Forest Carbon Monitoring

EO in support of quantifying Tree Planting

Lessons learnt from the ESA Forest Carbon Monitoring project

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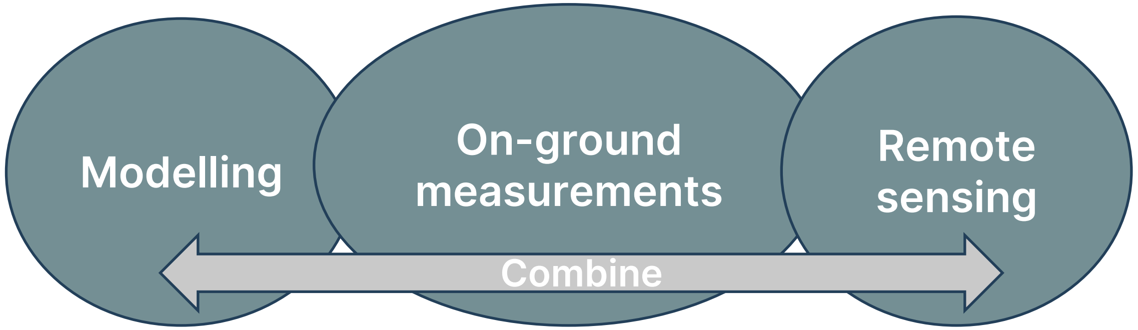
Presentation outline

- Short introduction of FCM project
- EO based forest mapping
  - Examples and achieved accuracies
- Data assimilation
  - Combining process-based modelling with EO-based mapping
- Integration of field sampling and EO-based mapping
  - Model-assisted estimation
  - Multi-step sampling schemes
- Conclusions

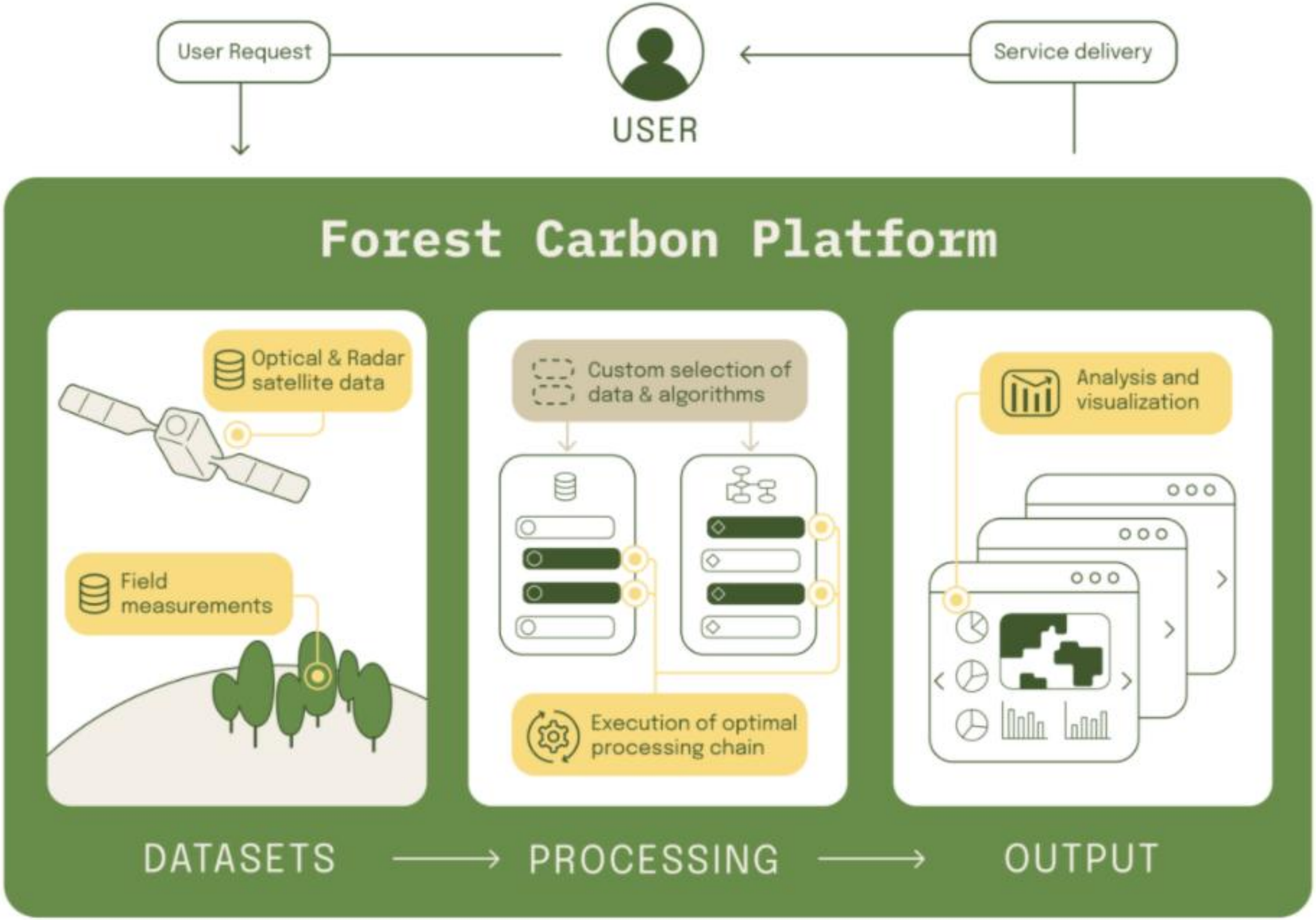
Quantification – three approaches*



*) From draft proposal

FCM concept

1. Integration of in-situ and EO data
2. Flexibility to user requirements
3. Process-based forest ecosystem modelling + data assimilation
4. Rigorous uncertainty assessment framework



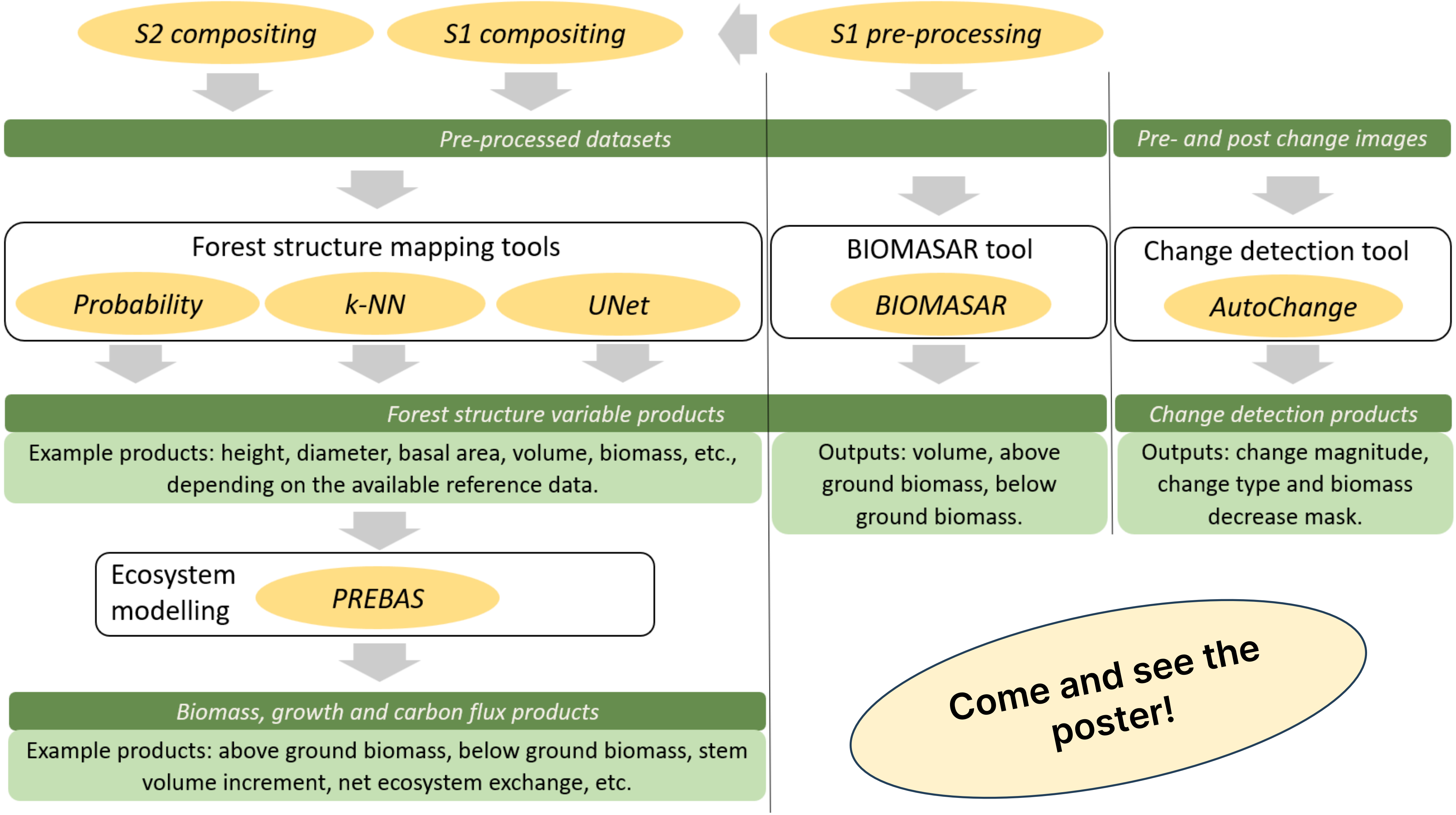
FCM toolset

1. Self-service at Forestry TEP: f-tep.com

Coming soon

2. Included in the NoR portfolio: nor-discover.org

3. Expert service through FCM project website



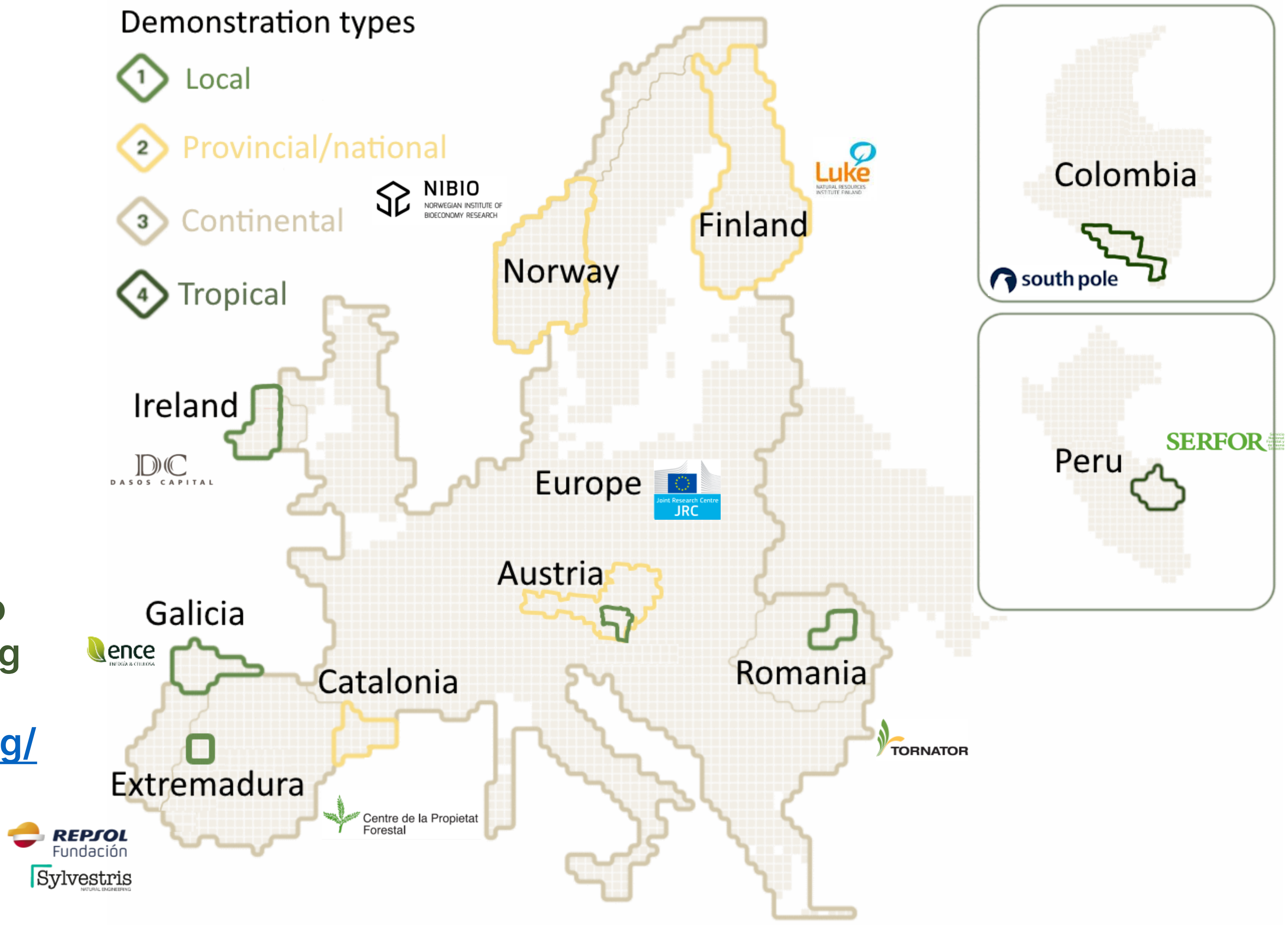
Come and see the poster!

Use case demonstrations

Primary EO data:
Sentinel-1 and Sentinel-2

Coverage:
From private company forests to European wide mapping

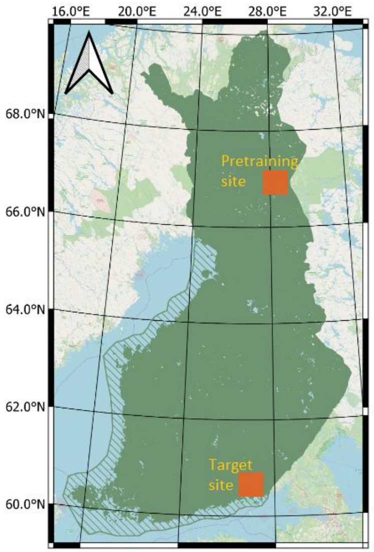
Outputs:
Over 100 products delivered to users. Example product viewing and downloading at: portal.forestcarbonplatform.org/



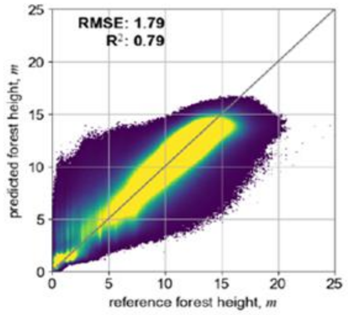
UNet for forest mapping

- Models trained with Airborne Laser Scanning (ALS) datasets
- Model transfer with limited number of field plots
- Improves accuracy compared to tradition machine learning methods
- Clear reduction in saturation effect

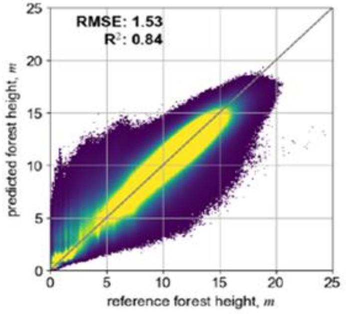
Pretraining over "source" site

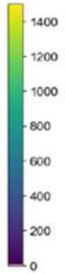


Sentinel-2 only



MS-EO



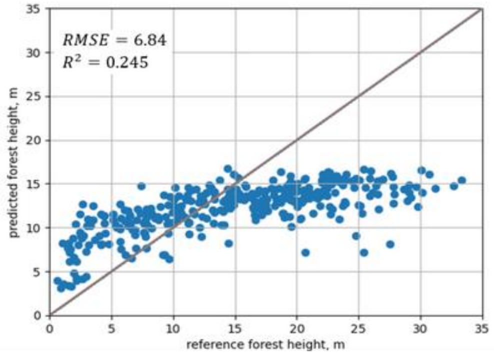


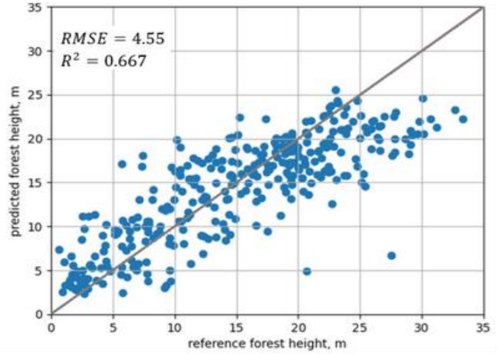
Application over "target" forest area

"Blind" prediction over target-site

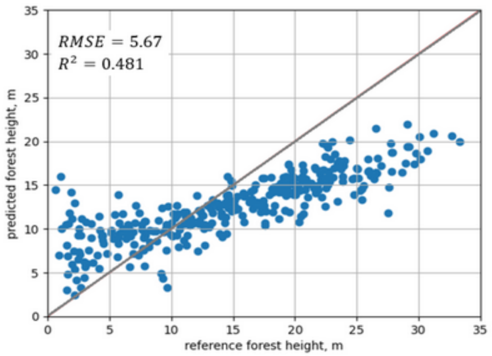
Prediction after finetuning

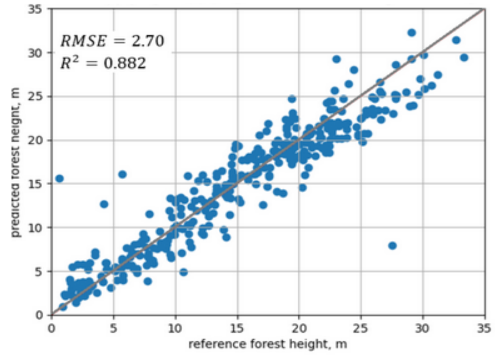
Sentinel-2 only





MS-EO: Sentinel-2, Sentinel-1, ALOS-2 PALSAR-2, TanDEM-X

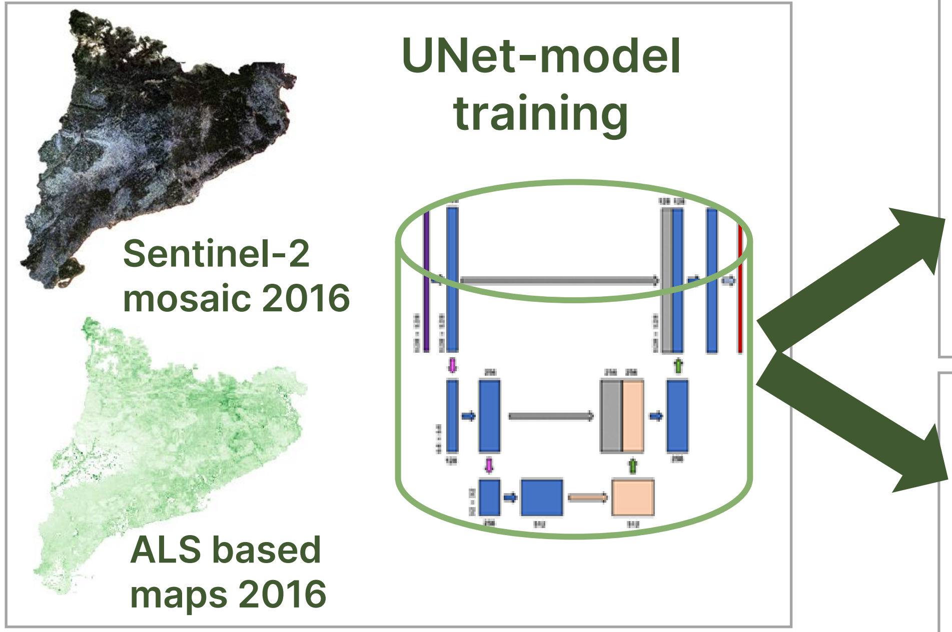


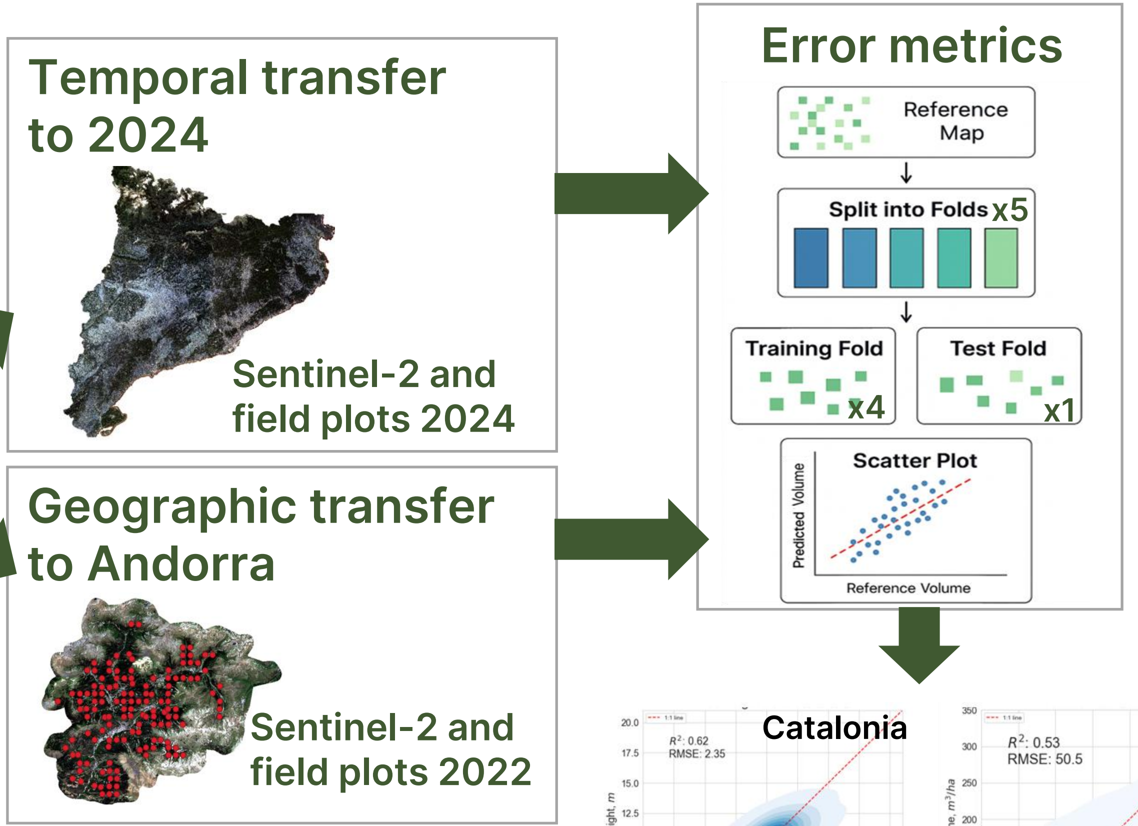


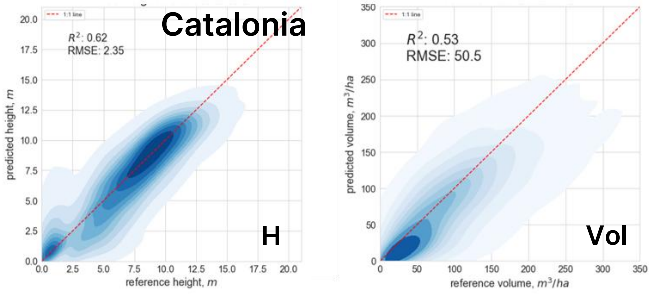
Ge et al. (2023) Deep learning models with transfer learning in boreal forest mapping using multi-source satellite SAR/InSAR and optical images, *Remote Sensing* 15: 5152. DOI: 10.3390/rs15215152

UNet for Catalonia and Andorra

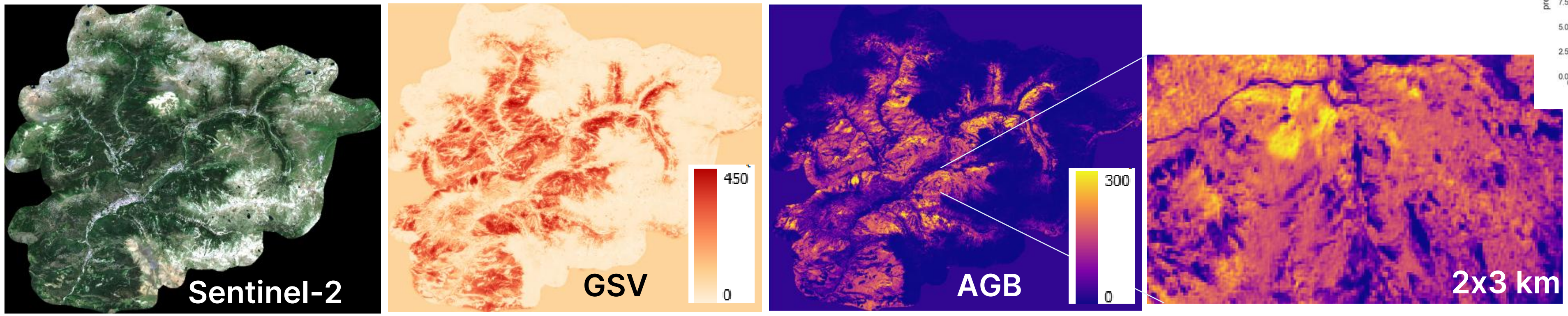
Approach:







Results:

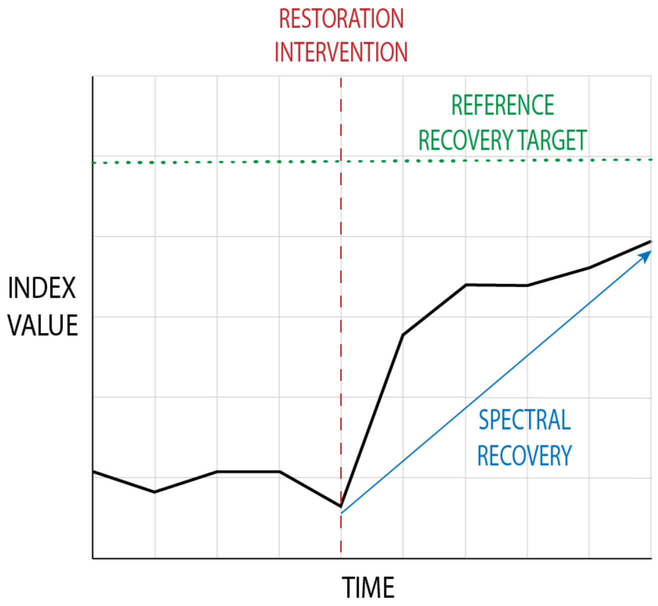


Andorra	H	D	G	V	AGB
RMSE	1.8	5.2	12.0	76.9	52.0
RMSE %	15.5	36.1	28.6	29.7	36.1
Bias	-0.3	-0.7	-0.9	-12.7	-6.7
Bias %	-2.5	-4.7	-2.1	-4.9	-4.7

Spectral recovery tool

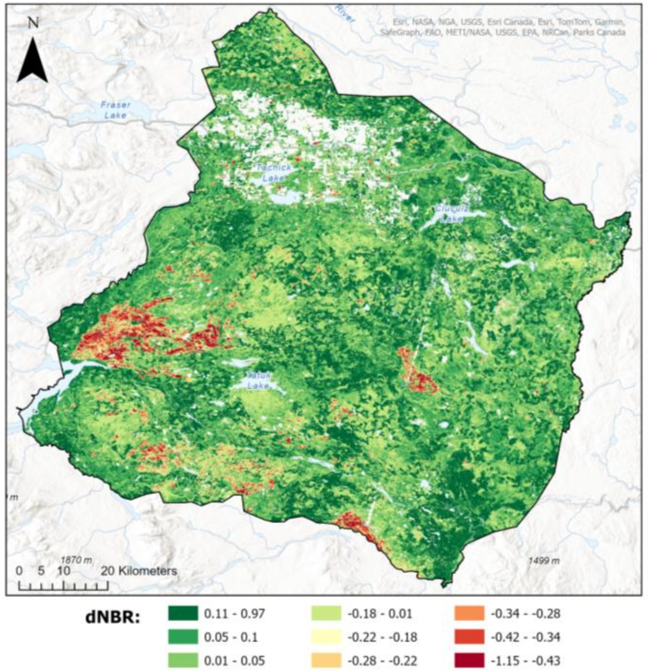
Designed for monitoring early tree growth

- Developed in ESA PEOPLE-ER project by UBC
- Available also in the Forestry TEP platform
- Website: https://www.people-er.info/
- Codes: https://github.com/PEOPLE-ER/spectral-recovery
- Webinar: https://youtu.be/2pGToi2kirM



Per-pixel NBR trend monitoring

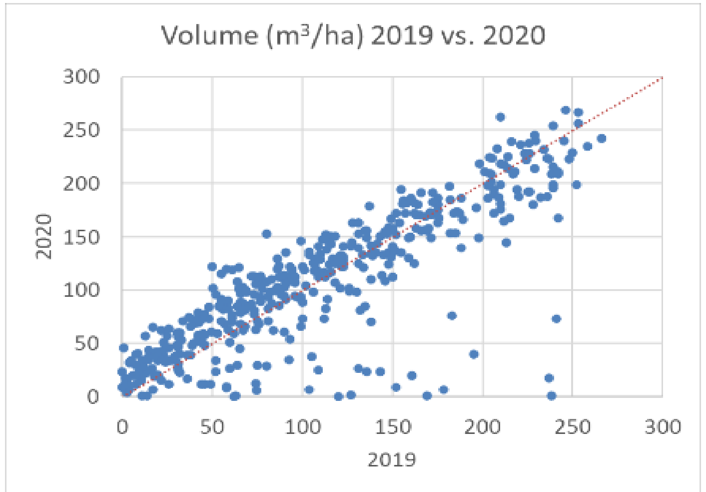
Landscape level monitoring



EO based mapping accuracy

Overview of the 13 use case demonstrations:

- Bias typically < 5% of the mean
- Plot level RMSE typically 20-60% of mean
- Inter-year consistency heavily dependent on remotely sensed imagery and/or availability of annual calibration data



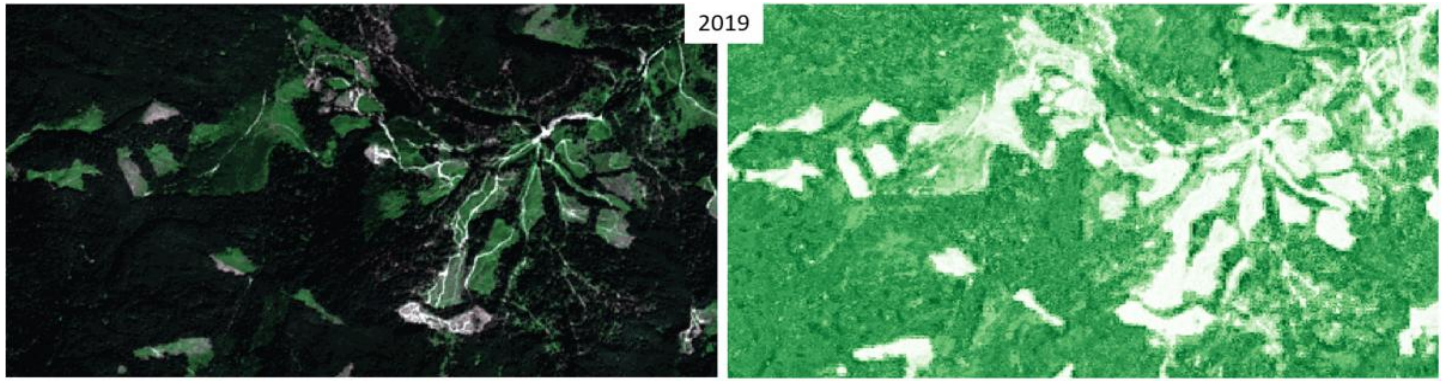
Year-to-year consistency for Volume in Galicia at stand level.

EO datasets	Accuracy (RMSE % of mean)* Tradional ML	Accuracy (RMSE % of mean)* Deep learning
Sentinel-1 only	50-80%	30-40%
Sentinel-2 only	20-60%	20-40%
Sentinel-2 + Sentinel-1 or PALSAR2	20-60%	20-40%
Sentinel-2 + Sentinel-1 + TanDEM-X coherence	20-50%	15-25%

* Typical plot level accuracy range between variables and sites.

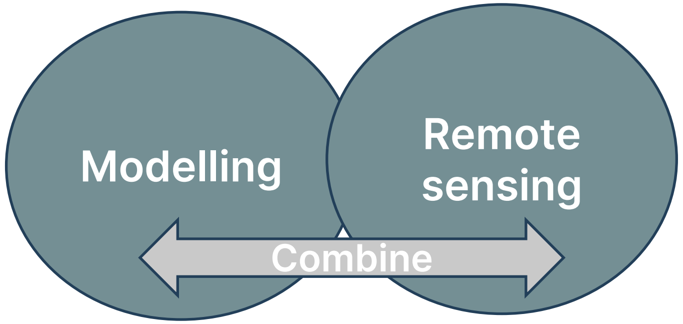
EO based maps:

- Provide detailed spatial distribution, but...
- Are not suitable (alone) for legal or financial quantification purposes



Annual time series of volume estimation in Romania

Data Assimilation



Data assimilation

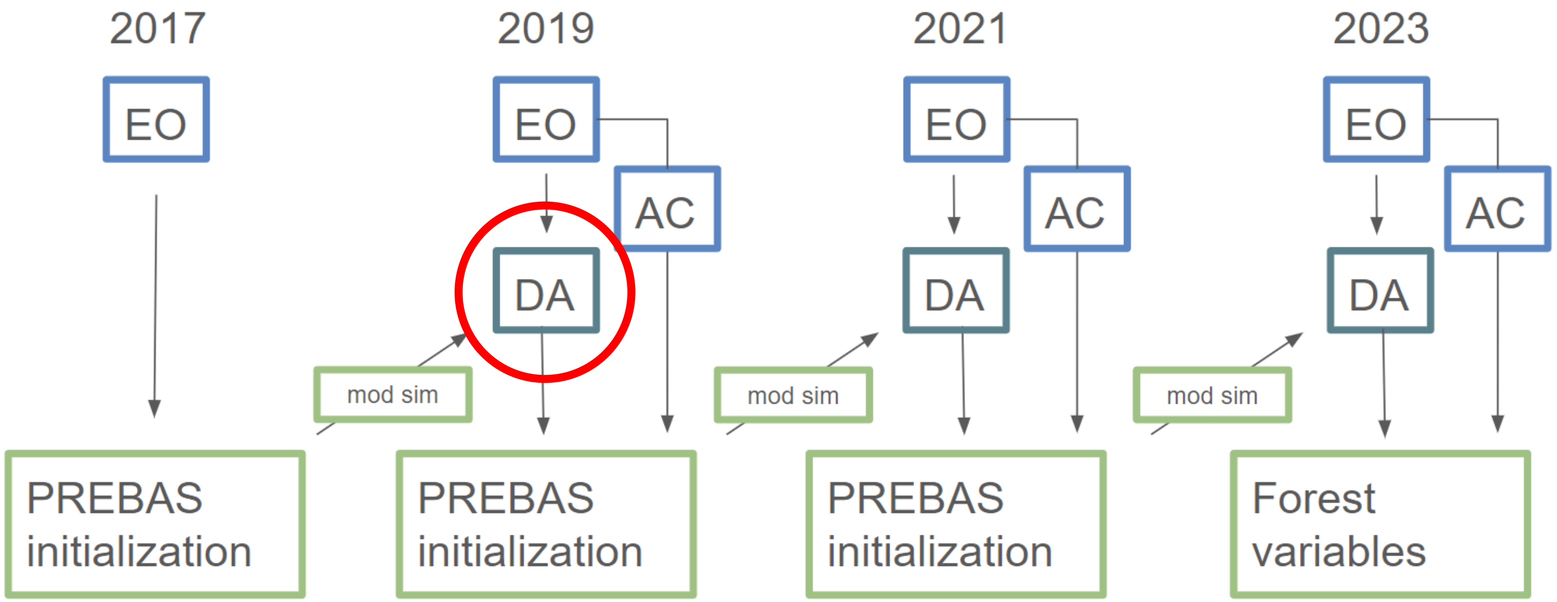
Basic idea:

- Combines process-based modelling with EO-based mapping
- Enables creation of consistent time series of EO-based forest resource maps, improves prediction accuracy and fills no-data gaps.

Example from Norway:

1. PREBAS model calibrated with NFI data
2. EO-based maps 2017-2023 as input
3. Data assimilation with PREBAS and maps
4. Accuracy evaluated with NFI plots

Data assimilation flow chart

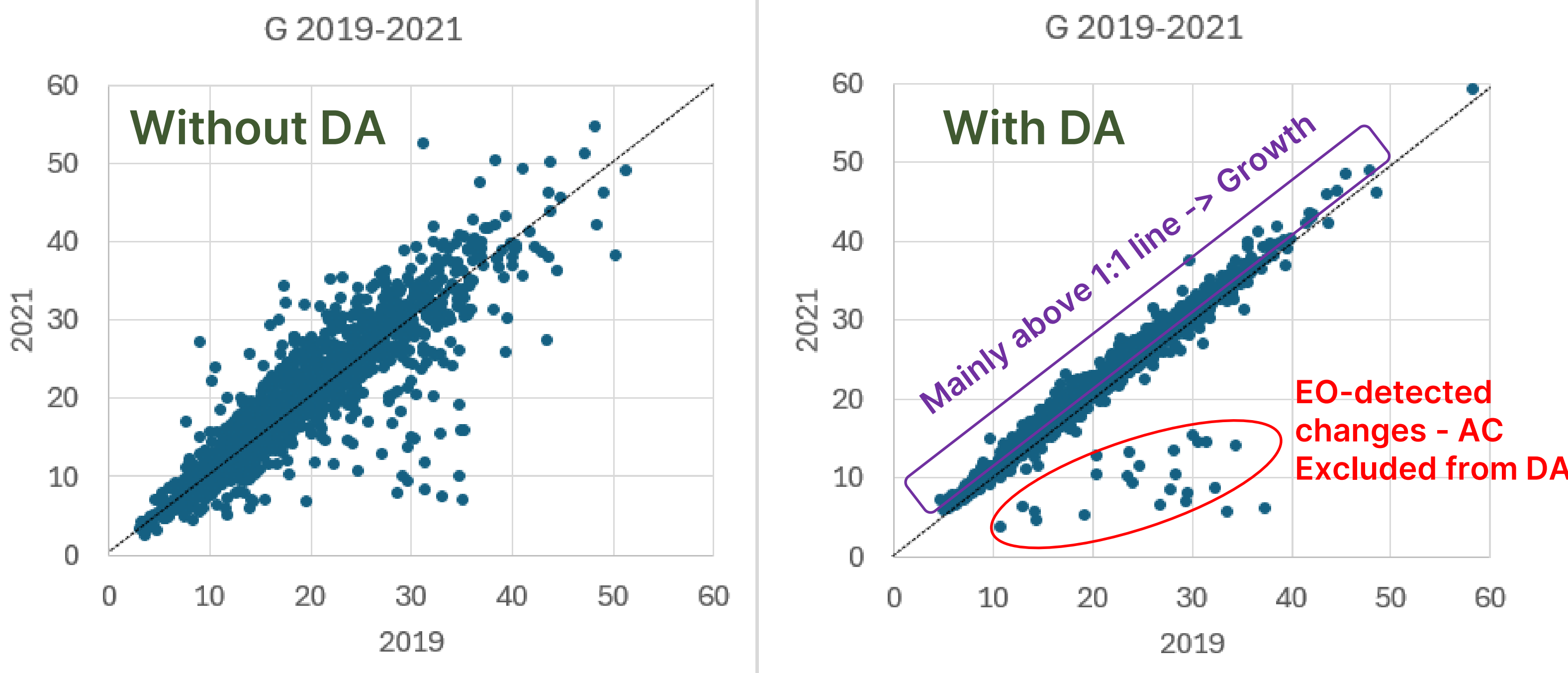


Minunno, F., Miettinen, J., Tian, X., Häme, T., Holder, J., Koivu, K. and Mäkelä, A. (2025) Data assimilation of forest status using Sentinel-2 data and a process-based model. *Agricultural and Forest Meteorology* 363: 110436. DOI: 10.1016/j.agrformet.2025.110436

Data assimilation

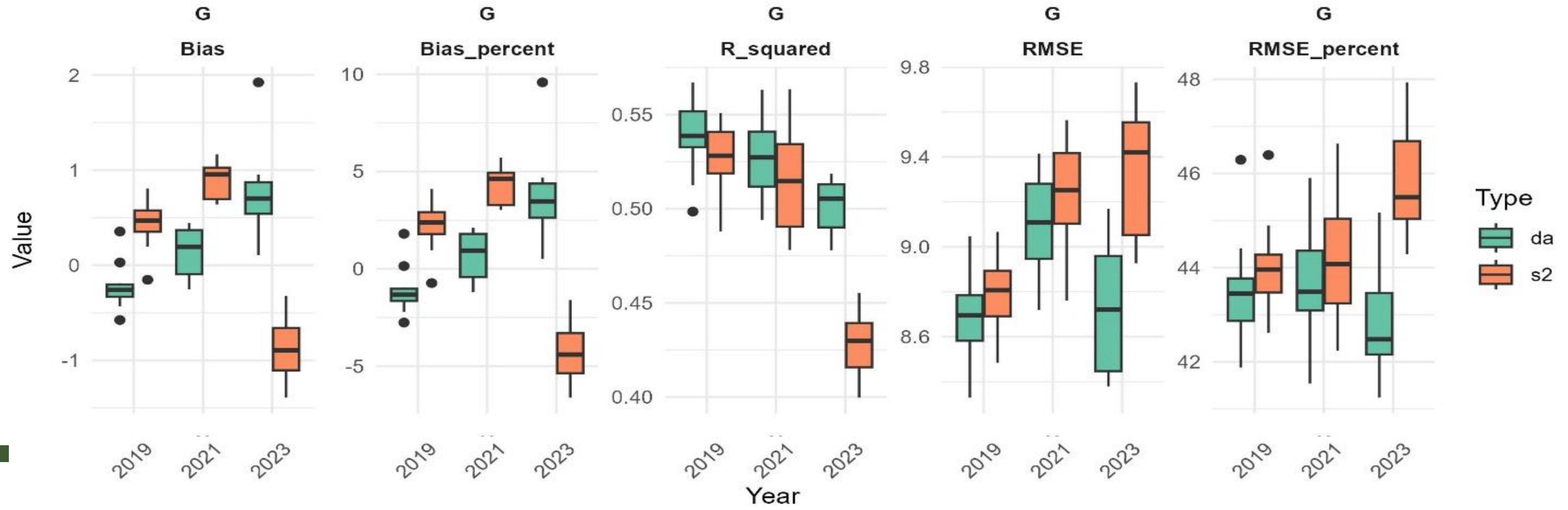
Creates consistency to pixel/plot level predictions:

- Year-to-year changes at pixel/plot level predictions follow realistic trends



Reduces uncertainty:

- Particularly bias reduced
- RMSE constantly smaller with DA



Data assimilation

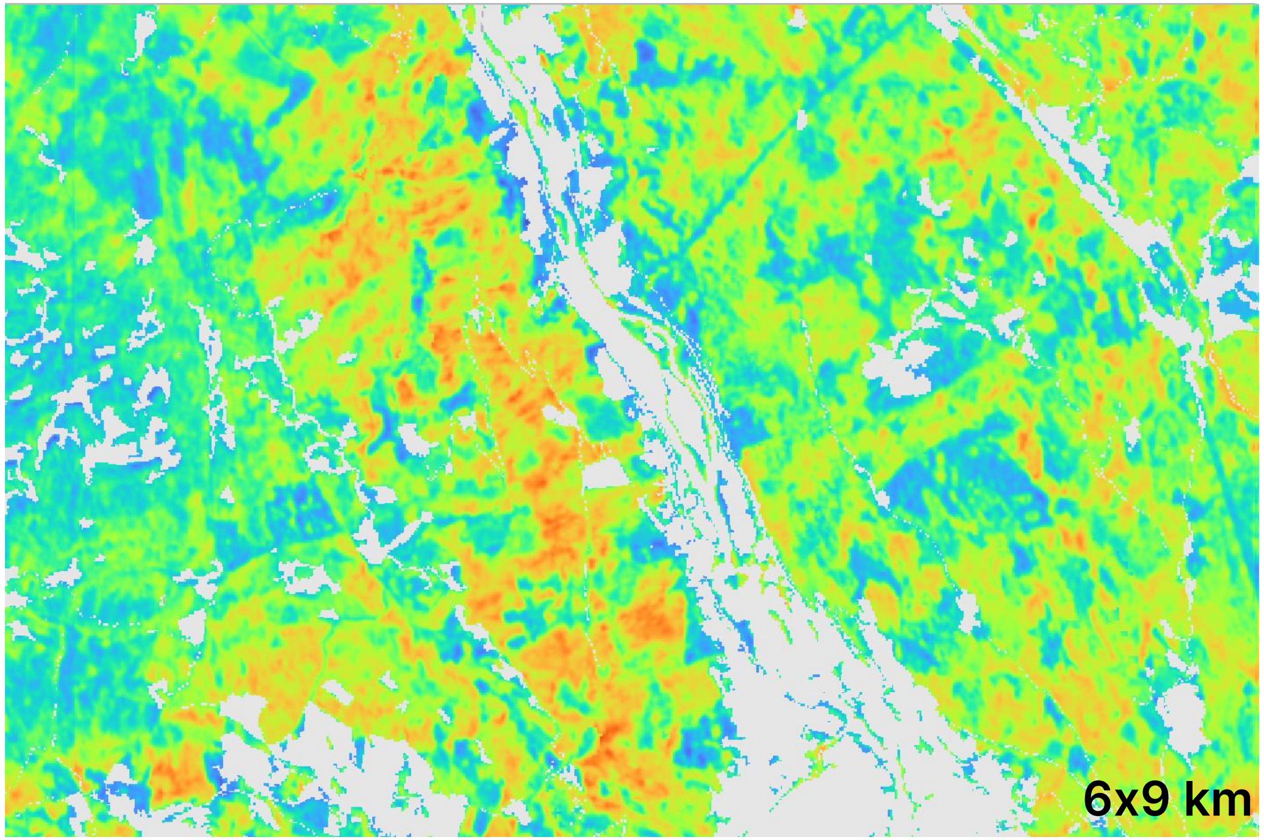
Improves consistency and removes no-data areas:

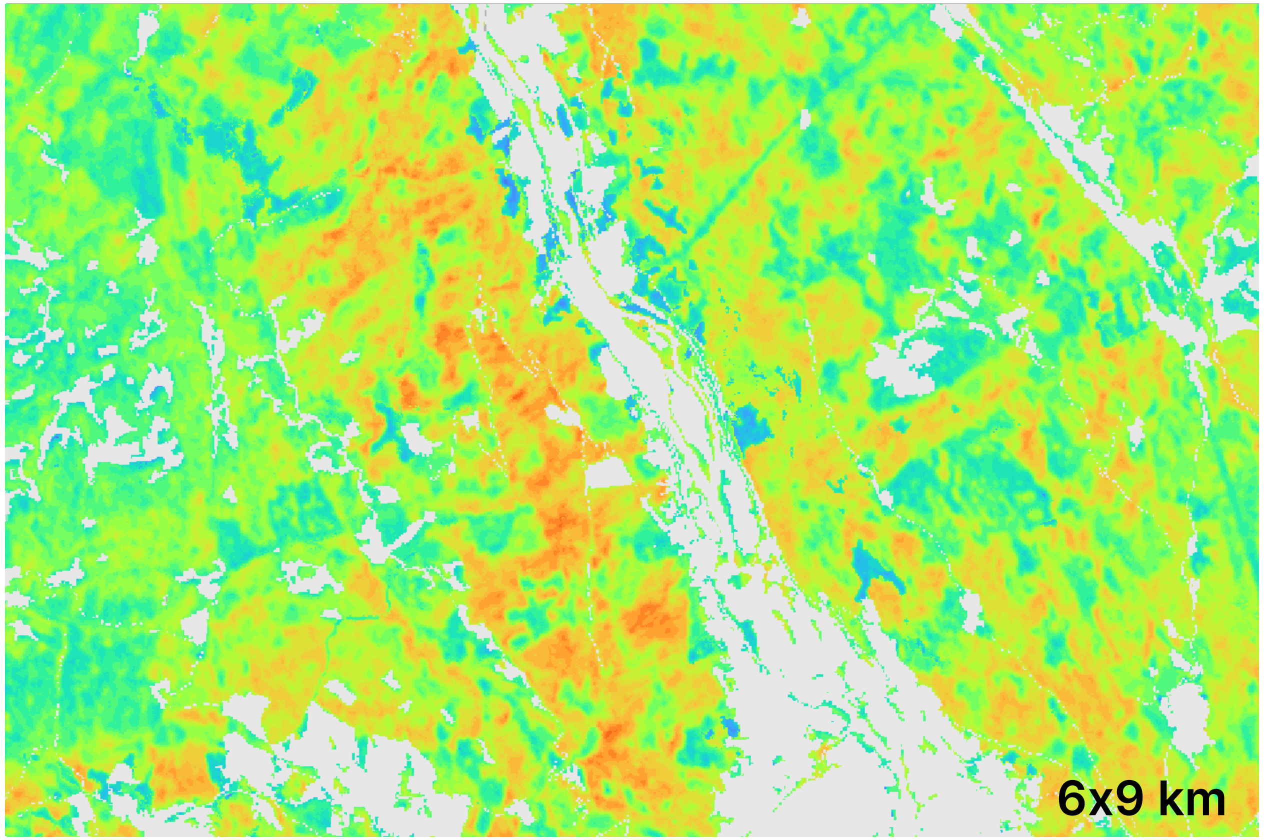
- Note particularly 2021-2023 transition

Satellite based prediction 2023

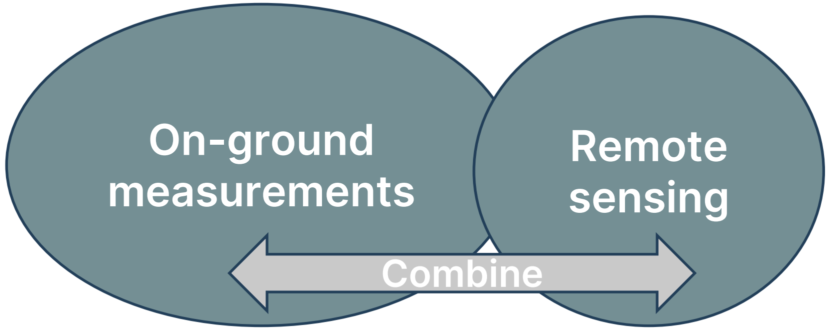
0 Height (m) 27

Data Assimilation 2023





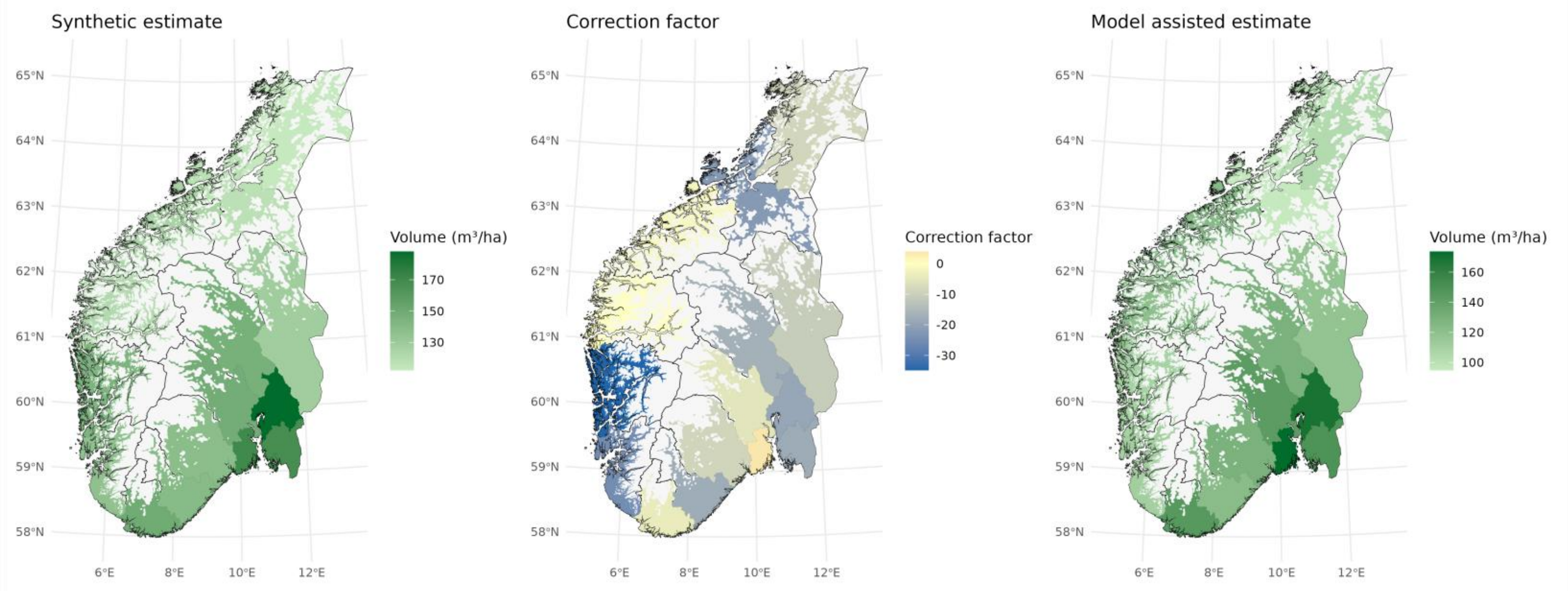
Integration of ground measurements and EO-based mapping

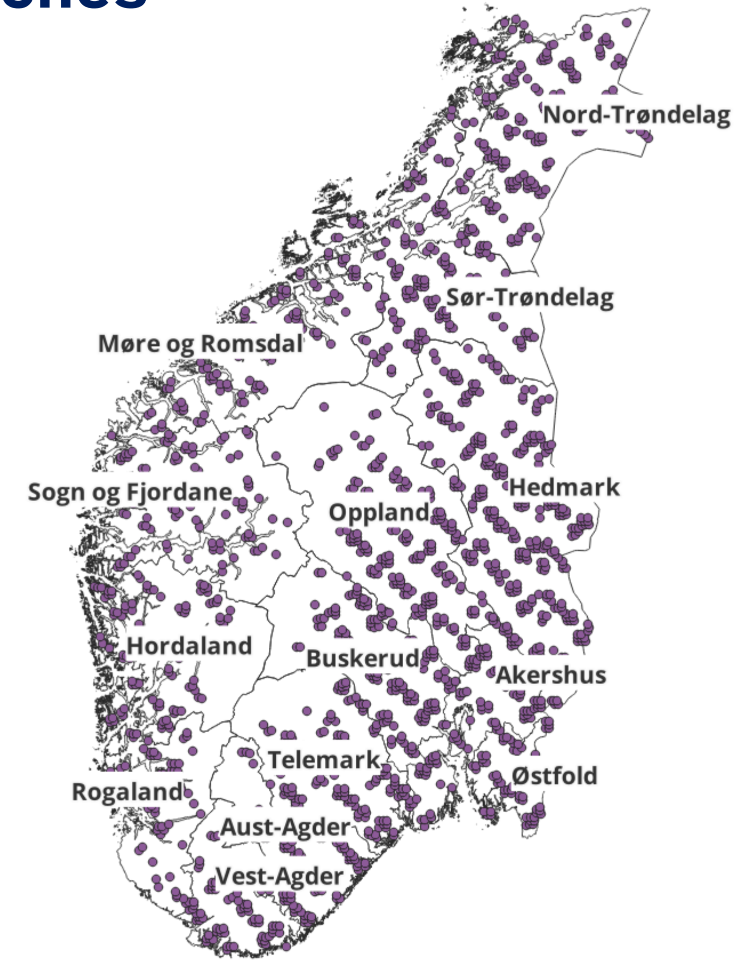


Model-assisted estimation
- integration of EO data into existing approaches

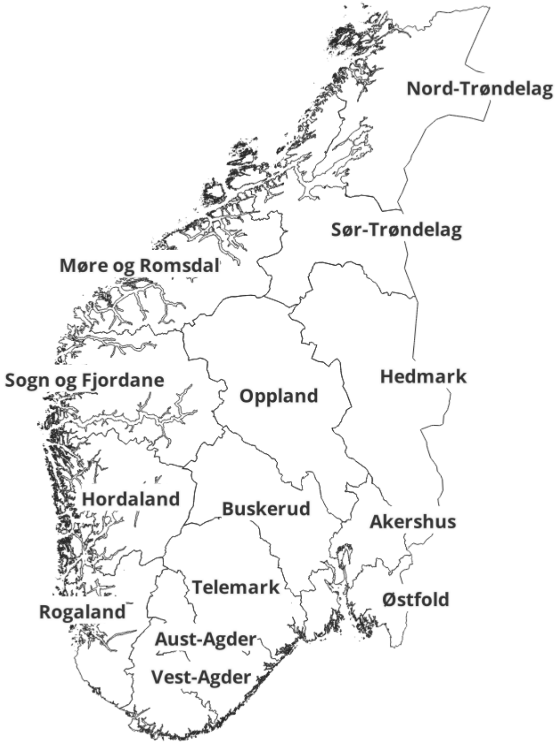
Implementation:

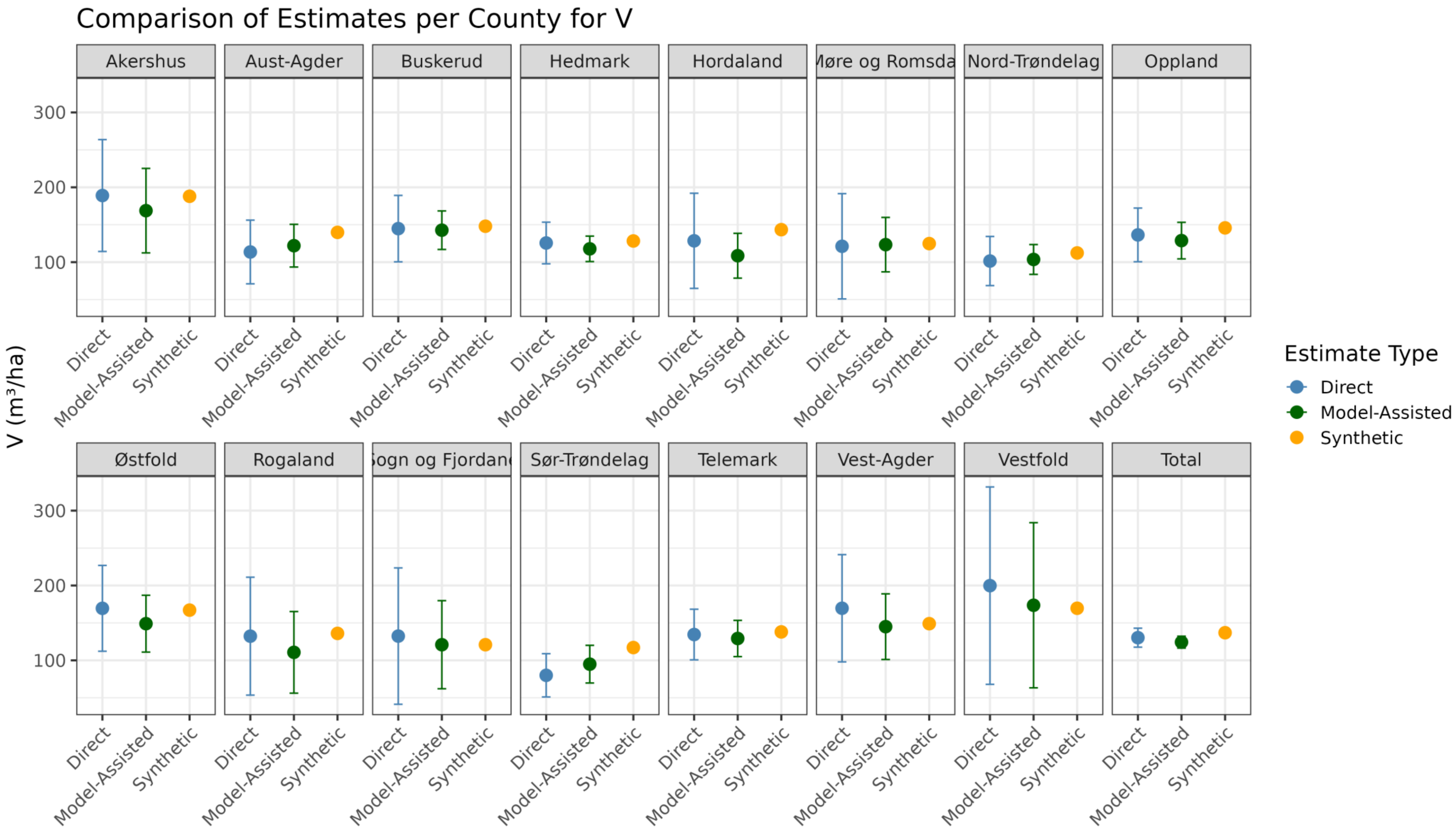
1. EO-based forest map – synthetic estimate (pixel counting) – no uncertainty for estimates
2. NFI plots (direct estimate) used to calculate correction factor and determine model assisted estimates
3. Outcome: Improved estimates with uncertainty metrics





Model-assisted estimation

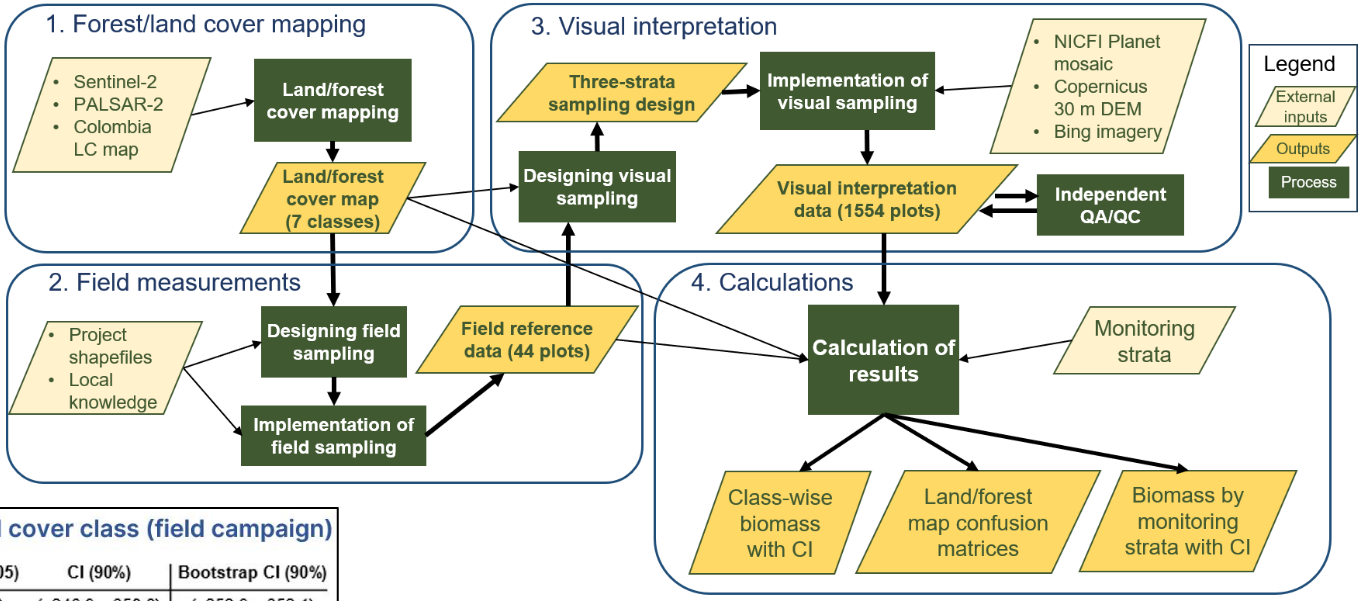




Two-step sampling

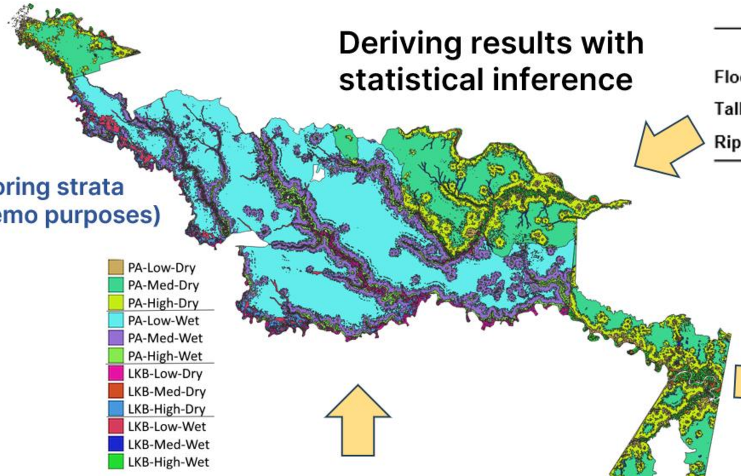
Statistical framework for deriving confidence intervals for AGB estimates

- Example of a multi-step approach
- Demonstrated in REDD+ context in the Colombia use case



Deriving results with statistical inference

Monitoring strata (for demo purposes)



Biomass statistics per forest/land cover class (field campaign)

Class	$\bar{x}$	s	n	$t_{n-1}(0.05)$	CI (90%)	Bootstrap CI (90%)
Forest	302.9	118.1	14	1.8	{ 246.9, 358.8}	{ 252.9, 352.1}
Flooded forest	289.2	156.1	11	1.8	{ 203.9, 374.5}	{ 201.9, 366.5}
Tall secondary	216.5	78.4	11	1.8	{ 173.6, 259.3}	{ 179.5, 254.3}
Riparian forest	317.6	62.5	10	1.8	{ 281.3, 353.8}	{ 288.0, 348.1}

Biomass estimates for monitoring strata

Strata	Biomass (Mt)	90% uncertainty (Mt)
PA-Low-Dry	660.2	527.1-779.2
PA-Med-Dry	235.6	187.8-278.4
PA-High-Dry	70.7	55.9-84.1
PA-Low-Wet	20.2	17.7-22.8
PA-Med-Wet	30.3	27.2-33.5
PA-High-Wet	58.9	52.8-65.3
LKB-Low-Dry	335.9	268.3-396.4
LKB-Med-Dry	187.8	149.8-221.8
LKB-High-Dry	60.2	47.6-71.7
LKB-Low-Wet	7.5	6.8-8.1
LKB-Med-Wet	15	13.5-16.6
LKB-High-Wet	39.6	34.7-44.6

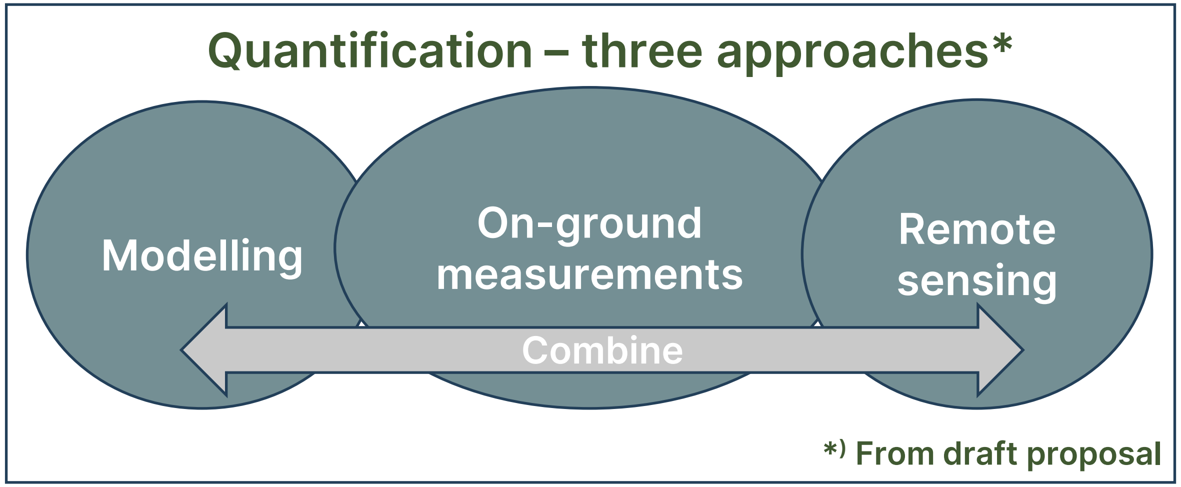
Forest/land cover distribution

LC class	Stratified mean (%/ha)	Standard error (%/ha)	Confidence interval (90%)
Forest	86.46	0.59	{ 85.49, 87.43}
Flooded forest	1.39	0.21	{ 1.04, 1.74}
Tall secondary	1.11	0.10	{ 0.95, 1.26}
Shrubland	0.06	0.01	{ 0.04, 0.08}
Open	0.05	0.03	{ 0, 0.10}
Water	0.09	0.01	{ 0.07, 0.11}
No data	0.90	0.28	{ 0.44, 1.37}
Riparian forest	10.00	0.44	{ 9.27, 10.73}

Reference measurements:

- Always needed for uncertainty estimation, but…
- Type may vary (field, TLS, ALS…)
- Multi-step procedures can be used to improve efficiency

Conclusions



- **EO based approaches have essential capabilities that cannot be overlooked**
  - Frequency, scalability, transparency, price, historical backlog, etc.
- **For legal and financial reporting, needs to be combined with other approaches**
  - Data assimilation with process-based modelling:
    - Temporal consistency
    - Improved accuracy
    - Filling no-data areas
  - Integration with field and other sampling schemes:
    - Model-assisted estimation or other approaches to combine with field-based monitoring
    - Multi-step statistical approaches for improved efficiency and improved confidence intervals

esa

Forest Carbon Monitoring

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