Classification of Sweden's Forest and Alpine Vegetation Using Optical Satellite and Inventory Data

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Cover: Looking for *Rhododendron lapponicum* near Vitnjul, Vindelfjällen
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Abstract

Creation of accurate vegetation maps from optical satellite data requires use of reference data to aid in interpretation or to verify map results. Reference data may be taken, for example, from field visits, aerial photo-interpretation, or ground-based inventories. National inventories are a potential source of reference data useful in land cover mapping projects.

This thesis addresses aspects of mapping forest and alpine vegetation in Sweden through combined use of optical satellite data and inventory data. Issues such as reference and satellite data pre-processing, spatial scale, quantity and quality of reference data, and classification methods have been examined. Optical satellite data with pixel sizes ranging from 10 to 300 m have been used together with reference data from the Swedish National Forest Inventory (NFI), National Inventory of Landscapes in Sweden (NILS), a point sample based on the Terrestrial Habitat Monitoring program (THUF), and a forest stand database.

Results include modifications to common remote sensing methods, such as introducing iterative adjustment of prior probabilities in Maximum Likelihood classification, and improved topographic normalization (C-correction) of satellite data. Probability-based samples such as NFI, NILS and THUF provide data necessary for assignment of prior probabilities, estimation of continuous values, and are useful as training and validation data. For managed boreal forest stands, coarser pixel (60 m) AWiFS data were nearly as effective for stem volume estimation as SPOT 5 data (10 m). On the other hand, the most accurate classification of detailed alpine vegetation types (72.9% overall accuracy) was from SPOT 5 data combined with elevation derivatives, while classifications of Landsat TM (25 m), AWiFS, and MERIS (300 m) were less accurate. Non-parametric methods (e.g., random forests, decision/regression trees) produced higher classification accuracies than traditional parametric methods for alpine vegetation. The quantity of reference data affected classification accuracy, as more reference data produced higher map accuracy, although other factors such as distribution and quality of the reference data should be considered. As seen in this thesis, the characteristics of the landscape exert an influence on satellite and training data requirements, classification methods and resulting map accuracy.

Keywords: alpine, classification, estimation, forest, inventory data, land cover mapping, optical satellite data, reference data, training data

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Vi behöver alla någon gång stillhet och perspektiv. Vi har alla våra medel att finna vad vi söker. De svenska fjällen ger ensamhet och distans icke genom verklighetsflykt utan genom mötet med en annan verklighet än arbetslivets och vardagens. (We all need stillness and perspective sometimes. We all have our means to find what we are seeking. The Swedish mountains provide solitude and distance – not through escape from reality – but through contact with a reality other than work and every-day life.)

Dag Hammarskjöld, *from Vägmärken*

Contents

List of Publications 6

Abbreviations 7

1 Introduction **9**
1.1 Optical satellite sensors 10
1.2 Land cover mapping 11
1.3 Landscape heterogeneity and satellite data pixel size 13
1.4 Combining satellite data and reference data for classification 15
1.5 Pre-processing of satellite data 17
1.6 Classification methods 18
1.7 Training data 20
1.8 Accuracy assessment 23
1.9 National inventories 24
1.10 National land cover mapping projects using optical satellite data 27
1.11 Optical remote sensing characteristics of forest and alpine/subalpine vegetation 29

2 Objectives **34**

3 Materials and methods **35**
3.1 Materials 35
3.2 Methods 38

4 Results and discussion **45**
4.1 A method for calibrated maximum likelihood classification of forest types 45
4.2 Using MERIS for mountain vegetation mapping and monitoring in Sweden 47
4.3 Comparison of Resourcesat-1 AWiFS and SPOT 5 data over managed boreal forest stands 48
4.4 C-correction of optical satellite data over alpine vegetation areas 50
4.5 Varying training data set size for supervised classification of alpine vegetation 52
4.6 Main findings 55
4.7 Concluding remarks 57

References **61**

Acknowledgements **75**

List of Publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I Hagner, O., and Reese, H. (2007). A method for calibrated maximum likelihood classification of forest types. *Remote Sensing of Environment* 110(4), 438-444.

II Reese, H., Nilsson, M., and Olsson, H. (2007). Using MERIS for mountain vegetation mapping and monitoring in Sweden. In *European Space Agency (Special Publication), Proceedings of the ENVISAT Symposium,* Montreux, Switzerland, 23-27 April.

III Reese, H., Nilsson, M., and Olsson, H. (2009). Comparison of Resource-sat-1 AWiFS and SPOT-5 data over managed boreal forest stands. *International Journal of Remote Sensing* 30(19), 4957-4978.

IV Reese, H. and Olsson, H. (2011). C-correction of optical satellite data over alpine vegetation areas: A comparison of sampling strategies for determining the empirical c-parameter. *Remote Sensing of Environment* 115(6), 1387-1400.

V Reese, H., Allard, A., Nilsson, M., and Olsson, H. Varying training data set size for supervised classification of alpine vegetation (manuscript).

Abbreviations

3-D	Three-dimensional
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
AWiFS	Advanced Wide Field Spectrometer
BRDF	Bi-directional Reflectance Distribution Function
CAVM	Circumpolar Arctic Vegetation Map
CBD	Convention on Biological Diversity
CIR	Color Infra-Red
CORINE	Coordination of Information on the Environment
DEM	Digital Elevation Model
EOS	Earth Observation Satellites
EOSD	Earth Observation for Sustainable Development of forest
ETM+	Enhanced Thematic Mapper Plus
FIA	Forest Inventory and Analysis
GAP	Gap Analysis Program
GEO	Group on Earth Observations
GIS	Geographic Information System
GMES	Global Monitoring for Environment and Security
GPS	Global Positioning System
GSD	Ground Sample Distance
HRG	High Resolution Geometrical
HRV	High Resolution Visible
kNN	k-Nearest Neighbors
LAI	Leaf Area Index
LDCM	Landsat Data Continuity Mission
LULC	Land Use Land Cover
MERIS	Medium Resolution Imaging Spectrometer

ML	Maximum Likelihood
MODIS	Moderate Resolution Imaging Spectroradiometer
MOTH	Monitoring Terrestrial Habitats
MSS	Multi-Spectral Scanner
MTCI	MERIS Terrestrial Chlorophyll Index
NDII	Normalized Difference Infrared Index
NDVI	Normalized Difference Vegetation Index
NFI	National Forest Inventory
NILS	National Inventory of Landscapes in Sweden
NIR	Near Infra-Red
NLCD	National Land Cover Database
PCA	Principal Components Analysis
QDA	Quadratic Discriminant Analysis
RF	Random Forest
RMSE	Root Mean Square Error
SAR	Synthetic Aperture Radar
SAVI	Soil Adjusted Vegetation Index
SLC	Scan Line Corrector
SLU	Sveriges Lantbruksuniversitet (Swedish University of Agricultural Sciences)
SMA	Spectral Mixture Analysis
SMAC	Simplified Method for Atmospheric Corrections
SPOT	Système Probatoire d'Observation de la Terre
SWIR	Short Wave Infra-Red
THUF	Terrestrial Habitat Monitoring (Terrester Habitatuppföljning)
TM	Thematic Mapper
VI	Vegetation Index

1 Introduction

Land cover maps are valuable data sources for environmental monitoring, natural resource inventory and management, policymaking and enforcement, climate change studies, and wildlife habitat mapping, to name just a few applications. The underlying primary data source for these maps is often remotely sensed data, whether from aerial- or satellite-borne sensors. Satellites provide a continuous and synoptic view of the globe, making wall-to-wall land cover mapping possible on local, regional and global scales. However, processing satellite data into map products requires the use of reference data, whether to aid in interpretation of the satellite data or to verify map results. Reference data may be derived from field visits, aerial photo-interpretation, or ground-based inventories, for example. National inventories are a potential source of reference data that can be applied to large-area land cover mapping projects.

An increasing number of countries have established National Forest Inventories (NFIs; Tomppo *et al.*, 2010), although the sampling design, sampling method, variables measured, and temporal cycle of the inventory may differ between countries (Lawrence *et al.*, 2010). The Nordic countries are among those with a long-established history of NFIs (Tomppo *et al.*, 2008) and Sweden's NFI started in 1923 (Axelsson *et al.*, 2010). Today, the Swedish NFI measures forest variables based on fixed-area GPS-located plots for all forested land within the country, running on a five-year cycle. Sweden also has a newly established (started 2003) terrestrial inventory program, the National Inventory of Landscapes in Sweden (NILS), measuring variables on fixed-area GPS-located plots for all land cover types (Ståhl *et al.*, 2011). Both the NFI and NILS are objectively collected, probability-based samples, providing a sound basis on which to assess and monitor resources and biodiversity over large regions. The possibility of combining Sweden's NFI data and satellite data has been researched and put into operational use for mapping forest types and parameters (Nilsson, 1997; Reese *et al.*, 2003). The relatively new NILS

program provides similar opportunities for mapping other land cover types, such as in the mountain areas.

The creation of land cover maps from the combination of satellite data and inventory data is seldom straightforward, and there are many factors that influence the final outcome. Factors that must be considered during the mapping process include geo-location of the reference data and co-location with satellite data; the spatial properties of the inventory unit, the satellite data, and the landscape to be mapped; the distribution and amount of the reference data; the radiometric pre-processing of the satellite imagery; the thematic classification scheme; methods used to classify the satellite data; and assembling a dataset for accuracy assessment. Despite the existence of inventories and satellite data over several decades, some aspects of their combined use are still in experimental as opposed to operational stages.

This thesis addresses the subject of land cover mapping using different sources of optical satellite data and inventory data. The study areas are located in both the forest and mountain areas of Sweden. Various challenges encountered in image processing, such as topographic normalization, image data pre-processing, scale issues, quantity and quality of reference data, and classification methods, have been addressed in the papers. In some cases, the work has been carried out in relation to an operational, nationwide mapping project or as steps towards such a project.

1.1 Optical satellite sensors

By the term "optical" satellite data, it is meant that the sensor operates within the optical spectrum (from 100 nm to 1 mm), of which the 400-780 nm wavelengths are visible to the human eye (e.g., blue, green, red). The optical sensors used in this thesis are concerned with those that operate in the visible, as well as near- and short-wave-infrared portions of the optical spectrum (Kramer, 2002; Lillesand *et al.*, 2008). The optical sensors recording reflected solar energy are considered "passive" sensors, whereas "active" sensors (e.g., radar, LiDAR) send out self-generated energy whose return signals are recorded by the sensor. This thesis restricts the scope of study to passive optical sensors carried on satellite platforms.

Optical satellite sensors have several important and variable properties, including the pixel resolution, nadir viewing versus off-nadir viewing capability, swath width, number of spectral bands and bandwidths, radiometric quantization of each band, and temporal resolution. Table 1 gives properties of the optical satellite data sources used in this thesis.

1.2 Land cover mapping

Land cover is defined as "the type of feature present on the surface of the earth" (e.g., forest, water, asphalt), while the term *land use* is "associated with human activity or economic function" (e.g., forestry or residential areas) (Lillesand *et al.*, 2008). Land use/land cover (LULC) is often used as a collective term, indicating that a map is either one or a mix of both types. The first LULC maps derived from remotely sensed data used aerial photography as a basis (Colwell, 1960). Early optical remote sensing efforts (the earliest known dating to 1858) involved placing cameras on balloons and kites (Lillesand *et al.*, 2008). Starting in the early 1900's, photographs were taken from airplanes, initially for military purposes, and later for civilian mapping purposes. In the 1960's, space-based cameras were introduced, and in the 1970's the era of operational satellite-borne sensors for earth resource monitoring began and continues today.

LULC maps derived from photographic data (e.g., aerial photographs) have commonly been interpreted visually by delineating polygons around homogenous land cover units. Detailed land cover mapping projects using aerial photos tended to be local or regional in area, due to labor-intensive interpretation and areal coverage of photographs. However, a few national LULC mapping projects using aerial photography have also been completed (e.g., Land Cover of Scotland 1988, Sweden's Mountain Vegetation Map).

A shift towards operational large-area LULC mapping projects was made possible with the launch of the first civilian Earth Observation (EO) satellite on July 23, 1972 (ERTS-1, later renamed Landsat-1; Kramer, 2002). The EO satellites provided digital data over the Earth's surface in a consistent manner, making data available for land cover mapping for all locations on the globe. In the 1970's and early 80's, analyzing a single satellite image or subset of an image was common. In the mid 1980's to early 90's, national and global mapping applications began to appear using coarse resolution meteorological satellite data (e.g., NOAA AVHRR) with a resolution of 4 km pixels (Townshend *et al.*, 1987), increasing to 1 km (Loveland *et al.*, 1991). Global scale mapping continues in the 21st century, using AVHRR data (Hansen *et al.*, 2000; Walker *et al.*, 2005) or other coarse resolution optical sensors such as SPOT-VEGETATION (Bartholome & Belward, 2005), ENVISAT MERIS (Arino *et al.*, 2008), or Terra/Aqua MODIS (Friedl *et al.*, 2010).

Table 1. *Properties of the satellite sensors used in this thesis.*

Satellite and Sensor	Swath width (km)	Number of bands	Spectral bandwidths (μm)	Pixel size (m)	Radiometric quantization
Landsat TM/ETM+	185	7/8[1]	Blue (0.45-0.52)	30	8-bit
			Green (0.52-0.60)	30	
			Red (0.63-0.69)	30	
			NIR (0.76-0.90)	30	
			SWIR1 (1.55-1.75)	30	
			SWIR2 (2.09-2.35)	30	
			Therm (10.40-12.50)	120/60[2]	
			Pan (0.50-0.90) [1]	13×15	
SPOT HRG	60-80	4	Green (0.50-0.59)	10	8-bit
			Red (0.61-0.68)	10	
			NIR (0.78-0.89)	10	
			SWIR (1.58-1.75)	20	
IRS-P6 Resourcesat-1 AWiFS	370[3]	4	Green (0.52-0.59)	60 (resampled from 56 at nadir)	10-bit
			Red (0.62-0.68)		
			NIR (0.77-0.86)		
			SWIR (1.55-1.70)		
ENVISAT MERIS[4]	575	15	1 (0.408-0.418)	300	16-bit
			2 (0.437-0.447)	300	
			3 (0.485-0.495)	300	
			4 (0.505-0.515)	300	
			5 (0.555-0.565)	300	
			6 (0.615-0.625)	300	
			7 (0.659-0.669)	300	
			8 (0.677-0.685)	300	
			9 (0.703-0.713)	300	
			10 (0.750-0.758)	300	
			11 (0.759-0.763)	300	
			12 (0.771-0.786)	300	
			13 (0.855-0.875)	300	
			14 (0.880 – 0.890)	300	
			15 (0.895-0.905)	300	
TERRA/ AQUA MODIS	2330	36[5]	Red (0.620-0-670)	250	16-bit
			NIR (0.841-0.876)	250	
			Blue (0.459-0.479)	500	
			Green (0.545-0.565)	500	
			NIR (1.230-1.250)	500	
			SWIR1 (1.628-1.652)	500	
			SWIR2 (2.105-2.155)	500	

[1]Panchromatic band (band 8) on Landsat ETM+ only. [2]Thermal band has 60 m resolution for Landsat ETM+ only. [3]Using one sensor, swath width is 370 km, while using both sensors gives a swath width of 740 km. [4]MERIS' bandwidths are programmable. At time of imaging, the bandwidths shown were used, ranging from violet to NIR. [5]Bands 1-7 only shown, bands 8-36 (from 0.405 up to 14.385 μm) have 1 km pixel size.

In the mid- to late-90's, more large-area, multiple scene mapping projects began using medium resolution satellite data (e.g., Landsat TM). This change was due to several factors including advances made in computer technology allowing processing of larger data amounts (Wulder *et al.*, 2003), the decreased cost of satellite data and cooperative buy-and-use agreements (Lauer *et al.*, 1991; Lins & Kleckner, 1996), and improved GPS-positioning, especially after 2000 when intentional degradation of GPS positioning ceased and better technology increased positional accuracy. For much of the 1980's, 90's and early 2000's, the Landsat series of satellites was the primary data source for LULC mapping projects. Landsat TM possessed a pixel size (30 m) suitable to many mapping purposes and a wide swath width (185 km), making it more practical and less expensive to use than SPOT data (60 km swath width). However, with the failure of Landsat 7's Scan Line Corrector (SLC) in May of 2003, alternative medium-resolution data sources were more actively sought for large area projects, such as AWiFS (Johnson, 2008), ASTER (Franklin *et al.*, 2011), and SPOT. While Landsat 5 TM acquired data long past its scheduled design lifetime, it has ceased to function on an operational level. The so-called "Landsat data gap" is now a reality, with lack of access to Landsat data before the next Landsat mission (i.e., Landsat Data Continuity Mission or LDCM) is to be launched as planned for December 2012 (Goward *et al.*, 2006; Franklin *et al.*, 2011).

Today, current motivators for the production of LULC maps include new directives regarding biodiversity monitoring and carbon accounting, with a need for data comparable across national boundaries. Some of these stem from the EU, such as The Habitats Directive of 1992 and Natura 2000 (Lengyel *et al.*, 2008), while others are of a global nature, such as the Kyoto Protocol and the Convention on Biological Diversity (CBD 2009). Other large area cooperative efforts are, for example, the Global Monitoring for Environment and Security (GMES) and Inspire directives in Europe, and the Group on Earth Observations (GEO) on the global level.

1.3 Landscape heterogeneity and satellite data pixel size

The importance of satellite data pixel size and scale issues deserves special attention in the case of land cover mapping. In the remote sensing context, Woodcock and Strahler (1987) use the term "*spatial resolution*" to refer to the sensors' ability to resolve the spatial detail of the landscape. Satellite data are often categorized by the pixel size (i.e., spatial resolution) as low (coarse; 200-1000 m pixel size), medium (moderate; 10-200 m), or high (fine; <10 m) resolution. Strahler *et al.* (1986) described two different types of models

representing the interaction between satellite spatial resolution and the scale of the objects being observed. These were *H*-resolution and *L*-resolution, in which *H*-resolution image pixels are smaller than the objects observed, and in *L*-resolution where the objects are smaller than the image pixels. As an example, for forests, *H*-resolution may translate to "several pixels per tree", while *L*-resolution translates to "many trees per pixel." Several studies have shown decreasing thematic classification accuracy with increasing spatial resolution (Woodcock & Strahler, 1987; Marceau *et al.*, 1994). In general, coarser resolution satellite data will have more pixels containing mixtures of cover types, making estimation of vegetation parameters more difficult (Lu, 2006). *H*-resolution imagery does not assure higher classification accuracies (Atkinson & Aplin, 2004), as aggregated spectral information of the landscape may be necessary for accurate classification. For example, not only the spectral reflectance from tree crowns but also the shadow cast by the tree crowns is an important source of information for the estimation of forest parameters. A moderate resolution pixel will capture both tree crown and its associated shadow. Higher spatial resolution data may provide more thematic detail, but the trade-off in pixel size is generally paid for with a smaller scene area coverage, resulting in a potentially more costly and complex mapping project.

Different landscapes present different levels of heterogeneity and transitions between land cover types can be distinct or fuzzy, and hard to define even in the field. The spatial composition of the landscape structure, such as the forest stand sizes present, and the diversity within it such as presence of elements like bedrock outcrops, wetlands, water bodies, and roads, may also have an effect on the result (Smith *et al.*, 2002; Aplin, 2006; Lam & Remmel, 2010). The properties of the landscape and the goals of the mapping project exert important influences on the appropriate choice of remotely sensed data that have an "optimal spatial resolution" (Woodcock *et al.*, 1988). Some research has been done on determining "optimal pixel size" (Stoy *et al.*, 2009), often involving the use of variograms (Woodcock *et al.*, 1988; Atkinson & Curran, 1995; Treitz & Howarth, 2000). Others have proposed using multiple-scale remotely sensed data for land cover classification (Ju *et al.*, 2005; Hilker *et al.*, 2009). The production of global land cover data often requires the use of coarse resolution data, which has stimulated the use of sub-pixel estimation methods to capture information about the heterogeneity within the larger pixel (Defries *et al.*, 2000). Lastly, it should be noted that the measured spectral response is related to the scale of observation, and may result in non-linear relationships between the scales of observation, in particular with NDVI (Chen, 1999; Jiang *et al.*, 2006).

1.4 Combining satellite data and reference data for classification

Reference data can be derived from many sources, such as high resolution remotely sensed data (e.g., aerial photographs, video, IKONOS, or LiDAR), map data, field-collected data, and inventory data. Reference data have assigned or measured variables describing properties of the sample plot (e.g., land cover class, percent shrub cover) and often have associated geographic coordinates. The satellite data are provided as geo-coded raster data with separate bands for each spectral wavelength. The common geographic locations allow the association of the spectral data to the variables from the reference data (see Figure 1). The aim is to associate known vegetation characteristics with spectral data, ideally having distinguishable spectral characteristics (i.e., "spectral signatures"), making creation of LULC maps from satellite data possible.

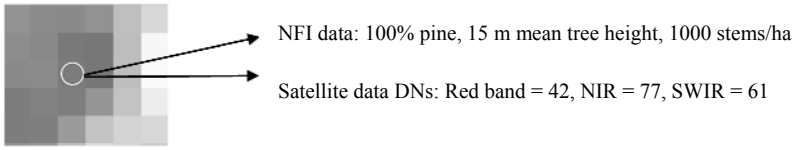

Figure 1. Example of a 10 m radius NFI plot corresponding to the same geographic location in Landsat TM data (25 m pixels).

The process of creating thematic LULC maps is often done using "classification" methods, which can be divided into two groups: supervised and unsupervised. Unsupervised classification methods first cluster the satellite data based on the statistics of the image, initially without use of reference data. Reference data are used afterwards to assign a class label to each cluster. Unsupervised methods are often used when reference data are sparse or inadequate (Cihlar *et al.*, 2000). Supervised classification is initially dependent on reference data. The reference data are used to identify a subset of the pixels in the image to build a model for the classification algorithm. The model is then applied to the entire satellite image. These reference data are referred to as "training data", and a good training data set should assign class labels to the range of spectral values present within the satellite image.

There are many different supervised classification methods, which can be separated into two groups: parametric methods, such as the maximum likelihood classification method (Hubert-Moy *et al.*, 2001; Tso & Mather, 2009), and non-parametric methods, such as decision and regression trees (Pal & Mather, 2003), random forests (Pal & Mather, 2005; Gislason *et al.*, 2006),

*k*NN (Tomppo *et al.*, 2008), support vector machines (Foody & Mathur, 2006; Tso & Mather, 2009), and neural networks (Atkinson & Tatnall, 1997). Parametric classifiers rely on defined statistical properties of the training data (e.g., normal distribution), whereas non-parametric do not. Classification can be carried out at the pixel level or at an aggregated level, such as segments (e.g., object-oriented classification). Classification methods can be combined, such as ensemble or majority-vote classifiers (Pal, 2005; Foody *et al.*, 2007), or guided clustering (Bauer *et al.*, 1994). Lu and Weng (2007) provide a recent review of image classification methods.

While this thesis focuses primarily on classification of satellite data, estimation methods should also be mentioned. Estimation methods for raster data use models to predict continuous values as an output, as opposed to a thematic class, for each pixel in the satellite data. Estimation of forest parameters is a common application (e.g., stem volume, percent forest cover). Estimation requires reference data and satellite data as input, and applies methods such as *k*NN (Nilsson, 1997; Tomppo *et al.*, 2008), regression, or regression trees (e.g., Olthof & Fraser, 2007). Raster output from continuous value estimation can also be used to assign a thematic class to a pixel. When continuous values are estimated with the goal of creating a thematic map, this is sometimes referred to as "soft" classification (Fernandes *et al.*, 2004). As a simple example, a raster output of percent forest cover can be converted to a two class thematic map of forest and non-forest by defining forest by the percent forest cover. Running *et al.* (1995) suggests that estimating continuous variables and creating thematic classes from the results allows for more flexibility and use of the results.

The availability of reference data (or lack thereof) is a major factor influencing many aspects of a mapping project. Much research has been conducted on classification methods, while relatively few guidelines have been published regarding methods of collection or properties of training data for operational mapping projects. In projects where reference data are scarce or not available, data for the purpose of the project are often collected, sometimes called "purpose-collected" training data. The training samples are often subjectively chosen locations, and homogenous groups of pixels, either identified in the field or by other means, and frequently in close proximity to roads. Subjective identification of training data is thus biased by the operator, however, it is the most common method of constructing a training data set. There may be advantages and disadvantages to using either subjectively or objectively collected training data. In operational projects, availability of data, cost of data collection, the characteristics of the landscape, the scale of the satellite data, and the aims of the mapping project (e.g., classification scheme

or accuracy goals) often determines what type of training data will be used. Reference data have another significant role in the image classification process, which is for accuracy assessment of the map.

1.5 Pre-processing of satellite data

Satellite data can be influenced by effects from the atmosphere, solar illumination angles, topography, and sensor view angles. Since these effects complicate the classification process and can decrease classification accuracy, a great deal of research has been carried out to develop methods to reduce their influence. However, in many large area projects, pre-processing beyond geometric correction is often not done (Franklin & Wulder, 2002). Vogelmann *et al.* (2001a) review the effects of radiometric calibration on landscape mapping.

One correction is the reduction of atmospheric effects in order to obtain reflectance values. There are two categories of corrections, namely absolute and relative. Absolute correction requires data regarding atmospheric conditions at the time of image acquisition, which are often difficult to obtain. Relative reflectance correction can be done by normalizing an image relative to another data source, for example, to another image which has already been corrected (Song *et al.*, 2001). Large area projects often need to use satellite images from different dates. If multiple scenes are used with extension of training data from one scene to another (Pax-Lenney *et al.*, 2001; Olthof & Fraser, 2007), reflectance normalization is a necessary pre-processing step. Clouds and haze are a common problem in mountainous and tropical environments. For Sweden's GSD-Land Cover map, a haze normalization process used NFI data to identify dense coniferous forest to construct a relative scene-wise haze index based on these areas (Hagner & Olsson, 2005).

Topographic characteristics of the landscape, such as slope and aspect, in combination with the solar zenith and azimuth angles, result in illumination differences within a satellite image. Topographic normalization methods adjust the spectral radiance in an image so that a vegetation class will have similar spectral values whether facing away from or towards the sun (Holben & Justice, 1980). While in mountainous areas the effects of topography and illumination angles are greater, topographic and illumination normalization is also performed for images over non-mountain areas. There are several categories of topographic normalization methods, such as photometric/photometric-empirical, statistical-empirical, sun-canopy-sensor, and physically based models (Soenen *et al.*, 2008). Based on the fact that non-Lambertian reflectance varies in degree with surface roughness and therefore

by vegetation characteristics (Holben & Justice, 1980; Teillet *et al.*, 1982), different topographic normalization methods are suggested for different vegetation types. Sun-canopy-sensor models or physically based models are more appropriate for forests, whose geotropic growth and canopy self-shadowing need to be taken into account (Gu & Gillespie, 1998). Semi-empirical normalization methods, such as the C-correction (Teillet *et al.*, 1982) and Minnaert correction (Smith *et al.*, 1980) are more appropriate for vegetation of shorter stature, such as that in the alpine areas.

Wide-angle sensors, such as AVHRR, MODIS, MERIS, and AWiFS, acquire data over such large swath widths that the radiance measured at nadir is not comparable to the radiance at the far edge of the image for the same vegetation class. The sensor viewing angles and solar illumination angles differ over the image area, but can be described by the Bidirectional Reflectance Distribution Function (BRDF) and thereby corrected (Li *et al.*, 1996). Such a correction is more critical in the case of physical parameter estimation as opposed to classification. The distributors of MODIS data provide Nadir BRDF-adjusted image products (Roman *et al.*, 2009).

1.6 Classification methods

1.6.1 Discriminant analysis and maximum likelihood

Discriminant analysis is a method by which one assigns class membership to an unknown observation based on a sample of data with known class memberships (Lachenbruch & Goldstein, 1979). For each class, a probability density function based upon the sample data distribution, as well as prior probability weights for each class (normally assigned by the user) are used to calculate the probability of getting the values in the sample data set. Then a posterior probability that an observation belongs to a certain class is calculated using the prior probabilities, the probability density function, and the probability of occurrence for that observation. These calculations are collectively also called the Bayes' rule. The maximum likelihood estimator is a rule used in Bayesian discriminant analysis, in which the observations are assigned to the most "likely" (i.e., highest probability) class, in order to maximize correct classification assignment. Discriminant analysis works best following the assumption that the data for each class and variable are normally distributed. In some cases, the covariance matrices of the different classes in the data may have the same distribution, and in this case, a linear discriminant analysis can be used. In cases where covariance matrices are not the same between classes, quadratic discriminant analysis should be used.

In remote sensing, practitioners often refer to the "Maximum Likelihood" (ML) supervised classification method (Lillesand *et al.*, 2008). Maximum likelihood classification was often used for land cover mapping projects in the 1980's and 90's, and is still used today. In practice, the application of ML classification in land cover mapping has often assumed equal prior probability of class occurrence due to lack of sufficient information about the frequency of class occurrence. When prior probabilities of occurrence can be assigned to the classes in the training data, this has sometimes been referred to in the remote sensing literature as an "extension of maximum likelihood" (Pedroni 2003).

In essence, when remote sensing practitioners refer to "maximum likelihood classification *using prior probabilities*", they are most often using Bayesian quadratic discriminant analysis, which uses prior probabilities. On the other hand, if a "maximum likelihood" classification without prior probabilities is used, then this is actually Bayesian discriminant analysis with equal prior probabilities for all classes. If equal probability is assumed and no weights are used in the training data, the result may be that more frequently occurring classes in the training data will be under-classified (errors of omission) in the resulting map and less frequently occurring classes will be over-classified in the map (errors of commission). Several remote sensing studies have pointed out the utility of including prior probabilities within the "maximum likelihood" classifier (Strahler, 1980; Skidmore & Turner, 1988; Pedroni, 2003), finding that it improved land cover classification accuracy, particularly for spectrally similar classes.

1.6.2 Decision trees, regression trees, and random forests

The use of non-parametric methods for land cover classification has increased in the past decade, with three methods being widely used, namely decision trees, regression trees and random forests. Decision trees produce a categorical output, regression trees produce continuous variables, and random forests is capable of producing both. The non-parametric methods have an important advantage over maximum likelihood classification in that data from different sources (e.g., spectral data, elevation derivatives, map data) can be combined, without the need for assumptions of normal distribution. In decision trees, a hierarchical tree is constructed from the training data. The tree consists of root nodes, interior nodes and terminal or leaf nodes (Tso & Mather, 2009). Data splitting rules are constructed at each non-terminal node based on the training data's spectral and class values. Splitting rules depend on the specific implementation of the decision tree, although most often they are based on determining the maximum information gain (Quinlan, 1993) and the lowest Gini impurity index (Breiman *et al.*, 1984) based on the input variables at each

node. In decision trees one variable is normally used for splitting at each node, although multivariate decision trees have been developed (Friedl & Brodley, 1997). Pruning of the trees is often necessary to avoid over-fitting of the data, often accomplished by setting aside a portion of the training data to use for pruning. Regression trees also consist of the same node system, however univariate or multivariate regression functions are built to estimate continuous values.

Random forests are a combination of decision or regression tree classifiers that use randomly chosen samples from the training data to construct each individual tree. Bootstrap samples are taken from the training data, and a decision or regression tree is fit using a binary partitioning of the data. Majority-voting by a user-specified number of trees (usually a large number) is used to assign the final class or continuous value. Random forests uses bagging (Breiman, 1996) as well as a random selection of the variables to consider at each node, therefore pruning of trees in random forests is not required. Use of the random forests classifier has produced classification results that are equally accurate (Pal, 2005) or more accurate than other methods (Gislason *et al.*, 2006; Na *et al.*, 2010), and it is relatively robust to outliers and noise (Breiman, 2001). Probability of class membership is based on the frequency of classes in the training data. Therefore, all the tree classification methods discussed here are subject to misclassifications due to imbalanced data (i.e., having an uneven distribution of training samples among the classes), and for this reason, weights and other improvements are sometimes added (e.g., McIver & Friedl, 2002; Chen *et al.*, 2004; Xie *et al.*, 2009). For a more thorough discussion of these methods, see Breiman *et al.* (1984), Friedl and Brodley (1997), Breiman (2001), Fernandes *et al.* (2004), and Tso and Mather (2009).

1.7 Training data

The “training data sample” refers to each individual reference plot with associated vegetation and spectral information. The “training data set” is the term referring to the collection of all training data samples into a data set. The number of training data samples needed, the scale of the training sample, the sampling scheme, the interaction between the classification method and characteristics of the training data set, and the quality of the training data are just a few of the issues revolving around training data for supervised classification. A sufficient number of training samples and their representativeness are clearly critical for image classifications (Hubert-Moy *et al.*, 2001; Chen & Stow, 2002; Mather, 2004). However, precise determination of the number of training data samples needed to achieve an accurate

classification is elusive. This is, in part due to the "catch-22" nature of needing detailed and accurate class and spectral information on which to base estimates of the number of training data samples needed. It is also due to the complex interaction of different factors that influence the classification results.

Firstly, the characteristics of the supervised classification method exert an influence on the requirements from the training data set. As an example, statistical classifiers using the mean vector for class assignment will be influenced less by outliers in the training data, while classifiers such as Neural Networks can be highly influenced by individual poor quality training data samples (Mather 2004). Some classifiers, such as maximum likelihood, require a minimum of p+1 (p = number of input variables) training samples per class to build statistics (e.g., covariance matrices). Based on this, Mather (2004) recommended that 10 to 30 times p training samples per class should be used. Non-parametric methods don't face this restriction, but are still affected by the total number and frequency of classes in the training data. The number of samples necessary to obtain adequate representation of the spectral variability present in a class can be determined statistically by sampling. This was done by Curran and Williamson (1986), however they based their calculations on only one spectral band or a two-band ratio, rather than on all input variables. Traditional distance measures of separation between classes are also often used (e.g., Jeffries-Matusita distance or Transformed Divergence), but these may be poor predictors of actual classification accuracy (Van Niel *et al.*, 2005), as they don't provide information about the adequacy of spectral representation of an individual class.

Not only the representation of a class' spectral variability needs to be taken into consideration, but also the spectral similarity or dissimilarity to other classes (Hubert-Moy *et al.*, 2001). As an example, water has a spectral signature so distinct from many vegetation types, that a full description of the spectral variability of water may not be necessary for accurate classification. Two very spectrally similar classes, such as willow and mesic heath require careful and full assignment of their spectral characteristics if one hopes to accurately classify these overlapping classes. Considering class spectral overlap, Van Niel *et al.*, (2005) found that only 2 to 4p training samples per class were sometimes necessary. Foody used neural networks (Foody, 1999) and Support Vector Machines (Foody and Mathur 2006) which depend on good separation between class boundaries in variable space, therefore only needing to include minimum and maximum variable values for all classes, allowing the training data set size to be smaller.

In the estimation of continuous values, a larger training data set is generally required. Mathys *et al.* (2009) found that for estimation of continuous

parameters, a training data set consisting of the whole range (0-100%) of the parameter was necessary. In fact, training samples containing mixes or 0% of the parameter were more important than training samples with 100% representation of the parameter.

The size of the sample plot used for training data is also important. Gong and Howarth (1990) suggested that training data were best selected using single pixels and a systematic sample, however Chen and Stow (2002) said this was more suitable for homogeneous land cover types. Chen and Stow (2002) tested training samples taken on single pixel level and in blocks of pixels, finding that training data set size mattered more when single pixel training samples were used, and that blocks of pixels produced higher accuracies for training in heterogeneous landscapes. However, their result may have been dependent on the urban land use classes particular to their study. When the landscape of a study area is complex and heterogeneous, selecting sufficient training samples becomes difficult (Lu and Weng 2007).

The frequency of the classes as represented in the training data has an influence on the results. In large area projects, it is desirable to have *a priori* information on the frequency of classes in the area (Cihlar 2000), as input to the supervised classification. For this reason, prior probabilities are assigned in Bayesian classifiers. Additionally, weights can be added in Decision and Regression Tree models to counteract imbalanced data (Xie 2009). Rare classes are often a desired class in map products, and sufficient training data may need to be collected specifically for this purpose.

There are also temporal aspects to recognize when using training data. Reference data may be collected from dates differing from the satellite imagery and this may cause erroneous class assignment. The timing of the image acquisition and the vegetation phenology must be considered in relation to the training data. In the case of the alpine landscape, the natural seasonal dynamics and change in moisture conditions that can occur within the growing season as well as from one year to another in the alpine region pose challenges to using training data and satellite data from different time points. Within managed forest landscapes, silvicultural activities such as thinning and clear-cutting need to be identified. In many large area projects satellite images from different dates may be used in mosaics, and may involve extension of training data, further complicating training data use (Pax-Lenney *et al.*, 2001; Olthof & Fraser, 2007).

Finally, several researchers emphasize the importance of quality control and refining training data in order to obtain accurate classifications (e.g., Foody & Arora, 1997; Chen & Stow, 2002; Frery *et al.*, 2009; Kavzoglu, 2009). Some authors suggest reducing the effects of outliers in the training data by

weighting training samples according to their quality (Mather 2004), or by subjecting training data to majority-vote classifiers to detect mislabeled data (Brodley & Friedl, 1999).

1.8 Accuracy assessment

Accuracy assessment of the map product is often an important element for the users of the data. It is sometimes not carried out, however, for large area projects, due to the lack of reference data, or limitations in project time or funding. An independent and objectively collected evaluation data set is essential to an unbiased assessment of the map product. Stehman and Czaplewski (2003) defined four criteria that should be met: 1) probability sampling, 2) adequate sample sizes with which to estimate user's accuracies with acceptable level of precision, 3) cost efficiency must be considered, and 4) spatial distribution of samples must be representative across the area of interest.

Stehman and Czaplewski (1998) have established three basic elements to consider in the design of an accuracy assessment plan: the sampling design, the response design, and the estimation and analysis protocol. The sampling unit may be a pixel, fixed-area plot or polygon, although the optimal unit depends on the application. Stehman *et al.* (2000) favor pixel-based evaluation units, as larger units render the results non-site specific. Polygon assessments also tend to lead to conservative estimates of classification accuracy (Verbyla & Hammond, 1995). Class homogeneity within the accuracy assessment unit is appealing, but not necessary, and if intentionally included, may bias the assessment of the map accuracy. A design-based sample with known inclusion properties is best, but the distances between plots should be large enough that potential spatial auto-correlation effects do not influence the result. Definitions constituting correct and incorrect responses should be established (e.g., if polygon accuracy assessment units are used, the rule may be that a "correct" classification requires a majority of the classified pixels to be correctly labeled as the dominant class, or the rule may be that the two most dominant classes must both be classified).

As with training data, questions regarding the sample size and sampling scheme of the accuracy assessment data need to be addressed. Stehman (2001) suggests that a sample size of 100 samples per class assures the population is estimated adequately. Congalton and Green (2009) suggest a minimum of 50 samples per class. To capture the necessary number of samples for rare classes, a stratified sample may be useful (Stehman, 2001). The quality of evaluation

data is of much importance, and a quality check of the evaluation data should be carried out before use.

Accuracy assessment is often presented in an "error matrix", with errors of commission (called "user's accuracy") and omission (called "producer's accuracy") for each class in the map, as well as a measure of overall accuracy. The kappa statistic, or k-hat, is also a measure of overall accuracy, and is intended to account for the chance of random agreement (Congalton and Green, 2009). A desired overall map accuracy of 85% is often given as a benchmark, but may not be realistic to achieve (Wulder *et al.*, 2006). Fuzzy accuracy assessment (Gopal & Woodcock, 1994; Foody, 2002) can be a useful measure of portraying different types of errors that may be more or less acceptable.

It is slightly more common that inventory data are used for accuracy assessment than for training (e.g., Riemann *et al.*, 2010). Wulder *et al.* (2006) encountered difficulties when applying 2 ha polygon-based inventory data due to differences between the raster and vector data, particularly because the polygon interpretation included heterogeneous cover. When purpose-collected video data were later photo-interpreted for accuracy assessment, the uncertainty in the photo-interpretation and the lack of a probability-based sample were drawbacks (Wulder *et al.*, 2007). One of the primary requests emerging after Canada's EOSD land cover mapping project was for improved collection strategies of calibration (training) and validation (accuracy assessment) data (Wulder *et al.*, 2008).

1.9 National inventories

Probability-based national inventories can be a source of high quality reference data. The initial development of such inventories was often for the purpose of estimating the quantity and quality of resources over a given area, with the aim of better planning and management of those resources (Cochran, 1977; Ståhl, 1994; Gregoire, 1998). Inventories may be focused on a particular resource, such as forest, or may be more encompassing, such as a terrestrial inventory. Today, many countries have some sort of national inventory program, but the scope and quality often depends on the economic importance of the resource to the country, political or legal requirements, and governmental support and administration.

Sampling techniques can be divided into those that are design- or probability-based ("objective") or non-probability based ("subjective"). There are inventories that are collected subjectively, such as wall-to-wall mapping of forest stands. Probability-based sampling methods are most often used in

inventory design because they can produce data with known statistical properties. Probability-based sample designs can differ in their layout, such as systematic, stratified random or two-stage cluster sampling. Likewise, the sampling unit varies and may be, for example, fixed-area plots or line transects (or a combination). Most often a fixed-area plot is used, such as a circular plot of a given radius, or square, rectangular, or hexagonal plots. The temporal resolution of an inventory is another factor, and plots may be re-surveyed on a fixed time cycle (i.e., "permanent plots", resurveyed every five years), or not ("temporary plots"), or have a combination of these. The variables measured are a key characteristic of the inventory and can differ widely in number and detail. Most inventories undergo moderation in design and methods in order to adapt to changing demands by the users of the data, new policy directives and new technology.

Many countries now have a National Forest Inventory program, although there are differences between them such as sampling design, definition of forest, method of sampling, variables measured, and temporal cycle of the inventory (Lawrence *et al.*, 2010). An overview of different NFIs is given in McRoberts et al. (2010c) and Tomppo et al. (2010). The Nordic countries are among those with a long-established history of NFIs (Tomppo *et al.*, 2008). Larger area countries such as Canada and the US tended until recently to have forest inventories conducted independently at provincial/territorial or state levels. However, a plot-based and aerial photograph-based NFI using a common method for the country as a whole was established in Canada (starting in 2000) (Gillis *et al.*, 2010) and in the US, the Forest Inventory Analysis (FIA) initiated consistent national level inventory in the 1990's (McRoberts *et al.*, 2010b).

The manner and degree to which remote sensing plays a part in different NFIs varies by country. There are synergistic uses of these data sources that may improve the results of using either data source alone. Remotely sensed data can be used within the context of NFIs in several ways, including as ancillary data or substitute for field visits, aiding the estimation of forest parameters, and mapping (McRoberts & Tomppo, 2007). Multi-source inventory is a term for the inventory system that combines inventory data and satellite data derived maps to calculate statistics of the resource under study (Tomppo & Tuomainen, 2010). Finland has an example of a true multi-source inventory, where forest maps are created from satellite data using the *k*NN algorithm (Tomppo *et al.*, 2008). In Finland and Sweden, satellite images are used as an ancillary data source to improve area statistics by post-stratification of the NFI statistics (Nilsson *et al.*, 2009; Axelsson *et al.*, 2010). Canada uses aerial photographs for inventory assessment in remote areas and Wulder *et al.*

(2010) have proposed the introduction of MODIS data for forest monitoring and inventory update. The US also uses satellite imagery for both pre-stratification and post-stratification in their FIA (McRoberts *et al.*, 2002) most recently with the use of model-based approaches (McRoberts, 2010) and to construct spatially explicit forest maps (McRoberts *et al.*, 2010a).

The nature of forest inventories has recently been influenced by importance of biodiversity indicators and carbon accounting. This has changed and expanded the spatial, temporal and categorical properties of many NFIs (Falkowski *et al.*, 2009; McRoberts *et al.*, 2010c). Within the latest cycle of the Swedish NFI, more fieldwork has been conducted within the mountain birch forest than in earlier cycles.

Some countries have sample-based inventory programs that cover all land cover types, regardless of the resource. The UK has conducted the British Countryside Survey (Haines-Young *et al.*, 2003), a terrestrial inventory, at regular intervals since 1978. More countries are initiating just such inventories, as was recently introduced with the Swedish NILS program. Inventory programs exceeding national borders are also being initiated, such as the European-wide LUCAS inventory that aims to provide a common reference data set for Europe with over 230,000 plots across the EU (Martino & Fritz, 2008). The process to harmonize European inventories used for environmental monitoring has also been initiated to enable sharing of data across national boundaries (Bunce *et al.*, 2008).

Sweden has a number of national inventory programs, three of which are described in the following sections. All of these inventories have their administrative and, in part, functional base within the Department of Forest Resource Management at the Swedish University of Agricultural Sciences. The placement of these inventory programs within a university allow for research to be conducted which can be used in the inventory program, and provides infrastructure for data sharing and communication among the sections at the Department, which includes the Section of Forest Remote Sensing.

1.9.1 The Swedish National Forest Inventory (NFI)

The NFI is a probability-based stratified sample that measures hundreds of variables on trees, vegetation, soil, and other aspects. Circular field plots (10 m radius for permanent plots, 7 m radius for temporary plots) are systematically arranged as tracts that vary in number, dimension, number of plots, and distance between plots, depending on the geographic stratum in which they are located. All permanent plots are re-surveyed every five to ten years, and GPS has been used for assigning plot coordinates since 1996 (Axelsson *et al.*, 2010). Over 10,000 plots are field-visited and measured each year.

1.9.2 The National Inventory of Landscapes in Sweden program (NILS)

The objective of the NILS program is to "provide data for and perform analyses of landscape biodiversity conditions and changes in terrestrial environments in Sweden" (Ståhl *et al.*, 2011). Towards this aim, a probability-based stratified sample inventory was established. The stratification is based on ten geographical regions within Sweden, and within each stratum 5 × 5 km squares are arranged systematically, forming the basic inventory units. There are a total of 631 squares, with distances between them depending on the geographic stratum. Within each 25 km^2 sample unit, the inner 1 × 1 km square is photo-interpreted using a full-coverage polygon delineation, and twelve systematically arranged (250 m between plot centers) fixed-area plots are field-visited, in addition to twelve 200 m long line transects for linear feature inventory between the field plots. The field plots are GPS-located and permanent, and all plots are re-surveyed on a five-year cycle. The field plots are based on concentric circles, with a 20 m, 10 m, and 3.5 m radius plot, with an addition three small plots of 0.28 m radius in a cluster arrangement from the plot center, with different variables measured in each of these plot sizes.

1.9.3 The Terrestrial Habitat Monitoring program (THUF)

The Terrestrial Habitat Monitoring program (THUF) is concentrated on vegetation types to be protected under the EU species and habitat directive. It is conducted in close cooperation with NILS. A project within THUF is the "Demonstration of an integrated North-European system for monitoring terrestrial habitats" project, or MOTH (Gardfjell & Hagner, 2011). Within the 25 km^2 squares of NILS, a point-sample is systematically arranged over a 2 × 5 km area and photo-interpreted from CIR aerial photographs. There are 200 points, arranged with 250 m between each point, and a vegetation class (based on Natura 2000 classification system) is recorded for the center point within a 10 m radius circle. Plots containing vegetation types of interest are field-visited.

1.10 National land cover mapping projects using optical satellite data

Among one of the first national land cover maps produced from moderate resolution data was the UK's 1990 Land Cover Map (LCM1990). The LCM is one of two complementary parts of the British Countryside Survey, the other part being a national field-based inventory of 508 1 × 1 km squares (Smart *et al.*, 2003). LCM 1990 used two-season Landsat TM data and subjectively chosen training data for a supervised classification (Fuller *et al.*, 1994).

Accuracy assessment was conducted with both subjectively chosen field-visited areas and some Countryside Survey field data. The LCM was repeated in 2000 (Fuller *et al.*, 2002) and 2007 (Morton *et al.*, 2011) using Landsat data and subjectively chosen reference data.

The CORINE project mapped land cover for European Union countries, using Landsat TM data from 1990 and repeated using Landsat TM/ETM+ data from 2000 (CLC1990 and CLC2000). The mapping was operated at a national level, with a common classification scheme and variable classification methods, ranging from manual visual interpretation to fully automated supervised classification. The UK and Sweden chose to first develop more thematically and spatially detailed national products which were then generalized to produce the 25 ha resolution CORINE land cover map (e.g., Fuller *et al.*, 2002; Hagner & Reese, 2007).

In the US, the Gap Analysis Program (GAP) began in 1987 to produce regional and national land cover maps from Landsat TM data to be used in habitat analyses. Classification was conducted at state or multiple-state levels. Supervised classification was carried out primarily with subjectively-chosen field data sites (e.g., Homer *et al.*, 1997), sometimes complemented with inventory data (e.g., Reese *et al.*, 2002; Lowry *et al.*, 2007). An updated nationwide GAP land cover map was recently completed in 2010. Concurrent to GAP, a mapping project called the National Land Cover Data set (NLCD 1992; Vogelmann *et al.*, 2001b) was initiated based on a single classification method for the whole country. NLCD 1992 employed an unsupervised classification of Landsat TM/ETM+ data and used aerial photographs as reference data. The project was repeated in 2001 (NLCD 2001; Homer *et al.*, 2007), this time using decision and regression trees with Landsat, DEM derivatives and other ancillary data, to produce both a thematic land cover map and continuous values (e.g, percent tree canopy and percent urban impervious surface). The training data were derived from map data, field-visited plots and FIA plot data. NLCD 2006 has been recently completed, which is an update to NLCD 2001 using change detection methods (Xian *et al.*, 2009).

Canada has produced a national land cover map referred to as EOSD Land Cover 2000 (Wulder *et al.*, 2008). Over 480 Landsat TM/ETM+ images were used to produce an unsupervised classification of 23 classes for the forested area. Provincial forest inventory data, aerial photo data, and local knowledge were used to assign class labels to the clusters. At the time of the EOSD LC 2000 project, the new Canadian NFI had not been completed, and was not available for operational use. Recently, classifications made from the integration of new NFI data and Landsat data (Remmel *et al.*, 2005) have been tested in British Columbia.

The number of operational large area classification projects employing national inventory data as training data is surprisingly few. The US NLCD 2001 map used FIA data together with Landsat data in a decision tree classification and regression tree estimation of percent tree cover (Homer *et al.*, 2007). In Sweden, NFI data were used in an automated, supervised maximum likelihood classification of Landsat data for the forest classification in CORINE and the more detailed national product, the GSD-Land Cover Map (Hagner & Reese, 2007). Within Canada's EOSD mapping project, although an unsupervised hyper-clustering approach was used for forest, a combination of provincial forest inventory data and aerial photo data were used to label the clusters (Wulder *et al.*, 2008). Such large-area operational projects are often made up of multiple satellite scenes, and often need to rely on some degree of automated processing in order to maintain consistent results between scenes, to enable reproduction of results, and to meet time and budget restraints (Aitkenhead & Aalders, 2011). However, use of automation is not widely prevalent, perhaps due to the intricacies and the "art" of classification, where manual intervention is seen as necessary.

Large area, medium-resolution map products which are predictions of continuous values (as opposed to thematic classifications) based on the combination of satellite data and NFI are more numerous, as the popularity of the *k*NN method (Tomppo, 1990) for forest parameter estimation spread from the Nordic countries. Finland started to produce nationwide wood volume databases by combining satellite data and NFI data in 1990, and Sweden produced a nationwide wood volume database in the same manner in 2000 (Reese *et al.*, 2003) and 2005, and the 2010 database is under production (skogskarta.slu.se). The US NLCD 2001 provides a nationwide map of percent tree cover, and several US states such as New Hampshire and Minnesota have produced *k*NN maps of wood volume (Lister *et al.*, 2005; McRoberts, 2010).

1.11 Optical remote sensing characteristics of forest and alpine/subalpine vegetation

Sweden's vegetation is dominated by forests, covering approximately 24.5 million ha or 60.4% of Sweden's land area (Anonymous, 2006). Scots pine (*Pinus sylvestris*) Norway spruce (*Picea abies*), and birch species (*Betula pendula, Betula pubescens*) are dominant, with other deciduous and coniferous species present. Sweden has a long history of forestry carried out by private, public and commercial actors, and much of the forest is managed, primarily in stands. The boreal forest zone stretches from the northern tip of Sweden

towards the Dal River ("Dalälven"), and the hemi-boreal forest zone is located from the Dal River and down to the southern tip of Sweden.

The ability to separate and classify coniferous and deciduous forests is well established in the remote sensing literature, as deciduous leaves reflect more of the NIR wavelength than coniferous trees (Lillesand *et al.*, 2008). Mixed deciduous/coniferous forests are more difficult to classify correctly due to the spatial arrangement and uneven mixtures of the deciduous and coniferous species within pixels. For boreal and managed coniferous forests, SPOT and Landsat data have a primarily negative correlation with wood volume in the visible and mid-infrared bands (Trotter *et al.*, 1997). Correlation with the near-infrared band is often more varied and might be lacking (Franklin, 1986). Forest canopy self-shadow has a large effect on the spectral response, yet it can be used to help derive stand parameters (Li & Strahler, 1986; Nilson & Peterson, 1994). For Swedish forest conditions, shadow is particularly important (Ardö, 1992) due to several factors including that coniferous tree species' crowns tend to cast more shadows than deciduous species and that the low sun angles occurring at Sweden's relatively high latitude produce more shadow and illuminate ground vegetation less (Nilson, 1992). The SWIR bands have been shown to be of significance in forest parameter estimation, most likely due to their sensitivity to shadow patterns (Olsson, 1994). As forests mature, the canopy tends to close, decreasing the amount of shadow and weakening the ability to determine forest parameters from optical satellite data (Franklin, 1986; Danson, 1987; Spanner *et al.*, 1990; Ekstrand, 1994; Trotter *et al.*, 1997). Trotter *et al.* (1997) found poor correlation between the SWIR band (TM band 5) and plantation forests, however, this was most likely due to the lack of complexity and shadows within the even-height plantation forests. The correlation between spectral data and wood volume tends to be stronger for younger stands than older stands (Franklin, 1986; Horler & Ahern, 1986; Peterson & Nilson, 1993). Horler and Ahern (1986) found Landsat's two SWIR bands to be the most sensitive to forest vegetation density, particularly in the case of regenerating forest stands. Clear-cuts are easily identifiable, with increased reflectance from the visible and SWIR bands and changes in the NIR reflectance (NIR may increase or decrease depending on the management activities and ground/field layer reflectance; Olsson, 2009). Determination of wood volume using Landsat and SPOT data has been hampered in several studies by the limited dynamic range of the spectral data (Trotter *et al.*, 1997), as reflectance of forest tends to be relatively low.

The Swedish alpine and subalpine areas make up approximately 6 million ha or 15% of the land area in Sweden (Anonymous, 2006). Regional alpine and subalpine zones have been defined based on elevation, and differ between the

northern and southern parts of the mountain chain (Rafstedt, 1985). The subalpine forest consists of two regions: the coniferous forest region, which generally occurs between 400 and 900 m elevation (depending on latitude), and the mountain birch region occurring between 600 to 950 m elevation. In the study area of this thesis, the coniferous forest reaches a maximum of 700 m, while the mountain birch region reached a maximum elevation of 900 m (with some individuals occurring over 900 m). The most common tree in the latter zone is subalpine mountain birch (*Betula pubescens* ssp. *czerepanovii*), which grows relatively sparsely, with undergrowth categorized as lichen-dominated, moss and shrub-dominated, or grass-forb dominated. Subalpine mountain birch forest classification has been studied more extensively than alpine vegetation classification due to interest in tree-line changes, biomass (carbon) assessment, and detection of anthropogenic or insect-related damages (Jepsen *et al.*, 2009). In northern Sweden, Dahlberg (2004) found the red band had the highest correlation with biomass and LAI of mountain birch, with NIR the second most correlated, and the SWIR2 (Landsat TM7) band also having a strong negative correlation. The Simple Ratio (Red/NIR) was the vegetation index with strongest correlation, and NDVI had the next strongest correlation. In Finland, Heiskanen (2006) used ASTER data and found the same correlations as Dahlberg (2004), also finding the SAVI index had strong correlations with biomass. Heiskanen and Kivinen (2008) used multi-temporal MODIS data to map continuous fields of tree cover along the tundra-taiga boundary. Heiskanen (2006) found that undergrowth vegetation and background reflectance were very likely to affect the relationship between spectral data and biophysical parameters. In Norway, changes in the mountain birch tree-line have been observed using multi-temporal remotely sensed data, including aerial photo based maps and Landsat data (Tømmervik *et al.*, 2009). The effect of solar zenith angles, tree growth on sloping topography, and the presence of shadows from the sparsely growing mountain birch trees are also important for understanding the observed spectral response from these areas.

The Swedish alpine region is characterized by three main vegetation zones: namely the low, middle, and high alpine regions (Rafstedt, 1985). In the study area of this thesis, the high alpine region is reported to begin at approximately 1500 m, the middle alpine region at 1200-1500 m, and the low alpine region starts at the tree-line and ends at approximately 1200 m (Curry-Lindahl, 1963; Rune, 1963), with the upper boundary often defined by growth of bilberry *(Vaccinium myrtillus;* Rafstedt, 1985). The high alpine belt consists primarily of exposed bedrock and boulders, glaciers, snowfields, and a general lack of coherent vegetation. The topographic gradient, access to water, the soil, climate, and aspect position play a large role in the vegetation composition

(Gould *et al.*, 2002). The vegetation tends to become sparser and shorter further up the elevation gradient. Alpine vegetation types are defined by their vegetation composition, height and density of the vegetation. In creating Sweden's Mountain Vegetation Map by photo-interpretation of CIR aerial photographs, Ihse and Wastenson (1975) established vegetation classes that could be determined with sufficient mapping accuracy. These vegetation classes have also been found to be discernable from optical satellite data (Boresjö-Bronge & Wester, 1999). Relative to forested ecosystems, the remote sensing of alpine vegetation is less well-studied. Alpine vegetation is characterized by multiple scales of spatial heterogeneity (McFadden *et al.*, 1998; Stow *et al.*, 2004) and researchers have reported that pixel sizes coarser than 10 m have not been adequate for mapping alpine vegetation in some areas (Stow *et al.*, 1993; Mosbech & Hansen, 1994). In Sweden, Dahlberg (2001) found that traditional classification methods were not suitable for the heterogeneous alpine vegetation types. Boresjö-Bronge and Wester (1999) developed a knowledge-based classification method. They determined from Landsat TM data that NIR and SWIR were the most important bands in classification of Swedish alpine vegetation types, but that the green band was not significant.

Other alpine vegetation classification projects using medium resolution optical satellite data have applied various classification methods with different levels of thematic detail. Olthof *et al*. (2009) used unsupervised classification of Landsat TM/ETM+ data in northern Canada, deriving 10 vegetation classes above the tree-line (four graminoid classes, three shrub classes, three sparse vegetation classes). Tømmervik *et al.* (2003) used a hybrid supervised/unsupervised classification of Landsat MSS and TM/ETM+ images and more than 500 field-visited plots for cluster labeling. The classes were birch forests, lichen-rich *Empetrum* birch forest, dwarf birch-*Empetrum-Vaccinum myrtillus* heaths, and two dwarf birch-lichen heath types. Johansen and Karlsen (2005) mapped alpine and subalpine vegetation over Finnmarksvida and northern Fennoscandia using Landsat data, DEM and other ancillary data. They derived several forest and wetland classes, seven alpine vegetation types, three snow-bed vegetation types, and other classes (gravel ridges, snow, water).

Many studies have found high correlations with NDVI for different alpine vegetation types (Deng *et al.*, 2007). Stow *et al.* (1993) were able to separate moist tundra, wet sedge and dry heath using SPOT HRV data, but found the 20 m resolution inadequate for capturing the necessary spatial detail. For alpine meadows, Gianelle *et al.* (2009) found NDVI and a Green-NIR-VI from spectrometer data and simulated Landsat TM and MODIS data to have the

most significant relationships with LAI and other biophysical parameters. Kushida (2009) found NDVI best correlated with the alpine sedge-shrub coverage ratio, but for green phytomass, NDII had the strongest correlation. Laidler *et al.* (2008) found NDVI to be highly correlated with percent cover of the vegetation type. The amount of soil and rock showing through the plant canopy is likely to play a strong role in the spectral response for the alpine vegetation types (Boresjö-Bronge & Wester, 1999; Laidler *et al.*, 2008; Montandon & Small, 2008).

2 Objectives

The objective of this thesis is to evaluate different aspects of combining inventory data and optical satellite data for the mapping of forest and alpine vegetation over large areas. The specific objectives for papers I-V are

I To develop and test a method in which the frequency of forest classes according to NFI data are used to adjust the prior probabilities in maximum likelihood classification, and therefore derive a classification of forest types reflecting area statistics in agreement with those from NFI data.

II To investigate the utility of ENVISAT MERIS data for mapping mountain vegetation in Sweden, and to test suitable training data and classification methods for use with coarse pixel size satellite data.

III To investigate the spectral and spatial properties of the newly available Resourcesat-1 AWiFS data in relation to boreal forest stand characteristics, such as stem volume and tree species, and to compare results from AWiFS data with those from SPOT 5 data.

IV To develop a reliable procedure for estimation of the *c*-parameter, used in the C-correction topographic normalization method, for the correction of optical satellite data over alpine areas.

V To evaluate the feasibility of mapping alpine and subalpine vegetation using a combination of optical satellite data and reference data; to evaluate use of different optical satellite data sources for mapping alpine vegetation classes; to assess the effect of using different amounts and configurations of training data for classification; and, to compare classification accuracy resulting from a parametric and non-parametric classification method.

3 Materials and methods

3.1 Materials

3.1.1 Study sites

The study sites in this thesis were located in the forested and mountainous areas of Sweden (Figure 2). Paper I had three evaluation areas, each corresponding to a Landsat scene, in forested areas of northern, central, and southern Sweden. Paper III covered two separate 3600 km^2 forested areas in Västerbotten Province. Papers II, IV and V were conducted in the mountains of Västerbotten and Norrbotten Provinces, with Paper II covering a 400 × 150 km area and Papers IV and V covering a 110 × 110 km area.

3.1.2 Remotely sensed data

The image data used for classification in this thesis ranged from the 10 m pixel size of SPOT 5 to the 300 m pixel size of ENVISAT MERIS (Table 2). While SPOT 5 and Landsat TM/ETM+ are well-established medium resolution sensors, the use of ENVISAT MERIS data and Resourcesat-1 AWiFS data were investigations into newly available image data sources.

Fifty Landsat 7 ETM+ images were classified using the method described in Paper I, and the evaluation results from three of these Landsat images are presented in Paper I. In Paper II a full resolution ENVISAT MERIS image was classified using training data from an unsupervised classification of three Landsat ETM+ images. Paper III used a Resourcesat-1 AWiFS image and two SPOT 5 images for classification of forest and prediction of stem volume. MODIS Nadir BRDF-adjusted reflectance 16-day composites were used as a data source for reflectance normalization in Papers III, IV and V. Paper IV tested a topographic normalization method using two Landsat 5 TM and two SPOT 5 HRG two-image mosaics. Paper V compared classifications of a two-image SPOT 5 mosaic, a Landsat 5 TM image and an AWiFS image.

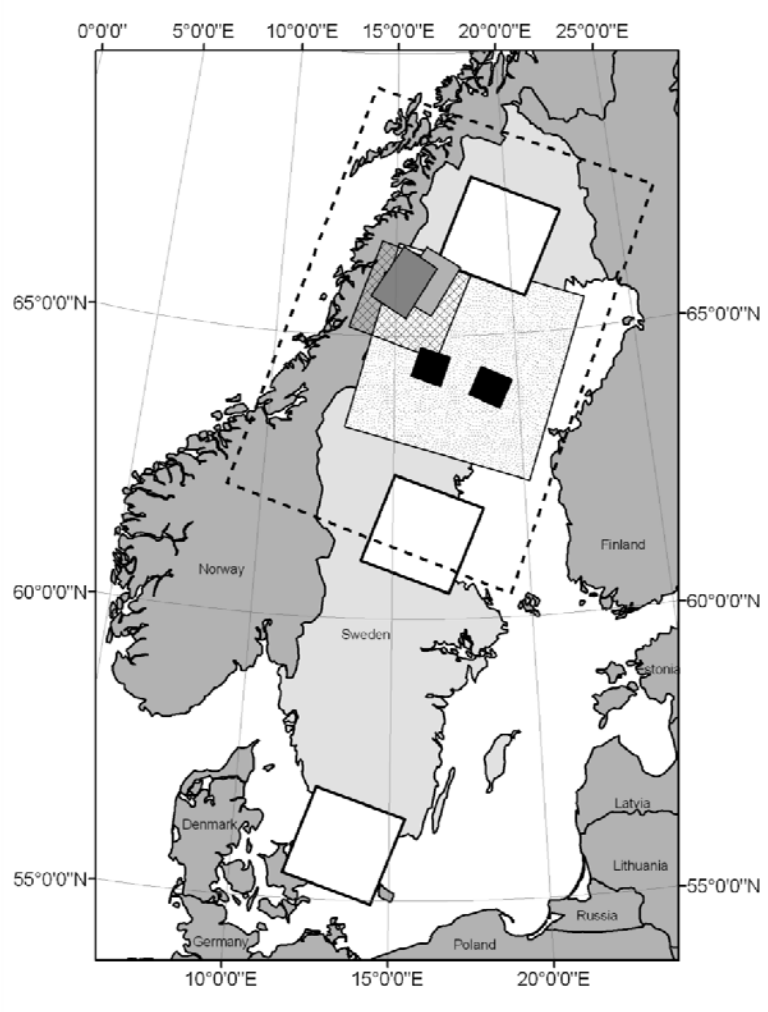

Figure 2. The images used in this thesis. Paper I used three Landsat 7 ETM+ scenes (white squares outlined in black); Paper II used one MERIS image, represented by a black dashed line; Paper III used an AWiFS image represented by the speckled square, and also two SPOT 5 images shown by the two black squares: Paper IV used two overlapping Landsat 5 TM images shown by the cross-hatched area, and two SPOT 5 two-image mosaics shown by two gray rectangles; Paper V used the same AWiFS image as Paper III, one of the Landsat 5 TM images shown by the cross-hatched area, and one of the SPOT 5 two-image mosaics, shown by the darker gray rectangle.

Table 2. *The optical satellite data used in this thesis.*

Sensor	Acquisition Date	Purpose	Paper
Landsat 7 ETM+	4 September 1999	Classification	I
Landsat 7 ETM+	10 July 1999	Classification	I
Landsat 7 ETM+	27 July 2000	Classification	I
Envisat MERIS	31 July 2005	Classification	II
Landsat 7 ETM+	29 July 2000	Training	II
SPOT 5 HRG XS	4 July 2005	Classification	III
SPOT 5 HRG XS	31 July 2005	Classification	III
AWiFS	31 July 2005	Classification	III, V
Landsat 5 TM	19 August 2006	Classification	IV
SPOT 5 HRG XS	29 July 2004	Classification	IV
SPOT 5 HRG XS	24 August 2008	Classification	IV, V
Landsat 5 TM	31 July 2005	Classification	IV, V
SPOT 5 HRG XS	28 July 2010	Classification	V
AWiFS	17 August 2008	Classification	V
MODIS[1]	28 July-12 August 2005	Reflectance Normal.	III, IV, V
MODIS[1]	27 July-11August 2004	Reflectance Normal.	IV, V
MODIS[1]	11 August-26 August 2008	Reflectance Normal.	IV, V
MODIS[1]	9 August-24 August 2006	Reflectance Normal.	IV, V
MODIS[1]	20 July-4 August 2010	Reflectance Normal.	V

[1] Nadir BRDF-Adjusted 16 day composite

For all papers, the Landsat images have been resampled with cubic convolution to 25 m pixels, to fit the grid used with Swedish national geographic data. Digital aerial photographs were also used for reference data collection in Papers IV and V. Twenty-one 5 × 5 km areas were covered by three overlapping (stereo) CIR aerial photographs at 1:30,000 scale from the NILS inventory, and seven 10 km × 1 km areas were covered by CIR aerial photographs at 1:2,000 scale in Paper V.

3.1.3 Reference data

National Forest Inventory data were used as reference data in Paper I. Within each Landsat scene, a complete five-year cycle of NFI plots was used, providing an average of 2,000 NFI plots per image. In Paper II, training data were derived from an unsupervised classification of Landsat ETM+ data, and also from NILS photo-interpreted polygons. The reference data used for production of categorical and continuous value predictions in Paper III was a stand-based forest inventory data set from the forestry company Sveaskog, which was derived from aerial photo interpretation and *in situ* field checks. The

inventory had a total of over 9,000 polygons, of which 3,950 were within the study area. Papers IV and V employed a point sample aerial photo-interpretation and NILS field data as reference data. The aerial photographs were based on the NILS systematic inventory, and a point sample photo-interpretation was carried out, similar to that done in the THUF/MOTH project.

3.1.4 Ancillary data

In all five Papers, the National GSD-DEM (50 m grid cell resolution), derived by interpolating elevation profiles measured manually from stereo aerial photograph models, was used for topographic normalization of the images, and in Papers II, IV and V, the DEM was used as ancillary data input to the classification. The Swedish Mountain Vegetation Map was used as reference data in Paper II, while the 1:100,000 scale GSD-Road Map was used for ancillary data, reference data, and map masks (Paper I, II, III, IV). The GSD-Land Cover map (earlier called the GSD-Land and Vegetation Cover map), derived from a classification of Landsat TM/ETM+ data, was used in Paper IV.

3.2 Methods

3.2.1 A method for calibrated maximum likelihood classification of forest types (Paper I)

Paper I describes and evaluates a modification to the Maximum Likelihood (ML) classification algorithm (referred to as “calibrated maximum likelihood”) used within Sweden’s part of the EU-CORINE land cover mapping project. The focus is on classification of forest cover types using Landsat TM/ETM+ data and NFI as reference data. In an extension of the maximum likelihood algorithm, class prior probabilities may be assigned; in this paper prior probabilities were initiated using class frequency determined from the NFI data. Even given prior probabilities, the ML classification output may still under-classify less frequent classes and over-classify more dominant classes. With calibrated maximum likelihood, the aim was to iteratively adjust prior probabilities so the classified output would more closely reflect class proportions as calculated from NFI data. Although this method was applied for an operational mapping project of the whole country (50 Landsat images), three representative Landsat scenes in northern, central, and southern Sweden were chosen for evaluation.

NFI plots from a minimum five-year time span within the Landsat scene's extent were used, which gave approximately 2,000 plots per Landsat scene. A plot-to-image matching routine was developed to better geo-locate plots measured previous to 1996 when GPS was introduced to the NFI, as well as for

plots geo-located after 1996, using estimated errors of GPS accuracy. Forest variables such as stem volume, age and tree height were updated or "back-dated" to the time of satellite image acquisition using growth estimation models (Soderberg, 1986). NFI variable measurements taken on plots with less than 10 m radius were adjusted to reflect a 10 m plot radius, better agreeing with the Landsat pixel size of 25 m (Hagner & Tingelöf, 2002). Pre-processing of the satellite data included reduction of within-image haze differences (Hagner & Olsson, 2005), topographic and illumination normalization (Teillet *et al.*, 1982), NFI plot-to-image geometry matching, and radiometric modeling (Hagner & Tingelöf, 2002). Many of these pre-processing steps used NFI data.

Nine primary forest classes were classified and spectrally homogenous subclasses of these nine primary classes were defined, resulting in a total of 32 subclasses. The first iteration of the ML classification was initialized using prior probabilities based on NFI-derived class frequencies within each scene, and afterwards the proportion of pixels per sub-class from the output was compared to the NFI-based class frequencies. Prior probability weights were adjusted proportionally to the representation error, being decreased if overrepresented and increased if underrepresented. This process was run iteratively until the output class proportions converged to the NFI-based class frequencies or when a maximum number of iterations (n=15) was reached. To compare the results from the calibrated-ML algorithm to those from a ML algorithm without iterative adjustment of prior weights, three Landsat images were processed using both methods. The area of each class within the scene after classification was compared to the NFI-based class frequencies, and additionally, overall classification error was determined using leave-one-out cross-validation.

3.2.2 Using MERIS for mountain vegetation mapping and monitoring in Sweden (Paper II)

The utility of data from the newly available coarse resolution ENVISAT MERIS sensor was tested for the mountain areas of Sweden. As the pixel size of MERIS is 300 m and the alpine and subalpine land cover is a heterogeneous mosaic, "soft" classification methods such as regression trees were investigated. Seven primary land cover types were classified: water, bare rock, grass heath, other heath (mesic and dry heath), meadow, wetland, and mountain birch.

Pre-processing of the MERIS data involved a Simplified Method for Atmospheric Correction (SMAC; Rahman & Dedieu, 1994) and topographic and illumination normalization using the C-correction (Teillet *et al.*, 1982). The MERIS Terrestrial Chlorophyll Index (MTCI) was calculated (Dash &

Curran, 2004), and principal components analysis (PCA) were used to transform the 13 spectral bands, from which the first two PCs were used (PC1, PC2). A training data set was built using 800 randomly selected 300 × 300 m areas from a Landsat-based classification, in addition to 100 homogenous areas from the NILS photo-interpretation. The input variables were PC1, PC2, MTCI, elevation, slope, and aspect. Regression trees and linear regression were used to estimate the fraction of the land cover types present within each pixel. The results were evaluated using 100 randomly selected 300 x 300 m plots from the Landsat-based classification.

3.2.3 Comparison of Resourcesat-1 AWiFS and SPOT 5 data over managed boreal forest stands (Paper III)

This study tested the utility of the newly available Resourcesat-1 AWiFS data for boreal forest information such as stem volume predictions and forest type classification. While the pixel size is coarser (60 m pixel) than Landsat or SPOT, the swath width of one AWiFS sensor is 370 km, allowing more inventory data plots to be included and possibly reducing multiple-date image processing complications. Comparisons between AWiFS and SPOT 5 data were made, such as band-wise correlations at different spatial aggregations, as well as stand-wise estimation of forest parameters using a polygon-based forest inventory database from Sveaskog. The influence of stand size on stem volume prediction from AWiFS and SPOT spectral data was investigated over a range of stand sizes.

The AWiFS and SPOT images were reflectance normalized relative to MODIS Nadir BRDF-adjusted reflectance data and topographically normalized using C-correction. Using a stand-wise forest inventory database as reference data, band-wise mean spectral values per stand were calculated. Multiple linear regression was used to determine relationships between the spectral data and stem volume. Correlations between the spectral data and stem volume were analyzed for the entire data set and also by stand size categories. Quadratic discriminant analysis of tree species and stem volume classes was performed. Finally, band-wise correlations between AWiFS and one of the SPOT 5 images (acquired 12 minutes after the AWiFS image) were performed on block aggregations of the data (60 m and 120 m).

3.2.4 C-correction of optical satellite data over alpine vegetation areas (Paper IV)

Topographic characteristics of the landscape, such as slope and aspect, in combination with the solar zenith and azimuth angles, result in illumination differences within a satellite image. Prior to classification, especially in the mountains, topographic normalization is a necessary pre-processing step for optical satellite data. Topographic normalization methods adjust an image so that a vegetation class will have similar spectral values whether facing away from or towards the sun (Holben & Justice, 1980). C-correction (Teillet *et al.*, 1982) is a commonly used topographic normalization method, suitable for alpine vegetation areas. However, details about deriving the C-correction's *c*-parameter are lacking in the published literature. This study looked at the influence of the sample used to determine the *c*-parameter, and the *c*-parameter's influence on topographic normalization results in an alpine area of Sweden. Four satellite images from different dates were used, each of which had different solar illumination and sensor viewing angles.

The C-correction consists of a modified cosine correction plus the empirical parameter *c*, which is derived from the linear relationship between the spectral data and the cosine of the solar incidence angle, *i*, with respect to surface normal (Teillet *et al.*, 1982). Cosine of *i* is calculated as a function of the local terrain slope and aspect, and the solar illumination angles upon the surface at the time of satellite data acquisition (Table 3, Eq. 1). Linear regression is used to estimate intercept (*b*) and gradient (*m*), using cosine of *i* as the independent variable and reflectance as the dependent variable (Eq. 2). The *c*-parameter is calculated as *b* divided by *m* (Eq. 3) for each wavelength band since the relationship between reflectance and cosine of *i* is wavelength dependent. The *c*-parameter is added to the numerator and denominator of the cosine correction to form the C-correction equation (Eq. 4). A sample from the satellite data used to determine *c* has commonly been taken in one of two ways: 1) selection (often subjective) of a relatively small number of observations ($n < 100$) for a target vegetation type over a range of topographic conditions, or 2) random sampling of a varying quantity of observations from either a subset or an entire image.

Table 3. *Symbols and their definitions (a) used in the equations (b) for C-correction.*

a) Symbols and definitions			
i	=	solar incidence angle with respect to surface normal	
z	=	solar zenith angle	
s	=	terrain slope angle	
a	=	solar azimuth angle	
a'	=	terrain aspect angle	
$\hat{\rho}_{\lambda t}$	=	topographically influenced ($_t$) reflectance of band λ	
b	=	intercept of linear regression	
m	=	gradient of linear regression	
c_λ	=	c-parameter for band λ	
$\hat{\rho}_{\lambda h}$	=	topographically normalized ($_h$) reflectance of band λ	
b) Equations			
Cosine of i (cos i)		$\cos i = \cos z * \cos s + \sin z * \sin s * \cos (a - a')$	(1)
Linear regression between reflect-ance and cos i		$\hat{\rho}_{\lambda t} = b + m * \cos i$	(2)
c-parameter		$c_\lambda = \frac{b}{m}$	(3)
C-correction		$\hat{\rho}_{\lambda h} = \hat{\rho}_{\lambda t} \frac{\cos z + c_\lambda}{\cos i + c_\lambda}$	(4)

Two Landsat TM images and two SPOT 5 image mosaics were first reflectance normalized relative to MODIS Nadir BRDF-adjusted reflectance data. Alpine vegetation and non-alpine vegetation were then separated using a map-mask. Three sampling methods for calculating the empirical *c*-parameter were tested: a random sample; a stratified random sample with stratification on north and south aspects; and, a stratified random sample with stratification by the cosine of the solar incidence angle, *i*. For the sample stratified by cosine of *i*, an optimal allocation method called power allocation (Bankier, 1988) was used to determine the quantity of observations for each stratum. Precision of *c* was assessed by taking the standard deviation of *c* as calculated from five separate samples, for each sampling method. Accuracy of *c* was tested by visual assessment, classification accuracy and two-sample independent *t*-tests.

3.2.5 Varying training data set size for supervised classification of alpine vegetation (Paper V)

Updating of vegetation maps over the mountainous areas of Sweden is currently of interest for several reasons. There are several challenges, however, in the use of optical satellite data for mapping detailed alpine vegetation classes. Alpine vegetation tends to be spatially heterogeneous and consist of complex mosaics of vegetation types. The pixel resolution of the satellite data

source needs to accommodate the structure of the landscape and will have an impact on the outcome of the map product. Mapping detailed vegetation classes can be difficult from spectral data alone, as there is a large degree of spectral overlap. Alpine class occurrence is highly dependent on topographic gradients, and the addition of DEM derivatives may improve classification accuracy. Reference data are needed for both the classification and evaluation of the satellite data, and Sweden's newly available NILS and THUF inventory programs may provide a data source for this purpose. In large area mapping projects, the question is often "How much training data is enough?" This study looks at the effect of the quantity and distribution of training data on classification accuracy. The results are presented for two different classification methods, and for three different optical satellite data sources.

Reference data were based on photo-interpreted plots within twenty-one 5 × 5 km squares. Each 5 × 5 km square contained 110 systematically arranged plots for which vegetation class and percent area coverage were photo-interpreted for the center point, and a 5, 10, 20, and 30 m circular radius around the center point. The data were quality controlled before use as training data. In summary, a total of six different training sets were tested: 2xNILS, 2xNILS50, 1xNILS, 1xNILS50, Subjective, and NILS Field.

- "2xNILS" is the complete data set after quality control, taken from all 21 of the 5 × 5 km primary sampling units, using all 110 secondary sample plots;
- "2xNILS50" uses all of the 21 5 × 5 km primary sampling units, but only half (55 of 110) of the secondary sample plots (every other plot);
- "1xNILS" uses all 110 secondary sample plots, but only 13 of the 5 × 5 km primary sampling units; these 13 primary sampling units are those used in the actual NILS inventory;
- "1xNILS50" uses only half (55 of 110) of the secondary sample plots (every other plot), and only 13 of the 5 × 5 km primary sampling units; these 13 primary sampling units are those used in the actual NILS inventory;
- "Subjective" refers to the training data samples chosen subjectively; all 21 of the 5 × 5 km primary units were used, and approximately 30 samples per 5 × 5 km area were taken;
- "NILS Field" is a training data set based on the field data collected in NILS. The data set was used for the AWiFS image only, and is taken from the area corresponding to the entire AWiFS image (i.e., larger than the 110 × 110 km study area), from a total of 31 NILS 5 × 5 km primary sampling units.

Each image from SPOT 5, Landsat 5 TM, and Resourcesat-1 AWiFS, was reflectance- and topographically normalized, and then subjected to supervised classification. Two different classification methods were used, namely Quadratic Discriminant Analysis (QDA) and random forests. The input to QDA was the spectral bands only, and to the random forests classification, spectral bands were combined with spectral indices and DEM derivatives such as elevation, slope, aspect and a topographic wetness index. Prior probabilities were assigned in the QDA according to class frequencies determined from the photo-interpretation of the systematic sample. The random forests algorithm was used to produce thematic classifications, and in the case of Landsat and AWiFS, fraction of land cover class was estimated as a continuous variable as well. Classification accuracy was assessed using photo-interpretation of a systematic sample of plots at multiple-scales (5, 10 and 30 m radius), using high resolution (1:2,000) CIR photographs.

4 Results and discussion

4.1 A method for calibrated maximum likelihood classification of forest types (Paper I)

The area statistics of the nine forest classes resulting from the output of the Maximum Likelihood (ML) and the calibrated-ML classifications show that the calibrated-ML algorithm classified the satellite images to more closely reflect class proportions from the NFI data (Table 4). Dominant classes over-represented by the ML classification were classified proportional to the NFI data using calibrated-ML. Cross-validation to check the effect on class accuracy revealed that accuracy did not decrease.

Table 4. *The percent of the scene area classified for the two most dominant classes and the single least prevalent class for each of the three Landsat scenes, using the calibrated maximum likelihood classification and maximum likelihood.*

Scene and class	Area (%) according to NFI	Area (%) Calibrated Max Like	Area (%) Max Like
South – Deciduous forest	25.9	25.8	28.3
South – Coniferous forest > 15m	32.6	34.9	41.1
South – Young Deciduous forest	3.3	4.6	1.8
Mid – Coniferous forest > 15m	32.3	32.9	41.1
Mid – Coniferous forest 5-15m	22.1	22.5	13.9
Mid – Deciduous forest	2.5	2.5	4.7
North – Regenerating forest	32.0	32.2	31.4
North – Coniferous forest 5-15m	22.2	21.8	24.0
North – Deciduous forest	2.4	2.4	6.4

The NFI data were useful for assigning and adjusting the prior probabilities used in ML classification since the NFI data are a probability-based sample,

lending themselves to estimation of forest parameters over regions. In projects where inventory data are not available, prior probabilities are either not assigned, or are based on other data, for example, maps or subjectively collected data. As seen in Paper I, even when prior probabilities were initiated based on an objective, probability-based sample such as the NFI, the ML classification may still tend to over-classify frequent classes and under-classify less frequent classes. The use of calibrated-ML with iteratively adjusted prior probabilities worked well with an area the size of a Landsat scene (185 × 185 km), which is more regional in nature. Using NFI data to calibrate the ML results over smaller areas, however, such as a SPOT scene (60 × 60 km) or a Landsat scene containing only small areas of forest, would be a questionable application of this method. This is because at local levels, the variance of estimates from NFI data is much higher and therefore less applicable. The effect of prior probabilities when using maximum likelihood for mapping individual vegetation classes has not been thoroughly studied (Pedroni, 2003).

Pre-processing of the NFI data was required in Paper I, such as the plot-to-image geo-location procedure, reconciling the forest variables to the date of the image as well as the resolution of the image pixel, and outlier detection with replacement of class label if necessary. These steps are a form of quality control of the training data. Performing this for thousands of NFI plots may seem tedious, but all processes were automated, making it a quick, robust and repeatable process. There are several sources of potential error in training data that should be investigated before the data are used, including labeling error, geo-location error, and mismatch between date of inventory and image data. However, it is important to maintain the integrity of the probability-based sample design (i.e., avoid removal of sample plots from the data set) if it is to be applied as it was in the calibrated-ML. An additional use of the NFI plots was the scene-wise haze normalization procedure, where the spatial distribution and variables measured in the NFI data made them well suited for this process.

The NFI data were also effective for use in the supervised classification of detailed forest classes. These classes were based on forest type and tree height (e.g., coniferous forest 5-15 m and coniferous forest > 15 m), and were spectrally separable using Landsat data. The classification outcome and the potential to develop new methods for applying NFI data is partly dependent on the characteristics of the land cover to be classified. A landscape that consists of managed coniferous boreal forest with relatively large and homogenous stands presents different conditions and challenges than, for example, a highly fractured landscape or a heterogeneous mix of land cover types.

4.2 Using MERIS for mountain vegetation mapping and monitoring in Sweden (Paper II)

When fractions of seven alpine and subalpine vegetation classes (bare rock, grass heath, other heath, meadow, wetland, mountain birch, and water) were estimated from MERIS data using a regression tree method and linear regression, the results were comparable. The regression tree produced an overall RMSE of 20.1% while linear regression produced a RMSE of 20.6%. When a thematic classification was produced from the class fraction results, regression trees provided a higher percent (65%) of correctly identified classes as compared to regression (61%). The seven land cover classes were rather general, and due to the spatial heterogeneity of the land cover types, it may be the limit of what is distinguishable using the coarse resolution MERIS sensor (300 m pixel). Aplin (2006) says that thematic class definitions appropriate for finer resolution data are not always appropriate for coarser resolution satellite data.

The geo-locational tie points supplied with the MERIS data resulted in a poor geo-referencing of the data. To remedy this, image to image geo-referencing with available Landsat data was necessary. This facilitated the use of an unsupervised classification from the same Landsat data as training data. Without the image to image geo-referencing, the locational accuracy of the MERIS data was too poor to carry out successful training using either NILS polygon-based photo-interpretation or the unsupervised Landsat classification. One of the most difficult stages in supervised classification of coarse resolution data is obtaining adequate calibration and validation data. Good geometry in coarse resolution data is essential, as it is difficult to correct afterwards.

The problem of classifying mixed pixels is not trivial to solve, and water often complicates separation of spectral values when it occupies just a portion of the pixel. When the pixel resolution is coarse, and the landscape is heterogeneous, use of "soft" classification methods as opposed to strictly thematic classification methods are more appropriate (Fernandes *et al.*, 2004). The use of regression tree to estimate fractions of land cover types or continuous values of other parameters is interesting, not only for coarse resolution imagery, but also for medium resolution sensors in a landscape with heterogeneous land cover (e.g., alpine areas) or if continuous value output is desired (e.g., Olthof & Fraser, 2007). Estimation methods used to identify fractions of cover types are increasingly being used to create data for monitoring purposes, such as the global MODIS percent tree cover data (Hansen *et al.*, 2002) or the US NLCD percent tree cover and percent impervious surface data from Landsat (Homer *et al.*, 2007). Using training data obtained from higher resolution remotely sensed data, as done in Paper V, or

map products from higher resolution data as done in Paper II are practical methods for the acquisition of training data for land cover fraction predictions.

4.3 Comparison of Resourcesat-1 AWiFS and SPOT 5 data over managed boreal forest stands (Paper III)

When stem volume was estimated using stand-wise mean spectral values from AWiFS (60 m pixel) and SPOT 5 (10 m pixel), the adjusted coefficient of determination (R^2_{adj}) resulting from AWiFS was comparable to that from SPOT 5 (Table 5).

Table 5. *The adjusted coefficients of determination (R^2_{adj}) based on multiple linear regression of AWiFS and SPOT 5 mean spectral data values to estimate stem volume.*

Analysis	AWiFS	SPOT 5
R^2_{adj} with stem volume	0.573	0.598
R^2_{adj} best two band combination	0.573 (NIR + Red)	0.595 (NIR + SWIR)
R^2_{adj} with stem volume for stands < 2ha	0.310	0.293
R^2_{adj} with stem volume for stands 20-30 ha	0.677	0.692
r between SWIR and stem volume	-0.651	-0.680
Discriminant Analysis of forest type (% correct)	65.6%	66.4%
Discriminant Analysis stand volume group (% correct)	61.9%	63.8%

For both AWiFS and SPOT 5, all four bands were negatively correlated with stem volume. The SWIR band had the single strongest correlation with stem volume, and was stronger for SPOT 5 than for AWiFS. For AWiFS the best two-band estimator of stem volume was a NIR and red band combination, while for SPOT 5 it was the NIR and SWIR bands. The different results for AWiFS might be explained by the increased radiometric resolution (10 bit) of all spectral bands and the larger coefficient of variation (CV) of the red band in AWiFS.

When stem volume was estimated by stand size, for stands less than 2 ha in size, AWiFS had slightly higher R^2_{adj} values than SPOT 5. This was surprising, but may have been due to the relatively "large" minimum stand size of 1.4 ha and that many small stands had similar conditions (usually higher volume) in neighboring stands. The strength of the relationship between stem volume and the spectral data increased with stand size, with the highest R^2_{adj} at 20 ha (Figure 3). Hyyppä and Hyyppä (2001) had similar findings, and suggested this resulted from sample size or landscape qualities. In Paper III, for stands 20 ha and larger the correlation between stem volume and NIR increased while it

decreased for the SWIR and visible bands. We concluded that the increase and then leveling off of R^2_{adj} with stand size was most likely due to changes in stem volume resulting from management practices at different stand sizes. For stands 20 ha and greater in size, there was an increased proportion of young re-generating forest, since the forestry company tended to carry out clear-felling operations at a minimum of 20 ha. The landscape characteristics had an effect on the outcome, as did the exclusive use of a forestry company's database as training data, and classification over an area managed by a large forestry company.

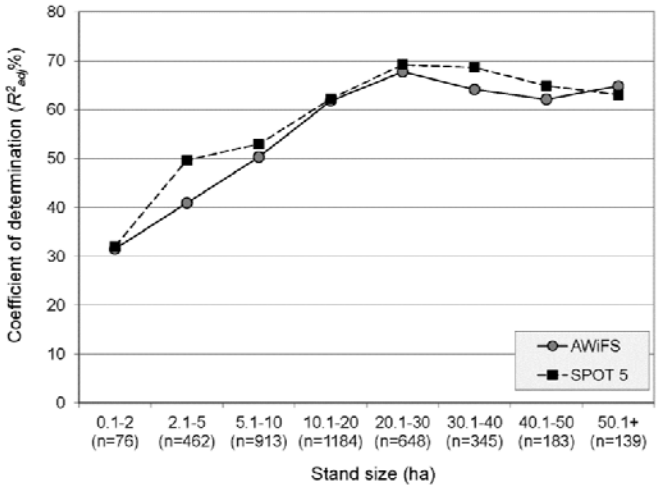

Figure 3. R^2_{adj} results of multiple linear regression of the AWiFS and SPOT 5 data as the independent variables and stem volume as the dependent variable for data subsets based on stand size.

Use of a polygon-based training data set worked well with AWiFS' 60 m pixel size, which was made easier by AWiFS' good geometric properties. Use of NFI data with the Resourcesat-1 AWiFS data was not tested, as applying the 10 m radius NFI plot to 60 m AWiFS pixels was more uncertain. To date, Resourcesat-1 AWiFS data have not been widely used, although they have been tested as a replacement for Landsat data in the annual estimation of crop area for the US Department of Agriculture (Johnson 2008). Resourcesat-3 AWiFS (scheduled for launch in 2013) will have 25 m pixels and a large swath width (300 m with one camera), encompassing many NFI plots, making AWiFS a potentially interesting future data source for classification and continuous value predictions over large areas using NFI data.

4.4 C-correction of optical satellite data over alpine vegetation areas (Paper IV)

Three different sampling schemes were tested from which the empirical parameter *c*, used in the C-correction for topographic normalization, was calculated. The sample stratified by cosine of the illumination angle, *i* ("cos*i* sample"), together with an optimal allocation of samples in the strata, produced the *c*-parameter with the highest precision and accuracy. The mean coefficients of determination (R^2_{adj}) from the linear regressions between cosine of *i* and the spectral data were much higher from the cos*i* sample (often double) as compared to the other sampling methods, for all bands and all four images tested. The random sample with n = 16,500 and the aspect sample (n = 5,000) also provided reasonably precise *c*-parameters, although the standard deviations (derived from repeated samples) were slightly higher. When *c* was calculated using the random sample with n = 1,600, instable (imprecise) values of *c* were obtained, accounting for some of the inconsistencies and problems in calculating *c* reported in the literature (e.g., Gu and Gillespie, 1998). It could be concluded that the sample used to calculate *c* influenced the value of *c* and the effectiveness of the topographic correction. The *c*-parameter is based on the linear relationship between the spectral data and cosine of *i*. Since *c* is calculated by dividing the linear regression's intercept by its gradient, the accurate determination of both intercept and gradient are important, which was best accomplished using a stratification based on cosine of *i*. Figure 4 shows the samples taken to calculate *c* for the NIR band from the 2008 SPOT 5 image.

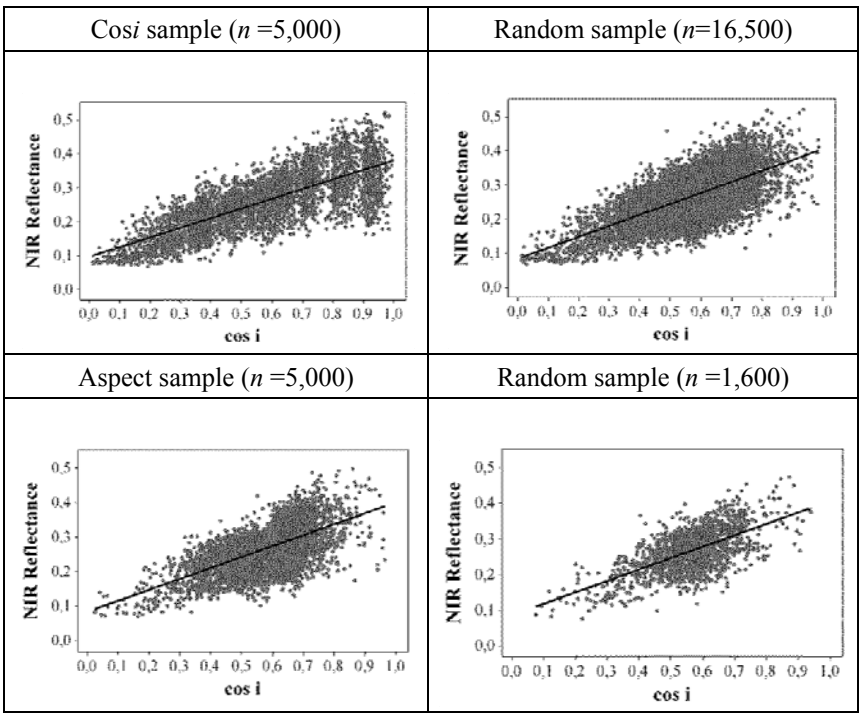

Figure 4. Scatterplots of NIR spectral reflectance (y-axis) versus cosine of *i* (x-axis) for four samples taken from the SPOT 5 image.

The cos*i* sample produced a larger value of *c* for the NIR band as compared to the other sampling methods, in particular for the SPOT 2008 and Landsat 2006 images. Previous studies found a need to adjust the empirical parameter used for correction of the NIR band, and was done by using a factor or simply changing the value (e.g., Civco, 1989; Ekstrand, 1994; Richter *et al.*, 2009). The use of an optimal allocation, namely power allocation (Bankier 1988), to allocate samples to each cosine of *i* stratum was important in the cos*i* sample. Power allocation allowed adjustment of sample allocation according to stratum importance, making increased allocation within small but important strata possible. With power allocation, more samples could be placed in strata having large variation in the spectral data, regardless of stratum size.

For all four satellite images, slightly higher classification accuracies were obtained when the *c*-parameters derived from the cos*i* sample were used. The two-sample independent *t*-tests indicated that optimal *c*-parameters may differ among the individual alpine vegetation classes. For the NIR band, dry alpine heath and alpine grass heath tended to have relatively higher *c*-parameters, mesic alpine heath was slightly lower, and alpine willow had relatively lower *c*-parameters, as did the alpine meadow classes. It could be seen that grass

heath and sparse vegetation had a different linear relationship within the NIR band sample than did dry/mesic heath, willow and alpine meadow. This may have been an influence of the soil background showing through a sparser vegetation canopy. Pinter *et al.* (1990) and Huete *et al.* (1992) determined that the amount of soil viewed through a vegetation canopy contributes to the surface anisotropy. It is possible that these vegetation types require separate topographic correction, and others (e.g., Bishop & Colby, 2002; Soenen *et al.*, 2008) suggest further study on vegetation-specific topographic normalization.

Pre-processing of the satellite imagery is an important step, and geometric quality, atmospheric correction, and topographic normalization contribute significantly to the classification outcome. These aspects are complex and, despite many years of research, are not fully studied or documented in the literature. The vegetation within the landscape and the topographic characteristics will determine the relationships and calculation of *c*, and these should be understood before conducting a topographic correction. It is possible that the sampling strategy proposed in Paper V for calculation of *c* would also be useful for the Minnaert constant, *k* (Smith *et al.*, 1980), and within the SCS+C method used for forest vegetation (Soenen *et al.*, 2005).

4.5 Varying training data set size for supervised classification of alpine vegetation (Paper V)

The random forests classification of alpine vegetation based on SPOT 5 and DEM data using the largest training data set (2xNILS) produced the most accurate classification of all combinations (overall accuracy of 72.9%, shown in Table 6). Classification of Landsat and AWiFS data resulted in lower overall classification accuracies, at best 62.7% and 51.2%, respectively.

Table 6. *Percent overall accuracy for the alpine vegetation classification, for the random forests (RF) and Quadratic Discriminant Analysis (QDA) classifications of SPOT 5, Landsat TM and AWiFS data, when using different training data sets. The evaluation data set was n = 483.*

	SPOT RF	**SPOT QDA**	**Landsat RF**	**Landsat QDA**	**AWiFS RF**	**AWiFS QDA**
2xNILS	72.9	60.7	62.7	61.5	46.5	38.9
2xNILS50	67.0	60.3	61.1	61.1	--[2]	--[2]
1xNILS	64.9	56.5	59.4	60.3	--[2]	--[2]
1xNILS50	63.6	54.4	59.4	59.2	--[2]	--[2]
1xNILS Field data	--[1]	--[1]	--[1]	--[1]	51.2	22.3
Subjective	69.9	60.3	56.5	60.3	45.9	33.9

[1] Too few NILS Field plots were available within the SPOT and Landsat image.
[2] AWiFS not classified with the smaller data sets due to initial poor results with 2xNILS data set.

Obtaining the best result from SPOT data is likely a result of the 10 m pixel size, suitable to the heterogeneous alpine landscape. The multiple-scale photo-interpretation showed that 10 m radius plots included on average more than one vegetation class, while 20 m radius plots included on average two vegetation classes.

The alpine vegetation classification in Paper V had thematic detail similar to the Swedish Mountain Vegetation Map. Individual class accuracies for bare rock, extremely dry heath, dry heath, mesic heath, and grass heath were generally above 75% from SPOT data. Classes below this level were wet heath, and short and tall alpine meadow, which may be improved by training data refinement. Willow also had low accuracy, as it had a high degree of spectral overlap with other classes, making correct classification difficult. The Saga Wetness Index improved classification accuracy of willow by 8% as it was the most important variable for willow, however, methods to improve mapping of willow are needed. The most important variables for classification of alpine vegetation types included many spectral indices such as NDVI and SAVI, and some DEM derivatives, presenting a very different case than for forest remote sensing. Several researchers (Stow *et al.*, 1993; Deng *et al.*, 2007; Laidler *et al.*, 2008) have noted the importance of NDVI for alpine vegetation. Rock and bare soil visible mixed with spectral information from the vegetation canopy influences the spectral signature of vegetation (Elvidge & Lyon, 1985; Boresjö-Bronge & Wester, 1999; Small, 2004; Olthof & Fraser, 2007; Gianelle *et al.*, 2009). This was supported by the high correlation ($r \geq 0.78$) found between spectral indices (Green-VI, NDVI and SAVI) and the percent vegetation cover.

An ISODATA unsupervised clustering was found effective for separation of subalpine forest vegetation from alpine vegetation (with 78% producer's accuracy for subalpine mountain birch forest classification using SPOT data). The Swedish Environmental Protection Agency has recently produced detailed subalpine forest classes (called "KNAS-5") from a combination of SPOT 5 data and texture measures from 1:30000 scale CIR digital aerial photographs for the entire Swedish mountain chain. Work done in Paper V therefore concentrated more on the classification of alpine vegetation.

Using AWiFS and Landsat data, fractions of detailed alpine vegetation classes estimated using random forests produced an overall RMSE of 33.1% for AWiFS and 28.6% for Landsat. Estimation of four simpler classes (shrub, forbs, grass and rock, and water) produced an overall RMSE of 23.9% for AWiFS and 19.7% for Landsat. In comparison, Olthof and Fraser (2007) estimated class fractions of bare, sedge and grass, deciduous shrub (alder,

willow, dwarf birch), conifer, and water with the lowest RMSE (16.4%) from regression trees and a resampled 90 m pixel of Landsat TM bands 3, 4 and 5.

The number of training data samples had an effect on classification accuracy, with the largest training data sets generally producing the highest accuracies. The largest changes in accuracy occurred using the RF classification of SPOT data, with the highest accuracy (72.9%) declining to 63.6% when the smallest training data set (1xNILS50) was used. Compared to SPOT, the decrease in classification accuracy from Landsat data after reducing training data set size was not as great. In all cases, higher accuracies were obtained using a denser distribution of the primary sampling units with fewer photo-interpretation plots (2xNILS50), than when using fewer primary sampling units yet more photo-interpretation plots (1xNILS). This may have been due to capturing more spectral variability using a wider spatial distribution of training areas, as well as that many of the NILS squares were located on mountain birch areas. The thematic classification of AWiFS data were in general poor, however the highest accuracy was obtained using the NILS field data (51.2%) which was surprising given the small training data set size and the difference between reference data plot size and pixel size. Accuracy increased to 62% when the four shrub-heath classes were simplified into a single heath class. A number of studies exist regarding influence of the number of training data samples on classification (Hubert-Moy *et al.*, 2001; Chen & Stow, 2002; Mather, 2004; Van Niel *et al.*, 2005), however, actual testing of different training sets is not common. Reference data for alpine areas are often difficult to obtain, and presents a limitation (Tømmervik *et al.*, 2009).

The accuracy of the QDA classifications were generally lower than for the RF classifier. While elevation derivatives used in the RF classification contributed to increased accuracy (8.9% in the case of SPOT), this was not the sole explanation for better accuracy; the classification method itself also played a role. The use of elevation data in the RF classification was most beneficial for separating dry heath and grass heath, improving the producer's accuracy of dry heath from 30.0% (with QDA) to 73.3% (with RF) using SPOT data.

The subjectively chosen training data produced lower accuracies than the larger 2xNILS objectively sampled training data, in the case of SPOT only marginally lower (3.0% for RF and 0.4% for QDA), and in the case of Landsat having rather different results (5.2% lower for RF and 1.2% lower for QDA). Given the smaller training data set size and the significantly shorter amount of time needed to collect the subjective training data, the relatively high classification results are of interest. On the other hand, while subjectively chosen training data are useful for classification, land cover fraction estimation using RF (or any CART method) requires mixed pixels with a full range of

values in the training data, and the subjectively collected data (which aims to collect plots with homogenous vegetation) is insufficient for this purpose. In addition, the establishment of a systematic training sample may allow for establishment of a long-term training data set, used in future classifications. Thirdly, the systematic sample provides information on the frequency of classes used in the prior probability assignment in maximum likelihood/QDA, and also affects the outcome of the RF classification.

4.6 Main findings

The demand for landscape scale land cover data continues to be high, due in part to directives on biodiversity monitoring, carbon accounting, habitat studies, and climate change's potential effect on vegetation. Over the past two decades the establishment of inventory programs has increased at both a national and international level. There is greater awareness that inventory programs and remotely sensed data offer complementary information, as new applications and improvements in both subjects are tested. Inventory data collected by probability-based sampling can provide statistical information about the landscape, while satellite data can provide spatially explicit, full coverage maps for repeated points in time. Combining inventory data and satellite data for the purpose of vegetation mapping is not always a simple process, and careful consideration should be given to several aspects of the mapping project beforehand.

The papers in this thesis contribute to the field of remote sensing, specifically the supervised classification of land cover, in several ways:

- Modifications to commonly used remote sensing methods were introduced. The maximum likelihood classification algorithm was modified by introducing iterative adjustment of prior probabilities based on class area estimates from NFI data (Paper I). Paper IV presented a new guideline for the C-correction topographic normalization method, regarding the calculation of the empirical parameter, *c*. The guideline suggests calculation of the *c*-parameter from a sample stratified by the cosine of the illumination angle, and optimal allocation (power allocation) of samples into each stratum. Use of a stratified sample allows calculation of *c* from data with stronger relationships (R^2 twice as large) between spectral data and the illumination angle, as compared to those typically derived. This allows for more robust and reliable C-

correction, and may be applicable to other topographic normalization methods, such as SCS+C or Minnaert correction.

- National inventory data provided a reference data source useful for the pre-processing and supervised classification of satellite data for both forest and alpine vegetation, and essential for the estimation of land cover fractions. Forest classification based on height and forest type was carried out for a national mapping project using a combination of NFI and Landsat satellite data (Paper I). Papers II and V represented the first use of NILS data for satellite data classification. Point sample reference data collected by aerial photo interpretation (modeled after the THUF/MOTH project) produced the highest overall classification accuracies of alpine vegetation from SPOT 5 data (72.9%). NILS field data produced the highest classification accuracy for AWiFS data (51.2% for detailed classes, and 62% for aggregated classes). This suggests that NILS field data may be useful as training data if enough plots can be assembled (through having larger scene sizes). Subjectively collected training data produced relatively good overall accuracy (69.9% for SPOT 5 with random forests classification) despite their smaller sample size (n = 200), and their suitability as training data should be considered.

- The number of training data samples had an effect on classification accuracy, more so for the non-parametric (random forests) classifier than the parametric classifier (Paper V). The largest number of samples generally produced the highest accuracy results for both classification methods, while decreasing the training data samples by one-quarter led to a larger reduction in accuracy when using random forests (going from 72.9% to 63.6%). Training data sample quantity was not the only influence on classification, as quality and spectral separation between classes were important. A wider distribution of fewer training data samples (n = 436) produced higher classification accuracies (67.0%) than using more training data samples (n = 532) from fewer sampling areas (64.9%).

- Resourcesat-1 AWiFS data (60 m pixel) were found to produce stand-wise stem volume predictions (R^2_{adj} = 0.573) similar to those from 10 m pixel SPOT 5 data (R^2_{adj} = 0.598) for a study site over a managed boreal forest (Paper III). However, when AWiFS data were used for thematic classification of alpine vegetation (Paper V), overall classification

accuracies were lower (51.2%) in comparison to those from SPOT 5 (72.9%) and Landsat TM (62.7%) data. The characteristics of the vegetation under study, such as forest stands managed by a large forestry company, or highly spatially heterogeneous vegetation such as that in the alpine landscape, influence the results and utility of the data.

- Detailed alpine vegetation (ten classes) classification was most accurate using SPOT 5 data (Paper V). Classification of SPOT's four spectral bands with quadratic discriminant analysis gave 60.7% overall accuracy, and with random forests, 62.3% overall accuracy. When combined with elevation derivatives the highest accuracies were produced, with 72.9% overall accuracy. The spatial heterogeneity of alpine vegetation was the most probable explanation for higher accuracy from SPOT 5 data than from Landsat TM, AWiFS, or MERIS data. Estimation of land cover fractions in the alpine landscape may be more appropriate for data with larger pixel sizes. Spectral vegetation indices such as NDVI and SAVI are important for identifying alpine vegetation types. The amount of vegetation cover versus visible bare soil and rock exert a strong influence on the spectral signatures of alpine vegetation, as seen from high correlations ($r \geq 0.78$) between percent vegetation cover and NDVI, SAVI and Green-VI from both SPOT and Landsat.

4.7 Concluding remarks

Creating spatially explicit maps from the combination of remotely sensed data and inventory data is a good synergistic use of both data sources. The use of national inventory data collected based on probability sampling, offers several advantages in regards to supervised classification of remotely sensed data. The data are often of high quality, well distributed spatially, have a large quantity of samples, are permanently located with GPS-assigned coordinates, surveyed multiple times, and provide reliable data on the frequency of vegetation type occurrence useful as prior probabilities. The frequency of divided plots obtained from a probability-based sample provides information about the vegetation heterogeneity of the landscape, which can be an advantage or disadvantage in training data, depending on the classification method used, the landscape characteristics and the desired output. Some difficulties of using inventory data might be that the inventory's spatial unit does not suit the purpose of the classification project, the variables measured are not sufficient, that there is insufficient representation of certain classes, and that quality control of the training data is perhaps even more important when using

inventory data. If the inventory variables don't meet the requirements for the training data, or if the inventory data have too few plots for rare cover types, the training data may need to be supplemented. In several operational large area land cover mapping projects (e.g., NLCD 2001), using a combination of training data sources (inventory data, aerial photo-interpretation, and field-visited data) is a common practice.

In some countries, national inventory data may not be available. However, this is slowly changing, due to new directives and the harmonization of inventory efforts over national boundaries. Even if national inventory data exist, there may be other hindrances to its use such as the quantity of data not being enough (it is enough for either training or accuracy assessment, but not both), or there may be locational and scale issues. There may be institutional hinders to using inventory data, such as secrecy regarding the location of the inventory sites, or a lack of cross-disciplinary communication between the administrators of the inventory data and the remote sensing analysts who wish to use the inventory data. Having people in the different organizations that are motivated to combine inventory data and remotely sensed data, as well as having the infrastructure for communication and data sharing, are catalysts for their combined use. The availability of national inventory data and its integration with satellite data to create better area statistics is increasing (e.g., Nilsson *et al.*, 2009; McRoberts, 2010), and is likely to do so in the future.

New optical satellite sensors will be launched in the coming years. The Indian Resourcesat-3 satellite, scheduled for launch in 2014, will carry an AWiFS sensor capable of acquiring large scenes (300 km swath width with one sensor) with a 25 m pixel size and an improved 12-bit radiometric resolution. The Landsat Data Continuity Mission (LDCM), scheduled for launch in 2012, will maintain the 185 km scene size and 30 m pixel size, but have an improved 12-bit radiometric resolution, and slightly different bandwidths than Landsat 7, including a new thermal-IR sensor. Sentinel-2 (part of the European GMES initiative and scheduled for launch in 2013) will be a two-satellite constellation with 10, 20 and 60 m pixels, 12-bit radiometric resolution of the visible, NIR and SWIR wavelength bands, and a scene size of 290 km. The SPOT series of satellites will launch a constellation of both SPOT 6 (scheduled for 2012) and SPOT 7 to provide data at a 6 m pixel size for the blue, green, red, and NIR bands, a 60 km swath width, and a daily revisit ability. Each of these satellites will provide new data useful for mapping forest and alpine landscapes.

Finally, the advancement of 3-D technology in remote sensing will also be of importance for land cover classification and continuous value predictions. Airborne laser-scanner data can be used to provide data on vegetation height and density, as well as to create high-resolution digital terrain models. Digital

aerial photographs are also a potential data source for automated digital surface models, and the TerraSAR/TanDEM-X radar mission will soon provide new global digital elevation models. Improved digital terrain models will certainly be useful for topographic normalization of optical satellite data as well as providing more detailed elevation derivatives as input to classification. Combining laser-derived parameters with optical satellite data has already been shown to improve the estimation of forest parameters (Nordkvist *et al.*, *in press*), as the two data sources provide complimentary information. It is anticipated that the addition of information on vegetation height and density from 3-D data sources together with the spectral information from optical satellite data will lead to improved classification of alpine vegetation types, as well as for forest.

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