Using different radiative transfer schemes for solar-induced chlorophyll fluorescence (SIF) in evergreen coniferous forests

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Abstract. Solar-induced chlorophyll fluorescence (SIF) is a small light signal emitted during the initial steps of photosynthesis and can be observed across scales (from photosystem level to satellite observation footprints). To be able to model SIF, we need to understand the mechanistic processes (including both physical and biological) leading to the observed SIF signal. In this study, we implemented a representation of SIF emission and transmission processes into the terrestrial biosphere model QUINCY ('QUantifying Interactions between terrestrial Nutrient CYcles and the climate system'). We tested the model across three different boreal coniferous forests located in North America and Europe that have eddy covariance derived $\mathrm{CO_2}$ fluxes and tower-based SIF observations. We found that different SIF radiative transfer approaches (one based on mSCOPE, one on two-stream radiative transfer model L2SM, and one empirically based) overestimated the SIF signal, but showed no large differences in the timing of their seasonal and diurnal predictions. The two-stream radiative transfer model approach, L2SM, provided stable performance while being comparatively computationally efficient. Our parameterization for sustained non-photochemical quenching was important for successfully simulating the timing of the SIF seasonal cycle. However, our parameterization did not perform equally well at all three sites, likely because of different temperature regimes at each sites. We further evaluated the potential of remote sensing -based SIF from TROPOMI (the TROPOspheric Monitoring Instrument) to provide accurate information on SIF and found that it could potentially be used in model development. This study demonstrated the usefulness of observations at various spatial scales and the linkages between SIF and GPP and their seasonal development at three different evergreen forest sites.

1 Introduction

Space-based observations can monitor the entire Earth's surface, and advances in remote sensing methods and satellite technology provide more data streams for carbon cycle studies (Schimel et al., 2019). The ability to observe sun-induced chlorophyll fluorescence (SIF) from space has led to numerous applications (Mohammed et al., 2019). SIF is linked to the light reactions of photosynthesis and can therefore provide information on terrestrial $\mathrm{CO_2}$ uptake (Porcar-Castell et al., 2021). Early research on SIF showed that the relationship between SIF and photosynthesis (gross primary productivity, GPP) is linear when measured from space (Frankenberg et al., 2011; Guanter et al., 2012; Joiner et al., 2011, 2013; Sun et al., 2017). Subsequent work has challenged this assumption, showing that the relationship between SIF and GPP is more complex (Damm et al., 2015; Magney et al., 2020; Martini et al., 2022; Sun et al., 2023b) even when using space-based observations (Balde et al., 2023). Therefore, process-based approaches are useful for understanding the mechanistic drivers of the SIF-GPP relationship.

Observations of leaf-level chlorophyll fluorescence (ChlF) have been widely used in plant physiological research for decades. Consequently, there is a thorough understanding of the mechanisms governing leaf-level ChlF (Baker, 2008; Maxwell and Johnson, 2000). When photons are absorbed by plant leaves, they have three main non-damage pathways: they can be used for photochemistry, emitted as ChlF, or dissipated as heat. Since these three pathways coexist, the amount of NPQ affects the relationship between ChlF and photochemistry. In ChlF, a small fraction of photons are re-emitted after giving up some of their energy at higher wavelengths (SIF spectrum is between 650 and 840 nm, as in Fig. 1) (Porcar-Castell et al., 2021). SIF is ChlF that takes place under natural illumination conditions, and measuring it is referred to as a passive measurement of ChlF.

When moving from the leaf level to the canopy level, the interpretation of the measured signal becomes more challenging. Scattering and re-absorption of ChlF take place within the canopy (Van Der Tol et al., 2019). These processes influence how much of the SIF signal located in the red part of the spectrum is absorbed compared to the near-infrared (NIR) (also called "far-red") region. The structural effects of the canopy play an important role in the transmission of the emitted SIF signal within the canopy (Paul-Limoges et al., 2018) and explain the anisotropy of the observed SIF at the top of the canopy (Joiner et al., 2020; Malenovský et al., 2021). The soil also contributes to the SIF signal observed at the top of the canopy, as observed signals include contributions from both vegetation and soil components (Yang et al., 2025b). The variability in radiative transfer through the canopy creates challenges for interpreting the measured SIF signal. By using radiative transfer and biological modelling, mechanistic drivers of the SIF signal can be disentangled, improving our interpretation of SIF (Damm et al., 2015).

The use of SIF in vegetation modeling has become widespread. The first leaf-level description for ChlF was in FluorModLeaf (Miller et al., 2005). A wide-spread leaf level model that was further developed from FluorModLeaf was within the Soil Canopy Observation of Photosynthesis and Energy fluxes (SCOPE) model (van der Tol et al., 2009). SCOPE is a site level model which combines the Farquhar photosynthesis model with a detailed radiative transfer scheme based on SAIL (van der Tol et al., 2009; Verhoef, 1984). A newer leaf level model, that was also implemented in SCOPE, was published a few years later (van der Tol et al., 2014) and further developments have also been made (Vilfan et al., 2016, 2018). The SCOPE model has been widely used in many applications, e.g. studying relationship of GPP and SIF in different ecosystems and under different fertilization treatments as well as water stress effects (e.g., Damm et al., 2015; Martini et al., 2019; Wang et al., 2023; Zhang et al., 2018). Recent model developments also allow the use of SIF to estimate GPP (Gu et al., 2019). These methods utilize the link between measured SIF and light reactions of photosynthesis and how these observations provide a link for actual electron transport from photosystem II to photosystem I. The model by Johnson and Berry (2021) has a tight coupling between photosynthesis and ChlF and allows for two-directional modelling, estimating SIF from GPP and vice versa.

Terrestrial biosphere models (TBMs) are large-scale models used to study the biogeochemical cycles and land–atmosphere interactions. They can be run at a large scale (regional and global), but site-scale simulations are still possible. The modelling community has implemented SIF models in TBMs with varying degrees of complexity. For example, Koffi et al. (2015) augmented the Biosphere Energy Transfer Hydrology (BETHY) model with the full SCOPE model. Lee et al. (2015) used a simple scheme to account for radiative transfer in the CLM implementation. Bacour et al. (2019) built a SCOPE emulator for an implementation in the ORCHIDEE model. Qiu et al. (2019) implemented SIF to the BEPS model and emphasized the importance of accounting for scattering in the modelling, and also data assimilation studies have been done with the BEPS model (Wang et al., 2021).

These different approaches balance simplifying the complex physical phenomenon of radiative transfer in plant canopies against the length of the simulation time. However, full 1D radiative transfer based on the SCOPE model is too computationally demanding for many large scale applications (Sun et al., 2023a) and some modelling teams have needed to use parameterizations instead of the full model (Miyauchi et al., 2025). The computational burden becomes even more relevant in different data assimilation approaches (Norton et al., 2019). An empirical approach used in some studies would be worth investigating (Liu et al., 2020; Zeng et al., 2019). One way to simplify the calculation of SIF signal's radiative transfer would be to use a two-stream radiative transfer model (Sun et al., 2023a). A recent two-stream radiative transfer model (Quaife, 2025) describes radiative transfer of emission originating from the canopy and therefore enables calculation of SIF signal's radiative transfer. The TBM studies mentioned used spaceborne data from Greenhouse gases Observing SATellite (GOSAT) (Kuze et al., 2009) and Orbiting Carbon Observatory (OCO)-2 (Frankenberg et al., 2014).

The northern latitudes are experiencing stronger climatic change than the rest of the globe (Rantanen et al., 2022). Boreal forests located in these regions are an important part of the global carbon cycle (Pan et al., 2024). Boreal forests are characterized by strong seasonality in environmental conditions, with harsh winter conditions and shoulder seasons when air and soil temperature and light availability drive the spring recovery and autumn drawdown of vegetation (Tanja et al., 2003; Thum et al., 2009; Vesala et al., 2010). The photosynthetic activity of evergreen forests in these ecosystems cannot be easily tracked by reflectance-based remote sensing alone, as the greenness is partially decoupled from the rate of photosynthesis (Walther et al., 2016). SIF observations have proven to be more reliable proxies for tracking photosynthesis in these ecosystems (Pierrat et al., 2024). Challenging conditions have led evergreen trees to develop different coping mechanisms. Sustained non-photochemical quenching (NPQ) is one of them and it increases in winter, at the same time as the capacity of photosystem II decreases (Porcar-Castell et al., 2008; Porcar-Castell, 2011; Adams et al., 2014). NPQ is a pH-independent mechanism associated with the retention of the xanthophyll cycle pigments zeaxanthin and antheraxanthin and allows the needles to dissipate the incoming radiation as heat (Demmig-Adams et al., 2014).

Sustained NPQ can only be estimated from the active ChlF observations, i.e. when a set of saturating light pulses are delivered to a leaf under dark- and light-adapted conditions. Therefore, it cannot be directly obtained from passive SIF observations, although progress is being made towards optical sensing of NPQ (Van Wittenberghe et al., 2024). Including description of sustained NPQ in large scale TBMs was started by Raczka et al. (2019), who used the state of acclimation, represented by a delayed temperature sum developed by Mäkelä et al. (2004) in the parameterization. Climate-induced changes will alter the seasonal cycle of vegetation, and the ability to have optical data to track photosynthetic activity is very helpful in understanding the changes in the carbon cycle.

The goal of this work was to improve the ChlF modelling so that a TBM can fully exploit the information provided by the ChlF related observations at different scales to improve our understanding of ecosystem processes related to biogeochemical cycles. Our objectives were 1) to test different radiative transfer approaches for SIF and 2) to assess the role of sustained NPQ in modelling. The research questions of our study are therefore:

- Which radiative transfer model calculation methods were sufficiently robust for reliable SIF model predictions?
- How could we account for the influence of sustained non-photochemical quenching in the modeled SIF signal?
- What was the benefit of in-situ observations versus satellite observations of SIF in model development?

To answer these questions, we run simulations of TBM QUINCY ('QUantifying Interactions between terrestrial Nutrient CYcles and the climate system') and compared them with tower observations of SIF at three coniferous evergreen sites that experience a strong seasonal cycle with harsh winters. In addition, we tested how spaceborn TROPOspheric Monitoring Instrument (TROPOMI) instrument (on board the Sentinel-5 Precursor (S5P) satellite) (Guanter et al., 2021) data capture the seasonal cycle at two of these sites and how its magnitude differs from the simulation results. The novel aspects of this study include using different radiative transfer schemes with one model, analyzing both red and far-red region observations from the tower observations of SIF, having sites in two different continents and having approaches that either include the SIF signal attenuation inside the leaf or not. Including both red and far-red regions in the analysis will help to evaluate potential challenges that the simulations will have in the red region, a fact that will become more relevant with new satellite missions covering whole SIF spectrum.

2 Materials and methods

2.1 Site descriptions and observations

The three study sites were Niwot Ridge (US-NR1) (Bowling et al., 2018; Burns et al., 2015; Magney et al., 2019a), USA, Saskatchewan (CA-Obs), Canada (Pierrat et al., 2021, 2022a) and Sodankylä (FI-Sod), Finland (Thum et al., 2007; Knorr et al., 2025). All of these sites are evergreen coniferous forests. The Canadian and Finnish sites are in the boreal zone, and Niwot

Table 1. The site characteristics of the three forests. LAI is one-sided and average value over summertime. Air temperature is annual average.

Abbreviation	Location (lat, lon)	Species and age (yrs)	Period	LAI ($\mathrm{m}^2\,\mathrm{m}^{-2}$)	Air temp. (°C)	SIF instrument
CA-Obs	53.99, -105.12	Black spruce (>100)	2019-2020	3.8	1.3	PhotoSpec
FI-Sod	67.36°, 26.64°	Scots pine (90)	2021	1.3-1.4	0.3	FloX
US-NR1	40.03°, -105.55°	Mixed evergreen coniferous (>100)	2017-2018	3.8–4.2	2.7	PhotoSpec

Ridge is a subalpine forest. Further details about the sites are given in Table 1. All sites have eddy covariance flux observations as well as a tower-mounted in-situ SIF instrument. The Sodankylä site is part of the ICOS network (https://www.icos-cp.eu/) and the North American sites are part of AmeriFlux (https://ameriflux.lbl.(gov/).

All of these sites exhibit strong seasonal cycle in vegetation activity, but it differs due to variations in latitude and elevation. The forest in CA-Obs experienced a strong seasonal cycle with low levels of photosynthetic activity between October and March. Although US-NR1 is located at a lower latitude than the other study sites, the high elevation conditions result in pronounced seasonal cycle, including below freezing winters. The forest at US-NR1 is photosynthetically active from May to September, with the shoulder season to winter occurring in October and December, and spring recovery occurring in April and May. FI-Sod is located 100 km north of the Arctic Circle. Therefore, the winter radiation drops to zero, and temperatures are low. Spring recovery occurs in April and May. The photosynthetically active period is from June to August and photosynthesis ceases in September and October.

2.2 SIF and CO_2 flux observations at the sites

At the North American sites, SIF was observed with PhotoSpec (Grossmann et al., 2018) in two different spectral regions. The red region is between 680 and 686 nm, and the far-red region is between 745 and 758 nm. These observations were made with a 2D scanning telescope. The retrieval method is based on the Fraunhofer line method (Grossmann et al., 2018). The field of view (FOV) is 0.7°. At US-NR1 a typical measurement included a scan from nadir to the horizon in 0.7° steps at two different azimuth direction (Magney et al., 2019a). At CA-Obs three vertical scans at three different directions (35°W, 0°N, 35°E) were done in sequence (Pierrat et al., 2021). The PhotoSpec retrievals were filtered by having an Normalized Difference Vegetation Index (NDVI) based threshold to ensure that only observations of vegetation were used. In this study we averaged over all the observations. More details of these observations can be found in Magney et al. (2019a) (US-NR1) and Pierrat et al. (2021) (CA-Obs). At US-NR1, observations were available from June 2017 until June 2018. At CA-Obs we used observations for whole years 2019 and 2020. In spring 2019 the eddy covariance observations were out of commission and until mid-2019 the GPP data was based on gap–filling.

In Sodankylä, the observations were made using a a FloX box (JB Hyperspectral Devices, Düsseldorf, Germany) (https://www.jb-hyperspectral.com/products/flox/). These observations were used to retrieve the SIF in the $\mathrm{O_2B}$ band at 687 nm in the red region and the$\mathrm{O_2A}$ band at 760 nm in the far-red region. The retrieval method used to process the data was the improved Fraunhofer

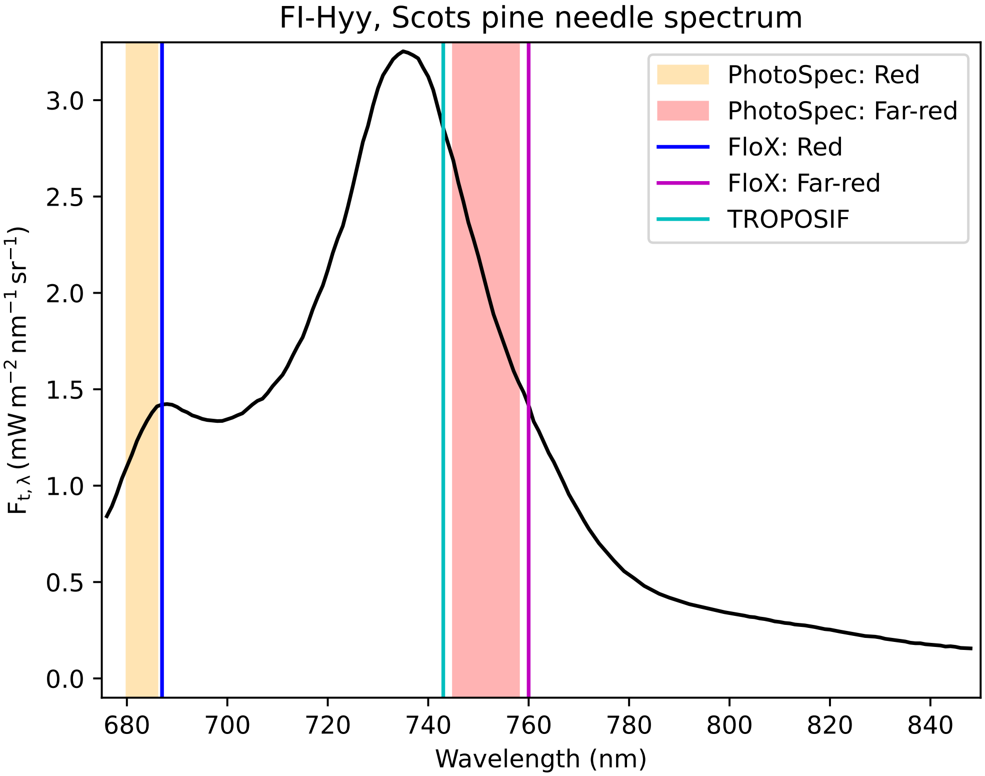

Figure 1. SIF emission spectrum for Scots pine located in the southern boreal zone (from Magney and Frankenberg (2019)) with wavelength regions of the observations. The lines indicate the bands for which the SIF signal was retrieved for the FloX observations and TROPOMI (TROPOSIF) and the shaded regions indicate the wavelength regions for which the SIF with the PhotoSpec was retrieved.

line method (Alonso et al., 2008; Cendrero-Mateo et al., 2019). In our study, we used close to nadir observations from June 2021 until the end of the year. The FOV is 25°. The different wavelengths of the retrieved SIF signals by the instruments are shown in Fig. 1, along with the SIF spectrum from observations of Scots pine needles in Hyytiälä, southern Finland (Magney and Frankenberg, 2019; Magney et al., 2019b).

Net ecosystem exchange of CO_2 was measured by the eddy covariance method. At CA-Obs the measurement height was 25 m, and the anemometer was CSAT3 (Campbell Scientific Inc., Logan, UT, USA) and the gas analyzer LI-7200 (Pierrat et al., 2021). At US-NR1 measurements were made at 21.5 m height with the CSAT3 and an LI-6262 gas analyzer (Magney et al., 2019a). At FI-Sod, measurements were made at 25 m with a Gill HS-50 sonic anemometer (Gill Instruments, Lymington, UK) and a LiCor LI-7200 gas analyzer (LiCor Inc., Lincoln, NE, USA) (Knorr et al., 2025). Flux partitioning and gap–filling at CA-Obs was done as described in Barr et al. (2004) and at US-NR1 using the Reichstein et al. (2005) method with the R package REddyProc (Wutzler et al., 2018). Gap–filling and partitioning of the measured net ecosystem exchange flux to gross primary production (GPP) and total ecosystem respiration was done at FI-Sod following Aurela et al. (2015). In Sodankylä, the fraction of absorbed photosynthetically active radiation (fAPAR) was measured using PQS1 instruments (Kipp & Zonen; Netherlands) (Knorr et al., 2025). Four of these sensors were installed below the canopy. These observations, together with aboveground canopy observations, were used to calculate fAPAR.

2.3 Remote sensing observations of SIF by TROPOMI

The TROPOMI is aboard the Copernicus Sentinel-5P mission and has been providing data since 2018 (Köhler et al., 2018). TROPOMI has global continuous spatial sampling with daily revisit times, because it has a nearly sun-synchronous orbit with a repeat cycle of 16 days and a wide swath of 2600 km (Köhler et al., 2018). The pixel size at nadir was 3.5 x 7.5 km^2 at the beginning of the mission and 3.5 x 5.5 km^2 after August 2019 (Guanter et al., 2021). We used the TROPOSIF product derived from the 743-758 nm window, at 743 nm (Guanter et al., 2021). The retrieval methodology is based on the Fraunhofer line in-filling principle (Plascyk and Gabriel, 1975) and a data-driven method is used (Guanter et al., 2015).

In this study we used 0.5° x 0.5° sampling area around two study sites, CA-Obs and FI-Sod. This corresponds to an area of approximately 56 km x 33 km at CA-Obs. According to the MODIS MCD12C1 from 2018 (Friedl and Sulla-Menashe, 2022), the land cover for CA-Obs in this region is 65 % woody savannah and 26 % evergreen needleleaf forest, with minor contributions from mixed forests and croplands. For FI-Sod the land cover was 83 % woody savannah and 17 % savannah. We also tested using a smaller sampling area around the region, extending 0.25° around the site. For this smaller region the land cover around CA-Obs was 45 % evergreen forest and 53 % woody savannah, with small contribution of mixed forests. For the FI-Sod site the smaller region had 92 % woody savannah and 8 % of savannah. We did not use TROPOMI data for US-NR1 because TROPOMI observations only covered part of the in situ observational period. TROPOMI's Level 2 cloud fraction product was applied for a strict cloud filtering, removing all SIF data for which the cloud fraction exceeded 0.2, as recommended by Guanter et al. (2021). In our analysis we used daily averages that we had calculated from instantaneous values.

2.4 Model description of QUINCY

The QUantifying Interactions between terrestrial Nutrient CYcles and the climate system (QUINCY) model is a terrestrial biosphere model that can be run on a single site or larger, such as regional or global, scales. QUINCY uses plant functional types (PFTs) to describe different ecosystems. In site level simulations, each site is described by a single PFT. Canopy can have up to ten layers. A brief description of the model is provided here; further details can be found in Thum et al. (2019).

The complete version of QUINCY has fully coupled carbon, energy, nitrogen and phosphorus cycles. The model has a modular structure that allows only some parts of the model to be run. We used the canopy module, which calculates fast biophysical processes of the model, including stomatal conductance, photosynthesis and radiative transfer within the canopy. Influence of soil is considered so that water uptake is constrained by soil moisture given a prescribed, PFT -specific root profile. Leaf area index (LAI) and leaf nitrogen content are prescribed with a constant value in the canopy module (otherwise these would be calculated prognostically inside the model). Leaf stoichiometry, i.e. the nitrogen to carbon ratio, is fixed in the canopy module. The calculation of leaf chlorophyll from the leaf nitrogen is described in Section S1.1.

Photosynthesis is calculated according to Kull and Kruijt (1998). This approach is based on the biochemical model of Farquhar et al. (1980), but instead of the regular implementation of having the minimum of the two branches limiting photosynthesis (light-limited rate of photosynthesis and carboxylation capacity limited rate), the amount of light-saturated region in the leaf is taken into account. In the non-light-saturated part, photosynthesis is calculated using the light-limited rate of photosynthesis based on the maximum electron transport rate parameter $J_{max,25}$ (the parameter has been scaled to 25 °C). For the light-saturated part, photosynthesis is calculated as the minimum of electron transport rate-limited photosynthesis and the carboxylation capacity limited photosynthesis (determined by the maximum carboxylation capacity parameter $V_{c(max),25}$). Photosynthesis is calculated separately for sunlit and shaded leaves in each canopy layer and coupled to the stomatal conductance (Medlyn et al., 2011), described in Section S1.2. Evergreen trees in cold environments adapt their photosynthesis during the shoulder seasons as described in Section S1.3.

2.4.1 Radiative transfer in QUINCY

The depth (in terms of LAI) of the canopy layers increases exponentially towards the lower canopy layers, of which there are a maximum of ten layers. The nitrogen gradient decreases with canopy depth according to observations (Niinemets et al., 1998), but is not connected to the leaf optical properties in the current model formulation. The fraction of sunlit and shaded leaves are calculated using the radiative transfer scheme based on the two-stream approach of Spitters (1986), and extended to include canopy albedo, clumping and attenuation of the shortwave backscatter from the ground. Radiative transfer is calculated separately for the visible (300-700 nm) and near-infrared (700-3000 nm) bands. Leaf reflectance is calculated based on the PFT-specific single leaf scattering albedo (SSA). Leaf transmissivity is assumed to be equal to reflectivity and absorptance is one minus SSA. Clumping index (Ω), non-random distribution of leaf elements, is described according to Campbell and Norman (1998):

$$\Omega = \Omega_0/(\Omega_0 + (1 - \Omega_0) \times e^{-k_{csf} \times acos(\gamma^*)^{\phi_{crown}}}), \tag{1}$$

where Ω_0 and ϕ_{crown} are the PFT-specific clumping factor at nadir (0.5 for conifers) and crown shape factor (2.19 for conifers), respectively, and k_{csf} is a correction factor (value 2.2). A seasonal cycle of Ω at FI-Sod site is shown in Fig. S1. Because all equations for leaf reflection and absorption coefficients are only valid for high solar elevation, the true zenith angle (γ) is constrained to values larger than 10° (γ^*). Otherwise the leaves are assumed to be distributed hemispherically. The soil albedo is set to a literature value (Bonan, 2008) for the visible and near infrared regions.

2.5 Models for the radiative transfer of the SIF signal

The leaf chlorophyll fluorescence yield was calculated using the model developed by (van der Tol et al., 2014). Its equations are shown in SI, Section 1.4. We did not change any of this model's default parameter values, and these parameters were kept constant for all the sites. The only change to the standard implementation of the model was caused by the different Farquhar et al. model formulation adapted to QUINCY, but this did not require any additional parameters.

The escape fraction describes how much of the emitted SIF signal reaches the top of the canopy. The total canopy SIF can be expressed using the escape fraction f_{esc} as (Sun et al., 2017):

$$SIF = PAR \cdot fAPAR \cdot \Phi_{F_t} \cdot f_{esc} \tag{2}$$

where SIF is the observed SIF, PAR is the photosynthetically active radiation, fAPAR is the fraction of absorbed PAR and Φ_{F_t} is the chlorophyll fluorescence yield. This section introduces three different ways to calculate the radiative transfer of SIF in the canopy that we used in this study. The first approach uses the mSCOPE model, which has been implemented in the QUINCY model. This approach is hyperspectral and considers the attenuation of the SIF signal within the leaf. The L2SM model is not implemented in QUINCY; rather it uses QUINCY's output. In our case, it utilizes two spectral regions. This approach considers the attenuation of the SIF signal within the leaf. The final approach is based on an empirical relationship and estimates the escape fraction using the fraction of absorbed PAR and leaf reflectance obtained from QUINCY. All approaches consider SIF emission to be a diffuse flux.

2.5.1 mSCOPE

The mSCOPE model (Yang et al., 2017) is a further development of the widely used SCOPE model (van der Tol et al., 2009) that has been eventually implemented in SCOPE 2.0 (Yang et al., 2021). In mSCOPE, the canopy is allowed to have a heterogeneous vertical canopy structure, whereas in SCOPE it is assumed to be homogeneous. The QUINCY model has a vertically varying canopy structure, as explained in Section 2.4. Therefore, the use of mSCOPE was more suitable than SCOPE for coupling with QUINCY.

In mSCOPE, the model Fluspect (Vilfan et al., 2016) calculates leaf reflectance, transmittance and ChlF. The radiative transfer of mSCOPE is described by two SAIL-based models (Verhoef, 1984): one, which calculates the radiative transfer of incident radiation, and another one, which calculates the radiative transfer of emitted ChlF. Homogeneity in the horizontal direction is assumed, but heterogeneity of leaf properties in the vertical direction is allowed. The probability of sunlight on leaves is described by a Poisson model. The shaded leaves are illuminated only by diffuse radiation and their absorbed radiation does not depend on geometry. For the sunlit leaves, the absorbed radiation is calculated for discrete leaf orientations, including 13 leaf inclinations and 36 leaf azimuth angles relative to the solar azimuth. The soil optical properties are represented by a linear combination of a dry and a saturated soil reflectance factors, weighted as a function of the ratio soil moisture content to field capacity. The mSCOPE model calculates the top of the canopy (TOC) value for the ChlF emission.

The mSCOPE model has been implemented in QUINCY (see conceptual figure in Fig. S2). This implementation replaces the original QUINCY radiative transfer model (Spitters, 1986). The vertical profile of leaf chlorophyll, that was calculated inside QUINCY (S1.1), was used to calculate the radiative properties of each layer. To calculate this, mSCOPE uses the PROSPECT model (Jacquemoud and Baret, 1990). mSCOPE runs over 60 canopy layers that were grouped to mimic the usual 10 layers in QUINCY as a function of the QUINCY layer LAI. mSCOPE outputs were then integrated for each layer group to represent each of the 10 QUINCY layers. For stability reasons, we also had to limit the calculation of the radiative transfer code to solar zenith angles below $80°$. To test the implementation, we performed a sensitivity analysis by running simulations with different parameter values in both mSCOPE and QUINCY-mSCOPE. The results were consistent (not shown), so we are confident that there are no major technical errors in the implementation. Using QUINCY with mSCOPE instead of QUINCY with the original radiative transfer model caused small differences in the simulated GPP, but overall the results were similar (for CA-Obs the Pearson correlation coefficient (r^2) was 0.99 for half-hourly values throughout the time period and the root mean squared error (RMSE) was 0.77 $\mu\mathrm{mol\,m^{-2}\,s^{-1}}$). The viewing angle was set to nadir in these simulations.

2.5.2 Layered two-stream model (L2SM)

The Layered canopy two-Stream Model (L2SM) (Knorr et al., 2025; Quaife, 2025) is a two-stream radiative transfer model based on the solutions provided by Meador and Weaver (1980). It allows the calculation of diffuse emissions originating from plant leaves. A conceptual figure showing how it is used in combination with QUINCY is shown in Fig. S3, and the equations of the model are in Section S1.5. The formulation of L2SM is a two-stream model, similar to the original radiative transfer model of QUINCY. Therefore it calculates the radiative transfer for the visible and near infrared region separately. Soil reflectance was assumed to be isotropic and leaf angle distribution was assumed hemispheric. We used L2SM with the leaf reflectance (which also equals transmissivity in QUINCY), the leaf area index for each layer, and the SIF emission per layer (as calculated by Eq. S15) as well as information on soil reflectance. In this implementation a novelty was that internal attenuation of the SIF signal was taken into account. While QUINCY is based on Spitters (1986), the L2SM approach is based on Meador and Weaver (1980). Therefore, the radiative transfer of incoming radiation used to calculate photosynthesis differs slightly from the way SIF is transferred within the canopy. A detailed derivation and description of the L2SM can be found in Quaife (2025).

2.5.3 Liu and Zeng approaches (LZ)

In addition to modelling the transfer of the SIF signal, we have also tested some simpler formulations to estimate the SIF leaving the canopy. A more empirical approach was based on the work of Liu et al. (2020) (for the visible region) and Zeng et al. (2019) (for the near-infrared/far-red region). We used the formulation presented by Hao et al. (2021) for the escape fraction (a conceptual figure is shown in Fig. S4). An empirically based formulation for the escape fraction f_{esc} is:

$$f_{esc}^{reg} = \frac{\rho_{can}^{reg}}{fAPAR \cdot \sigma^{reg}} \tag{3}$$

where reg is either visible (vis) or near-infrared (nir) region, ρ_{can} is the reflectance of green vegetation and σ is the single leaf scattering albedo, which is the sum of reflectance and transmittance. Therefore, this escape fraction is calculated separately for the visible and the near-infrared regions. The soil was assumed to be black, i.e. non-reflectant. To estimate the escape fraction from QUINCY in this way, we used the modelled vegetation reflectance for the whole canopy, fAPAR and the constants for single-leaf scattering albedo. After calculating the escape fraction, the upscaled SIF emission (calculated as the sum of canopy layer SIF emissions from Eq. (S15) which were multiplied by the canopy LAI) was multiplied by to obtain the estimate of the SIF signal.

2.6 Converting the units of SIF from modelled to observed

The output of the radiative transfer approaches in Sections 2.5.1-2.5.3 is in flux units, i.e. $\mu\mathrm{mol\,m^{-2}\,s^{-1}}$. To be able to compare the model output with the observations, which are typically in units of $\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$, we need to convert the units of the model output. This procedure was similar as described in Knorr et al. (2025).

In the unit conversion, the Planck equation is used to obtain the energy E of photons per mole as

$$E = \frac{N_a hc}{\lambda_\phi} \tag{4}$$

where N_a is Avogadro's number (value is $6.022 \cdot 10^{23}$), h is the Planck's constant ($6.626 \cdot 10^{-34}\ Js$), c is the speed of light ($3.0 \cdot 10^{8}\ m\,s^{-1}$) and λ_ϕ is the wavelength of the SIF photons (unit m).

The emittance of SIF from the top of the canopy is assumed to be isotropic, so the conversion to steradians is done using a constant factor of $\frac{1}{\pi}$. The final step is to weight the relative strength of the emissions at wavelengths λ_ϕ compared to a reference SIF spectrum as:

$$w = \frac{e_s(\lambda_\phi)}{\sum_i e_s(\lambda_{\phi,i})}, \tag{5}$$

where e_s is the emission spectrum in relative units. The emission was calculated for the wavelengths of the observing instruments (PhotoSpec or FloX). Similarly to Knorr et al. (2025), we used a spectrum observed at Hyytiälä Scots pine forest, located in central Finland (Magney et al., 2019a; Magney and Frankenberg, 2019) for the LZ approach. Observations of four trees were made at a light level of 1200 $\mu\mathrm{mol\,m^{-2}\,s^{-1}}$ and these spectra were then averaged. For the L2SM we used mathematically constructed estimate of the *in vivo* leaf spectrum (Gordon, 1979), which was based on double Gaussian curve and normalized to one. This was done, since the current version of L2SM includes the leaf attenuation of the SIF signal.

Using this information, the unit conversion of the original SIF, $SIF_{unit,flux}$, to the SIF in measured units, $SIF_{unit,eng}$ is obtained as follows:

$$SIF_{unit,eng} = SIF_{unit,flux}\frac{e_{sw}}{\pi}. \tag{6}$$

The QUINCY run with mSCOPE provides fluorescence radiance units, and is therefore independent of this approach.

2.7 Sustained non-photochemical quenching ($\mathbf{NPQ_s}$)

Sustained non-photochemical quenching ($\mathrm{NPQ_s}$) is a process that is relevant to plants that retain needles through the winter. This is another NPQ mechanism in addition to the reversible NPQ that we introduced in the S1.4 section (Eq. S14). In previous work with the Community Land Model (CLM) model (Raczka et al., 2019), a parameterization for sustained NPQ based on the state of acclimation was developed. We have already used state of acclimation in the photosynthesis model of QUINCY (Eq. S5). Following the earlier work and similarly to the state of acclimation, we obtained for K_{N_s}:

$$K_{N_s} = \frac{K_{N_{s,max}}}{1 + e^{b_{NPQ_s}(S - T_{NPQ_s})}} \tag{7}$$

where $\mathrm{K_{N_{s,max}}}$, $\mathrm{b_{NPQ_s}}$ (°C^{-1}) and $\mathrm{T_{NPQ_s}}$ (°C) are parameters, set to 8.0, 0.5 °C^{-1} and 5.0 °C, respectively. The difference between this equation and Eq. (S5) is that it has large values in winter, while Eq. (S5) has large values during the summer. S is obtained from Eq. (S4). To estimate the parameters in the Eq. (7) we used SIF observations from US-NR1 and tuned the values to get the best match with our model considering the whole observational time period. The previous study by Raczka et al. (2019) had developed the parameterization for this site using active leaf level observations from coniferous forest Hyytiälä in Finland. We tested different values and chose those that best fit the data. A seasonal cycle of $\mathrm{K_{N_s}}$ and and S at Sodankylä in 2021 are shown in Fig. S5.

When both reversible and sustained NPQ were taken into account, $\mathrm{K_N}$ was then a sum of them, as

$$K_N = K_{N_{rev}} + K_{N_s}. \tag{8}$$

2.8 Site scale flux simulation protocol

All the sites of the study were classified as boreal coniferous evergreen forests PFT in QUINCY. Therefore also the soil reflectance was described similarly for all the sites. In this work we took advantage of the modular structure of QUINCY and used only the canopy model in our simulations. The LAI and leaf nitrogen content were prescribed so that the average summertime GPP level matched the observations. The meteorological forcing (air temperature, precipitation, atmospheric pressure, vapor pressure deficit, wind speed, short and longwave radiation) to run the model was obtained from the site measurements. In addition, we used atmospheric $\mathrm{CO_2}$ concentration and N deposition, but the N cycle was not active in the canopy model simulations. The canopy model does not require any spinup and the simulations were performed for the years of the observations. The leaf single scattering albedo used to calculate reflectance for conifers was 0.15 in the visible wavelength region and 0.73 in the near infrared (Otto et al., 2014). The soil albedo for all the sites was estimated to be 0.15 in the visible and 0.30 in the near infrared. The LAI values have been set to lower values than observations, to make a better match with the observed magnitude of GPP. The LAI was set to 2.5 $\mathrm{m^2\,m^{-2}}$ in CA-Obs, 3.6 $\mathrm{m^2\,m^{-2}}$ in US-NR1 and 1.2 $\mathrm{m^2\,m^{-2}}$ in FI-Sod. When presenting the results in Section 3.1, we had used the sustained NPQ presentation for the CA-Obs and US-NR1 sites, but not for the FI-Sod site.

2.9 Evaluation methodology

The metrics to assess the model performance were coefficient of correlation (r^2) (Wright, 1921), bias and root mean square error (RMSE) (Hastie et al., 2009) as well as its systematic and random components (Willmott, 1981). These formulas have been shown in Section S1.6.

For many of the figures we used averaging window of 15 days to smooth the daily values, so that the seasonal cycle would be easy to distinguish. Without satisfactory modelling performance of GPP, the simulation of the SIF would not be successful, as output from the photosynthesis model was used in our approach to calculate the leaf level emissions of SIF and this is why we also showed evaluation of GPP. We show for the subdaily time scale separately metrics for the model performance on morning (6 a.m. to 9:30 a.m.), midday (10 a.m. to 1:30 p.m.) and afternoon (2 p.m. to 5:30 p.m). All of these times are local winter time.

Since the mSCOPE was run inside QUINCY and the two other approaches outside QUINCY, the wall time calculation differed. For the mSCOPE version the wall time was calculated as the time it took for QUINCY to simulate one year at FI-Sod. For the L2SM and the LZ approaches QUINCY was first run for one year at Sodankylä, and then the calculation outside QUINCY in Python was added to this wall time value.

3 Results

The diurnal monthly cycles and the seasonal cycles of the observed and simulated SIF signals for the years 2019 and 2020 at CA-Obs are shown in Fig. 2. This was the final result we obtained after testing for different radiative transfer schemes and adding the description for sustained NPQ. The following sections describe how we arrived at these results. In the main text, we focus on the results from the CA-Obs site, for which we had the most data. In the supplement, we present the results for the other two sites.

3.1 Performance of the radiative transfer models

3.1.1 CA-Obs

The different radiative transfer schemes were all tested at all three sites. The monthly diurnal cycles and midday values (10 a.m. to 1:30 p.m.) for GPP, red region SIF and far-red SIF at CA-Obs (Fig. 3) showed large overestimation with all the different SIF transfer schemes. The midday values are shown here to give a better insight into how the magnitude of the variables changes, thus removing the strong influence of the change in day length on the results. QUINCY was able to capture the seasonal behaviour at the site. The large overestimation of the SIF simulation results will be discussed also later in this paper.

The model performance of GPP in CA-Obs was generally good (Table 2). The simulation of GPP was best at midday, and slightly less in morning hours. Since there was a long gap in observed GPP in and we instead used gap–filled GPP, we also checked the r^2 of daily GPP values for the two years separately. For 2019 the r^2 was 0.89 and for 2020 0.86, possibly reflecting the fact that simulations did not capture the turbulent nature of eddy covariance observations, but were potentially closer to gap–filled values that estimate the average behaviour of the ecosystem.

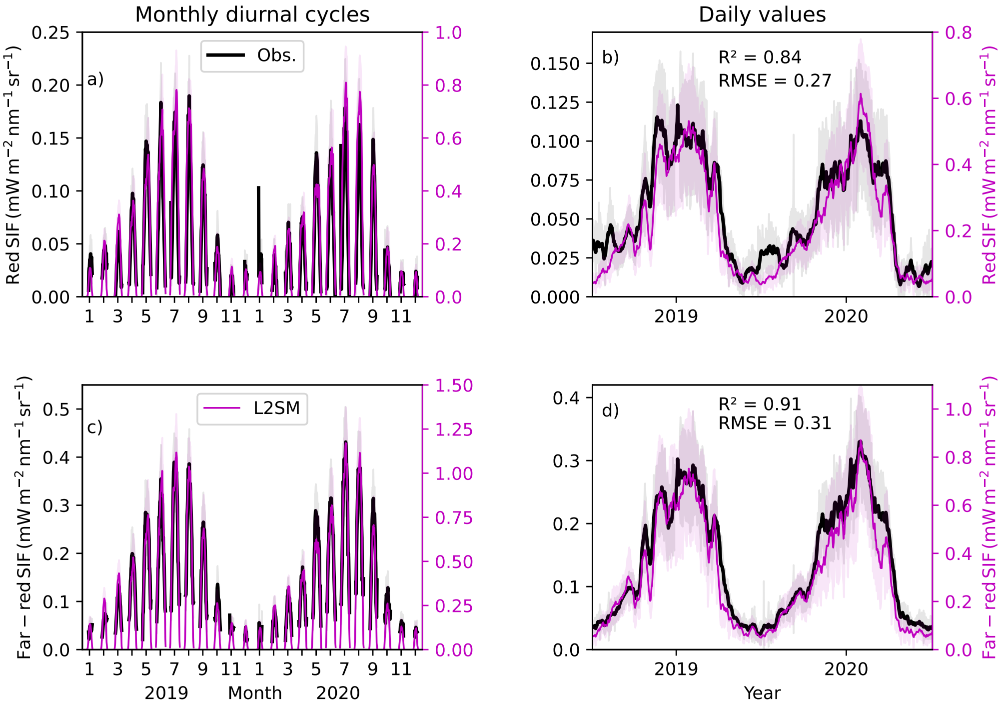

Figure 2. Monthly diurnal cycles for (a) red region SIF and (c) far-red SIF and daily values for (b) red region SIF and (d) far-red SIF at CA-Obs. The black line is the observation for all plots, magenta for the L2SM. All the lines for daily values have been smoothed with a 15-day long window. The shaded regions denote standard deviation. The metrics shown have been calculated from daily, non-smoothed values. The RMSE is in units $\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$.

The daily r^2 values for SIF were close to those of GPP (Table 2). Overall, modelling of SIF was more successful in the far-red region than in the red region. The r^2 values in both wavelength regions were better in the midday and afternoon than in the morning. When investigating whether the different months showed clearly different patterns in model behaviour (Fig. 4), it was seen that the highest simulated midday values in summer were higher than the linear fit between observations and simulations would imply, suggesting that the model had a tendency to overestimate these values relative to other time periods.

The performance of the different modelling approaches was quite comparable when looking at the r^2 values (Table 2). The RMSE values showed greater variation. Of the three different radiative transfer approaches, L2SM appeared to have a consistent level of performance in both wavelength ranges and different times of the day. Overall, the r^2 values were quite

Table 2. The r^2 and RMSE values of simulated versus observed SIF values in the red and far-red regions in 2019-2020, according to different radiative transfer approaches at CA-Obs. The metrics are also shown for the GPP derived from the standard QUINCY configuration. The morning values are from 6 a.m. to 9:30 a.m., the midday values from 10 a.m. to 1:30 p.m., and the afternoon values from 2 p.m. to 5:30 p.m.

Variable (unit) / r^2 (RMSE)	Daily	Morning	Midday	Afternoon
GPP ($\mu\mathrm{mol\,m^{-2}\,s^{-1}}$)	0.88 (1.47)	0.83 (2.71)	0.87 (2.19)	0.84 (2.15)
Red region SIF ($\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$)				
mSCOPE	0.85 (0.21)	0.68 (0.23)	0.88 (0.29)	0.82 (0.32)
L2SM	0.84 (0.27)	0.68 (0.27)	0.86 (0.31)	0.84 (0.34)
LZ	0.83 (0.59)	0.68 (0.54)	0.86 (0.66)	0.83 (0.72)
Upscaled	0.84 (1.45)	0.68 (1.34)	0.88 (1.89)	0.84 (1.70)
Far-red region SIF ($\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$)				
mSCOPE	0.92 (0.18)	0.87 (0.21)	0.91 (0.27)	0.89 (0.28)
L2SM	0.91 (0.31)	0.87 (0.31)	0.90 (0.38)	0.92 (0.38)
LZ	0.91 (1.20)	0.87 (1.13)	0.90 (1.49)	0.92 (1.43)

similar between the approaches, showing that the different approaches did not have a pronounced influence on the temporal patterns of the simulated SIF.

3.1.2 US-NR1 and FI-Sod

Running the same simulations at other sites allowed further evaluation of model performance and possible influences of instrumentation on the diurnal dynamics. The model performance for simulating GPP and SIF was lower in US-NR1 than in CA-Obs (Table S2, Fig. S6). For SIF this is clearly seen in the amount of scatter between simulated and observed values in Fig. S7. The model seemed to have difficulty in capturing the variation in midday values during the summer months. The seasonal cycle of SIF in US-NR1 was not as well reproduced as in CA-Obs (Fig. S6b vs. Fig. 5b), although the spring recovery of GPP seemed to be well simulated (Fig. S5b). Similar to CA-Obs, the r^2 values for SIF were generally higher in the far-red region than in the red region at US-NR1 (Table S2). The model performance was best at midday.

QUINCY was more successful in simulating GPP at FI-Sod than at the other two sites (Fig. S8, Table S3). Modelling SIF was less successful than modelling of GPP in FI-Sod (Table S3, Fig. S9). In both spectral regions, the model performed best in the morning and midday, and worse in the afternoon. Differences between the radiative transfer approaches were not pronounced.

3.1.3 Comparison performance between sites and computational efficiency

The magnitude of the observed SIF was similar in both the red and far-red regions at the two sites with the PhotoSpec observations (Table S4) for the July-August midday values. Compared to these values, the FI-Sod value observed with FloX

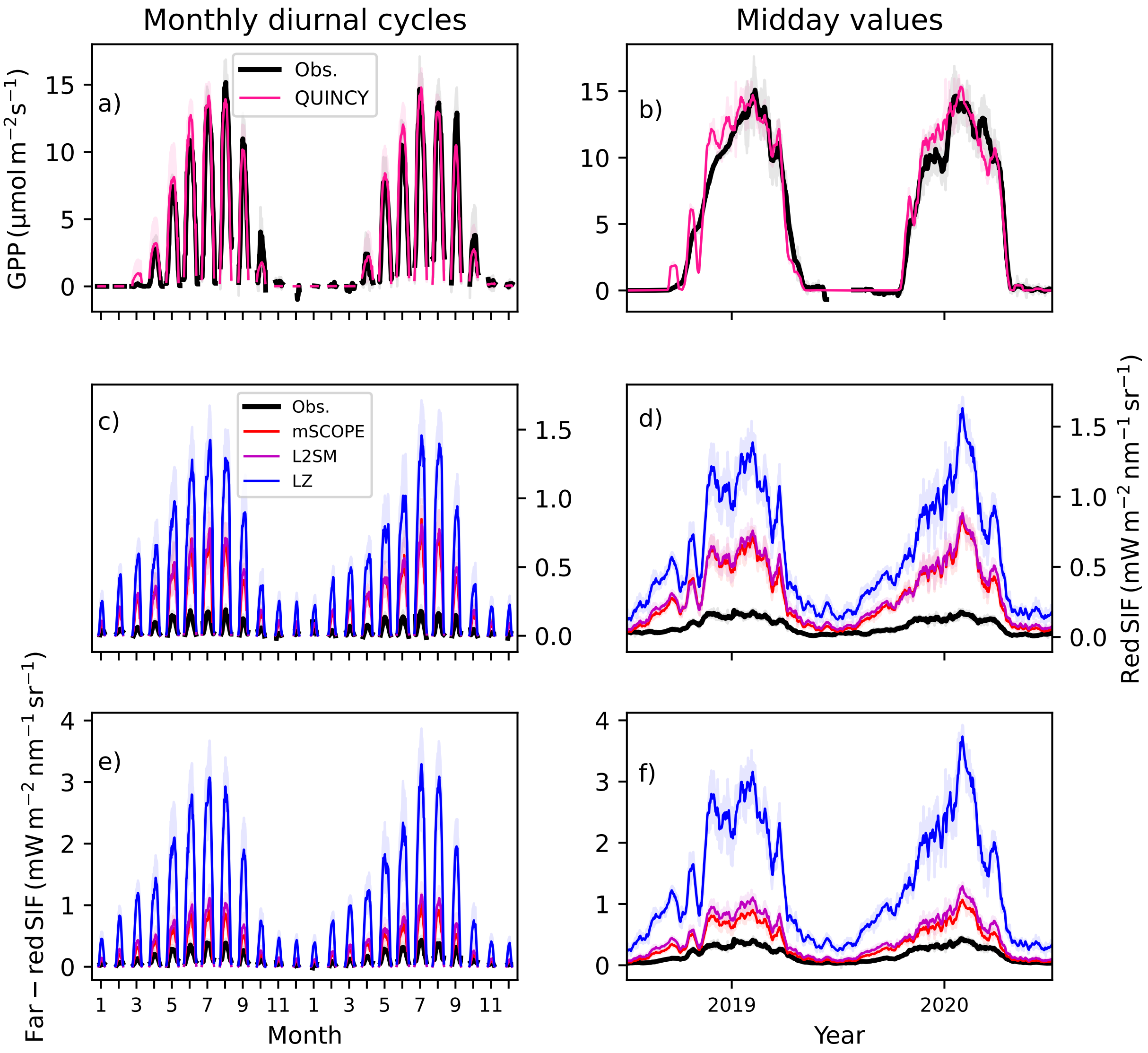

Figure 3. Monthly diurnal cycles for (a) GPP, (c) red region SIF and (e) far-red SIF and midday values, calculated from winter time between 10 a.m. and 1:30 p.m., for (b) GPP, (d) red region SIF and (f) far-red SIF in CA-Obs. The black line is the observation in all plots, the pink line in the GPP plots is the QUINCY simulation. For the SIF plots the red line is the mSCOPE result, magenta the L2SM and blue the LZ approach. All the lines for midday values have been smoothed with a 15-day long window.

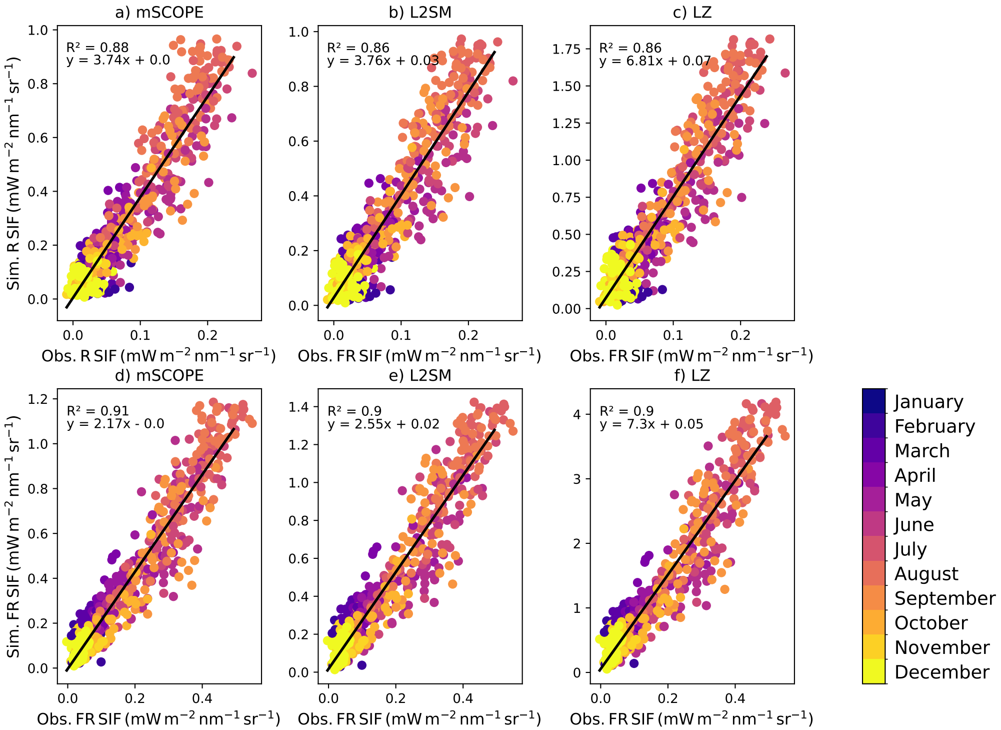

Figure 4. Observed vs. modelled SIF midday values in the red (denoted with R in the figure) region (a: mSCOPE, b: L2SM, c: LZ) and far-red (denoted with FR in the figure) region (d: mSCOPE, e: L2SM: f: LZ) at CA-Obs. Values from different months are color-coded. The black line shows a fit with the corresponding parameters shown in each panel.

was higher in the red region and lower in the far-red region, which was consistent with what we see in the spectral shape of the SIF emission (Fig. 1). In the far-red region this difference was more pronounced and was half of the value observed with PhotoSpec (Table S4). The overestimation of SIF by the different radiative transfer methods was most pronounced for the sites 390 with PhotoSpec observations in the red region. In the far-red region, mSCOPE had the lowest overestimation, while the LZ approach had the highest. The same was true when looking at the metrics for all the sites combined (Table 3. The LZ approach had the highest bias and systematic RMSE across the sites. Otherwise, generally mSCOPE had the best performance metrics, but the other approaches were not much worse. In the North American sites the model approaches performed better in the far red region.

395 As the simulation time is relevant for large scale applications, we calculated wall times for the simulations for one year at FI-Sod (Table 4). LZ was 419 times faster than the mSCOPE approach, while L2SM took twice as long as LZ while being 210 times faster then the mSCOPE approach.

Table 3. The r^2, bias, $\mathrm{RMSE}_{\mathrm{sys}}$ and $\mathrm{RMSE}_{\mathrm{ran}}$ values of simulated versus observed SIF values in the red and far-red regions according to different radiative transfer approaches at the three sites. The metrics are also shown for the GPP derived from the standard QUINCY configuration. The values are calculated on daily values.

Variable (unit)	r^2	Bias	$\mathrm{RMSE}_{\mathrm{sys}}$	$\mathrm{RMSE}_{\mathrm{sys}}$
CA-Obs: Red region SIF ($\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$)				
mSCOPE	0.85	0.15	0.21	0.01
L2SM	0.84	0.21	0.27	0.02
LZ	0.83	0.47	0.59	0.02
CA-Obs: Far-red region SIF ($\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$)				
mSCOPE	0.92	0.12	0.18	0.03
L2SM	0.91	0.24	0.31	0.03
LZ	0.91	0.95	1.20	0.03
US-NR1: Red region SIF ($\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$)				
mSCOPE	0.67	0.25	0.29	0.02
L2SM	0.62	0.27	0.30	0.03
LZ	0.63	0.60	0.67	0.03
US-NR1: Far-red region SIF ($\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$)				
mSCOPE	0.74	0.25	0.28	0.06
L2SM	0.70	0.33	0.36	0.07
LZ	0.73	1.23	1.36	0.06
FI-Sod: Red region SIF ($\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$)				
mSCOPE	0.65	0.14	0.15	0.04
L2SM	0.58	0.33	0.35	0.04
LZ	0.57	0.81	0.86	0.04
FI-Sod: Far-red region SIF ($\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$)				
mSCOPE	0.65	0.20	0.21	0.03
L2SM	0.59	0.34	0.36	0.04
LZ	0.59	1.25	1.32	0.04

Table 4. Wall times in seconds for different radiative transfer approaches.

	mSCOPE	L2SM	LZ
Wall time (seconds)	4191	20	10

3.2 Importance and generality of sustained NPQ modelling

SIF modelled without sustained NPQ showed a strong relationship with the absorbed PAR (aPAR) at CA-Obs (Fig. 5a). A CA-Obs simulation was carried out to assess the performance of the parameterization carried out at US-NR1. QUINCY was successful in simulating the aPAR at CA-Obs at midday (Fig. 5a, Table 5). The seasonal cycle was strong with winter values of aPAR around 200 $\mu\mathrm{mol\,photons\,m^{-2}\,s^{-1}}$. The increase towards summer values in aPAR started earlier than for the observed GPP, as the low temperatures prevented the spring recovery of vegetation. The increase towards summer values of aPAR started already in the first part of the year, much earlier than the SIF values started to increase strongly (Fig. 5). The simulated SIF without the described $\mathrm{NPQ_s}$ followed the behaviour of the absorbed PAR. The simulated SIF with the $\mathrm{NPQ_s}$ was more similar to the observed seasonal behaviour (Fig. 5b, Table 5). The magnitudes between the simulations and observations differed for SIF, but the general timing was better for the simulation with $\mathrm{NPQ_s}$. The $\mathrm{NPQ_s}$ had a strong influence on the chlorophyll fluorescence yield (Φ_F) in the model (Fig. 5c).

As US-NR1 is more southerly than CA-Obs, the absorbed PAR did not show a pronounced seasonal cycle (Fig. S10a). The simulated SIF without $\mathrm{NPQ_s}$ followed the seasonal cycle of absorbed PAR. In order to simulate the seasonal variation seen in the SIF observations, it was necessary to include $\mathrm{NPQ_s}$ in the modelling. However, the formulation used for $\mathrm{NPQ_s}$ delayed the spring recovery in 2018 too much. The formulated $\mathrm{NPQ_s}$ also slightly affected the summer time values, which is physiologically unlikely to happen in reality. Inclusion of $\mathrm{NPQ_s}$ improved the simulations results considerably in terms of r^2, RMSE and bias.

As FI-Sod is located north of the Arctic Circle and the absorbed PAR had a pronounced seasonal cycle (Fig. S11a). The absorbed PAR caused the simulated SIF values to start to increase already in February, well before the start of the vegetation active period (Fig. S11). There were no tower flux SIF observations at the site at that time, but it is not likely that the SIF would have increased considerably so early. Therefore, it seems that the same parameterization that gave reasonably satisfactory results at the other two sites was not as functional at this more northern site with different climatic characteristics (Fig. S11b). The aPAR observed by the above- and belowground canopy PAR sensors showed much better resemblance to simulations than the aPAR estimated from the FloX measurements (Table 5). This suggests that the shadow effects in the footprint of the FloX observations likely influence the observation and in a way set the limit to which model simulations can be successful. The temperature response of the chlorophyll fluorescence yield (Φ_F) showed further the pronounced difference depending on whether the $\mathrm{NPQ_s}$ was included or not (Fig. S12). There were no differences between the sites. Temperature response of the ratio daily far-red SIF divided by GPP showed that the ratio increased in cold temperatures at the North American sites in both

Table 5. The metrics (r^2, RMSE and bias) of the simulated absorbed PAR (aPAR) and far-red region (FR) SIF at the three sites for midday values with and without the formulation for $\mathrm{NPQ_s}$. The units of RMSE and bias are $\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$ for far red region SIF and $\mathrm{\mu mol\,m^{-2}\,s^{-1}}$ for APAR.

Site and variable	r^2	RMSE	Bias
CA-Obs			
aPAR	0.94	91.6	13.4
FR SIF, no $\mathrm{NPQ_s}$	0.71	0.59	0.51
FR SIF, with $\mathrm{NPQ_s}$	0.90	0.43	0.32
US-NR1			
aPAR	0.83	256.1	205.3
FR SIF, no $\mathrm{NPQ_s}$	0.24	0.76	0.72
FR SIF, with $\mathrm{NPQ_s}$	0.71	0.42	0.37
FI-Sod			
aPAR (FloX)	0.70	159.9	71.4
aPAR (PAR sensors)	0.96	73.9	-13.2
FR SIF, no $\mathrm{NPQ_s}$	0.70	0.31	0.23
FR SIF, with $\mathrm{NPQ_s}$	0.69	0.28	0.18

the observations and simulations (Fig. S13). The simulated values showed much larger SIF:GPP values than the observations. Observations at FI-Sod did not cover enough wide range in temperature to show such a variation.

3.3 Dependencies between far-red SIF, GPP and PAR

Noticeable differences were found comparing the relationship between GPP and far-red SIF in the observations and simulations with L2SM for June and July (Fig. 6). The observations presented equally high far-red SIF values for CA-Obs and US-NR1, although the observed GPP values were higher at CA-Obs (Fig. 6a). Both observed GPP and far-red SIF values were lower at FI-Sod compared to the North American sites (Fig. 6a). The simulated values showed much less scatter for the SIF-GPP relationship than the observations (Fig. 6b). The highest far-red SIF values were obtained at CA-Obs, although the highest GPP values were obtained at US-NR1. When looking at the GPP and far-red SIF light responses (Fig. 7 e, g) it was noticed that the simulated far-red SIF values were highly correlated with the PAR values, while simulated GPP values had more scatter.

We made a hyperbolic fit to these relationships, fitting parameters a and b of function y=ax/(b+x) (Damm et al., 2015; Pierrat et al., 2022b). The fitted lines are shown in Fig. 6 and the fitted parameter values with their associated uncertainties are shown in Table S5. Goodness of the hyperbolic fits (Table S5) were better for the simulated GPP vs. SIF relationship than for the observed (averaged over three sites r^2= 0.73 for the simulated, r^2=0.45 for the observed.) Also the RMSE of the fit

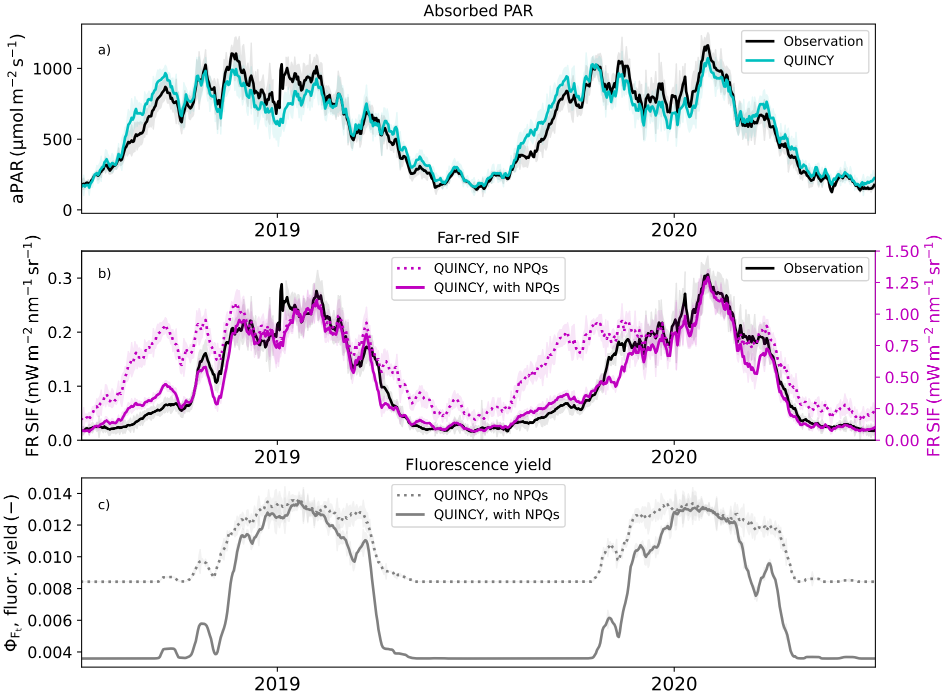

Figure 5. (a) The observed and simulated absorbed photosynthetically active radiation at CA-Obs, (b) far red (FR) region SIF values with and without sustained NPQ simulated with L2SM and (c) simulated chlorophyll fluorescence yields with and without sustained NPQ. Values are averages of midday values (10 a.m. to 1:30 p.m.), the standard deviation is shown as shaded areas. All the lines for midday values were smoothed with a 15-day long window.

was smaller for the simulations vs. observations for all the three sites. The worst behaviour of fits (in terms of r^2) happened at FI-Sod for the observations, potentially reflecting the fact that the GPP vs. SIF relationship looks quite linear for that site.

Given the worse model performance for SIF at US-NR1, the diurnal cycle during the summer was examined in more detail for all three sites. First, we calculated the r^2 and RMSE values for the instantaneous values over five days versus the averaged diurnal cycle over five days. The improvement in r^2 and RMSE when moving from instantaneous to averaged values was considerable (Table 6).

The r^2 values of the averaged diurnal cycle were comparable for GPP and SIF in the far-red region at CA-Obs (Table 6). On day of year (DOY) 187, the simulated GPP showed an almost sinusoidal diurnal behaviour, which resulted from simulation under high irradiance conditions (Fig. 7a). The observed GPP showed more variation than simulated GPP during the day. The light response of the observed GPP was much more scattered than that of the simulations (Fig. 7e). The simulated far-red SIF values with all the approaches were able to capture variations quite successfully on DOY 189 (Fig. 7c), when variations in radiation occurred.

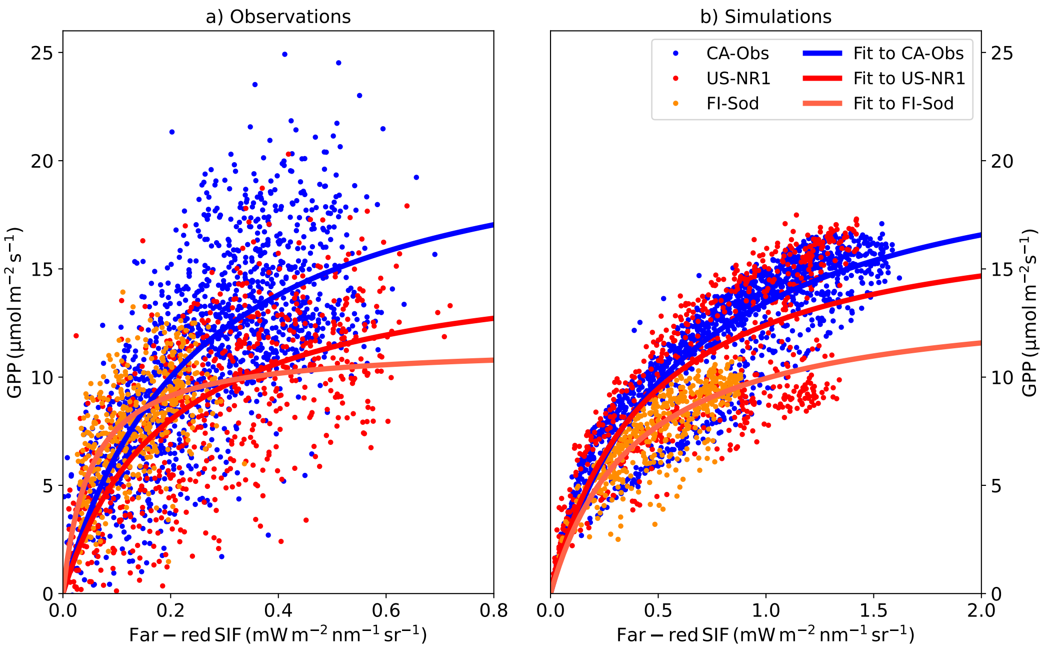

Figure 6. (a) The observed and (b) simulated GPP vs. far-red region SIF relationship at three different sites for half-hourly values for all points in June and July using the L2SM approach in the simulations. CA-Obs has half-hourly values and FI-Sod and US-NR1 hourly values. Hyperbolic fits are shown as solid lines in the figure.

Table 6. Model performance in terms of r^2 and RMSE for GPP and SIF in the far-red region at three sites for half-hourly values during five summer days and the averaged diurnal cycle over the five days. Calculated for half-hourly values at CA-Obs and hourly values at US-NR1 and FI-Sod. RMSE for GPP is in units $\mu\mathrm{mol\,m^{-2}\,s^{-1}}$ and for SIF in $\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$.

	CA-Obs	US-NR1	FI-Sod
GPP, r^2 (RMSE)			
half-hourly	0.60 (3.42)	0.26 (2.77)	0.98 (0.59)
averaged	0.80 (2.08)	0.51 (1.79)	0.99 (0.50)
SIF, r^2			
half-hourly	0.69 (0.57)	0.29 (0.52)	0.40 (0.54)
averaged	0.83 (0.51)	0.66 (0.46)	0.50 (0.53)

At US-NR1 the model performance remained significantly lower for GPP than at the other two sites (Table 6) even after calculating the average over five days. The light response curves of the observed GPP and SIF in the far-red region were quite

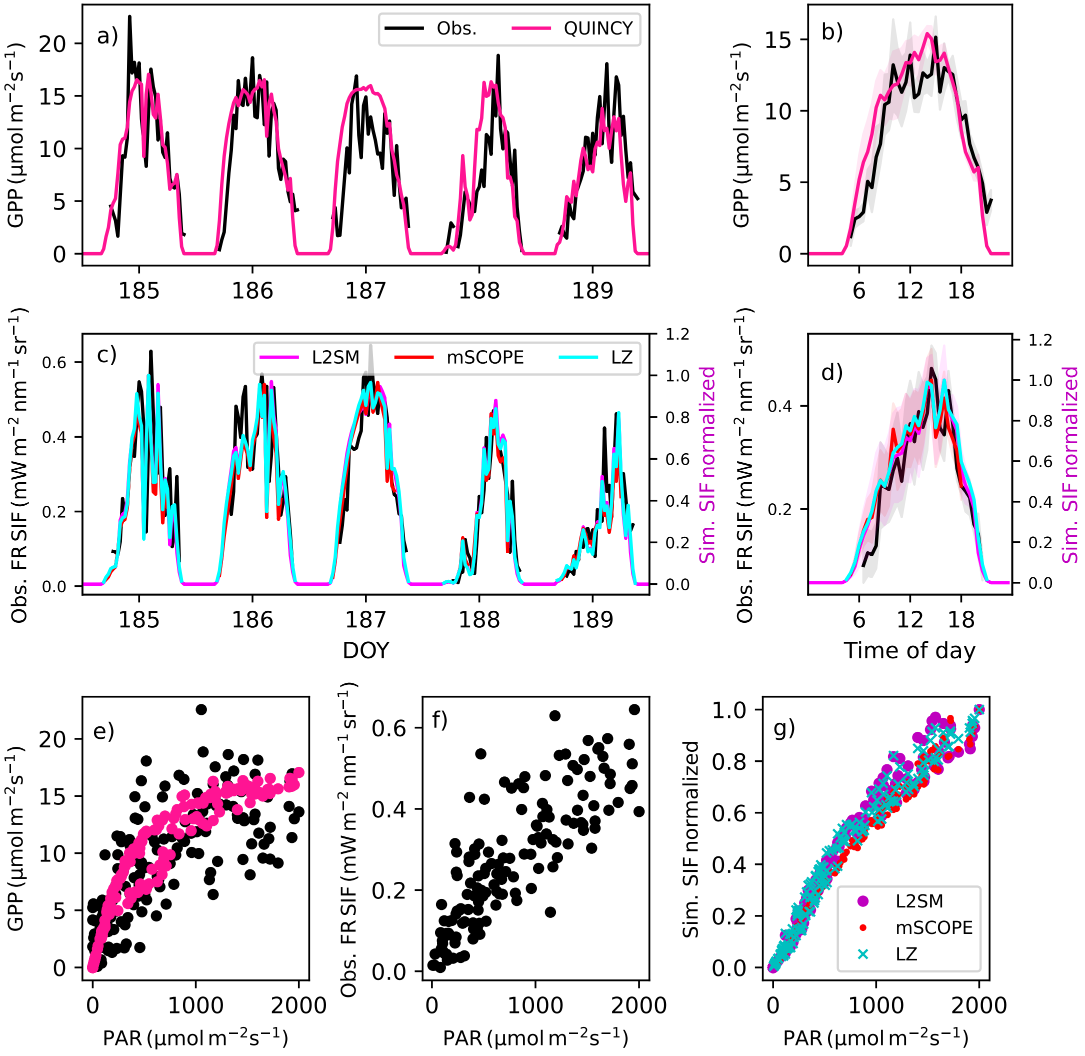

Figure 7. (a) The observed and simulated GPP and (c) far-red (denoted as FR in the figure) region SIF for days 185-189 (5 July-8 July 2020) and averaged over these five days (b for GPP and d for far-red region SIF) at CA-Obs. The shaded regions in b and d show the standard deviations of the averaged values. (e) The light response of the observed and simulated GPP for these five days, (f) the observed far-red region SIF and the (g) simulated far-red region SIF. The observations are in black, the simulated GPP is in pink and the simulated far-red SIF from L2SM is in magenta, from mSCOPE in red and from LZ approach in cyan. The simulated SIF values have been normalized to one.

scattered at this site (Fig. S14e, f). The model performed very well for GPP at Sodankylä (Table 6, Fig. S15). The modelled diurnal cycle of far-red SIF did not capture the variation in the observations (Fig. S8c, d).

Table 7. The metrics (r^2, RMSE and bias) of the simulated SIF at CA-Obs and FI-Sod against the TROPOSIF observations. The simulated values have been calculated from the midday values and TROPOSIF values are daily averages. The values are separately region around the site expanding to 0.50° x 0.50° or 0.25° x 0.25°. The units of RMSE and bias are $\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$.

Site and region	r^2	RMSE	Bias
CA-Obs (0.50° x 0.50°)	0.48	0.57	0.45
CA-Obs (0.25° x 0.25°)	0.46	0.64	0.55
FI-Sod (0.50° x 0.50°)	0.15	0.61	0.51
FI-Sod (0.25° x 0.25°)	0.26	0.64	0.58

3.4 Comparison of simulated SIF to satellite observations

The magnitude of the simulated SIF was large compared to the tower-based observations at all sites (Figs. 3, S6, S8). Comparison with satellite observations at CA-Obs showed a better agreement between the simulated and observed magnitudes (Fig. 8c) than proximal sensing (Fig. 8b). In 2019, the seasonal cycle of TROPOSIF was smoother than that of the simulated SIF and PhotoSpec observations at the site. In 2020, the seasonal cycle was smoother in the PhotoSpec observations and the simulated seasonal cycle was more consistent with TROPOSIF. The simulation results and the TROPOSIF are shown on different scales because the magnitude of the winter TROPOSIF observations is below zero due to the retrieval method, but the minimum of the simulated SIF is zero and using different scales helps to see the seasonality of the two observations together. The simulations for the period July-August overestimated the observations by 30 %.

At FI-Sod (Fig. S16) the TROPOSIF time series expanded also to spring, thus covering also for the period not available from the FloX observations. There was a lot of variation in the springtime TROPOSIF observations (shaded region in Fig. S16, from April 9th to May 17th) and when the values started to increase for the last time in May (the vertical line in Fig. S16 showing May 29th) the observed GPP was already at higher level than in early spring. The variation in TROPOSIF and simulated SIF during summer followed the same pattern. Overestimation of the simulations compared to TROPOSIF observations for the July-August period was 45 %.

The performance metrics for simulated SIF against TROPOSIF were better at CA-Obs than at FI-Sod (Table 7. This was partly contributed to the fact that the sustained non-photochemical quenching was not simulated at FI-Sod. The FloX observations alone were not sufficient to assess that, as the spring was missing from those, but one can see from the Fig. S16, that the increase should start later than it started here. Despite the large differences in the springtime at FI-Sod, the RMSE and bias were quite similar at the two sites for the larger region (having 0.50° x 0.50° region around the region). When constraining to a smaller region, RMSE and bias got worse for both of the sites, but the r^2 increased at FI-Sod, even though it was still quite small.

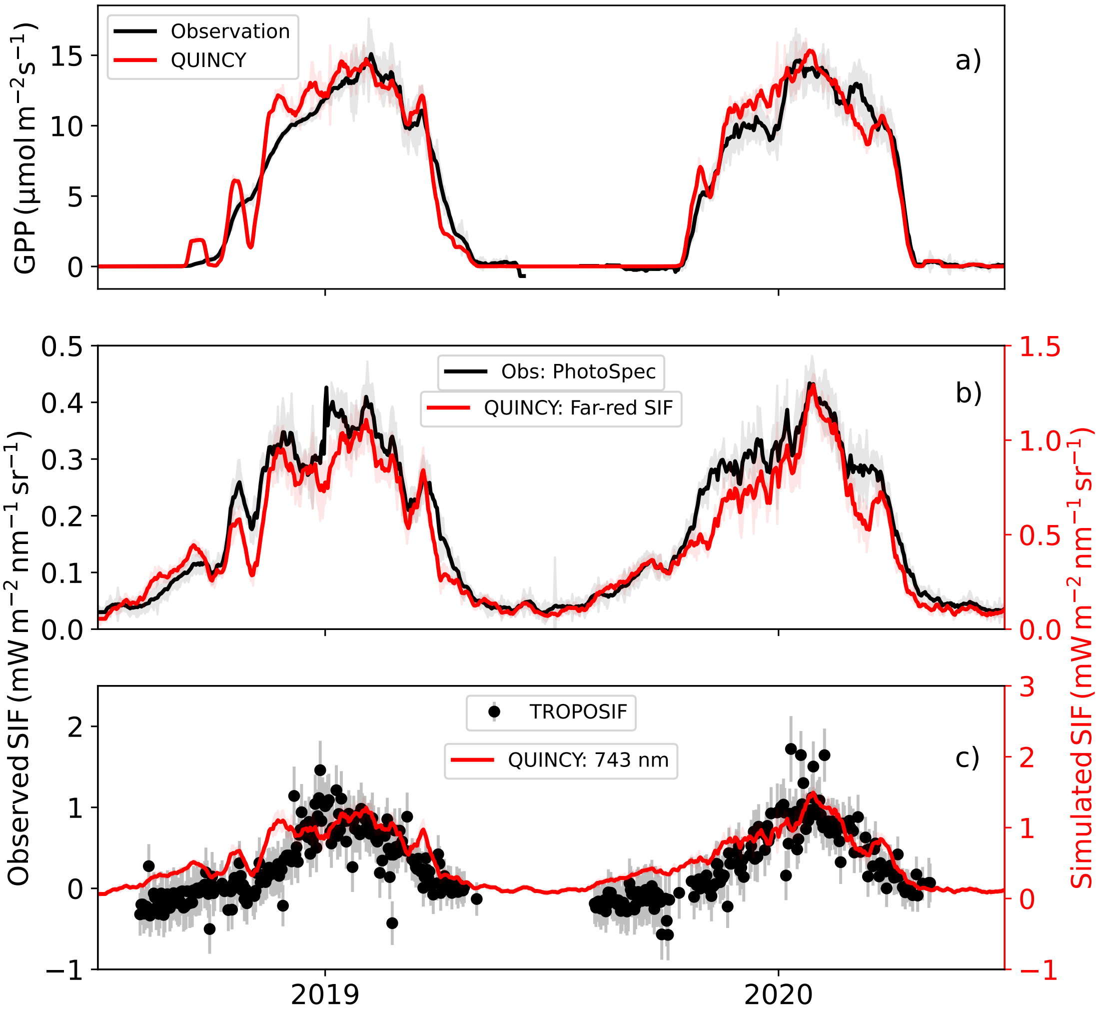

Figure 8. In (a) the observed and simulated GPP at CA-Obs, (b) near-infrared SIF from PhotoSpec observations and simulations with L2SM and (c) and TROPOSIF observations and simulations with L2SM at 743 nm. The other values than TROPOSIF are averages of midday (10 a.m. to 1:30 p.m.) values, with standard deviation is shown as shaded areas and TROPOSIF uncertainty from the retrievals shown in error bars (c). TROPOSIF values are daily. All the lines for midday values have been smoothed with a 15-day long window.

4 Discussion

4.1 Magnitude of the simulated SIF

All of the approaches that we tested overestimated the in situ observed SIF considerably (Table S4). The differences were less pronounced in the comparison against the satellite observations. The leaf level model was consistent across all our approaches. In that model, we used only the default parameters, which were held constant across all sites. The leaf level model provided the chlorophyll fluorescence yield, which was applied differently by each approach to obtain the top of canopy value.

Therefore, the reason for the overestimation of the SIF could originate from either the leaf level model or the radiative transfer calculation. The leaf level model provided the Ft, which was consistent with values in the literature (e.g., the original model formulation, (van der Tol et al., 2014); another modelling study for US-NR1 (Raczka et al., 2019); and site level observations (Kim et al., 2021)). However, there are other types of estimates for these values, including some of these sites. For example, Pierrat et al. (2024) provide a higher leaf level chlorophyll fluorescence yield value from MoniPAM observations. In any case, the magnitude is subject to choices made in the post-processing of the data, so it is also not easy to compare the simulated value to these observations.

It is likely that the overestimation originated from the radiative transfer part of the model. Despite testing different approaches, they all led to overestimated SIF. Two approaches that included attenuation of the SIF signal inside the leaf (mSCOPE and L2SM) resulted in smaller overestimation than the approach that did not account for attenuation (LZ). Additionally, the version of the LZ approach employed here assumed black, or non-reflective, soil. Some recent developments may help overcome this issue (Yang et al., 2025a). The simulated far-red region SIF showed lower overestimation than the simulated red region SIF. This model behaviour suggests issues with attenuation in the red region. The modelling of SIF is also related to the modelling of absorbed PAR. At US-NR1, the simulations overestimated absorbed PAR, whereas at the other two sites, the bias in aPAR was smaller (Table 5. It has been noted, that parameters related to aPAR are important for SIF modelling (Fan et al., 2025).

The overestimation of SIF in evergreen conifer forests has also occurred in other modelling studies (Li et al., 2022), and our results are close to the model average shown in a model comparison study conducted at US-NR1 (Parazoo et al., 2020). Preliminary model tests with QUINCY on other ecosystems did not reveal such significant discrepancies between the magnitude of the simulation results and in situ observations (results not shown). Therefore, it may be that the characteristics of the in situ sampling in this type of ecosystem to provide smaller SIF signals than expected. A comparison to satellite observations did not reveal such a large overestimation of the simulated SIF. One can keep in mind that also other processes may also play a role, such as reversible NPQ. The leaf level model that we used has been parameterized for cotton (van der Tol et al., 2014). (Raczka et al., 2019) used leaf level MoniPAM observations from Hyytiälä to parameterize reversible NPQ and improved the performance of their SIF model. This could be a way to improve modelling for new ecosystems.

4.2 On the choice of radiative transfer approach

First, we tested different ways of describing the radiative transfer of the SIF to determine a robust method for feasible calculations in a large-scale model. When considering the r^2 metric for the different approaches, we found that the simple LZ method did not perform significantly worse than the more sophisticated approaches (Tables 2, S2, S3). This justifies the rather simple approaches previously used in the radiative transfer of SIF (e.g., Lee et al., 2015; Thum et al., 2017), but it contrasts with some other studies (Li et al., 2022). The mSCOPE model performed similarly to the other approaches across all sites and often provided the most accurate estimates. However, its longer computation time (20 times longer than the other approaches in our comparison) makes it impractical for large scale applications (Li et al., 2022). The radiative transfer model in mSCOPE is based on SAIL, which was originally developed for croplands (van der Tol et al., 2009). The radiative transfer model in QUINCY was also originally developed for croplands, so neither model was designed to consider the unique characteristics of radiative transfer in the conifer forests. A study by Li et al. (2022) found that including clumping in their model significantly improved SIF modeling in CLM compared to simulation without clumping. Failing to consider clumping can lead to significant errors in SIF modelling (Zeng et al., 2020). QUINCY describes clumping in a relatively simple way. There is potentially room for improvement in SIF modelling if clumping were also included in the radiative transfer of SIF, e.g. in L2SM. In conifer ecosystems, the challenge is that the clumping of the canopy exposes more ground vegetation visible to optical measurements, which affects the remotely sensed signal (Gopalakrishnan et al., 2023).

The structure of the vegetation affects the observed SIF signal (Magney et al., 2019b; Sun et al., 2023a). This is something that could be addressed by including vegetation NIRv, a near-infrared reflectance, in the analysis. NIRv has very similar interactions within the canopy to the far-red region SIF. Including NIRv in helping to interpret the SIF signal in the analysis would allow the attribution of the structural effects seen in the SIF signal (Zeng et al., 2019; Dechant et al., 2022). This analysis could be conducted using in situ or spaceborne observations. Another approach would be to consider the 3D structure of the canopy in QUINCY and the SIF RT model. This would allow for consistent modulation of both the GPP and SIF (Stretton et al., 2025).

4.3 Modelling performance of GPP and SIF at subdaily scale

Compared to the simulated GPP, the observed GPP showed more variation on a subdaily scale at the sites (Figs. 7, S14, S15). This variation may be due to canopy shading, understorey vegetation and turbulence conditions. The lower performance at CA-Obs in the morning may be due to sun-view geometry and the 3D structure of the canopy, which casts shadows within the spectroradiometer's measurement footprint. These shadows were not reproduced by 1D radiative transfer models.

At FI-Sod, the FloX footprint might be partially shadowed during certain periods on sunny days, resulting in discrepancies between the observed and simulated far-red SIF (Fig. S15c,d). This may partly explain the lower model performance observed in the afternoon (Table S3), as the shadow effects may be more pronounced during the shoulder seasons at a high latitude sites. Designing an observation that excludes shadow effects would be very challenging at such high latitudes, where the days are very long days in the summer.

4.4 On the use of optical properties

Although L2SM supports vertically varying optical properties, this study set it up with properties that remain unchanged throughout the canopy profile. However, the vertical profile of leaf chlorophyll content could be used to adjust the optical properties of each layer. In the current version of QUINCY, the chlorophyll content increases with depth within canopy layers. The single leaf scattering albedo of forest plant functional types in QUINCY is based on a study by Otto et al. (2014). Values commonly used to calculate reflectance and transmittance in terrestrial biosphere models have been criticized, and some new approaches based on more data have been proposed (Majasalmi and Bright, 2019). Since reflectance was also used in the calculation of the LZ approach calculation, it would also influence these results as well. The assumption of equal reflectance and transmittance in QUINCY can be debated and further developed, as discussed in Majasalmi and Bright (2019). The simplification of using only two radiative bands (visible and near infrared) may introduce biases in the results at certain wavelengths.

Using of the L2SM and the LZ approaches requires the use of SIF spectra for unit conversion from the modelled to observed units (see Section 2.6). For the LZ approach, we used spectra measured in a Finnish Scots pine forest. To extend this approach to other PFTs, it would be necessary to use different measured SIF spectra. This approach has limitations in terms of generalizability because these spectra differ between species (Liu et al., 2025; Magney et al., 2017). Therefore, using a single spectrum for a PFT may introduce uncertainties. Furthermore, the spectral shape of SIF emission changes under stress conditions. For example, photosystems I and II respond differently to stress (Magney et al., 2019a), which will further limit our approach, and require careful investigation of the stress effects. For the L2SM approach we used a theoretical estimate of the in vivo spectrum. Further testing with observed in vivo spectra would also benefit this approach.

4.5 Uncertainties in the observations

Using the Fraunhofer line method with PhotoSpec instruments is less susceptible to atmospheric attenuation than using the oxygen lines with FloX. At FI-Sod, the distance from the soil for FloX was around 19-20 m, and the distance to the canopy was less. Therefore, the measurement distance is less than 20 meters, the threshold at which the data must to be corrected for atmospheric effects (Sabater et al., 2018; van der Tol et al., 2023). FI-Sod has a sparser canopy than the other sites, which implies that the footprint of the observing optical fiber is susceptible to environmental influences other than the canopy, such as the understory. The nearly linear relationship between GPP and SIF in the observations may indicate understory contribution (Fig. **??**a).

The measurements that we used have several sources of uncertainty. The tower SIF observations are relatively new observations and have uncertainties related to instrumentation, the retrieval method, and the spatial matching of the optical and flux footprints (Buman et al., 2022; Cendrero-Mateo et al., 2019; Pacheco-Labrador et al., 2019). Our results showed that using averaging for the model evaluation could be a useful method for evaluating the model. The eddy covariance observations are subject to uncertainty due to the measuring equipment, the heterogeneity of the footprint, and the stochastic nature of turbulence (Richardson et al., 2006). Gap-filling introduces additional uncertainties to the data (Vekuri et al., 2025).

Comparing the satellite observations to a site level observations introduces several uncertainties. The fact that the TROPOSIF estimates remain close to zero by the end of May, despite the GPP levels advancing towards summer levels, indicates that these observations must be handled with caution. Clouds make interpreting the signal more challenging, which is why we used the strict cloud filtering criterion recommended for this type of study. The is a large mismatch in scale between the satellite and flux tower observations. However, constraining the region did not improve the modelling results. This may be because more points help to smooth out the random error of the satellite observations. When only pixels where the site was located were chosen from the satellite retrievals, there were so few points that no significant seasonal cycle was detected at the sites (data not shown). The data aggregation performed for TROPOSIF involves averaging over several viewing geometries because the viewing angle varies due to the wide swath. This introduces additional uncertainty to the data. The land cover classes within the TROPOSIF product that are derived from the MODIS product obviously have issues in the high latitudes, which is a known issue (Liang et al., 2019). However, the land cover class does not impact the retrieved SIF because it is only used to identify water bodies and glaciers. An overall uncertainty of $\sim$ 0.50 $\mathrm{Wm^{-2}s^{-1}nm^{-1}sr^{-1}}$ has been found for the TROPOSIF product, as reported in Du et al. (2023), which emphasizes that the low values during the shoulder seasons for these northern sites are very uncertain. Site heterogeneity influences the the accuracy of TROPOSIF (Du et al., 2023), as do the geolocation shifts (Zeng et al., 2024).

4.6 Model uncertainties and limitations

Our model only simulates one plant functional type per site and is horizontally homogeneous. Thus, the influence of the understory is ignored, even though it may be relevant, e.g., at FI-Sod, where the site has a low LAI and the footprint of the tower SIF observation is static. QUINCY has a representation of clumping, but L2SM does not. Therefore, including clumping in the radiative transfer of SIF in L2SM could improve the results in coniferous forests. Examining the entire diurnal cycle revealed discrepancies between the simulation results and the observations, which could be due to the effects of shadows. More rigorous modelling tools, such as a 3D description of forest structure, would be required to account for these effects. In reality, directional effects also influence the observed optical signal, but our approach did not account for them (Hilker et al., 2008b, a). A comparison of simulated and observation based estimates of aPAR from FloX box and PAR sensors revealed that the model's inability to capture certain dynamics observed by the FloX box may be due to its small footprint.

The scatter of the observed SIF against the observed GPP values, as well as the fact that model was unable to fully capture this behaviour (Fig. 6), raises questions about whether the simulated SIF provides reasonable results in water-stressed conditions. However, due to the scattered nature of the SIF observations, having a more comprehensive dataset than the one used in this study would be helpful.

4.7 Role of sustained NPQ

Our results showed a strong influence of sustained NPQ for these sites, where the plants cannot use the energy of the incoming radiation due to temperature constraints and winter dormancy (see also (Pierrat et al., 2024)). ChlF is closely related to photosynthesis, as both result from the functioning of the leaf biochemical machinery. In the current framework, there is currently no feedback from the modelling of SIF back to the photosynthesis part of the QUINCY model, so describing the $\mathrm{NPQ_s}$ did not influence modelling of GPP. However, similar mechanism based on state of acclimation as used in $\mathrm{NPQ_s}$ has been implemented for spring recovery of GPP in the QUINCY model already earlier.

In general, simulating NPQ has been a challenge in the modelling community, as it is composed of many processes (Zaks et al., 2013) and active measurements have been needed to quantify it. However, recent advances in the use of spectral imaging of xanthophyll cycle pigments are advancing and making it possible to quantify NPQ also from the optical observations (Pescador-Dionisio et al., 2025; Van Wittenberghe et al., 2024), thus making remote sensing of NPQ feasible. Also some studies have combined vegetation indices to help in parameterization of NPQ (Jiang et al., 2023). Some new parameterizations for NPQ based on site-level observations have also become available (Martini et al., 2022).

A more thorough analysis on additional data at Sodankylä (including longer time series of the FloX observations and active ChlF observations with MoniPAM) will be carried out to develop a formulation for sustained NPQ applicable to the site. The current results showed (when comparing the spring time against satellite observations, Fig. S16) that the formulation that was successful at other sites likely caused a too early increase in simulated SIF in spring. It could be that the colder temperature and light regime of high latitudes together causes the FI-Sod has a different dormancy level and mechanisms for coping with stress caused by winter conditions than the sites located in North America. Study from South Korean evergreen coniferous forest showed lower values for observed chlorophyll fluorescence yield (Φ_F) showed lower values of Φ_F for low temperatures than our parameterization allowed (Fig. S12). Therefore, it is likely that the parameterization could be improved for the FI-Sod, while still maintaining realistic values for Φ_F. While similar parameterization for GPP based on state of acclimation was successful across the sites, the same was not true for a parameterization based on similar principles for sustained NPQ. This could be caused by the closer link of the ChlF to pigment pool changes than GPP (Kim et al., 2021). The cold protection mechanisms of conifers are complex and include additionally changes in the absorption cross-section of the antenna complexes, as well as down-regulation of photosystem II activity with simultaneous energy tranfer from photosystem II to photosystem I (Bag et al., 2020). The ratio between GPP and SIF has been shown to vary in low temperatures in earlier studies (Chen et al., 2022, 2025) and it is important to be able to model dynamics of this behaviour so that we understand the coupling between GPP and SIF.

A recent study combining PAM observations worldwide evaluated the photosynthetic capacity of photosystem II (Neri et al., 2024). The study showed that this capacity depends more on the temperature regime of the environment where the vegetation grows than on the species of plant. The study also quantified of this dependence. The ultimate goal is to obtain a sufficiently general parameterization for the entire coniferous evergreen forest region, using the results of (Neri et al., 2024), possibly with the help of TROPOMI observations. Using the same model for photosynthesis and ChlF (Johnson and Berry, 2021) could potentially circumvent this problem. However, the current photosynthesis parameters in QUINCY are directly influenced by nitrogen content and also leaf chlorophyll content is closely coupled to photosynthesis (Thum et al., 2025). Leaf chlorophyll content could be useful as a metric related to nitrogen cycling in model evaluation (Miinalainen et al., 2025). This is a much-needed metric (Kou-Giesbrecht et al., 2023). Additionally, the amount of leaf chlorophyll influences how much of the SIF emitted from leaves that is attenuated in the canopy within the visible spectrum. Therefore, including both leaf chlorophyll and SIF in a model such as QUINCY would be beneficial for understanding Earth system processes and their temporal variations. The amount of chlorophyll in leaves also affects the shape of the SIF spectrum. Since we used a fixed SIF spectrum to convert from the total SIF flux to SIF at a given wavelength (Magney et al., 2019b), this topic could benefit from some further investigation.

5 Conclusions

We have implemented chlorophyll fluorescence into the QUINCY model and tested different canopy transfer approaches of the SIF signal. On a seasonal scale, many of the approaches performed similarly, and did not show clear differences in performance when looking at day-to-day variation and the ability to simulate different times of day. The magnitude of the tower-based SIF observations was greatly overestimated in the simulations, but the timing and seasonality were captured successfully. Of the approaches studied, L2SM showed consistent performance across the sites and is computationally feasible to implement in a large-scale model. We hypothesize that the consistent overestimation might arise from the misrepresentation of conifer leaves and canopy with the commonly used 1D canopy, and leaf plate-theory-based radiative transfer models. However, no fluorescence emission has been implemented in needle-like leaf radiative transfer models, and 3D canopy transfer modules are too computationally demanding for TBMs. Thus, simpler modeling solutions should be explored to improve the representation of fluorescence emission in conifer forests, with the help of proximal sensing measurements

Sustained NPQ was relevant in decoupling the simulated SIF from the observed absorbed PAR and the same parameterization improved model performance at the North American sites but appeared less suitable at the Finnish site. This process is likely linked to the air temperature regime of the sites. The TROPOSIF product from satellite was able to capture the low spring values observed at CA-Obs and could therefore probably serve as additional data when implementing the parameterization of sustained NPQ in a global model. However, for more northern site FI-Sod the amount of points in spring was sparse and an increase in TROPOSIF occurred later than for GPP. Use of TROPOSIF observations additionally in model evaluation and development seems feasible, given that the springtime behaviour seems to follow better site level observations of SIF than absorbed PAR.

The next step of this work will be to extend it to other ecosystems, using both in situ and satellite observations as evaluation data. Together with QUINCY's diagnostic leaf chlorophyll content, a variable which can be observed from space, this work brings QUINCY closer to being a tool for comprehensive analysis of biogeochemical cycles.

Code and data availability. The scientific part of the QUINCY code is available under a GPL v3 license. The source code is available online (https://doi.org/10.17871/quincy-model-2019), but its access is restricted to registered users. Readers interested in running the model should request a username and password via the Git repository.

L2SM-code by T. Quaife is available at Zenodo in doi: 10.5281/zenodo.13753268. The FloX observations with meteorology and CO_2 fluxes from Sodankylä are available at https://zenodo.org/records/12725765. The PhotoSpec observations and CO_2 flux observations from CA-Obs are available at https://zenodo.org/records/10048770 and from US-NR1 at https://data.caltech.edu/records/meh5c-wy279. The meteorological data for the North American sites is available from Ameriflux (https://ameriflux.lbl.gov/). The simulation results of SIF are available at https://fmi.b2share.csc.fi/records/8847a0c06c374668b01e345094d373cd.

Author contributions. TT designed the study, implemented Fluspect to version of QUINCY including mSCOPE, performed all the simulations and analysis and was responsible for the first draft of the manuscript. ZP and JS conducted the Photospec observations at CA-Obs, where AB and BJ were responsible for the CO_2 flux and meteorological observations. TM and JS were responsible for the PhotoSpec observations at US-NR1. MH conducted the FloX observations at FI-Sod in collaboration with HL. HL contributed the satellite data. MA was responsible for the CO_2 flux and meteorological observations at FI-Sod. JPL made original implementation of mSCOPE to the QUINCY model. TQ provided the L2SM code and help with its use as well as the code for the unit conversion. SZ provided help with the QUINCY model. All the authors contributed to discussing the results and writing of the manuscript.

Competing interests. At least one of the (co)-authors is a member of the editorial board of Biogeosciences..

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