Assimilation of fluorescence observations to constrain the gross primary production in a land surface model

F. Maignan, C. Bacour, L. Leverne, C. Abadie, Y. Zhang, V. Bastrikov, N. Raoult, P. Peylin et al.

Scientific goal: Understanding of GPP-related processes from leaf to large scales under various conditions

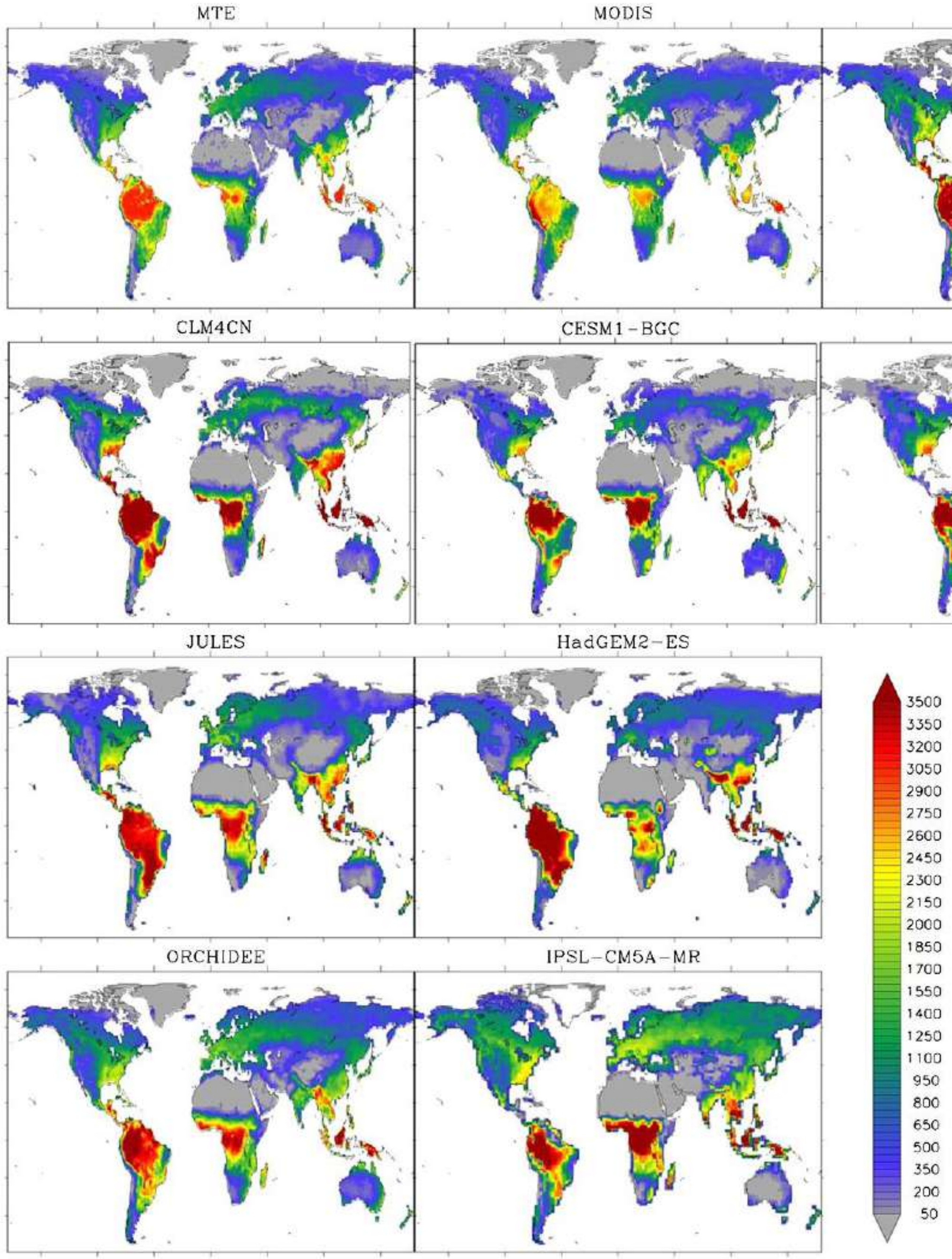
Tools:

Land Surface Model ORCHIDEE

Data: Satellite (Sun-Induced Fluorescence, SIF) and in situ

Data Assimilation ORCHIDAS

GROSS PRIMARY PRODUCTION (GPP): A VERY UNCERTAIN FLUX



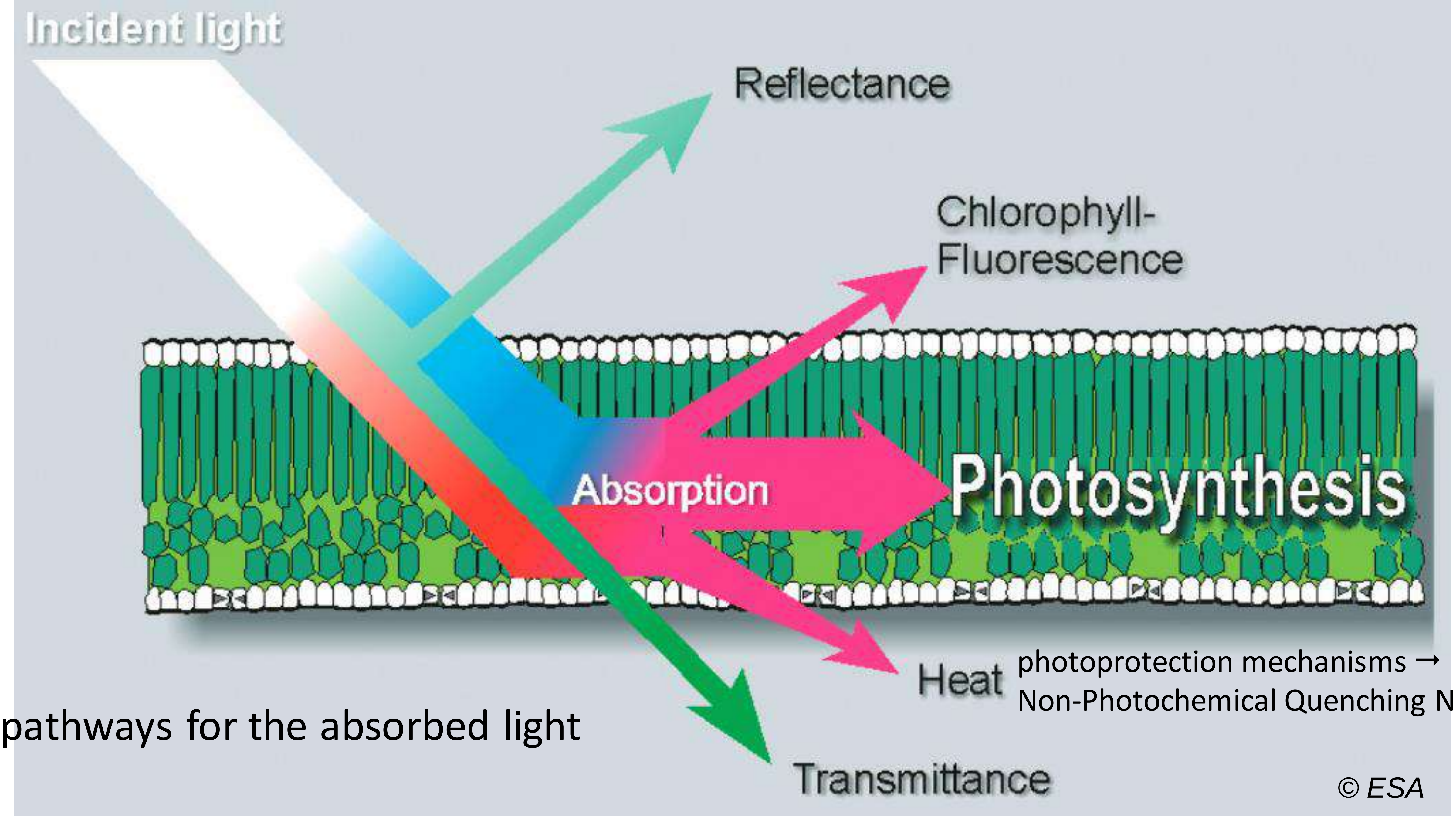
Anav et al. (2015)

1990-2009
gC m^{-2} yr^{-1}

GPP cannot be measured at scales larger than leaf.

- Extrapolation from in situ measurements (FLUXNET)
- Based on satellite observations (e.g. MODIS)
- Land surface models

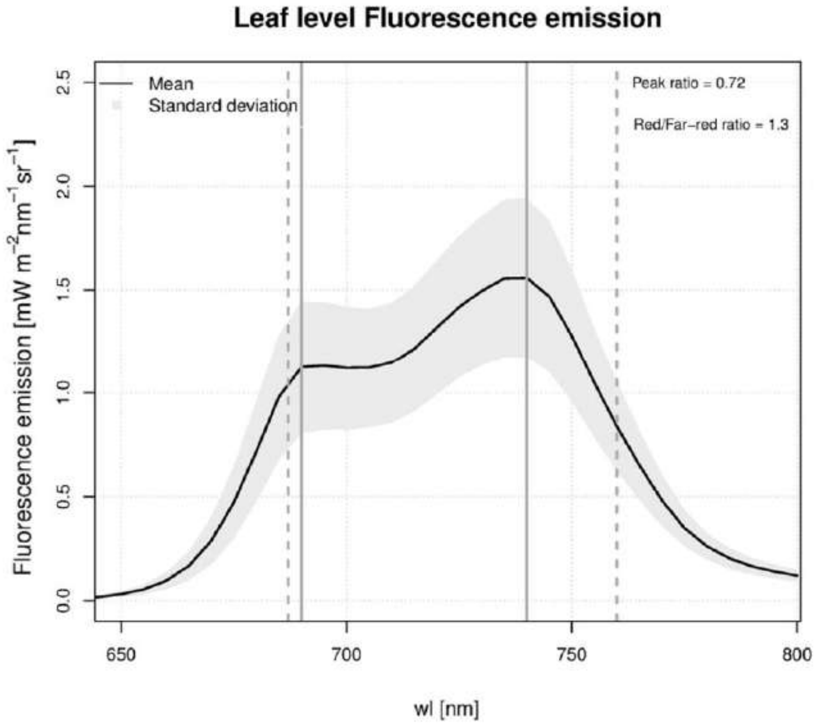
WHY IS FLUORESCENCE RELATED TO PHOTOSYNTHESIS?



photoprotection mechanisms → Non-Photochemical Quenching NPQ

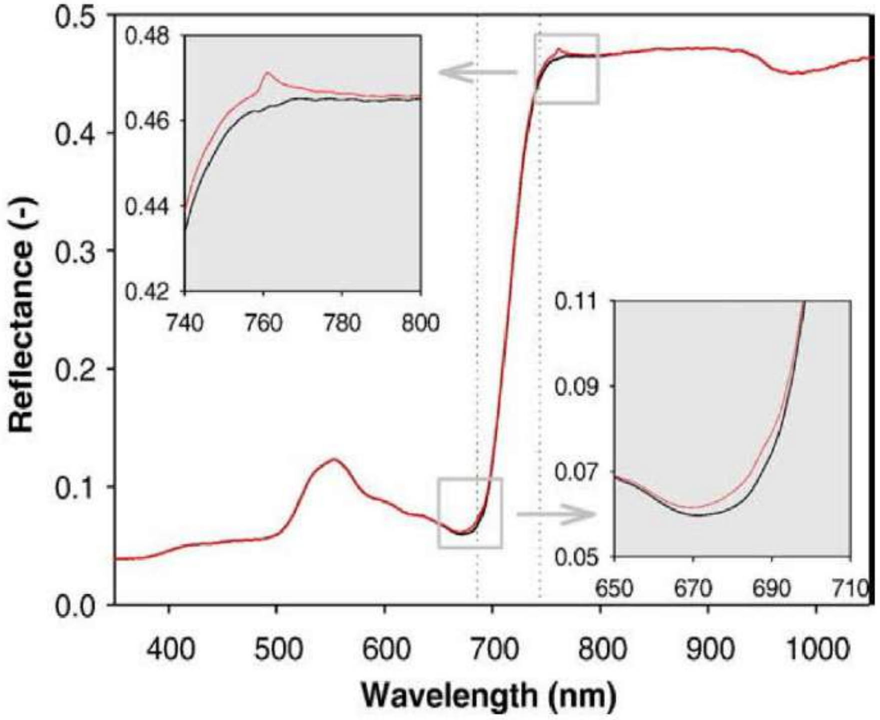
3 pathways for the absorbed light

Leaf level



Julitta et al., 2016

Canopy level

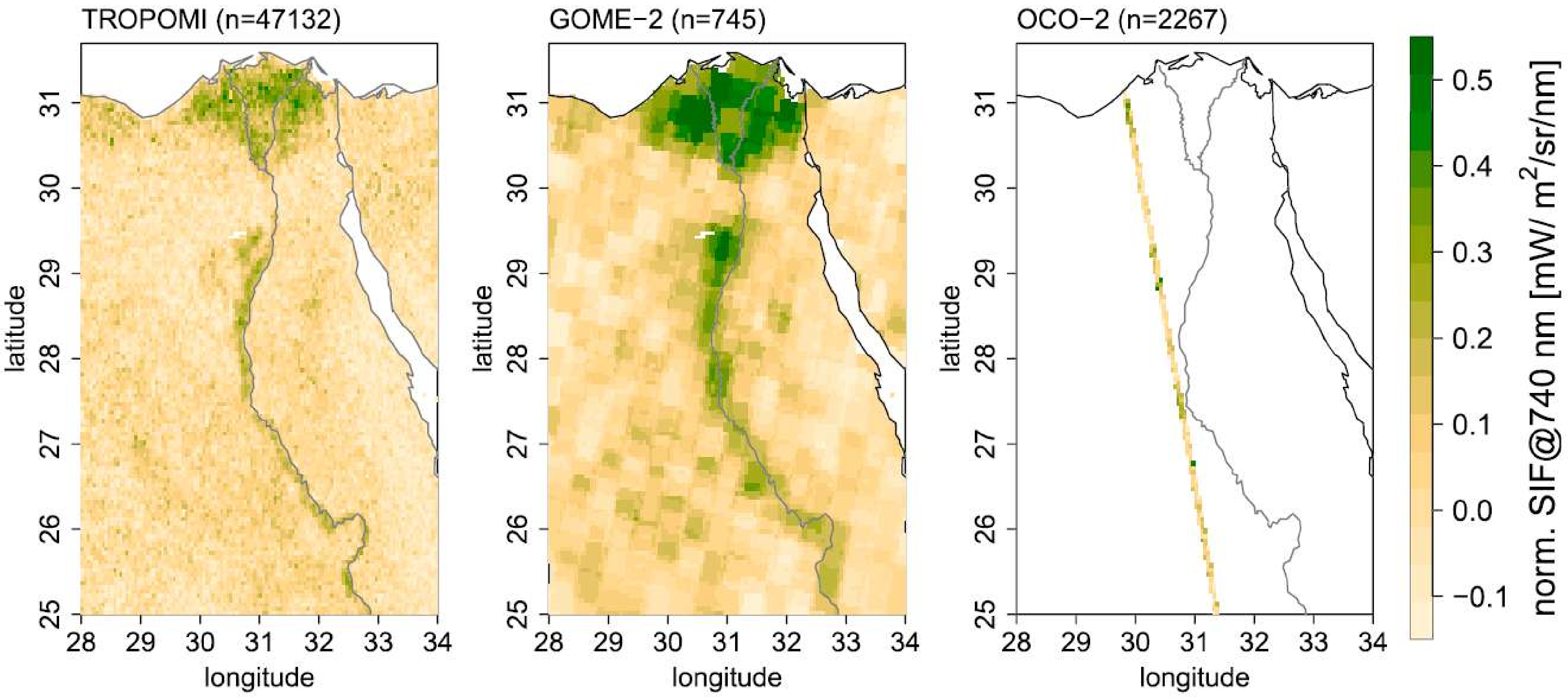


Meroni et al., 2009

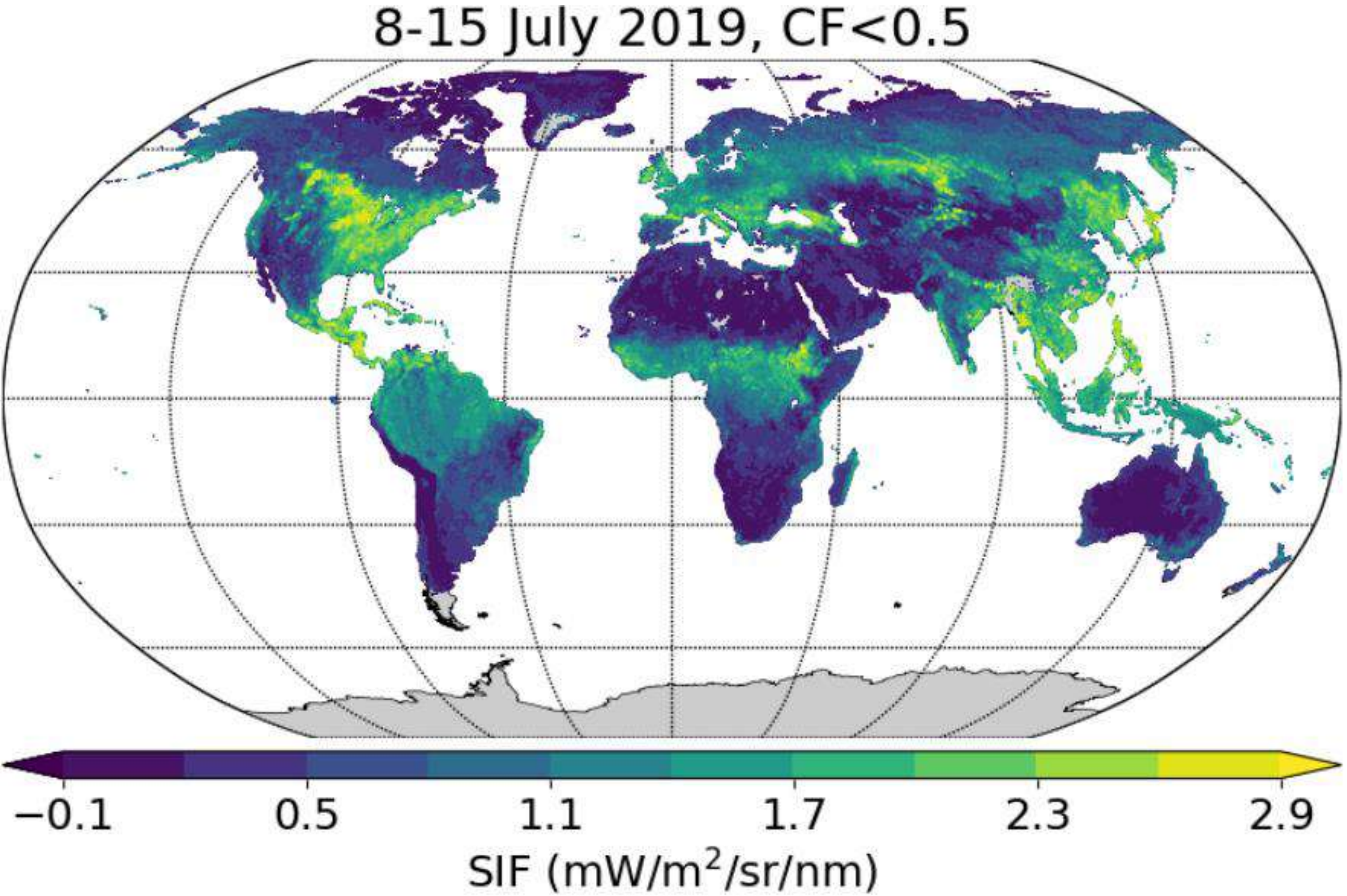
Satellite instruments for SIF estimates

	GOME-2	SCIAMACHY	GOSAT	OCO-2	TROPOMI
Spatial resolution	40x40 km²	30x60 km²	0.5x0.5 km²	1.3x2.25 km²	3.5 km x 5.5 km²
Revisit frequency	3 days	6 days	3 days	16 days	~ 1 day
Overpass time	9:30	10:00	13:00	13:30	13:30
Spectral resolution	~ 0.5 nm	~ 0.5 nm	~ 0.025 nm	~ 0.05 nm	0.38 nm

+ ESA FLEX (2025) 300m



Köhler et al. (2018)



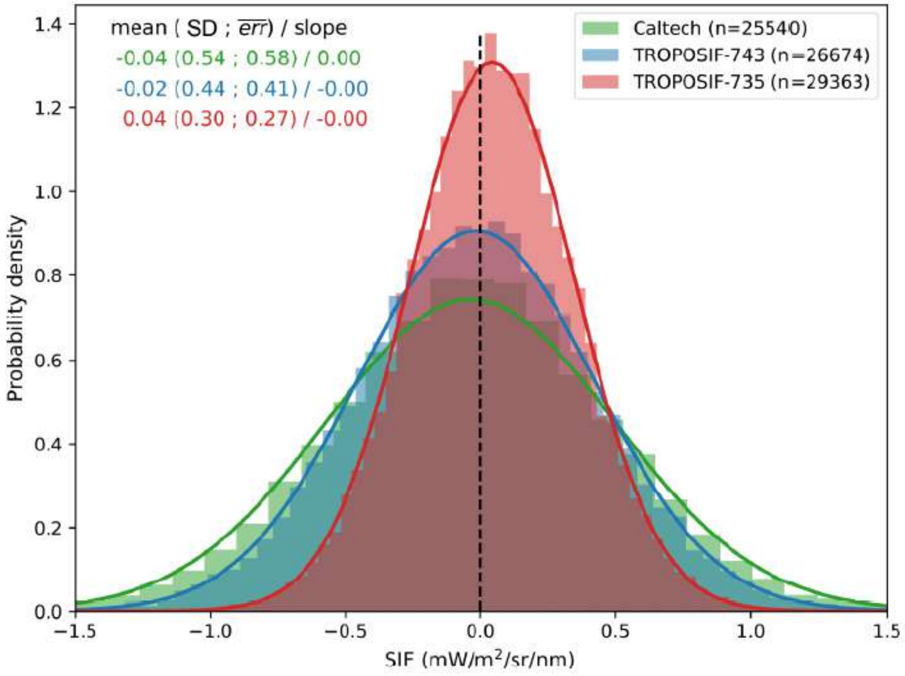


Figure 10. Histogram of all available TROPOMI-based SIF estimates at 10 PICS over the 2018–2020 period, for Caltech SIF and TROPOSIF SIF estimates from the 743–758 and 735–758 nm fitting windows. The distributions were fitted using a Gaussian function; the corresponding mean (bias) and standard deviation (SD) are provided for each SIF product. The mean slope of the SIF temporal variations over the 10 PICS is given in brackets.

- The bias is evaluated at invariant calibration sites and close to 0.
- The retrieval error for TROPOSIF is typically 0.5 mW m^{-1} sr^{-1} nm^{-1}.
- Directional effects

→ Data are aggregated temporally and/or spatially to reduce noise.

Guanter, Bacour et al. (2021)

AGU ADVANCING EARTH AND SPACE SCIENCE
Global Biogeochemical Cycles
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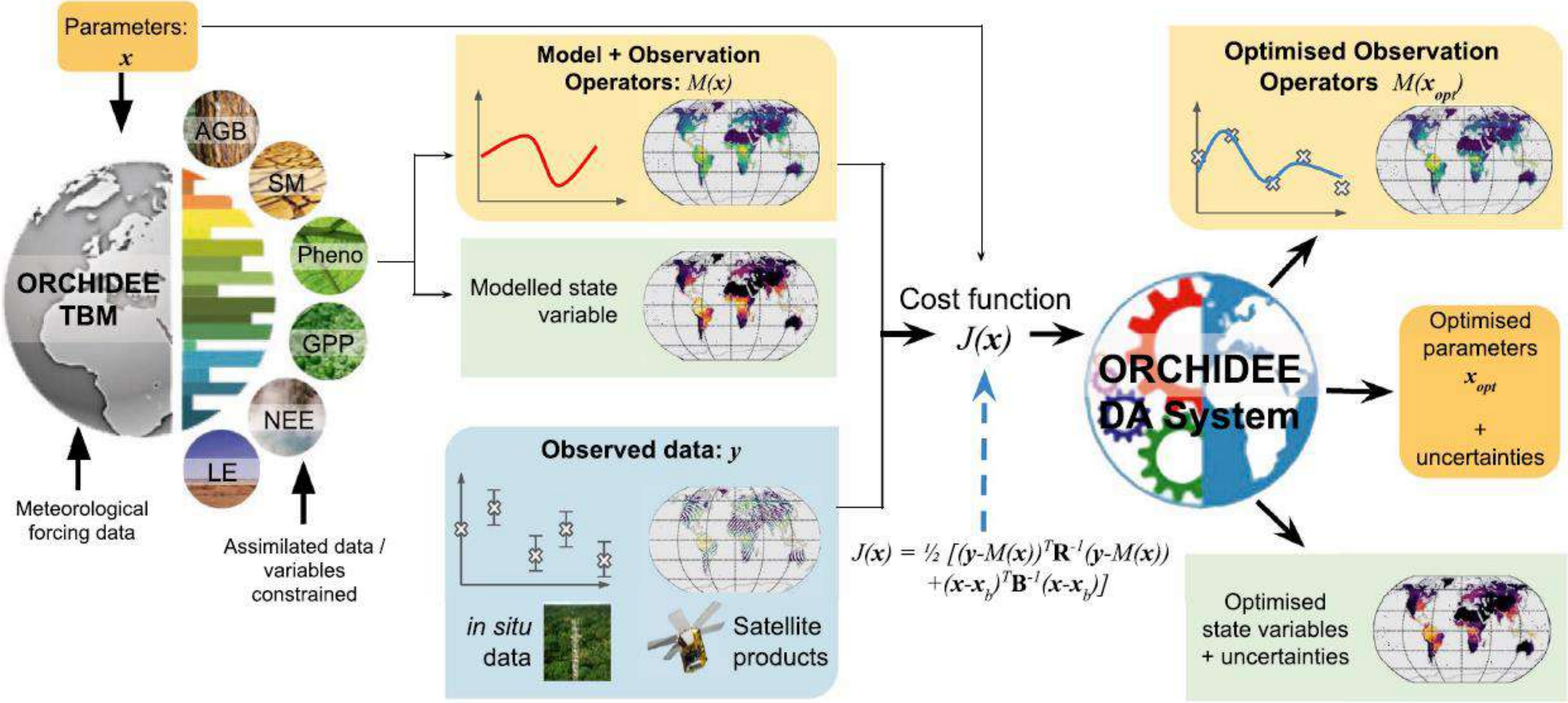


Figure 1. Schematic showing the different components of the ORCHIDEE Data Assimilation System.

MacBean, Bacour et al. (2022)

Bayesian framework: x_{opt} minimizes the misfit function *J(x):*

$$J(x) = \frac{1}{2}\Big[\underbrace{(M(x) - y)^T \mathbf{R}^{-1}(H(x) - y)}_{\text{observation term}} + \underbrace{(x - x_b)^T \mathbf{B}^{-1}(x - x_b)}_{\text{prior parameter term}}\Big]$$

M(x) model outputs
y observation vector
R observation and model error covariance matrix

x parameter vector
x_b a priori parameter values
B prior par. error cov. matrix

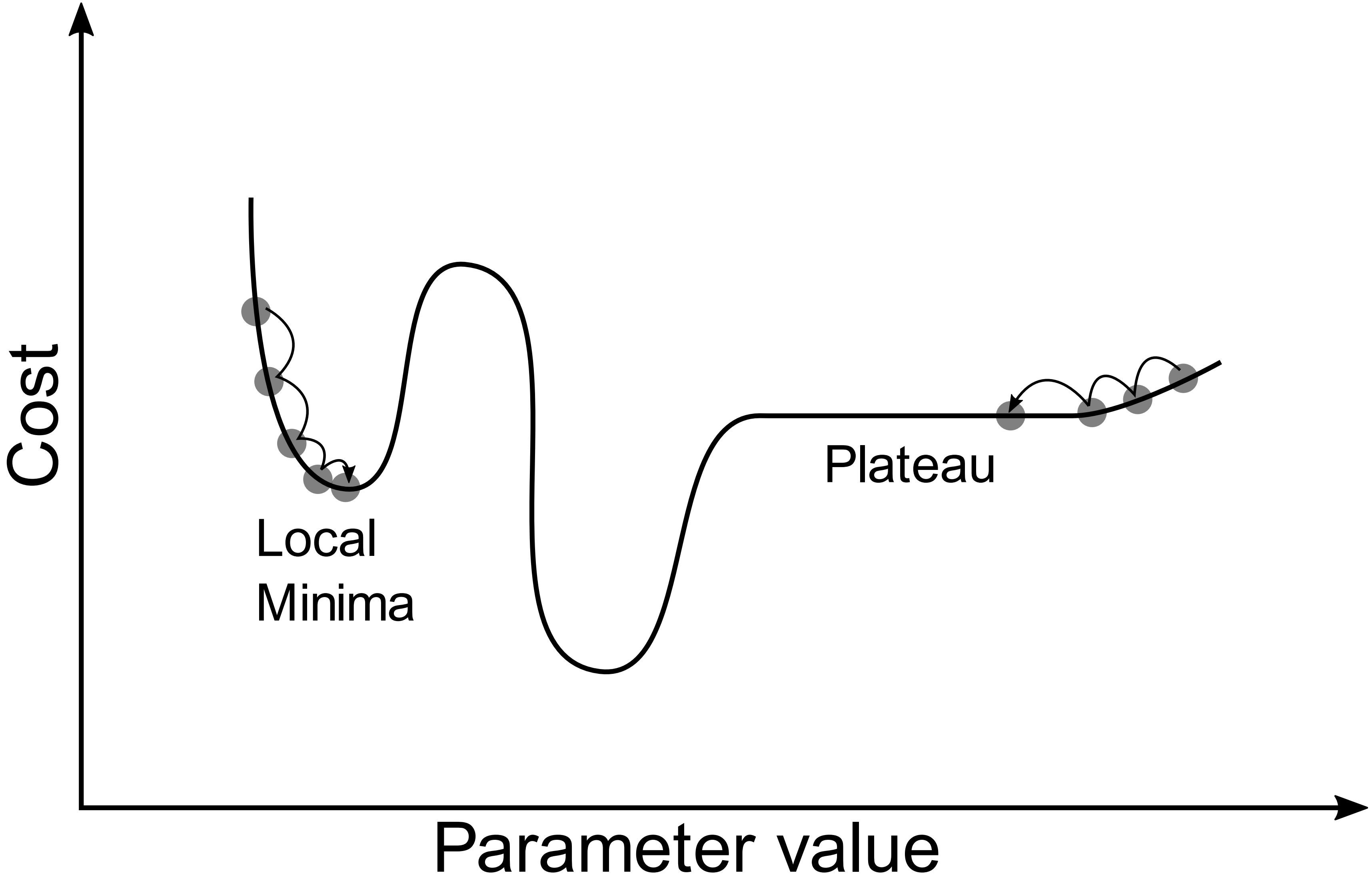
(Tarantola, 1987)

Technical challenges:

- **R** and **B** are diagonal → We do not consider any correlation (temporal, spatial, between parameters).
- The authorized range variations of parameters is prescribed based on literature reviews and expertise of the researchers.
- The prior uncertainty is typically assumed to be 25% of the parameter value range.
- The observation and model error covariance matrix (**R**) is based on the RMSE between the observations and the model.

…

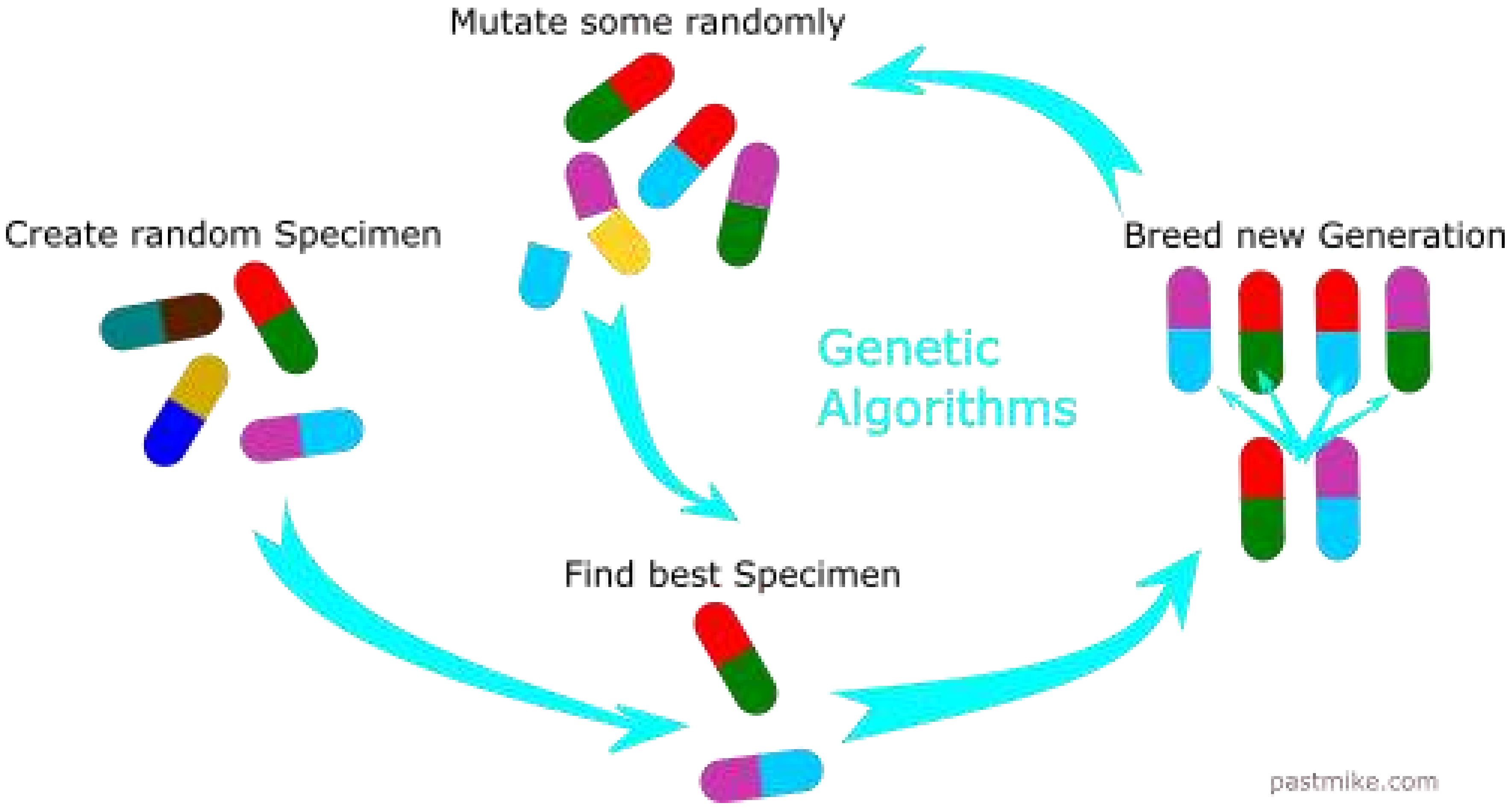
Minimization algorithms: local gradient-based vs global random search



https://winder.ai/402-optimisation-and-gradient-descent/

High risk to be stuck in a local minima for non-linear models.

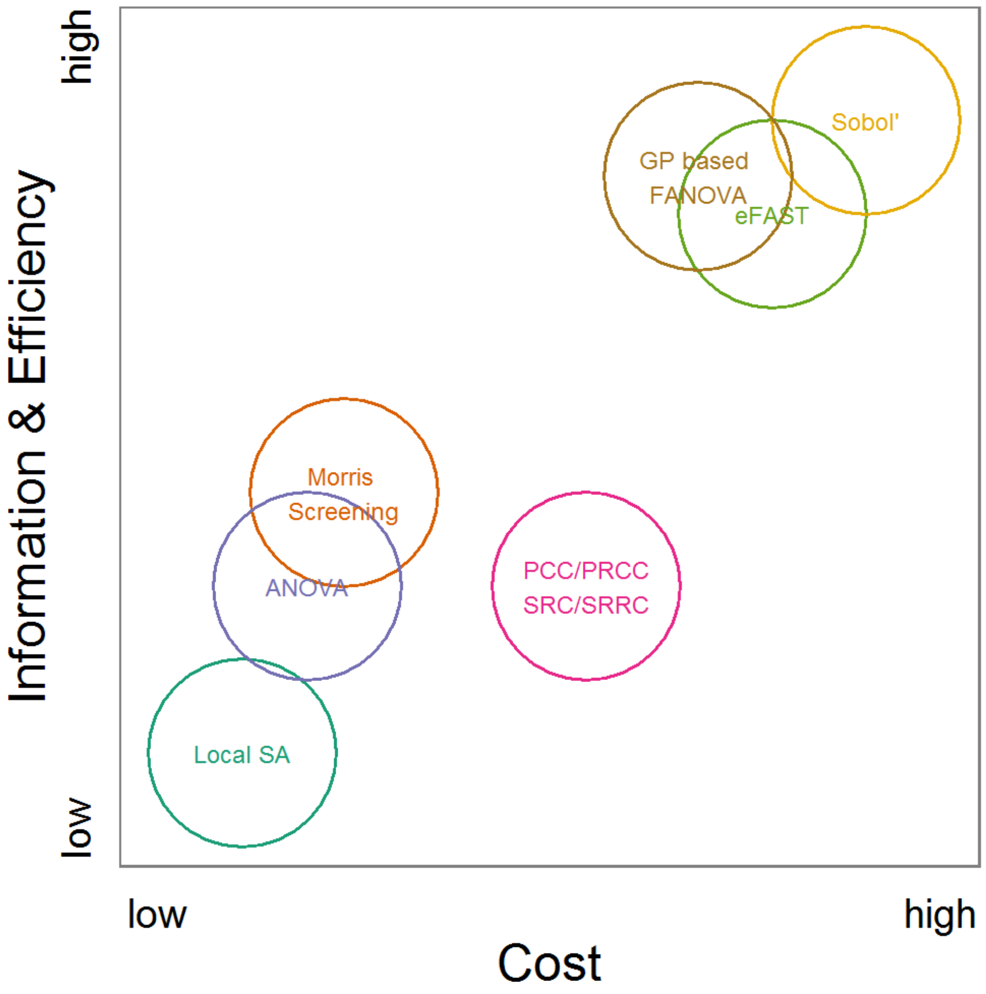
https://pastmike.com/what-is-a-genetic-algorithm/



Geoscientific Model Development
Open Access
EGU

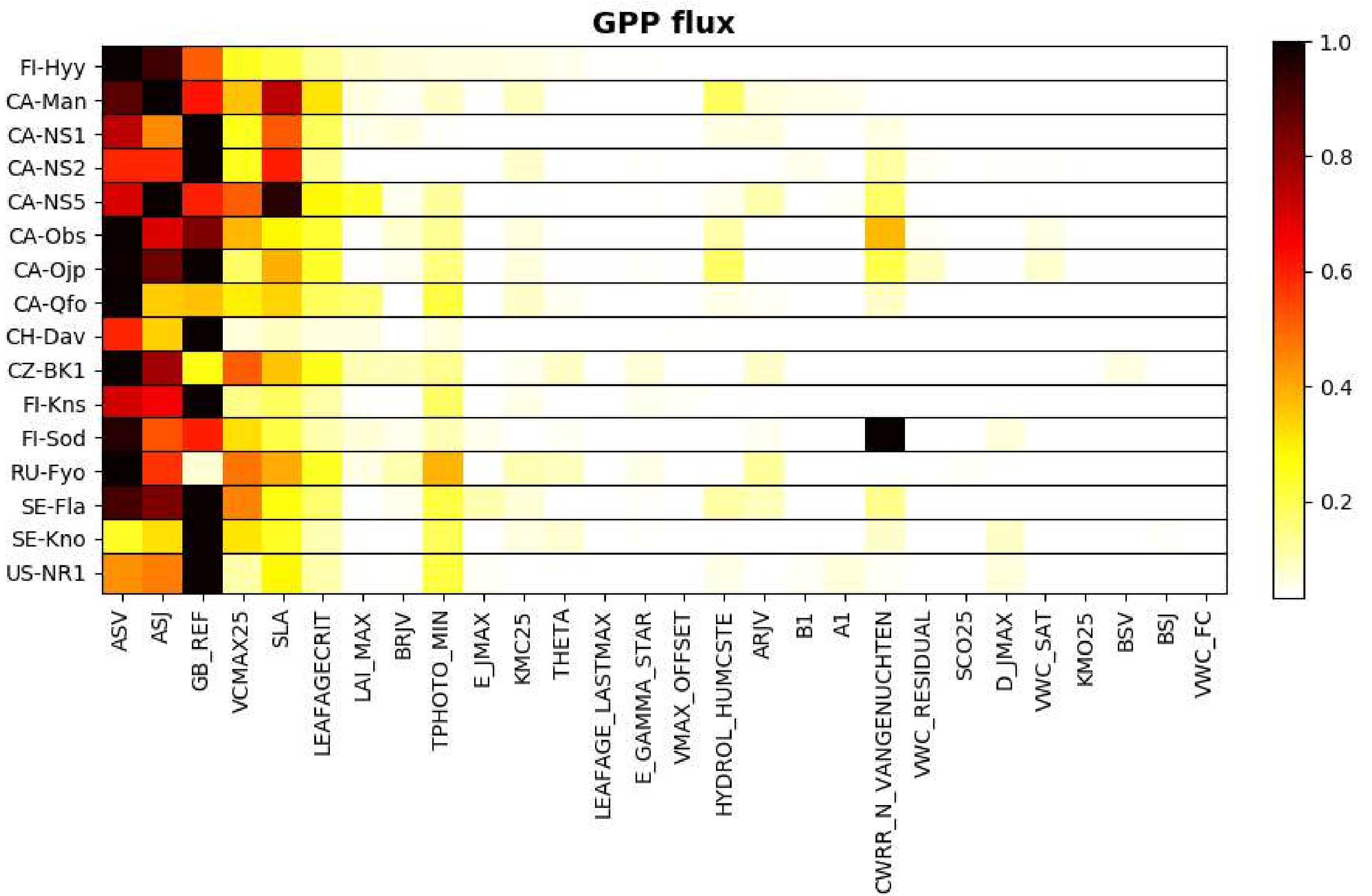
Land surface model parameter optimisation using in situ flux data: comparison of gradient-based versus random search algorithms (a case study using ORCHIDEE v1.9.5.2)

Vladislav Bastrikov[1,2], Natasha MacBean[1,a], Cédric Bacour[3], Diego Santaren[1], Sylvain Kuppel[4], and Philippe Peylin[1]



Thiele et al. (2014)

Example with the Morris approach:



Abadie et al. (in prep.)

The ranking largely depends on the authorized range variation.

Virtual workshops:
Tackling Technical Challenges in Land Data Assimilation, June 14-16, 2021 (https://aimesproject.org/lda_workshop/)
New Directions in Land Data Assimilation, June 13-15, 2022 (https://aimesproject.org/lda_workshop_2022/)

BAMS
Meeting Summary

Building a Land Data Assimilation Community to Tackle Technical Challenges in Quantifying and Reducing Uncertainty in Land Model Predictions

Natasha MacBean, Hannah Liddy, Tristan Quaife, Jana Kolassa, and Andrew Fox

DEVELOPING A SIF OBSERVATION OPERATOR

We first hypothesized a **linear relationship between SIF and GPP**, and assimilated GOME-2 data at a monthly time-scale and a 0.5° spatial resolution.

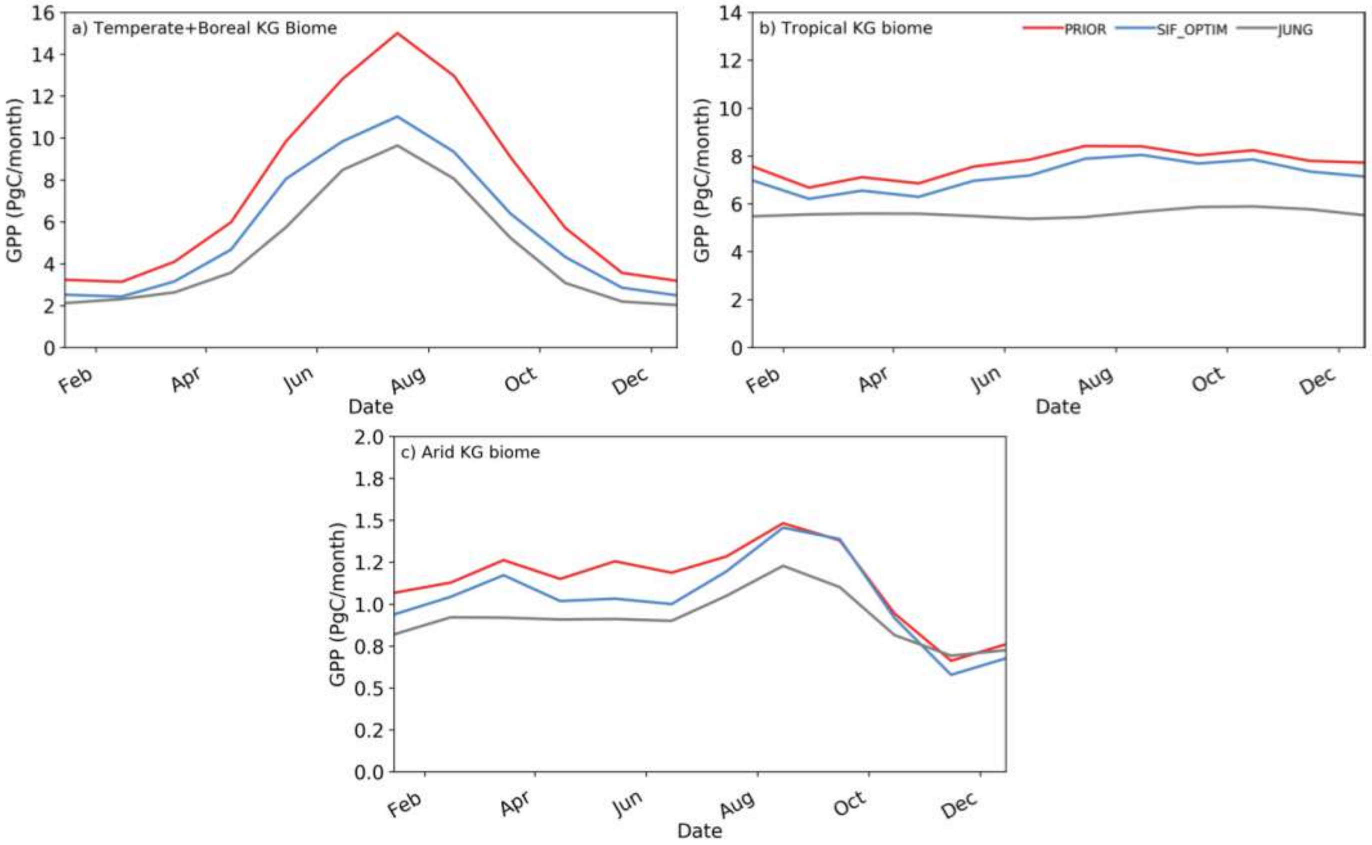


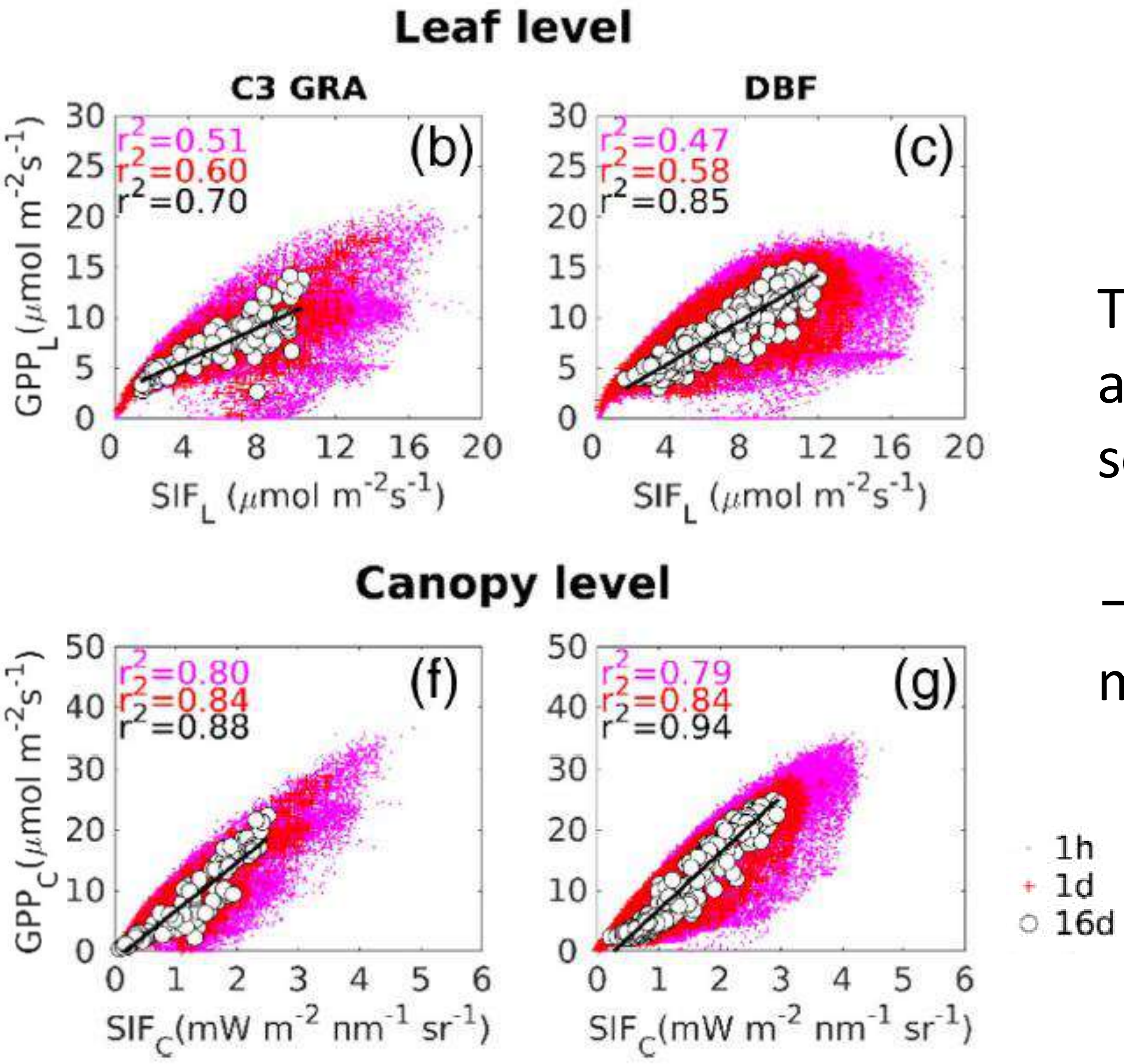
Figure 3. Mean monthly GPP seasonal cycle over 2007–2011 period (PgC/month) for: (**a**) temperate and boreal Köppen-Geiger (KG) biomes (approximately equivalent to northern hemisphere >60°N); (**b**) tropical KG biomes (approximately equivalent to tropical latitudes 30°S to 30°N); (**c**) arid KG biomes. The prior simulation is shown in the red curve, and the posterior in blue. The grey curve shows a comparison with the JUNG up-scaled FLUXNET data-driven GPP product by Jung M. *et al.*[18]. Köppen-Geiger classification based on Peel M. C. *et al.*[53].

$$SIF = aGPP + b$$

→ Simulated GPP improved both in amplitude and seasonality

MacBean, Maignan, Bacour et al. (2018)

But: The SIF-GPP relationship is scale-dependent.

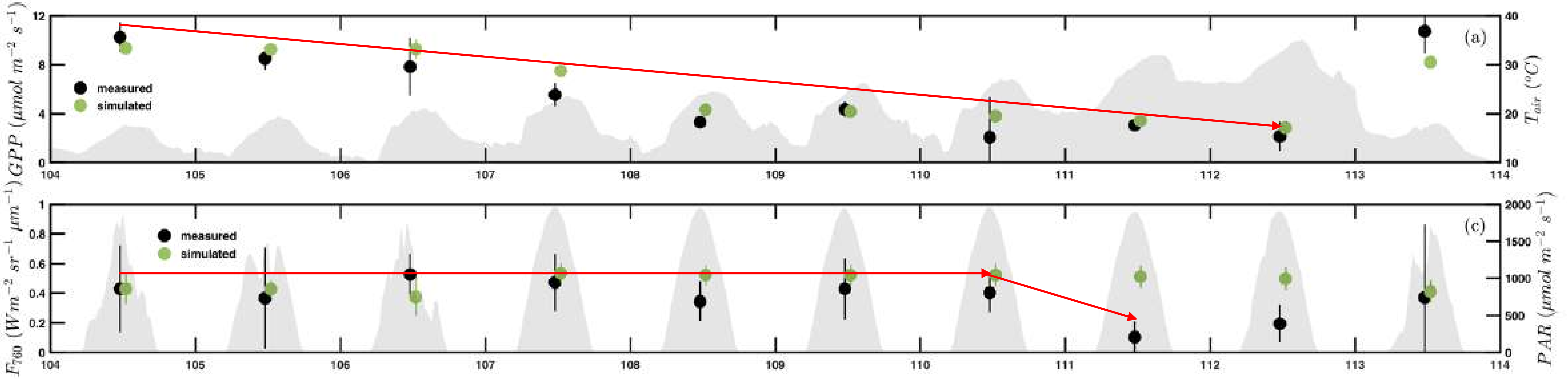


The SIF-GPP relationship is not linear at leaf and high-frequency time scales.

→ Need to use SIF process-based models.

Zhang et al. (2016)

But: SIF and GPP are decoupled during droughts and heatwaves.



Wohlfahrt et al. (2018)

Heatwave monitored during April 2017, at the Yatir forest, Israël

→ Need to understand the underlying mechanisms in stress conditions.

- **Principle**

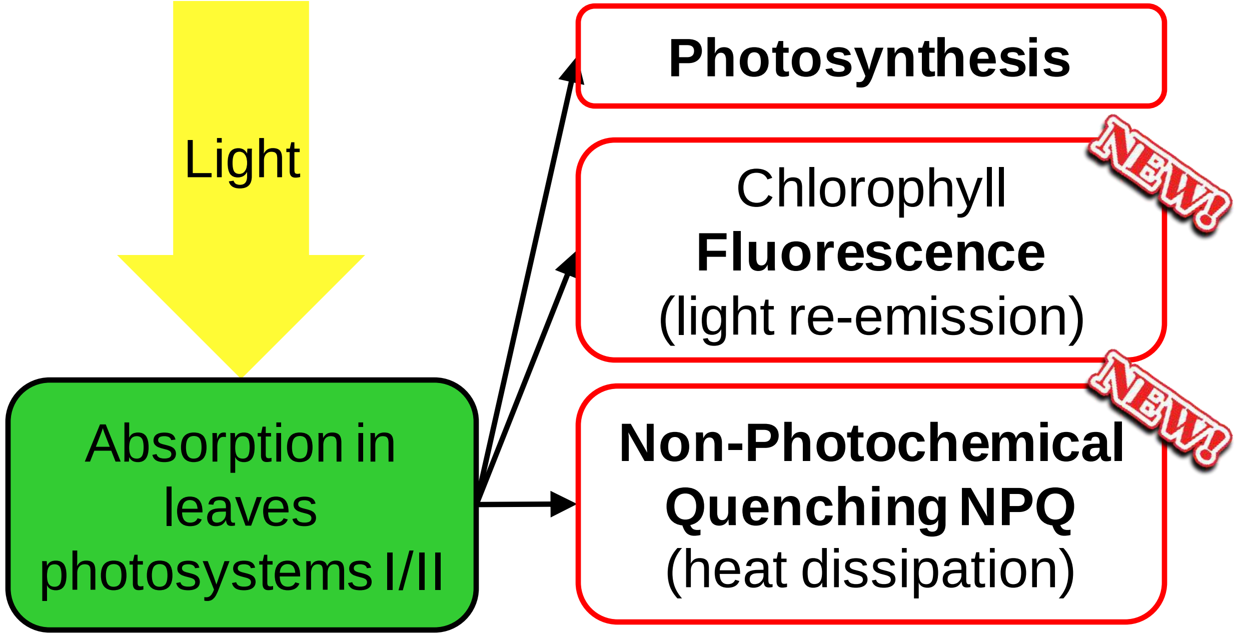
based on the SCOPE model (*Van der Tol et al., 2009*)

fluorescence emission: $$F^{\lambda} = F^{\lambda}_{PSI} + \varepsilon F^{\lambda}_{PSII}$$

- **Canopy level**

$F^{\lambda}_{PSI/PSII}$ fluorescence emission from photosystem (PS) I/II at canopy level for wavelength λ

- **Leaf level**



$$\varepsilon = \frac{\varphi_F}{\varphi_{F_0}}$$

regulation factor due to environmental conditions computed for a Top Of Canopy leaf

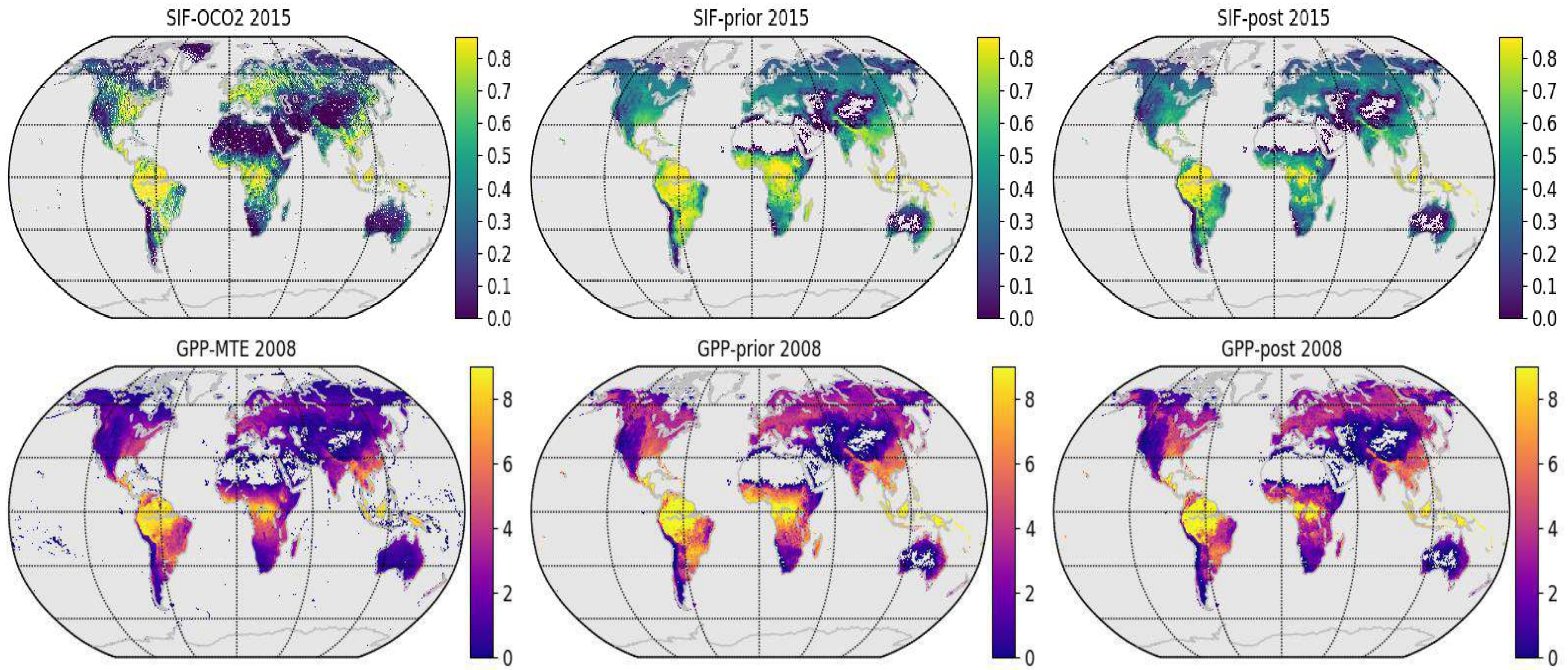
φ_F fluorescence yield

φ_{F_0} for dark adapted leaves

Assimilation of OCO-2 SIF

SIF (2015)

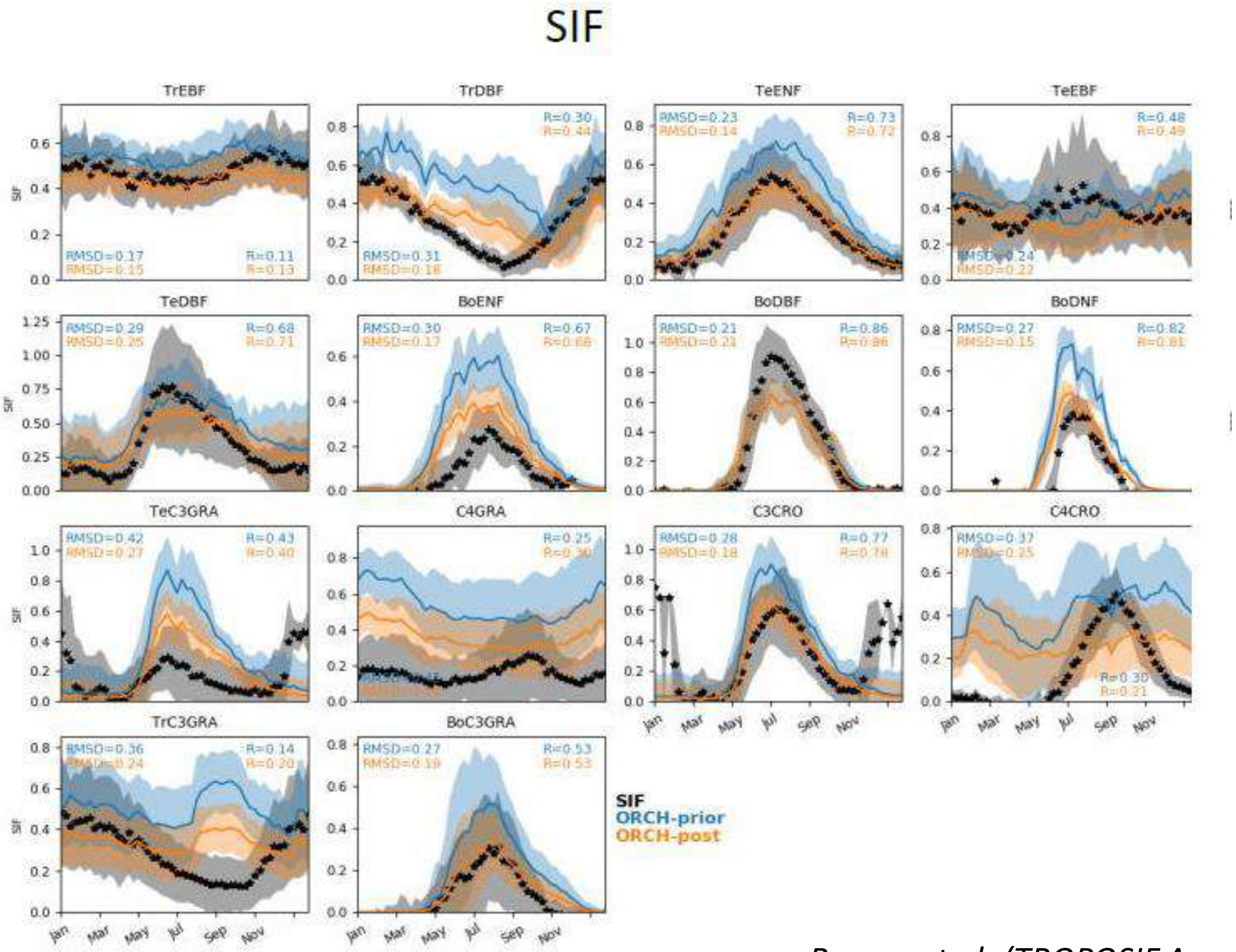
GPP (2008)



→Improvement of GPP magnitude and seasonality

Bacour, Maignan, MacBean et al. (2019)

Assimilation of TROPOMI SIF data

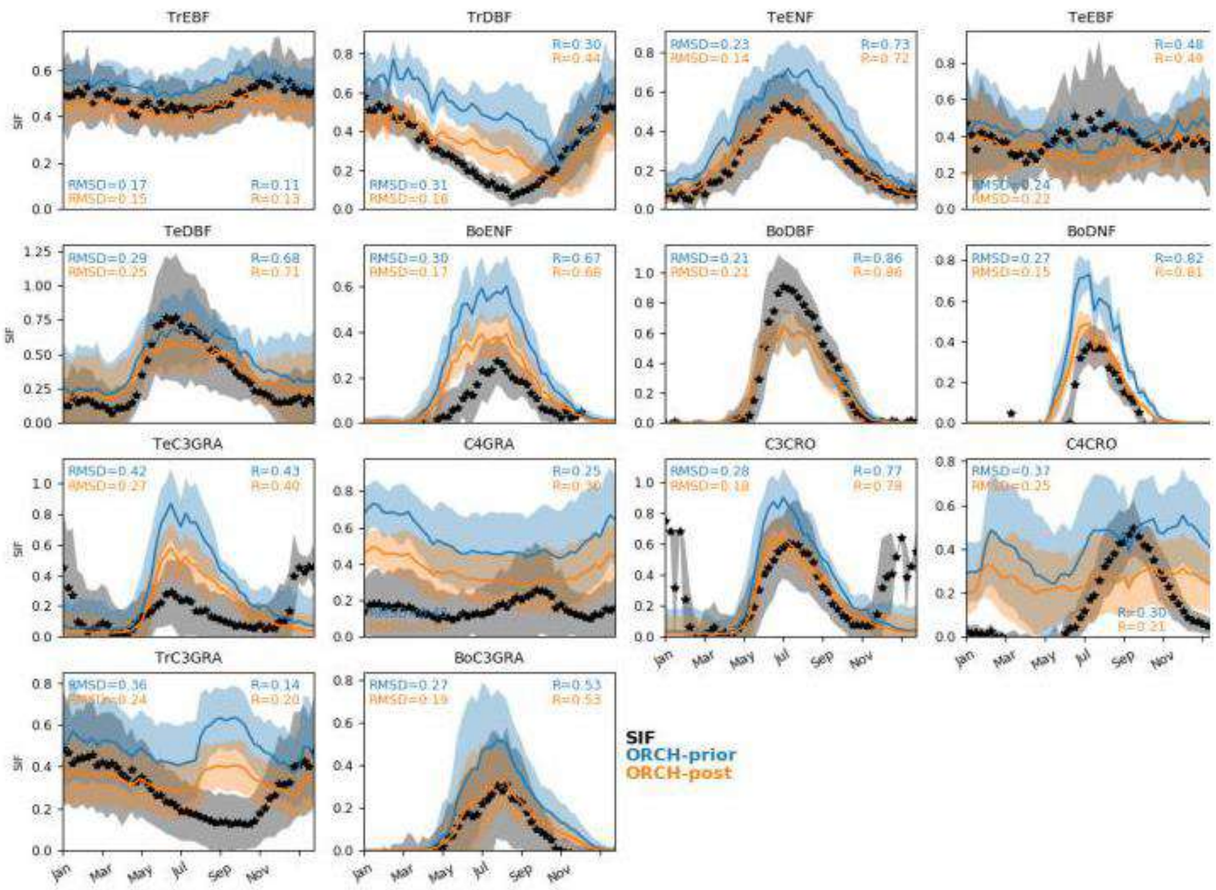


Bacour et al. (TROPOSIF Assessment Report, 2021)

Assimilating SIF-only results in GPP degradation for a majority of PFTs.

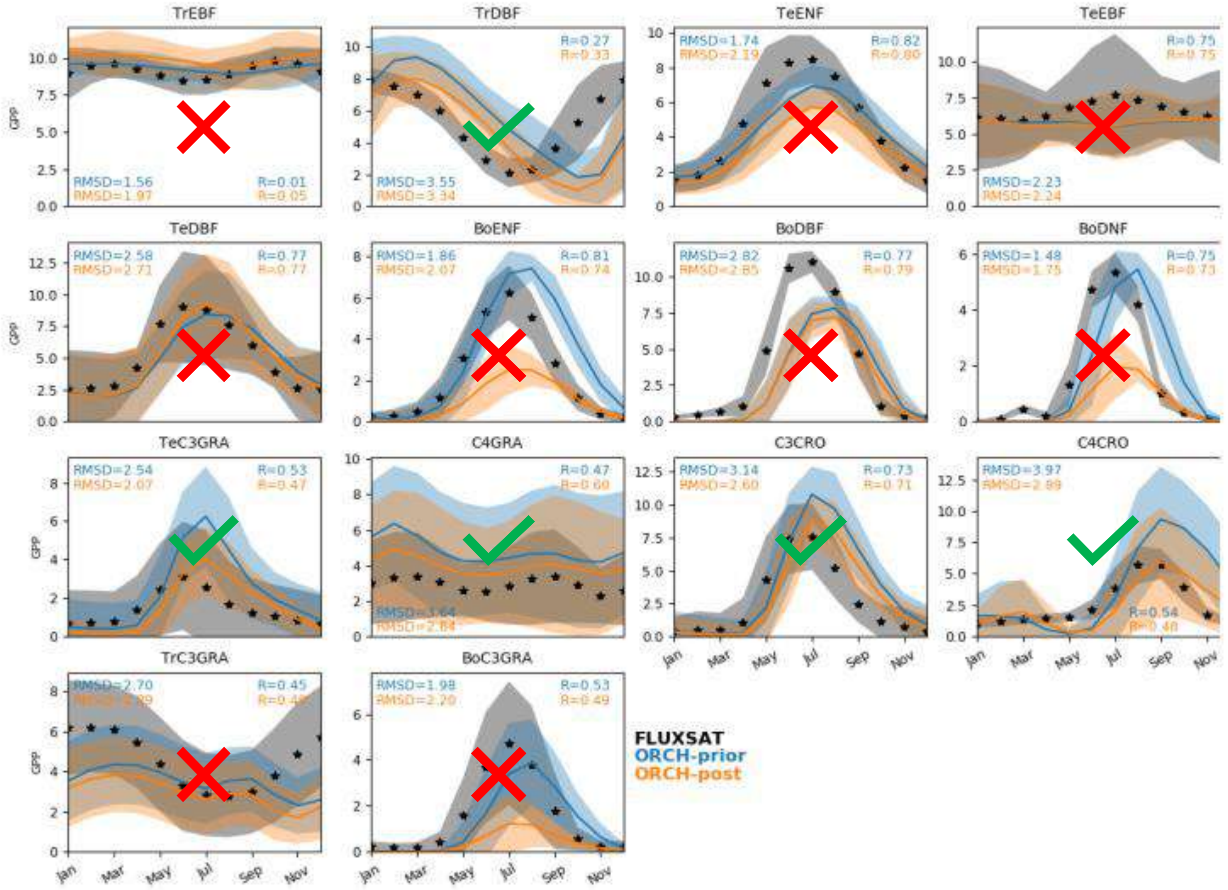
GRIDDED TROPOMI PRODUCT

SIF



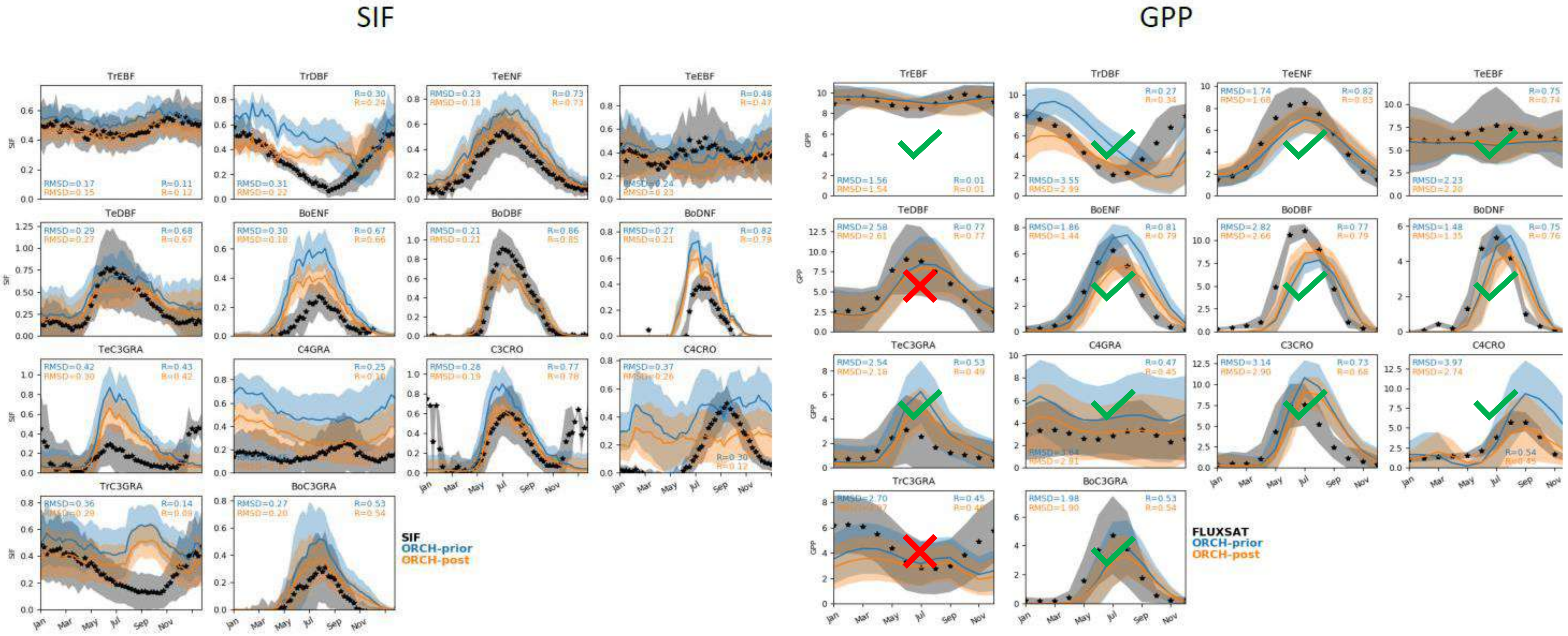
GRIDDED FLUXSAT PRODUCT

GPP



Bacour et al. (TROPOSIF Assessment Report, 2021)

Co-assimilation of SIF and GPP is required to optimize both variables.



Bacour et al. (TROPOSIF Assessment Report, 2021)

→ We are now currently co-assimilating TROPOMI SIF satellite data and in situ FLUXNET GPP estimates, managing the different spatial scales.

OUTLOOKS

Reducing model structural errors:

- Improving the radiative transfer model (Zhang et al., 2020).
- Improving the photosynthesis scheme (Johnson and Berry, 2021).
- Improving the NPQ model (PhD Lucas Leverne).
- Participating in Model Intercomparison Projects (SIFMIP2).

Data:

- Development of a network of in situ SIF observations

Data assimilation:

- Co-assimilation of SIF and Carbonyl Sulfide (COS), SIF and Vegetation Optical Depth (VOD) (PhD Camille Abadie)
- Co-assimilation of SIF and XCO2 (OCO-2, MicroCarb)
- Implementation of the History Matching approach in ORCHIDAS (use of emulators)