Benchmarking Earth Observation Embeddings for Large Scale Aboveground Biomass Density Mapping

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ML4EO
Machine Learning for Earth Observation, 22- 24 June 2026

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https://cordis.europa.eu/project/id/101218854 European Commission

Overviews

Objectives

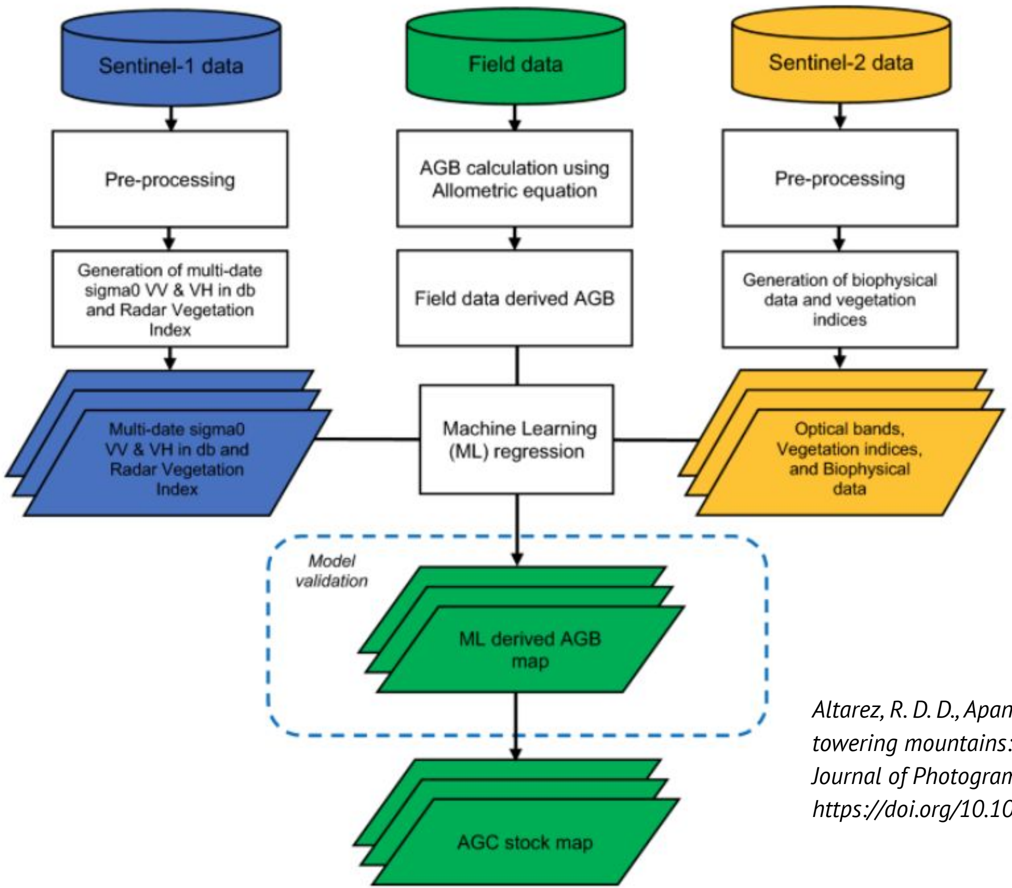
- Country-based evaluation of aboveground biomass mapping

Gaps:

- How well different **EO settings** performs?
- Which **ML/DL model** is better capturing AGB distribution and spatial pattern?

The Intergenerational Open Geospatial Carbon Registry (OGCR). Grant agreement ID: 101218854.

Machine Learning Framework for AGB



Variables

- Field data: Reference AGB
- Sentinel-1: Forest structure
- Sentinel-2: Vegetation abundance

More ref. Nuthammachot et al. (2020), Ghosh and Behera (2018)

Altarez, R. D. D., Apan, A., & Maraseni, T. (2024). Uncovering the hidden carbon treasures of the Philippines' towering mountains: A synergistic exploration using satellite imagery and machine learning. PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 92(1), 55–73. https://doi.org/10.1007/s41064-023-00264-w

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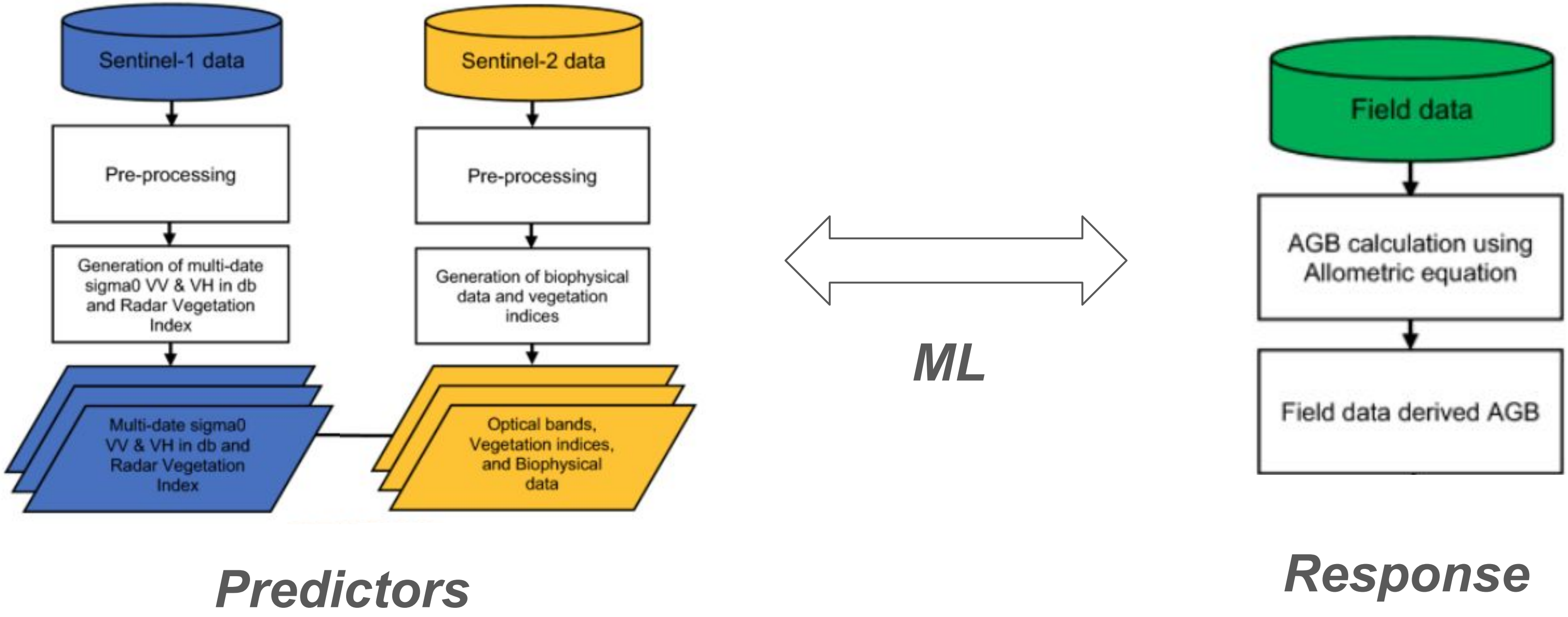

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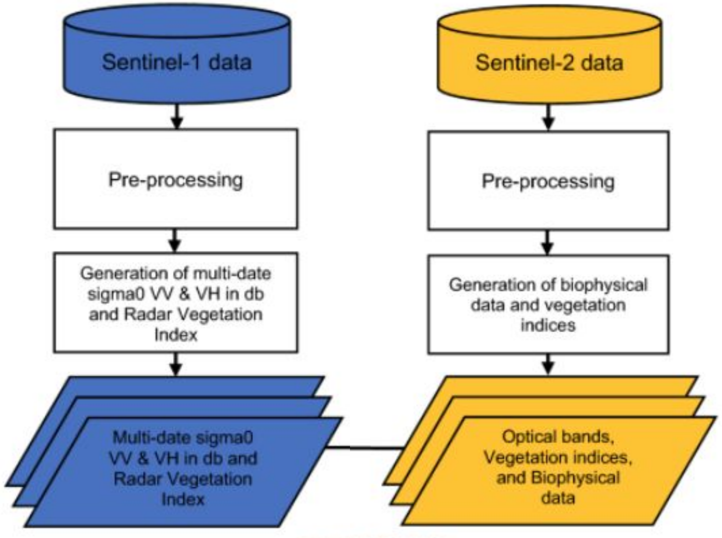
Machine Learning Framework for AGB



Predictors

Not an easy task for large scale mapping...

- High resolution,
- Multiple bands,
- Challenging pre-processing,
- **High frequent revisit**

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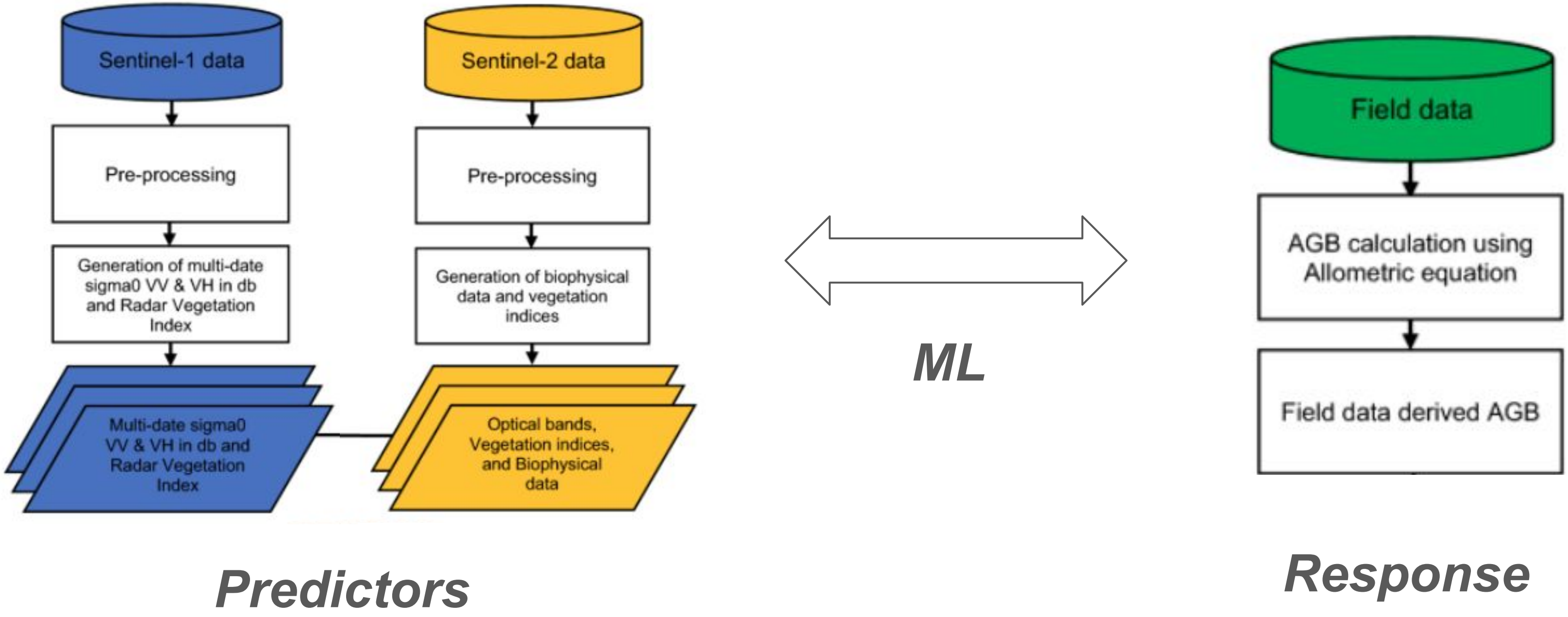
Machine Learning Framework for AGB



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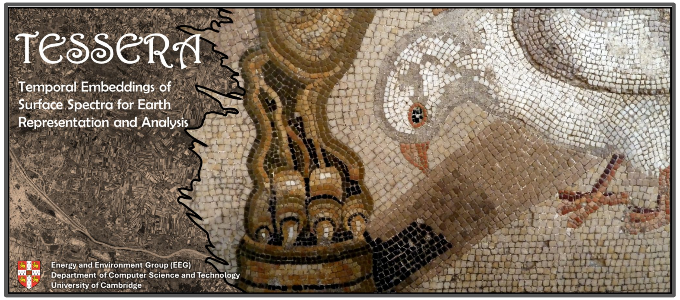
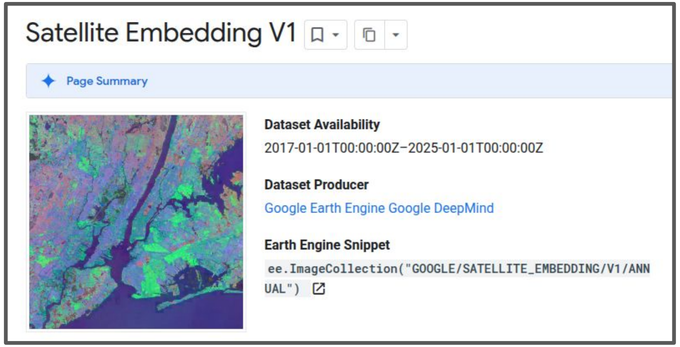
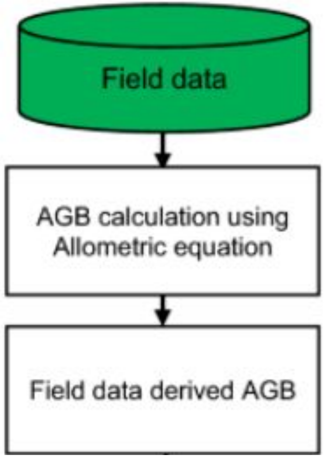




Predictors

ML



Response

https://github.com/ucam-eo/tessera

https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL

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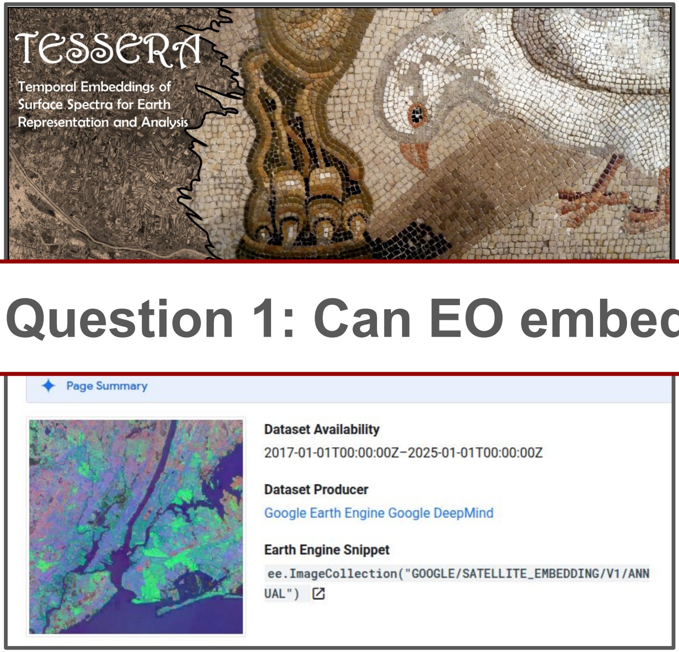
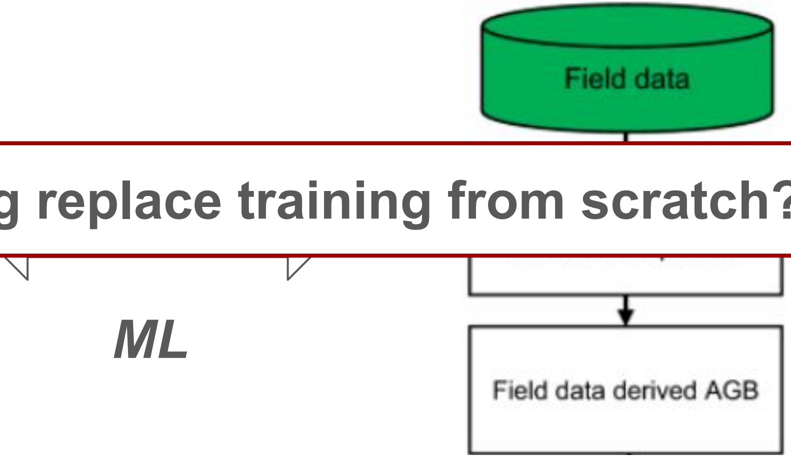
Machine Learning Framework for AGB



Question 1: Can EO embedding replace training from scratch?



ML

Predictors

Response

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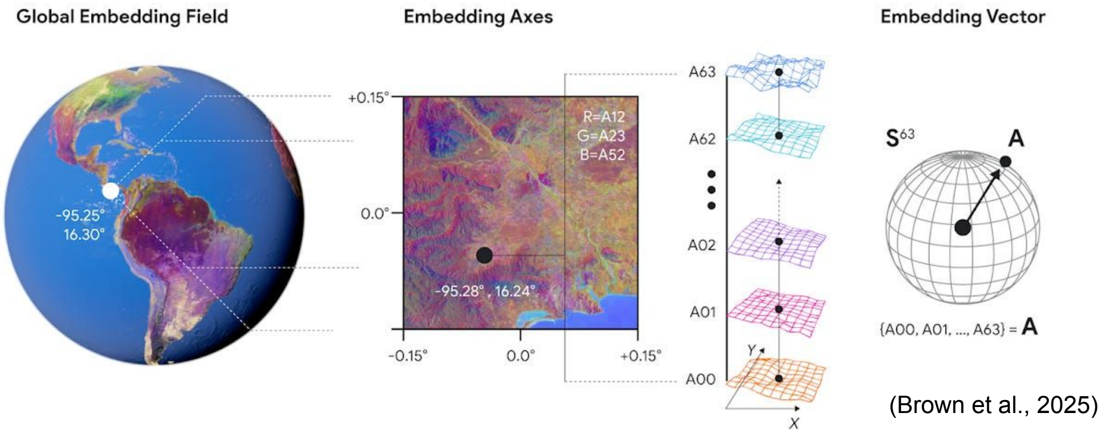
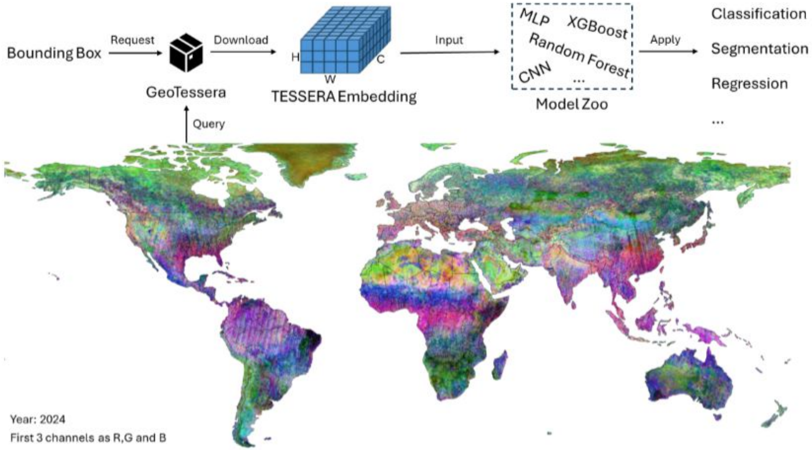
EO Embedding dataset

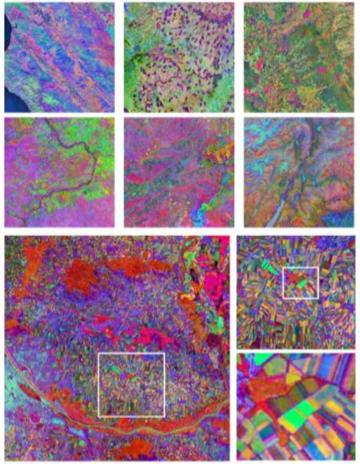


(Brown et al., 2025)

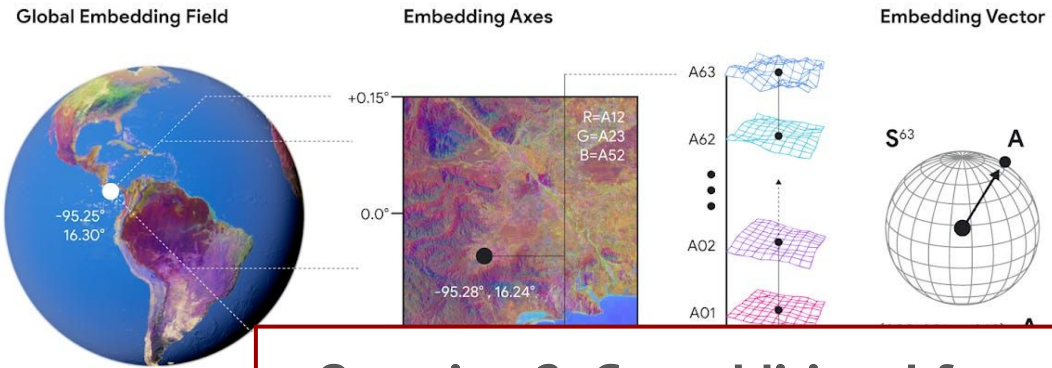
1. Numerical vectors stored as any other **raster layers**
2. Easy to build **downstream** models with **non-limit choices**.
3. Flexibility to add **additional features** or do **feature engineering**

(Feng et al., 2025)





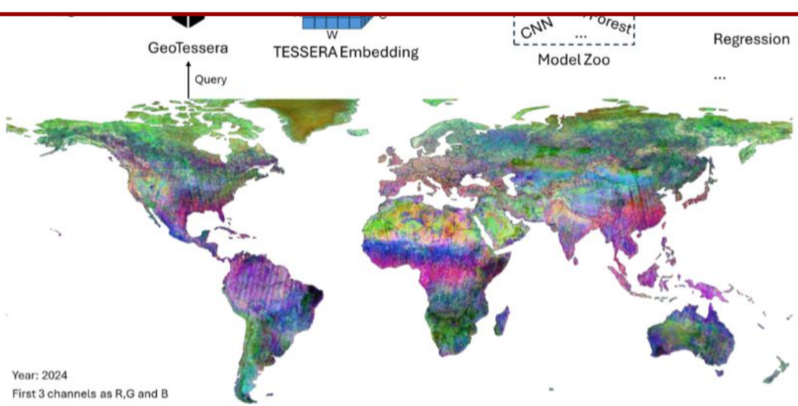
EO Embedding dataset

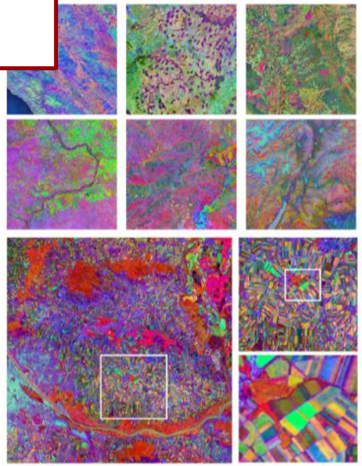


1. Numerical vectors stored as any other **raster layers**
2. Easy to build **downstream** models with **non-limit choices**.

Question 2: Can additional features further increase model performance?

3. Flexibility to add **additional features** or do **feature engineering**

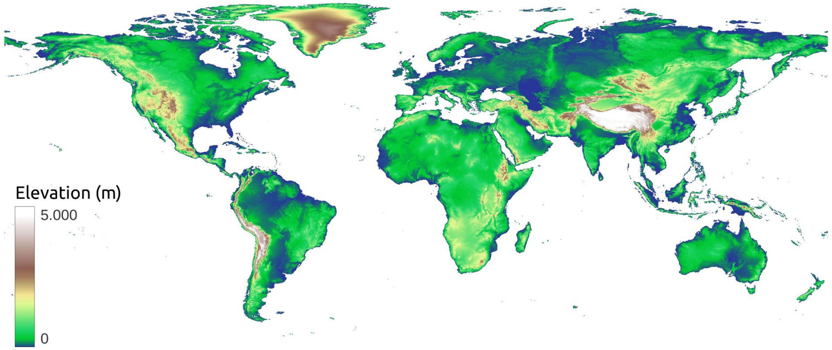


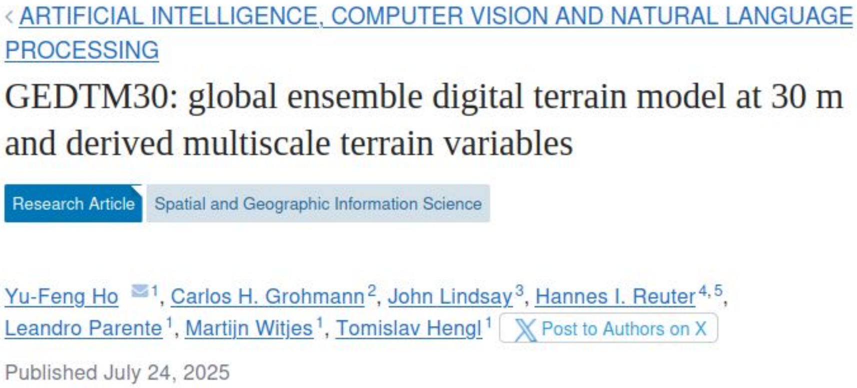


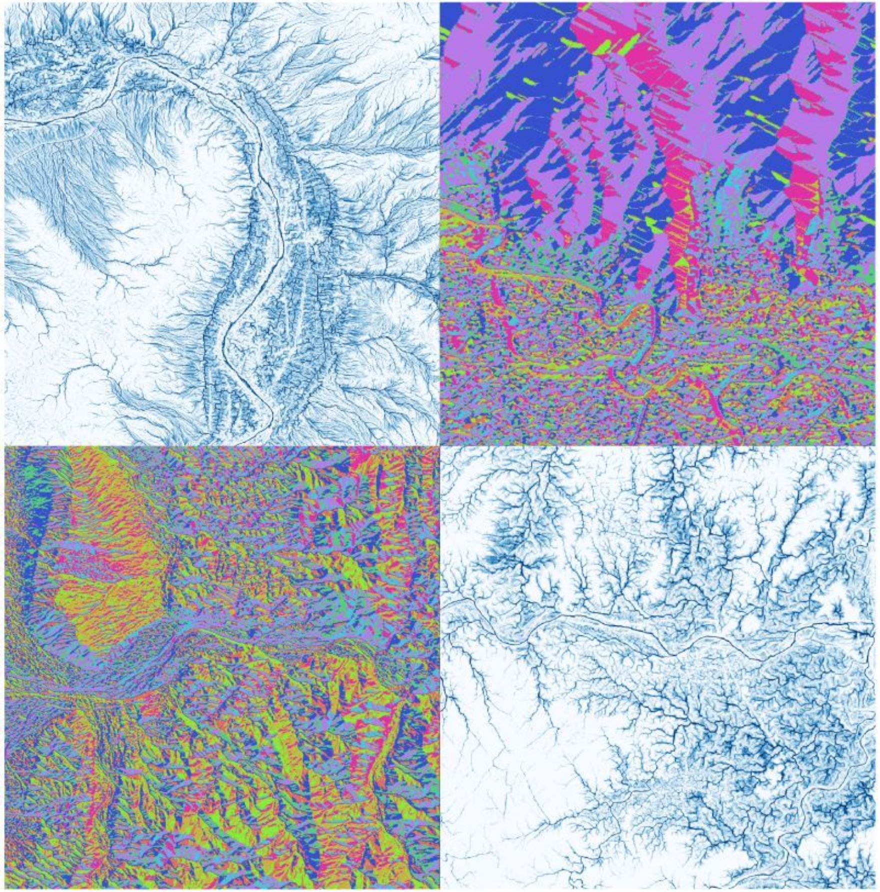
(Feng et al., 2025)

Topographic attributes as additional features

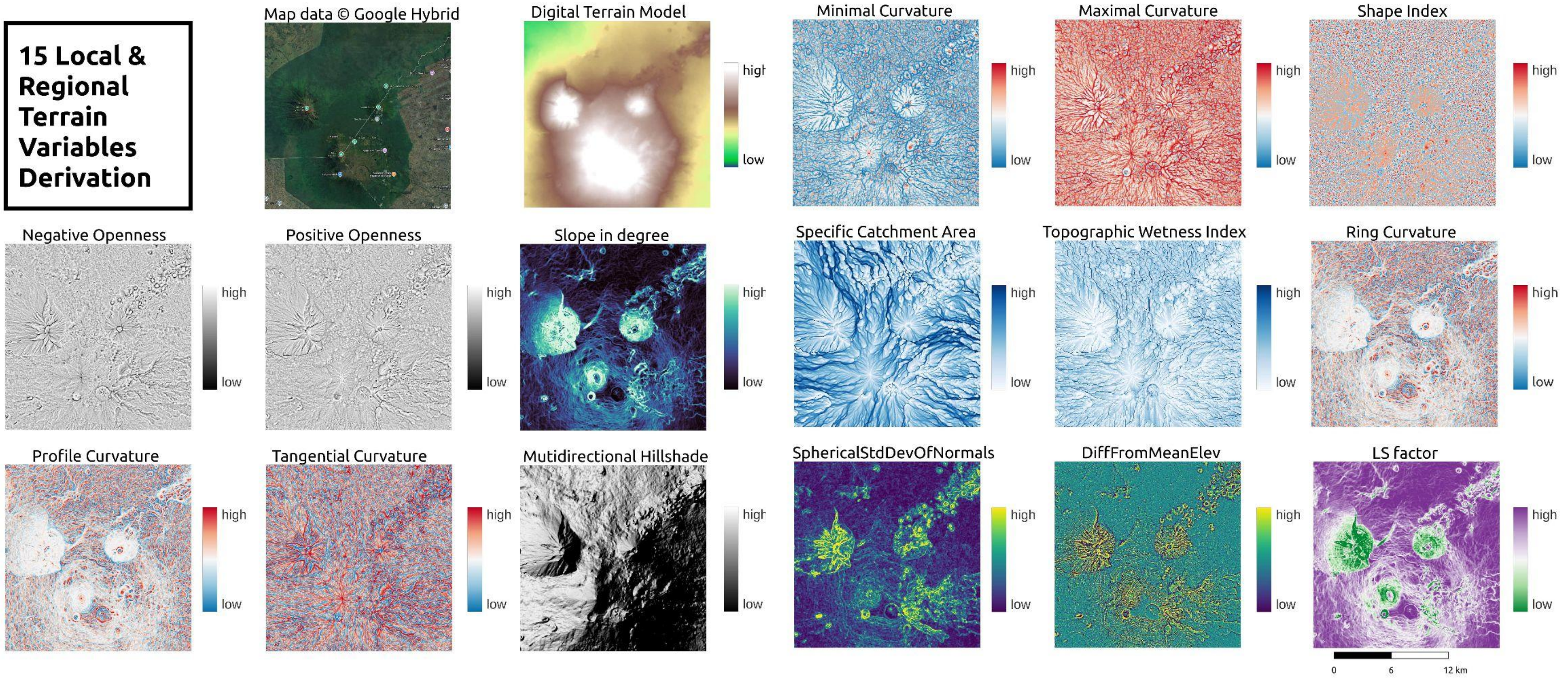
Global Ensemble Digital Terrain Model in 30m (GEDTM30)







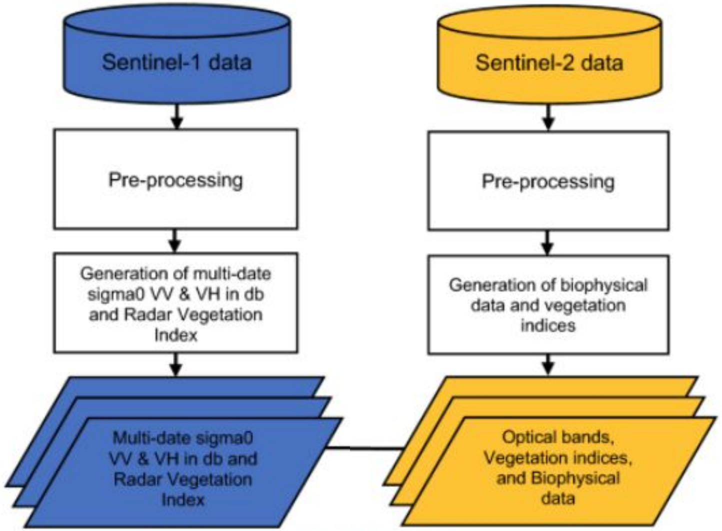
Topographic attributes as additional features



Topographic features underlie the natural process...

Ho, Y. F., Grohmann, C. H., Lindsay, J., Reuter, H. I., Parente, L., Witjes, M., & Hengl, T. (2025). GEDTM30: Global ensemble digital terrain model at 30 m and derived multiscale terrain variables. PeerJ, 13, e19673.

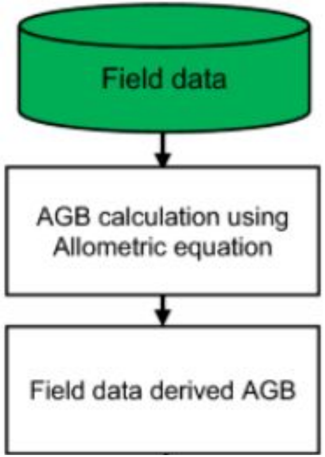
Machine Learning Framework for AGB



Predictors

ML

Question 3: Which downstream ML model performs the best?



Response

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ML model - Quantile Random Forest

Q: which EO embedding setup has better performance?

- High Accuracy
- Lower Uncertainty

Quantile Random Forest Regressor
- Scalable
- Per-pixel uncertainty
- Easy to implement (Scikit-learn)

To produce per-pixel uncertainty, we use the TB-QRF (Meinshausen, 2006), where the output of each single tree in the RF has been used to derive the prediction intervals:

$$\begin{aligned} \widehat{y1}_{\mathrm{stb}_{1,1}} &= [P_{1,1}, P_{1,2}, P_{2,1}, P_{2,2}] \\ \widehat{y2}_{\mathrm{stb}_{1,1}} &= [P_{1,1}, P_{1,2}, P_{2,1}, P_{2,2}] \\ \widehat{y3}_{\mathrm{stb}_{1,1}} &= [P_{1,1}, P_{1,2}, P_{2,1}, P_{2,2}] \\ &\cdots \\ \widehat{yN}_{\mathrm{stb}_{1,1}} &= [P_{1,1}, P_{1,2}, P_{2,1}, P_{2,2}] \end{aligned} \tag{13}$$

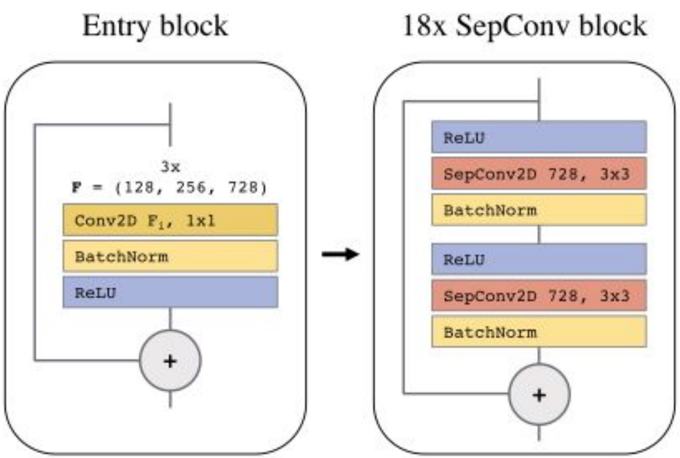
where $\widehat{y1}_{\mathrm{stb}_{1,1}}$ is the mean prediction from the individual tree (out of a total of N trees). These are then used to derive the lower and upper 68 % probability quantiles:

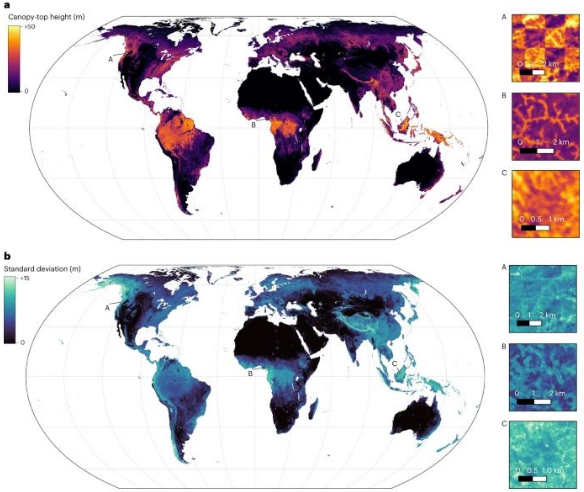
$$\widehat{y}_{\mathrm{lower}} = Q_{0.16}\left(\left\{\widehat{y1}_{\mathrm{stb}_{1,1}}, \widehat{y2}_{\mathrm{stb}_{1,1}}, \cdots, \widehat{yN}_{\mathrm{stb}_{1,1}}\right\}\right), \tag{14}$$

$$\widehat{y}_{\mathrm{upper}} = Q_{0.84}\left(\left\{\widehat{y1}_{\mathrm{stb}_{1,1}}, \widehat{y2}_{\mathrm{stb}_{1,1}}, \cdots, \widehat{yN}_{\mathrm{stb}_{1,1}}\right\}\right). \tag{15}$$

Hengl, T., Consoli, D., Tian, X., Nauman, T. W., Nussbaum, M., Isik, M. S., ... & Harris, N. (2026). OpenLandMap-soildb: global soil information at 30 m Spatial resolution for 2000–2022+ based on Spatiotemporal machine learning and harmonized legacy soil samples and observations. Earth System Science Data, 18(2), 989-1036.

DL model - Xception CNN Architecture

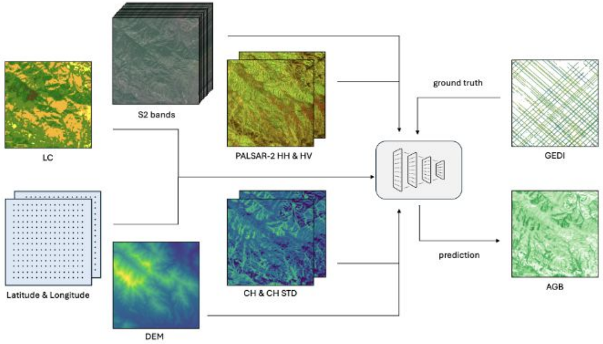




Lang, N., Jetz, W., Schindler, K., & Wegner, J. D. (2023). A high-resolution canopy height model of the Earth. *Nature Ecology & Evolution*, *7*(11), 1778-1789.

Lang, N., Schindler, K., & Wegner, J. D. (2019). Country-wide high-resolution vegetation height mapping with Sentinel-2. *Remote Sensing of Environment*, *233*, 111347.

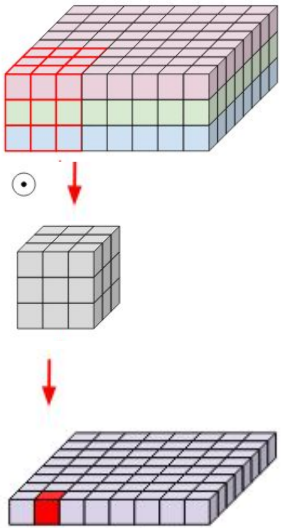
Methods						
GBDT (1×1)	FCN (15×15)	FCN (25×25)	UNet (15×15)	UNet (25×25)	Lang et al. (15×15)	Lang et al. (25×25)
70.73 ±0.18	69.29 ±0.16	69.33 ±0.07	69.08 ±0.08	68.54 ±0.12	68.54 ±0.27	68.11 ±0.24
72.92 ±0.18	64.97 ±0.25	64.75 ±0.11	63.14 ±0.29	61.97 ±0.09	61.60 ±0.13	60.39 ±0.19
69.41 ±0.11	63.52 ±0.22	63.48 ±0.08	62.00 ±0.09	60.69 ±0.05	60.36 ±0.13	59.15 ±0.22
66.48 ±0.05	62.40 ±0.19	62.47 ±0.12	61.09 ±0.18	59.99 ±0.12	59.65 ±0.10	58.82 ±0.14
67.57 ±0.06	62.43 ±0.24	61.78 ±0.69	60.47 ±0.67	59.33 ±0.40	58.55 ±0.19	57.90 ±0.21
67.27 ±0.08	61.95 ±0.19	61.81 ±0.18	60.59 ±0.14	59.27 ±0.11	59.12 ±0.11	58.22 ±0.23
65.16 ±0.02	60.97 ±0.05	60.97 ±0.19	59.84 ±0.10	58.50 ±0.16	58.16 ±0.15	57.14 ±0.29
63.76 ±0.09	60.98 ±0.23	60.92 ±0.23	60.18 ±0.36	58.33 ±0.47	58.04 ±0.31	57.52 ±0.41

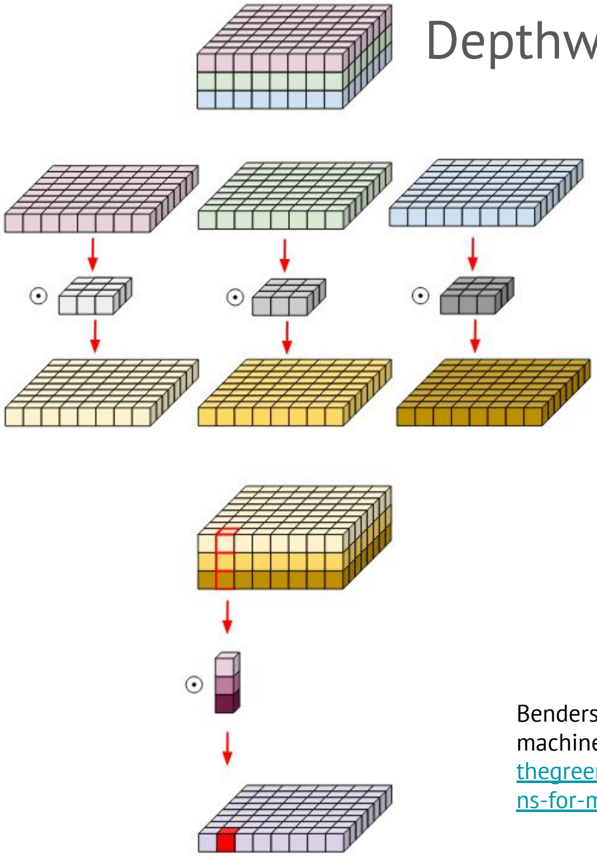


Sialelli, G., Peters, T., Wegner, J. D., & Schindler, K. (2024). Agbd: A global-scale biomass dataset. *arXiv preprint arXiv:2406.04928.*

DL model - Xception CNN Architecture

Traditional Convolution



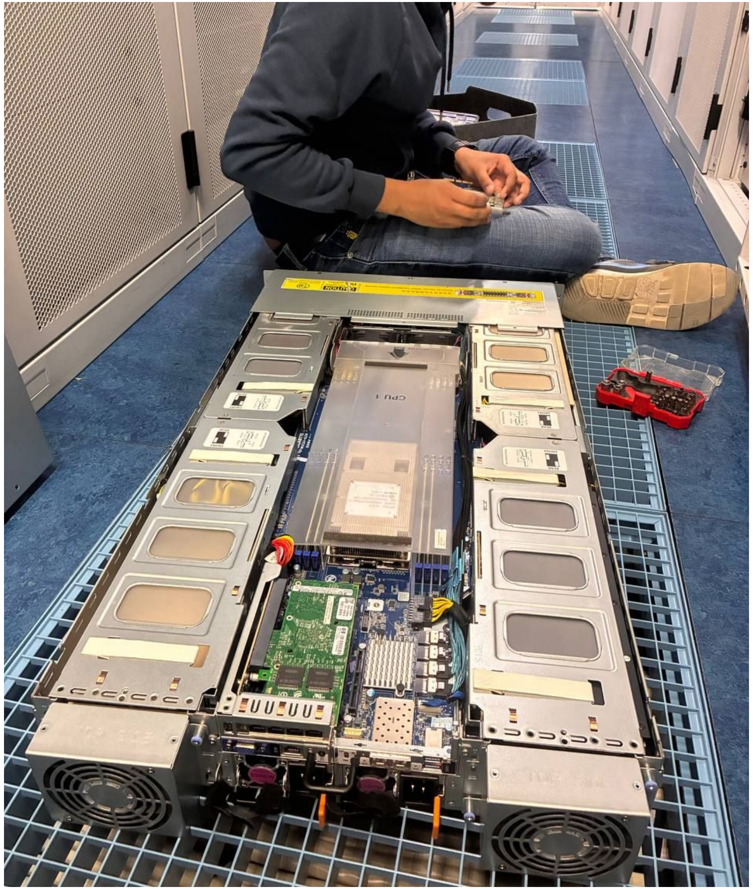


Depthwise separable Convolution (SepConv)

- Lower computational cost
- Fewer parameters

Bendersky, E., 2018. Depthwise separable convolutions for machine learning. https://eli.thegreenplace.net/2018/depthwise-separable-convolutions-for-machine-learning

DL model - Xception CNN Architecture



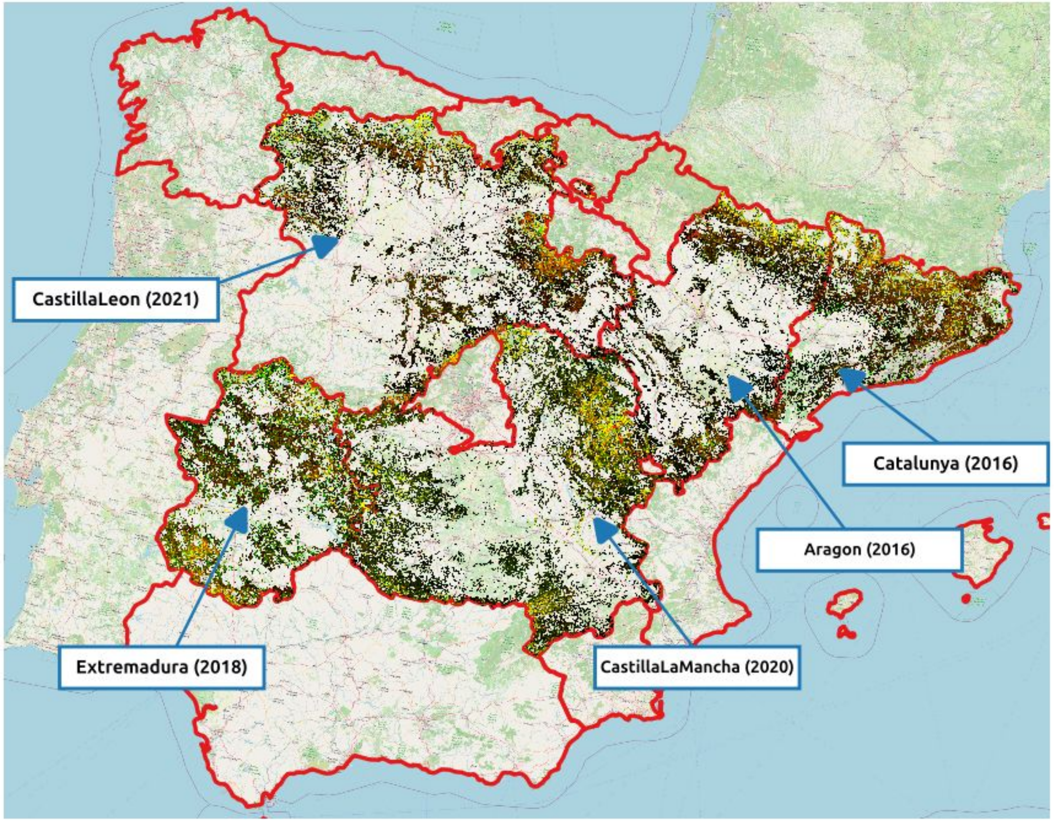
Just installed and configured the GPU server on our cluster **last week**...

↓

Disclaimer: results of Xception model are still underdevelopment.

Result

Study Site



- 5 regions of Spain
- 2016-2021

Tanase, M. A., Martini, J. P., Garcia, D. G., Zavala, M., & Ruiz-Benito, P. (2026). Forest structure and its changes from multi-temporal lidar data: a homogeneously derived database forpeninsular Spain. *Annals of Forest Research*, *69*(1), 3-20.
Link: https://www.afrjournal.org/index.php/afr/article/view/4341/1355

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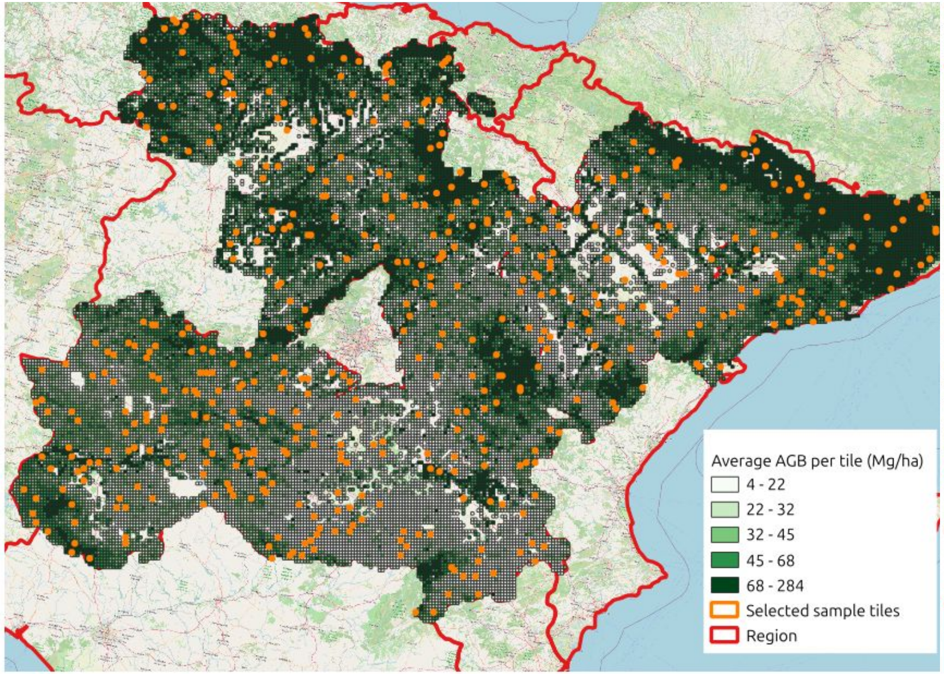
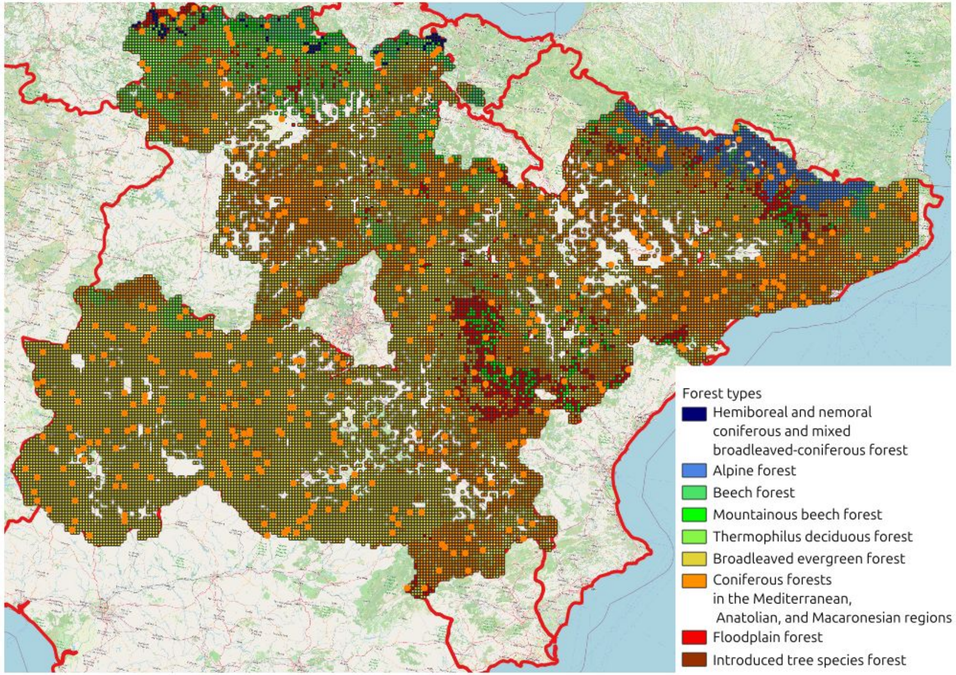
Study Site





Random sampling across spain, capturing representation of forest type and aboveground biomass

- *500 tiles*
- *Each tile 300x300 pixels*

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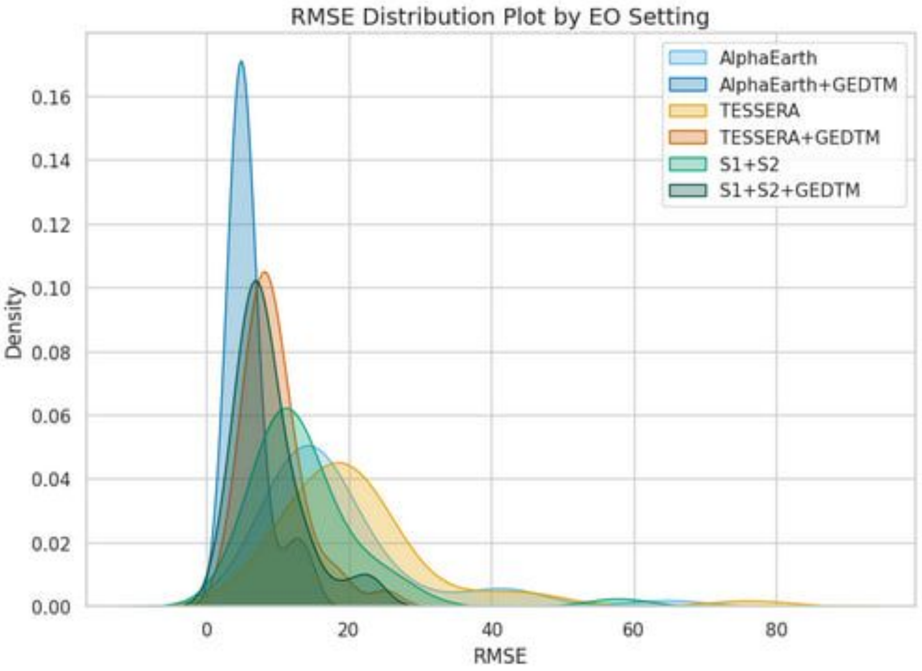
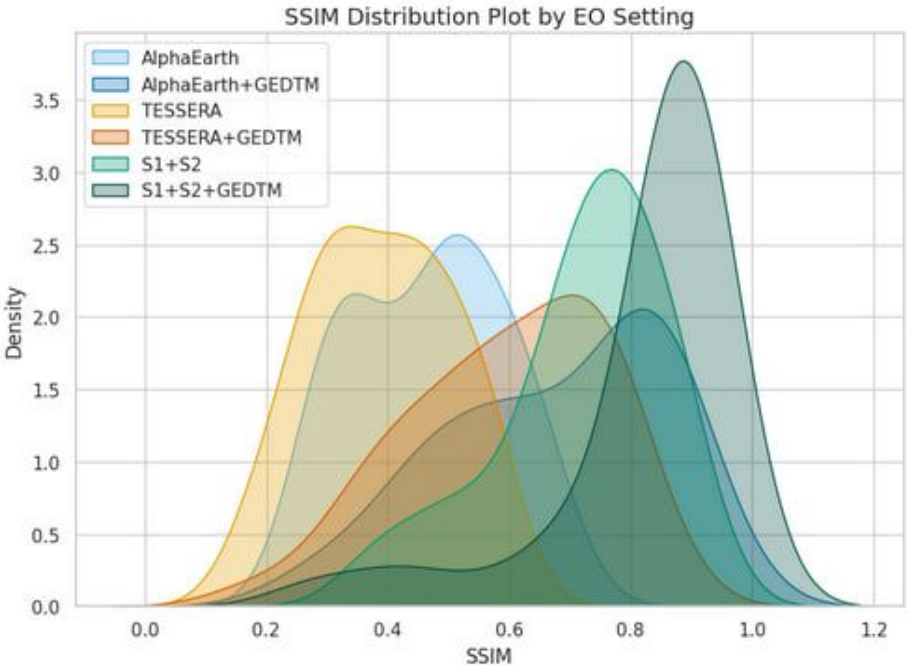
Comparison of different EO settings

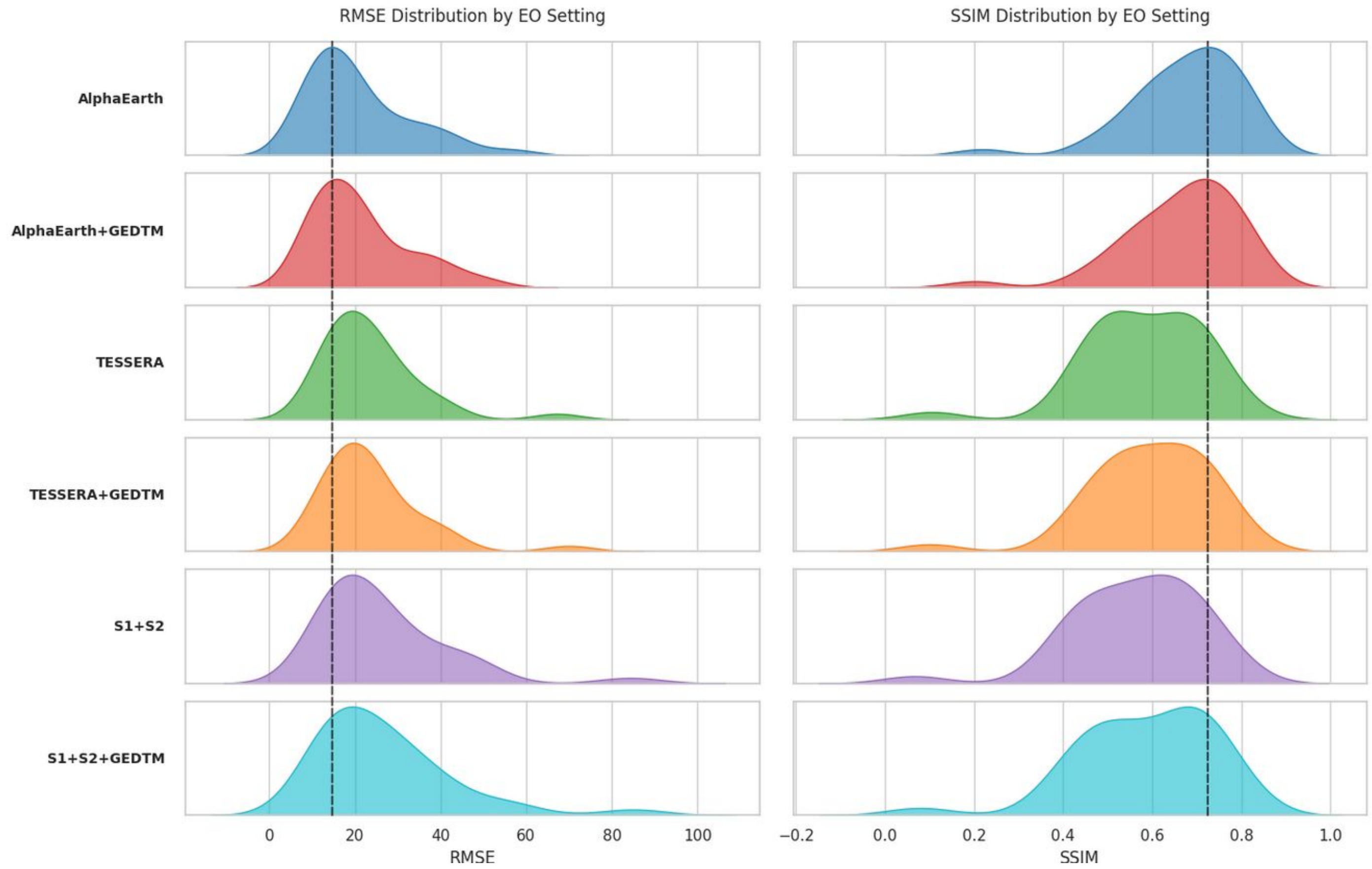




n=50

- *Downstream model:* ***random forest (RF)***
- *Topographic attributes contribute to prediction accuracy*
- *RMSE: TESSERA or AlphaEarth > S1+S2 / SSIM: S1+S2 > TESSERA or AlphaEarth*
- *AlphaEarth performs slightly better than TESSERA (v1.1)*

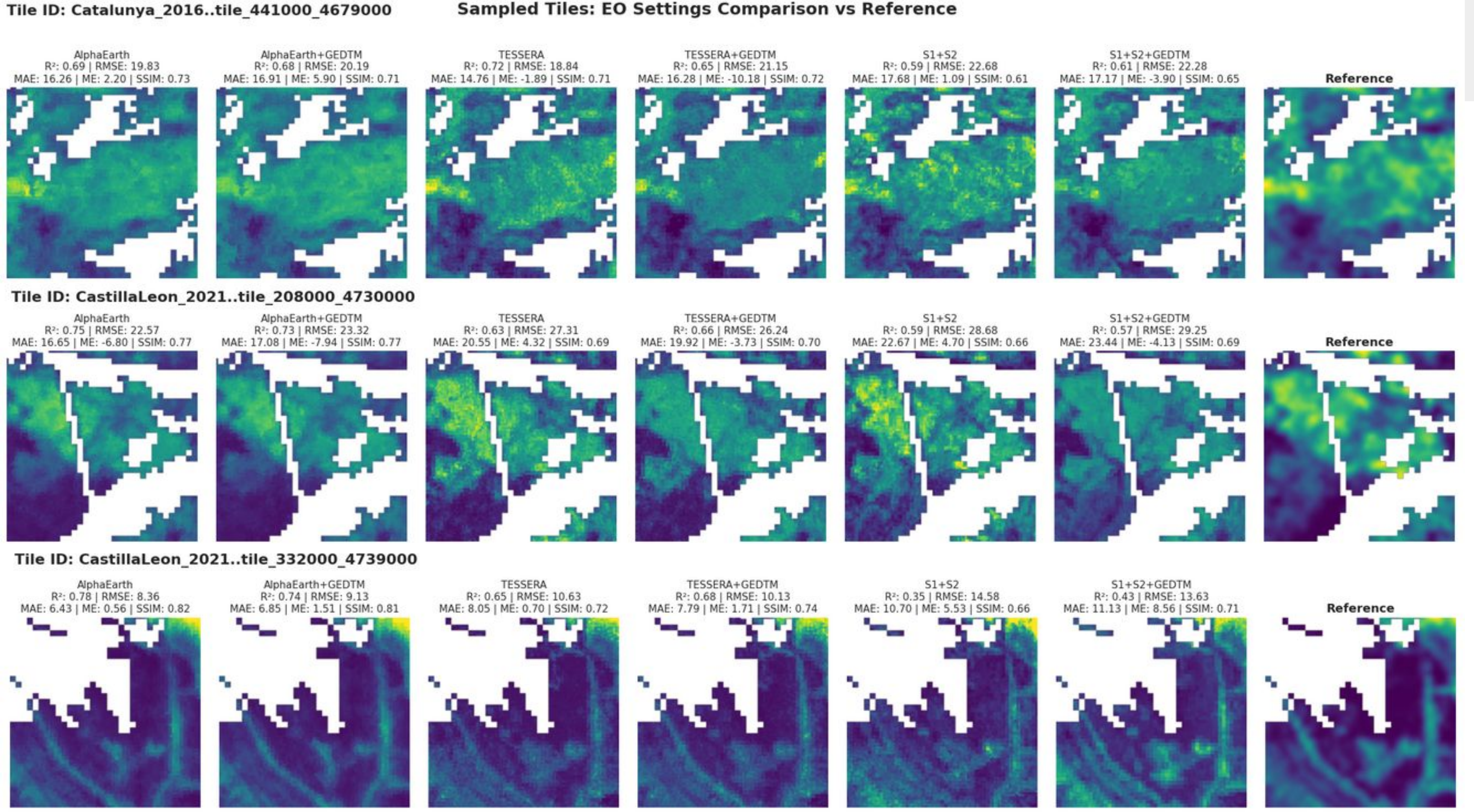
Comparison of different EO settings



- *Downstream model: **random forest (RF)***
- *Trained by 450 training tiles (cross validation)*
- *Distribution of RMSE & SSIM by test tiles (n=50)*

v1!

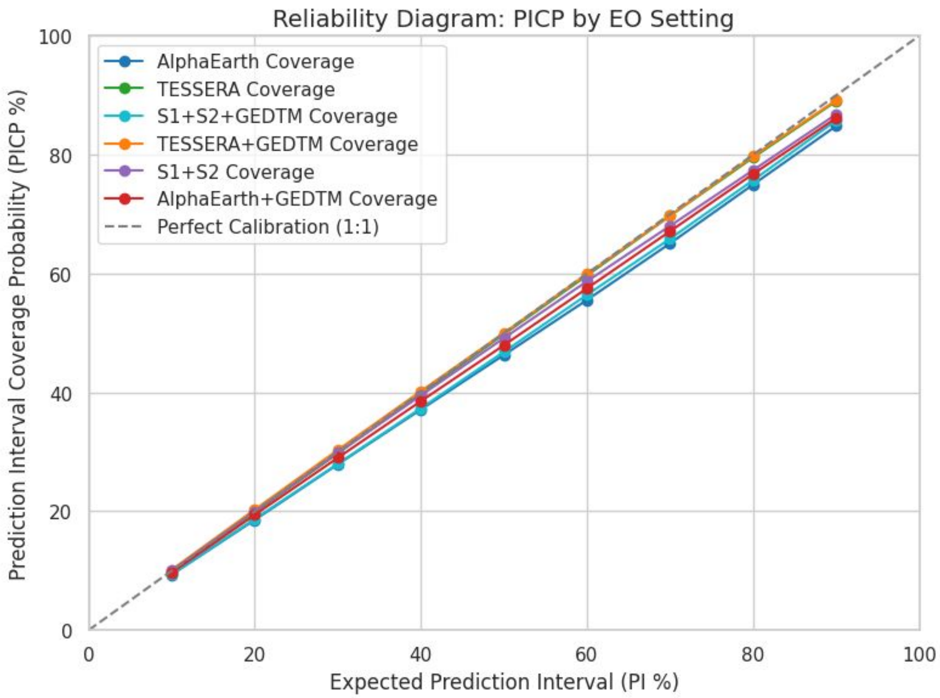
- *Topographic attributes does not contribute to prediction accuracy*
- *AlphaEarth performs slightly better than **TESSERA (v1)** and **S1+S2***

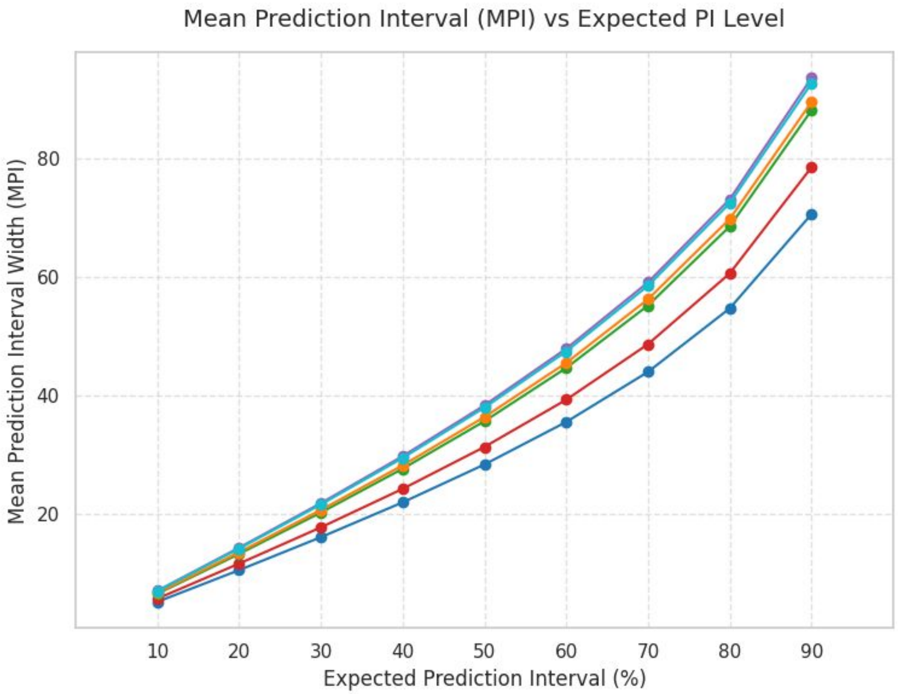

Sampled Tiles: EO Settings Comparison vs Reference
Tile ID: Catalunya_2016..tile_441000_4679000
AlphaEarth
R²: 0.69 | RMSE: 19.83
MAE: 16.26 | ME: 2.20 | SSIM: 0.73
AlphaEarth+GEDTM
R²: 0.68 | RMSE: 20.19
MAE: 16.91 | ME: 5.90 | SSIM: 0.71
TESSERA
R²: 0.72 | RMSE: 18.84
MAE: 14.76 | ME: -1.89 | SSIM: 0.71
TESSERA+GEDTM
R²: 0.65 | RMSE: 21.15
MAE: 16.28 | ME: -10.18 | SSIM: 0.72
S1+S2
R²: 0.59 | RMSE: 22.68
MAE: 17.68 | ME: 1.09 | SSIM: 0.61
S1+S2+GEDTM
R²: 0.61 | RMSE: 22.28
MAE: 17.17 | ME: -3.90 | SSIM: 0.65
Reference
Tile ID: CastillaLeon_2021..tile_208000_4730000
AlphaEarth
R²: 0.75 | RMSE: 22.57
MAE: 16.65 | ME: -6.80 | SSIM: 0.77
AlphaEarth+GEDTM
R²: 0.73 | RMSE: 23.32
MAE: 17.08 | ME: -7.94 | SSIM: 0.77
TESSERA
R²: 0.63 | RMSE: 27.31
MAE: 20.55 | ME: 4.32 | SSIM: 0.69
TESSERA+GEDTM
R²: 0.66 | RMSE: 26.24
MAE: 19.92 | ME: -3.73 | SSIM: 0.70
S1+S2
R²: 0.59 | RMSE: 28.68
MAE: 22.67 | ME: 4.70 | SSIM: 0.66
S1+S2+GEDTM
R²: 0.57 | RMSE: 29.25
MAE: 23.44 | ME: -4.13 | SSIM: 0.69
Reference
Tile ID: CastillaLeon_2021..tile_332000_4739000
AlphaEarth
R²: 0.78 | RMSE: 8.36
MAE: 6.43 | ME: 0.56 | SSIM: 0.82
AlphaEarth+GEDTM
R²: 0.74 | RMSE: 9.13
MAE: 6.85 | ME: 1.51 | SSIM: 0.81
TESSERA
R²: 0.65 | RMSE: 10.63
MAE: 8.05 | ME: 0.70 | SSIM: 0.72
TESSERA+GEDTM
R²: 0.68 | RMSE: 10.13
MAE: 7.79 | ME: 1.71 | SSIM: 0.74
S1+S2
R²: 0.35 | RMSE: 14.58
MAE: 10.70 | ME: 5.53 | SSIM: 0.66
S1+S2+GEDTM
R²: 0.43 | RMSE: 13.63
MAE: 11.13 | ME: 8.56 | SSIM: 0.71
Reference

Comparison of different models

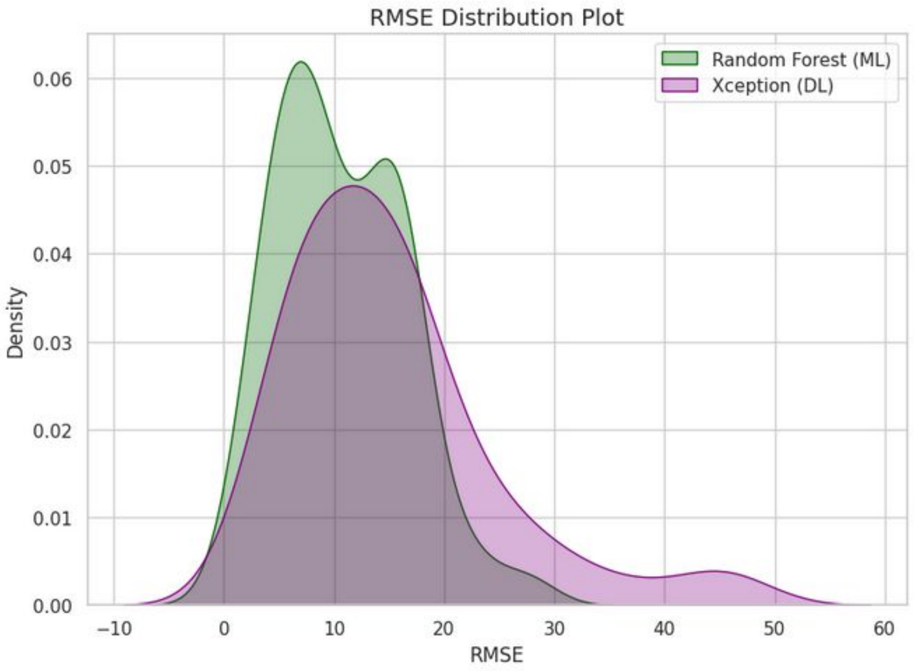
- *Uncertainty quantification is reasonable (PICP aligns 1:1 Calibration)*
- *AlphaEarth earns the lowest uncertainty range*

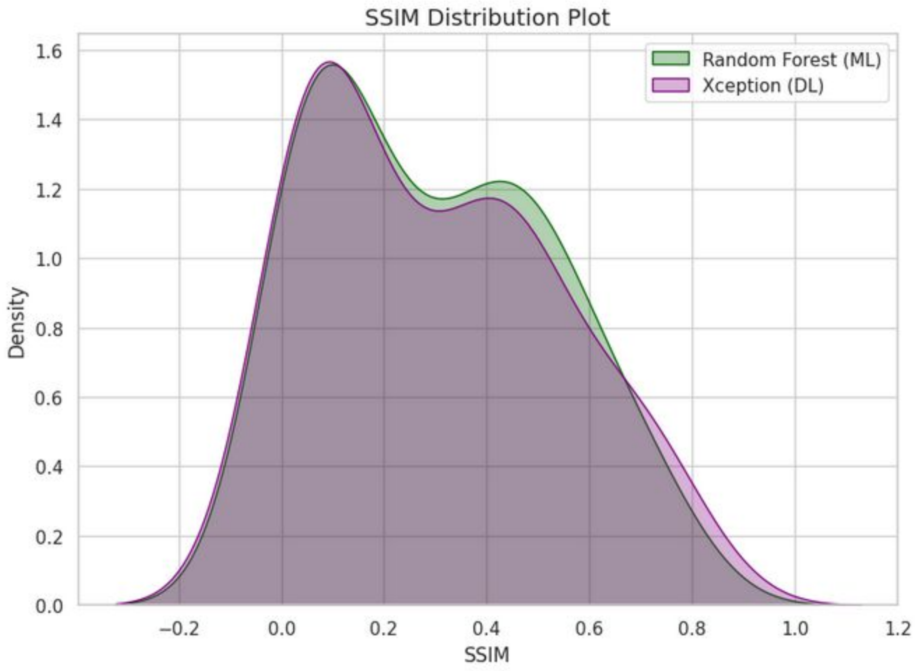
Uncertainty-per-pixel, what does it says?





Comparison of different models

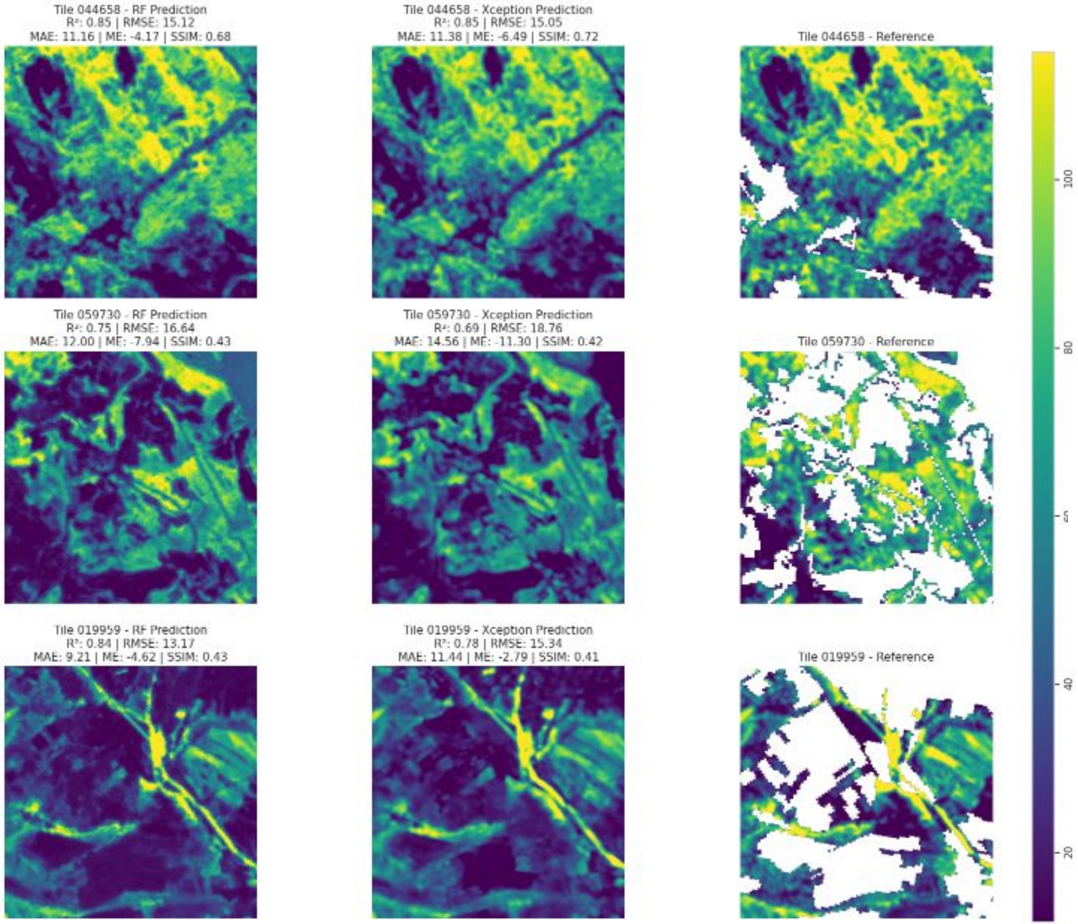




(Still in investigation)

- *Method - 450 training tiles / 50 test tiles, model training (cross validation for RF / train-val epoch for Xception)*
- *~58,000 (25x25) patches in total for Xception model (13.1M parameters)*
- *Random forest is robust, and show no significant differences to Xception model*

Comparison of different EO settings



AGB (t/ha)

Random forest demonstrates discrete prediction, whereas **Xception CNN** gives slightly smooth prediction

Discussion and Conclusion

Conclusion

- AlphaEarth and TESSERA can possibly replace annual aboveground biomass mapping.
- AlphaEarth performs slightly better than TESSERA **(v1)** and Sentinel-1 and 2
- Random forest and Xception do not perform significantly different on AlphaEarth-based model.

Next steps

- Increase training patches for Xception Models
- Test differents models for all EO settings
- Add more countries?

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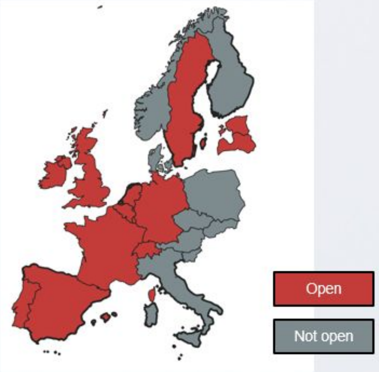
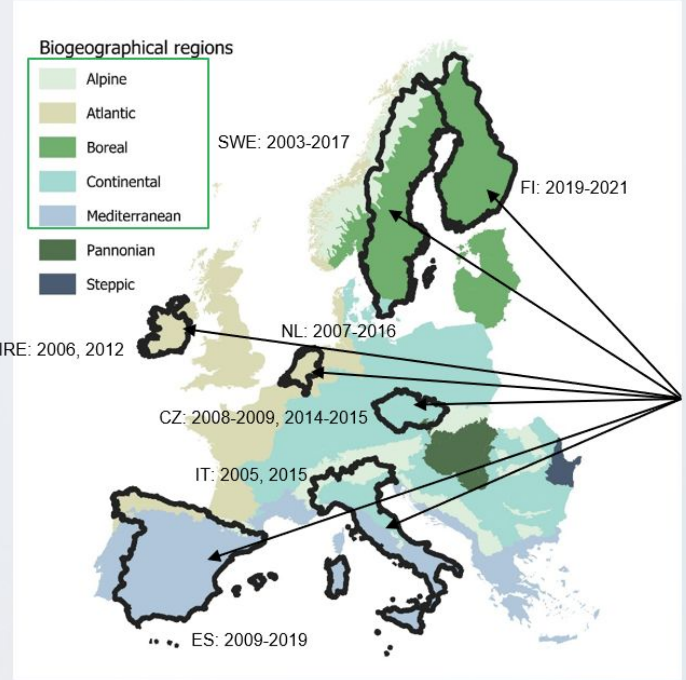
Large scale? Next step!

Overview

Current data covers the **five** most important biogeographical regions* in Europe



Distributions of Ground Data + ALS data



Processed or under processing

* The biogeographical regions map is acquired from https://www.eea.europa.eu/en/analysis/maps-and-charts/biogeographical-regions-in-europe-2.

The Intergenerational Open Geospatial Carbon Registry (OGCR). Grant agreement ID: 101218854.

Open-Earth-Monitor OEMC Global workshop 2026

Thank you for your attention!

Open Geospatial Carbon Registry

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