Global high resolution land fluxes estimate using physics-constrained machine learning

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Water JPI · Water Works 2017 · 2018 JOINT CALL

UNIVERSITY OF TWENTE. ITC

1. Introduction and motivation

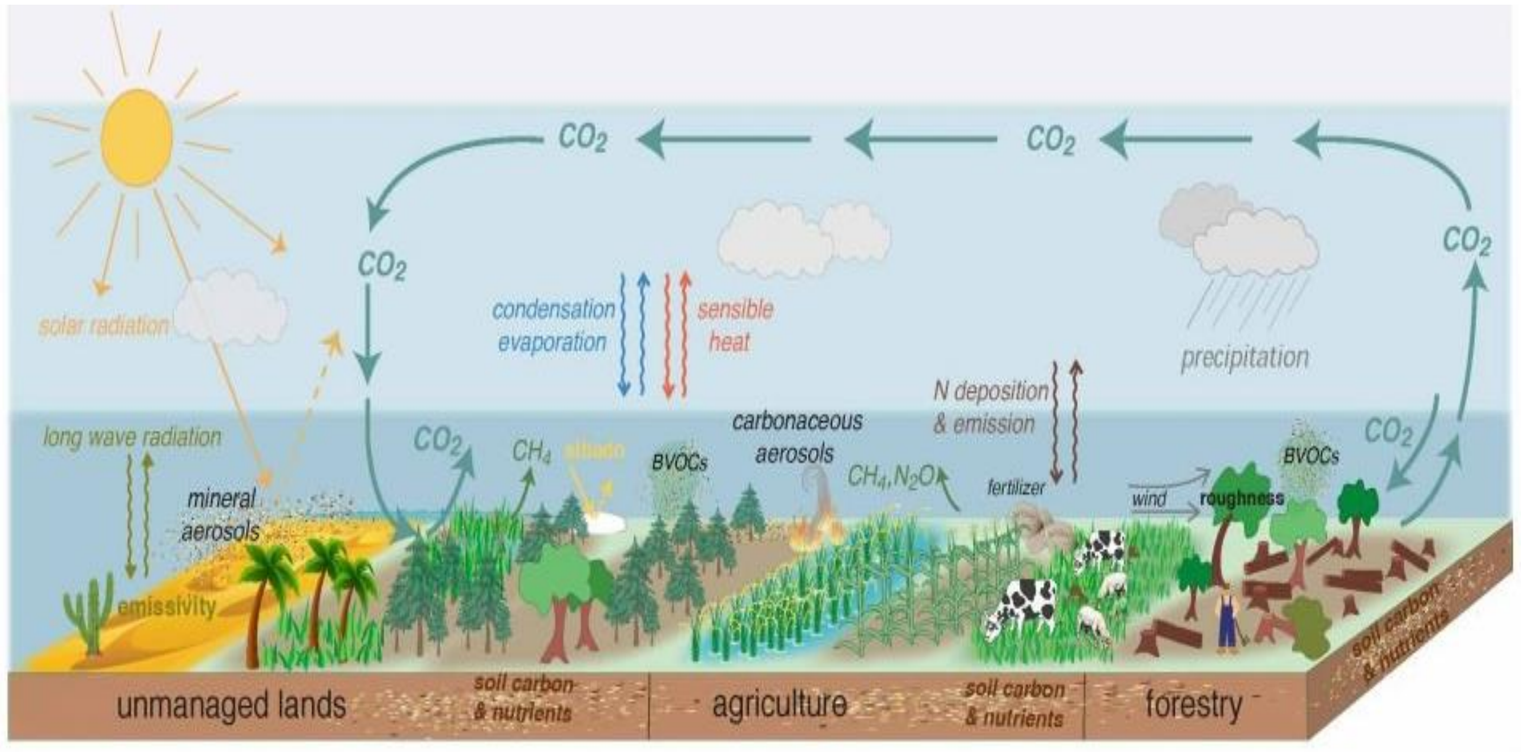


Fig.1. Picture of carbon, water and energy cycle by IPCC in 2019

The dynamic variation of terrestrial water, energy, and carbon fluxes is crucial to understand Earth's climate system and land–atmosphere processes.

- Research questions:

1. What is the highest spatial resolution of fluxes datasets?
2. What is the highest temporal resolution of fluxes dataset?
3. Can we manage to explore the fluxes change based on the existing fluxes datasets?

This study aims to predict high spatial and temporal resolution fluxes at the global scale, with physics-constrained machine learning (ML) algorithms taking into account remote sensing indices, climatological and meteorological data.

2. Main method

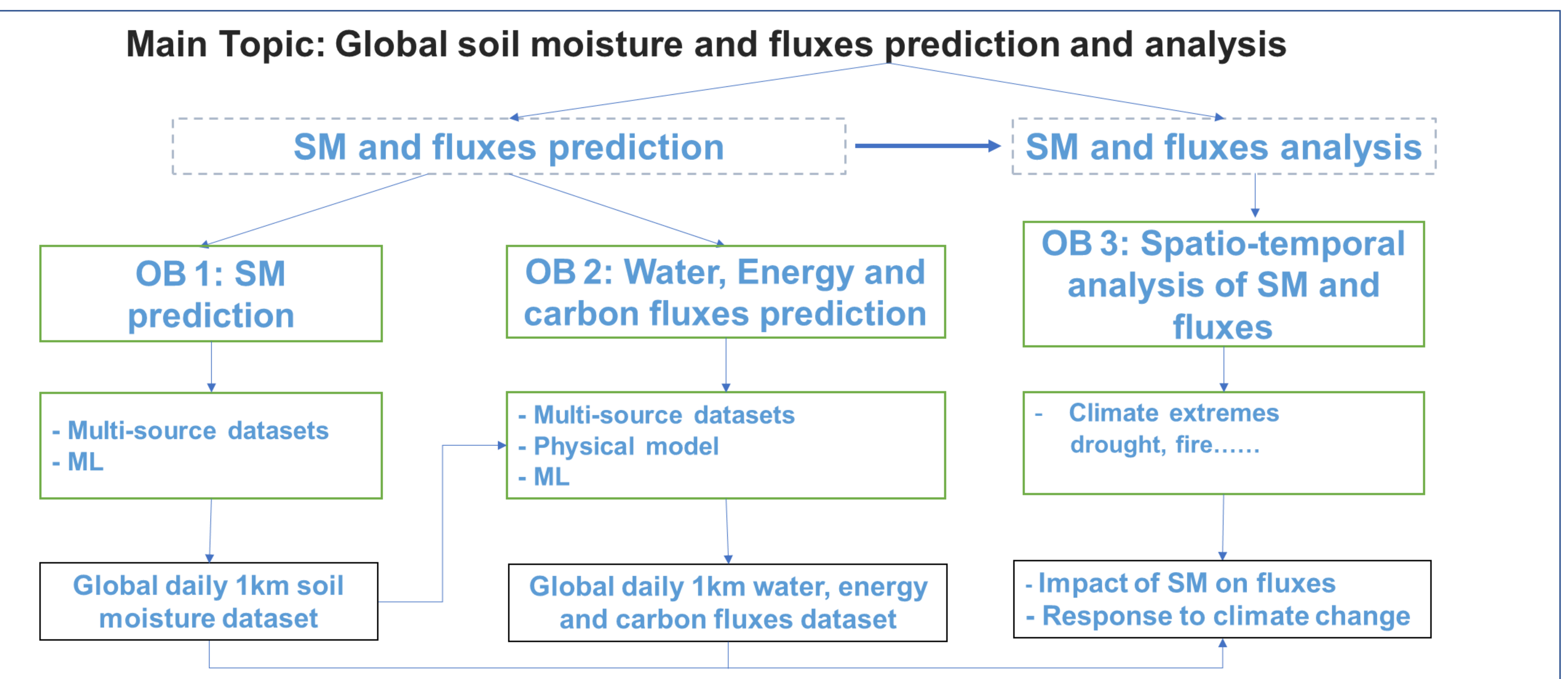


Fig.2. Research framework

The research framework
*OB = Objective; ML= Machine Learning; SM=Soil Moisture

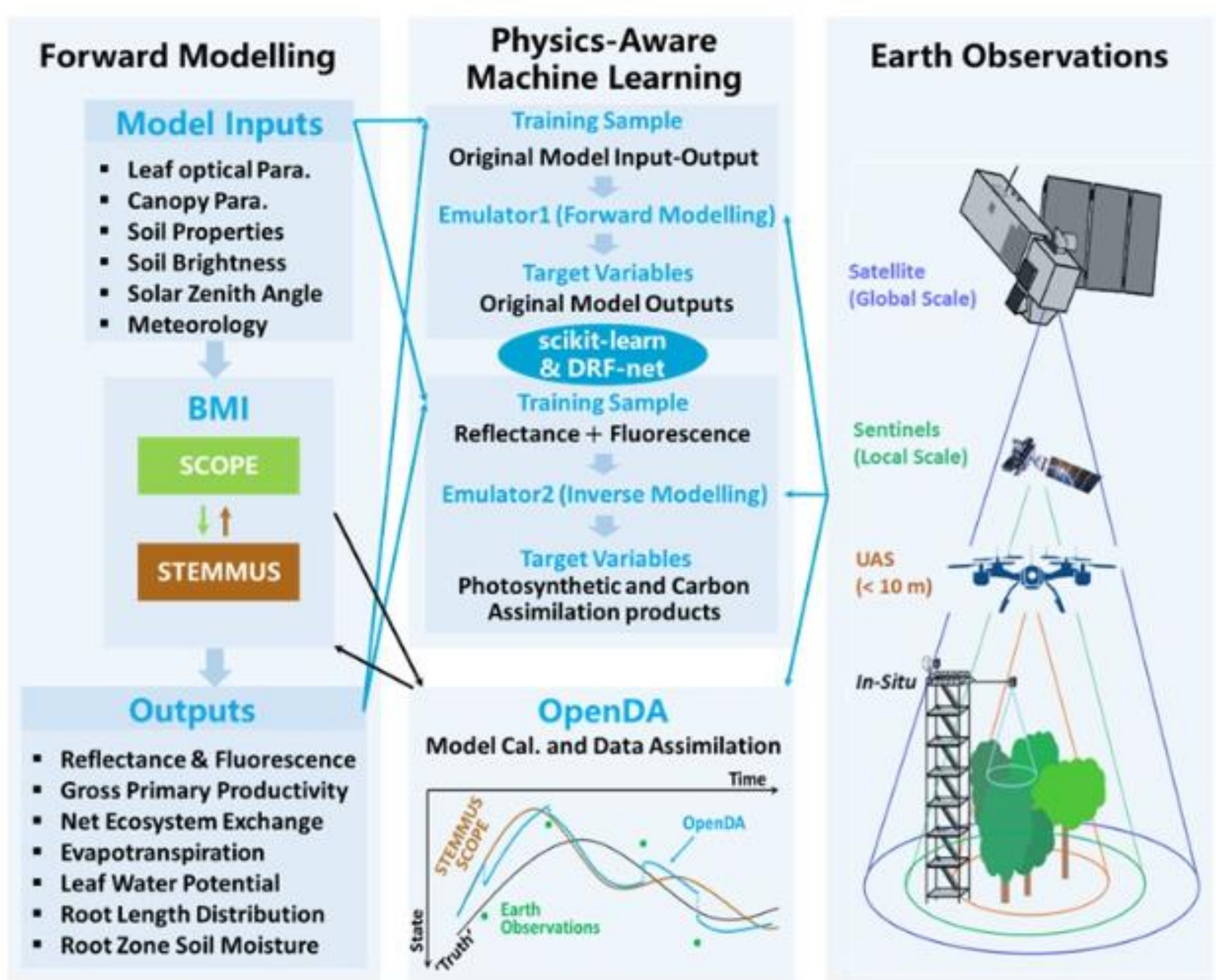


Fig.3. Conceptual Workflow for Developing Emulators with Physics-Informed Machine Learning.

Acknowledgement: The authors would like to thank the European Commission and (Netherlands Organisation for Scientific Research (NWO)) for funding in the frame of the collaborative international consortium (iAqueduct) financed under the 2018 Joint call of the WaterWorks2017 ERA-NET Cofund. This research has been funded by The Netherlands Organisation for Scientific Research (NWO) KIC, WUNDER project (grant no. KICH1. LWV02.20.004).

3. Results

Global Surface Soil Moisture (GSSM1km) provides surface soil moisture (0-5 cm) at 1 km spatial and daily temporal resolution over the period 2000-2020. The performance of the GSSM1km dataset is evaluated with testing and validation datasets, and via inter-comparisons with existing soil moisture products. The root mean square error of GSSM1km in testing set is 0.05 cm^3/cm^3, and correlation coefficient is 0.9.

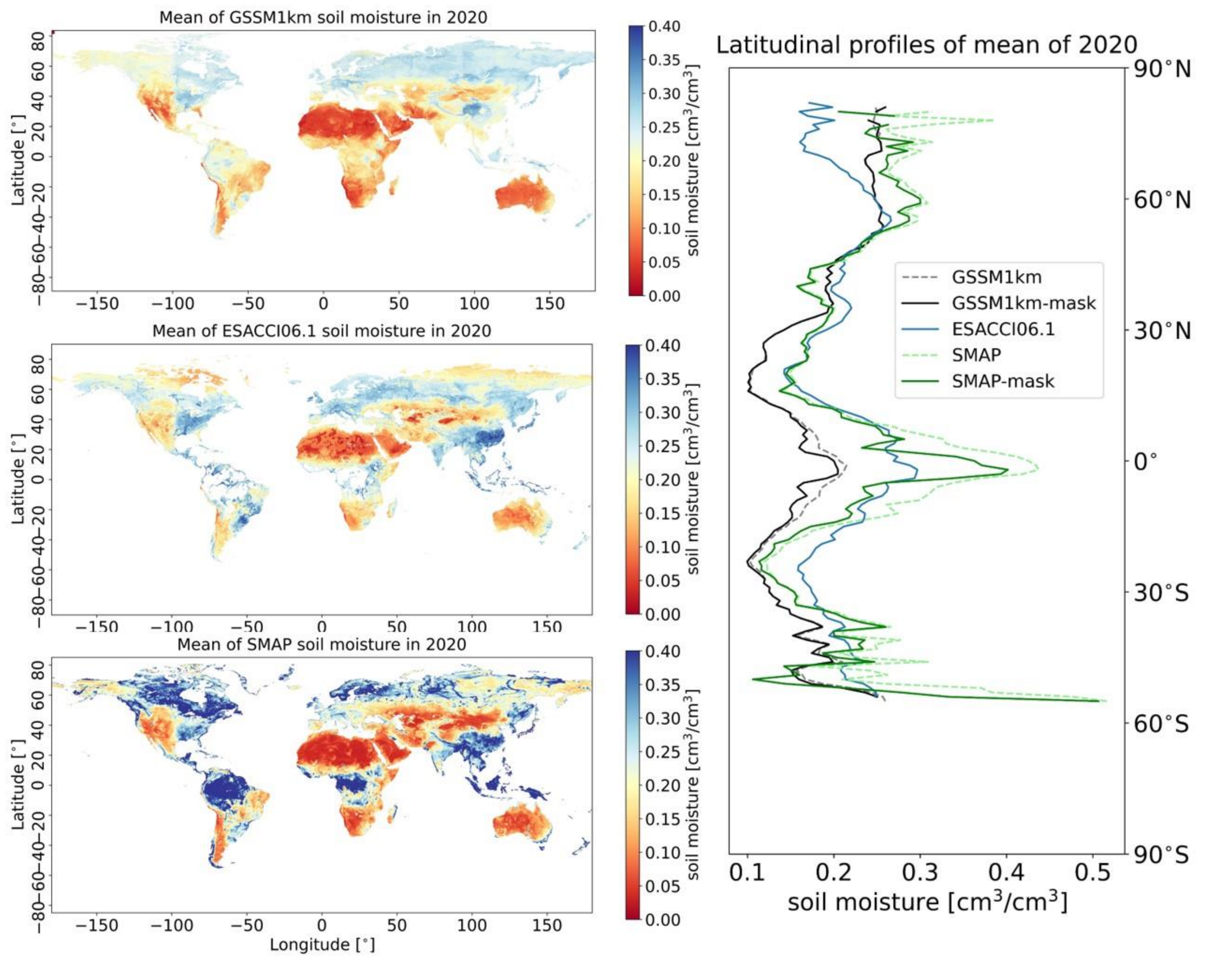
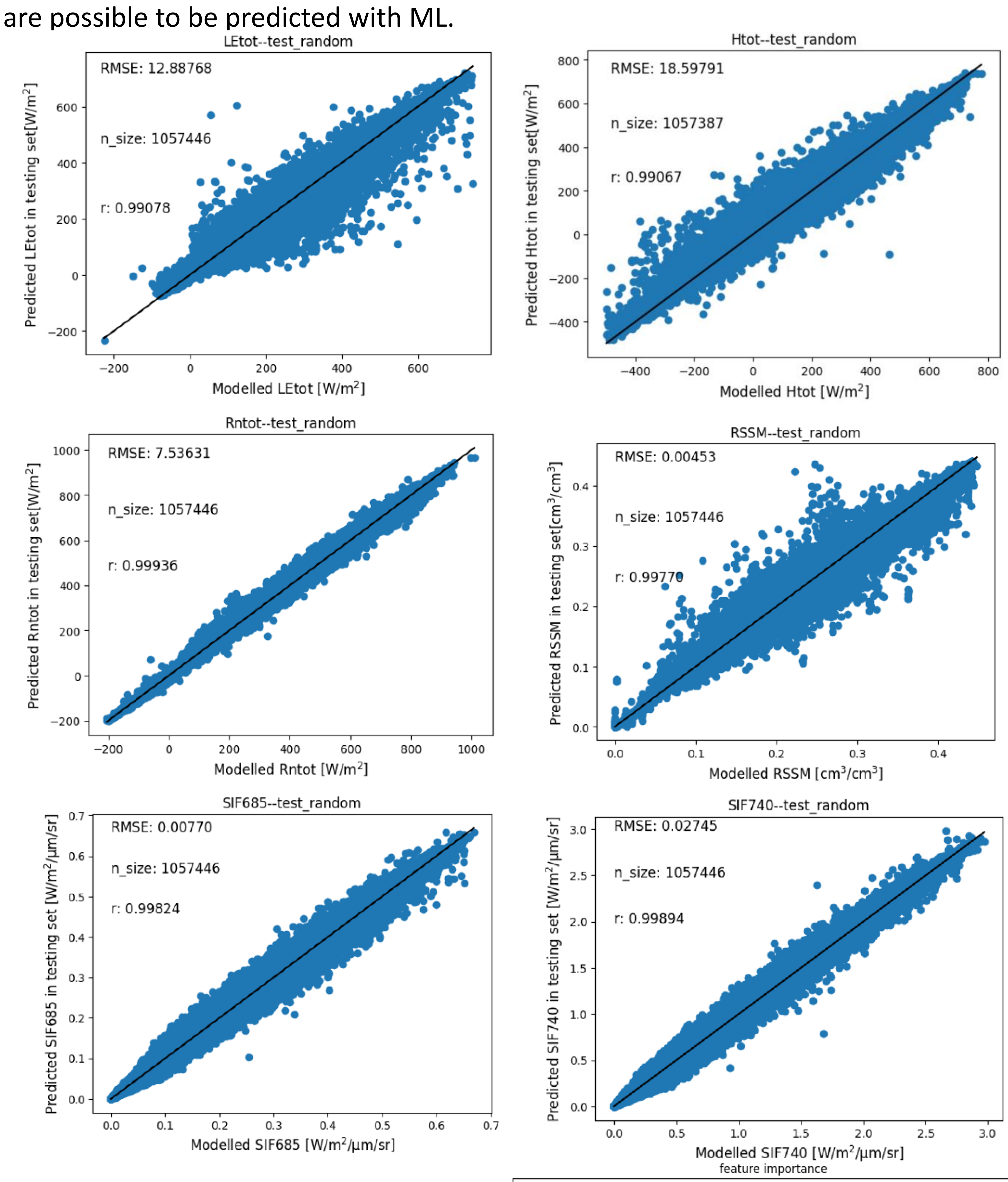


Fig.4. Global mean SSM map of 2020, (a) GSSM1km; (b) ESA-CCI06.1; (c) SMAP. Areas in white means no data. (d) Comparison of latitudinal profiles among GSSM1km, GSSM1km-mask, ESA-CCI06.1, and SMAP, SMAP-mask. ESACCI06.1 is used as a mask for GSSM1km and SMAP because it has missing data.

Based on GSSM1km and STEMMUS-SCOPE model, LE (latent flux) and H (sensible flux) are possible to be predicted with ML.



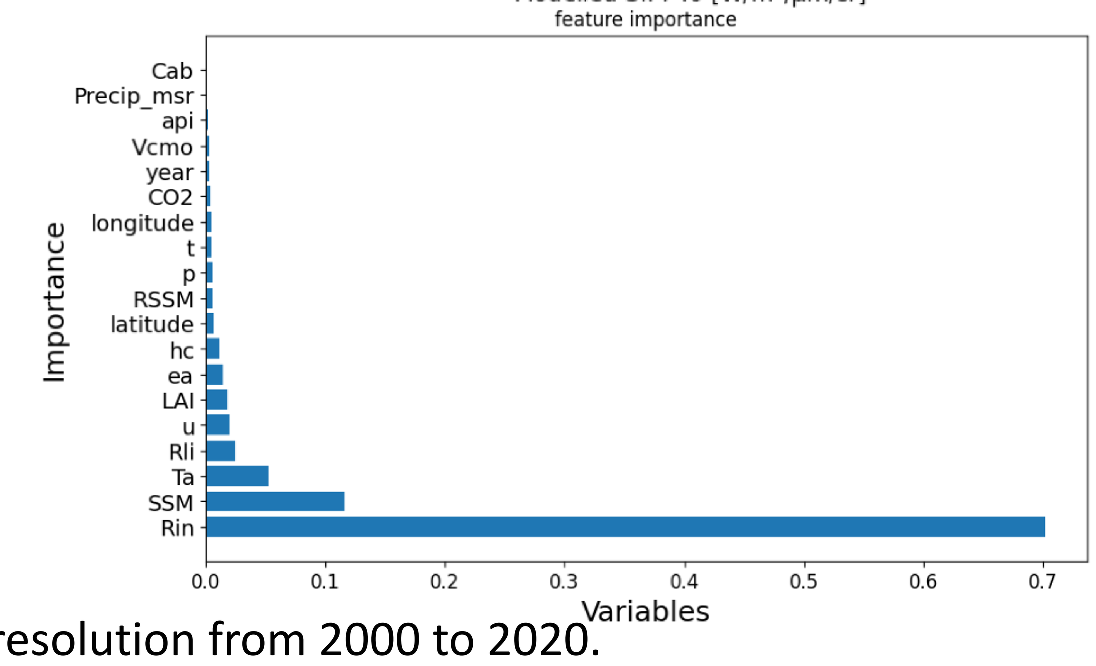


Fig.5. Testing performance and feature importance

Future work:

Predict global fluxes with high resolution from 2000 to 2020.

References

[1] Han, Q., Zeng, Y., Zhang, L., Wang, C., Prikaziuk, E., Niu, Z. and Su, B., 2023. Global long term daily 1 km surface soil moisture dataset with physics informed machine learning. Scientific Data, 10(1), p.101.

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