Exploiting SIF and NIR_v anomalies to enhance biosphere flux estimates in an atmospheric CO_2 inversion

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CO_2 Human Emissions

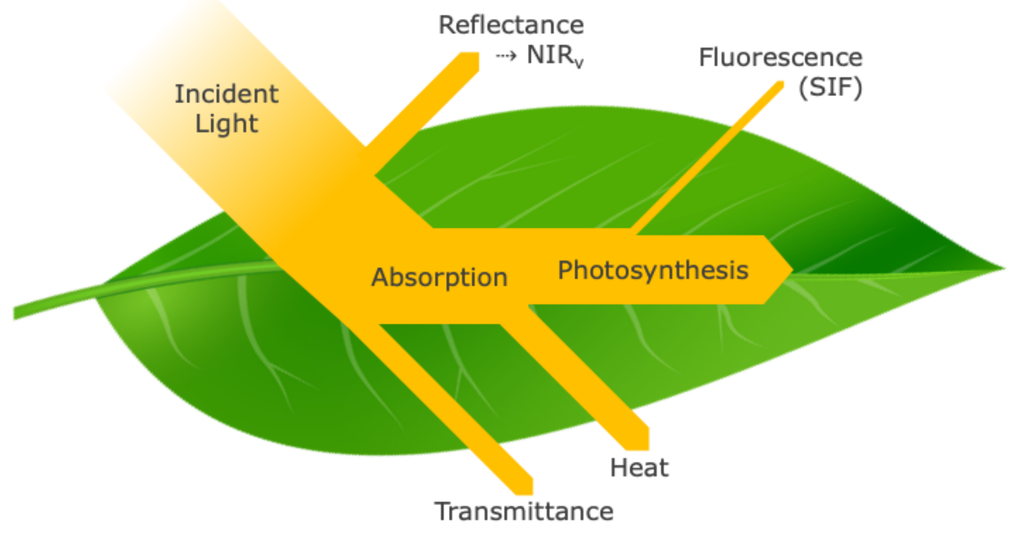
Motivation & Objective

One of the challenges in obtaining accurate estimates of CO_2 fluxes at the Earth's surface is the still high uncertainty related to biogenic carbon exchange. Estimates for the net ecosystem exchange (NEE) are typically obtained by assimilating measurements of atmospheric CO_2 mole fractions into an inversion framework that uses biogenic surface fluxes resulting from process-based models as prior estimate. Due to sparse coverage of observation locations NEE fluxes remain only weakly constrained by observations, and the computational cost related to this set-up prevents long-window runs.

In this study we explore the use of an alternative inversion set-up, which directly makes use of remote-sensing observations of SIF and NIR_v, both proxies for biogenic production. This set-up is particularly suited for long-window runs, thus allowing to constrain also slow processes by CO_2 observations. Moreover, improvements in large-scale variability as well as the sensitivity to interannual climate variations of NEE estimates are expected.

The presented approach is inspired by the work of Rödenbeck et al. (2018), who demonstrated the effectivity of estimating NEE responses in an inversion based on temperature anomalies.

SIF & NIR_v proxy for photosynthetic production



Sun Induced Fluorescence (SIF)

= the re-emission of light during photosynthesis. Approximately 1% of the light absorbed by chlorophyll is re-emitted at longer wavelengths, with peaks at 737 nm. These SIF signatures can be measured with space-based spectrometers. Several studies have shown a strong correlation between remotely-sensed SIF and primary production (Frankenberg et al. 2011, Parazoo et al. 2014), thereby allowing for quantification of the impact of anomalous climatological events on the carbon cycle (Koren et al. 2018).

In this study we make use of monthly averaged SIF from the SIFTERv2 dataset (http://www.temis.nl/surface/sif.html), retrieved from the GOME-2A instrument aboard of MetOp satellites.

Near-infrared reflectance of terrestrial vegetation (NIR_v)

= product of total near-infrared (NIR) reflectance and NDVI, the normalized difference vegetation index. It represents the portion of reflectance attributable to vegetation. NIR_v shows strong linear correlation with GPP and SIF (Badgley et al. 2017). Datasets can be produced at moderate-resolution with excellent spatiotemporal coverage due to the availability of satellite observations for several decades. For this study NIR_v was calculated based on MODIS data.

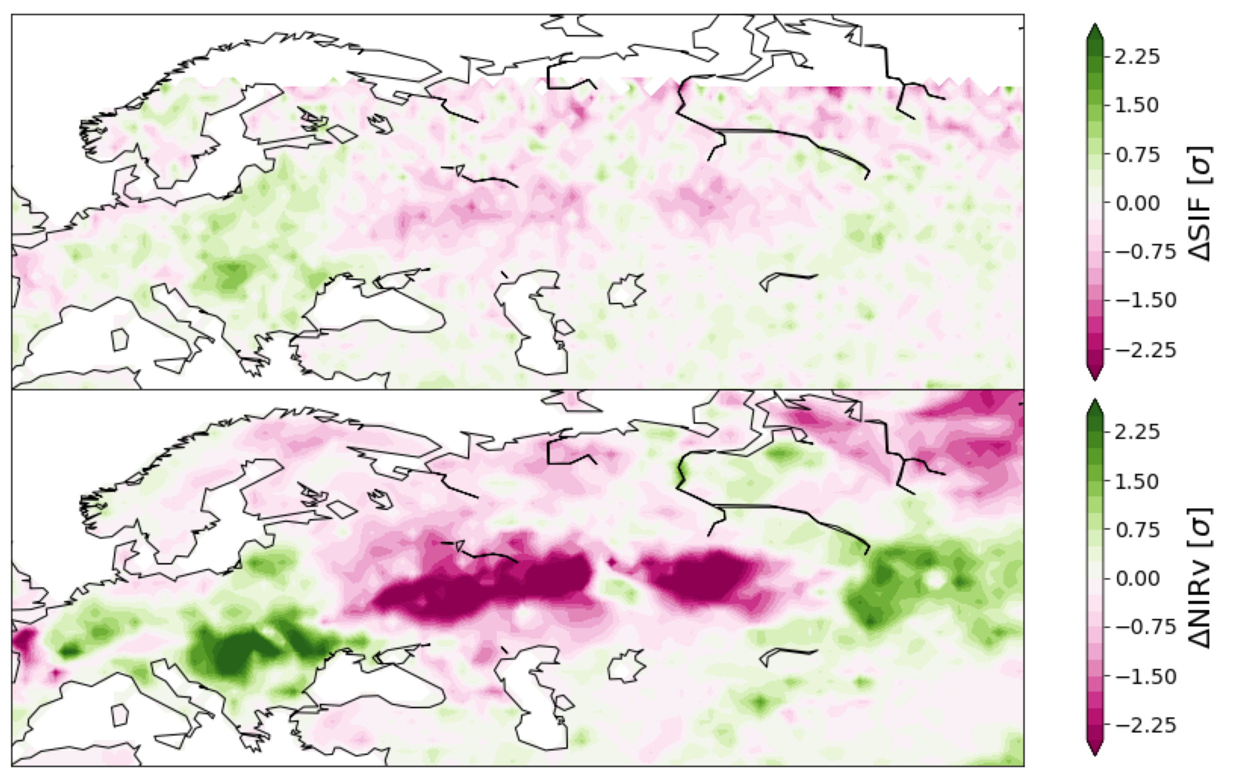
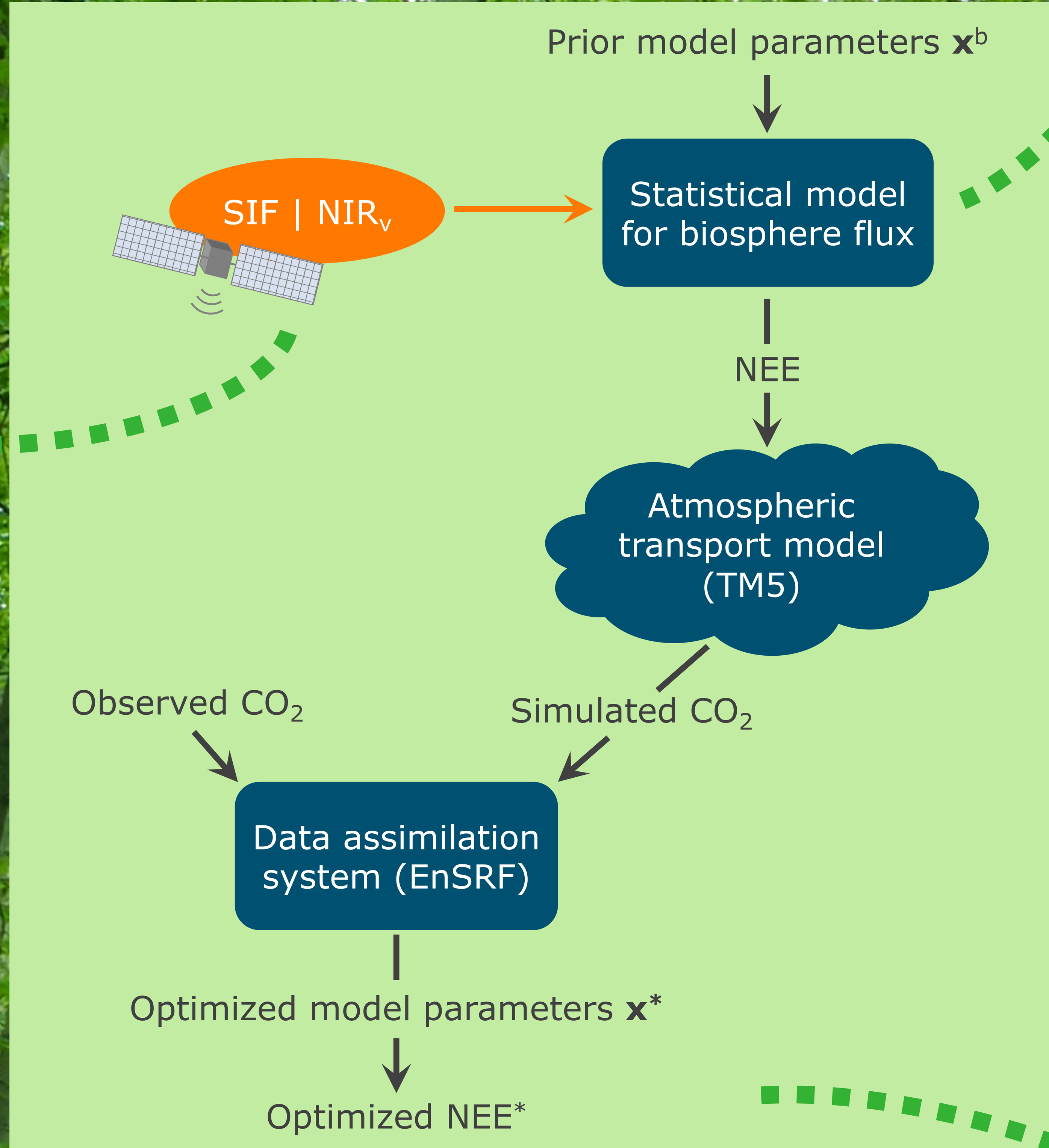


Figure 1: Anomalies in SIF (top) and NIR_v (bottom) during the drought in Russia in the summer of 2010. Results are averaged over the months July, August, September.



Results

A new state vector was implemented in the Carbon Tracker Europe (CTE) data assimilation system, which is based on a sequential ensemble square root (EnSRF) filter algorithm (Peters et al. 2005). The new system, referred to as CTSF, allows for direct optimization of the NEE statistical function parameters.

A first test of the system was performed for the 5-year period 2010-2014, using flask measurements of CO_2 mole fractions at 64 locations and simulating atmospheric transport on a global grid with 6x4 deg spatial resolution. Our prior NEE estimate consisted of a sine-wave yearly cycle with latitude-dependent amplitude. The same fossil fuel, fire and ocean fluxes were imposed as for the CTE 2018 inversion.

Our first results prove the flexibility of the system to correct poor NEE estimates such as to obtain good correspondence with atmospheric CO_2 observations (figure 2) and to incorporate spatiotemporal patterns from direct observations of climate proxies (figures 4 and 5).

Net Ecosystem Exchange (NEE) Statistical Model

Assumptions

- Mean NEE per ecoregion can be represented by a polynomial function combined with harmonics of yearly cycle (Based on CCGCRV function for CO_2 of Thoning et al. 1989)
- Linear correlation between local variations in NEE and anomalies in photosynthesis proxy P (i.e. SIF, NIR_v)

$$NEE(x,y,t) = \underbrace{x_0 + x_1 t + x_2 t^2 + \sum_{n=1}^{4}\left[(a_n + b_n t)\cos\left(\frac{2\pi}{T}nt\right) + (c_n + d_n t)\sin\left(\frac{2\pi}{T}nt\right)\right]}_{\text{Long-term mean, seasonal cycle, temporal trend}} + \underbrace{\gamma^P \Delta P(x,y,t)}_{\text{Spatial \& interannual variability}}$$

Parameters to be optimized

- One set of parameters per ecoregion (i.e. Olson ecosystem type per TRANSCOM region)
- Sensitivity parameters γ additionally vary per calendar month

→ For $n = 4$ statevector contains $31 * 134 = 4154$ parameters to be optimized for entire temporal window

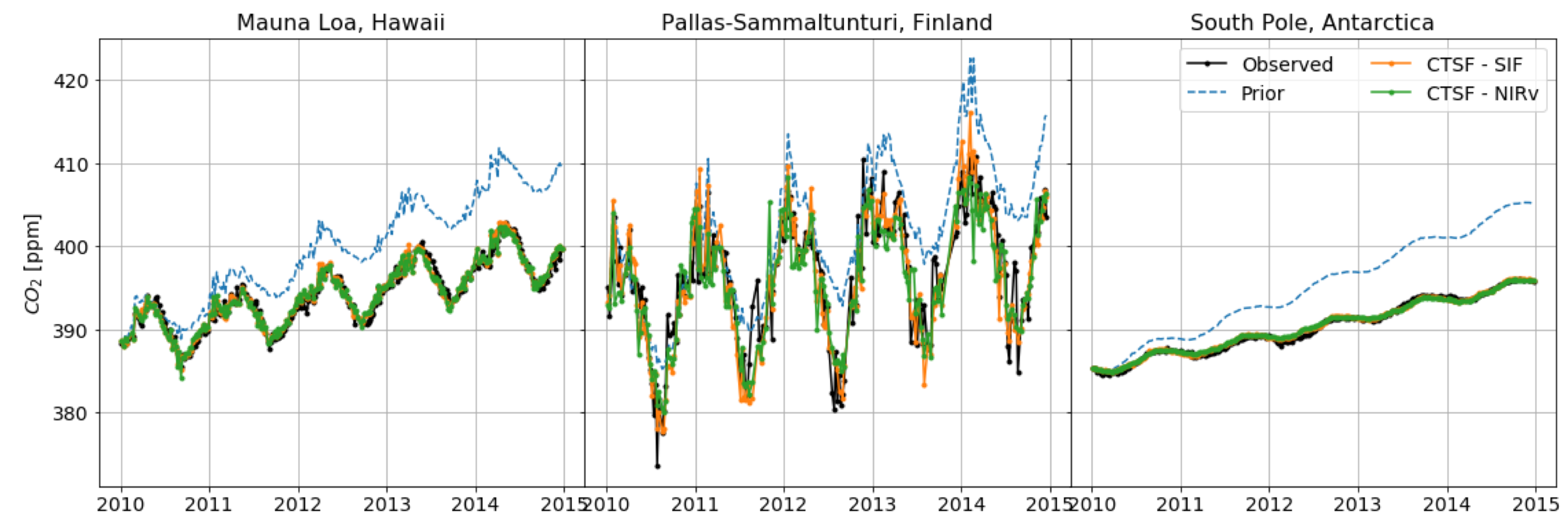


Figure 2 (left): Time series of atmospheric CO_2 mole fractions as observed by flask measurements ('observed') and as simulated with the prior or optimized ('CTSF-SIF' and 'CTSF-NIR_v') biosphere fluxes.

Figure 5 (under): Anomalies of the optimized NEE with respect to the local mean seasonal cycle, averaged for July-August-September 2010. Compared to the CTE 2018 result, the results of both the CTSF-SIF and CTSF-NIR_v inversions show larger spatial variability in NEE anomalies and some reduced uptake of CO_2 in Russia during the 2010 drought.

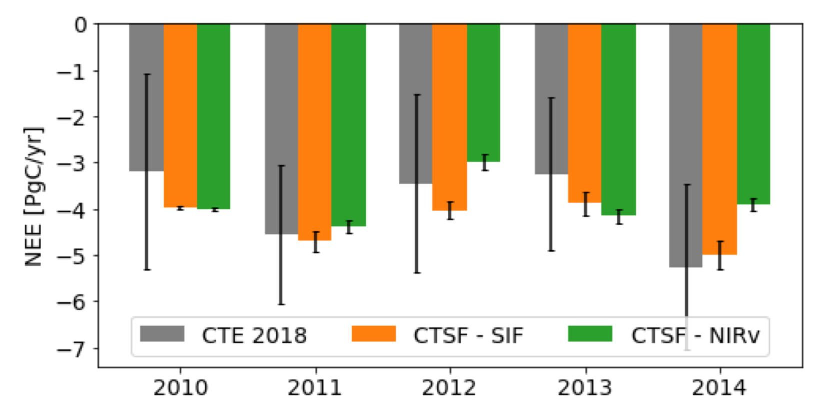


Figure 3: Annual global total biosphere fluxes.

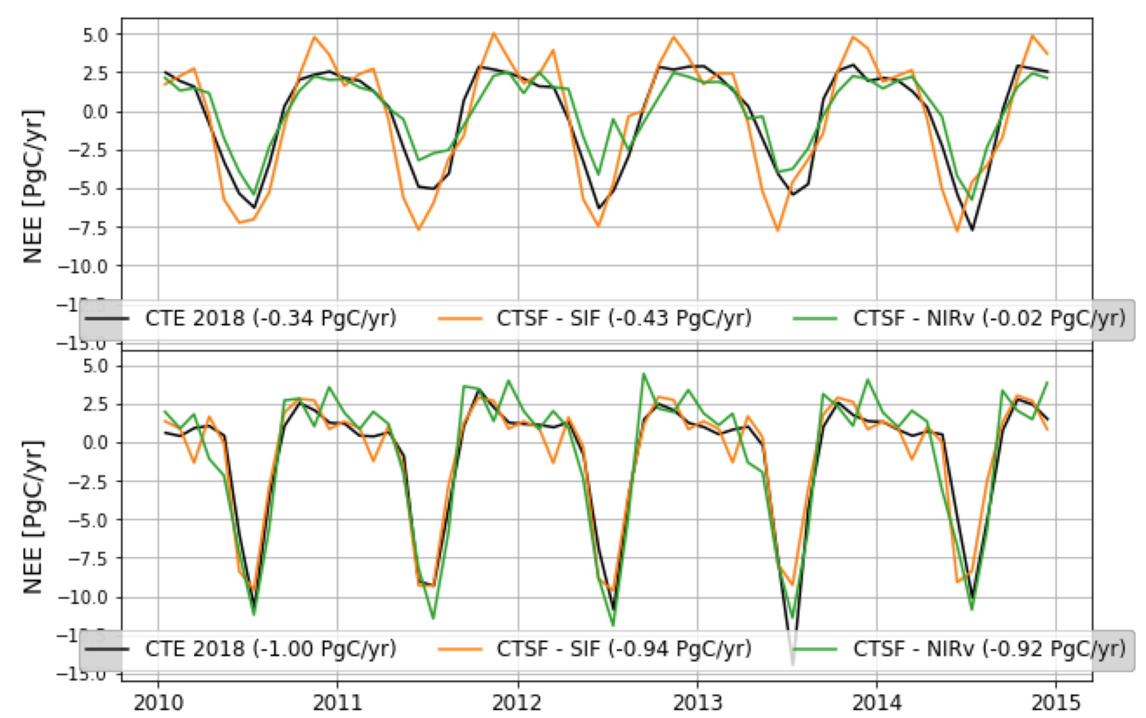


Figure 4: Monthly mean NEE for the North American Temperate (top) and Eurasia Boreal (bottom) Transcom regions, with included the mean yearly uptake for this 5-year period.