4th Carbon from Space Workshop

Multiscale photosynthesis productivity estimation from Sentinel satellites

25/10/2022

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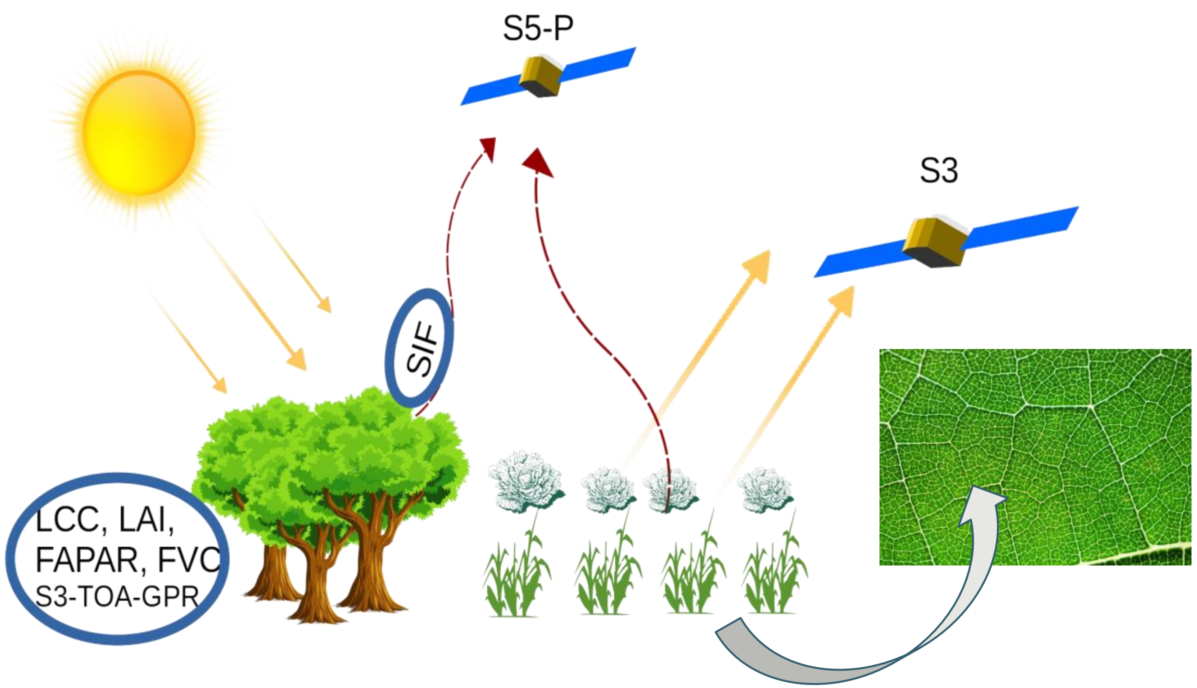
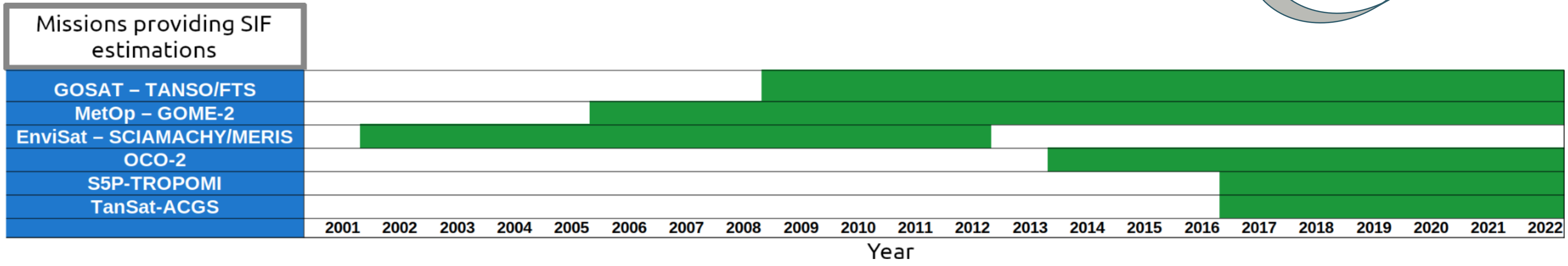
Estimating carbon fluxes

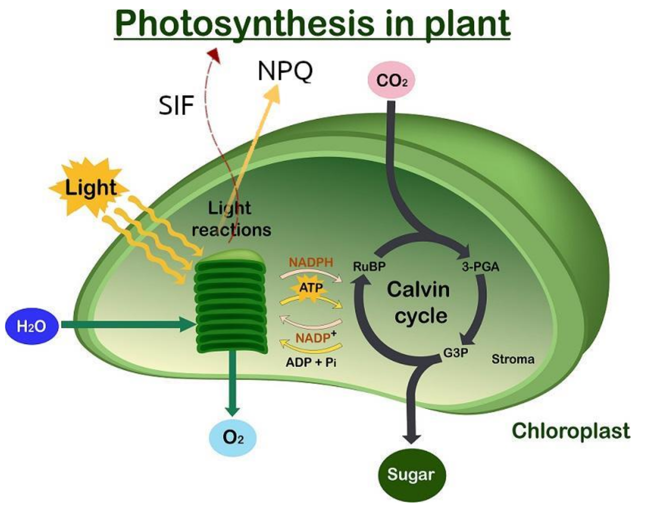
- Objectives:
    - Applying **machine learning** on synergistic data to estimate vegetation productivity related variables
    - Integrating **S3-OLCI based vegetation products** and **S5-P TROPOMI SIF** data within our workflow
- **Fluorescence** as a key variable in photosynthesis, offered by different missions
- Prototype models potentially usable in the context of the upcoming **FLEX** mission.

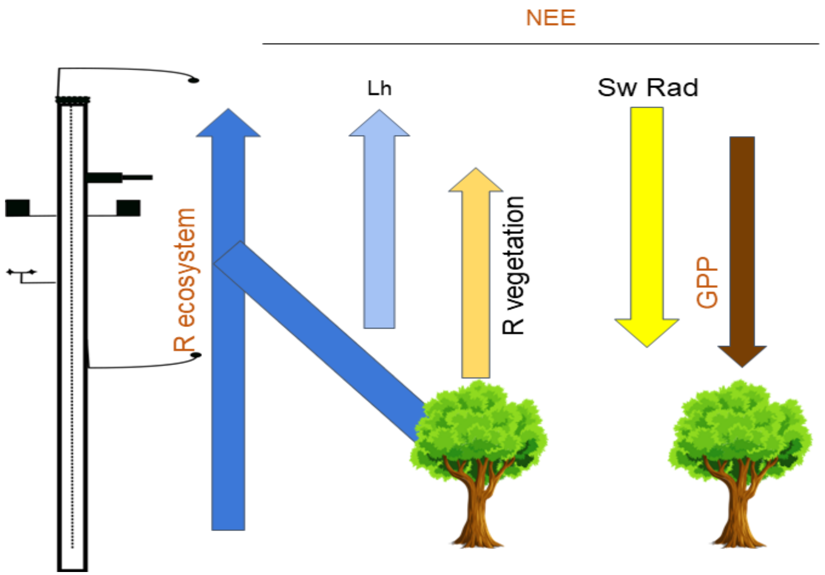




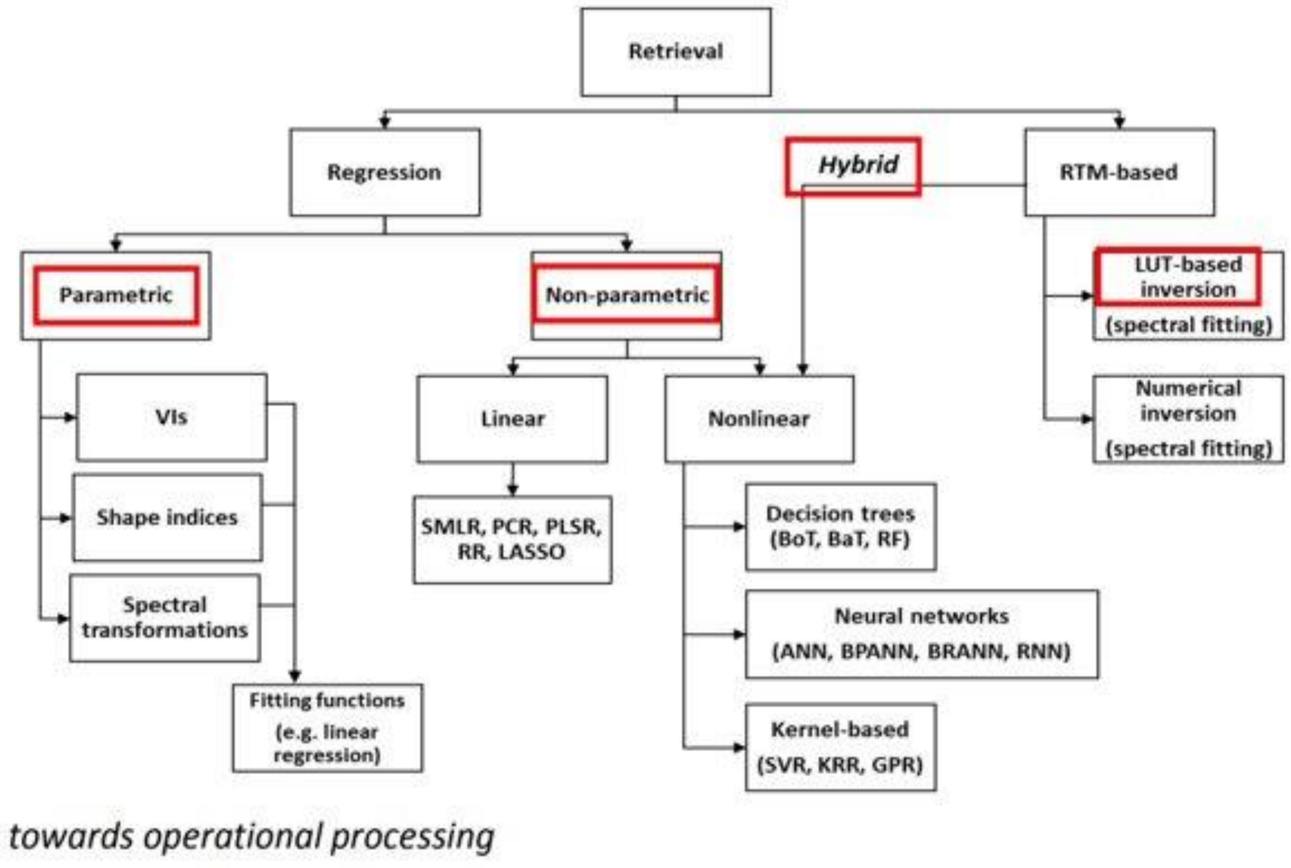
Estimating GPP, NPP, NEE and Respiration:

- **Gross primary productivity** (GPP)
  - Currently calculated from different approaches:
    - LUE models: based on empirical coefficients and APAR
    - Parameterization of photosynthesis processes (Vcmo, electron transport rate, etc.)
    - Chlorophyll fluorescence emissions linked GPP
- **Net Primary Productivity** NPP = GPP - R vegetation*
- **Net ecosystem exchange** NEE = GPP - R ecosystem
  - Measured by flux towers
  - Includes heterotrophic respiration

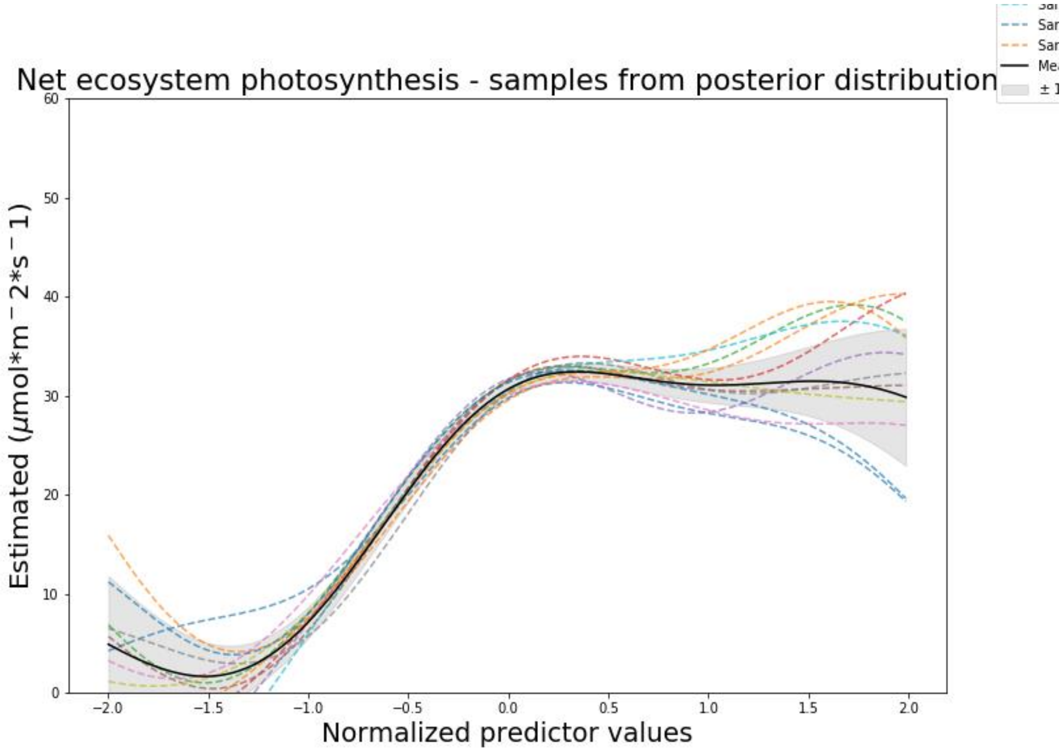




Estimating carbon fluxes: Hybrid methods



Verrelst, J et al. (2019). Quantifying vegetation biophysical variables from imaging spectroscopy data: a review on retrieval methods. *Surveys in Geophysics*, 40(3), 589-629.

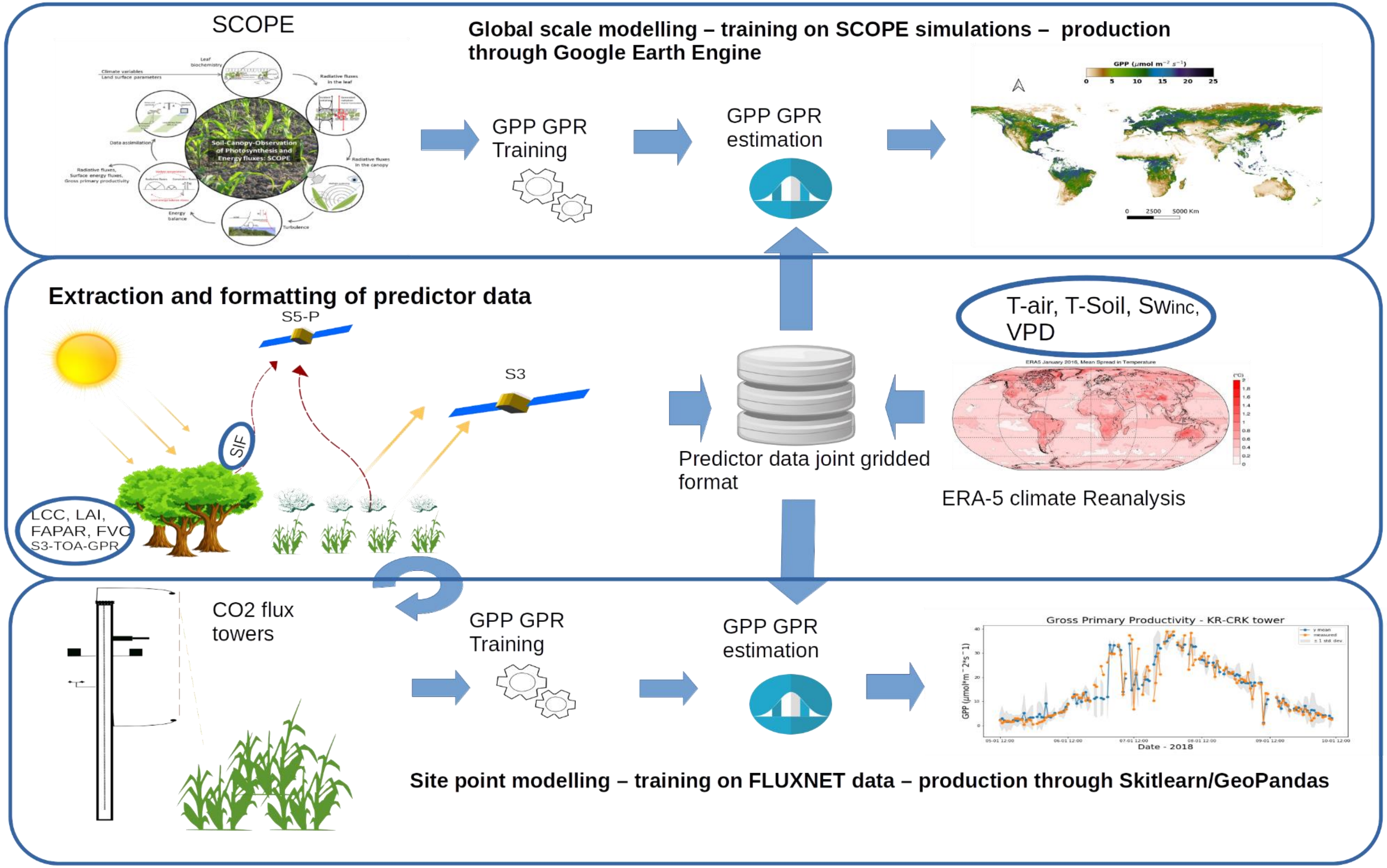


$$f(x) \sim GP(m(x), k(x, x'))$$

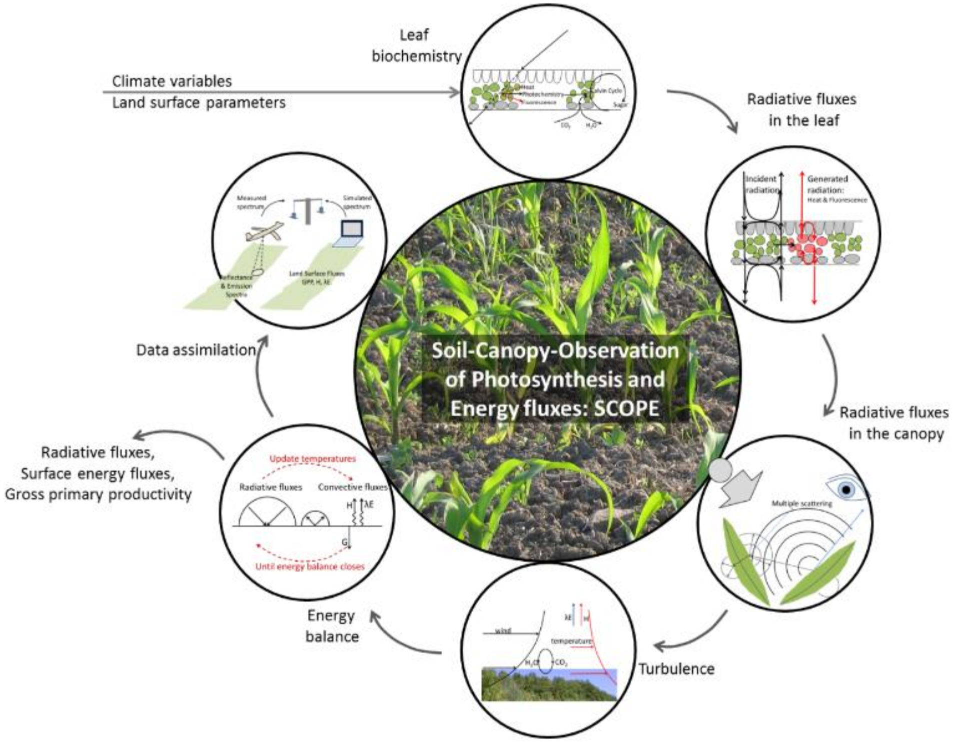
X -> [SWinc, VPD, ST, LCC, LAI, FAPAR, FVC, SIF]

GPR maximize estimates likelihoods and provides uncertainties

Estimating carbon fluxes: workflow



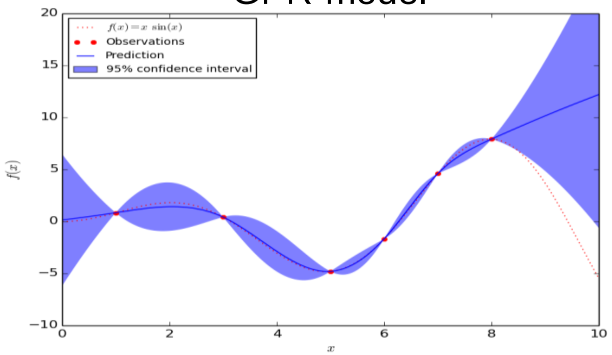
Training data set generation - SCOPE 1.7



	Variable	lower bound	higher bound	n samples
Meteo	Rs (W / m^2)	0	1400	100
	Tª air (º C)	-10	50	60
	Ev (hPa)	0.0	150	15
Leaf parameters	Chlorophyll	0	100	20
	Cw	0	0.5	5
Leaf biochemical	Vcmo	40	80	10
Canopy	LAI	0	8	30
	LIDF	-1	1	10

Training

GPR-model



Sentinel based products

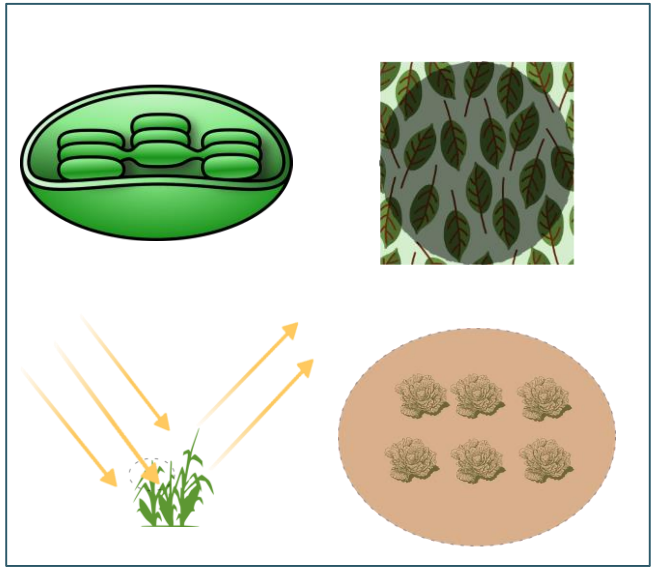
- S3-TOA-GPR products: **LCC, LAI, FAPAR, FVC**

Retrievals from OLCI (400 nm - 1020 nm, 21 bands)

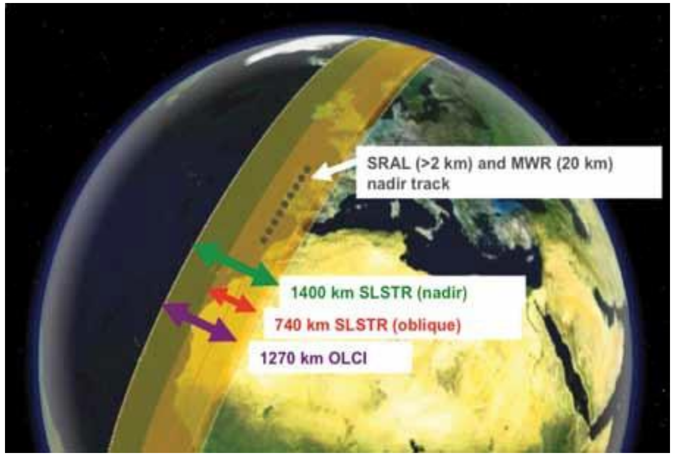
- Spatial resolution: 300 m
- Temporal resolution: ~ daily (middle and high latitudes)

- S5P-TROPOMI: **SIF** (743 - 758 nm windows)
  - Spatial resolution (7 km x 3.5 km^2)
  - Temporal resolution < 1 days

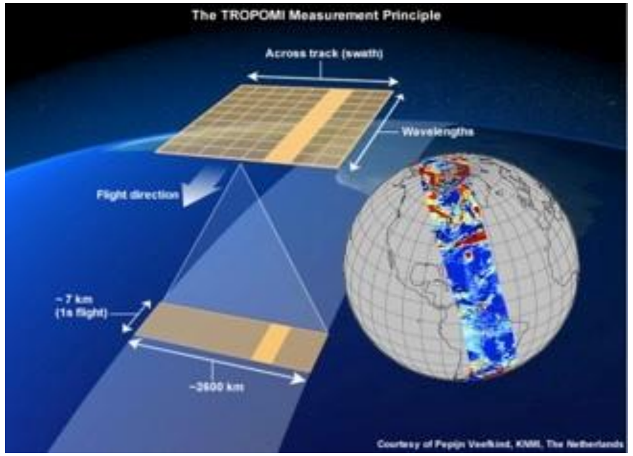
S3 products



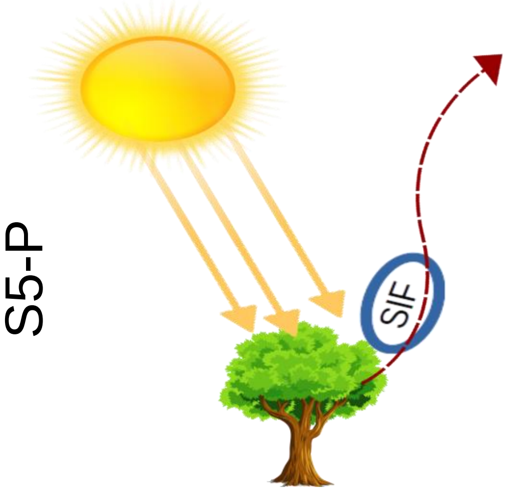
S3



S5-P



S5-P



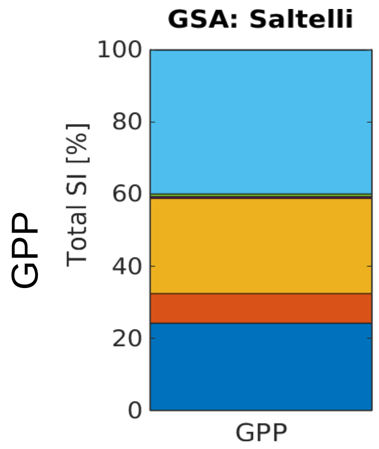
SCOPE simulations and GPR trained models

Analysis of predictors strength:

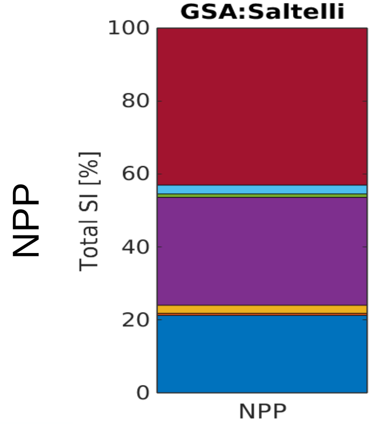
The sensitivity analysis carried out from SCOPE simulations revealed that **Vcmax, LAI and Short-Wave Incident Radiation** were the predictors with maximal influence.

The analysis of variance from GPR models shows that **SIF, FAPAR and LAI** were the variables more important after trained.

Global Sensitivity Analysis calculated from SCOPE inputs	Variance of GPP - NPP due to different predictors from GPR



- Incoming shortwave radiation
- Vcmo (maximum carboxylation capacity)
- LAI



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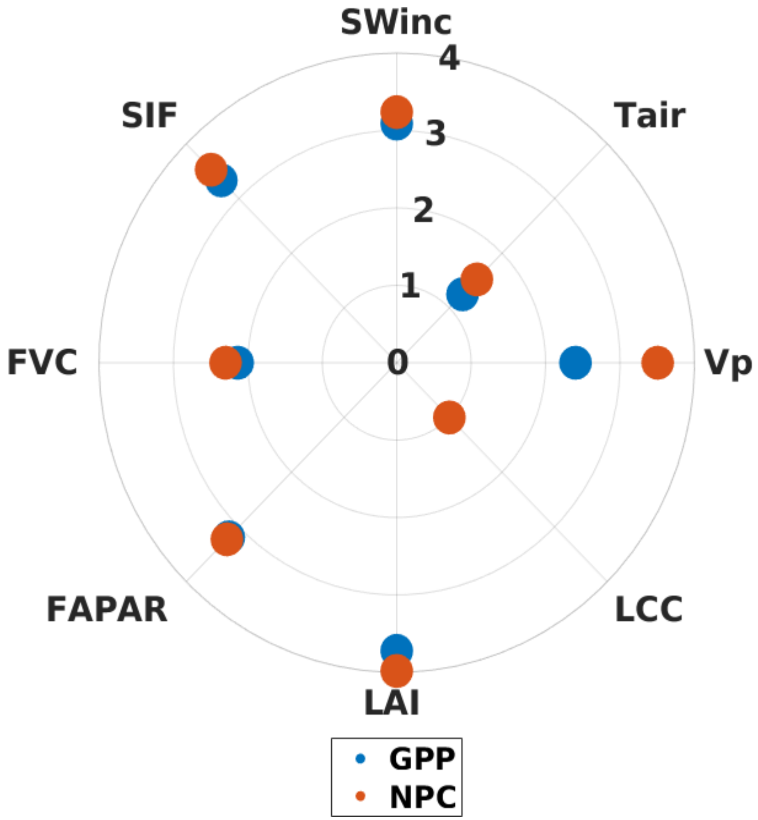


Mapping GPP: Global and continental maps

Spatial distribution:

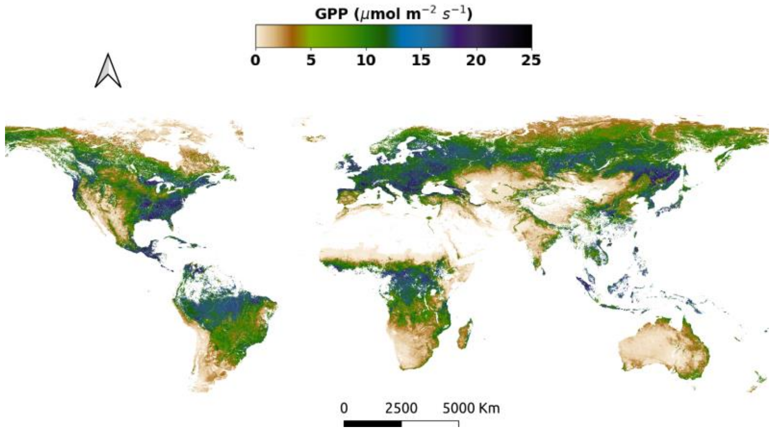
Tropical forests, Taiga and temperate forests reaching peaks of GPP

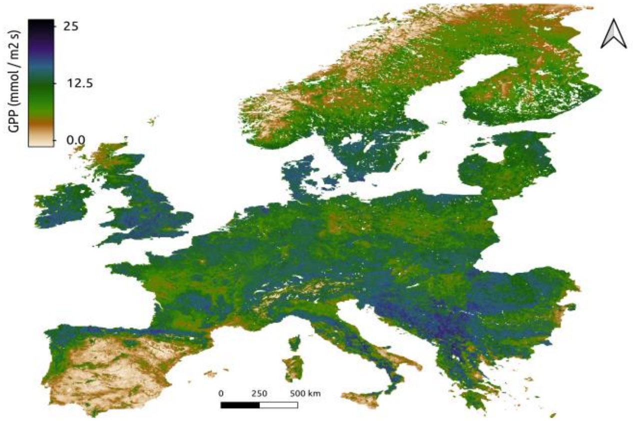
The best performing model included 8 variables leading to **deviations** (second row) of around **20 % of estimates**

At European scale, peaks of GPP on forest areas: Dinaric Alps.

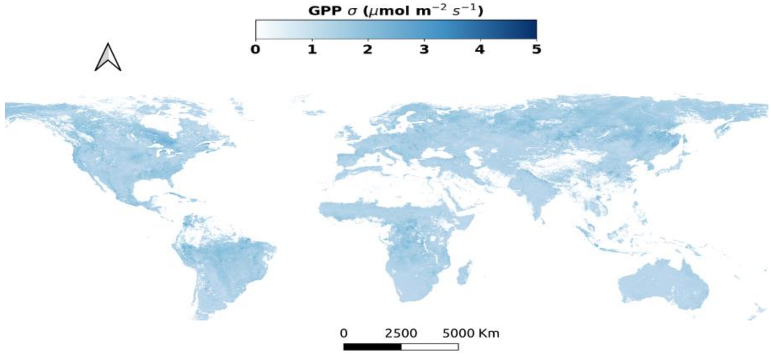
Estimates and uncertainties on 16-06-2019–13:00:00	Estimates and uncertainties on 16-06-2019–13:00:00

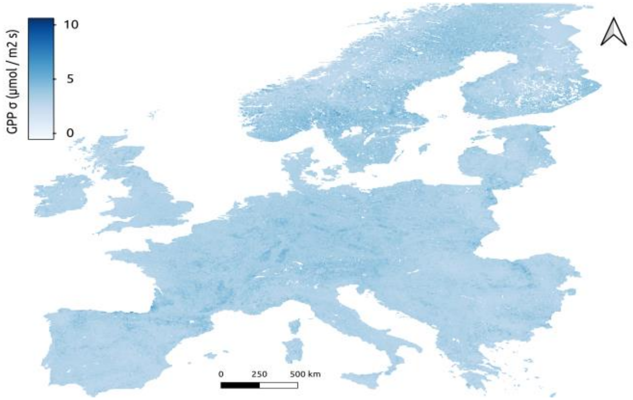
Estimates





Uncertainties



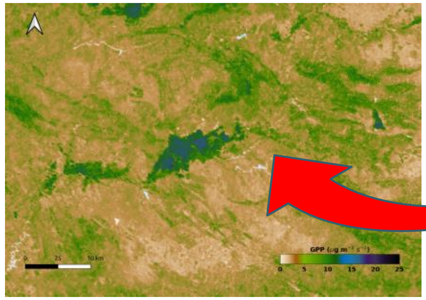


Mapping GPP: Regional maps

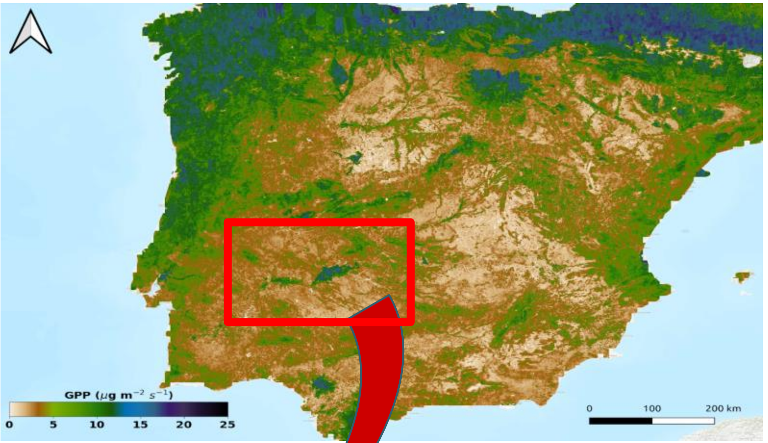
Spatial distribution:

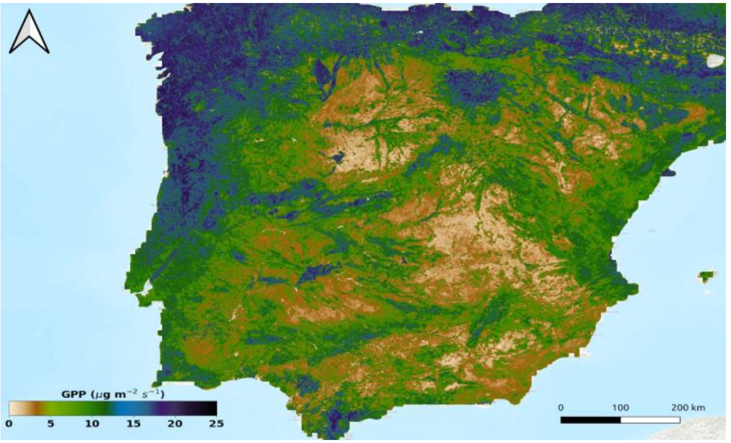
Regional scale map highlighting diverse land cover types, with peak values over forest and agricultural areas.

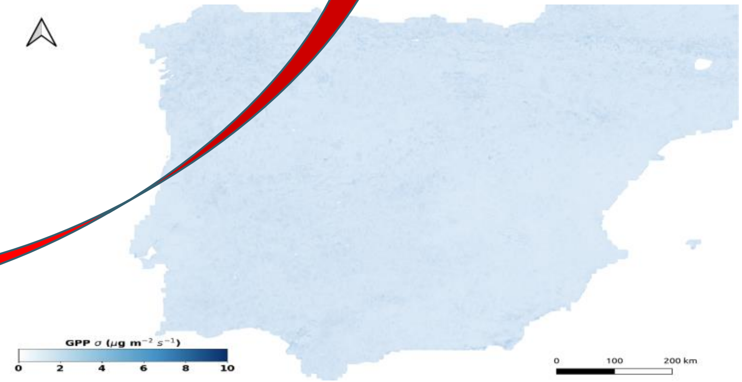
Model including SIF (8 vars) throw most consistent results with lower uncertainties (under 20 %)

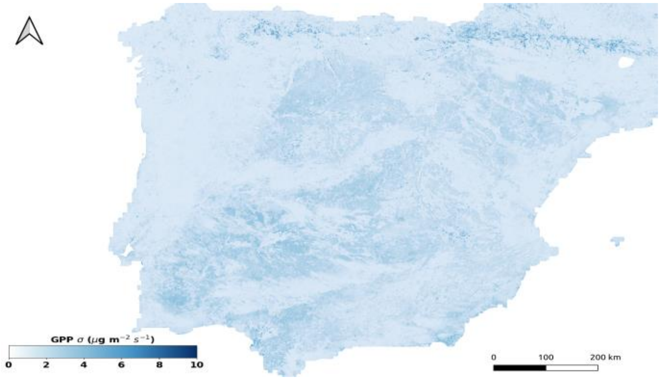


Estimates and uncertainties on 16-06-2019–13:00:00 (**SIF**)	Estimates and uncertainties on 16-06-2019–13:00:00 (**No SIF**)







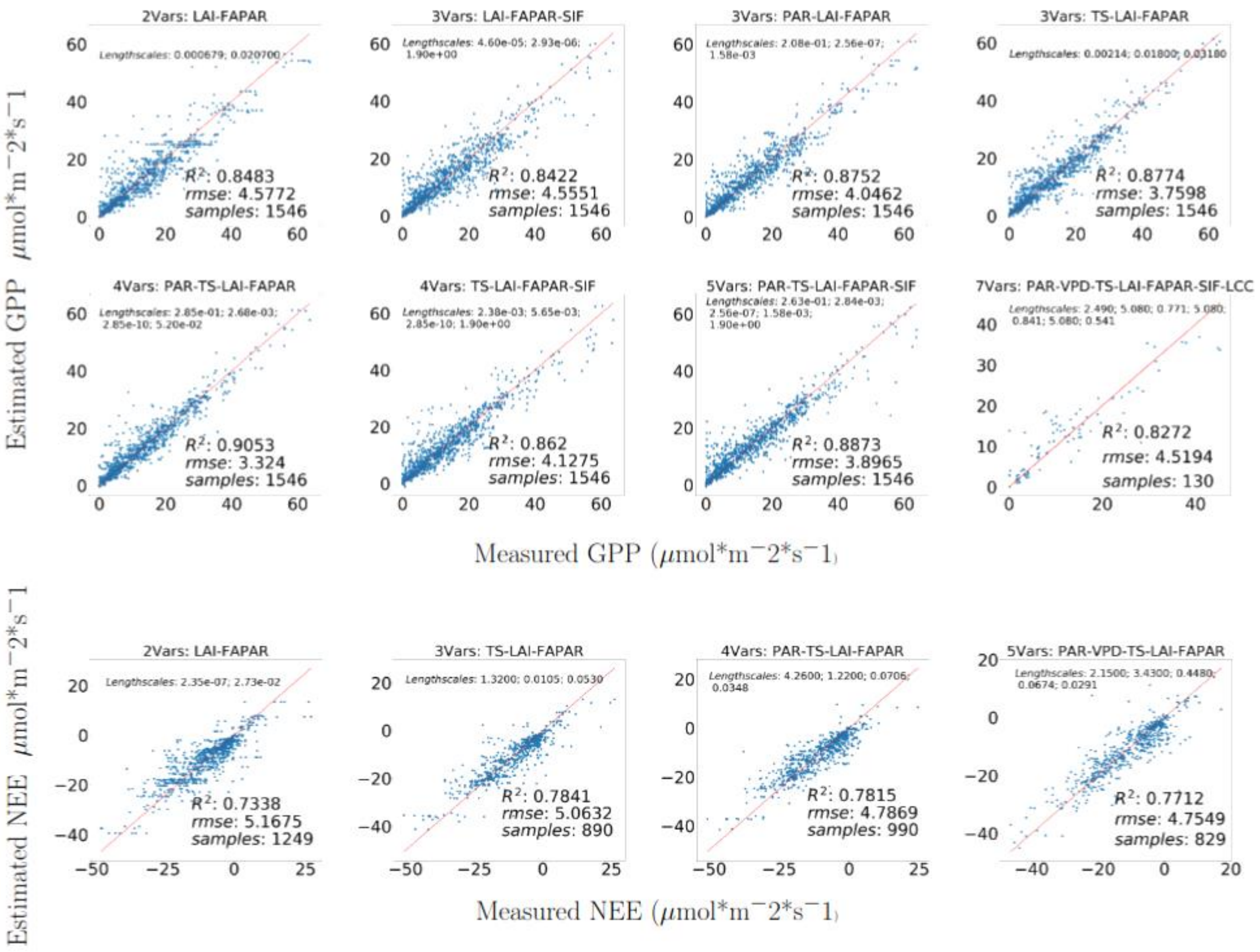


Validating GPP – NEE: Models performance at tower sites

Validation against flux tower data (all sites together):

Best performance for the combination of 4 variables: **SWin, ST, LAI and FAPAR** explaining an $\mathbf{R^2}$ of of **0.90** and an rmse of 3.32 (GPP) and **0.78** and 4.79 (NEE)

The model based only on LAI and FAPAR explained an R^2 of 0.85 (GPP) and 0.73 (NEE)

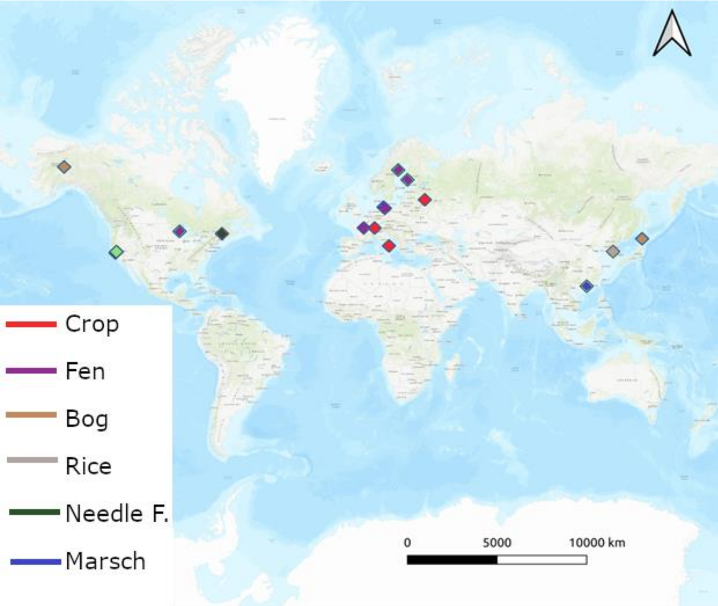


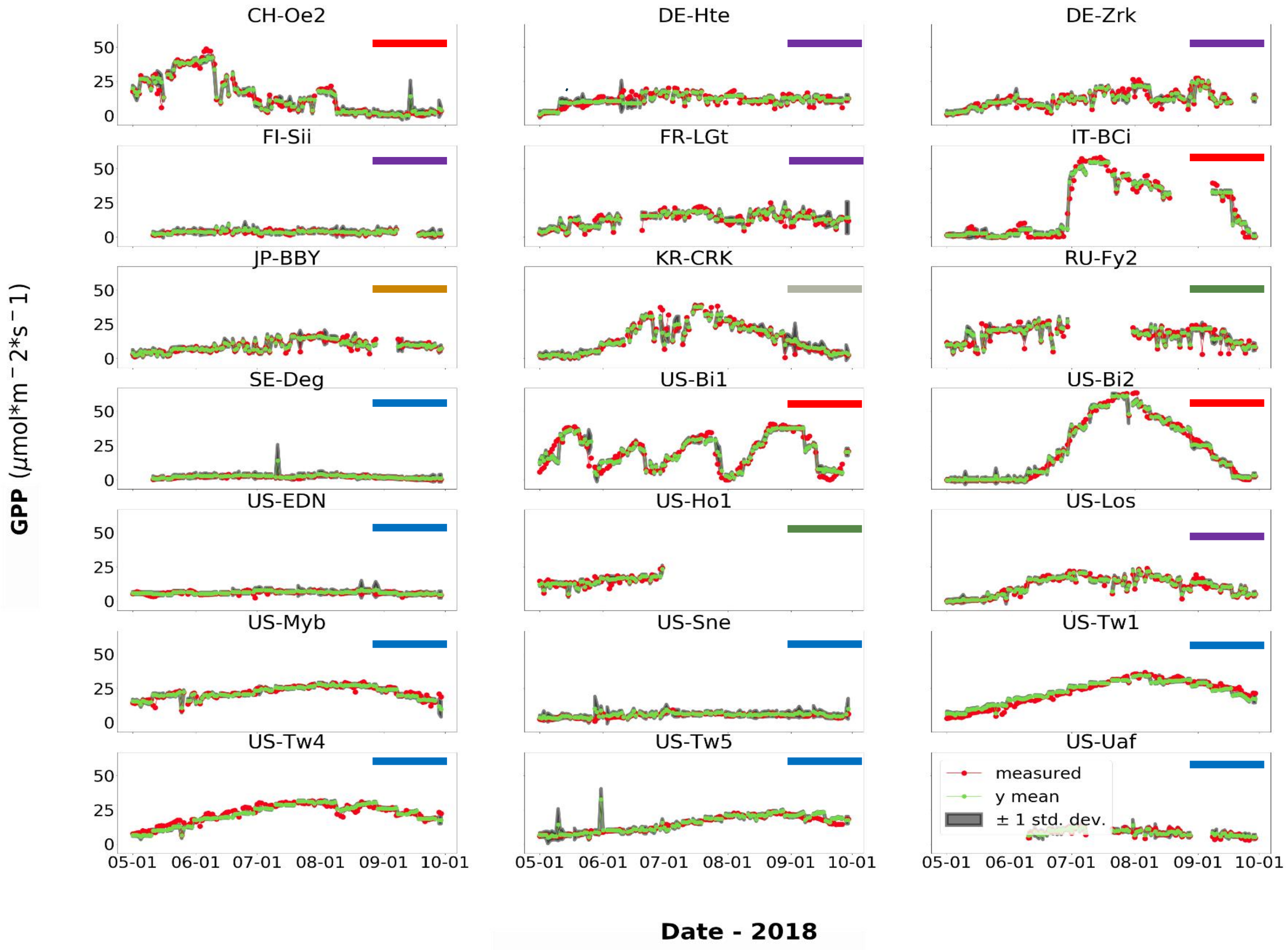
Estimating GPP: Tower sites

GPP Time evolution:

Observed time-variability according to ecosystem type.

Crop sites presenting higher variability over time. Marsch sites presenting lower variability over time.





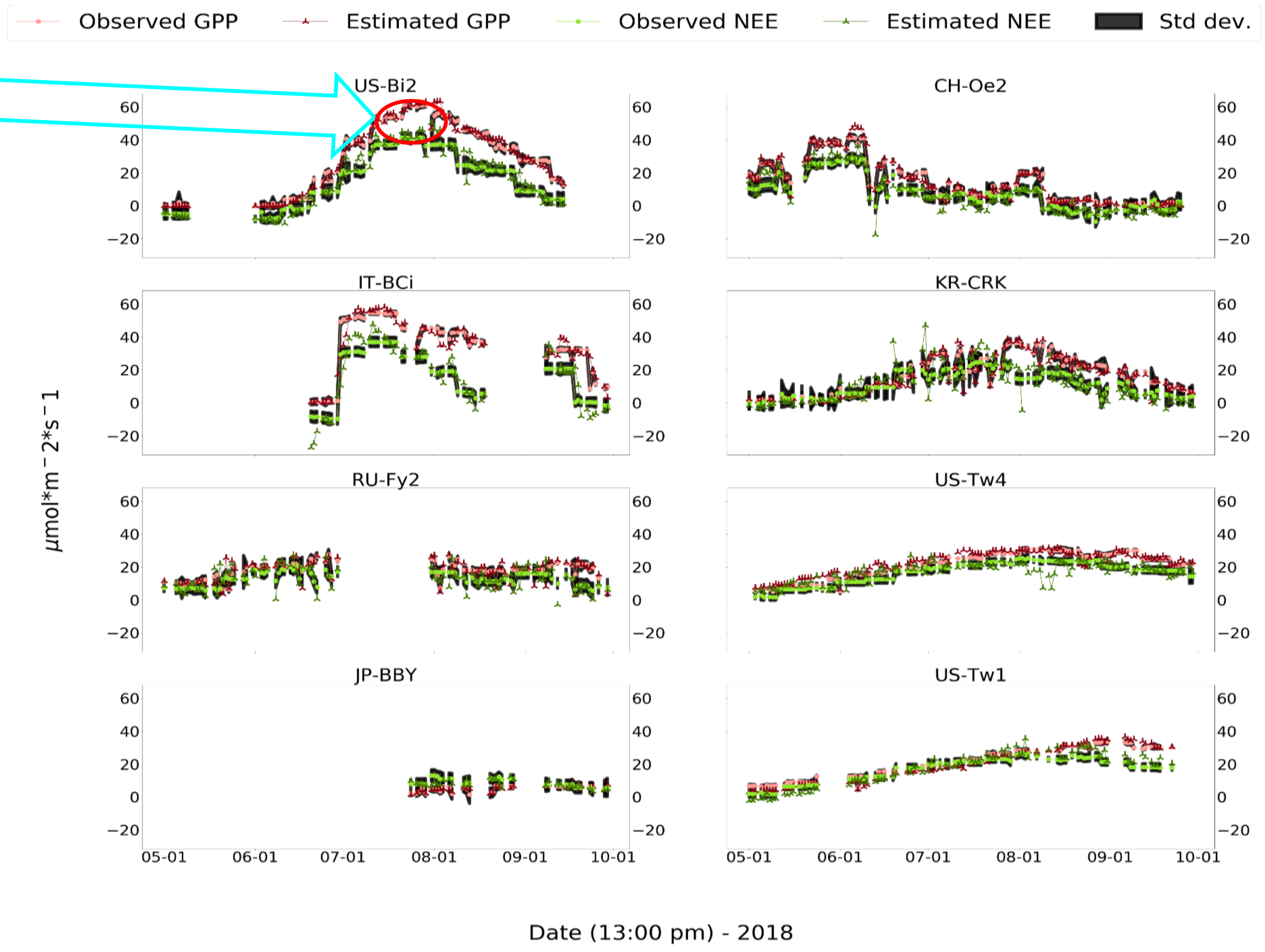
Estimating GPP/NEE relation: Tower sites

GPP/NEE evolution:

Total ecosystem respiration as **Respiration** = GPP - NEE

Bigger differences between GPP and NEE found on crop sites (US-Bi2 IT-BCi)

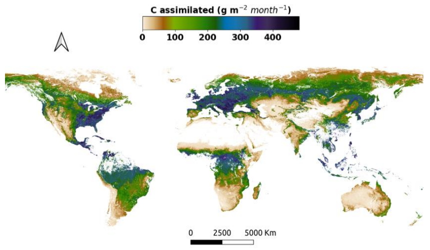
Marsch sites presenting closest values of GPP and NEE

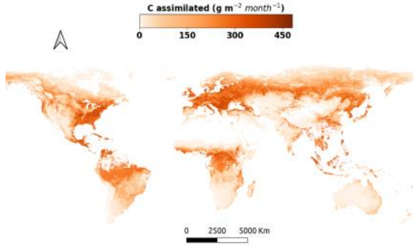


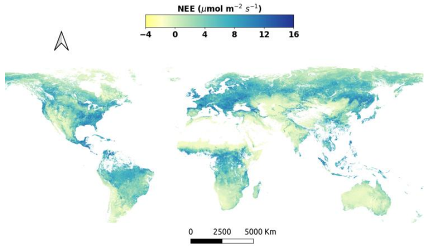
Conclusions and future works

An efficient method for estimating vegetation productivity variables based on the usage of GPR and a multisource data catalogue

SIF, LAI and FAPAR were found the most important variables for global mapping productivity (GPP, NPP). SIF prediction ability was constrained at tower site scales (resolution downscaling is needed)



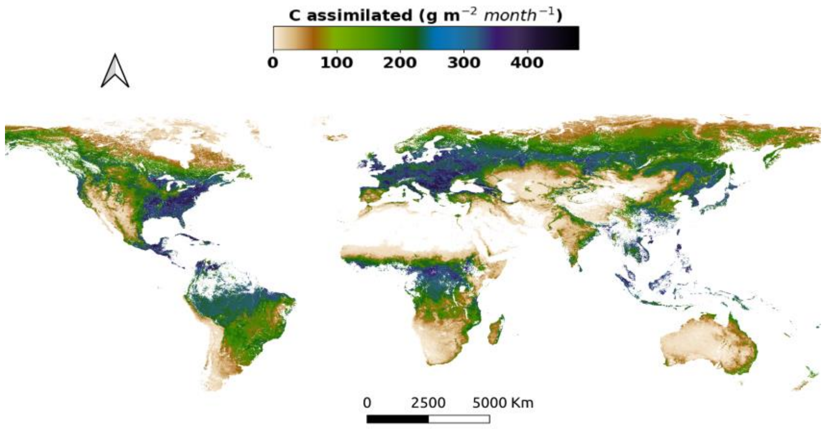


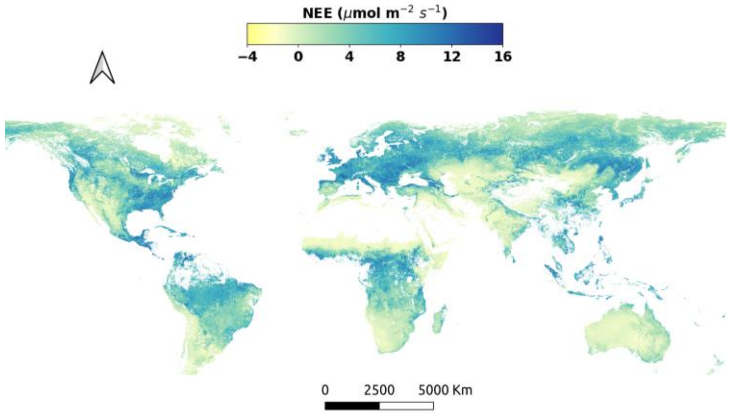


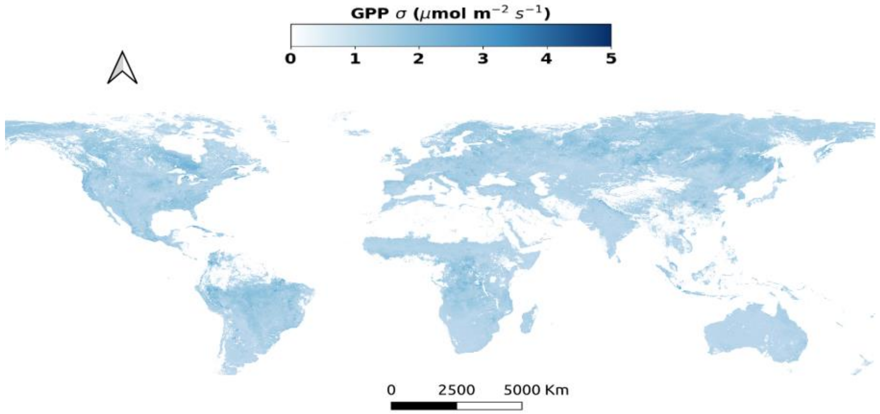
Future worklines:

- Integrating carbon assimilated over time and gap filling techniques
- Validations on different ecosystem types
- Downscaling Tropomi-SIF data for usage at tower scale
- Applications of the models on data sources coming from different missions (e.g, SLSTR, S2, future FLEX mission)

Thanks for your attention!!







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