Development and Refinement of New Products from Multi-Angle Remote Sensing to Improve Leaf Area Index Retrieval

by

Jan Pisek

A thesis submitted in conformity with the requirements for the degree of Doctor of Philosophy
Graduate Department of Geography
University of Toronto

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University of Toronto
2009

Abstract

Remote sensing provides methods to infer vegetation information over large areas at a variety of spatial and temporal resolutions that is of great use for terrestrial carbon cycle modeling. Understory vegetation and foliage clumping in forests present a challenge for accurate estimates of vegetation structural information. Multi-angle remote sensing was used to derive and refine new information about the vegetation structure for the purpose of improving global leaf area index mapping.

A field experiment with multi-angle, high resolution airborne observations over modified and natural backgrounds (understory, moss, litter, soil) was conducted in 2007 near Sudbury, Ontario to test a methodology for the background reflectivity retrieval. The experiment showed that it is feasible to retrieve the background information, especially over the crucial low to intermediate canopy density range where the effect of the understory vegetation is the largest. The tested methodology was then applied to background reflectivity mapping over conterminous United States, Canada, Mexico, and Caribbean land
mass using space-borne Multi-angle Imaging SpectroRadiometer (MISR) data. Important seasonal development of the forest background vegetation was observed across a wide longitudinal and latitudinal span of the study area.

The previous first ever global mapping of the vegetation clumping index with a limited eight-month multi-angular POLDER 1 dataset was expanded by integrating new, complete year-round observations from POLDER 3. A simple topographic compensation function was devised to correct negative bias in the data set caused by topographic effects. The clumping index reductions can reach up to 30% from the topographically non-compensated values, depending on terrain complexity and land cover type. The new global clumping index map is compared with an assembled set of field measurements, covering four continents and diverse biomes.

Finally, inclusion of the new vegetation structural information, including background reflectivity and clumping index, gained from the multi-angle remote sensing was then shown to improve the performance of LAI retrieval algorithms over forests.
Acknowledgments

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<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>ADEOS</td>
<td>ADvanced Earth Observation System</td>
</tr>
<tr>
<td>AF</td>
<td>Anisotropy Factor</td>
</tr>
<tr>
<td>APAR</td>
<td>Absorbed Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>AGRO</td>
<td>agricultural BigFoot site near Bondville, Illinois, USA.</td>
</tr>
<tr>
<td>ASDC</td>
<td>Atmospheric Science Data Center</td>
</tr>
<tr>
<td>BELMANIP</td>
<td>BEnchmark Land Multisite ANalysis and Intercomparison of Products</td>
</tr>
<tr>
<td>BOREAS</td>
<td>BORreal Ecosystem Atmosphere Study</td>
</tr>
<tr>
<td>BRDF</td>
<td>Bidirectional Reflectance Distribution Function</td>
</tr>
<tr>
<td>BRF</td>
<td>Bidirectional Reflectance Factor</td>
</tr>
<tr>
<td>CASI</td>
<td>Compact Airborne Spectrographic Imager</td>
</tr>
<tr>
<td>CCD</td>
<td>Charge-Coupled Device</td>
</tr>
<tr>
<td>CEOS</td>
<td>Committee on Earth Observation Satellites</td>
</tr>
<tr>
<td>CHRIS/PROBA</td>
<td>Compact High-Resolution Imaging Spectrometer/Project for On-Board Autonomy</td>
</tr>
<tr>
<td>DAAC</td>
<td>Distributed Active Archive Center</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>DOY</td>
<td>Day Of Year</td>
</tr>
<tr>
<td>ETM</td>
<td>Enhanced Thematic Mapper</td>
</tr>
<tr>
<td>EOS</td>
<td>Earth Observing System</td>
</tr>
<tr>
<td>fAPAR</td>
<td>fraction of Absorbed Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>GLC2000</td>
<td>Global Land Cover 2000</td>
</tr>
<tr>
<td>GO</td>
<td>Geometrical-Optical</td>
</tr>
<tr>
<td>GPP</td>
<td>Gross Primary Productivity</td>
</tr>
<tr>
<td>HARV</td>
<td>HARVard forest BigFoot site, Massachusetts, USA</td>
</tr>
<tr>
<td>IDL</td>
<td>Interactive Data Language</td>
</tr>
<tr>
<td>IFOV</td>
<td>Instantaneous Field of View</td>
</tr>
<tr>
<td>IGBP</td>
<td>International Geosphere-Biosphere Programme</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>ISR</td>
<td>Infrared Simple Ratio</td>
</tr>
<tr>
<td>KONZ</td>
<td>KONZa prairie BigFoot site, Kansas</td>
</tr>
<tr>
<td>LACC</td>
<td>Locally Adjusted Cubic-spline Capping</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>--------------</td>
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</tr>
<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
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<tr>
<td>LC</td>
<td>Land Cover</td>
</tr>
<tr>
<td>LUT</td>
<td>Look Up Table</td>
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<tr>
<td>MAE</td>
<td>Mean Absolute Error</td>
</tr>
<tr>
<td>MISR</td>
<td>Multiangle Imaging SpectroRadiometer</td>
</tr>
<tr>
<td>MODTRAN</td>
<td>MODerate resolution atmospheric TRANsmission</td>
</tr>
<tr>
<td>MODIS</td>
<td>MOderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>NDHD</td>
<td>Normalized Difference between Hotspot and Darkspot</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NIR</td>
<td>Near Infra-Red</td>
</tr>
<tr>
<td>NOBS</td>
<td>NOrthern Boreal Spruce BigFoot site, Manitoba, Canada</td>
</tr>
<tr>
<td>NPP</td>
<td>Net Primary Productivity</td>
</tr>
<tr>
<td>OLS</td>
<td>Ordinary Least Squares</td>
</tr>
<tr>
<td>PAR</td>
<td>Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>PE</td>
<td>Percentage Error</td>
</tr>
<tr>
<td>PHI</td>
<td>relative azimuth angle</td>
</tr>
<tr>
<td>POLDER</td>
<td>P0larization and Directionality of the Earth’s Reflectance</td>
</tr>
<tr>
<td>RAE</td>
<td>Relative Absolute Error</td>
</tr>
<tr>
<td>RE</td>
<td>Relative Error</td>
</tr>
<tr>
<td>RMA</td>
<td>Reduced Major Axis</td>
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<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
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<td>RS</td>
<td>Remote Sensing</td>
</tr>
<tr>
<td>RSR</td>
<td>Reduced Simple Ratio</td>
</tr>
<tr>
<td>RT</td>
<td>Radiative Transfer</td>
</tr>
<tr>
<td>SMAC</td>
<td>Simplified Method for Atmospheric Correction</td>
</tr>
<tr>
<td>SOA</td>
<td>Southern Old Aspen site</td>
</tr>
<tr>
<td>SOM</td>
<td>Space Oblique Mercator</td>
</tr>
<tr>
<td>SPOT-VGT</td>
<td>Satellite Pour l'Observation de la Terre – VeGeTation</td>
</tr>
<tr>
<td>SR</td>
<td>Simple Ratio</td>
</tr>
<tr>
<td>SZA</td>
<td>Solar Zenith Angle</td>
</tr>
<tr>
<td>TRAC</td>
<td>Tracing Radiation and Architecture of Canopies</td>
</tr>
<tr>
<td>UTM</td>
<td>Universal Transverse Mercator</td>
</tr>
<tr>
<td>VALERI</td>
<td>VALidation of European Remote sensing Instruments</td>
</tr>
<tr>
<td>VeMP</td>
<td>VEGeTation Misr Polder</td>
</tr>
<tr>
<td>VGT</td>
<td>VeGeTation</td>
</tr>
</tbody>
</table>
VI
Vegetation Index

VZA
View Zenith Angle

WGS84
World Geodetic System 1984
1 Introduction

Modeling terrestrial ecosystems and the terrestrial carbon cycle requires observations of key surface characteristics provided at relevant spatial and temporal resolutions. Among these characteristics, the leaf area index (LAI) and the clumping index have been shown to be important parameters for any process-based canopy-scale photosynthesis modeling because of their effects on radiation absorption and distribution in the canopy.

Remote sensing observations allow monitoring the seasonal and interannual LAI variability, and multiple LAI products have become available to the science community at both global and regional extents. It was observed repeatedly that LAI products can vary significantly. The presence of understory vegetation is a long time recognized problem that limits the accuracy of satellite-estimated forest LAI. Not accounting for the foliage clumping in LAI retrieval algorithms can lead to substantial underestimation of actual LAI. Prior to the advent of multi-angle remote sensing, it was not possible to retrieve the structural information about the foliage clumping and understory using conventional mono-angle, nadir-spectral optical remote sensing techniques.

This chapter serves three objectives: (i) to provide a broader picture of the significance of the undertaken research in the field of the terrestrial ecosystems/carbon cycle modeling and climate change, (ii) to briefly introduce the initial studies in the field of multi-angle remote sensing that define the starting point of this dissertation, and (iii) to outline the research objectives and structure of this dissertation.

1.1 Climate, carbon cycle modeling, and the role of remote sensing

It is well known that the concentration of greenhouse gases has increased remarkably since the industrial revolution, especially in the last century. The concentration of carbon dioxide has risen from
280 ppm before the industrial revolution to over 383 ppm (Blasing, 2008; IPCC, 2007). This rapid rise in atmospheric carbon dioxide concentrations occurs due to the imbalance between the rates at which anthropogenic and natural sources emit carbon dioxide and the rate at which the global carbon sinks remove carbon dioxide from the atmosphere (Canadell et al., 2007). Carbon dioxide, as a key greenhouse gas, enhances gradual warming of the Earth’s temperature (IPCC, 2007).

In terrestrial ecosystems, vegetation is one of the most important assimilators of carbon dioxide with gross primary productivity reaching around 120 GtCy⁻¹ (IPCC, 2007). Plants assimilate carbon dioxide from the atmosphere and incorporate it into the biomass through photosynthesis, and part of the assimilated carbon is emitted into the atmosphere through plant respiration (autotrophic respiration). The rate of carbon uptake from the atmosphere through photosynthesis, the gross primary productivity (GPP), is arguably the most variable component of the terrestrial carbon cycle. Our ability to model this component accurately is critical in global carbon cycle and climate research (Alton et al., 2007; Chen et al., 2009).

The portion of carbon that remains in the living biomass after accounting for autotrophic respiration is called the net primary productivity (NPP). Current NPP models used to simulate carbon fixation can be classified into light use efficiency (empirical) models and process-based models. The light use efficiency models calculate NPP through the energy conversion efficiency and photosynthetically active radiation (PAR) absorbed by vegetation (Running and Coughlan, 1988; Potter et al., 1993; Landsberg and Waring, 1997; Running et al., 2004). Despite being computationally efficient, the generalization of empirical parameters in these models is sometimes difficult and these models are not applicable to project future responses of the carbon cycle to climate change.

Process-based models are based on physiological and ecological processes. Photosynthesis, evapotranspiration, autotrophic respiration, and dry matter partition are used to estimate NPP (Spitters,
3

1986; Kim and Verma, 1991; Sellers et al., 1992, 1996; Amthor, 1994; Baldocchi and Harley, 1995; Leuning et al., 1995, 1998; Wang and Leuning, 1998; Dai et al., 2004). Process-based models have been widely used in estimating the distribution of NPP and researching the carbon cycle at the regional or global scale because of their well-established theoretical foundations.

Process-based models can use different approaches to upscale the leaf-level Farquhar biochemical model (Farquhar et al., 1980) to the canopy by treating the canopy as a big leaf (Friend, 1995; Sellers et al., 1996), two leaves (sunlit-shaded leaf model) (Wang and Leuning, 1998; Arain et al., 2002; Chen et al., 2003a), or as multiple-layers of leaves (Bonan, 1993; Foley, 1995; Grant et al., 2001). Big-leaf models assume a plant canopy to function as a big leaf. They calculate photosynthesis for a leaf at the top of the canopy and then scale up to the whole canopy by considering the attenuation of solar radiation inside the canopy (Sellers et al., 1996; Friend et al., 1997; Dickinson et al., 1998). The sunlit-shaded leaf models stratify the canopy into leaves that belong to the sunlit and shaded regimes (Wang and Jarvis, 1990; Leuning et al., 1995). Studies show that sunlit-shaded leaf models are a large improvement over big-leaf models which do not capture the non-linearities associated with the canopy biophysics (Chen et al., 1999). The sunlit-shaded leaf models are also computationally efficient relative to multiple-layer canopy models (Wang and Leuning, 1998; Dai et al., 2004), where the carbon fixation is estimated for each leaf surface of multi-specific plant canopies, defined by height, azimuth, inclination, and exposure (Grant et al., 2001).

Leaf area index (LAI), defined as one half of the total green area per horizontal ground surface area (Chen and Black, 1992; Jonckheere et al., 2004), is the parameter needed for any process-based canopy-scale photosynthesis modeling activity (Wang et al., 2007). However, the single LAI parameter is insufficient to describe the effect of canopy architecture on radiation absorption and distribution in the canopy (Chen et al., 2003b). Conifer forests may be the most highly organized, with structures such as shoots, branches, whorls, tree crowns and tree groups, while grasses and crops are lacking similar
structures (Chen et al., 2005). The leaf spatial distribution pattern can be effectively described by the foliage clumping index (Nilson, 1971; Chen, 1996a; Weiss et al., 2004). The clumping index quantifies the degree of the deviation of foliage spatial distribution from the random case. The use of clumping index is critical in any photosynthesis models, either empirical through the calculation of absorbed photosynthetically active radiation (APAR) or process-based through the calculation of the average PAR irradiance on all leaves or on sunlit and shaded leaves separately. However, the clumping index is a particularly important input in sunlit/shaded leaf models (Chen et al., 2003b) as its value greatly modifies the amounts of sunlit and shaded leaves. As foliage clumping increases at a given LAI, i.e., leaves are more aggregated in clumps, the amount of sunlit leaves decreases and that of shaded leaves increases, changing the final outcome of canopy photosynthesis. The use of the clumping index therefore captures the ecological importance of the existing canopy architectural difference of various vegetation types.

In order to estimate carbon fixation by terrestrial vegetation, datasets at the relevant spatial and temporal resolution are required (Cayrol, et al., 2000). The general consensus is that such data sets over large areas can be regularly obtained only from remote sensing (Myneni et al., 1997; Chopping et al., 2008a; Pinty et al., 2008).

1.2 Estimating leaf area index from remote sensing and its limitations

Driven by the need to monitor global vegetation under changing climate, many space-borne observing systems have been successfully launched. In the past five years, multiple LAI products have become available to the science community at both global and regional extents. For year 2002 only, at least six different global LAI and nine fraction of Absorbed Photosynthetically Active Radiation (fAPAR) products were developed (Weiss et al., 2007). With the available spectral measurements from satellite data, two kinds of methods were generally applied for estimating LAI, namely canopy radiation models and vegetation indices. The first approach is based on the inversion of canopy radiation models (Goel,
1989; Myneni et al., 1997; Weiss and Baret, 1999). Theoretically this approach is preferable, since these models simulate physical processes and their derived variables have a physical basis to their interpretation. Numerical methods (Bicheron and Leroy, 1999; Jacquemoud et al., 2000), Look Up Table (LUT) (Knyazikhin et al., 1998a) and neural network (Weiss and Baret, 1999; Gastellu-Etchegorry et al., 2003; Bacour et al., 2006; Baret et al., 2007) are the main inversion techniques used to retrieve LAI based on radiative transfer models (Garrigues et al., 2008). Numerical optimisation techniques traditionally used for direct model inversion either tend to have a high computational cost or are sensitive to initial parameter values (e.g. Jacquemoud et al., 2000). Therefore the use of computationally efficient LUT or neural networks procedures are currently used (Casa and Jones, 2005). The second approach to estimate LAI is to use semi-empirical relationships between LAI and vegetation indices (Baret and Guyot, 1991). Vegetation indices are computed by transformation and combination of multispectral reflectance data. The most commonly used are indices such as the normalized difference vegetation index (NDVI) (Baret and Guyot, 1991; Carlson and Ripley, 1997), the simple ratio (SR) and reduced simple ratio (RSR) (Brown et al., 2000; Chen et al., 2002; Stenberg et al., 2004), and the infrared simple ratio (ISR) (Butson and Fernandes, 2004). Many LAI products have been produced with various degrees of accuracy, although the problem of saturations of reflectances in the various spectral bands at high LAI values (Goel, 1989; Bicheron and Leroy, 1999) is always a major cause for concern using the VI-based methods.

The multitude of these products prompted the need for their validation and intercomparison (Baret et al., 2006). It was observed repeatedly that LAI products can vary significantly (Buermann et al., 2002; Tian et al., 2004; Abuelgasim et al., 2006; Bacour et al., 2006; Pisek et al., 2007; Weiss et al., 2007; Garrigues et al., 2008). Beside the variation of atmospheric characteristics, angle effects (sensor and sun angles) and the application of the algorithms to a range of vegetation types and environmental conditions (i.e. the extrinsic sources), the biggest source of uncertainty in canopy LAI estimates is related to the manner in which canopy architecture is represented in LAI retrieval algorithms. First, this concerns the spatial variation of leaf area density leading to foliage clumping. Not accounting for the foliage
clumping in LAI retrieval algorithms leads to substantial underestimation of the actual LAI, especially for needleleaf forest (Chen et al., 1997a). Second, canopy vertical heterogeneity is also generally not properly taken into account in current retrieval algorithms (Garrigues et al., 2008). The presence of understory vegetation is a long time recognized problem that limits the accuracy of satellite-estimated forest LAI (Peddle et al., 1999; Gemmel, 2000; Ni and Li, 2000; Chopping et al., 2006; Eriksson et al., 2006). The presence of an understory layer can substantially amplify the canopy LAI estimates (Chen et al., 1997b). However, prior to the advent of multi-angle remote sensing, it was not possible to retrieve the structural information about the foliage clumping and understory using conventional mono-angle, nadir-spectral remote sensing techniques since structural surface properties are largely confounded in nadir-spectral measures (Chopping, 2008).

1.3 Multi-angle remote sensing and retrieval of forest background and foliage clumping information

Multi-angular observations can be collected by viewing the same target from several angles in one overpass of a space-borne or airborne sensor or by observing the target during several overpasses (Asner et al., 1998; Diner et al., 1999). Multi-angle remote sensing delivers additional information about vegetation in terms of directional characteristics related to its vertical structure (Diner et al., 1999, 2005; Leblanc et al., 1999; Verstraete et al., 1996; Chopping, 2008), and there have been a number of studies carried out to extract information on optical properties and structure of vegetation from the multi-angle data (e.g. Bicheron et al., 1997; Deering et al., 1999; Sandmeier and Deering, 1999; Lacaze et al., 2002; Zhang et al., 2002a, b; Chen et al., 2003b; Gao et al., 2003; Cierneyewski et al., 2004; Heiskanen, 2006; Armston et al., 2007; Schull et al., 2007; Chopping et al., 2008a; Rautiainen et al., 2008b). A recent study of the ability of multi-angle remote sensing for retrieving forest background optical properties over a boreal region in Canada provided some encouraging results (Canisius and Chen, 2007). Due to the lack of field measurements, the verification of the derived background reflectivity estimates was rather limited. Further work on the methodology, its validation and upgrade into a mature remote sensing algorithm was yet to be done.
Global mapping of the vegetation clumping index was attempted for the first time using multi-angular POLDER 1 data by Chen et al. (2005). This work built on previous research by Lacaze et al. (2002) and Chen et al. (2003b), where an angular index obtained from multi-angle remote sensing and that characterizes reflectance anisotropy was successfully related to ground measurements of clumping index. The original ~6 km resolution POLDER 1 global clumping map by Chen et al. (2005) had still several limitations including limited spatial coverage due to clouds, presence of topographic effects, and a lack of evaluation with field measurements. It is therefore an integral part of this thesis research to improve this global clumping index map using new POLDER data in order to use it for improving global LAI mapping.

1.4 Research Objectives and Thesis Outline

The objectives of this dissertation are as follows:

(1) to investigate the recently in-house developed LAI algorithms by Deng et al. (2006) using reference data from a set of validation sites in North America and the MODIS LAI product that has been routinely produced and increasingly used for various global and local studies (Myneni et al., 2002; Lotsch et al., 2003). Chapter 2, entitled “Comparison and validation of MODIS and VEGETATION global LAI products over four BigFoot sites in North America” (Pisek and Chen, 2007), examines the performance of the two global LAI products, VGT LAI of Deng et al. (2006) and MODIS LAI Collection 4 of Myneni et al. (2002). It focuses on the issues of comparisons with estimates from validation sites and the role of the uncertainties that need to be addressed.

(2) to undertake field experiments in order to better understand the role of background on the optical properties of the vegetation stands. Chapter 3, entitled “Mapping forest background reflectance in a boreal region using multi-angle Compact Airborne Spectrographic Imager (CASI) data” (Pisek et al., 2009a), focuses on the initial testing of the retrieval methodology, with unique field work including
modifications to the understory, and an orchestrated multi-angle airborne sensor campaign over a study area near Sudbury, Ontario. The effects of uncertainties in the input forest structural parameters on this retrieval strategy are also explored.

(3) to apply the findings from the field experiments with an airborne sensor in developing algorithms for determining the forest background reflectivity from the multi-angle satellite observations. In Chapter 4 entitled “Mapping forest background reflectivity over North America with Multi-angle Imaging SpectroRadiometer (MISR) data“ (Pisek and Chen, 2009), the refined background reflectivity mapping methodology is transformed into a set of operational algorithms and applied over the conterminous United States, Canada, Mexico, and the Caribbean land mass. Temporal, spatial and overstory vegetation-dependent variations of the forest background reflectivities are explored.

(4) to address the limitations of the global clumping map by Chen et al. (2005), namely its limited spatial coverage, its neglect of topographic effects, and its lack of evaluation with field measurements. The first ever global mapping of the vegetation clumping index with a limited eight-month multi-angular POLDER 1 dataset by Chen et al. (2005) is expanded in Chapter 5 by integrating new, complete year-round observations from POLDER 3. Entitled “Refining global mapping of foliage clumping index with multi-angular POLDER 3 measurements: evaluation and topographic compensation“ (Pisek et al., 2009b), this chapter further offers a method to compensate for the topographic effects in the map. The improved map is evaluated over a limited set of available ground measurements covering four continents and various biomes.

(5) to incorporate the above findings and products into the global LAI algorithm of Deng et al. (2006) and to evaluate the new LAI product. Chapter 6, entitled “Impact of including forest understory and foliage clumping information from multi-angular measurements on the Leaf Area Index product over North America” (Pisek et al., 2009c), effectively brings together products from multiple sensors with complementing capabilities - SPOT-VGT (Chapter 2), MISR (Chapter 3, 4), and POLDER (Chapter 5) in a new LAI dataset with 10-day intervals corrected for the influence of understory and foliage clumping
over North America for one year. Via the means of indirect and direct validation, it is explored if the fusion of data inputs between multiple sensors can lead indeed to improved products and if multi-angle remote sensing can help us to address effectively the issues (separating the signal from the understory and overstory, foliage clumping) that could not be solved via the means of the conventional mono-angle, nadir-spectral remote sensing.

Conclusions and directions for future work are provided in Chapter 7.
2 Comparison and validation of MODIS and VEGETATION global LAI products over four BigFoot sites in North America

This chapter is based on the paper published in Remote Sensing of Environment:

2.1 Abstract

A new set of recently developed leaf area index (LAI) algorithms has been employed for producing a global LAI dataset at 1 km resolution and in time-steps of 10 days, using data from the Satellite pour l'observation de la terre (SPOT) VEGETATION (VGT) sensor. In this paper, this new LAI product is compared with the global MODIS Collection 4 LAI product over four validation sites in North America. The accuracy of both LAI products is assessed against seven high resolution ETM+ LAI maps derived from field measurements in 2000, 2001, and 2003. Both products were closely matched outside the growing season. The MODIS product tended to be more variable than the VGT product during the summer period when the LAI was maximum. VGT and ETM+ LAI maps agreed well at three out of the four sites. The median relative absolute error of the VGT LAI product varied from 24% to 75% at 1-km scale and it ranged from 34% to 88% for the MODIS LAI product. The importance of correcting field measurements for the clumping effect is illustrated at the deciduous broadleaf forest site (HARV). Inclusion of the sub-pixel land cover information improved the quality of LAI estimates for the prairie grassland KONZ site. Further improvement of the global VGT LAI product is suggested by production and inclusion of pixel-specific global foliage clumping index and forest background reflectance maps that would serve as an input into the VGT LAI algorithms.

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1 Elsevier and my co-author Dr. Chen allowed me to include this previously published paper as a chapter in my dissertation. Dr. Chen provided suggestions about the manner of comparing the datasets pixel-by-pixel over the validation sites and edited the paper draft. I produced the VGT LAI data set, performed all analyses, and composed the manuscript.
2.2 Introduction

Exchanges of energy (Bonan, 1995; Sellers et al., 1994), water (Band et al., 1991; Nouvellon et al., 2000; Su, 2000) and greenhouse gases (Liu et al., 1997; Nouvellon et al., 2000; Coops et al., 2001; Frank, 2002) between the land surface and the atmosphere depend greatly on the functioning of plant leaves. Models that simulate these exchanges require quantitative information on the area and density of vegetation (Dickinson, 1995). Leaf Area Index (LAI) is a key quantitative information in this context (Buermann et al., 2002), where LAI is defined as one half of the total green leaf area per unit ground surface area (Chen and Black, 1992).

For effective use in ecosystem models for large area applications, LAI data must be collected for a long period of time and should represent every region of the terrestrial surface (Myneni et al., 2002). Also, due to different definitions of LAI, different measurement protocols and instruments and different considerations of canopy architecture, LAI products can vary significantly, and it is desirable to have accurate and consistent products for global and regional applications (Deng et al., 2006). Satellite remote sensing is the most effective means of collecting such global fields on a regular basis. Global LAI estimates have been routinely produced using MOderate Resolution Imaging Spectroradiometer (MODIS) data at 1-km resolution and time intervals of 8 days (Myneni et al., 2002). In the MODIS algorithm, a three-dimensional canopy radiative transfer model is used to derive relationships between the spectral signatures of a vegetated canopy and its structural characteristics (Myneni et al., 1997; Knyazikhin et al., 1998a,b). These relationships are used to relate LAI to measured spectral reflectances at various observation angles. Various levels of accuracy and success have been reported in MODIS product evaluation studies (Abuelgasim et al., 2006; Cohen et al., 2006a, 2003; Fensholt et al., 2004; Huemmrich et al., 2005; Tan et al., 2005; Wang et al., 2004).
Based on previous work (Brown et al., 2000; Chen, 1996b; Chen and Cihlar, 1997; Chen and Leblanc, 1997, 2001; Chen et al., 2002; Roujean et al., 1992), Deng et al. (2006) developed a new set of LAI algorithms for the purpose of deriving an alternative global LAI product, using SPOT-4 VEGETATION (VGT) data. The initial validation of this new product included seven sites in Canada (Pisek et al., 2007). A limited mutual comparison of MODIS and VGT LAI products was also carried out. However, there was an obvious need for further validation outside of Canada to demonstrate the reliability of this global product. In this study, we carry out comparisons of MODIS and VGT LAI products over a set of LAI reference sites.

One set of LAI data that is optimal for this study is from the BigFoot sites (http://www.fsl.orst.edu/larse/bigfoot/) (Running et al., 1999). The BigFoot project covers nine flux tower sites from Alaska to Brazil in order to represent different biomes. Field data were collected over 25 km², and Landsat-7 Enhanced Thematic Mapper Plus (ETM+) image data and ecosystem process models were used to characterize an area of 7 km × 7 km around each tower (Cohen et al., 2006a, 2003). Since the BigFoot LAI ETM+ maps are estimated by measurements independent of both MODIS and VGT products, direct comparisons of BigFoot data with MODIS- and VGT-derived products can help us to assess the quality of these products and the sources of their errors. The validation procedures are in agreement with the outlines presented in Morisette et al. (2006). At most BigFoot sites, there is an existing program of long-term measurements offering LAI data from various years within the growing season. The use of this dataset can thus offer insights into the inter-annual and seasonal variations of LAI.

The aim of this paper is to conduct MODIS and VGT LAI product validation to assess their quality. Four sites with multiple year data from the BigFoot project were selected for this validation. The mutual comparisons of these two products were also made over the seasonal cycles at the four sites in 2000, 2001, and 2003.
Figure 2-1. Locations of BigFoot study sites in North America. And comparison of original unsmoothed and temporally smoothed annual LAI cycle at an agricultural system at AGRO site near Bondville, IL for year 2003.

2.3 Materials

2.3.1 Study sites

The four BigFoot sites included in this study were AGRO (an agricultural system in Bondville, Illinois, USA), HARV (Harvard Forest, Massachusetts, USA), KONZ (Konza Prairie, Kansas, USA), and NOBS (Northern Old Black Spruce, Manitoba, Canada) (Figure 2-1). Campbell et al. (1999) provide detailed descriptions of these sites. The AGRO site is centered at 40.01° N and 88.29° W. The land cover consists of fields with annually harvested crops (Cohen et al., 2003) and a rural community occupying the southeastern corner of the site. The Harvard forest site (HARV; 42.37° N, 72.25° W) represents a temperate mixed forest (Magill et al., 2004). In addition to the closed forest canopies there were a few areas of wetlands, grasslands and water bodies. KONZ (39.08° N, 96.62° W) is predominantly a tall grass prairie. In the northern part of the site there were areas of deciduous broadleaf forest (Hall et al., 1990). The NOBS site (55.88° N, 98.48° W) has a cover of up to 70% of black spruce forest, comprised of mature stands of trees from 60–120 years in age with tree heights ranging from 7–18 m (Kimball et al.,...
Table 2-1. BigFoot sites and dates of maps used for validation

<table>
<thead>
<tr>
<th>Site</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Location</th>
<th>Vegetation</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGRO</td>
<td>40.00</td>
<td>-88.29</td>
<td>Illinois, USA</td>
<td>cropland</td>
<td>11-Aug-2000</td>
</tr>
<tr>
<td>HARV</td>
<td>42.53</td>
<td>-72.17</td>
<td>Massachusetts, USA</td>
<td>mixed forest</td>
<td>4-Aug-2000, 26-28-Jul-2001</td>
</tr>
<tr>
<td>KONZ</td>
<td>39.09</td>
<td>-96.57</td>
<td>Kansas, USA</td>
<td>tall grass</td>
<td>6-Jun-2000, 18-Jun-2001</td>
</tr>
<tr>
<td>NOBS</td>
<td>55.89</td>
<td>-98.48</td>
<td>Manitoba, Canada</td>
<td>black spruce</td>
<td>14-Jul-2000, 14-Jul-2001</td>
</tr>
</tbody>
</table>

1997). This site was previously used in the Boreal Ecosystem Atmosphere Study (BOREAS, Sellers et al., 1997). A fire damaged the extreme southern part of the study site in 1981, but the forest has largely recovered since then.

2.3.2 ETM+ imagery

Table 2-1 presents a list of seven ETM+ LAI scenes (UTM projection, pixel resolution resampled to 25 m) that were acquired from the BigFoot database (Cohen et al., 2006b). Two scenes were obtained for each site—one map in 2000 and the other in 2001. There was only one scene available from the AGRO site in 2000. Since the site is predominantly occupied by annually harvested crops and no significant differences were expected between the various years in the seasonal LAI cycle, the identical scene was used for the approximate validation of the VGT product performance during 2001 as well. For each scene, the IGBP land cover information was also acquired (Cohen et al., 2006a). AGRO land cover classification included BigFoot labels (for the IGBP cropland label, it is specified as soybean or corn).

ETM+ LAI estimates were directly linked to the field measurements using methods described by Gower et al. (1999). Cohen et al. (2003) discusses the conversion of the ETM+ spectral data to Tasseled Cap indices. The indices were subsequently related to the field LAI measurements by means of Ordinary Least Squares (OLS) and Reduced Major Axis (RMA) regressions. Cohen et al. (2003) also provide details on the LAI prediction accuracy (overall in excess of 80%; 88% across sites). It is important to note that during field measurements not all land cover types were sampled (e.g. deciduous broadleaf forest at the KONZ site), and Cohen et al. (2003) used LAI values from the literature for these cover types.
2.3.3 VGT LAI product

Based on a geometrical optical model (Four Scale; Chen and Leblanc, 1997) with a multiple scattering scheme (Chen and Leblanc, 2001) and LAI algorithms previously derived for Canada-wide applications, Deng et al. (2006) produced a new algorithm for the global retrieval of LAI. The algorithm makes use of red, near infra-red, and shortwave infra-red bands from a satellite sensor. Global scenes of VGT data are acquired over a large ranges of solar zenith and satellite view angles, and a bidirectional reflectance distribution function (BRDF) is needed for correcting these angular effects and standardization to a common geometry (Schaaf et al., 2002). While the usual approach is to conduct BRDF normalization prior to the input of reflectance values into LAI algorithms (Chen, 1996b; Chen et al., 2002), BRDF is considered explicitly in Deng et al. (2006). The issue is solved by using the Four Scale model for simulating the relationships between LAI and the spectral bands. Since the vegetation structure is distinctly different among land cover types, the simulations were made separately for different plant functional types. The global land cover classification for the year 2000 (GLC2000) dataset (Bartholomé and Belward, 2005; Loveland et al., 2000) has been used for retrieving the land cover information. The cover types with similar structural characteristics were combined to form six groups based on canopy architecture. The six biomes were (i) needleleaf forest, (ii) tropical forest, (iii) broadleaf forest, (iv) mixed forest, (v) shrub, (vi) cropland and grassland. Snow/ice, water body classes, and bare rock were assigned the value of zero in LAI retrieval.

Based on the model simulations, Deng et al. (2006) fit the key coefficients in the BRDF kernels with Chebyshev polynomials of the second kind. In the kernel function approach, the land surface brightness variation is modelled statistically by a class of simple functions. The spectral bands were then combined into Simple Ratio (SR) and the Reduced Simple Ratio (RSR) for LAI retrieval. More detail of the theoretical basis of the algorithms is given in Deng et al. (2006).
Since VGT is a single-view angle sensor at each ground location per overpass, the reflectances are mostly affected by the canopy gap fraction at the view angle (Chen, 1996b; Harding et al., 2001; Weiss et al., 2000). An assumption of the random leaf spatial distribution is made to invert from gap fraction to LAI. Under this assumption, the inverted LAI is termed the “effective LAI” rather than the true LAI (Chen et al., 1997a). It is necessary to convert the effective LAI using the clumping index to retrieve true LAI values. Chen et al. (2005) recently undertook the first ever global mapping of the vegetation clumping index using POLDER measurements. Using their results, mean values for different land cover types were retrieved and used as inputs into the LAI algorithms. It was not possible to include the specific value for clumping index for every pixel on a given date because only eight months of global POLDER-1 at ~6 km resolution were available (Lacaze et al., 2002).

The VGT data used in this study were acquired in the form of 10-day composite (S10) scenes from the SPOTIMAGE/VITO distribution site (http://free.vgt.vito.be/), already atmospherically corrected with the simplified method for the atmospheric correction (SMAC) by Rahman and Dedieu (1994). The spatial resolution is 1 km, and the data use plate–carree projection with the WGS84 coordinate system. The annual global VGT LAI product consists of 36 scenes that cover the whole year. We used the data from 2000 and 2001 to match with the maximum number of available ETM+ scenes from the BigFoot project. Since the global VGT LAI product was originally produced for the year 2003, we included these data for the comparison with MODIS LAI as well.

The downloaded VGT data were already atmospherically corrected by the application of the Simplified Method for Atmospheric Correction (SMAC) (Rahman and Dedieu, 1994). However, the residual atmospheric effects were still considerable, as abnormally low values within the LAI product were observed, e.g., erratic reductions of LAI up to a value of 6 over 10 days. To minimize these residual atmospheric effects, Chen et al. (2006a) developed a procedure named Locally Adjusted Cubic-spline Capping (LACC) to reconstruct the seasonal trajectory of LAI. A series of cubic spline curves is applied
to the annual cycle of LAI, and optimum local smoothing coefficients are assigned to every LAI value based on the curvature of the initially fitted curve with an average global smoothing coefficient. In this way, the resulting capping curve is automatically adjusted to both rapid and slow variations in LAI in various seasons. This procedure avoids the problem of rigid seasonal trajectory shapes by simple overlapping of a few harmonics in the existing FASIR (Sellers et al., 1994) and ABC3 (Cihlar et al., 1997) methods. The performance of the LACC method is illustrated in Figure 2-1 for one pixel within the AGRO site. The LACC method has been applied to every pixel of the global VGT LAI product.

2.3.4 MODIS LAI product

The MODIS Collection 4 LAI product and land cover classification schemes were acquired in a form of ASCII subsets from the Distributed Active Archive Center (DAAC) database of Oak Ridge National Laboratory (http://www.modis.ornl.gov/modis/index.cfm). The subset profiles are presented in 1-km resolution with a time-interval of 8 days. The prepared ASCII subsets have already been re-projected and they match the BigFoot sites' layout. The available ASCII subsets were downloaded for the years 2000, 2001, and 2003 to cover the same periods as the VGT LAI product. All mentions of the MODIS product in this paper refer to MODIS Collection 4 unless noted otherwise.

Along with the LAI fields, the Quality Flags for the MODIS product were obtained. Under optimal circumstances, a lookup-table (LUT) method is used to achieve inversion of a three-dimensional radiative transfer model (Myneni et al., 2002). When this method fails to localize a solution, a back-up method based on a relationship between the normalized difference index (NDVI) and LAI (Knyazikhin et al., 1998a; Myneni et al., 1995) is utilized. The Quality Flags serve to determine the origin of the calculated value or mark pixels where no retrievals were made. Cohen et al. (2003) originally noted the actual descriptions of the Quality Flags in Collection 4 were not easy to understand. The Quality Flags scheme
was simplified here to display only whether the value was calculated by the main algorithm, backup algorithm, or if the value was not retrieved.

2.4 Methods

The overall quality of LAI products depends on a few key factors that influence the accuracy of the retrievals. The first factor is the uncertainty in the input land cover data. The effect of land cover misclassification for MODIS and VGT products varies depending on the degree of similarity among biomes. MODIS LAI algorithm also employs a six class biome suite defined in Myneni et al. (2002). Myneni et al. (2002) calculated this LAI difference to be up to 50% when distinct cover types were interchanged. We assessed relative proportions of land cover types within every BigFoot site first. This assessment offered an insight into the role of uncertainties in land cover information in actual LAI retrievals that were compared in the next step. Both MODIS and the BigFoot project use the IGBP classification, but the share of the land cover classes present might vary due to the different image resolutions (25 m vs. 1 km). GLC2000 land cover types used with the VGT images were transferred into IGBP equivalents.

Uncertainties and errors in input surface reflectances are another source of possible error in the LAI retrievals (Chen et al., 2002; Fernandes et al., 2003; Yang et al., 2006a). These uncertainties are mainly due to different atmospheric corrections and the length of the composite period. These uncertainties might be larger in the case of the VGT sensor as the composite period is longer than that used for the MODIS sensor. The selected VGT reflectances might come from dates further away from the BigFoot ETM+ maps by a few days. The original reflectance values were available only for the VGT product. Pisek et al. (2007) calculated the mean difference between VGT and Landsat-5 TM vegetation indices to be 14.5% for their set of validation scenes in Canada. We believe the magnitude of the uncertainties introduced by discrepancies in input reflectances between the high resolution and coarse resolution scenes is similar here.
The main step in the validation procedure consisted of placing the BigFoot +ETM LAI data on the graphs containing the MODIS and VGT LAI trajectories for the years 2000, 2001, and 2003. Each data point on the graph has been produced by averaging the LAI values over a 7 km×7 km BigFoot site. The products were compared over the multi-pixel (patch) rather than on the pixel-by-pixel basis in this step. This strategy reduces errors due to coregistration and overlapping uncertainties between various products (Yang et al., 2006a). Since the LAI values from MODIS can come from the main RT or the back-up algorithm, averages over the BigFoot sites were computed first with main RT retrievals only and then with included back-up values. Tan et al. (2005) advise using back-up algorithm retrievals with caution as they are generated from surface reflectances with high uncertainties. The relative proportion of main and back-up algorithm retrievals has been also assessed to obtain an insight into the seasonal course of plotted MODIS LAI trajectories.

The relatively small size (7 km×7 km) of the study sites poses limits for testing and comparison of these products via scatter-plots. This is mainly linked to the difficulties of securing the needed close spatial match between the high resolution and low resolution scenes. Also, because of the point spread function behavior of the incoming signal in low resolution sensors, the retrieved value usually comes from a greater area than the actual spatial resolution of the sensor (Cihlar et al., 2003; Cracknell, 1998). Puyou-Lascassies et al. (1994) and Oleson et al. (1995) further demonstrate that the weight of the signal is also not constant over the field of view and decreases with increasing distance from the center. Bearing these limitations in mind, we produced a set of scatter-plots for each BigFoot site. Acquired ASCII subsets of the MODIS product were already pre-processed to fit the 7 km×7 km sites. Aggregating the values to 1 km resolution produced the equivalent ETM+ LAI estimates. High resolution ETM+ land cover classifications were also used as input into the VGT LAI algorithm. Alternative LAI values for 1-km
Table 2-2. List of IGBP land cover classes, present at BigFoot sites, and their codes as used in Figure 2-2.

<table>
<thead>
<tr>
<th>IGBP class code</th>
<th>Land cover type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Needleleaf evergreen forest</td>
</tr>
<tr>
<td>4</td>
<td>Deciduous forest</td>
</tr>
<tr>
<td>5</td>
<td>Mixed forest</td>
</tr>
<tr>
<td>6</td>
<td>Closed shrubland</td>
</tr>
<tr>
<td>7</td>
<td>Open shrubland</td>
</tr>
<tr>
<td>8</td>
<td>Woody savanna</td>
</tr>
<tr>
<td>9</td>
<td>Savanna</td>
</tr>
<tr>
<td>10</td>
<td>Grasslands</td>
</tr>
<tr>
<td>11</td>
<td>Permanent wetlands</td>
</tr>
<tr>
<td>12</td>
<td>Cropland</td>
</tr>
<tr>
<td>13</td>
<td>Urban/built-up area</td>
</tr>
<tr>
<td>14</td>
<td>Cropland/natural vegetation</td>
</tr>
<tr>
<td>16</td>
<td>Barren</td>
</tr>
<tr>
<td>0</td>
<td>Water</td>
</tr>
</tbody>
</table>

Pixels were then retrieved by weighting the various land cover types by their area fractions within the pixel. The goal of this exercise was to see how the LAI retrievals would change with the inclusion of information about the contexture of low resolution pixels (Chen, 1999) within the validation sites.

2.5 Results and discussion

2.5.1 Land cover comparison

Table 2-2 includes a list of all IGBP classes present at the four sites. The greatest agreement among these classification schemes was observed at the AGRO site (Figure 2-2). This was expected, as the AGRO site was quite homogenous in the BigFoot high resolution image with 88% of pixels classified as cropland. The built-up area in the southeastern corner occupied 10% of the total image area. In the MODIS classification all pixels were classified as cropland, and 94% of pixels were identified as cropland.
Figure 2-2. Relative proportions of land cover types at each site in 2000, as mapped by BigFoot, MODIS, and VGT (GLC2000). See Table 2-1 for class names.

in the GLC2000 classification with 6% classified as a deciduous forest. The KONZ site results were also satisfying. Grasslands occupied 78% and 80% in GLC2000 and MODIS classifications, respectively. The share of grassland in the BigFoot image was lower, at 63% with 17% and 9% classified as open shrubland and woody savanna, respectively, and 7% marked as deciduous forest. The differences among the classifications were due to the distributed pattern of deciduous broadleaf forest patches and open shrublands in the BigFoot image, as both low resolution classifications were unable to produce a similar level of detail. The relative share of forest area agrees well in MODIS and BigFoot classifications for the HARV site. MODIS consists of deciduous broadleaf and mixed forest, while BigFoot classifies 12% of pixels as needleleaf evergreen forest. There is a small share of grasslands and permanent wetlands in BigFoot as well. The whole HARV area is classified as broadleaf deciduous forest in GLC2000. Since the
RSR-based algorithm is applied for forest pixels in the case of VGT LAI, the land cover discrepancy should not significantly affect the range of retrieved LAI values, as Brown et al. (2000) demonstrated that use of Reduced Simple Ratio (RSR) index reduces the dependence of algorithms on land cover types. The most striking difference in land cover classifications among the low resolution images and BigFoot was observed on the NOBS site. MODIS considers most of the area to be needleleaf evergreen forest whereas BigFoot mapped the site as open shrubland, savanna and woody savanna, and permanent wetland. GLC2000 considered the whole area as a needleleaf evergreen forest. The coniferous forest has been classified as shrubland or woody savanna in the BigFoot project mainly due to the relatively lower density of the forest stands. Random VGT pixels from NOBS site were first marked as a coniferous forest and then as a woody savanna for the LAI algorithm. A difference of LAI>2 (38%) had been observed for July 21, 2000—the peak of boreal summer. An additional map source has been consulted for verification of the land cover. It was decided to keep the VGT pixels classified as conifer forest for the next step of constructing the seasonal trajectories of LAI.

2.5.2 BigFoot–MODIS–VGT comparison: Seasonal trajectories

MODIS LAI estimates were available from February 26, 2000 (day 57) at all sites. Only the MODIS LAI values with the highest quality flags were used for the construction of the seasonal trajectories. At the AGRO site, both VGT and MODIS products follow the beginning and the end of the growing season reasonably well, and the differences between the products were minimal (Figure 2-3). However, during the peak of the growing season MODIS delivers unstable results. The LACC smoothing method is not used in the MODIS product, although Chen et al. (2006) demonstrated the improvement of the MODIS LAI product if this method is applied. Tan et al. (2005) reported similar unstable behavior for broadleaf and crop pixels for the MODIS Collection 3 product due to mismatch between the modeled and observed MODIS surface reflectances. Yang et al. (2006b) reported that the problem was caused by
increased aerosol contamination of surface reflectances. As aerosol contamination increased, the scatter of surface reflectances increased and more data were found to be out of the retrieval domain of the main RT algorithm. This resulted in the failure of the main algorithm. The BRDF effects were not taken into account within the back-up LAI–NDVI relationships (Shabanov et al., 2005) and the algorithm generates rather unreliable estimates of LAI, especially for extreme view/illumination geometries. Results from Figure 2-3 indicated that the problem persisted in Collection 4 for this agricultural site. The median relative absolute error (RAE) was 88% for the MODIS LAI product, while the RAE of the VGT LAI product was 43%. VGT retrievals after smoothing match the expected seasonal trajectory very well. The maximum LAI value occurs around July 20 (day 202) and it is in good agreement with the seasonal
Table 2-3. Summary of LAI statistics of the four ETM+ maps and those of VEGETATION and MODIS over the same scenes in 2000.

<table>
<thead>
<tr>
<th></th>
<th>AGRO</th>
<th>HARV</th>
<th>KONZ</th>
<th>NOBS</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETM+</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average LAI</td>
<td>3.12</td>
<td>4.1</td>
<td>2.16</td>
<td>3.18</td>
</tr>
<tr>
<td>S.D.</td>
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<td>0.46</td>
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</tr>
<tr>
<td>VGT</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average LAI</td>
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<td>4.81</td>
<td>1.64</td>
<td>3.42</td>
</tr>
<tr>
<td>S.D.</td>
<td>0.67</td>
<td>0.54</td>
<td>0.29</td>
<td>0.32</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.5</td>
<td>1.05</td>
<td>0.79</td>
<td>0.65</td>
</tr>
<tr>
<td>MODIS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average LAI</td>
<td>1.52</td>
<td>6.01</td>
<td>1.78</td>
<td>4.32</td>
</tr>
<tr>
<td>S.D.</td>
<td>0.81</td>
<td>0.79</td>
<td>0.34</td>
<td>0.32</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.61</td>
<td>2</td>
<td>0.88</td>
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</table>

maximum LAI around 4 observed around nearby flux tower sites according to FLUXNET ground measurements (http://www-eosdis.ornl.gov/FLUXNET/). The BigFoot LAI for August 11 also closely agrees with the seasonal trajectory of VGT.

The MODIS and VGT LAI trajectories were in very good agreement up to August 4 at KONZ. MODIS LAI does not decrease below 1 until the beginning of October, while VGT does so two months earlier. At this site, the MODIS LAI estimate is closer to BigFoot +ETM LAI than VGT. The difference is still only around LAI of 0.5 between VGT and BigFoot +ETM LAI (Table 2-3). MODIS estimates for the deciduous HARV site do not decrease below LAI of 2 during the entire year. However, Yang et al. (2006a) recently reported that in the new prototype Collection 5 product winter LAI already decreases to <0.5 at this location. This is in better agreement with the VGT product. MODIS produces fairly stable values around LAI of 6 during the summer, while the VGT trajectory is more variable due to a series of poorer quality data from the mid-summer. The BigFoot +ETM LAI of 4.1 is smaller than the VGT and MODIS values. In the case of MODIS the difference reaches a magnitude of 2. The field measurements were acquired using LICOR-2000 instrument according to the methodology outlined by Gower et al. (1999). However, clumping index values were not obtained for the site and the BigFoot HARV data were
not corrected for foliage clumping, i.e. the effect of non-random leaf spatial distribution. The BigFoot data were thus arguably underestimated in comparison with the true LAI values.

The NOBS site is marked by a very simple seasonal cycle with a linear increase in LAI with the peak around July 20 and a subsequent linear decrease (Figure 2-3). BigFoot matches relatively closely VGT in terms of LAI with a difference of less than 0.5. The clumping correction was not an issue with BigFoot in this case as the field estimates were established via allometric methods (Cohen et al., 2006a, 2003). MODIS tended to greatly over-estimate LAI, especially during the late summer, but there was a close agreement between VGT and MODIS during the early summer. It must be acknowledged that the modeled seasonal trajectory by the VGT LAI product outside the growing season is spurious for high latitudes. Yang et al. (2006c) and Cohen et al. (2006a) identified poor illumination conditions, extreme
Figure 2-5. Same as in Figure 2-3, but for year 2003. BigFoot data, shown for comparison, come from year 2000.

solar zenith angles, snow and cloud contamination, and the signal from the understory as the main factors for the similarly poor performance of the MODIS LAI product at high latitudes. The same factors also affect the quality of the VGT LAI product for high latitude estimates during the winter season, but we believe that leaf chlorophyll content may also be an important factor.

BigFoot +ETM LAI validation data were also available for 2001 except for the AGRO site. Seasonal trajectories were further produced from MODIS and VGT for 2003. Figures 2-4 and 2-5 show the results. The greatest difference among the various years was observed at AGRO. This was caused by the variation of crops present at the site during different years. NOBS was characterized by the smallest inter-annual differences in the trajectory. In 2001 VGT estimates were also closely matched with BigFoot ETM+ LAI for NOBS. MODIS LAI retrievals for NOBS were rather unstable and over-estimated. On the
other hand, VGT tended to underestimate LAI for the KONZ site in 2001; both MODIS and VGT estimates were again very similar during 2003. Seasonal trajectories during the main growing season were also reasonably similar for the HARV site in 2001 and 2003. Similar discrepancies were observed between BigFoot and the low resolution products in 2000 and 2001. This further confirms the systematic nature of these underestimated BigFoot data due to an unaccounted clumping effect and its importance in producing reliable validation data (Chen and Cihlar, 1996; Leblanc et al., 2005a). MODIS was characterized by a greater standard deviation of the LAI predictions than VGT for every site and year in which the comparisons were made.

**Figure 2-6.** Relative proportions of pixels with shown origin of calculated LAI value at each site in 2001, as represented in MODIS LAI product.
Table 2-4. Comparison of calculated average LAI values over BigFoot sites from MODIS data, using available Quality 0 level estimates only, and averages calculated by using back-up algorithms values as well.

<table>
<thead>
<tr>
<th>day</th>
<th>AGRO Q1 back-up</th>
<th>AGRO Q1 back-up</th>
<th>HARV Q1 back-up</th>
<th>KONZ Q1 back-up</th>
<th>NOBS Q1 back-up</th>
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</tbody>
</table>

The relative instability of MODIS estimates was further examined by comparing the changing proportions of values produced by the main RT and back-up algorithm through the year. The results offer very similar patterns for all three years and only results for 2001 are presented here (Figure 2-6). With the
exception of NOBS, a large amount of MODIS retrievals comes from a back-up algorithm during the peak of the growing season (KONZ, HARV) or is not produced at all (AGRO). This is not an optimal situation since most of the validation effort is usually carried out during the summer period. The comparison of site averages, calculated from the main RT values only and then with back-up results included for year 2001, is shown in Table 2-4. The biggest differences were observed at the HARV site, where the inclusion of back-up values actually resulted in lower LAI averages. The differences were negligible in most of the cases for AGRO and KONZ sites. Differences around LAI of 1 were observed for the NOBS site from day 249 to day 281. However, BigFoot ETM+ LAI was available for day 195 when both alternatives of MODIS product closely matched.

The findings presented above document that the VGT product seems to deliver reliable information about the seasonal cycle of LAI at the four BigFoot sites within the snow free growing season. The seasonal trajectories matched very closely with MODIS during the start and end of the growing season in most cases except for evergreen conifers. VGT tended to produce good and stable results during the maximum growing period. Both MODIS and VGT LAI values seemed to underestimate LAI at the KONZ site. The standard deviation of VGT LAI during the growing season is smaller than that of MODIS LAI. The use of the LACC smoothing method in the VGT LAI production procedure is considered to be effective in securing a good quality of the product. VGT estimates were also shown to match closely with BigFoot data at three out of four sites.

It is interesting to observe that results from both VGT and MODIS main algorithm approaches tend to deliver mutually consistent retrievals for grassland and cropland biomes (AGRO, KONZ). The one-dimensional RT model is invoked for these biomes in the MODIS approach (Knyazikhin et al., 1998a). Minimal leaf clumping and leaf distribution were very close to the assumed values the current MODIS RT methodology originally evolved from (Myneni et al., 1991, 1997), i.e., the canopy is assumed to be a homogeneous medium of infinitesimal scatters (Goel, 1989; Myneni et al., 1989; Pinty and Verstraete,
However, these assumptions do not hold for forest canopies and the full 3-D method is applied for the biomes in both algorithms, although the VGT algorithm is based on a GO model (Four Scale) with a multiple scattering scheme. The largest differences between these two products were observed in forested sites, with VGT LAI retrievals being mostly closer to the field LAI estimates than the MODIS retrievals.

We believe the core of the problem lies in the way the radiation interaction with forest canopies with complex structures is modeled. MODIS LUTs of the main algorithm store only a single-scattering albedo at a reference wavelength and at the red and NIR wavelengths (Shabanov et al., 2005), and this single scattering albedo is used to estimate multiple scattering in successive orders in turbid media (Knyazikhin et al., 1998a). The multiple scattering scheme, used for producing the LUTs in the VGT LAI algorithm, addresses the geometrical effects on higher order scattering that can not be accounted for within turbid media-based RT models because the mutual shadowing effects among large geometrical structures (e.g. tree crowns) can not be effectively modeled without explicit mathematical description of these structures. The Four-Scale multiple scattering scheme is based on view factors among sunlit and shaded parts of tree crowns in the canopy, the background and the sky (Chen and Leblanc, 2001). This scheme can thus capture the strong multiple scattering among tree crowns which is the major scattering component in forest canopies, although multiple scattering within tree crowns is still a weakness in this GO model. This scheme is also effective in simulating the angular dependence of the first, second, and higher order scattering as affected by sun and view angles and the canopy structure and in particular the strong enhancement of reflectance due to multiple scattering around the hotspot —the feature that turbid media RT approaches can not easily simulate with reasonable radiance magnitude and angular width. For the coming MODIS Collection 5 product, a new stochastic RT model has been applied to achieve a better consistency of simulated and MODIS surface reflectances (Shabanov et al., 2005). It remains to be seen if the modification will improve the quality of MODIS retrievals in comparison with ground data.

The quality of the retrievals is also influenced by the length of the compositing period. Shabanov et al. (2005) documented, using a prototype Collection 5 product, that extending the MODIS compositing period from 8 to 10 days reduces the number of back-up LAI values by 15%. This also includes a
Figure 2-7. Comparisons of MODIS (grey) and VGT (black) LAI values for year 2000 with those retrieved from ETM+ map of BigFoot sites. The VGT and MODIS LAI were calculated at 1-km resolution, and the ETM+ LAI was calculated at 25-m resolution. The effect of improving the LAI relationship with weighting LAI retrievals land cover fractions within coarse resolution VGT pixels is shown for the KONZ site. See text for further details.

decrease in the retrieval uncertainties, assuming that the phenological changes during the compositing period were not significant.

2.5.3 BigFoot–MODIS–VGT comparison: pixel-by-pixel

Although pixel-by-pixel comparisons were not attempted in previous MODIS LAI validations (Cohen et al., 2006a, 2003; Tan et al., 2005; Yang et al., 2006a), we believe that a validation is not complete without doing this comparison. Figure 2-7 shows four selected scatter-plots for the pixel-by-
pixel comparisons of the LAI products. BigFoot estimates were aggregated from 25-m to 1-km resolution and matched with corresponding low-resolution pixels of MODIS and VGT. VGT and MODIS scenes were selected according to their acquisition period to overlap with the dates of BigFoot ETM+ scenes. The scatter-plot for the AGRO site confirms the effectiveness of applying the LACC smoothing method. Both VGT and MODIS original retrievals were poor in quality due to unfavorable atmospheric conditions. The VGT LAI values were under-estimated for the KONZ site. The main MODIS RT algorithm failed and the back-up filtered values were produced instead. Figure 2-7 shows that the LACC method succeeded in improving the relationship between the final VGT product and BigFoot +ETM LAI values as the values were equally occupying the sides of the 1:1 regression line. In contrast, MODIS retrievals bear virtually no relationship with BigFoot data. The median relative absolute error (RAE) for the AGRO site was 88% for the MODIS LAI product, while the RAE of the VGT LAI product was half of this value. The RAE value was 25% for the VGT LAI estimate and 35% for the MODIS LAI estimate at the HARV site. The over-estimation of LAI values by VGT and MODIS in the HARV scatter-plot can be explained by the omission of the clumping effect in the BigFoot retrievals. RAE values for the NOBS site were 37% for the VGT LAI product and 65% for the MODIS LAI product. MODIS LAI estimates had smaller RAE value (47%) than VGT LAI product (76%) at the KONZ site. Figure 2-7 further demonstrates the effect of including the contextual information in the input land cover map for the VGT LAI algorithm at the KONZ site. Weighting LAI according to the land cover fractions within each 1 km×1 km pixel improved the slope and the BigFoot–VGT relationship (from R²=0.04 to R²=0.35 vs. MODIS R²=0.15) as it follows a similar vector direction as the 1:1 regression line. The treatments were carried out for other sites as well, but the results did not differ from the original plots due to the homogeneity and limited variation of the land cover within these sites.

The scatter-plots were produced for very small areas (7 km×7 km). Geolocation uncertainties and pixel-shift errors due to point spread function may not change the general trends in the plotted values of the coarse resolution products and BigFoot data, but they can contribute to the observed scattering of the
Figure 2-8. Colour-coded global map of (a) VEGETATION and (b) MODIS LAI fields from the peak of boreal summer - July 2003.

values in the plots.

2.5.4 MODIS and VGT global LAI maps

Both global LAI products are displayed in Figure 2-8 from the peak period of the boreal summer. Figure 2-5 offers an explanation for the difference in LAI values for boreal forests.

At NOBS, MODIS tended to greatly overestimate the LAI values obtained by BigFoot or VGT. The similar behavior over boreal forest areas can be observed in Figure 2-8. This concurs with the
Figure 2-9. VGT-MODIS July 2003 global map differences by land surface area. Values of ΔLAI smaller than zero signify LAI over-estimation by MODIS relative to VGT, values larger than zero mark higher LAI values in the VGT product.

findings of Shabanov et al. (2005) about the anomalies of retrievals over woody vegetation in the Collection 4 data. Shabanov et al. (2005) concluded that this behavior at high LAI values in Collection 4 was due to the errors in BRDF modeling for black soil sub-problem of the algorithm.

Smaller LAI differences (LAI diff.<0.5; Figure 2-9) were present over certain areas with herbaceous vegetation. This is linked to the poorer data quality of the MODIS retrievals during winter and summer months, when a large number of values were then produced by the back-up algorithm. Tan et al. (2005) showed the back-up algorithm overestimates can amount up to a world-wide difference of LAI=1.5 against RT-algorithm retrievals during the peak boreal summer. With respect to the VGT performance over the KONZ site in 2003 (Figure 2-5), an under-estimation of LAI (LAI diff.<0.5) by the VGT algorithm within certain types of herbaceous vegetation cannot be excluded as well.
2.6 Conclusions

This research is focused on the validation of a new global LAI product from SPOT4-VGT data. This validation was carried out by means of comparing seasonal LAI trajectories with the MODIS Collection 4 product over four BigFoot sites in 2000, 2001, and 2003. BigFoot ETM+ LAI maps in 2000 and 2001, directly based on field measurements, were used for verification of the retrievals. A reasonable agreement was found between MODIS and VGT seasonal trajectories at the BigFoot sites. This was the case especially at the start and end of the growing season except for the NOBS site. However, they differed during the summer periods. A good agreement between VGT and BigFoot was observed at three out of four sites. MODIS values tended to be unstable with large standard deviations and generally overestimated LAI during the peak of the growing seasons. The median relative absolute errors of the products ranged from 25% (VGT LAI estimate for the HARV site) to 88% (MODIS LAI product for the AGRO site). It was demonstrated that the relatively poor performance of MODIS Collection 4 is caused by the failure of the main radiative transfer (RT) based algorithm to produce LAI values. Following Tan et al. (2005), this may be due to the persistent problems of MODIS Collection 4 to match modeled and measured reflectances from the MODIS sensor. Yang et al. (2006a) reported improved LAI retrievals in the prototype Collection 5 version of the MODIS product, where the amount of over-estimation of the LAI retrievals should be further limited, especially outside the growing season.

At the HARV site, the importance of correcting the field measurements for clumping effects was demonstrated. Since this correction was not done in this BigFoot site, its LAI values were lower than both MODIS and VGT estimates for this site. The use of the sub-pixel land cover information in retrieving LAI with VGT data considerably improved the quality of LAI estimates for the KONZ site in comparison with a BigFoot ETM+ LAI map. This is in agreement with our validation results for seven selected scenes in Canada (Pisek et al., 2007). Similar improvements for the other three BigFoot sites were very small due to their land cover homogeneity.
The results of this study suggest that the new global VGT product could be a sound alternative to the MODIS product, although further validations of both products are still needed in other regions. The validation is needed particularly during the key phenological periods and the in-situ measurement activities in this direction are encouraged. Additional combinations of the ground measurements at Fluxnet sites (Baldocchi et al., 2001) and remote sensing data could also improve the representativeness of algorithms validated. As this study recognized the importance of the correct assessment of the foliage clumping effect, future work will be dedicated to the production of global pixel-specific clumping index and forest background reflectance maps that would serve as an input for the VGT LAI algorithms.
3 Mapping forest background reflectance in a boreal region using multi-angle Compact Airborne Spectrographic Imager (CASI) data²

This chapter is based on the paper published in IEEE Transactions on Geoscience and Remote Sensing:


3.1 Abstract

Forest background, consisting of understory, moss, litter and soil, contributes significantly to optical remote sensing signals from forests in the boreal region. In this article we present results of background reflectance retrieval from multi-angle, high-resolution CASI sensor data over a boreal forest area near Sudbury, Ontario, Canada. Modifications of the background by white and black plastic sheets at two sites provide two extreme limits for the development and testing of an algorithm for retrieving the background information from multi-angle data. Measured background reflectances in red and near-infrared bands at six sites in the vicinity of these modified sites are used to validate the algorithm. We also explore the effect of uncertainties in the input forest structural parameters on this retrieval. The results document a) capability of the algorithm to retrieve meaningful background reflectance values for various forest stand conditions, especially in the low to intermediate canopy density range; b) the effect of background bidirectional reflectance distribution function (BRDF) on retrieved values; c) performance of

²IEEE and my co-authors allowed me to include this accepted paper as a chapter in my dissertation. Dr. Chen stood behind the idea of organizing the field campaign. Dr. Chen was the author of the original idea about the possibility of using multi-angle approach for the background information retrieval. Dr. Miller was responsible for providing the CASI sensor and acquisition of the images according to the provided guidelines. James Freemantle carried atmospheric corrections and co-registration of the CASI images. Dr. Peltoniemi provided the BRDF profiles of the white and black plastic. Anita Simic helped with the field measurements. I was responsible for planning the field work and collecting the data, I did all the data and image processing, modified the retrieval methodology parameterization, carried out model inversions, analyzed the results, and wrote the manuscript.
the algorithm using data with different cross angle values; and d) verification of the internal consistency of the geometric-optical 4-Scale model used. The results provide an important platform for the operational estimation of the vegetation background reflectance from the spectral BRFs observed by the MISR instrument.

3.2 Introduction

Leaf area index (LAI), defined as one half of the total green leaf area per unit horizontal ground surface area (Baret, 2007) after (Chen and Black, 1992), is a key surface characteristic for modelling carbon, water, and energy exchanges between the earth surface and the atmosphere. Since ecosystem models are often applied over large areas, a lot of attention has been paid to the estimation of LAI using remote sensing data ( Sellers et al., 1996; Myneni et al., 2002). The typical approach is to place the emphasis on determining the relationship between LAI and the canopy optical properties, and the properties of understory/ground layer are given as an input based on simplifying assumptions (Kuusk, 2001). However, the validation of various LAI products derived from remote sensing data has revealed the importance of background reflectance on the accuracy of canopy LAI estimation (Brown et al., 2000; Eklundh et al., 2003; Garrigues et al., 2008; Pisek et al., 2007; Rautiainen, 2005; Stenberg et al., 2004). Lang et al. (2007) observed higher correlation between stand reflectances and LAI for forests with higher canopy cover with the understory increasingly obscured and its contribution to stand reflectance reduced. Stenberg and Rautiainen (2005) reported that the contribution of understory reflectance can range up to 95% for LAI below 0.5. Previous LAI validation efforts have resulted in the recognition that understory cannot be neglected in reflectance modelling (Chopping et al., 2004), especially in the case of low to intermediate canopy cover. Unifying the definitions by (Kuusk, 2001; Chen et al., 2002; Gemmell, 2000), by the term forest background we refer to all the materials below the forest canopy such as understory vegetation, leaf litter, grass, lichen, moss, rock, soil, snow, or their mixtures, which are detectable through the overstorey canopy from above.
Few approaches have been suggested to account for, or minimize, the variable understory effect on the stand reflectance. In the majority of forest reflectance models, the background reflectance is given by a fixed value at each wavelength (Kuusk and Nilson, 2000) or modeled bidirectional reflectance distribution function (BRDF) (Dangel et al., 2005) using field observations (Chopping et al., 2003). Kuusk et al. (2004) proposed the understory spectra to be estimated from forestry databases or spectral data banks. Peltoniemi et al. (2005a) reported their initial efforts to create such a spectral data bank for the most common understory species in Finland. However, if we consider large areas on a continental or global scale, such an approach would be tremendously demanding with regard even to account for the common understory types. Several authors also noted the large variations even among the same species (Peltoniemi et al., 2005a; Bubier et al., 1997; Sonnentag et al., 2007). Seasonal variations of the background composition and their optical properties would present a further challenge.

Alternatively, Deng et al. (2006) tried to minimize the effect of the background/understory on LAI retrieval for forest stands by developing the relationships using Reduced Simple Ratio (RSR). However, during the validation of this LAI product it was noted the understory effect still might have not been entirely removed (Rautiainen, 2005; Pisek and Chen, 2007; Chapter 2), and direct inclusion of seasonally-variable background vegetation spectra into the algorithms is desirable.

Multi-angle remote sensing has been shown to enable us to describe properties of terrestrial surfaces by means that are not possible using mono-angle, nadir-spectral data (for the overview of recent progress in the multi-angle remote sensing see the review of Chopping (2008)). Initial studies of the ability of multi-angle remote sensing for retrieving background optical properties provided some encouraging results (Canisius and Chen, 2007; Chopping et al., 2006). In particular, Canisius and Chen (2007) used the 4-Scale model (Chen and Leblanc, 1997; Leblanc et al., 1999) to examine the feasibility of determining the understory reflectance over a boreal region given two viewing geometries with an inversion approach using Multi-angle Imaging SpectroRadiometer (MISR; Diner et al., 1998) data. Due to
the lack of field measurements, the verification of the derived background reflectivity estimates was limited to assessment of seasonal trajectories. It is therefore highly desirable to acquire high-resolution airborne and in-situ measurements to further validate the methodology. This validation is a necessary step for us to exploit MISR data for mapping the background reflectance globally, in order to improve our global LAI mapping.

In this article we present results of background reflectance retrieval from multi-angle, high-resolution CASI data for three dominant boreal forest species: black spruce (*Picea mariana*), jack pine (*Pinus banksiana*), and trembling aspen (*Populus tremuloides*). The theory underpinning the proposed algorithm for deriving background reflectance is further investigated by means of modifying and controlling the understory properties. Finally, we carry out simulations to test the inner consistency of the 4-Scale geometrical-optical (GO) model used in this study and to explore the effect of uncertainties in the input canopy structural parameters on the retrieval of the background reflectance.

### 3.3 Methodology

#### 3.3.1 Background reflectivity retrieval theory

In geometrical optical modeling, the total canopy reflectance is expressed as a linear combination of the contributions from sunlit and shaded crown (*R*<sub>T</sub> and *R*<sub>ZT</sub>) and background (*R*<sub>G</sub> and *R*<sub>ZG</sub>) components (Chen et al., 2000; Li and Strahler, 1985):

\[
R = R_T \cdot k_T + R_G \cdot k_G + R_{ZT} \cdot k_{ZT} + R_{ZG} \cdot k_{ZG}
\]  

(3-1)

where *k*<sub>T</sub>, *k*<sub>G</sub>, *k*<sub>ZT</sub> and *k*<sub>ZG</sub> are the corresponding proportions of the four components in the instantaneous field of view (IFOV). The contributions of the components to the total reflectance change with view angle as the proportions vary with view angle. Assuming that the sun is at a fixed angle and observations are made along a plane where target reflectances change little with angle, the variation of total reflectance
with view angle for a given stand should follow opposite trajectories for two contrasting backgrounds, where one background type is with higher and the other one with lower reflectivity than that of the overlying forest canopy. This concept is illustrated in Figure 3-1. In both scenes (Figure 3-1, Case A and B), the background contribution is the largest at nadir, while the contribution of the overlying forest canopy increases with increasing view zenith angle. The total reflectance increases (Case A) or decreases (Case B) with view angle depending on the background reflectivity. If the background reflectance is lower than that of the overlying forest canopy (i.e. dark background), the total reflectance increases with view zenith angle; the opposite is true for bright (e.g. snow) background. We provide the validation of this first step in the theory of the background retrieval in the results section.

Our algorithm is based on the premise that the reflectance of the overstory and the understory at a given illumination angle changes little between chosen view angles or this change can be well estimated.
within the algorithm. Forward-scattering reflectances of various targets were shown to be fairly constant (Bacour and Bréon, 2005; Deering et al., 1999; Kaasalainen and Rautiainen, 2005; Sandmeier, 2004), especially when not too close to the principal plane (Peltoniemi et al., 2005a). The observed reflectance at nadir \( R_n \) and at an angle in forward direction \( R_a \) can be then described by the following set of equations:

\[
R_n = R_T \cdot k_{Tn} + R_G \cdot k_{Gn} + R_{ZT} \cdot k_{ZTn} + R_{ZG} \cdot k_{ZGn}
\]

\[
R_a = R_T \cdot k_{Ta} + R_G \cdot k_{Ga} + R_{ZT} \cdot k_{ZTn} + R_{ZG} \cdot k_{ZGa}
\]  

(3-2) 

(3-3)

Next, shaded components of trees and ground can be expressed as functions of their sunlit parts and the multiple scattering factor (White et al., 2001; White et al., 2002a; White et al., 2002b), giving

\[
R_{ZT} = M \cdot R_T \quad \text{and} \quad R_{ZG} = M \cdot R_G,
\]

where \( M = R_z / R \) for a reference target, with \( R_z \) representing its shaded reflectance. Solving Eqs. (3-2) and (3-3), the background reflectivity \( R_G \) can be then calculated as:

\[
R_G = \frac{R_n \left( k_{Ta} + k_{ZTa} \cdot M \right) - R_a \left( k_{ZTn} \cdot M \right)}{-k_{Tn} \cdot k_{Ga} + k_{Gn} \cdot k_{Ta} + M \left( -k_{Tn} \cdot k_{ZGa} + k_{Ga} \cdot k_{ZTa} - k_{Ga} \cdot k_{ZTn} + k_{Ta} \cdot k_{ZGa} \right) + M^2 \left( -k_{ZTn} \cdot k_{ZGa} + k_{ZGn} \cdot k_{ZTa} \right)}
\]

(3-4)

where the total reflectances \( R_n \) and \( R_a \) are acquired from the nadir and a forward direction, \( M \) is predetermined by model inversion, and the proportions of the components can be predicted from the GO model. These scene components are estimated using a LUT constructed with 4-Scale (Chen and Leblanc, 2001), which takes into account their variations with solar and view angles with given LAI and the best estimates of other stand structure parameters such as tree height, crown radius, and stand density, as described in the following section.
3.3.2 4-Scale model

4-Scale is a geometric-optical radiative-transfer model with an emphasis on the structural composition of forest canopies at different scales (Chen and Leblanc, 1997; Leblanc et al., 1999; Chen and Leblanc, 2001). From the model output, only the proportions of the components were used in the background reflectance retrieval from the study area. Stand structure in the reflectance model is characterized by trees with internal structures. The non-random spatial distribution of trees is simulated using the Neyman type A distribution (Neyman, 1939) that creates patchiness of a forest stand. The tree surface created by the crown volume (cone and cylinder, or spheroid) is treated as a complex medium rather than a smooth surface so that shadowed foliage can be observed on the sunlit side and sunlit foliage on the shaded side. Besides the total reflectance, the model provides the needed outputs of the proportions of sunlit and shaded tree and ground components. Inputs to 4-Scale were obtained directly from the stand parameter measurements described in Section 3.4.1. View and solar angles were specified according to their configuration during individual flights as described in Section 3.4.2.

3.3.3 Uncertainty in the background reflectance estimates

Understanding the impact of uncertainty in a retrieved parameter and the following implications is an important part of any algorithm validation effort (Disney et al., 2006). Since the ultimate goal of the herein tested methodology is to retrieve the forest background reflectance over large areas where not all canopy parameters are known, we explored the effect of uncertainty in the input canopy parameters on the retrieval of the background reflectance. We chose a method that assessed both the possible bias within the algorithm (Eq. (3-4)) and the amount of bias introduced by factors other than the algorithm in the process of background reflectance retrieval.
The sensitivity of input to 4-Scale and its output was examined by (Zhang et al., 2008). Compared to LAI, the effects of stand density on the 4-Scale output were small (Zhang et al., 2008). We created two scenarios to represent the increase of LAI of a forest stand. In one scenario, we keep the stand density constant at 2000 trees/ha while increasing the size of the trees in regular steps. At each step, the vertically-projected crown area was calculated. The same crown area coverage was also achieved in the second scenario by keeping tree dimensional parameters constant for all steps while increasing the stand density. Close-to-reality configurations might be then found in the space bounded by these two scenarios for every step. The parameters for each step and scenario are presented in Table 3-4.

In the first test, the 4-Scale model was run with the input parameters from Table 3-4 for every step of both scenarios and the angular constellation set to correspond to the situation during the CASI flight. The background reflectance was then calculated from Eq. (3-4) with total canopy reflectances and proportions of the components as predicted by the 4-Scale model. If there is no bias in the 4-Scale model and Eq. (3-4), the retrieved background reflectances would not change with increasing canopy foliage, as all the changes in predicted stand reflectances should appear due to changes of the foliage only.

The stand parameters, such as tree height or stand density, might still not be perfectly known during the operational use of the algorithm over large areas despite the promising advances in their retrieval (Chopping et al. 2008b; Heiskanen, 2006; Hill et al., 2008; Schull et al., 2007). The error due to the uncertainty in the input stand parameters was assessed in the second test. The background reflectances were again calculated for every scenario and every step, but the total nadir and angular reflectances were held constant and corresponded to CASI data over one study site with known stand parameters, instead. The proportions of components were the same as in the first test. The comparison of background reflectances allowed us to see the effect of incorrectly specified stand parameters on the results.
3.4 Study Area

3.4.1 Study sites and field measurements

The study sites include four black spruce stands (labeled SB7, 11, 12, 17), one trembling aspen (AS19) and one young jack pine site (PJ21) located near Sudbury, Ontario, Canada (Figure 3-2). Canopy-Site configurations range from young to mature and from sparse to dense. The understory vegetation at black spruce sites consisted mainly of feather moss (*Hylocomium splendens*) with varying contributions from labrador tea (*Ledum groenlandicum*) and leather leaf (*Chamaedaphne calyculata*). Bare soil was the dominant ground cover at the aspen and young jack pine sites. Sites SB7 and SB11 had two parts with
Table 3-1. Characteristics of the investigated stands.

<table>
<thead>
<tr>
<th>site</th>
<th>AS 19</th>
<th>SB 7B</th>
<th>SB 11B</th>
<th>SB 12</th>
<th>SB 17</th>
<th>PJ 21</th>
</tr>
</thead>
<tbody>
<tr>
<td>tree species</td>
<td>trembling aspen</td>
<td>black spruce</td>
<td>black spruce</td>
<td>black spruce</td>
<td>black spruce</td>
<td>young jack pine</td>
</tr>
<tr>
<td>latitude</td>
<td>47.1762</td>
<td>47.1616</td>
<td>47.1635</td>
<td>47.1600</td>
<td>47.1638</td>
<td>47.1619</td>
</tr>
<tr>
<td>longitude</td>
<td>81.7378</td>
<td>81.7454</td>
<td>81.7452</td>
<td>81.7509</td>
<td>81.7599</td>
<td>81.7490</td>
</tr>
<tr>
<td>stand density (trees/ha)</td>
<td>2000</td>
<td>2000</td>
<td>4000</td>
<td>4000</td>
<td>4000</td>
<td>8000</td>
</tr>
<tr>
<td>zenith gap fraction</td>
<td>0.11 (25º)</td>
<td>0.51 (27º)</td>
<td>0.08 (39º)</td>
<td>0.06 (39º)</td>
<td>0.12 (40º)</td>
<td>0.44 (59º)</td>
</tr>
<tr>
<td>canopy LAI</td>
<td>3.65</td>
<td>2.65</td>
<td>5.5</td>
<td>4.57</td>
<td>4.04</td>
<td>2</td>
</tr>
<tr>
<td>element clumping index</td>
<td>0.9</td>
<td>0.73</td>
<td>0.88</td>
<td>0.89</td>
<td>0.81</td>
<td>-</td>
</tr>
<tr>
<td>tree height (m)</td>
<td>13.5</td>
<td>5.6</td>
<td>12.7</td>
<td>10.6</td>
<td>15.9</td>
<td>1.8</td>
</tr>
<tr>
<td>DBH (cm)</td>
<td>32.3</td>
<td>19.3</td>
<td>27.1</td>
<td>36.9</td>
<td>53</td>
<td>-</td>
</tr>
<tr>
<td>understory species</td>
<td>bare soil</td>
<td>feather moss</td>
<td>feather moss</td>
<td>feather moss</td>
<td>feather moss</td>
<td>bare soil</td>
</tr>
<tr>
<td></td>
<td>bush honeysuckle</td>
<td>labrador tea</td>
<td>labrador tea</td>
<td>labrador tea</td>
<td>labrador tea</td>
<td>rotten wood</td>
</tr>
<tr>
<td></td>
<td>lichen hazelnut</td>
<td>rotten wood</td>
<td>rotten wood</td>
<td>rotten wood</td>
<td>rotten wood</td>
<td>honeysuckle</td>
</tr>
</tbody>
</table>

unmodified and modified understory. At the modified sites SB7 and SB11, we cut and removed all understory and covered the ground with white plastic. At SB7, we additionally laid a layer of black plastic. This layer was removed after the first flight and white plastic was exposed for the second flight. The unmodified parts are identified with a subscript B.

Quadratic plots of 30 m side length with a central east-west oriented transect line were established at each site. Along each transect a forestry flag was placed every 10 m. At each plot, measurements of forest structural variables and forest background reflectance were carried out within a week of the CASI flight date, 28 June 2007. Stand variables for the sites are summarized in Table 3-1.

The effective LAI ($L_e$) was measured using the LAI-2000 Plant Canopy Analyzer (LI-COR, Lincoln, NE) instrument. Measurements at each flag along the site transect were taken under diffuse sky conditions (i.e. overcast sky or at dusk). We assessed the multiple scattering effect by comparing $L_e$ based on rings 1-3 (corresponding to the zenith angle range from 0º to 45º) and rings 1-5 (0º to 75º). Interestingly enough, we observed the same average difference between these two ways of $L_e$ calculation.
(16%) as the previous study (Chen et al., 2006b) for stands collected from the whole of Canada. We have increased by 16% for all $L_e$ values from LAI-2000 calculated using rings 1-5 to account for the multiple scattering effect.

Beyond-shoot clumping ($\Omega_E$) was quantified using the element clumping index and measured directly in the field during sunny days along the same transects using the TRAC instrument (Third Wave Engineering, Ottawa, Canada) based on a canopy gap size distribution theory (Chen and Cihlar, 1995; Leblanc, 2002). Values of woody-to-total leaf area ratio ($\alpha$) and needle-to-shoot ratio ($\gamma_E$) were used as provided by Chen et al. (2006b) and Gower et al. (1999) and were comparable with estimates of Zhang et al. (2008) for different sites within the same study area.

For the estimation of forest background reflectance, we first took photos around each forest flag with a digital camera pointing perpendicularly to the ground. The sunlit reflectance of the present forest floor types was measured using a FieldSpec Pro spectroradiometer (Analytical Spectral Devices Inc., Boulder, Colorado, USA). To capture the inter-species variability as well as the intra-species variability in spectral reflectance as influenced by different moisture and environmental conditions, we took several sets of spectral reflectance measurements at different locations at each site. All spectral reflectance measurements were taken in the nadir direction under clear sky conditions at a height of about 3 cm above sunlit targets (leaves or moss/lichen layer, ground). The solar position during the understory spectra measurements was consistent with the configuration during CASI flights. The measurements were standardized to reflectance using a Spectralon diffuse reflectance target (Labsphere, North Sutton, New Hampshire). The average nadir forest background reflectance for each site was obtained based on the reflectance of the cover types weighted by their area fractions as derived from the photos. Finally, the spectra of plastic sheets were measured in a laboratory with Finnish Geodetic Institute Field Goniospectrometer (Suomalainen et al., 2008). The light source was positioned at zenith angle of 38º that corresponded to the sun position during the second flight.
3.4.2 CASI data and processing

Two CASI flights took place on 28 June 2007 at an altitude of 1524 m (5000 ft) above the ground between 18:10 and 20:38 GMT at the solar zenith angle of 25.2º to 44.3º. CASI was operated in the hyperspectral mode (72 channels; spectral range 408-947 nm; bandwidth 7.5 nm) with 2-m spatial resolution (Haboudane et al., 2008). Variable viewing zeniths were obtained by mounting the camera on a tilting bracket and adjusting the tilt along the flight line. The view zenith angles were 0º (nadir), -30º, and +40º for the first flight, and 0º, -40º, +40º, and +45º for the second flight. Following the convention of Chopping et al. (2004), negative values indicate the backscattering hemisphere and positive values indicate the forward-scattering hemisphere. The view angles for the back-scattering hemisphere were set to be close to solar zenith position during individual flights. Cross angles (absolute angle difference from the principal plane; Φ) varied with flights in order to see the effect of the deviation from the principal plane on the understory reflectance retrieval. Φ was 29º for the first flight and Φ = 3º for the second flight with the camera set at VZA = 40º. For the view angle of 45º during the second flight, Φ = 15º. In the following text, the results are indicated by the value of the cross angle.

The multi-angle images were radiometrically calibrated using the latest radiance scale factors for the CASI sensor and atmospherically corrected to at-ground reflectance using MODTRAN 4 in the PCI atmospheric correction package (PCI Geomatics, Richmond Hill, Canada). Direct measurements of atmospheric parameters were not available during the CASI overflights; however, aerosol optical depth was estimated from nearby measurements of visibility. Methodological measurements from Environment Canada gave the conditions as clear with a visibility of 25 km. Other atmospheric parameters were allowed to default to MODTRAN mid summer, mid latitude values. The reflectance images were geometrically corrected using Itres’ geometric correction software (Itres, Calgary, Canada) and roll, pitch and location information from an on-board navigation system. Geometric correction based on this system was further adjusted using ground control points measured in the field. These ground control points
include 2 m × 2 m white plastic sheets placed on the road sides near the sites, and identifiable ground features such as road crossings, or rock outcrops. Geometrically-corrected off-nadir images were then registered to the nadir images. The final spatial resolution of the images is 3 meters. The roll and pitch were quite pronounced in the off-nadir images making geometric correction very difficult. The final RMSE for the whole scenes were 5-6 pixels. However, since all the sites were located close to distinct features (white/black plastic, roads), it has been verified that the reflectance data for various view angles cover nearly identical areas. Also, the background mapping was not carried out on individual pixels, but on averaged plots of size 30 m × 30 m (i.e. 100 pixels). If the accuracy could not be guaranteed due to roll and pitch distortions over particular sites in the image, we did not carry out the calculations. All sites were located on flat terrain and there were no topographic effects that needed to be taken into account in our image analysis.

The hyperspectral mode data were finally aggregated to create MISR-like responses for red and NIR bands. We averaged the CASI hyperspectral bands that cover the corresponding MISR red and NIR spectral bandwidths as provided by Diner et al., (1998). The new bands were centered at 671.3 nm (vs. 671.7 nm for MISR) and 866.1 nm (vs. 866.4 nm for MISR).

3.5 Results and discussion

3.5.1 Changes of total reflectance with view angle

The verification of the predicted total reflectance changes with view angle in the field by modifying the background properties with black and white plastic presented the first important step in our research. To our knowledge this is for the first time the forest understory has been completely controlled and studied at such a spatial extent (30m × 30m and 20m × 20m plots in stands with different densities). Complete understory removal was previously performed by Liames et al., (2004), but the effect of
understory was assessed only indirectly via observing the changes in the scene NDVI between pre- and post-treatment IKONOS imagery.

The total reflectances obtained from the CASI data were examined at two viewing angles. The total reflectances increased with view angle for the dark background and decreased for the white background situation for the SB7 site with the modified understory (Figure 3-1). This behavior confirmed the first step in the theory of the background reflectance retrieval as described in the Methodology section. The Anisotropy Factor (AF), calculated by normalizing the reflectance in a specific view direction by nadir reflectance for a given wavelength (Sandmeier and Itten, 1999), was more pronounced for both red and NIR band values from the second flight with white plastic background below. The higher AF values were also observed during the second CASI flight over SB11 site, where white background was present for both flights. The angular measurements during the first flight were taken on a plane further away from the principal plane than during the second flight (i.e. $\Phi = 29^\circ$ vs. $\Phi = 3^\circ$). Observed behavior of AF values confirms first the reflectances of components (canopy and background) change less with viewing angle on a plane further away from the principal plane and therefore the data from the first flight are more appropriate for the background reflectance retrieval.

3.5.2 Background reflectance

The retrievals of background reflectance using Eq. (3-4) were validated first over the sites with modified understory. Testing the new algorithm over the control sites revealed important impacts of our algorithm assumption of the Lambertian isotropic background. While the CASI-retrieved values were very close to field measurements in both bands in the case of dark background over SB7 (lower stand density), significant disagreement between values in the red band was present over the same site with the white background (Figure 3-3a). The percentage error (PE) was 43% for the flight with and $\Phi = 15^\circ$ and 28% with $\Phi = 3^\circ$, respectively. Interestingly, all the retrievals in red band over the other modified site SB 11
Figure 3-3. Nadir reflectance spectra (BRF) from the measurements (lines) and as calculated from CASI data (point markers) for two black spruce stands with modified background. Numbers indicate the angular difference of CASI flights and the principal plane.

(higher stand density) were also underestimated, but the error margin was smaller with PE < 15% (Figure 3-3b).

Analysis of the complete BRFs of black and white plastic explains this behavior (Figure 3-4). The BRFs of all the plastics have huge specular reflectance. The anisotropy effect is usually the most pronounced along the principal plane (Ni and Li, 2000), and it was shown to decrease with increasing angular distance from the principal plane (Tsay et al., 1998). The width of the specular reflectance effect along the principal plane varies between the plastics. The effect is very narrow for the black plastic and the dark background configuration was observed by CASI camera with $\Phi = 29^\circ$. The background reflectance thus did not change very much with view angle, and the retrieved values were very close to the field measurements. The bright (white plastic) background configuration was observed with smaller cross-angle values, $\Phi = 3^\circ$ and $\Phi = 15^\circ$. The angles were not enough to avoid the spike in the forward scattering direction due to the specular reflectance, and background reflectances then varied with view angle. The assumption of the Lambertian target was violated, which resulted in biased background reflectance retrievals. If we decreased the total angular reflectance by the percentage difference between
Figure 3-4. The BRDF of (a) white and (b) black plastic in red band. Lamp zenith angle is 38 degrees. The concentric colored rings clarify zenith angles.
the angular and nadir reflectance of the white plastic as measured during the BRF reconstruction of the material in the lab, the background reflectance predicted from the algorithm closely matched the one measured in the field. This effect was not so pronounced for SB11 (Figure 3-3b) due to the higher stand density (twice as high as for SB7). The proportions of visible background were much lower for SB11 and for all angles trees occupied more than half of the instantaneous field of view (IFOV). The background was a dominant component for all angles at SB7. It can be concluded that if the BRDF of the understory for given solar position is known, the corrections to the algorithm input reflectances can be done to produce appropriate nadir background reflectance. The results might point to a possible lower accuracy of the background reflectance retrieval over very bright surfaces with strong specular reflectance such as snow in winter (Kokhanovsky et al., 2005). However, our initial results with satellite-based MISR data (Pisek et al., 2008) seem to indicate the algorithm can produce meaningful background retrievals over natural areas with snow in winter as well.

The performance of the algorithm over sites with unmodified background is described in Figure 3-5 and Table 3-2. The retrievals were validated with field measurements, collected over transect locations at every site. Similar to Peltoniemi et al. (2005a) and Bubier et al. (1997), sometimes optical spectra measured at nadir at various locations even just a few meters apart could be quite different among the same species. The degree of understory vegetation cover can also vary considerably within one stand (Eriksson et al., 2006). The retrieved nadir background reflectances match reasonably well with the in-situ measurements in absolute terms, with scatter mainly due to uncertainties in the estimated angular reflectance pattern of the background measured in field, overstory parameterization, and the pixel co-registration. The algorithm seems to perform relatively well for various black spruce, jack pine and aspen stands. The results indicate the robustness of the algorithm for estimating the forest background reflectance over diverse palettes of understory situations.
Table 3-2. A comparison of measured and calculated stand BRF from CASI data in red and NIR band over six stands in 2007. Numbers in brackets are relative absolute errors from the in-field measured values.

<table>
<thead>
<tr>
<th>band</th>
<th>site</th>
<th>measurement</th>
<th>View Angle 40°</th>
<th>View Angle 45°</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Φ = 29°</td>
<td>Φ = 3°</td>
</tr>
<tr>
<td>red (671 nm)</td>
<td>SB7B</td>
<td>0.0501</td>
<td>0.0610 (0.22)</td>
<td>0.0627 (0.25)</td>
</tr>
<tr>
<td></td>
<td>SB11B</td>
<td>0.0513</td>
<td>0.0476 (0.07)</td>
<td>0.0598 (0.17)</td>
</tr>
<tr>
<td></td>
<td>SB12</td>
<td>0.0501</td>
<td>0.0525 (0.05)</td>
<td>0.0455 (0.09)</td>
</tr>
<tr>
<td></td>
<td>SB17</td>
<td>0.0506</td>
<td>0.0469 (0.07)</td>
<td>0.0532 (0.05)</td>
</tr>
<tr>
<td></td>
<td>PJ21</td>
<td>0.1009</td>
<td>0.1155 (0.14)</td>
<td>0.0773 (0.23)</td>
</tr>
<tr>
<td></td>
<td>AS19</td>
<td>0.0927</td>
<td>0.0767 (0.17)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SB7B</td>
<td>0.0501</td>
<td>0.0610 (0.22)</td>
<td>0.0627 (0.25)</td>
</tr>
<tr>
<td></td>
<td>SB11B</td>
<td>0.0513</td>
<td>0.0476 (0.07)</td>
<td>0.0598 (0.17)</td>
</tr>
<tr>
<td></td>
<td>SB12</td>
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<td>0.0525 (0.05)</td>
<td>0.0455 (0.09)</td>
</tr>
<tr>
<td></td>
<td>SB17</td>
<td>0.0506</td>
<td>0.0469 (0.07)</td>
<td>0.0532 (0.05)</td>
</tr>
<tr>
<td></td>
<td>PJ21</td>
<td>0.1009</td>
<td>0.1155 (0.14)</td>
<td>0.0773 (0.23)</td>
</tr>
<tr>
<td></td>
<td>AS19</td>
<td>0.0927</td>
<td>0.0767 (0.17)</td>
<td></td>
</tr>
<tr>
<td>NIR (866 nm)</td>
<td>SB7B</td>
<td>0.4475</td>
<td>0.4289 (0.04)</td>
<td>0.4340 (0.03)</td>
</tr>
<tr>
<td></td>
<td>SB11B</td>
<td>0.4268</td>
<td>0.3980 (0.07)</td>
<td>0.4490 (0.05)</td>
</tr>
<tr>
<td></td>
<td>SB12</td>
<td>0.4028</td>
<td>0.3639 (0.10)</td>
<td>0.2855 (0.29)</td>
</tr>
<tr>
<td></td>
<td>SB17</td>
<td>0.3774</td>
<td>0.3010 (0.20)</td>
<td>0.3574 (0.05)</td>
</tr>
<tr>
<td></td>
<td>PJ21</td>
<td>0.1782</td>
<td>0.1906(0.12)</td>
<td>0.1993 (0.07)</td>
</tr>
<tr>
<td></td>
<td>AS19</td>
<td>0.4444</td>
<td>0.4889 (0.10)</td>
<td></td>
</tr>
</tbody>
</table>

Figure 3-5. Nadir reflectance spectra (BRF) from the measurements (lines) and as calculated from CASI data (point markers) for six stands with unmodified background. Numbers indicate the angular difference of CASI flights and the principal plane.
The availability of the CASI data at different azimuthal angles relative to the sun also permitted a look at the effect of the angular distance from the principal plane on the quality of retrievals. For the analyzed collection of the stands, results were slightly improved with increasing cross angle. Mean PE was the worst for retrievals with $\Phi = 3^\circ$ (16% in red and 12% in NIR) and the best at 12% (red) and 10% (NIR) for retrievals with $\Phi = 29^\circ$. Both these results and the findings from the Section 3.5.1 confirm that angular observations further away from the principal plane are indeed more appropriate for the background reflectance retrieval, in agreement with the proposal of Canisius and Chen, (2007) that angular observations near the perpendicular plane would be optimal for background retrieval. This may be due to two reasons: (1) the BRDF effect of the background is minimized and (2) the shadow fraction of the overstorey varies the least along the perpendicular plane. The angular configuration of our CASI measurements near the principal plane was designed for the purpose of clumping index retrieval (Simic et al., 2009), while the same data are used for background retrieval. Although this configuration is not optimal, it was encouraging to see that the background information can still be reliably retrieved, and this further demonstrates the robustness of our background algorithm.

Our results further suggest that at least for observations with larger sun-view azimuthal angle differences ($\Phi = 29^\circ$ and $\Phi = 15^\circ$), the CASI sensor at smaller view zenith angles delivered slightly more accurate background reflectance retrievals. This is probably caused by larger proportions of background seen at smaller view zenith angles. Although the view zenith angle varied only less than 5 degrees during our CASI acquisition, our results indirectly support findings by Rautiainen et al. (2008a), who observed smaller contributions from the understory with more oblique viewing angles for CHRIS PROBA data.

Subsequently, a background reflectance map was produced for a sub-scene of the study area with minimal co-registration errors between two images at different view angles (Figure 3-6). The inputs were CASI data from the first flight with $\Phi = 29^\circ$ and the scene proportions calculated for SB11B, since this
Figure 3-6. CASI background reflectance map (left-red band; right-NIR band) over a subset area of the scene from Figure 3-2. near Sudbury, Ontario, Canada. The spatial resolution of the image is 20 x 20 m.

site was deemed to be the most representative of the stand conditions in the sub-scene. The area was revisited in late June 2008 and the map was validated with background reflectance measurements at randomly placed sites. The compatibility of the measurements coming from different years (CASI data from June 2007; field data from June 2008) was assured by visiting the transect at SB12 and re-measuring all present understory species. The averaged background site spectral curves for 2007 and 2008 closely agreed with PE of 4%.

Background values were produced only for coniferous stands in the map (deciduous stands were not present in the area). Areas covered with peatland, bare soil, or gravel hold their original nadir reflectances. Table 3-3 includes the results of the background map validation. Location J0 corresponds to a road and the PE of CASI data to the field measurements was under 10% for both red and NIR band. This confirms the minimal effect of atmosphere on the data observed by CASI during the flights over the study area. In agreement with Sandmeier and Deering (1999), exposed road showed relatively isotropic reflectance characteristics and was bright in all viewing directions. The other sites (J1-J5) corresponded to various coniferous stands (both black spruce and jack pine). The retrievals were again reasonably close to the field measurements with few exceptions in the red band. Overall, background retrievals in the NIR
Table 3-3. A comparison of measured and calculated background BRF from CASI data (June 2007) in red and NIR band over additional sites, measured in June 2008. Numbers in brackets are relative absolute errors from the in-field measured values.

<table>
<thead>
<tr>
<th>site</th>
<th>red band (671 nm)</th>
<th>NIR band (866 nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>in situ</td>
<td>CASI</td>
</tr>
<tr>
<td>J 0</td>
<td>0.1543</td>
<td>0.1441 (0.07)</td>
</tr>
<tr>
<td>J 1</td>
<td>0.0517</td>
<td>0.0576 (0.12)</td>
</tr>
<tr>
<td>J 2</td>
<td>0.0985</td>
<td>0.0762 (0.23)</td>
</tr>
<tr>
<td>J 3</td>
<td>0.1092</td>
<td>0.0709 (0.35)</td>
</tr>
<tr>
<td>J 4</td>
<td>0.0884</td>
<td>0.0796 (0.10)</td>
</tr>
<tr>
<td>J 5</td>
<td>0.0349</td>
<td>0.0581 (0.67)</td>
</tr>
</tbody>
</table>

Figure 3-7. (a) Distribution of the total reflectances (dark grey) and calculated background reflectances (light grey) for the pixels in the CASI background reflectance map over a subset area of the scene from Figure 3-2. near Sudbury, Ontario, Canada. The highlighted points indicate the differences between the total and background reflectances for the sites from Table 3-3. For clarity, calculated background reflectances only are shown in (b).

Band tend to be more stable than the ones in the red band. This may be due to an effect of higher multiple scattering in NIR that balances out local differences and results in smoother BRDF of these stands.

Figure 3-7 illustrates the importance of not neglecting the background reflectance. The background reflectances tend to be higher in both the red and the NIR band than the total reflectances. The relative increase tends to be higher in the red band than in the NIR band, which results in decreased SR values for
the background in comparison with the total reflectance at the stand level. Our ground-truth data may still be insufficient for validating the small regional map produced by CASI, but the pronounced shifts in the spectral space from total reflectance positions in Figure 3-7 underline the fact that the background reflectance and the role of understory cannot be ignored in the canopy LAI retrieval.

### 3.5.3 Stand reflectance simulations

To gain confidence in our approach, we tested the internal consistency of the 4-Scale model inversions. While the model-predicted stand reflectances were increasing with canopy foliage, the background reflectance, calculated with Eq. (3-4) based solely on the outputs from the model, was staying almost constant (Figure 3-8). This behavior confirms that the 4-Scale model itself through the predicted proportions of components introduces only a minimal bias into the calculations of the background reflectance. However, the uncertainties in the input parameters to the model would be other sources of errors.

In this study, we acquired detailed information about the stand structure. Component proportions could be then predicted fairly well with 4-Scale. What happens if all this stand structure information is not available? The effects of input stand parameters were therefore investigated. Inputs into the Eq. (3-4)

<table>
<thead>
<tr>
<th>Scenario number</th>
<th>tree height (m)</th>
<th>crown depth (m)</th>
<th>crown radius (m)</th>
<th>vertical projected crown area (m²)</th>
<th>corresponding stand density (trees/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0.85</td>
<td>0.34</td>
<td>713.64</td>
<td>404</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>1.70</td>
<td>0.48</td>
<td>1427.27</td>
<td>808</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>3.39</td>
<td>0.67</td>
<td>2854.55</td>
<td>1616</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
<td>5.09</td>
<td>0.83</td>
<td>4281.82</td>
<td>2424</td>
</tr>
<tr>
<td>5</td>
<td>8</td>
<td>6.79</td>
<td>0.95</td>
<td>5709.09</td>
<td>3232</td>
</tr>
<tr>
<td>6</td>
<td>10</td>
<td>8.48</td>
<td>1.07</td>
<td>7136.36</td>
<td>4040</td>
</tr>
<tr>
<td>7</td>
<td>12</td>
<td>10.18</td>
<td>1.17</td>
<td>8563.64</td>
<td>4848</td>
</tr>
</tbody>
</table>
Figure 3-8. Changes in simple ratio (SR) of 4-Scale simulated scene components with increasing LAI/vertically projected crown area by altering tree size/stand density. Line ‘Grow trees’ corresponds to results achieved with constant stand density and increasing tree size (lower x-axis or Table 3-4); line ‘Grow forest’ corresponds to results achieved by keeping tree dimensional parameters constant while increasing the stand density (upper x-axis or Table 3-4). Line ‘Average case’ represents the mean value between the two scenarios at each step.

were proportions of components as provided by 4-Scale for every step in each scenario; total nadir and angular reflectances were kept constant and corresponded to observations over SB7B site (i.e. lower stand density, unmodified background) with $\Phi = 29^\circ$. The retrieved background reflectance changes with increasing canopy foliage this time (Figure 3-9). Illustrated with simulations for the red band, the results
Figure 3-9. Sensitivity of the background reflectance estimates to the input stand parameters. The 4-Scale model calculated the scene background components as tree size/stand density increased, while the stand reflectance was kept constant as observed over SB-7 site by CASI. For the legend explanation see Figure 3-8.

indicate that the algorithm performs well for low to intermediate stand densities - that is, the situation when the background reflectance does have an important contribution to the total reflectance of the canopy - but with increasing canopy foliage, the error progressively increases. If the assumed canopy foliage is twice the amount observed in the field, PE reached up to 100% in the red band. This is not very encouraging. However, one has to bear in mind that in these cases of dense vegetation canopies, LAI is greater than 5. A high accuracy of the background retrievals for dense canopies is not possible due to low visibility of the understory through the dense canopy (Lang et al., 2007; Eriksson et al., 2006; Nilson, 1999) and the role of the background understory is then also not so critical. The stand reflectance at high LAI values is nearly independent of view directions (e.g. Rautiainen et al., 2008a, demonstrated this for VZA 7.6° up to 56.7°), and, as mentioned, the background has only a very small contribution to the total forest reflectance (Kaufmann et al., 2000; Zarco-Tejada et al., 2001; Zhang et al., 2002). The background plays an important role mainly at low to intermediate stand densities, and the results in Figure 3-9 indicate
the algorithm is less sensitive to the input stand parameters in this domain. As the main purpose for our background reflectance is to improve LAI mapping, which is more sensitive to the background when the LAI is small, this expected limitation in our methodology therefore does not defeat our goal of using multi-angle data for LAI mapping.

3.6 Conclusion

This investigation offers new insights into the possibilities and limitations of multi-angle data use for estimating the forest background reflectance with a GO model. Through an intensive field campaign, including multi-angle airborne remote sensing and concurrent ground measurements in forest stands with modified and natural backgrounds, we validated, for the first time, our background reflectance retrieval algorithm. While other authors noted that multi-angular data can reduce the effect of understory (Heiskanen, 2006; Rautiainen et al., 2008a), we show that under appropriate zenith and azimuth angular sensor configuration we can achieve the opposite as well - the retrieval of the signal from forest background. We demonstrated that it is feasible to retrieve the background reflectance with two-angle remote sensing, one at nadir and the other at an off-nadir angle. Although the off-nadir remote sensing is theoretically optimal on the plane perpendicular to the solar plane, our current study shows that the retrieval can also be successful if the background reflectance directionality is considered in the retrieval algorithm.

Several studies have proposed the inclusion of the measurement of the understory component into the canopy LAI algorithms (Morisette et al., 2006). While the understory LAI measurements are part of the field protocol, for example, for the VALERI group (VALERI, 2007) or other networks (Baret et al., 2006), the information about the forest understory has not been retrieved from remote sensing data. The previous progress in retrieving the combined soil-understory responses by Chopping et al. (2006; 2008a) focused on grass- and shrub-dominated areas and the acquired results cannot be simply extrapolated into
the forest domain. In this sense, we have made one step forward in retrieving the forest background information from remote sensing data.

However, the successful retrieval also depends on the estimation of various scene fractions used in the algorithm. These scene fractions depend strongly on the LAI, which is a required input to the algorithm, but also depend on other stand parameters, such as stand density and tree size. As these parameters are often lacking for large regions, we conducted sensitivity tests of our model, and demonstrated that for low and moderate density stands with LAI < 5, the error in the retrieved background reflectance would be within 16% in the red band and 12% in the NIR band. These results suggest that it is feasible to retrieve the background information from two-angle remote sensing with only LAI as the additional input. Our next goal is to apply this algorithm over large areas with MISR data (Diner et al., 1998), which provide satellite observations at multiple viewing and illumination angles. This study has provided, in addition to the necessary validation of the theory with airborne and in-situ measurements, an insight into the sources of uncertainties affecting the performance of the algorithm that will need to be taken into account for large area mapping. Once the seasonal variations of the background optical properties can be retrieved from remote sensing, our regional and global LAI mapping can be significantly improved.
4 Mapping forest background reflectivity over North America with Multiangle Imaging SpectroRadiometer (MISR) data\textsuperscript{3}

This chapter is based on the paper published in *Remote Sensing of Environment*:


4.1 Abstract

The spatial and temporal patterns of the forest background optical properties are critically important in retrieving the biophysical parameters of the forest canopy (overstory) and in ecosystem modeling. In this paper we carry out background reflectivity mapping over conterminous United States, Canada, Mexico, and the Caribbean land mass using Multi-angle Imaging SpectroRadiometer (MISR) data at 1.1-km resolution. The refined methodology uses the nadir and 45\textdegree forward directions of the MISR camera images. The background reflectivity is shown to vary between coniferous and deciduous stands, particularly in the near-infrared band, and with the overall amount of overstory vegetation. The largest seasonal differences were observed over a boreal region. The main drawback is a high amount of missing MISR data due to the presence of clouds and other atmospheric effects. The paper also contains a demonstration of the effect on LAI estimates when the dynamic background reflectivity information is inserted into a global LAI algorithm. Multi-angular remote sensing is thus shown to enable us to effectively map yet another forest structure parameter over large areas, which was not possible using mono-angle, andir-spectral data.

\textsuperscript{3} Elsevier and my co-author Dr. Chen allowed me to include this submitted paper as a chapter in my dissertation. Dr. Chen provided suggestions about the manner of temporal and spatial interpolation of the data and edited the paper draft. I was responsible for the methodology and data production chain, conducted simulations to produce look-up tables (LUTs), analyzed the results, and wrote the manuscript.
4.2 Introduction

Quantitative description of vegetation structure has been identified as one of the key requirements for major improvement in modeling the terrestrial carbon cycle and global biosphere (Turner et al., 2004). Vegetation canopy structure and its energy absorption capacity can be described by leaf area index (LAI), defined as half the total developed area of green leaves per unit ground horizontal area (Chen and Black, 1992) and by the Fraction of Photosynthetically Active Radiation (FAPAR) absorbed by the leaves. It was noted that for models of climate, hydrology, and ecology it is probable that only the LAI, FAPAR, and information about the forest floor albedo have to be estimated spatially (Diner et al., 2005). Other parameters can be derived from LAI or taken from the literature (Manninen and Stenberg, 2009).

While retrieving the information about forest vegetation structure such as LAI, it is the spectral signal from the forest canopy (overstory, see Figure 4-1) that is the target in many remote sensing (RS) applications, and not the background. However, the sensor receives a signal from both the target and the background (Olofsson and Eklundh, 2007; Peltoniemi et al., 2005a). By the term forest background, we refer to all the materials below the forest canopy such as understory, shrubs, leaf litter, grass, lichen, moss, rock, soil, snow, or their mixtures (Figure 4-1). The stand is thus conceptually divided into tree canopy and background material + soil (Chopping et al., 2006).

The lack of spatial information about forest background and its importance has recently gained increased attention (e.g. Eriksson et al., 2006; Kuusk et al., 2004; Rautiainen, 2005). Particularly within relatively open forest canopies, understory vegetation, its contrasting greenness and senescence can be quite important to relationships between vegetation indices (VI) and overstory LAI (Pocewicz et al., 2007). Further, Garrigues et al. (2008) noted in their validation and intercomparison of global LAI products that the forest understory LAI is not systematically taken into account in ground LAI measurements. This can result in substantial differences with the satellite LAI product derived from the vertical integration of the radiometric signal within the canopy (Abuelgasim et al., 2006; Chen et al.,
Figure 4-1. Conceptual scheme of a forest stand. In vertical dimension the forest consists of overstory tree canopy; everything below (in purple) is considered to be the forest background. In horizontal dimension, the total reflectance of the stand is the sum of (a) sunlit tree, (b) shaded tree, (c) shaded ground, and (d) sunlit ground fractions.

1997; Iiames et al., 2008; Wang et al., 2004;). It is equally important to take the understory vegetation into account when measuring FAPAR, particularly in open canopies (Olofsson and Eklundh, 2007).

Driven by these calls, a few efforts were carried out at collecting various understory components and/or creating limited spectral banks (Lang et al., 2002; Miller et al., 1997; Peltoniemi et al., 2005a,b; Rautiainen et al., 2007; Rees et al, 2004). Monitoring the environment at a continental or global scale over periods of multiple years requires access to continuous fields of geophysical quantities, and satellite RS is the only technology currently able to provide consistent data at these scales (Pinty et al., 2008). The information conveyed about canopy structure is small in the case of a mono-angle instrument, whose footprint does not spatially resolve individual scene elements (Figure 4-1). Therefore, specifically in reference to LAI, a wide range of natural variation in LAI and soil or understory reflectance can result in the same value of the remotely sensed signal. This results in a high uncertainty in retrieved values of LAI (Hu et al., 2003). Before the era of simultaneously acquired multi-angle RS data by sensors such as MISR (Diner et al., 1998) or POLDER (Leroy and Lifermann, 2000) really started, Gemmel (2000)
summarized that in the large majority of situations, the background spectral characteristics cannot be effectively obtained from the mono-angle, nadir-spectral RS data.

The use of multi-angle RS for characterizing surface properties represents a new paradigm in optical RS application (Nolin, 2004), where the variation in reflectance with view angle is considered a source of new information rather than noise. Multi-angle RS enables us now to describe surface properties by means that are not possible using mono-angle data (for a comprehensive review of the progress, see Chopping, 2008).

In this paper, we intend a) to document an improved retrieval strategy for the background reflectivity retrieval using geometrical optical modeling theory with the 4-Scale model and MISR data from the initial study published by Canisius and Chen (2007); b) to examine the optical properties and seasonal changes of the forest background over conterminous United States, Canada, Mexico and the Caribbean land mass over the year 2007; and c) to present on the example of the existing global LAI algorithms of Deng et al. (2006) a preliminary analysis of the effects of using the new background information dataset to correct the forest LAI estimates.

The improved strategy has been previously field-tested with multi-angle airborne Compact Airborne Spectrographic Imager (CASI) data (Pisek et al., 2009a; Chapter 3). The current paper presents, for the first time, a forest background dataset retrieved from MISR data at a continental scale and the implications for global LAI mapping.

4.3 Materials and Methods

4.3.1 Background Reflectivity Algorithm

Since radiance is additive, the total spectral reflectance of a pixel (R) can be expressed as a linear
combination of the contributions from the scene components (Li and Strahler, 1985; Bacour and Breon, 2005; Chen et al., 2000; Chopping et al., 2008a):

\[
R = R_T \cdot k_T + R_G \cdot k_G + R_{ZT} \cdot k_{ZT} + R_{ZG} \cdot k_{ZG}
\]  

(4-1)

where \( R_T, R_G, R_{ZT}, \) and \( R_{ZG} \) are the reflectances of the sunlit tree crowns, sunlit background, shaded tree crown, and shaded background. \( k_j \) are the proportions of the four components in the instantaneous field of view (IFOV). By using the observed reflectance at nadir and at another angle one can derive the background reflectivity \( (R_G) \). The first condition is that the observations are made along a plane where the target reflectances change little with view angle. The directional dependence of reflectance factors is the greatest in the principal solar plane and decreases fast as the viewing azimuth angle moves away from this plane (Bicheron et al., 1997, Peltoniemi et al., 2005b, Sandmeier and Deering, 1999). MISR is an operational sensor overpassing the equator at approximately 10:30 local time while descending that provides high quality calibrated multi-angular measurements taken along an oblique plane, not so close to the principal plane (Diner et al., 2002). The influence of BRDF is then minimized and it has been observed that the azimuthal dependency of the reflectance of forest floor in particular is typically not that strong (Peltoniemi et al., 2005b) and forward-scattering reflectances of various targets were shown to be fairly constant (Bacour and Breon, 2005; Deering et al., 1999; Kaasalainen and Rautiainen, 2005). The reflectance at nadir \( (n) \) and another zenith angle \( (a) \) can be then expressed by the Eqs. (4-2) and (4-3):

\[
R_n = R_T \cdot k_{Tn} + R_G \cdot k_{Gn} + R_{ZT} \cdot k_{ZTn} + R_{ZG} \cdot k_{ZGn}
\]  

(4-2)

\[
R_a = R_T \cdot k_{Ta} + R_G \cdot k_{Ga} + R_{ZT} \cdot k_{ZTn} + R_{ZG} \cdot k_{ZGn}
\]  

(4-3)

Canisius and Chen (2007) originally assumed the shaded reflectivities (i.e. \( R_{ZT} \) and \( R_{ZG} \)) to be comparatively small and replaced them by a constant value \( (R_Z = R_{ZT} = R_{ZG}) \) for individual wavelengths. However, Gemmel (2000) observed that reflectances from different shaded crowns could
differ up to a factor or two. Pisek et al. (2009a; Chapter 3) tackled the issue in the new version of the algorithm (Eqs. (4-2),(4-3) and used in this study for the first time with satellite RS data), by expressing shaded components of trees and ground dynamically as functions of their sunlit part and the multiple scattering factor (White et al., 2001, 2002a, b), giving \( R_{ZT} = M \cdot R_T \) and \( R_{ZG} = M \cdot R_G \), where \( M = R_z / R \) for a reference target. Solving Eqs. (4-2) and (4-3), the background reflectivity \( R_G \) can be then calculated as:

\[
R_G = \frac{R_n (k_{Ta} + k_{ZTa} \cdot M) - R_a (k_{ZTn} \cdot M)}{-k_{Tn} \cdot k_{Ga} + k_{Ga} \cdot k_{Tn} + M (-k_{Tn} \cdot k_{ZGa} + k_{Ga} \cdot k_{ZTn} - k_{Ga} \cdot k_{ZTn} + k_{Ta} \cdot k_{ZGa}) + M^2 (-k_{ZTn} \cdot k_{ZGa} + k_{ZGa} \cdot k_{ZTn})}
\]

(4-4)

where the total reflectances \( R_n \) and \( R_a \) are acquired from the nadir and chosen angle direction, \( M \) is predetermined by the 4-Scale model inversion, and the proportions of the components can be predicted from a GO model. We compare the performance of the algorithms by Canisius and Chen (2007) and Pisek et al. (2009a; Chapter 3) using MISR data in the results section.

### 4.3.2 Estimating Probabilities of Viewing Scene Components

The proportions of the components in Eq. (4) are calculated using the 4-Scale model (Chen and Leblanc, 1997; Leblanc et al., 1999; Chen and Leblanc, 2001). This is a geometric-optical radiative-transfer model with an emphasis on the structural composition of forest canopies at different scales. From the model output, only the proportions of the components were used in the background reflectivity retrieval. The two most important properties of the 4-Scale from this point of view are:

a) Tree crowns are simulated as discrete geometrical objects: cone and cylinder for conifers, and spheroid for deciduous species, as this has been found to be an important parameter for correct BRDF model inversions (Rautiainen et al., 2004; 2008b). The non-random spatial
Table 4-1. Input parameters to 4-Scale.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Coniferous</th>
<th>Deciduous</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stand density</td>
<td>Trees/ha</td>
<td>500,1000, 2000</td>
<td>500,1000, 2000</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3000,4000</td>
<td>3000,4000</td>
</tr>
<tr>
<td>Clumping index ($\Omega_E$)</td>
<td></td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>Tree shape</td>
<td></td>
<td>Cone+cylinder</td>
<td>Spheroid</td>
</tr>
<tr>
<td>Crown base height</td>
<td>m</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Crown vertical</td>
<td></td>
<td>12</td>
<td>15</td>
</tr>
<tr>
<td>dimension</td>
<td>m</td>
<td>0.75</td>
<td>2</td>
</tr>
</tbody>
</table>

distribution of trees is simulated using the Neyman type A distribution (Neyman, 1939).

b) The tree surface created by the crown volume is treated as a complex medium rather than a smooth surface so that shadowed foliage can be observed on the sunlit side and sunlit foliage on the shaded side.

Although the 4-Scale model requires many input parameters, it can be run with a fixed set of general parameters. Simulations by Nilson and Peterson (1994) pointed to the main factors in geometric-optical modeling of stand reflectances being LAI, canopy closure, tree type, and background reflectivity. Since according to their results parameters such as stand density, tree height, and tree stem diameter were not the most important factors, we used fixed values for these tree architectural parameters of coniferous and deciduous types as input to the 4-Scale model (Table 4-1). The parameters such as LAI, solar and view zenith angles (SZA and VZA), the relative azimuth angle between the sun and the viewing camera (PHI) varied between pixels. These parameters were obtained from the satellite images as described in the following section.

Running 4-Scale on multi-angle images pixel by pixel is computationally impractical with regard to the size of the assembled data. An alternative method of look-up tables (LUTs) has been previously
applied for similar large dataset processing (Gobron et al., 2000; Weiss et al., 2000; Myneni et al., 2002). Ten LUTs, five for the coniferous and deciduous forest type each, were developed using the 4-Scale model. Ranges of values agree with the original LUT dimensions of Canisius and Chen (2007): LAI from 0.1 to 10, SZA from 0º to 70º, PHI from 100º to 170º along with the nominal VZA of MISR cameras. Despite advances in the retrieval of stand density from multi-angle RS (Nolin, 2004; Heiskanen, 2006), operational retrieval of the parameter over large areas is yet to be seen. However, the performance of the background reflectivity algorithm was shown not to be critically sensitive to the assumed stand density in case of low to intermediate densities (Pisek et al., 2009a; Chapter 3) when the influence of the background reflectance on the total canopy signal is the greatest (Rautiainen et al., 2007). The background reflectivity is thus calculated here as an average value of five results predicted with MISR data and multiple scattering factor M dependent on the wavelength while component fractions are retrieved from LUTs for five different stand densities for the given biome (Table 4-1).

4.3.3 MISR Data and Processing

The multi-angular satellite data were provided by MISR, which is onboard the Earth Observing System (EOS) satellite Terra (Diner et al., 1998, 2002). MISR consists of nine cameras; four point to the forward direction (denoted as AF, Bf, Cf, Df in the order of increasing off-nadir angle), one points towards the nadir (An) and four point to the aftward direction (Aa, Ba, Ca, Da). The nominal view angles of the cameras are 0º, ± 26.1º, ± 45.6º, ± 60.0º, and ± 70.5º. Each of the nine cameras obtains images at four spectral bands: blue (centered at 446nm; bandwidth 42 nm), green (558nm; 29nm), red (672 nm, 22nm) and near infrared (NIR) (866 nm; 40nm) (Diner et al., 1998). MISR data employed in this study were acquired from all blocks arranged in orbits covering the North America in 2007. The data were provided by the Atmospheric Science Data Center (ASDC) at NASA Langley Research Center and ordered online with the MISR Order Tool.
A set of standard MISR data products is available, ranging from the raw instrument data to the calibrated and geolocated radiances, and geophysical retrievals of atmospheric and surface properties (Bothwell et al., 2002). MISR Level 2 products are resampled to 1.1 km resolution and are screened for contamination from sources such as clouds, cloud shadows, sun glitter over water, and topographically shadowed regions (Bothwell et al., 2002). MISR Level 2 MIL2ASLS Land Surface Parameters (surface bidirectional reflectance factor (BRF) and LAI), MISR Level 1B2 MI1B2GEOP Geometric Parameters (sun/view, zenith/azimuth angles), and MISR Ancillary Geographic Product (longitude and latitude of pixels) were used here.

MISR Level 2 products were provided in the Space Oblique Mercator (SOM) projection in equally sized blocks of an ellipsoidal surface defined by the World Geodetic System 1984 (WGS84). The block construct enables the co-registration of nine-angle, four-band images and allows stacking all the blocks of an orbit into a single dataset.

The MISR Level 2 Land Surface Product also includes biome information. Since Hu et al. (2003) observed incorrect assignment in 80% of pixels across five biomes, and serious misclassifications were noted in other papers as well (e.g. Pocewicz et al., 2007), we used the biome information from the GLC2000 dataset (Loveland et al., 2000; Bartholome and Belward, 2005), instead. The same classification is used as an input into the global LAI algorithms of Deng et al. (2006) that are used later in the paper for the demonstration of the background reflectivity effect on LAI retrieval. Internal consistency between the two algorithm inputs (background reflectivity and LAI) is thus secured.

An IDL code was developed to read the data stored in stack-block and compute background reflectivity \( R_g \) from nadir and angular images. Canisius and Chen (2007) used a 60º (Cf) camera for the angular information; 45.6º camera (Bf) is used in this paper. Previously, small co-registration errors were found for the Bf camera, but the revised algorithm fixed this and co-registration for all channels
meets the expected goals now (Jovanovic et al., 2007). Smaller view angles than 60º are theoretically better due to the probability of observing larger proportions of background. Indeed, Pisek et al. (2009a; Chapter 3) observed slightly more accurate background reflectivity retrievals at smaller view zenith angles. These conclusions are also indirectly supported by findings of Rautiainen et al. (2008a), who noted that if the viewing azimuth angle is at the least 20º away from the principal plane (i.e. oblique plane), 56.7º view zenith angle is considerably more efficient than 37.2º in excluding the influence of the background especially in coniferous stands. The smaller view zenith angle also allows us to avoid the observed slight increase of BRF in the largest view angles in the forward scattering direction in broadleaved species in particular, caused by the high canopy transmission and specular reflectance from the leaves (Deering et al., 1999).

The code was developed for a global application and automatically switches between forward and backward positioned cameras according to the relative azimuth angle, as the scattering directions change with the sensor-sun configuration across the Earth. The background reflectivities were retrieved for the red and the NIR band and every orbit over North America in 2007. The orbit retrievals were then re-projected and combined into 10-day composite scenes in the Plate-Carree projection with the WGS84 coordinate system. The spatial and temporal interpolations, described below, were carried out on pixels within a latitude / longitude bounding box about the conterminous United States, Northern Canada, and the Caribbean landmass. The intent is to use a geographic domain of sufficient extent to illustrate the seasonal and regional variations while simultaneously restricting the computing time to a manageable level.

4.3.4 The Spatial and Temporal Consistency

The global coverage time is 9 days for MISR (Diner et al., 2005), while the large-scale LAI algorithms produce results at around 10-day time steps (Myneni et al., 2002; Fernandes et al., 2003; Baret et al., 2007; Pisek et al., 2007). Figure 4-2a,b shows the quantity and spatial coverage of retrieved
background reflectivity values at 10-day time steps at the original MISR spatial resolution. Cloud contamination, persistent clouds, and other suboptimal atmospheric or illumination conditions can reduce the data quality and cause missing values in MISR Land Surface Products. About 20% of all forest pixels in the domain do not have a single successful retrieval; the percentage of pixels quickly drops with the number of retrieved background reflectivities. Additionally, the retrievals were not distributed evenly across the temporal domain, either.

Figure 4-2. (a) The spatial coverage and (b) quantity of retrieved forest background reflectivity values within the study area (red box) aggregated by 10-day time steps at original MISR spatial resolution of 1.1 km. (c) The distribution of values by the number of retrievals after aggregating the results to 1-degree resolution.
Figure 4-3. Example of reconstructing seasonal-variation curves in the red band. Location of the sample area is 50º N, 77º W. The missing data were replaced first with the mean value (circles) of the valid observations (crosses) recorded in the preceding and subsequent time period. The smoothed values with a 40-day moving average window and the largest and the smallest values discarded before every averaging step (grey line); final monthly mean background reflectivity values (black line).

Interpolation is essential under these conditions to reach continuous series free of missing data and of acceptable quality, as required by many climate modeling applications at the continental scale. Combination of spatial and temporal approaches offers superior interpolative capabilities to any single method, and in fact, generation of continuous data fields requires a hybrid approach such as this (Borak and Jasinski, 2009). The satisfactory temporal coverage, which enabled further temporal interpolation and reconstructing seasonal trajectories, was reached by upscaling the within one standard deviation background reflectivity retrievals to 1 decimal degree spatial resolution (Figure 4-2c). Initial local window operations over the pixels with missing data, similar to the approach of Gao et al. (2008), with an automatic increasing of the spatial domain from 5 x 5 km/pixels in search of the successful retrievals were slow, prone to the outliers bias and overall were not effective due to the occurrence of extensive areas of missing data.
Figure 4-3 illustrates the consequent procedures of temporal interpolation and seasonal trajectories reconstruction with a series of moving temporal windows. The still missing data were replaced with the mean value of the observations recorded for that location in the preceding and the subsequent time period. A 5-value moving window was run next with the largest and the smallest value dropped before averaging. Finally, the monthly mean background reflectivity maps in the red and NIR band were produced.

4.3.5 Global LAI algorithms

Based on previous studies (Roujean et al., 1992; Chen, 1996b; Chen and Cihlar, 1997; Chen and Leblanc, 1997, 2001; Brown et al., 2000; Chen et al., 2002), Deng et al. (2006) developed a set of LAI algorithms for the purpose of deriving global LAI products from multiple sensors. The algorithms are used for the production of the GLOBCARBON LAI product (Plummer et al., 2007). This set of algorithms has some unique features, including (a) explicit consideration of BRDF, (b) separate algorithms for several structurally distinct biomes, and (c) derivation of the effective rather than the true LAI from spectral indices. Deng et al. (2006) provide full accounts and theories for the algorithms used in this study. The input into the algorithms can also include background reflectivity data or vegetation clumping; if not specified, empirical values of background reflectivity and clumping index for different land cover types are used. Presence of an understory layer can substantially amplify the canopy LAI estimate (Chen et al., 1997b; Eriksson et al., 2006) and it is an acknowledged source of uncertainty in global LAI modeling (Garrigues et al., 2008). Here, for the first time, we document the effect of using the derived MISR background reflectivity dataset on the output from the global LAI algorithms.

4.4 Results

4.4.1 Total and background reflectivity

The evaluation of the effect of the background brightness on forest reflectance and the
improvements of the background reflectance algorithm are demonstrated first. As an example, we will now examine the retrievals covering path 21, orbit 18572 (mid-June) over Canada (Figure 4-4). The orbit has been selected due to the excellent cloud-free conditions, a relatively high share of both deciduous and

Figure 4-4. The coverage of MISR path 21, orbit 018572, over Ontario, Quebec, Hudson Bay and a part of Michigan. The MISR red, green and blue bands are used to create the color image, which has been clipped and gamma-stretched to make cloud, ocean and land features visible (Original image a property of NASA Langley Research Center Atmospheric Sciences Data Center).
coniferous pixels (for each of the categories more than 15,000 pixels are reliable), and the coverage of the area of the original validation of the algorithm with in-situ spectral measurements and airborne CASI data (Pisek et al., 2009a; Chapter 3). The performance of the algorithm can be studied without the effect of later spatio-temporal interpolation and smoothing procedures, described in Section 4.3.4.

Figure 4-5 illustrates the importance of not neglecting the background reflectance on the example of coniferous forest. The plotted background BRFs show non-negligible shifts in the spectral space from the total reflectances. The behaviour is the same as the one observed by Pisek et al. (2009a; Chapter 3) with airborne data. The background BRFs tend to be higher in both the red and the NIR band than the total reflectances. This is because the large shadow fractions at the stand level reduce the overall apparent reflectances from above the stand, while the background reflectance refers to its inherent ability to reflect solar radiation.

**4.4.2 Dynamic vs. constant shaded background reflectivities**

Next, Table 4-2 offers a comparison of the retrievals to the ones using the algorithm of Canisius and Chen (2007) over the area in Figure 4-4. The algorithms deliver different frequency distribution of
the results for both the coniferous and deciduous forest, particularly in the red band. The differences are the largest in case of deciduous forest, where the algorithm of Canisius and Chen (2007) predicts 62.3% of the reflectivities in the red band to be higher than 0.12. This would indicate a presence of a very bright background such as snow (Peltoniemi et al., 2005b) in June. The algorithm of Canisius and Chen (2007) was originally developed for mapping over a limited area of boreal region only, with only a small fraction of deciduous forest. The variation of the background might have been then smaller and the constant shaded values corresponded to local conditions; results from Table 4-2 indicate this approach might not be optimal for a large-scale mapping. The current version with the non-constant shaded reflectivities places most of the values in the red band within the 0.04-0.08 reflectance interval, as would be expected at this time of the season.

**Table 4-2.** Distribution of forest background reflectances in the red and the NIR bands, as predicted by the algorithm with dynamic and static reflectances by shaded fractions. The break-down of the negative retrievals (in bold) is provided in Table 4-3.

<table>
<thead>
<tr>
<th>band</th>
<th>R_{c1}, R_{z1}</th>
<th>dynamic (coniferous)</th>
<th>static (coniferous)</th>
<th>dynamic (deciduous)</th>
<th>static (deciduous)</th>
</tr>
</thead>
<tbody>
<tr>
<td>671.7 nm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(red)</td>
<td></td>
<td>less than zero</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.1</td>
<td>0.2</td>
<td>0.2</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.02-0.039</td>
<td>7.9</td>
<td>0.5</td>
<td>5.9</td>
</tr>
<tr>
<td></td>
<td>0.04-0.059</td>
<td>36.1</td>
<td>6.7</td>
<td>23.4</td>
<td>1.8</td>
</tr>
<tr>
<td></td>
<td>0.06-0.079</td>
<td>34.3</td>
<td>23.1</td>
<td>29.5</td>
<td>11.1</td>
</tr>
<tr>
<td></td>
<td>0.08-0.099</td>
<td>16.2</td>
<td>33.6</td>
<td>18.5</td>
<td>14.0</td>
</tr>
<tr>
<td></td>
<td>0.1-0.119</td>
<td>4.1</td>
<td>24.3</td>
<td>11.5</td>
<td>10.6</td>
</tr>
<tr>
<td></td>
<td>&gt;0.12</td>
<td>1.1</td>
<td>11.4</td>
<td>10.0</td>
<td>62.3</td>
</tr>
<tr>
<td>866.4 nm</td>
<td></td>
<td>less than zero</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(NIR)</td>
<td></td>
<td>0.0</td>
<td>0.4</td>
<td>0.4</td>
<td>11.7</td>
</tr>
<tr>
<td></td>
<td>0.0-0.09</td>
<td>0.1</td>
<td>0.5</td>
<td>1.1</td>
<td>2.1</td>
</tr>
<tr>
<td></td>
<td>0.1-0.19</td>
<td>2.7</td>
<td>3.7</td>
<td>2.6</td>
<td>3.8</td>
</tr>
<tr>
<td></td>
<td>0.2-0.29</td>
<td>27.9</td>
<td>16.9</td>
<td>8.7</td>
<td>7.5</td>
</tr>
<tr>
<td></td>
<td>0.3-0.39</td>
<td>54.9</td>
<td>42.4</td>
<td>24.1</td>
<td>14.7</td>
</tr>
<tr>
<td></td>
<td>0.4-0.49</td>
<td>13.8</td>
<td>30.0</td>
<td>37.5</td>
<td>21.7</td>
</tr>
<tr>
<td></td>
<td>0.5-0.59</td>
<td>0.8</td>
<td>5.5</td>
<td>20.4</td>
<td>23.3</td>
</tr>
<tr>
<td></td>
<td>&gt;0.6</td>
<td>0.0</td>
<td>0.6</td>
<td>5.1</td>
<td>15.3</td>
</tr>
</tbody>
</table>
Table 4-3. Distribution of negative forest background reflectivities by the stand LAI. Their percentage share on the total number of pixels in given LAI interval is in brackets.

<table>
<thead>
<tr>
<th>BG BRF &lt;0</th>
<th>0.1</th>
<th>0.0</th>
<th>0.2</th>
<th>0.4</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>coniferous</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LAI</td>
<td>number of pixels</td>
<td>red</td>
<td>NIR</td>
<td>number of pixels</td>
</tr>
<tr>
<td>0-1</td>
<td>24994</td>
<td>90 (0.4)</td>
<td>3 (0.0)</td>
<td>415</td>
</tr>
<tr>
<td>1-2</td>
<td>23972</td>
<td>3 (0.0)</td>
<td>6585</td>
<td>1 (0.0)</td>
</tr>
<tr>
<td>2-3</td>
<td>27302</td>
<td>2 (0.0)</td>
<td>3305</td>
<td>1 (0.0)</td>
</tr>
<tr>
<td>3-4</td>
<td>5567</td>
<td>3 (0.0)</td>
<td>1117</td>
<td>6 (0.5)</td>
</tr>
<tr>
<td>4-5</td>
<td>484</td>
<td>1 (0.0)</td>
<td>1602</td>
<td>23 (1.4)</td>
</tr>
<tr>
<td>5-6</td>
<td>246</td>
<td>1 (0.0)</td>
<td>1602</td>
<td>23 (1.4)</td>
</tr>
<tr>
<td>&gt;6</td>
<td>7</td>
<td>3 (1.1)</td>
<td>39 (14.1)</td>
<td></td>
</tr>
</tbody>
</table>

The algorithm can occasionally predict negative background reflectivities that are screened out from the final results. Their share is not very high (maximum is 0.4% of retrievals over deciduous forest in the sample area of Figure 4-4; Table 4-2), but the break-down of negative retrievals by canopy LAI offers an insight into the role of overstory in the process (Table 4-3). The share of negative retrievals increases with canopy LAI in the case of deciduous forest, where a large portion of the biome within the path area (Figure 4-4) does attain LAI > 4. The higher amount of canopy LAI makes the understory more difficult to see from above, particularly from the slanted view angle. A high accuracy of the background retrievals for dense canopies is not possible due to this low visibility of the understory through the dense canopy. The stand reflectance at high LAI values is nearly independent of view directions, and as mentioned, the background has only a very small contribution to the total forest reflectance (Kaufmann et al., 2000; Zarco-Tejada et al., 2001; Zhang et al., 2002a). If there is almost no visible understory, then there is no ability to measure background reflectivity. This inability results in the production of the negative values. The role of the background is not important then as well, as the background does not affect the total signal in case of these dense canopies (Lang et al., 2002; Olofsson and Eklundh, 2007). The dominant role of the spectral properties of understory compositions is at low canopy cover (Rautiainen et al., 2007), and the algorithm delivers stable results in this domain.
4.4.3 Changing spectral properties of background with canopy LAI

The background spectral properties change with canopy openness, overall growing conditions, and the seasonal cycle (Fuller et al., 1997, Rautiainen et al., 2009). These variations can be observed in derived background reflectivities in June over both types of forest (Figure 4-6). The range of values in the red and NIR band is quite wide for canopies with low LAI due to two reasons: first, similarly high values in the red band and in the NIR band correspond to surfaces with exposed bare soil and a minimum of vegetation cover, as the overall growing conditions are not favorable and result in low canopy LAI. Where the climatic and substrate growing conditions are more favorable to the understory vegetation,
sufficient light can penetrate the overstory of open sites, and increasing amount of present understory vegetation lowers the reflectivity in the red band via higher absorption of chlorophylls and increases it in the NIR band, respectively (Haboudane et al., 2004; Nilson et al., 2003). It is at these extremely low coverages where the difficulties of canopy RS are the greatest due to the overwhelming influence of soil and understory background on the spectral signature (DeFries et al., 2000). As the general growing conditions improve, both the canopy LAI and the amount of understory vegetation increase to the point where the decreasing amount of light transmitted through the overstory starts becoming a limiting factor (LAI=3-4; Figure 4-6). The amount of understory vegetation can start decreasing after this point and so does the reflectivity in the NIR band. The behavior in the red band seems to be slightly different between deciduous and coniferous stands at high LAI values (Figure 4-6a, c). This may be a result of the observed greater aggregation of foliage in coniferous forests (Rautiainen and Stenberg, 2005), which permits more light to reach the understory layer. The degree of understory vegetation cover can be higher then in coniferous stands than in deciduous stands having the same LAI.

4.4.4 Differences in background reflectivity between coniferous and deciduous forests

Reflectances from coniferous and broadleaved trees differ significantly especially in the NIR band (Hame et al., 1997). Does the overall background reflectivity differ between coniferous and deciduous forests as well? Two background reflectivity sets at 1 decimal degree were created for June 2007, the first one by upscaling 1-km resolution retrievals over coniferous forest, the other one with deciduous forest only. There are no statistically significant differences (p<0.05) between the two forest backgrounds in the red band (Figure 4-7). The retrieval differences are normally distributed around zero. The differences in the NIR band between the upscaled background reflectivities from the two biomes are normally distributed as well, but the coniferous forest background reflectance in NIR tends to have lower values than that of deciduous forest (Figure 4-7). Our results are in line with field measurements of Goward et al. (1994), who observed higher NIR reflectance of broad-leaf shrubs and herbs, such as sworn fern, big leaf maple, or blackberry, whereas moss and litter dominated under the coniferous forest.
Figure 4-7. Distribution of differences between the deciduous and coniferous forest background in the red and NIR bands if both types of forests were found within the corresponding 1-degree pixel. Negative values signify lower values for coniferous forest.

4.4.5 Seasonal maps of forest background reflectivity

The seasonal changes of the forest background signal are best illustrated over the red band, as this wavelength region with low mean reflectance (e.g. the red spectral region around 672 nm) exhibits a relatively large reflectance variation compared to a high reflectance region with a rather small variation (e.g., the NIR region; Strub et al., 2003). Wide ranges of forest background reflectivities are present over the continent in January-March (Figure 4-8). The presence of snow increases the foreground/background contrast in forest. The regions with very high red band reflectivities indicate the presence of the snow and the high values are close to the observed reflectances of snow by Miller et al. (1997) and Peltoniemi et al.
The southern parts of the continent are then characterized lower reflectances than snow, corresponding to bare soil or understory vegetation. Melting of snow implies dramatic changes occurring at the forest floor (Pinty et al., 2008). This can be observed especially over Canada during the period from March to June (Figure 4-8). The maps show the disappearance the snow over the mid-west as well with the gradual transition to bare soil or low cover of the understory. The continental distribution is fairly
stable during the main growing period from June to September, when both overstory and understory BRFs in the red band decrease over a large extent of the continent because of the high absorption by the chlorophylls as leaf area of canopy layers increases (Heiskanen, 2006). The picture starts to change again in October when the background reflectivity increases. This corresponds to the decay of absorbing chlorophylls and the beginning of the senescence period. By December a highly reflecting background covered by snow can be observed over most of the continent. The understory showed in this study exhibits vegetation indices that may be lower than but fall within a similar range of the overstory canopies, which are in agreement with the field studies by Goward et al. (1994) and Miller et al. (1997) over different parts of the United States and Canada. It should be noted there is a larger uncertainty in the estimates over Caribbean as the forest structure can differ from representations specified by the input parameters into 4-Scale to produce LUTs with probabilities of observing the individual four scene components (Table 4-1).

### 4.4.6 Inclusion of the background reflectivity information in global LAI algorithms

These background reflectivity maps enable us to examine the realistic effect of forest background on LAI retrieval. The effect is illustrated with an example of an LAI map derived with the global LAI algorithm of Deng et al. (2006) and SPOT-VEGETATION satellite data over North America for June 2007. Two LAI maps were produced: the first one with the original version of the algorithms that uses constant background values corresponding to the bare soil (Figure 4-9a), and another one where the dynamic forest background reflectivity retrievals from MISR were incorporated into the algorithm (Figure 4-9b). The biggest difference between the two maps can be observed in a boreal region (Figure 4-9c), where the background reflectivity information from MISR reduces the estimates of LAI by over 1. The reductions are in agreement with measured understory LAI in a boreal region e.g. by Sonnentag et al. (2007). The largest relative differences between the two LAI maps correspond to regions with low to intermediate canopy cover. Regions with higher canopy cover experience smaller reductions in LAI, as the influence of background reflectivity on total stand reflectance decreases. In addition, the understory
vegetation might not be as abundant as well, as illustrated in Section 3.3. The reductions in LAI might not appear very large, yet the amounts correspond to the range of overestimations between various global LAI products and reference measurements over forest stands as observed by Garrigues et al. (2008). The dynamic background reflectivity maps from MISR thus definitely show the potential of filling the existing gap and may help us to bring the canopy LAI estimates from RS data in closer agreement with field observations.

Figure 4-9. VEGETATION LAI fields over North America from the peak of boreal summer – July 2007. (a) constant forest background value for all pixels, (b) dynamic forest background from MISR data, (c) difference between the two maps over forest stands from MISR data.
4.5 Discussion

Given the rich content of multi-angular imagery, the analyses performed on the data have just begun to capitalize on the information provided by this measurement approach (Diner et al., 2005). The main reasons for the recent spark in the interest in forest understory are that the signal from the understory can be used, for example, (1) to remove the influence of understory in estimating canopy biophysical variables (e.g. LAI, FAPAR) from remotely sensed images (Garrigues et al., 2008), (2) to develop and test canopy radiative transfer models (Widlowski et al., 2007), and (3) in forestry applications to separate forest site types (Rautiainen et al., 2009). In this study we demonstrate the applicability of the produced background reflectivity dataset to the first application.

It is encouraging to see the multi-angle view approach is capable of differentiating between different understory optical properties. However, separating understory cover components is not yet feasible, as the spectral properties of the individual species in the understory vegetation are generally similar, and the understory reflectance depends more on their abundance than on their spectral difference (Peltoniemi et al., 2005a; Korpela, 2008). For this task, a method of Rautiainen et al. (2007) with using visible bands of satellite images in sparse canopies or of Sonnentag et al. (2007) to account for a spectrally varying background using mixture signal decomposition might be more appropriate.

The rendering of the spring understory development sequence as shown in Figure 4-8 would be useful for monitoring canopy phenology from satellite data such as MODIS (Wang et al., 2005; Ahl et al., 2006). As the canopy cover can be quite low in spring and the understory has been observed to start developing earlier than the overstory to take the advance of the light availability in the early growing season (Komiyama et al., 2001), the influence of the understory on the total signal and its variation can be quite important especially during this season (Pocewicz et al., 2007).
The compilation of the background reflectivity dataset using MISR data also showed a few drawbacks. First, in a marginal number of retrievals, the algorithm can predict negative reflectivity values. This is due to the effect of incorrect biome/initial LAI input information, or due to very low visibility of the understory through dense canopies which preclude a successful retrieval. However, the negative retrievals formed at maximum only 0.4% of all retrievals over the study area. Additionally, background has only a very small influence on LAI retrieval at high LAI values. Another drawback to be considered is the low resolution of the upscaled dataset tracking the seasonal development of the background reflectivity. Cloud contamination, persistent clouds, and other suboptimal atmospheric or illumination conditions caused large swaths of missing values in the input MISR Surface Parameters data. However, the background in low and medium density forest stands is often similar within a geographical area (Kellomaki and Vaisanen, 1991; Reinikainen et al., 2001; Muukkonen and Heiskanen, 2005), although small scale variability may exist between stands of different densities in close proximity. As these coarse resolution background maps are mostly useful for low to medium density stands, this shortcoming of low resolution may be overcome in their application for regional and global LAI mapping. Furthermore, with respect to the mentioned application of the forest background information in canopy radiative transfer and GO models, Kuusk et al. (2004) looked at the sensitivity of their hybrid type model to input understory parameters and they recommended using typical (average) parameter values while representing understory. Assembling multi-angle observations from multi-year time series of MISR data to fill in the missing areas could be an alternative strategy.

Unfortunately, we were unable to directly validate the derived background reflectivity values with measurement data. To our knowledge, there are currently no recorded, continuous measurements of the seasonal changes of spectral properties of understory layers. The general seasonal patterns and background spectral properties found in our study agree with the measurements done by e.g. Goward et al. (1994), Miller et al. (1997), Lang et al. (2002), Peltoniemi et al. (2005a,b) or Pisek et al. (2009a; Chapter 3). This leads us to believe the observed temporal trends and spatial patterns are real.
4.6 Conclusions

In this study we demonstrate the capability of our refined approach and multi-angle RS data to retrieve meaningful background reflectivity information over large areas. For the first time, the forest background seasonal maps at a continental scale are presented here.

The retrieved background reflectivity shows the following characteristics:

(a) There are differences between the reflectances from the forest background and the total stand. This confirms that forest background cannot be ignored while retrieving canopy biophysical parameters from remotely sensed data. This is particularly true for stands with low to intermediate canopy cover.

(b) Background reflectivity changes with the amount of canopy cover. This is primarily caused by the overall variation in the growth condition at different sites and the amount of light penetrating through the overstory.

(c) Forest background slightly differs between coniferous and deciduous stands, particularly in the NIR band. This may be linked to differences in prevailing understory species in these forest types.

(d) Significant seasonal development of the forest background vegetation can be observed across a wide longitudinal and latitudinal span of the study area. The seasonal trajectories are reasonable with respect to biome types and snow cover.

The future work will focus on the full incorporation of the background vegetation values into global LAI algorithms. It remains to be seen if the information about the background helps us to reduce its effect on canopy LAI retrievals and improve the quality of various LAI products, a task much needed as suggested by Garrigues et al. (2008).
5 Refining global mapping of foliage clumping index with multi-angular POLDER 3 measurements: evaluation and topographic compensation

This chapter is based on the paper submitted to *ISPRS Journal of Photogrammetry and Remote Sensing*:


5.1 Abstract

The first ever global mapping of the vegetation clumping index with a limited eight-month multi-angular POLDER 1 dataset is expanded by integrating new, complete year-round observations from POLDER 3. We show that terrain-induced shadows can enhance bi-directional reflectance distribution function variation and negatively bias the clumping index (i.e. indicating more vegetation clumping) in hilly regions. Using a global high-resolution digital elevation model, a topographic compensation function is devised to correct for this terrain effect. The clumping index reductions can reach up to 30% from the topographically non-compensated values, depending on terrain complexity and land cover type. The new global clumping index map is compared with an assembled set of 32 different site field measurements, covering four continents and diverse biomes.

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4 My co-authors allowed me to include this submitted paper as a chapter in my dissertation. Dr. Chen was the author of the original methodology for retrieval of the clumping index map from POLDER 1. Dr. Chen edited the paper draft. Dr. Lacaze kindly provided POLDER-3 data. Dr. Sonnentag kindly provided field measurement data for TONZI site and valuable suggestions about the original draft. Krista Alikas helped with field measurements in Estonia. I adjusted the original POLDER-1- tailored clumping index retrieval algorithms to be compatible with POLDER-3 data, devised the topographic compensation method, assembled the field data from the literature, carried the evaluation, and wrote the manuscript.
5.2 Introduction

Clumping index ($\Omega$) quantifies the spatial variation of leaf area density from a random distribution (Nilson, 1971; Weiss et al., 2004). The clumping index is useful in ecological and meteorological models because it provides new structural information to the effective leaf area index (Chen and Black, 1991) retrieved from mono-angle remote sensing, which does not correct for the non-random distribution of foliage in the canopy (Chen et al., 1997a). Clumping, through a better separation of sunlit and shaded leaves, has profound effects on the radiation regime of a plant canopy and photosynthesis (Baldocchi and Harley, 1995; Mottus et al., 2006). As the clumping index can vary considerably for a land cover type, it is highly desirable to map the spatial distribution of this index using remote sensing data (Chen et al., 2003b). The clumping index ($\Omega$) larger than unity implies the foliage is regularly distributed; $\Omega = 1$ for a random distribution and in the case of foliage more clumped than random, $\Omega < 1$.

Previous studies have shown that the clumping index is related to the shape of bidirectional reflectance distribution function (BRDF) (Lacaze et al., 2002; Chen et al., 2003b). Quantitatively, the clumping index can be associated with an angular index formulated using the hotspot (where the sun and view angles coincide) and the darkspot (where the reflectance is at its minimum) values from the BRDF curve along the principal plane (Leblanc et al., 2005b). The normalized difference between hotspot and darkspot (NDHD) has been found to be linearly related to the clumping index (Chen et al., 2003b, Simic et al., 2009). It is defined as:

$$NDHD = \frac{\rho_h - \rho_d}{\rho_h + \rho_d}$$  \hspace{1cm} (5-1)

where $\rho_h$ and $\rho_d$ are the reflectance at the hotspot and darkspot, respectively. The clumping index information is included in the darkspot reflectance, whereas the hotspot can be seen as the normalizing factor when used in NDHD (Chen et al., 2003b). The relationship between clumping index and darkspot exists mostly because clumped canopies cast dark shadows and decrease the darkspot reflectance.
(Leblanc et al., 2005b). The relationship was previously used to derive a first ever global clumping index map using multi-angular POLDER 1 satellite data from ADEOS-1 (Chen et al., 2005). The original POLDER 1 global clumping map had several limitations that are addressed by this study: lack of comprehensive spatial coverage, topographic effects, and a lack of evaluation with field measurements.

5.3 Expanding the global clumping index map with POLDER 3

The POLDER radiometer is designed to measure directional and polarized reflectances of the surface-atmosphere system (Deschamps et al., 1994). The instrument concept consists of a rotating wheel equipped with and without polarized filters, a CCD matrix array detector, and a wide field of view lens (114°) that gives a swath about 2400 km, which allows the same ground area to be viewed during successive orbital passes. During a single satellite overpass, a surface target is scanned up to 14 times (POLDER 1) or 16 times (POLDER 3) under different viewing angles. The view illumination directional configuration changes every day as the orbit shifts. Therefore, after a few days, assuming clear atmospheric conditions, the measurements provide a sample of the BRDF within the sensor field of view. POLDER is best used at the global scale because of its ~6 km nadir resolution and high angular resolution. For the expansion of the global clumping map, we used data from POLDER 3 onboard PARASOL microsatellite (Lier and Bach, 2008). Available POLDER 3 data, provided by MEDIAS-France/POSTEL Service Centre, cover the whole year 2005.

The clumping index was calculated using the NIR band and relationship between NDHD and $\Omega$, i.e.,

$$\Omega = a + b \text{NDHD}$$  \hspace{1cm} (5-2)

where $a$ and $b$ are coefficients determined by the linear regression, based on a set of model simulations made with 4-Scale model in Chen et al. (2005). The coefficients are the same as for POLDER 1 data and vary with solar zenith angle (SZA) and vegetation type (see Table 2 in Chen et al., 2005). Pinty et al.
(2002) assert the wavelength should be chosen to maximize the reflectance/absorption contrasts between vertically clumped elements and the background, i.e. the red band should be more appropriate due to weaker multiple scattering (Pinty et al., 2009). However, a stronger relationship between NDHD and $\Omega$ in the NIR band was observed previously both with 4-Scale modeled (Chen et al., 2005) and CASI airborne data (Simic et al., 2009). This, coupled with the greater accuracy limitations in the atmospheric correction in the red band for satellite data, led to the choice of the NIR band for clumping index retrieval here.

The land cover information was obtained from Global Land Cover 2000 (GLC2000) database (Bartholomé and Belward, 2005). POLDER 3 data improved the global coverage with valid $\Omega$ retrievals over vegetated areas by 7.5% up to 95%, mainly over North America and North Asia. However, even more important was the possibility to finally obtain $\Omega$ during the periods of peak growth in the Northern Hemisphere, as POLDER 1 was active only from November 1996 to June 1997, while POLDER 3 data were available for the whole year 2005. The remaining gaps are mainly in the tropic regions due to persistent cloud cover.

5.4 Reduction of topographic effects in the global clumping index map

Topography might have a severe impact on NDHD due to shadowing, adjacent hill illumination, sky occlusion, and slope orientation with respect to the BRDF of the land cover type (Schaaf et al., 1994). The reliable reconstruction of the BRDF to obtain non-biased hotspot and darkspot values in rugged terrain is more challenging than it is from a similarly vegetated flat region as the BRDF is no longer symmetrical on the principal plane (Schaaf et al., 1994). Direct correction of the BRDF would be impractical here due to the global spatial extent, frequency and the number of different angular configurations during POLDER observations. A simple and robust correction for influences of rugged terrain is required.
A global digital elevation model (DEM) GTOPO30 with 30-arc seconds (~ 1 km) grid spacing from U.S. Geological Survey's EROS Data Center in Sioux Falls, South Dakota (http://edc2.usgs.gov/geodata/index.php), was used to examine effects of topographic variation on the NDHD and $\Omega$. Average elevation, standard deviation and slope were calculated within each POLDER pixel (~ 6 km resolution). A negative correlation (i.e. vegetation more clumped with increasing values of terrain parameters) was observed across all vegetation land cover types. The strongest relationship was obtained for standard deviation of elevation within POLDER pixels (Fig. 5-1(a)). High elevation variation induces terrain shadows that can also enhance the BRDF variation (Sandmeier and Itten, 1997). Additionally, canopy mutual shadowing also increases with terrain complexity (Soenen et al., 2005). Since the information about the vegetation clumping is mainly included in the darkspot (Chen et al., 2005), shadows cast from neighboring terrain features and increased self-shadowing result in negatively biased values of $\Omega$. The observed change in $\Omega$ is not linear with the variation of elevation (Fig. 5-1(a)). The change course is also similar to the modeling work of Kane et al. (2008), where the non-linearity was related to the changing role of sunlit and shaded areas of canopy on the total reflectance.

Topographically uncorrected $\Omega$ values from Eq. (2) are formed by the contributions from (a) land cover type-independent, terrain-induced shadows, and (b) the actual structural properties of foliage (e.g. leaf area distribution within crowns, organization of needles into shoots and whorls), which at the coarse ~ 6 km resolution of POLDER instrument scale shall not be closely dependent on the topographic complexity. In other words, topographically-corrected $\Omega$ from POLDER data is not expected to show any trend with increasing standard deviation of elevation ($\sigma$). The effect of topography, demonstrated through the increasing difference between $\Omega$ at $\sigma_{i=0}$ (flat terrain) and $\Omega$ at $\sigma_{i+1,j+2,...,i+y}$ (increasing topographic variation) in Fig. 1(a), was removed in four steps. First, all valid clumping index retrievals from the compiled global clumping index map in Section 2 were binned into 50-m interval classes by the value of the standard deviation of elevation ($\sigma$) for given pixel. The mean clumping index value was retrieved then for every class interval (Fig. 5-1(a)). Second, a polynomial function was fitted to the observed decrease in
\( \Omega \) with the increasing standard deviation of elevation \( \sigma \) by the following polynomial function \((R^2=0.991)\) (Fig. 5-1(a)):

\[
\Omega_T = -0.0001\sigma^3 + 0.0142\sigma^2 - 0.6869\sigma + 70.477 \tag{5-3}
\]

where \( \Omega_T \) values describe primarily the observed across-biome, terrain shadow-induced decreasing trend in \( \Omega \) with increasing topographic complexity \((\sigma)\). Since this polynomial function is fitted to the mean values coming from both forest and non-forest pixels at each \( \sigma \) interval, the foliage structure effect in \( \Omega_T \) values is suppressed. The area fractions of biome types in each \( \sigma \) range might have influenced this regression, but as the critical forest fraction varies in a limited range \((0.42-0.66)\) (Fig. 5-1(a)), this influence would be less than 0.05 in the final \( \Omega \) value. Next, for each POLDER pixel the difference \( \delta \) between original \( \Omega \) and \( \Omega_T \) was calculated. Finally, \( \delta \) was added to the intercept from Eq. (5-3). In this way, the across-biome difference in the topographical effect was removed, while the role of foliage structure was retained. The topographically corrected global average clumping index still decreases with the standard deviation of the elevation, however now this is related to the increased share of forest (i.e. more clumped) areas in the hilly regions (Fig. 5-1(a)). The new forest-only clumping index values oscillate around \( \Omega=0.66 \) and become independent of terrain complexity. Despite rather smaller area of more topographically complex terrain (e.g. only around 15% of all ~ 6 km resolution POLDER pixels with vegetation have a standard deviation of elevation \( \sigma \) greater than 100 m; their share drops to 5% by \( \sigma \) of 250 m), the clumping index reductions can reach up to 30% in the new topographically-corrected global clumping index map (Fig. 5-1(b)), depending on terrain complexity and land cover type. Average statistics for the topographically corrected clumping index values then still retain the relative differences between the various land cover types (Table 5-1). Finally, the gaps in the global coverage by POLDER observations (5% of vegetated areas, mainly in the tropics due to persistent cloud cover) are filled with mean clumping index values calculated from the successful retrievals over the identical biomes (Table 5-1) for the dominant LC types from GLC2000 map to obtain the new updated clumping index map of the world (Fig. 5-1(b)).
Table 5-1. Average Statistics Calculated with the Topographically Corrected Clumping Index Values over Vegetated Areas

<table>
<thead>
<tr>
<th>Class</th>
<th>Class names</th>
<th>mean</th>
<th>stan. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tree Cover, broadleaf, evergreen</td>
<td>0.64</td>
<td>0.11</td>
</tr>
<tr>
<td>2</td>
<td>Tree Cover, broadleaf, deciduous, closed</td>
<td>0.69</td>
<td>0.08</td>
</tr>
<tr>
<td>3</td>
<td>Tree Cover, broadleaf, deciduous, open</td>
<td>0.72</td>
<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>Tree Cover, needleleaf, evergreen</td>
<td>0.63</td>
<td>0.12</td>
</tr>
<tr>
<td>5</td>
<td>Tree Cover, needleleaf, deciduous</td>
<td>0.78</td>
<td>0.07</td>
</tr>
<tr>
<td>6</td>
<td>Tree Cover, mixed leaf type</td>
<td>0.72</td>
<td>0.11</td>
</tr>
<tr>
<td>7</td>
<td>Tree Cover, regularly flooded, fresh water</td>
<td>0.67</td>
<td>0.15</td>
</tr>
<tr>
<td>8</td>
<td>Tree Cover, regularly flooded, saline water</td>
<td>0.78</td>
<td>0.17</td>
</tr>
<tr>
<td>9</td>
<td>Mosaic: Tree Cover / Other natural vegetation</td>
<td>0.70</td>
<td>0.05</td>
</tr>
<tr>
<td>10</td>
<td>Tree Cover, burnt</td>
<td>0.78</td>
<td>0.15</td>
</tr>
<tr>
<td>11</td>
<td>Shrub Cover, closed-open, evergreen</td>
<td>0.77</td>
<td>0.17</td>
</tr>
<tr>
<td>12</td>
<td>Shrub Cover, closed-open, deciduous</td>
<td>0.74</td>
<td>0.09</td>
</tr>
<tr>
<td>13</td>
<td>Herbaceous Cover, closed-open</td>
<td>0.77</td>
<td>0.12</td>
</tr>
<tr>
<td>14</td>
<td>Sparse herbaceous or sparse shrub cover</td>
<td>0.78</td>
<td>0.16</td>
</tr>
<tr>
<td>15</td>
<td>Reg. flooded shrub and/or herbaceous cover</td>
<td>0.80</td>
<td>0.14</td>
</tr>
<tr>
<td>16</td>
<td>Cultivated and managed areas</td>
<td>0.78</td>
<td>0.11</td>
</tr>
<tr>
<td>17</td>
<td>Mosaic: Cropland / Tree Cover / Natural veg</td>
<td>0.77</td>
<td>0.12</td>
</tr>
<tr>
<td>18</td>
<td>Mosaic: Cropland / Shrub and/or grass cover</td>
<td>0.76</td>
<td>0.05</td>
</tr>
</tbody>
</table>

5.5 Evaluation of the new global clumping index map

At the scale of the POLDER data (~ 6 km), it is very difficult to evaluate the clumping index map and in fact this has never been done before. Larger ground truth plots are necessary for clumping index evaluation because of the POLDER resolution. The considered sites had a dominant land cover type at ~ 6 km resolution (i.e. a single GLC2000 land cover type containing over 65% of area within the corresponding POLDER pixel) that was coincident with the land cover type sampled in the field. Another difficulty for direct comparison stems from the fact that the POLDER-derived clumping index quantifies the total effect of canopy structures at all levels on radiation interception and photosynthesis by the canopy (Lacaze et al., 2002). The total clumping index $\Omega$ can be separated into two components, namely
Figure 5-1. (a) Global mean clumping index ($\Omega$) values over vegetated areas against standard deviation ($\sigma$) of elevation within POLDER pixels. The polynomial function (Eq. 5-3) is fitted to the topographically uncorrected $\Omega$ values (blue circles). The decreasing trend in the topographically corrected $\Omega$ values (in violet) is caused by increasing share of forested area in hilly regions. Topographically corrected $\Omega$ values for forest-only areas oscillate around a constant value (red line). In the legend, NC – $\Omega$ topographically not compensated, TC – $\Omega$ topographically compensated. (b) The new, topographically corrected global vegetation clumping index map derived from POLDER 1 and POLDER 3 data using the normalized difference between interpolated hotspot and darkspot NIR reflectance and applied to vegetated land cover.

Clumping at a scale larger and smaller than the shoot, which are measured separately in the field:

$$\Omega = \frac{\Omega_E}{\gamma_E} \quad (5-4)$$

where $\Omega_E$ is the clumping of foliage elements, leaves for broadleaf species and shoots for needleleaf species; and $\gamma_E$ is the needle-to-shoot area ratio, which accounts for clumping of needles into shoots; for broadleaves $\gamma_E = 1$ (Chen et al., 1997a). Further, different methods and equations exist for obtaining $\Omega_E$ from field measurements, although most of them are highly correlated (for a brief list and comparison see Gonsamo and Pellikka; 2009). $\Omega_E$ has been also shown to be dependent on solar zenith angle (Kucharik et al., 1999; Ryu et al., 2009), but the angular dependence follows patterns that allow it to be estimated from only one angular measurement of clumping with instrument such as Tracing Radiation and Canopy Architecture (TRAC) (Chen, 1996a). For the preliminary evaluation we compiled a
### Table 5-2. Characteristics and Results from the Validation Sites and POLDER Retrievals

<table>
<thead>
<tr>
<th>ID</th>
<th>Site</th>
<th>Location</th>
<th>Overstory</th>
<th>Dates</th>
<th>Transect</th>
<th>Lengths (m)</th>
<th>$r_E$</th>
<th>Field Method</th>
<th>Field $\Omega$</th>
<th>POLDER $\Omega$</th>
<th>Ref</th>
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<td>CC 0.76</td>
<td>0.77</td>
<td>1</td>
</tr>
<tr>
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<td>Botswana</td>
<td>OW</td>
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<td>0.71</td>
<td>1</td>
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<tr>
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<td>Botswana</td>
<td>MW</td>
<td>2000/3</td>
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<td>CC 0.76</td>
<td>0.77</td>
<td>1</td>
</tr>
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<td>4</td>
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<td>Botswana</td>
<td>Osh</td>
<td>2000/3</td>
<td>Transect</td>
<td>3 x 750</td>
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<td>0.57</td>
<td>CC 0.57</td>
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<td>Osa</td>
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<td>3 x 750</td>
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<td>1</td>
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<td>7</td>
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<td>USA</td>
<td>BO, CFP</td>
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<td>4 x 90</td>
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<td>CC 0.82</td>
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<td>OJP</td>
<td>1994/S</td>
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<td>1.42</td>
<td>0.82</td>
<td>CC 0.58</td>
<td>0.59</td>
<td>4</td>
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<tr>
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<td>OJP</td>
<td>1994/S</td>
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<td>1994/S</td>
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<td>OBS</td>
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<td>1993/9</td>
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<td>PP</td>
<td>1997/9</td>
<td>Transect</td>
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<td>0.65</td>
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<td>LpP</td>
<td>1999/S</td>
<td>Transect</td>
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<td>0.42</td>
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<td>1999/S</td>
<td>Transect</td>
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<td>A, BP</td>
<td>1999/S</td>
<td>Transect</td>
<td>10 x 10</td>
<td>1</td>
<td>0.87</td>
<td>CC N 0.87</td>
<td>0.87</td>
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<tr>
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<td>BS</td>
<td>2005/08</td>
<td>Transect</td>
<td>100</td>
<td>1.36</td>
<td>0.87</td>
<td>CC N 0.64</td>
<td>0.64</td>
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<td>0.66</td>
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<td>CC 0.93</td>
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<td>LbP</td>
<td>2003/8</td>
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<td>0.74</td>
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<td>2002-2003/7,8</td>
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<td>0.83</td>
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<td>Transect</td>
<td>60, 90</td>
<td>1</td>
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<td>CC N 0.93</td>
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<td>Transect</td>
<td>60, 90</td>
<td>1</td>
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<td>CC N 0.93</td>
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<td>0.93</td>
<td>CC N 0.93</td>
<td>0.93</td>
<td>17</td>
</tr>
<tr>
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<td>NS_Y</td>
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<td>1.526</td>
<td>0.89</td>
<td>CC N 0.58</td>
<td>0.58</td>
<td>18</td>
</tr>
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<td>30</td>
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<td>Czech Rep.</td>
<td>NS_O</td>
<td>2006/09</td>
<td>Transect</td>
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<td>1.422</td>
<td>0.89</td>
<td>CC N 0.47</td>
<td>0.47</td>
<td>18</td>
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</tbody>
</table>

**Note:** "Lat", "Lon", "Ref" stand for "latitude", "longitude" and "reference", respectively. In the column "Site" the number indicates the ID of the site. In the column "Overstory" W – woodland, OW – open woodland, MW – mopane woodland, Osh – open savanna, AM – alpine meadow, BO – blue oak, CFP – California foothill pine, OJP – old jack pine, YJP – young jack pine, OBS – old black spruce, RP – red pine, JP – jack pine, PP – ponderosa pine, LpP – lodgepole pine, WS – white spruce, A – aspen, BP – balsam poplar, BS – black spruce, T – tamarack, JO – Japanese oak, LbP – Loblolly pine, AP – Aleppo pine, B – birch, NS – norway spruce, SP – Scots pine, NS 0 – norway spruce old, NS Y – norway spruce young. In the column "Dates", S stands for summer. In the column "Method" CC stands for the Chen and Cihlar (1995) method of calculating $\Omega_E$, CCN stands for the normalized CC method by Leblanc (2002), R stands for the method in Ryu et al. The column "Ref" indicates the associated references for the validation sites. The numbers refer to 1: (Privette et al., 2004), 2: (Lu et al., 2005), 3: (Ryu et al.) 4: $\gamma_E$ from (Chen et al., 1996), 5: $\gamma_E$ from (Chen, 1996), 6: (Law et al., 2001), 7: (Hall et al., 2003), 8: (Chen et al., 2006), 9: (Sonnentag et al., 2007), 10: (Pisek et al., 2009), 11: (Nasahara et al., 2008), 12: (Iiames et al., 2004), 13: (Iiames et al., 2008), 14: (Iiames et al., 2006), 15: (Pocewicz et al., 2007), 16: (Sprintsin et al., 2007), 17: (Pisek and Alikas, 2008), 18: (Homolova et al., 2007). All the measurements were taken within the solar zenith range of 30º-60º.
Figure 5-2. Comparisons of POLDER $\Omega$ values with those from field measurements. Numbers in brackets correspond to site ID numbers in Table 5-2.

database of 32 different site field measurements of clumping index with TRAC, covering four continents and diverse biomes (Table 5-2). However, it must be acknowledged that the spatial and biome coverage
of the available measurements is still limited and can be considered rather biased towards temperate/boreal regions (62% of the sites are in Canada; 82% of the sites are over the 40° N parallel; only 31% of the sites are non-coniferous; no measurements from tropical forests). As a result, the clumping values may be most uncertain for tropical ecosystems, and additional validation for tropical regions is needed before the clumping map can be reliably used for global applications. The field data should be optimally integrated with high-resolution imagery to allow a real product validation (Morisette et al., 2006). Unfortunately, with an exception of a limited extent high resolution map of clumping index (< 1 km²) by Simic et al. (2009), no such image maps are currently available, and only a limited evaluation can be carried out. In absence of high-resolution maps of clumping index, the measurements of $\Omega_E$ with TRAC are the most suitable for comparison with the retrievals from POLDER data as the instrument is walked along transects that are in range of tens or hundreds of meters. While $\Omega_E$ estimates can be obtained also from hemispherical photography (HP) (see e.g. Gonsamo et al., 2009; Leblanc et al., 2005a; Walter et al., 2003), the length of suitable angular rings (30-60° view zenith angles; Leblanc and Chen, 2001) is significantly smaller compared to the length of TRAC-sampled transects (Table 5-2). The clumping at larger landscape scales as observed by POLDER can be then underestimated if HP retrievals are used. $\gamma_E$ values were used as reported in the original papers (Table 5-2); otherwise default values for the tree species were used as suggested by Chen et al. (2006b).

The agreement is very encouraging over woodland and savannas in Africa and USA, although the number of measurements is not very high (Fig. 5-2(a)). The disagreement between the field measurements for forest sites during the period of 1993-2001 (Fig. 5-2(b)) and 2002-2008 (Fig. 5-2(c)) is due to the missing normalization factor in the original derivation of $\Omega_E$ applied before 2002 (Leblanc, 2002). The effect of this correction can be confirmed by the relatively even distribution of the retrievals around 1:1 line for the post-2001 measurements (Fig. 5-2(c)), while non-normalized $\Omega_E$ values from 1993-2001 indicated rather higher clumping than retrievals from POLDER (Fig. 5-2(b)). The normalization effect is of concern in highly clumped stands (Law et al., 2001; Leblanc, 2002); the results over the presented
savanna and woodlands should not be greatly affected, as the field $\Omega$ values with an exception of Okwa River site ($\Omega = 0.58$) indicate rather less clumped type of vegetation. The mean absolute error (MAE) is 0.027 over savanna and woodland sites from Fig. 2a, MAE = 0.046 for the forest sites measured from 2001-2008. However, these preliminary evaluation results of the expanded global clumping index map should be still treated with caution due to the limited coverage of the compiled dataset especially over the non-boreal region, and the coarse resolution (~ 6 km) of the POLDER clumping map, particularly while considering its application to higher resolution/individual stand studies. For example, POLDER retrieval greatly underestimates the clumping index value (i.e. indicating more clumped foliage) for Pijnven site ($\Delta = -0.27$, not shown) with Scots Pine stand in Belgium (Jockheere et al., 2005). The land cover is very fragmented in this area and the dominant land cover type from GLC2000 dataset for POLDER resolution is cultivated and managed areas, instead. The modeled results by Chen et al. (2005) also suggested that areas with less than 25% vegetation coverage or fragmented land cover should be treated with caution. Overall the new clumping index map achieves a good agreement with the homogeneous vegetation field site estimates. In the light of the findings presented above, it is recommended to use the mean $\Omega$ values for land cover types from Table 5-1 in cases of heterogeneous land cover mosaic.

### 5.6 Conclusion

Multi-angle remote sensing techniques are so far underutilized for ecological applications. Leaf area index and clumping index are two canopy structural parameters of comparable importance for plant growth and terrestrial carbon cycle modeling. In this context, it is expected that the findings and improvements of this study (a) will have a strong impact on the use of the clumping index to improve the assessment of terrestrial productivity and carbon cycle before higher resolution global maps of clumping index are available, and (b) will stimulate much needed efforts in acquisition of additional field-measured clumping index values, if by TRAC or HP methods, for under-represented regions and biomes. The new clumping index map shown here can be provided with quality flags upon request.
6 Impacts of including forest understory and foliage clumping information from multi-angular measurements in leaf area index mapping over North America

This chapter is based on the paper submitted to Journal of Geophysical Research-Biogeosciences:


6.1 Abstract

A new LAI dataset in 10-day intervals with consideration of the understory reflectance and foliage clumping effects over North America for one year is developed. The dataset effectively brings together measurements from multiple sensors with complementary capabilities (SPOT-VEGETATION, MISR, POLDER). First, the temporal consistency analysis indicated the new product is on-par with other available LAI datasets used currently by the community. Second, with the removal of the background (understory in forests, moss, litter and soil) effect on the forest overstory LAI retrieval, slightly different LAI reductions were found between needleleaf and broadleaf forests. This is caused by the more clumped nature of needleleaf forests especially at higher LAI values that allows more light to penetrate through the overstory canopy, making the understory more visible for equal LAI than broadleaf forests. This is found over a representative set of 105 BELMANIP sites in North America used for indirect validation. Third, the dataset was directly validated and compared with MODIS Collection 5 LAI product using results from the BigFoot project for available forest test sites. This study demonstrates that the fusion of data inputs between multiple sensors can lead indeed to improved products and multi-angle remote sensing can help

5 My co-authors allowed me to include this paper intended for publication in Journal of Geophysical Research as a chapter in my thesis. Dr. Chen and Feng Deng were the original authors of the VGT LAI algorithms. Dr. Chen edited the first draft. Krista Alikas helped with the evaluation of the product temporal consistency. I was responsible for the multiple sensor data integration, I performed the product evaluation and validation and composed the manuscript.
us to address effectively the issues (separating the signal from the understory and overstory, foliage clumping) that could not be solved via the means of the conventional mono-angle remote sensing.

6.2 Introduction

The importance of vegetation in studies of global climate and biogeochemical cycles has been well recognized (Sellers et al., 1996). This is especially the case with respect to carbon, with about a quarter of atmospheric carbon dioxide potentially fixed by terrestrial vegetation annually (Canadell et al., 2007). In order to estimate carbon fixation by terrestrial vegetation and exchanges between the land surface and the atmosphere, leaf area index (LAI), defined as half the total developed area of green leaves per unit ground horizontal area (Chen and Black, 1992; Jonckheere et al., 2004), is required as a basic and indispensable key parameter. For a few years, LAI has been operationally estimated from remotely sensed optical imagery at a global scale in the context of several international initiatives that use different sensor data, methods and approaches (Verger et al., 2008). Recent validation studies have outlined significant discrepancies among several existing LAI products and ground measurements (e.g. Abuelgasim et al., 2006; Verger et al., 2006; Weiss et al., 2007). These results were used by the Committee for Earth Observation Satellite to state that none of the available LAI products are yet performing globally within the threshold accuracy requirements for LAI around ±0.5 (CEOS, 2006) (Verger et al., 2008). This threshold accuracy requirement is based on the expected variability on diurnal, seasonal and decadal timescales.

In the most comprehensive intercomparison study up to this date, Garrigues et al. (2008) investigated the performances of four major global LAI products. The best agreement between products was reached over grasslands and croplands, while non-negligible differences could be observed over forests (Garrigues et al., 2008). Beside the quality of surface reflectances, it was suggested that the global LAI products need to be improved by better accounting for the vegetation structure, namely the effects of the background and foliage clumping.
The vegetation background includes all the materials below the forest canopy such as grass, shrub, moss, leaf litter, rock, soil, snow, etc. (Pisek et al., 2009a; Chapter 3). The effect of the background on the relationship between LAI and reflectance has been repeatedly pointed out (e.g. Gemmel, 2000; Kuusk et al., 2004; Eriksson et al., 2006; Rautiainen et al., 2007; Liames et al., 2008; Kobayashi et al., 2009). Forest understory can vary both with space and time with its own temporal cycle in reflectance properties due to differences in species phenology and foliar display as well as diurnal and solar illumination through a seasonally varying overstory canopy (Pocewicz et al., 2007). Very often the understory is spectrally similar to the overstory canopy (Miller et al., 1997). Various approaches were tried to account for or minimize the effect of background on global LAI retrievals (Myneni et al., 2002; Deng et al., 2006), but during the validations and intercomparisons it has been repeatedly noted that the understory effect is still not entirely removed (Pisek and Chen, 2007; Chapter 2; Garrigues et al., 2008) and direct inclusion of seasonally and spatially variable forest understory information into the algorithms is desirable. Based on a refined methodology tested with airborne data (Pisek et al., 2009a; Chapter 3), Pisek and Chen (2009; Chapter 4) produced a 1-degree monthly forest background reflectivity dataset over North America using multi-angular MISR data (Diner et al., 1998). However, the MISR-derived background vegetation values and their effects were not fully incorporated into any of the global LAI algorithms or used to assess the uncertainty in model results yet.

Foliage clumping refers to the confined distribution of leaves within distinct canopy structures, such as tree crowns, shrubs, and row crops, relative to a random distribution (Nilson, 1971; Weiss et al., 2004). Not accounting for foliage clumping both in LAI retrieval algorithms and ground measurements leads to substantial underestimation of the LAI, especially for needleleaf forest (Chen et al., 1997a). Chen et al. (2005) published the first global clumping index map using multi-angular POLDER 1 satellite data from ADEOS-1. However, the map application in global studies was restrained due to limited spatial and seasonal phenology coverage, topographic effects, and a lack of evaluation with field measurements. Recently, Pisek et al. (2009c; Chapter 5) expanded the spatial and temporal coverage with POLDER-3
data and devised a strategy to reduce the topographic effects with a high-resolution digital elevation model. The new clumping map was also evaluated with field observations over various biomes. While the remaining issue is a coarse resolution of the dataset (~6 km of POLDER instrument in nadir view; Deschamps et al., 1994), the new map provides updated spatially explicit estimates of foliage clumping that can improve the assessment of global LAI products.

The objectives of this paper are threefold: (1) to investigate with the sample LAI dataset and algorithms of Deng et al. (2006), if information about the background from MISR and foliage clumping from POLDER instruments can help us to reduce their effects on canopy LAI estimates and improve the quality of LAI maps; (2) to conduct an intercomparison of the new background and clumping-corrected LAI retrievals over North America with the latest version of the global MODIS LAI product (Collection 5 - Myneni et al., 2002; Shabanov et al., 2005); and (3) to evaluate directly the new LAI maps over a set of four forest validation sites with ground measurements from BigFoot project according to the methodology proposed by Weiss et al. (2007) for the validation of global LAI products. Finally, conclusions are drawn and implications of findings are discussed.

6.3 Data and Methods

6.3.1 VGT LAI product

Based on previous studies (Roujean et al., 1992; Chen, 1996b; Chen and Cihlar, 1997; Chen and Leblanc, 1997; 2001; Brown et al., 2000; Chen et al., 2002), Deng et al. (2006) developed a set of LAI algorithms for the purpose of deriving global LAI and the fraction of photosynthetically active radiation absorbed by the canopy ($f_{\text{PAR}}$) from multiple sensors. This set of algorithms has some unique features, including:

(i) explicit consideration of bi-directional reflectance distribution function (BRDF) as part of the algorithms. No BRDF normalization is necessary prior to the input of reflectance values into LAI algorithm.
(ii) separate algorithms for several structurally distinct biomes (conifer; tropical; deciduous; mixed forest; shrub; cropland, grassland, and others). The present biome is determined based on the GLC2000 global land cover dataset of Bartholome and Belward (2005).

(iii) derivation of the effective rather than the true LAI from spectral indices, since the effective LAI is the key input into the f_{APAR} calculations (Fensholt et al., 2004). The actual value of LAI is converted from the effective LAI using a clumping index (Chen and Black, 1992; Weiss et al., 2004).

(iv) utilization of the reduced simple ratio (RSR) for forests to limit the effect of understory (Brown et al., 2000, Stenberg et al., 2004).

The SPOT-VEGETATION (VGT) data used in this study were acquired in the form of 10-day composite (S10) scenes over North America for the year 2002 from the SPOTIMAGE/VITO distribution site (http://free.vgt.vito.be/). The spatial resolution is 1 km, and the data are in plate–carree projection with the WGS84 coordinate system. The VGT LAI product consists of 36 scenes that cover the whole year. The 10-day values are further subjected to a smoothing procedure (Chen et al., 2006a) in order to minimize residual atmospheric effects and reconstruct a seasonal trajectory of LAI for each pixel.

Inputs to the original LAI algorithms included a global land cover classification dataset (GLC2000) (Bartholome and Belward, 2005), reflectance and angular values from the VGT sensor, and empirical values of clumping index for different land cover types as provided by Chen et al. (2005).

6.3.2 Inclusion of the new information about understory and foliage clumping in the VGT LAI algorithms

The spectral signatures of the background values vary geographically as well as temporally with moisture and the understory vegetation composition (Bubier et al., 1997; Rautiainen et al., 2007). As the differences in spectral signatures between soil and understory vegetation are much larger than those
among different soil types, Deng et al. (2006) decided to include all the vegetation (understory+canopy) in the calculated LAI before a sound background information could be acquired. In carbon cycle modeling, overstory LAI and background LAI are treated differently because carbon fixed through net primary productivity (NPP) has different residence times for these different vegetation components in forest ecosystems (Vogel and Gower, 1998; Rentch et al., 2003). However, prior to the multi-angle remote sensing, mono-angle remote sensing did not allow differentiating between these layers of vegetation (Gemmel, 2000). Based on the results of Chen et al. (2002), the background SR value of 2.4 was used in all of the simulations for forest types and the development of the original VGT LAI algorithms (Deng et al., 2006) and the SR corresponding to bare soil was applied in the actual LAI retrieval (Pisek et al., 2007). In the new version of the LAI algorithms with the forest background information derived from multi-angular MISR data as described in Pisek and Chen (2009; Chapter 4), a scheme based on Chen et al. (1999b) is fully adopted to adjust for the effect of the difference between the actual background $SR_B$ and the standard background values used in model simulations ($SR=2.4$). The adjusted SR for the pixel to be used in LAI inversion is:

$$SR = (2.4 - SR_B) \cos(\theta_v, \theta_s, \phi) \frac{SR_{MAX} - SR_T}{SR_{MAX} - SR_B} + SR_T$$  \hspace{1cm} (1)$$

where $SR_{MAX}$ is the maximum SR value of the algorithm for a cover type at a specific angle $(\theta_v, \theta_s, \phi)$ combination and $SR_T$ is the original (understory+canopy) value of SR from VGT. In Eq. (1), $\cos(\theta_v, \theta_s, \phi) \frac{SR_{MAX} - SR_T}{SR_{MAX} - SR_B}$ represents the probability of seeing the background through the canopy, i.e. the gap fraction (Chen et al., 1999b). This adjustment to SR is equivalent to adjusting effective LAI – SR relationship to fit a specific background and account for the difference from the $SR_B$ value of 2.4, originally used for the LAI algorithm development. Since the understory layer is accounted for in this way, the LAI retrievals correspond to the overstory effective LAI only. It must be noted the used background reflectivity maps are of a low 1-degree resolution because of the often missing
measurements in MISR 1 km observations. This is due to the cloud cover and other suboptimal atmospheric or illumination conditions (Pisek and Chen, 2009; Chapter 4). At the same time, the background is often similar over a wide geographic area, although small-scale variability may exist between stands of different densities in close proximity (Serbin et al., 2009; Steinberg et al., 2006). A small uncertainty is thus present in the assessment of background at 1 km resolution while using the current background maps.

The true LAI values are now converted from the effective LAI using spatially explicit values of clumping index from the POLDER data derived map using the updated results from Pisek et al. (2009b; Chapter 5). While overall the results do not differ greatly from the mean values presented in Chen et al. (2005), the expanded temporal and spatial coverage with POLDER-3 data, topographic effect removal, and limited evaluation with ground measurements increase our confidence in the updated map. The fusion of the inputs from the three complementary sensors thus forms the new VeMP (VEGETATION, MISR, POLDER) LAI_o (overstory) product analyzed in this study.

6.3.3 Validation sites

A subset from the network of sites dedicated to the intercomparison of land biophysical products, the CEOS’ Benchmark Land Multisite Analysis and Intercomparison of Products (BELMANIP) (Baret et al., 2006) is used in this paper. This benchmark network was designed to provide a good sampling of biomes and land surface types over the globe and brings together 404 sites (full list at http://lpvs.gsfc.nasa.gov/laiintercomp.hp) extracted from several existing networks (AERONET, FLUXNET, VALERI, BigFoot, and others). The VGT LAI and VeMP LAI_o are first investigated over a subset of 105 sites in North America in 2002. Although ground measurements are not available for every site, the BELMANIP network is very useful to complement the direct validation presented later in the paper by providing a good sampling both in space and time. Using 105 locations over one year with 10-day frequency of VGT and VeMP LAI retrievals, 3780 observations are thus made available for
intercomparison from each product.

To perform any intercomparison or validation, the target must obviously match the same area, i.e. to correspond to the same geographic location and size. Geolocation uncertainties, differences in projection systems and point spread functions have to be accounted for (Weiss et al., 2007). The geolocation uncertainty is not an issue here as both VGT LAI products come from the identical input dataset in plate-carree grid. Considering the spatial dimension and the effect of point spread function of the VGT sensor (Fillol et al., 2006), a 3 km x 3 km support area at each site was considered for the analysis as recommended by Weiss et al. (2007). The median LAI value over 3 x 3 pixels area was used. Using the median value instead of the average value of LAI allows removing most outliers inside the 3 km x 3 km area. In addition, using the median makes a better match with the 'dominant class' if the class is assumed to be the main driver of variability between pixels in the 3 km x 3 km area (Verger et al., 2008).

The biome information about the site location was retrieved from the GLC2000 dataset classified into six biomes. Original ECOCLIMAP (Masson et al., 2003) classification was not used, because some misclassification was observed from within ECOCLIMAP and from comparison with GLC2000. Since the VGT LAI/VeMP LAI<sub>e</sub> products use the identical biome information, the used biome classification will not introduce any additional bias.

The direct validation of the new VeMP LAI<sub>e</sub> product and intercomparison of seasonal trajectories with the LAI results from MODIS Collection 5 is carried out over four forest sites from the BigFoot project (Gower et al., 1999; Cohen et al., 2006a). The four sites with available ETM+ LAI maps for 2002 include CHEQ, a mixed forest of northern hardwoods and aspen at Chequamegon, Wisconsin, USA (Burrows et al., 2002); METL, a temperate ponderosa pine forest at Metolius, Oregon, USA (Law et al., 2001); HARV - Harvard Forest, Massachusetts, USA (Magill et al., 2004); and NOBS - Northern Old
Black Spruce site, Manitoba, Canada (Cohen et al., 2003). ETM+ LAI estimates at each site were directly linked to the field measurements using methods described by Gower et al. (1999) and Cohen et al. (2006a).

The field measurements could be derived from several devices and interpretation techniques, and may provide estimates of effective LAI values (Weiss et al., 2004) or true LAI values when leaf clumping is accounted for (Chen et al., 2006b). The most accurate measurement is achieved using destructive samplings for foliage element estimates, and locally calibrated allometric relationships to scale these estimates over plots (Chen et al., 1997a; Jonckheere et al., 2004). The allometric method was applied at NOBS site; optical analyzer LAI-2000 (LI-COR, Lincoln, Nebraska, USA) was used at the other sites (Cohen et al., 2006a). Additionally, Law et al. (2001) measured clumping index at METL site. NOBS and METL estimates thus provide information about true LAI, while CHEQ and HARV retrievals refer to effective LAI only, instead.

6.3.4 MODIS Collection 5 LAI product

MODIS Collection 5 products were acquired in a form of ASCII subsets over the study sites from the Distributed Active Archive Center (DACC) database of Oak Ridge National Laboratory (http://daac.ornl.gov/MODIS/). Collection 5 is marked by few changes in the LAI algorithms to improve the quality of LAI retrievals and their consistency with field measurements. The acquired MODIS LAI product is composited every 8 days using a main retrieval algorithm based on a three dimensional radiative transfer model tuned for eight (up from six) main biome classes (Shabanov et al., 2005). New Look-Up-Tables (LUT) were used to compare observed and modeled red and NIR BRFs for a combination of canopy structures, leaf optical properties and soil/background patterns that represent an expected range of typical conditions for a given biome type (Knyazikhin et al., 1998a,b; Myneni et al., 1997). Under optimal circumstances, this LUT method is used to achieve inversion of a stochastic three-dimensional radiative transfer model (Shabanov et al., 2005) and the output represents a mean LAI value
over the set of acceptable solutions for which simulated and measured MODIS surface reflectances differ within specified levels of uncertainties (Myneni et al., 2002). In contrast with the VGT/VeMP LAI algorithms of Deng et al. (2006), the effect of foliage clumping is supposed to be incorporated indirectly in the formulation of the extinction and the differential scattering coefficients of the stochastic 3-D radiative transfer model (Myneni et al., 1997). If the main algorithm fails, a back-up procedure is used to estimate LAI from biome specific LAI-NDVI relationships (Myneni et al., 1997). The back-up algorithm produces LAI retrievals of lower accuracy (Yang et al., 2006c), mostly due to residual clouds and poor atmospheric correction (Wang et al., 2001), and it is recommended to use only the retrievals from the main algorithm in validation/intercomparison studies. The information about the algorithm origin of the retrieved MODIS LAI values was acquired along with the subsets. Only the values retrieved with the main algorithm were selected for the comparison with VGT LAI products and BigFoot results.

6.4 Indirect validation

Indirect validation consists of evaluating the performances of different products, without comparing them to actual ground measurements (Weiss et al., 2007). The temporal continuity and consistency of VGT LAI and VeMP LAI is investigated first. Next, we compared the statistical distributions for the several biome classes. The understory effect, its dependency on the canopy closure, and the LAI corrections using the forest background information from MISR are documented and illustrated on example sites.

6.4.1 Temporal consistency

Seasonal variation patterns of remotely sensed surface parameters can provide first quality assurance of the LAI products (Cihlar et al., 1997). Apart from the abrupt changes in land use such as fire or flooding, vegetation structure variables such as LAI vary continuously with time. The incremental nature of biomass production and allocation processes from which the leaf area index results, leads to a slow variation of this variable. A smooth temporal course of a LAI product is therefore expected. The
Figure 6-1. Box plot of $\delta$ value as a function of LAI(t) value for VGT LAI (left) and VeMP LAI$_o$ (right) products. The horizontal line in the box indicates mean and median values. The box contains 50% of the data, black lines show the 95% confidence interval and stars represent outliers.

The original VGT LAI product was characterized by relatively smooth seasonal trajectories with no gaps, which is required for most applications including investigations on global biochemical cycles and climate (Buermann et al., 2001). Preservation or improvement of the temporal consistency in the VeMP LAI$_o$ dataset would be thus desirable.

Temporal consistency was evaluated by the smoothness level of the temporal profiles over 105 BELMANIP sites in 2002. Following Weiss et al. (2007), to qualify the ‘smoothness’ of products, the difference between the LAI (t) product value at time $t$ and the mean value between the two bracketing dates was computed:

$$\delta = \frac{1}{2} \left( \frac{(LAI(t + \Delta t) + (LAI(t - \Delta t))) - LAI(t)}{\Delta t} \right)$$

(2)

where $\Delta t$ is the temporal sampling interval. Difference $\delta$ is computed only if the two bracketing LAI values exist. The smoother the temporal evolution, the smaller the $\delta$ difference should be.
Results (Figure 6-1) show that the original VGT LAI product had a very smooth temporal profile with no $\delta$ values exceeding $\pm 1$, suggesting that the possible noise in the LAI algorithm outputs is effectively tackled by the cubic spline seasonal smoothing procedure by Chen et al. (2006b). The dissymmetry observed for higher LAI values is due to the low probability of getting a LAI value at time $t + \Delta t$ and $t - \Delta t$ when LAI($t$) is high. The understory-corrected VeMP LAI$_o$ product displays even smoother behavior (Figure 6-1) with residues of only two outliers exceeding $\pm 0.5$. The VeMP LAI$_o$ thus shows improved temporal consistency. Inclusion of vegetation understory information from MISR and clumping index values from POLDER into the LAI algorithms does not introduce any signs of abrupt changes in the temporal profiles of overstory LAI profiles.

To put these results into perspective, we compare them with other products. Weiss et al. (2007) reported the residues of MODIS LAI temporal profiles to vary between $-3$ and 3. The root mean square error (RMSE) between LAI($t$) and the two bracketing dates is also lower (0.07) for VeMP LAI$_o$ than for CYCLOPES (0.13) and MODIS (0.58), although Weiss et al. (2007) was carrying the comparison over the full BELMANIP dataset during period 2000-2003. At the same time, little LAI variability between the years was observed, and the numbers can be thus considered to be comparable. The maximum VeMP LAI$_o$ value over the subset of 105 BELMANIP sites was over 8, which signifies the new product is also capable of estimating the LAI values over the broader range than MODIS (LAI < 7; Shabanov et al., 2005) or CYCLOPES (around 5; Baret et al., 2007).

**6.4.2 Statistical distributions per biome**

Histograms of VGT LAI/VeMP LAI$_o$ product values were investigated for each of the five present main biome types used as an input into the VGT-based LAI algorithms. The values were again sampled as medians over the 3 x 3 km$^2$ areas of 105 BELMANIP sites in North America in 2002.
Figure 6-2. Histogram of VGT LAI (gray thick line) and VeMP LAI₀ products (black line) for the main biome classes. Results are computed over 105 BELMANIP sites, 3 x 3 km² during the period January-December 2002 (3780 observations).

Histograms of LAI/LAI₀ values (Figure 6-2) show consistent distributions across all biomes between the two products derived from the same original VGT data. The histograms are identical for grasslands, croplands and shrubs (Figure 6-2), since the vegetation understory was considered only in the case of forest biomes. The small reduction around LAI of 2.5 for shrubs in Figure 6-2 is caused by heterogeneous nature of GLC2000 land cover classification over few BELMANIP sites, where some of the pixels over the 3 x 3 km² area belonged to forest biomes. Overall, the removal of the understory effect reduced the overstory LAI and shifted the value of the median slightly to lower values as well. The highest share of LAI values close to zero in all histograms is caused by considering the values from the whole year including the winter season. Overall, the distributions over non-forest biomes are in a good
agreement with the results for other products published elsewhere (Verger et al., 2008). Garrigues et al. (2008) also observed the best agreement between various LAI products over non-forested biomes.

For the needleleaf forest (Figure 6-2), the increased number of VeMP values in the range of LAI 1 to 2 is caused by the shift of the values from both the lower and higher values in the original VGT LAI. The forest background reflectivity maps produced from MISR by Pisek and Chen (2009; Chapter 4) capture the presence of the snow on the ground in the winter with SR very close to 1. Since this value is lower than the constant background SR value used in the VGT LAI algorithms to characterize bare soil, the new VeMP LAI, values can be actually higher than in VGT LAI product. The other addition to the increased number of values in the LAI range from 1-2 in VeMP comes from the removal of the understory enhancement of LAI values during the main growing season.

Differences between the distributions over both broadleaf and mixed forest biomes show similar characteristics of the consistent shift from higher LAI values of VGT to slightly reduced values (by LAI 0.5 to 1) of VeMP. This reduction corresponds to field measurements of understory LAI at various locations over North America found in the literature (Miller et al., 1997; Liames et al., 2008; Sonnentag et al., 2007; Serbin et al., 2009).

6.4.3 Changes of forest overstory LAI with canopy closure and time

Scatter plots between VGT LAI products were generated to better describe their agreement and/or differences. This comparison was again applied to 105 BELMANIP sites, using the median value computed over the 3 x 3 km² extent during the year 2002. Only the results over the forest sites are shown (Figure 6-3), as the scatter plots for grasslands, croplands and shrubs form 1:1 line.
Figure 6-3. VGT LAI versus VeMP LAI, as a function of the forest biome classes over 105 BELMANIP sites.

The LAI, values are corrected over the full LAI range with the smaller reductions towards higher LAI values as the canopy closure increases and the understory becomes less visible. The new VeMP product thus still clearly keeps the wide range of LAI up to 8 over the BELMANIP needleleaf and mixed forest sites (Figure 6-3). The width of the reductions along the 1:1 line in the scatter plots also indicates a similar understory effect from overstory LAI of 2 to about 4. While the absolute value of the LAI reduction might be the same, the relative reduction value to the total LAI will change, being more pronounced over less dense or more clumped stands with plenty of penetrating light to sustain abundant understory vegetation contributing to the total stand reflectance (Goward et al., 1994).

The relative median LAI reduction and its distribution with the total LAI are different between needleleaf and broadleaf forests (Figure 6-4). The median LAI reduction reaches the highest values around LAI of 3 for broadleaf forests. This coincides with the most optimal conditions for the understory vegetation growth as revealed by the analysis of the forest understory from MISR by Pisek and Chen (2009; Chapter 4). The needleleaf forests experience the highest LAI reductions at LAI greater than 3 (Figure 6-4). This is made possible by the more clumped foliage of the needleleaf forests (Chen et al., 1997a), allowing more light penetration through the overstory and making the understory more visible.
**Figure 6-4.** Distribution of median LAI reductions in percents from the original VGT LAI values sorted by LAI.

**Figure 6-5.** Temporal evolution of original VGT (white dots) and VeMP LAI<sub>o</sub> (black dots) LAI in 2002 over two 3 x 3 km<sup>2</sup> sites.

than for the broadleaf type which is less clumped and more uniform (Gower et al., 1999). However, overall the higher LAI reductions are reached for broadleaf forests. This points to more vigorous
understory layer in broadleaf forests than in the case of the needleleaf forest understory, which is in agreement with previous studies (Goward et al., 1994; Serbin et al., 2009).

To better document the temporal behavior of LAI products, we present time courses over two sites with different biomes: BOREAS SOA (Old Aspen), corresponding to a boreal broadleaf forest with hazelnut understory (Chen et al., 1997b), and a Fluxnet site in the British Columbia (BEMANIP ID 83), representing a needleleaf forest according to the GLC2000 land cover classification. Those sites were chosen since they represent a typical behavior over other BELMANIP sites, and illustrate well the understory effect, its removal, and remaining issues of the seasonal LAI mapping.

The Fluxnet site in British Columbia presents a simple seasonal trajectory with a broad peak of constant overstory LAI values in summer (Figure 6-5). The forest background contributed by LAI close to 1 in the original VGT LAI estimates in the middle of the summer when the understory is the greenest. The clumped needleleaf overstory with LAI around 2 allows enough light to penetrate to the ground and sustain a vivid understory layer. A broad peak in summer months such as that in the case of VeMP LAI, would be expected in the case of boreal needleleaf forests, as an average leaf turnover (total foliage mass/new foliage mass) for needleleaf foliage is slow at around 4 years (Chen, 1996b) up to 12 years (Gower et al., 1997). The results indicate that the seasonality in understory vegetation can indeed partly explain the observed vegetative cycles over boreal needleleaf stands recorded with remotely sensed LAI data (e.g. Yang et al., 2006b). The LAI values drop to zero values in the winter months according to both VGT LAI/LAI, products. Previously, Yang et al. (2006c) and Cohen et al. (2006a) identified poor illumination conditions, extreme solar zenith angles, snow and cloud contamination, and the signal from the understory as the main factors for the similarly poor performance of the MODIS LAI product at high latitudes. Here the signal from the snow-covered understory clearly does not alleviate the problem. Another important factor might be then lower levels of chlorophyll content in needles in winter as well (Lundmark et al., 1888; Strand and Lundmark, 1995; Zhang et al., 2008).
Results for SOA site indicate the beginning of the leaf emergence about DOY (day of year) 113 (Figure 6-5). This is in a very good agreement with an estimate of DOY 110 by Chen et al. (1997b) from the field measurements in the area. The hazelnut understory clearly forms an important part of the total LAI during the whole growing season. The VeMP LAI$_o$ reaches a peak median LAI value of 2.95 in mid-July. This corresponds with the maximum aspen overstory LAI value of 2.88 in the meteorological footprint of the tower at the site suggested by Chen et al. (1997b). Figure 6-5 shows quite early start of leaf senescence with LAI$_o$ around 2 by DOY 230 (middle August). Previously, Serbin et al. (2009) observed the mean onset of senescence on DOY 253 ± 10 days in the BOREAS study area for 2004 through 2006. The difference can be explained by a very dry summer of 2002 with very little precipitation over the area and this might have sped up the leaf senescence process in that year.

6.5 Direct validation and comparison with MODIS Collection 5 LAI product

In this section, the medians of the VeMP LAI$_o$ estimates were compared with MODIS Collection 5 and direct ground measurements of effective or true LAI over four 7 x 7 km forest sites from the BigFoot project in 2002 (Figure 6-6). The methods used to scale up local measurements to the ETM+ site level maps are described in Cohen et al. 2003; 2006a). Note that ground measurements could be derived from several devices and interpretation techniques, and may provide estimates of effective LAI values or true LAI values when the foliage clumping is accounted for (Chen et al., 2006b).

Results show the VeMP LAI$_o$ follows similar seasonal trajectory over the NOBS site to the one in Figure 6-6 over another needleleaf forests. The BigFoot LAI over the site for DOY 195 (23 June 2002) is 2.74; the VeMP retrieval for DOY 192 is 2.54 (the relative error (RE) 7.6%) and 3.43 (RE = 24.7%) for DOY 193 from MODIS Collection 5. The NOBS BigFoot LAI value refers to the true (clumping accounted) LAI, since allometry method was used in the field (Cohen et al., 2006a). The flat summer peak in VeMP LAI$_o$ profile seems more reasonable that the strong unimodal, albeit similarly close to ground truth data, trajectory of the original VGT LAI product over the NOBS site, shown in Pisek and
Figure 6-6. VeMP (overstory) LAI\(_o\), original VGT LAI and MODIS Collection 5 2002 LAI trajectories for BigFoot sites. Means and one standard deviation values are shown. BigFoot data are shown as diamonds. Black diamond signalizes true, clumping-corrected LAI value; white diamond marks effective LAI.

Chen (2007; Chapter 2). The spurious performance in the winter half of the year over needleleaf forests still remains the issue for both products.

METL site offers another possibility of comparing the LAI products for forest sites with rather low true LAI. Similar to NOBS, the VeMP LAI\(_o\) underestimates (RE=15.9\%) and MODIS Collection 5 overestimates (RE=25.9\%) the field-measured LAI. MODIS Collection 5 shows an improved stabilized seasonal trajectory over METL to the result from the previous Collections 3 and 4 (Cohen et al., 2006a)
that is more realistic with the seasonal dynamics at the site (Law et al., 2001).

Both products seem to strongly overestimate the BigFoot LAI value for the CHEQ site (VeMP RE=57.2%; MODIS Collection 5 RE=65.8%). However, the BigFoot LAI corresponds to the effective LAI as the field measurements were carried with LAI-2000 instrument and the clumping index was assumed to be unity (Burrows et al., 2002). After applying the clumping correction for the mixed forest from the results of Pisek et al. (2009b; Chapter 5), the true LAI for the site is 4.58 (Figure 6-6, CHEQ), and the RE is reduced to 13.3% for VeMP and 19.4% for MODIS Collection 5 for the closest DOY LAI retrievals, respectively.

The dense overstory of the broadleaf/mixed forest at HARV during the summer dominates the reflectance signal, and the VeMP LAI_o values in Figure 6-6 do not differ substantially from the original VGT retrievals shown in Pisek and Chen (2007; Chapter 2). The BigFoot estimates correspond to the effective LAI (Cohen et al., 2006a). Corrected for the clumping, the RE of the VeMP product is only 4.2%, and it is 4.5% for MODIS Collection 5. This result agrees with Shabanov et al. (2005), who reported an improved performance of the Collection 5 over HARV with an increased number of retrievals from the main algorithm. Interestingly in contrast to NOBS, both products seem to be capable of delivering reasonable LAI retrievals (LAI~0.5-0.8) at HARV during the winter. However, the seasonal trajectory of MODIS Collection 5 can still show unstable behavior, which is not present in the VeMP LAI_o product, partly due to the application of the locally adjusted cubic-spline capping method of Chen et al. (2006b) to minimize the residual cloud effects.

After the indirect validation, the VeMP LAI_o product thus delivers improved outputs over the selected forest sites with direct ground measurements as well. The results may indicate a level of performance superior to both MODIS Collection 5 and the original VGT LAI product analyzed by Pisek and Chen (2007; Chapter 2). The VeMP LAI_o product meets the threshold accuracy requirements by
CEOS (Morisette et al., 2006) for LAI around 0.5 at all four sites. This was not the case of the original VGT LAI product (see Pisek et al., 2007; Pisek and Chen, 2007; Chapter 2). Finally, note also that the standard deviation is very low for the new VeMP LAI_o product whereas it can be large for some of the sites for MODIS. However, more validations are needed to see if the accuracy is maintained for other sites.

6.6 Spatial variation of the difference between VGT and VeMP LAI over North America

Both VGT LAI and VeMP LAI_o maps over North America from June 2002 are shown in Figure 6-7 to provide an overall picture about the spatial distribution of LAI reductions at the onset of the growing season by accounting for understory effect in VeMP LAI_o. Differences between the two maps can be observed most clearly in a boreal region. The largest relative differences between the two maps (up to $\delta$ LAI over 1) correspond to regions with low to intermediate canopy cover, where the fraction of radiation reaching the forest floor can stimulate the understory development that can contribute to overall signal observed (Bond-Lamberty and Gower, 2007; Ross et al., 1986). The reductions in LAI might not appear very large, however it must be remembered, as mentioned in Section 6.2.2, that a partial understory signal was already considered during the development of VGT LAI algorithms of Deng et al. (2006). In that sense, the difference between the two maps in Figure 6-7 corresponds to the additional reduction in LAI due to the more abundant understory vegetation as mapped by MISR (Pisek and Chen, 2009; Chapter 4) than the one assumed during the original LAI algorithm development by Feng et al. (2006). Furthermore, the relative contribution of the understory LAI to LAI will also decrease with higher overstory LAI such as in Ontario, Quebec and the eastern U.S. (Figure 6-7), as the canopy closure becomes a limiting factor for the understory growth and its contribution to the total signal observed (Lang et al., 2007; Serbin et al., 2009). Albeit not very large, the relative differences between the various products, as illustrated in the previous sections and in Figure 6-7, correspond to the range of overestimations in global LAI products observed recently by Garrigues et al. (2008) or Kobayashi et al. (2009).
Figure 6-7. Color-coded maps of VGT LAI (above), VeMP LAI_o (center) fields and their difference over forested areas (below) over North America from June 2002.
6.7 Conclusions

A new dataset of LAI in 10-day intervals, corrected for understory and foliage clumping effects over North America is discussed in this article. The new VeMP dataset effectively brings together measurements from multiple sensors with complementary capabilities (VEGETATION, MISR, POLDER). This strategy follows the calls for fusion of various sensor measurements to improve LAI products and to address the uncertainties in the current LAI products, namely effects of the understory and foliage clumping on the canopy LAI estimates (Garrigues et al., 2008), in order to satisfy the requirements for global biochemical and climate modeling (Bonan, 1993; Sellers et al., 1996).

First, we evaluated the temporal consistency of the VeMP LAI₀ product. The analysis indicated the new product is on par with, if not better than, other available LAI datasets currently used by the community. Second, we showed that the LAI reductions after removing the forest background contribution were slightly different between needleleaf and broadleaf forests. This is caused by the more clumped nature of needleleaf forests, especially at higher LAI values that allow easier penetration of light through the canopy, making the understory more visible. This difference is found to be larger at higher LAI values. This evaluation was made over the subset of 105 BELMANIP sites in North America used for indirect validation. Kobayashi et al. (2009) recently concluded that, despite the importance of clumping, the understory is the more crucial parameter to derive correct LAI₀ estimates. In this paper we showed that the foliage clumping itself can greatly influence the impact of understory as well. Third, the dataset was directly validated using results from the well-established BigFoot project and compared to another LAI data set (MODIS Collection 5) widely used by the community over the four forest sites. The VeMP product meets the threshold accuracy requirements by CEOS (Morisette et al., 2006) for LAI around 0.5 at all four sites. At the same time, the importance of accounting for the clumping index both in the remotely sensed and field measurements data is highlighted in order to deliver comparable and true LAI estimates.
The new VeMP dataset still has its limitations. The spurious performance of the various LAI products in winter, over needleleaf forests in particular, still remains an important issue. Next, the current input background maps are of coarse 1-degree resolution and the uncertainty about the small-scale variation of the understory is not entirely removed. Higher resolution background reflectivity maps would be desirable. This issue will be addressed in depth in the future research. Similarly, higher resolution 1-km maps of clumping index would be of benefit to other LAI products such as CYCLOPES (Baret et al., 2007) as well. Unfortunately, the POLDER-based ~ 6 km resolution map is the only available global map as of now. Through this study, we encourage the development of new multi-angle sensors at a higher resolution than POLDER.

In this study, we demonstrated that physically-based fusion of data from multiple sensors can indeed lead to improved products and multi-angle remote sensing can help us to address effectively the issues that could not be resolved via the means of the conventional mono-angle remote sensing.
7 Summary

This thesis examined the application of multi-angle remote sensing for obtaining new information about the canopy architecture and its incorporation into global leaf area index algorithms. More specifically, this thesis focused on a) assessing the performance of a selection of current global leaf area index products and identifying areas where multi-angle remote sensing could help reduce uncertainties in these products and improve their performance, b) deriving and refining information about understory vegetation, foliage clumping from different and complementary multi-angle sensors (MISR, POLDER), and c) providing an evaluation for a leaf area index data set obtained through the combined use of information from multiple sensors. The main conclusions of the thesis are their limitation as well as possible future directions are summarized as follows:

1. **Global leaf area index values agree better with field data over croplands and grasslands than over forests, where differences in vegetation structure representation between algorithms can lead to substantial differences.** Ignoring the canopy vertical heterogeneity, in particular the presence of an understory layer, can overestimate the forest overstory LAI. Comparison with field measurements is then also difficult, because forest understory (consisting of grass and shrubs) is not systematically taken into account in ground LAI measurements. Information about foliage clumping is also crucial both for the algorithms and during ground measurements in order to secure accurate estimates of true LAI. Spurious seasonal variability of vegetation over evergreen needleleaf forests is often retrieved from optical remote sensing because of the seasonal variation in the background, especially in winter, when it is covered by snow is also not realistic and results in highly saturated and contaminated surface reflectances.

2. **Meaningful forest background reflectance values can be retrieved using multi-angle remote sensing.** The methodology presented in Chapter 2 was tested during a field campaign over a full range of boreal forest stands both with modified and natural backgrounds. Even though the airborne remote
sensing configuration was not optimally set with respect to the off-nadir azimuth angle (too close to the principal plane in our case), the retrieval of the background reflectivity was successful when the directionality of the background reflectivity is considered. Further measurements of the bi-directional distribution function of various targets are very important for gaining more confidence about the validity of the assumed near-Lambertian behaviour of the forest background in the forward part of the off-principal plane domain.

(3) **Observed forest background reflectance changes between different types of forests and with their canopy closure.** Forest background reflectance, despite being often fairly homogeneous, cannot be considered invariable both across and within various forest biomes. The existing variability is caused by the interplay between the climatic and substrate conditions and the amount of light transmitted through the overstory. The current parameterizations of the overstory layer correspond to broadleaf and needleleaf forests. The uncertainty in the background reflectance retrievals also depends on the input structural parameters of the overstory such as stand density and tree size. The sensitivity analysis showed the algorithm provides stable results for the crucial low to intermediate canopy density range; however, the uncertainty of the retrievals could have been further reduced if the information about the overstory structure in terms of tree height or stand density were better known.

(4) **The negative bias in the remote sensing estimates of clumping index in hilly regions can be compensated using higher resolution digital elevation model.** The terrain-induced shadows can enhance the bi-directional distribution function variation of the target and bias the clumping index value. The relationship between the elevation variation at ~1 km resolution and the clumping index from the current ~6 km resolution map has been traced and compensated for. Higher resolution maps of clumping index are needed and efforts are under way to produce them in the near future. The topographic effects will be most likely present in the new estimates as well; higher resolution digital elevation models or
other tools and approaches could be used to refine the compensation for the topographical effects on clumping retrieval.

(5) Although the limited evaluation of the global clumping index map from POLDER is encouraging, the results should be still treated with caution in medium and high resolution applications. The coarse ~6-km resolution of the POLDER clumping map provides limited means to describe mixed biomes in heterogeneous land cover mosaics. Higher spatial sampling sensor observations must be developed to better capture surface spatial heterogeneity. Further, field data should be optimally integrated with high-resolution imagery to allow a real product validation (Morisette et al., 2006). Unfortunately, with an exception of a limited extent high resolution clumping index map (< 1 km²) by Simic et al. (2009), no such image maps are currently available. Studies with high resolution (airborne) imagery would be thus of a great benefit for validating the current and upcoming global clumping index maps. More insight into the uncertainties linked with (4) could be thus also acquired.

(6) Inclusion of the new vegetation structural information gained from the multi-angle remote sensing improves the performance of LAI algorithms over forests. The demonstrated integration of the inputs is an important step forward in fusing data from several sensors with complementary qualities. The next logical step would be along the propositions of Verger et al. (2008) to look into possible ways of building ‘virtual constellations’ from different sensors, and exploiting them in synergy. However, for now the uncertainties in surface reflectance measurements during winter seem to persist and other strategies for the rectification must be found.

Given the rich content of multi-angular imagery, the analyses and advancements performed in this dissertation are only some additions in the ever increasing number of studies that have begun to capitalize on the information provided by this measurement approach (Liang et al., 2000; Diner et al., 2005; Chopping, 2008). Hopefully the results of this dissertation will stimulate and inspire further
attempts to utilize the multi-angular approach in the quest to improve our understanding of the world by providing accurate estimates of carbon uptake by terrestrial vegetation.
8 References


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