

Remote sensing of boreal land cover: estimation of forest attributes and extent

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Academic dissertation

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ABSTRACT

Remote sensing provides methods to infer land cover information over large geographical areas at a variety of spatial and temporal resolutions. Land cover is input data for a range of environmental models and information on land cover dynamics is required for monitoring the implications of global change. Such data are also essential in support of environmental management and policymaking. Boreal forests are a key component of the global climate and a major sink of carbon. The northern latitudes are expected to experience a disproportionate and rapid warming, which can have a major impact on vegetation.

This thesis examines the use of optical remote sensing for estimating aboveground biomass, leaf area index (LAI), tree cover and tree height in the boreal forests and tundra–taiga transition zone in Finland. The continuous fields of forest attributes are also required for improved detection of forest extent. The thesis focuses on studying the feasibility of satellite data at multiple spatial resolutions, assessing the potential of multispectral, -angular and -temporal information, and provides regional evaluation for global land cover data. The reference data consist of field measurements, forest inventory data and fine resolution land cover maps. The preprocessed ASTER, MISR and MODIS image products are the principal satellite data.

Fine resolution studies demonstrate how statistical relationships between biomass and satellite data are relatively strong in single species and low biomass mountain birch biotopes in comparison to higher biomass coniferous stands. The combination of forest stand data and fine resolution ASTER images provides a method for biomass estimation using medium resolution MODIS data. The multiangular data improve the accuracy of land cover mapping in the sparsely forested tundra–taiga transition zone, particularly in the mires. Similarly, multitemporal data improve the accuracy of coarse resolution tree cover estimates in comparison to the peak of the growing season data. Furthermore, the peak of the growing season is not necessarily the optimal time for land cover mapping in the northern boreal regions. The evaluated coarse resolution land cover data sets have considerable shortcomings in northernmost Finland and should be used with caution in similar regions. The quantitative reference data and upscaling methods for integrating multiresolution data are required for calibration of statistical models and evaluation of land cover data sets. The preprocessed satellite data products have potential for wider use as they can considerably reduce the time and effort used for data processing.

Keywords: vegetation, biomass, tree cover, multiangular, multitemporal, accuracy assessment, tundra–taiga boundary

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LIST OF ORIGINAL ARTICLES

This thesis is a summary of the following articles which are referred to in the text by their Roman numerals:

- I Heiskanen J (2006). Estimating aboveground tree biomass and leaf area index in a mountain birch forest using ASTER satellite data. *International Journal of Remote Sensing* 27, 1135–1158.
- II Muukkonen P & J Heiskanen (2005). Estimating biomass for boreal forests using ASTER satellite data combined with standwise forest inventory data. *Remote Sensing of Environment* 99, 434–447.
- III Muukkonen P & J Heiskanen (2007). Biomass estimation over a large area based on standwise forest inventory data and ASTER and MODIS satellite data: a possibility to verify carbon inventories. *Remote Sensing of Environment* 107, 617–624.
- IV Heiskanen J (2006). Tree cover and height estimation in the Fennoscandian tundra–taiga transition zone using multiangular MISR data. *Remote Sensing of Environment* 103, 97–114.
- V Heiskanen J & S Kivinen. Assessment of multispectral, -temporal and -angular MODIS data for tree cover mapping in the tundra–taiga transition zone. *Remote Sensing of Environment*, accepted for publication.
- VI Heiskanen J. Evaluation of global land cover data sets over the tundra–taiga transition zone in northernmost Finland. *International Journal of Remote Sensing*, accepted for publication.

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AUTHOR'S CONTRIBUTION

I was the sole author for Papers I, IV and VI. Dr. Petteri Muukkonen was responsible for writing Papers II and III. The Papers were planned and many of the data analyses made together. I also contributed to the writing. I was responsible for writing Paper V, but the statistical analyses were planned and conducted together with Dr. Sonja Kivinen.

ABBREVIATIONS

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BRDF	Bidirectional reflectance distribution function
BRF	Bidirectional reflectance factor
CCA	Canonical correlation analysis
CORINE	Coordination of Information on the Environment
DEM	Digital elevation model
EOS	Earth Observing System
ETM+	Enhanced Thematic Mapper Plus
GIS	Geographical information systems
GLC2000	Global Land Cover 2000
GLC2000-NE	GLC2000 Northern Eurasia land cover product
GLM	Generalized linear models
GPS	Global Positioning System
HDRF	Hemispherical-directional reflectance factor
IGBP	International Geosphere-Biosphere Programme
LAI	Leaf area index
MAE	Mean absolute error
MERIS	Medium Resolution Imaging Spectrometer
MISR	Multiangule Imaging SpectroRadiometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MODIS-IGBP	MODIS land cover product, IGBP legend
MODIS-VCF	MODIS vegetation continuous fields product
NASA	National Aeronautics and Space Administration
NBAR	Nadir BRDF-adjusted surface reflectance
NDVI	Normalized Difference Vegetation Index
NFI	National Forest Inventory
NIR	Near-infrared
OLS	Ordinary least squares
RMA	Reduced major axis
RMSE	Root mean square error
SPOT	Satellite Probatoire d'Observation de la Terre
SR	Simple Ratio
SVI	Spectral vegetation index
SWIR	Shortwave infrared
TIR	Thermal infrared
TM	Thematic Mapper
VNIR	Visible and near-infrared

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1. INTRODUCTION

1.1 Land cover, boreal forests and remote sensing

Land cover refers to the observed (bio)physical cover of the Earth's surface, the description of vegetation being a key component of it (DiGregorio 2005). Land cover and vegetation have a central role in the climate, hydrology and biogeochemical cycling. They also provide humans with a vast natural resource base. Land use refers to the human activities to produce, change and maintain land cover (DiGregorio 2005). Land use has a major impact on the environment (Foley *et al.* 2005), for example, to the rate of carbon exchange between the Earth's surface and the atmosphere (Houghton 2003) and to biodiversity (Chapin *et al.* 2000). Information on land cover and land cover change is required to understand and manage the environment at variety of spatial and temporal scales. It is essential for monitoring global change and for sustainable management of natural resources. It is also input data for a range of environmental models (Hall *et al.* 1995; Sellers *et al.* 1997). Furthermore, policy-driven needs, particularly the international agreements, motivate the production of land cover information for the climate models, quantification of carbon cycle and biodiversity assessments (DeFries & Belward 2000; Rosenqvist *et al.* 2003).

The circumpolar boreal vegetation zone extends across the northern hemisphere south of the treeless arctic zone, or tundra. The boreal zone is mainly characterized by coniferous forests and is almost synonymous with taiga (Heikkinen 2005). Boreal forests and tundra ecosystems are critical components of the Earth's climate system (Bonan *et al.* 1992, 1995). The boreal forests are also a major carbon sink (Goodale *et al.* 2002; Dong *et al.* 2003). The boreal forest and treeless arctic zone are separated by the northern timberline (Hustich 1966; Heikkinen 2005), or tundra–taiga transition zone (Callaghan *et al.* 2002a, 2002b), which is a latitudinal gradient of forest attributes, such as tree cover and tree height, modified by the topography and presence of rivers and peatlands. Mountain birch ecosystems are characteristic for this transition zone in Fennoscandia (Wielgolaski 2001). This transition zone is sensitive to changes in climate and human land use, and it is where the changes in the northern extent of the boreal forest biome occur. The northern latitudes are expected to experience a disproportionate and rapid warming in response to global climate change, which can have a major impact on vegetation distribution in the tundra–taiga ecotone (Grace *et al.* 2002; Skre *et al.* 2002) and feedback effects to the climate (Foley *et al.* 1994; Harding *et al.* 2002). Several studies have observed recent changes in the high latitude vegetation and photosynthetic activity (Myneni *et al.* 1997; Suarez *et al.* 1999; Kullman 2001; Sturm 2001; Slayback *et al.* 2003; Tape *et al.* 2006; Karlsen *et al.* 2007). The boreal forests and the northern extent of forest are also subject to change due to natural disturbances, particularly fires and insects, and anthropogenic influences, such as timber harvesting and land cover conversion (Gromtsev 2002; Vlassova 2002).

Satellite remote sensing provides capabilities for gathering land cover information over large areas in a synoptic and spatially explicit manner. The science- and policy-driven needs for land cover information, the unprecedented variety of remotely sensed data, and improved computing resources and data analysis tools have created new opportunities for major improvements in the global and regional land cover characterization (DeFries & Belward 2000). Remote sensing also provides information to assess the state of forests and to manage forest resources in a sustainable manner (Franklin 2001).

A great deal of progress has been made in the remote sensing of boreal forests since the launch of the first Earth observation satellites in 1970s (Kasischke *et al.* 2004; Boyd & Danson 2005). However, due to the great diversity of forests, the feasibility of methods needs to be evaluated in a range of environments. Although the boreal forests are well-inventoried in many countries, the land cover and vegetation of the climatically sensitive tundra–taiga transition zone has remained poorly characterized (Callaghan *et al.* 2002a, 2002b). For example, the Fennoscandian mountain birch forests are prone to land cover changes, but the estimation of forest attributes using remote sensing has been studied

insufficiently (Dahlberg 2001; Tømmervik *et al.* 2005). So far, classification has been the most popular method for land cover characterization, but its intrinsic limitations at coarse spatial resolution and change detection have turned the attention towards continuous field estimation (DeFries *et al.* 1995b; Lambin & Linderman 2006). The development of better methods is also required for more accurate biomass estimation and carbon stock accounting (Brown 2002; Rosenqvist *et al.* 2003; Lu 2006). The successful exploitation of remote sensing relies on defining the link between the remotely sensed data and surface variable of interest. Therefore, novel strategies are needed for upscaling field observations to match the coarse resolution pixels for calibration and validation of remote sensing models and land cover data sets (Liang 2004).

A number of new satellite sensors designed more specifically for observing land cover and land cover changes have been launched recently. These provide improved data in terms of spatial, spectral and angular resolutions, and atmospheric, radiometric and geometric correction. However, land cover mapping is most often based on the spectral information although, for example, the angular sampling of the sensors has improved considerably (Asner *et al.* 1998; Diner *et al.* 1999). Furthermore, new medium spatial resolution sensors have good temporal resolution, which increases the potential applications of temporal information in cloud-prone northern latitudes. For example, the NASA's Earth Observing System (EOS) sensors ASTER, MODIS and MISR are used to make available a range of preprocessed data products in support of a variety of applications. Higher level data products include, among others, global land cover maps (Friedl *et al.* 2002) and retrievals of biophysical parameters, such as leaf area index (Myneni *et al.* 2002). These data are distributed together with extensive meta-data over the Internet free of charge or at low price. Furthermore, the temporal continuation of the satellite observations is important for monitoring long-term land cover changes. The threat of a possible data gap in the very popular Landsat program has motivated the search for substitutive data sources (Goetz 2007). EOS sensor ASTER, for example, could provide supplementary data, which has been used so far only rarely to study land cover and forests.

1.2 Objectives of the thesis

This thesis contributes to our knowledge on the application of optical remote sensing for estimation of forest attributes in the boreal forests and tundra–taiga transition zone in Finland. The forest attributes under interest were aboveground biomass, leaf area index (LAI), tree cover and tree height. More specifically, this thesis is investigating the feasibility of new satellite data at multiple spatial resolutions, assessing the potential of multispectral, -angular and -temporal information, and providing regional evaluation for global scale land cover data sets. The constituting Papers I–VI are summarized in Figure 1.

Paper I examines the potential of the fine resolution multispectral ASTER data for biomass and LAI estimation in single species mountain birch forests in northernmost Finland. The low biomass mountain birch ecosystems form the treeline both towards north and at high elevations in northern Fennoscandia. The statistical relationships between the plot level field measurements and ASTER data are studied using linear and non-linear regression analyses. The examined spectral features include the single spectral bands, several spectral vegetation indices and canonical correlation analysis transformed reflectance.

Paper II examines the statistical relationships between the ASTER data and biomass in the southern boreal forests. Contrary to Paper I, the study area is characterized by coniferous and mixed forests, and much higher biomass levels. The ground reference data consist of stand level forest inventory data. The non-linear regression models and neural networks are used for statistical analyses. Paper III applies the statistical models calibrated in Paper II and medium resolution MODIS data to estimate biomass and stand volume for the forests of southern Finland.

Paper IV examines the potential of moderate and coarse resolution multiangular MISR data to improve the accuracy of tree cover and height estimates. The study area is located in the tundra–taiga transition zone in northernmost Finland and it is characterized by treeless heaths, mountain birch forests and woodlands, sparse coniferous forests and open mires. Neural networks are employed to study how the accuracy of the tree cover and tree height estimates depends on the utilized spectral-angular band combination. The ground reference data consist of biotope inventory polygons, which have been interpreted from aerial photographs. The explanatory power of coarse resolution multispectral, -temporal and -angular MODIS data is examined in Paper V using the same calibration data as in Paper IV. The generalized linear models are used for statistical modelling and for studying the explanatory power of different variable groups. The selected models are employed to map tree cover and forest–non-forest boundary over northernmost Finland.

In Paper VI, the selected coarse resolution land cover data sets are evaluated in northernmost Finland. The evaluated data sets differ from each other in terms of the legend definition, input data and mapping methodology, and provide a comprehensive sample of the current land cover mapping at continental and global scales.

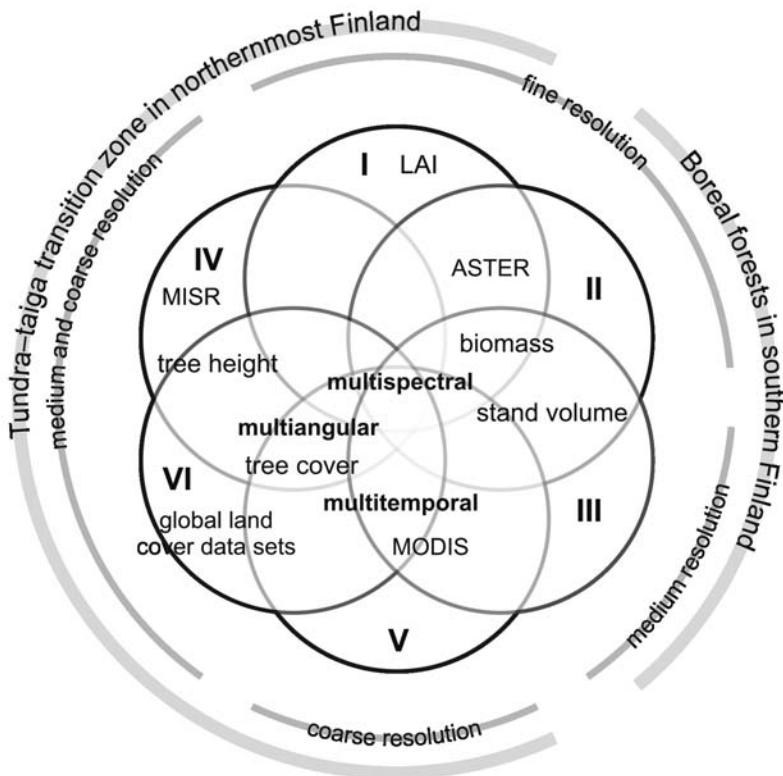


Figure 1. Summary of the geographical areas, spatial resolution, remote sensing data and forest attributes examined in Papers I–VI.

2. BACKGROUND

The aim of terrestrial remote sensing is to infer information on the physical, biological and chemical conditions of the Earth's surface from the measurements of reflected, emitted or scattered electromagnetic radiation. The amount of radiation is measured by a variety of passive and active sensors, which are typically onboard air- and spaceborne platforms and operate over a wide range of the electromagnetic spectrum from visible to microwave wavelengths. The focus of this thesis is on optical satellite remote sensing in the visible to shortwave infrared (SWIR) spectral region, i.e. approximately in the range of 400–2500 nm.

2.1 Key properties of optical remote sensing data

In the visible to SWIR spectral region, most of the radiation measured by the sensor is emitted from the Sun. The atmosphere scatters and absorbs the radiation on its path from the Sun to Earth's surface and from Earth's surface to the sensor. The sensors designed to study the land surface operate in spectral wavebands in which the atmospheric transmission is high (atmospheric windows). Reflectance is the interaction between the solar radiation and the Earth's surface, which creates the information on the images. The amount of reflected radiation varies as a function of wavelength, angle (direction), time, polarization and location, which enables the inference of surface properties from the measured reflectance (Barnsley 1999).

The spectral (i.e. wavelength dependent) variability of reflectance is probably the most utilized information source in the remote sensing of land surfaces. The vegetation shows typically a low reflectance in the visible range of the spectrum, particularly in the blue and red wavelengths, a steep increase in reflectance around 700 nm (red edge) and high reflectance in the near infrared (NIR). The principal chemical and physical characteristics determining the leaf optical properties are plant pigments, particularly chlorophylls a and b, carotenoids and xanthophylls, leaf mesophyll structure and water content (Gates *et al.* 1965; Tucker & Sellers 1986). The reflectance varies also as a function of the illumination and viewing angles (Kimes 1983; Kleman 1987). This angular dependence of the reflectance is described by the bidirectional reflectance distribution function (BRDF). Surface reflectance refers usually to the more specific measures of bidirectional reflectance factor (BRF) or hemispherical-directional reflectance factor (HDRF) (Martonchik *et al.* 2000). The reflectance of forests is typically highly anisotropic and determined by the optical properties of canopy components, canopy- and landscape-level structural characteristics, and topography (Asner *et al.* 1998). The reflectance of the land surfaces can also vary considerably as a function of time due to the seasonality of vegetation and snow cover.

The spectral, radiometric, angular, spatial and temporal resolutions describe how the surface leaving radiation is recorded by the sensor. Polarization is outside the scope of this study. The measurements are typically made in several wavebands (multispectral data), which are described by their spectral sensitivity functions. The spectral resolution refers to the number and bandwidth of the wavebands, and radiometric resolution to the sensors ability to distinguish different levels in observed radiance. Multiangular observations can be collected by viewing the target from several angles near-simultaneously or by observing the target during several overpasses (Asner *et al.* 1998; Diner *et al.* 1999). The range of the view and solar illumination angles over which data can be acquired is controlled by the sensor viewing geometry and satellites orbital characteristics (Barnsley *et al.* 1994). Spatial resolution refers to the level of spatial detail that is provided by the image (Aplin 2006). The content of the pixel is determined by the sensors instantaneous field of view on the ground and spatial response function. The pixel size denotes to the area on the ground covered by a single pixel in the image. The temporal resolution refers to the average revisit period at a constant site (Aplin 2006). It depends on various factors, including the swath width, satellites orbital altitude, sensor view angle,

sensor tilting capabilities and latitude. In the optical range, the probability of obtaining cloud free observations is directly related to the temporal resolution.

None of the image resolutions or image extent can be increased without increasing the amount of data. The trade-off between the spatial and temporal resolutions is one of the key issues in the selection of the remotely sensed data for any application (Lefsky & Cohen 2003; Aplin 2006; Figure 2). Cihlar (2000) divides the land cover mapping over large areas roughly into two categories: those that use fine spatial resolution data and those that use coarse spatial resolution data. In the ‘fine’ resolution studies, the spatial resolution is relatively high (typically 5–30 m) but the extent of the data is relatively small and temporal resolution poor. The extent of the fine resolution data can be increased by mosaicking several cloud free images together (Virtanen *et al.* 2004). In the ‘coarse’ resolution studies, data cover larger areas with good temporal resolution, but the spatial resolution is rather low (typically around 1 km). In these studies, it is common to composite data for multiple days to reduce cloud contamination (Holben 1986). However, this division has recently diminished somewhat because of the ‘medium’ spatial resolution sensors (e.g., Terra/Aqua MODIS and Envisat MERIS) and improved tilting capabilities of the fine resolution sensors.

The land cover and vegetation mapping and monitoring require data at multiple spatial resolutions (Stow *et al.* 2004). Fine resolution data have been used frequently in the local to regional scale studies. Medium and coarse spatial resolution sensors are particularly useful for monitoring the seasonal and annual variability of vegetation over larger areas. In the cloud prone regions, such as northern latitudes, the high temporal resolution is essential for regular land cover monitoring (Rees *et al.* 2002; Roy *et al.* 2006). Multitemporal data can be also required for distinguishing certain land cover types. The coarse resolution analyses of land cover change help in focusing the attention on the areas experiencing the most rapid land cover changes (Hansen & DeFries 2004; Lepers *et al.* 2005). Townshend & Justice (1988) determined that a resolution finer than 1 km is desirable for global

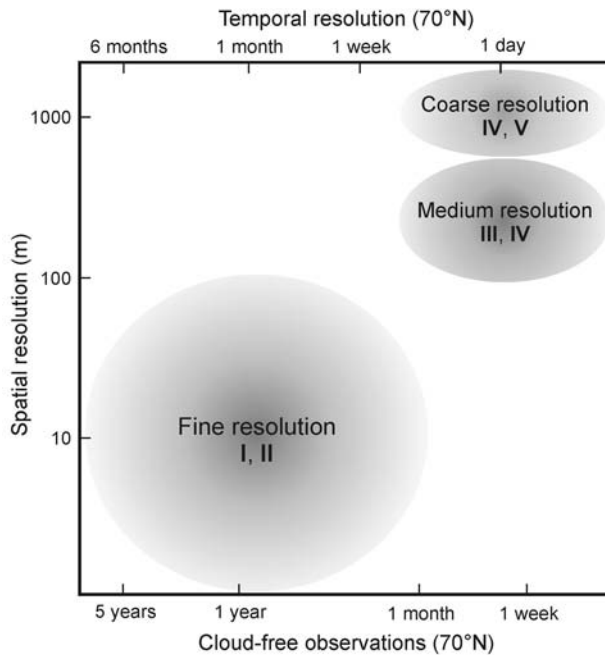


Figure 2. The spatial resolution of fine, medium and coarse resolution satellite data against the average revisit period and typical cloud-free revisit period of the sensors at 70°N latitude. Temporal scales from Rees *et al.* (2002).

scale vegetation monitoring and a resolution of 250 m is needed to depict human-induced land cover changes. The less frequent imaging with fine spatial resolution sensors is useful for calibration and validation of lower resolution observations and enables more detailed analyses of land cover change (Stow *et al.* 2004).

Although it is common to categorize the image data according to the absolute pixel size, the spatial resolution is probably best understood relative to the size of objects that we want to sense. Strahler *et al.* (1986) developed a taxonomic structure for remote sensing models and introduced the concepts of L- and H-resolution. Important concepts are scene and image, and size of the scene objects and spatial resolution of the image. In the H-resolution case, the scene varies at a lower spatial frequency than image sampling and features can be resolved. Conversely, in L-resolution case, the scene objects are smaller than the spatial resolution of the image. Mixed pixels are a typical L-resolution problem, occurring when two or more scene objects of interest fall within a single pixel. The spatial resolution is also closely related to the selection of image processing methods (Strahler *et al.* 1986; Woodcock *et al.* 1987).

2.2 Approaches to extract land cover information

The success of the remote sensing analysis depends on finding the accurate way to represent relationship between the radiance measured by the sensor and the land surface properties. The basic types of remote sensing models are physical models and empirical (statistical) models, although many variations and hybrids exist (Liang 2004). The optical remote sensing system can be physically modelled as a selection of several subsystems, which describe how the land surface properties relate to the remotely sensed data. The most important subsystems are scene, atmosphere and sensor models, but the data are also affected by navigation model and mapping and binning methods (Liang 2004). In the image interpretation, the physical models have to be inverted to predict what caused the observed signal. Although the physical models can have great explanatory power and are not as site-specific as empirical models, they can be difficult to implement in practice and often require measurement of variables that are hard to acquire (Nilson *et al.* 2003). The empirical models do not account for physical processes, but are fitted statistically between the land surface attributes and remotely sensed data. The advantage of empirical models is that they can use data very effectively, but the applicability depends primarily on the strength of the relationship between remotely sensed data and the variable of interest. The disadvantage is that statistical models are usually highly site and time specific and not transferable to other areas (Foody *et al.* 2003).

The methods for extracting land cover information can be classified according to the type of information they produce: discrete classes or continuous estimates. Classification is the most common method for mapping the discrete land cover attributes, such as land cover type (Tso & Mather 2001; Franklin & Wulder 2002). The classification assigns the pixels to a set of categories described in the classification legend. The land cover type is a 'hybrid' variable, as classes are typically defined in terms of several characteristics, for example, according to the vegetation composition and structure. Ideally, the legend should consist of non-overlapping, all encompassing, mutually exclusive and quantitatively defined classes (Cohen *et al.* 2003b). In the 'hard' classification, the sub-pixel heterogeneity can be taken into account by defining classes for mixed and complex land cover types. The classification has been historically the most popular method to produce land cover data, which according to the DeFries *et al.* (2000a) stems from the tradition in bioclimatology.

Another approach is to estimate land cover characteristics as continuous variables. Sub-pixel classification aims to estimate fractional covers of different land cover types. Furthermore, the land cover can be characterized by vegetation structural and biophysical attributes. In the forest ecosystems, the typical attributes include tree cover, tree height, stand volume, aboveground biomass and LAI. Opposite from the fractional cover estimates, the continuous fields approach assumes that there is

no spatial covariation among land cover attributes within the pixel (Fernandes *et al.* 2004). Some of the variables can be estimated by inverting the physical models (e.g., Myneni *et al.* 2002), but more commonly those are estimated through empirical relationships. Various methods have been used for calibrating models between ground reference data and satellite data, for example, linear spectral unmixing, regression analysis, k-nearest-neighbours method (k-*nn*) and neural networks (Boyd *et al.* 2002; Tomppo *et al.* 2002; Fernandes *et al.* 2004). The combination of spectral vegetation indices (SVIs) and empirical modelling has been particularly common in the estimation of vegetation attributes. The numerous SVIs have been designed to isolate the contribution of vegetation from the contribution of other materials (background, atmosphere) to the reflectance (Asner *et al.* 2003). The most common SVIs are either ratios or linear combinations of spectral bands, typically calculated from red and near infrared data, such as Normalized Difference Vegetation Index (NDVI; Rouse *et al.* 1973; Tucker 1979).

The image processing algorithm is applied assuming either L-resolution or H-resolution (Strahler *et al.* 1986; Woodcock & Strahler 1987). Classification is an H-resolution method, because the scene objects of interest are larger than pixels. If the objects are relatively homogeneous at the level of the sensors spatial resolution, discrete land cover labels may be appropriate. Also image segmentation can be applied to delineate homogeneous units for analysis (Pekkarinen 2004). The physical and empirical models relating biophysical attributes to multispectral measurements are proper methods in the L-resolution case. When classification is applied to the L-resolution case, problems occur because land cover appears as mixtures and mosaics. The classification of coarse resolution pixels typically results in underestimation of the less abundant and more fragmented classes (Braswell *et al.* 2003; Virtanen *et al.* 2004). The subjectivity and poor reproducibility of the classification are another problem (Cihlar 2000). The analyst's role cannot be eliminated because the class distinctions are always to some degree artificial. Classification relies on the analyst's skills in labelling training sites or clusters. The third limitation is related to the change detection, because the classification based methods overemphasize the land cover conversions and neglect the more subtle land cover modifications within land cover categories (Lambin & Linderman 2006).

The continuous field estimation can better exploit the inherent variability of the images and provide more appropriate land cover characterizations for the ecotones and spatially fragmented regions. It provides also means for detecting subtle temporal changes in land cover (DeFries *et al.* 1995b; Fernandes *et al.* 2004; Lambin & Linderman 2006). Furthermore, the flexibility of continuous fields enables the derivation of several classifications from the same data (Cohen *et al.* 2001). If classification is based on continuous fields, the subjectivity of the classification is reduced (Cihlar 2000). The continuous fields allow also better parameterization of the environmental models (DeFries *et al.* 1995b).

2.3 Land cover characterization of boreal forests and tundra–taiga transition zone

2.3.1 Estimation of the forest structural and biophysical attributes

The application of aerial photography has long traditions in vegetation mapping and forest resource management (Colwell 1960). Therefore, it is natural that satellite remote sensing has received considerable attention in land cover mapping since the early 1970s when the first Landsat satellite was launched. The fine resolution studies have focused mainly on the classification of forests according to the composition and estimation of forest inventory variables (e.g., stand volume). More recently, the quantification of the carbon cycle and mapping of biophysical variables for parameterization of the ecosystem process models has got also more attention (Franklin 2001; Boyd & Danson 2005). Now the value of continuous fields has been realized in a range of applications, for example in the large-scale habitat mapping (McDermid *et al.* 2005). Although the continuous field estimation has

been common in the boreal zone and treeless arctic regions (Wulder 1998; Laidler & Treitz 2003; Kasischke *et al.* 2004), the land cover of the tundra–taiga transition has been mapped almost exclusively by classification (Clark *et al.* 1985; Käyhkö & Pellikka 1994; Rees *et al.* 2002; Kharuk *et al.* 2003; Tømmervik *et al.* 2003; Virtanen *et al.* 2004) and continuous field estimation has received only little attention (Ranson *et al.* 2004a; Olthof & Fraser 2006). For example, only a few studies have tried to map forest biophysical attributes in the Fennoscandian mountain birch forests (Dahlberg 2001; Tømmervik *et al.* 2005).

The forest attributes can be grouped to the canopy cover, canopy height (structure) and stand composition related attributes (Lefsky & Cohen 2003). The attributes related to the canopy cover include, for example, tree cover and LAI. Tree cover can refer either to the tree crown or tree canopy cover, depending on if within canopy gaps are included or excluded from the cover (Hansen *et al.* 2002). The canopy cover is important variable in the reflectance of the forest stand and therefore the canopy cover related variables have been estimated rather successfully by optical remote sensing (Wulder 1998; Franklin 2001; Nilson *et al.* 2003). LAI is defined as one half of the total leaf area per unit ground surface area (Chen & Black 1991) and it is an important biophysical variable controlling many biological and physical processes (Waring & Running 1999). LAI is also a key factor in the forest growth and its accurate estimation is a prerequisite for derivation of the improved forest growth estimates by ecosystem process models (Franklin 2001). The estimation of LAI is complicated by the fact that LAI has an asymptotic relationship with canopy cover, because additional layers of leaves have little effect on canopy cover after a particular LAI. As the stand reflectance is mainly affected by the canopy cover, the reflectance tends to saturate at high LAI values. Also the reflectance of background and undergrowth vegetation hinders the estimation of canopy cover related variables (Spanner *et al.* 1990; Baret & Guyot 1991).

Tree height, stand volume and aboveground biomass are forest attributes which usually show weaker relationships with optical remote sensing data than those related to the canopy cover (Nilson *et al.* 2003; Kasischke *et al.* 2004). For example, the accuracy of the stand volume estimates is usually too inaccurate for purposes of forest management (Franklin 2001). The problem is that in many forest types, the basal area and other stand properties continue to evolve after the canopy cover reaches its maximum, but the stand reflectance is not significantly affected by those increases (Nilson & Peterson 1994). Therefore, the applicability of the remote sensing data is determined by the relationship of canopy cover and the forest attribute. When canopy is closed, the success in the estimation of forest attribute depends on the extent to which a closed canopy can predict them (Franklin 2001).

The third group of attributes is related to the composition, including the species composition, leaf type (broadleaved vs. needleleaf) and leaf longevity (deciduous vs. evergreen) (Lefsky & Cohen 2003). The composition is typically viewed as a categorical attribute (e.g., forest type). Therefore, the success in mapping is dependent on the type and detail of the classification legend. However, for example, leaf type and leaf longevity information can be estimated also as continuous variables (DeFries *et al.* 1995b).

2.3.2 Potential and limitations of optical information sources

The spectral information, i.e. multispectral images and SVIs, are the most utilized source of information in the land cover characterization. As mentioned above, the spectral information lacks sensitivity to forest attributes at the moderate and high biomass levels (Lu 2006). The stand reflectance is also affected by the background and understory characteristics, particularly in sparse and open regions (Spanner *et al.* 1990; Rautiainen *et al.* 2007). Furthermore, the spectral confusion between the non-forest and forest vegetation, for example, the confusion between open mires, low shrublands and forests are common problems in the northern regions (Kalliola & Syrjänen 1991; Käyhkö & Pellikka 1994; Häme *et al.* 1997; Tomppo *et al.* 2002; Rees *et al.* 2002). Because of the limitations of the

spectral information, the angular and temporal information seems attractive for improving the land cover characterizations. The spatial domain of optical images (Wulder 1998) and, for example radar and lidar techniques (Rees *et al.* 2002; Ranson *et al.* 2004b), could also improve the estimates of forest attributes and accuracy of land cover mapping, but those were outside the scope of this thesis

Sometimes the angular information may have higher sensitivity to land cover variability than purely spectral information (Barnsley *et al.* 1997). The BRDF research has focused on the development and implementation of mathematical models to normalize the satellite observations to the common viewing and illumination geometry, and to derive information on certain biophysical properties of the Earth's surface (Roberts 2001). Although the applications of multiangular data for land cover mapping are still relatively rare, the potential of multiangular data for land cover characterization has been demonstrated by several studies (Abuelgasim *et al.* 1996; Barnsley *et al.* 1997; Bicheron *et al.* 1997; Sandmeier & Deering 1999a, 1999b; Grant 2000; Lovell & Graetz 2002; Zhang *et al.* 2002). The angular information has been input into the empirical models in the form of multiangular images (Barnsley *et al.* 1997), multiangular indices (Sandmeier & Deering 1999a; Gao *et al.* 2003; Chen *et al.* 2005) and fitted BRDF-model parameters (Brown de Colstoun & Walthall 2006; Armston *et al.* 2007). As the structural differences between the forest and tundra vegetation are large, but spectral differences of some land cover types are small, the multiangular data could improve the land cover depiction in the tundra–taiga transition zone.

The seasonality of the vegetation is an important feature of the northern latitudes. The simplest way to exploit the temporal domain is to acquire data at the time of maximum contrast between the land cover types (Kasischke *et al.* 2004). The phenological development can also be utilized for inferring the land cover characteristics. The multitemporal data have been employed particularly in the global scale mapping (Lloyd 1990; DeFries *et al.* 1995a; Hansen *et al.* 2005), but it has also been used at finer spatial resolution studies for land cover classification and prediction of forest attributes (Wolter *et al.* 1995; Lefsky *et al.* 2001; Toivonen & Luoto 2003). Furthermore, multitemporal data can improve the wetland classification and help to separate wetlands from the other land cover types (Ozesmi & Bauer 2002). The analysts can use directly a temporal series of satellite images or seasonal variability can be characterized by a set of phenological variables or metrics, which are derived, for example, from the temporal NDVI profile (DeFries *et al.* 1995a). The advantage of the latter approach is that differences in the timing of the seasonal events are normalised. The data are also 'compressed' into a fewer numbers of bands (Hansen *et al.* 2005). The temporal information have been used only rarely for land cover characterization of the tundra–taiga transition zone (Ranson *et al.* 2004a), but the mapping is usually based on peak of the growing season images (Rees *et al.* 2002; Kharuk *et al.* 2003; Olthof & Fraser 2006). The short growing season, cloudiness, snow cover and low solar elevation angles complicate the use of multitemporal data in the northern latitudes (Häme *et al.* 1997; Rees *et al.* 2002).

2.3.3 Upscaling issues in the model calibration and validation

The model calibration is an important step in developing the statistical models for forest attributes. Validation (accuracy assessment) is the process of assessing the accuracy of data products derived from the system outputs by independent means and it determines the usefulness of the product for specific purposes (Morissette *et al.* 2002). The validation of the continuous estimates is usually based on the correlative analysis of the satellite derived products and ground reference data. The classified data are usually assessed using the error (confusion) matrix (Foody 2002). The calibration and validation of remote sensing models have in common that they require the integration of remotely sensed and ground reference data. This can be complicated, because the area represented by the field measurements does not necessarily correspond to area of remotely sensed pixels, particularly at coarse spatial resolution. The land cover tends to be also very heterogeneous at the sensor resolution. Therefore, the

methods for upscaling the field measurements to the resolution of remote sensing data are central in the calibration and validation (Liang 2004).

The field observations are typically made at the scale of field plots. Although some attributes can be difficult to measure even at the scale of relatively fine resolution data (e.g., Landsat ETM+), the field plots usually correspond rather well with pixels at that resolution. Therefore, the fine resolution data have been popular for upscaling plot level data to the landscape scale for calibration and validation of low resolution models (Iverson *et al.* 1989; Häme *et al.* 1997, 2001; Tomppo *et al.* 2002; Cohen *et al.* 2003b). However, when relating plot level measurements with high resolution satellite data, the co-registration errors between the field and satellite data can deteriorate the estimation results (Halme & Tomppo 2001). The collection of new field data is usually time-consuming and expensive. Sometimes the fine resolution reference data is available (e.g., land cover map) and can be used directly for calibration or validation.

The ground reference data can be also over stands or some administrative units. The forest stand, or compartment, is an area of relatively homogeneous forest attributes and it is typically the smallest unit in the forest management (Poso 1983; Koivuniemi & Korhonen 2006). The stands are handled as polygons in the geographical information systems (GIS). Traditionally the stands are delineated from aerial photographs and forest attributes measured in the field or estimated from the photographs. As stands are typically larger than fine resolution satellite image pixels, models can be developed per stands (Poso *et al.* 1987; Ardö 1992; Kilpeläinen & Tokola 1999). However, if stands are plenty, they can be used directly for calibrating and validating coarse resolution models. The estimates can be also validated over larger areas than stands, typically as mean values over some administrative areas. The National Forest Inventory (NFI) statistics provide appropriate reference data at this level.

The accuracy assessment of global land cover classifications has got lots of attention as new products have been released lately (Loveland *et al.* 2000; Friedl *et al.* 2002; Bartholomé & Belward 2005). Similarly, the validation of biophysical retrievals has received mounting attention (Cohen *et al.* 2003b; Morisette *et al.* 2006). The accuracy assessment is difficult because of the large areas to be sampled. It is also complicated by the difficulties to observe categorical variables at coarse resolution. Land cover types have poor scalability and it is difficult to determine representative land cover labels for heterogeneous pixels, although fine resolution reference data would be available (Cihlar 2000; Foody 2002). The statistically sound validation of land cover data sets has been based on the interpretation of reference data from fine resolution satellite images and other existing data sources by regional experts (Scepan 1999; Mayaux *et al.* 2006). Some studies have compared the global land cover data sets to identify the areas where they agree or disagree (Hansen & Reed 2000; Latifovic *et al.* 2004; Giri *et al.* 2005; McCallum *et al.* 2006). The other studies have concentrated on more regional study areas (Cohen *et al.* 2003b, 2006; Schwarz & Zimmermann 2005; Waser & Schwarz 2006). Although these case studies cannot state the accuracy of the whole data set, they can provide valuable information on the data deficiencies and suggest improvements to the future products. However, such evaluations are rare over the tundra–taiga transition zone (Virtanen & Kuhry 2006).

3. STUDY AREAS

The study areas of this thesis concentrate on two regions, one located in southern Finland (II, III) and another in northernmost Finland (I, IV–VI, Figure 3). Finland is part of Fennoscandia and has a relatively warm climate in comparison to the other regions in the equivalent latitudes due to the strong influence of Atlantic Gulf Stream (Tikkanen 2005). In north to south direction Finland stretches across the whole boreal vegetation zone, which is bordered with treeless arctic zone towards the north and with temperate zone towards the south (Ahti *et al.* 1968). The northernmost parts of Finland belong to the hemiarctic and orohemiarctic subzones of the northern boreal zone (Heikkinen 2005). In general, the biomass of the vegetation is decreasing towards the north with decreasing temperatures and shorter growing season. Therefore, the studied areas correspond to two ends of biomass gradient in the Finnish boreal forests.

The most common tree species in Finland are Scots pine (*Pinus sylvestris*), Norway spruce (*Picea abies*), silver birch (*Betula pendula*) and downy birch (*B. pubescens*). Typically the forest stands consist of more than one tree species. Pure pine stands occur in rocky terrain, on dry sandy soils and in forested mires. Natural spruce stands occur in richer soils. Birch is commonly found as an admixture, but can also form pure stands. Mountain birch (*B. pubescens* ssp. *czerepanovii*) forms the transitional forests towards north and on the fell slopes almost everywhere in the Fennoscandia (Wielgolaski 2001). Mountain birch biotopes range from forests and woodlands (Figure 4) to low growing shrublands (Sihvo 2002). The typical undergrowth vegetation in the Finnish forests includes dwarf shrubs, particularly crowberry (*Empetrum hermaphroditum*), cowberry (*Vaccinium vitis-idaea*) and blueberry (*V. myrtillus*), and mosses and lichen in variable proportions. Various kinds of peatlands and mires are also important in the Finnish landscape (Vasander 1996; Seppä 2002). Most of the Finland is

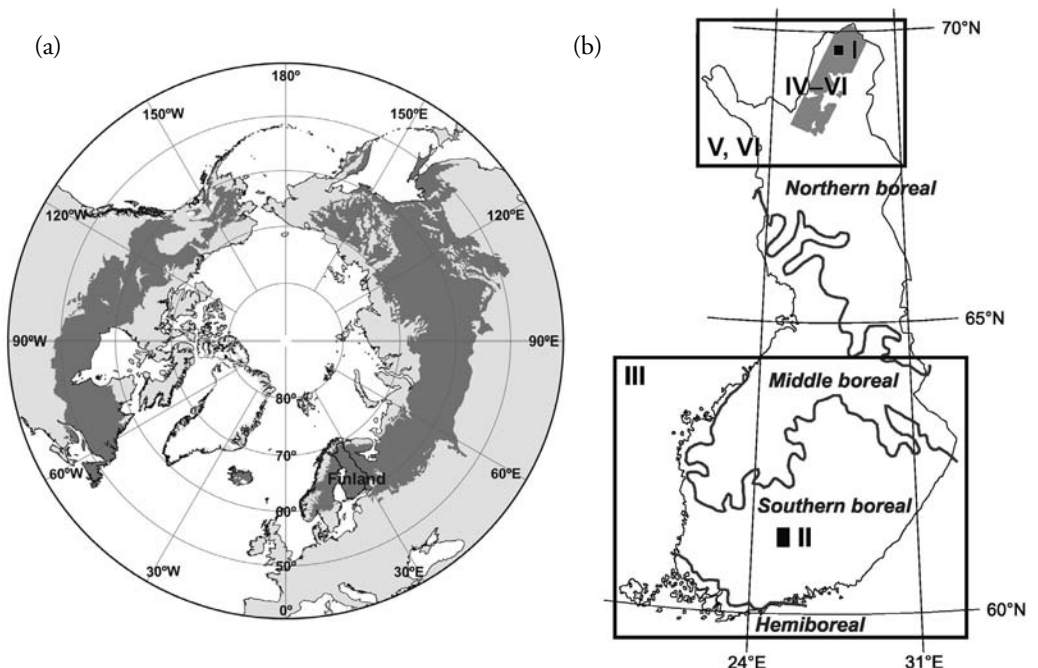


Figure 3. (a) The location of Finland relative to the circumpolar boreal forests. Boreal forests are shown in dark gray and based on Olson *et al.* (2001). (b) The location and extent of the study areas of Papers I–VI relative to the boreal vegetation zones (Ahti *et al.* 1968). The northernmost parts of the northern boreal zone belong to the hemiarctic and orohemiarctic subzones (Heikkinen 2005).



Figure 4. Mountain birches in the study area of Paper I ($69^{\circ}36'1''\text{N}$, $27^{\circ}15'5''\text{E}$).

characterized by gently undulating terrain. About 80% of the country lies below 200 m and may be classified as lowland (Tikkanen 1994). The highest fells are over 1000 m high and located in north-westernmost Finland.

Nearly all the productive forest land in Finland is intensively managed. Despite the active harvesting and reduction of national territory after the Second World War, the biomass of the Finnish forests is now greater than during the 20th century and continues to increase (Liski *et al.* 2006). Most of the non-productive forest land and the largest protected areas are located in northern Finland. The effect of natural disturbances on Finnish forests is relatively small as the forest fires are effectively suppressed. Reindeer herding is an important form of land use in the northernmost Finland, having also considerable effects on land cover (Käyhkö & Pellikka 1994; Helle 2001). The mountain birch forests are also regularly defoliated by insects herbivores (Seppälä & Rastas 1980; Neuvonen *et al.* 2001).

4. MATERIALS AND METHODS

4.1 Reference data

The overview of the materials and methods used in this thesis is given in Figure 5.

The ground reference data on aboveground biomass and LAI of mountain birch woodlands and forests were surveyed in northernmost Finland in July 2004 (I). The measurements were made in four 1 km² study sites covering a range of mountain birch biotopes. The total number of field plots was 128. The plot size was 100 m² in the site having the highest tree density and 200 m² in the three sparser sites. The plots were located using a GPS-device. The basic stand parameters (diameter at breast height, height) were measured for scrubs and trees taller than 1.3 m. The biomasses of the tree components were estimated using the allometric models developed for mountain birch by Starr *et al.* (1998). The leaf area was estimated using the estimated leaf biomass and specific leaf weight data from literature.

The stand level forest inventory data were used in Papers II and III. Two data sets were used: the statistical models were calibrated using one data set and models evaluated by another data set. The data were provided by Metsähallitus and Finnish Forest Research Institute (Metla). The stand volume

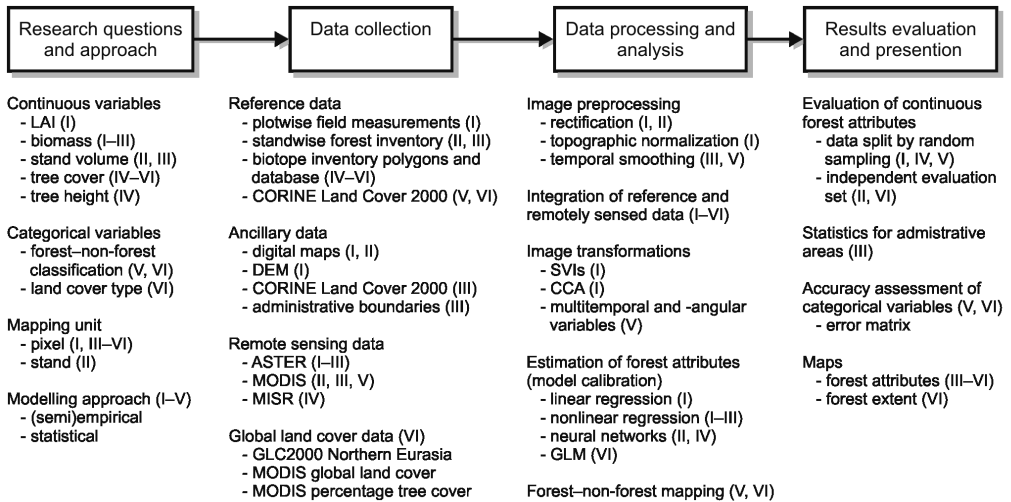


Figure 5. Summary of Papers I–VI relative to the typical steps of remote sensing analysis.

and stand age were used for calculating the aboveground biomass of tree components and understory vegetation. Only forest stands in mineral soils were examined, since the available biomass conversions (Lehtonen *et al.* 2004; Muukkonen & Mäkipää 2006) were applicable only to those conditions.

The biotopes of the nature reserves, wilderness areas and national parks of northernmost Finland have been inventoried between 1996 and 1999 by Metsähallitus (Sihvo 2001, 2002). According to the definition, biotope is an area with uniform soil, tree stand and human impact. The survey is based on 1:20 000 scale colour-infrared aerial photographs, the minimum mapping unit being approximately one hectare. In addition to the biotope classification, the database includes quantitative data on tree crown cover, species composition, tree height and shrub cover. The data have been stored in a GIS-database in vector format. The biotope inventory data were used for regional model calibration and evaluation (IV, V) and for assessment of global land cover data sets (VI). The data were used from approximately 250 km long and 60 km wide transect (Figure 3b).

Finnish Environment Institute (SYKE) has produced a fine resolution land cover database for the whole of Finland as a part of European CORINE Land Cover 2000 project (CLC2000-Finland 2005). The Finnish CORINE land cover map has a resolution of 25 m and it is based on the data integration of automated Landsat 7 ETM+ image interpretation and existing GIS data. The continuous forest variables have been estimated using an unsupervised clustering and cluster labelling method. CORINE data were used for deriving a forest mask (III) and validating forest–non-forest maps (V, VI).

4.2 Satellite data and preprocessing

The technical specifications of the utilized satellite sensors are summarized in Table 1, and satellite data products and global land cover data sets in Table 2. All the satellite data were obtained through NASA's EOS Data Gateway (<http://edcimswww.cr.usgs.gov/pub/imswelcome/>).

The fine resolution Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is onboard NASA's Terra satellite, which was launched in December 1999 (Yamaguchi *et al.* 1998). The atmospherically corrected surface reflectance data (Abrams 2000) were used in Papers I and II. The surface reflectance product has three spectral bands in the visible and near-infrared (VNIR) and

six bands in the SWIR spectral regions at 15 and 30 m spatial resolution. The VNIR bands have been designed particularly for vegetation assessment, but SWIR bands mainly for the purpose of surface soil and mineral mapping (Yamaguchi *et al.* 1998). ASTER also provides five bands in the thermal infrared (TIR) spectral region at 90 m spatial resolution, but this data were not used. ASTER images were rectified to the national coordinate system by using ground control points collected from digital topographic maps and first order polynomials. In Paper I, the image data were also topographically normalized by using digital elevation model (DEM) at 25 m resolution and C-correction (Teillet *et al.* 1982). Several SVIs were also calculated (I: Table 1).

Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Terra and Aqua satellites provides multispectral, -temporal and -angular data for medium and coarse resolution land cover characterization (Justice *et al.* 1998, 2002). MODIS has 36 spectral bands, seven being particularly designed for land applications; three bands in the visible, one band in NIR and three bands in SWIR spectral ranges. The spatial resolution of MODIS data is either 250 m, 500 m or 1 km depending on spectral band and data product. Terra MODIS data are available since 2000 and Aqua MODIS data since 2002.

Table 1. Technical specifications of the ASTER (bands 1–9), MODIS (bands 1–7) and MISR sensors.

Sensor	Band	Bandwidth (nm)	Spectral region	Spatial resolution	Swath width	Reference
ASTER	1	520–600	green	15 m	60 km	Yamaguchi <i>et al.</i> 1998
	2	630–690	red	30 m		
	3	760–860	NIR			
	4	1600–1700	SWIR			
	5	2145–2185	SWIR			
	6	2185–2225	SWIR			
	7	2235–2285	SWIR			
	8	2295–2365	SWIR			
	9	2360–2430	SWIR			
MODIS	1	620–670	red	250 m	2330 km	Barnes <i>et al.</i> 1998
	2	841–876	NIR	500 m		
	3	459–479	blue			
	4	545–565	green			
	5	1230–1250	SWIR			
	6	1628–1652	SWIR			
	7	2105–2155	SWIR			
MISR*	1	425–467	blue	275 m, 1.1 km**	360 km	Diner <i>et al.</i> 1998
	2	543–572	green			
	3	661–683	red			
	4	847–886	NIR			

* MISR has nine cameras pointing to 0°, ±26.1°, ±45.6°, ±60.0° and ±70.5° view zenith angles.

** The nadir viewing camera and all the red bands are at 275 m resolution and other bands at 1.1 km resolution.

In Paper III, the atmospherically corrected MODIS reflectance for red and NIR bands at 250 m resolution were used. The data for three 8-day periods from the growing season 2001 (July 4th–11th, August 13th–20th, August 21st–28th) were obtained. The average reflectance of three data sets was also calculated.

In Paper V, MODIS BRDF model parameters and nadir BRDF-adjusted surface reflectance (NBAR) products were used (Schaaf *et al.* 2002). This data are provided at 1 km resolution for 16-day periods. MODIS BRDF/Albedo algorithm makes use of a kernel-driven linear BRDF model, which relies on the weighted sum of an isotropic parameter and two functions (kernels) of viewing and illumination geometry. The BRDF model parameters are provided for MODIS bands 1–7 and three broadbands. The model parameters are used for producing the NBAR data for bands 1–7. In principle, MODIS NBAR data correspond to temporal composite data, which have been normalised for BRDF effects. MODIS data were obtained for the snow-free period (9 June–13 September) of the years 2000–2006. The data were used for calculating average of nadir-view BRF and NDVI, average BRDF model parameters and selected multiangular indices for the peak of the growing season period (V: Table 2). The temporal variability of the reflectance was described by the mean, maximum and range of BRF and NDVI over the growing season (DeFries *et al.* 1995a). Three cloud-free MODIS granules at 1 km resolution were used for comparison.

Table 2. Summary of the preprocessed ASTER, MODIS and MISR data products, and global land cover data sets.

Data product	Description	Reference	Used in
<i>ASTER</i>			
<i>AST_07</i>	ASTER level 2 surface reflectance, version 2.8. Bands 1–9. Pixel size 15/30 m.	Abrams 2000	I–III
<i>MODIS</i>			
MOD021KM MYD021KM	MODIS level 1B radiance, collection 5. Bands 1–7. Pixel size 1 km.	MCST 2006	V
MOD09Q1	MODIS surface reflectance, collection 4. Bands 1 and 2. Pixel size 250 m.	Vermote <i>et al.</i> 2002	III
MOD43B1	MODIS BRDF model parameters, collection 4. Bands 1–7. Pixel size 1 km.	Schaaf <i>et al.</i> 2002	V
MOD43B4	MODIS nadir BRDF-adjusted reflectance, collection 4. Bands 1–7. Pixel size 1 km.	Schaaf <i>et al.</i> 2002	V
<i>MISR</i>			
MI1B2T	MISR terrain projected top-of-atmosphere radiance, version F02_0020. Pixel size 275 m/1.1 km.	Bothwell <i>et al.</i> 2002	IV
MIL2ASLS	MISR surface bidirectional reflectance factor (BRF), version F04_0013. Pixel size 1.1 km.	Bothwell <i>et al.</i> 2002	IV
<i>Global land cover data set</i>			
MODIS-IGBP (MOD12Q1)	MODIS global land cover, IGBP legend, collection 4. Pixel size 1 km.	Friedl <i>et al.</i> 2002	VI
MODIS-VCF (MOD44B)	MODIS vegetation continuous fields, collection 3. Pixel size 500 m.	Hansen <i>et al.</i> 2003	VI
GLC2000-NE	Global Land Cover 2000 Northern Eurasia. Based on SPOT-4 VEGETATION data. Pixel size (1/112) ^o .	Bartalev <i>et al.</i> 2003	VI

Multispectral and -angular data (Diner *et al.* 1998, 2002). MISR has nine cameras: four cameras point in forward direction, one points towards nadir and four point in aftward direction. The nominal view angles of the cameras are 0° , $\pm 26.1^\circ$, $\pm 45.6^\circ$, $\pm 60.0^\circ$ and $\pm 70.5^\circ$. Each of the nine cameras has four bands in the VNIR spectral range. MISR data are acquired at a spatial resolution of 275 m, but in the 'global mode' the original resolution is preserved only for the red bands and nadir camera, the other bands being averaged to 1.1 km resolution.

A range of standard MISR data products are 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). Terrain projected top-of-atmosphere radiance data and surface bidirectional reflectance factors for 29 July 2000 were used (IV).

4.3 Global land cover data sets

Three global scale land cover data sets were evaluated in Paper VI: Global Land Cover 2000 Northern Eurasia map (GLC2000-NE), MODIS global land cover map IGBP legend (MODIS-IGBP) and percentage tree cover layer of MODIS vegetation continuous fields product (MODIS-VCF). These products differ in terms of classification legends, employed satellite data and mapping methodology.

The GLC2000 land cover database has been produced by an international partnership of over 30 research groups, coordinated by European Commission's Joint Research Centre (Bartholomé & Belward 2005). The database consists of 18 separately produced continental and regional scale maps, which have been harmonized also to a global map. Most of the maps have been produced by unsupervised classification, the main input data being the SPOT-4 VEGETATION data for 1999 and 2000. The data are delivered in the Lat/Lon projection and have the spatial resolution of $(1/112)^\circ$, which corresponds to resolution of 1 km at the equator. The legend of GLC2000-NE map has 27 classes (Anon. 2003; Bartalev *et al.* 2003).

The MODIS-IGBP map at approximately 1 km resolution has been produced by Boston University (Friedl *et al.* 2002). A supervised decision tree classifier, a global database of training sites interpreted from fine resolution images and MODIS data for the year 2001 have been used in the classification. The MODIS IGBP legend has 17 classes.

The MODIS-VCF has been produced by University of Maryland (Hansen *et al.* 2003). The evaluated version of the product includes percentage tree cover, percentage non-tree vegetation and percentage bare layers at 500 m resolution, but only the tree cover layer was studied. The layers have been generated using global training data and phenological variables derived from monthly MODIS composites for November 2000 – December 2001. A regression tree algorithm has been used in model calibration.

4.4 Integration of multiresolution reference and satellite data

Several approaches were required to integrate multiresolution reference and satellite data in Papers I–VI. The selected method depended on the type of ground reference data and spatial resolution of the satellite data (Figure 6).

In Paper I, ASTER data at 15 and 30 m resolution were used together with plotwise field measurements. The reflectance was averaged for 25 m buffer zones around the field plots (on average nine VNIR pixels and two SWIR pixels). The averaging was used for reducing the geometric errors both in the GPS measurements and image rectification, and to account for difference in the pixel size of VNIR and SWIR bands.

In Paper II, ASTER reflectance was averaged for forest stands. A large number of pixels were located on the borders of the forest stands because the mean stand size is relatively small (II: Figure 3). Therefore only the pixels located in the core areas of the forest stands (i.e. pixels not crossing the stand boundary) were used in calculation of average reflectance (Kilpeläinen & Tokola 1999; Mäkelä & Pekkarinen 2004). This operation should compensate for the geometric errors in the remote sensing data and stand maps. The forest stands are too small to be integrated directly with 250 m resolution MODIS pixels. Therefore, the standwise models developed in Paper II were applied to MODIS data (III) after intercalibration of the ASTER and MODIS red and NIR bands by linear regression (Häme *et al.* 1997; III: Figure 4). The procedure avoids the calibration of the mixed pixels and averaging of the ground reference data.

In Papers IV and V, the ground reference data (biotope inventory polygons) is comparable to Papers II and III (forest stands), but the satellite data have coarser resolution. Therefore, the ground reference data were averaged for pixels. All the biotope inventory data were rasterized and transformed to the projections of the satellite data, which avoided resampling it. Then percentage tree cover (IV, V), tree height (IV) and some ancillary variables (percentage shrub cover, fractional covers of water and mire) were calculated for the pixels.

The reference percentage tree cover data were derived for evaluating the MODIS-VCF data using the previous method (VI). However, the determination of the representative land cover labels for the coarse resolution pixels was more challenging. First, the biotope inventory polygons were labelled to match the GLC2000-NE and MODIS-IGBP classes according to the tree cover, tree height, species composition, shrub cover and biotope class (VI: Table 1). The land cover class was determined for coarse resolution pixels by majority rule (VI: Figure 2). First, it was tested if a pixel is land or water. If the majority of the pixel was land, the class in the next level was determined, and then in the third level, if necessary. The method compensates for the different level of detail in the different classes. For example, none of the forest classes necessarily cover the majority of the pixel area although the forest classes together might cover the majority of the pixel. If pixel was forested, the forest class was determined according to the fractional covers of needleleaf and broadleaf trees. The method also enables the identification of complex classes, because fractional covers of different classes are known. The reference forest extent from CORINE data was determined from a forest–non-forest mask by majority rule (V, VI).

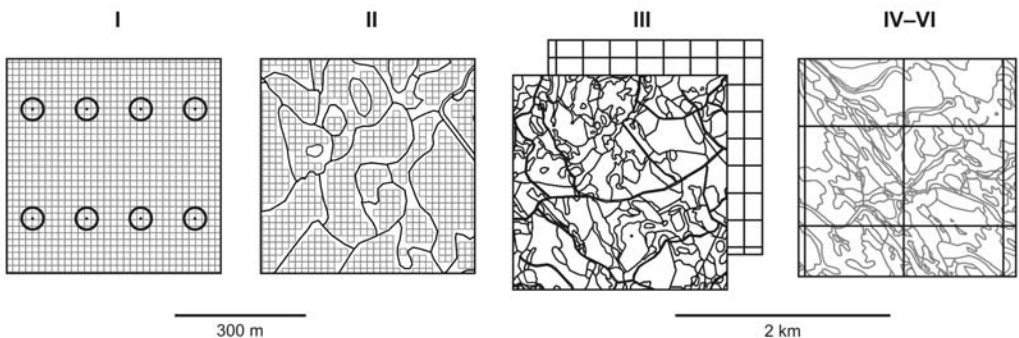


Figure 6. Summary of the methods used for integrating multiresolution reference and satellite data in Papers I–VI. The fine resolution satellite data were averaged for field plots (I) or stands (II). In Paper III, the models developed for stands (II) were applied to the medium resolution pixels without spatial overlay of the data sets. In Papers IV–VI, the attributes and land cover labels were determined for medium and coarse resolution pixels by averaging the standwise reference data (IV–VI) or by majority rule (V, VI).

4.5 Model calibration and evaluation

A variety of methods were applied to examine the strengths of statistical relationships and to calibrate models for forest attributes. The principal methods were correlation analysis (I, II), linear regression (I), nonlinear regression (I, II), neural networks (II, IV) and generalized linear models (V). The independent calibration and evaluation sets were used in all the papers. The data sets were either split randomly (I, IV, V) or two separate data sets were used (II).

In Paper I, the reduced major axis (RMA) regression was used for simple linear regression between biomass, LAI and ASTER data (Cohen *et al.* 2003a). The more commonly used ordinary least squares (OLS) regression is often an inappropriate method to relate remotely sensed data and forest attributes (Curran & Hay 1986; Ardö 1992; Cohen *et al.* 2003a). OLS requires the specification of independent and dependent variables, it assumes that independent variable is measured without error, and the estimates have attenuated variation in the direction of estimation in comparison to the observed values. The canonical correlation analysis (CCA) was used in order to apply the RMA regression in a multiple regression context. CCA is a multivariate procedure that maximizes the correlation between two sets of variables, providing a set of weights to align the spectral bands with the variation in the forest attribute or attributes. The resulted CCA scores can be used equally to more traditional SVIs in simple linear regression (Cohen *et al.* 2003a).

In Papers I and II, the nonlinear relationships were studied by data transformations and nonlinear regression analysis. In Paper I, logarithmic transformations of ASTER bands and applicability of power law and exponential models were studied. The models were linearized and model parameters estimated using RMA regression. In Paper II, stand volume and biomass components were estimated using nonlinear multiple regression. The models using ASTER red and NIR bands were applied to medium resolution MODIS data (III).

Neural networks were used for modelling stand volume and biomass (II), and for estimating tree cover and height using multiple MISR band combinations (IV). Neural networks are general-purpose computing tools that can solve complex non-linear problems (Bishop 1995). Their major attraction in estimation of forest attributes using remotely sensed data is that they can be applied without making assumptions about the data distribution (Boyd *et al.* 2002; Fernandes *et al.* 2004). Feed-forward multilayer neural networks were used in Papers II and IV. The models were trained separately for all target variables by investigating various network architectures having one and two hidden layers and variable number of hidden units. The networks were trained using Levenberg-Marquardt algorithm, and early stopping was adopted in order to avoid overfitting of the models (Bishop 1995).

In Paper V, the generalized linear models (GLM) were used for calibrating statistical models between tree cover, coniferous cover, broadleaved cover and MODIS data. GLMs are an extension of linear regression to model non-normal data. GLMs allow a wide range of distributions for the response variable and do not require constant variances. The response variable is connected to the linear predictor through a link function (Dobson 2002). The binomial GLM with logit link (logit or logistic regression) was used for calibrating statistical models between the response variables and MODIS data. The method has been used only rarely to estimate vegetation continuous fields from remotely sensed data (Schwarz & Zimmermann 2005). However, the method has been used for other purposes, for example, to burned area mapping (Koutsias & Karteris 1998) and change detection (Morissette *et al.* 1999). Logit regression is appropriate model for a binomially distributed and bounded (0–100%) response variable, such as tree cover (Schwarz & Zimmermann 2005). The explanatory variables were selected using backward elimination with a strict criterion for variable inclusion (Chisq, $p < 0.0001$). Both linear and quadratic terms of explanatory variables were included to the models. The benefit of using the multiangular variables together with multispectral and -temporal variables was assessed by variation partitioning, which is based on a series of (partial) regression models (Borcard *et al.* 1992). The tree cover models were used for predicting tree cover fields for the northernmost Finland.

The model fit of the linear and nonlinear regression models was assessed by the coefficient of determination (r^2) and fit of the logit regressions by percentage deviance explained (D^2). The agreement of the observed and estimated continuous variables was studied by Pearson correlation coefficient (r) (I, IV–V) or concordance correlation coefficient (r_c) (Cox 2006; VI). The accuracy of the estimates was assessed by the mean absolute error (MAE), root mean square error (RMSE), bias and their relative counterparts, MAE_r , $RMSE_r$ and $bias_r$ (Hyvönen 2002; Mäkelä & Pekkarinen 2004; Schwarz & Zimmermann 2005). The stand volume and biomass estimates were also compared to the municipality and forestry centre level forest inventory statistics (II, III). The categorical variables, i.e. forest–non-forest maps (V) and global land cover maps (VI), were assessed using error (confusion) matrix and standard accuracy statistics, percentage correctly classified, user's and producer's accuracy and kappa coefficient (Foody 2002). In Paper VI, percentage average mutual information (percentage AMI) was also used for assessing the similarity of the maps (Finn 1993).

5. RESULTS AND DISCUSSION

5.1 Continuous field estimation at fine resolution: the sensitivity of reflectance data to forest attributes

The fine resolution satellite images are particularly suitable for examining the sensitivity of reflectance to forest structural and biophysical attributes as it is relatively easy to integrate satellite data with field plots (I) and forest stands (II). The sensitivity of satellite data can be studied also at coarser resolution (IV, V), but the interpretation of the statistical relationships is complicated due to the heterogeneity of land cover within pixels. The fine resolution data also enable the landscape scale mapping of the forest attributes (e.g., Heiskanen 2005) and provides calibration (III) and validation (Morissette *et al.* 2006) of coarser resolution data.

The mountain birch forests and woodlands in northernmost Finland are characterized by low biomass levels and open canopies (I). The mean tree biomass of the field data was only 8.35 t ha⁻¹ and canopy closure of the densest plots around 50–60%. The ASTER red band showed the strongest correlation with biomass ($r = -0.83$) and LAI ($r = -0.85$). Also the NIR band showed a strong positive and the SWIR band 4 a strong negative correlation with the attributes (I: Table 5, Figure 3). The strong correlation with the red band and the direct relationship of forest attributes and NIR data are typical for mountain birch (Dahlberg 2001) and other broadleaved forests (Häme *et al.* 1997; Eklundh *et al.* 2003). The plant pigments in the green leaves absorb radiation effectively in the red spectral range and the canopy reflectance is inversely related to the quantity of the pigments. In NIR range, the leaf reflectance of broadleaf trees is high and the canopy reflectance increases with increasing leaf area. In SWIR range, the reflectance decreases with increasing leaf area as the absorption of water increases (Gates *et al.* 1965; Tucker & Sellers 1986). The logarithmic transformations improved the linear correlations in most bands. Simple Ratio (SR) and NDVI were SVIs having the strongest relationships with biomass and LAI. The linear model was the best for SR and the exponential model for NDVI. The results agree with the other comparisons of SVIs in broadleaved forests (Häme *et al.* 1997; Dahlberg 2001; Eklundh *et al.* 2003) and low and medium LAI values (Broge & Leblanc 2000). However, the SVIs using also SWIR band have been often better than SR and NDVI in the coniferous stands (Nemani *et al.* 1993; Brown *et al.* 2000; Stenberg *et al.* 2004).

The mountain birch biomass and LAI were predicted most accurately by CCA scores (I: Figure 5). The logarithmic transformations of the bands were used as they improved the linear relationships. CCA is comparable to the multiple regression analysis (Cohen *et al.* 2003a), which usually offers substantial improvement over simple regressions (Fassnacht *et al.* 1997; Dahlberg 2001; Eklundh *et al.* 2003). CCA scores explained 84% and 85% of the variability in biomass and LAI, respectively.

The lowest RMSE was 3.45 t ha⁻¹ (41.0%) for biomass and 0.28 m² m⁻² (37.0%) for LAI. The models were applied by Heiskanen (2005) to map biomass and LAI at a landscape scale, and to derive biomass and LAI statistics for mountain birch biotopes. The results were reasonable in comparison to biomass and LAI estimates in the literature. However, the advantage of the remotely sensed estimates is that summary statistics for different mountain birch biotopes are based on a relatively large number of stands in comparison to the field studies (Heiskanen 2005; Tømmervik *et al.* 2005).

The biomass levels in Paper II were much higher than in Paper I (mean tree biomass > 100 t ha⁻¹). The dominant tree species were also coniferous. The correlations between stand averaged ASTER reflectance and forest attributes were statistically significant although not particularly strong (II: Table 3). The green band had the strongest correlation with stand volume and most biomass components (r between -0.67 and -0.69). The NIR band had the strongest correlation with stand age (r -0.40) and biomass of understory vegetation (r -0.36). The band 4 was the SWIR band showing the highest correlations. In the coniferous forests, green and SWIR reflectance have typically had the strongest correlations with stand volume (Ardö 1992; Hyvönen 2002) and LAI (Fassnacht *et al.* 1997). The correlation of the stand age with NIR data have been also reported (Hyvönen 2002). All the relationships were inverse, which is typical for coniferous stands (Ardö 1992; Nilson & Peterson 1994; Häme *et al.* 1997; Hyvönen 2002; Eklundh *et al.* 2003). In contrast to the broadleaved stands, the reflectance of coniferous stands is reduced in the NIR range, because of the pronounced within-shoot scattering (Rautiainen & Stenberg 2005). The results also show that it does not make a significant difference if biomass conversion for stand volume is done before or after the model calibration.

In Paper II, red and NIR reflectance predicted the forest attributes more accurately than any other single band or band combination (II: Table 5). The fits of non-linear regression models were the best for stand volume, biomass components of trees and total biomass of all forest vegetation with only minor differences (r^2 between 0.54 and 0.59). The model fits were worse for stand age and biomass of understory vegetation. When the regression models were applied to the validation data, RMSE_v varied mostly between 24.6% and 53.7%. Low biomass levels were overestimated and high biomass levels underestimated. The biases were significant for almost all the attributes. The neural networks produced slightly better model fits and lower biases but the differences were not statistically significant (II: Table 6, Figure 5).

The model fits in Paper I are comparable or better than in most of the similar studies in broadleaved or coniferous forests (Ardö 1992; Häme *et al.* 1997; Dahlberg 2001; Chen *et al.* 2002; Eklundh *et al.* 2003; II). In Paper II, the estimation error of stand volume is also lower than in many previous studies in boreal coniferous and mixed forests (II: Table 7). The typical broadleaved stands in the boreal and temperate zone consist of multiple tree species, which weakens the relationships (Eklundh *et al.* 2003). Therefore, the relatively strong relationships observed in mountain birch forests are partly explained by the single tree species. In the mountain birch forests LAI is also relatively low and reflectance is not saturated as severely as in the higher biomass forests. However, in the open mountain birch stands the undergrowth vegetation has a strong effect to the reflectance. The undergrowth vegetation is the most luxuriant in the forest type having the highest overstory LAI. On the other hand, the undergrowth is scarce in the sparsest mountain birch biotopes. Therefore, the correlation of the undergrowth and overstory LAI can partly explain the strong relationships. The effect of undergrowth vegetation could also explain why SVIs using the SWIR band could not improve the models in comparison to SR and NDVI. The forest reflectance simulations could clarify the role of undergrowth vegetation in the reflectance of mountain birch stands (Kuusk *et al.* 2004; Rautiainen *et al.* 2007).

5.2 Continuous field estimation at medium and coarse resolution: biomass estimates for a large area and assessment of optical information sources

In Paper III, the non-linear regression models developed for biomass and stand volume (II) were applied to medium resolution MODIS data (red and NIR bands at 250 m resolution). The estimation was limited to the forests on mineral soils by using forest mask derived from the CORINE data. The validation of biomass estimates is often limited by the lack of appropriate reference data (Lu 2006). Because the estimation accuracy of the stand volume was approximately the same as that of biomass, the stand volume estimates were compared to the Forestry Centre level estimates provided by the Finnish NFI (III: Table 2, Figures 5a & 6). The differences in Forestry Centre level stand volumes varied between -16.0 and $10.6 \text{ m}^3 \text{ ha}^{-1}$ (-12.7% and 8.0%). The estimation error for the whole of southern Finland was $-4.0 \text{ m}^3 \text{ ha}^{-1}$ (-3.6%). Furthermore, the biomass estimates for southern Finland were rather close to the biomass estimates based on NFI data (Liski *et al.* 2006; III: Table 3).

Paper III demonstrates that models based on standwise forest inventory and fine resolution ASTER data can be applied to the medium resolution MODIS data. The accuracy of large area estimates is relatively good if the small amount of calibration data is considered. However, the per-pixel accuracy of the estimates might be poor. The fine resolution satellite data have been used commonly as an intermediate step in linking the reference data with medium and coarse resolution data (Iverson *et al.* 1989; Tomppo *et al.* 2002). However, the models have been typically calibrated separately between the reference and fine resolution data, and between fine resolution maps and coarser resolution data. Therefore, the advantage of the method used in Paper III is that regression models need to be calibrated only once. This could also reduce the co-registration errors between the reference and satellite data (discussed in 5.4). The models based on forest stands also correspond better to the scale of medium resolution pixels than models based on field plots and fine resolution data.

Paper IV examined the potential of multiangular information for tree cover and tree height estimation in Northernmost Finland using single-orbit MISR data. The MISR BRF had a strong dependence on view zenith angle (IV: Figures 5 & 6), although the view azimuth angle did not correspond exactly to the principal plane (IV: Figure 3). The directional reflectance of forest stands is typically characterised by strong reflectance in the backscatter direction with a peak in the hot spot. The directional dependency of reflectance is usually weaker in the forward scatter direction and reflectance reduces quickly as view azimuth angle diverges from the principal plane (Kleman 1987; Russell *et al.* 1997; Deering *et al.* 1999). The atmospheric correction has a major effect on the directional reflectance because of the path radiance and directional scattering of the atmosphere, particularly in the shortest wavelengths and largest view angles (Deering & Eck 1987; Barnsley *et al.* 1997).

In Paper IV, the most accurate tree cover and height estimates were produced by neural networks when using all the spectral-angular bands as input data. The multiangular data produced more accurate estimates than the equivalent nadir-view bands (IV: Tables 2 & 3, Figures 7 & 8). The smallest RMSEs were 6.5% and 2.0 m for tree cover and tree height at 275 m resolution (RMSE_t 56.1% and 37.6%), and 4.1% and 1.3 m at 1.1 km resolution (36.9% and 25.4%). The relative estimation errors were considerably larger when coniferous and broadleaved tree cover were estimated separately, which is typical in species-wise estimation of forest attributes (Tokola & Heikkilä 1997; Hyvönen 2002; Mäkelä & Pekkarinen 2004). The tree cover and broadleaved tree cover were estimated most accurately by the multiangular red bands and coniferous tree cover by the NIR bands. The green bands were the best in the tree height estimation, but the difference to the red and NIR bands was small. The largest estimation errors occurred in the mires and low shrublands, but the multiangular bands reduced the overestimation in these sparsely wooded regions (IV: Figures 13–16).

The assessment of optical information sources was continued in Paper V, which examined the feasibility MODIS data at 1 km resolution for tree cover mapping. According to the results, the multitemporal and -angular variables increase the accuracy of tree cover estimates and forest–non-forest

mapping in comparison to the peak of the growing season nadir-view multispectral data (V: Tables 4 & 8). The tree cover estimates and forest–non-forest maps were the most accurate when produced by the multitemporal and -angular explanatory variables together. The smallest RMSE of the tree cover estimates was 4.6% (RMSE_r 42.2%). Although the pure effect of the multiangular variables was small in the models (V: Figure 4), the improvement was substantial in the low tree covers and mires in comparison to the peak of the growing season nadir-view data and multitemporal variables (V: Figures 6 & 8). The season of the data acquisition also affected the model fit and accuracy, the late-spring and early-summer data being superior to mid- and late-summer data (V: Tables 4 & 7).

The per-pixel accuracy has been assessed only rarely for forest attributes at medium and coarse resolution (Hansen *et al.* 2002). However, the estimation accuracies in Papers IV and V seem to be comparable with other regional scale studies (e.g., Schwarz & Zimmerman 2005). The results clearly demonstrate how optical satellite data typically overestimates forest attributes in open forests and non-forested areas. This occurs because the reflectance of undergrowth and other non-tree vegetation resembles to some extent the reflectance of trees. Typically the reflectance also saturates in the dense forests, which causes underestimation of forest attributes (DeFries *et al.* 2000b).

The potential of the angular information to improve the discrimination of land cover classes and estimation accuracy of continuous fields have been indicated by several studies in a multitude of environments (Abuelgasim *et al.* 1996; Barnsley *et al.* 1997; Bicheron *et al.* 1997; Sandmeier & Deering 1999a, 1999b; Grant 2000; Lovell & Graetz 2002; Zhang *et al.* 2002; Braswell *et al.* 2003; Brown de Colstoun & Walthall 2006; Armston *et al.* 2007; Su *et al.* 2007). Papers IV and V support the conclusions of the earlier studies, which have stated that multiangular data have increased sensitivity to the vegetation structure, it has reduced sensitivity to the variability of undergrowth vegetation, and that use of it can reduce the confusion of the structurally different but spectrally similar land cover types, such as mires and forests (Barnsley *et al.* 1997; Sandmeier & Deering 1999a; Gemmel 2000). Although the potential of multiangular data has been demonstrated, the use of such data remains rare in land cover mapping. In Paper IV, MISR data was used for examining the potential of multiangular data for tree cover and height estimation, but MISR images are not suitable for large scale land cover mapping without atmospheric correction and use of an appropriate BRDF model. MODIS BRDF model parameters product used in Paper V provides data that is more readily applicable to land cover mapping, either in the form of model parameters or multiangular indices.

The advantage of using multitemporal information has been demonstrated at a variety of scales and spatial resolutions (Wolter *et al.* 1995; Toivonen & Luoto 2003; Hansen *et al.* 2005). Hansen *et al.* (2005) compared the single-date images, monthly composites and phenological metrics for tree cover mapping and demonstrated that the advantages of the data sets depend on the extent of the study area. Single-date images were superior at local and regional scales and image composites and temporal metrics at continental and global scales. The effect of seasonality on the estimation accuracy has been studied only occasionally. Chen & Cihlar (1996) found that late spring Landsat TM images were superior to summer images for determining overstory LAI for boreal coniferous stands. Ranson *et al.* (2004a) found that tundra–taiga boundary was sharply distinguished by the maximum red band reflectance in the spring time. At coarse spatial resolution, the interpretation of the phenological effects is complicated by the land cover heterogeneity within pixels. However, early-summer seems to be the most appropriate time for estimating broadleaved cover in northernmost Finland, because the mires are wet, and mire, heath and undergrowth vegetation are not yet fully developed, but birch leaves are almost full-sized. Furthermore, the contrast between the dark coniferous forests and other land cover types seems to be the best in the mid- and late-summer, when mires are drier, birch leaves are full-sized and mire and heath vegetation is most luxuriant.

5.3 Perspectives from the global scale land cover data

The evaluation of the global scale land cover data sets in northernmost Finland (VI) gives perspective on the current limitations of the coarse resolution land cover mapping in the tundra–taiga transition zone. The evaluation also demonstrates the differences of the categorical and continuous land cover data and provides a global scale reference for the regionally calibrated tree cover estimates (IV, V) and forest–non-forest maps (V).

According to the results, the categorical land cover depictions (GLC2000-NE, MODIS-IGBP) are inaccurate over northernmost Finland if assessed in the most detailed level of the classification legend (VI: Figures 3–5, Table 4). The maps have difficulties in classifying evergreen needleleaf and deciduous broadleaved (mountain birch) forests according to the class descriptions (VI: Table 1). Wetlands (mires) are also either lacking from the maps or misclassified. The results support the conclusion of Cohen *et al.* (2006), who state that MODIS-IGBP map is based more on colloquialism than strict class definitions. Therefore, the accuracy is poor if quantitative class definitions are strictly followed in the map assessment. Naturally, inaccuracies in the classifications appear very evident over vegetation transitions, where the class boundaries should follow the exact tree cover and height thresholds. The MODIS-VCF tree cover estimates are inaccurate in comparison to the regionally calibrated models in Papers IV and V (VI: Table 5, Figure 7). Similarly to the regional scale models, MODIS-VCF overestimates low tree cover values and underestimates large values (VI: Figure 8), which is in line with previous assessments (Schwarz & Zimmerman 2005; White *et al.* 2005). However, although the accuracy of the maps is low when strict class definitions are followed, the land cover data sets can depict the CORINE forest–non-forest boundary (tree cover threshold 15%) rather accurately (VI: Table 6). The most accurate forest–non-forest masks have only slightly lower accuracy than regionally calibrated masks at 1 km resolution (V).

There are many factors, which could explain the low accuracy of the global land cover data sets. The difficulty of mapping open forests, shrublands and wetlands has been considered as a major reason for the disagreement of global land cover data sets (Latifovic *et al.* 2004; Giri *et al.* 2005). The reasons for tree cover over- and underestimation in MODIS-VCF are likely to be the same as in the regional scale studies (IV, V), i.e. the effect of undergrowth vegetation, the spectral confusion of forest and non-forest vegetation and the saturation of reflectance. The GLC2000-NE map is also based on the unsupervised classification and it is unlikely that clusters would correspond exactly to the specific tree cover and height thresholds. On the other hand, the accuracy of the MODIS-IGBP and MODIS-VCF products based on supervised methods is dependent on the quality of the training data. There is only a small amount of training data from the regions comparable to the study area and from wetlands, which show huge variability at global scale (Anon. 2006).

The definition of classification legend is a very important part of the categorical land cover characterization (DiGregorio 2005). The smaller the map extent, the more regional emphasis can be given in the legend. On the other hand, the global legend has to work everywhere on Earth and it is inevitably a compromise when evaluated in a regional context. This difference is evident when the legends of GLC2000-NE and MODIS-IGBP are compared. The class names and class descriptions of GLC2000-NE are familiar to the region and regionally important classes related to tundra and wetlands have been taken into account. However, the GLC2000 map can not be considered as a true global land cover classification because it has been combined from several separately classified regional/continental scale maps (Hansen *et al.* 2005). Therefore, the land cover map is not consistent in the global scale, not even in the circumpolar scale, which is a major weakness of the data set. A well-defined legend is also a prerequisite for the successful accuracy assessment, as overlapping, incomplete and vaguely defined classes complicate the determination of the reference class (Cohen *et al.* 2003b). A novel tool for the legend definition is described in DiGregorio (2005).

The potential of continuous field products to provide improved land cover characterization over classification has been noted by several authors (DeFries *et al.* 1995b; Fernandes *et al.* 2004; Hansen & DeFries 2004; Lambin & Linderman 2006). In principle, the continuous field estimation could provide improved methods for unbiased land cover characterization over large areas by using coarse resolution data, and for depicting the spatial gradients and temporal changes. These improvements would be important in the regions where land cover is heterogeneous and composed of spatial gradients, like in the tundra–taiga transition zone. The flexibility of the continuous field databases (DeFries *et al.* 1995b; Cohen *et al.* 2001) would also enable the depiction of the forest extent by variable criteria (V: Figure 7). The categorical and continuous land cover characterizations have been usually evaluated separately. For example, MODIS-VCF has been excluded from the recent studies on the agreement of the global land cover products (Latifovic *et al.* 2004; Giri *et al.* 2005; McCallum *et al.* 2006; Waser & Schwarz 2006) although the forest extent is key information, which can be derived from both types of maps. The one disadvantage of the continuous field estimation is the need for quantitative calibration data, which have limited availability and are more expensive to collect than qualitative training data for classification (Kasischke *et al.* 2004). However, in some regions, such data exists in the forest inventory databases and that data could be used more efficiently (II, IV, V). Another disadvantage is the need to produce separate data layers for all the required land cover characteristics (Kasischke *et al.* 2004). Furthermore, all the land cover characteristics are not easily translated into quantitative variables to be inferred from satellite data (Cihlar 2000). Wetlands and mires are a good example of such land cover type.

5.4 Factors affecting the estimation accuracy and sources of uncertainty

The estimation of forest attributes such as biomass and tree cover from remotely sensed data is a complex procedure in which many factors interactively affect the estimation accuracy (e.g., Lu 2006). In addition to the sensitivity of the optical remote sensing data to forest attributes, the other factors include, among others, the spatial resolution, the correspondence of the reference and satellite data, data quality, and the selection of estimation and evaluation methods. Understanding and identifying the sources of uncertainty in the models is indispensable for improving estimates of the forest attributes and land cover characterizations.

The spatial resolution of the satellite data has a major effect on the estimation accuracy, the estimation errors typically decreasing with coarser pixel size (Hagen *et al.* 2002; Hansen *et al.* 2003; IV). This is partly explained by the reduced variation in data when it is averaged to the lower resolution. However, the spatial averaging reduces also the adjacency effects and improves the spatial correspondence between the reference and satellite data (Townshend *et al.* 2000; Huang *et al.* 2002; Tan *et al.* 2006). Similarly, if forest attributes are estimated for stands, the estimation errors are typically the largest for the smallest stands (Hyypä *et al.* 2000; Hyypä & Hyypä 2001; Mäkelä & Pekkarinen 2004; II: Figure 8). The estimates also improve as the extent of inventoried area is increased (Tokola & Heikkilä 1997; III).

When relating ground reference data to remotely sensed data, it is important that reference data represent a similar area to the pixel of the image (Wulder 1998). The area represented by plotwise field data corresponds roughly to the pixel size of fine resolution images, such as Landsat TM and ASTER. Therefore the models are applicable to the fine resolution images and resulting maps provide necessary upscaling for calibration and evaluation of coarse resolution models (Iverson *et al.* 1989; Tomppo *et al.* 2002; Cohen *et al.* 2003b, Morissette *et al.* 2006). However, the pixels do not correspond to any meaningful unit in the field. Also the precise co-registration of the field and satellite data can be difficult (Halme & Tomppo 2001). The advantage of the standwise data is that map objects correspond to ‘homogeneous’ units (forest stands) avoiding the mixed pixels. However, the regression models are not directly applicable to the fine resolution pixels, but the image should be first segmented to stands

of similar size (Pekkarinen 2004). In Paper III, the models were applied to the satellite data having approximately the same pixel size with the stands. If inventory polygons are plenty and have relatively small size in relation to the pixel resolution, the continuous attributes can be averaged within pixels (IV, V).

The uncertainty in co-registration of field and satellite data is another source of unexplained variation. Although the georegistration accuracy of the preprocessed ASTER product was not sufficient for relating field plots directly with pixels, the fine spatial resolution VNIR bands enabled the accurate geometric correction (I, II). The effect of co-registration errors was also reduced by using buffer zones in the retrieval of reflectance values for the field plots (I). The stand level field data is also assumed to be less sensitive to the co-registration errors than plot-level data (Kilpeläinen & Tokola 1999; Hyvönen 2002; Mäkelä & Pekkarinen 2004; II). In the medium and coarse resolution studies the co-registration errors are likely to be smaller (Hagen *et al.* 2002; IV–VI). The mean georegistration error of MISR data is below 60 m (standard deviations ranging from 100 to 300 m) and the co-registration of most of the cameras is within one pixel (Diner *et al.* 2002; Jovanovic *et al.* 2002). The MODIS data have also sub-pixel georegistration accuracy (Wolfe *et al.* 2002). The mismatch between grid cells and observations create gridding artifacts to the MODIS data used in Papers III and V (Wolfe *et al.* 1998; Tan *et al.* 2006). Those have implications for the algorithm calibration and validation at the pixel level, because the average overlap between observations and grid cells is less than 30% (Tan *et al.* 2006). One way to improve the correspondence would be to aggregate data to coarser resolution. An advantage of the method used in Paper III is that it does not require spatial overlay of the reference and MODIS data, which minimizes the effects of georegistration errors and gridding artifacts.

The inaccuracies in calibration and validation data can also reduce model fit and bias accuracy statistics. The errors in the field measurements and allometric models create uncertainty to the biomass and LAI models in Paper I. The accuracy of the standwise reference data in Papers II and III is determined by the errors in standwise inventory and in biomass conversions. The standard error of standwise inventory is typically around 20–30% (Poso 1983; Koivuniemi & Korhonen 2006). The errors of the biotope inventory data (IV–VI) have also been estimated to be within the typical error of the standwise inventory (Kunnari 2000). The averaging of the biotope inventory data to the resolution of MISR and MODIS is likely to increase its accuracy (IV, V). The geometric and thematic accuracy of the Finnish CORINE Land Cover 2000 data is reported by Törmä (2005). Some disagreements between the forest–non-forest maps (V: Figure 10) could be due to the classification errors in the CORINE data. However, the thematic aggregation of the map to the forest–non-forest level and upscaling of it to 1 km resolution is likely to improve the accuracy (V, VI).

Another source of uncertainty is data quality. The topographic normalization can produce artifacts to the image data because of the mismatch in DEM and image resolution (Gu & Gillespie 1998). The topographic correction of ASTER data is unlikely to affect the results of Paper I, because the field plots were not located on steep slopes. However, the artifacts of topographic normalization could be important when images are used for mapping biomass and LAI fields (Heiskanen 2005). The medium and coarse resolution temporal composites contain typically more artifacts than single images. Therefore, it can be preferable to use single images in local and regional scale studies (Hansen *et al.* 2005). The noise is also emphasized when multitemporal and multiangular variables are derived (V). The artifacts can originate from the gridding and compositing of the satellite data (Tan *et al.* 2006), from the inaccurate surface reflectance retrieval (atmospheric correction) or from the integration of several data sets at multiple resolutions (IV). The missing data, sub-pixel snow patches and phenological variability can also create noise. Also the topography can affect the multiangular data (Schaaf *et al.* 1994; V). Sometimes averaging seems to provide a possible means for noise reduction (III, V). The high temporal repeatability is a major advantage of the medium and coarse resolution data, but this advantage is diminished by temporal averaging. In paper V, the noisiness of the MODIS BRDF/Albedo data might reduce somewhat the explanatory power of multiangular variables (V: Figure 4). The future MODIS products having higher spatial resolution and combining MODIS

and MISR data should provide better data quality, because the number of cloud free observations is increased (Roy *et al.* 2006).

Several statistical methods have been used for estimating the continuous fields of land over and forest attributes (e.g., Fernandes *et al.* 2004). Several methods were also employed in this thesis. The linear regression models are simple to fit and apply. RMA regression is better suited for remote sensing data than ordinary least squares method and CCA enables the use of RMA comparably to the multiple regression analysis (Cohen *et al.* 2003a; I). The transformations of the explanatory variables and non-linear regression models can be used for modelling the non-linear relationships when the data amount is little and/or the statistical relationships are relatively simple, for example, the analysis is restricted to one land cover or forest type (I, II). The non-parametric neural networks are an appropriate method when data are readily available, the assumptions of the regression analysis are difficult to meet and statistical relationships are complex, for example, due to the heterogeneity of land cover (IV). However, the neural networks can be time consuming to fit and difficult to apply to satellite data. In Paper II, the regression models and neural networks performed very similarly (II: Figure 5), which is equal to results of Hyypä *et al.* (2000). GLMs are also suitable for modelling complex relationships. The logit regression models are easy to fit and models produce values only in a realistic range (Schwarz & Zimmerman 2005). The models are also easy to apply for predictions in GIS (V). Variation partitioning provides a method for studying the relative explanatory power of different explanatory variable groups (V). However, when studying the explanatory power of the optical domains, it can be difficult to separate spectral, temporal and angular information as domains are not independent but overlap (Asner *et al.* 2003).

The problem of the empirical (statistical) models is that they are site and sensor specific. Therefore, the statistical models of forest attributes are only rarely applicable outside the area of calibration (Foody *et al.* 2003). Many physical reflectance models have been developed (e.g., Verhoef 1984; Li & Strahler 1985; Kuusk & Nilson 2000) and can be used for simulating the effect of different stand characteristics on canopy reflectance, and for inverse modelling to estimate canopy characteristics by numerical inversion techniques (Asner *et al.* 2003; Nilson *et al.* 2003). The promise of the forest reflectance models is that they could provide an interface between forestry databases and satellite data (Nilson *et al.* 2003). However, so far the use of more physically based approaches has been limited mainly to the derivation of biophysical variables at global scale (e.g., Myneni *et al.* 2002).

The greatest source of uncertainty in the evaluation of coarse resolution land cover data sets is related to the determination of reference classifications (VI). To reduce the subjectivity of the assessment, it is important to define classes quantitatively and have quantitative reference data, which enable the classification of the reference data according to the class descriptions (Cohen *et al.* 2003b, 2006). The flexibility of the quantitative reference data also allows the evaluation of several land cover maps by using the same data. The map legends are also resolution dependent. Therefore it is not necessarily feasible to classify fine resolution data (e.g., Landsat ETM+ data, 30 m resolution) by using a legend designed for coarse resolution mapping. The biotope inventory polygons provided a good compromise, because relatively large polygons can be classified by using the coarse resolution legend. The fine resolution land cover maps with fixed legends are more conventional evaluation data. Sometimes the maps are made particularly for the validation purposes, but very often the existing land cover data sets are used (e.g., Waser & Schwarz 2006). If legends are inconsistent, the comparison is difficult. The maps might agree too well, which is particularly true if both maps are based more on colloquialism than quantitative data. Another problem of the remotely sensed reference data is that it might repeat some of the errors in the lower resolution map leading to false agreement. The Finnish CORINE Land Cover 2000 map has been derived using continuous forest attributes (CLC2000-Finland 2005), which reduces the subjectivity of the classification. Furthermore, the data combination with the existing GIS data enabled the accurate mapping of the mires (CLC2000-Finland 2005). Therefore CORINE data provided good reference data for evaluating the forest–non-forest depiction using a regionally meaningful tree cover threshold (V, VI). However, it is important to note that for-

est–non-forest map, which is based on the fine resolution land cover map and majority rule, does not correspond perfectly to map which has been derived from the coarse resolution tree cover estimates by applying a threshold value (V).

6. CONCLUSIONS AND FURTHER STUDIES

This thesis examined the application of optical remote sensing for estimating forest attributes in the boreal forests and tundra–taiga transition zone. More specifically, this thesis focused on investigating the feasibility new satellite data at multiple spatial resolutions, assessing the multispectral, -angular and -temporal information, and providing regional evaluation for the global scale land cover data sets. The study areas were located in the tundra–taiga transition zone in northernmost Finland and in boreal forests of southern Finland. The main conclusions of the thesis are:

- 1) **The statistical relationships between biomass, LAI and fine resolution ASTER data are strong in the single species and low biomass mountain birch biotopes in comparison to higher biomass coniferous stands.** The regression models developed for mountain birch are applicable for estimating the biomass and LAI at local and landscape scales. However, the factors affecting the reflectance of mountain birch stands, particularly the effect of the undergrowth vegetation, should be examined more carefully by a physical forest reflectance model.
- 2) **The combination of standwise forest inventory and fine resolution ASTER data provide a novel method for integrating the ground reference data with medium resolution MODIS data.** The stand level models are less sensitive to mixed pixels and co-registration problems than the pixel level models. The demonstrated approach provides a method for cost-effective biomass estimation over large areas when more accurate national or large scale forest inventories do not exist or independent verification data are needed. However, the applicability of the current method is somewhat limited by the need for a forest mask and further studies should quantify the role of forest mask in the estimation and should consider also peatlands.
- 3) **The multiangular satellite data show potential for improving the accuracy of land cover characterization in the tundra–taiga transition zone.** In northernmost Finland, the use of multiangular data reduced the overestimation of tree cover and tree height in the open mires and low shrublands. The use of BRDF model parameters and multiangular indices are one way to use multiangular data for large scale land cover mapping. Further studies should consider using more physically based models for better utilization of multiangular observations. The finer spatial resolution of the forthcoming data products and coupling of observations from several sensors, for example from MODIS and MISR, will provide improved data for land cover mapping in the near future. Furthermore, as global land cover data sets are usually based on the spectral-temporal information, the use of multiangular data could increase the accuracy of the global scale mapping in the tundra–taiga transition zone.
- 4) **The multitemporal nadir-view data can improve tree cover estimates in comparison to the peak of the growing season data. The coarse resolution data also suggests that the peak of the growing season is not necessarily the optimal time to acquire image data for land cover mapping purposes in northernmost Finland.** Although the availability of multitemporal fine resolution data is limited in the northern latitudes, the medium and coarse resolution data are more readily available. However, to better understand how the time of growing season affects to the estimation accuracy, the observations should be validated by using finer resolution data, which can be related more precisely with field observations.

- 5) **The global land cover data sets have considerable shortcomings in northernmost Finland and should be used with caution in tundra–taiga transition zone.** The accuracy of the land cover maps is difficult to evaluate in the most detailed level of classification, but the accuracy seems to be low in the studied area. Also the global tree cover estimates are biased and inaccurate in comparison to the regionally calibrated estimates. However, if data sets are aggregated to the forest–non-forest level, the agreement with reference data is rather good. The spatial resolution of the data sets is not too coarse for general land cover characterization at circumpolar scale, but the improvement of the spatial resolution could enhance the accuracy. The land cover product calibrated only for the northern boreal forests and tundra, and based on quantitative reference data from the region could have an improved accuracy in comparison to global scale data set. Although this thesis focused on passive optical remote sensing, the use of other remote sensing techniques, such as spaceborne lidar (Ranson 2004b), could provide major improvements to the land cover mapping in tundra–taiga transition zone.
- 6) **The land cover classification and the continuous field estimation do not need to be considered as two separate branches of land cover characterization.** The mapping of the tundra–taiga transition zone as continuous fields is tempting because it is composed of the gradients of forest attributes, such as tree cover and height, particularly at coarser spatial resolutions. There is also potential for the wider use of continuous fields in support of classification. For example, the depiction of the forest classes and extent should be based on the continuous tree cover and tree height fields. The estimation demands quantitative calibration data but can improve the quantitative content of the classes and reduce the subjectivity of the classification.
- 7) **The sensors and preprocessed data sets studied in this thesis have potential for wider use in the remote sensing of land cover and forests.** The possible discontinuity of the Landsat program has turned the attention towards other sensors providing data for similar applications. ASTER images have been used only rarely to study land cover and forests. The extensive use of ASTER is hindered by the relatively small image extent and non-systematic data collection. However, the good spatial resolution of the VNIR bands and spectral correspondence to the other sensors make it a potential data source for fine resolution studies. ASTER SWIR data had only little explanatory power in the estimation of the forest attributes. The medium resolution data, such as MODIS red and NIR bands at 250 m resolution, bridge the gap between the fine and coarse resolution data. MISR has been used only rarely for land cover mapping, but it provides multiangular data in the red spectral band at approximately the same resolution. The preprocessed ASTER, MISR and MODIS data products were principal data in this thesis. All the data were available for free in the Internet. Although some image processing was needed to improve the geometric and radiometric properties of the data, these data products (e.g., surface reflectance data) have potential to reduce considerably the time and effort consumed to the preprocessing of satellite data.
- 8) **The calibration and evaluation of land cover depictions require quantitative reference data and methods for upscaling the reference data to the resolution of satellite data.** As quantitative data is expensive and time consuming to collect, the more effective use of existing digital databases should be encouraged. The standwise forest inventory and biotope inventory databases provided quantitative reference data that were already upscaled to match the medium and coarse resolution pixels. The continuously recorded forest attributes in the biotope inventory database were necessary to reveal that global land cover maps have poor correspondence with quantitative class descriptions. The users who hold accurate regional data sets can have an important role in the independent evaluation of land cover data sets and hence in the improvement of the future products. However, to facilitate the independent evaluation of the land cover maps, the data providers should also reduce the ambiguity of the class descriptions.

REFERENCES

- Abrams M (2000). The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER): data products for the high spatial resolution imager on NASA's Terra platform. *International Journal of Remote Sensing* 21, 847–859.
- Abuelgasim AA, S Gopal, JR Irons & AH Strahler (1996). Classification of ASAS multiangle and multispectral measurements using artificial neural networks. *Remote Sensing of Environment* 57, 79–87.
- Ahti T, L Hämet-Ahti & J Jalas (1968). Vegetation zones and their sections in northwestern Europe. *Annales Botanici Fennici* 5, 169–211.
- Anon. (2003). The Northern Eurasia Land Cover Map Classes (version v3). Available online at: http://www-gym.jrc.it/glc2000/Products/neurasia/ne_v3_legend.pdf.
- Anon. (2006). Validation of the consistent-year V003 MODIS land cover product. Available online at: <http://www-modis.bu.edu/landcover/>.
- Aplin P (2006). On scales and dynamics in observing the environment. *International Journal of Remote Sensing* 27, 2123–2140.
- Ardö J (1992). Volume quantification of coniferous forest compartments using spectral radiance recorded by Landsat Thematic Mapper. *International Journal of Remote Sensing* 13, 1779–1786.
- Armston JD, PF Scarth, SR Phinn & TJ Danaher (2007). Analysis of multi-date MISR measurements for forest and woodland communities, Queensland, Australia. *Remote Sensing of Environment* 107, 287–298.
- Asner GP, JA Hicke & DB Lobell (2003). Per-pixel analysis of forest structure: vegetation indices, spectral mixture analysis and canopy reflectance modeling. In Wulder MA & SE Franklin (eds.): *Remote sensing of forest environments: concepts and case studies*, 209–254. Kluwer Academic, Boston.
- Asner GP, BH Braswell, DS Schimel & CA Wessmen (1998). Ecological research needs from multiangle remote sensing data. *Remote Sensing of Environment* 63, 155–165.
- Baret F & G Guyot (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment* 35, 161–173.
- Barnes WL, TS Pagano & VV Salomonson (1998). Prelaunch characteristics of the Moderate Resolution Imaging Spectroradiometer (MODIS) on EOS-AM1. *IEEE Transactions on Geoscience and Remote Sensing* 36, 1088–1100.
- Barnsley MJ (1999). Digital remotely sensed data and their characteristics. In Longley PA, MF Goodchild, DJ Maguire & DW Rhind (eds.): *Geographical information systems: principles, techniques, applications and management*, 567–580. John Wiley & Sons, New York.
- Barnsley MJ, D Allison & P Lewis (1997). On the information content of multiple view angle (MVA) images. *International Journal of Remote Sensing* 18, 1937–1960.
- Barnsley MJ, AH Strahler, KP Morris & J-P Muller (1994). Sampling the surface BRDF: 1. Evaluation of current and future satellite sensors. *Remote Sensing Reviews* 8, 271–311.
- Bartalev SA, AS Belward, DV Erchov & AS Isaev (2003). A new SPOT4-VEGETATION derived land cover map of Northern Eurasia. *International Journal of Remote Sensing* 24, 1977–1982.
- Bartholomé E & AS Belward (2005). GLC2000: a new approach to global land cover mapping from Earth observation data. *International Journal of Remote Sensing* 26, 1959–1977.
- Bicheron P, M Leroy, O Hautecoeur & FM Bréon (1997). Enhanced discrimination of boreal forest covers with directional reflectances from the airborne polarization and directionality of Earth reflectances (POLDER) instrument. *Journal of Geophysical Research* 102, 29517–29528.
- Bishop CM (1995). *Neural networks for pattern recognition*. 482 p. Clarendon Press, Oxford.
- Bonan GB, FS Chapin & SL Thompson (1995). Boreal forest and tundra ecosystems as components of the climate change. *Climate Change* 29, 145–167.

- Bonan GB, D Pollard & SL Thompson (1992). Effects of boreal forest vegetation on global climate. *Nature* 359, 716–718.
- Borcard D, P Legendre & P Drapeau (1992). Partialling out the spatial component of ecological variation. *Ecology* 73, 1045–1055.
- Bothwell GW, EG Hansen, RE Vargo & KC Miller (2002). The Multi-angle Imaging SpectroRadiometer science data system, its products, tools, and performance. *IEEE Transactions on Geoscience and Remote Sensing* 40, 1467–1476.
- Boyd DS & FM Danson (2005). Satellite remote sensing of forest resources: three decades of research development. *Progress in Physical Geography* 29, 1–26.
- Boyd DS, GM Foody & WJ Ripple (2002). Evaluation of the approaches for forest cover estimation in the Pacific Northwest, USA, using remote sensing. *Applied Geography* 22, 375–392.
- Braswell BH, SC Hagen, SE Froking & WA Salas (2003). A multivariable approach for mapping sub-pixel land cover distributions using MISR and MODIS: application in the Brazilian Amazon region. *Remote Sensing of Environment* 87, 243–256.
- Broge NH & E Leblanc (2000). Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. *Remote Sensing of Environment* 76, 156–172.
- Brown L, JM Chen, SG Leblanc & J Cihlar (2000). A shortwave infrared modification to the simple ratio for LAI retrieval in boreal forests: an image and model analysis. *Remote Sensing of Environment* 71, 16–25.
- Brown S (2002). Measuring carbon in forests: current status and future challenges. *Environmental Pollution* 116, 363–372.
- Brown de Colstoun EC & CL Walthall (2006). Improving global scale land cover classifications with multi-directional POLDER data and a decision tree classifier. *Remote Sensing of Environment* 100, 474–485.
- Callaghan TV, BR Werkman & RMM Crawford (2002a). The tundra–taiga interface and its dynamics: concepts and applications. *Ambio Special Report* 12, 6–14.
- Callaghan TV, RMM Crawford, M Eronen, A Hofgaard, S Payette, WG Rees, O Skre, B Sveinbjörnsson, TK Vlassova & BR Werkman (2002b). The dynamics of the tundra–taiga boundary: an overview and suggested coordinated and integrated approach to research. *Ambio Special Report* 12, 3–5.
- Chapin FS III, ES Zavaleta, VT Eviner, RL Naylor, PM Vitousek, HL Reynolds, DU Hooper, S Lavorel, OE Sala, SE Hobbie, MC Mack & S Díaz (2000). Consequences of changing biodiversity. *Nature* 405, 234–242.
- Chen JM & TA Black (1991). Measuring leaf-area index of plant canopies with branch architecture. *Agricultural and Forest Meteorology* 57, 1–12.
- Chen JM & J Cihlar (1996). Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sensing of Environment* 55, 153–162.
- Chen JM, CH Menges & SG Leblanc (2005). Global mapping of foliage index using multi-angular satellite data. *Remote Sensing of Environment* 97, 447–457.
- Chen JM, G Pavlic, L Brown, J Cihlar, SG Leblanc, HP White, RJ Hall, DR Peddle, DJ King, JA Trofymow, E Swift, J Van der Sanden & PKE Pellikka (2002). Derivation and validation of Canada-wide coarse resolution leaf area index maps using high-resolution satellite imagery and ground measurements. *Remote Sensing of Environment* 80, 165–184.
- Cihlar J (2000). Land cover mapping of large areas from satellites: status and research priorities. *International Journal of Remote Sensing* 21, 1093–1114.
- Clark MJ, AM Gurnell, EJ Milton, M Seppälä & M Kyöstitä (1985). Remotely-sensed vegetation classification as a snow depth indicator for hydrological analysis in sub-arctic Finland. *Fennia* 163, 195–216.
- CLC2000-Finland (2005). *Final report*. 65 p. Finnish Environment Institute, Helsinki.

- Cohen WB, TK Maersperger, ST Gower & DP Turner (2003a). An improved strategy for regression of biophysical variables and Landsat ETM+ data. *Remote Sensing of Environment* 84, 561–571.
- Cohen WB, TK Maersperger, TA Spies & DR Oetter (2001). Modelling forest cover attributes as continuous variables in a regional context with Thematic Mapper data. *International Journal of Remote Sensing* 22, 2279–2310.
- Cohen WB, TK Maersperger, Z Yang, ST Gower, DP Turner, WD Ritts, M Berterretche & SW Running (2003b). Comparison of land cover and LAI estimates derived from ETM+ and MODIS for four sites in North America: a quality assessment of 2000/2001 provisional MODIS products. *Remote Sensing of Environment* 88, 233–255.
- Cohen WB, TK Maersperger, DP Turner, WD Ritts, D Pflugmacher, RE Kennedy, A Kirschbaum, SW Running, M Costa & ST Gower (2006). MODIS land cover and LAI collection 4 product quality across nine sites in the western hemisphere. *IEEE Transactions on Geoscience and Remote Sensing* 44, 1843–1857.
- Colwell RN (1960 ed.). *Manual for photographic interpretation*. 868 p. The American Society of Photogrammetry, Washington D.C.
- Cox NJ (2006). Assessing agreement of measurement and predictions in geomorphology. *Geomorphology* 76, 332–346.
- Curran PJ & AM Hay (1986). The importance of measurement error for certain procedures in remote sensing at optical wavelengths. *Photogrammetric Engineering & Remote Sensing* 52, 229–241.
- Dahlberg U (2001). Quantification and classification of Scandinavian mountain vegetation based on field data and optical satellite images. 23 p. Licentiate thesis, Swedish University of Agricultural Sciences, Department of Forest Resource Management and Geomatics.
- Deering DW & TF Eck (1987). Atmospheric optical depth effects on angular anisotropy of plant canopy reflectance. *International Journal of Remote Sensing* 8, 893–916.
- Deering DW, TF Eck & B Banerjee (1999). Characterization of the reflectance anisotropy of three boreal forest canopies in spring-summer. *Remote Sensing of Environment* 67, 205–229.
- DeFries RS & AS Belward (2000). Global and regional land cover characterization from satellite data: an introduction to the special issue. *International Journal of Remote Sensing* 21, 893–916.
- DeFries RS, MC Hansen & JRG Townshend (1995a). Global discrimination of land cover types from metrics derived from AVHRR pathfinder data. *Remote Sensing of Environment* 54, 209–222.
- DeFries RS, MC Hansen & JRG Townshend (2000a). Global continuous fields of vegetation characteristics: a linear mixture model applied to multi-year 8 km AVHRR data. *International Journal of Remote Sensing* 21, 1389–1414.
- DeFries RS, MC Hansen, JRG Townshend, AC Janetos & TR Loveland (2000b). A new global 1-km dataset of percentage tree cover derived from remote sensing. *Global Change Biology* 6, 247–254.
- DeFries RS, CB Field, I Fung, CO Justice, S Los, PA Matson, E Matthews, HA Mooney, CS Potter, K Prentice, PJ Sellers, JRG Townshend, CJ Tucker, SL Ustin & PM Vitousek (1995b). Mapping the land surface for global atmosphere-biosphere models: toward continuous distributions of vegetation's functional properties. *Journal of Geophysical Research* 100, 20867–20882.
- Diner DJ, JC Beckert, GW Bothwell & JI Rodriguez (2002). Performance of the MISR instrument during its first 20 months in Earth orbit. *IEEE Transactions on Geoscience and Remote Sensing* 40, 1449–1466.
- Diner DJ, GP Asner, R Davies, Y Knyazikhin, J-P Muller, AW Nolin, B Pinty, CB Schaaf & J Stroeve (1999). New directions in Earth observing: scientific applications of multi-angle remote sensing. *Bulletin of the American Meteorological Society* 80, 2209–2228.
- Diner DJ, JC Beckert, TH Reilly, CJ Bruegge, JE Conel, RA Kahn, JV Martonchik, TP Ackerman, R Davies, SAV Gerstl, HR Gordon, J-P Muller, RB Myneni, PJ Sellers, B Pinty & MM Verstraete (1998). Multiangle Imaging SpectroRadiometer (MISR) instrument description and experiment overview. *IEEE Transactions on Geoscience and Remote Sensing* 36, 1072–1087.

- DiGregorio A (2005). *Land Cover Classification System: classification concepts and user manual. Software version 2*. 190 p. FAO, Rome.
- Dobson AJ (2002). *An introduction to generalized linear models*. 2nd ed. 225 p. Chapman & Hall/CRC, Boca Raton.
- Dong J, RK Kaufmann, RB Myneni, CJ Tucker, P Kauppi, J Liski, W Buermann, V Alexeyev & MK Hughes (2003). Remote sensing estimates of boreal and temperate forest woody biomass: carbon pools, sources, and sinks. *Remote Sensing of Environment* 84, 393–410.
- Eklundh L, K Hall, H Eriksson, J Ardö & P Pilesjö (2003). Investigating the use of Landsat thematic mapper data for estimation of forest leaf area index in southern Sweden. *Canadian Journal of Remote Sensing* 29, 349–362.
- Fassnacht KS, ST Gower, MD MacKenzie, EV Nordheim & TM Lillesand (1997). Estimating the leaf area index of North Central Wisconsin forests using the Landsat Thematic Mapper. *Remote Sensing of Environment* 61, 229–245.
- Fernandes R, R Fraser, R Latifovic, J Cihlar, J Beaubien & Y Du (2004). Approaches to fractional land cover and continuous field mapping: a comparative assessment over the BOREAS study region. *Remote Sensing of Environment* 89, 234–251.
- Finn JT (1993). Use of the average mutual information index in evaluating classification error and consistency. *International Journal of Geographical Information Systems* 7, 349–366.
- Foley JA, JE Kutzback, MT Coe & S Levis (1994). Feedbacks between climate and boreal forests during the Holocene epoch. *Nature* 271, 52–54.
- Foley JA, R DeFries, GP Asner, C Barford, G Bonan, SR Carpenter, FS Chapin, MT Coe, GC Daily, HK Gibbs, JH Helkowski, T Holloway, EA Howard, CJ Kucharik, C Monfreda, JA Patz, IC Prentice, N Ramankutty & PK Snyder (2005). Global consequences of land use. *Science* 309, 570–574.
- Foody G (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment* 80, 185–201.
- Foody GM, DS Boyd & MEJ Cutler (2003). Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. *Remote Sensing of Environment* 85, 463–474.
- Franklin SE (2001). *Remote sensing for sustainable forest management*. 407 p. CRC Press, London.
- Franklin SE & MA Wulder (2002). Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. *Progress in Physical Geography* 26, 173–205.
- Friedl MA, DK McIver, JCF Hodges, XY Zhang, D Muchoney, AH Strahler, CE Woodcock, S Gopal, A Schneider, A Cooper, A Baccini, F Gao & C Schaaf (2002). Global land cover mapping from MODIS: algorithms and early results. *Remote Sensing of Environment* 83, 287–302.
- Gao F, CB Schaaf, AH Strahler, Y Jin & X Li (2003). Detecting vegetation structure using a kernel-based BRDF model. *Remote Sensing of Environment* 86, 198–205.
- Gates DM, HJ Keegan, JC Schleiter & VR Weidner (1965). Spectral properties of plants. *Applied Optics* 4, 11–20.
- Gammel F (2000). Testing the utility of multi-angle spectral data for reducing the effects of background spectral variations in forest reflectance model inversion. *Remote Sensing of Environment* 72, 46–63.
- Giri C, Z Zhu & B Reed (2005). A comparative analysis of the Global Land Cover 2000 and MODIS land cover datasets. *Remote Sensing of Environment* 94, 123–132.
- Goetz S (2007). Crisis in Earth observation. *Science* 315, 1767.
- Goodale CL, MJ Apps, RA Birdsey, CB Field, LS Heath, RA Houghton, JC Jenkins, GH Kohlmaier, W Kurz, S Liu, GJ Nabuurs, S Nilsson & AZ Shvidenko (2002). Forest carbon sinks in the northern hemisphere. *Ecological Applications* 12, 891–899.
- Grace J, F Berninger & L Nagy (2002). Impacts of climate change on the tree line. *Annals of Botany* 90, 537–544.

- Grant IF (2000). Investigation of the variability of the directional reflectance of Australian land cover types. *Remote Sensing Reviews* 19, 243–258.
- Gromtsev A (2002). Natural disturbance dynamics in the boreal forests of European Russia: a review. *Silva Fennica* 36, 41–55.
- Gu D, AR Gillespie, J Adams & R Weeks (1999). A statistical approach for topographic correction of satellite images by using spatial context information. *IEEE Transactions on Geoscience and Remote Sensing* 37, 236–246.
- Hagen S, BH Braswell, S Frolking, WA Salas & X Xiao (2002). Determination of subpixel fractions of nonforested area in the Amazon using multiresolution satellite sensor data. *Journal of Geophysical Research* 107, 8049.
- Hall FG, JR Townshend & ET Engman (1995). Status of remote sensing algorithms for estimation of land surface parameters. *Remote Sensing of Environment* 51, 138–156.
- Halme M & E Tomppo (2001). Improving the accuracy of multisource forest inventory estimates by reducing plot location error – a multicriteria approach. *Remote Sensing of Environment* 78, 321–327.
- Hansen MC & RS DeFries (2004). Detecting long-term global forest change using continuous fields of tree-cover maps from 8-km Advanced Very High Resolution Radiometer (AVHRR) data for the years 1982–99. *Ecosystems* 7, 695–716.
- Hansen MC & B Reed (2000). A comparison of the IGBP DISCover and University of Maryland 1 km global land cover products. *International Journal of Remote Sensing* 21, 1365–1373.
- Hansen MC, JRG Townshend, RS DeFries & M Carrol (2005). Estimation of tree cover using MODIS data at global, continental and regional/local scales. *International Journal of Remote Sensing* 26, 4359–4380.
- Hansen MC, RS DeFries, JRG Townshend, L Marufu & RA Sohlberg (2002). Development of a MODIS tree cover validation data set for Western Province, Zambia. *Remote Sensing of Environment* 83, 320–335.
- Hansen MC, RS DeFries, JRG Townshend, M Carroll, C Dimiceli & RA Sohlberg (2003). Global percent tree cover at a spatial resolution of 500 meters: first results of the MODIS vegetation continuous fields algorithm. *Earth Interactions* 7, 1–15.
- Harding R, P Kuhry, TR Christensen, MT Sykes, R Dankers & S van der Linden (2002). Climate feedbacks at the tundra-taiga interface. *Ambio Special Report* 12, 47–55.
- Heikkinen O (2005). Boreal forests and northern and upper timberlines. In Seppälä M (ed.): *The physical geography of Fennoscandia*, 185–200. Oxford University Press, Oxford.
- Heiskanen J (2005). Remote sensing of mountain birch forest biomass and leaf area index using ASTER data. *Proceedings of the 31st International Symposium on Remote Sensing of Environment*, 20–24.6.2005, Saint Petersburg.
- Helle T (2001). Mountain birch forests and reindeer husbandry. In Wielgolaski FE (ed.): *Nordic mountain birch ecosystems*, 279–291. Unesco, Paris and Parthenon, Carnforth.
- Holben BN (1986). Characteristics of maximum-value composite images for temporal AVHRR data. *International Journal of Remote Sensing* 7, 1435–1445.
- Houghton RA (2003). Revised estimates of the annual net flux of carbon to the atmosphere from changes in land use and land management 1850–2000. *Tellus B* 55, 378–390.
- Huang C, JRG Townshend, S Liang, SNV Kalluri & RS DeFries (2002). Impact of sensor's point spread function on land cover characterization: assessment and deconvolution. *Remote Sensing of Environment* 80, 203–212.
- Hustich I (1966). On the forest-tundra and the northern tree-lines. *Reports from the Kevo Subarctic Research Station* 3, 7–47.
- Hyvönen P (2002). Kuvioittaisten puustotunnusten ja toimenpide-ehdotusten estimointi k-lähimmän naapurin menetelmällä Landsat TM -satelliittikuvan, vanhan inventointitiedon ja kuviotason tukiaineiston avulla. *Metsätieteen aikakauskirja* 3, 363–379.

- Hyyppä HJ & JM Hyyppä (2001). Effects of stand size on the accuracy of remote sensing-based forest inventory. *IEEE Transactions on Geoscience and Remote Sensing* 39, 2613–2621.
- Hyyppä J, H Hyyppä, M Inkinen, M Engdahl, S Linko & Y-H Zhu (2000). Accuracy comparison of various remote sensing data sources in the retrieval of forest stand attributes. *Forest Ecology and Management* 128, 109–120.
- Häme T, A Salli, K Andersson & A Lohi (1997). A new methodology for the estimation of biomass of conifer-dominated boreal forest using NOAA AVHRR data. *International Journal of Remote Sensing* 18, 3211–3243.
- Häme T, P Stenberg, K Andersson, Y Rauste, P Kennedy, S Folving & J Sarkeala (2001). AVHRR-based forest proportion map of the Pan-European area. *Remote Sensing of Environment* 77, 76–91.
- Iverson LR, EA Cook & RL Graham (1989). A technique for extrapolating and validating forest cover across large regions: calibrating AVHRR data with TM data. *International Journal of Remote Sensing* 10, 1805–1812.
- Jovanovic VM, MA Bull, MM Smyth & J Zong (2002). MISR in-flight camera geometric model calibration and georectification performance. *IEEE Transactions on Geoscience and Remote Sensing* 40, 1512–1519.
- Justice CO, JRG Townshend, EF Vermote, E Masuoka, RE Wolfe, N Saleous, DP Roy & JT Morisette (2002). An overview of MODIS Land data processing and product status. *Remote Sensing of Environment* 83, 3–15.
- Justice CO, E Vermote, JRG Townshend, R Defries, DP Roy, DK Hall, VV Salomonson, JP Privette, G Riggs, A Strahler, W Lucht, RB Myneni, Y Knyazikhin, SW Running, RR Nemani, Z Wan, A Huete, W Leeuwen, RE Wolfe, L Giglio, J-P Muller, P Lewis & MJ Barnsley (1998). The moderate resolution imaging spectroradiometer (MODIS): land remote sensing for global research. *IEEE Transactions on Geoscience and Remote Sensing* 36, 1228–1249.
- Kalliola R & K Syrjänen (1991). To what extent are vegetation types visible in satellite imagery? *Annales Botanici Fennici* 28, 45–57.
- Karlsen SR, I Solheim, PSA Beck, KA Høgda, FE Wielgolaski & H Tømmervik (2007). Variability of the start of the growing season in Fennoscandia, 1982–2002. *International Journal of Biometeorology* 51, 513–524.
- Kasischke ES, S Goetz, MC Hansen, SL Ustin, M Ozdogan, CE Woodcock & J Rogan (2004). Temperate and boreal forests. In Ustin SL (ed.): *Remote sensing for natural resource management and environmental monitoring*, 147–238. John Wiley & Sons, Hoboken.
- Kharuk VI, KJ Ranson, TA Burenina & EV Fedotova (2003). Mapping of Siberian forest landscapes along the Yenisey transect with AVHRR. *International Journal of Remote Sensing* 24, 23–37.
- Kilpeläinen P & T Tokola (1999). Gain to be achieved from stand delineation in LANDSAT TM image-based estimates of stand volume. *Forest Ecology and Management* 124, 105–111.
- Kimes DS (1983). Dynamics of directional reflectance factor distributions for vegetation canopies. *Applied Optics* 22, 1364–1372.
- Kleman J (1987). Directional reflectance factor distributions for two forest canopies. *Remote Sensing of Environment* 23, 83–96.
- Koivuniemi J & KT Korhonen (2006). Inventory by compartments. In Kangas A & M Maltamo (eds.): *Forest inventory – methodology and applications*, 271–278. Springer, Dordrecht.
- Koutsias N & M Karteris (1998). Logistic regression modelling of multitemporal Thematic Mapper data for burned area mapping. *International Journal of Remote Sensing* 19, 3499–3514.
- Kullman L (2001). 20th century warming and tree-limit rise in the southern Scandes of Sweden. *Ambio* 30, 72–80.
- Kunnari J (2000). Metsähallituksen Ylä-Lapin luonnonhoitoalueen ja Urho Kekkosen kansallispuiston luontokartoitus: menetelmän luotettavuus. 33 p. Masters thesis, Forest Planning and Economics, University of Joensuu.

- Kuusik A & T Nilson (2000). A directional multispectral forest reflectance model. *Remote Sensing of Environment* 72, 244–252.
- Kuusik A, M Lang & T Nilson (2004). Simulation of the reflectance of ground vegetation in sub-boreal forests. *Agricultural and Forest Meteorology* 126, 33–46.
- Käyhkö J & P Pellikka (1994). Remote sensing of the impact of reindeer grazing on vegetation in northern Fennoscandia using SPOT XS data. *Polar Research* 13, 115–124.
- Laidler GJ & P Treitz (2003). Biophysical remote sensing of arctic environments. *Progress in Physical Geography* 27, 44–68.
- Lambin EF & M Linderman (2006). Time series of remote sensing data for land change science. *IEEE Transactions on Geoscience and Remote Sensing* 44, 1926–1928.
- Latifovic R, Z Zhu, J Cihlar, C Giri & I Olthof (2004). Land cover mapping of North and Central America—Global Land Cover 2000. *Remote Sensing of Environment* 89, 116–127.
- Lefsky MA & WB Cohen (2003). Selection of remotely sensed data. In Wulder MA & SE Franklin (eds.): *Remote sensing of forest environments: concepts and case studies*, 13–46. Kluwer Academic, Boston.
- Lefsky MA, WB Cohen & TA Spies (2001). An evaluation of alternate remote sensing products for forest inventory, monitoring, and mapping in Douglas-fir forests of western Oregon. *Canadian Journal of Forest Research* 31, 78–87.
- Lehtonen A, R Mäkipää, J Heikkinen, R Sievänen & J Liski (2004). Biomass expansion factors (BEFs) for Scots pine, Norway spruce and birch according to stand age for boreal forests. *Forest Ecology and Management* 188, 211–224.
- Lepers E, EF Lambin, AC Janetos, R DeFries, F Achard, N Ramankutty & RJ Scholes (2005). A synthesis of information on rapid land-cover change for the period 1981–2000. *BioScience* 55, 115–124.
- Li X & AH Strahler (1985). Geometric-optical modeling of a conifer forest canopy. *IEEE Transactions on Geoscience and Remote Sensing* 23, 705–721.
- Liang S (2004). *Quantitative remote sensing of land surfaces*. 534 p. John Wiley & Sons, Hoboken.
- Liski J, A Lehtonen, T Palosuo, M Peltoniemi, T Eggers, P Muukkonen & R Mäkipää (2006). Carbon accumulation in Finland's forests 1922–2004 – an estimate obtained by combination of forest inventory data with modelling of biomass, litter and soil. *Annals of Forest Science* 63, 687–697.
- Lloyd D (1990). A phenological classification of terrestrial vegetation cover using shortwave vegetation index imagery. *International Journal of Remote Sensing* 11, 2269–2279.
- Loveland TR, BC Reed, JF Brown, DO Ohlen, Z Zhu, L Yang & JW Merchant (2000). Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing* 21, 1303–1330.
- Lovell JL & RD Graetz (2002). Analysis of POLDER-ADEOS data for the Australian continent: the relationship between BRDF and vegetation structure. *International Journal of Remote Sensing* 23, 2767–2796.
- Lu D (2006). The potential and challenge of remote sensing-based biomass estimation. *International Journal of Remote Sensing* 27, 1297–1328.
- Martonchik JV, CJ Bruegge & A Strahler (2000). A review of reflectance nomenclature used in remote sensing. *Remote Sensing Reviews* 19, 9–20.
- Mayaux P, H Eva, J Gallego, AH Strahler, M Herold, S Agrawal, S Naumov, EE De Miranda, CM Di Bella, C Ordoyne, Y Kopin & PS Roy (2006). Validation of the Global Land Cover 2000 map. *IEEE Transactions on Geoscience and Remote Sensing* 44, 1728–1739.
- McCallum I, M Obersteiner, S Nilson & A Shvidenko (2006). A spatial comparison of four satellite derived 1 km global land cover datasets. *International Journal of Applied Earth Observation and Geoinformation* 8, 246–255.

- McDermid GJ, SE Franklin & EF LeDrew (2005). Remote sensing for large-area habitat mapping. *Progress in Physical Geography* 29, 449–474.
- MCST (2006). MODIS level 1B product user's guide, for level 1B version 5.0.6 (Terra) and version 5.0.7 (Aqua). 57 p. MCST Document PUB-01-U-0202-REV B, MCST Internal Memorandum M1054. Available online at: <http://www.mcst.ssai.biz/mcstweb/L1B/product.html>.
- Morisette JT, S Khorram & T Mace (1999). Land-cover change detection enhanced with generalized linear models. *International Journal of Remote Sensing* 20, 2703–2721.
- Morisette JT, JL Privette & CO Justice (2002). A framework for the validation of MODIS Land products. *Remote Sensing of Environment* 83, 77–96.
- Morisette JT, F Baret, JL Privette, RB Myneni, JE Nickeson, S Garrigues, NV Shabanov, M Weiss, RA Fernandes, SG Leblanc, M Kalacska, G Sánchez-Azofeifa, M Chubey, B Rivard, P Stenberg, M Rautiainen, P Voipio, T Manninen, AN Pilant, TE Lewis, JS Iames, R Colombo, M Meroni, L Busetto, WB Cohen, DP Turner, ED Warner, GW Petersen, G Seufert & R Cook (2006). Validation of global moderate-resolution LAI Products: a framework proposed within the CEOS Land Product Validation subgroup. *IEEE Transactions on Geoscience and Remote Sensing* 44, 1804–1817.
- Muukkonen P & R Mäkipää (2006). Empirical biomass models of understorey vegetation in boreal forests according to stand and site attributes. *Boreal Environment Research* 11, 355–369.
- Myneni RB, CD Keeling, CJ Tucker, G Asrar & RR Nemani (1997). Increased plant growth in the northern high latitudes from 1981 to 1991. *Nature* 386, 698–702.
- Myneni RB, S Hoffman, Y Knyazikhin, JL Privette, J Glassy, Y Tian, Y Wang, X Song, Y Zhang, GR Smith, A Lotsch, M Friedl, JT Morisette, P Votava, RR Nemani & SW Running (2002). Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. *Remote Sensing of Environment* 83, 214–231.
- Mäkelä H & A Pekkarinen (2004). Estimation of forest stand volumes by Landsat TM imagery and stand-level field-inventory data. *Forest Ecology and Management* 196, 245–255.
- Nemani R, L Pierce, S Running & L Band (1993). Forest ecosystem processes at the watershed scale: sensitivity to remotely-sensed leaf area index estimates. *International Journal of Remote Sensing* 14, 2519–2534.
- Neuvonen S, K Ruohomäki, H Bylund & P Kaitaniemi (2001). Insect herbivores and herbivory effects on mountain birch dynamics. In Wielgolaski FE (ed.): *Nordic mountain birch ecosystems*, 207–222. Unesco, Paris and Parthenon, Carnforth.
- Nilson T & U Peterson (1994). Age dependence of forest reflectance: analysis of main driving factors. *Remote Sensing of Environment* 48, 319–331.
- Nilson T, A Kuusk, M Lang & T Lük (2003). Forest reflectance modelling: theoretical aspects and applications. *Ambio* 32, 535–541.
- Olson DM, E Dinerstein, ED Wikramanayake, ND Burgess, GVN Powell, EC Underwood, JA D'amico, I Itoua, HE Strand, JC Morrison, CJ Loucks, TF Allnutt, TH Ricketts, Y Kura, JF Lamoreux, WW Wettengel, P Hedao & KR Kassem (2001). Terrestrial ecoregions of the world: a new map of life on Earth. *BioScience* 51, 933–938.
- Olthof I & RH Fraser (2006). Mapping northern land cover fractions using Landsat ETM+. *Remote Sensing of Environment* 107, 496–509.
- Ozesmi SL & ME Bauer (2002). Satellite remote sensing of wetlands. *Wetlands Ecology and Management* 10, 381–402.
- Pekkarinen A (2004). Image segmentation in multisource forest inventory. *The Finnish Forest Research Institute, Research Papers* 926. 35 p.
- Poso S (1983). Kuvioittaisen arvioimismenetelmän perusteita. *Silva Fennica* 17, 313–349.
- Poso S, R Paananen & M Similä (1987). Forest inventory by compartments using satellite imagery. *Silva Fennica* 21, 69–94.

- Ranson KJ, G Sun, VI Kharuk & K Kovacks (2004a). Assessing tundra-taiga boundary with multi-sensor satellite data. *Remote Sensing of Environment* 93, 283–295.
- Ranson KJ, G Sun, K Kovacks & VI Kharuk (2004b). Landcover attributes from ICESat GLAS data in central Siberia. *IGARSS '04. Proceedings* 2, 753–756.
- Rautiainen M & P Stenberg (2005). Application of photon recollision probability in coniferous canopy reflectance simulations. *Remote Sensing of Environment* 96, 98–107.
- Rautiainen M, J Suomalainen, M Möttöus, P Stenberg, P Voipio, J Peltoniemi & T Manninen (2007). Coupling forest canopy and understory reflectance in the Arctic latitudes of Finland. *Remote Sensing of Environment* 110, 332–343.
- Rees G, I Brown, K Mikkola, T Virtanen & B Werkman (2002). How can the dynamics of the tundra-taiga boundary be monitored? *Ambio Special Report* 12, 56–62.
- Roberts G (2001). A review of the application of BRDF models to infer land cover parameters at regional and global scales. *Progress in Physical Geography* 25, 483–511.
- Rosenqvist Å, A Milne, R Lucas, M Imhoff & C Dobson (2003). A review of remote sensing technology in support of the Kyoto Protocol. *Environmental Science and Policy* 6, 441–455.
- Rouse JW, RH Haas, JA Schell & DW Deering (1973). Monitoring vegetation systems in the Great Plains with ERTS. *Proceedings of the third Earth resources technology satellite-1 symposium*, NASA SP-351, 309–317. NASA, Washington, DC.
- Roy DP, P Lewis, C Schaaf, S Devadiga & L Boschetti (2006). The global impact of cloud on the production of MODIS bi-directional reflectance model based composites for terrestrial monitoring. *IEEE Transactions on Geoscience and Remote Sensing Letters* 3, 452–456.
- Russell CA, JR Irons & PW Dabney (1997). Bidirectional reflectance of selected BOREAS sites from multiangle airborne data. *Journal of Geophysical Research* 102, 29505–29516.
- Sandmeier ST & DW Deering (1999a). Structure analysis and classification of boreal forests using airborne hyperspectral BRDF data from ASAS. *Remote Sensing of Environment* 69, 281–295.
- Sandmeier ST & DW Deering (1999b). A new approach to derive canopy structure information for boreal forests using spectral BRDF data. *IGARSS'99 Proceedings* 1, 410–412.
- Scepan J (1999). Thematic validation of high-resolution global land-cover data sets. *Photogrammetric Engineering & Remote Sensing* 65, 1051–1060.
- Schaaf CB, X Li & AH Strahler (1994). Topographic effects on bidirectional and hemispherical reflectances calculated with a geometric-optical canopy model. *IEEE Transactions on Geoscience and Remote Sensing* 32, 1186–1193.
- Schaaf CB, F Gao, AH Strahler, W Lucht, X Li, T Tsang, NC Strugnell, X Zhang, Y Jin, J-P Muller, P Lewis, M Barnsley, P Hobson, M Disney, G Roberts, M Dunderdale, C Doll, RB d'Entremont, B Hu, S Liang, JL Privette & D Roy (2002). First operational BRDF, albedo nadir reflectance products from MODIS. *Remote Sensing of Environment* 83, 135–148.
- Schwarz M & NE Zimmermann (2005). A new GLM-based method for mapping tree cover continuous fields using regional MODIS reflectance data. *Remote Sensing of Environment* 95, 428–443.
- Sellers PJ, RE Dickinson, DA Randall, AK Betts, FG Hall, JA Berry, GJ Collatz, AS Denning, HA Mooney, CA Nobre, N Sato, CB Field & A Henderson-Sellers (1997). Modeling the exchanges of energy, water, and carbon between continents and the atmosphere. *Science* 275, 502–509.
- Seppä H (2002). Mires of Finland: regional and local controls of vegetation, landforms, and long-term dynamics. *Fennia* 180, 43–60.
- Seppälä M & J Rastas (1980). Vegetation map of northernmost Finland with special reference to subarctic forest limits and natural hazards. *Fennia* 158, 41–61.
- Sihvo J (2001). *Ylä-Lapin luonnonhoitoalueen ja Urho Kekkosen kansallispuiston luontokartoitus. Loppuraportti osa 1: projektikuvaus*. 76 p. Metsähallitus, Vantaa.
- Sihvo J (2002). *Ylä-Lapin luonnonhoitoalueen ja Urho Kekkosen kansallispuiston luontokartoitus. Loppuraportti osa 2: Ylä-Lapin luontotyypit*. 175 p. Metsähallitus, Vantaa.

- Skre O, R Baxter, RMM Crawford, TV Callaghan & A Fedorkov (2002). How will the tundra-taiga interface respond to climate change. *Ambio Special Report 12*, 37–46.
- Slayback DA, JE Pinzon, SO Los & CJ Tucker (2003). Northern Hemisphere photosynthetic trends 1982–99. *Global Change Biology* 9, 1–15.
- Spanner MA, LL Pierce, DL Peterson & SW Running (1990). Remote sensing of temperate coniferous forest leaf area index. The influence of canopy closure, understory vegetation and background reflectance. *International Journal of Remote Sensing* 11, 95–111.
- Starr M, M Hartman & T Kinnunen (1998). Biomass functions for mountain birch in the Vuoskojärvi Integrated Monitoring area. *Boreal Environment Research* 3, 297–303.
- Stenberg P, M Rautiainen, T Manninen, P Voipio & H Smolander (2004). Reduced simple ratio better than NDVI for estimating LAI in Finnish pine and spruce stands. *Silva Fennica* 38, 3–14.
- Stow DA, A Hope, D McGuire, D Verbyla, J Gamon, F Huemmrich, S Houston, C Racine, M Sturm, K Tape, L Hinzman, K Yoshikawa, C Tweedie, B Noyle, C Silapaswan, D Douglas, B Griffith, G Jia, H Epstein, D Walker, S Daeschner, A Petersen, L Zhou & R Myneni (2004). Remote sensing of vegetation and land-cover change in Arctic tundra ecosystems. *Remote Sensing of Environment* 89, 281–308.
- Strahler AH, CE Woodcock & JA Smith (1986). On the nature of models in remote sensing. *Remote Sensing of Environment* 20, 121–139.
- Sturm M, C Racine & K Tape (2001). Climate change – increasing shrub abundance in the Arctic. *Nature* 411, 546–547.
- Su L, MJ Chopping, A Rango, JV Martonchik & DPC Peters (2007). Differentiation of semi-arid vegetation types based on multi-angular observations from MISR and MODIS. *International Journal of Remote Sensing* 28, 1419–1424.
- Suarez F, D Binkley, MW Kaye & R Stottlemeyer (1999). Expansion of forest stands into tundra in the Noatak National Preserve, northwest Alaska. *Ecoscience* 6, 465–470.
- Tan B, CE Woodcock, J Hu, P Zhang, M Ozdogan, D Huang, W Yang, Y Knyazikhin & RB Myneni (2006). The impact of gridding artifacts on the local spatial properties of MODIS data: Implications for validation, compositing, and band-to-band registration across resolutions. *Remote Sensing of Environment* 105, 98–114.
- Tape K, M Sturm & C Racine (2006). The evidence for shrub expansion in Northern Alaska and the Pan-Arctic. *Global Change Biology* 12, 686–702.
- Teillet PM, B Guindon & DG Goodenough (1982). On the slope-aspect correction of multispectral scanner data. *Canadian Journal of Remote Sensing* 8, 84–106.
- Tikkanen M (1994). Suomen pinnanmuodot. *Terra* 106, 181–192.
- Tikkanen M (2005). Climate. In Seppälä M (ed.): *The physical geography of Fennoscandia*, 97–112. Oxford University Press, Oxford.
- Toivonen T & M Luoto (2003). Landsat TM images in mapping of semi-natural grasslands and analysing of habitat pattern in an agricultural landscape in south-west Finland. *Fennia* 181, 49–67.
- Tokola T & J Heikkilä (1997). Improving satellite image based forest inventory by using a priori site quality information. *Silva Fennica* 31, 67–78.
- Tomppo E, M Nilson, M Rosenberg, P Aalto & P Kennedy (2002). Simultaneous use of Landsat-TM and IRS-1C WiFS data in estimating large area tree stem volume and aboveground biomass. *Remote Sensing of Environment* 82, 156–171.
- Townshend JRG & CO Justice (1988). Selecting the spatial resolution of satellite sensors required for global monitoring of land transformations. *International Journal of Remote Sensing* 9, 187–236.
- Townshend JRG, C Huang, SNV Kalluri, RS DeFries, S Liang & K Yang (2000). Beware of perpixel characterization of land cover. *International Journal of Remote Sensing* 21, 839–843.
- Tso B & PM Mather (2001). *Classification methods for remotely sensed data*. 322 p. Taylor & Francis, London.

- Tucker CJ (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment* 8, 127–150.
- Tucker CJ & PJ Sellers (1986). Satellite remote sensing of primary production. *International Journal of Remote Sensing* 7, 1395–1416.
- Tømmervik H, KA Høgda & I Solheim (2003). Monitoring vegetation changes in Pasvik (Norway) and Pechenga in Kola Peninsula (Russia) using multitemporal Landsat MSS/TM data. *Remote Sensing of Environment* 85, 370–388.
- Tømmervik H, FE Wielgolaski, S Neuvonen, B Solberg & KA Høgda (2005). Biomass and production on a landscape level in the mountain birch forests. In Wielgolaski FE (ed.), PS Karlsson, S Neuvonen & D Thannheiser (ed. board): *Plant ecology, herbivory, and human impact in Nordic mountain birch forests*, 53–70. Springer-Verlag, Berlin, Heidelberg.
- Törmä M (2005). Suomen IMAGE2000 ja CORINE land cover 2000 tarkkuuden arviointi. 45 p. Finnish Environment Institute, Helsinki.
- Vasander H (1996 ed.). *Peatlands in Finland*. 168 p. Finnish Peatland Society, Helsinki.
- Verhoef W (1984). Light scattering by leaf layers with application to canopy reflectance modeling: the SAIL model. *Remote Sensing of Environment* 16, 125–141.
- Vermote EF, N El Saleous & CO Justice (2002). Atmospheric correction of MODIS data in the visible to middle infrared: first results. *Remote Sensing of Environment* 83, 97–111.
- Virtanen T & P Kuhry (2006). Comparison of a regional Landsat image based land cover classification to global data sets in Northeast European Russia. *Reports on Polar and Marine Research* 520, 133–138.
- Virtanen T, K Mikkola & A Nikula (2004). Satellite image based vegetation classification of a large area using limited ground reference data: a case study in the Usa Basin, north-east European Russia. *Polar Research* 23, 51–66.
- Vlassova TK (2002). Human impacts on the tundra-taiga zone dynamics: the case of the Russian lesotundra. *Ambio Special Report* 12, 30–36.
- Waring RH & SW Running (1998). *Forest ecosystems: analysis at multiple scales. 2nd edition*. 370 p. Academic Press, San Diego.
- Waser LT & M Schwarz (2006). Comparison of large-area land cover products with national forest inventories and CORINE land cover in the European Alps. *International Journal of Applied Earth Observation and Geoinformation* 8, 196–207.
- White MA, JD Shaw & RD Ramsey (2005). Accuracy assessment of the vegetation continuous field tree cover product using 3954 ground plots in the south-western USA. *International Journal of Remote Sensing* 26, 2699–2704.
- Wielgolaski FE (2001 ed.). *Nordic mountain birch ecosystems*. 390 p. Unesco, Paris and Parthenon, Carnforth.
- Wolfe RE, D Roy & E Vermote (1998). MODIS land data storage, gridding, and compositing methodology: Level 2 grid. *IEEE Transactions on Geoscience and Remote Sensing* 36, 1324–1338.
- Wolfe RE, M Nishihama, AJ Fleig, JA Kuyper, DP Roy, JC Storey & FS Patt (2002). Achieving sub-pixel geolocation accuracy in support of MODIS land science. *Remote Sensing of Environment* 83, 31–49.
- Wolter PT, DJ Mladenoff, GE Host & TR Crow (1995). Improved forest classification in the Lake States using multi-temporal Landsat imagery. *Photogrammetric Engineering & Remote Sensing* 61, 1129–1143.
- Woodcock CE & AH Strahler (1987). The factor of scale in remote sensing. *Remote Sensing of Environment* 21, 311–332.
- Wulder M (1998). Optical remote-sensing techniques for the assessment of forest inventory and biophysical parameters. *Progress in Physical Geography* 22, 449–476.

- Yamaguchi Y, A Kahle, H Tsu, T Kawakami & M Pniel (1998). Overview of Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). *IEEE Transactions on Geoscience and Remote Sensing* 36, 1062–1071.
- Zhang Y, Y Tian, RB Myneni, Y Knyazikhin & CE Woodcock (2002). Assessing the information content of multiangle satellite data for mapping biomes. *Remote Sensing of Environment* 80, 418–434.

ERRATA

The author regrets the following errata in Papers II and III:

Paper II 1) The equations for calculating bias and bias_r should be corrected as follows:

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) \quad (6)$$

$$\text{Bias}_r = \frac{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)}{\bar{y}} \times 100 \quad (7)$$

where \hat{y}_i is the modeled value, y_i is the observed value, \bar{y} is the mean of the observed values and n is the number of the observations. The results were calculated correctly. Therefore, the negative biases correspond to the underestimation and positive biases to the overestimation of observed values.

2) Tokola & Heikkilä (1997) is cited incorrectly in Table 7. Instead of 82.0%, the relative standard error of stand volume was 70.3% for field plots and 37.4% for simulated areas size of 1 ha.

Paper III Relative RMSE for district-level mean stand volume given in the abstract should be 7.6% (III: Table 2), not 9.9%.