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Spatially downscaling sun-induced chlorophyll fluorescence leads to an improved temporal correlation with gross primary productivity

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ABSTRACT

Sun-induced chlorophyll fluorescence (SIF) is known to relate directly to leaf and canopy scale photosynthesis. Retrieving SIF from space can thus provide an indication on the temporal and spatial patterns of the terrestrial gross primary productivity (GPP). Recent studies have successfully demonstrated the serendipitous retrieval of SIF from satellite remote sensing instruments originally destined to atmospheric studies. However, the finest spatial resolution achieved by these products is 0.5°, which remains too coarse for many applications, including the early detection of drought impacts on vegetation and the integration with ground GPP measurements from flux-towers. This paper proposes a methodology to spatially disaggregate the information contained within each coarse SIF pixels by using a non-linear model based on the concept of light use efficiency (LUE). The strategy involves the aggregation of high-resolution (0.05°) remote sensing biophysical variables to calibrate the downscaling model locally and independently at each time step, which can then be applied to non-aggregated data to create a new layer, denoted SIF*, with a spatial resolution of 0.05°. A global SIF* dataset is generated by applying this methodology globally to 7 years of monthly GOME-2 SIF data. SIF* is shown to be a better proxy for GPP than the original coarse spatial resolution product according to flux-tower eddy covariance measurements. Its performance is comparable to dedicated GPP products despite that (unlike SIF*) these are calibrated based on the same flux towers, driven by meteorological data and not hampered by the large noise caused by the SIF retrieval. To further illustrate the added-value of the global SIF* product, this paper also presents: (1) an ecosystem level assessment showing a considerable reduction of noise with respect to the original SIF; (2) a spatio-temporal inter-comparison with existing GPP products; and (3) estimations of global terrestrial productivity per selected vegetation types based on SIF*.

1. Introduction

Photosynthesis is the main process governing the global carbon cycle. Gross primary productivity (GPP), defined as the amount of carbon that terrestrial ecosystems assimilate per unit of area and time, is the largest planetary CO_2 flux (123 ± 8 Pg C y^{-1}, Beer et al., 2010). GPP drives the inter-annual variability of the CO_2 mixing ratio and may substantially affect the future climate trajectory (Le Quéré et al., 2015). The quantification of the spatio-temporal variations of GPP is therefore fundamental for the detection of biogeochemical signals in the terrestrial biosphere, as driven by climate and other environmental drivers connected to global change like atmospheric CO_2 concentration and nitrogen deposition. Accurate data-driven estimates of GPP are also required to evaluate and improve biogeochemical land surface models used in Earth system models to predict future climate trajectories.

Techniques to estimate GPP range from eddy-covariance measurements at flux towers sites (Baldocchi, 2003; Baldocchi et al., 2001) to globally-distributed mechanistic land surface model simulations (Friedlingstein et al., 2006; Sitch et al., 2008). At point level GPP can be derived from the partitioning of the net ecosystem exchange as measured with the eddy covariance techniques at a global network of sites. While arguably the most reliable estimations of GPP, eddy-covariance measurements are limited by the uncertainty in the partitioning method (Lasslop et al., 2012), by the restricted area covered by their observation footprints and by the limited and biased spatial distribution of towers across the globe (Schimel et al., 2015). On the other side, land surface models can simulate GPP over a range of spatial and temporal scales across the globe, but the reliability of such estimation is heavily dependent on both the input data and the strong modelling assumptions made about the system, which do not always hold in space or time. Between these extremes are various data-driven approaches that try to remain as close as possible to observations while tolerating a variable degree of modelling abstraction (Durgun, Gobin, Gilliams, Duveiller, & Tychon, 2016; Jung et al., 2011; King, Turner, & Ritts, 2011; Mäkelä et al., 2007; Ogutu, Dash, & Dawson, 2013; Papale &

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Valentini, 2003; Ruimy, Dedieu, & Saugier, 1996; Running et al., 2004; Veroustraete, Sabbe, & Eerens, 2002; Zhao, Heinsch, Nemani, & Running, 2005).

Data-driven methods for globally distributed GPP estimations generally rely, at least partly, on satellite Earth Observation (EO) either as driving variables or to calibrate model parameters. A typical approach to link remotely-sensed data to GPP involves the light-use efficiency (LUE) approach proposed by Monteith (Monteith, 1972, 1977), which states that GPP is proportional to the product of incoming photosynthetically active radiation (PAR), the fraction absorbed by vegetation (fAPAR), and the efficiency at which absorbed radiation is used in the process of photosynthesis (ε_P):

$$\mathrm{GPP} = \mathrm{PAR} \times \mathrm{fAPAR} \times \varepsilon_P. \tag{1}$$

Much research effort has been devoted on estimating the first two terms of this equation from satellite remote sensing (see reviews: Hilker, Coops, Wulder, Black, & Guy, 2008; Malenovský, Mishra, Zemek, Rascher, & Nedbal, 2009. The spatio-temporal variations of fAPAR, which can be derived either from empirical relationships with vegetation indices (VIs) or from inversion of radiative transfer models (Baret et al., 2013; Gobron et al., 2007; Myneni et al., 2002), are typically the major remote sensing contribution to GPP estimations. However, the presence of chlorophyll, which is estimated by fAPAR or certain VIs, is a required but not sufficient condition for the occurrence of photosynthesis. The photosynthetic efficiency (ε_P) varies in space and time depending on both vegetation type and key climate drivers, such as air temperature and soil water content. GPP models (e.g. Running et al., 2004) commonly assume a potential LUE, ideally set to a different value for every major plant functional type (PFT), and then downregulate it based on environmental constrains. Such methodologies are heavily dependent on the availability and quality of both climatic and land-cover data, along with strong assumptions on the capability of these variables to drive the spatio-temporal variations of ε_P (Garbulsky, Peñuelas, Papale, & Filella, 2008). Given that important short and long-term dynamics in ecosystem carbon fluxes such as GPP depend on variations in the physiological properties of plant canopies combined with the trends in environmental drivers (Reichstein, Bahn, Mahecha, Kattge, & Baldocchi, 2014), there is an increasing interest in improving the representation of ε_P in satellite-based GPP estimations (Garbulsky, Filella, Verger, & Peñuelas, 2014; Grace et al., 2007). Fortunately, photosynthesis emits an optical electromagnetic signal, called chlorophyll *a* fluorescence, that is sensitive not only to PAR and FAPAR, but also to ε_P (Porcar-Castell et al., 2014).

Chlorophyll *a* fluorescence originates from the core of the photosynthetic machinery and consists of a re-emission of absorbed photons at lower energy wavelengths (from 650 to 850 nm, with peaks at approximately 690 and 740 nm). It is considered to be a mechanism that photosynthetic organisms developed to respond instantaneously to rapid perturbations in environmental conditions of light, temperature and water availability, before the heat dissipation mechanism of non-photochemical quenching can be triggered (Maxwell & Johnson, 2000). Chlorophyll *a* fluorescence has been extensively studied in laboratory at scales ranging from the subcellular up to the leaf for the past

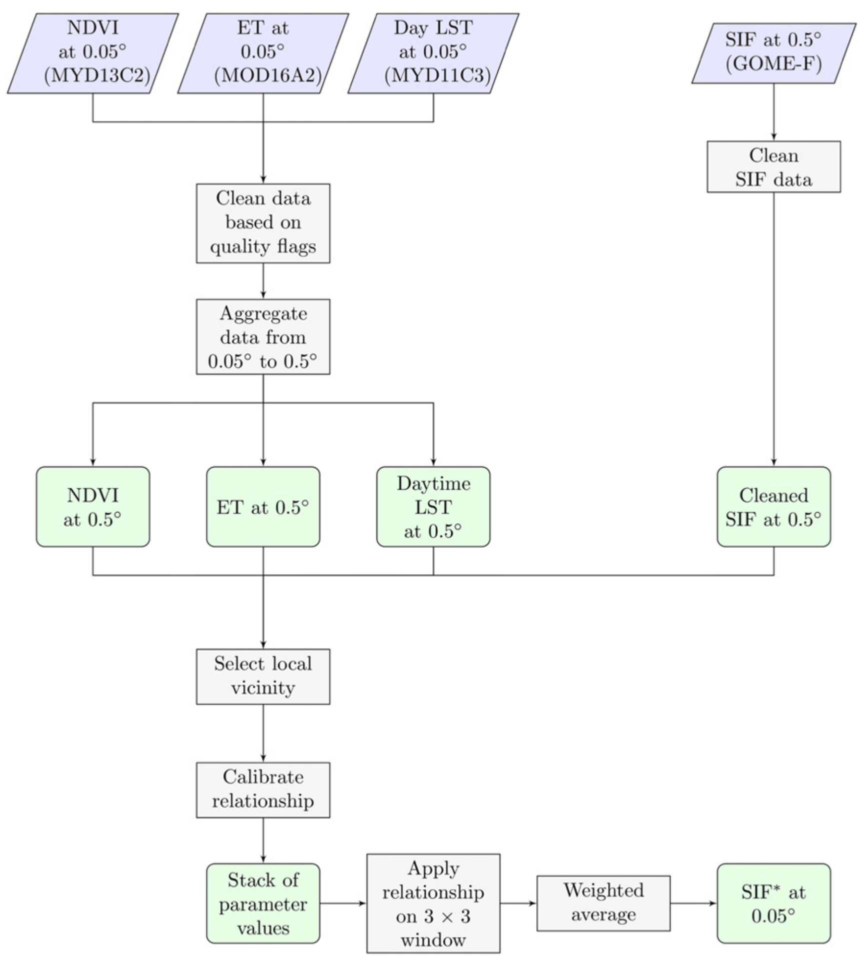

Fig. 1. Flowchart of the processing steps taken to generate SIF*, which is a proxy of gross primary productivity derived from downscaling a sun-induced fluorescence (SIF) signal at a spatial resolution of 0.5° using three explanatory variables at 0.05° spatial resolution: Normalized difference vegetation index (NDVI), evapotranspiration (ET) and land surface temperature (LST). Violet boxes represent input data, grey boxes represent processing steps and green boxes represent output or intermediary datasets.