Modelling carbon uptake in Nordic forest landscapes using remote sensing

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Sofia Junttila

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Abstract:

Boreal forests and peatlands store over 30% of the global terrestrial carbon in their vegetation and soil, but changing climate can compromise the current carbon stock. Rising air temperatures, changing precipitation patterns and increased risk of natural disturbances can impact the ability of the boreal ecosystems to absorb and store carbon, reducing their effectiveness as carbon sinks. Reliable estimates of carbon fluxes between these ecosystems and the atmosphere are crucial for understanding the ecosystem response to climate change. This thesis focuses on developing remote sensing-based models of the vegetation carbon uptake i.e. gross primary production (GPP) in Nordic forests and peatlands, and upscaling the estimates from sites to landscape and regional levels.

The results demonstrate that spectral vegetation indices EVI2 and PPI can capture the seasonal dynamics of GPP well. In general, other environmental variables that further helped to improve the results were air temperature, photosynthetically active radiation (PAR), and vapour pressure deficit (VPD) that expresses atmospheric demand for water. Another finding was that the spatial resolution of the satellite instrument had less influence on the accuracy of GPP estimates than the model formulation and selection of the input data. The result suggested that vegetation productivity can be monitored at various scales with high accuracy using satellite remote sensing data. Fine-scale estimates are beneficial when monitoring individual forest stands or spatially heterogeneous ecosystems like peatlands.

Various model formulations were tested to estimate GPP with remotely sensed data. The site-specific calibration gave more accurate results, but the single parameter set per ecosystem type was more applicable for upscaling GPP for a larger area. In addition, we found that PPI performed well and provided a useful tool for estimating GPP at local and regional scales. Despite the good agreement with the eddy covariance-derived GPP, the models could be further improved to capture the spatial heterogeneity between the sites by adding e.g. soil moisture data. Finally, we applied a PPI-based model to estimate annual GPP in Sweden's forests and peatlands with a 10-meters spatial resolution. This thesis highlights that satellite remote sensing has a great potential for monitoring variations changes in vegetation carbon uptake in Nordic forest and peatland ecosystems.

Key words: Forest, peatland, remote sensing, Sentinel-2, carbon exchange, gross primary production, CO2, climate change, boreal region

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Author contributions

I. **SJ** contributed to the design of the study, contributed to the analysis of remote sensing and environmental data, interpreted the results with co-authors, and contributed to writing, reviewing, and editing the manuscript.

II. **SJ** conceived and designed the study with JK and LE, conducted the Sentinel-2 data processing, performed GPP and NEE modelling, interpreted the results with JK and LE, prepared the original draft of the manuscript, and led the reviewing and editing with contributions from all co-authors.

III. **SJ** conceived and design the study with LE, performed the data processing with support from NK, ZC and HJ, carried out the data analysis, interpreted the results with LE, JA and TT, prepared the original draft of the manuscript, and led the reviewing and editing with contributions from all co-authors.

IV. **SJ** conceived and designed the study with LE, conducted the data analysis with support from ZC and HJ, interpreted the results with all co-authors, and prepared the manuscript with editing support by all co-authors.

Popular summary

Boreal regions play a key role in the global carbon cycle due to the large amounts of carbon stored in their vegetation and soils, especially in the form of peat. Carbon dioxide (CO_2) is the key greenhouse gas driving the current climate change, and the uptake and release of CO_2 largely define if an ecosystem is a carbon sink or source. CO_2 is absorbed by vegetation through photosynthesis, and released by plant respiration and soil microbes as they decompose organic matter. When forests or peatlands are disturbed, for example through limited water availability, fire, insect outbreaks, loggings, or other forms of land use change, the stored carbon might be released back into the atmosphere as CO_2, contributing to climate change. Changing climate is expected to increase the frequency and magnitude of disturbances, which can create a positive feedback loop accelerating global warming.

Given the broad extent of the boreal region and the large amounts of carbon stored within it, the health and stability of these ecosystems are critical for regulating the global carbon cycle and mitigating the climate change. Monitoring carbon uptake and release in boreal forests and peatlands can help to preserve the carbon storage in these ecosystems through sustainable land use practices and limiting the impacts of different disturbances.

This thesis focuses on modelling and upscaling the carbon uptake by vegetation, known as gross primary production (GPP), in Nordic forest and peatland ecosystems using satellite remote sensing data. The thesis compiles four papers and aims to identify the main drivers controlling carbon exchange in northern ecosystems, develop and test various remote sensing-based models to estimate GPP, examine the effect of the spatial resolution of the satellite instrument on the accuracy of GPP estimation, and finally, to upscale GPP from ecosystems to a larger area.

The results demonstrated that spectral vegetation indices measured from satellite can explain the vegetation carbon uptake well. In general, other environmental variables that further helped to improve the results were air temperature, photosynthetically active radiation (PAR), and vapour pressure deficit (VPD) that expresses atmospheric demand for water. Another finding was that the spatial resolution of the satellite instrument had less influence on the accuracy of GPP estimates than the model formulation and selection of the input data. The result suggested that vegetation productivity can be monitored at various scales with good accuracy. Fine-scale estimates are beneficial when monitoring individual forest stands or spatially heterogeneous ecosystems like peatlands.

We tested various models to estimate GPP with remotely sensed data. The models were calibrated using GPP measurements from eddy covariance towers. The calibration was done either for a specific site, or by using a single parameter set for several sites. The site-specific calibration gave more accurate results but, on the other hand, the single parameter set was more useful for upscaling the carbon uptake for a larger area. In addition, we found that the plant phenology index (PPI) performed well and provided a useful tool for estimation of GPP at local and regional scales. Despite the good agreement with the ground-measured GPP, the models could be further improved to capture the difference between the sites. Soil moisture is a possible variable to be included in the models, as it is an important driver of carbon exchange in peatlands, but it could also improve the forest GPP models. Finally, we applied a PPI-based model to estimate annual GPP in Sweden’s forests and peatlands with a 10-meters spatial resolution.

In 2018, central and northern Europe experienced a severe drought with persistent high air temperatures and reduced water availability. This thesis provides valuable information on the responses of different ecosystems to droughts. The analysis revealed that the response to the drought varied between the ecosystem classes and the regions. Carbon uptake in peatland and forest ecosystems was mostly decreased due to the drought, although some sites showed no change or even increased productivity due to the longer and warmer growing season. The alternating response to the drought emphasize the importance of taking into account the spatial heterogeneity of the ecosystems when modelling carbon uptake. The results highlight the great potential of Sentinel-2 based high-resolution GPP for monitoring changes in vegetation productivity under climate stresses and other disturbances.

The current global warming greatly influences the environmental conditions in the boreal region. Reliable carbon flux estimates are essential for predicting how ecosystems response to changing conditions and disturbances, for monitoring the carbon sink strength, and for supporting sustainable management practices.

Abbreviations

APAR	Absorbed photosynthetically active radiation
CH_4	Methane
CO_2	Carbon dioxide
EC	Eddy covariance
ER	Ecosystem respiration
EVI	Enhanced vegetation index
EVI2	Two-band enhanced vegetation index
fAPAR	Fraction of absorbed photosynthetically active radiation
GPP	Gross primary production
LST	Land surface temperature
LUE	Light use efficiency
MSI	MultiSpectral Instrument
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized difference vegetation index
NEE	Net ecosystem exchange
PAR	Photosynthetically active radiation
PPI	Plant phenology index
T_{air}	Air temperature
VI	Vegetation index
VPD	Vapour pressure deficit

Introduction

The role of boreal ecosystems in the global carbon cycle

Boreal land ecosystems play a key role in global carbon cycle. The boreal forest is the second largest forest ecosystem covering over 1200 million ha (Keenan et al., 2015; Tagesson et al., 2020), whereas 80% of Earth's peatlands are located in boreal and subarctic areas in northern hemisphere (Limpens et al., 2008). Together, these two ecosystems contain more than 30% of the global terrestrial carbon, most of which is located in soil and peat, and the rest in living biomass (Bradshaw & Warkentin, 2015; Pan et al., 2011). Boreal ecosystems are not only a big carbon storage, but also a potential source of carbon emissions into the atmosphere, primarily through natural disturbances (e.g. forest fires, insect outbreaks and extreme weather events), deforestation or land degradation by human activity (Bradshaw & Warkentin, 2015; van der Werf et al., 2009). Understanding and predicting the carbon fluxes between the terrestrial biosphere and the atmosphere is important since they have an ability to control the atmospheric carbon concentrations and thus, offer a mitigation strategy for the current climate change (Beer et al., 2010; Gauthier et al., 2015).

The carbon balance in boreal land ecosystems is mainly dominated by the uptake and release of carbon dioxide (CO_2) (Chi et al., 2020), which is also the most important driver of anthropogenic climate change (Heimann & Reichstein, 2008). Other important components of the carbon balance in a boreal landscape are methane (CH_4) fluxes especially in peatlands, aquatic exports of dissolved carbon and carbon loss via harvest (Chi et al., 2020). A measure representing the CO_2 balance between a land ecosystem and the atmosphere is net ecosystem exchange (NEE). NEE is a difference between two reversed fluxes, gross primary production (GPP) and ecosystem respiration (ER). GPP is the uptake of CO_2 through vegetation photosynthesis, and ER is the total release of CO_2 by vegetation respiration (autotrophic respiration) and microbial decomposition (heterotrophic respiration). The carbon that has been assimilated in photosynthesis and not lost through autotrophic respiration, is stored as plant tissues, forming plant biomass. Hence, GPP drives the vegetation growth and is the basis for food, fiber and wood production.

Ecosystem carbon balance is influenced by several external drivers, depending on the ecosystem type, and spatial and temporal scales. Photosynthesis is a light-driven phenomenon, so GPP does not occur at nights or winters in the boreal region due to lack of sunlight. Furthermore, air temperature (Keenan & Riley, 2018) and water availability (Babst et al., 2019) are considered to be the most important environmental variables regulating GPP and ER in boreal ecosystems. The spatial variation of GPP and ER in boreal forest ecosystems is mainly related to the leaf area index (LAI) (Launiainen et al., 2022; Ueyama et al., 2013). LAI is the one-sided green leaf area per unit ground area (m^2m^{-2}) and determines radiation absorption and transmission by the canopy.

Globally, terrestrial GPP is the largest carbon flux (Beer et al., 2010), but in boreal ecosystems ER contributes also greatly to NEE (Lindroth et al., 1998). Boreal forests may act either as CO_2 sinks or as sources depending on species compositions, stand age and climatic variability (Hadden & Grelle, 2016, 2017; Litvak et al., 2003), whereas boreal pristine peatlands are usually CO_2 sinks (Yu, 2012). In both ecosystems, a small change in either GPP or ER might determinate whether an ecosystem is a sink or source of atmospheric CO_2. Natural disturbances, land use changes, and changing environmental conditions due to the climate change have a tendency to increase the CO_2 release (by increasing ER or decreasing GPP) and thus weaken the ecosystem CO_2 sink strength (Gauthier et al., 2015; Qiu et al., 2020). This thesis primarily focuses on studying GPP in boreal forest and peatland ecosystems, with some attention to peatland NEE and ER.

Boreal ecosystems under global change

Global warming has a major effect on the regional mean temperature, precipitation and soil moisture. Due to the feedback mechanisms in the climate system, Artic and boreal regions are impacted more than areas close to the equator (IPCC, 2021). Depending on the climate change scenario, the mean annual temperature in the boreal zone might increase 1.5–6 °C and precipitation 5–30% by 2100, compared to the period 1981–2000 (IPCC, 2021). The annual range of precipitation and soil water storage is predicted to increase, indicating that wet seasons will become wetter and dry seasons drier in northern high latitudes (Wu et al., 2015).

Overall, increasing temperatures, longer growing seasons and the elevation of the atmospheric CO_2 concentration are able to enhance GPP and biomass growth in forests, but changing climate can also cause contrary effects (Hyvönen et al., 2007; Reyer et al., 2017). Warmer and drier summer conditions are expected to increase droughts, forest fires and insect attacks, while warmer and wetter winters will lead to increasing damage by windstorms, heavy snow loading and pathogens (Venäläinen et al., 2020). Peatlands are also sensitive to the rise of temperatures and to changes in water table depth. Like in boreal forests, climate change can enhance peatland GPP, although the CO_2 fertilization effect on plant growth is predicted to be smaller in peatlands than in other boreal ecosystems (Qiu et al., 2020). On the other hand, warming temperatures might increase peatland ER due to accelerated decomposition and increased soil respiration (Lund et al., 2010).

Forest management to enhance carbon sink

Forests in Nordic countries are actively managed, whereas the management in the rest of the boreal region (Alaska, Canada, Russia) is less intense. The predominant forest management method in the Fennoscandian region is rotation forestry, which usually consists of several thinning operations before the clear-cut harvest, followed by soil scarification and planting or natural regeneration (Högberg et al., 2021). Consequently, this management method can increase spatial heterogeneity at the landscape level by creating a mosaic of even-aged forest stands with a distinct age class, regeneration phase, growth rate and carbon dynamics (Peichl et al., 2023).

There is an ongoing debate about alternative forest management strategies (e.g. continuity forestry) within the Fennoscandian region to strengthen the carbon sink but also enhance other forest ecosystem services like biodiversity. Peichl et al. (2023) and Lundmark et al. (2014) emphasize the importance of developing strategies that optimize tree biomass production to mitigate the climate change, whereas Skytt et al. (2021) suggest that the greatest short-term climate benefits are achieved by reduced harvest levels in productive forests. Felton et al. (2020) present that mixed-species stands, uneven-aged forest management and longer rotations times are potential methods to not only enhance biodiversity but also aid climate change adaptation and mitigation.

Several studies have suggested that the impact of drought on forest can be altered by management activities. Schäfer et al. (2019) found that drought-sensitive Norwegian spruce benefited from the mixture with more drought-resistant European beech trees under drought conditions. On the other hand, Laurent et al. (2003) and Cabon et al. (2018) suggested that moderate to heavy thinning can improve the resistance of forest stands to drought stress.

Peatland conservation and restoration

Boreal peatlands are not regularly managed like forests, but they either remain undisturbed or they have been mined or drained for agriculture and forestry. Until now, undisturbed peatlands have been persistent carbon sinks, and if they continue to absorb and store carbon in the future, conserving pristine peatlands provides a simple and inexpensive climate change mitigation method (Qiu et al., 2020).

Drainage for forestry, agriculture and peat extraction compromise the climate regulations that pristine peatlands provide, as it induces CO_2 emissions from the peat into the atmosphere and usually makes drained peatlands a net source of CO_2

(IPCC, 2021). Within the boreal region, forestry-drained peatlands may act either as a net carbon sink or source (Lohila et al., 2011; Meyer et al., 2013; Minkkinen et al., 2018; Ojanen et al., 2013).

Peatland restoration by rewetting drained peatlands has a substantial potential for climate change mitigation (Helbig et al., 2020; Leifeld & Menichetti, 2018). Rewetting peatlands might cause a short-term warming effect by increasing CH_4 emissions, but a long-term cooling effect due to assimilated CO_2 (Günther et al., 2020). Since CH_4 has a greater warming potential but shorter lifespan in the atmosphere than CO_2, the cooling effect by CO_2 fixation has been considered to outweigh the warming effect caused by increased CH_4 emissions (Frolking & Roulet, 2007; Günther et al., 2020). However, Ojanen and Minkkinen (2020) suggest that tropical peatlands and agricultural peatlands in temperate and boreal regions have the highest potential for climate change mitigation by rewetting, whereas abandoning tree stands may be a more beneficial mitigation method in temperate and boreal forestry-drained peatlands.

Estimating carbon fluxes

Eddy Covariance measurements

Accurate accounting of CO_2 fluxes (namely, NEE, GPP and ER) in boreal regions is essential for understanding the global carbon cycle and the climate change impacts on terrestrial ecosystems. The eddy covariance (EC) system mounted on a tower (Figure 1) provides direct measurements of NEE and nighttime ER at the ecosystem level and those measurements can be subsequently partitioned into GPP and daytime ER (Baldocchi, 2003). Thus, EC-derived GPP and ER are actually modelled estimates, although they are usually considered to be ground reference data for modelled fluxes (Lasslop et al., 2010). Footprint models are an essential part of the EC method, as they provide the field-of-view of the tower and reveal the area that contributes to the measured fluxes (Schmid, 2002). However, there is only limited number of EC sites in the world. Hence, additional measurements and modelling are required to extend the spatial coverage of carbon flux estimates, and to represent ecosystems with different age classes and species diversity (Lagergren et al., 2006).

Figure 1. The eddy covariance tower at the Norunda site. Photogprah: Sofia Junttila

Remote sensing of GPP

GPP or ER cannot be measured directly by satellite instruments, but there are certain biophysical properties of vegetation that can be related to the CO_2 fluxes and to vegetation spectral properties measured by satellites. Remote sensing-based models often rely on empirical relationships between EC-derived fluxes and the spectral properties of vegetation or, alternatively, mechanistic models with remotely sensed inputs. In general, empirical models are simple yet easy to apply but they lack the theory of plant physiology or ecosystem function whereas mechanistic models describe physiological processes in detail but are limited by data availability as well as temporal and spatial scaling (Feng et al., 2007).

To estimate GPP with satellite remote sensing, spectral vegetation indices (VI) play a key role. These indices usually express the greenness of the vegetation and are closely related to biophysical variables such as LAI or the fraction of photosynthetically active radiation absorbed by green vegetation (fAPAR). Widely used indices, like the Normalized Difference Vegetation Index (NDVI; Tucker, 1979) and the Enhanced Vegetation Index (EVI; Huete et al., 2002), have a linear or near-linear relationship with fAPAR (e.g. Gitelson, 2019; Xiao et al., 2005), whereas the recently-developed Plant Phenology Index (PPI; Jin & Eklundh, 2014) is strongly related to LAI.

The groundwork for remote sensing-based productivity models was laid by Running (1986) who applied the light used efficiency (LUE) concept by Monteith (1972). The LUE model expresses GPP as the product of photosynthetically active radiation (PAR) incident on vegetation, fAPAR, and the efficiency with which vegetation convert radiation to carbon. Currently, one of the most well-established remote sensing approaches based on the LUE model is the MODIS GPP/NPP (MOD17) product (Running et al., 2004). The MOD17 product uses spectral data from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard the Terra and Aqua satellites. In addition, it uses a look-up table containing biome specific information about the maximum LUE coefficient and the constraining functions based on air temperature (T_{air}) and vapour pressure deficit (VPD). The MOD17 is widely acknowledged but it has also been questioned due to the coarse resolution meteorological input data and to lack of sufficient flux measurements for validation and calibration of the algorithm (Turner et al., 2006; Wang et al., 2013; Zhao et al., 2005). For example, the look-up table does not include parameters for peatlands.

LUE-based GPP models assume that the relationship between GPP and absorbed PAR (APAR, i.e. incident PAR multiplied by fAPAR) is linear, although it is only a partly correct assumption. The GPP-APAR relationship generally has an asymptotic shape at the daily time step, but it can be considered as near-linear over monthly or annual periods (Falge et al., 2001; Tagesson et al., 2012). Another uncertainty of the LUE models is that it does not take into account the spatial and temporal variation of the LUE coefficient. LUE varies among vegetation types (Madani et al., 2014; Turner et al., 2003), under environmental stresses (Running et al., 2004) and between phenological phases (i.e. spring green-up and autumn senescence) (Jenkins et al., 2007).

To overcome these uncertainties in the LUE approach, alternative empirical models have been developed. Some of the models are simpler than the LUE model avoiding one or more parametrizations of the LUE model, or they rely on site-specific relationships and additional data like land surface temperature (LST) (Hashimoto et al., 2012; Olofsson et al., 2008; Schubert et al., 2012; Sims et al., 2008). Another direction is to estimate GPP with more complex data-driven models, e.g. using machine learning (Xiao et al., 2010; Zhang et al., 2017). The underlying assumption of the approach is that complex models are more flexible in structure than the LUE approach and are able to account for possible nonlinear relationships between remotely sensed predictor variables and GPP. The disadvantage is that purely data-driven models might lack the mechanistic understanding about vegetation functioning. An approach that has a strong physiological background and accommodates for the nonlinear relationship between GPP and PAR, is the light response function (Falge et al., 2001). The light response function parameters can be derived from EC-measured GPP and PAR, and then spatially and temporally extrapolated in relation to a VI (Tagesson et al., 2017; Tagesson et al., 2021).

Remote sensing of ER and NEE

In comparison to GPP, there is significantly fewer remote sensing–based ER models. Most of the models are based on the know relationship between temperature and respiration (Lloyd & Taylor, 1994). Hence, remotely sensed land surface temperature (LST) has been successfully used to estimate ER (Olofsson et al., 2008; Schubert et al., 2010). The key challenge in modelling ER is that is a combination of aboveground and belowground processes, induced by vegetation and microbes. It has been argued that the temperature-based ER model represents mainly the heterotrophic respiration, whereas autotrophic respiration could be described by adding vegetation productivity data (e.g. GPP or a VI) into an ER model (Gao et al., 2015).

It is challenging to model NEE with remote sensing data, as NEE is a difference between two large fluxes driven by separated processes with different seasonal dynamics. In the boreal region, annual NEE is often close to zero, which can generate a high relative error and a weak correlation in the modelled results (Olofsson et al., 2008). NEE can be modelled as a difference between modelled GPP and ER (Olofsson et al., 2008), with a multiple regression model (Schubert et al., 2010) or, like most recently, with machine learning techniques (Cho et al., 2021; Virkkala et al., 2021).

Upscaling carbon fluxes

Remote sensing-based methods are essential for predicting carbon fluxes across larger areas (i.e., upscaling), based on small scale measurements. Fluxes can be upscaled from the ecosystem level (m^2 to km^2) to the local (10–100 km^2), regional (10^3–10^6 km^2) or global levels (10^7–10^8 km^2). This dissertation focuses on upscaling GPP from the EC sites to the local level, and after that to the regional level covering the whole of Sweden.

In principle, all above-mentioned remote sensing-based models can be used to upscale GPP, ER or NEE, if the required data sets are available in the target area. The model accuracy and generalizability is the key to ensure the robustness of the upscaled flux estimates. In addition, it is essential that the observational data used for model training represent the vegetation properties well at the target ecosystem. Simple linear models (e.g. the LUE approach) can be a powerful tool in upscaling due to their ease of extrapolation and interpretation, whereas nonlinearity in the models limits their scalability. Re-parameterization would be necessary if the nonlinear models were to be applied at a different spatial or temporal scale for which they were developed.

One major challenge in upscaling carbon fluxes with remote sensing methods is the spatial heterogeneity of vegetation properties across an ecosystem. It is crucial to identify what kind of area (and vegetation) is contributing the EC measurements at each time and how well the measurements represent the ecosystem as a whole (Kljun et al., 2015). Hence, accurate footprint estimation is essential, especially in boreal peatlands that show large variability in vegetation species, microtopography and hydrology (Lees et al., 2018).

Another limitation for accurate GPP estimations is the mismatch of spatial resolutions between remote sensing data and the flux tower footprint, since vegetation dynamics have traditionally been monitored by satellite sensors with relatively low spatial resolutions (hundred meters to kilometres) (Balzarolo et al., 2019; Huang et al., 2022). The new Sentinel-2A and 2B satellites with the MultiSpectral Instrument (MSI) provide a great opportunity to study GPP in heterogeneous landscapes with 10 m spatial resolution and with 2-3 days' revisit frequency at high latitudes. However, the LST data, that is important for estimating ER, is limited by coarse spatial and temporal resolutions. MODIS provides LST with 1 km spatial and 1-2 days temporal resolutions, whereas Landsat has 60 m and 16 days resolutions, respectively.

Coarse resolution GPP, ER or NEE estimates are practical when studying the carbon balance at the global level. However, high resolution CO_2 flux estimates are beneficial especially at the local and regional scales. Upscaling flux tower measurements to landscape level increases the feasibility of the data for carbon assessments and modelling, and potentially improves the accuracy of national carbon emissions accounting. Local-scale remote sensing data may become important in assessing effects of different forest management regimes or peatland conservation. Overall, the extended geographical coverage of the flux estimates improves our understanding of the spatial patterns and regional budgets of terrestrial ecosystem CO_2 fluxes.

Aims

The principal aim of this thesis is to improve the methodology for estimating and upscaling local-scale CO_2 fluxes in boreal ecosystems. The dissertation focuses on estimating ecosystem gross primary production (GPP) in Nordic peatland and forest ecosystems using satellite remote sensing data.

The specific objectives of the thesis are:

- To identify the major biophysical drivers controlling temporal and local-scale variability of the carbon fluxes in northern regions and to examine if these drives can be determined using remote sensing data.
- To assess the influence of the spatial resolution of the satellite instrument on the accuracy of carbon flux estimations.
- To evaluate the performance of various model formulations and spectral vegetation indices to explain carbon fluxes.
- To upscale GPP to local and regional levels and to demonstrate the applicability of the upscaled GPP estimates.

Methods

Paper I

This study investigates the potential of high resolution Sentinel-2 MSI data to improve the accuracy of GPP estimation across northern land ecosystems, in comparison to the MODIS-derived estimates. Sentinel-2 provides data with 10 m, 20 m and 60 m spatial resolutions and with 2-3 days temporal resolution in high latitudes. In this study, we used 10 m spectral data to calculate the two-band Enhanced Vegetation Index (EVI2; Jiang et al., 2008). EVI2 was also calculated from the MODIS reflectance data with 250 m and 500 m resolutions. MODIS measurements are available with 1-2 days temporal resolution. In addition, we used EC-derived GPP, T_{air}, PAR and VPD at eight Nordic sites, including four coniferous and one deciduous forest sites, two peatland sites and one agriculture site. Figure 2 shows the locations of all the sites that have been used in this thesis. We analysed data from 2016 to 2017. We evaluated if the spatial resolution of the satellite data effects the performance of the GPP estimate, and additionally, how much EVI2 and the biophysical variables contribute to the EC-derived GPP.

The EVI2 data from both instruments were gap-filled and smoothed using the TIMESAT software system (Jönsson & Eklundh, 2004) to produce smooth daily time series for each of the sites. We applied a different method to select the pixels that contributed to the GPP measurements for each remote sensing data set. For the 500 m MODIS data, the pixel matching the tower location was used to represent each site. For the 250 m MODIS data, maximum four pixels around the tower were used to calculate daily average of EVI2. For the Sentinel-2 data, we modelled the annual EC flux footprints using the Flux Footprint Prediction (FFP) model by Kljun et al. (2015). Then, we calculated weighted averages of the pixels that contributed to 80% of the annual footprint. The EC-derived data was averaged with a 7-day moving window to match with temporal scale of the remote sensing data.

To estimate GPP, we tested linear regression models following Schubert et al. (2012) with various combinations of the input data:

$$GPP = a \times EVI2 \times E + b \qquad (1)$$

where EVI2 is the daily averaged EVI2 either from Sentinel-2, 250 m MODIS or 500 m MODIS. *E* is an environmental variable: PAR, T_{air}, VPD or a product of them.

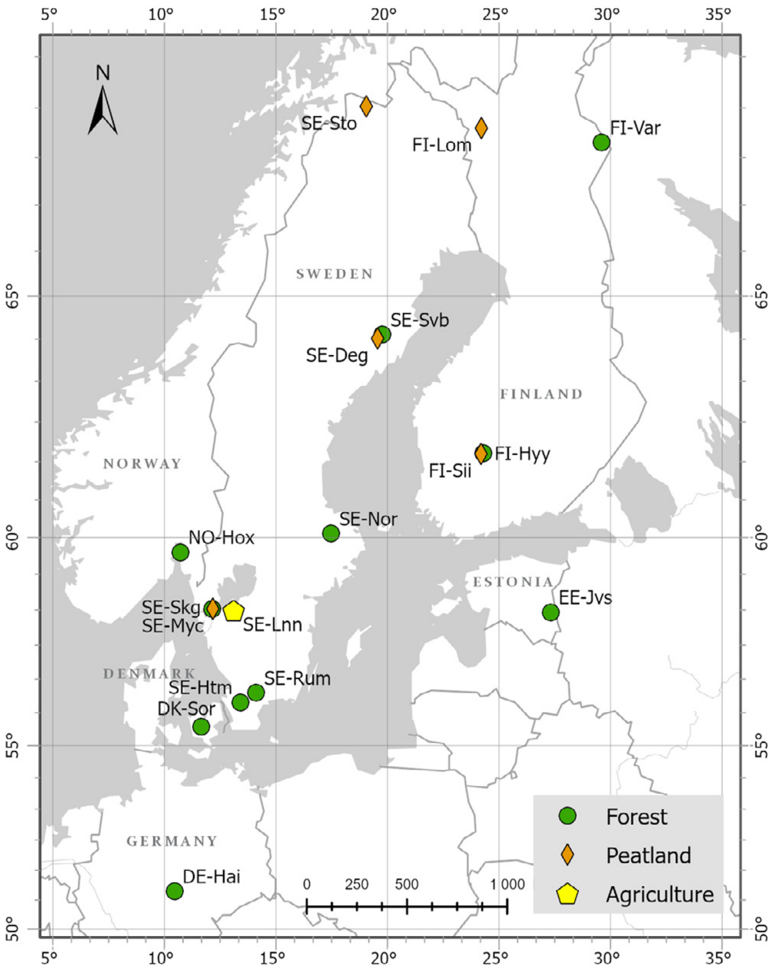

Figure 2. Eddy covariance sites used in this thesis.

Paper II

In Paper II, we develop models for estimating peatland CO_2 fluxes (NEE, GPP and ER) using satellite remote sensing data. EC-data from five Nordic peatlands between 2017 and 2019 was used to calibrate the empirical regression models (Figure 3).

We used data from Sentinel-2 to calculate EVI2 with 10 m spatial resolution and NDWI (Normalized Difference Water Index; Gao, 1996) with 20 m resolution. NDWI was used to calculate a water scalar to represent the variations of moisture conditions interannually and between the sites. The MODIS products MOD11A1 and MYD11A1 provided LST data with 1 km spatial resolution.

The remote sensing data was gap-filled and smoothed using a spline function in TIMESAT (Jönsson & Eklundh, 2004) to create daily products of EVI2, NDWI and LST for each site. The EC data was also smoothed with TIMESAT. For the Sentinel-2 data, we used the Flux Footprint Prediction (FFP) model (Kljun et al., 2015) to create the daily flux footprint and to calculate weighted averages of the pixels within the 80% footprint area. Due to the coarse resolution of the MODIS data, we extracted LST values from the pixel where the EC tower was located at each site.

Our GPP model was based on previous work by Schubert et al. (2010). We investigated how satellite-derived EVI2, LST, and the NDWI-based water scalar along with site-measured environmental variables (T_{air}, PAR, water table depth and annual precipitation) were contributing to EC-derived GPP. Based on the analysis, EVI2, the water scalar and LST were included into the GPP model.

$$GPP = a \times EVI2 \times LST \times W_{scalar} \tag{2}$$

The ER model was based on work by Gao et al. (2015) and included daytime LST and EVI2. We also tested whether using EVI2 and NDWI scalars, as well as modelling the dormant and growing season separately, improved the ER model fit. We modelled NEE in two ways, by subtracting modelled ER from modelled GPP and by parameterizing the ER and GPP models together.

The GPP, ER and NEE models were first parameterized for each site individually and then an average model parameter set was acquired using leave-one-out-cross-validation based on the data from all the sites. Therefore, we could evaluate how well an empirical model with averaged parameters was able to predict the fluxes and explain the differences between the sites.

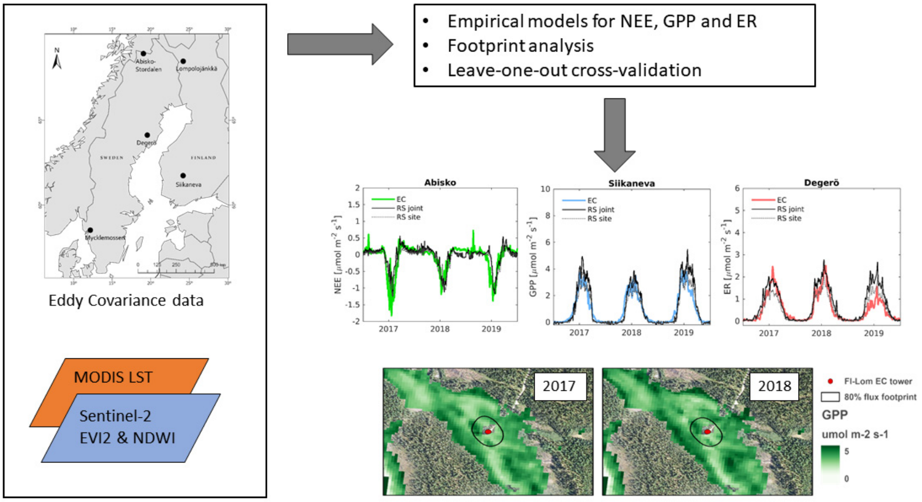

Figure 3. Reproduced from Paper II, a general overview of the stydy estimating GPP, ER and NEE in five northern peatlands.

Paper III

The aim of Paper III was to evaluate various satellite remote sensing-based GPP models in eleven forest sites in northern Europe in 2017–2020. We compared six purely empirical models, a light use efficiency model, and a light response function model. All models were based on either EVI2 or PPI, both derived from Sentinel-2 spectral data with 10 m spatial resolution. EC-derived GPP, PAR, T_{air} and VPD were used to parametrized and evaluate the models.

The EC data was smoothed and averaged to daily values using a 7-day moving average with a 1-day time step. The vegetation indices were smoothed and gap-filled with a combined double-logistic and spline function in TIMESAT (Jönsson et al., 2018). We used the Flux Footprint Prediction model to create the daily time series of the remote sensing data in the same way as in Paper II.

The light use efficiency model was based on the MOD17 algorithm by Running et al. (2004), but in our model, EVI2 was used as a proxy for fAPAR instead of NDVI. The light response function model parameters were first estimated with EC-derived GPP and PAR, following work by Tagesson et al. (2021), and then upscaled using EVI2. Preliminary we tested nine empirical regression model formulations fitted between GPP and PPI, EVI2 and PAR using all available site-years. For the final analysis we included three EVI2-based models and three PPI-based models.

The models were parametrized separately for evergreen needleleaf and deciduous broadleaf forest ecosystems with a leave-one-out cross validation. The GPP estimates were constrained with T_{air} and VPD functions (following the MOD17 algorithm) in order to take into account the main environmental drivers limiting GPP.

Paper IV

The aim of the Paper IV was to upscale forest and peatland GPP to the whole of Sweden, and to demonstrate the applicability of the upscaled GPP estimates. We wanted to study the spatial and temporal patterns of estimated annual GPP in Sweden from 2017 to 2021, and investigate the vegetation response to the drought events in 2018 and 2019.

We applied a novel high-resolution phenology data set, which is based on Sentinel-2 –derived PPI across European ecosystems. PPI was found robust for GPP estimation in Paper III. We therefore used the sum of all daily PPI values during a growing season and converted it into GPP units with a linear regression model and EC-derived annual GPP measurements. Thus, we obtained the estimated annual GPP at a 10-m spatial resolution across Swedish forest and peatland ecosystems from 2017 to 2021. The annual GPP was average for four large regions in Sweden to study the variability of GPP at a regional level. Furthermore, we calculated the percent difference of estimated GPP for each year using the average of the whole study period GPP as the reference. Then we were able to quantify annual GPP variation between the years in the four regions, and also between the ecosystems types. In addition, we calculated the standardized precipitation-evapotranspiration index (SPEI; Vicente-Serrano et al., 2010) at a scale of 3 months (SPEI3) and 12 months (SPEI12) to reveal the drought severity in the different years and across the Swedish regions.

Results and discussion

Relationships between GPP and explanatory variables

In remote sensing-based studies, a vegetation index is usually the main variable to explain GPP. We used two indices in this thesis project: the 2-band enhanced vegetation index (EVI2) was used in Papers I-III, and the plant phenology index (PPI) was used in Papers III and IV.

In Paper I, daily EVI2 from Sentinel-2 MSI and MODIS showed linear relationships with EC-derived GPP giving the coefficient of determination (R^2) between 0.45 and 0.93. The differences were found between the study sites and ecosystems, rather than the satellite instruments. A similar range of R^2 was found in Paper II for four peatlands sites (R^2 = 0.61), as well as in Paper III for eleven forest sites (R^2 = 0.57–0.78), both derived from a linear relationship between daily mean EVI2 from Sentinel-2 and EC-derived GPP. The linear relationship between PPI and GPP in forest sites in Paper III gave a similar agreement, R^2 = 0.62–76. Vegetation productivity, in general, is easier to model in deciduous broadleaf forest or in agriculture, as these ecosystems have distinct seasonal dynamics (leaf emergence, leaf senescence and leaf fall or harvest), that can be accurately captured by remote sensing data (Yuan et al., 2014). The leaf phenology in evergreen coniferous forest, on the other hand, is subtler (Xiao et al., 2004).

In Paper IV we compared the sum of daily PPI over growing seasons and the growing season sum GPP from EC sites. The three studied ecosystems (coniferous forest, deciduous forest and peatland) gave similar agreements, R^2 = 0.54–0.64. The number of data points is significantly smaller when studying annual sums in comparison to daily values, which makes the relationship sensitive to outliers. The overcome the issue, we used a robust linear regression instead of the ordinary least-squares linear regression. The iteratively re-weighted least squares method assign a weight to each data point which makes it less sensitive to outliers (Bañuelos-Cabral et al., 2017).

PAR, T_{air} and VPD are the most common environmental variables to include in remote sensing –based GPP models with a vegetation index, as light, temperature, and water availability widely control the vegetation photosynthesis. In Paper I we found that GPP correlated well with T_{air} at most of the sites, whereas PAR showed high agreement with GPP only in southern sites. This can be explained by the large latitudinal range (55–68 °N), as in the northern part of the Nordic area the growing season begins when the temperature exceeds the temperature limit, which occurs well after the amount of light has reached sufficient levels for photosynthesis. When comparing the ecosystem types, we found that PAR seems to be more important in forest sites (Papers I and III) than in peatlands (Papers I-II) to describe GPP.

Peatlands are unique ecosystems due to their high water table, and several studies have suggested that water table depth and temperature are the variables that most widely affect peatland GPP (Harris & Dash, 2011; Lund et al., 2012). Therefore, in Paper II we included remotely-sensed LST and NDWI-based water index into the GPP model to improve the accuracy of GPP estimations. However, NDWI is a spectral index expressing the influence of soil moisture on the vegetation rather than an actual soil moisture index, and it did not fully capture the seasonal variations in water table depth at sites. Further studies are needed to establish a method to capture variations in water table depth or soil moisture in remote sensing-based models. For example, Huang et al. (2020) assimilated regional soil moisture network data, remote sensing data, and high-resolution land surface parameters to develop an empirical soil moisture model.

Soil moisture data could also be used in forest GPP models in addition or instead of VPD. In Papers I and III we found that VPD did not contribute to GPP as much as PAR or T_{air}, although remote sensing-based GPP models commonly assume that VPD is able to capture the effect of water deficit on GPP (Running et al., 2004; Zhao & Running, 2010). Several studies (e.g., Stocker et al., 2019; Tagesson et al., 2021) have suggested, instead, that soil moisture is a critical variable constraining vegetation productivity, and should be taken into account in GPP modelling. However, Zhang et al. (2022) questions the quality of the soil moisture data currently available, especially at high latitudes.

Spatial resolution and footprint modelling

In Paper I we compared remote sensing data at three spatial resolutions for estimating GPP: 10 m resolutions Sentinel-2 MSI, 250 m resolutions MODIS and 500 m resolutions MODIS. It was expected that the higher spatial resolution would improve the accuracy of the GPP estimation (Gelybó et al., 2013). However, we found that there was almost no difference in the results generated from Sentinel-2 MSI data and MODIS data sets. The main reason for this might be the homogeneity of the vegetation surrounding the EC measurement towers (which is a requirement for establishing an EC site) in combination with the large footprints especially at the forest sites. In addition, the time series smoothing and gap-filling might reduce the differences between the remote sensing data set even more. Hence, in Paper I we concluded that the model formulation and the selection of the additional input data might play more important roles than the spatial resolution of the remote sensing data. Similar performances of Sentinel-2 and MODIS data sets is encouraging as the instruments together are able to create a coherent data set for estimating vegetation productivity.

However, in Paper I we also found a topic to further develop regarding the footprint modelling. In Paper I, we use the Flux Footprint Prediction (FFP) model with half-hourly EC-derived data as input to obtain annual flux footprint climatology contours and contribution weights in the 10 m grid matched to Sentinel-2 pixel. To further improve the match between EC-derived data and remote sensing data, we applied daily rather than annual footprint climatologies in Papers II and III. In general, the accurate selection and weighting of the remote sensing imagery pixels is more important when studying spatially heterogeneous ecosystems, like peatlands. The footprint modelling might be less essential e.g. in large homogeneous forest areas, but is still recommended if there is micrometeorological data available.

GPP model formulation

In Papers I-II and IV we used a linear regression model to estimate GPP, whereas Paper III focused on developing and testing a set of different GPP models for forest ecosystems. Linear GPP models (often following the light use efficiency approach) are widely used within the remote sensing community due to their scalability. However, several studies have also investigated nonlinear models between observed GPP and an explanatory variable to find even closer relationships (Noumonvi & Ferlan, 2020; Verma et al., 2015).

The results in Papers I and II showed that a linear regression model can be a simple yet effective approach to estimate GPP. The linear model with Sentinel-2 input and site-specific parametrization in Paper I gave strong agreement with EC GPP: the root square mean error (RSME) was 1.23 g C m^{-2} day^{-1}, and R^2 = 0.84 was an average for all the sites. Similar results were found with the GPP model in Paper II with site-specific parameters, RMSE = 0.49 µmol m^{-2} s^{-1}, normalized RMSE (NRMSE) of 10% of the maximum flux, and R^2 = 0.83 on average for all the sites. In Paper II we also parameterized the GPP model using the leave-one-out cross validation method. The goodness-of-fit statistics gave slightly poorer results in comparison to site-specific parameterization (RMSE = 0.68 µmol m^{-2} s^{-1}, NMRSE = 14%, R^2 = 0.70), but, on the other hand, we obtained more general model parameters that can be used in upscaling.

Leave-one-out cross validation was also used in Paper III, where we tested several different GPP modelling approaches. We found that no single model was clearly superior to the others but several models provided good performances at daily level (up to RMSE = 1.96 g C m^{-2} day^{-1}, NRMSE = 9%, R^2 = 0.78) and annually (RMSE

= 246 g C m^{-2} $year^{-1}$, NRMSE = 16%, R^2 = 0.74 at the best). Paper III highlighted what was also observed in Paper II: applying an averaged parameter set for a range of ecosystems is suitable for some sites and unsuitable for others. Both underestimation and overestimation of modelled GPP occurred, although the models were generally able to capture the seasonal dynamics of GPP well. In Paper III, the underestimation of daily GPP tended to be more common than overestimation, especially during the peak growing season. A fundamental issue causing underestimation in GPP estimates is pervasive cloud cover in the boreal regions. It has been observed that diffuse light under cloudy conditions can enhance the photosynthesis in comparison to direct radiation (Chen et al., 2021; Knohl & Baldocchi, 2008). However, optical satellite remote sensing provides information about vegetation characteristics only under cloud-free conditions, and gaps in the data caused by cloud cover are filled using cloud-free observations. This may lead to underestimation of GPP of more than 20% in coniferous forest (Choudhury, 2001). The difference between cloudy and sunny conditions have also been observed at the leaf level. Chen et al. (2020) suggest that the bias of modelled GPP is larger in more clumped canopies (i.e. forests) than less clumped canopies due to high portion of shaded leaves. Therefore, the portions of sunlit and shaded leaves in the canopy should be considered for more accurate GPP estimation at regional scale.

In Paper II and III, we also noticed that the GPP-VI relationship varied between the phenophases i.e., the spring green-up phase and the senescence phase. The hysteresis is derived from the variability of the light use efficiency across seasons that has been widely observed (Jenkins et al., 2007; Madani et al., 2014). Therefore, modelling GPP separately for the spring green-up, growing season peak and senescence phases is suggested. Our initial testing in Paper II, however, revealed that separating the modelling between the seasonal phases was not straightforward, as the level of hysteresis varied between sites and years, causing difficulties to model especially the peak season accurately. Hence, we decided to use a single model for the whole year in Papers II and III, but we recommend that further studies should be undertaken to resolve the challenge.

Observed nonlinear relationships between GPP and explanatory variables provided a reason to test several model formulations, both linear and nonlinear, in Paper III. We concluded that several models were able to capture the seasonal dynamics of GPP well, but none of the models showed clear superiority to others. However, the choice to use a specific model to estimate GPP could depend on the aim of the use, the target ecosystem type and what input data is available. The main disadvantage of nonlinear models is the scale dependency, which limits their applicability. A nonlinear model should be applied at the same spatial and temporal scale for which it has been parameterized. Linear models, on the other hand, might simplify the relationship between GPP and a vegetation index, but still provide a convenient tool for estimating GPP. For instance, the simplest model in Paper III, a linear regression model with PPI, performed well besides the more complex models. A scalable model with a low number of input datasets, yet reasonable accurate, would provide a feasible tool for operational remote sensing, e.g. for forest management or peatland conservation purposes.

Upscaling GPP

In this thesis, upscaling simply means applying a model on larger spatial scale for which it has been developed. In Paper II, we demonstrated the applicability of the carbon flux models by upscaling GPP beyond the EC flux footprint area. Figure 4 shows similar results, but applying the linear PPI model from Paper III for the forest site Norunda (SE-Nor) from 2017 to 2020. Such maps can be used to assess the spatial variability of the carbon fluxes within and beyond the EC flux footprint, locate hotspots of carbon fluxes and evaluate how well the flux footprint represents the ecosystem a whole.

To verify the accuracy of the upscaled maps, they need to be validated against other data source than EC data. Chamber measurements could be suitable for hotspot measurements of carbon fluxes for relative small areas (Schrier-Uijl et al., 2010), whereas other remotely sensed variables provide the information at ecosystem or landscape level. An alternative way to estimate either GPP or the ecosystem light use efficiency, is to use the remotely sensed solar induced fluorescence (SIF) (Mohammed et al., 2019). Currently, SIF is available only with coarse spatial resolution, but it will be generated at the ecosystem scale in future from the forthcoming Fluorescence Explorer (FLEX) satellite mission by ESA. Another approach to estimate LUE using remote sensing methods is the photochemical reflectance index (PRI; Gamon et al., 1997). PRI alone is not a good GPP estimator, but it provides added explanation value to GPP models (Hilker et al., 2008). However, the wavelength bands to calculate PRI are not available with Sentinel-2, but only with coarser resolution satellite instruments. Unfortunately, small scale variations in Sentienel-2 derived GPP or LUE cannot be validated with current PRI or SIF products due to their coarse spatial resolution.

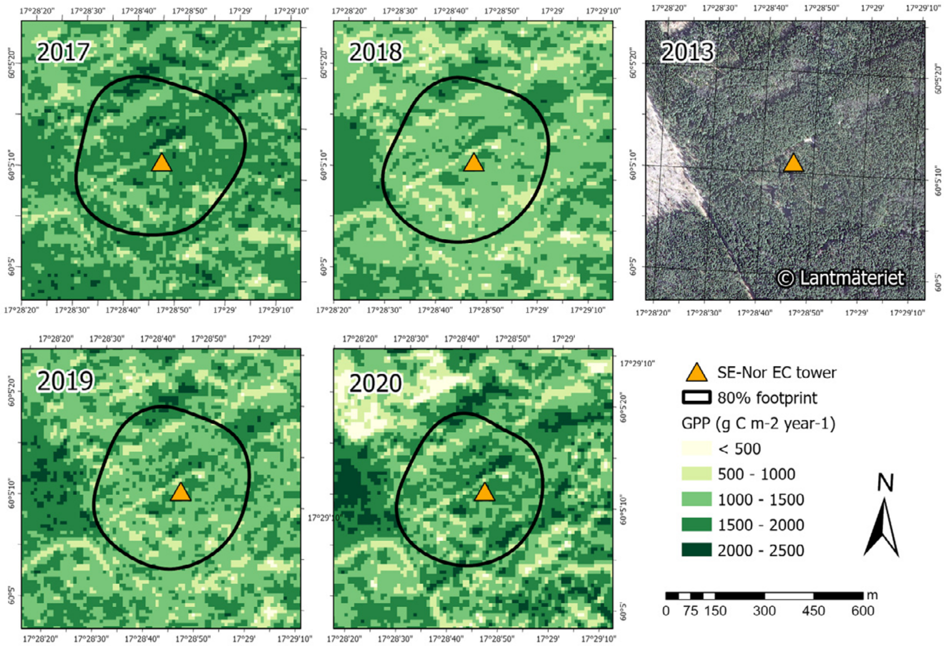

Figure 4. Upscaled annual GPP based on the linear PPI model from Paper III at the Norunda (SE-Nor) site in 2017-2020. The black line shows the 80% of the annual EC flux footprint climatologies. The reference image is an aerial photography recorded in 2013 by Lantmäteriet (the Swedish Land Survey).

In Paper IV we upscaled annual GPP to Sweden from 2017 to 2021 (Figure 5). The study focused on coniferous forest, deciduous forest and peatlands in Sweden. Other vegetated ecosystems like agriculture, grassland and shrubland were excluded due to lack of EC data for the model calibration. As the estimated GPP has not been validated beyond the EC flux footprints, there are still uncertainties on the accuracy of the results. Therefore, the maps are suitable for studying relative changes within an area or making comparisons between areas.

We noticed that GPP in coniferous forests and peatlands increased gradually from north to south, which is expected due to the span of climatic conditions across Sweden. The deciduous forest class, however, showed only small variability across the regions as well as between the years. Peatland GPP was decreased in 2018, which was a severe drought year in Sweden. Coniferous forests, on the other hand, showed declined GPP in 2018 and even more so in 2019. The effects of drought on forest and peatland carbon fluxes are further discussed in the next section.

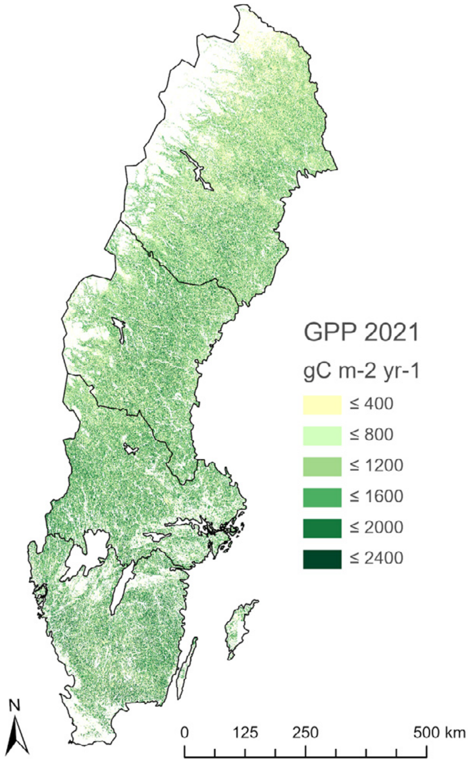

Figure 5. Reproduced from Paper IV, estimated annual GPP in Sweden's forests and peatlands in 2021 at a 10-m spatial resolution.

Effects of drought on forest and peatland GPP

In the summer 2018 northern Europe experienced a severe drought as a result of a heatwave and reduced precipitation (Sjökvist et al., 2019). The drought induced water stress and reduced GPP at several northern peatland (Rinne et al., 2020) and forest sites (Lindroth et al., 2020). The summer 2019 was also dry in Europe, although the 2019 drought was centered on eastern Europe (Blauhut et al., 2022).

In Paper II, we modelled GPP, ER and NEE at five Nordic peatlands. The study period (2017-2019) was strongly influenced by droughts. We found some variations showing that the peatlands were affected by the 2018 drought. EC-derived NEE was decreased in 2018 in comparison to 2017 and/or 2019 at three sites, Abisko-Stordalen (SE-Sto), Degerö (SE-Deg) and Siikaneva (FI-Sii), but not at Lompolojänkkä (FI-Lom). Rinne et al. (2020) made the same observation that Lompolojänkkä was less sensitive to the 2018 drought than other northern peatlands, probably due to local hydrological characteristics. The decrease in NEE was mainly originated from reduced GPP, although increased ER in 2018 was also observed at Siikaneva. Modelling GPP was challenging at Degerö in 2019, which was a dryer than average year decreasing GPP and ER at the site. However, the dry conditions did not correspond to the spectral properties of vegetation. Observed EVI2 in 2019 was at the same level as in 2017, which was a normal year regarding the weather. EC-derived GPP, on the other hands, was similar in 2019 as in the drought year 2018. This mismatch caused an overestimation of modelled GPP in 2019. It is also possible the 2018 drought has a legacy effect in 2019, i.e., the vegetation did not fully recover from the drought in the previous year, and therefore both GPP and ER were low in 2019 at Degerö. Another site with slightly poorer performance was Mycklemossen (SE-Myc). Mycklemossen experienced droughts both in 2017 and 2018 (Rinne et al., 2020), and was also the southern-most site in Paper II. Sites in southern Sweden have higher temperatures than more northern sites and are more light-dominated, as we noticed in Paper I. These aspects may partly explain why our GPP, ER, NEE models with the average parameters performed poorest there. Overall, it is difficult to draw strong conclusions about the temporal variations of the fluxes with only two or three years of data, especially if a severe drought has been experienced at a site.

In Paper III, we also found some differences between the forest sites regarding the responses to the drought events. The largest effect of drought can be observed at the deciduous beech forest sites Sorø (DK-Sor) and Hainich (DE-Hai). At both sites, EC-derived GPP decreased drastically during the 2018 growing season. Although the vegetation indices EVI2 and PPI did not decline as much, the VPD-based scalar helped to model GPP well at these sites. The effect of the 2018 drought on GPP at coniferous forest sites seemed to be milder than at deciduous forest sites. An abrupt decrease and fast recovery of GPP was observed at Hyltemossa (SE-Htm) and Norunda (SE-Nor) during the peak growing season 2018, but none of the models were able to detect this variation. On the other hands, the warm temperatures in 2018 also lead to increased annual GPP at Norunda, probably due to a longer growing season. None of the models, however, were able to capture the lengthened growing season, but all models underestimated the annual GPP 2018 at Norunda.

In Paper IV, we studied the drought effects at regional level instead of individual ecosystems. The drought index at a 3-months scale (SPEI3) showed clearly increased drought severity in 2018 all over Sweden, emphasizing the southern part of Sweden. SPEI3 did not suggest large drought severity in 2019, but a slightly increased situation in 2020, especially in central Sweden. The relative variations in the estimated annual GPP in forest and peatland ecosystems, however, showed slightly different patterns. The estimated annual GPP in peatlands declined clearly in 2018 in all regions, but more in central and northern Sweden than in southern Sweden, although the SPEI3 indicated the most severe drought in the southernmost part of Sweden. Slightly positive difference in peatland GPP was also found, mainly in northern Sweden, indicating that not all peatlands suffered from the 2018 drought.

Other studies have notices that the sensitivity of peatland GPP to drought is also rather complex and depends on several factors, including timing and severity of the drought, peatland type, vegetation composition and mean water table depth (Laine et al., 2019; Lund et al., 2012) . GPP might decrease during the drought due to water stress or increase because of the higher oxygen and nutrient availability to plant roots in drier conditions (Aurela et al., 2007; Laine et al., 2019).

Forest ecosystems in Paper IV showed only slightly decreased GPP in 2018 at regional level, yet more declined GPP was observed in the whole Sweden in 2019. The impact of drought on forest is complex and modulated by local conditions, e.g. soil type, moisture and elevation (Adams & Kolb, 2005; Rehschuh et al., 2017). Lindroth et al. (2020) found large variations in forest GPP during the 2018 drought in Northern Europe. They observed large to minor decrease in GPP in most of the sites, although two northern forest sites benefitted from the warmer weather conditions and showed increased annual GPP in the drought year. The delayed impact on the modelled GPP may be related soil moisture that allowed trees to sustain moisture during the dry summer but made them vulnerable during the bud-setting period towards the end of the season (e.g., Meier & Leuschner, 2008), thus affecting next year's growth. It has been observed that many coniferous trees have a response time to moisture deficiencies of up to a year, however, varying with site conditions and physiology of the trees (Lévesque et al., 2013; Vicente-Serrano et al., 2013). It has also been observed that remote sensing based models often underestimate drought impacts on photosynthesis, most likely due to lack of soil moisture data (Stocker et al., 2019).

Future perspectives

Satellite remote sensing is able to provide information about vegetation characteristics that can be converted into a carbon uptake estimate. Robust estimates are essential for predicting how ecosystems will respond to future environmental change. However, there are several issues that need to be considered in order to further improve the accuracy of GPP models.

As discussed before, the accuracy of GPP estimations could be improved by separating the model parameterization for different phenophases (e.g., spring green-up, peak growing season, and senescence), including soil moisture or the portion of sunlit and shaded leaves into the model, or improved selection of validation data. Paper II and III highlighted that model parameterization based purely on the ecosystem type (i.e., peatland, coniferous forest, and deciduous forest) is not necessarily sufficient. Other possible indicators taking into account the spatial variability could be forest stand age, LAI, soil type, soil fertility, latitude or elevation (Marushchak et al., 2013; Tagesson et al., 2017; Virkkala et al., 2021).

Currently, most remote sensing-based models do not consider the fertilization effect of increasing atmospheric CO_2 concentration, although it has been observed to enhance vegetation productivity. The effect of understory vegetation is not usually addressed in remote sensing-derived GPP models, although it as it can notably contribute to the spatial and temporal variability of forest carbon exchange (Chi et al., 2021; Martínez-García et al., 2022) and, furthermore, affects spectral reflectance and estimates of LAI in northern forests (Eriksson et al., 2006). The influence of understory vegetation on GPP modelling can be significant especially at the beginning and the end of the growing season, when lack of leaves is able create optimal light conditions at the forest floor (Palmroth et al., 2019).

Similarly, in peatlands the mixture of mosses and vascular plants with different spectral properties can complicate the carbon exchange modelling. Huemmrich et al. (2010) recommends to treat peatlands as a two-level environment with a moss understory and a vascular canopy, and to separate their contributions in remote sensing models. The vegetation assemblages and dominating species are strongly related to the peatland type (i.e., bog or fen), which can influence the relationships between remote sensing vegetation indices and peatland CO_2 fluxes (Kross et al., 2013). In addition, bogs and fens have also been shown to respond differently to changes in water table and air temperature (Helbig et al., 2019; Sulman et al., 2010).

Hence, future studies could focus on modelling the carbon fluxes separately for bogs and fens.

Improved accuracy and robustness of the model are important for moving towards operational monitoring and prediction of forest and peatland carbon uptake. Currently, Sentinel-2 MSI data with a 10-m spatial resolution enables monitoring of vegetation productivity in spatially heterogeneous ecosystems (e.g. peatlands) or landscapes (e.g. mosaic of even-aged forest stands). Models in Paper II provide a foundation for monitoring peatland carbon fluxes across northern Europe. The same models could be applied for evaluating the carbon sink strength in restored peatlands. Hence, re-parameterization with data from a rewetted peatland would be required in addition to water table depth or soil moisture data. Models for estimating forest GPP (Papers I, III and IV) provide a useful tool for evaluating the effect of different forest management activities on forest productivity and could be routinely applied as part of forest management operations in future.

Conclusions

Studying carbon exchange in terrestrial ecosystems is essential for understanding and quantifying the response of the biosphere to climate change and human activity. Reliable estimates of carbon fluxes can help to offset increasing CO_2 emissions and thus to mitigate global warming. In addition, they can support decision-making regarding the management and conservation of natural resources. This doctoral thesis has contributed to environmental studies by developing methods to model gross primary production (GPP) across forested landscapes and regions using satellite remote sensing data and by widening the understanding of the factors driving and constraining carbon exchange in boreal forest and peatland ecosystems.

This thesis has demonstrated that the seasonal dynamics of vegetation carbon uptake can be well captured using satellite instruments with different spatial resolutions. The comparison between Sentinel-2 MSI instrument at 10-meters spatial resolution and MODIS at 250 m and 500 m spatial resolution showed only small differences. The consistent results suggested that vegetation productivity can be monitored at various scales depending on the purpose of study. Sentinel-2 is able to provide detailed GPP estimation across the boreal region, which is a benefit for monitoring spatially heterogeneous ecosystem or landscapes.

In the thesis, several model formulations have been developed and tested, specifically for northern European coniferous forest, deciduous forest and peatland ecosystems. The empirical models performed better when the model parameters were estimated separately for each site in comparison to the average parameters acquired with a leave-one-out cross validation. However, a single parameter set per model is more appropriate approach for upscaling GPP to regional level, although it also led to underestimation of the peak growing season GPP at some sites and overestimation at other sites. The results suggested that a model based purely on the ecosystem type is not able to fully capture the spatial variability among the sites, indicating a need for additional factors to explain the variability. Soil moisture is a possible variable to further improve the model accuracy, as it is an important driver of carbon exchange in peatlands, but it could also benefit forest GPP models.

A simple linear regression model with the plant phenology index (PPI) performed well, suggesting PPI as a convenient tool for a local and regional scale GPP estimation. A simple model with reasonable accuracy yet low number of input datasets is a crucial step towards predicting how ecosystems response to changing conditions and disturbances. The 2018 drought in Europe affected ecosystems strongly and thus provides an opportunity to study how high air temperature and reduced water availability impacted on the vegetation carbon uptake in the boreal ecosystems. The analysis revealed that the ecosystem response to the drought varied between the ecosystem classes and the regions. Carbon uptake in peatland and forest ecosystems was mostly decreased due to the drought, although some sites showed no change or even increased productivity due to the longer and warmer growing season. The alternating response to the drought emphasizes the importance of taking into account the spatial heterogeneity of the ecosystems when modelling carbon uptake.

The current global warming greatly influences the climatic conditions in the boreal region. Therefore, robust models and reliable carbon flux estimates are essential for monitoring the carbon sink strength in northern ecosystems and supporting sustainable management practices.

References

Adams, H. D., & Kolb, T. E. (2005). Tree growth response to drought and temperature in a mountain landscape in northern Arizona, USA. *Journal of Biogeography, 32*(9), 1629-1640. doi:https://doi.org/10.1111/j.1365-2699.2005.01292.x

Aurela, M., Riutta, T., Laurila, T., Tuovinen, J.-P., Vesala, T., Tuittila, E.-S., Rinne, J., Haapanala, S., & Laine, J. (2007). CO2 exchange of a sedge fen in southern Finland-the impact of a drought period. *Tellus B: Chemical and Physical Meteorology, 59*(5), 826-837. doi:10.1111/j.1600-0889.2007.00309.x

Babst, F., Bouriaud, O., Poulter, B., Trouet, V., Girardin, M. P., & Frank, D. C. (2019). Twentieth century redistribution in climatic drivers of global tree growth. *Science Advances, 5*(1), eaat4313. doi:10.1126/sciadv.aat4313

Baldocchi, D. D. (2003). Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: past, present and future. *Global Change Biology, 9*(4), 479-492.

Balzarolo, M., Peñuelas, J., & Veroustraete, F. (2019). Influence of landscape heterogeneity and spatial resolution in multi-temporal in situ and MODIS NDVI data proxies for seasonal GPP dynamics. *Remote Sensing, 11*(14), 1656.

Bañuelos-Cabral, E. S., Gutiérrez-Robles, J. A., & Gustavsen, B. (2017). Rational Fitting Techniques for the Modeling of Electric Power Components and Systems Using MATLAB Environment. In C. Eduardo Salvador Banuelos, G.-R. Jose Alberto, & G. Bjorn (Eds.), *Rational Fitting Techniques for the Modeling of Electric Power Components and Systems Using MATLAB Environment* (pp. Ch. 1). Rijeka: IntechOpen.

Beer, C., Reichstein, M., Tomelleri, E., Ciais, P., Jung, M., Carvalhais, N., Rödenbeck, C., Arain, M. A., Baldocchi, D., & Bonan, G. B. (2010). Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate. *Science, 329*(5993), 834-838.

Blauhut, V., Stoelzle, M., Ahopelto, L., Brunner, M. I., Teutschbein, C., Wendt, D. E., Akstinas, V., Bakke, S. J., Barker, L. J., Bartošová, L., Briede, A., Cammalleri, C., Kalin, K. C., De Stefano, L., Fendeková, M., Finger, D. C., Huysmans, M., Ivanov, M., Jaagus, J., Jakubínský, J., Krakovska, S., Laaha, G., Lakatos, M., Manevski, K., Neumann Andersen, M., Nikolova, N., Osuch, M., van Oel, P., Radeva, K., Romanowicz, R. J., Toth, E., Trnka, M., Urošev, M., Urquijo Reguera, J., Sauquet, E., Stevkov, A., Tallaksen, L. M., Trofimova, I., Van Loon, A. F., van Vliet, M. T. H., Vidal, J. P., Wanders, N., Werner, M., Willems, P., & Živković, N. (2022). Lessons from the 2018–2019 European droughts: a collective need for unifying drought risk management. *Nat. Hazards Earth Syst. Sci., 22*(6), 2201-2217. doi:10.5194/nhess-22-2201-2022

Bradshaw, C. J., & Warkentin, I. G. (2015). Global estimates of boreal forest carbon stocks and flux. *Global and Planetary Change, 128*, 24-30.

Cabon, A., Mouillot, F., Lempereur, M., Ourcival, J.-M., Simioni, G., & Limousin, J.-M. (2018). Thinning increases tree growth by delaying drought-induced growth cessation in a Mediterranean evergreen oak coppice. *Forest Ecology and Management, 409*, 333-342.

Chen, B., Arain, M. A., Chen, J. M., Wang, S., Fang, H., Liu, Z., Mo, G., & Liu, J. (2020). Importance of shaded leaf contribution to the total GPP of Canadian terrestrial ecosystems: evaluation of MODIS GPP. *Journal of Geophysical Research: Biogeosciences, 125*(10), e2020JG005917.

Chen, S., Sui, L., Liu, L., & Liu, X. (2021). Effect of the Partitioning of Diffuse and Direct APAR on GPP Estimation. *Remote Sensing, 14*(1), 57.

Chi, J., Nilsson, M. B., Laudon, H., Lindroth, A., Wallerman, J., Fransson, J. E., Kljun, N., Lundmark, T., Ottosson Löfvenius, M., & Peichl, M. (2020). The Net Landscape Carbon Balance—Integrating terrestrial and aquatic carbon fluxes in a managed boreal forest landscape in Sweden. *Global Change Biology, 26*(4), 2353-2367. doi:10.1111/gcb.14983

Chi, J., Zhao, P., Klosterhalfen, A., Jocher, G., Kljun, N., Nilsson, M. B., & Peichl, M. (2021). Forest floor fluxes drive differences in the carbon balance of contrasting boreal forest stands. *Agricultural and Forest Meteorology, 306*, 108454. doi:https://doi.org/10.1016/j.agrformet.2021.108454

Cho, S., Kang, M., Ichii, K., Kim, J., Lim, J.-H., Chun, J.-H., Park, C.-W., Kim, H. S., Choi, S.-W., Lee, S.-H., Indrawati, Y. M., & Kim, J. (2021). Evaluation of forest carbon uptake in South Korea using the national flux tower network, remote sensing, and data-driven technology. *Agricultural and Forest Meteorology, 311*, 108653. doi:https://doi.org/10.1016/j.agrformet.2021.108653

Choudhury, B. J. (2001). Estimating gross photosynthesis using satellite and ancillary data: Approach and preliminary results. *Remote Sensing of Environment, 75*(1), 1-21.

Eriksson, H. M., Eklundh, L., Kuusk, A., & Nilson, T. (2006). Impact of understory vegetation on forest canopy reflectance and remotely sensed LAI estimates. *Remote Sensing of Environment, 103*(4), 408-418.

Falge, E., Baldocchi, D., Olson, R., Anthoni, P., Aubinet, M., Bernhofer, C., Burba, G., Ceulemans, R., Clement, R., & Dolman, H. (2001). Gap filling strategies for defensible annual sums of net ecosystem exchange. *Agricultural and Forest Meteorology, 107*(1), 43-69.

Felton, A., Löfroth, T., Angelstam, P., Gustafsson, L., Hjältén, J., Felton, A. M., Simonsson, P., Dahlberg, A., Lindbladh, M., Svensson, J., Nilsson, U., Lodin, I., Hedwall, P. O., Sténs, A., Lämås, T., Brunet, J., Kalén, C., Kriström, B., Gemmel, P., & Ranius, T. (2020). Keeping pace with forestry: Multi-scale conservation in a changing production forest matrix. *Ambio, 49*(5), 1050-1064. doi:10.1007/s13280-019-01248-0

Feng, X., Liu, G., Chen, J. M., Chen, M., Liu, J., Ju, W. M., Sun, R., & Zhou, W. (2007). Net primary productivity of China's terrestrial ecosystems from a process model driven by remote sensing. *Journal of Environmental Management, 85*(3), 563-573. doi:https://doi.org/10.1016/j.jenvman.2006.09.021

Frolking, S., & Roulet, N. T. (2007). Holocene radiative forcing impact of northern peatland carbon accumulation and methane emissions. *Global Change Biology, 13*(5), 1079-1088.

Gamon, J. A., Serrano, L., & Surfus, J. S. (1997). The photochemical reflectance index: an optical indicator of photosynthetic radiation use efficiency across species, functional types, and nutrient levels. *Oecologia, 112*(4), 492-501. doi:10.1007/s004420050337

Gao, B.-C. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment, 58*(3), 257-266.

Gao, Y., Yu, G., Li, S., Yan, H., Zhu, X., Wang, Q., Shi, P., Zhao, L., Li, Y., Zhang, F., Wang, Y., & Zhang, J. (2015). A remote sensing model to estimate ecosystem respiration in Northern China and the Tibetan Plateau. *Ecological Modelling, 304*, 34-43. doi:https://doi.org/10.1016/j.ecolmodel.2015.03.001

Gauthier, S., Bernier, P., Kuuluvainen, T., Shvidenko, A. Z., & Schepaschenko, D. G. (2015). Boreal forest health and global change. *Science, 349*(6250), 819-822.

Gelybó, G., Barcza, Z., Kern, A., & Kljun, N. (2013). Effect of spatial heterogeneity on the validation of remote sensing based GPP estimations. *Agricultural and Forest Meteorology, 174*, 43-53.

Gitelson, A. A. (2019). Remote estimation of fraction of radiation absorbed by photosynthetically active vegetation: generic algorithm for maize and soybean. *Remote Sensing Letters, 10*(3), 283-291. doi:10.1080/2150704X.2018.1547445

Günther, A., Barthelmes, A., Huth, V., Joosten, H., Jurasinski, G., Koebsch, F., & Couwenberg, J. (2020). Prompt rewetting of drained peatlands reduces climate warming despite methane emissions. *Nature Communications, 11*(1), 1644. doi:10.1038/s41467-020-15499-z

Hadden, D., & Grelle, A. (2016). Changing temperature response of respiration turns boreal forest from carbon sink into carbon source. *Agricultural and Forest Meteorology, 223*, 30-38. doi:https://doi.org/10.1016/j.agrformet.2016.03.020

Hadden, D., & Grelle, A. (2017). Net CO2 emissions from a primary boreo-nemoral forest over a 10year period. *Forest Ecology and Management, 398*, 164-173. doi:https://doi.org/10.1016/j.foreco.2017.05.008

Harris, A., & Dash, J. (2011). A new approach for estimating northern peatland gross primary productivity using a satellite-sensor-derived chlorophyll index. *Journal of Geophysical Research: Biogeosciences, 116*(G4). doi:https://doi.org/10.1029/2011JG001662

Hashimoto, H., Wang, W., Milesi, C., White, M. A., Ganguly, S., Gamo, M., Hirata, R., Myneni, R. B., & Nemani, R. R. (2012). Exploring Simple Algorithms for Estimating Gross Primary Production in Forested Areas from Satellite Data. *Remote Sensing, 4*(1), 303-326.

Heimann, M., & Reichstein, M. (2008). Terrestrial ecosystem carbon dynamics and climate feedbacks. *Nature, 451*, 289. doi:10.1038/nature06591

Helbig, M., Humphreys, E., & Todd, A. (2019). Contrasting temperature sensitivity of CO2 exchange in peatlands of the Hudson Bay Lowlands, Canada. *Journal of Geophysical Research: Biogeosciences, 124*(7), 2126-2143.

Helbig, M., Waddington, J. M., Alekseychik, P., Amiro, B., Aurela, M., Barr, A. G., Black, T. A., Carey, S. K., Chen, J., Chi, J., Desai, A. R., Dunn, A., Euskirchen, E. S., Flanagan, L. B., Friborg, T., Garneau, M., Grelle, A., Harder, S., Heliasz, M., Humphreys, E. R., Ikawa, H., Isabelle, P.-E., Iwata, H., Jassal, R., Korkiakoski, M., Kurbatova, J., Kutzbach, L., Lapshina, E., Lindroth, A., Löfvenius, M. O., Lohila, A., Mammarella, I., Marsh, P., Moore, P. A., Maximov, T., Nadeau, D. F., Nicholls, E. M., Nilsson, M. B., Ohta, T., Peichl, M., Petrone, R. M., Prokushkin, A., Quinton, W. L., Roulet, N., Runkle, B. R. K., Sonnentag, O., Strachan, I. B., Taillardat, P., Tuittila, E.-S., Tuovinen, J.-P., Turner, J., Ueyama, M., Varlagin, A., Vesala, T., Wilmking, M., Zyrianov, V., & Schulze, C. (2020). The biophysical climate mitigation potential of boreal peatlands during the growing season. *Environmental Research Letters, 15*(10), 104004. doi:10.1088/1748-9326/abab34

Hilker, T., Coops, N. C., Wulder, M. A., Black, T. A., & Guy, R. D. (2008). The use of remote sensing in light use efficiency based models of gross primary production: A review of current status and future requirements. *Science of the Total Environment, 404*(2), 411-423. doi:https://doi.org/10.1016/j.scitotenv.2007.11.007

Högberg, P., Ceder, L., Astrup, R., Binkley, D., Dalsgaard, L., Egnell, G., Filipchuk, A., Genet, H., Ilintsev, A., & Kurz, W. (2021). Sustainable boreal forest management challenges and opportunities for climate change mitigation.

Huang, J., Desai, A. R., Zhu, J., Hartemink, A. E., Stoy, P. C., Loheide, S. P., Bogena, H. R., Zhang, Y., Zhang, Z., & Arriaga, F. (2020). Retrieving Heterogeneous Surface Soil Moisture at 100 m Across the Globe via Fusion of Remote Sensing and Land Surface Parameters. *Frontiers in Water, 2*(38). doi:10.3389/frwa.2020.578367

Huang, X., Zheng, Y., Zhang, H., Lin, S., Liang, S., Li, X., Ma, M., & Yuan, W. (2022). High spatial resolution vegetation gross primary production product: Algorithm and validation. *Science of Remote Sensing, 5*, 100049. doi:https://doi.org/10.1016/j.srs.2022.100049

Huemmrich, K., Gamon, J., Tweedie, C., Oberbauer, S., Kinoshita, G., Houston, S., Kuchy, A., Hollister, R. D., Kwon, H., & Mano, M. (2010). Remote sensing of tundra gross ecosystem productivity and light use efficiency under varying temperature and moisture conditions. *Remote Sensing of Environment, 114*(3), 481-489.

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment, 83*(1), 195-213. doi:https://doi.org/10.1016/S0034-4257(02)00096-2

Hyvönen, R., Ågren, G. I., Linder, S., Persson, T., Cotrufo, M. F., Ekblad, A., Freeman, M., Grelle, A., Janssens, I. A., Jarvis, P. G., Kellomäki, S., Lindroth, A., Loustau, D., Lundmark, T., Norby, R. J., Oren, R., Pilegaard, K., Ryan, M. G., Sigurdsson, B. D., Strömgren, M., van Oijen, M., & Wallin, G. (2007). The likely impact of elevated [CO2], nitrogen deposition, increased temperature and management on carbon sequestration in temperate and boreal forest ecosystems: a literature review. *New Phytologist, 173*(3), 463-480. doi:10.1111/j.1469-8137.2007.01967.x

IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group 1 to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jenkins, J., Richardson, A. D., Braswell, B., Ollinger, S. V., Hollinger, D. Y., & Smith, M.-L. (2007). Refining light-use efficiency calculations for a deciduous forest canopy using simultaneous tower-based carbon flux and radiometric measurements. *Agricultural and Forest Meteorology, 143*(1-2), 64-79.

Jiang, Z., Huete, A. R., Didan, K., & Miura, T. (2008). Development of a two-band enhanced vegetation index without a blue band. *Remote Sensing of Environment, 112*(10), 3833-3845. doi:https://doi.org/10.1016/j.rse.2008.06.006

Jin, H., & Eklundh, L. (2014). A physically based vegetation index for improved monitoring of plant phenology. *Remote Sensing of Environment, 152*, 512–525. doi:10.1016/j.rse.2014.07.010

Jönsson, P., Cai, Z., Melaas, E., Friedl, M. A., & Eklundh, L. (2018). A method for robust estimation of vegetation seasonality from Landsat and Sentinel-2 time series data. *Remote Sensing, 10*(4), 635.

Jönsson, P., & Eklundh, L. (2004). TIMESAT—a program for analyzing time-series of satellite sensor data. *Computers & Geosciences, 30*(8), 833-845. doi:https://doi.org/10.1016/j.cageo.2004.05.006

Keenan, R. J., Reams, G. A., Achard, F., de Freitas, J. V., Grainger, A., & Lindquist, E. (2015). Dynamics of global forest area: Results from the FAO Global Forest Resources Assessment 2015. *Forest Ecology and Management, 352*, 9-20. doi:https://doi.org/10.1016/j.foreco.2015.06.014

Keenan, T. F., & Riley, W. J. (2018). Greening of the land surface in the world's cold regions consistent with recent warming. *Nature Climate Change, 8*(9), 825-828. doi:10.1038/s41558-018-0258-y

Kljun, N., Calanca, P., Rotach, M. W., & Schmid, H. P. (2015). A simple two-dimensional parameterisation for Flux Footprint Prediction (FFP). *Geosci. Model Dev., 8*(11), 3695-3713. doi:10.5194/gmd-8-3695-2015

Knohl, A., & Baldocchi, D. D. (2008). Effects of diffuse radiation on canopy gas exchange processes in a forest ecosystem. *Journal of Geophysical Research: Biogeosciences, 113*(G2). doi:https://doi.org/10.1029/2007JG000663

Kross, A., Seaquist, J. W., Roulet, N. T., Fernandes, R., & Sonnentag, O. (2013). Estimating carbon dioxide exchange rates at contrasting northern peatlands using MODIS satellite data. *Remote Sensing of Environment, 137*, 234-243. doi:https://doi.org/10.1016/j.rse.2013.06.014

Lagergren, F., Grelle, A., Lankreijer, H., Mölder, M., & Lindroth, A. (2006). Current Carbon Balance of the Forested Area in Sweden and its Sensitivity to Global Change as Simulated by Biome-BGC. *Ecosystems, 9*(6), 894-908. doi:10.1007/s10021-005-0046-1

Laine, A. M., Mäkiranta, P., Laiho, R., Mehtätalo, L., Penttilä, T., Korrensalo, A., Minkkinen, K., Fritze, H., & Tuittila, E. S. (2019). Warming impacts on boreal fen CO2 exchange under wet and dry conditions. *Global Change Biology, 25*(6), 1995-2008.

Lasslop, G., Reichstein, M., Papale, D., Richardson, A. D., Arneth, A., Barr, A., Stoy, P., & Wohlfahrt, G. (2010). Separation of net ecosystem exchange into assimilation and respiration using a light response curve approach: critical issues and global evaluation. *Global Change Biology, 16*(1), 187-208. doi:10.1111/j.1365-2486.2009.02041.x

Launiainen, S., Katul, G. G., Leppä, K., Kolari, P., Aslan, T., Grönholm, T., Korhonen, L., Mammarella, I., & Vesala, T. (2022). Does growing atmospheric CO2 explain increasing carbon sink in a boreal coniferous forest? *Global Change Biology, 28*(9), 2910-2929. doi:https://doi.org/10.1111/gcb.16117

Laurent, M., Antoine, N., & Joël, G. (2003). Effects of different thinning intensities on drought response in Norway spruce (Picea abies (L.) Karst.). *Forest Ecology and Management, 183*(1-3), 47-60.

Lees, K. J., Quaife, T., Artz, R. R. E., Khomik, M., & Clark, J. M. (2018). Potential for using remote sensing to estimate carbon fluxes across northern peatlands – A review. *Science of the Total Environment, 615*, 857-874. doi:https://doi.org/10.1016/j.scitotenv.2017.09.103

Leifeld, J., & Menichetti, L. (2018). The underappreciated potential of peatlands in global climate change mitigation strategies. *Nature Communications, 9*(1), 1071. doi:10.1038/s41467-018-03406-6

Lévesque, M., Saurer, M., Siegwolf, R., Eilmann, B., Brang, P., Bugmann, H., & Rigling, A. (2013). Drought response of five conifer species under contrasting water availability suggests high vulnerability of Norway spruce and European larch. *Global Change Biology, 19*(10), 3184-3199. doi:https://doi.org/10.1111/gcb.12268

Limpens, J., Berendse, F., Blodau, C., Canadell, J. G., Freeman, C., Holden, J., Roulet, N., Rydin, H., & Schaepman-Strub, G. (2008). Peatlands and the carbon cycle: from local processes to global implications – a synthesis. *Biogeosciences, 5*(5), 1475-1491. doi:10.5194/bg-5-1475-2008

Lindroth, A., Grelle, A., & Morén, A. S. (1998). Long-term measurements of boreal forest carbon balance reveal large temperature sensitivity. *Global Change Biology, 4*(4), 443-450.

Lindroth, A., Holst, J., Linderson, M.-L., Aurela, M., Biermann, T., Heliasz, M., Chi, J., Ibrom, A., Kolari, P., & Klemedtsson, L. (2020). Effects of drought and meteorological forcing on carbon and water fluxes in Nordic forests during the dry summer of 2018. *Philosophical Transactions of the Royal Society B, 375*(1810), 20190516.

Litvak, M., Miller, S., Wofsy, S. C., & Goulden, M. (2003). Effect of stand age on whole ecosystem CO2 exchange in the Canadian boreal forest. *Journal of Geophysical Research: Atmospheres, 108*(D3). doi:https://doi.org/10.1029/2001JD000854

Lloyd, J., & Taylor, J. A. (1994). On the Temperature Dependence of Soil Respiration. *Functional Ecology, 8*(3), 315-323. doi:10.2307/2389824

Lohila, A., Minkkinen, K., Aurela, M., Tuovinen, J.-P., Penttilä, T., Ojanen, P., & Laurila, T. (2011). Greenhouse gas flux measurements in a forestry-drained peatland indicate a large carbon sink. *Biogeosciences, 8*(11), 3203-3218.

Lund, M., Christensen, T. R., Lindroth, A., & Schubert, P. (2012). Effects of drought conditions on the carbon dioxide dynamics in a temperate peatland. *Environmental Research Letters, 7*(4), 045704.

Lund, M., Lafleur, P. M., Roulet, N. T., Lindroth, A., Christensen, T. R., Aurela, M., Chojnicki, B. H., Flanagan, L. B., Humphreys, E. R., Laurila, T., Oechel, W. C., Olejnik, J., Rinne, J., Schubert, P., & Nilsson, M. B. (2010). Variability in exchange of CO2 across 12 northern peatland and tundra sites. *Global Change Biology, 16*(9), 2436-2448. doi:doi:10.1111/j.1365-2486.2009.02104.x

Lundmark, T., Bergh, J., Hofer, P., Lundström, A., Nordin, A., Poudel, B. C., Sathre, R., Taverna, R., & Werner, F. (2014). Potential Roles of Swedish Forestry in the Context of Climate Change Mitigation. *Forests, 5*(4), 557-578.

Madani, N., Kimball, J. S., Affleck, D. L., Kattge, J., Graham, J., Van Bodegom, P. M., Reich, P. B., & Running, S. W. (2014). Improving ecosystem productivity modeling through spatially explicit estimation of optimal light use efficiency. *Journal of Geophysical Research: Biogeosciences, 119*(9), 1755-1769.

Martínez-García, E., Nilsson, M. B., Laudon, H., Lundmark, T., Fransson, J. E. S., Wallerman, J., & Peichl, M. (2022). Overstory dynamics regulate the spatial variability in forest-floor CO2 fluxes across a managed boreal forest landscape. *Agricultural and Forest Meteorology, 318*, 108916. doi:https://doi.org/10.1016/j.agrformet.2022.108916

Marushchak, M. E., Kiepe, I., Biasi, C., Elsakov, V., Friborg, T., Johansson, T., Soegaard, H., Virtanen, T., & Martikainen, P. J. (2013). Carbon dioxide balance of subarctic tundra from plot to regional scales. *Biogeosciences, 10*(1), 437-452. doi:10.5194/bg-10-437-2013

Meier, I. C., & Leuschner, C. (2008). Leaf Size and Leaf Area Index in Fagus sylvatica Forests: Competing Effects of Precipitation, Temperature, and Nitrogen Availability. *Ecosystems, 11*(5), 655-669. doi:10.1007/s10021-008-9135-2

Meyer, A., Tarvainen, L., Nousratpour, A., Björk, R. G., Ernfors, M., Grelle, A., Kasimir Klemedtsson, Å., Lindroth, A., Räntfors, M., Rütting, T., Wallin, G., Weslien, P., & Klemedtsson, L. (2013). A fertile peatland forest does not constitute a major greenhouse gas sink. *Biogeosciences, 10*(11), 7739-7758. doi:10.5194/bg-10-7739-2013

Minkkinen, K., Ojanen, P., Penttilä, T., Aurela, M., Laurila, T., Tuovinen, J. P., & Lohila, A. (2018). Persistent carbon sink at a boreal drained bog forest. *Biogeosciences, 15*(11), 3603-3624. doi:10.5194/bg-15-3603-2018

Mohammed, G. H., Colombo, R., Middleton, E. M., Rascher, U., van der Tol, C., Nedbal, L., Goulas, Y., Pérez-Priego, O., Damm, A., & Meroni, M. (2019). Remote sensing of solar-induced chlorophyll fluorescence (SIF) in vegetation: 50 years of progress. *Remote Sensing of Environment, 231*, 111177.

Monteith, J. L. (1972). Solar Radiation and Productivity in Tropical Ecosystems. *Journal of Applied Ecology, 9*(3), 747-766. doi:10.2307/2401901

Noumonvi, K. D., & Ferlan, M. (2020). Empirical vs. light-use efficiency modelling for estimating carbon fluxes in a mid-succession ecosystem developed on abandoned karst grassland. *PLOS ONE, 15*(8), e0237351. doi:10.1371/journal.pone.0237351

Ojanen, P., & Minkkinen, K. (2020). Rewetting Offers Rapid Climate Benefits for Tropical and Agricultural Peatlands But Not for Forestry-Drained Peatlands. *Global Biogeochemical Cycles, 34*(7), e2019GB006503. doi:https://doi.org/10.1029/2019GB006503

Ojanen, P., Minkkinen, K., & Penttilä, T. (2013). The current greenhouse gas impact of forestry-drained boreal peatlands. *Forest Ecology and Management, 289*, 201-208. doi:https://doi.org/10.1016/j.foreco.2012.10.008

Olofsson, P., Lagergren, F., Lindroth, A., Lindström, J., Klemedtsson, L., Kutsch, W., & Eklundh, L. (2008). Towards operational remote sensing of forest carbon balance across Northern Europe. *Biogeosciences, 5*(3), 817-832. doi:10.5194/bg-5-817-2008

Palmroth, S., Bach, L. H., Lindh, M., Kolari, P., Nordin, A., & Palmqvist, K. (2019). Nitrogen supply and other controls of carbon uptake of understory vegetation in a boreal Picea abies forest. *Agricultural and Forest Meteorology, 276-277*, 107620. doi:https://doi.org/10.1016/j.agrformet.2019.107620

Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., Phillips, O. L., Shvidenko, A., Lewis, S. L., Canadell, J. G., Ciais, P., Jackson, R. B., Pacala, S. W., McGuire, A. D., Piao, S., Rautiainen, A., Sitch, S., & Hayes, D. (2011). A Large and Persistent Carbon Sink in the World's Forests. *Science, 333*(6045), 988-993. doi:10.1126/science.1201609

Peichl, M., Martínez-García, E., Fransson, J. E. S., Wallerman, J., Laudon, H., Lundmark, T., & Nilsson, M. B. (2023). Landscape-variability of the carbon balance across managed boreal forests. *Global Change Biology, 29*(4), 1119-1132. doi:https://doi.org/10.1111/gcb.16534

Qiu, C., Zhu, D., Ciais, P., Guenet, B., & Peng, S. (2020). The role of northern peatlands in the global carbon cycle for the 21st century. *Global Ecology and Biogeography, 29*(5), 956-973.

Rehschuh, R., Mette, T., Menzel, A., & Buras, A. (2017). Soil properties affect the drought susceptibility of Norway spruce. *Dendrochronologia, 45*, 81-89. doi:https://doi.org/10.1016/j.dendro.2017.07.003

Reyer, C. P. O., Bathgate, S., Blennow, K., Borges, J. G., Bugmann, H., Delzon, S., Faias, S. P., Garcia-Gonzalo, J., Gardiner, B., Gonzalez-Olabarria, J. R., Gracia, C., Hernández, J. G., Kellomäki, S., Kramer, K., Lexer, M. J., Lindner, M., van der Maaten, E., Maroschek, M., Muys, B., Nicoll, B., Palahi, M., Palma, J. H. N., Paulo, J. A., Peltola, H., Pukkala, T., Rammer, W., Ray, D., Sabaté, S., Schelhaas, M.-J., Seidl, R., Temperli, C., Tomé, M., Yousefpour, R., Zimmermann, N. E., & Hanewinkel, M. (2017). Are forest disturbances amplifying or canceling out climate change-induced productivity changes in European forests? *Environmental Research Letters, 12*(3), 034027. doi:10.1088/1748-9326/aa5ef1

Rinne, J., Tuovinen, J.-P., Klemedtsson, L., Aurela, M., Holst, J., Lohila, A., Weslien, P., Vestin, P., Łakomiec, P., Peichl, M., Tuittila, E.-S., Heiskanen, L., Laurila, T., Li, X., Alekseychik, P., Mammarella, I., Ström, L., Crill, P., & Nilsson, M. B. (2020). Effect of the 2018 European drought on methane and carbon dioxide exchange of northern mire ecosystems. *Philosophical Transactions of the Royal Society B: Biological Sciences, 375*(1810), 20190517. doi:doi:10.1098/rstb.2019.0517

Running, S. W. (1986). Global primary production from terrestrial vegetation: Estimates integrating satellite remote sensing and computer simulation technology. *Science of the Total Environment, 56*, 233-242.

Running, S. W., Nemani, R. R., Heinsch, F. A., Zhao, M., Reeves, M., & Hashimoto, H. (2004). A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production. *BioScience, 54*(6), 547-560. doi:10.1641/0006-3568(2004)054[0547:ACSMOG]2.0.CO;2

Schäfer, C., Rötzer, T., Thurm, E. A., Biber, P., Kallenbach, C., & Pretzsch, H. (2019). Growth and tree water deficit of mixed Norway spruce and European beech at different heights in a tree and under heavy drought. *Forests, 10*(7), 577.

Schmid, H. P. (2002). Footprint modeling for vegetation atmosphere exchange studies: a review and perspective. *Agricultural and Forest Meteorology, 113*(1–4), 159-183. doi:https://doi.org/10.1016/S0168-1923(02)00107-7

Schrier-Uijl, A., Kroon, P., Hensen, A., Leffelaar, P., Berendse, F., & Veenendaal, E. (2010). Comparison of chamber and eddy covariance-based CO2 and CH4 emission estimates in a heterogeneous grass ecosystem on peat. *Agricultural and Forest Meteorology, 150*(6), 825-831.

Schubert, P., Eklundh, L., Lund, M., & Nilsson, M. (2010). Estimating northern peatland CO2 exchange from MODIS time series data. *Remote Sensing of Environment, 114*(6), 1178-1189. doi:https://doi.org/10.1016/j.rse.2010.01.005

Schubert, P., Lagergren, F., Aurela, M., Christensen, T., Grelle, A., Heliasz, M., Klemedtsson, L., Lindroth, A., Pilegaard, K., Vesala, T., & Eklundh, L. (2012). Modeling GPP in the Nordic forest landscape with MODIS time series data—Comparison with the MODIS GPP product. *Remote Sensing of Environment, 126*(Supplement C), 136-147. doi:https://doi.org/10.1016/j.rse.2012.08.005

Sims, D. A., Rahman, A. F., Cordova, V. D., El-Masri, B. Z., Baldocchi, D. D., Bolstad, P. V., Flanagan, L. B., Goldstein, A. H., Hollinger, D. Y., & Misson, L. (2008). A new model of gross primary productivity for North American ecosystems based solely on the enhanced vegetation index and land surface temperature from MODIS. *Remote Sensing of Environment, 112*(4), 1633-1646.

Sjökvist, E., Abdoush, D., & Axén, J. (2019). *Sommaren 2018 - en glimt av framtiden?* (SMHI report Klimatologi no. 52). Retrieved from SMHI: https://www.smhi.se/publikationer/publikationer/sommaren-2018-en-glimt-av-framtiden-1.149088

Skytt, T., Englund, G., & Jonsson, B.-G. (2021). Climate mitigation forestry—temporal trade-offs. *Environmental Research Letters, 16*(11), 114037. doi:10.1088/1748-9326/ac30fa

Stocker, B. D., Zscheischler, J., Keenan, T. F., Prentice, I. C., Seneviratne, S. I., & Peñuelas, J. (2019). Drought impacts on terrestrial primary production underestimated by satellite monitoring. *Nature Geoscience, 12*(4), 264-270. doi:10.1038/s41561-019-0318-6

Sulman, B. N., Desai, A. R., Saliendra, N. Z., Lafleur, P. M., Flanagan, L. B., Sonnentag, O., Mackay, D. S., Barr, A. G., & van der Kamp, G. (2010). CO2 fluxes at northern fens and bogs have opposite responses to inter-annual fluctuations in water table. *Geophysical Research Letters, 37*(19).

Tagesson, T., Ardö, J., Cappelaere, B., Kergoat, L., Abdi, A., Horion, S., & Fensholt, R. (2017). Modelling spatial and temporal dynamics of gross primary production in the Sahel from earth-observation-based photosynthetic capacity and quantum efficiency. *Biogeosciences, 14*(5), 1333-1348. doi:10.5194/bg-14-1333-2017

Tagesson, T., Mastepanov, M., Tamstorf, M. P., Eklundh, L., Schubert, P., Ekberg, A., Sigsgaard, C., Christensen, T. R., & Ström, L. (2012). High-resolution satellite data reveal an increase in peak growing season gross primary production in a high-Arctic wet tundra ecosystem 1992–2008. *International Journal of Applied Earth Observation and Geoinformation, 18*(Supplement C), 407-416. doi:https://doi.org/10.1016/j.jag.2012.03.016

Tagesson, T., Schurgers, G., Horion, S., Ciais, P., Tian, F., Brandt, M., Ahlström, A., Wigneron, J.-P., Ardö, J., & Olin, S. (2020). Recent divergence in the contributions of tropical and boreal forests to the terrestrial carbon sink. *Nature Ecology & Evolution, 4*(2), 202-209.

Tagesson, T., Tian, F., Schurgers, G., Horion, S., Scholes, R., Ahlström, A., Ardö, J., Moreno, A., Madani, N., Olin, S., & Fensholt, R. (2021). A physiology-based Earth observation model indicates stagnation in the global gross primary production during recent decades. *Global Change Biology, 27*(4), 836-854. doi:https://doi.org/10.1111/gcb.15424

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment, 8*(2), 127-150. doi:https://doi.org/10.1016/0034-4257(79)90013-0

Turner, D. P., Ritts, W. D., Cohen, W. B., Gower, S. T., Running, S. W., Zhao, M., Costa, M. H., Kirschbaum, A. A., Ham, J. M., Saleska, S. R., & Ahl, D. E. (2006). Evaluation of MODIS NPP and GPP products across multiple biomes. *Remote Sensing of Environment, 102*(3), 282-292. doi:https://doi.org/10.1016/j.rse.2006.02.017

Turner, D. P., Urbanski, S., Bremer, D., Wofsy, S. C., Meyers, T., Gower, S. T., & Gregory, M. (2003). A cross-biome comparison of daily light use efficiency for gross primary production. *Global Change Biology, 9*(3), 383-395. doi:doi:10.1046/j.1365-2486.2003.00573.x

Ueyama, M., Iwata, H., Harazono, Y., Euskirchen, E. S., Oechel, W. C., & Zona, D. (2013). Growing season and spatial variations of carbon fluxes of Arctic and boreal ecosystems in Alaska (USA). *Ecological Applications, 23*(8), 1798-1816. doi:10.1890/11-0875.1

van der Werf, G. R., Morton, D. C., DeFries, R. S., Olivier, J. G. J., Kasibhatla, P. S., Jackson, R. B., Collatz, G. J., & Randerson, J. T. (2009). CO2 emissions from forest loss. *Nature Geoscience, 2*(11), 737-738. doi:10.1038/ngeo671

Venäläinen, A., Lehtonen, I., Laapas, M., Ruosteenoja, K., Tikkanen, O.-P., Viiri, H., Ikonen, V.-P., & Peltola, H. (2020). Climate change induces multiple risks to boreal forests and forestry in Finland: A literature review. *Global Change Biology, 26*(8), 4178-4196. doi:https://doi.org/10.1111/gcb.15183

Verma, M., Friedl, M. A., Law, B. E., Bonal, D., Kiely, G., Black, T. A., Wohlfahrt, G., Moors, E. J., Montagnani, L., Marcolla, B., Toscano, P., Varlagin, A., Roupsard, O., Cescatti, A., Arain, M. A., & D'Odorico, P. (2015). Improving the performance of remote sensing models for capturing intra- and inter-annual variations in daily GPP: An analysis using global FLUXNET tower data. *Agricultural and Forest Meteorology, 214-215*, 416-429. doi:https://doi.org/10.1016/j.agrformet.2015.09.005

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate, 23*(7), 1696-1718. doi:10.1175/2009jcli2909.1

Vicente-Serrano, S. M., Gouveia, C., Camarero, J. J., Beguería, S., Trigo, R., López-Moreno, J. I., Azorín-Molina, C., Pasho, E., Lorenzo-Lacruz, J., Revuelto, J., Morán-Tejeda, E., & Sanchez-Lorenzo, A. (2013). Response of vegetation to drought time-scales across global land biomes. *Proceedings of the National Academy of Sciences, 110*(1), 52-57. doi:doi:10.1073/pnas.1207068110

Virkkala, A.-M., Aalto, J., Rogers, B. M., Tagesson, T., Treat, C. C., Natali, S. M., Watts, J. D., Potter, S., Lehtonen, A., Mauritz, M., Schuur, E. A. G., Kochendorfer, J., Zona, D., Oechel, W., Kobayashi, H., Humphreys, E., Goeckede, M., Iwata, H., Lafleur, P. M., Euskirchen, E. S., Bokhorst, S., Marushchak, M., Martikainen, P. J., Elberling, B., Voigt, C., Biasi, C., Sonnentag, O., Parmentier, F.-J. W., Ueyama, M., Celis, G., St.Louis, V. L., Emmerton, C. A., Peichl, M., Chi, J., Järveoja, J., Nilsson, M. B., Oberbauer, S. F., Torn, M. S., Park, S.-J., Dolman, H., Mammarella, I., Chae, N., Poyatos, R., López-Blanco, E., Christensen, T. R., Kwon, M. J., Sachs, T., Holl, D., & Luoto, M. (2021). Statistical upscaling of ecosystem CO2 fluxes across the terrestrial tundra and boreal domain: Regional patterns and uncertainties. *Global Change Biology, 27*(17), 4040-4059. doi:https://doi.org/10.1111/gcb.15659

Wang, X., Ma, M., Li, X., Song, Y., Tan, J., Huang, G., Zhang, Z., Zhao, T., Feng, J., Ma, Z., Wei, W., & Bai, Y. (2013). Validation of MODIS-GPP product at 10 flux sites in northern China. *International Journal of Remote Sensing, 34*(2), 587-599. doi:10.1080/01431161.2012.715774

Wu, W.-Y., Lan, C.-W., Lo, M.-H., Reager, J. T., & Famiglietti, J. S. (2015). Increases in the annual range of soil water storage at northern middle and high latitudes under global warming. *Geophysical Research Letters, 42*(10), 3903-3910. doi:https://doi.org/10.1002/2015GL064110

Xiao, J., Zhuang, Q., Law, B. E., Chen, J., Baldocchi, D. D., Cook, D. R., Oren, R., Richardson, A. D., Wharton, S., Ma, S., Martin, T. A., Verma, S. B., Suyker, A. E., Scott, R. L., Monson, R. K., Litvak, M., Hollinger, D. Y., Sun, G., Davis, K. J., Bolstad, P. V., Burns, S. P., Curtis, P. S., Drake, B. G., Falk, M., Fischer, M. L., Foster, D. R., Gu, L., Hadley, J. L., Katul, G. G., Matamala, R., McNulty, S., Meyers, T. P., Munger, J. W., Noormets, A., Oechel, W. C., Paw U, K. T., Schmid, H. P., Starr, G., Torn, M. S., & Wofsy, S. C. (2010). A continuous measure of gross primary production for the conterminous United States derived from MODIS and AmeriFlux data. *Remote Sensing of Environment, 114*(3), 576-591. doi:https://doi.org/10.1016/j.rse.2009.10.013

Xiao, X., Hollinger, D., Aber, J., Goltz, M., Davidson, E. A., Zhang, Q., & Moore, B. (2004). Satellite-based modeling of gross primary production in an evergreen needleleaf forest. *Remote Sensing of Environment, 89*(4), 519-534. doi:https://doi.org/10.1016/j.rse.2003.11.008

Xiao, X., Zhang, Q., Hollinger, D., Aber, J., & Moore III, B. (2005). Modeling gross primary production of an evergreen needleleaf forest using MODIS and climate data. *Ecological Applications, 15*(3), 954-969.

Yu, Z. C. (2012). Northern peatland carbon stocks and dynamics: a review. *Biogeosciences, 9*(10), 4071-4085. doi:10.5194/bg-9-4071-2012

Yuan, W., Cai, W., Xia, J., Chen, J., Liu, S., Dong, W., Merbold, L., Law, B., Arain, A., Beringer, J., Bernhofer, C., Black, A., Blanken, P. D., Cescatti, A., Chen, Y., Francois, L., Gianelle, D., Janssens, I. A., Jung, M., Kato, T., Kiely, G., Liu, D., Marcolla, B., Montagnani, L., Raschi, A., Roupsard, O., Varlagin, A., & Wohlfahrt, G. (2014). Global comparison of light use efficiency models for simulating terrestrial vegetation gross primary production based on the LaThuile database. *Agricultural and Forest Meteorology, 192-193*, 108-120. doi:https://doi.org/10.1016/j.agrformet.2014.03.007

Zhang, Y., Xiao, X., Wu, X., Zhou, S., Zhang, G., Qin, Y., & Dong, J. (2017). A global moderate resolution dataset of gross primary production of vegetation for 2000–2016. *Scientific Data, 4*(1), 170165. doi:10.1038/sdata.2017.165

Zhang, Z., Li, X., Ju, W., Zhou, Y., & Cheng, X. (2022). Improved estimation of global gross primary productivity during 1981–2020 using the optimized P model. *Science of the Total Environment, 838*, 156172. doi:https://doi.org/10.1016/j.scitotenv.2022.156172

Zhao, M., Heinsch, F. A., Nemani, R. R., & Running, S. W. (2005). Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment, 95*(2), 164-176. doi:https://doi.org/10.1016/j.rse.2004.12.011

Zhao, M., & Running, S. W. (2010). Drought-Induced Reduction in Global Terrestrial Net Primary Production from 2000 Through 2009. *Science, 329*(5994), 940-943. doi:10.1126/science.1192666

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