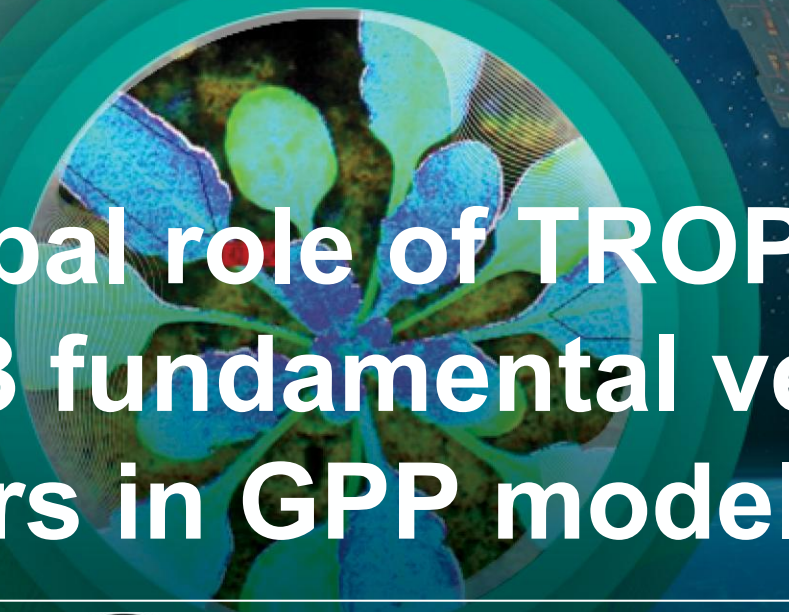
FLEX-Fluorescence 2026 Workshop

03 – 06 March | Bonn University, Germany



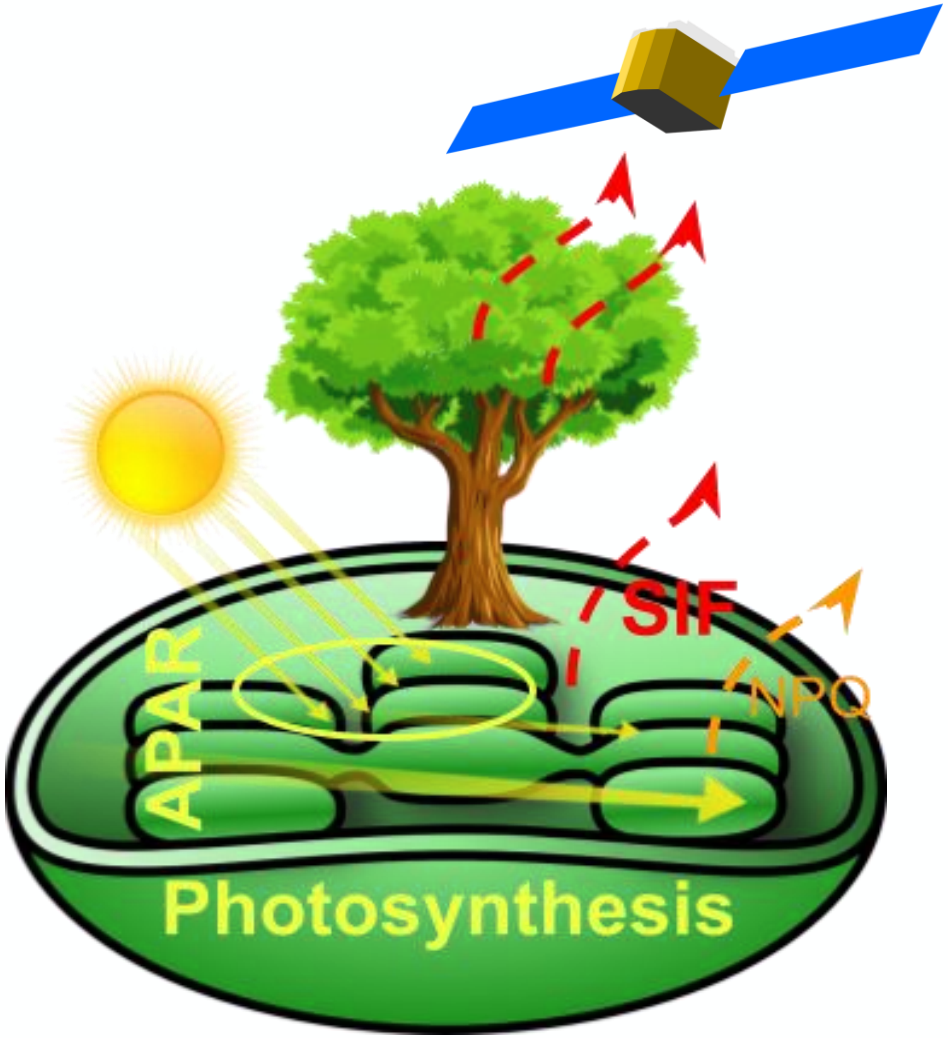
Analyzing the global role of TROPOMI-derived SIF and Sentinel-3 fundamental vegetation traits as proxy predictors in GPP models

Pablo Reyes Muñoz, Dàvid D. Kovacks, Yuxin Zhang, Jochem Verrelst - University of Valencia

Objectives

Interpretation of the link between SIF, GPP and meteorological constraints through satellite-derived products.

- Intercomparison of GPP products driven by diverse inputs, including satellite-SIF and soil meteorological information.
- To analyse the correlation/causality of diverse meteorological constraints on satellite-SIF response at large scale.
- To explore if satellite-SIF along with satellite-canopy variables embeds meteorological information for prediction of GPP



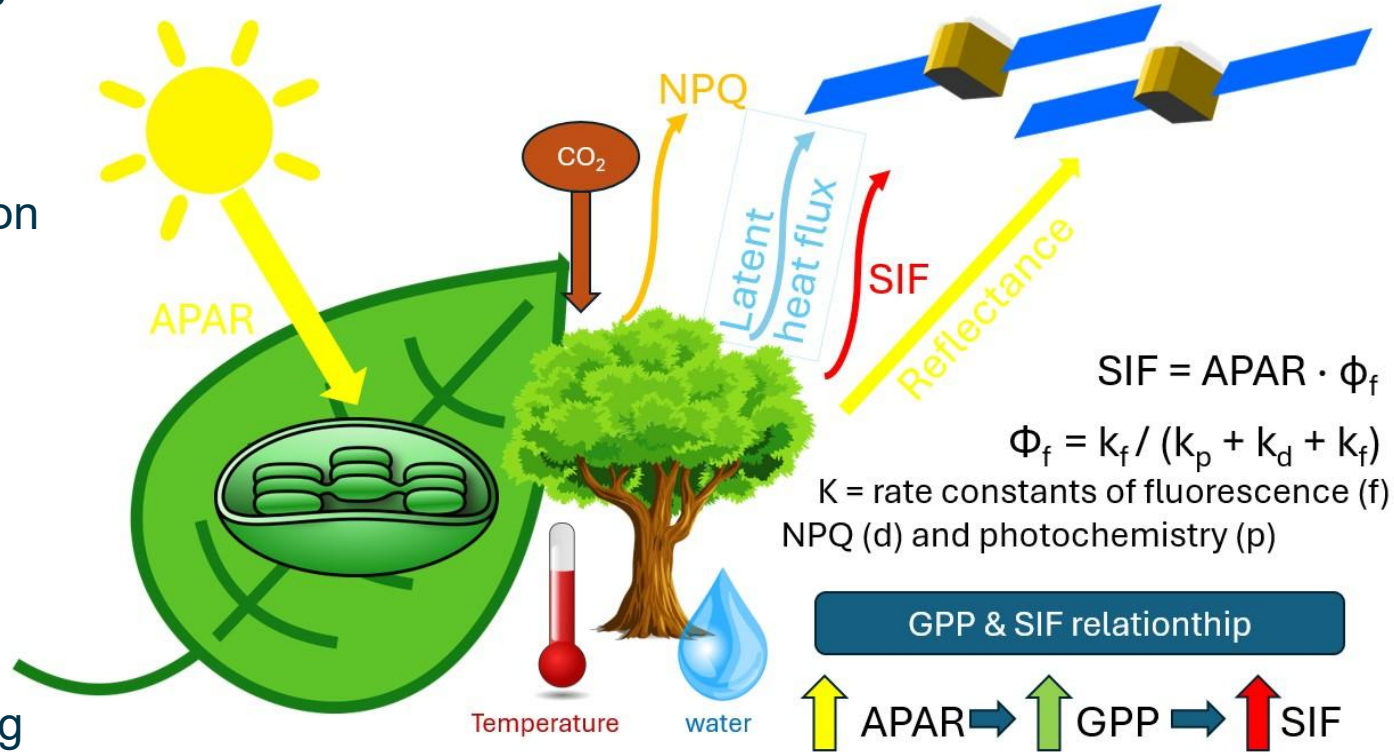
Introduction

- SIF, the most direct measurable indicator of photosynthesis activity from satellite, represents a physiological response (energy regulation).

- At canopy, SIF and GPP have positive correlation with APAR (Absorbed Photosynthetically Active Radiation)

- APAR depends on canopy structural variables: LAI, FAPAR and meteorology (PAR)

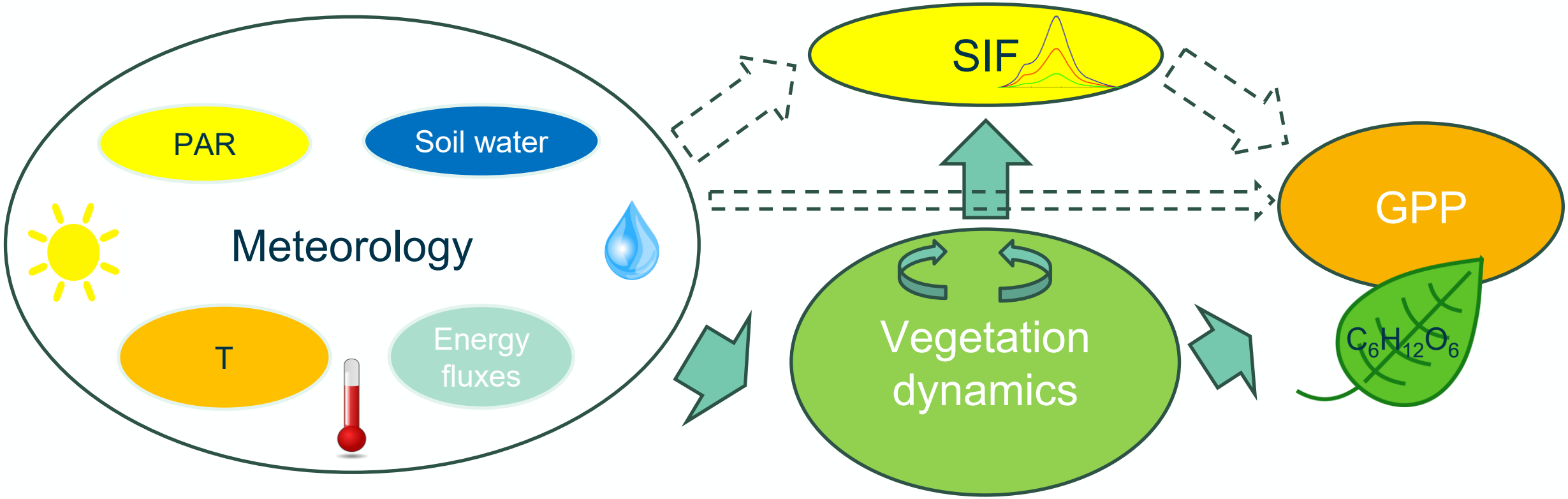
- LAI and FAPAR, derivable from Sentinel-3, flying in tandem with FLEX are crucial therefore for the interpretation of the SIF signal and GPP.



Introduction

Assessing **SIF as a proxy variable for prediction of GPP**

- Meteorology influences vegetation dynamics, including SIF and GPP
- SIF is measureable from satellite and it is correlated with GPP and indirectly controlled by meteorology.



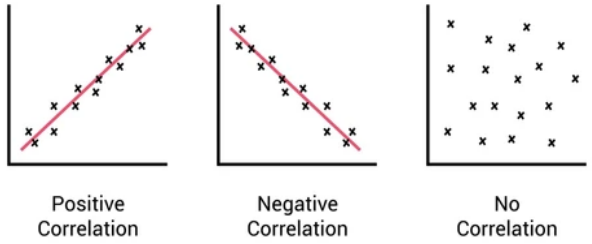
Methods

Analyzing inter-variables relationships:

1) Pearson Correlation: Measures linear co-variation (symmetric):

$$r_{XY} = \frac{\sum_{t=1}^{T}(X_t - \bar{X})(Y_t - \bar{Y})}{\sqrt{\sum_{t=1}^{T}(X_t - \bar{X})^2}\sqrt{\sum_{t=1}^{T}(Y_t - \bar{Y})^2}}$$

$$r_{XY} = \cos(\theta)$$

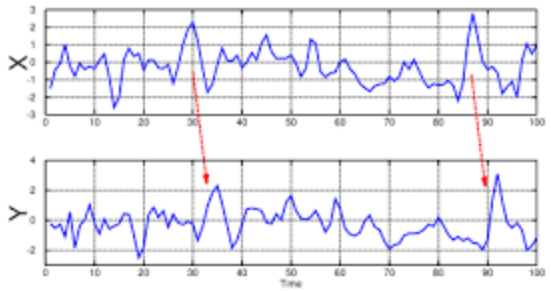


2) Granger Causality: Test prediction information flow (directionality, autoregression).

$$Y_t = \alpha_0 + \sum_{i=1}^{p}\alpha_i Y_{t-i} + \varepsilon_t$$

$$Y_t = \beta_0 + \sum_{i=1}^{p}\beta_i Y_{t-i} + \sum_{i=1}^{p}\gamma_i X_{t-i} + u_t$$

$$F = \frac{(RSS_r - RSS_u)/p}{RSS_u/(T-2p-1)}$$



3) Multivariate Granger

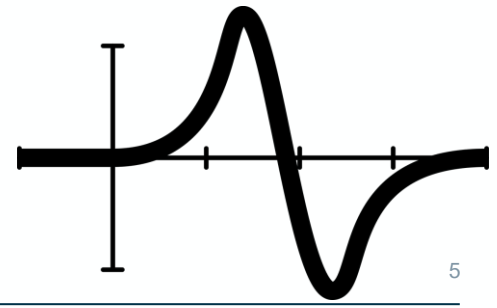
$$\mathbf{Z}_t = A_1\mathbf{Z}_{t-1} + \ \ldots\ + A_p\mathbf{Z}_{t-p} + \varepsilon_t$$

$$\mathbf{Z}_t = (\mathrm{SIF}_t,\ T_t,\ SWC_t,\ LE_t)^\top$$

4) Statistical significance through multiple tests: Benjamin Hochberg

$$p_{(k)} \leq \frac{k}{m}\alpha$$

$$\mathrm{FDR} = \mathbb{E}\left(\frac{V}{R}\right)$$

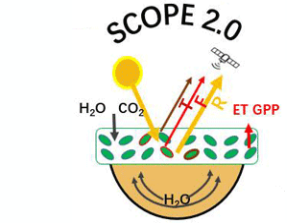


Methods Data

- Data used in correlation analysis (constrained to year 2019)

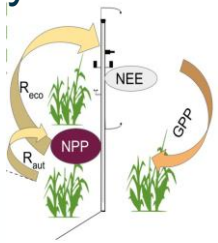
TROPOSIF[1]: daily scaled at 7 x 3.5 km, global coverage

ERA5-Land: reanalysis product ~9Km, global coverage

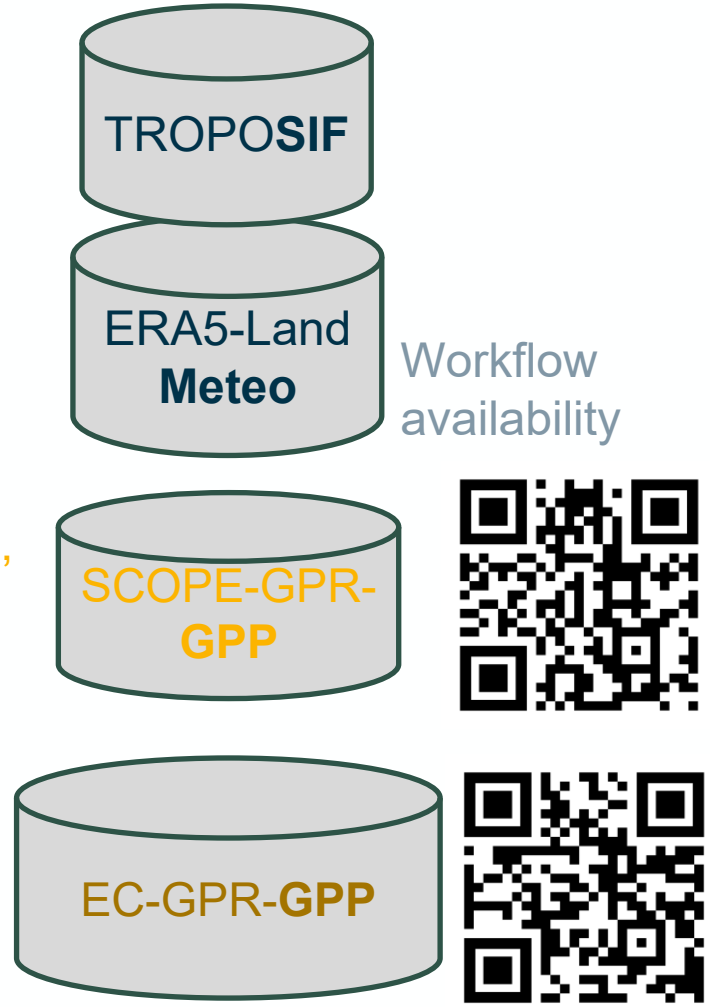


SCOPE-GPR-GPP[2]: Hybrid model of GPP driven by TROPOSIF, S3-derived vegetation traits and ERA5-Land as input features

Eddy-covariance



EC-GPR-GPP[3]: Data-driven model of GPP with ERA5-Land and MODIS-derived LAI



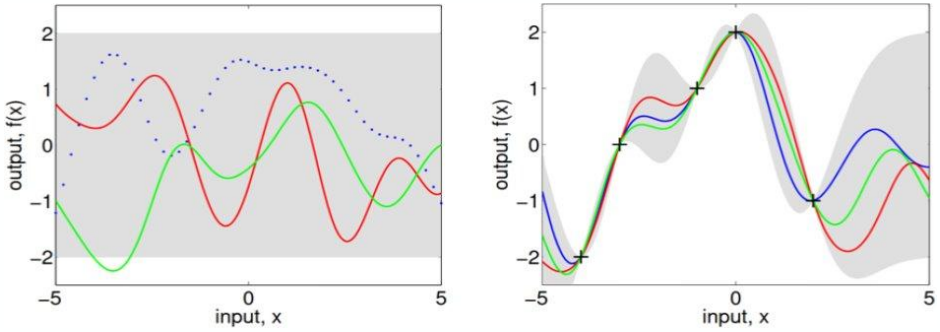
[1]Guanter et al., 2021 [2]Reyes-Muñoz et al., 2024 [3]Reyes-Muñoz et al., 2025

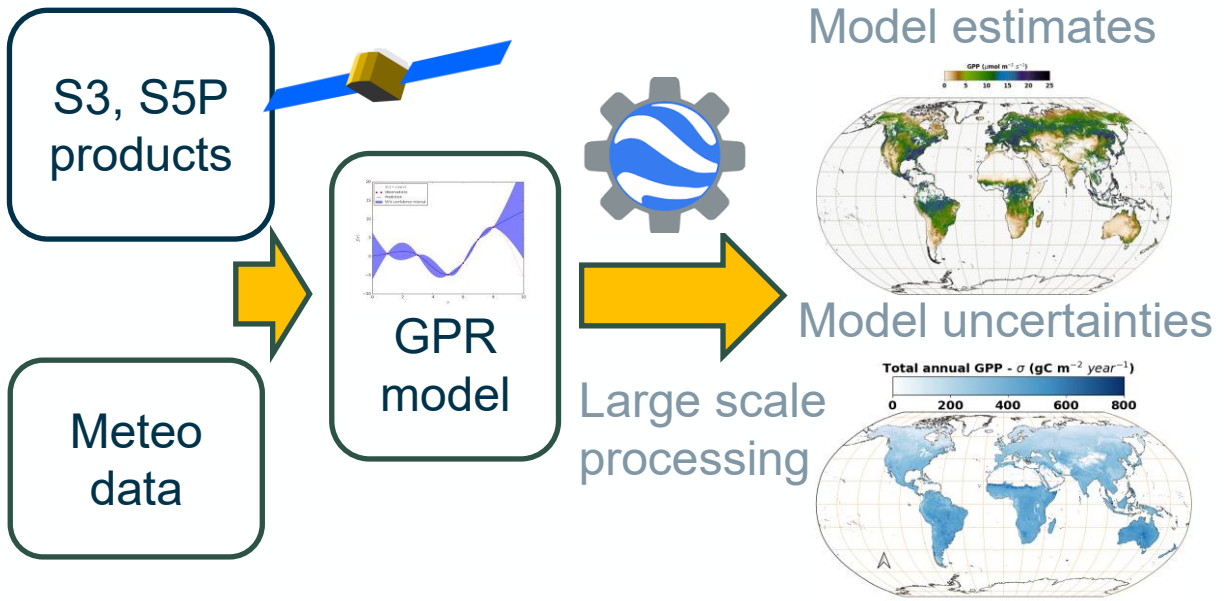
Methods – Gaussian process regression

A non-parametric, non-linear regression method.
A probabilistic approach implemented through kernel functions.

GPR facilitates **band ranking analysis and** provides **epistemic uncertainty estimates**

The model is applied in Google Earth Engine through algebra of multidimensional arrays.





1) SCOPE-GPR-GPP: Global time series 2019, 8-days steps. Driven by TROPOSIF, S3-derived vegetation products and ERA5-Land

2) EC-GPT-GPP: Global time series 2004-2023, 8 days steps. Driven by LAI and ERA5-Land

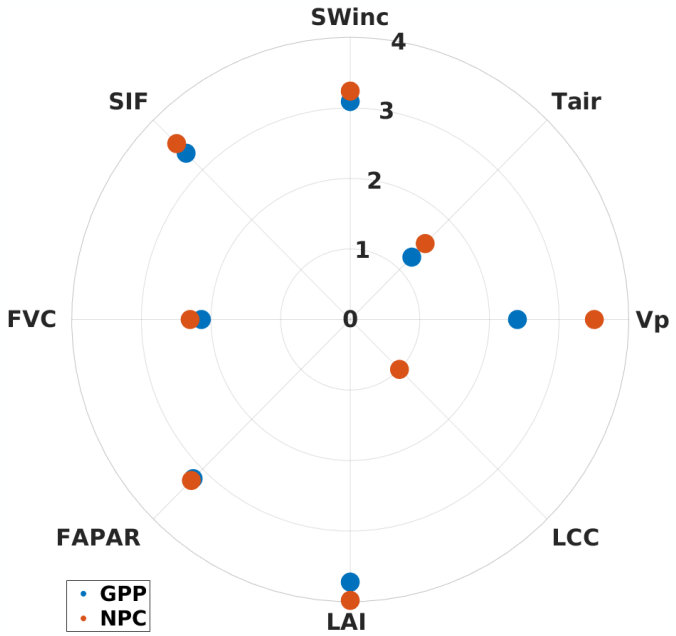
Reyes-Muñoz, Pablo, et al. "Inferring global terrestrial carbon fluxes from the synergy of Sentinel 3 & 5P with Gaussian process hybrid models." *Remote Sensing of Environment*

Results – Intercomparing GPP products

GPR-based GPP products:

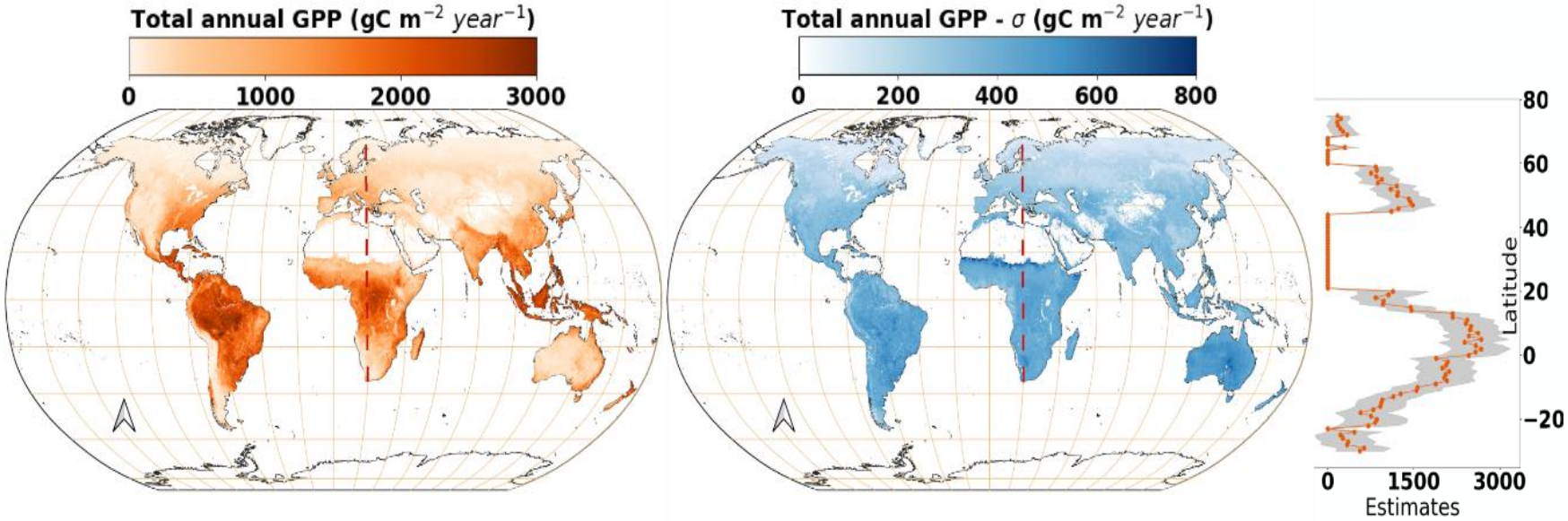
- SCOPE-GPR-GPP[1] -> An hybrid physically-informed model trained with Gaussian process regression (GPR). It includes 8 predictors -> 5 vegetation products (with SIF)

SCOPE-GPR – training polar plot



Estimates **Uncertainties**

Yearly GPP (g C ·m^{-2} · year^{-1}) 2019



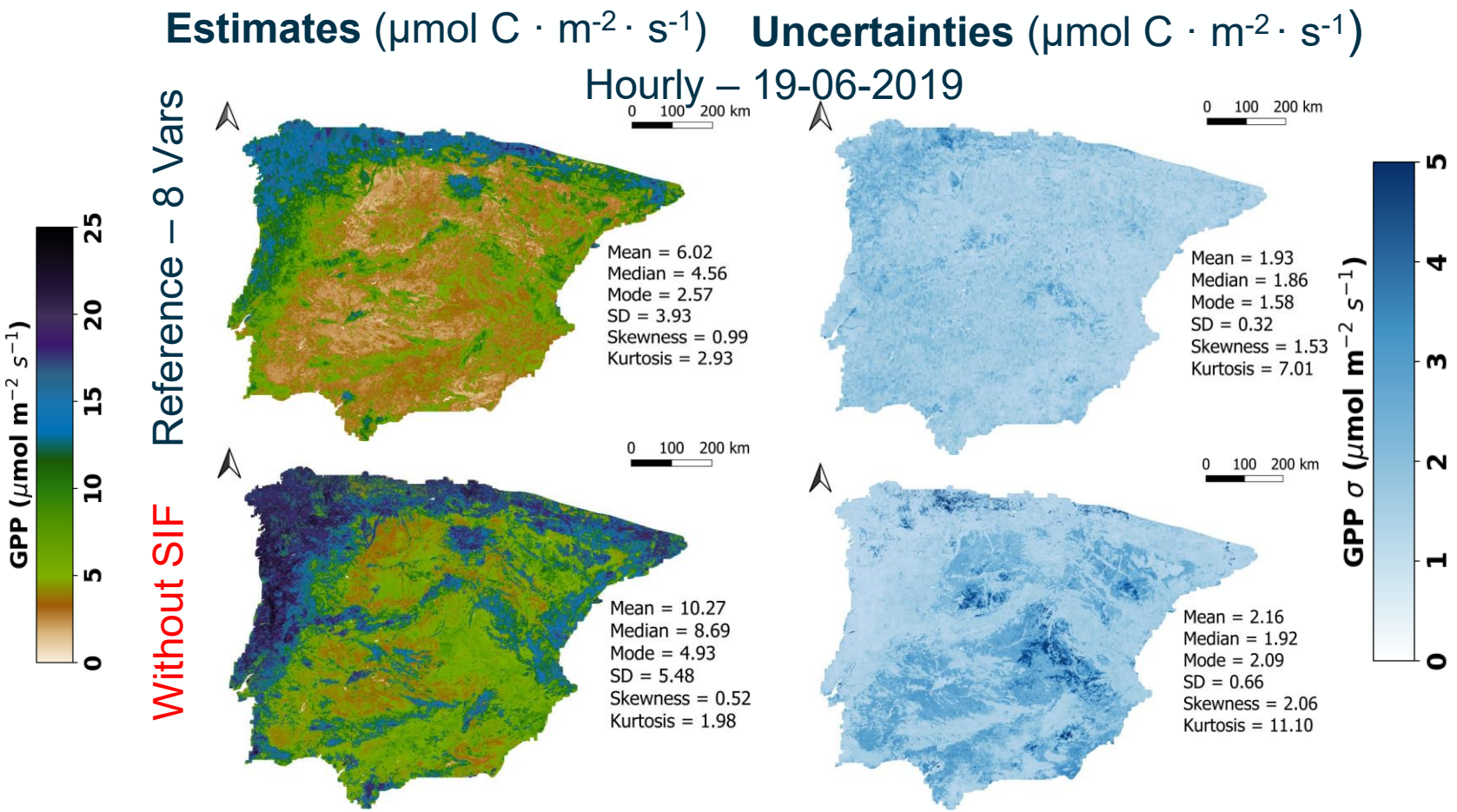
Reyes-Muñoz, Pablo, et al. "Inferring global terrestrial carbon fluxes from the synergy of Sentinel 3 & 5P with Gaussian process hybrid models." *Remote Sensing of Environment*

Results – SIF and hybrid GPP model

GPR-based GPP products:

- SCOPE-GPR-GPP[1] -> An hybrid physically-informed model trained with Gaussian process regression (GPR)

- **SCOPE-GPR-GPP** models were applied at the **Iberian peninsula at 300 m resolution.**
- At the **production stage the importance of predictors** were tested through versions of the model excluding these predictors.



[1]*Reyes-Muñoz et al., 2024*

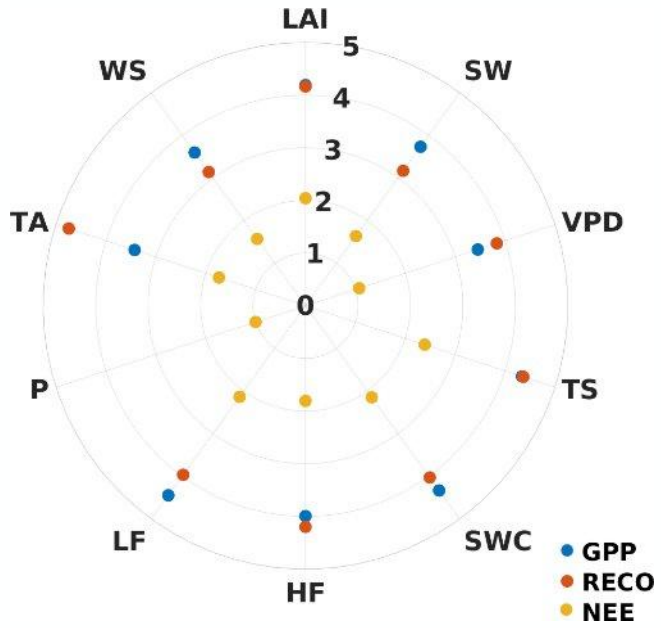
Results – Tower-based models

GPR-based GPP products:

- EC-GPR-GPP[2] -> A data-driven empirical model trained with Gaussian process regression (GPR)

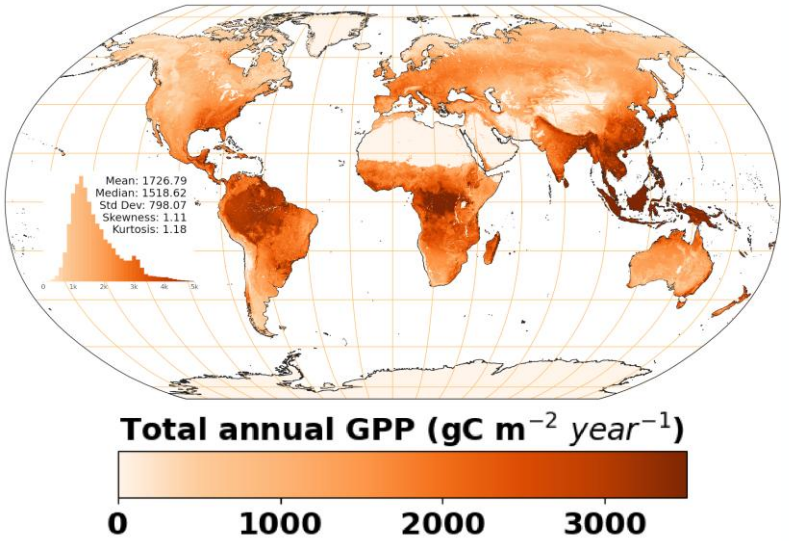
  It includes 10 predictors -> 9 meteorological variables

GPR – training polar plot

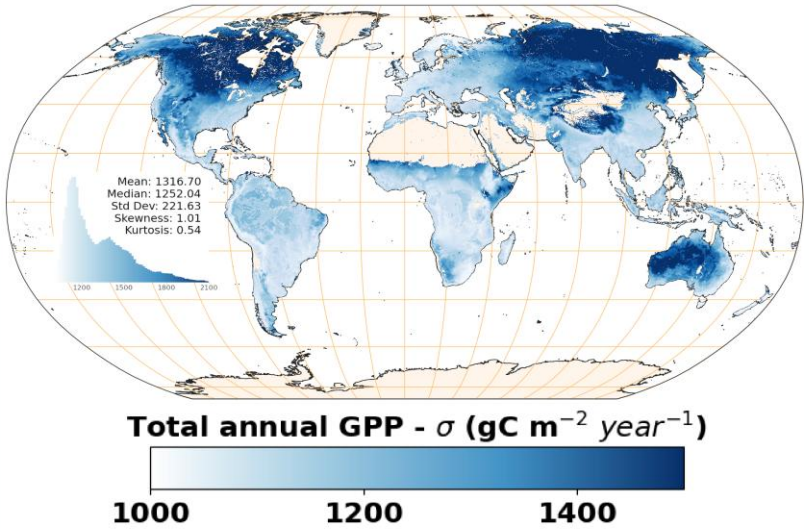


Estimates

Yearly (g C ·m^{-2} · year^{-1}) 2004-2023



Uncertainties



Reyes-Muñoz, Pablo, Dávid D. Kovács, and Jochem Verrelst. "Tower-to-global upscaling of terrestrial carbon fluxes driven by MODIS-LAI, Sentinel-3-LAI and ERA5-Land data." *Ecological Indicators*

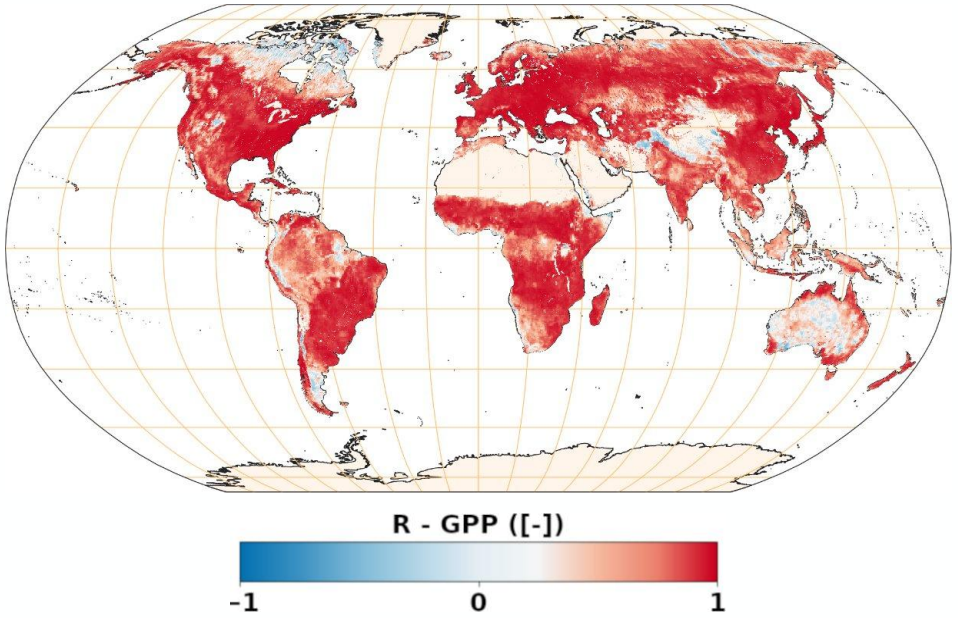
Results – Intercomparison between GPP products

Intercomparison between GPR-based GPP products (2019):

- Agreement between SCOPE-GPR and EC-GPR **suggest that TROPOSIF along with S3-derived vegetation products may act as proxies of meteorological variables for predicting TCFs**

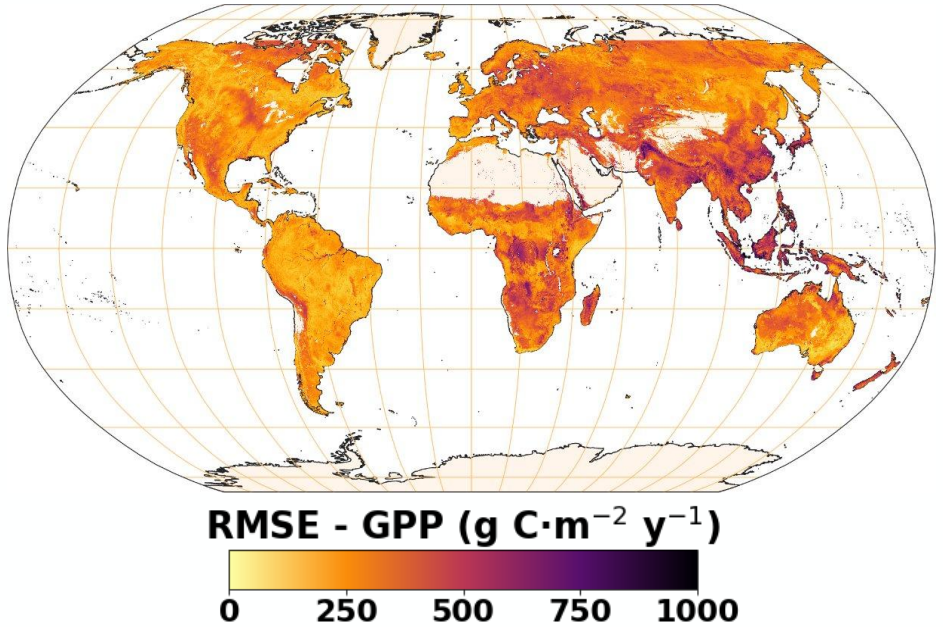
R EC-GPR Vs SCOPE-GPR

Median = 0.76 Std. dev. = 0.33

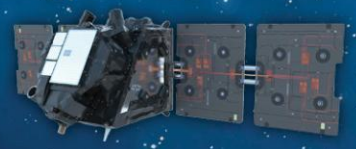


RMSE EC-GPR Vs SCOPE-GPR

Median = 500 g C·m^{-2} y^{-1} Std. dev. = 300 g C·m^{-2} y^{-1}

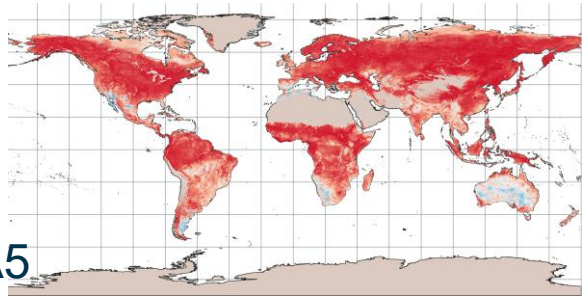


Results – Multiple correlation



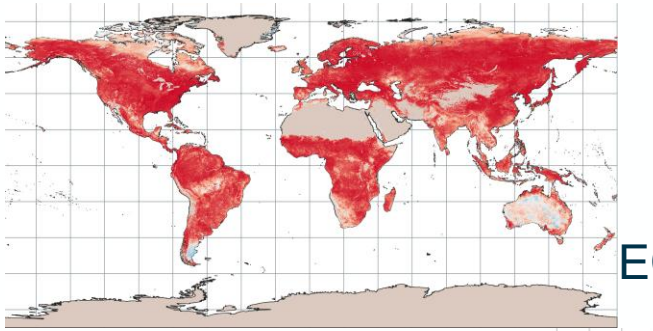
R ([-])
−1 0 1

EC-GPR-GPP Vs FAPAR



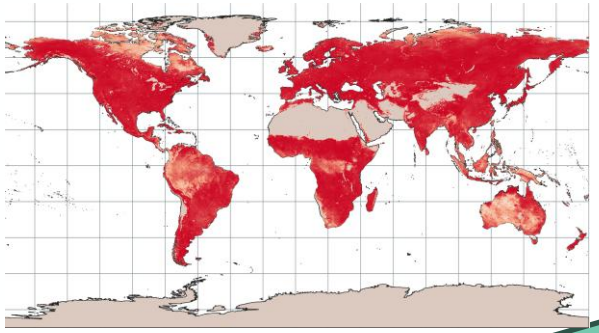
GPP

EC-GPR-GPP Vs LAI

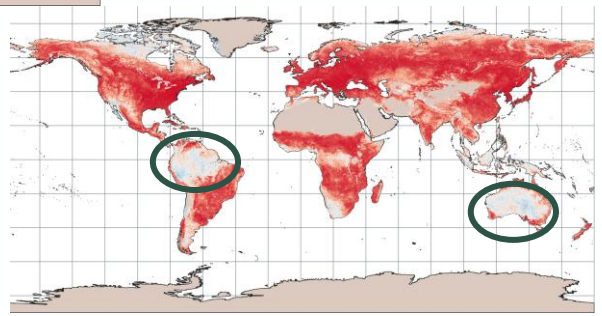


R ([-])
−1 0 1

EC-GPR-GPP Vs ERA5



EC-GPR-GPP Vs SIF



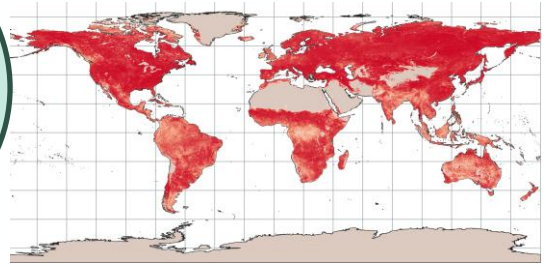
Correlation all Vs EC-GPR-GPP

Vegetation

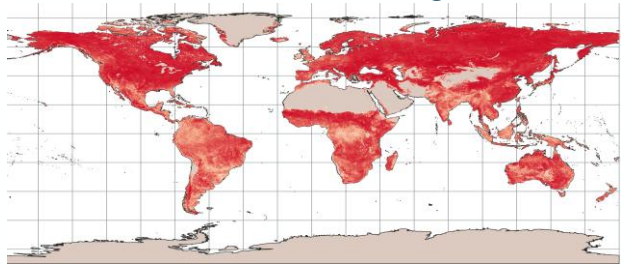
Multivariate correlation LAI/FAPAR/SIF Vs meteo

Meteo/ERA5 (SW, T, SWC, LE)

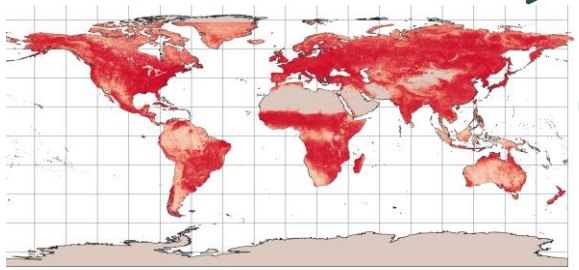
LAI Vs ERA5



FAPAR Vs ERA5



SIF Vs ERA5



VPs/SIF

Results – Granger causality

Multivariate Granger F statistic: ERA5-Land data: shortwave incoming radiation - soil temperature – soil water content – latent heat flux) and LAI causality on **SIF**

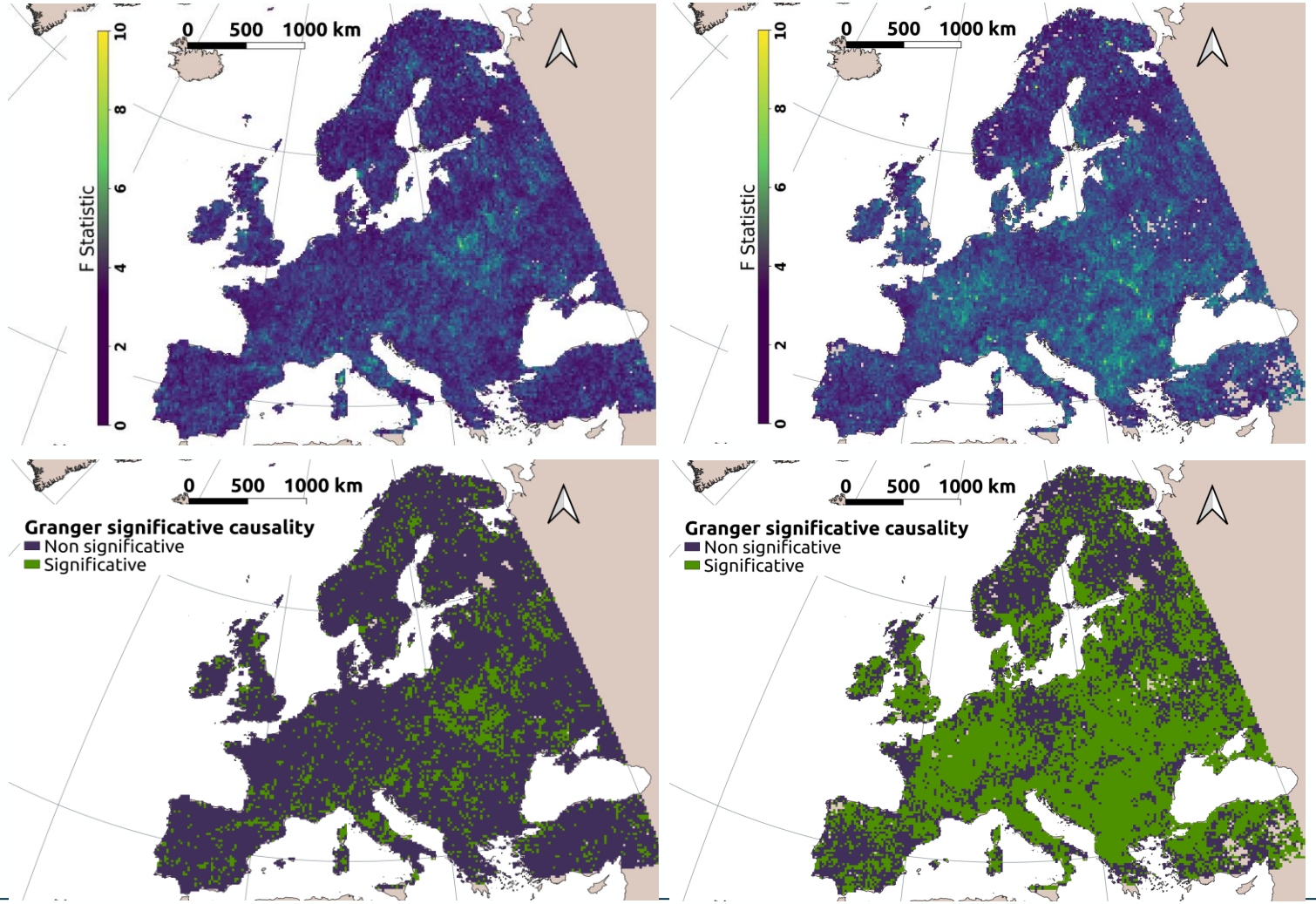
Significance of test causality drastically expanded when adding LAI as predictor

ERA5-Land -> SIF

ERA5-Land + LAI -> SIF

F- statistic

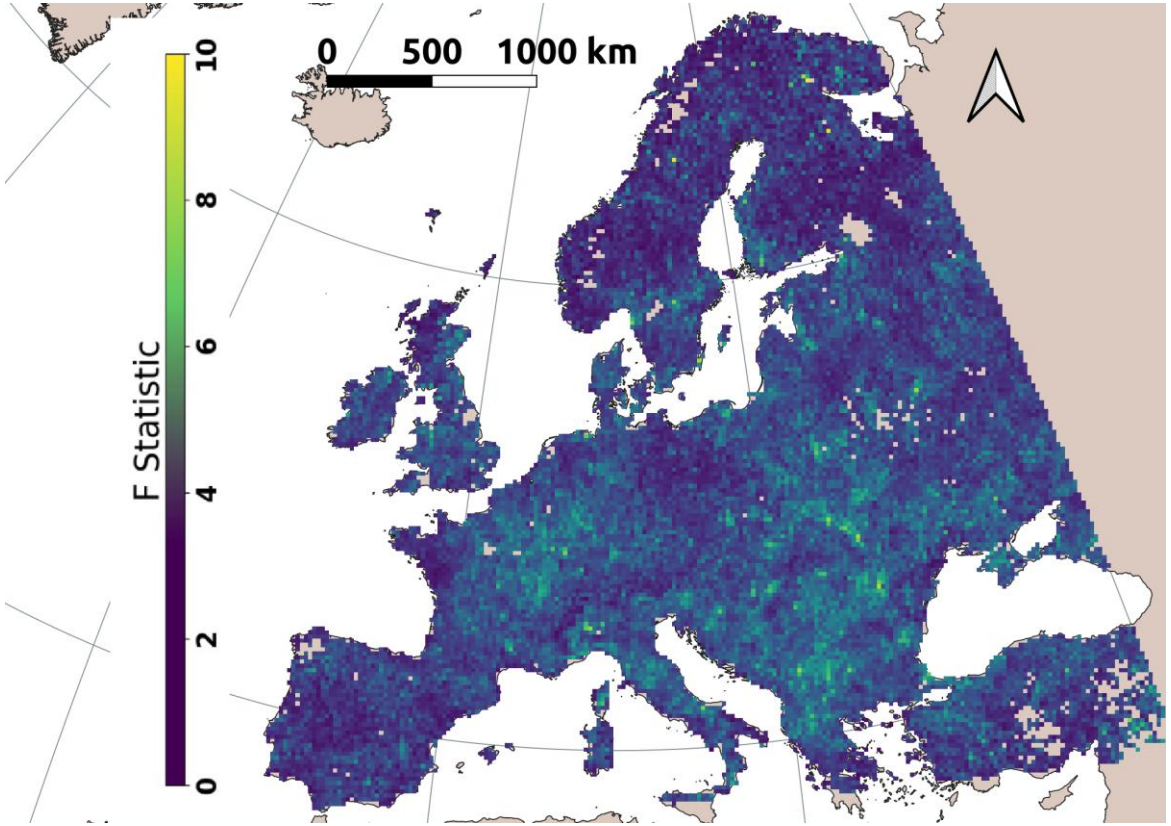
Statistical signigicance

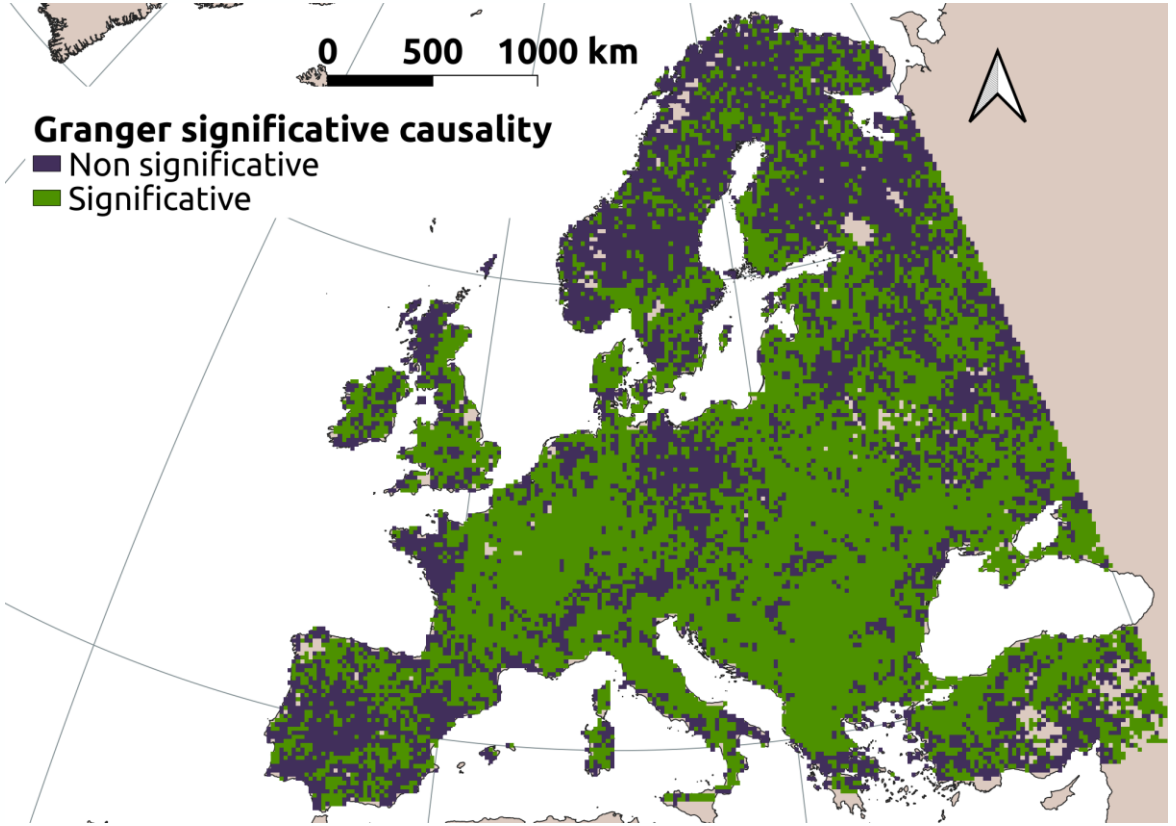


Results – Granger causality

Multivariate Granger F statistic (corrected for false detection): Causality on 56.2% of the surface was significative

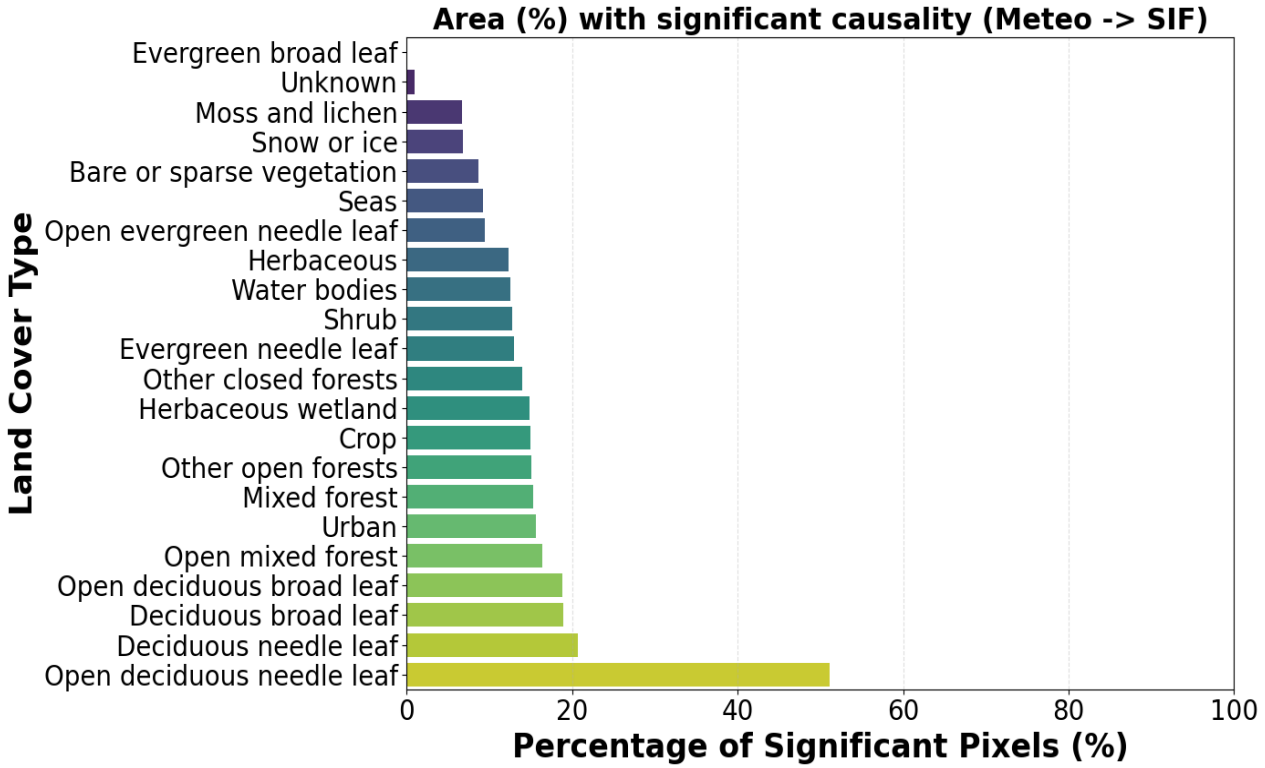
- Shortwave incoming radiation – Soil temperature – Soil water content – Latent heat flux – **LAI**

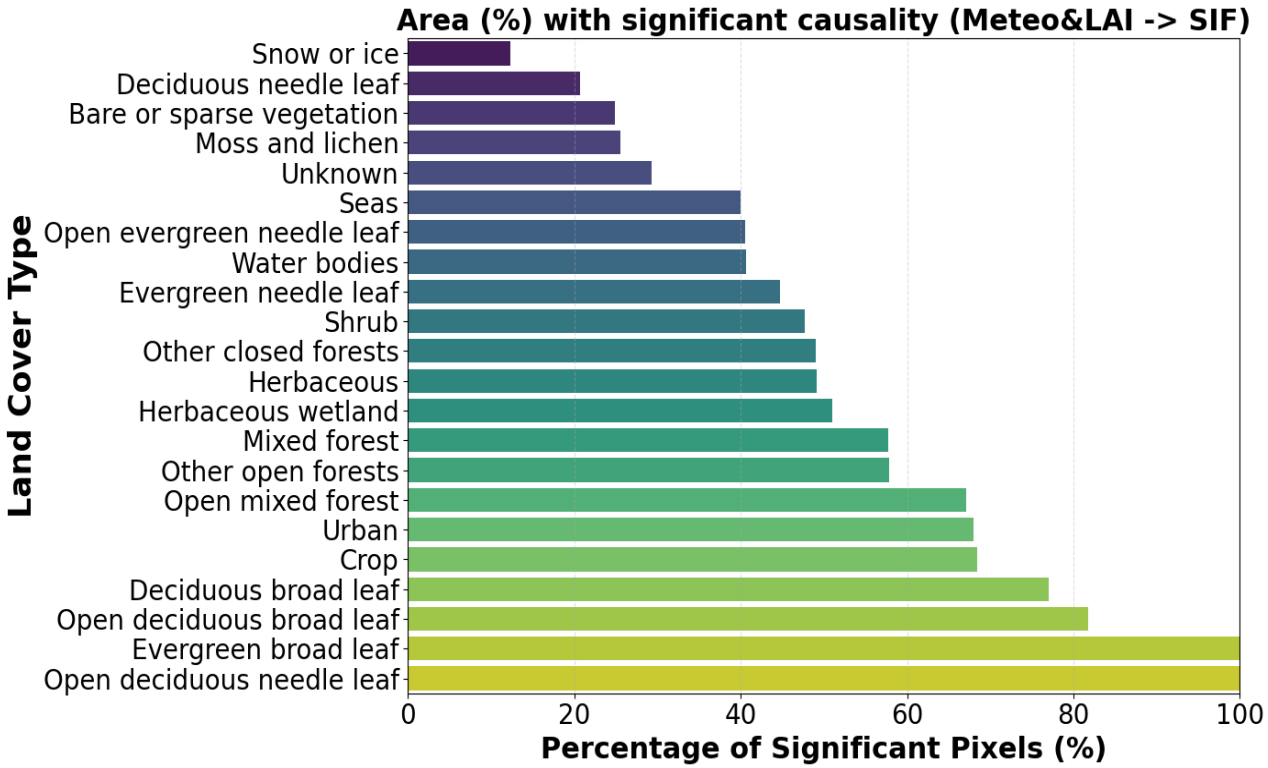




Results – Granger causality

Multivariate Granger - Causality significance (Meteo -> SIF) was more frequent on open deciduous forests, with maximum of ~50% in open deciduous needle leaf. The areas linked with sgnificant causality dramatically increase when adding **LAI** in the multivariate Granger analysis.





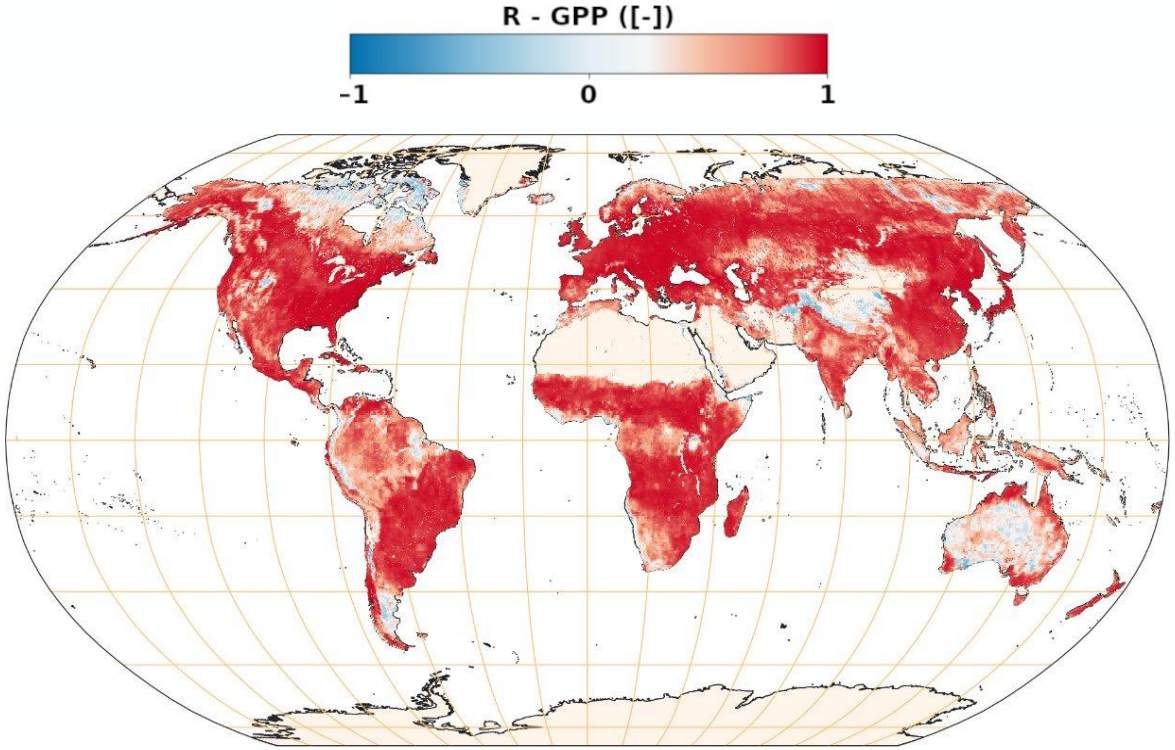
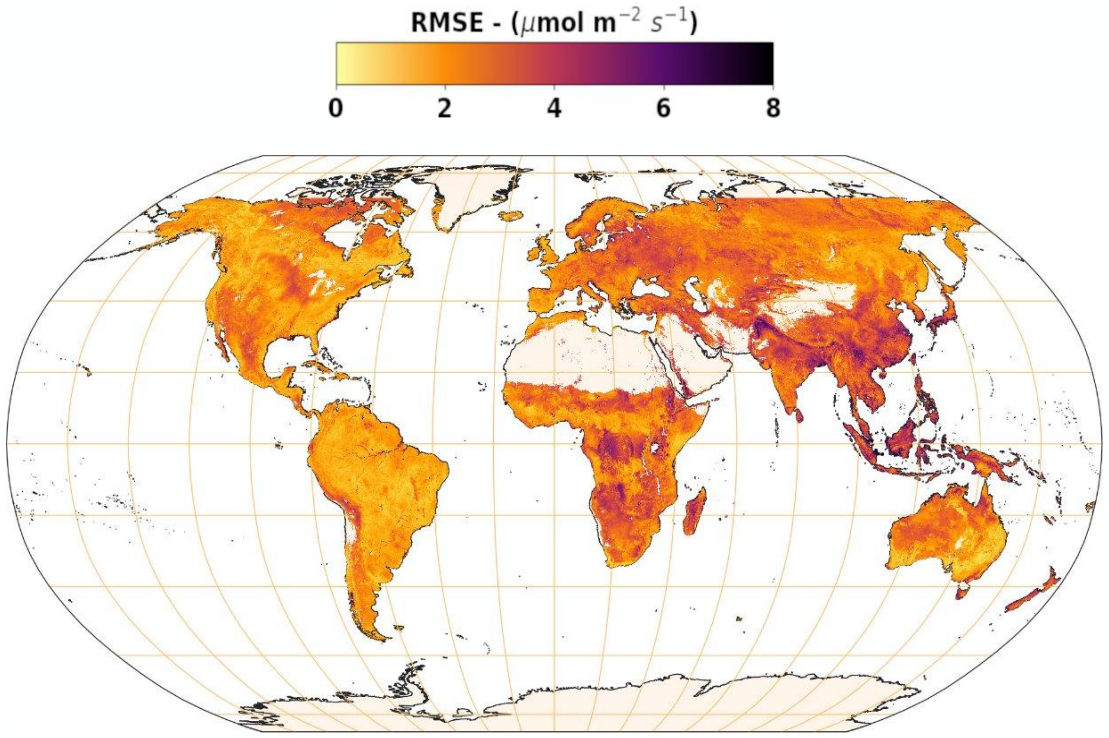
Outlook and future work

1. In preparation for FLEX, this study advances in the interpretation of the SIF dynamics from satellite data, particularly as a predictor of GPP.

2. The analysis of this work highlighted a **good match** between two GPP models, suggesting that TROPOSIF and S3-derived vegetation products **proxy meteorological information for prediction of GPP.**

3. **TROPOSIF data enhanced the consistency of the hybrid GPP models**, reducing the epistemic uncertainty.

4. Granger causality helps to identify **sites where satellite-SIF dynamics are caused by combined-meteorological dynamics.**

5. The analysis was experimentally conducted with TROPOSIF for one year of data (2019). The workflows will be applied to improved SIF data from FLEX.

Thanks for your attention