**Dissertationes Forestales 187**

# Estimation of leaf area index and the fraction of absorbed photosynthetically active radiation in a boreal forest

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Academic dissertation

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## ABSTRACT

The aim of this dissertation is to assess the accuracy of different ground reference methods used to validate satellite based leaf area index (LAI) and the fraction of absorbed photosynthetically active radiation (fPAR) products. LAI and fPAR are strongly linked, although they principally and practically measure different properties: LAI quantifies the areal interphase between soil and atmosphere, whereas fPAR quantifies the energy available for photosynthesis. Until now, the development of remote sensing based methods to estimate LAI and fPAR in a boreal forest has been hindered by the scarcity of ground data, which is required to validate and develop existing algorithms. The aim of the first part of this dissertation was to assess the impacts of different methodological approaches to estimate LAI in boreal forests, and to validate satellite based LAI products. Results showed that the accuracy of ground based LAI estimates is sensitive to both the retrieval methods and sampling scheme used to collect the optical LAI data. The satellite based measurements of LAI demonstrated a large temporal variability in LAI. The second part of the dissertation focused on measuring and modeling fPAR in a boreal forest. A new scheme for measuring and modeling ground reference fPAR based on photon recollision probability was presented in this dissertation. Ground reference fPAR is usually estimated only for the forest canopy layer. This study is among the first ones to validate the new global satellite based fPAR product called GEOV1 using data of both the forest canopy and understory layers from boreal forests. Results showed that satellite based fPAR products may correspond better with the total fPAR, instead of only the forest canopy fPAR as has often been presumed.

**Keywords:** LAI, fPAR, global vegetation product, TRAC, LAI-2000, photon recollision probability

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Now it has finally come the time to thank those people who have helped me through the last years, and there are many of them.

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Most importantly, my journey from MSc to PhD was guided by two extremely wise and skillful researchers, Prof. Pauline Stenberg and Dr. Miina Rautiainen to whom I owe my most humble gratitude - I do not have words to thank you enough, and without the endless patience, scientific insight and warm support you provided, this dissertation would certainly not exist.

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Helsinki, February 2015

Titta Majasalmi

## LIST OF ORIGINAL ARTICLES

This thesis is based on the following research articles, which are referred to in the text by their Roman numerals. Articles I-VI are reprinted with the permission of publishers.

I. Majasalmi T., Rautiainen M., Stenberg P., Lukeš P. (2013). An assessment of ground reference methods for estimating LAI of boreal forests. Forest Ecology and Management 292: 10-18. http://dx.doi.org/10.1016/j.foreco.2012.12.017

II. Majasalmi T., Rautiainen M., Stenberg P., Rita H. (2012). Optimizing the sampling scheme for LAI-2000 measurements in a boreal forest. Agricultural and Forest meteorology 154-155: 38-43. http://dx.doi.org/10.1016/j.agrformet.2011.10.002

III. Heiskanen J., Rautiainen M., Stenberg P., Mõttus M., Vesanto V.-H., Korhonen L., Majasalmi T. (2012). Seasonal variation in MODIS LAI for a boreal forest area in Finland. Remote Sensing of Environment 126: 104-115. http://dx.doi.org/10.1016/j.rse.2012.08.001

IV. Rautiainen M., Mõttus M., Heiskanen J., Akujärvi A., Majasalmi T., Stenberg P., (2011). Seasonal reflectance dynamics of common understory types in a northern European boreal forest. Remote Sensing of Environment 115: 3020-3028. http://dx.doi.org/10.1016/j.rse.2011.06.005

V. Majasalmi T., Rautiainen M., Stenberg P. (2014). Modeled and measured fPAR in a boreal forest: Validation and application of a new model. Agricultural and forest meteorology 189-190: 118-124. http://dx.doi.org/10.1016/j.agrformet.2014.01.015
Corrigendum to study V (2015). http://dx.doi.org/10.1016/j.agrformet.2015.01.016

VI. Majasalmi T., Rautiainen M., Stenberg P., Manninen T. (2015). Validation of MODIS and GEOV1 fPAR products in a boreal forest site in Finland. Remote Sensing 7: 1359-1379. http://dx.doi.org/10.3390/rs70201359

### Authors' contributions

Study I: Majasalmi was responsible for the calculations and interpretation of the results and had a leading role in writing the paper. Field data were measured by Rautiainen. R-code for the inversion of the canopy radiation model was written by Lukeš. Study II: Majasalmi developed the measurement design and carried out the field work and data analysis, and had a leading role in writing the paper. Study III: Majasalmi was responsible for measurements and preprocessing of LAI data, commented the manuscript. Study IV: Majasalmi participated in measuring understory spectra, and measured the LAI data. Study V: Majasalmi planned and carried out the field work and data analysis, and had a leading role in writing the paper. Stenberg reformulated an earlier model by Stenberg et al. 2013. Study VI: Majasalmi developed the measurement design, did the canopy transmittance and LAI measurements, was responsible for analysis of the field and satellite data and interpretation of the results, and had a leading role in writing the paper.

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**ABBREVIATIONS AND DEFINITIONS**

LAI = Leaf Area Index, one sided or hemisurface area of the leaves or needles to horizontal ground surface area (Watson 1947; Chen and Black 1992)
fPAR = fraction of Photosynthetically Active Radiation (PAR, 400-700 nm) absorbed by vegetation
ECV = Essential Climate Variable
GCOS = Global Climate Observing Systems
RAMI = Radiative Transfer Model Intercomparison
MODIS = Moderate-resolution Imaging Spectroradiometer satellite by NASA
GEOV1 = Satellite based fPAR product based on SPOT VEGETATION sensor's data
CC = Canopy Cover, vertical cover fraction of forest canopies
NFI = National Forest Inventory
NPP = Net Primary Production
SLA = Specific Leaf Area, ratio of fresh foliage area to dry foliage mass
DHP = Digital Hemispherical Photography
FOV = Field-of-View, defines as the area 'seen' by the optical sensor
TRAC = Tracing Radiation and Architecture of Canopies, optical instrument with a narrow FOV for measuring canopy transmittance and ground surface reflectance
LUE = Light Use Efficiency
APAR = Absorbed PAR
PRI = Photochemical Reflectance Index
VALERI = Validation of Land European Remote Sensing products network
CEOS WGCV = Committee on Earth Observation Satellites Working Group on Calibration and Validation
NDVI = Normalized Difference Vegetation Index
RSR = Reduced Simple Ratio
HYPERION = Medium spatial resolution imaging spectrometer satellite by NASA
Landsat = Medium spatial resolution satellite sensors with multispectral scanners, satellite program by NASA
SPOT = Satellite Pour l'Observation de la Terre, medium spatial resolution satellite mission by the French Space Agency
LUT = Look-Up Table
LAI-2000 = Optical instrument with hemispherical FOV for measuring canopy transmittance and LAI
STAR = Silhouette to Total Area Ratio of a shoot
PAI = Plant Area Index, fraction of plant material within the sensors' FOV
BAI = Branch Area Index, fraction of branch area within the sensors' FOV
ISR = Infrared Simple Ratio
MOD = Satellite data obtained from MODIS TERRA sensor
MYD = Satellite data obtained from MODIS AQUA sensor
MCD = Combined data obtained from TERRA and AQUA sensors
DIFN = Diffuse non-interceptance, fraction of radiation penetrating through gaps in the canopy under isotropic illumination
NIR = Near Infrared
SWIR = Shortwave Infrared
ALS = Airborne Laser Scanning

# 1 BACKGROUND

## 1.1 International significance of LAI and fPAR

Boreal forests, also referred to as taiga, extend across the northern hemisphere. They constitute nearly one third (13.7 million $km^2$) of the Earth's forests (Graze 2004) and contain almost 30% of all carbon stored in terrestrial biomes (Pan et al. 2011). Boreal carbon sink forms approximately 20% of the global carbon sink (Pan et al. 2011). According to the Intergovernmental Panel on Climate Change (IPCC) (Smith et al. 2014), mitigation actions in forests are divided into four groups: reducing deforestation, reforestation, restoration practices and improving forest management (e.g. favoring longer rotation cycles, reducing damage to remaining trees and the amount of logging residue, the conservation of soils, fertilizing, and using wood more efficiently). Currently, there is an urgent need for quantitative forest data on a global level to establish appropriate mitigation actions. Remote sensing of Leaf Area Index (LAI) and the fraction of Photosynthetically Active Radiation (fPAR) absorbed by green vegetation may be effectively used to monitor the health and growth of forests globally. The LAI quantifies the amount of foliage forming the interface between land surfaces and the atmosphere, and is a physical measure of the tissue capable of photosynthesis. The fPAR (in a wavelength region of 400-700 nm) controls the photosynthetic activity of vegetation and serves as an indicator for vegetation health and productivity. It may also be used to quantify carbon storing. LAI and fPAR are classified as biophysical variables because they have a direct impact on the radiative transfer of vegetated canopies and belong to the group of Essential Climate Variables (ECVs as defined by the network of Global Climate Observing Systems (GCOS 2012)). GCOS was established in 1992 to ensure that physical, chemical, and biological observations of atmosphere, ocean and land surfaces are properly measured and archived.

The rapid increase in different forms of remotely sensed data used for environmental monitoring and modeling applications has underlined the need for ground truth data to validate and develop existing models, for example, the Radiative Transfer Model Intercomparison (RAMI) initiative or satellite based estimates such as MODIS LAI/fPAR and BioPAR GEOV1 (McCallum et al. 2010; Widlowski et al. 2011; Camacho et al. 2013). In addition, monitoring vegetation cover over large areas for long time periods is only feasible using remote sensing techniques. Many studies have reported on the performance of different satellite based products for monitoring forest productivity, yet our understanding of the seasonal dynamics of boreal forests remains incomplete. To interpret satellite based data correctly, the phenological phases typical of the boreal region need to be linked with changes in forest reflectance. Climate change models are used to predict climate-vegetation interactions under different environmental scenarios (Diffenbaugh and Field 2013), and field data is needed to evaluate and improve both seasonal and long term climate projections. International efforts to build up existing databases to validate different satellite based data products and climate change models have been limited by the small number and spatial representativeness of the research sites. From the perspective of international politics, spatially and temporally accurate maps of biophysical variables such as LAI and fPAR can be used to assess the impacts of international commitments (e.g. sustainable development of forest resources and climate change mitigation actions), as well as providing indicators for desertification, vegetation stresses, and carbon sinks and sources.

## 1.2 Estimation of LAI

Forest inventories are conducted to quantify changes in forest growing stock and extent, and to assist forest management. After remote sensing based methods became popular for estimating global forest resources and international obligations to report sustainability practices started, there was a clear need to standardize the definition of a forest. According to the Food and Agricultural Organization (FAO), the international definition of forest is based on Canopy Cover (CC - proportion of ground covered by vertical projection of tree crowns) (Jennings et al. 1999). In the context of this thesis, 'forest structure' may be defined not only as an aggregation of above ground biomass components, i.e. stems, branches and foliage, but also as a collection of different hierarchical structures containing clumping at different spatial scales e.g. needles grouped into shoots (Oker-Blom and Smolander 1988), and clumping at larger scales than shoot-level (Chen and Cihlar 1996).

The Finnish National Forest Inventory (NFI) was established by the Finnish Research Institute in 1921 to assess the productivity of forests with a possibility to estimate forest income (METLA, 2014). Noteworthy is that the continuous historical record of the Finnish NFIs is one of the longest in the world (Tomppo et al. 2010). LAI has never belonged to conventional forest inventory variables in Finland, despite the fact that both the growth and health of a tree depend on the amount of foliage, but it may be estimated based on forest variables and allometric modeling techniques. Currently, ground reference LAI is needed as an input in many models estimating carbon cycling or Net Primary Production (NPP), and to validate satellite based estimates of LAI. The sampling methods adopted by the Finnish NFI have undergone many changes since 1921 and have been studied intensively during past decades (Tomppo et al. 2010). However, the optical measurement techniques (e.g. Welles 1990) needed to estimate LAI or fPAR have been studied far less than the sampling techniques adopted by the NFI in a boreal forest.

In forest inventories, both stand-level and tree-level variables are collected systematically. One of the most important stand-level forest variables is the basal area, which is a measure of the area of a given section of land that is occupied by the cross-section of tree stems at breast height (= 1.3 m above the ground) ($m^2$/ha). In Finnish stand-wise forest inventory, tree-level forest variables are measured only for the basal area median tree: diameter at breast height, tree height and age. Crown length is measured in NFI. These forest variables cannot be used as such to validate satellite based estimates because satellite sensors are only able to measure biophysical variables (i.e. variables such as LAI controlling the radiative transfer in plant canopies). LAI and fPAR are not included in traditional forest inventories, and different modeling approaches (e.g. radiative transfer models and allometric biomass models (described in chapter 2.2)) may be used to relate forest variables with biophysical measures, which can then be used to validate satellite based products. Crown length is one of the most important forest canopy variables, and thus it is included in most of the allometric and radiative transfer models. According to Repola (2009), including crown length as a predictor variable in allometric biomass equations significantly improves the reliability of the predictions for crown biomass. Crown length is also contained in radiative transfer models (e.g. Nilson 1999), because it is one of the most important parameters defining the canopy volume which comprises the LAI.

The difficulty in obtaining field estimates of biophysical variables such as the LAI and fPAR needed to validate satellite based products, is due to the fact that neither of the variables is directly measurable over large geographical extents. Historically, LAI was defined for flat leaves as the one sided area of leaves per unit of horizontal ground area

(Watson 1947). Later the definition was extended to be applicable to non-flat coniferous needles by replacing the one-sided area by the hemi-surface area (Chen and Black 1992). LAI may be measured using destructive measurement techniques, i.e. foliage harvests, together with measurements of Specific Leaf Area (SLA, ratio of fresh foliage area to dry foliage mass). Monitoring the seasonal development of LAI is possible using leaf traps. However, foliage harvests are not suitable for continuous monitoring and neither of these methods is suited for application over large geographical extents. Obtaining direct estimates of LAI is important for calibration of the LAI estimates produced using different methods.

Optical measurement techniques (Figure 1) which describe radiation transmission through forest canopies have become a popular option by which to estimate LAI, instead of laborious and time-consuming destructive measurement techniques. The simplest optical method for estimating LAI is based on the inversion of the Beer's law equation. This describes radiation attenuation through a turbid medium, and was modified from atmosphere physics to vegetated canopies by Monsi and Saeki (1953). Radiation attenuates through plant canopies as a function of LAI, which characterizes the optical thickness of the canopy, and directionally varies with the leaf orientation. In the inversion from canopy transmittance (directional gap fractions) to LAI, the effect of leaf orientation is cancelled out by integration over the hemisphere (Miller 1967). However, more sophisticated inversion methods are needed to take into account that the spatial distribution of foliage elements may deviate from the random distribution assumed by the Beer's law equation.

**Figure 1.** Digital Hemispherical Photographs (DHP) belong to the group of optical measurement techniques.

Indirect approaches for estimating LAI were originally developed for broadleaved tree species or agricultural crops (Warren Wilson 1960; Gower and Norman 1991), and have been found to underestimate LAI in boreal coniferous forests. Optical approaches underestimate 'true' LAI because of shoot-level clumping (e.g. Stenberg et al. 1994) (Figure 2), which is the primary source of clumping in coniferous forests (Stenberg 1996a). Optical instruments are not able to differentiate between foliage and woody areas, and the presence of woody areas increases the optical LAI. In addition, optical instruments also tend to lose their sensitivity to changes in LAI, after the LAI reaches three or four (Myneni et al. 1997). The optically measured LAI is often referred to as the 'effective' LAI, in contrast to the true LAI which is obtained after the effective LAI is corrected for woody area and foliage clumping. For example, a gap frequency model by Nilson (1999) strives to estimate true LAI based on measured canopy transmittance readings and a predefined set of input parameters (e.g. shoot-level clumping, crown shape and the spatial pattern of trees).

Shoot-level clumping correction has frequently been used to correct the optically measured effective LAI, for example, in remote sensing applications (e.g. Myneni et al. 1997; Rautiainen and Stenberg 2005). According to Stenberg et al. (2003), optical measurement techniques underestimate the true LAI and this underestimation is more dependent on shoot-level clumping and the fraction of woody area, than changes in stand density. In addition, LAI may also be estimated based on allometric biomass models which relate woody structures to foliage mass. Foliage mass can be converted to LAI using the SLA parameter. The drawback of allometric biomass models is that the accuracy of the models depends on the representativeness of the data used to create the model (e.g. size of trees, geographic location, climate, and soil properties), and are also not suitable for seasonal monitoring of LAI.


**Figure 2**. Demonstration of shoot-level clumping. Clumping is typical for coniferous species with shoot structures like a) pine and b) spruce, but not so obvious for deciduous species like c) birch

To estimate LAI over large geographical areas, the most advanced option is to use reflectance models which run using forestry databases and allometric biomass models (Rautiainen 2005). Forest reflectance models (e.g. Kuusk and Nilson 2000) provide the most advanced option to estimate stand or landscape level LAI based on satellite measurements. The models may be used to simulate forest reflectance based on traditional forest inventory parameters, and an additional set of parameters defining the forest structure and optical properties with different levels of LAI. One of the simplest options to retrieve LAI is based on comparing simulated and satellite measured reflectances, and finding the LAI which gives the best fit between measured and simulated values.

Large LAI databases are needed for example: 1) to model carbon cycling using biosphere-atmosphere models, 2) to validate global remotely sensed data products (e.g. Camacho et al. 2013), 3) as an input for forest canopy-gap models to study forest dynamics (e.g. Xiaodong and Shugart 2005) or 4) as process-based models to simulate NPP of biomes (e.g. Running and Hunt 1993). To create these extensive LAI databases, different methods may be used. The LAI estimates may be produced using optical measurement techniques, allometric biomass models, remote sensing techniques or destructive measurements. The LAIs estimated using different methods are often assumed to similarly estimate LAI. However, in forested environments the LAI estimates produced using different methods are not similar in terms of absolute values of LAI, because of biases and discrepancies arising from theoretical assumptions and the technical limitations of different instruments (Bréda 2003; Jonckheere et al. 2004). Currently, it is unclear how different LAI estimates are produced by different methods in a boreal forest. In a temperate coniferous forest, for example, the allometric LAI was nearly two LAI units larger than the optical LAI, and the allometric LAIs were the largest among all of the methods (Jonckheere et al. 2005). Although the representativeness of the measured optical data depends on the spatial sampling design, no systematic comparisons of different sampling schemes have been made in forest conditions. Thus, using optimized sampling schemes would improve the accuracy of the LAI measurements and enable time-savings.

### 1.3 Estimation of fPAR

fPAR is a dynamic variable having a large temporal variability compared to LAI, which has relatively small temporal variability in boreal coniferous forests (Muukkonen and Lehtonen 2004; Muukkonen 2005) except during spring (leaf emergence and development) and autumn (leaf senescence). For modeling applications, temporal averages of fPAR over e.g. a few days or seasons, are necessary. The fPAR of a forest stand depends on LAI, solar altitude, the distribution of incoming PAR, vegetation structure and the optical properties of the foliage. Estimation of fPAR *in-situ* requires simultaneous measurements of PAR both above and below the canopy. The most commonly used approach to estimate fPAR is based on measuring incident and reflected PAR above the canopy, incident PAR below the canopy, and reflected PAR at the ground layer (e.g. Gower et al. 1999) (Figure 3). This approach is applicable for most measuring instruments, and suitable for both stationary and mobile measurements. Incident PAR above the forest canopies may be estimated based on flux tower measurements. There are several instruments capable of measuring transmitted PAR. These instruments may have either hemispherical Field-of-View (FOV) (e.g. AccuPAR, SunScan) or narrow effective FOV (e.g. TRAC, Tracing Radiation and Architecture of Canopies (Leblanc et al. 2002)). The TRAC instrument was designed to address the problem with foliage clumping at scales larger than the shoot, by introducing measurements of gap size distribution. Canopy gap size distribution characterizes the spatial variability of canopy transmittance at different hierarchical levels (i.e. the level of tree crowns, whorls and branches), and thus quantifies the clumping effects at different hierarchical levels (Miller and Norman 1971).

Canopy transmittance is relatively easy to obtain using optical instruments such as TRAC (Figure 4). TRAC records transmitted solar radiation in the sun's direction with three LI-COR PAR sensors, and needs to be operated under cloudless skies. However, TRAC is difficult to use in boreal conditions because of low sun angles (TRAC measurements should be conducted at sun altitudes of more than 30 degrees) and relatively frequent cloudiness. The PAR reflected by the understory can be measured using hand-held spectroradiometers (e.g. Iwata et al. 2013) or instruments with down-looking PAR sensors (like TRAC). Spectroradiometers are instruments capable of measuring broader wavelength regions than PAR sensors (e.g. FieldSpec Hand-Held UV/NIR: 325-1075 nm), and have a larger number of bands (e.g. 200 bands) compared to PAR sensors with only one band to cover the whole PAR region. Yet, measuring the fPAR of an understory is not an easy task due to low vegetation and constantly fluctuating light conditions under the tree canopy (e.g. Mõttus et al. 2012; Liu et al. 2013). As an alternative to measuring fPAR with a spectroradiometer, the fPAR of the understory may be approximated using fractional cover estimates of different plant species (Pickett-Heaps et al. 2014). The third term required to calculate fPAR, namely reflected PAR by the forest canopy, is the most difficult variable to obtain. This is partly due to the large number of PAR sensors needed to reach accurate estimates of canopy reflectance in heterogeneous coniferous forests (e.g. Mõttus et al. 2012), and partly due to the scarcity of towers which may be used for setting up the instruments. For these reasons, values derived from literature or measured from a flux tower (e.g. Thomas et al. 2006) are commonly used to approximate reflected PAR by the forest canopy. In general, the large number of instruments needed to measure forest canopy fPAR, limits the extent that may be sampled and complicates efforts e.g. to validate satellite based fPAR products.

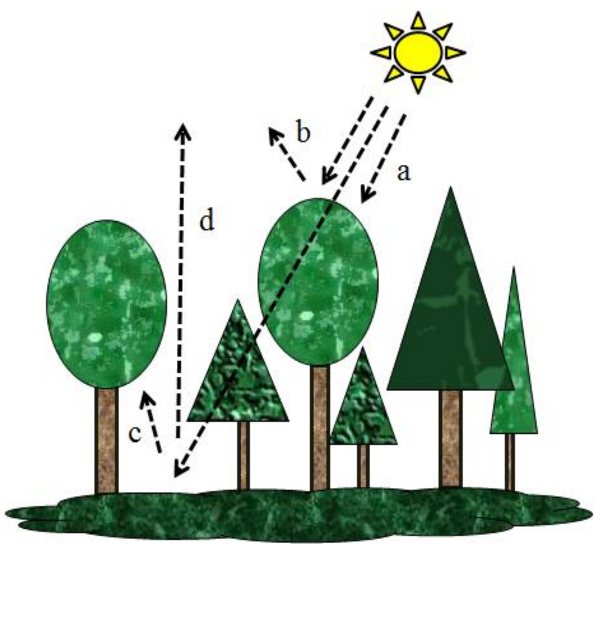


**Figure 3.** Incident PAR may be a) absorbed or b) reflected by a forest canopy, or transmitted through the canopy. The transmitted PAR may be reflected by the ground and then c) absorbed or d) reflected by the canopy.

**Figure 4.** The TRAC instrument has three LI-COR PAR sensors. Two sensors point upwards to record PAR transmittance and one downward to record the PAR reflected by the understory.

All radiative transfer models of plant canopies consist of three common components which they must deal with: reflectance (R), transmittance (T) and absorptance (A). As the energy balance equation can be written as $A=1-R-(1-\alpha)T$, where $\alpha$ is the background albedo (e.g. Widlowski et al. 2011), all radiative transfer models are able to approximate fPAR. Currently, there are many radiative transfer models with varying degrees of complexity (from 1D models for agricultural crops to 3D models for forest canopies). More complex 3D models (e.g. Forest Reflectance and Transmittance model (FRT), Common Land Model (CoLM) and MixFor3D) (Widlowski et al. 2011)) need detailed descriptions of forest canopies and they are developed to test hypotheses (e.g. the sensitivity analysis of different factors affecting canopy radiation transfer) or to validate simpler models (Mariscal et al. 2004; Roupsard et al. 2008). However, the problem with the complex 3D models is how to measure or acquire all of the input variables (Kuusk and Nilson 2000; Widlowski et al. 2011). Also, comparing results from different models is difficult because of different model formulations and underlying assumptions. To overcome these issues, the RAMI initiative was established (Pinty et al. 2001) to provide a base where different models could be systematically compared using modeled descriptions of structural, spectral and illumination related parameters, instead of measured values to decrease ambiguity. Although canopy radiation models are desirable tools for estimating fPAR, the differences between models (e.g. CoLM, MixFor3D) tend to be large for complex canopies like coniferous forests (Widlowski et al. 2011). fPAR may also be modeled using simplified descriptions of forest canopies (Kim et al. 2011). Knowing which variables may be simplified helps people to concentrate on the most important variables influencing the fPAR. For example, Kim et al. (2011) found that if shoot-level clumping is ignored, then fPAR is always overestimated in conifer stands, but the amount of overestimation depends on LAI: at LAI=2, the overestimation of fPAR was 40%, but at LAI=10, the overestimation of fPAR decreased to 25%.

According to the Light Use Efficiency (LUE) theory by Monteith (1972), the NPP of an ecosystem is directly proportional to the Absorbed PAR (APAR). However, to estimate NPP, the LUE term ($\varepsilon$ = NPP/APAR) is required. The estimate of $\varepsilon$ may be obtained from previous studies or flux tower measurements of net ecosystem exchange and incoming PAR (Cheng et al. 2014). The potential maximum $\varepsilon$ varies between biomes and is usually downscaled according to environmental conditions (e.g. temperature, water availability, phenological phases of plants). Although instantaneous values of $\varepsilon$ have been found to vary significantly between different biomes (Gower 1999), the temporal averages tend to stay more constant and can be used to approximate the ε. The advantage of the LUE based model is its general simplicity and the fact that fPAR may be estimated using remote sensing (e.g. Myneni et al. 1995; Landsberg et al. 1997). There have been several attempts to estimate ε from space, e.g. using the Photochemical Reflectance Index (PRI) (Hilker et al. 2008). If ε is assumed to stay relatively 'constant' (Yuan et al. 2014), then improving the estimates of NPP would be possible through a more accurate estimation of fPAR.

### 1.4 Remote sensing of LAI and fPAR

Large areas of boreal regions are inaccessible and thus remote sensing is the only alternative to monitor the health or development status of vegetation. In addition, producing global maps of LAI and fPAR is only feasible using remote sensing techniques. The initial goal of all organizations producing and delivering the satellite based LAI and fPAR products is to ensure continuous long-term availability of the products, because detecting changes (e.g. in the case of large inter-annual variability), requires access to long time series. Satellite agencies like the National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA) produce and deliver global satellite based LAI and fPAR products with a spatial resolution of 1 km × 1 km every 1-2 weeks. Previously, research institutions like the European Commission's Joint Research Centre (JRC) have been active in producing global satellite based LAI and fPAR products. Global satellite based LAI and fPAR maps could be provided on a daily basis, yet a more popular option is to use composites, which are temporally aggregated maps. Composite LAI and fPAR maps are far more accurate than daily products, because daily products are prone to errors caused by clouds and atmospheric conditions. Obtaining ground based measurements of LAI and fPAR is now more important than ever, due to an increased demand for accurate satellite based estimates linked to the rapid increase in satellite based data featured in global environmental monitoring programs. Validation of different satellite based algorithms for LAI and fPAR (e.g. MODIS, GEOV1) is not possible without ground reference data. There have been several networks (VALERI, FLUXNET, BIGFOOT) formed to produce ground reference data, and the Committee on Earth Observation Satellites Working Group on Calibration and Validation (CEOS WGCV) has started coordinating the creation of a centralized database for ground reference measurements of LAI. Currently, no ground reference network for fPAR exists, but platforms such as the On Line Interactive Validation Exercise (OLIVE) could potentially fulfill this function (Weiss et al. 2014).

The past decade has been a golden era for satellite based LAI and fPAR products. Time series of the MODIS LAI and fPAR products (Knyazikhin et al. 1999) have been available from the year 2000. To preserve data continuity between different sensors, all the data from the oldest sensors (e.g. SeaWiFS) to those currently operating (e.g. MODIS) have been inter-calibrated, and new satellite sensors are being sent to replace the older instruments. The most recent LAI and fPAR provider is GEOV1 (Geoland BioPAR) (Baret et al. 2013). In the past, satellite based vegetation indices like the Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974) have been popular in estimating vegetation status (i.e. LAI and fPAR) from space. Common approaches to validate global satellite based LAI and fPAR products have involved three steps: 1) collecting *in situ* data, 2) using high resolution products to upscale the ground measurements, and 3) aggregating the high resolution satellite images to lower spatial resolution (i.e. similar to LAI/fPAR products). Vegetation indices based on bands affected by water absorption (e.g. Reduced Simple Ratio (RSR)) have performed reasonably well in estimating boreal forest LAI (Stenberg et al. 2004), but the Root Mean Square Errors (RMSE's) are still high between satellite based and field measured estimates of LAI (Heiskanen et al. 2013). In addition, most vegetation indices have been found to be insensitive to the whole range of variation in LAI (i.e. for small or large values) (e.g. Myneni et al. 1997), and are also influenced by understory (Eriksson et al. 2006), and view and illumination angles. Relatively recently, satellite based imaging spectroscopy data (e.g. from HYPERION) has improved the LAI estimation from space compared to broadband sensors (e.g. MODIS, Landsat, SPOT) (Heiskanen et al. 2013). Although a slightly better accuracy of LAI may be obtained using imaging spectroscopy data compared to broadband sensors, the use of imaging spectroscopy data remains complicated due to the laborious preprocessing of the data, and because the hyperspectral data is neither systematically nor globally available (i.e. hyperspectral sensors scan only predefined locations on request). At present, NASA is preparing a new LAI product based on medium spatial resolution Landsat data (30 m × 30 m) (Ganguly et al. 2012).

Currently, the global LAI/fPAR products by MODIS are based on the inversion of a radiative transfer model using a Look-Up Table (LUT) with biome-specific parameters, which are used to compute LAI and fPAR values (Knyazikhin et al. 1999). The GEOV1 LAI/fPAR algorithm, on the other hand, uses neural networks, which were trained using data from MODIS and CYCLOPES to estimate LAI and fPAR (Baret et al. 2013). Currently, there is a lack of ground reference data to quantify the seasonal variability of different biomes (Garrigues et al. 2008). Seasonal variation of LAI has a direct impact on forest reflectance, which is recorded by satellite sensors. In addition, data characterizing the temporal reflectance cycle of a boreal forest is needed for both the forest canopy and the understory layer (Rautiainen et al. 2009a). In a boreal region, the seasonal development of LAI has three distinct phenological phases (leaf emergence, growth and senescence), which are characterized by certain changes in both optical and structural properties of foliage. Using only field data collected at the peak of the growing season (Morisette et al. 2006), is not sufficient for monitoring seasonal dynamics of vegetated land surfaces, and seasonal trajectories of LAI are an important input for many climate and NPP related models.

In order to validate satellite based LAI products, a series of measurements for both understory LAI and forest canopy LAI is needed. Although the contribution of understory LAI is contained in the remotely sensed estimates of LAI, the understory LAI is rarely measured because it is difficult to measure in field conditions (Garrigues et al. 2008). Understory LAI (or fPAR) may significantly influence the total LAI (or fPAR) (Rautiainen et al. 2012), and thus it should be considered in remote sensing studies concentrating on forests. In burned boreal forest, the contribution of understory LAI to total LAI has been found to range between 11% and 85% (absolute LAI units ranged from 0.46 to 1.16) (Serbin et al. 2009). For the same stands, the contribution of understory fPAR to total fPAR varied between 9% and 59% (absolute fPAR units range from 0.07 to 0.34) (Serbin et al. 2009). According to Iwata et al. (2013), understory fPAR varied by around 0.1 fPAR units when the understory was composed of only mosses.

Although there have been many efforts to validate MODIS LAI products, only a few studies have assessed LAI (Collection 5, available from 2007) of a boreal coniferous forest (De Kauwe et al. 2011). This is probably because few studies have had seasonal series of field measured LAI (Rautiainen et al. 2012). Boreal coniferous forests have a relatively small seasonal variation in forest canopy LAI due to the fact that only a small portion of the needles is shed each year (Muukkonen and Lehtonen 2004; Muukkonen 2005). However, MODIS LAI is reported to have a larger variation than is expected based on ground reference LAI (Rautiainen et al. 2012). Currently it is not known how well MODIS LAI is able to detect the phenological phases of a boreal forest, and how the variation of LAI depends on the season.

fPAR has obtained less attention than LAI in remote sensing studies, although it is more readily retrievable from space than LAI. In addition, fPAR has stronger temporal dynamics than LAI because it depends on the solar elevation. As LAI is not measurable from space, it is estimated based on the NDVI and a large set of other variables (e.g. meteorological data, biome-specific LUT) (Knyazikhin et al. 1999). Despite the apparent simplicity of estimating fPAR using satellite based measurements, recent research has shown that different fPAR products yield substantially different results, especially for forested biomes (D'Odorico et al. 2014). Validation of satellite based fPAR products with ground based fPAR is also complicated by the fact that satellite based fPARs are often based on theoretical illumination conditions instead of prevalent illumination (Widlowski 2010). Satellite based fPAR is commonly defined as instantaneous fPAR assuming only direct radiation, yet the ground reference fPAR is calculated as a sum of direct and diffuse radiation components (Olofsson and Eklundh 2007; D'Odorico et al. 2014). Validation of satellite based fPAR products have focused on comparing different satellite based fPAR products, because measuring ground reference fPAR is difficult and requires data collection over several days (Mõttus et al. 2012). In addition, the development of the algorithms for estimating fPAR in boreal forests is hindered by the lack of ground reference fPAR data (McCallum et al. 2010; Camacho et al. 2013; D'Odorico et al. 2014). Direct validation activities are therefore the only option to quantify uncertainty, which is required by different organizations utilizing remotely sensed fPAR products (e.g. GCOS).

## 1.5 Aim and structure of the thesis

This thesis focuses on developing methods for measuring and modelling LAI and fPAR in a boreal forest. Understanding the role of forest structural variables and LAI in determining forest canopy fPAR is important in modeling forest productivity, and for the development of remote sensing based retrieval methods for both LAI and fPAR. Currently, there is a shortage of *in situ* measurement techniques applicable over large spatial extents to validate global satellite based fPAR products. The aim of this thesis is to present a new scheme for measuring and modeling ground reference fPAR in a boreal forest. For the first time, the theory of spectral invariants is applied to producing ground based estimates of fPAR, and a thorough set of ground reference measurements are used to validate global satellite based fPAR products. Since different approaches are common in estimating LAI and as fPAR is highly dependent on LAI, the first part of this dissertation investigates the accuracy of different ground reference methods and sampling schemes on LAI. In addition, a seasonal series of a ground reference LAI is used to validate satellite based estimates of LAI. The second part of this dissertation concentrates on developing methods for measuring and modelling boreal forest fPAR in order to validate satellite based fPAR products.

Structurally this dissertation is divided into four parts comprising six studies, with their specific aims as follows:

● First, the effect of different LAI estimation methods on the accuracy of LAI was investigated (study I), and followed by an analysis of the effect of sampling scheme on the accuracy of optical LAI (study II). The goal was to find out to what degree LAI estimates produced using different methods or measured using different sampling schemes (studies I and II) differ from each other.

● Next, the seasonal series of remotely sensed estimates of LAI was validated with concurrent ground measurements of LAI (study III). The aim was to find out how well the remotely sensed estimates of LAI correspond to ground based measurements of LAI, and what is the role of the boreal forest understory in satellite based measurements of LAI (study IV). The accuracy of the ground reference LAI was obtained from earlier studies.

● Then, a canopy radiation budget model by Stenberg et al. (2013) was adopted to an fPAR model (study V). The specific research questions raised in the study were: How accurate are the measured and modeled values of fPAR in a boreal forest? How much do forest canopy structure and LAI affect the diurnal and seasonal courses of forest canopy fPAR?

● Finally, the new fPAR model was used to validate global satellite based fPAR products (study VI). Field measurements were planned based on earlier studies. The focus was on answering the questions: How accurate are satellite based fPAR products in a boreal forest, and how large is the contribution from understory to total fPAR in satellite based estimates?

# 2 MATERIALS AND METHODS

## 2.1 Study sites

This dissertation is based on data drawn from Hyytiälä (24°17' E, 61°50' N), Saarinen (27°29' E, 62°40' N) and Puumala (28°42' E, 61°31' N) which are located in the southern boreal forest zone of Finland (Figure 5). The areas are mainly dominated by Norway spruce (*Picea abies* L. *Karst*) and Scots pine (*Pinus sylvestris* L.) (Figure 6). Stands dominated by birches (*Betula spp.* L.) are rare, but birches are common in stands with mixed species. The forest understory is typically composed of two layers, where the upper understory layer is composed of dwarf shrubs, pteridophytes, herbaceous species, and graminoids, and the lower ground layer populated by mosses, lichens and litter. For Saarinen and Puumala, a systematic grid (0.65 km × 1.4 km and 1.0 km × 1.0 km, respectively) was established, and the distance between forest plots was 50 m. In Hyytiälä (~15 $km^2$), forest plots were selected according to species composition and stand characteristics. Data from Puumala (number of plots (n) =334) and Saarinen (n=327) were used in study I, whereas data from Hyytiälä (n=390) was used in other studies (II-VI). The data used in studies I-VI is summarized in Table 1.

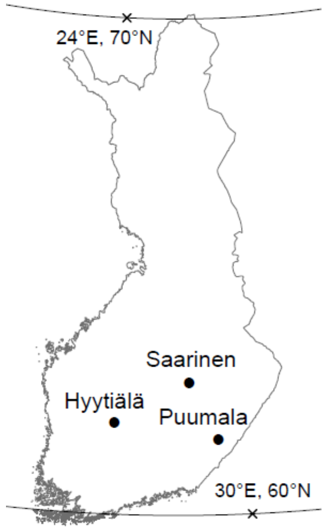


**Figure 5.** Location of the study sites.

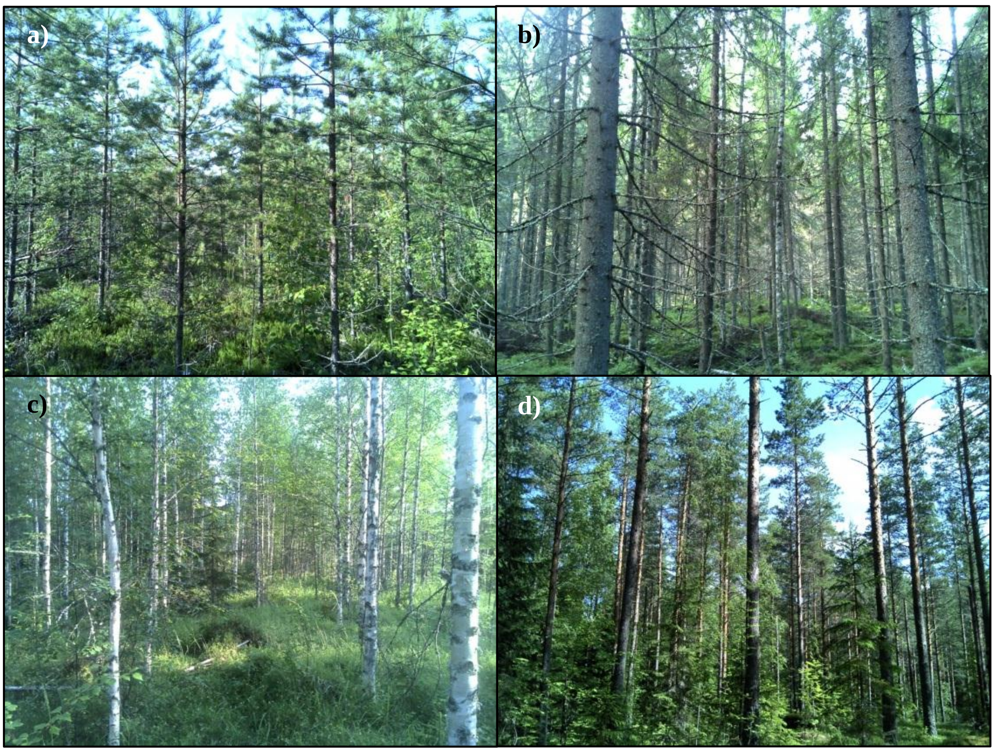


**Figure 6.** Boreal forest dominated by a) pine b) spruce c) birch and d) mixed species.

**Table 1.** Ground based measurements. Plots = total number of forest plots, Time = time of the field measurements, Inventory = forest inventory was conducted, LAI-2000 = LAI-2000 instrument, DHP = Digital Hemispherical Photography, TRAC = TRAC instrument, Spectrom = ASD FieldSpec UV/NIR, FCU = fractional cover of understory and ground layer species. Note, satellite based data were also used in studies III and VI.

| Study | Plots | Time | Inventory | LAI-2000 | DHP | TRAC | Spectrom | FCU |
|---|---|---|---|---|---|---|---|---|
| I | 661 | June, July | yes | yes | no | no | no | no |
| II | 6 | July | yes | yes | no | no | no | no |
| III | 64 | May-October | yes | yes | yes | no | no | no |
| IV | 4 | May-October | yes | yes | no | no | yes | yes |
| V | 9 | June | yes | yes | no | yes | no | no |
| VI | 307 | June-August | yes | yes | no | yes | no | yes |

## 2.2 LAI estimation

### *2.2.1 Optical measurement methods for LAI*

Currently, measurements by the LAI-2000 (or LAI-2200) Plant Canopy Analyzer (LI-COR 1992) is a standard option used to estimate LAI. The LAI-2000 sensor measures diffuse sky irradiance in the blue wavelength region (320 – 490 nm), where light scattering from leaves is minor, and in five zenith angle bands (0-13°, 16-28°, 32-43°, 47-58° and 61-74°) (Figure 7). The LAI-2000 measurements made in our studies were always started by inter-calibrating two LAI-2000 instruments, used simultaneously to obtain above and below canopy readings (Figure 8). The reference ‘above canopy’ sensor was located in the middle of an open field or in a tower close to the study sites. Canopy gap fractions are obtained for five zenith angle bands for each plot by combining the data from two instruments.

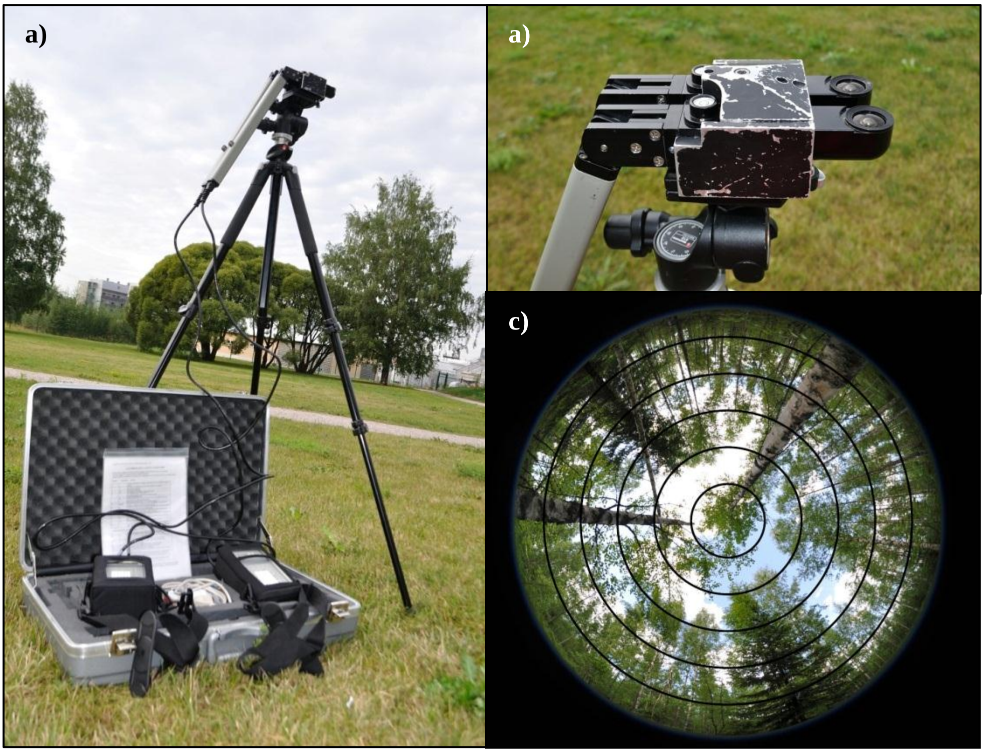


**Figure 7.** LAI-2000 instrument**.** a) Two LAI-2000 units were always inter-calibrated before measurements were started using b) a special clamp to hold the sensors. Figure c) demonstrates the five zenith bands of the LAI-2000 sensor.

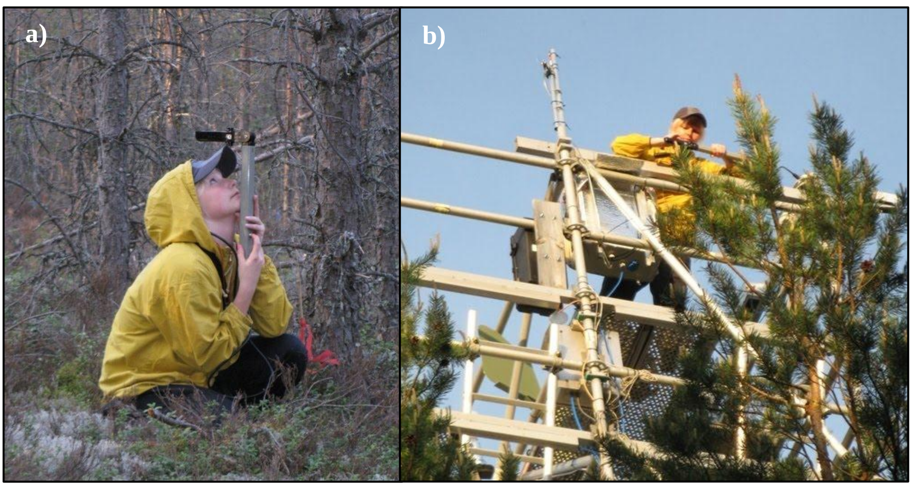


**Figure 8.** LAI-2000 readings taken from a) below and b) above a forest canopy. © Matti Mõttus.

The direct output of the LAI-2000 instrument is called an effective LAI or optical LAI, in contrast to the true LAI, which cannot be measured using optical instruments. Optical measurement techniques, which are based on Beer's law, tend to underestimate the true LAI, because the assumption of randomly distributed foliage does not hold true in boreal coniferous forests (e.g. Gower and Norman 1991). Since a large part of the clumping in coniferous forests is apparently caused by shoot-level clumping (e.g. Stenberg 1996a), simply applying a shoot-level clumping correction has become a popular option to correct for the underestimation of optical LAI (e.g. Rautiainen and Stenberg 2005). The shoot-level clumping corrected optical LAI is obtained by dividing the optical LAI with a 4 × mean Silhouette to Total Area Ratio (STAR) - Oker-Blom and Smolander (1988). According to Thérézien et al. (2007) there may be a large variation between mean STAR values of different species (e.g. ranges from 0.091 to 0.222). For pine, the mean STAR has been reported to vary between 0.142 and 0.161, and for spruce between 0.147 and 0.216 (Thérézien et al. 2007). In studies I, V and VI, a mean STAR value 0.147 was used for pine and 0.161 for spruce.  For deciduous species no correction was applied.

Optical instruments cannot be used to separate foliage from woody structures (stems and branches), and thus the output of optical measurements corresponds to the Plant Area Index (PAI). Although most branches (80-90%) are masked by leaves and needles in boreal coniferous forest, the stem remains visible (comprising 30-50% of the total woody area), and thus the contribution of the woody area cannot be ignored (Kucharik et al. 1998). Canopy radiation models may be used to correct for both the clumping of foliage and the contribution of the woody area. In study I, the gap frequency model presented by Nilson (1999), which contained corrections for both foliage clumping and woody area, was used to estimate the true LAI.

Some researchers (Chen and Cihlar 1995; Leblanc et al. 2002) have argued that in addition to shoot-level clumping, a second correction for clumping at scales larger than a shoot (i.e. crowns, whorls, branches) (henceforth referred to as crown-level clumping) should be applied. However, the new software included in the LAI-2000 instrument partially accounts for clumping at scales larger than a shoot (calculated as the mean of the logarithms of the gap fraction readings), and thus additional correction for shoot-level clumping is primarily needed (this applies to all my studies). The clumping correction at scales larger than a shoot quantifies the spatial arrangement of foliage, and thus depends on canopy cover, crown shape and height of the canopies (Ryu et al. 2010a).

LAI-2000 was used to measure LAI for more than a thousand forest plots (n=1003) (Table 1, Figure 9). In study II, the optical LAIs were calculated as an average of the point-specific LAIs, but plot-specific averages were used in studies I and III-VI. In study III, the stands were measured every two-three weeks between May 3$^{rd}$ and October 20$^{th}$. In addition, to increase the sample size in study III, a separate set of hemispherical photographs of pure coniferous stands (n=44) taken two years earlier were included in the analysis. LAI-2000 measurements were usually performed under diffuse sky conditions in order to avoid direct sun light reaching the sensors (studies II-VI). Although LAI-2000 is operated under diffuse sky conditions the measured gap fraction reading is slightly overestimated by scattering effects between plant elements and ground (Kobayashi et al. 2013). View restrictors (90 degrees) were used to block out the sun during daytime measurements (study I). Understory LAI was estimated based on fractional cover estimates, which were upscaled using relative abundances of different site fertility types derived from a forestry database.

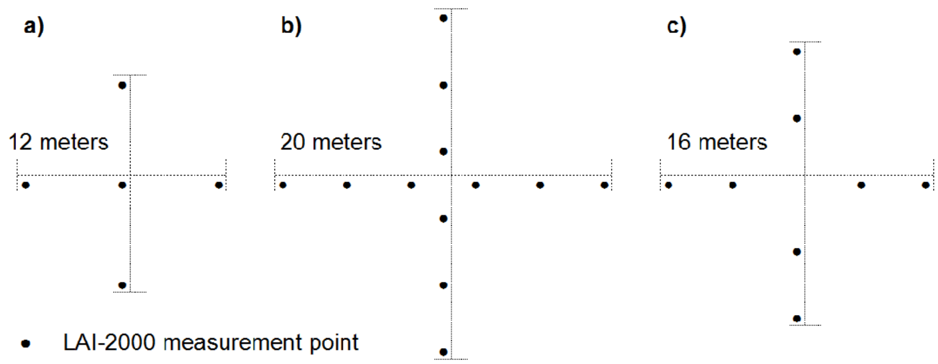


**Figure 9.** Sampling schemes used in different studies. Scheme a) was used in study I. Scheme b) was used in studies III, IV and V. Scheme c) was used in study VI. Note: the sampling schemes used in study II are not shown here, but are described in Majasalmi et al. (2012).

*2.2.2 Allometric biomass models for LAI*

Allometric biomass models describe relations between woody structures and foliage, and may be used to estimate tree or stand-level LAI. Several allometric biomass models were used in study I to obtain independent estimates of LAI. Data from the same latitudes as the study area was used to create the allometric models and thus the models were assumed to be suitable for the study area. The LAI estimates obtained by different allometric biomass models were compared to optically measured LAI estimates to investigate how similar estimates may be obtained using different approaches. Allometric regression models may have one or several input variables. If the model inputs are assumed to be reliable, the accuracy of the allometric foliage biomass models is assumed to increase as more input variables are given. Tree-level forest variables are used to produce an estimate of dry foliage mass, which is then converted to LAI using species-specific estimates of SLA and stand density.

Currently, only a few allometric foliage mass models exist for boreal tree species applicable for southern Finland. Three different allometric foliage mass models were used to estimate foliage masses: Repola's (2008, 2009) models for pine, spruce and birch, Marklund's (1988) models for pine and spruce, and Johansson's (1999) model for birch. The largest difference between the models is the number of input variables, which varied from one to three in study I. Repola's models are based on a multivariate procedure, whereas Marklund's and Johansson's models are based on common linear regression. The multivariate procedure ensures that spatial dependencies among regression equations for the different biomass components of the tree are taken into account (tree-level and stand-level error terms may be separated). In addition, Repola's models contain variance correction terms (u and e) which are applied to correct for logarithmic bias caused by logarithmic transformations. However, in Marklund's models, the bias correction terms are built-in. Allometric regression models estimate foliage mass for individual trees, and since the aim was to estimate foliage mass at stand-level, the stand-level foliage mass was calculated by upscaling the median tree ('standard' method) and by applying a theoretical stem diameter distribution (described in detail in study I). The standard method for estimating LAI is:

$$LAI_{Standard} = \sum_{i=1}^{i=3} \frac{n_i}{10000} \times Bio_i \times SLA_i \qquad (1)$$

where i denotes the species (either pine, spruce or birch), $n_i$ is the species-specific number of trees per hectare, and $Bio_i$ is the foliage mass of the median tree in kilograms. Species-specific SLA values (spruce: Stenberg et al. (1999); pine: Palmroth and Hari (2001); birch: Lintunen et al. (2011)) were used to convert foliage mass to LAI.

### *2.2.3 Inversion of a canopy radiation model to estimate LAI*

In study I, a gap frequency model by Nilson (1999) was used to correct for the clumping of foliage and the woody area of optical LAI, because the model can be run using measured canopy transmittance values and traditional forest variables. The model takes into account variables like shoot-level clumping, crown shape and the spatial pattern of trees. Required input parameters include standard forest inventory variables, measured canopy gap fractions (obtained e.g. from LAI-2000 measurements) and some additional forest parameters including shoot-level clumping (STAR), Branch Area Index (BAI), Fisher's grouping index and crown shape.

### *2.2.4 Satellite based estimation of LAI*

The most validation studies focusing on boreal forest LAI have been conducted during 'peak-season', yet understanding the seasonal dynamics is highly important for the development of products. In study III, ground based LAIs were measured from 64 stands (20 stands using the LAI-2000, and 44 stands using the DHP). Currently, no high spatial resolution LAI products exist, and thus medium resolution data is used to upscale field measurements to the low spatial resolution of the global LAI products. The canopy area 'seen' by the optical instruments, for example LAI-2000 measurements in a forest, corresponds roughly to the size of a pixel of a medium satellite sensor (e.g. 30 m × 30 m). Different vegetation indices (e.g. RSR and Infrared Simple Ratio (ISR)) were calculated using medium spatial resolution data products (e.g. SPOT and Hyperion, Table 2). Because of geo-registering errors, 3 × 3 pixel windows around the stand center points were used to extract the mean values for the stands. These mean values were used to create empirical regression models, which were used to transform vegetation index maps into LAI. Understory LAI values were estimated based on the fractional cover of understory species (Schleppi et al. 2011). The understory LAI estimates were upscaled to the level of the study area using relative abundances of different site fertility types derived from a forestry database. Finally, the stand-level measurements of forest canopy and understory LAI were upscaled using empirical regression models and medium spatial resolution satellite data. These medium resolution maps of LAI were then aggregated into MODIS pixels resolution to validate satellite based MODIS LAI products (Table 3).

**Table 2.** Description of the medium resolution satellite data

| Satellite | Sensor | Spatial resolution (m) | Spectral resolution | Number of bands | Campaign year |
|---|---|---|---|---|---|
| SPOT 4 | HRVIR1 | 20 m | 70 - 170 nm | 4 | 2010 |
| SPOT 4 | HRVIR2 | 20 m | 70 - 170 nm | 4 | 2010 |
| EO-1 | Hyperion | 30 m | ~ 10 nm | 242 | 2010 |
| Landsat 8 | OLI | 30 m | 30 - 80 nm | 9 | 2013 |

**Table 3.** Description of the global satellite based LAI/PAR products.

| Satellite product | MODIS LAI | MODIS fPAR | GEOV1 fPAR |
|---|---|---|---|
| Definition | Hemisurface LAI | Green veg. fPAR (10:30 am) | Green veg. fPAR (~10:15 am) |
| Sensor | MODIS TERRA /& AQUA | MODIS TERRA | SPOT VEGETATION |
| Algorithm | Inversion of 3D model | Inversion of 3D model | Trained neural networks |
| Acronyms | MOD/MYD15A2, MCD15A2/A3 | MOD15A2, MCD15A2 | g2_BIOPAR_FAPAR |
| Prior data | Landcover map (MCD12) | Landcover map (MCD12) | Fused & scaled CYCLOPES & MODIS |
| Parameters | 8 biomes | 8 biomes | Global |
| Spatial resolution | 1 km | 1 km | 1 km |
| Temporal resolution | 4-8 days | 8 days | 10 days |
| Reference | Myneni et al. 2002 | Myneni et al. 2002 | Baret et al. 2013 |
| Data provider | NASA/Boston university | NASA/Boston university | Geoland2 |
| Campaign year | 2010 | 2013 | 2013 |

MODIS LAI products are based on the inversion of a radiative transfer model, which is applied to retrieve LAI from coarse spatial resolution data (pixel size ~1 km × 1 km). MODIS LAI data acquired between March 30$^{th}$ and November 8$^{th}$ in 2012 were studied. MODIS LAI composites were produced using data from TERRA (MOD) and AQUA (MYD) sensors, and a combined dataset from the two sensors (MCD). The study area (~15 km$^2$) was determined by the location of the ground reference plots and the coverage of the LAI maps with medium spatial resolution. MODIS LAI products are provided with pixel-specific quality control layers. Quality control data shows, for example, if the main algorithm or the backup algorithm had been used and if clouds were present. In addition, for each pixel, a standard deviation of LAI (or fPAR) is given. It is calculated based on pixel-wise daily LAI (or fPAR) values during the 8 day composition period. The larger is the standard deviation, and the lower is the expected accuracy of that pixel (Knyazikhin et al. 1999; Myneni et al. 2002). MODIS LAI products were studied by retrieval type and cloud state to observe their seasonal variation and relation to LAI.

## 2.3 fPAR estimation

### *2.3.1 Measurements of fPAR*

There are many PAR sensors available which may be used to quantify fPAR or canopy transmittance and reflectance. Instrument systems are usually operated below the canopy, which means that above canopy readings must be measured separately. Sensor systems can be divided into hemispherical (integrate over the hemisphere) or directional (measurements with a narrow FOV) instruments (e.g. Mõttus et al. 2012). Hemispherical sensors systems (AccuPAR, SunScan, SunFleck, and quantum sensors) have been more popular in measuring PAR, because they allow better spatial sampling compared to directional sensor systems. Instruments with a narrow FOV (TRAC, DEMON) assume different approximations of forest structure, or measure around a zenith angle of 57.5$^{o}$ where canopy transmittance does not depend on foliage orientation (Warren Wilson 1963). However, in measuring only at angles around 57.5$^{o}$ the FOV of the sensor would be very narrow and would thus increase the number of measurements needed to obtain a representative sample. The drawback of these sensor systems is that the sensors are not able to differentiate radiation absorbed by woody material (stems, branches) and the leaf area, which may lead to an overestimation of fPAR. In addition, a large number of sensors are required to preserve spatial sampling in heterogeneous forests (up to several hundred sensors in coniferous forest (Reifsnyder et al. 1972)), and data should be collected over several days to get a representative average of diurnal fPAR.

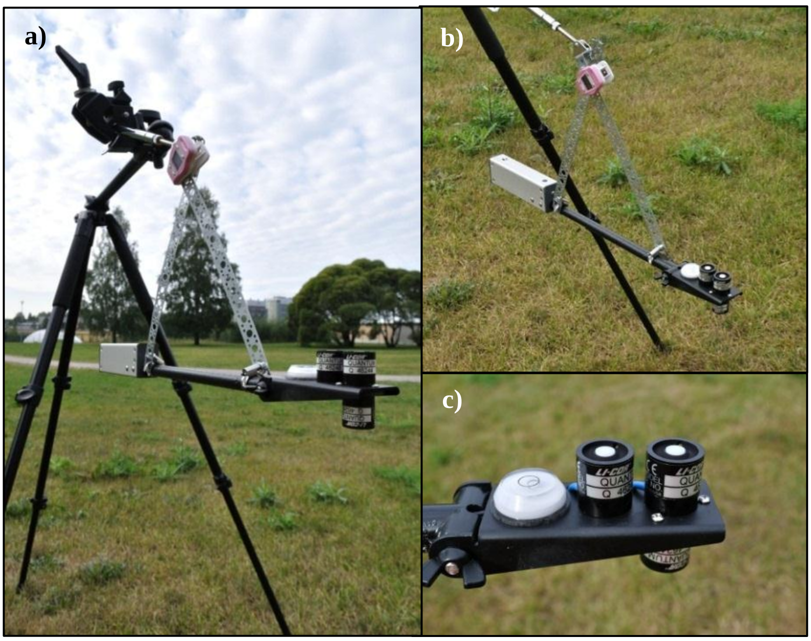


**Figure 10.** The TRAC instrumentation. a) The TRAC is leveled using an extension arm held by a tripod. b) The extension arm held by a person was used to level the (c) three PAR sensors during the field measurements, and a metronome was used to keep a constant walking pace.

The TRAC is a less common instrument for measuring transmitted PAR by the forest canopy and reflected PAR by the understory (Leblanc et al. 2002) (Figure 10). TRAC data has mainly been published by researchers from Canada (Chen et al. 1997; Kucharik et al. 1999; Hall et al. 2003; Leblanc et al. 2005; Simic et al. 2010; He et al. 2012). The data from TRAC has been used to quantify canopy architecture and correct for the clumping of optical LAI. In addition, TRAC measurements have been conducted in Estonia (Pisek et al. 2011), Sweden (Eriksson et al. 2006), Africa (Privette et al. 2002), France (Govind et al. 2013), Belgium (Jonckheere et al. 2005), and the USA (Law et al. 2001; Ryu et al. 2010b). Only Chen (1996a) has used TRAC to estimate fPAR. Chen's equation to calculate fPAR was based on LAI, and should be therefore be run with data from LAI-2000 instead of TRAC, because it allows better angular and spatial sampling (Chen et al. 2006).

TRAC records transmitted radiation at PAR wavelengths (400-700 nm) at a high frequency (32 Hz), and using three LI-COR PAR sensors (two pointing upwards and one downwards). Sampling is performed by measuring transects oriented perpendicularly to the sun's direction. Measurements have to be made under clear sky conditions, and when the sun zenith angle is less than 60 degrees to make sure the forest canopies are measured. TRAC may also be used to estimate LAI and foliage clumping at spatial scales larger than a shoot. Measurements are based on the inversion of a canopy gap size distribution using the measured light transmittance profiles.

In studies V and VI, a metronome was used to keep the walking pace constant (~0.3 m/s), because TRAC records the radiation as a function of time, not as a function of distance. The measurement height was 0.7 m using an extension arm to level the instrument. The above canopy PAR readings were obtained from a similar LI-COR PAR sensor located at the top of a flux tower next to the study area. TRAC sensors were inter-calibrated with the flux tower sensor. fPAR from TRAC was approximated using above canopy ($PAR_{TOWER}$ = downwelling PAR) and below canopy readings ($PAR_{TRAC(\downarrow)}$ = transmitted PAR, and $\rho_G$ = reflected PAR by the understory (ratio of upwelling and downwelling PAR)) expressed as:

$$\mathrm{fPAR_{TRAC}} \approx \frac{PAR_{TOWER}-PAR_{TRAC(\downarrow)}}{PAR_{TOWER}} + \rho_G\left(\frac{PAR_{TRAC(\downarrow)}}{PAR_{TOWER}}\right)\left(1-\frac{PAR_{TRAC(\downarrow)}}{PAR_{TOWER}}\right) \quad (2)$$

TRAC measurements were performed in the summers of 2012 and 2013, and the data was used in studies V and VI. In study V, nine stands were measured. In each stand, five 20-m transects, located 4- apart, were established and TRAC measurements were performed at two different sun angles. In study VI, 18 stands were measured and measurements were made similarly to those in study V, except that six transects were used instead of five.

### *2.3.2 Modeling forest canopy fPAR*

Measuring fPAR requires a large number of sensors and is time-consuming, because of its spatial and temporal dynamics, and thus, modeling fPAR may be preferred (Liang et al. 2012; Mõttus et al. 2012). Still, acquiring all the parameters needed for modeling fPAR in heterogeneous environments (e.g. coniferous forests) is complicated (Widlowski et al. 2011). Simple fPAR models should be preferred in practical applications, because they are easy and fast to apply, and applicable for large area applications. However, more detailed fPAR models are needed to test the performance of the simpler models. Estimates of fPAR are required in many LUE based models (Monteith 1972), which are used to estimate the NPP.

Relatively recently, the theory of canopy spectral invariants (Panferov et al. 2001) has been applied in modeling the radiation budget of vegetation (Knyazikhin et al. 2011). In this dissertation, the radiation budget model by Stenberg et al. (2013) was reformulated to serve as an fPAR model. The fPAR model is based on relationship between LAI and the recollision probability (p), which is a wavelength independent canopy structural parameter (Smolander and Stenberg 2005). To calculate fPAR, several variables are needed: the p, understory reflectance, canopy transmittance, optical LAI and canopy Diffuse non-interceptance (DIFN). The p may be calculated using the formula offered by Stenberg (2007), and the other parameters (canopy transmittance, optical LAI and DIFN) may be obtained directly from the LAI-2000 measurements. The optical LAI may be corrected for shoot-level clumping by dividing the optical LAI with 4STAR (Oker-Blom and Smolander 1988; Stenberg et al. 1994). Instantaneous fPAR under incident irradiation $I_0(\theta,\alpha)$ arriving from a sky position $(\theta,\alpha)$ ($\theta$ = zenith angle, $\alpha$= azimuth angle) was calculated by numerical approximation of the integral:

$$fPAR_{MODEL} = \frac{\int_0^{2\pi}\int_0^{\pi/2} fPAR(\theta) I_0(\theta,\alpha) sin\theta d\theta d\alpha}{\int_0^{2\pi}\int_0^{\pi/2} I_0(\theta,\alpha) sin\theta d\theta d\alpha} \tag{3}$$

In study V, the fPAR model was validated by comparing measured and modeled estimates of fPAR for nine forest stands. To estimate the seasonal courses of fPAR, canopy transmittance and LAI were assumed to stay constant in coniferous stands over the growing season. Atmospheric clear sky transmittance was assigned a theoretical value of 0.7, and the direct and diffuse radiation components were calculated according to Liu and Jordan (1960). The angular distribution of diffuse sky irradiance under clear and overcast conditions was estimated according to Kittler and Darula (2006), and the instantaneous radiation falling on a surface was calculated as the sum of the direct and diffuse components.

### *2.3.3 Satellite based estimation of fPAR*

At present, there are two operational, global satellite based fPAR products available: MODIS fPAR and GEOV1 fPAR. The main difference between the two products is that GEOV1 applies neural networks for the retrieval of fPAR, but the MODIS fPAR is based on the inversion of a radiative transfer model. However, in the past, NDVI based approaches have been popular in estimating fPAR from space. Both NDVI and fPAR estimation are based on measuring the reflected radiation of land surfaces covered by green vegetation. The relationship between fPAR and NDVI is close to linear (e.g. Chen 1996b; Sellers et al. 1996). Yet, the linearity between NDVI and fPAR is achieved by the rescaling of the NDVI distribution separately for each biome. This requires additional information such as land cover maps, which may in-turn introduce additional errors. To understand the physical reasons why radiation absorption differs between biomes, radiative transfer models have been used in modeling fPAR. Validation and intercomparison studies have shown that satellite based fPAR products do not yield mutually similar results, and that the differences are most severe in forested environments (D’Odorico et al. 2014). The newest approach to retrieving fPAR from satellites is based on neural networks, which are trained using fused and scaled data from other satellite sensors.

The MODIS fPAR product (Table 3) has been available for approximately fifteen years, and may be used as a benchmark for other fPAR products. The MODIS radiative transfer model for fPAR uses surface reflectances in red and Near Infrared (NIR) bands, and land cover classification (based on vegetation structure) to create an LUT, which contains several possible biome-specific canopy realizations (Knyazikhin et al. 1999). The newest version of the algorithm is called Collection 5 (C5) and it is parameterized for 8 biomes (Friedl et al. 2010). The LUT approach is based on comparing measured and modeled canopy radiances using a cost function, which is optimized to minimize the difference between the two. An NDVI based back-up algorithm is applied if the main algorithm fails. The fPAR product is provided as an eight-day composite, which is obtained by selecting the maximum fPAR within the composition period for each pixel. In addition, uncertainty information is provided for each pixel.

The newest satellite based fPAR product, the GEOV1 fPAR, is processed using neural networks. The design of neural networks imitates the neural system of the human brain and is capable of learning in a similar way to the brain (Kriesel 2007). Neural networks are interconnected computing systems, which are used to solve problems that require flexibility and they cannot be achieved using traditional rule-based programming. For GEOV1 fPAR (Table 3) the neural network was trained using data from MODIS and CYCLOPES, but the estimation of fPAR is based on SPOT VEGETATION data. The main advantage of the use of a neural network compared to a radiative transfer model is that it does not implicitly use land cover information, which can contain spatial and temporal inconsistencies (Camacho et al. 2013). The composition period of GEOV1 fPAR is 30 days, but the composite is provided every ten days, which means that the MODIS fPAR product is provided more often than the GEOV1 fPAR product. In addition, the GEOV1 fPAR composite is created using the 70 percentile of the cumulative fPAR within the composition period, instead of the maximum fPAR. In study VI, these two different approaches to estimate fPAR were compared and validated in boreal conditions using ground based estimates of fPAR.

In study VI, two-month series of both MODIS fPAR and GEOV1 fPAR were studied to analyze the temporal profiles of the products. Validation of the fPAR products was conducted during the peak-season (from mid-June to mid-August) when leaves are fully developed. In addition, rescaling of the NDVI based approach to estimate fPAR was tested, because NDVI data is available with different spatial resolutions and more frequently than the fPAR products. The MODIS NDVI-fPAR relationship (Knyazikhin et al. 1999) was used to convert Landsat (Table 2) and MODIS NDVI values to fPAR. Only pixels classified as good quality were used in study VI. Because satellite based estimates of fPAR contain both forest canopy fPAR and understory fPAR, the contribution of understory fPAR was modeled based on the fractional cover of the understory species (Pickett-Heaps et al. 2014). The contribution of understory fPAR to total forest fPAR was obtained by multiplying the understory fPAR with canopy transmittance in the sun’s direction at the moment of satellite overpass.

# 3 RESULTS

## 3.1 Ground based measurements of LAI

Currently, it is unclear how different LAI estimates are produced by different methods and sampling schemes in a boreal forest. Based on study I, Marklund's models with diameter at breast height and tree height as input produced on average 30% larger foliage biomass values for conifers than Repola's models, which additionally included crown length. The overall trend was that as the number of input variables increased (from one to three), the estimates of foliage biomass decreased. Because Repola's models had the largest number of input variables (diameter at breast height, tree height and crown length) and the data used to create the model were from Finland, it was selected as a reference method among the allometric models.

Optical and allometric estimates of LAI had a different range in LAI values, because of the saturation of the optical LAI estimates. Allometric estimates of LAI were on average 36% larger than the optical measurements of LAI (Figure 11). Shoot-level clumping correction of optical LAI improved the fit between optical and allometric LAI (RMSE = 1.38). The allometric models produced on average 12% smaller LAI values, compared to the shoot-level clumping corrected LAI. However, when the canopy radiation model was used to correct for the shoot-level clumping and contribution of stems and branches, the difference between allometric and optical estimates increased (RMSE = 1.81). The allometric LAI was 19% smaller than LAI inverted by the model. The slope (=0.89) between shoot-level clumping corrected LAI and LAI inverted using the canopy radiation model suggested that including some additional clumping correction, e.g. at crown-level, could possibly improve the fit between the two LAI estimates. The differences between optical and allometric values were the smallest for pine and largest for birch.

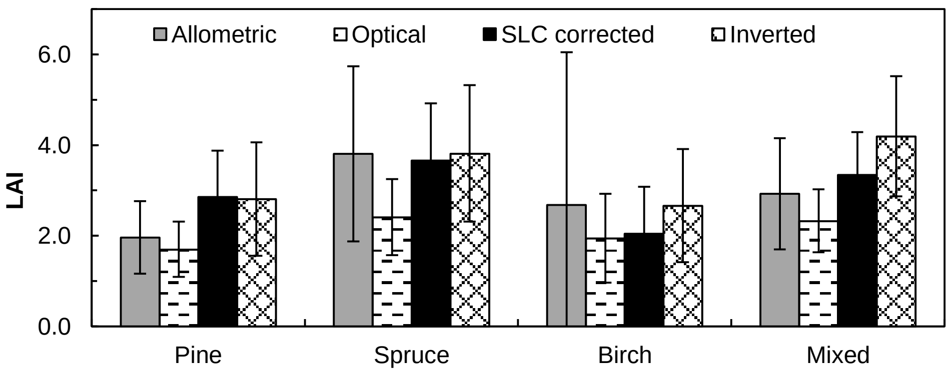


**Figure 11.** Comparison of different approaches to estimate LAI. LAI estimates produced using different methods: Allometric = LAI based on Repola's allometric models, Optical = optically measured LAI, SLC corrected = optical LAI corrected for shoot-level clumping, and Inverted = LAI inverted using the gap frequency model by Nilson (1999).

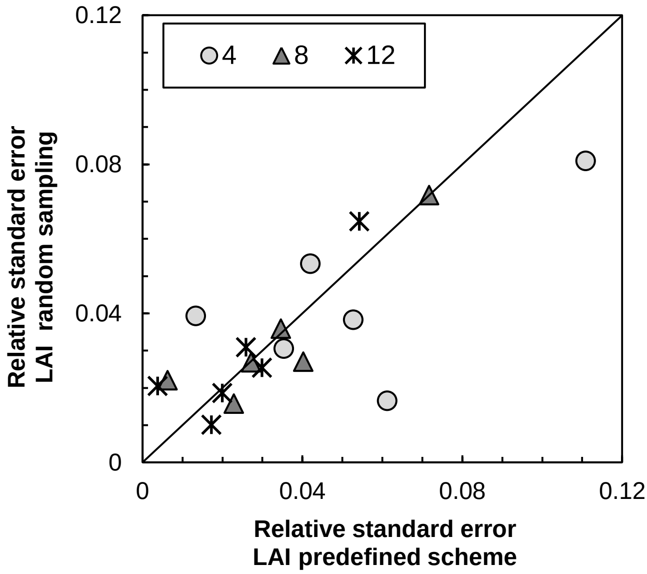


**Figure 12.** Comparison of random and predefined sampling schemes with similar numbers of measurement points.

The effect of sampling scheme on the accuracy of optical LAI values was studied in six differently structured boreal forest stands (study II). The studied plots covered a ground area of 36 m × 36 m (approximately 0.13 ha). The LAI was investigated using random, systematic and predefined sampling schemes. According to the results, relatively few measurement points (for example 8) are required to obtain LAI estimates with a relative standard error of less than 0.1 (Figure 12). Adding more points only moderately improved the estimates. Because random sampling is difficult to perform in practice, predefined sampling schemes are preferable. The best performing sampling schemes had individual measurement points organized systematically either in a square or a cross form. Using spatially more scattered sampling schemes like a square or cross instead of transect schemes, may be recommended for measuring boreal forest LAI. However, having four or less measurement points resulted in large errors, and thus schemes with eight to twelve measurement points organized in either a square or cross form, are recommended to obtain LAI estimates with an accuracy of 0.08 LAI units and a bias of less than 3%.

### 3.2 Validation of satellite based LAI products

Satellite based LAI products have usually been validated only at the peak of the growing season, because validation covering longer time periods would require measuring or estimating seasonal series of both understory and forest canopy layer LAI, which is laborious. In study III, seasonal series of understory and forest canopy LAI were used to assess the performance of the MODIS LAI products. The estimates of understory LAI were obtained from fractional cover estimates for different site fertility types (xeric, sub-xeric, mesic and herb-rich - study IV), which were upscaled using relative abundances of the different site fertility types. According to study III, the seasonal variation of forest canopy LAI was small (between 5 and 11%) for coniferous stands compared to stands with deciduous trees. Forest canopy LAI increased rapidly in stands dominated by birches from mid-May (LAI between 0.5 and 1.5) to the end of June (LAI between 2.5 and 3.4). Based on study IV, the largest seasonal changes between the understory types were observed in the most fertile sites (herb-rich and mesic sites) and the smallest in driest sites (xeric and sub-xeric). It was noticed that stands with the strongest dynamics in understory reflectance also have the strongest dynamics in forest canopy structure (LAI). Results from study IV showed that the differences between understory types were most evident at the peak of the growing season.

In study III, the average of understory LAI increased from spring to end of July, from 0.1 to 0.4. Meanwhile, the mean of MODIS LAI ranged from 0.5 (April) to 5 (mid-July). Results showed anomalous seasonal changes in MODIS LAI over coniferous forests. The variation in MODIS LAI was unrealistically large, even for deciduous forests, based on ground reference measurements. MODIS LAI was closer to the forest canopy LAI in spring and autumn, whereas during the summer it was more similar to the total LAI (canopy and understory) (Figure 13). Saturation of MODIS LAI caused relatively large composite-to-composite variation between the LAI products. Based on study III, the best time of year to validate the satellite based LAI products is either during spring or august, when saturation of LAI does not occur. According to study IV, the smallest differences between the understory types were seen in spring, because of the decay of plant material during the winter - the largest differences occurred during the summer.

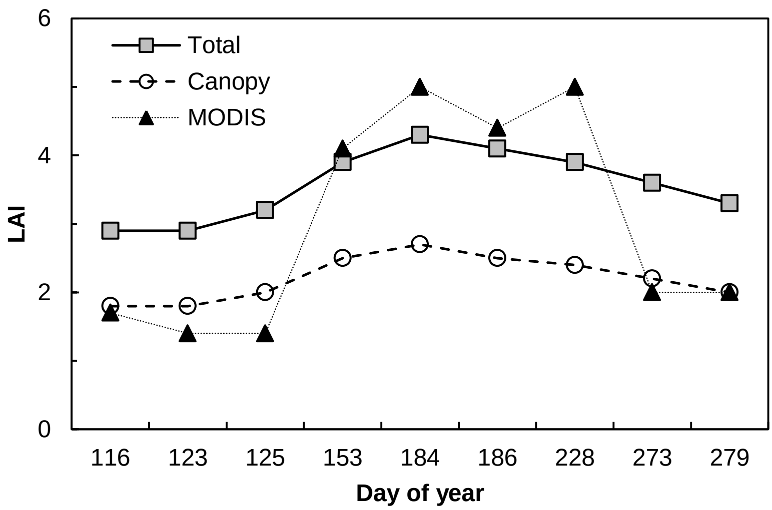


**Figure 13**. The seasonal course of ground reference LAI, Canopy = forest canopy LAI (optical LAI), and Total = forest canopy and understory LAI, and MODIS = satellite based LAI (MCD15A2).

### 3.3 Modeling ground reference fPAR

Measuring fPAR requires a large number of PAR sensors and is time-consuming, and thus modeling has become a popular option to approximate fPAR. However, obtaining all the model inputs for modeling the fPAR is challenging. The fPAR model presented in study V is based on a relationship between LAI and photon recollision probability and has a simple formulation. The measured and modeled fPAR estimates agreed generally well, and the average RMSE was less than 0.05. However, fPAR measured earlier in the morning showed a systematically better fit with the modeled values (RMSE = 0.03) than the fPAR measurements performed during the afternoon (RMSE = 0.06) (Figure 14). Results showed that the more heterogeneous the canopy structure, the larger is the variation in the diurnal courses of fPAR. Heterogeneity in forest structure was induced by small crowns and large gaps between the crowns in stands of low LAI. The difference between measured and modeled fPAR were the largest at noon (solar zenith angle ~40 degrees). Results showed that as the difference in stand-level optical LAI was 1, the maximum difference between the instantaneous fPAR was almost 0.2. During clear sky conditions the differences in diurnal courses of stand-level fPAR were the largest. Based on seasonal courses of fPAR, for July slightly smaller fPAR values were observed due to the higher sun elevation. The modeled 'Canopy' (Figure 14) fPAR (RMSE = 0.05) was almost systematically smaller than measured fPAR in study VI, because there was a 1 m difference in measurements heights between the two measurement devices.

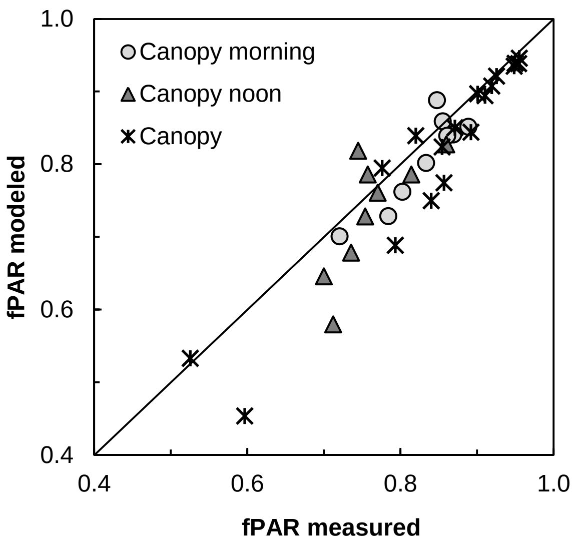


**Figure 14.** Measured and modeled fPAR. The morning and noon measurements and modeling of canopy fPAR are described in detail in study V, and canopy fPAR in study VI.

### 3.4 Validation of satellite based fPAR products

At present, there is a scarcity of ground reference fPAR data available from boreal forests to validate the satellite based fPAR products and to develop the retrieval algorithms. In this study the peak-season fPAR products were validated using modeled ground reference fPAR dataset of both forest canopy (study V) and understory fPAR. Results from study VI showed that the GEOV1 fPAR corresponded better to the total fPAR (RMSE = 0.05) (including forest canopy fPAR and understory fPAR) than to forest canopy fPAR (Figure 15). In contrast, MODIS fPAR was more similar to the forest canopy fPAR (RMSE = 0.12). MODIS fPAR demonstrated larger temporal variation and had a smaller number of good quality retrievals than GEOV1 fPAR during the peak-season. Seasonal variation in MODIS fPAR values ranged from 0.3 to 0.9 fPAR units, whereas the variation in the GEOV1 fPAR product stayed at around 0.8 (±0.15) fPAR units. GEOV1 fPAR was on average 0.15 fPAR units larger than fPAR MODIS during the peak-season, and its mean standard deviation (sd = 0.05) was one third of that of MODIS fPAR (sd = 0.16). Rescaling the NDVI into fPAR produced relatively similar results as the MODIS and GEOV1 fPAR products: MODIS NDVI based fPAR was found to correspond better to total fPAR than to canopy fPAR whereas Landsat NDVI based fPAR was more similar to forest canopy fPAR. For the 16 MODIS 1 km × 1 km pixels the contribution of understory fPAR ranged between 0.09 and 0.26 fPAR units, and was 0.18 on average.

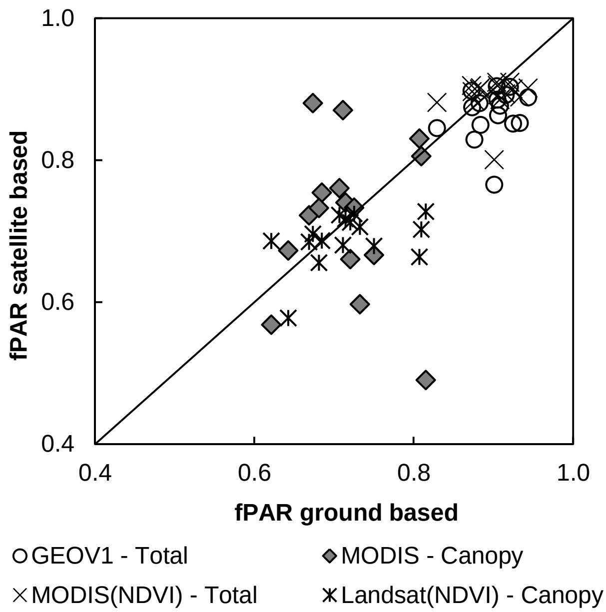


**Figure 15.** Comparison of the satellite based GEOV1 and MODIS fPAR products, and Landsat NDVI and MODIS NDVI based fPAR estimates to ground based fPAR. For MODIS fPAR and GEOV1 fPAR products the peak-season averages are shown for the 16 (1 km × 1 km) pixels. Ground based total fPAR is the sum of forest canopy and understory fPAR.

# 4 DISCUSSION

## 4.1 Estimation of ground reference LAI and fPAR

In this thesis, the national foliage biomass models for three boreal species were for the first time compared to optical measurements of LAI in a boreal region. Results showed that allometric models which had the largest number of input parameters, produced relatively similar results to the optical estimates, which were corrected for shoot-level clumping and branch area (assuming constant BAI). Since allometric and optical methods were found to produce similar results, a national database of LAI may be created based on forestry databases. However, since the number of input variables influences the foliage biomass estimates and thus LAI, caution is needed in model selection. Nationwide maps of LAI can be produced based on the results from study I. This has not been previously possible as the datasets of earlier studies have consisted of only a limited number of sample plots.

To analyze the effect of sampling scheme on the accuracy of optical LAI estimates, three different optical sampling techniques were compared: regular, systematic and predefined schemes. Large gaps between tree crowns are typical feature for managed boreal forests, and thus the spatial sampling scheme has to be considered if optical measurement techniques are used. The number of measurements points needed to estimate LAI with a predefined precision is described by an exponential function, and thus the accuracy of measurements increases relatively fast as the sample size is increased. A relatively small number of measurement points (e.g. 8-12, plot size 0.13 ha) were found to be sufficient for the estimation of LAI in a boreal forest.

All of the methods of LAI estimation have associated strengths and weaknesses, and thus the selection of the best LAI estimation method depends on the spatial and temporal monitoring needs. For example, if LAI estimates are required to cover large geographical areas, then the most applicable method is to use allometric foliage mass models that may be run using data from forestry databases. On the other hand, optical field measurements are applicable for smaller areas (< a few $km^2$) and may be used to detect fast changes in LAI, and to estimate seasonal and abrupt changes like defoliation or insect outbreaks. Using automatic observation systems (e.g. cameras and LED spectral sensors (Ryu et al. 2014)) for monitoring changes in LAI or spring phenology would offer time savings by reducing the visiting frequency to study areas. However, automated sensor systems should be able to cope with harsh environmental conditions (e.g. large temperature variations), and this therefore limits the number of systems available for monitoring boreal forests.

Both allometric and optical methods have their limitations, for example in estimating seasonal changes in LAI, but for different reasons. Allometric biomass models cannot be used to estimate seasonal development of LAI, because they do not include any variables to describe for example changes in plant metabolism or the seasonal changes in SLA which is needed to convert foliage mass to LAI. Obtaining a representative SLA value remains complicated, because the SLA is influenced by canopy position, site conditions, leaf/needle age and shading (Kellomäki and Oker-Blom 1981; Ross et al. 1986; Niinemets and Kull 1995; Stenberg et al. 1999). Optical measurement techniques which assume optically black foliage (e.g. LI-COR 1992) are not able to detect the color changes of coniferous needles. However, the senescence of deciduous species can be detected using optical instruments based on litterfall rather than changing leaf color. Optical instruments which measure several spectral regions such as hemispherical photographs, can be used to detect phenological changes at least in stands dominated by deciduous trees (Nagai et al. 2013). Yet, to detect the color changes of the foliage, hemispherical photographs should be taken under direct illumination conditions to preserve the foliage color information which would be lost under diffuse sky conditions.

fPAR is a dynamic variable and changes temporally as the sun moves along its path. Estimation of fPAR is not independent of LAI, because LAI quantifies the areal interphase, which absorbs and converts light energy into biomass. The log-linear relationship between optical LAI and fPAR is slightly less steep after shoot-level clumping correction is applied (Figure 16a). The fPAR model presented in study V is the first canopy absorption model that is based on photon recollision probability, and is suitable for forested environments because it takes into account multiple scattering effects. The novelty is that the fPAR model is made widely applicable by using data from different optical field instruments, and in that all model inputs are measurable. Measuring ground reference fPAR requires a large number of ground reference sensors and thus the modeling of fPAR serves a more practical approach. The fPAR model has a simple formulation, because it is based on the spectral invariance of scattering and absorption features at both leaf and canopy scale, and also of the scattering asymmetry parameter which describes fractions of upward and downward scattered radiation (Mõttus and Stenberg 2008). However, the nature of the required input parameters means that the model's sensitivity to, for example, traditional forestry variables cannot be assessed. More advanced canopy radiation models could be used to study our fPAR model's sensitivity to different stand architectures. However, the drawback of the advanced canopy radiation models is that acquiring all the required parameters remains challenging, and thus they are not suitable for large area applications.

The fPAR was measured using the TRAC instrument, which measures in the direction of the sun. As the sun zenith angle decreased, smaller fPAR values were obtained because in boreal forests, canopy openness increases towards the zenith. This also implies that the transect length which is used to estimate fPAR should be longer when the solar zenith angle is smaller. Therefore the sampling may be biased if too short transect length is used. Better correspondence between measured and modeled fPAR values was obtained in the morning, rather than during the afternoon, probably because the canopy transmittance was more homogeneous due to the smaller proportion of gaps in the canopies. The sky may also be clearer in the morning, because air temperature limits the water vapor, and as the temperature increases, more vaporized water may be contained within the atmosphere - the more clouds there are in the sky, the larger the ratio of diffuse to total incident radiation (e.g. Mõttus et al. 2012). The diurnal and seasonal courses of fPAR were simulated using three stands with different stand LAI (Figure 16b). The steepness of the diurnal fPAR curves is defined by the stand-specific pattern of gaps between the crowns. The bowl-shape trend of the diurnal fPAR is due to changes in solar zenith angle. In general, fPAR should be higher under diffuse than direct radiation conditions because diffuse radiation is able to penetrate deeper into the canopy. In the morning, the instantaneous fPAR increases along with increasing intensity of both direct and diffuse radiation components. However, the fPAR starts to decrease as the direct radiation component becomes larger than the diffuse radiation component, and as the portion of gaps within the canopies increases towards nadir. The sparser the stand, the larger the differences in diurnal and seasonal fPAR curves.

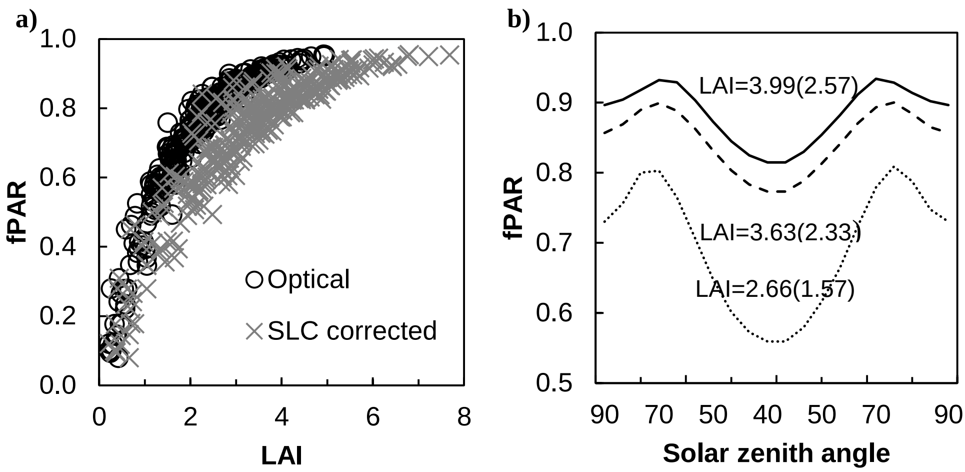


**Figure 16.** Relationship between LAI and fPAR. a) Optical LAI and LAI corrected for shoot-level clumping. b) Diurnal fPAR curves for clear sky conditions (Optical LAI is given inside parenthesis).

The reliability of the fPAR model depends on the accuracy of the input data and the validity of the model assumptions. Naturally the model may not be used if all of the model input cannot be determined. The fPAR model assumes that the ground surface is a Lambertian reflector and that forest canopy scattering is symmetrical for both upward and downward directions. To apply the fPAR model, estimates for understory reflectance and the optical properties of leaves and needles are also needed.

The fPAR model is based on ‘p-theory’, according to which canopy scattering and leaf scattering at the same wavelengths are related by a spectrally invariant canopy structural variable ‘p’ (Knyazikhin et al. 1998). p may be calculated based on LAI and canopy Diffuse non-interceptance (DIFN), which can be obtained from optical measurements (e.g. from LAI-2000 or DHP). The optical LAI and DIFN, which quantifies the fraction of radiation penetrating through canopy gaps under isotropic illumination, are exponentially related in boreal forests (Rautiainen et al. 2009b). Yet, the calculation of p requires that the true LAI is known. Shoot-level clumping correction of optical LAI may be used to approximate the true LAI, but in reality, in order to obtain the true LAI, a correction for the woody area and possible crown-level clumping is also required. Shoot-level clumping correction is based on species-specific STAR values, which have been found to display a large variation, even within a tree (Thérézien et al. 2007). However, the species-specific mean STAR has been found to stay relatively constant (Thérézien et al. 2007), and thus simple shoot-level clumping corrections appears to be a suitable option by which to correct for optical LAI estimates.

### 4.2 Estimation of LAI and fPAR by remote sensing

Remote sensing techniques are able to estimate the biophysical variables of LAI and fPAR, which have a direct influence on the scattering and absorption of plant canopies. In this thesis, several new ground reference methods to validate satellite based LAI and fPAR products have been presented. For the first time a complete seasonal series of simultaneous understory and forest canopy layer measurements was conducted, and used to quantify the seasonal dynamics of different understory types, and to validate satellite based LAI products. In addition the satellite based estimates of fPAR were also validated using a ground based dataset of both forest canopy and understory fPAR.

Satellite based estimates of LAI and fPAR are retrieved assuming only green plant material and, for example, the MODIS LAI or fPAR products have no separate green understory layers on top of the bare soil surface (as GEOV1 fPAR does (Baret et al. 2013)). This simple parameterization does not allow for any separation between foliage and woody compartments, or between different layers of vegetation, but is easy to apply to different biomes, computationally efficient and applicable to global monitoring. Optical instruments such as the LAI-2000 are equally unable to differentiate between foliage and a woody area, and are only able to estimate forest canopy PAI. This is why optical measurements are not directly comparable to satellite based measurements of LAI. To improve the fit between ground based and satellite based estimates of LAI, a shoot-level clumping correction is commonly applied. Satellite based LAI is known to correspond better with shoot-level clumping corrected LAI, rather than optical LAI (Weiss et al. 2007; Garrigues et al. 2008). As the fPAR is calculated based on LAI (Knyazikhin et al. 1999), inaccuracies in LAI retrieval may result in even larger inaccuracies of fPAR.

Results showed that the satellite based estimates of LAI display anomalous seasonality, compared to ground based measurements of LAI. The satellite based estimates of LAI showed relative large composite-to-composite variation, and were smaller than ground based estimates during spring and autumn, whereas during summer the satellite based estimates were larger than the ground based estimates of LAI. The results from study III support findings by others (e.g. De Kauwe et al. 2011; Rautiainen et al. 2012). Some researchers have suggested that including Shortwave Infrared (SWIR) band in MODIS LAI retrieval could potentially improve LAI estimates for coniferous forests (Wang et al. 2004; Abuelgasim et al. 2006). Currently, the accuracy of satellite based LAI is restricted by the low spatial resolution of the data. At present, NASA is developing a global LAI product based on medium spatial resolution Landsat data (Ganguly et al. 2012). The new LAI product will hopefully solve the problems caused by heterogeneous forest structure and the small stand size of European forests, and thus ease the parameterization of different biomes.

Managed boreal forests in Finland are typically composed of small forest stands, and the average stand size is only 1-2 hectares. Individual forest stands are usually grown as even-aged, but larger forest areas often consist of stands with different development stages. Thus, measuring the average fPAR to cover just one satellite based fPAR pixel (~1 km × 1 km) requires measuring the fPAR for 25-100 forest stands, which is extremely laborious. Medium spatial resolution data has been used to separate different forest stands, because the pixel size (~30 m × 30 m) is relatively similar to the area, which may be measured using optical instruments within a forest. Medium spatial resolution data has been used to validate coarse spatial resolution fPAR products using transfer functions to link between ground and satellite based data (e.g. Morisette et al. 2006). Vegetation indices have been popular in estimating LAI or fPAR based on remote sensing data, because indices are applicable to different sensors and independent of the spatial resolution of the satellite data. However, the applicability of vegetation indices is restricted by the fact that plant absorption varies due to changes in plant structure (e.g. plant growth: changes in leaf shape, size and orientation), and also environmental conditions such as drought or competition of light. There is a large variation in structural and physiological conditions between different biomes (and within a biome), and thus using biome-specific parameters to scale vegetation indices to e.g. fPAR may produce inaccurate estimates (e.g. Liang et al. 2012).

Satellite based estimates of LAI and fPAR are instantaneous, because data is collected in a few seconds. The LAI stays constant over a day outside the green up and senescence phases, however the fPAR changes dynamically in relation to the sun zenith angle and plant structure. The difficulty in measuring instantaneous values of fPAR is that measurements should be conducted simultaneously with satellite image acquisition, which is rarely possible, especially if ground based data needs to be measured from several places. The satellite based fPAR products are often defined as instantaneous black sky fPAR around 10:00 which is a close approximation of the daily integrated fPAR (Baret et al. 2012; Camacho et al. 2013). Liang et al. (2012) pointed out that many of the current fPAR algorithms do not separate between direct and diffuse radiation components, and so to achieve higher retrieval accuracy, these two radiation components should be modeled separately.

Satellite based fPAR products have been said to overestimate fPAR in northern latitudes for most of the year (Steinberg et al. 2006). Study VI is based on extensive field measurements of forest canopy transmittance and the cover fraction of different understory types, and highlights the important role of understory vegetation in the total fPAR, obtained by satellite based measurements. The results support those of Serbin et al. (2009) who conducted a similar study for wildfire originated stands, which may be very different from the managed boreal forests of Finland. According to Iwata et al. (2013), moss understory increased fPAR on average by 0.1 units, whereas our stands comprised two layers of different understory species and the average understory fPAR was 0.18 units (± 0.15 units). The general result that total fPAR (comprising both understory and forest canopy layer) varied less than the forest canopy fPAR, simply implied that the forest understory adapts its structure based on prevailing light conditions.

Finally, in study VI, the new product called GEOV1 fPAR was validated using ground reference data of both the forest canopy and understory. The study VI was among the first ones to report validation results from boreal forests. The GEOV1 fPAR produced larger estimates than the MODIS fPAR, which has been used to benchmark other satellite based fPAR products. The results showed that GEOV1 fPAR values were more similar to ground reference total fPAR, whereas MODIS fPAR agreed better with forest canopy fPAR. One notable difference between the satellite based fPAR products was that GEOV1 had a larger number of pixels classified as good quality compared to MODIS, and smoother temporal dynamics. Based on this study, the GEOV1 fPAR is a more suitable option to estimate boreal forest fPAR than MODIS fPAR. Nevertheless, the problems associated with northern locations (low sun angles and cloudiness), will still restrict the accuracy of the remote sensing products in estimating vegetation LAI or fPAR in a boreal region.

### 4.3 Future prospects

First of all, allometric measurements need to be parameterized properly, so as to take into account seasonal changes in the size of foliage elements. My idea is that an allometric model could be used to estimate seasonal changes in LAI, if the SLA value which is used to convert foliage mass to area, could be linked to temperature sum or growth degree days. This would allow generation of nationwide LAI statistics based on forestry databases and meteorological observations. Optical LAI measurement techniques need measurements of shoots to quantify the seasonal changes in shoot-level clumping caused by the growth of needles and changes in the needle angle (Stenberg et al. 1994). This would require measuring a large number of shoot samples over different species, development stages, age groups and site conditions. In addition, for each tree, several shoots with predefined locations should be sampled to get a representative average, because a shoot's geometry changes along the light gradient (e.g. Stenberg 1996b).

Next, the relationship between PAI and LAI should be quantified in order to estimate the true LAI by optical measurement techniques. The correction for woody area would most probably have most influence in broadleaved stands, where the fraction of woody area to foliage area is larger during spring and autumn compared to summer. A method by which to quantify the PAI-LAI relation could possibly be developed based on hemispherical photography, because the data allows visual separation of foliage and woody areas when they do not overlap, and also post-processing of the data. A more accurate determination of foliage and woody area could be based on terrestrial laser scanning, because woody parts and foliage reflect differently, for example, at 1500 nm. Côté et al. (2009) have demonstrated using simulated data that foliage and woody parts of trees can be separated by selecting the darkest and brightest points from the simulated point cloud. Another option is to use full waveform terrestrial lidar to separate non-ground hits of woody parts and foliage, based on the relative width of return pulse (Yang et al. 2013). However, under natural conditions, determination of the reflectance thresholds for woody parts and foliage remains difficult due to the variation in spectra and surface orientation (Côté et al. 2009) and clumping at the scale of the pulse width.

Airborne Laser Scanning (ALS), currently adopted by the Finnish stand-level forest management inventories, is a valid method for forest inventory purposes (Hyyppä et al. 2008) and estimating total biomass (Næsset and Gobakken 2008). ALS data cannot be used to directly estimate the true LAI (Solberg et al. 2009), however it may be used to estimate the effective LAI, which can be obtained based on gap fraction (Solberg et al. 2009). Currently, terrestrial laser scanning techniques are used to measure lower parts of the canopies, and could thus be used to obtain canopy gap fraction or the inputs needed for the allometric foliage biomass models. For example, the length of the living crown is difficult to obtain from ALS, but may be estimated based on terrestrial laser scanning data.

Optical measurement techniques are widely applied in modeling LAI and fPAR due to their simplicity and efficiency. Since optical measurement techniques are not applicable for use over areas larger than a few square kilometers, some key variables like the p should be linked with NFI data or combined with land cover classification to create national maps of p. A national map of p could allow for more detailed environmental monitoring and validation of global remote sensing products, because remotely sensed estimates of LAI (Rautiainen et al. 2009b), fPAR or albedo (Lukeš et al. 2014) could be corrected using independent data. Alternatively, nationwide maps of fPAR or albedo could be created based on forest variables and meteorological databases. Both fPAR and albedo vary between 0 and 1, and thus the models could be based on beta regression techniques (Ferrari and Cribari-Neto 2004). The calculation of p from ground based data requires estimates of true LAI and DIFN. The DIFN may be calculated based on canopy transmittance, which may be obtained either by optical measurements or by terrestrial laser scanning techniques (Van Leeuwen et al. 2013). However, since the true LAI remains unknown, the value of p depends on shoot-level clumping correction. The p-LAI relationship may be solved only by understanding the workings of the PAI-LAI relationship.

The development of remote sensing techniques and instruments may help to separate reflected signals originating from forest canopy and understory layers, and to broaden our understanding of different plant processes. If the contributions from different layers could be separated, the accuracy of NPP prediction would improve. Finer spatial resolution and multi-angular satellite measurements may be used to separate the contributions from both layers, because a smaller spatial resolution allows the selection of more homogeneous targets (e.g. mono-cultural forests). Additionally, different view angles may be used to detect the reflected portions of the forest understory layer (Pisek et al. 2012). Hyperspectral remote sensing (imaging spectroscopy) which uses narrow spectral bands and band combinations, may provide more detailed information on different plant processes, when compared to broadband sensor data. For example, Heiskanen et al. (2013) demonstrated that by using narrow spectral bands, a higher correlation was obtained between satellite based and ground based optical LAI.

The accuracy of satellite based products to estimate biophysical variables such as LAI and fPAR is restricted by either spatial or spectral resolution, because the finer the spatial or spectral resolution, the lower is the signal-to-noise ratio. Currently, applying narrow spectral bands to estimate biophysical variables such as LAI and fPAR seems to hold the most potential, because some of the physiological responses of plants to different environmental factors are seen only at specific wavelengths. For example, the red edge inflection point, corresponding to the wavelength of the most rapid increase in spectra around 700 nm, is sensitive to vegetation chlorophyll (Pu et al. 2003), and thus could be useful in estimating fPAR because higher chlorophyll content may also denote an increase in fPAR. Finer spatial resolution data may also be more accurate in areas with fragmented landscapes like the boreal forests of Finland. Hopefully, the development will lead towards other finer spatial resolution satellite products, for example global fPAR products.

Currently, the Earth system is monitored from space in near real-time, because people have the expertise, instruments and techniques to do so, as well as a hunger for information. However, it is good to remember that the accuracy of these satellite based measurements depends on the accuracy of the ground based data which was used to develop the algorithms. As long as optical remote sensing techniques are used to survey the state of the biosphere, ground reference data will be required to quantify the structural and optical properties of vegetation, to unravel the signals measured by satellite sensors, and to validate and develop satellite based products.

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