Benchmarking Earth Observation Embeddings for large scale aboveground biomass mapping

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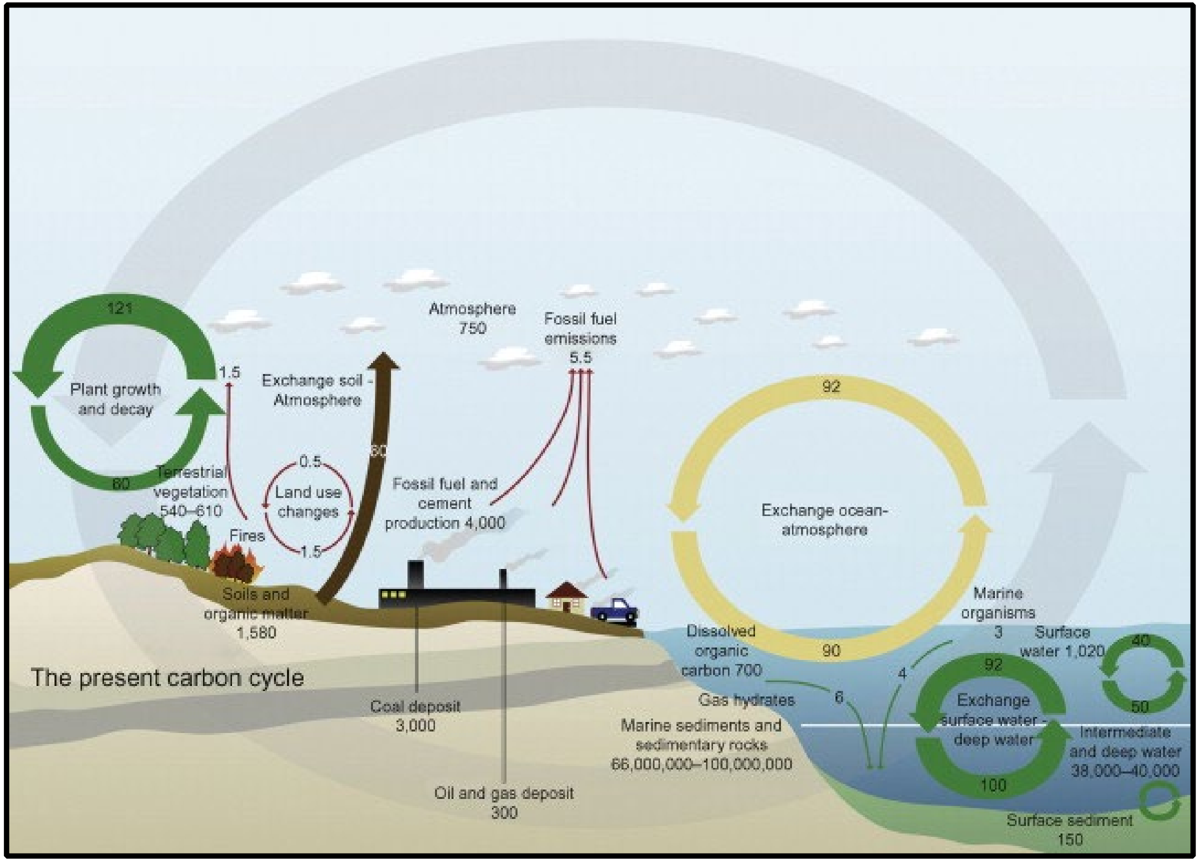
Bologna 15 april, 2026

This research project is sponsored by: Open Geospatial Carbon Registry
https://cordis.europa.eu/project/id/101218854

Aboveground Biomass in Carbon Cycle

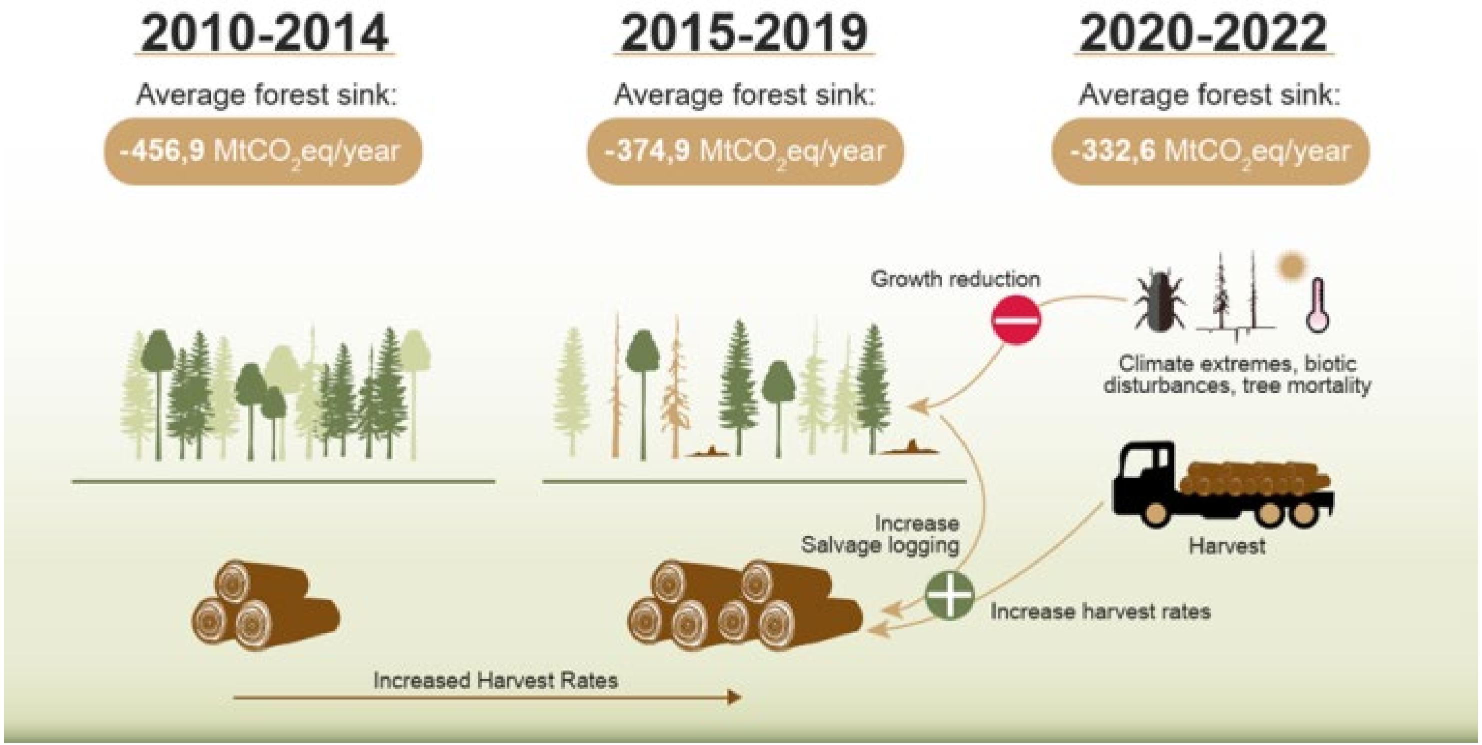
Although the major carbon stock is located in sediments under the sea, plant growth and **decay of terrestrial vegetation contribute a relatively huge portion of the carbon flux.**



(Courtesy of UNEP/GRID-Arendal)

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

Aboveground Biomass in Carbon Cycle



EU Forest works as **carbon sink**, but is **decreasing** and lack of **monitoring**

https://joint-research-centre.ec.europa.eu/jrc-news-and-updates/european-forest-carbon-sink-declining-can-we-reverse-trend-2025-07-30_en

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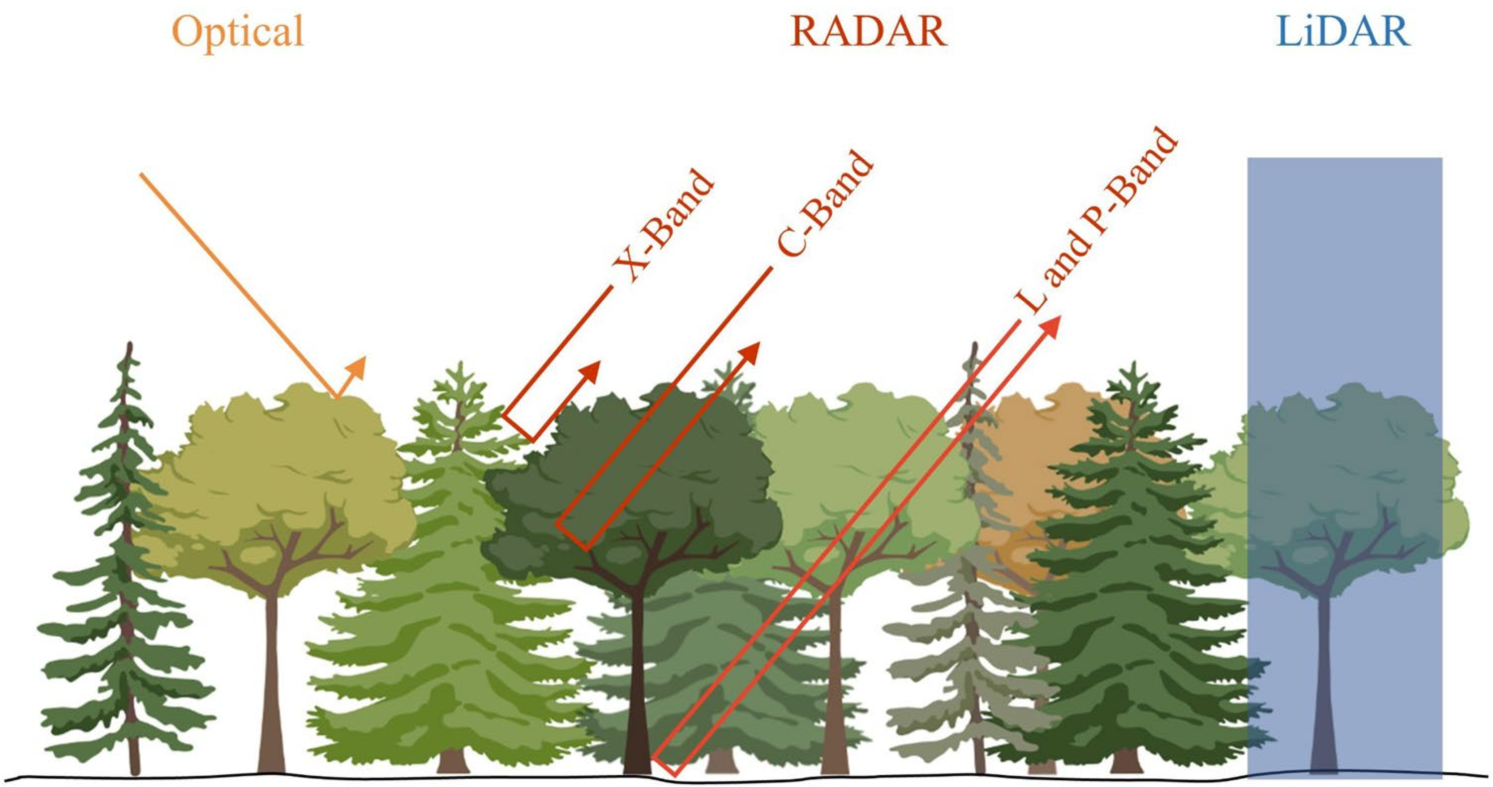
Earth Observation for Aboveground Biomass



Tian, L., Wu, X., Tao, Y., Li, M., Qian, C., Liao, L., & Fu, W. (2023). Review of remote sensing-based methods for forest aboveground biomass estimation: Progress, challenges, and prospects. *Forests*, *14*(6), 1086.

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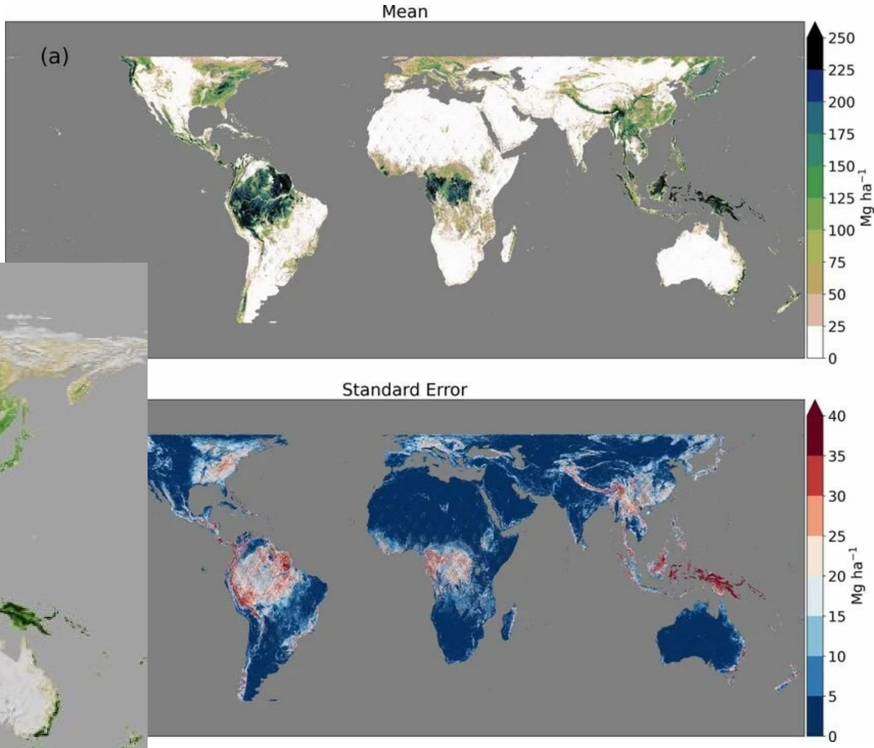
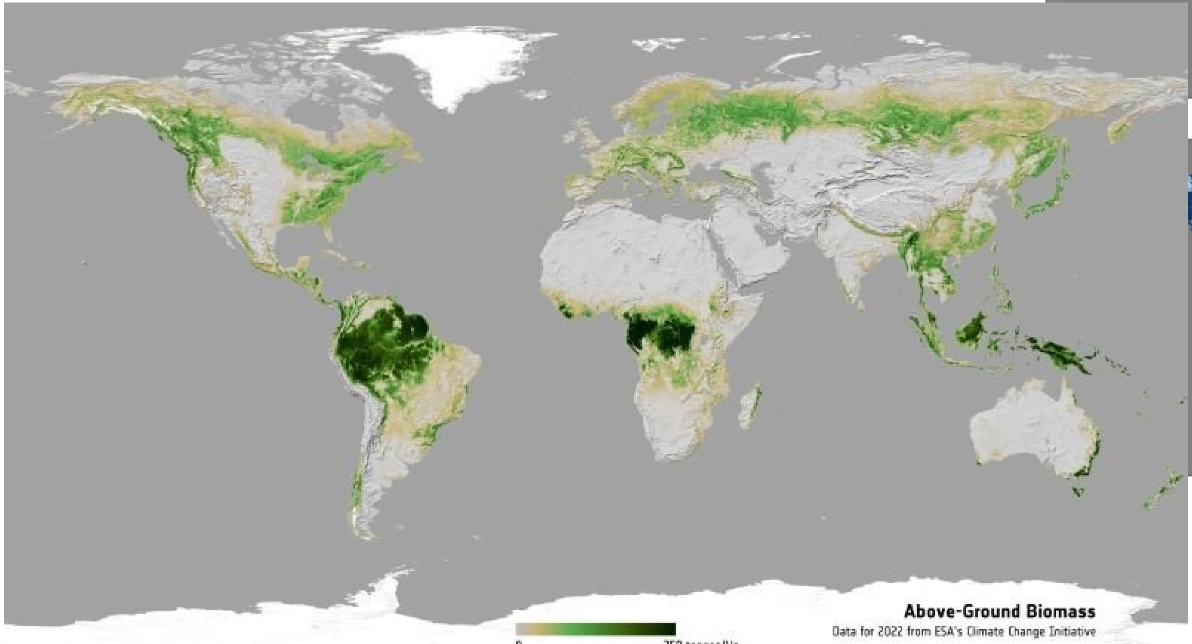
Aboveground Biomass Mapping

Santoro, M., & Cartus, O. (2023). *ESA Biomass Climate Change Initiative (Biomass_cci): Global datasets of forest above-ground biomass for the years 2010, 2017, 2018, 2019 and 2020, v4.* Centre for Environmental Data Analysis.





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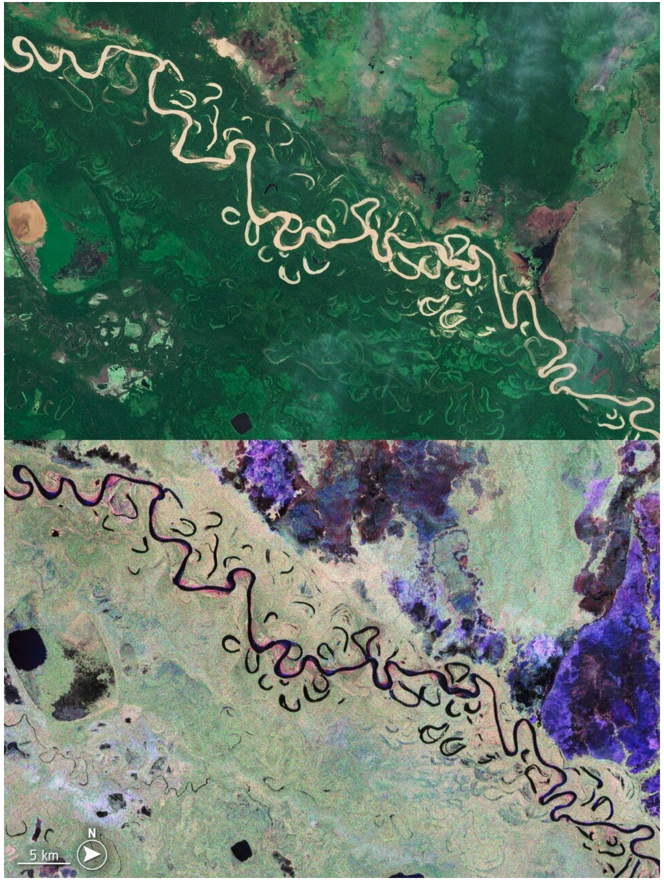
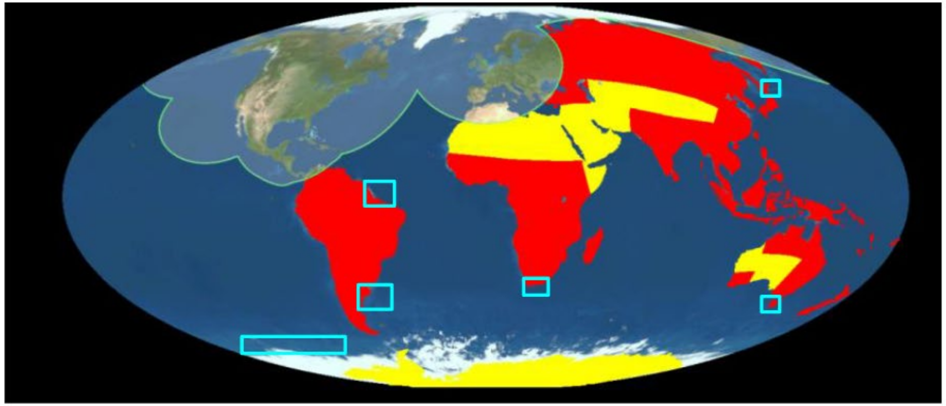
Dubayah, R.O., J. Armston, S.P. Healey, Z. Yang, P.L. Patterson, S. Saarela, G. Stahl, L. Duncanson, and J.R. Kellner. 2022. GEDI L4B Gridded Aboveground Biomass Density, Version 2. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/2017

Aboveground Biomass Mapping



ESA's new mission (P-band radar) to monitor forest biomass of 200m of the world, **but exclude US and EU**



(Red = Primary objective coverage mask, Yellow = Secondary objective coverage mask)

https://earth.esa.int/eogateway/missions/biomass/description

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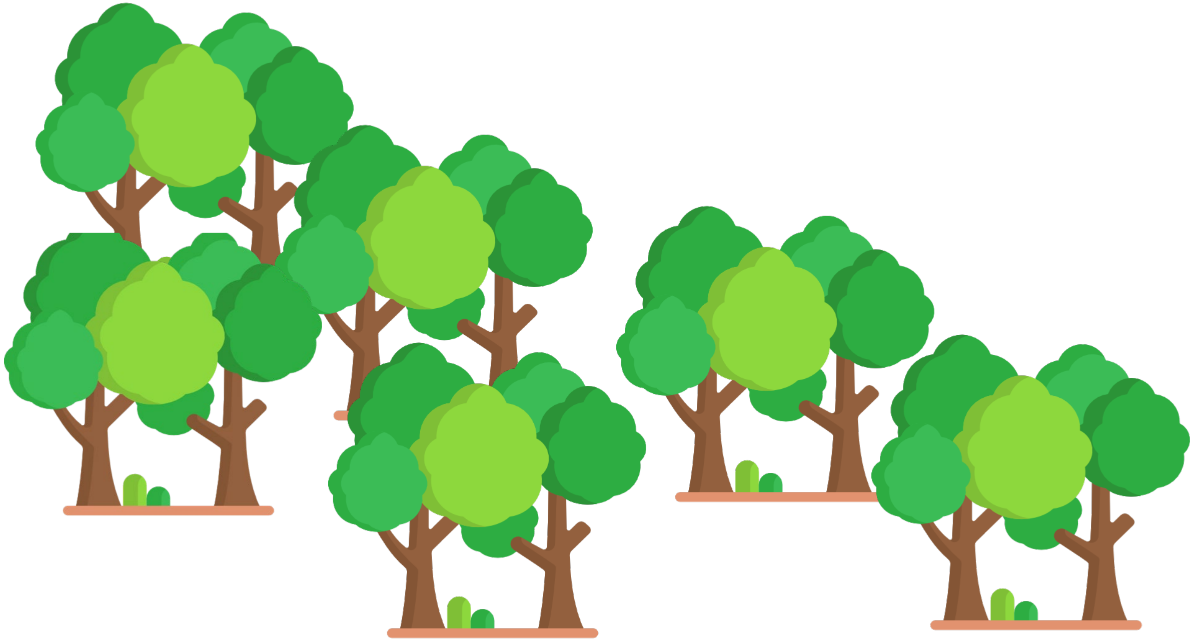
Forest monitor / AGB estimate



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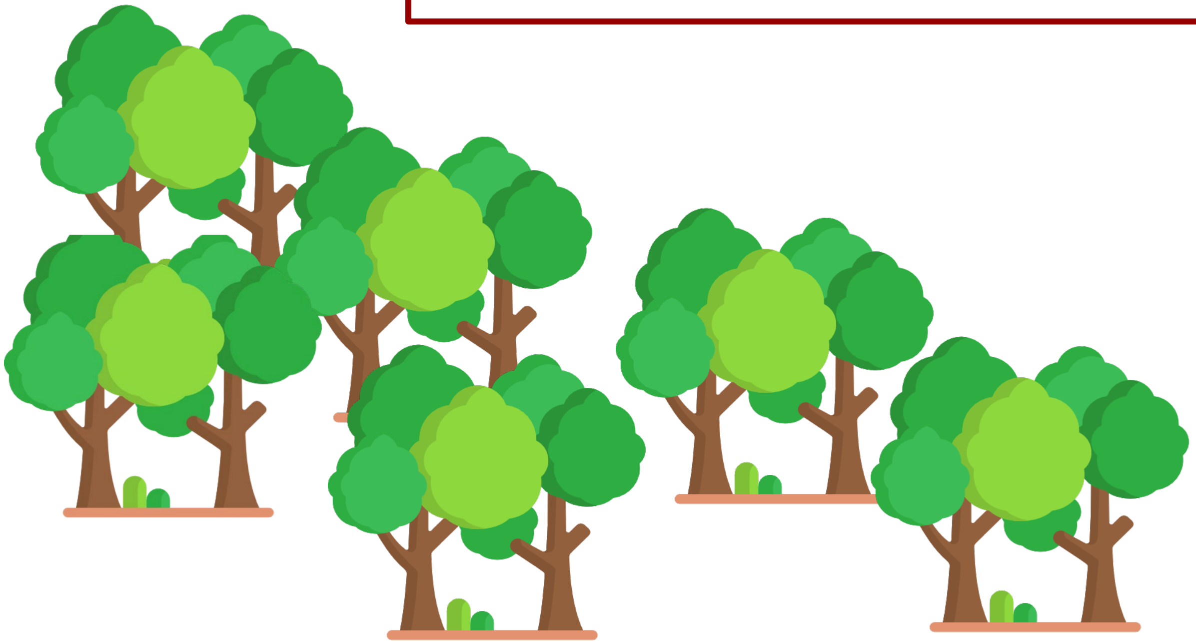
Forest monitor / AGB estimate

Forest inventory
(Field data: tree height, diameter, species)



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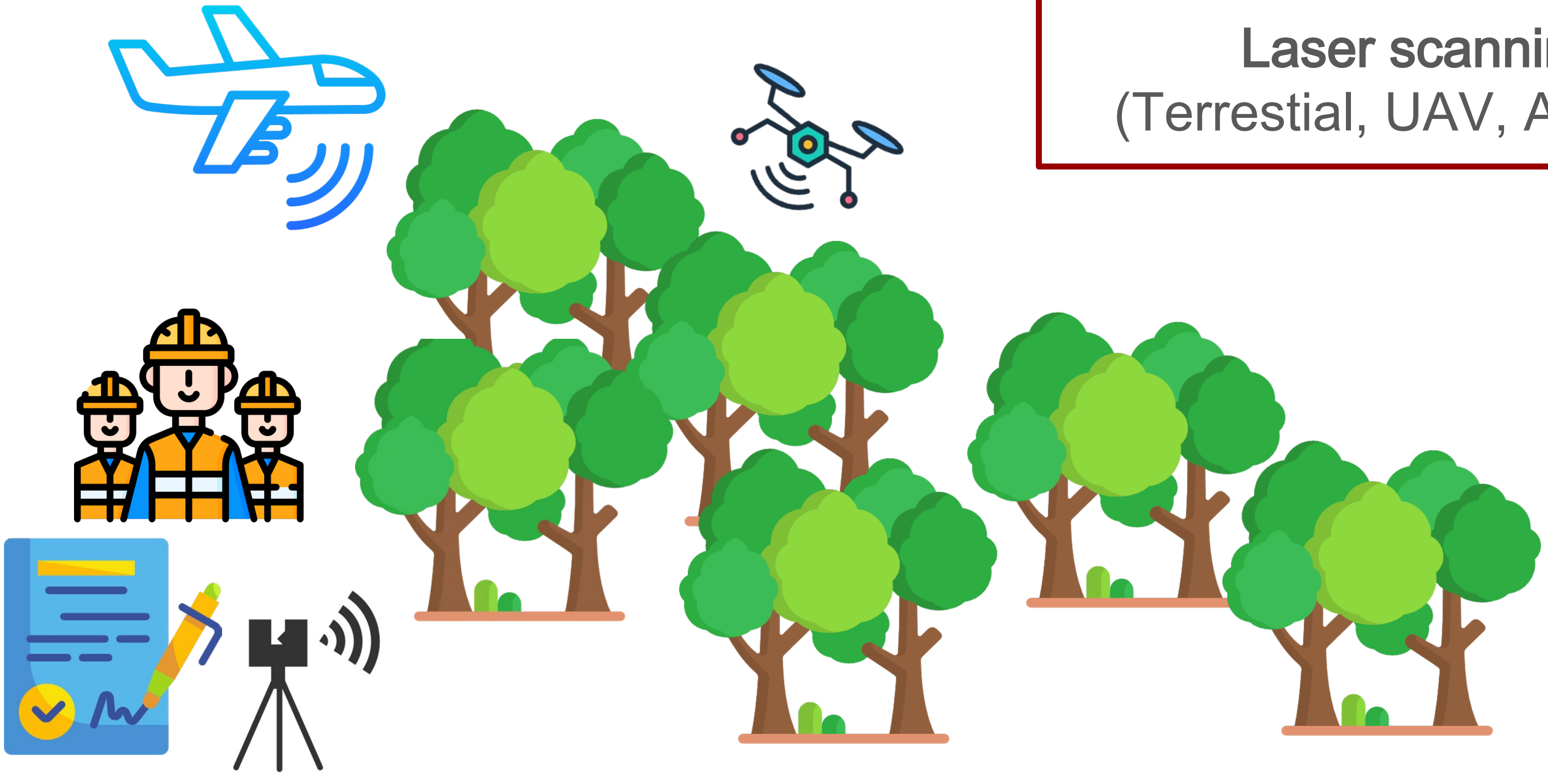
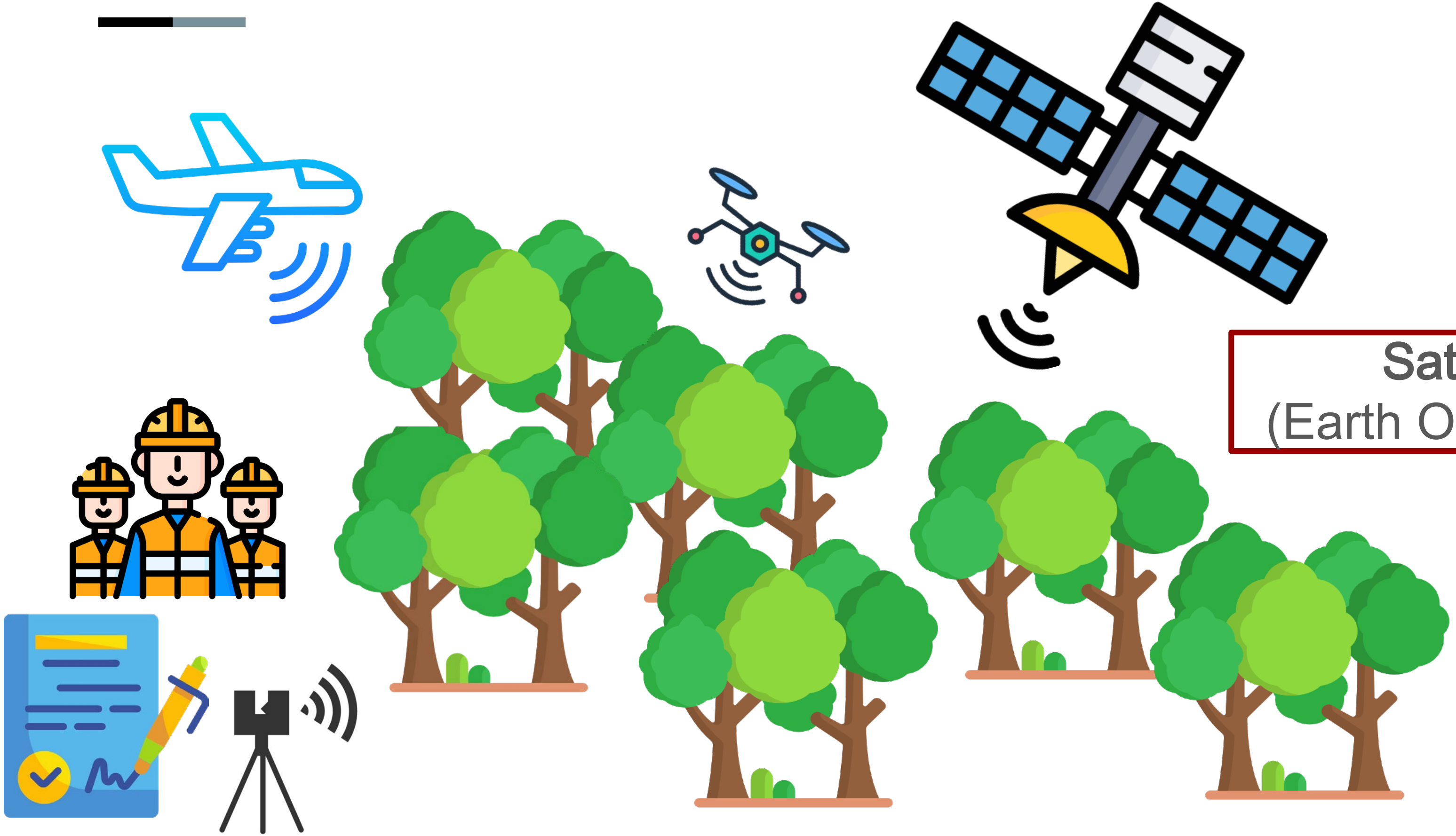
Forest monitor / AGB estimate



Laser scanning
(Terrestial, UAV, Airborne)

Forest monitor / AGB estimate



Satellite
(Earth Observation)

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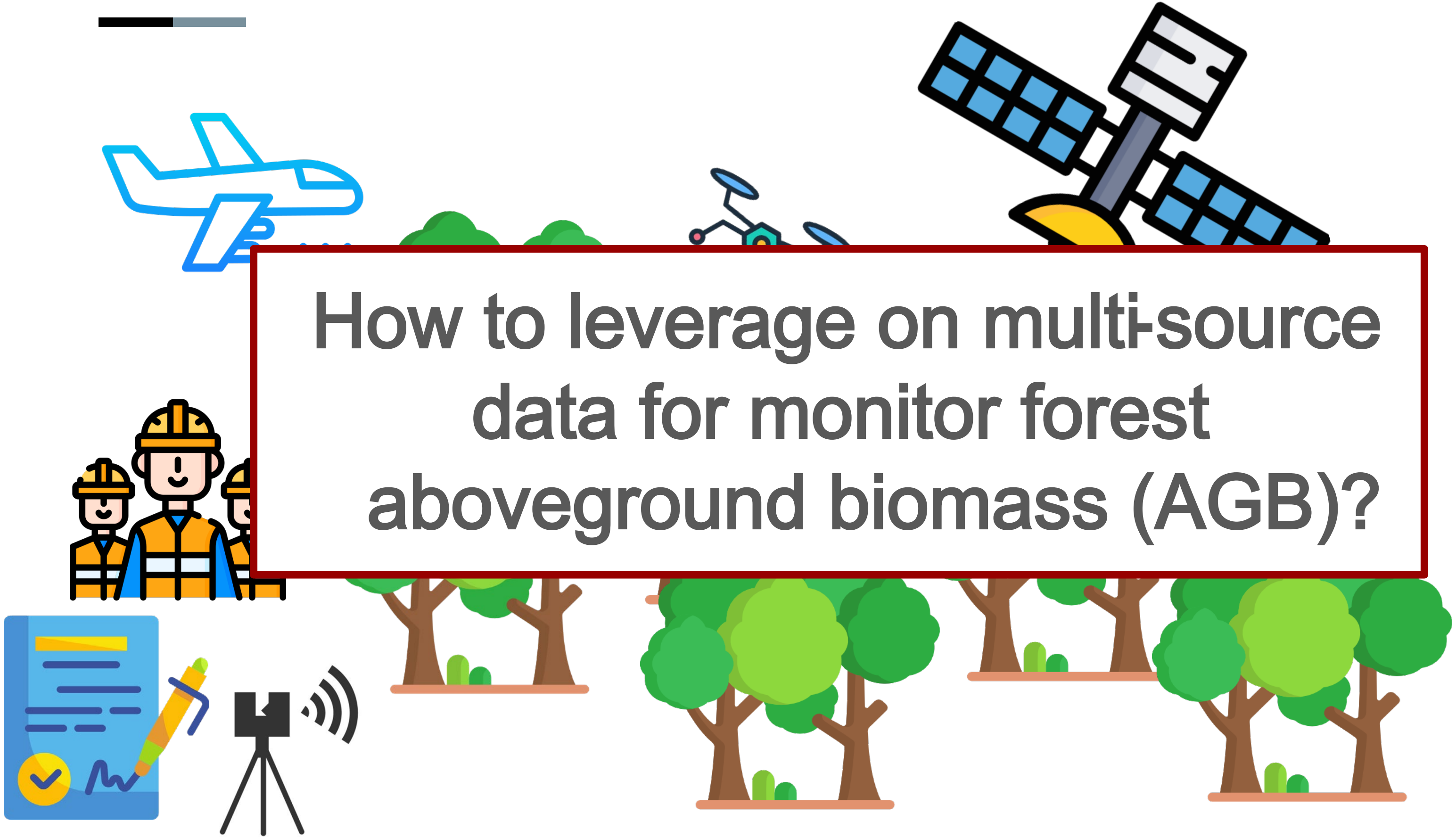
Forest monitor / AGB estimate



How to leverage on multi-source data for monitor forest aboveground biomass (AGB)?

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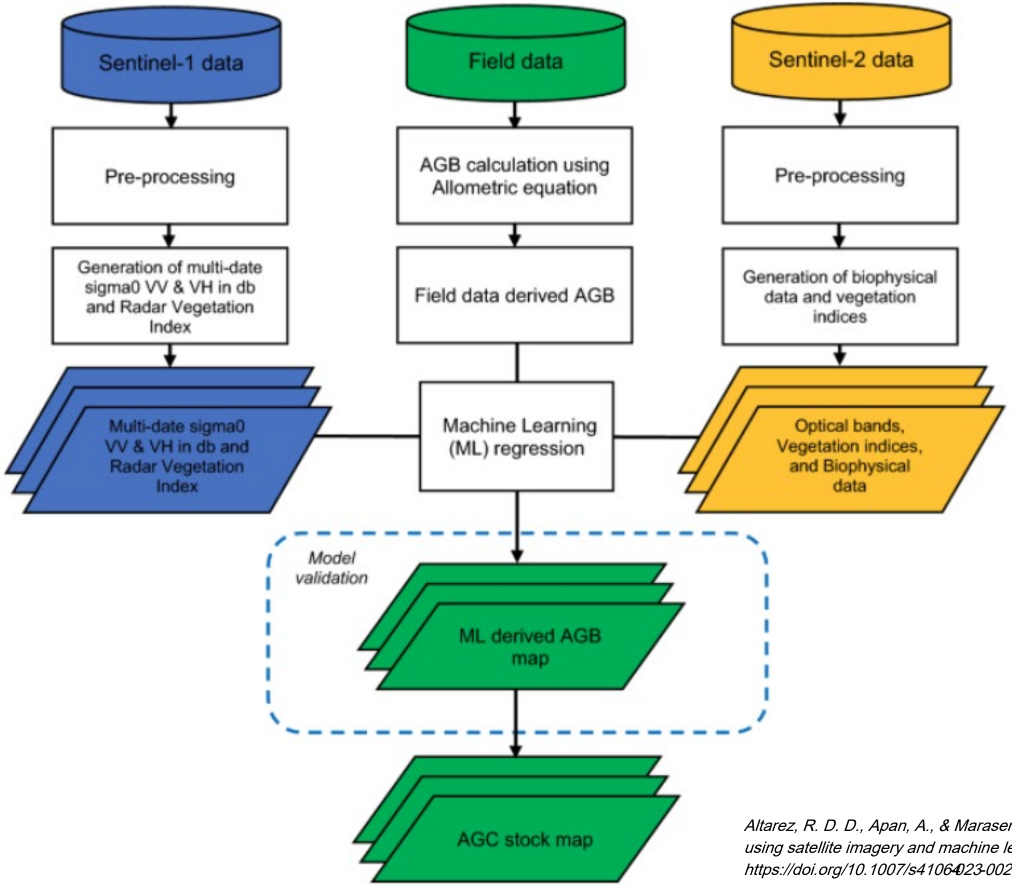
Machine Learning Framework for AGB



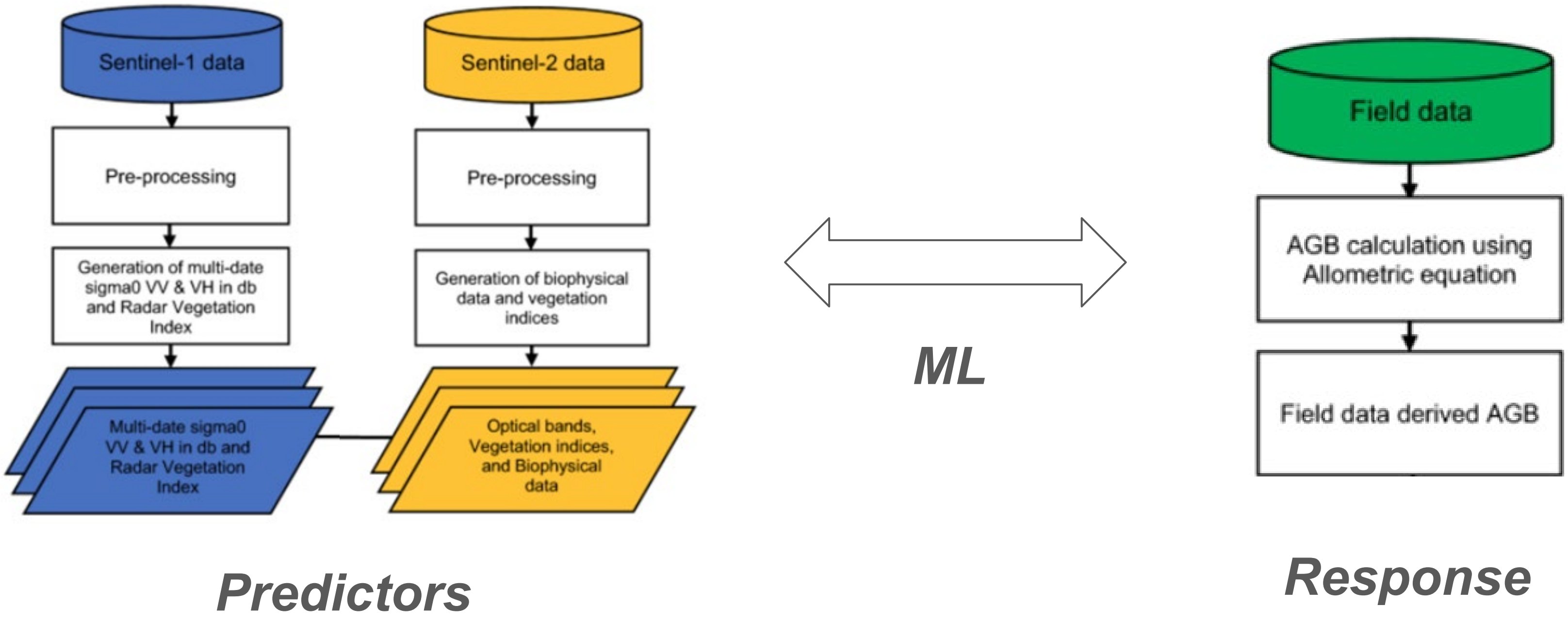
Variables

- 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

Machine Learning Framework for AGB



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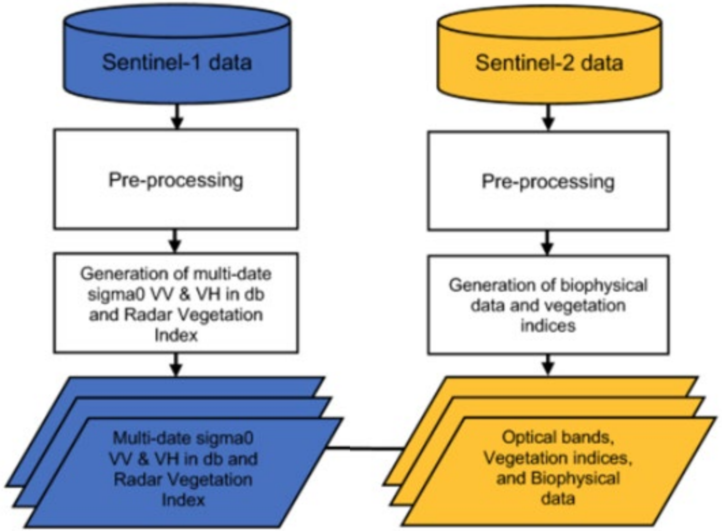
Machine Learning Framework for AGB



Predictors

Not an easy task for large scale mapping…

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

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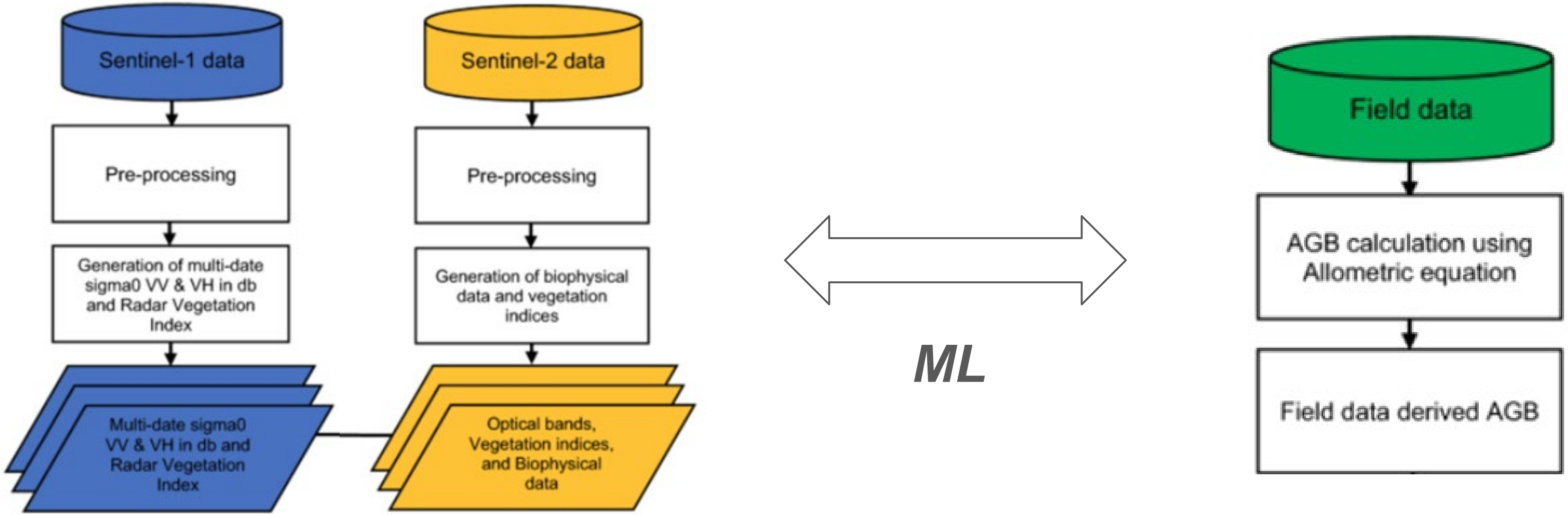
Machine Learning Framework for AGB



Predictors

Response

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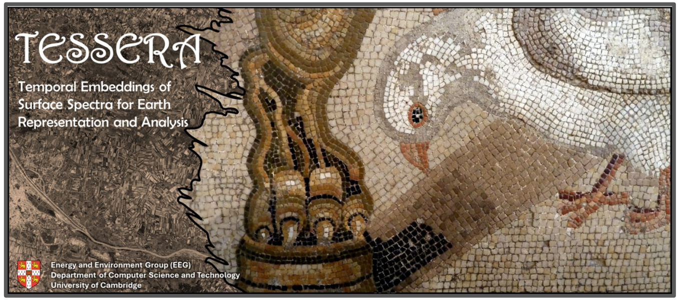
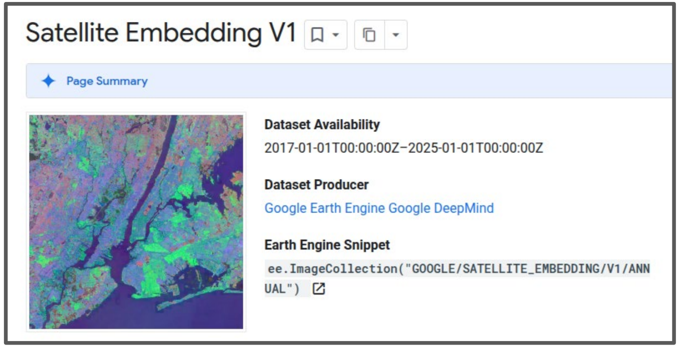
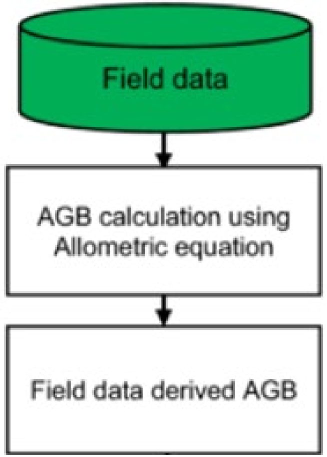
Machine Learning Framework for AGB





ML



Predictors

Response

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

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

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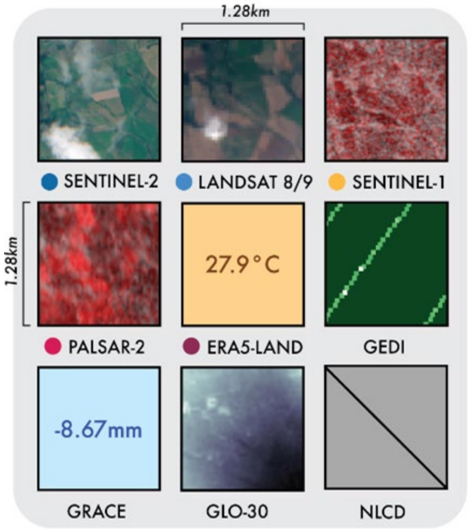
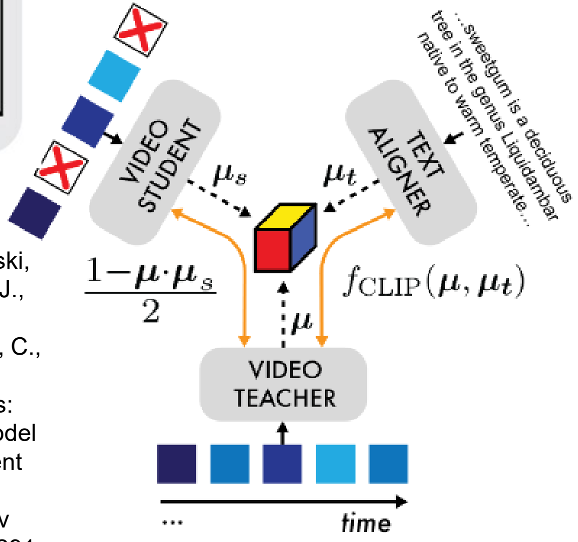
AlphaEarth Foundations

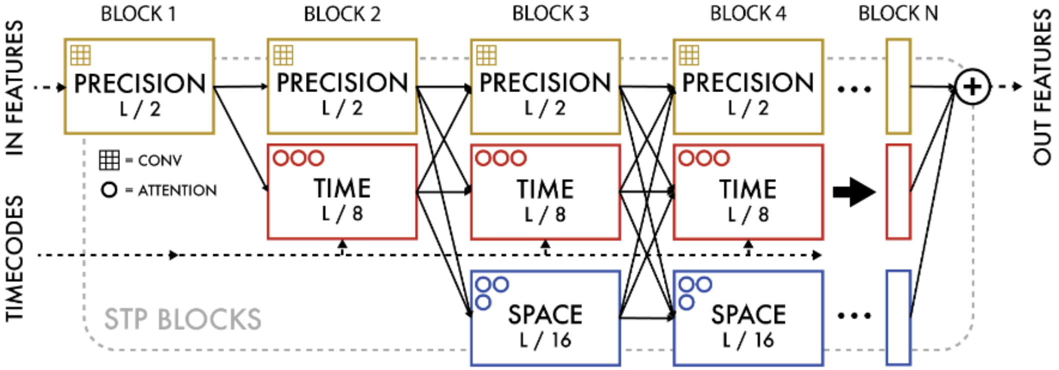
Data sources



Model concept

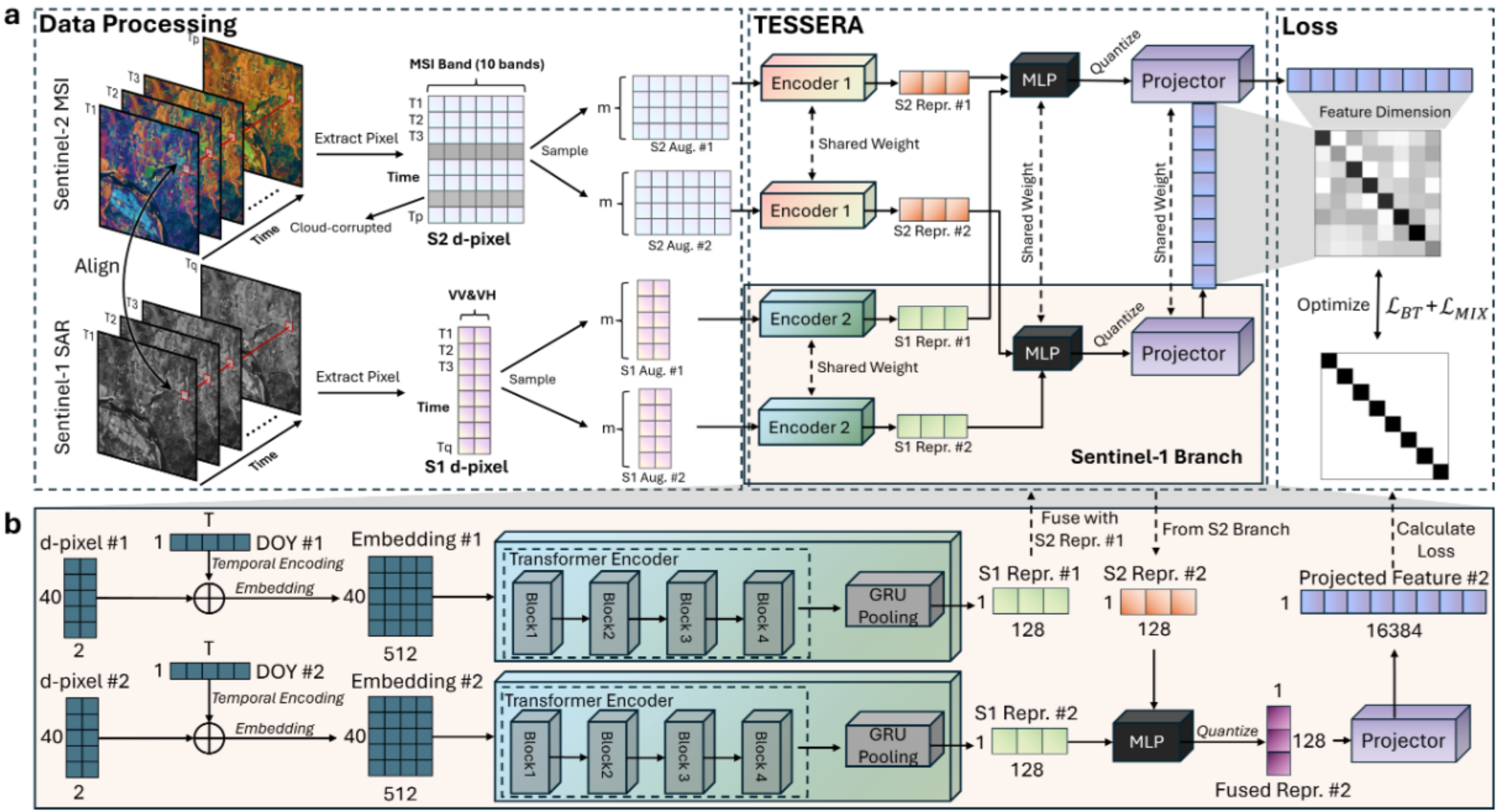


Modeling framework



Brown, C. F., Kazmierski, M. R., Pasquarella, V. J., Rucklidge, W. J., Samsikova, M., Zhang, C., ... & Kohli, P. (2025). Alphaearth foundations: An embedding field model for accurate and efficient global mapping from sparse label data. arXiv preprint arXiv:2507.22291.

TESSERA

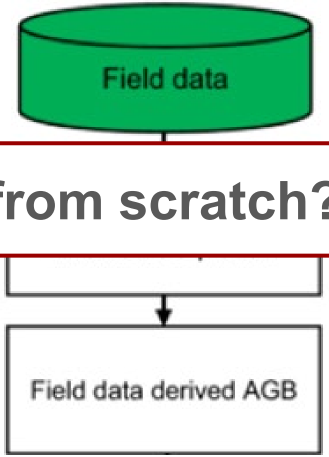


Feng, Z., Atzberger, C., Jaffer, S., Knezevic, J., Sormunen, S., Young, R., ... & Keshav, S. (2025). Tessera: Temporal embeddings of surface spectra for earth representation and analysis. *arXiv preprint arXiv:2506.20380*.

Machine Learning Framework for AGB

Question 1: Can EO embedding replace training from scratch?

ML



Predictors

Response

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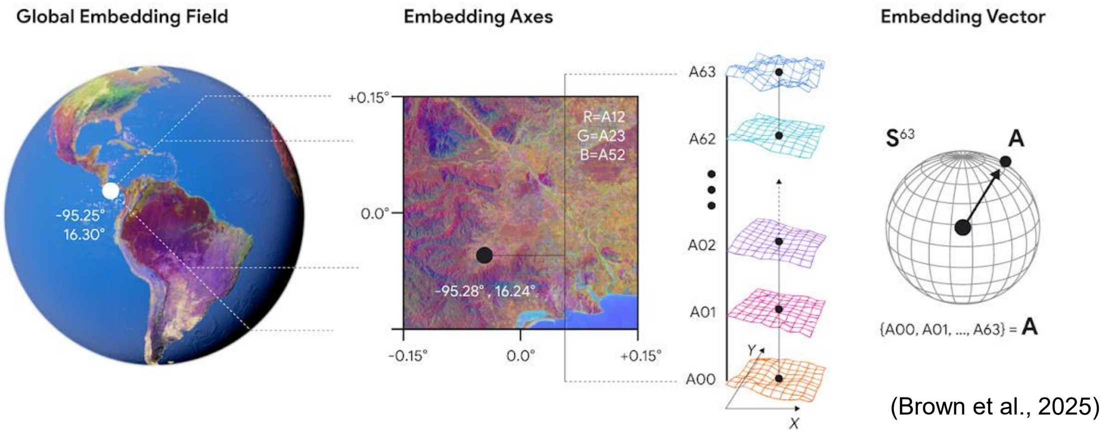
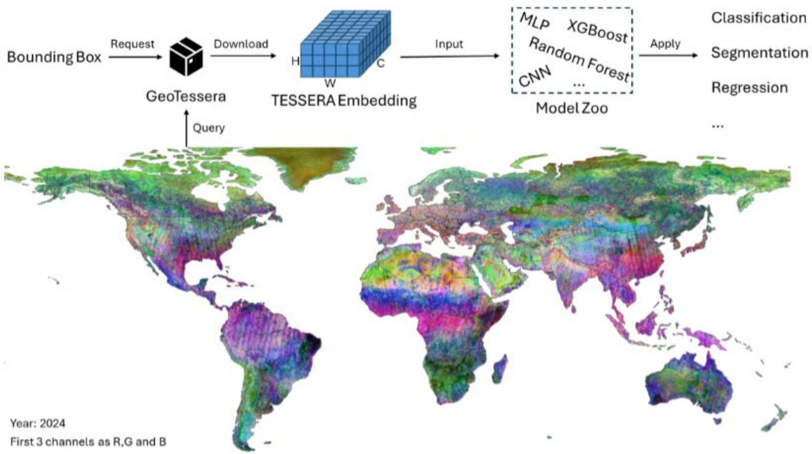
EO Embedding dataset

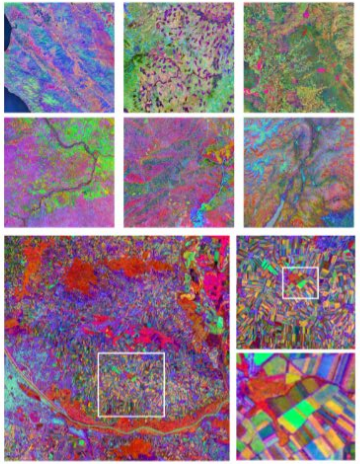


1. Numerical vectors stored as any other **raster layers**
2. Easy to build **downstream** models with **non-limit choices.**

(Brown et al., 2025)

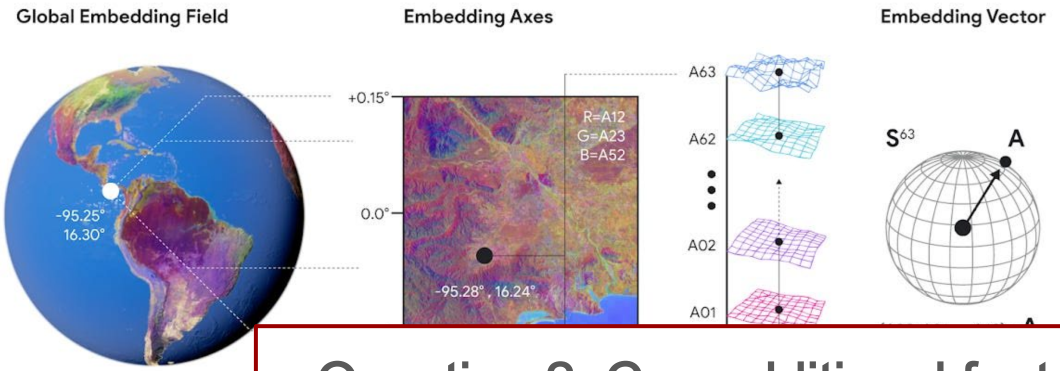
3. Flexibility to add **additional features** or do **feature engineering**





(Feng et al., 2025)

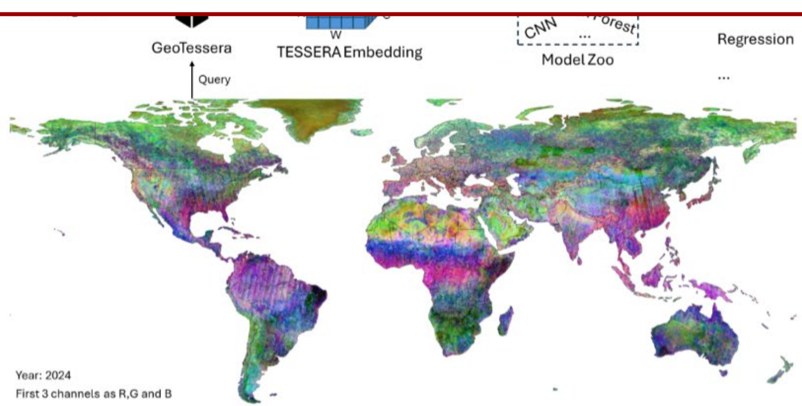
EO Embedding dataset

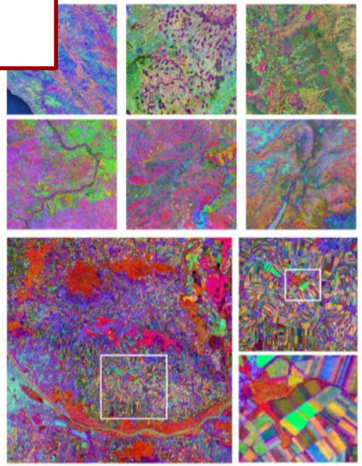


1. Numerical vectors stored as any other **raster layers**
2. Easy to build **downstream** models with **non-limit choices**

Question 2: Can additional features further increase model performance?

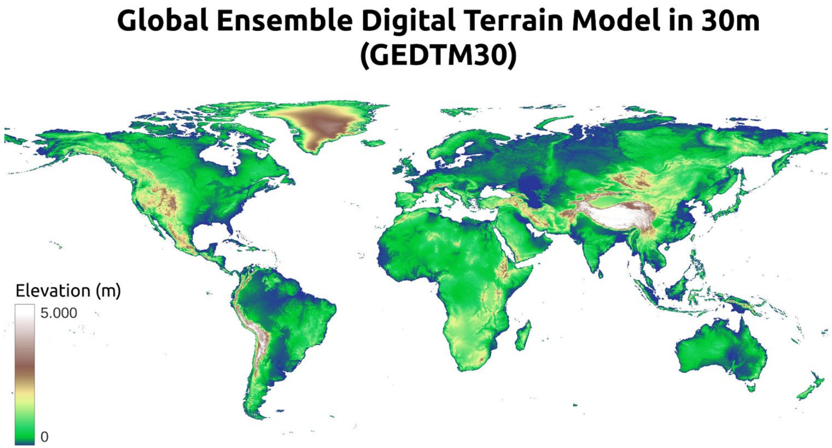
3. Flexibility to add **additional features** or do **feature engineering**





(Feng et al., 2025)

Topographic attributes as additional features



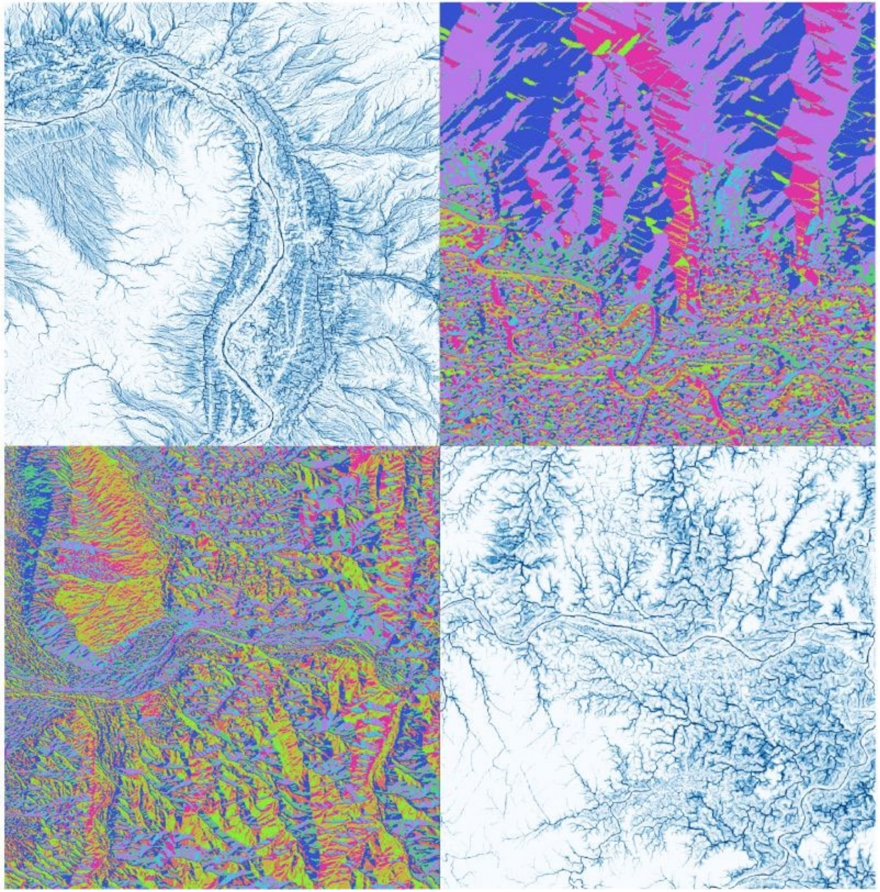
‹ ARTIFICIAL INTELLIGENCE, COMPUTER VISION AND NATURAL LANGUAGE PROCESSING

GEDTM30: global ensemble digital terrain model at 30 m and derived multiscale terrain variables

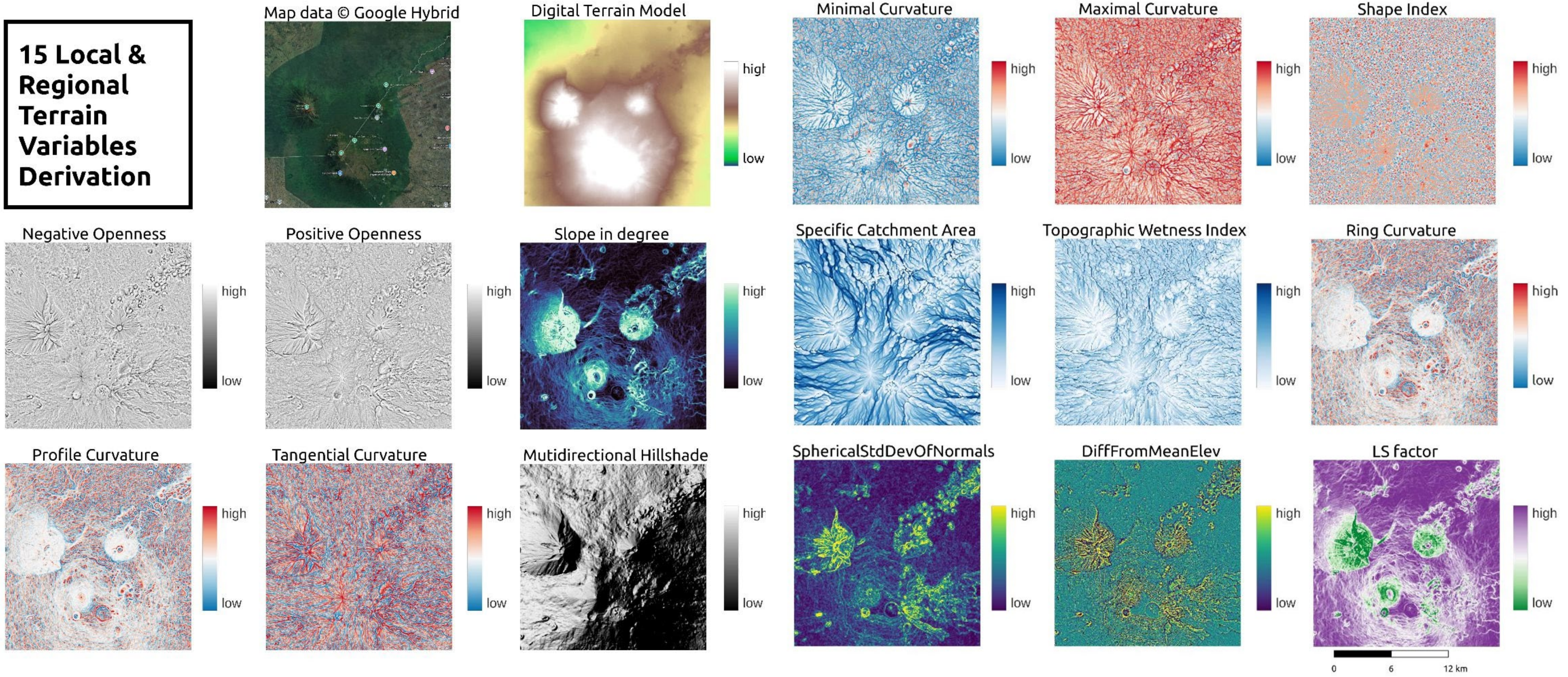
Research Article | Spatial and Geographic Information Science

Yu-Feng Ho [1], Carlos H. Grohmann [2], John Lindsay [3], Hannes I. Reuter [4,5], Leandro Parente [1], Martijn Witjes [1], Tomislav Hengl [1] Post to Authors on X

Published July 24, 2025



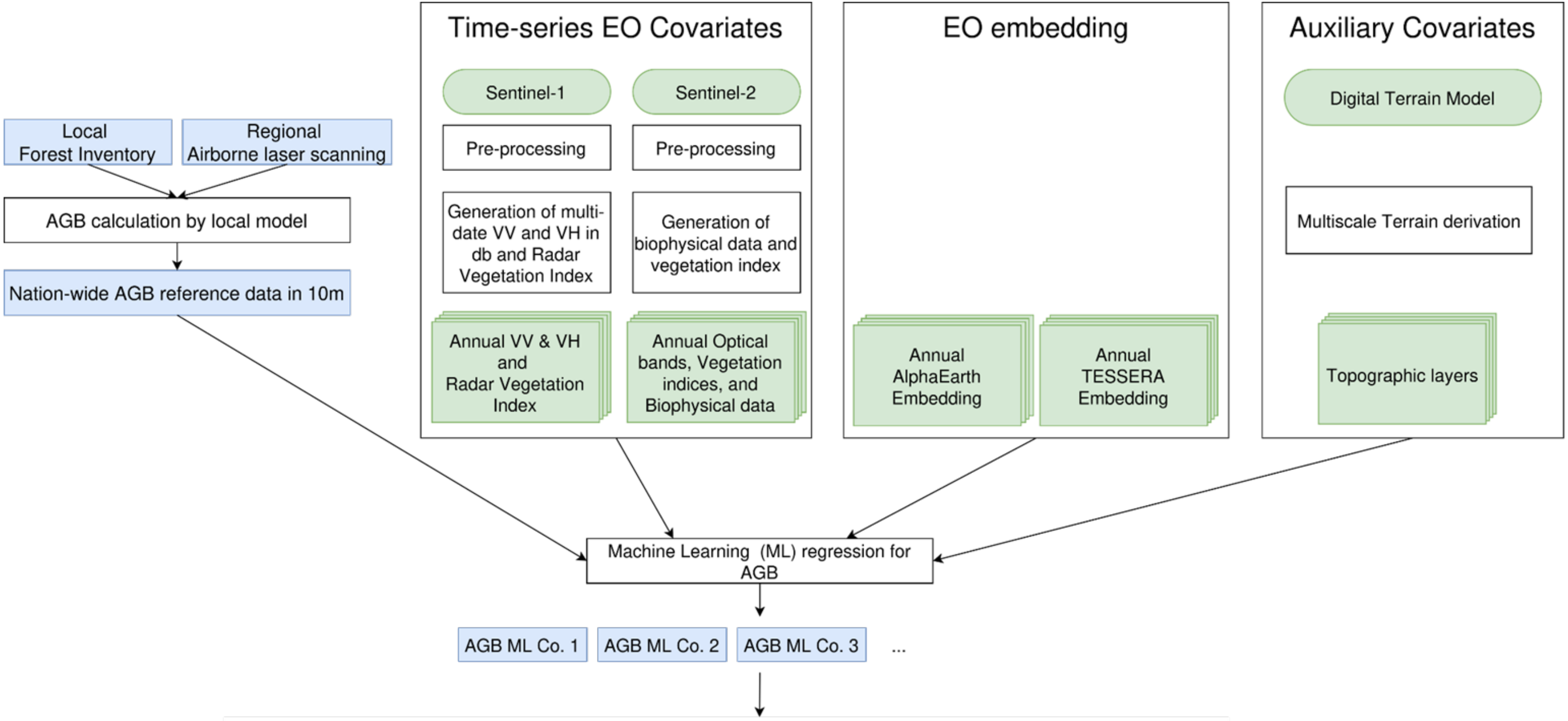
Topographic attributes as additional features



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.

General Framework



What is the optimal setup for large scale aboveground biomass mapping?

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Evaluation by Machine Learning Method

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:

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

where $\widehat{y1}_{\text{stb}_{1,1}}$ 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:

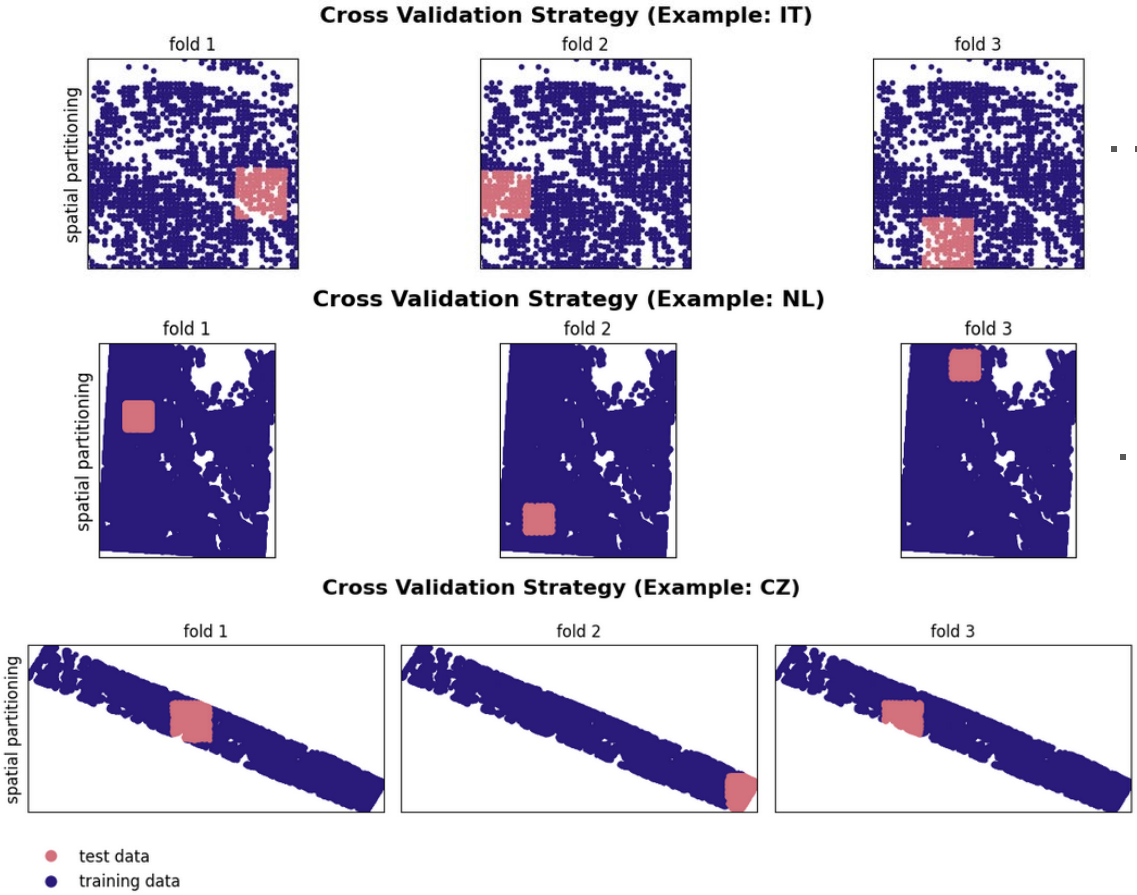
$$\widehat{y}_{\text{lower}} = Q_{0.16}\left(\left\{\widehat{y1}_{\text{stb}_{1,1}}, \widehat{y2}_{\text{stb}_{1,1}}, \cdots, \widehat{yN}_{\text{stb}_{1,1}}\right\}\right), \tag{14}$$

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

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), 999-1036.

Cross validation- Spatial Blocking

```
Automatic Spatial Range Detected: 115.95 meters
Remaining samples after filtering zeros: 1359
```



. . .

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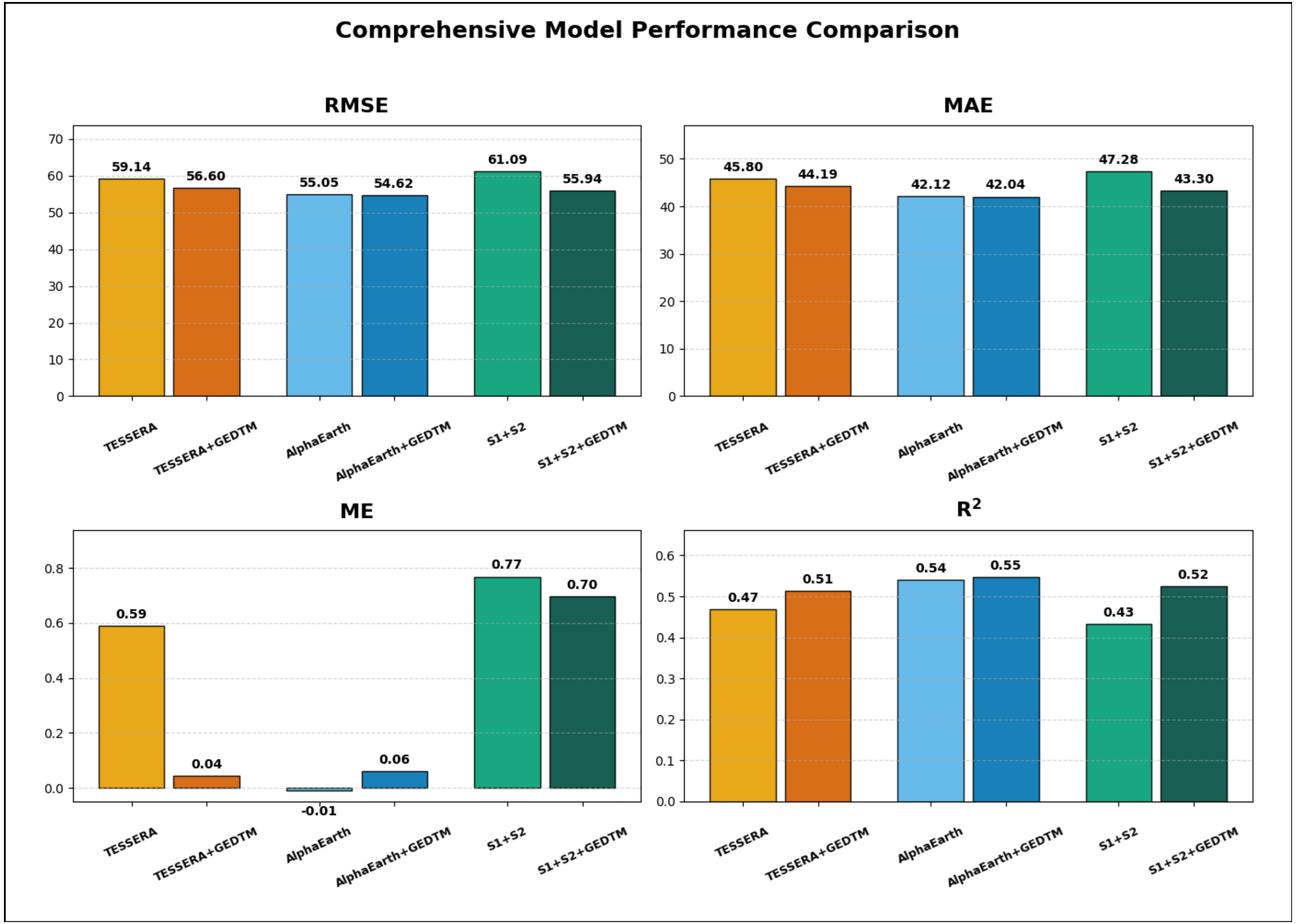
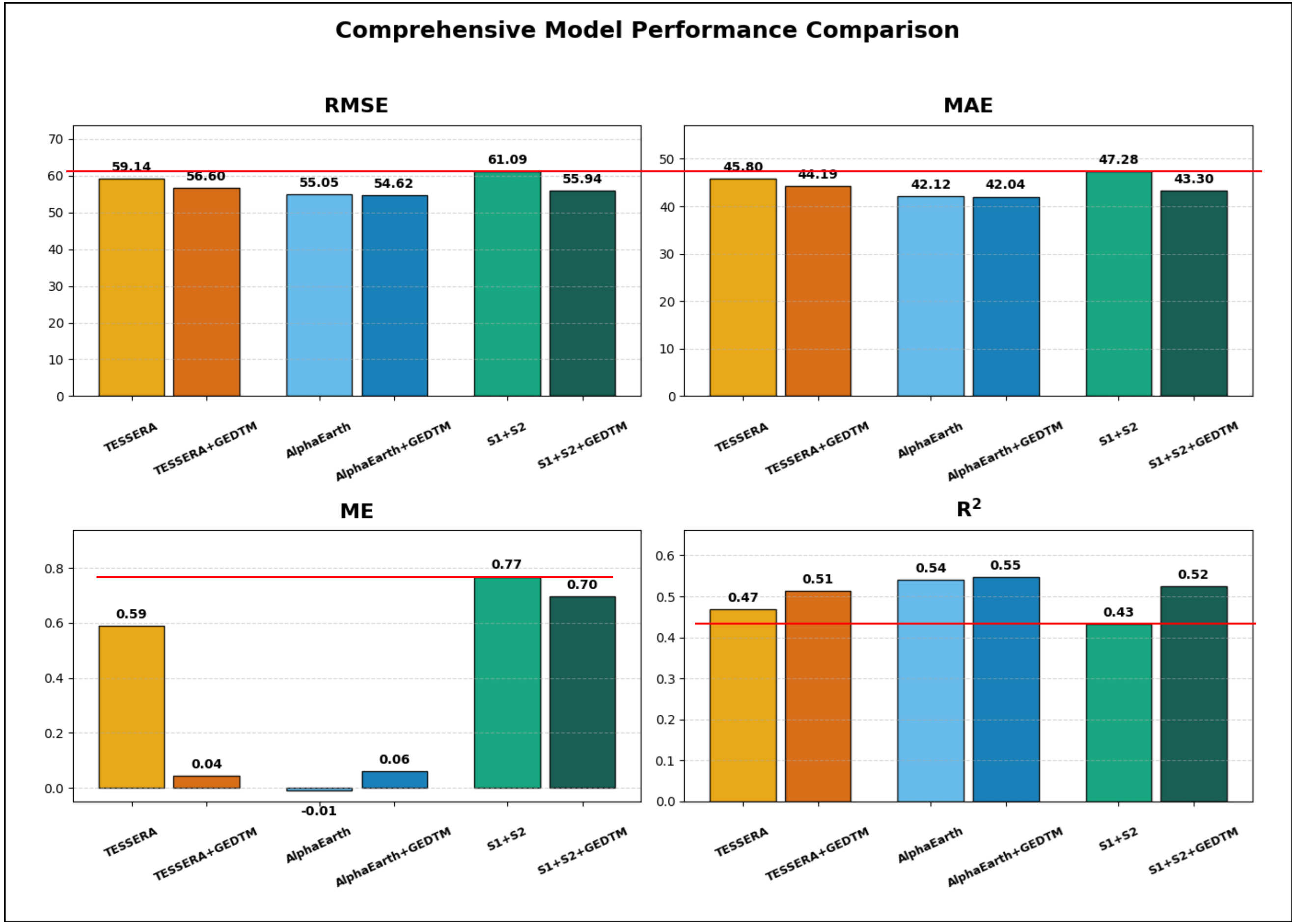
- Minimal blocksize: semivariogram
- Crosscountry modeling:
  1. block aggregation
  2. 5-fold cross validation through radom blocks

Result - accuracy assement

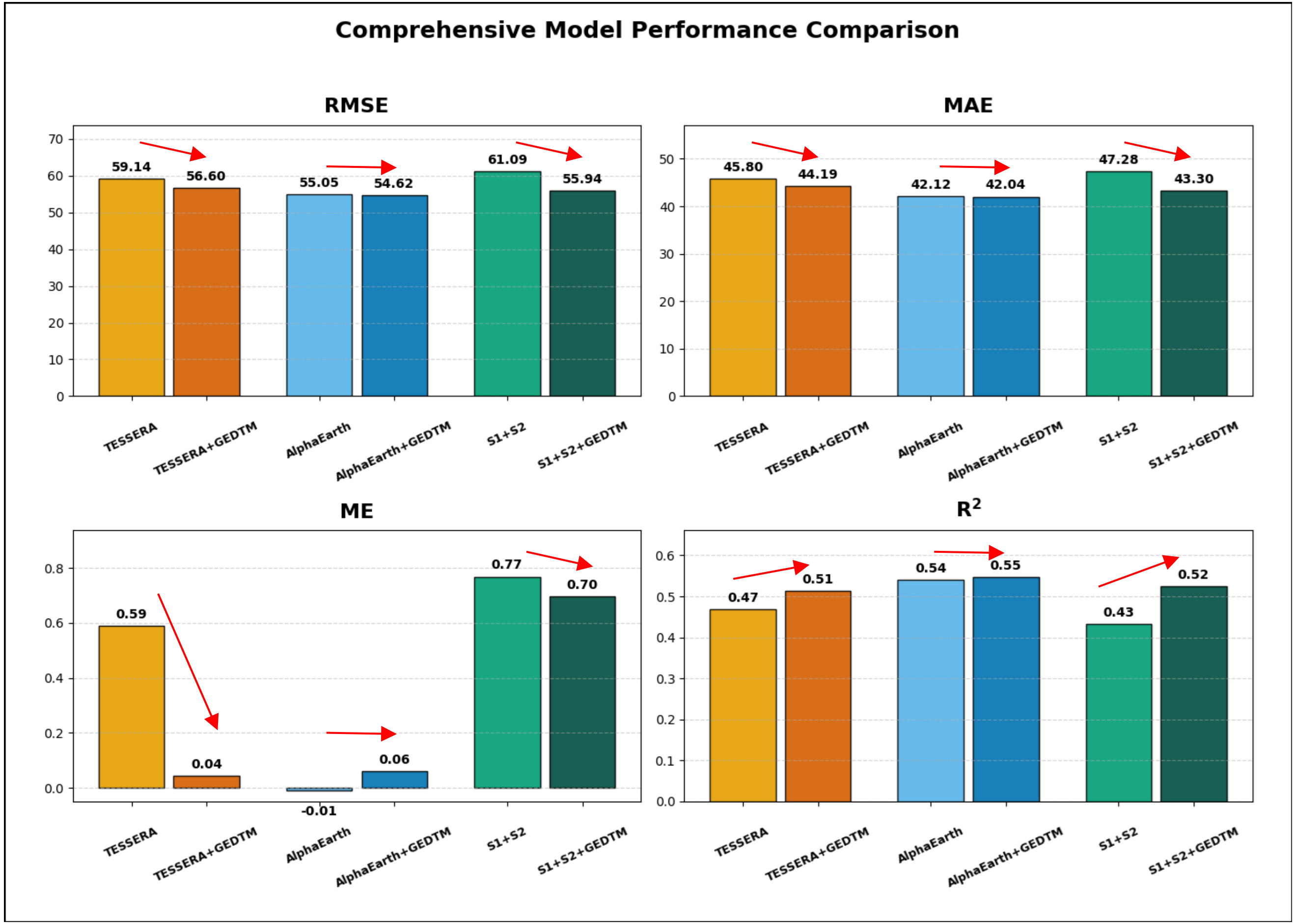


Result - accuracy assement



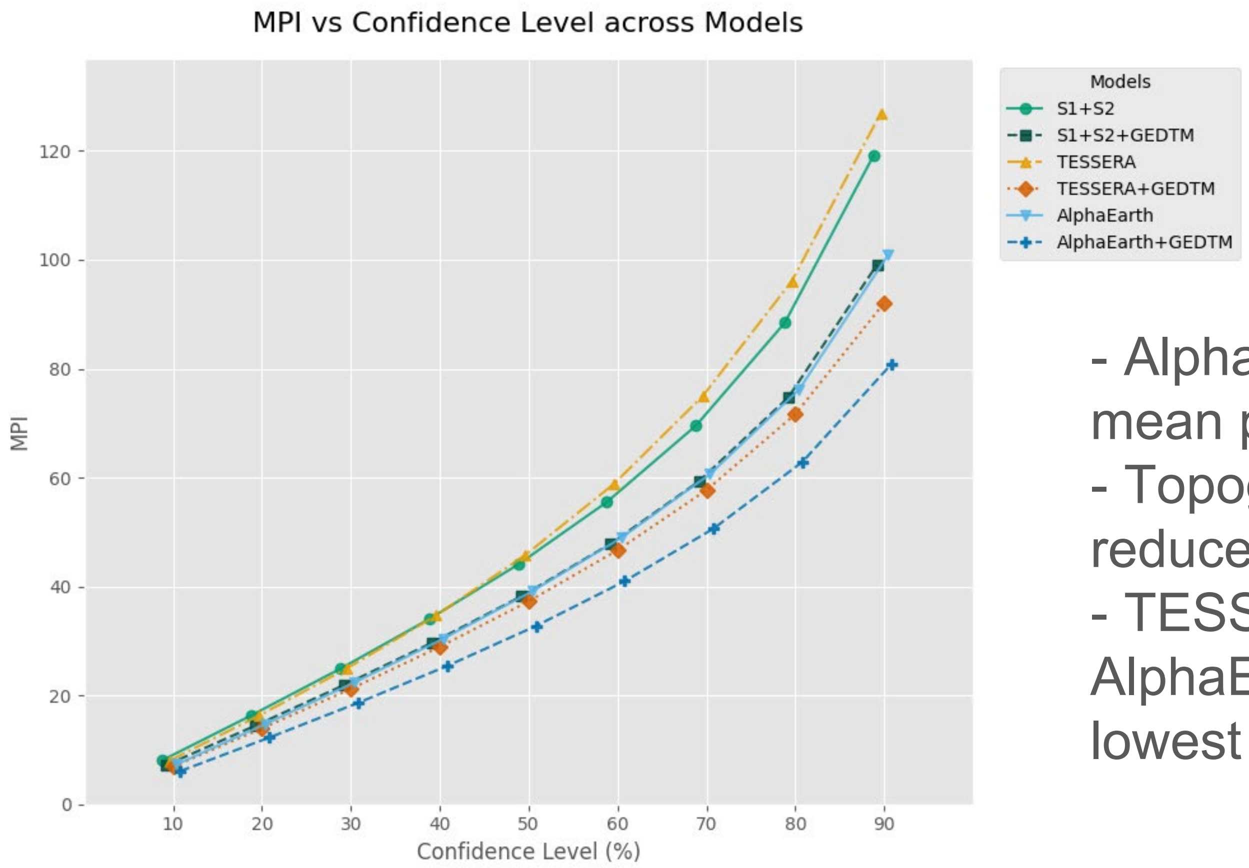
- TESSERA & AlphaEarth performs better than S1+S2
- AlphaEarth performs slightly better than TESSERA

Result - accuracy assement



- Topographic attributes contribute to prediction accuracy
- Except for AlphaEarth

Result - uncertainty assessment



- AlphaEarth has the lower mean prediction interval (MPI)
- Topographic attributes reduces MPI
- TESSERA+GEDTM & AlphaEarth+GEDTM has the lowest MPI

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Discussion and Conclusion

- EO embedding has **comparable** model performance to baseline Sentinel-1/2 model.
- Topographic attributes improve both **prediction accuracy** and **uncertainty**, except for AlphaEarth's point estimate accuracy.
- AlphaEarth integrates GEDI and COPDEM in training modeling. The self-supervised learning model has learnt the topographic attributes.
- More probablisitc deep learning model should be included in this benchmark (e.g. Bayesian Neural Network).
- Expansion to **climatic datasets** could reinforce the benefit of additional features.

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Thank you for your attention!

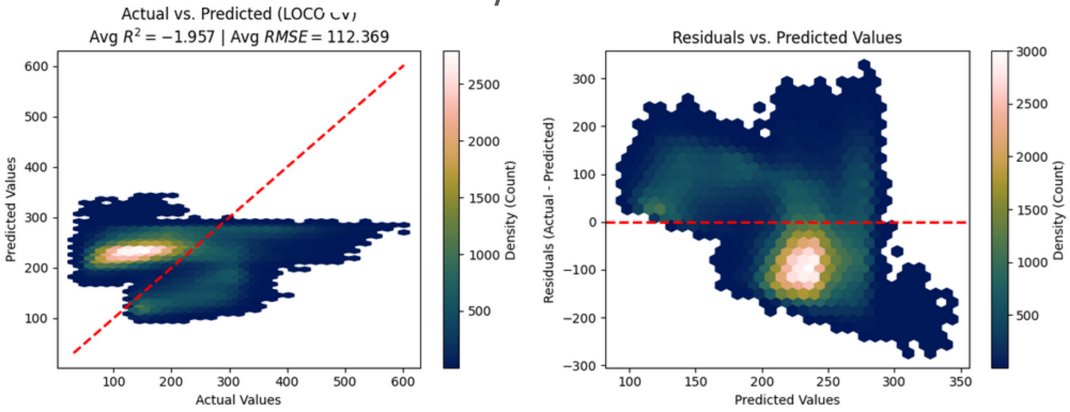
Open Geospatial Carbon Registry

Partnership with...

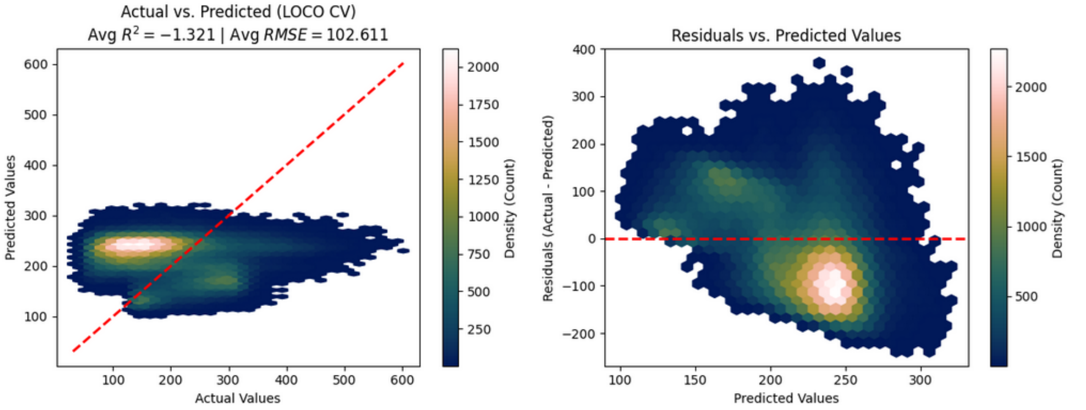
The Intergenerational Open Geospatial Carbon Registry (OGCR). Grant agreement ID: 101218854.

Can we do pan-EU mapping now?

AlphaEarth



TESSERA



Leave-one-country-out (LOCO) was performed. Models were trained on 2 countries and were validated by the third one.

It shows a poor performance, indicates the extrapolation to other countries is currently impossible