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Synergy between sun-induced chlorophyll fluorescence (SIF), surface spectral reflectance and reflectance-based indices on quantifying gross primary productivity (GPP)

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INTRODUCTION

- Due to climate change such as frequent occurring heatwaves and wildfires, it has become imperative to assess the role of terrestrial ecosystems in terms of carbon, water and energy exchanges. The gross primary productivity (GPP), which is the amount of carbon taken up by vegetation through photosynthesis, is the largest CO_2 flux between the atmosphere and the terrestrial ecosystems. Being able to quantify GPP at global and regional scales accurately is important to understand the ecosystems functioning, as well as to help us to cope with climate change. However, we still do not have an accurate estimation of the temporal and spatial variations of GPP yet, especially at ecosystem and larger scales. Luckily, the sun-induced chlorophyll fluorescence (SIF) has recently emerged as a promising remote sensing tool for monitoring canopy photosynthesis activity [1]. SIF is a faint signal emitted by the chlorophyll pigments during the photosynthetic activity [2]. SIF is fundamentally and functionally different from reflectance based vegetation indices such as normalized difference vegetation index (NDVI) and near-infrared reflectance of vegetation (NIRv) [3], which can only capture the significant changes in canopy structure and biochemical properties.

OBJECTIVES

- Evaluate how SIF is related to tower-based GPP at site scale and vegetation type;
- Assess whether mixed models of SIF and spectral reflectance would make a better prediction of GPP;
- And ultimately examine which inputs variables contribute the most to GPP prediction.

STUDY SITES AND DATA

- This study was carried out in 40 Integrated Carbon Observatory System (ICOS) ecosystem sites (figure 1). The flux sites span diverse Plant Functional Types (PFT): mixed forests croplands, deciduous broadleaf forests, evergreen broadleaf forest, evergreen needleleaf forests, grasslands, open shrubland, and wetlands. GPP data, from February 2018 to December 2020, were obtained from ICOS database portal (https://www.icos-cp.eu/data-services). Daily GPP values were used.

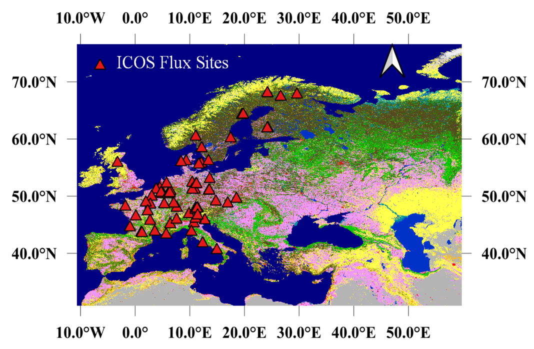

***Figure 1** ICOS flux sites localisation*

MODIS Terra and Aqua: Both contain 16 spectral bands of which the spatial resolution from B1 to B7 is 500m, and 1 km for the remaining. Daily corrected reflectance and vegetation indices (NDVI, NIRv, and photochemical reflectance index (PRI)) were used.

TROPOMI SIF data: daily estimated near infrared SIF (743-758nm) [4]. Its spatial resolution is 7 km along track and 3.5 km across track. Daily ungridded SIF (SIFd: $mWm^{-2}sr^{-1}nm^{-1}$) pixels whose center is at 5 km away from the ICOS site were used.

METHODS

- To evaluate the strength of the relationship between SIFd and GPP for each site and each PFT, a linear regression model was used.
- **Random Forest (RF) regression models** based on the combination of the inputs variables:
  - only surface spectral reflectance values (**RF-R**);
  - spectral reflectance values plus SIF_d (**RF-SIF-R**);
  - spectral reflectance plus SIFd and the vegetation type as categorical variable (**RF-SIF-R-PFT**);
  - and eventually, SIFd plus VIs (namely NDVI, NIRv, and PRI) (**RF-SIF-VI**).
  - 80% of the data for training and the 20% for testing our model (hyperparameters tuning).
- Models performance evaluation included: the coefficient of determination (R^2) , Adjusted R^2, the root mean squared error (RMSE), and p-value metrics. The relative importance of each variable was used to evaluate the part of the contribution of each inputs variable to predict GPP.

RESULTS

- **Site- and PFT-dependent relationship between ICOS ground-based GPP and SIF_d.**
  - The figure 2 shows that the slopes and offsets of the linear regression between GPP and SIFd are site-and PFT-dependent.
  - These results suggest that the difference in canopy structure, plant functional types, and spatial heterogeneity across sites may affect the relationship between GPP and SIFd.

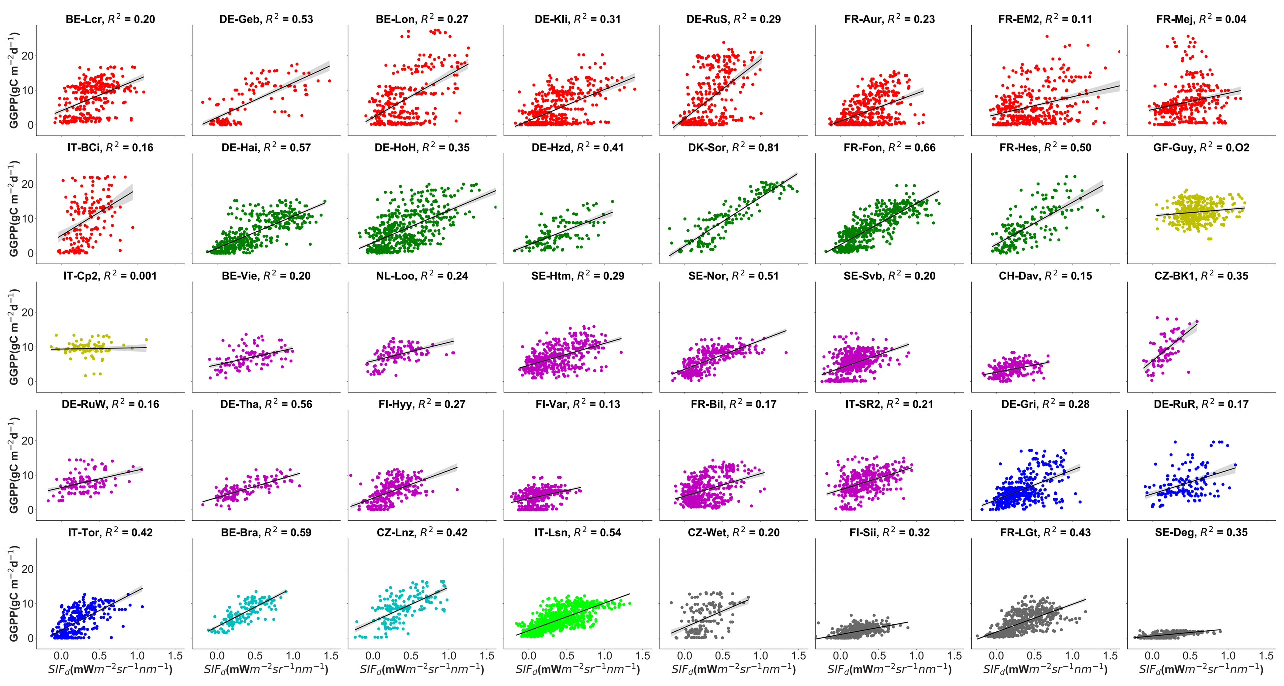

***Figure 2 :** the color code represents the eight different vegetation types encountered in the study sites: Red color stands for **CRO** (croplands), green for **DBF** (deciduous broadleaf forests), yellow for **EBF** (evergreen broadleaf forests), magenta for **ENF** (evergreen needleleaf forests), blue for **GRA** (grasslands), Cyan for **MF** (mixed forests), lime for **OSH** (open shrubland), and dimgrey for **WET** (wetland).*

- **Performance of GPP estimates by RF model:**
- Overall, all RF predicted GPP showed a high agreement with observed GPP.
- Yet, the **RF-R** model had the strongest prediction by explaining 86% of GPP variance, while the **RF-SIF-VI** model explained 75% of observed GPP, the lowest prediction.

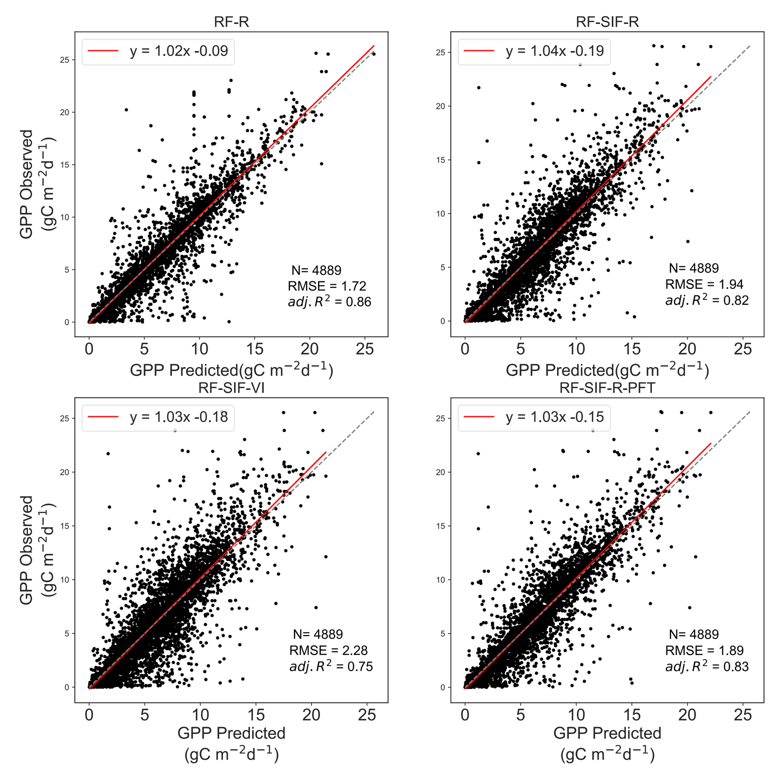

***Figure 3** the performance of the RF predicted GPP against observed GPP.*

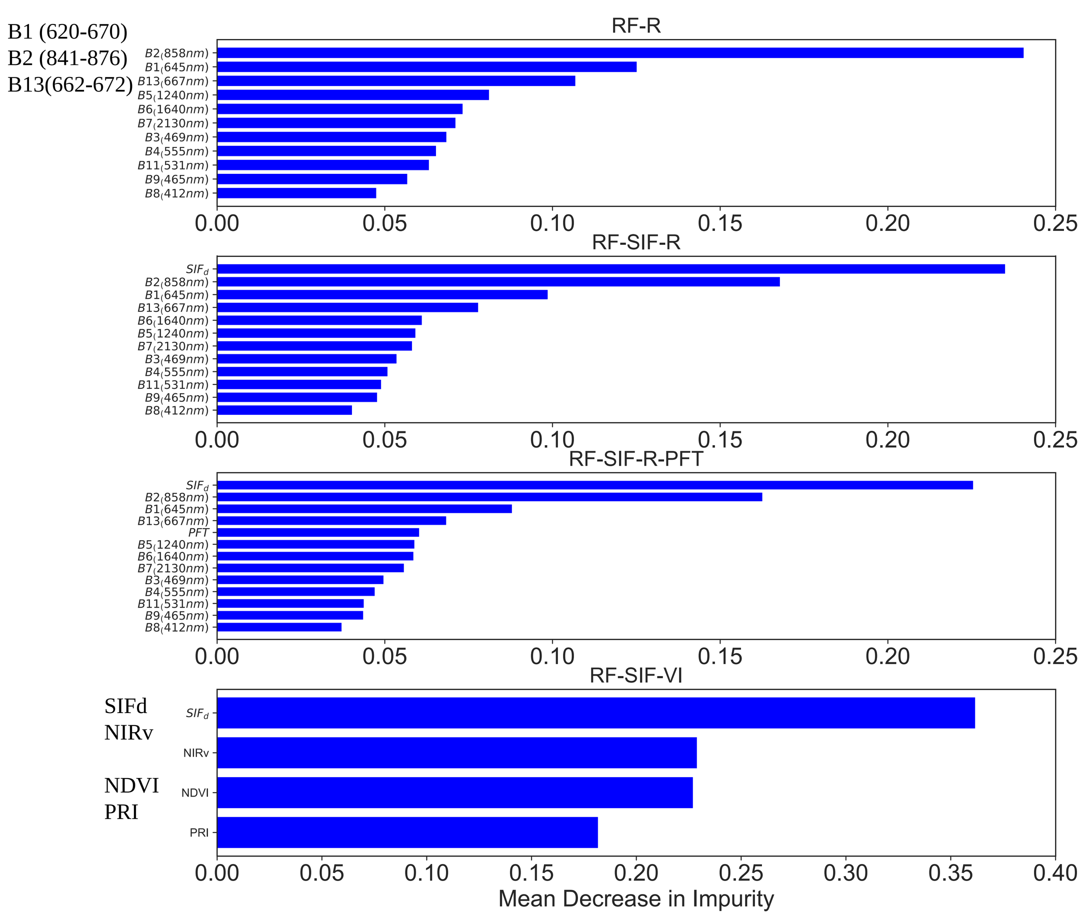

***Figure 4**, performance of the RF predicted GPP against observed GPP*

- The results in the figure 4 showed that SIF_d, the spectral reflectance in the near infrared band (B1), red band (B2), far-red band (B13), as well as NIRv and NDVI provide the most useful information for the prediction of GPP.
- B1 and B2 are well-known for characterizing vegetation seasonal phenology and canopy structure and leaves biochemical properties.
- While SIF_d exhibited the highest relative importance, SIF_d may lose its physiological information and most likely reflect phenological, structural and illumination at this limited spatial resolution (7 km x 3.5 km).
- SIF_d remains a better predictor of GPP than each reflectance band individually.

CONCLUSION AND PERSPECTIVES

- The strength of the relationship between GPP and SIF was strongly site- and PFT-dependent.
- SIF coupled with reflectance observations, explains over 80% of the GPP variability across diverse ecosystems, but bring same ability to predict GPP compared to reflectance alone at coarse spatial scales (~5 km).

Works on progress:

- Measurements of GPP, SIF and laser induced fluorescence (LIF) at the forest ICOS site of Barbeau Fontainebleau (ESE).
- Studying the link between SIF, LIF and GPP, to disentangle the physiological and structural information of SIF signal.
- Investigating the effects of heatwave and drought on these variables.

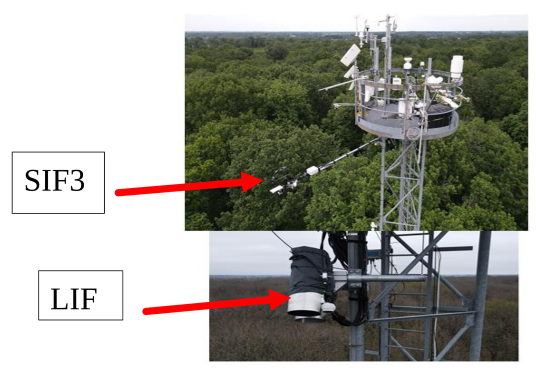

***Figure 5**, ground-based sun-induced chlorophyll fluorescence (SIF), Laser induced chlorophyll fluorescence (LIF), and GPP measurements at the forest site Barbeau Fontainebleau.*

This study is available at : Balde, H., Hmimina, G., Goulas, Y., Latouche, G., and Soudani, K.: Synergy between TROPOMI sun-induced chlorophyll fluorescence and MODIS spectral reflectance for understanding the dynamics of gross primary productivity at integrated carbon observatory system (ICOS) ecosystem flux sites, EGUsphere [preprint], (https://doi.org/10.5194/egusphere-2022-640).

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