



TOWARDS AN INTERGENERATIONAL OPEN GEOSPATIAL CARBON REGISTRY (OGCR)

EO for Monitoring, Reporting, and Verification of Carbon Removals 2025

Copenhagen, Denmark

9th October, 2025



This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101218854.





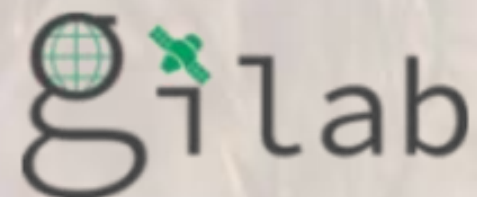
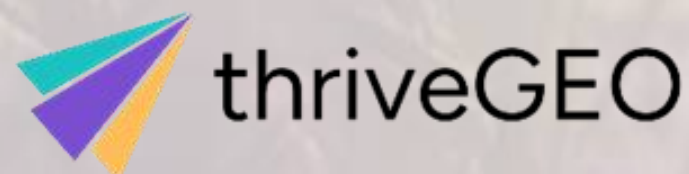
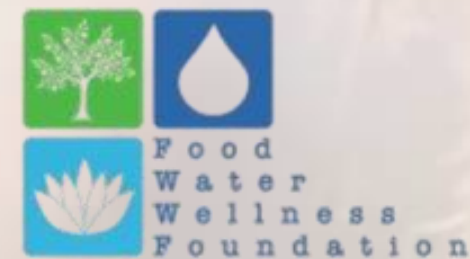
Dr. ICHSANI WHEELER
FOUNDER/RESEARCH COORDINATOR
OGCR PROJECT COORDINATOR

Summer Schools 2007 → OpenGeoHub Foundation



- 15+ summer schools
- 20+ tailored trainings
- 10+ hackathons
- 1000+ hours of teaching & video archive
- 3000+ students

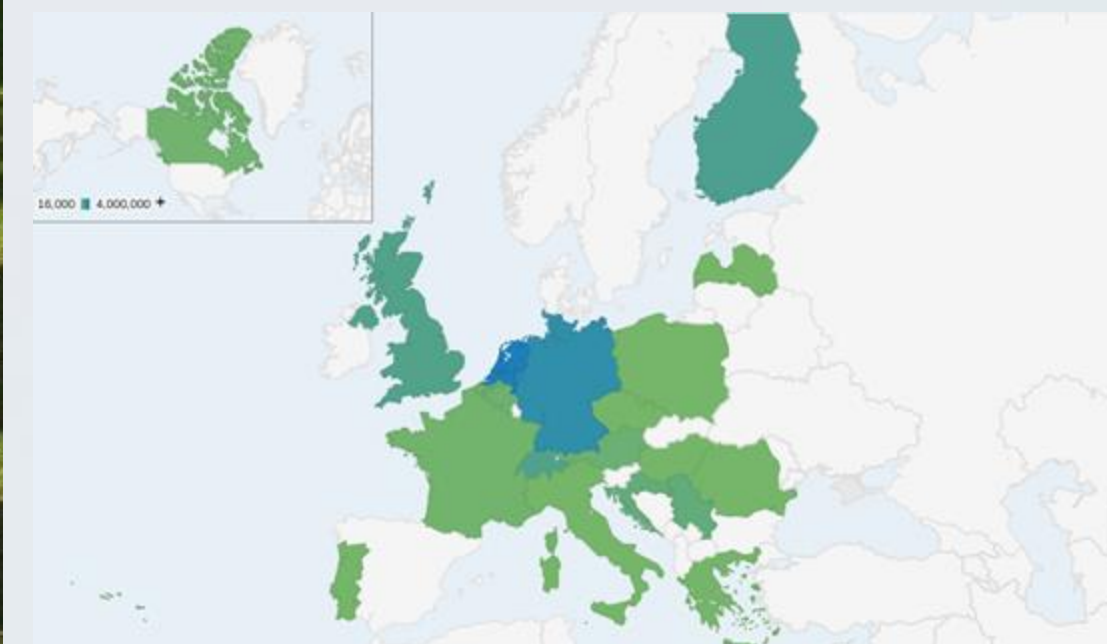
OGCR Project partners



Project consortium



20 partners
11 associated



OGCR in a nutshell → Three working areas

1



Carbon Farming

2



Carbon Products

3



~~Permanent Carbon~~
Centennial
Removals

OGCR in a nutshell → Participatory Tier 3 (all land)



1

To provide a low-cost / easy access system, which connects the 9.1m farmers & forest managers

2

To build an open-source, FAIR & CARE-compliant MRV ecosystem from parcel to continental scale

3

To provide unified frameworks for all major carbon farming categories, with uncertainty calculations, to standardise carbon removals / reductions

4

To support a just transition for rural communities promoting environmental integrity, social fairness, and economic viability

OGCR in a nutshell → Participatory Tier 3 (all land)

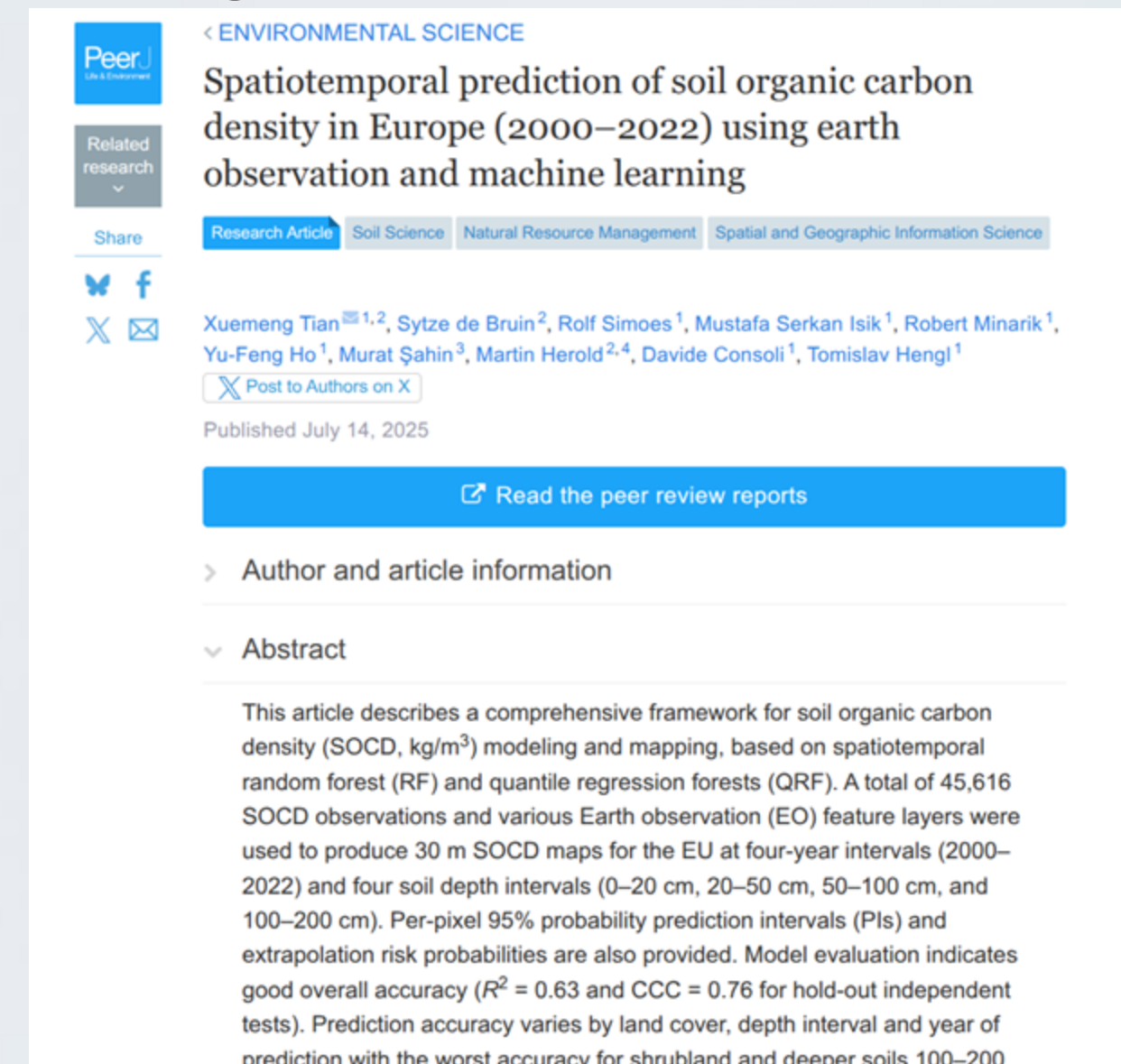


→ Build robust, open-source geospatial data infrastructure using **participatory monitoring**, remote sensing, new AI & hybrid ML methods & blockchain technology

→ We recently produced spacetime (2-year) predictions of SOC for pan-EU (0–20 cm, 20–50 cm and 50–100 cm) with uncertainty (for the needs of the [AI4SoilHealth.eu](https://www.ai4soilhealth.eu) project)

→ The results were promising, although uncertainty is much wider than for the above ground biomass estimates

→ Data was made available via Zenodo, [EcoDataCube.eu](https://www.ecodatacube.eu) + the code is available via [Github.com](https://github.com)



Funded by
the European Union

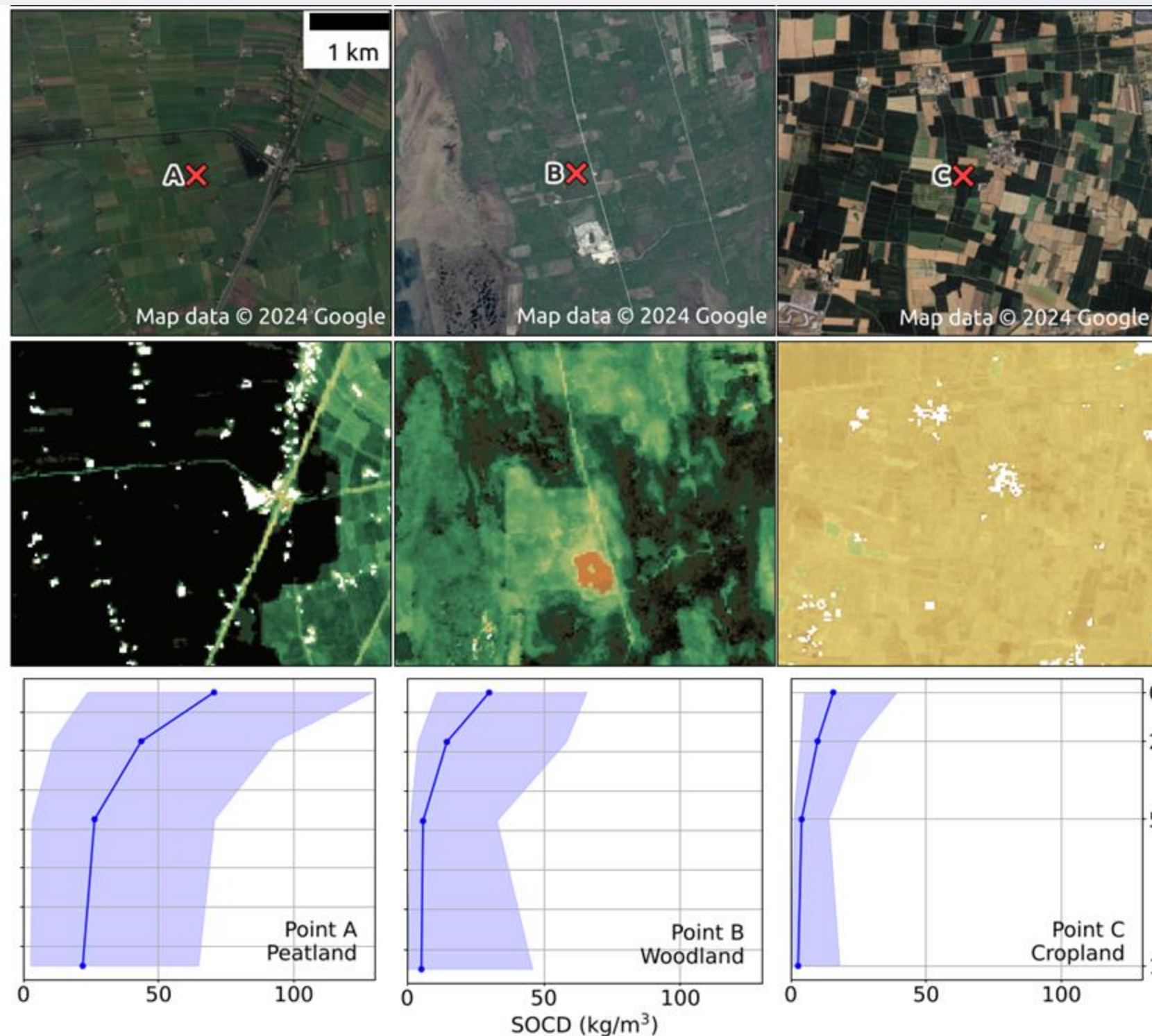
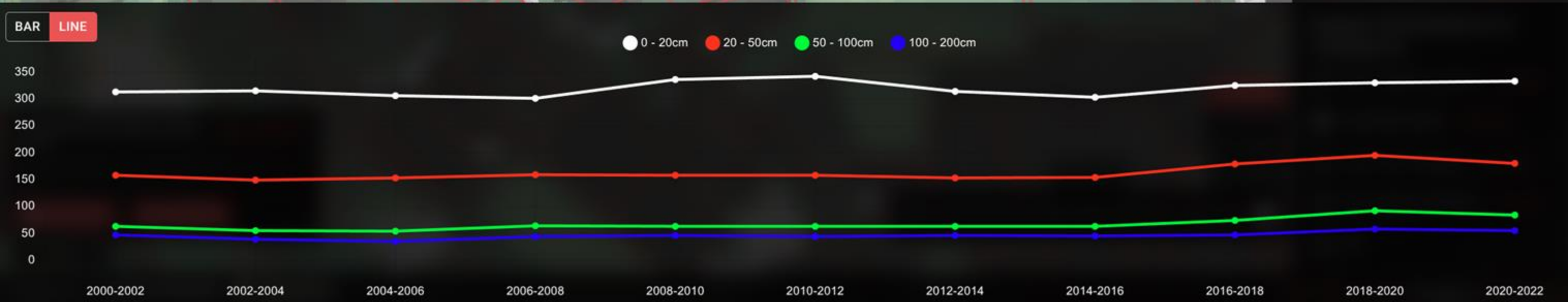


Figure 14 SOCD predictions for the topsoil (0–20 cm) across continental Europe from 2020 to 2022 (available at <https://doi.org/10.5281/zenodo.13754343>). The top row presents an overview of the predictions (middle), including the upper bound (P0.975 at left) and lower bound (P0.025 at right). The middle two rows provide zoomed-in SOCD predictions and corresponding satellite images for the same period at three specific locations: (A) a peatland site in the Netherlands (lon: 6.177, lat:52.583), (B) a woodland area in Finland (lon: 22.531, lat: 62.351), and (C) a cropland site in Italy (lon: 10.339, lat: 45.101). The bottom row illustrates the variation of SOCD predictions with depth at these three points, with the pale blue shading indicating the corresponding PI. Google Maps (2024, CNES/Airbus, Maxar Technologies), available through <https://www.google.com/maps/>, last accessed: 30 August 2024.

Full-size  DOI: [10.7717/peerj.19605/fig-14](https://doi.org/10.7717/peerj.19605/fig-14)

- Can we use these estimates to detect changes? What if the uncertainty of estimates is much wider than actual difference?
- There are obvious limits to using EO data for soil carbon mapping.
- How many years do we have to wait until the change in carbon is “detectable”?
- How can we reduce local uncertainty

Planet Lab 51m parcels → cadastral/legal parcels



Global SOC → monitoring challenges common



Earth System Science Data

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Preprint

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Abstract Assets Discussion Metrics

24 Jun 2025



Status: this preprint is currently under review for the journal ESSD.

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

Tomislav Hengl, Davide Consoli ✉, Xuemeng Tian, Travis W. Nauman, Madlene Nussbaum, Mustafa Serkan Isik, Leandro Parente, Yu-Feng Ho, Rolf Simoes, Surya Gupta, Alessandro Samuel-Rosa, Taciara Zborowski Horst, José Lucas Safanelli, and Nancy Harris

Abstract. There is increasing interest in global dynamic soil information with changes in soil properties mapped over time and at high spatial resolution. Thanks to long-term, multi-temporal, and fine- and medium-resolution satellite missions such as Landsat, MODIS, Copernicus Sentinel and similar, it is possible to produce globally consistent predictions of key soil variables that match other 10–30 m spatial resolution global data sets. This paper describes data preparation, modeling, and production of OpenLandMap-soildb: global dynamic predictions of soil organic carbon content, soil organic carbon density, bulk density, soil pH in H₂O, soil texture fractions (clay, sand and silt) and USDA subgroup soil types (USDA soil taxonomy subgroups) at 30 m spatial resolution based on spatiotemporal Machine Learning (Quantile Regression Random Forest with output predictions showing the mean plus the lower and upper prediction intervals of 68 % probability). To train the models, a large compilation of soil samples imported from legacy soil projects was used: 216,000 soil samples with soil carbon density (kg m⁻³), 408,000 soil samples with soil carbon content (g kg⁻¹), 272,000 samples with soil pH in H₂O, 363,000 samples with clay, silt, and sand (%), and 134,000 samples with bulk density oven dry (t m⁻³). Soil carbon and soil pH were mapped with 5 year time-intervals; soil texture fractions, bulk

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Short summary

We used satellite data and thousands of soil samples to create detailed global maps showing how...
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Carbon
Lab



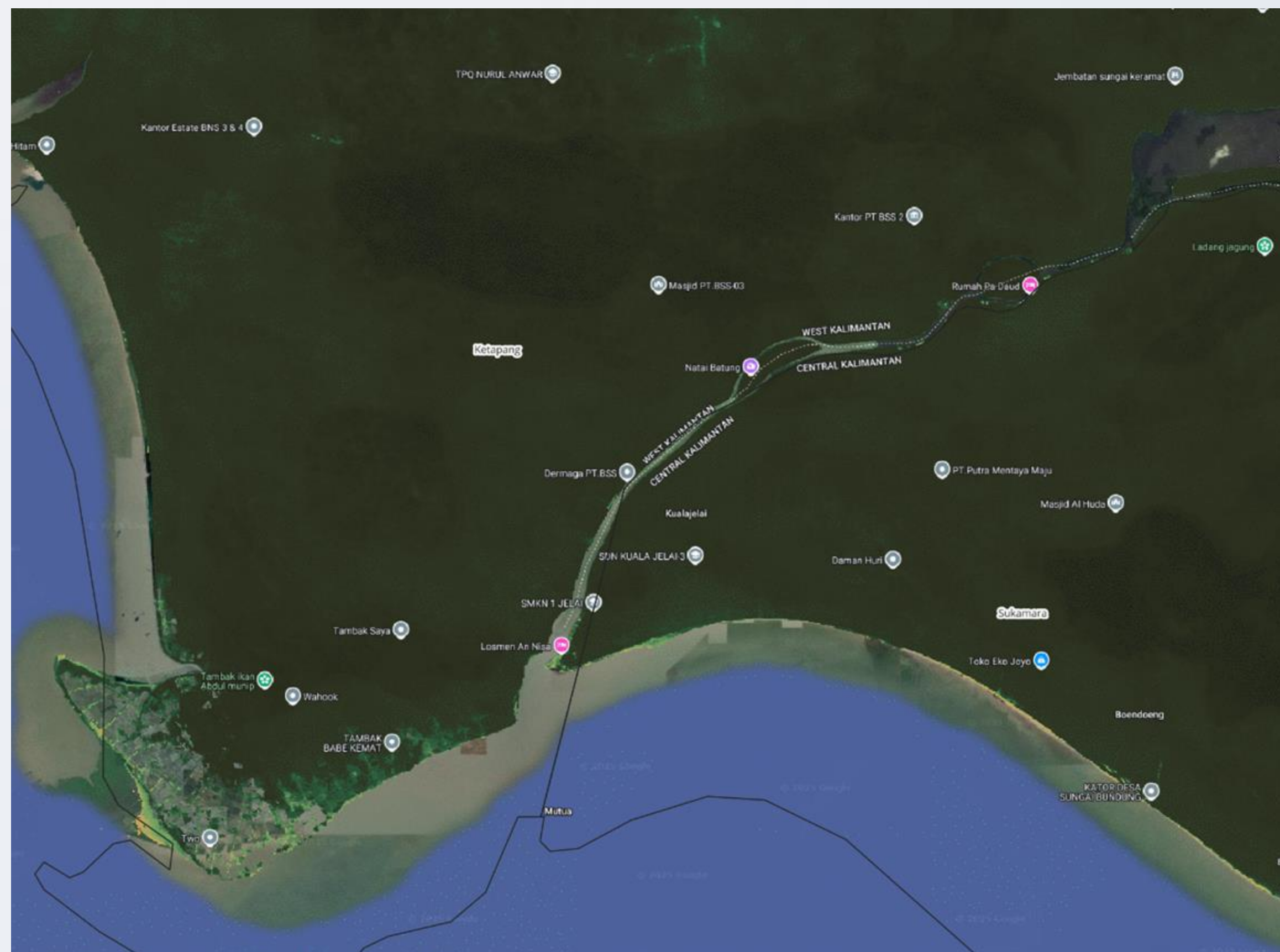
WORLD
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<https://doi.org/10.5194/essd-2025-336>

Global SOC → LULUCF is visible



- Example from Kalimantan (Indonesia)
- Deforestation of tropical forests clearly leads to a loss in SOC
- Land degradation comes also with a loss of SOC / loss of soil health



Global SOC → LULUCF challenges common

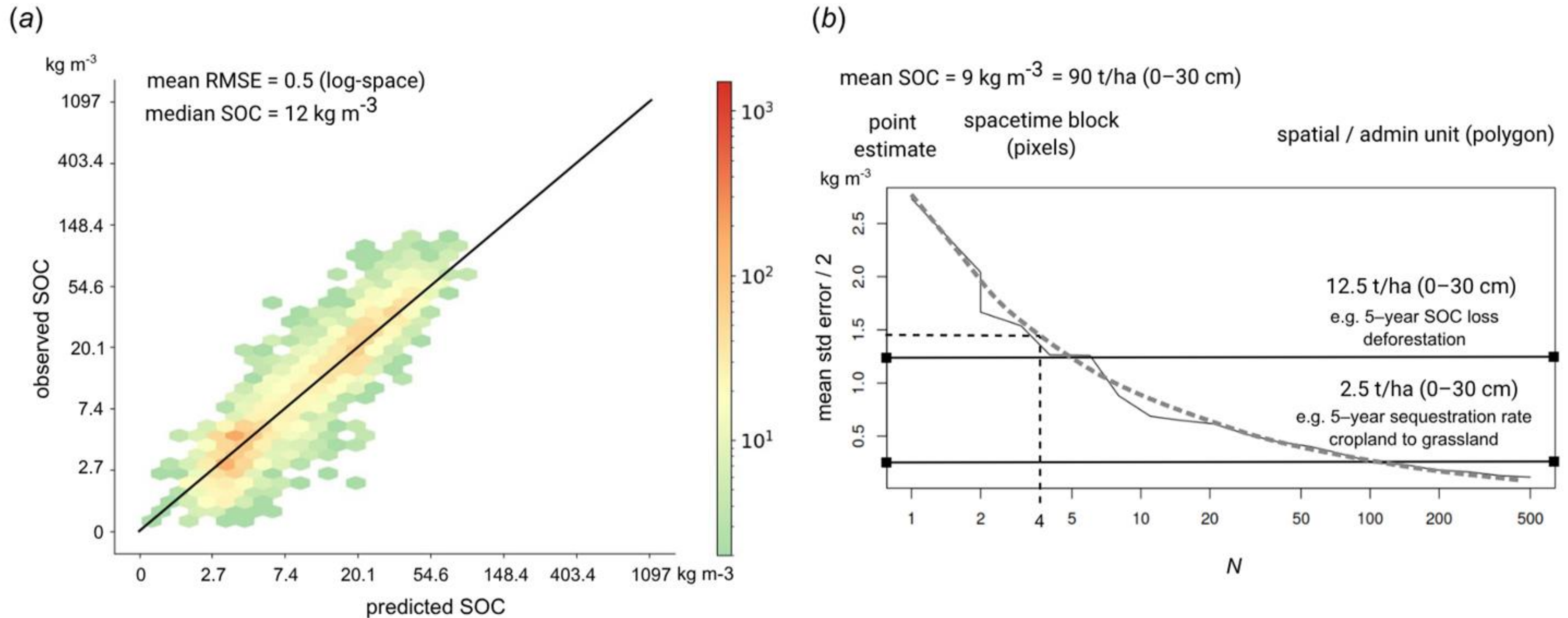


Figure 21. Simulated example of how SOC density prediction errors estimated through validation (a) relate to detection limits for different SOC sequestration / SOC loss rates (b).

Global SOC → LULUCF with local updating

Initial + sampling



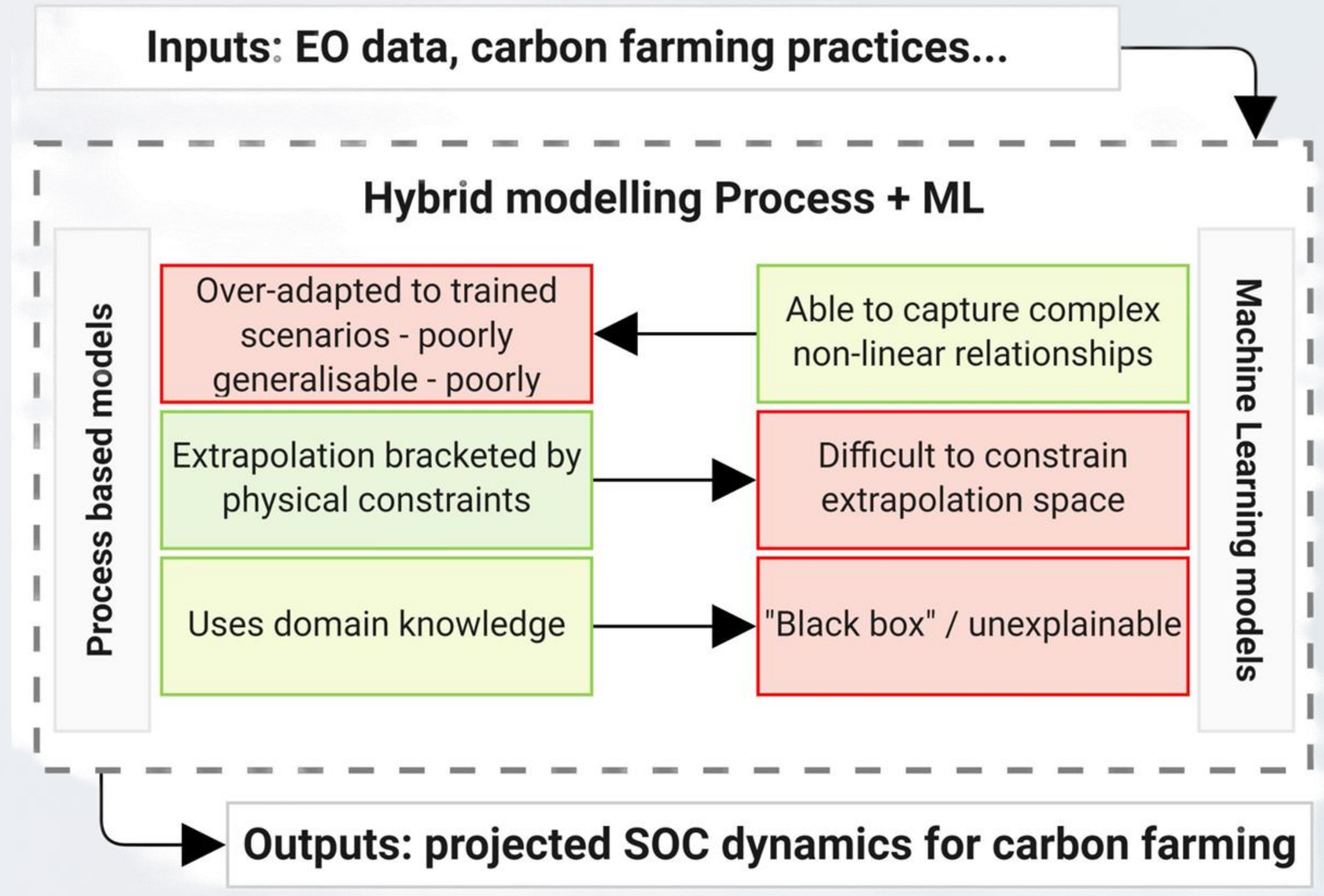
Updated (local)



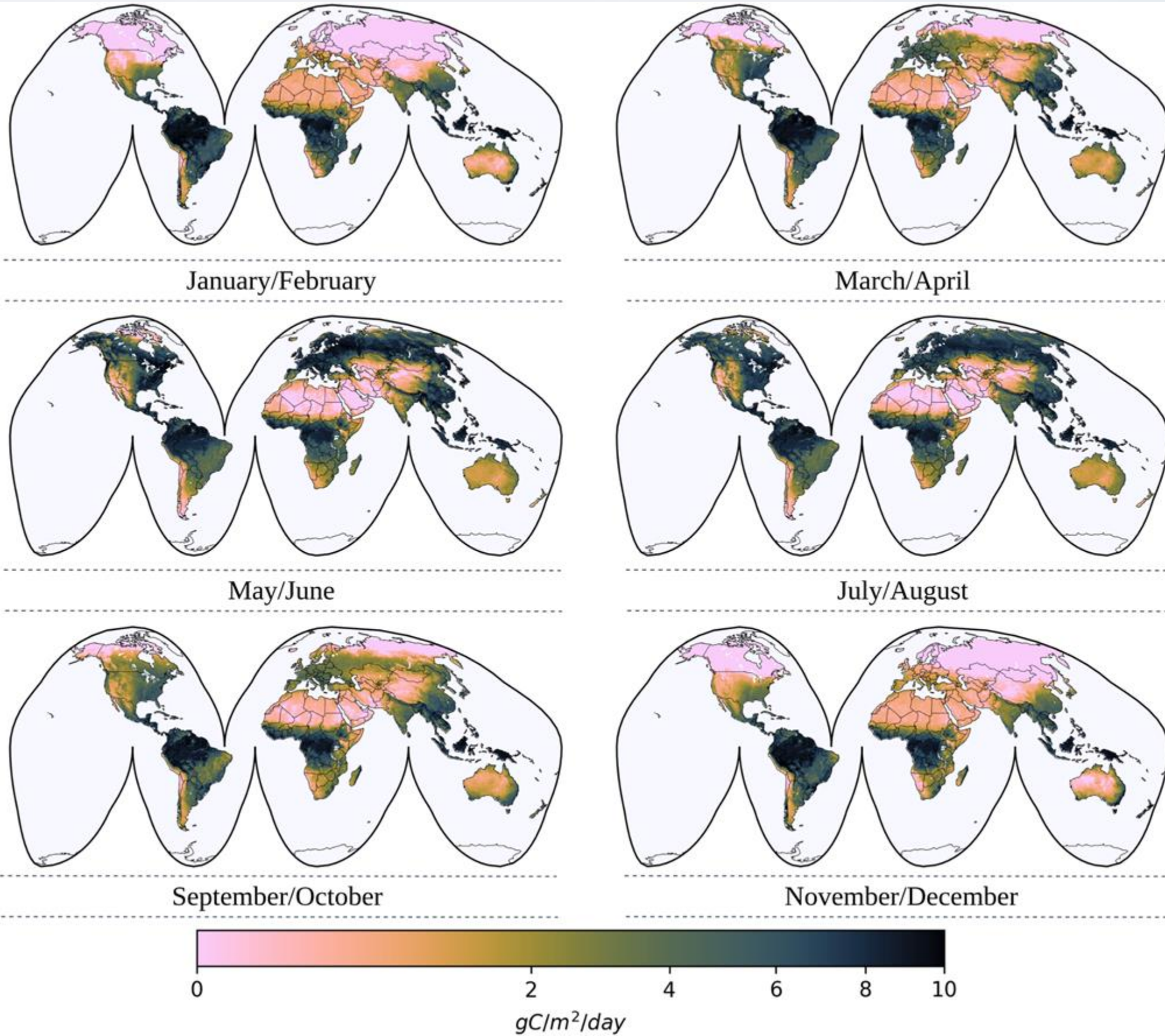
1. Initial predictions g/kg (global)
2. Generate a sampling design using uncertainty of the global predictions
3. Do field work and sample SOC (e.g. 20 locations)

4. Add new samples and re-run global models (**re-analysis**)
5. Update and share predictions (uncertainty for specific farm much smaller)

ML Data driven vs process models → HYBRID:)



ML Data driven vs process models → HYBRID:)



Related research

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Light use efficiency (LUE) based bimonthly gross primary productivity (GPP) for global grasslands at 30 m spatial resolution (2000–2022)

Data report/analysis Ecosystem Science Natural Resource Management Environmental Impacts

Spatial and Geographic Information Science

Mustafa Serkan Isik¹, Leandro Parente¹, Davide Consoli¹, Lindsey Sloat², Vinicius Vieira Mesquita³, Laerte Guimaraes Ferreira³, Simone Sabbatini⁴, Radost Stanimirova², Nathalia Monteiro Teles³, Nathaniel Robinson⁵, Ciniro Costa Junior⁶, Tomislav Hengl¹ [Post to Authors on X](#)

Published August 12, 2025

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> Author and article information

Abstract

The article describes production of a high spatial resolution (30 m) bimonthly



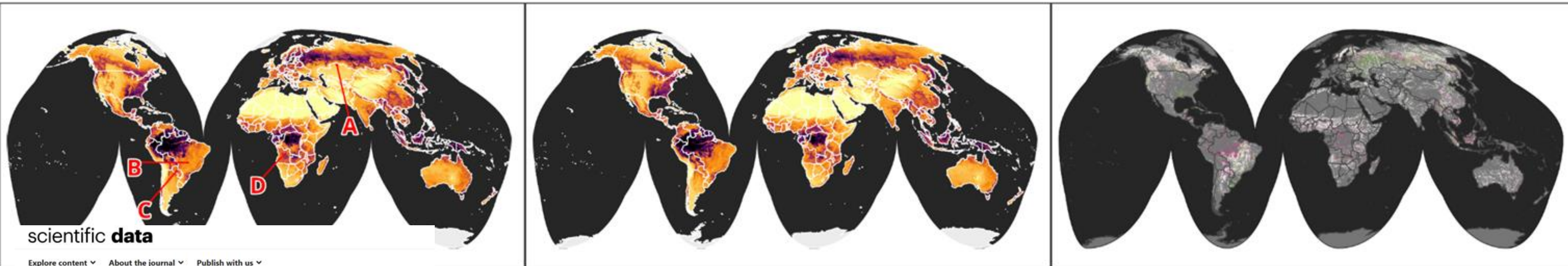
Structure monitoring → + local lidar surveys



2000

2022

Trend map



scientific data

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nature > scientific data > data descriptors > article

Data Descriptor | Open access | Published: 23 August 2025

Global 30-m annual median vegetation height maps (2000–2022) based on ICESat-2 data and Machine Learning

Maria O. Hunter, Leandro Parente, Yu-feng Ho, Carmelo Bonannella, Laerte Guimarães Ferreira, Douglas Morton, Davide Consoli & Lindsey Sloat

Scientific Data 12, Article number: 1470 (2025) | Cite this article

4047 Accesses | 6 Altmetric | Metrics

Abstract

Accurately measuring vegetation height is essential for understanding ecosystem structure, carbon storage, and biodiversity, yet global height models have overwhelmingly focused on forests, excluding ecosystems with shorter herbaceous vegetation or shrubs. To address this gap in vegetation structure data, we developed the first global estimate of median vegetation height annually from 2000–2022 at 30 m resolution, using ICESat-2 satellite Lidar, Landsat cloud free composites, and other Earth Observation raster data. Thirty two (32) million ICESat-



2016

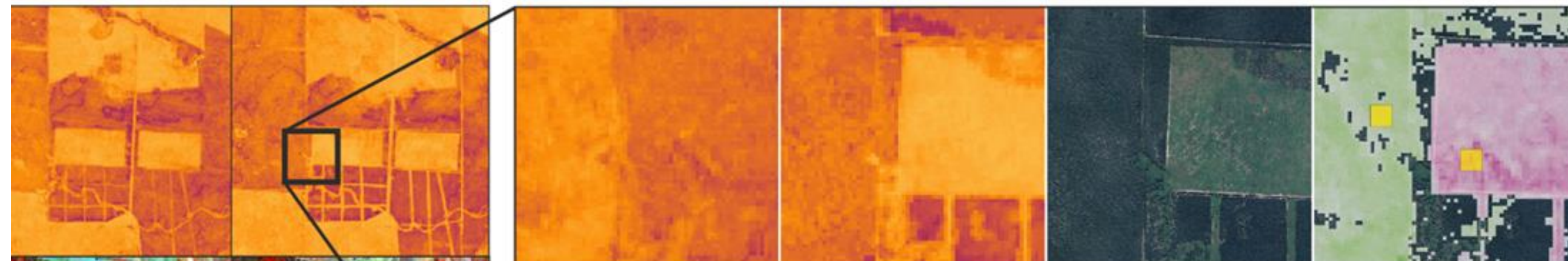
2022

2000

2022

Google Maps

Trend map



Serranópolis, Brazil



Cloud-free reconstructed Landsat long-term trend of min. Normalized Difference Lillage Index (NDTI)

Slope flitted with Theil-Sen estimator on annual minNDTI time series...

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500 m



trend

Opacity (11%)

Imagery (BSF)
Slope flitted with Theil-Sen estimator on annual BSF time series between 2000 and 2022.

Cloud-free reconstructed Landsat long-term trend of min. Normalized Difference Lillage Index (NDTI)

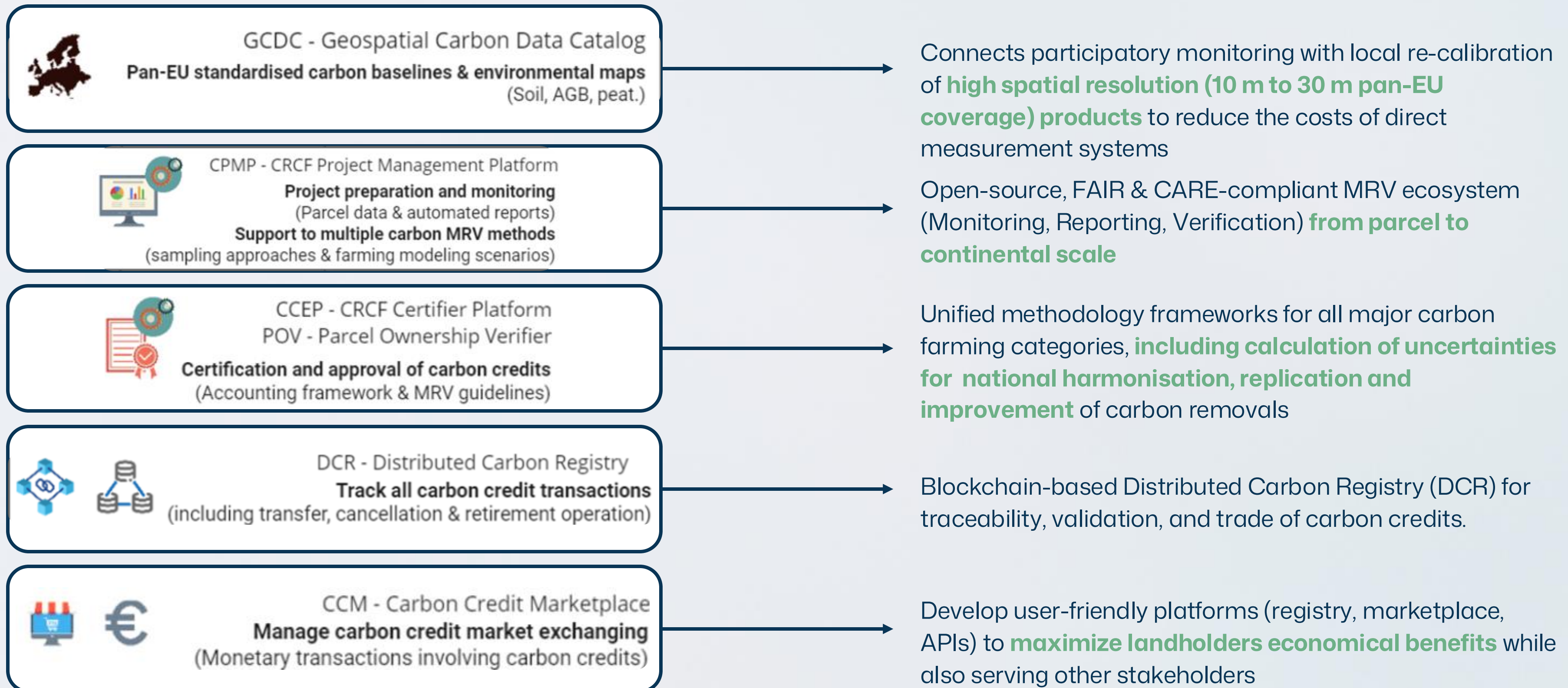
Slope flitted with Theil-Sen estimator on annual minNDTI time series between 2000 and 2022.

Regions, Field Boundaries & Training Data

- NUTS Regions Level-3 [\(Source\)](#)
- Field Boundaries [\(Source\)](#)
- Land Cover Samples [\(Source\)](#)
- Tree Species Samples [\(Source\)](#)
- Off



OGCR geospatial infrastructure → MODULAR:)



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