Student thesis series INES nr 374

Assessment of the relationship between the Photochemical Reflectance Index and Light Use Efficiency: A study of its seasonal and diurnal variation in a sub-arctic birch forest, Abisko, Sweden

Elsa Lindevall

2016
Department of
Physical Geography and Ecosystem Science
Lund University
Sölvegatan 12
S-223 62 Lund
Sweden

Elsa Lindevall (2016).
Assessment of the relationship between the Photochemical Reflectance Index and Light Use Efficiency: A study of its seasonal and diurnal variation in a sub-arctic birch forest, Abisko, Sweden
Utvärdering av förhållandet mellan ett fotokemiskt vegetationsindex (Photochemical Reflectance Index; PRI) och den fotosyntetiska effektiviteten (Light Use Efficiency; LUE): En studie av dess säsongs- och dygnsvariation i en subarktisk björkskog, Abisko, Sverige
Bachelor degree thesis, 15 credits in *Physical Geography and Ecosystem Science*
Department of Physical Geography and Ecosystem Science, Lund University

Level: Bachelor of Science (BSc)

Course duration: *March* 2016 until *June* 2016

Disclaimer

Assessment of the relationship between the Photochemical Reflectance Index and Light Use Efficiency: A study of its seasonal and diurnal variation in a sub-arctic birch forest, Abisko, Sweden

---

Elsa Lindevall

Bachelor thesis, 15 credits, in *Physical Geography and Ecosystem Science**

Supervisor:
Helena Eriksson
Department of Physical Geography and Ecosystem Science
Lund University

Exam committee:
Vaughan Phillips
Department of Physical Geography and Ecosystem Science
Lund University

Abstract

Photosynthesis, which describes the uptake of carbon from the atmosphere by vegetation, is key to the natural mitigation of anthropogenic climate change. Its accurate assessment is therefore of vital importance for correct estimates of the global carbon balance and the understanding of global carbon dynamics. This uptake of carbon is referred to as the gross primary productivity (GPP) and can be remotely sensed by utilising models that are based on the concept of light use efficiency (LUE). However, LUE is difficult to derive directly from remote sensing and therefore alternative approaches has been suggested for its derivation. One such approach is the photochemical reflectance index (PRI) which measures the reflectance signal of the photoprotective mechanism of the xanthophyll cycle. Even though the PRI and LUE has been shown to be correlated, no generalised relationship has yet been established and more research needs to be conducted for different species, climates and temporal scales in order for this to be achieved. This report shows that for a birch forest in a sub-arctic climate, PRI does not approximate LUE over diurnal and seasonal time scales. The correlation between PRI and LUE were generally higher over the seasonal time scale compared to the diurnal analysis, which exhibited varying correlations throughout the season. The majority of these correlations were not significant ($p<0.05$), suggesting that PRI cannot be considered as a proxy for LUE in these environments. This contradicts the few studies conducted for other deciduous forests in sub-arctic climates and the research field of PRI as a whole. Therefore, it is likely that it is the design of the study that gives rise to these results and not that the relationship between PRI and LUE does not hold true. The findings of this study therefore comply with and contribute to the body of evidence that suggest that PRI is a sensitive index, highly influenced by external factors.

Sammanfattning

Fotosyntes, vilket beskriver upptaget av koldioxid från atmosfären av vegetationen, är nyckeln till den naturliga förmildringen av den antropogena klimatförändringen. Dess korrekta skattning är därför av avgörande betydelse för korrekta bedömningar av den globala kolbalansen och förståelsen av det globala kolets kretslopp. Detta upptag av kol kallas bruttoprimärproduktionen (Gross Primary Productivity; GPP) och kan fjärranalyseras genom att utnyttja modeller som är baserade på konceptet av fotosyntetisk effektivitet (Light Use Efficiency; LUE). Det är dock svårt att härleda LUE direkt från fjärranalys och därför har alternativa metoder föreslagits för dess härledning. Ett sådant tillvägagångssätt är det fotokemiska reflexions indexet (Photochemical Reflectance Index; PRI), som mäter reflexionen av den ljusskyddande mekanismen xantofyll cykeln. Trots att PRI och LUE har visat sig vara korrelerade, har inget allmänt samband ännu fastställts och mer forskning måste genomföras för olika arter, klimat och tidsskalor för att detta skall kunna uppnås. Denna rapport visar att för en björkskog i ett subarktiskt klimat, approximerar inte PRI LUE över de dagliga eller säsongsmässiga tidsskalorna. Korrelationen mellan PRI och LUE var i allmänhet högre för den säsongsmässiga tidsskalan jämfört med dygnsanalysen, som uppvisade varierande korrelationer under hela säsongen. Majoriteten av dessa korrelationer var inte signifikant ($p<0,05$), vilket tyder på att PRI inte kan betraktas som ett substitut för LUE i dessa miljöer. Detta motsäger de få studier som genomförts för andra lövskogar i subarktiska klimat och forskningsområdet om PRI som helhet. Därför är det troligt att det är utformningen av denna studie som ger upphov till dessa resultat och inte att förhållandet mellan PRI och LUE inte överensstämmer. Resultaten av denna studie bidrar därför till den mängd bevis som tyder på att PRI är ett känsligt index som i hög grad påverkas av yttre faktorer.

Table of contents

List of abbreviations

APAR	Absorbed Photosynthetically Active Radiation by vegetation
EC	Eddy Covariance
fAPAR	fraction of Absorbed Photosynthetically Active Radiation by vegetation
GPP	Gross Primary Productivity
LUE	Light Use Efficiency
NDVI	Normalised Difference Vegetation Index
NEE	Net Ecosystem Exchange
PAR	Photosynthetically Active Radiation
PRI	Photochemical Reflectance Index

1.Introduction

There has been a large focus on the global carbon cycle, both publically and scientifically, since the recognition of anthropogenic climate change (Ciais et al. 2013). There is a large interest in the realistic quantification of each pool and flux of this cycle in order to evaluate the current and future state of the carbon balance in an accurate fashion. Of particular interest is the vegetation's role in carbon cycling since primary producers naturally mitigate atmospheric CO_2 levels through the process of photosynthesis. This uptake of carbon between vegetation and atmosphere is termed the gross primary productivity (GPP).

As a result of this process, approximately 50% of anthropogenic CO_2 emissions released into the atmosphere have been taken up by oceanic and terrestrial ecosystems for the last 50 years (Ballantyne et al. 2012). In particular, the temperate and sub-arctic terrestrial biomes have potentially acted as significant carbon sinks (Goodale et al. 2002; Pan et al. 2011). This exemplifies the importance of vegetation in the global carbon cycle and thus further highlights the need to estimate the global GPP more accurately.

There are several methods for the estimation of GPP. Ground observations are commonly obtained through the use of the eddy covariance (EC) technique (Baldocchi 2003) where GPP is partitioned from the sampled net ecosystem exchange (NEE) (Reichstein et al. 2005). NEE is the balanced measure of carbon uptake and carbon loss in the form of plant respiration for an ecosystem (Schlesinger and Bernhardt 2013). Even though measurements are point based, the EC technique encompasses similar spatial scales to satellite imagery (~1 km^2) (Turner et al. 2003; Eklundh et al. 2011). But to establish new EC towers is expensive (Eklundh et al. 2011) and gives rise to errors when performed over heterogeneous surfaces (Baldocchi 2003). As a result of all these factors, the EC technique lacks the spatial coverage needed for global GPP estimates. Therefore, modelling methods exist which utilize remote sensing to overcome these limitations.

Several models can be applied through the use of remote sensing to fulfil the limitations of estimating GPP from EC towers (Landsberg and Sands 2011b). Most of these models are alterations of the light use efficiency model (Monteith 1972, 1977), which describes GPP as the product of the absorbed light by vegetation (APAR) and an efficiency factor termed LUE. This factor describes how much of the absorbed light that is used for photosynthesis and therefore the stress constraints limiting the assimilation of carbon (Goerner et al. 2011). This model has been proven effective in uniform vegetation with stable (laboratory) conditions (Russell et al. 1989). However, these settings are rarely found in nature and the specific LUE for a given location is therefore difficult to derive with remote sensing (Hilker et al. 2008b). Consequently, there is a need for an alternative method to derive a value for the constraints limiting the efficiency of carbon assimilation.

One such approach has been suggested to overcome the limitation of deriving LUE with remote sensing. This approach is referred to as the photochemical reflectance index (PRI) (Gamon et al. 1992). This index makes use of the reflectance signal of the specific photoprotective mechanism termed the xanthophyll cycle which is initiated when the plant experience stress from excessive light conditions (Demmig-Adams 1990). PRI has been shown to correlate with LUE (Garbulsky et al. 2011) since they both describe the stress factors limiting the efficiency of carbon assimilation. The value of PRI is therefore thought to be interchangeable with the LUE parameter in Monteith's GPP model, thus removing the need to remotely sense the LUE directly.

However, there is still debate within the literature regarding PRI's suitability as a substitute for LUE since PRI has been shown to be sensitive to external influences (Barton and North 2001). As stated by Zhang et al. (2015) "It is still a challenge to derive a generalized relationship between LUE and PRI", which means that PRI cannot yet be applied with confidence at a wider scale. In order to achieve this, more research needs to be conducted regarding PRI and LUE for different species, climates and temporal scales (Busch et al. 2009; Zhang et al. 2015) to expand the current knowledge of its functioning and variability.

Even though this is currently being done through the expanding interest in the research field of PRI (Garbulsky et al. 2011), the PRI for many biomes and its temporal variability have not yet been researched. Particularly little research has been done in sub-arctic environments. The few studies that exist for this climate have mainly focused on coniferous forests (Nichol et al. 2000; Hilker et al. 2011; Porcar-Castell et al. 2012; Gamon et al. 2015; Wong and Gamon 2015b, a) and only a few include deciduous stands (Nichol et al. 2000; Drolet et al. 2005; Hilker et al. 2011; Gamon et al. 2015). Thus, a limited number of deciduous tree species in sub-arctic environments have as to date been researched. Therefore, there is a need to conduct further research in these environments in order to assess the wider applicability of PRI.

1.1. Aim

The aim of this study is to evaluate the ability of PRI to approximate LUE of a sub-arctic birch forest (*Betula pubescens*) at canopy scale. This relationship will be analysed over both seasonal and diurnal time scales.

2. Background

This section will briefly develop the theoretical background governing the concepts that were presented in the Introduction. First is a description of LUE, its application in GPP modelling and its limitations. Second is a description of PRI, why it is considered to be an appropriate substitute to LUE and what factors affect its application.

2.1. Light Use Efficiency (LUE)

As mentioned previously, LUE describes the efficiency of photosynthesis, i.e. how much of the light that is absorbed by the vegetation that is used for photosynthesis (Monteith 1972). This efficiency is governed by abiotic stress factors, which is determined by the access to water, nutrients and sufficient lighting (Landsberg and Sands 2011a). These factors are hard to separate into their individual components as they often act simultaneously. LUE overcomes this by aggregating all of these stresses into a single parameter (Goerner et al. 2011).

Initially, the LUE was considered constant since plants and vegetation had been shown to grow proportionally to the light absorbed by the canopy (Monteith 1972, 1977). However, this relationship only holds true for uniform stands during vegetation growth and ideal environmental conditions (Russell et al. 1989), which rarely exists in reality. Consequently, the LUE has been observed to vary between biomes, days and seasons (Turner et al. 2003), which complicates its derivation. Therefore, a single value of LUE cannot be attributed to a specific species or environment.

It was Monteith (1972, 1977) that first proposed the concept of LUE in his light use efficiency model of GPP. Here, the LUE is combined with the incoming light, also known as photosynthetically active radiation (PAR), and the fraction of PAR that is absorbed by vegetation (fAPAR). PAR includes the visible light between 400 and 700 nanometres and fAPAR is considered as stable and not affected by stress factors. The model is denoted as follows:

$$GPP = PAR \cdot fAPAR \cdot LUE \qquad \text{Equation (1)}$$

where GPP is the gross primary productivity (μmol m^{-2} s^{-1})
PAR is the photosynthetically active radiation (μmol m^{-2} s^{-1})
fAPAR is the fraction of absorbed PAR (μmol m^{-2} s^{-1})
LUE is the light use efficiency

A direct measure of GPP from remote sensing is problematic since only two of the three model components can be directly estimated with remote sensing. These components are the fAPAR, which has been highly correlated with the normalised difference vegetation index (NDVI) (Rouse et al. 1974; Running et al. 2000; Rossini et al. 2012), and the PAR which can be estimated through satellite measurements (see Hilker et al. (2008b) for a good summary). As of yet, the third component LUE is difficult to derive solely from remote sensing (Hilker et al. 2008b) due to the complex factors governing LUE and their variability.

Modern remote sensing variations of Monteith's GPP model attempt to incorporate the LUE variation by basing the LUE on a biome specific theoretical maximum LUE. This factor is then downscaled by the air temperature and vapour pressure deficit (Running et al. 1999) to simulate the abiotic stresses. The need to know the specific theoretical maximums for a given biome means that the method needs some predefined variables which are not remotely sensed and still based on experimentation (Running et al. 2000). Such models are still too simplistic to sufficiently quantify the LUE, which gives rise to errors in the estimation of GPP (He et al. 2013; Zhang et al. 2015). Therefore, there is an interest to investigate the use of PRI as an estimate of LUE.

2.2. Photochemical Reflectance Index (PRI)

When a plant absorbs more light than can be utilised for photosynthesis, the redundant light can cause damage to the plant (Demmig-Adams and Adams 1992). Several photoprotective mechanisms operate simultaneously during these conditions in order to protect the plant from photoinhibition (Kyle et al. 1987). One of these photoprotective mechanisms is the dissipation of excessive PAR through the xanthophyll cycle, where the pigment violaxanthin is de-epoxied by the excessive PAR into the pigment zeaxanthin through the pigment antheraxanthin (Demmig-Adams 1990). The process is reversed during limiting light conditions (see Figure 1). This cycling of pigments can be remotely sensed through the use of PRI (Gamon et al. 1992) since the concentration of zeaxanthin generates a reflectance signal centred around 531 nanometres. This reflectance is normalised by a reference wavelength that is not affected by the reflectance signal of the xanthophyll cycle in order for the index to measure the level of light stress.

$$PRI = \frac{\rho_{531} - \rho_{ref}}{\rho_{531} + \rho_{ref}} \qquad \text{Equation (2)}$$

where PRI is the photochemical reflectance index
ρ_{531} is the reflectance at wavelength 531 (%)
ρ_{ref} is the reflectance of the reference wavelength (%)

The index ranges between -1 and 1, with values decreasing with excessive sunlight (Peñuelas et al. 1995). The reference wavelength is typically centred at 570 nanometres but there is a debate regarding the optimal reference wavelength since good results have been obtained at wavelengths of 550 nanometres too (Gamon et al. 1992). Also, if PRI should be derived from satellites other reference wavelengths has to be investigated since contemporary satellites are not equipped with instruments that measure at the original wavelengths of PRI (Drolet et al. 2005; Drolet et al. 2008).

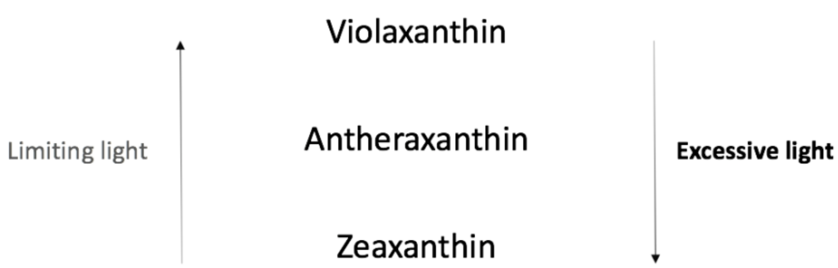

Figure 1. *A scheme of pigment concentrations in the xanthophyll cycle depending different light regimes. Modified from Demmig-Adams (1990).*

Excessive light conditions not only occur with increasing incoming light but can be caused during stable light conditions through the increased occurrence of other abiotic stresses, e.g. water or nutrient limitation, which limits the plant’s ability to photosynthesise (Demmig-

Adams 1990). It is on this basis that the xanthophyll cycle, through the use of PRI, is assumed to be a useful proxy for the LUE. Based upon the assumption that fAPAR in the LUE model remains constant and is only affected by the varying LUE.

2.2.1. Causes of spectral variability

Just as for other spectral indexes related to vegetation, the reflectance PRI measures are influenced by a number of factors. These are mainly related to the physical properties and constituents of vegetation but atmospheric conditions and instrumentation also impact the observed reflectance.

2.2.1.1. Vegetation

When it comes to the vegetation itself, it is mainly the canopy structure and density that contributes to the uncertainties of PRI. Intra canopy dynamics such as leaf orientation (Barton and North 2001; Drolet et al. 2008; Suárez et al. 2008; Gamon et al. 2015), leaf shadowing, occurrence of sun- and dark adapted leaves (Méthy 2000; Barton and North 2001; Stylinski et al. 2002; Hall et al. 2008), and the visibility of soil and branches from above (Méthy 2000; Stylinski et al. 2002; Suárez et al. 2008), all contribute to the variation in reflectance used for estimating PRI.

It has also been demonstrated that the factors controlling the PRI signal is altered temporally. Over shorter time scales, i.e. days, PRI is controlled by changes in the xanthophyll cycle (Gamon et al. 1992; Gamon et al. 2015). On seasonal time scales however, PRI is instead controlled by changes to the concentrations of chlorophyll and carotenoid (Stylinski et al. 2002; Fréchette et al. 2015; Gamon et al. 2015; Wong and Gamon 2015b, a). These two controls on PRI has been termed the facultative and constitutive PRI response, where the facultative PRI is controlled by the xanthophyll cycle and the constitutive PRI is controlled by changing pigment pool concentrations (Gamon and Berry 2012).

2.2.1.2. Atmospheric conditions

Atmospheric conditions influence PRI as these conditions both affect the physical state of the vegetation and the composition of the atmosphere through which the reflection travels at the point of measurement. The physical state of vegetation is mainly driven by meteorology and will be discussed first while the atmospheric composition will be discussed later.

During extreme meteorological events that causes stress upon the vegetation, the relationship between the xanthophyll cycle and PRI can be decoupled. This has been observed both in a coniferous forest undergoing stress induced by cold temperatures (Wong and Gamon 2015b) and for sunflower crops experiencing drought (Peñuelas et al. 1994). This decoupling due to meteorological events can therefore introduce uncertainty or outliers in the PRI measurements when analysed over longer time periods.

When it comes to the composition of the atmosphere, PRI has been shown to be highly sensitive to atmospheric scattering in the form of Rayleigh scattering (Barton and North 2001). Thus, when sampling PRI from a satellite, atmospheric corrections has to be performed (Barton and North 2001). When sampling at ground level, the cloud cover has been seen to affect the PRI signal as overcast conditions reduces the PAR. It has been observed that the PRI fluctuates more with increasingly clear sky conditions (Hilker et al. 2008a) and stronger correlations between PRI and LUE has been observed when no clouds are present (Soudani et al. 2014). However, the exact effects of cloud cover on PRI, or rather the effect of decreasing

PAR, has still not been established. These effects are amplified when sampling is conducted at large solar zenith angles (Barton and North 2001).

2.2.1.3. Instrumentation settings

PRI has been shown to vary significantly depending on the instrumentation used for sampling (Castro-Esau et al. 2006; Harris et al. 2014) since the index is based upon narrow bandwidths (Castro-Esau et al. 2006). Not only the instrument but how it is positioned effects the value of PRI. As stated previously, the solar zenith angle amplify the effects of atmospheric conditions on PRI when larger angles are employed (Barton and North 2001) and this also holds true for larger view angles. This is the result of that larger view angles incorporates a higher proportion of shaded leaves in the reflectance measurement, which affects the PRI negatively (Hilker et al. 2008a). Thus, the use of near-nadir viewing angles would improve the correlation between PRI and LUE (Goerner et al. 2011). The instrumentation and their differing settings are therefore important to take into consideration when comparing results in-between studies.

2.2.2. Alternative ways of calculating PRI

Due to the prosperous future use of PRI in GPP modelling, there is an interest from the scientific community to further develop the PRI equation so that the effects of spectral variability discussed above is reduced. Alternative ways of calculating PRI has therefore been proposed, where only a few will be presented here. To account for differing view and solar zenith angles when sampling, Hilker et al. (2008a) merged the PRI equation with the Bidirectional Reflectance Distribution Function (BRDF) (Nicodemus et al. 1977). The uncertainty arising from different canopy structures can be minimised by calculating the canopy shadow-fraction and multiplying it with the PRI, which enables PRI comparison between biomes (Hall et al. 2008; Hilker et al. 2010). It is also possible to remove the reflectance originating from dark adapted leaves from the value of PRI by subtracting the so called PRI_0 (Hmimina et al. 2014), which is the value at the intercept of PRI and APAR for the dark adapted leaves in a forest stand. Due to time and data limitations, none of these alternative PRI estimations have been included in the analysis of this study.

3. Materials and methods

3.1. Area of study

The data was obtained from Lars Eklundh and Honxiao Jin, Lund University. Sampling was conducted at two sites located close to Abisko, Sweden (Figure 2) over the course of two years, 2010 and 2011. The climate at the study area is classified as sub-arctic and between 1981 and 2010 it experienced a mean annual temperature of -0.14°C and an annual precipitation of 332 mm (ICOS Sweden 2016). The area of study is dominated by birch (*Betula pubescens*) which are on average four meters high and has a density of 1300 trees per hectare (Eklundh et al. 2011). As seen in Figure 2, the two sites of sampling are located adjacent to Lake Torneträsk and are connected by the road E10 which runs between Luleå, Sweden and Narvik, Norway.

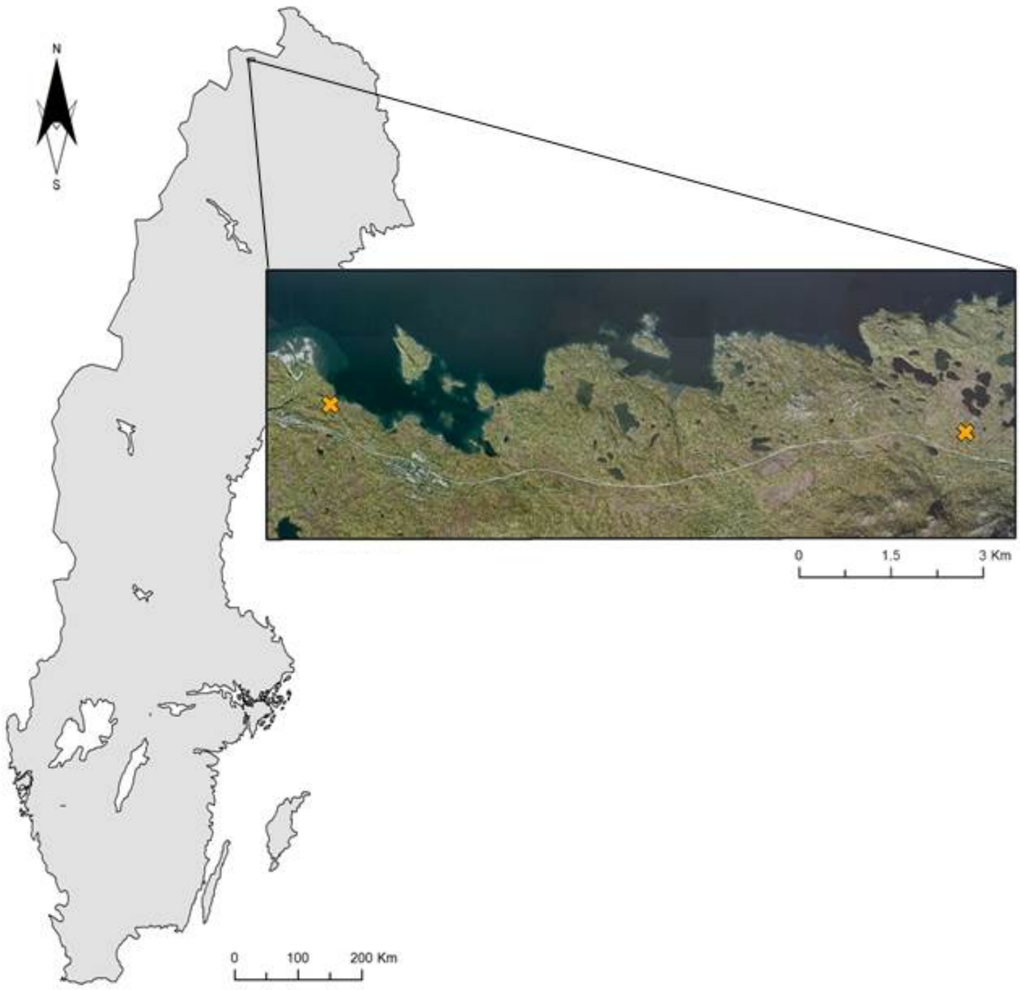

Figure 2. *The location of the study area and the two sampling sites. The cross to the left is the spectral mast and the cross to the right is the EC tower. The map of Sweden is based upon the Swedish municipality borders obtained from Statistiska Centralbyrån (SCB) and the aerial photo of the study site is the "GSD-Ortofoto 1m" © Lantmäteriet.*

3.2. Data

3.2.1. Sampling at the spectral mast

At the western site of sampling (68°21'36"N, 18°48'0"E), a spectral mast is present that is situated at 340 meters above sea level (Eklundh et al. 2011). Spectral sensors are mounted 55° off-nadir on the mast 8 meters above the canopy (Eklundh et al. 2011). The view azimuth angle is 261° and in combination with a field-of-view (FOV) of 60°, the sensors sample an area of 1961 m^2 at canopy level (Eklundh et al. 2011). With a four-channel SKR-1850A spectral sensor, wavelengths centred around 529 and 569 nanometres was sampled every 10 minutes. The reflectance for each wavelength was calculated as follows (Lillesand et al. 2015):

$$\rho_\lambda = \frac{E_R(\lambda)}{E_I(\lambda)} \qquad \text{Equation (3)}$$

where ρ_λ is the reflectance for a specific wavelength (%)
$E_R(\lambda)$ is the reflected energy at the specific wavelength (μmol m^{-2} s^{-1})
$E_I(\lambda)$ is the incident energy at the specific wavelength (μmol m^{-2} s^{-1})

It should be noted that the wavelengths used in this study differ from those originally used by Gamon et al. (1992) due to the properties of the sensor. However, since the reference wavelength centre is within the range (~550 to ~570 nanometres) reported suitable for the estimation of PRI (Gamon et al. 1992), the use of this reference waveband should be sufficient to accurately estimate PRI. Also, the utilised sensor bandwidth of 10 nanometres (Eklundh et al. 2011) is within the required sensor bandwidth range (3-10 nanometres) for PRI estimation (Grace et al. 2007).

At the same sampling site, four additional PAR fluxes were sampled every 10 minutes, but with a JYP-1000 PAR sensor. These PAR fluxes are incoming PAR above the canopy (PAR_0), total reflected PAR ($RPAR_{eco}$), canopy transmitted PAR below the canopy (TPAR) and the ground reflection ($RPAR_g$). These four fluxes were then combined in order to estimate fAPAR. This estimation was done according to the methodology described in Eklundh et al. (2011).

$$fAPAR = \frac{PAR_0 + RPAR_g - TPAR - RPAR_{eco}}{PAR_0} \qquad \text{Equation (4)}$$

3.2.2. Sampling at the EC tower

At the eastern site of sampling (68°20'53"N, 19°02'59"E), an EC flux tower is present that is situated at 397 meters above sea level (Heliasz et al. 2011). This tower is part of the FLUXNET network (Baldocchi et al. 2001) and is located about 10 kilometres east of the spectral mast (see Figure 2). A JYP-1000 PAR sensor and an EC system are here mounted 7.5 meters above the ground (Heliasz et al. 2011), which causes the instrumentation to rise 3.5 meters above the canopy. The incoming PAR was sampled at 30 minute intervals by the JYP-1000 PAR sensor. The NEE was measured by the EC system and the GPP was partitioned from the sampled NEE based on the methodology of Reichstein et al. (2005). The NEE was also sampled in 30-minute intervals. A detailed description of the instrumentation used for the sampling of NEE and PAR can be found in Heliasz et al. (2011).

3.2.3. Calculation of LUE

The light use efficiency was estimated by combining the GPP and PAR sampled at the EC tower and the fAPAR sampled at the spectral mast. LUE was estimated by rearranging Equation 1:

$$LUE = \frac{GPP}{PAR \cdot fAPAR} \qquad \text{Equation (5)}$$

where LUE is the light use efficiency
GPP is the gross primary productivity (μmol m^{-2} s^{-1})
PAR is the photosynthetically active radiation (μmol m^{-2} s^{-1})
fAPAR is the fraction of absorbed PAR (μmol m^{-2} s^{-1})

3.3. Temporal analysis

3.3.1. Seasonal analysis

To enable analysis over the course of a season, data harmonisation was conducted due to the differences in sampling frequency between the different measurements. All variables were averaged between 11:30 and 12:00 for each day since the solar noon fluctuated in-between this time frame throughout both 2010 and 2011 (National Oceanic and Atmospheric Administration). This was done in order to minimise the solar zenith angle and therefore reduce its variation between days since PRI has been shown to be sensitive to varying illumination conditions (Harris et al. 2014).

GPP and PAR was only sampled between May and September during both years, thus limiting the seasonal analysis to this period. Further analysis was performed over a finer temporal resolution based on the period of full leaf growth of the forest. This temporal reduction was based on the period of NDVI stability for the sake of minimising the temporal effects of leaf pigment concentrations during leaf maturity and senescence. This has been done in other studies, e.g. Hmimina et al. (2014) and Soudani et al. (2014), as it is believed to yield better estimates of PRI. When NDVI is stable, the canopy is also assumed stable, thus the changes in PRI should in theory only be attributed to the xanthophyll cycle.

3.3.2. Diurnal analysis

For the diurnal analysis of PRI, five days were chosen for analysis, the 28th of May, the 15th of June, the 24th of July, the 10th of August and the 3rd of September. These days were chosen since they exhibited the highest daily average of PAR for their corresponding month, which would ensure a high PAR and possibly result in better correlations between PRI and LUE (Soudani et al. 2014). The extraction of one day per month were chosen in order to investigate the seasonal variability of the daily correlations. The diurnal data sampled at 10 minute intervals were then averaged over 30 minutes within 6 hours before and after the solar noon, i.e. between 05:30 and 17:50, in order to analyse the data over a 12-hour period, i.e. a day.

3.3.3. Statistical analysis

The same statistical analysis was performed on the daily and seasonal datasets over the course of the two years. Firstly, the correlation (expressed as the correlation coefficient *r*) between the two variables were calculated to see the association between LUE and PRI. Secondly, the significance of this relationship was tested with the following equation (Smith and Smith 2007):

$$F = \frac{(n-2)\cdot r^2}{1-r^2} \qquad \text{Equation (6)}$$

where n is the number of pairs being compared
r is the correlation coefficient

3.4. Estimation of uncertainties

For the entire season of 2010, a local sensitivity analysis was performed for PRI and LUE separately in order to evaluate which input parameters that influence the two model outputs the most. This was also conducted to see if both models were behaving as expected and how the model outputs were generally affected by larger or smaller values in the distribution. Each input parameter to the PRI and LUE models were changed based on the range of one standard deviation from the seasonal sample mean. New PRI and LUE model outputs were then calculated by running through the values of each input parameter one at a time while the other input parameters were kept constant at their mean. This result was evaluated by plotting the new PRI and LUE outputs against the range of values within one standard deviation of each input parameter.

Over the same period of time, i.e. the entire season, a global uncertainty analysis was conducted to evaluate how the uncertainty of the input parameters generally propagate into the uncertainty of the output. For each input parameter, a thousand random values were generated within the range of uncertainty from the parameter's seasonal mean. For the inputs to PRI, i.e. the reflectance at 529 and 569 nanometres, the measurement uncertainty is ±5% (Skye Instruments Ltd). The measurement uncertainty for the inputs to LUE was not available (Eklundh et al. 2011) but was assumed to be ±10%. The randomly generated values were then used simultaneously to calculate new PRI and LUE outputs, which were then plotted against each input parameter to check the correlation between the variables. The input parameters which exhibit high correlations with the output are termed important (Smith and Smith 2007) since their uncertainty is propagated into the uncertainty of the output. A histogram was also produced which shows the possible range and variability of the generated output values when it has an unknown error within the given range in precision of the instrument. If the input parameter had no uncertainty the output value would be a single number. Since the uncertainty analysis was based on the mean of each input parameters, its results should only be seen as an indicator of the uncertainty of PRI and LUE. If absolute results should be obtained, this analysis should be performed for the specific measurement of interest.

3.5. Evaluation of the study design

In order to evaluate and justify the use of data from two different locations, the only data that was sampled at both locations were plotted against each other. This was the PAR sampled at the EC tower and the PAR_0, which was sampled at the spectral mast and used as an input for the estimation of fAPAR (Equation 4). The data was plotted over the five days used in the diurnal analysis to see the variation over a short time scale. Paired t-tests were also performed in order to see if the PAR measurements came from the same population.

4. Results

4.1. Temporal analysis

4.1.1 Seasonal analysis

The period of NDVI stability, as defined by low variation around the seasonal maximum, occurred between the 6th of July and 24th of August in 2010 and between the 20th June and 29th of August in 2011 (Figure 3). Between these dates, the NDVI reached above the index value of 0.8 and will be referred to as the period of full leaf development from through the rest of the report. As can be seen in the graph, the NDVI is increasing from the beginning of May during both years, starts to decline towards the end of August/beginning of September and then increases slightly again in the middle of September. The pattern for the two years is similar, showing two plateaus, one in May/June and one in July/August. The difference between the two years is that the second plateau occurs earlier in 2011 and expands for a longer period of time, resulting in a longer period of analysis in 2011.

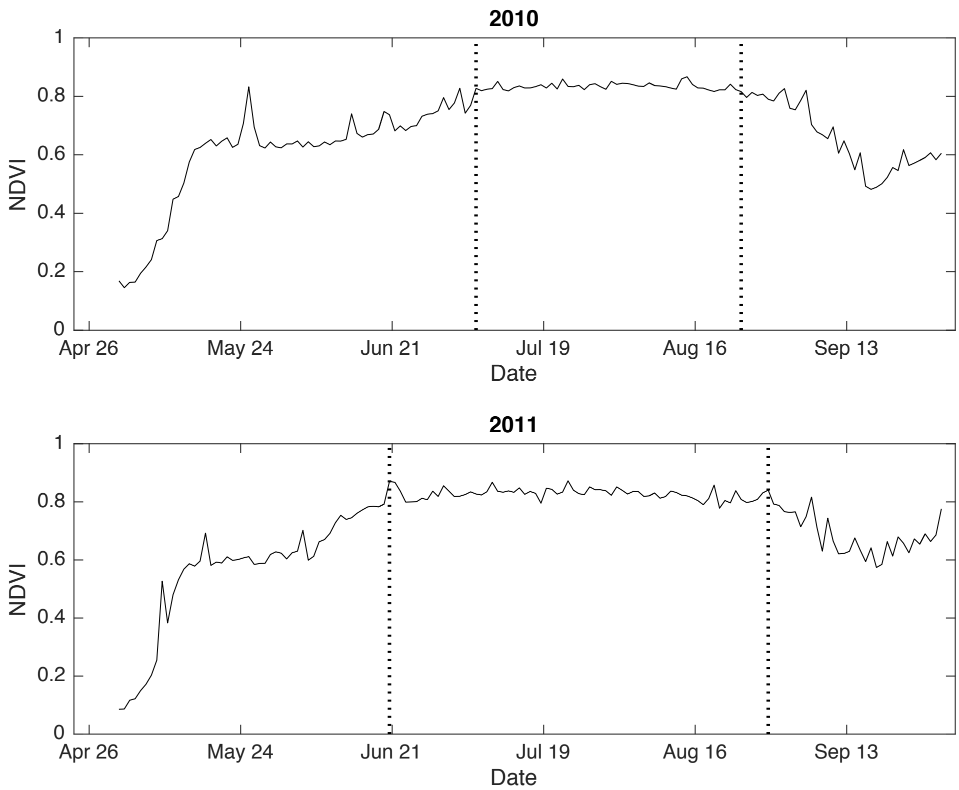

Figure 3. *The seasonal pattern of NDVI during 2010 and 2011. The dotted vertical lines indicate the beginning and end of full leaf development, which is the 6th of July and 24th of August in 2010 and the 20th of June and 29th of August in 2011.*

The temporal variability of PRI and LUE over the two years and different time periods can be seen in Figure 4. PRI is approximately ten times as large as LUE and are both fluctuating in-between days. From the middle to the end of September 2010 (Figure 4a) there is a sudden drop of the PRI, with resulting values of around -0.9. Since this exceeds the range of observed index values prior to the deviation, which had a minimum value of -0.14, the measurements of roughly -0.9 are most likely erroneous and considered as outliers. Therefore, these measurements have been removed from the further analysis.

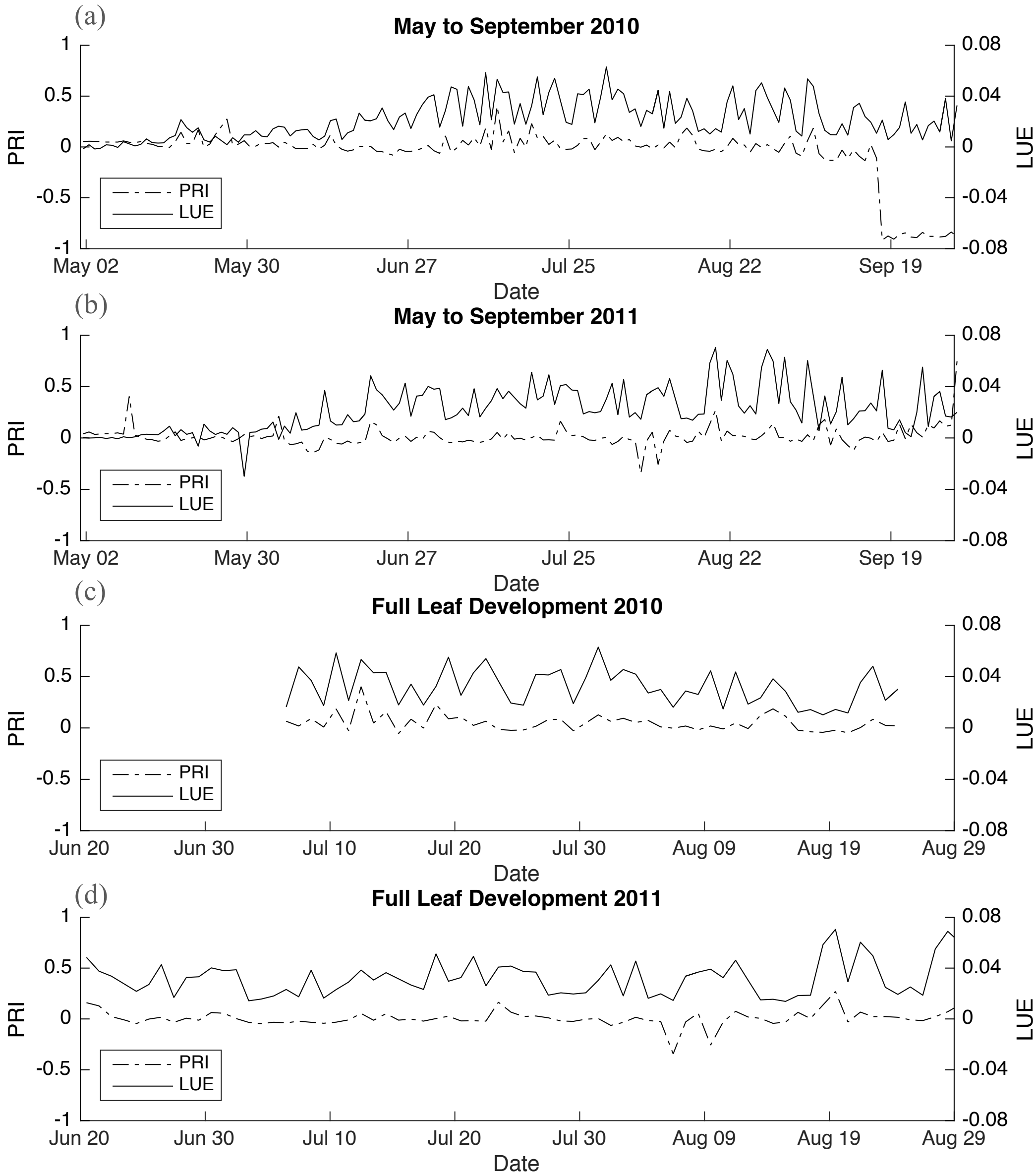

Figure 4. *Time series of PRI and LUE between May and September 2010 (a) and 2011 (b) and during full leaf development in 2010 (c) and 2011 (d).*

As seen in Figure 5a, the correlation between PRI and LUE is twice as large during 2010 (r=0.2990) compared to 2011 (r=0.1310) (Figure 5b). Over the period of full leaf development (Figure 5c, d), the correlation between PRI and LUE is much higher compared to the full season. The correlation between the years is similar where 2010 shows a higher correlation (r=0.5981) compared to 2011 (r=0.5487). However, none of the observed correlations are significant ($p<0.05$) except during May to September 2011 (Figure 5b).

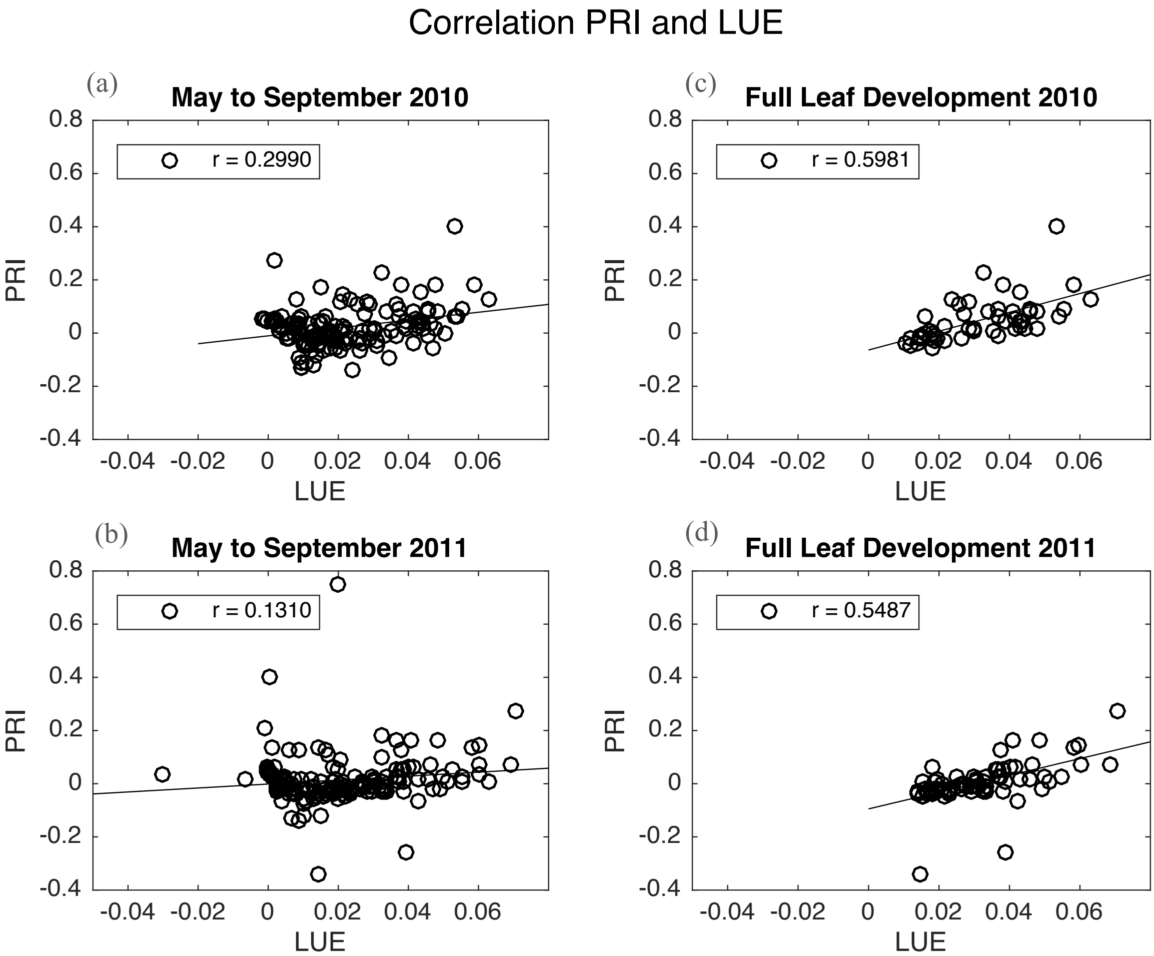

Figure 5. *Correlation of PRI and LUE between May and September 2010 (a) and 2011 (b) and during full leaf development in 2010 (c) and 2011 (d).*

4.1.2. Diurnal analysis

Just as over the seasonal time scale, the LUE and PRI fluctuates over the course of a day (Figure 6). These fluctuations do not follow each other and vary to different extents, hence no clear diurnal pattern of PRI or LUE can be observed. The order of magnitude is the same over the diurnal time scale as for the seasonal time scale, i.e. the PRI manifests values about 10 times larger than LUE. The last record of PRI on the 3rd of September (Figure 6e) is potentially an outlier but has not been removed from the further analysis.

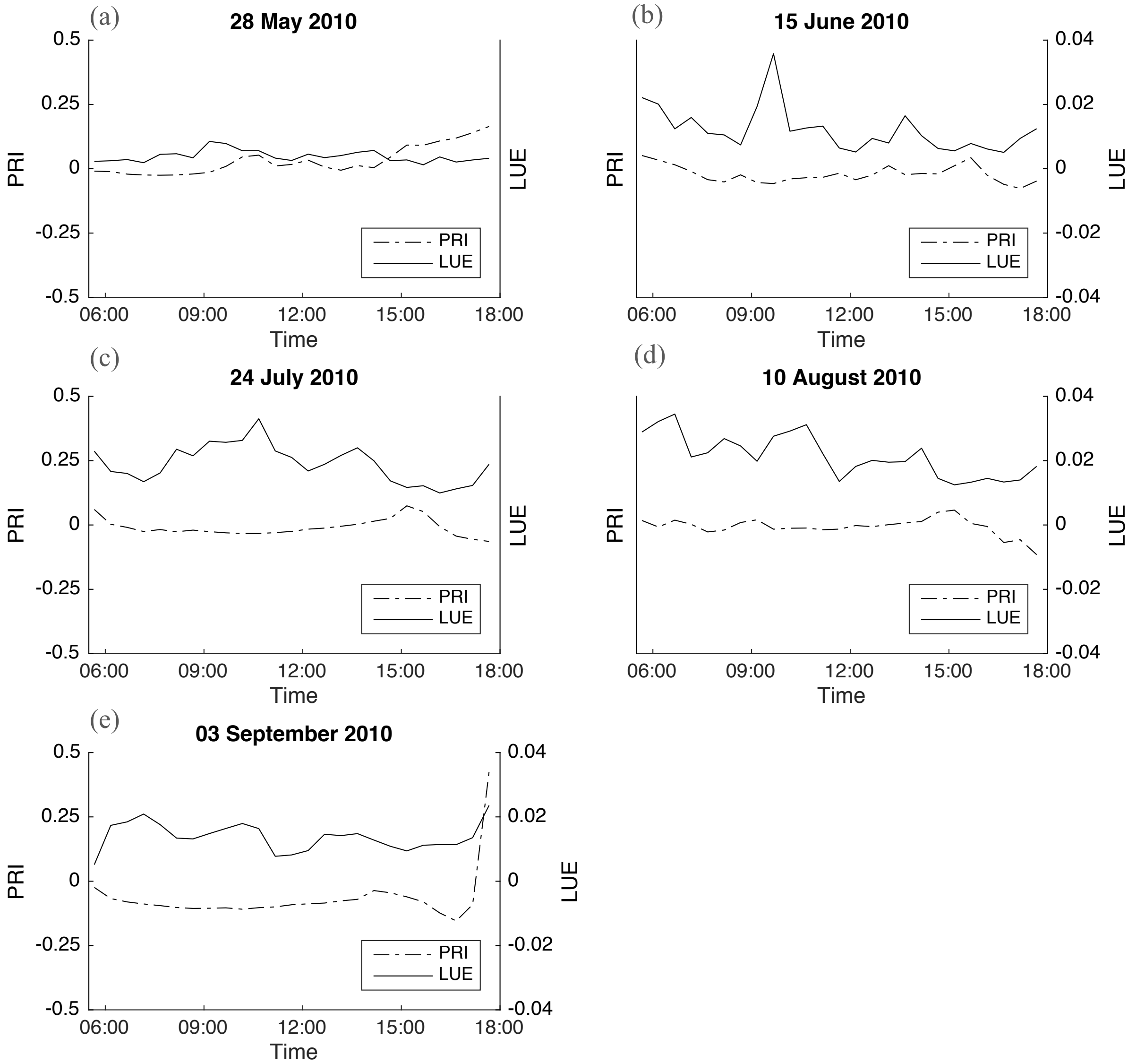

Figure 6. *Diurnal variation of PRI and LUE during the 28th of May (a), 15th of June (b), 24th of July (c), 10th of August (d) and the 3rd of September (e) in 2010.*

The correlation of PRI and LUE over the daily time scale, generates no general relationship (Figure 7). On the 28th of May (Figure 7a) and the 24th of July (Figure 7c) the correlations are negative (r=-0.2765 and r=-0.2492 for May and July respectively) and significant ($p<0.05$). In June (Figure 7b) and August (Figure 7d), the correlation is close to zero (r=0.0229 and r=0.0834 for June and August respectively), i.e. there is no correlation between the variables. These relationships are both significant ($p<0.05$). The day in September (Figure 7e), shows a positive and the strongest correlation between PRI and LUE (r=0.4077) but this relationship is not significant ($p<0.05$).

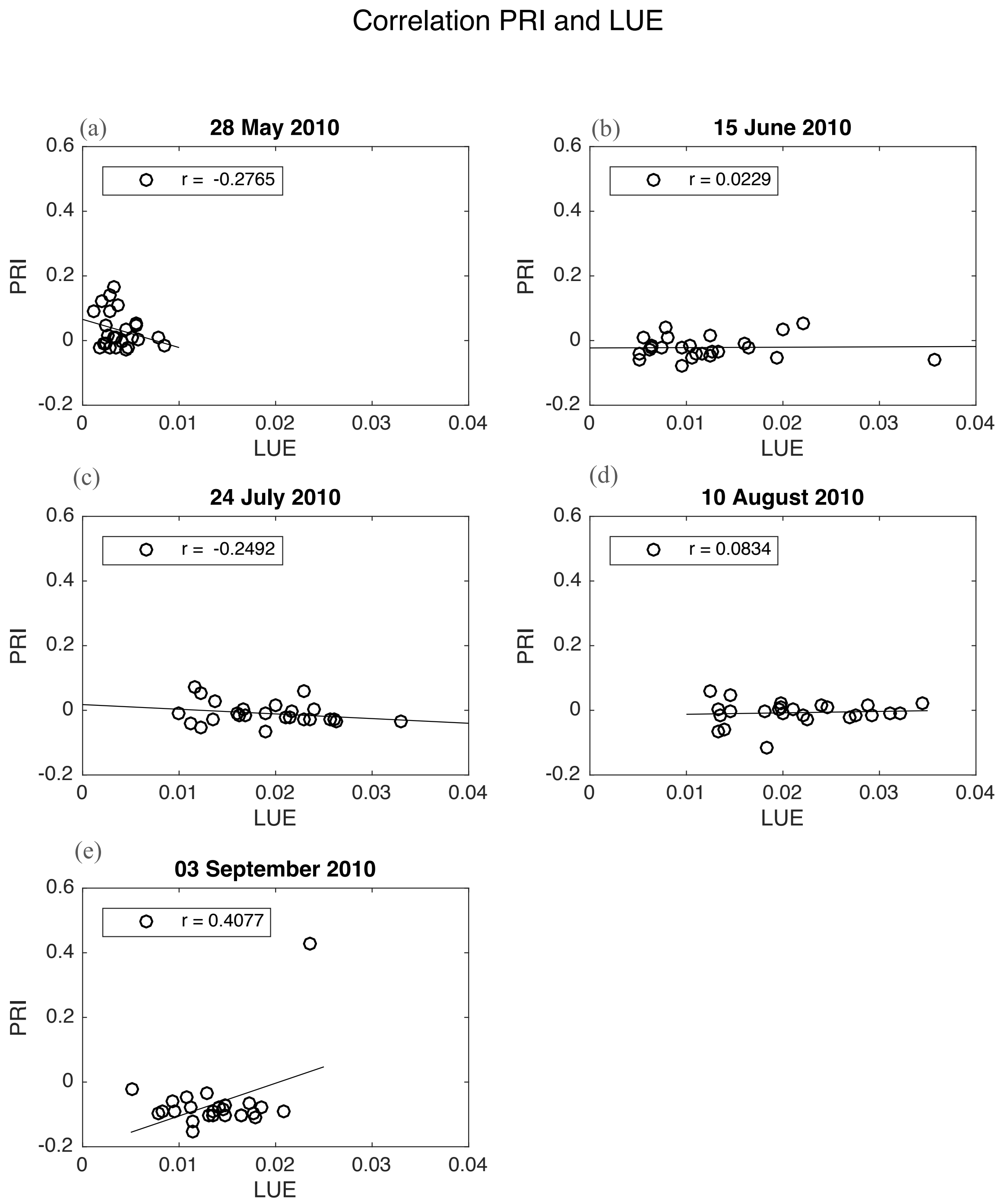

Figure 7. *Diurnal correlation between PRI and LUE during the 28th of May (a), 15th of June (b), 24th of July (c), 10th of August (d) and the 3rd of September (e) in 2010.*

The PAR curves in Figure 8, all follow the typical daily pattern where the PAR increases until noon and then decreases. The PRI is weakly following the inverse of this pattern in the morning and then deviates from being inversed and fluctuates throughout the day. On the 28th of May (Figure 8a) and on the 3rd of September (Figure 8e) the PRI increases again in the evening whereas it decreases on the 15th of June (Figure 8b), the 24th of July (Figure 8c) and on the 10th of August (Figure 8d).

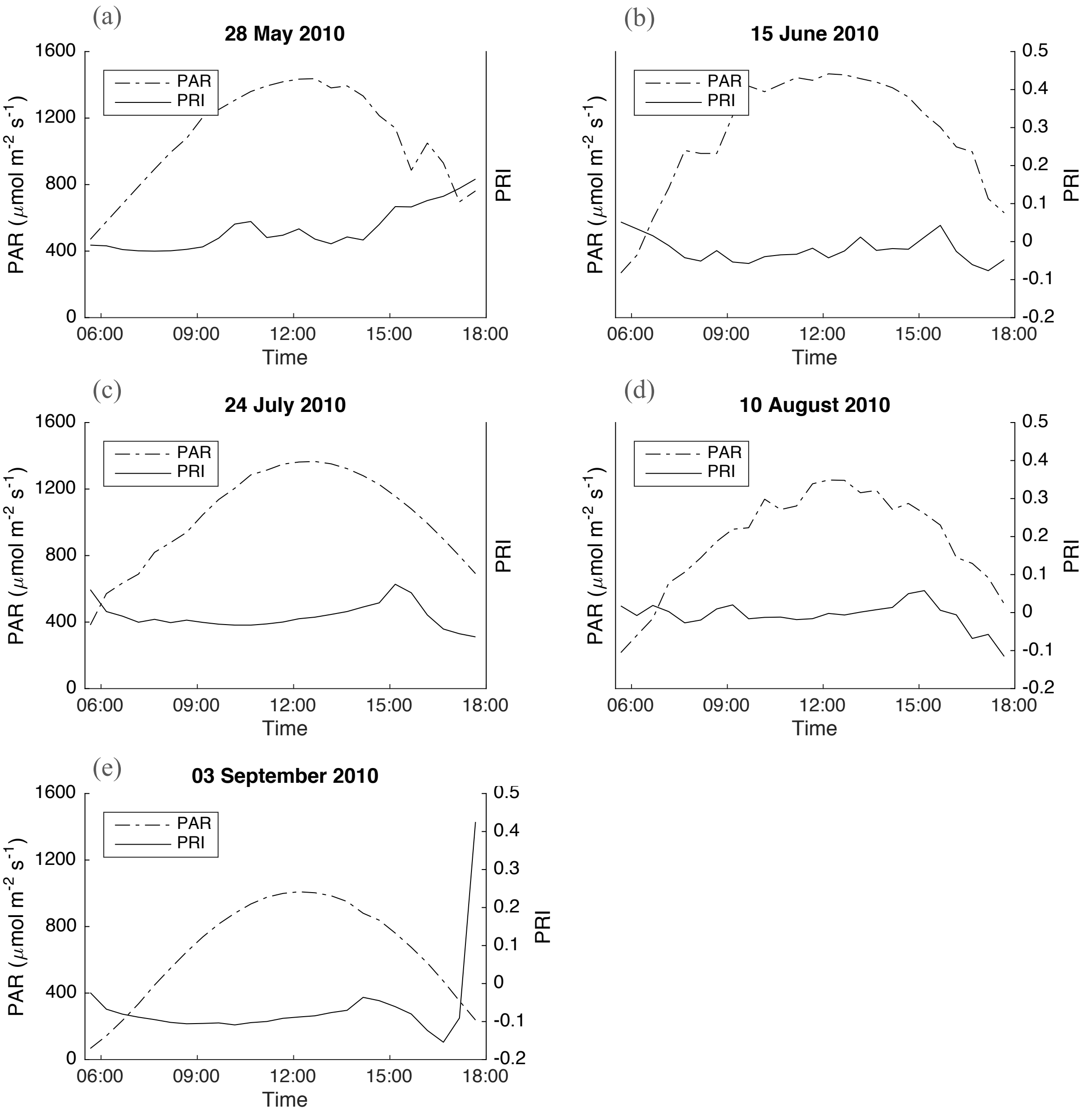

Figure 8. *Diurnal variation of PRI and PAR during the 28th of May (a), 15th of June (b), 24th of July (c), 10th of August (d) and the 3rd of September (e) in 2010.*

4.2. Estimation of uncertainties

In Figure 9a, PRI can be seen to be equally sensitive to the reflectance at 529 and 569 nanometres. When all other input parameters are held constant and the reflectance at 529 nanometres is increased, PRI increases exponentially. The opposite is observed for the reflectance at 569 nanometres. The mirrored relationship of these two curves therefore visualise the normalising behaviour of the PRI equation (Equation 2). When it comes to LUE (Figure 9b), the output is also sensitive to all input parameters but mostly sensitive to the value of GPP due to their linear relationship. Thus, a small change in GPP will give rise to a large change in LUE. The PAR and fAPAR exhibit a similar trend in relation to LUE and when these input parameters increase, the PRI decreases exponentially.

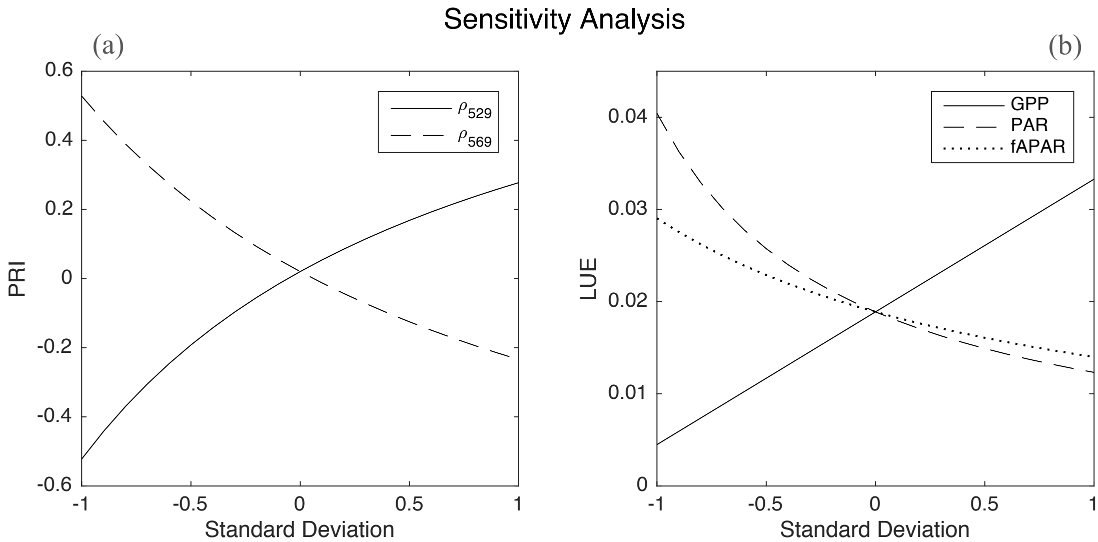

Figure 9. *Sensitivity analysis of PRI (a) and LUE (b) to their respective input parameters.*

The uncertainty analysis of PRI (Figure 10) shows that the input parameters ρ_{529} (Figure 10a) and ρ_{569} (Figure 10b) influence the output to an equal extent due to their similar correlation coefficients (r=0.7075 and r=-0.6902 for ρ_{529} and ρ_{569} respectively). The histogram (Figure 10c) shows that when the model is run with the seasonal means of the input parameters and the error of ±5%, the estimated PRI value could fall anywhere within the range of -0.03 and 0.07, resulting in a variation in PRI of 0.1

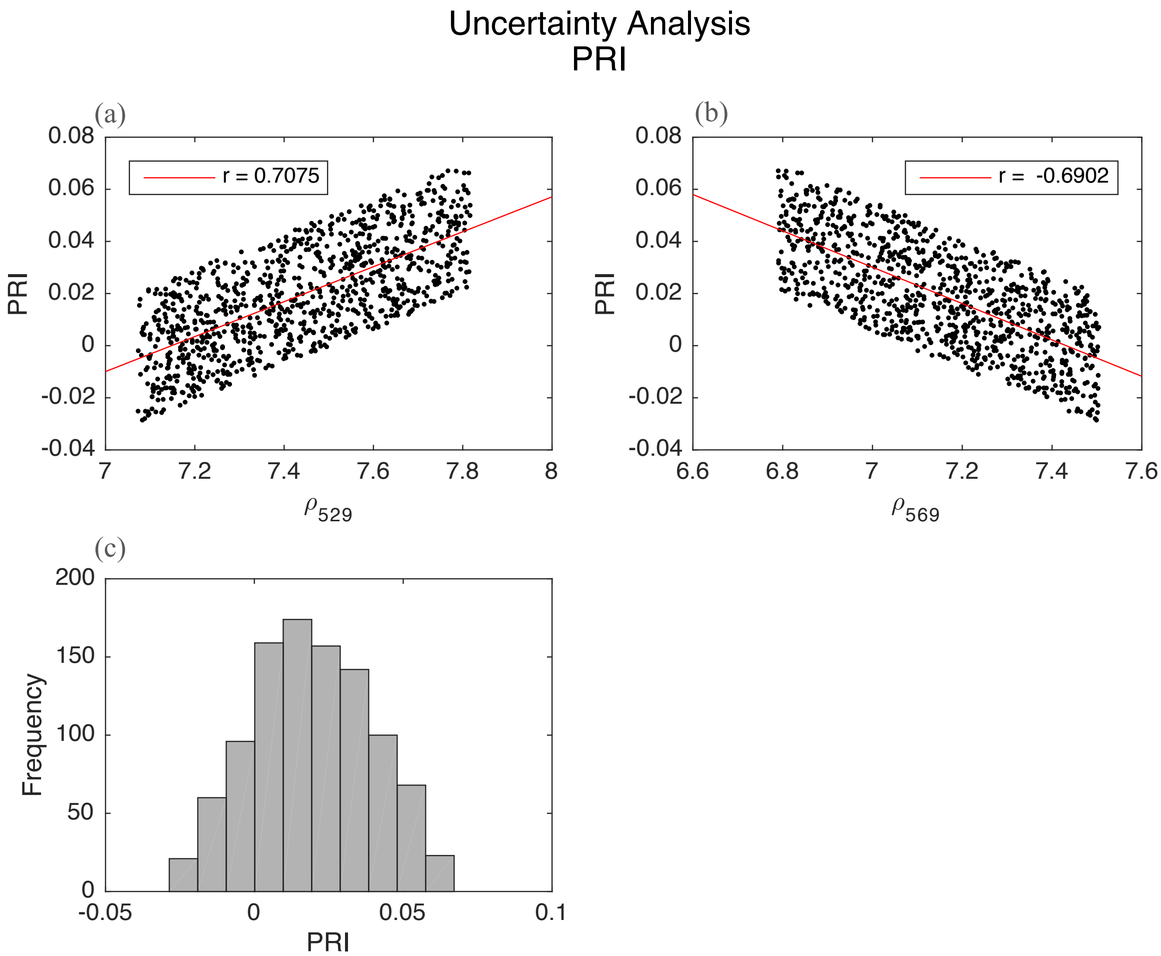

Figure 10. *Uncertainty analysis of PRI and its input parameters ρ_{529} (a) and ρ_{569} (b). The histogram (c) shows the possible range of PRI values based on the randomly generated input parameters within ±5% of the seasonal mean of each input parameter.*

The uncertainty analysis of LUE (Figure 11) also shows that its input parameters equally contribute to the uncertainty in LUE. The correlation (r=0.5987) between LUE and GPP (Figure 11a) is slightly higher compared to the correlation between LUE and PAR (Figure 11b) and LUE and fAPAR (Figure 11c), which exhibits r-values of -0.5596 and -0.5475 respectively. Here, the histogram (Figure 11d) show that when the model is run with the seasonal means of the input parameters and the error of ±10%, the estimated LUE could fall anywhere within the range of 0.015 and 0.025, which results in a variation of 0.01.

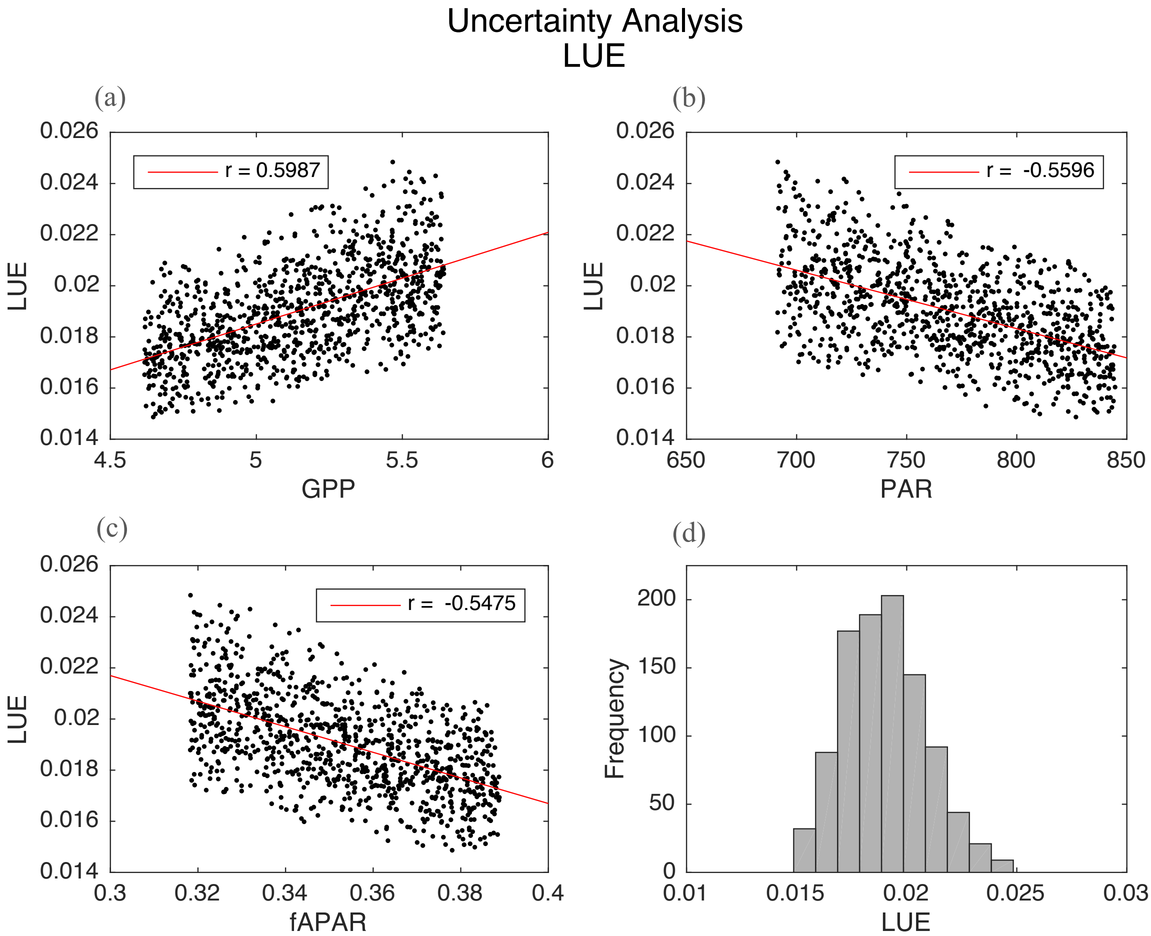

Figure 11. *Uncertainty analysis of LUE and its input parameters GPP (a), PAR (b) and fAPAR (c). The histogram (d) shows the possible range of LUE values based on the randomly generated input parameters within ±10% of the seasonal mean of each input parameter.*

4.3. Evaluation of the study design

When comparing the PAR measurements obtained at the two sampling sites, the values can be seen to differ (Figure 12). The data sampled at the EC tower all show a similar pattern, where the PAR increases until noon, reaching a value between a 1000-1500 μmol m^{-2} s^{-1}, and then decreases. For the data sampled at the spectral mast, this feature is not as clearly visible during all of the days. In July (Figure 12c) and September (Figure 12e) the daily PAR values follow the previous description of the incremental rise and decline. The days in May (Figure 12a), June (Figure 12b) and August (Figure 12d) however, do not. For these days the signal appears noisy since the initial increase is followed by fluctuations during the middle of the day. The PAR measurements obtained in May, July and September significantly differ ($p<0.05$) from each other while the PAR values in June and August do not.

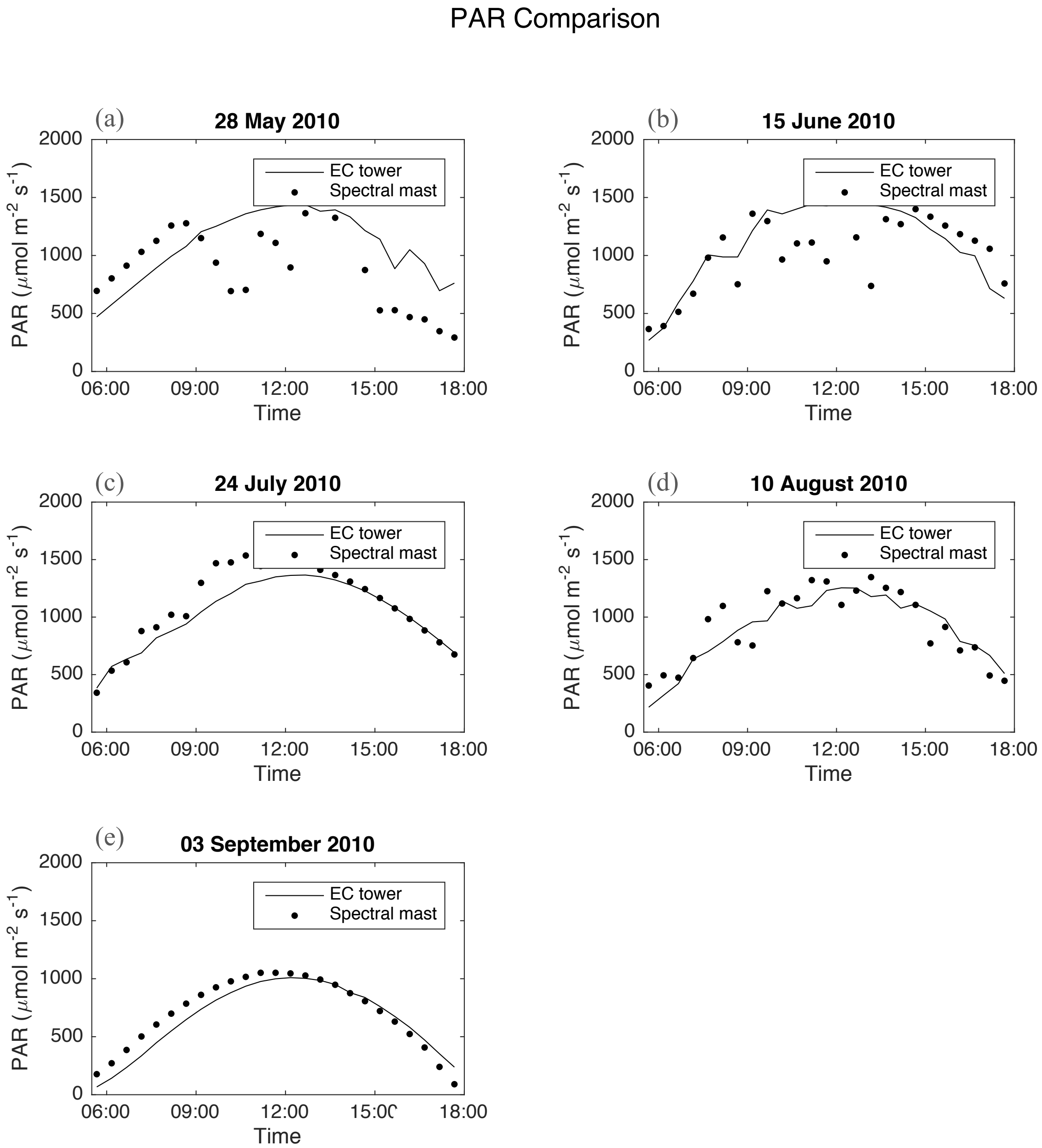

Figure 12. *A comparison of the PAR values measured at the EC tower (solid line) and the spectral mast (dotted line) over the course of the 28th of May (a), 15th of June (b), 24th of July (c), 10th of August (d) and the 3rd of September (e) in 2010.*

5. Discussion

5.1. Temporal analysis

In this study, the analysis over the seasonal and diurnal time scales yield differing results. The seasonal analysis generally yields higher correlations between PRI and LUE compared to the diurnal time scale which exhibits varying correlations throughout the season that are generally low. This is unexpected since PRI was developed for short time scales (Gamon et al. 1990; Gamon et al. 1992) and weaker correlations are typically observed over the seasonal time scale (Garbulsky et al. 2011). The following discussion will try to disentangle these findings by firstly going through the results from the different time scales and then go on to discuss the uncertainties in the measurements. This will then be followed by an evaluation of the construction and design of the study and its future improvements.

5.1.1. Seasonal analysis

Between May and September and the period of full leaf development, both measurements of PRI and LUE appear to be noisy. The correlations during May to September is therefore low, with r-values ranging between 0.1310 (2011) and 0.2990 (2010) (Figure 5a, c). Over the period of full leaf development, the correlation between PRI and LUE are higher compared to the entire season, with r-values ranging between 0.5487 (2011) and 0.5981 (2010) (Figure 5b, d). The correlations at this temporal scale are within the range of observed correlations for PRI and LUE in other studies (Garbulsky et al. 2011).

Due to the large improvement of the relationship between PRI and LUE during the period of full leaf development, the observed low correlation of PRI and LUE between May and September are probably due to noise in the data. This noise is probably originating from the exposure of soil and branches (Méthy 2000; Suárez et al. 2008) during the phase of leaf growth in the beginning of the growing season and the peculiar PRI behaviour of senescent leaves towards the end of the growing season (Nakaji et al. 2006), which both influence the measured reflectance used in the estimation of PRI.

The noisy data for May to September could also stem from the presence of snow, which a number of authors have found to negatively affect the vegetation index NDVI (Gamon et al. 2006; Bradley et al. 2007). Since PRI is a spectral vegetation index just like NDVI, it could be assumed that the same effects can be observed for PRI. The negative effect is a result of the spectral distribution of snow, which differs from vegetation or soil (Wang et al. 2015) and thus alters the measured reflectance. At least in 2010, snow was still present when the analysis commenced since the end of snow melting occurred on the 10^{th} of May (Eklundh et al. 2011). It is thus highly likely that snow affected the PRI signal when sampling begun during both years even though no data is available of the date of snow melting in 2011, which would affect the correlation with LUE negatively.

The majority of the observed correlations between PRI and LUE on the seasonal scale (Figure 5), both between May to September and during full leaf development, are not significant. This suggests that the use of PRI as a proxy of LUE over the seasonal scale fails and consequently the findings of this study cannot be applied on other forests in similar climates.

5.1.2. Diurnal analysis

Over the diurnal time scale, PRI and LUE exhibit low correlations during the majority of the days (Figure 7). The diurnal correlations vary in-between the days through the season which is to be expected since several studies have observed this variation in seasonal PRI and LUE correlations (Nakaji et al. 2006; Soudani et al. 2014; Zhang et al. 2015). The negative correlations observed in May and July (Figure 7a, c) are peculiar and unexpected but could be the result of rain as discussed in the study by Zhang et al. (2015). When GPP is sampled with an open path EC system as in this study, the wetting of the sensor causes the accuracy of the measured flux to decrease (Leuning and Judd 1996). This therefore affects the estimated LUE value and consequently also the correlation between PRI and LUE. Additionally, the accumulation of rain on leaves during rain events will affect the leaves' reflectance signal (Zhang et al. 2015), which in turn influence the PRI signal and its correlation to LUE. The diurnal correlations of PRI and LUE are likely to be more sensitive to the rain since it includes fewer observations, which would explain why the negative relationships only can be observed over the diurnal time scale. Since no precipitation data was sampled, the effects of rain on the measurements cannot be verified.

Due to the nature of the xanthophyll cycle, PRI is inversely related to PAR since the index decreases with excessive sunlight (Peñuelas et al. 1995). In this study, the diurnal variability of PRI does not show as clear inverse relationships to PAR (Figure 8) as in other studies (e.g. Louis et al. (2005) and Merlier et al. (2015)). Either, this indicates that the incoming light never became excessive at the area of study or the PAR/PRI relationship is concealed due to the definition of a day in the study (05:30-18:00). If all the hours between sunrise and sunset would have been included in the diurnal analysis, the inverse pattern might have revealed itself and been more clear.

On the diurnal time scale, the only significant correlations between PRI and LUE were obtained during the days with the lowest correlations (Figure 7a, b, c, d). The PRI does therefore not seem to be a suitable proxy of LUE over the diurnal time scale, which contradicts the previous research conducted within the field (Grace et al. 2007). This either means that the theoretical concept of PRI as a proxy for LUE does not hold true or that there are errors in the measurements used in this study which gives rise to the observed results.

5.1.3. Comparison with other studies

In general, it is a difficult task to compare the results of PRI and LUE between different studies. Not only does the species composition and climate need to correspond but the spatial and temporal resolution as well as the instrumentation settings also need to be similar. Since no other studies have been conducted for birch forests in sub-arctic climates, no direct comparison is possible for the results in this study. Only two other studies for deciduous forests in sub-arctic climates have been found that can be used as some sort of reference. Unsurprisingly, they obtained significantly different results compared to the ones in this study. In the first study, Nichol et al. (2000) observed a significant correlation between PRI and LUE of 0.78 for an aspen stand in Saskatchewan, Canada. The temperature at the time of sampling was similar to the daily temperatures in this study but the PAR was higher. For the same aspen stand, Hilker et al. (2010) found a correlation between PRI and LUE of 0.88 when sampling between June and November. Even though a direct comparison with these studies are impossible as stated previously, the much higher observed correlations of PRI and LUE in these studies compared to this one indicate that the design of this study has led to unexpected results, not that the correlation between PRI and LUE does not hold true.

5.2. Estimation of uncertainties

Only a few values in this study were clear outliers and subsequently removed from the analysis (Figure 4a). A much greater number of values are potential outliers but were not removed since they did not exhibit as clear deviations as the removed outliers. Some examples of the more uncertain outliers are the two most negative PRI values during the beginning of August in 2011 (Figure 4d and Figure 5d) and the last PRI value during the 3rd of September (Figure 6e). If these values were to be removed, the analysis could potentially have been improved and yielded more clear and strong results.

The results show that PRI is equally sensitive to its input parameters, the reflectance at 529 nanometres and the reflectance at 569 nanometres (Figure 9a). When the input parameters are altered by a function of their standard deviation, both show a mirrored exponential relationship. This mirrored relationship and the equal sensitivity is not unexpected as this demonstrates the normalising behaviour of the PRI equation.

The uncertainty analysis of PRI based on the seasonal mean of all of the input parameters plus or minus the stated uncertainty of 5%, shows that the uncertainty in both inputs propagates equally (approximately r=0.7) into the output value of PRI (Figure 10). With high correlations in both parameters they can be considered as important. Again, this is unsurprising as the PRI equation is equally sensitive to both input parameters and the uncertainty is the same in both. For this specific example, the PRI values ranges between -0.03 and 0.07 (Figure 10c). This result gives some indication of the variability of a given PRI estimate.

For the LUE equation, it would appear that the resulting LUE value is most sensitive to GPP as seen by the steep linear trend in Figure 9b. This trend is visible through the whole range of values within plus/minus one standard deviation. PAR and fAPAR are approximately equally sensitive with one another at plus one standard deviation. However, in the lower values this similarity separates and PAR becomes the most sensitive parameter, i.e. a small change in PAR will result in a large change in LUE at minus one standard deviation.

For the uncertainty in LUE (Figure 11), where the seasonal mean of each input parameter is attributed an error of ±10%, the expected result is found. As each of the inputs has the same uncertainty, the uncertainty in the output is related to how the model is sensitive to its input parameters. As GPP was the most sensitive parameter, most of the uncertainty in the LUE value can be attributed to it (r=0.5987). Therefore, each of the remaining input parameters propagates less uncertainty in the value of LUE with r-value of -0.5596 and -0.5475 for PAR and fAPAR respectively. The strength of this correlation is relatively high and thus all of the inputs can be considered important. As a result, in this particular case the maximum and minimum value of LUE are 0.015 and 0.025 (Figure 11d).

Based on these findings from the sensitivity and uncertainty analysis for these test scenarios, the approximate error or uncertainty in a given LUE or PRI value can be found. This error estimate could be useful when trying to compare or correlate the LUE and PRI values as it gives a range of values in which one should try to be within. Although this is a generalised estimate, it gives an indication of which input parameters contribute mostly to the uncertainty based upon the equations and highlights key areas where more precise input values should be sought after. This indication shows that there is a potentially large variation or uncertainty in the LUE values which may contribute to the reduced correlation with PRI. There are fewer inputs to the PRI equation which are also more precisely known, suggesting that the uncertainty in the PRI output is not as likely to effect the correlation with LUE.

5.3. Evaluation of the study design

As stated previously, the weak and insignificant correlations between PRI and LUE obtained in this study most likely stems from the utilised sampling strategy. The following section will therefore go through the potential flaws of this strategy and what needs to change in order to obtain more robust results, which evaluate the relationship between PRI and LUE that are not a consequence of noise.

As mentioned in the Background, PRI varies depending on which instrumentation that is used. A study conducted by Harris et al. (2014) found that the SKY1800 sensor (which is similar to the SKY1850A sensor used in this study) performs badly at tracking the diurnal variations of the xanthophyll cycle. This sensor was concluded to be better at tracking the seasonal variability of PRI which could explain the observed higher correlations between PRI and LUE over the seasonal scale as found in this study. Thus, if the correlations between PRI and LUE should be improved over the diurnal time scale, other types of instrumentation have to be utilised when sampling.

It is also possible that the bandwidth used in this study, 10 nanometres, is too large. Grace et al. (2007) states in their study that the required bandwidth when sampling the reflectance for the estimation of PRI lies between 3-10 nanometres as mentioned in the Materials and methods. However, Nichol et al. (2000) find in their study that even though a bandwidth of 10 nanometres is sufficient to use when sampling PRI, it does introduce significant scatter in the data. Thus, if more accurate estimates of PRI should be obtained in the future, the sampling at smaller bandwidths should be investigated and applied if possible.

It is likely that it is the large view angle utilised in this study (55° off-nadir) that gives rise to the low diurnal correlation between PRI and LUE. When sampling off-nadir, a higher proportion of dark adapted leaves are included in the reflectance measurement (Hilker et al. 2008a). Since dark adapted leaves are more susceptible to excessive light, they will alter the PRI signal when they are included in the measurement. Since the diurnal values were obtained during varied illuminations hitting the canopy at different angles as compared to the seasonal values which was sampled around solar noon, more errors were probably introduced in the diurnal measurements as a larger portion of dark adapted leaves were included. This could therefore explain the low correlations observed between PRI and LUE at the diurnal time scale and a smaller view angle should be employed if these results should be improved.

In order to correct for the varying solar angles over the diurnal time scale as discussed in the previous paragraph, a BRDF-model can be integrated into the PRI estimate as suggested by Hilker et al. (2008a). When doing so the authors improved their observed correlation of PRI and LUE from $r=0.37$ to $r=0.82$. Even though the view angle was held constant throughout the period of sampling in this study, the low diurnal correlation between PRI and LUE suggests that the variation of the solar angle is large enough to introduce errors. The integration of a BRDF-model is therefore advisable and should be applied in future studies.

As seen in the comparison of the PAR measurements sampled at the two different locations, the majority of the PAR measurements differ significantly (Figure 12). During all of the days, the values at least follow similar trends but they are rarely compatible and can therefore not be assumed equal. This is either an effect of that the distance between the two sampling sites is large enough to give rise to differing local meteorological conditions or one of the PAR sensors is not sampling correctly. Regardless, it is highly likely that the way in which the data from the two masts has been used in this study gives rise to errors which cannot be neglected.

Considering the observed difference in the PAR measurements, the estimation of LUE is particularly dubious since the PAR data from both masts is combined in its estimation. Not only is the data originating from the two masts combined in this equation, but the two different PAR measurements are used simultaneously, which might actually be faulty since they do not exhibit the same values. It would have been more correct to use the PAR obtained at the spectral mast in the estimation of LUE rather than from the EC tower. This does not however remove the errors that exists as a result of the data being used from two locations since the GPP still would be included. In order to remove this error, GPP has to be sampled at the same location as the spectral measurements.

As discussed in this section, there is a number of factors that can have affected the observed results. Since no quantification of these errors have been done, it is not possible to pin point which of these factors that has had the largest impact on the measurements. What can be said is that the fundamental assumption of the study, i.e. that the data from the two sampling sites are equal, does not seem to hold true. Since the way in which the data has been combined and compared influences the results regardless of its quality, the assumption of equality should be regarded as the most serious flaw of this study.

5.4. Further improvements of the study

As stated above, it is likely that the relationship between LUE and PRI in this study is a consequence of the study design. The flaws of the current sampling settings therefore need to be improved in order to obtain results that describe this relationship adequately. A good start in doing this would be to implement the suggested improvements to the study design as presented in the previous section.

Possible improvements can also be achieved by changing the way in which some of the data was handled before analysis. For example, the data used for the seasonal analysis was extracted and averaged within the temporal range of the annual fluctuations of the solar noon. For future improvements, the extracted data should be linked to the specific solar noon for each individual day. This would help to further minimise the solar zenith angle and reduce its variation between the days and thus also reduce the errors introduced from it.

Similarly, the true diurnal variation could have been analysed if data had been available on each day’s sunrise and sunset. The values for the diurnal analysis could then have been extracted based on these times and analysed over the entire course of a day rather than during a 12-hour period. By including more values, the diurnal patterns of PRI, LUE and PAR might have been more clear and the correlations might have been more robust.

Figure 5c, which displays the correlation between PRI and LUE during May to September 2011, show that there are a number of values included in the analysis which are widely spread, i.e. that the data is noisy. From this figure it is difficult to attribute the deviations to the correct variable and to a specific point in time and thus removing them as outliers. Instead, it could have been a good idea to smooth the data by performing a moving average. The smoothed output could then have been used as the input to the analysis in order to improve the relationship between PRI and LUE. Another method of doing this could have been by only conducting the analysis on cloud free days as done by Drolet et al. (2005).

6. Conclusion

The ability of PRI to approximate LUE, was in this study found to differ depending on the scope of the temporal analysis. The seasonal analysis generally yielded higher correlations between PRI and LUE compared to the diurnal analysis, which varied throughout the season. The majority of these correlations were not significant which suggests that PRI cannot be considered as a proxy for LUE in these environments. Since, this contradicts the few studies conducted for other deciduous forests in sub-arctic climates and the research field of PRI as a whole, it is likely that the it is the design of this study that gives rise to these results and not that the relationship between PRI and LUE does not hold true. The insignificant low correlations of PRI and LUE are probably a result of the utilised instrumentation, its positioning in relation to nadir, the sampled bandwidth, the lack of correction for differing solar angles during the diurnal analysis and the interchangeable usage of data from two locations. The latter should be considered the largest flaw of this study since the fundamental assumption of data equality between the two sampling sites were proven not to be true. The findings of this study therefore contribute to the body of evidence that suggest that PRI is a sensitive index, highly influenced by external factors.

References

Baldocchi, D., E. Falge, L. Gu, R. Olson, D. Hollinger, S. Running, P. Anthoni, C. Bernhofer, et al. 2001. FLUXNET: A New Tool to Study the Temporal and Spatial Variability of Ecosystem–Scale Carbon Dioxide, Water Vapor, and Energy Flux Densities. *Bulletin of the American Meteorological Society,* 82**:** 2415-2434. DOI: doi:10.1175/1520-0477(2001)082<2415:FANTTS>2.3.CO;2

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**:** 479-492. DOI: 10.1046/j.1365-2486.2003.00629.x

Ballantyne, A. P., C. B. Alden, J. B. Miller, P. P. Tans, and J. W. C. White. 2012. Increase in observed net carbon dioxide uptake by land and oceans during the past 50 years. *Nature,* 488**:** 70-72.

Barton, C. V. M., and P. R. J. North. 2001. Remote sensing of canopy light use efficiency using the photochemical reflectance index: Model and sensitivity analysis. *Remote Sensing of Environment,* 78**:** 264-273. DOI: 10.1016/S0034-4257(01)00224-3

Bradley, B. A., R. W. Jacob, J. F. Hermance, and J. F. Mustard. 2007. A curve fitting procedure to derive inter-annual phenologies from time series of noisy satellite NDVI data. *Remote Sensing of Environment,* 106**:** 137-145. DOI: 10.1016/j.rse.2006.08.002

Busch, F., N. P. A. Hüner, and I. Ensminger. 2009. Biochemical constrains limit the potential of the photochemical reflectance index as a predictor of effective quantum efficiency of photosynthesis during the winter spring transition in Jack pine seedlings. *Functional Plant Biology,* 36**:** 1016-1026. DOI: 10.1071/FP08043

Castro-Esau, K. L., G. A. Sánchez-Azofeifa, and B. Rivard. 2006. Comparison of spectral indices obtained using multiple spectroradiometers. *Remote Sensing of Environment,* 103**:** 276-288. DOI: 10.1016/j.rse.2005.01.019

Ciais, P., C. Sabine, G. Bala, L. Bopp, V. Brovkin, J. Canadell, A. Chhabra, R. DeFries, et al. 2013. Carbon and Other Biogeochemical Cycles. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,* eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley, 465–570. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Demmig-Adams, B. 1990. Carotenoids and photoprotection in plants: A role for the xanthophyll zeaxanthin. *Biochimica et Biophysica Acta (BBA) - Bioenergetics,* 1020**:** 1-24. DOI: 10.1016/0005-2728(90)90088-L

Demmig-Adams, B., and W. W. Adams. 1992. Photoprotection and other responses of plants to high light stress. *Annual Review of Plant Physiology and Plant Molecular Biology,* 43**:** 599-626. DOI: 10.1146/annurev.pp.43.060192.003123

Drolet, G. G., K. F. Huemmrich, F. G. Hall, E. M. Middleton, T. A. Black, A. G. Barr, and H. A. Margolis. 2005. A MODIS-derived photochemical reflectance index to detect inter-annual variations in the photosynthetic light-use efficiency of a boreal deciduous forest. *Remote Sensing of Environment,* 98**:** 212-224. DOI: 10.1016/j.rse.2005.07.006

Drolet, G. G., E. M. Middleton, K. F. Huemmrich, F. G. Hall, B. D. Amiro, A. G. Barr, T. A. Black, J. H. McCaughey, et al. 2008. Regional mapping of gross light-use efficiency using MODIS spectral indices. *Remote Sensing of Environment,* 112**:** 3064-3078. DOI: 10.1016/j.rse.2008.03.002

Eklundh, L., H. Jin, P. Schubert, R. Guzinski, and M. Heliasz. 2011. An optical sensor network for vegetation phenology monitoring and satellite data calibration. *Sensors (Basel),* 11**:** 7678-7709. DOI: 10.3390/s110807678

Fréchette, E., C. Y. S. Wong, L. V. Junker, C. Y.-Y. Chang, and I. Ensminger. 2015. Zeaxanthin-independent energy quenching and alternative electron sinks cause a decoupling of the relationship between the photochemical reflectance index (PRI) and photosynthesis in an evergreen conifer during spring. *Journal of Experimental Botany,* 66**:** 7309-7323. DOI: 10.1093/jxb/erv427

Gamon, J. A., and J. A. Berry. 2012. Facultative and constitutive pigment effects on the Photochemical Reflectance Index (PRI) in sun and shade conifer needles. *Israel Journal of Plant Sciences,* 60**:** 85-95. DOI: 10.1560/ijps.60.1-2.85

Gamon, J. A., Y. Cheng, H. Claudio, L. MacKinney, and D. A. Sims. 2006. A mobile tram system for systematic sampling of ecosystem optical properties. *Remote Sensing of Environment,* 103**:** 246-254. DOI: 10.1016/j.rse.2006.04.006

Gamon, J. A., C. B. Field, W. Bilger, O. Björkman, A. L. Fredeen, and J. Peñuelas. 1990. Remote sensing of the xanthophyll cycle and chlorophyll fluorescence in sunflower leaves and canopies. *Oecologia,* 85**:** 1-7. DOI: 10.1007/bf00317336

Gamon, J. A., O. Kovalchuck, C. Y. S. Wong, A. Harris, and S. R. Garrity. 2015. Monitoring seasonal and diurnal changes in photosynthetic pigments with automated PRI and NDVI sensors. *Biogeosciences,* 12**:** 4149-4159. DOI: 10.5194/bg-12-4149-2015

Gamon, J. A., J. Peñuelas, and C. B. Field. 1992. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. *Remote Sensing of Environment,* 41**:** 35-44. DOI: 10.1016/0034-4257(92)90059-S

Garbulsky, M. F., J. Peñuelas, J. Gamon, Y. Inoue, and I. Filella. 2011. The photochemical reflectance index (PRI) and the remote sensing of leaf, canopy and ecosystem radiation use efficienciesA review and meta-analysis. *Remote Sensing of Environment,* 115**:** 281-297. DOI: 10.1016/j.rse.2010.08.023

Goerner, A., M. Reichstein, E. Tomelleri, N. Hanan, S. Rambal, D. Papale, D. Dragoni, and C. Schmullius. 2011. Remote sensing of ecosystem light use efficiency with MODIS-based PRI. *Biogeosciences,* 8**:** 189-202. DOI: 10.5194/bg-8-189-2011

Goodale, C. L., M. J. Apps, R. A. Birdsey, C. B. Field, L. S. Heath, R. A. Houghton, J. C. Jenkins, G. H. Kohlmaier, et al. 2002. Forest carbon sinks in the Northern hemisphere. *Ecological Applications,* 12**:** 891-899. DOI: 10.1890/1051-0761(2002)012[0891:FCSITN]2.0.CO;2

Grace, J., C. Nichol, M. Disney, P. Lewis, T. Quaife, and P. Bowyer. 2007. Can we measure terrestrial photosynthesis from space directly, using spectral reflectance and fluorescence? *Global Change Biology,* 13**:** 1484-1497. DOI: 10.1111/j.1365-2486.2007.01352.x

Hall, F. G., T. Hilker, N. C. Coops, A. Lyapustin, K. F. Huemmrich, E. Middleton, H. Margolis, G. Drolet, et al. 2008. Multi-angle remote sensing of forest light use efficiency by observing PRI variation with canopy shadow fraction. *Remote Sensing of Environment,* 112**:** 3201-3211. DOI: 10.1016/j.rse.2008.03.015

Harris, A., J. A. Gamon, G. Z. Pastorello, and C. Y. S. Wong. 2014. Retrieval of the photochemical reflectance index for assessing xanthophyll cycle activity: a comparison of near-surface optical sensors. *Biogeosciences,* 11**:** 6277-6292. DOI: 10.5194/bg-11-6277-2014

He, M., W. Ju, Y. Zhou, J. Chen, H. He, S. Wang, H. Wang, D. Guan, et al. 2013. Development of a two-leaf light use efficiency model for improving the calculation of terrestrial gross primary productivity. *Agricultural and Forest Meteorology,* 173**:** 28-39. DOI: 10.1016/j.agrformet.2013.01.003

Heliasz, M., T. Johansson, A. Lindroth, M. Mölder, M. Mastepanov, T. Friborg, T. V. Callaghan, and T. R. Christensen. 2011. Quantification of C uptake in subarctic birch

forest after setback by an extreme insect outbreak, Auxiliary Material. *Geophysical Research Letters,* 38**:** L01704. DOI: 10.1029/2010GL044733
Hilker, T., N. C. Coops, F. G. Hall, T. A. Black, M. A. Wulder, Z. Nesic, and P. Krishnan. 2008a. Separating physiologically and directionally induced changes in PRI using BRDF models. *Remote Sensing of Environment,* 112**:** 2777-2788. DOI: 10.1016/j.rse.2008.01.011
Hilker, T., N. C. Coops, M. A. Wulder, T. A. Black, and R. D. Guy. 2008b. 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**:** 411-423. DOI: 10.1016/j.scitotenv.2007.11.007
Hilker, T., A. Gitelson, N. C. Coops, F. G. Hall, and T. A. Black. 2011. Tracking plant physiological properties from multi-angular tower-based remote sensing. *Oecologia,* 165**:** 865-876. DOI: 10.1007/s00442-010-1901-0
Hilker, T., F. G. Hall, N. C. Coops, A. Lyapustin, Y. Wang, Z. Nesic, N. Grant, T. A. Black, et al. 2010. Remote sensing of photosynthetic light-use efficiency across two forested biomes: Spatial scaling. *Remote Sensing of Environment,* 114**:** 2863-2874. DOI: 10.1016/j.rse.2010.07.004
Hmimina, G., E. Dufrêne, and K. Soudani. 2014. Relationship between photochemical reflectance index and leaf ecophysiological and biochemical parameters under two different water statuses: towards a rapid and efficient correction method using real-time measurements. *Plant, Cell & Environment,* 37**:** 473-487. DOI: 10.1111/pce.12171
ICOS Sweden. 2016. Abisko-Stordalen. Retrieved 17 May 2016, from http://www.icos-sweden.se/station_stordalen.html.
Kyle, D. J., C. B. Osmond, and C. J. Arntzen. 1987. Photoinhibition. In *Topics in Photosynthesis,* ed. J. Barber, 315. Amsterdam: Elsevier Science Publisher B. V.
Landsberg, J., and P. Sands. 2011a. Chapter 3 - Physiological Processes. In *Terrestrial Ecology*, 49-79. Elsevier.
Landsberg, J., and P. Sands. 2011b. Chapter 8 - Modelling Tree Growth: Concepts and Review. In *Terrestrial Ecology*, 221-240. Elsevier.
Leuning, R. A. Y., and M. J. Judd. 1996. The relative merits of open- and closed-path analysers for measurement of eddy fluxes. *Global Change Biology,* 2**:** 241-253. DOI: 10.1111/j.1365-2486.1996.tb00076.x
Lillesand, T., R. W. Kiefer, and J. Chipman. 2015. *Remote Sensing and Image Interpretation*. Wiley.
Louis, J., A. Ounis, J.-M. Ducruet, S. Evain, T. Laurila, T. Thum, M. Aurela, G. Wingsle, et al. 2005. Remote sensing of sunlight-induced chlorophyll fluorescence and reflectance of Scots pine in the boreal forest during spring recovery. *Remote Sensing of Environment,* 96**:** 37-48. DOI: 10.1016/j.rse.2005.01.013
Merlier, E., G. Hmimina, E. Dufrêne, and K. Soudani. 2015. Explaining the variability of the photochemical reflectance index (PRI) at the canopy-scale: Disentangling the effects of phenological and physiological changes. *Journal of Photochemistry and Photobiology B: Biology,* 151**:** 161-171. DOI: 10.1016/j.jphotobiol.2015.08.006
Méthy, M. 2000. Analysis of Photosynthetic Activity at the Leaf and Canopy Levels from Reflectance Measurements: A Case Study. *Photosynthetica,* 38**:** 505-512. DOI: 10.1023/a:1012449104831
Monteith, J. L. 1972. Solar Radiation and Productivity in Tropical Ecosystems. *Journal of Applied Ecology,* 9**:** 747-766. DOI: 10.2307/2401901

Monteith, J. L. 1977. Climate and efficiency of crop production in Britain. *Philosophical Transactions of the Royal Society of London Series B-Biological Sciences,* 281**:** 277-294. DOI: 10.1098/rstb.1977.0140

Nakaji, T., H. Oguma, and Y. Fujinuma. 2006. Seasonal changes in the relationship between photochemical reflectance index and photosynthetic light use efficiency of Japanese larch needles. *International Journal of Remote Sensing,* 27**:** 493-509. DOI: 10.1080/01431160500329528

National Oceanic and Atmospheric Administration, E. S. R. L., Global Monitoring Division. NOAA Solar Calculator. Retrieved 15 April 2016, from http://www.esrl.noaa.gov/gmd/grad/solcalc/index.html.

Nichol, C. J., K. F. Huemmrich, T. A. Black, P. G. Jarvis, C. L. Walthall, J. Grace, and F. G. Hall. 2000. Remote sensing of photosynthetic-light-use efficiency of boreal forest. *Agricultural and Forest Meteorology,* 101**:** 131-142. DOI: 10.1016/S0168-1923(99)00167-7

Nicodemus, F. E., J. C. Richmond, J. J. Hsia, I. W. Ginsberg, and T. Limperis. 1977. *Geometrical Considerations and Nomenclature for Reflectance*. Washington D.C., USA: US Department of Commerce, National Bureau of Standards.

Pan, Y., R. A. Birdsey, J. Fang, R. Houghton, P. E. Kauppi, W. A. Kurz, O. L. Phillips, A. Shvidenko, et al. 2011. A Large and Persistent Carbon Sink in the World's Forests. *Science,* 333**:** 988-993. DOI: 10.1126/science.1201609

Peñuelas, J., I. Filella, and J. A. Gamon. 1995. Assessment of photosynthetic radiation-use efficiency with spectral reflectance. *New Phytologist,* 131**:** 291-296. DOI: 10.1111/j.1469-8137.1995.tb03064.x

Peñuelas, J., J. A. Gamon, A. L. Fredeen, J. Merino, and C. B. Field. 1994. Reflectance indices associated with physiological changes in nitrogen- and water-limited sunflower leaves. *Remote Sensing of Environment,* 48**:** 135-146. DOI: 10.1016/0034-4257(94)90136-8

Porcar-Castell, A., J. I. Garcia-Plazaola, C. J. Nichol, P. Kolari, B. Olascoaga, N. Kuusinen, B. Fernandez-Marin, M. Pulkkinen, et al. 2012. Physiology of the seasonal relationship between the photochemical reflectance index and photosynthetic light use efficiency. *Oecologia,* 170**:** 313-323. DOI: 10.1007/s00442-012-2317-9

Reichstein, M., E. Falge, D. Baldocchi, D. Papale, M. Aubinet, P. Berbigier, C. Bernhofer, N. Buchmann, et al. 2005. On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm. *Global Change Biology,* 11**:** 1424-1439. DOI: 10.1111/j.1365-2486.2005.001002.x

Rossini, M., S. Cogliati, M. Meroni, M. Migliavacca, M. Galvagno, L. Busetto, E. Cremonese, T. Julitta, et al. 2012. Remote sensing-based estimation of gross primary production in a subalpine grassland. *Biogeosciences,* 9**:** 2565-2584. DOI: 10.5194/bg-9-2565-2012

Rouse, J. W., R. H. Haas, J. A. Scheel, and D. W. Deering. 1974. Monitoring Vegetation Systems in the Great Plains with ERTS. In *3rd Earth Resource Technology Satellite (ERTS) Symposium,* ed. S. C. Freden, E. P. Mercanti, and M. A. Becker, Washington D. C.: NASA, 48-62.

Running, S. W., R. Nemani, J. M. Glassy, and P. Thornton, 1999. MODIS daily photosynthesis (PSN) and annual net primary production (NPP) product (MOD17). Algorithm Theoretical Basis Document., NASA, Report 59 pp. [in Swedish, English summary]

Running, S. W., P. E. Thornton, R. Nemani, and J. M. Glassy. 2000. Global Terrestrial Gross and Net Primary Productivity from the Earth Observing System. In *Methods in*

Ecosystem Science, eds. O. E. Sala, R. B. Jackson, H. A. Mooney, and R. W. Howarth, 44-57. New York, NY: Springer New York.

Russell, G., P. G. Jarvis, and J. L. Monteith. 1989. Absorption of radiation by canopies and stand growth. In *Plant Canopies: Their Growth, Form and Function,* eds. G. Russell, B. Marshall, and P. G. Jarvis, 21-40. Cambridge: Cambridge University Press.

Schlesinger, W. H., and E. S. Bernhardt. 2013. *Biogeochemistry (Third Edition): An Analysis of Global Change*. Boston: Academic Press.

Skye Instruments Ltd. 2 – Channel Light Sensor. In *Product Manuals*. Llandrindod Wells: Skye Instruments Ltd.

Smith, J., and P. Smith. 2007. *Introduction to Environmental Modelling*. New York: Oxford University Press.

Soudani, K., G. Hmimina, E. Dufrêne, D. Berveiller, N. Delpierre, J. M. Ourcival, S. Rambal, and R. Joffre. 2014. Relationships between photochemical reflectance index and light-use efficiency in deciduous and evergreen broadleaf forests. *Remote Sensing of Environment,* 144**:** 73-84. DOI: 10.1016/j.rse.2014.01.017

Stylinski, C., A. J. Gamon, and W. Oechel. 2002. Seasonal patterns of reflectance indices, carotenoid pigments and photosynthesis of evergreen chaparral species. *Oecologia,* 131**:** 366-374. DOI: 10.1007/s00442-002-0905-9

Suárez, L., P. J. Zarco-Tejada, G. Sepulcre-Cantó, O. Pérez-Priego, J. R. Miller, J. C. Jiménez-Muñoz, and J. Sobrino. 2008. Assessing canopy PRI for water stress detection with diurnal airborne imagery. *Remote Sensing of Environment,* 112**:** 560-575. DOI: 10.1016/j.rse.2007.05.009

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

Wang, X.-Y., J. Wang, Z.-Y. Jiang, H.-Y. Li, and X.-H. Hao. 2015. An Effective Method for Snow-Cover Mapping of Dense Coniferous Forests in the Upper Heihe River Basin Using Landsat Operational Land Imager Data. *Remote Sensing,* 7**:** 17246-17257. DOI: 10.3390/rs71215882

Wong, C. Y. S., and J. A. Gamon. 2015a. The photochemical reflectance index provides an optical indicator of spring photosynthetic activation in evergreen conifers. *New Phytologist,* 206**:** 196-208. DOI: 10.1111/nph.13251

Wong, C. Y. S., and J. A. Gamon. 2015b. Three causes of variation in the photochemical reflectance index (PRI) in evergreen conifers. *New Phytologist,* 206**:** 187-195. DOI: 10.1111/nph.13159

Zhang, Q., W. Ju, J. M. Chen, H. Wang, F. Yang, W. Fan, Q. Huang, T. Zheng, et al. 2015. Ability of the Photochemical Reflectance Index to Track Light Use Efficiency for a Sub-Tropical Planted Coniferous Forest. *Remote Sensing,* 7**:** 16938-16962.

Institutionen för naturgeografi och ekosystemvetenskap, Lunds Universitet.

Student examensarbete (Seminarieuppsatser). Uppsatserna finns tillgängliga på institutionens geobibliotek, Sölvegatan 12, 223 62 LUND. Serien startade 1985. Hela listan och själva uppsatserna är även tillgängliga på LUP student papers (https://lup.lub.lu.se/student-papers/search/) och via Geobiblioteket (www.geobib.lu.se)

The student thesis reports are available at the Geo-Library, Department of Physical Geography and Ecosystem Science, University of Lund, Sölvegatan 12, S-223 62 Lund, Sweden. Report series started 1985. The complete list and electronic versions are also electronic available at the LUP student papers (https://lup.lub.lu.se/student-papers/search/) and through the Geo-library (www.geobib.lu.se)

340 Elisabeth Maria Farrington (2015) The water crisis in Gaborone: Investigating the underlying factors resulting in the 'failure' of the Gaborone Dam, Botswana
341 Annie Forssblad (2015) Utvärdering av miljöersättning för odlingslandskapets värdefulla träd
342 Iris Behrens, Linn Gardell (2015) Water quality in Apac-, Mbale- & Lira district, Uganda - A field study evaluating problems and suitable solutions
343 Linnéa Larsson (2015) Analys av framtida översvämningsrisker i Malmö - En fallstudie av Castellums fastigheter
344 Ida Pettersson (2015) Comparing Ips Typographus and Dendroctonus ponderosas response to climate change with the use of phenology models
345 Frida Ulfves (2015) Classifying and Localizing Areas of Forest at Risk of Storm Damage in Kronoberg County
346 Alexander Nordström (2015) Förslag på dammar och skyddsområde med hjälp av GIS: En studie om löv- och klockgroda i Ystad kommun, Skåne
347 Samanah Seyedi-Shandiz (2015) Automatic Creation of Schematic Maps - A Case Study of the Railway Network at the Swedish Transport Administration
348 Johanna Andersson (2015) Heat Waves and their Impacts on Outdoor Workers – A Case Study in Northern and Eastern Uganda
349 Jimmie Carpman (2015) Spatially varying parameters in observed new particle formation events
350 Mihaela – Mariana Tudoran (2015) Occurrences of insect outbreaks in Sweden in relation to climatic parameters since 1850
351 Maria Gatzouras (2015) Assessment of trampling impact in Icelandic natural areas in experimental plots with focus on image analysis of digital photographs
352 Gustav Wallner (2015) Estimating and evaluating GPP in the Sahel using MSG/SEVIRI and MODIS satellite data
353 Luisa Teixeira (2015) Exploring the relationships between biodiversity and benthic habitat in the Primeiras and Segundas Protected Area, Mozambique
354 Iris Behrens & Linn Gardell (2015) Water quality in Apac-, Mbale- & Lira district, Uganda - A field study evaluating problems and suitable solutions
355 Viktoria Björklund (2015) Water quality in rivers affected by urbanization: A Case Study in Minas Gerais, Brazil
356 Tara Mellquist (2015) Hållbar dagvattenhantering i Stockholms stad - En riskhanteringsanalys med avseende på långsiktig hållbarhet av Stockholms stads dagvattenhantering i urban miljö
357 Jenny Hansson (2015) Trafikrelaterade luftföroreningar vid förskolor – En studie om kvävedioxidhalter vid förskolor i Malmö
358 Laura Reinelt (2015) Modelling vegetation dynamics and carbon fluxes in a high Arctic mire

359 Emelie Linnéa Graham (2015) Atmospheric reactivity of cyclic ethers of relevance to biofuel combustion
360 Filippo Gualla (2015) Sun position and PV panels: a model to determine the best orientation
361 Joakim Lindberg (2015) Locating potential flood areas in an urban environment using remote sensing and GIS, case study Lund, Sweden
362 Georgios-Konstantinos Lagkas (2015) Analysis of NDVI variation and snowmelt around Zackenberg station, Greenland with comparison of ground data and remote sensing.
363 Carlos Arellano (2015) Production and Biodegradability of Dissolved Organic Carbon from Different Litter Sources
364 Sofia Valentin (2015) Do-It-Yourself Helium Balloon Aerial Photography - Developing a method in an agroforestry plantation, Lao PDR
365 Shirin Danehpash (2015) Evaluation of Standards and Techniques for Retrieval of Geospatial Raster Data - A study for the ICOS Carbon Portal
366 Linnea Jonsson (2015) Evaluation of pixel based and object based classification methods for land cover mapping with high spatial resolution satellite imagery, in the Amazonas, Brazil.
367 Johan Westin (2015) Quantification of a continuous-cover forest in Sweden using remote sensing techniques
368 Dahlia Mudzaffar Ali (2015) Quantifying Terrain Factor Using GIS Applications for Real Estate Property Valuation
369 Ulrika Belsing (2015)The survival of moth larvae feeding on different plant species in northern Fennoscandia
370 Isabella Grönfeldt (2015) Snow and sea ice temperature profiles from satellite data and ice mass balance buoys
371 Karolina D. Pantazatou (2015) Issues of Geographic Context Variable Calculation Methods applied at different Geographic Levels in Spatial Historical Demographic Research -A case study over four parishes in Southern Sweden
372 Andreas Dahlbom (2016) The impact of permafrost degradation on methane fluxes - a field study in Abisko
373 Hanna Modin (2016) Higher temperatures increase nutrient availability in the High Arctic, causing elevated competitive pressure and a decline in *Papaver radicatum*
374 Elsa Lindevall (2016) Assessment of the relationship between the Photochemical Reflectance Index and Light Use Efficiency: A study of its seasonal and diurnal variation in a sub-arctic birch forest, Abisko, Sweden