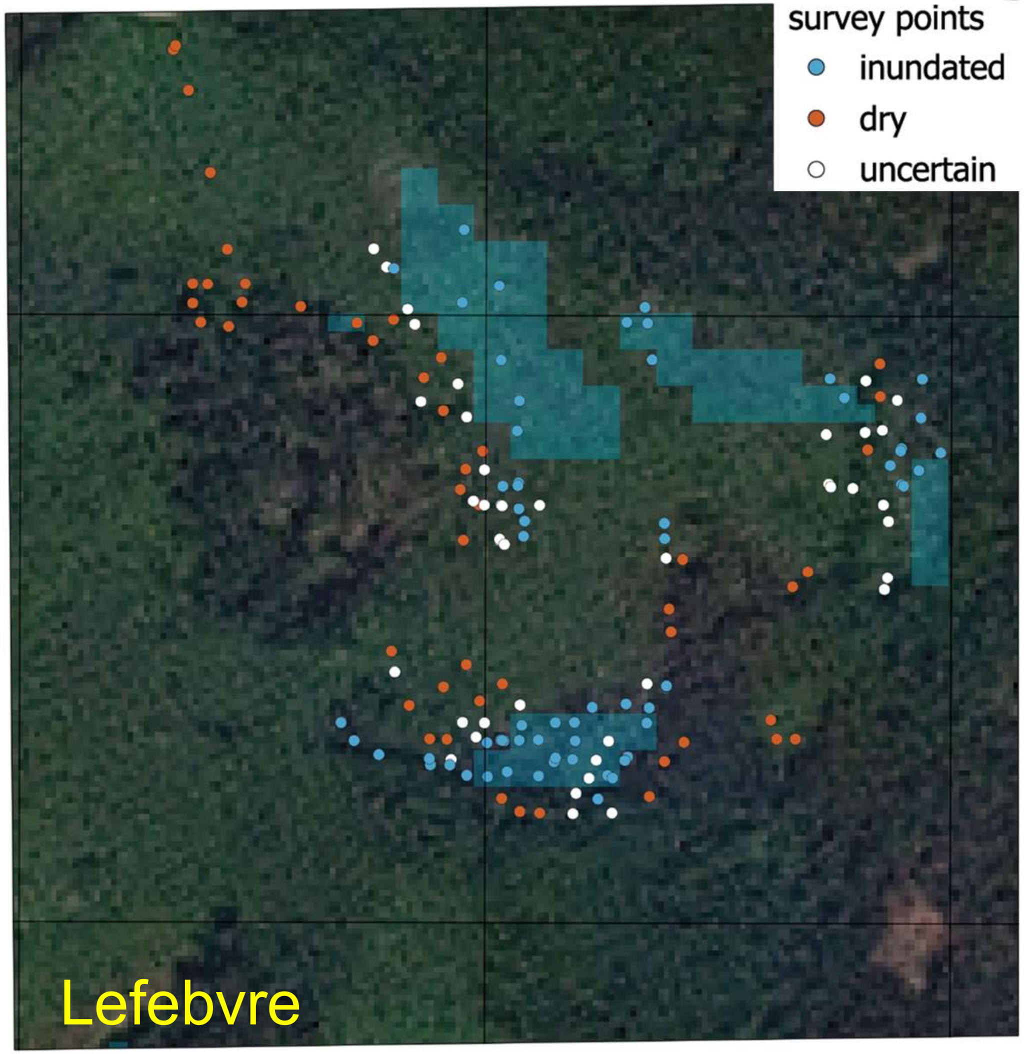
Inundation Jussila vs Lefebvre (Czech Republic)



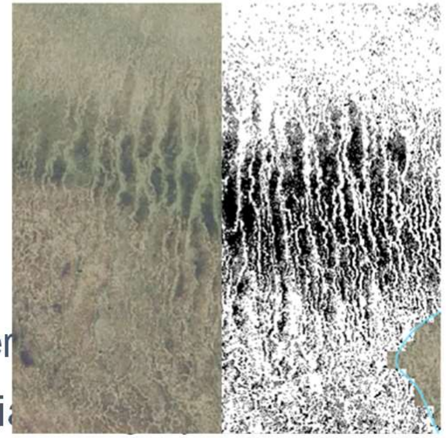


Field validation (Kramarka)



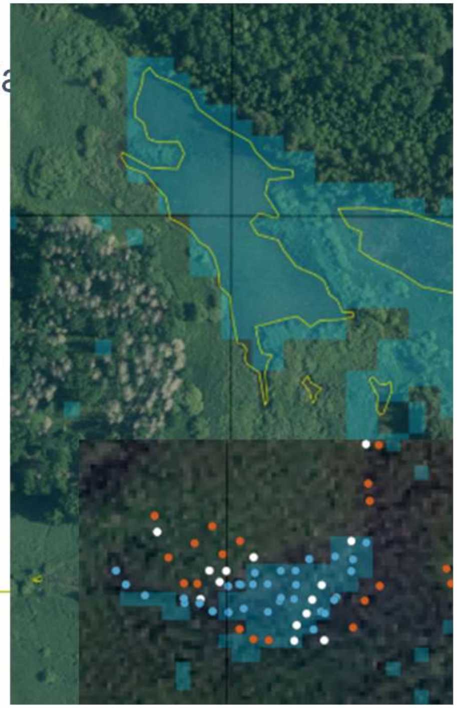


Training and reference data crucial



1. Visual evaluation based on aerial images.
2. Utilising existing habitat mapping information (Czechia, Fi
3. Point sample collected based on aerial imagery interpretation (Finl

4. Segmentation algorithms for semi-automated delineation of wet su
   (Flanders, others?).
5. Generating high-resolution reference rasters by unsupervised clas



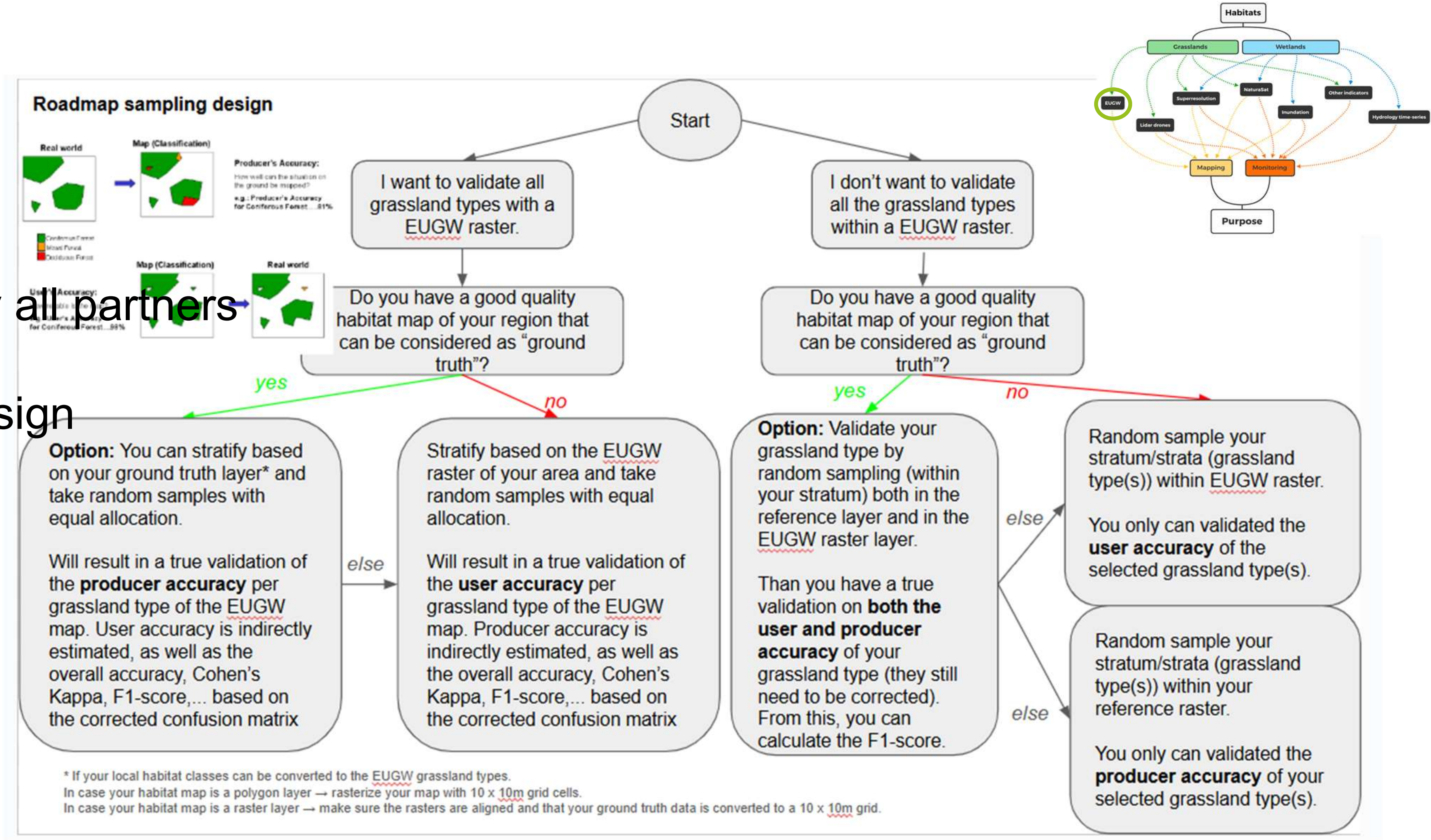
6. Field visits in August 2025: validation points (Czechia, Finland).
7. Field visits with a drone (Sweden, Slovakia).
8. Multitemporal validation? (Flanders, ~~Finland~~)
9. WTD loggers for multitemporal validation? (Flanders)

Validation EUGW

- Performed by all partners possible
- Validation design

Point stratification

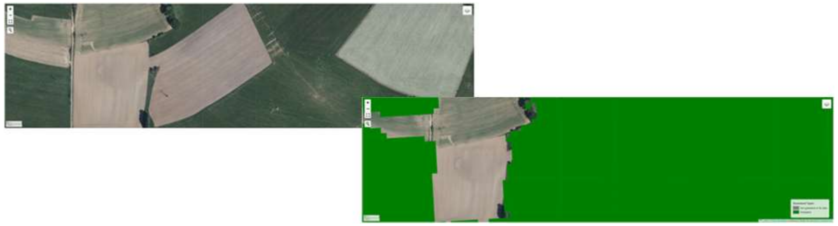
Tool for validation



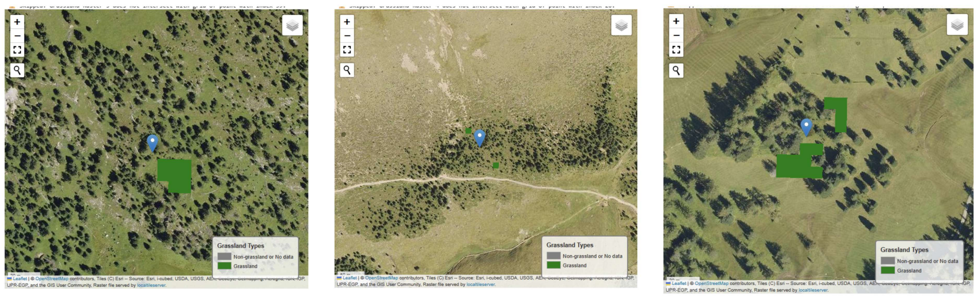
Validation EUGW – guidelines for ”hard to interpret cases”

Forest borders, tree lines, mixed pixels

Agricultural areas (with temporary grasslands or crops similar to grass)

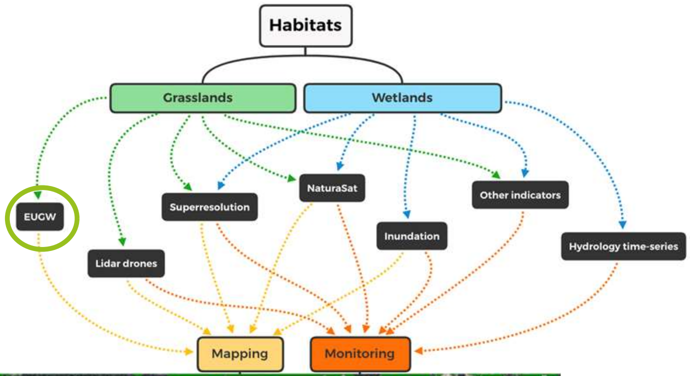


Sparsely wooded grasslands



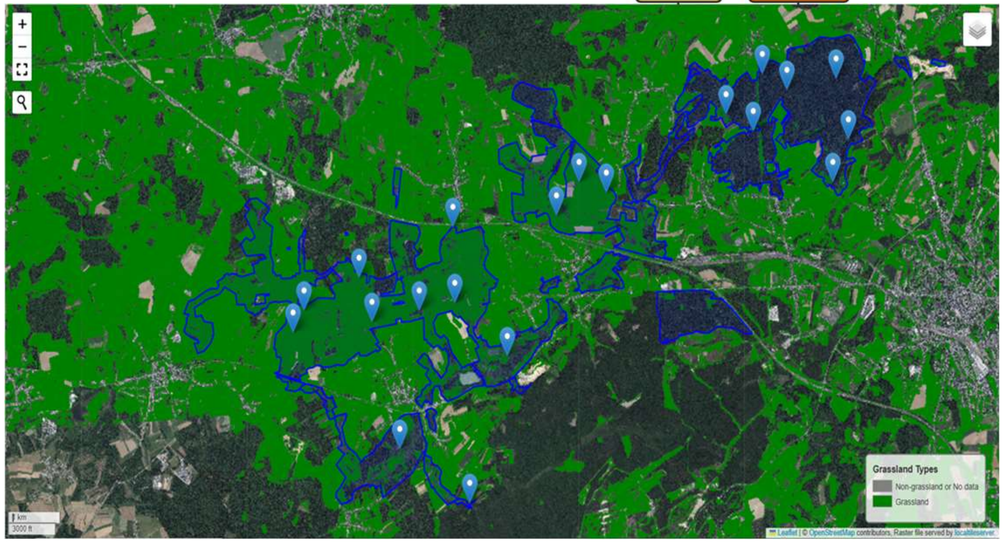
Validation of EU Grassland Watch classification

Not available in all partner countries



Analysis workflow

1. Binary conversion
2. Raster pixel sampling
   a. >< grid sampling (previous notebook)
   b. stratified random sampling with equal allocation
      i. 200 locations in grassland
      ii. 200 locations in non-grassland
   c. limited to sampling with the SAC area (?)
   ➢ limit the sampling in agricultural and recreational grasslands

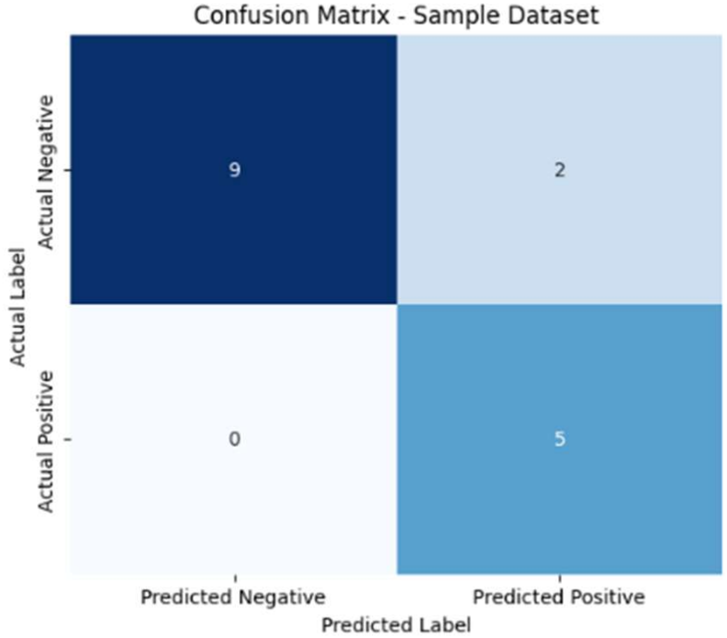


Analysis workflow

1. Binary conversion
2. Raster pixel sampling
3. Interactive widget for labelling
4. Accuracy assessment report
    a. Confusion matrix
    b. Corrected confusion matrix

```
=== Analysis: Sample Dataset ===
Total labels: 20
Uncertain labels: 4
Percentage of uncertain labels: 20.00%

--- Metrics for Certain Labels (TP, TN, FP, FN) ---
True Positives (TP): 5
True Negatives (TN): 9
False Positives (FP): 2
False Negatives (FN): 0
Total certain labels: 16
```

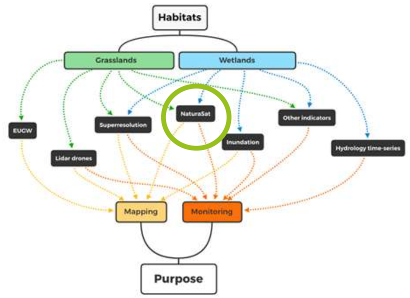


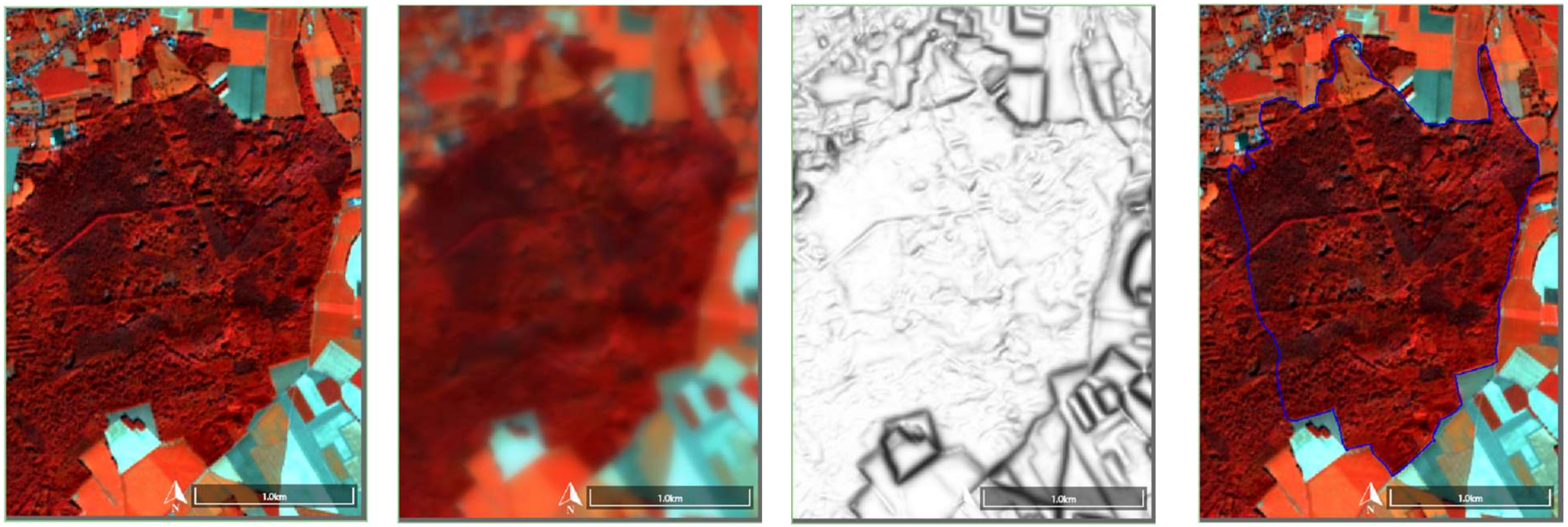

```
Overall Accuracy: 0.8750
Precision (Positive Class): 0.7143
Recall (Sensitivity - Positive Class): 1.0000
F1 Score (Positive Class): 0.8333

--- Additional Notes ---
Interpretation of labels for confusion matrix context:
- 'TP': Correct Positive (e.g., Grassland predicted as Grassland)
- 'TN': Correct Negative (e.g., Not Grassland predicted as Not Grassland)
- 'FP': Incorrect Positive (e.g., Not Grassland predicted as Grassland)
- 'FN': Incorrect Negative (e.g., Grassland predicted as Not Grassland)
```

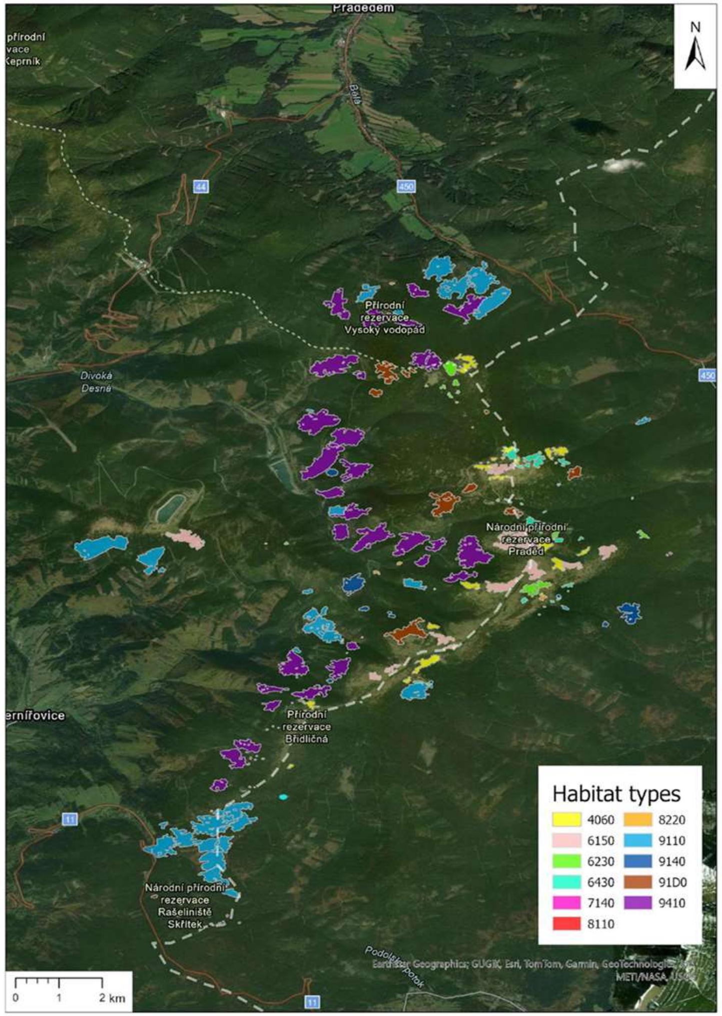
Segmentation semi-automatic (NaturaSat)

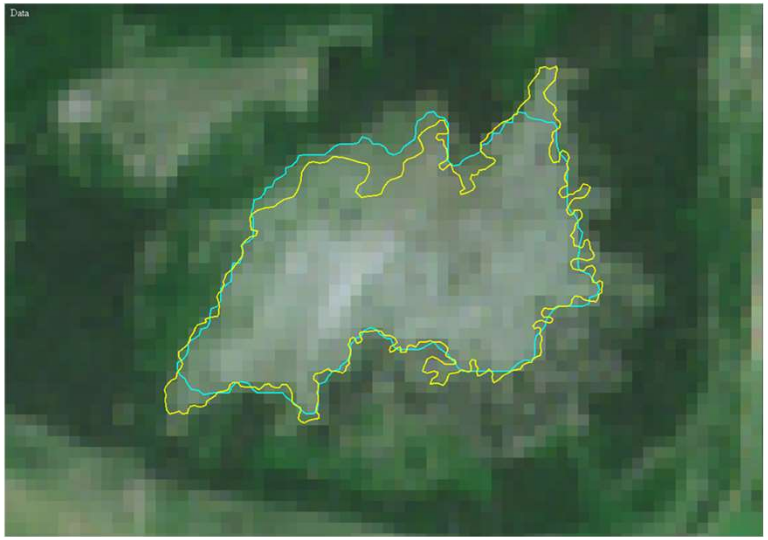
Input image enhancement → Edge detection → Segmentation

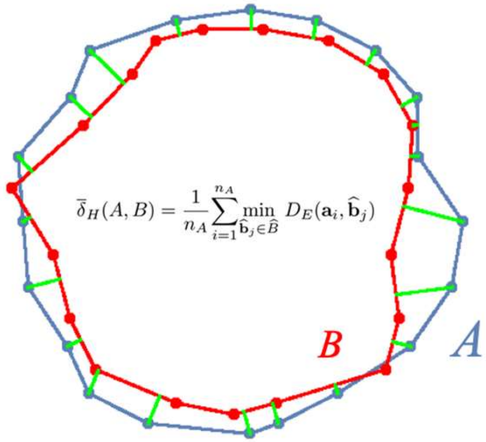




Segmentation validation



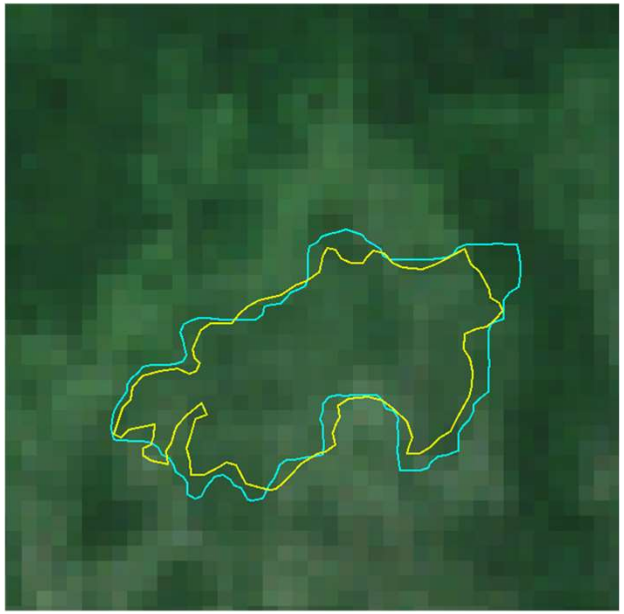




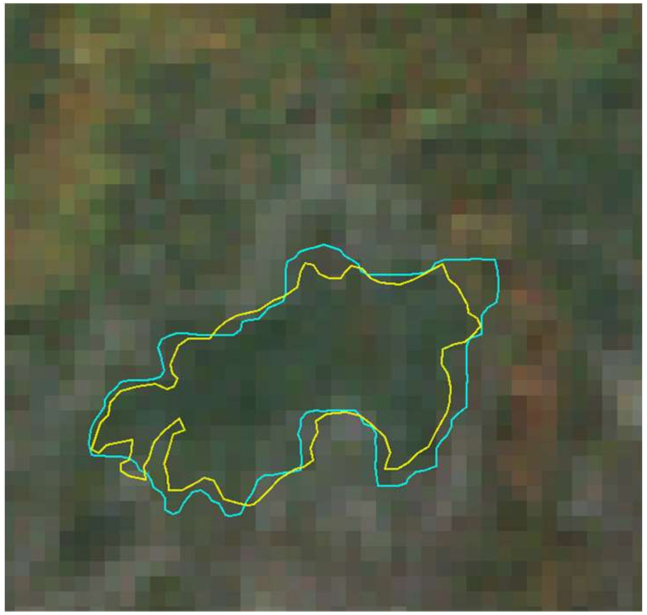
Hausdorff distance

Segmentation of juniperus formations

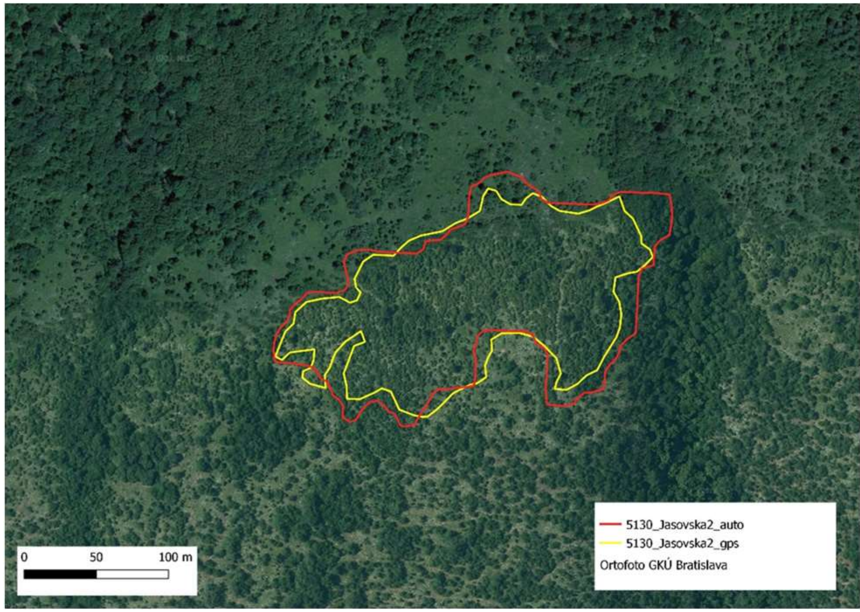
5130 *Juniperus* communis formations on heaths or calcareous grasslands – mean accuracy 10.19m



Vegetation season



Autumn



Aerial photograph

- Better delineation during the non-vegetation period, when contrast to surroundings trees are higher

biodiversa+

European Biodiversity Partnership

Habitat Mapping & Quality Monitoring, Biodiversa+ Habitat Pilot 2024-2025 – Main contacts

- Co-led by the Swedish Environmental Protection Agency (SEPA) and the Finnish Ministry of Environment (MoE_Fi)
- SEPA coordination team: Sara Wiman, Mona Naeslund, *Ola Inghe (retired)*
- SYKE (/MoE_FI) coordination team: Risto Heikkinen, Tytti Jussila

Thank you for your attention!