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Multi-source forest inventory data for forest production and utilization analyses at different levels

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Academic dissertation

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ABSTRACT

National forest inventory (NFI) data are commonly used in national and regional scenario analyses on forest production and utilization possibilities. There is an increased demand for similar analyses at the sub-regional level, and further, to incorporate spatially explicit data into the analyses. However, the fairly sparse network of NFI sample plots allows analyses only for large areas. The present dissertation explored whether satellite imagery, NFI sample plot data and the *k* nearest neighbour estimation method can be employed in generating spatial forest data for scenario analyses at the local level. The method was first applied in the area of two villages in Eastern Finland to quantify the effects of administrative land use and technical land-form constraints on timber production. Secondly, the impacts of three alternative regional felling strategies on suitable habitat for the Siberian flying squirrel (*Pteromys volans*) were assessed.

As a scenario analysis tool, the Finnish forestry dynamics model MELA was used. Management units for simulations of forest development and management activities were delineated by means of image segmentation and digital maps on restriction areas, and new weights for NFI sample plots, that is, the representativeness in these units, were estimated by means of satellite image data. The performance of different segmentation methods and different spectral features in the estimation were examined. Image segments corresponding to forest stands enabled the use of patch- and landscape-level models in the prediction of suitable habitat.

Satellite image-based estimation of new NFI sample plot weights was found to be a feasible method for generating forest data for scenario analyses in areas smaller than is possible with the plot data only, for example, for municipalities. Satellite imagery with large geographic coverage and continuous NFI field measurements provide cost-efficient data sources for versatile impact and scenario analyses at the local level.

Keywords: Forest planning, forestry scenario modelling, *k* nearest neighbour estimation, Landsat satellite image, remote sensing, spatially explicit constraint

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Helsinki, July 2017

Helena Haakana

LIST OF ORIGINAL ARTICLES

This dissertation is based on the following four articles, which are referred to by their Roman numerals in the text. The articles are reprinted with the kind permission of the publishers.

I Mäkelä H., Pekkarinen A. (2001). Estimation of timber volume at the sample plot level by means of image segmentation and Landsat TM imagery. Remote Sensing of Environment 77(1): 66–75. https://doi.org/10.1016/S0034-4257(01)00194-8

II Mäkelä H., Hirvelä H., Nuutinen T., Kärkkäinen L. (2011). Estimating forest data for analyses of forest production and utilization possibilities at local-level by means of multi-source National Forest Inventory. Forest Ecology and Management 262: 1245–1359. https://doi.org/10.1016/j.foreco.2011.06.027

III Kärkkäinen L., Nuutinen T., Hirvelä H., Mäkelä H. (2011). Effects of administrative land-use and technical land-form constraints on timber production at the landscape level. Scandinavian Journal of Forest Research, 26(2): 120–127. https://doi.org/10.1080/02827581.2010.536568

IV Haakana H., Hirvelä H., Hanski I. K., Packalen T. (2017). Comparing regional forest policy scenarios in terms of predicted suitable habitats for the Siberian flying squirrel (*Pteromys volans*). Scandinavian Journal of Forest Research 32(2): 185–195. https://doi.org/10.1080/02827581.2016.1221991

In I, data preparation and analyses were carried out by Haakana. Pekkarinen was responsible for developing and implementing image segmentation and estimation algorithms. In II – IV, Haakana was responsible for data preparation and estimation, and Hirvelä for scenario analyses. In IV, the habitat models were derived by Haakana and Hanski, and Haakana was responsible for applying the models in forest scenarios. The work was designed and the articles were jointly written by the authors (I – IV).

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1 INTRODUCTION

1.1 Information needs for policy support

Forests are renewable natural resources, and, to use the resources in a sustainable way, information on the amount and state of forests is required. National forest inventories (NFIs) and monitoring systems have been established to provide this information for policy support and strategic forest planning at the national and regional levels. NFIs in Finland and in other Scandinavian countries were started as early as in the 1920s to assess and monitor the state of forests. At the beginning the driving force was concern about the availability of timber resources after the slash and burn system in agriculture and intensive fellings for tar burning and raw material for the ship industry. Since then various information needs have emerged to which the NFIs have been adjusted to respond, such as intensive forestry programmes to guarantee raw material for the increasing forest industry in the 1950s, concern about forest damage due to air pollution in the 1980s and concern about loss of forest biodiversity in the 1990s.

Multiple goals in forestry, such as safeguarding biodiversity, the mitigation of climate change and ecosystem products and services beyond wood, have brought further challenges to forest management in the 21st century. Forests and wood products play a key role in international climate policy, as they can store carbon, and, in addition, wood-based products can be used to replace materials and energy from non-renewable sources. Carbon credits and increased demand for bioenergy (European Commission 2009; 2013; 2014) have again arisen concern about the availability of wood recourses (Hänninen and Kallio 2007; Nabuurs et al. 2007; Alberdi et al. 2016; Barreiro et al. 2016; Packalen et al. 2016). At the same time, political decisions have been made to preserve forest biodiversity (United Nations 1992; European Commission 2006; 2011) and, consequently, to increase areas set-aside for conservation and encourage ecologically oriented forest management. These competing demands may restrict the supply of raw material for the forest industry and have economic impacts on the forest sector (Hänninen and Kallio 2007; Nabuurs et al. 2007). In cross-sectoral policy making and decision support there is an increased need for information on future wood production potentials and, further, on the effects of alternative forest utilization.

The projection of forest resources into the future by means of scenario modelling enables the evaluation of different forest management strategies and their trade-off values. A scenario is describing a possible future situation and the course of events leading from the original situation to the future situation (Godet and Roubelat 1996). Scenarios provide a useful tool for decision makers to analyse the consequences of different forest policies. Many countries have projection systems based on tree-level growth models and the simulation of specific management activities and natural events, such as thinnings, regeneration fellings and mortality (e.g. Siitonen et al. 1996; Kaufmann 2001; Wikström et al. 2011; Packalen et al 2014; Barreiro et al. 2016). These forestry scenario models are mainly developed for large-scale timber production analyses at the strategic level of forest management to assist policy makers. The traditional objective is to assess future felling potentials at the national or regional scale (e.g. Salminen and Salminen 1998; Nuutinen et al. 2000; 2007a). However, the forestry scenario models are continuously developed to better meet the emerging information needs and expectations from diverse stakeholders. These include information on different ecosystem functions and services and on the effects of the conservation of forest biodiversity, of forests' carbon sequestration and of climate change on forests' growth and vitality (Eid et al. 2002; Backéus et al. 2005; Johnson et al. 2007; Kramer et al. 2010; Barreiro 2016).

Forest planning has a hierarchical structure and is generally divided into three levels: strategic, tactical and operational levels corresponding to the level of the decision-making process, the area and the time scale of planning (Weintraub and Cholaky 1991; Martell et al. 1998). This dissertation focuses on the strategic level, which deals with the long-term management strategy taking into account sustainability and policy issues such as regulations and recommendations. Long-term forest planning is a complex process because of the multitude of alternative management actions, their spatial and temporal hierarchy and the multiple objectives set for forest management (Martell et al. 1998). The decisions at the lower level as regards the allocation and timing of fellings and other silvicultural treatments are taken to fulfil the goals set at the strategic level. Mathematical planning tools, or rather decision support systems (DSSs) based, for example, on classical utility theory and linear programming (LP) have been developed to deal with the complexity and to select management schedules that best meet the set objectives (e.g. Kilkki et al. 1975; Kilkki 1987; Johnson et al. 2007; Wikström et al. 2011). DSSs help in evaluating alternative management scenarios (decisions) and studying the long-term impacts of forest management.

1.2 NFI and forestry scenario modelling

NFIs are designed to produce reliable and unbiased information on the current state of forests and through repeated inventories on their changes. For reasons of cost-efficiency and statistical validity, NFIs are commonly based on sampling, which covers all land use categories and ownership groups. In Finland the NFI sampling is designed for reliable estimates of the forest attributes of interest at the national and regional scales. As regional units, the 19 provinces and, previously, the regional Forest Centres have been applied. In 2015 the 13 regional Forestry Centres were reorganized as the Finnish Forest Centre, which is a state-funded administrative forestry unit responsible for, for example, promoting forestry and related livelihoods, advising landowners and enforcing forestry legislation. The Forest Centre together with the regional Forestry Councils also formulates regional forest programmes, which are strategic development and working plans for regional forestry (Maa- ja metsätalousministeriö 2006; Weckroth et al. 2009; Maa- ja metsätalousministeriö 2015).

For forest policy support, the sample plot data of NFIs are commonly used in analyses of forest production and utilization possibilities at the national and regional levels (e.g. Eid and Hobbelstad 2000; Eid et al. 2002; Nuutinen et al. 2000; 2007a; 2009; Eriksson et al. 2007; Matala et al. 2009; Barreiro 2016). In Finland, a forestry dynamics model, the MELA model (Siitonen et al. 1996), was designed in the 1970s to analyse wood production potentials at the regional and national levels based on the sample plot data collected in the NFI. Since then analyses of forestry dynamics have been used in forest policy support, primarily to assess future felling potentials (e.g. Salminen and Salminen 1998; Hirvelä et al. 1998; Nuutinen et al. 2000; Nuutinen and Hirvelä 2006; Nuutinen et al. 2007a; Salminen et al. 2013) but increasingly also in supporting energy and climate policy (Kärkkäinen et al. 2014; Haatanen et al. 2014; Kallio et al. 2016; Lehtonen et al. 2016).

MELA is a stand simulator based on tree-level models and it includes an optimization package based on linear programming, JLP (Lappi 1992). Management units can be described by forest stands or sample plots representing a forest stand (Siitonen et al. 1996; Redsven et al. 2007). The Scandinavian counterparts are AVVIRK2000 in Norway (Eid and Hobbelstad 2000) and the Hugin and Heureka systems in Sweden (Lundström and Söderberg 1996; Lämås and Eriksson 2003; Wikström et al. 2011). Heureka is developed for analyses and planning at different spatial levels, and it includes following three applications (Lämås and Eriksson 2003; Wikström et al. 2011): an interactive simulator for stand-level analyses (StandWise), a forest-level planning tool with optimization (PlanWise), and a simulation model (RegWise) for long-term scenario analyses on large scales (Wikström et al. 2011). The Hugin was a simulation model designed for regional analyses on wood production potentials based on plot-level data (Lundström and Söderberg 1996), but it has been replaced by the RegWise module in Heureka.

The NFIs cover all land areas, but the relatively sparse network of the sample plots enables analyses only for large areas. However, there is an increasing demand to also localize policy support at the sub-regional level to support complicated decision-making situations, for example, at the municipality and village levels. In rural areas forestry is often an important part of local livelihoods, and other forest uses may cause conflicts between market players such as forest owners, companies, government and consumers of different ecosystem products and services (Nuutinen et al. 2011; Carlsson et al. 2015). Bio-energy investments, the trading of nature and recreational values and hunting tourism are other examples that increase the demand for strategic planning at the local level. In some areas governmental regulations concerning, for example, nature conservation and land use policy restrict or totally prohibit possibilities to use forest resources. This is likely to decrease a community's income from forestry and increase the price of wood for the forest industry because of an expanded procurement area (Leppänen et al. 2005; Hänninen and Kallio 2007; Kärkkäinen et al. 2017a).

In Finland, the land use planning system is hierarchical and is defined by the Land Use and Building Act (1999). Regional land use plans drafted by regional councils are general plans setting out the principles of land use and community structure as well as areas for regional development at the province level. The regional plans steer local master plans, which are legally binding land use plans at the municipality level. Local master plans in turn coordinate and control the preparation of local detailed land use plans for construction and other intensive land use. In connection with land use planning, the long-term impacts of implementing the plan, including socio-economic, social, cultural and other impacts, must be assessed. The local master plans should not cause unreasonable harm to landowners, and, if the landowner is unable to use his land in a manner generating reasonable return, he is entitled to compensation for the losses (Land Use and Building Act 1999). However, harmonized procedures and objective tools in land use planning for analysing the effects of regulations defined in local master plans are currently missing (Huhtinen and Vainio 2016). The use of a forest DSS enabling impact analyses and the comparison of alternative options has been, therefore, also proposed for local land use planning (Huhtinen and Vainio 2016; Kärkkäinen et al. 2017b).

Information on nature conservation and other site-specific constraints on wood production are taken into account in the Finnish NFI if they occur on a sample plot. A variable determining the cause and level of the restriction is recorded for the sample plots. Some restrictions such as nature conservation areas are identified from other data sources before field work commences. In addition, field teams can record the existence of restrictions to forestry due to specific natural values, aesthetical values or other values found at the site. With the help of this information, NFI results are presented separately for all forest land as well as forest land available for wood production. In addition, information on restrictions determined, for example, in land use plans can be assigned to the sample plots to calculate their influence on the forest resources under protection (Mattila and Korhonen 2010). Consequently, future wood availability and the effects of conservation on the availability can be analysed at the regional and national scales. Because of relatively sparse sampling, the NFI cannot, however, capture small restriction areas or rare occurrences of threatened species, and is not suitable, for example, for assessing and monitoring all natural forest habitat types (Raunio et al. 2008). Similarly, with respect to land use restrictions originating from local master plans which are typically concentrated around urban areas and relatively small in size, their effects on forestry are of interest at the local rather than the regional scale.

Furthermore, NFI data collected from sample plots do not allow for analyses at the landscape level. To incorporate nature and biodiversity values, such as the habitat requirements of threatened species, into the scenario analyses, spatially explicit data with full coverage are often required. Habitat models based on linking empirical species' survey data with habitat characteristics, in addition to land cover and forest attributes, with different landscape metrics, have become common (e.g. Pereira and Itami 1991; Edenius and Mikusiński 2006; Stighäll et al. 2011; Bradley et al. 2012). The increased concern about forest biodiversity has led to complex planning problems with multiple objectives and a need to comprise both temporal and spatial dimensions. In previous studies information on valuable habitats or other biodiversity indicators has been combined with simulation of forest stand data to assist in the evaluation of alternative management strategies in forest planning (e.g. Nalli et al. 1996; Næsset 1997a; Öhman and Eriksson 1998; Carlsson 1999; Kliskey et al. 1999; Kurttila et al. 2002; Öhman and Eriksson 2002; Schwenk et al. 2012). Forest management planning systems linking georeferenced forest stand data, projection models and an LP model are powerful tools allowing decision makers to explore trade-offs between multiple objectives and analyse the economic consequences of alternative developments (Carlsson 1999). Methodologies for multi-objective forest management planning have been developed to support forest owners in decision making, that is, long-term strategic planning at the forest holding level (see Kangas et al. 2015; Pukkala 2008; 2016). These require spatially explicit information on production possibilities, such as forest attributes, habitats and recreation, at the same scale, traditionally at the forest stand level (Pukkala 2008).

There is clearly a need for similar analyses at the larger, sub-regional scale to assess the potential impacts of different forest policies on valuable habitats and provide support in decision making (Edenius and Mikusiński 2006; Packalen et al. 2014; Vauhkonen and Ruotsalainen 2017). To apply spatially explicit habitat models, spatial data on forest resources over larger areas of interest ranging from villages to provinces are needed. However, full coverage of up-to-date stand-level forest data is rarely available due to institutional and economic reasons. In Finland, forest stand data are traditionally collected for operational forest management planning, especially for providing information on felling possibilities and scheduling forest operations at the forest holding level. The NFI sample plot data otherwise used in national and regional impact analyses are not adequate alone, but remote sensing provides a means to generate spatially explicit forest data for sub-regional analyses.

1.3 Remote sensing in forest inventory

NFIs typically produce forest statistics, that is, estimates of means and totals of forest variables such as forest area, volume, biomass and growth of the growing stock, for large areas using field data measured on sample plots. The requirement for diverse, geo-referenced and timely information on forest resources at low cost has contributed to innovations in the use of remote sensing and related statistical estimation techniques in forest inventory (see e.g. McRoberts and Tomppo 2007; Barret et al. 2016). The integration of aerial photography with the field data has a long tradition in forest inventory, and satellite imagery has been used as ancillary data in inventory applications since the 1970s (e.g. Poso and Kujala 1971; Poso et al. 1984; Kilkki and Päivinen 1987; Muinonen and Tokola 1990; Tomppo 1991). Advances in technology such as GIS and the availability of free Landsat satellite imagery and other digital map data have further enhanced the use of remote sensing in forest inventory (Barret et al. 2016).

McRoberts and Tomppo (2007) have listed four primary ways how remote sensing has been used to enhance NFIs: 1) providing a fast and less expensive method than field sampling to estimate certain forest attributes; 2) increasing the precision of the large-area inventory estimates by means of stratification (e.g. Nilsson et al. 2003; McRoberts et al. 2002; 2006); 3) estimating forest attributes for areas smaller than are possible with required accuracy using relatively sparse field sampling; and 4) producing forest information in geo-referenced form, that is, as thematic maps that can be used, for example, in timber procurement or ecological studies. Digital forest maps have also been used in sampling design studies (Tomppo et al. 2001; 2014b). In addition, satellite image data have also been widely used in land cover classification and change detection.

The production of raster maps on forest attributes has been implemented as a part of operational NFIs, for example, in Finland and Sweden (Tomppo et al. 1998; 2008; Reese et al. 2003) and tested in many other countries (e.g. Trotter et al. 1997; Franco-Lopez et al. 2001; McRoberts at al. 2002; Maselli et al. 2005; Gjertsen 2007; Koukal et al. 2007; Scheuber 2010). In Finland, the Multi-Source National Forest Inventory (MS-NFI) system based on satellite imagery (see Tomppo et al. 2008) provides raster maps of different forest attributes and forest statistics for municipalities every other year (Tomppo et al. 1998; 2008; 2009; 2012; 2013; 2014a; Mäkisara et al. 2016). In Sweden raster maps are produced approximately every fifth year (Fridman et al. 2014). These remote sensing-based inventories offer invaluable information on forest resources and specifically on the spatial variation and location of the resources. The applications in forest and ecological studies utilizing raster maps are various, including the estimation of bioenergy potential (Muinonen et al. 2013), habitat modelling (e.g. Reunanen et al. 2002b; Hurme et al. 2007; Manton et al. 2005; Stighäll et al. 2011; Santangeli et al. 2013) and the cost-effective selection of reserves for forest biodiversity conservation (Mikusiński et al. 2007; Juutinen et al. 2008; Vauhkonen and Ruotsalainen 2017).

The advantages of optical satellite data such as Landsat and SPOT include the coverage of a large area, fast availability and low cost. For example, the size of one Landsat 7 scene is approximately 170 km × 183 km, with a temporal resolution of 16 days. The Landsat programme has the longest history in providing satellite imagery with coarse or medium spatial resolution (e.g. 30 m × 30 m for Landsat 7) and wide spectral resolution (8 bands) for applications in, for example, agriculture, forestry and regional planning. The first version, Landsat I, was launched in 1972, and since 2011 the images have been freely available (Wulder et al. 2016). However, cloud-free images may be difficult to obtain for a desired growing season. For example in Sweden, 28 Landsat scenes were theoretically required to cover the whole country, but because of clouds 50 scenes were actually needed to obtain a cloud-free forest classification (Reese et al. 2003).

During recent decades, several satellite imaging systems providing images with a spatial resolution higher than 5 metres have been developed to contribute to the fields of resource mapping and monitoring. Some examples of these commercial systems are the Advanced Land Observing Satellite (ALOS), QuickBird, IKONOS, RapidEye, WorldView-2 and Sentinel-2. The Sentinel-2 mission, by the European Space Agency (ESA), provides multi-spectral imagery with high resolution (10 m), a swath width of 290 km and frequent revisits (5 days) to support, for example, land cover mapping, change detection and forest monitoring (Drusch et al. 2012). The first Sentinel-2A satellite was launched in June 2015.

At the same time, the availability of remote sensing materials with very high spatial resolution acquired by airborne imaging spectrometers (e.g. AISA and CASI) and active sensors such as radars (e.g. TerraSAR-X) and airborne laser scanners (ALS) has increased, and their applicability in forest inventory has been actively studied (e.g. Holmström and Fransson 2003; Holopainen et al. 2010).

For forest management inventories, ALS has proven to be the most useful remote sensing technique (Næsset 1997b; Means et al. 1999; Næsset 2002; 2004; Holmgren 2004; Næsset et al. 2004; Maltamo et al. 2006; Packalén and Maltamo 2006; 2007; Hyyppä et al. 2008; Hudak et al. 2009). For example in Finland, the traditional stand-level field assessment for forest planning was replaced by a new inventory system based on ALS, aerial photographs and field measurements on reference sample plots (Maltamo and Packalen 2014). The inventory proceeds area by area and is targeted for completion in 10 years (2010–2020). In Sweden, ALS has been used in constructing a nationwide forest database (Nilsson et al. 2016) and in Norway and Austria, for example, for district-level forest management inventories (Næsset 2004; Hollaus et al. 2009). Due to technical advances in aerial digital cameras and data processing, photogrammetric point clouds also provide a competent data source for forest inventory. Digital stereo imagery can be used to generate a surface model of forest canopy and a canopy height model if a digital terrain model is available, such as that derived from ALS or other sources (e.g. Vastaranta et. al 2013; Pitt et al. 2014; Gobakken et al. 2015).

ALS has been shown to provide accurate estimates of stand-level forest variables, but the high cost of the data acquisition limits its use in NFIs. It is not feasible to acquire full coverage ALS data, or other very high resolution RS data, continuously over large geographical regions (McRoberts and Tomppo 2007; Næsset et al. 2013). In addition, the use of different ALS devices, flying and scanning parameters and differences in forest structure between regions complicate data analyses and the applicability of nationwide models (Kotivuori et al. 2016). As an alternative, the use of ALS data as auxiliary data for two-phase sampling surveys has shown promising results in national and regional inventories (Gregoire et al. 2011; Næsset et al. 2013; Ene et al. 2016). While research on new techniques and RS materials is ongoing, optical satellite imagery provides a cost-efficient data source for operational NFIs.

1.4 Estimation of forest attributes

In combining satellite data and field plot data to produce raster maps and estimate forest attributes for small areas, different estimation techniques have been investigated. The estimation is based on the assumption that the spectral values of an image correlate with timber volume and other volume-related forest variables. Parametric regression models can be formulated to predict forest variables for each image pixel or forest stand (e.g. Franklin 1986; Tomppo 1987; Häme et al. 1988; Ardö 1992) as well as provide estimates for small areas such as municipalities by aggregating pixel predictions. However, each variable is usually predicted separately, and the estimates do not have the natural variation of original forest attributes or retain the relationships between the attributes (Moeur and Stage 1995). To overcome these drawbacks, the non-parametric *k* nearest neighbour (*k*nn) technique has been used extensively in inventory applications employing satellite imagery (e.g. Kilkki and Päivinen 1987; Muinonen and Tokola 1990; Tokola 1990; Tomppo 1991; Tokola et al. 1996; Nilsson 1997; Trotter et al. 1997; Franco-Lopez et al. 2001; McRoberts et al. 2002; Reese et al. 2002; Katila and Tomppo 2001; Katila 2006; Kajisa et al. 2008; Tomppo et al. 2008). One advantage of the *k*nn method is that several forest variables of interest can be estimated simultaneously while preserving much of the correlation structure among the variables (Moeur 1987; McRoberts and Tomppo 2007; McRoberts et al. 2007). Further, because the method is non-parametric, no assumptions regarding the distributions of variables are required. The method is versatile and can be used with different reference data and remote sensing materials. The *k*nn estimator has also been used widely, for example, in the studies on ALS in forest inventory (e.g. Maltamo et al. 2006; Breidenbach et al. 2010; Tuominen and Haapanen 2011; Gagliasso et al. 2014).

The basic principle of the *k*nn method in a mapping approach is that for each image pixel, *k* spectrally nearest pixels associated with a field plot are searched, and forest attributes for the pixel in question are estimated as a weighted mean of the field measured attributes; weights are inversely proportional to the squared spectral distance. For the distance metric, most often the Euclidian distance (e.g. Franco-Lopez et al. 2001; Katila and Tomppo 2001; Reese et al. 2003; Tomppo et al. 2008) and also the Mahalanobis distance (Tokola et al. 1996; Nilsson 1997; Fazakas et al. 1999; Muinonen et al. 2001) as well as similarity measure based on canonical correlation (Mouer and Stage 1995; Muinonen et al. 2001) have been used. In small area estimation, sample plot weights can be interpreted as the area of similar forest as the plot represents in the total inventory area (Kilkki and Päivinen 1987; Tomppo 1996; Lappi 2001). Inventory area refers to the sub-regional, small area, such as a municipality, for which the forest statistics are calculated. Area interpretation is possible if the weights are positive and the same for all target variables (Tomppo 1996; Lappi 2001). However, the chosen nearest neighbours may not add up to unbiased or statistically optimal estimates for the total area (Lappi 2001).

Resampling techniques such as cross-validation (leave-one-out) can be used to assess the quality, often the root mean square error (RMSE), and bias of the estimates at the pixel level. In this method, forest variables are predicted for each field plot pixel (a pixel associated with a field plot) in turn with the help of the other field plots. The cross-validation is also frequently applied in selecting the size of the neighbourhood, that is, the value of *k*, and other parameters, such as spectral features, distance metric and weighing and selecting the geographical reference area where nearest neighbours are searched (e.g. Nilsson 1997; Katila and Tomppo 2001). In this case, the objective is to minimize the mean square error of the key variables and at the same time retain the variation of the forest variables. However, there is no analytical variance estimator available to assess errors of *k*nn predictions in target areas of different sizes. Model-based approaches to error estimation have been developed (Kim and Tomppo 2006; McRoberts et al. 2007; Magnussen et al. 2009; 2010; McRoberts et al. 2011), but the methods are not yet operational. Consequently, the accuracy of *k*nn estimates for small areas have been assessed empirically using independent datasets based, for example, on aerial photographs or intensive field sampling (Tokola and Heikkilä 1997; Hyyppä et al. 2000; Katila 2006). The bias of small area estimates in the Finnish MS-NFI have been studied comparing them with the estimates based on NFI field data in sub-regions (groups of municipalities), which are large enough to enable the estimation of forest variables and their standard errors (Katila et al. 2000).

One weakness of the *k*nn method is that the estimates at the pixel level are potentially biased, especially in the neighbourhood of extreme observations (Altman 1992; Nilsson 1997; Katila and Tomppo 2001; McRoberts et al. 2002). This is due to the convex relationship between spectral values and forest variables, such as volume. Inverse distance weighing of the neighbours reduces the bias, but for extreme observation, all *k* neighbours are mostly smaller, or larger respectively, than the observation itself. Using a small value for *k* decreases the bias and preserves the variability of the observations but at the same time increases the mean standard error of estimates. However, with a *k* value of one it can be even larger than the variance of the observations, which means that using the mean of the observations for each prediction would result in a smaller error (McRoberts et al. 2002). Consequently, the selection of k is a compromise between precision and bias, and further, the variation of the estimates (Altman 1992; Moeur and Stage 1995). Increasing the number of neighbours leads to more precise but also more average predictions.

In the Finnish MS-NFI the *k*nn method has been used for both the mapping and estimation of forest variables for municipalities (e.g. Tomppo et al. 1998; 2008; 2009; 2012). The method has been continuously developed, and new features have been implemented within the operational MS-NFI. For example, to reduce the effect of map errors a calibration method based on the confusion matrix between land use classes of the field sample plots and corresponding map information has been developed (Katila et al. 2000). Further, ancillary data such as site fertility and peat land maps can be used as a priori information for the stratification of data to improve the accuracy of *k*nn predictions (Tokola and Heikkilä 1997; Katila and Tomppo 2002). In Sweden the *k*nn was applied to produce nationwide raster maps, but the small area (sub-county) statistics were estimated using post-stratification, where the *k*nn maps were used for stratification (Reese et al. 2003; Nilsson et al. 2003; Fridman et al. 2014). One reason for this was problems with land use classification (Fridman et al. 2014).

The *k*nn method results in high RMSEs of the forest variable estimates at the plot level, that is, the pixel level when Landsat image data are used. The reported relative RMSEs for the mean volume estimated by means of Landsat image data and sample plot data in boreal forests range typically between 60% and 80% and are even higher for volumes by tree species (Tokola et al. 1996; Fazakas et al. 1999; Katila and Tomppo 2001; Reese et al. 2002). One reason for the high estimation errors at the pixel level may be errors in the image registration and locations of sample plots (Halme and Tomppo 2001). The RMSE decreases when it is calculated for a larger area, that is, when the number of pixels increases. At the forest stand level, a relative RMSE of about 40−60% has been reported (Hyyppä et al. 2000; Mäkelä and Pekkarinen 2004) but decreased to 20% when the area was larger than 30 ha (Tokola and Heikkilä 1997). An RMSE of about 10–15% is reached for areas of 100 ha (Nilsson 1997; Tokola and Heikkilä 1997; Tomppo et al. 1998; Fazakas et al. 1999; Reese et al. 2002; Katila 2006) and 5% for an area of 10,000 ha (Katila 2006). Fazakas et al. (1999) pointed out that using only NFI sample plots, the mean volume with a 10% RMSE can be estimated for an area of 25,000 ha in Sweden.

The *k*nn tends to overestimate small volumes and underestimate large volumes. At the plot level the bias may be rather large and also significant in small areas (100 ha) depending on the location and characteristics of the area in regard to the whole reference area from where the field plots are employed (Fazakas et al. 1999; Katila et al. 2000; Katila 2006). In areas of 10,000 ha and larger (groups of municipalities), the bias could be reduced by correcting the effect of map errors (Katila et al. 2000). Further, adding coarse-scale forest variables, such as volumes of tree species or age, height and site index, as ancillary variables in the *k*nn estimation has been reported to reduce the bias (Holmgren et al. 2000; Tomppo and Halme 2004). It is also important to have enough field plots that represent the entire variation of the forest attributes in the inventory area.

Because of the small size of forest stands in boreal conditions and, consequently, high RMSEs at the stand level, stand variables estimated by means of satellite imagery and NFI sample plots are not accurate enough to support operational forest planning, that is, timing and allocation of forest operations. However, the use of satellite images could provide a valuable data source for the strategic analysis of forest production possibilities at the sub-regional level. Previously, Bååth et al. (2002) combined Swedish NFI sample plot data with satellite image data to estimate input data for the forestry planning system Hugin

(Lundström and Söderberg 1996) to assess future forest fuel potentials at the local level. They used the *k*nn estimation with one neighbour, that is, each image pixel was represented by one NFI sample plot (Bååth et al. 2002). The potential amount of forest fuels was forecasted for the coming 50 years in two different scenarios: according to a standard silvicultural programme and a programme with a spatial restriction (Bååth et al. 2002). The current dissertation had a similar approach, aiming to utilize NFI sample plot data for scenario analyses at the local level by means of satellite image data.

1.5 Image segmentation in forest inventory

A basis for forest management planning and operations in practice is a forest stand. Forest stands are homogenous units in terms of site properties (e.g. mineral soil or peatland), the structure of the growing stock (age, density, dominant tree species etc.) and management history. Forest site potential and the current state of the growing stock determine optional management schedules in the future, and, therefore, information on the stand characteristics at the starting point is crucial in the analyses of forest production and utilization possibilities. Consequently, forest information for management purposes has been traditionally collected and presented as means and totals for forest stands delineated, for example, with the help of aerial photographs. In national and regional impact and scenario analyses based on NFI sample plots in Finland, the simulation of feasible management activities is based on stand-level forest characteristics recorded for the sample plots (Hirvelä et al. 1998, Nuutinen et al. 2000; Nuutinen and Hirvelä 2001; Nuutinen et al. 2007a).

Satellite imagery provides a means to generate spatial forest data and, consequently, associate the forest data with other relevant information in scenario analyses, for example, on valuable habitats. By means of satellite imagery forest attributes can be estimated for each image pixel. A pixel map is, however, not a traditional presentation of forest and not suitable for analyses of forest production possibilities as such, especially considering the large estimation errors at the pixel level. One possibility for creating more traditional management units approximating forest stands is image segmentation.

Image segmentation is the division of an image into spatially continuous, disjoint and spectrally homogeneous regions. In the context of remote sensing, the objective is to delineate regions that correspond to identifiable objects, such as forest stands or tree crowns in the ground. Automated image segmentation is a commonly used technique in the fields of computer vision and pattern recognition, and a multitude of segmentation algorithms have been developed (e.g. Pal and Pal 1993). The segmentation techniques applied in forestry can be classified into three main groups: pixel-, edge- and region-based methods (Pekkarinen 2002a). Pixel-based methods include thresholding or, more generally binarization, and clustering in the feature space. In thresholding, objects of interest are separated from the background using a threshold value based on a priori information or, for example, by locating local maxima to detect individual trees in aerial images (Pitkänen 2001). Image clustering is the grouping of image pixels into homogenous groups (clusters) within the feature space, which correspond to natural classes of interest such as land use categories or vegetation types. The results of thresholding and clustering contain several units belonging to the same class (cluster) that are not necessarily spatially connected. To produce a segmentation, spatially continuous regions can be identified and re-labelled, for example, by means of connected component labelling (Jain et al. 1995). In edge-based segmentation methods, edges, that is, the locations of significant intensity changes in the image, are detected first and then linked to compose boundaries; and finally, segments are defined as regions inside these boundaries (Jain et al. 1995). In region-based segmentation, neighbouring pixels that are similar enough are assigned to the same segment. Region-growing algorithms typically start with initial low-level segments or individual pixels and aggregate adjacent regions or pixels based on their spectral properties iteratively until the criteria given for the similarity or the segment size are met (Hagner 1990; Baaz and Schäpe 2000; Pekkarinen 2002a; Castilla 2003). There are several algorithms based on region growing, merging or splitting and, further, their combinations with other segmentation approaches. For example, a segmentation method used in forest inventory applications, “Image segmentation with directed trees” by Narendra and Goldberg (1980), combines the features of edge-detection and region-growing.

In forest inventory applications, image segmentation has been used to divide an area into spectrally homogenous units representing forest stands. With low-resolution satellite imagery, the ultimate objective has been the estimation of forest stand variables for forest management purposes (Tomppo 1987; Tokola 1990; Häme 1991; Parmes 1992; Woodcock and Harward 1992; Mäkelä and Pekkarinen 2004) or the improvement of estimation results by means of stratification (Kilpeläinen and Tokola 1998). With high spatial resolution imagery, such as IKONOS or QuickBird satellite images, aerial photographs and ALS data, image segmentation has been used in the delineation of forest stands or, further, micro-stands for the estimation of forest characteristics for management planning (e.g. Baatz and Schäpe 2000; Hay et al. 2005; Mustonen et al. 2008; Pascual et al. 2008; Wulder et al. 2008) and in extracting segment-based image features to improve estimation results (Pekkarinen 2002b; Hyvönen et al. 2005; van Aardt et al. 2006; Tuominen and Haapanen 2011). Moreover, segmentation techniques have been applied in detecting individual trees in high spatial resolution imagery (e.g. Brandtberg and Walter 1998; Hyyppä and Inkinen 1999; Leckie et al. 2003; Maltamo et al. 2003; 2004), aiming at the estimation of forest stand characteristics for management planning.

1.6 Objectives

The main objective of this dissertation was to explore whether satellite imagery and NFI sample plot data can be employed in generating spatial forest data for analyses of forest production and utilization possibilities at the sub-regional level, that is, for areas smaller than is possible using the NFI plot data only. There is an increasing demand for local impact and scenario analyses, including a spatial component also, due to changes in the operational environment in forestry. The driving force behind the present dissertation, especially in the studies II–IV, was to respond to these needs. The Finnish forestry dynamics model MELA is a powerful tool for versatile scenario analyses at different levels, but often spatial data with a full geographic coverage over the area of interest are not available or can be out of date. The operative MS-NFI provides forest statistics for municipalities and thematic forest maps, and the possibility to use the same approach in estimating forest data for scenario analyses by the MELA model was investigated. Technically, NFI sample plot data, Landsat satellite imagery and digital map data were applied in the estimation of new weights (representativeness) for the sample plots in different areas of interest (management units), and these sample plot data were used in MELA calculations. In the estimation, the *k*nn method was used, and different estimation units and spectral features were tested.

Image segmentation was applied to delineate spectrally homogenous units corresponding to forest stands. Segments were employed for four different purposes, as follows: 1) to extract spectral features in the homogenous neighbourhood of a sample plot

(Study I); 2) to apply segments as estimation units and, further, as management units in the simulation, for which forest attributes were estimated (studies II–IV); 3) to incorporate small-scale constraints on wood production into the scenario analyses (Study III); and 4) to enable the use of patch- and landscape-level habitat models (Study IV). It should be noted that in 2, the objective was to generate stand-level forest data represented by NFI sample plots for scenario analyses at the sub-regional scale and not to estimate stand-level forest characteristics as such.

The objectives of the studies included in the dissertation were as follows:

- Study I: To investigate whether the accuracy of timber volume estimates can be improved by using segment-based features instead of those of fixed-sized windows or plot pixels only. In addition, the performance of different segmentation methods in delineating homogenous units, preferably corresponding to the units of interest (forest stands) in the feature extraction were studied.
- Studies II–III: To estimate management-unit level forest data for strategic analyses of forest production and utilization possibilities at the village level. Image segmentation and spatially explicit constrains were applied in the delineation of management units. Additional objectives were to test two different spectral features in the estimation of the sample plot weights and to integrate spatial constraints into the scenario analyses. An overall objective of studies II–III was to support the outlining of a local forestry programme for an area of two villages in North Karelia.
- Study IV: To estimate forest data with full geographic coverage for scenario analyses and enable the use of spatially explicit habitat models, that is, the use of patch- and landscape-level variables in the prediction. The overall objective of the Study IV was to assess the impacts of forest management according to three different regional forest policies on the future state of suitable habitats for the Siberian flying squirrel (*Pteromys volans*) in Southern Finland.

2 MATERIALS

2.1 Study areas

The studies were carried out in three different areas in Southern Finland, which were determined by the objectives of and data available for the study in concern. The studies demonstrate two different levels of impact analyses, local and regional. Study I covered an area corresponding to a part of a municipality, and studies II–III covered an area of two villages, previously the typical size of a local forest planning area in private forests. The study area in IV comprised the whole of South Finland, including the areas of 10 regional Forestry Centres in the mainland. In Study IV, the impacts of different forest policies on a special conservation value, the Siberian flying squirrel in this case, were studied by the Forestry Centres.

The study area in I was located in South Finland, south from the city of Suonenjoki. It was 60 × 52 kilometres in size and delineated to cover a forest planning area called Suontee in the area of Forestry Centre Pohjois-Savo (Northern Savonia) (Mäkelä and Pekkarinen 2004). At the time of the research, Suontee was chosen as a test area for a joint research project entitled “Assessment and Updating of Forest Information”, funded by the Ministry of Agriculture and Forestry during the years 1999–2001, and there were both new NFI and stand-level forest inventory data available for the area. The area belonging to the Forestry Centre Etelä-Savo (Southern Savonia) in the southern part of the 60 × 52 km square was excluded, because there were no NFI data from the same time point available.

The study area was a rural landscape characterized by managed forests and agricultural land broken up by several lakes, especially in the north western part of the area. The total area was 277,565 ha, of which 64% was forestry land according to the digital map data. The dominant tree species were Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* (L.) Karst.), and birch (*Betula* spp.) and other deciduous trees had a lower proportion.

In studies II and III, the study area was located in the province of North Karelia in Eastern Finland. The area covered the villages of Koli and Hattusaari, which were selected for a case study to formulate a local forestry programme (Nuutinen et al. 2007b; 2011) as a part of the international project "Enhancing Local Activity and Values from Forest Land through Community-led Strategic Planning". The total study area was 11,372 ha, of which 9,821 ha was land in forestry use comprising private forest holdings and a part of Koli National Park. The Koli and Hattusaari villages were chosen because of intensive multiple uses of forests and opportunities for the local livelihoods offered by the forests in the area. On the other hand, in addition to the national park, there were other administrative and site-specific constraints, such as a local master plan and a local detailed plan (shore plan), which restricted the use of forests for timber production in the Koli and Hattusaari area.

Concurrent with the interactive and collaborative strategic planning at the village level, the regional Forestry Centre Pohjois-Karjala (North Karelia) was carrying out a stand-level field inventory for forest management planning and offered support in decision making at the forest holding level. Hence, there were up-to-date forest data based on field measurements available for the evaluation of the estimation results on the private forests. Similarly, for the Koli National Park, there were up-to-date stand-level forest data available, provided by the Finnish Forest Research Institute (since 2015, Natural Resources Institute Finland), which previously owned and managed the park area.

The Koli and Hattusaari study area was located on the western side of the lake Pielinen and was characterised by Koli hills rising about 300 metres above sea level. The lowland forests and fertile slopes were dominated by spruce and birch, and the rocky tops and poorer soils by Scots pine. The private forests represented typical managed forest with a fairly even distribution of different development classes. Regeneration and seedling stands covered 30% and mature stands 30% of the forest land area. The core area of Koli National Park was old forest, but the park also included young forests in the areas connected to the conservation area by the time of its establishment in 1991.

In IV, the study extended across the whole of South Finland, covering about 17.8 million ha, and included almost the entire distribution of the flying squirrel in Finland. The Finnish Museum of Natural History conducted a nationwide survey of the species in 2003–2005 to assess its distribution (Hanski 2006), and the Finnish Ministry of the Environment provided funding for a research project to link the occurrence data with the MS-NFI data. Project objectives were to study the species' association with habitat characteristics (Santangeli et al. 2013) and the development of potential habitats in different cutting scenarios in 2005–2055. The study area was restricted to the 10 southernmost Forestry Centres in Finland, though the flying squirrel also occurs in small numbers in southern parts of North Finland, specifically, in the provinces of Pohjois-Pohjanmaa and Kainuu (Hokkanen et al. 1982; Mönkkönen et al. 1997; Reunanen et al. 2000; 2002a; 2002b).

In South Finland, forests dominate the landscape, accounting for 73% of the land area (Metsätilastollinen vuosikirja 2014). The most common tree species are pine, spruce and birch, with proportions of 44%, 35% and 16%, respectively, of the total volume of the growing stock (Metsätilastollinen vuosikirja 2014). Most of the forests are available for wood production, while nature reserves and other protected areas cover 5% of the forestry land area (Metsätilastollinen vuosikirja 2014). Other land uses include agricultural areas, human infrastructures and water bodies, with some variation between the provinces. Agricultural land is more common in the southwestern part and lakes in the eastern part of the country. The habitat characteristics of the flying squirrel were studied at the landscape level, and, therefore, other land use areas were included in habitat composition and configuration.

2.2 Field data

The sample plot data of the 9th NFI (NFI9) were used in studies I–III and those of the 10th NFI (NFI10) in Study IV. The study areas in I–III were in the sampling density region “Central Finland”, where one sampling unit, that is, a cluster, in the NFI9 consisted of 18 relascope sample plots located at 300-m intervals along the sides of a rectangle (Tomppo et al. 2011). The distance between the clusters was 7 km in both east-west and north-south directions, and, on every fourth cluster, sample plots were established as permanent. Field teams located the positions of the sample plots by measuring distances and bearings to the plot centre starting from a point which was exactly identifiable both on the base map (scale 1:20,000) and in the field, such as a corner in a forest holding boundary or a crossing of two boundaries. In navigation and positioning, a measuring tape of 20 metres and a Suunto direction compass (400°) were applied. In cases where the field team noticed a deviation of more than 10 metres from the true sample plot location, they recorded the deviation and corrected the bearing used in measuring the locations of the remaining sample plots in the cluster.

Trees belonging to a sample plot were selected by a relascope, that is, using restricted angle count sampling (probability proportional to size) with the basal area factor 2 m^2/ha and a maximum radius of 12.52 m. Every seventh tallied tree was measured as a sample tree. Stand-level characteristics were measured and assessed from those stands that intersected the sample plot area (referred to as sample plot stands). For the forest stands where a sample plot centre happened to locate, all stand characteristics describing, for example, site quality, soil properties, growing stock, damages and accomplished fellings and silvicultural measures were recorded. The stand description represented the whole stand, not only the plot area. If there was a stand border in the plot area and trees belonging to the sample plot were measured from the intersecting forest stand, a separate stand description was also recorded for the intersecting stand. In cases where there were no trees belonging to the sample plot on the intersecting forest stand, only certain main attributes, such as land use category and land use changes, were recorded. Because of the tree sampling method, the plot area varied between the plots depending on the size of the largest tree measured on the sample plot. If the largest tree on the plot was larger than 34.4 cm at breast height, the maximum radius was applied, that is, the plot size was fixed.

The NFI9 field measurements in the Forestry Centre Pohjois-Savo were carried out in 1996, and the total number of sample plots located in study area I was 1,065. Of these only sample plots on forestry land and that were completely inside their respective forest stand, 466 plots in total, were applied in Study I. Sample plots intersected by a stand border and divided into two or more forest stands were excluded. In the Forestry Centre Pohjois-Karjala, the NFI9 was carried out in 2000. All sample plots both within the Forestry Centre boundary and the Landsat image scenes chosen, a total of 6,935 plots, were used as field data in studies II and III.

In Study IV, the NFI10 sample plots measured in 2004 and 2005 were applied. The sampling design was similar to that in the NFI9, but the locations of temporary clusters were shifted 1 km north and west from the previous locations (Korhonen et al. 2013). Further, the number of sample plots on a cluster was reduced to meet the intensified rotation of the NFIs, which was set to five years. In the NFI10, sample plot centres were located by means of a GPS device. Trees to be measured on sample plots were selected using restricted angle count sampling, and every seventh tree was measured as a sample tree, as in the NFI9. The stand-level measurements were similar to those in the NFI9, but the growing stock was described in more detail, that is, by tree layers and tree species (Korhonen et al. 2013).

The study area in IV covered the whole of South Finland, and in the estimation NFI10 sample plots within each satellite image scene in question were used. Consequently, sample plots locating in North Finland, that is, in the areas of Forestry Centres Pohjois-Pohjanmaa and Kainuu, were applied as well. The sample plots intersecting forestry land and other land use, such as agricultural land, human infrastructure and waterbodies, were rejected from the field dataset. Further, sample plots treated with a clear cut between the field measurement and satellite image acquisition as well as sample plots covered by clouds or their shadows were excluded (Tomppo et al. 2008; 2009).

Other field data used in Study II for evaluation included two separate sets of forest stand data. The first consisted of a delineation and the attributes of 1,763 forest stands in Koli National Park and the other also of a forest stand map but only summary information of 5,458 stands in the private forests in the Koli and Hattusaari study area. Both datasets were collected with a traditional stand-level field assessment, for the national park during 1996–2000 and for the private forests in 2005–2006. The stand data measured before 2000 in the national park had been computationally updated to correspond to the year 2000. The two forest stand maps were applied to delineate the study area in II, that is, only the areas covered by the stand data for comparison were included in II. Consequently, the study areas in II and III were slightly different, and data preparation and estimation were carried out separately for these studies.

In Study IV, field data on the occurrence of the flying squirrel in South Finland were applied in the modelling of the species' presence. The data were collected with a field survey carried out to assess the species distribution and density in Finland in 2003–2005 (Hanski 2006; Santangeli et al. 2013). The survey was based on sampling and field assessment on sample plots of 300 m × 300 m (9 ha) in size. The presence of flying squirrels on a plot was based upon the detection of faecal pellets.

2.3 Satellite image data and pre-processing

As satellite image material, Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced TM Plus (ETM+) images were applied (Table 1). The TM and ETM+ spectral bands 1–5 and 7 record the wavelengths of visible and infrared light (0.450–2.350 µm) and the band 6 thermal-infrared light (10.40–12.50 µm), the ETM+ band 8 is panchromatic (all wavelengths of visible light). The images were originally procured for the use of the operational MS-NFI (Tomppo et al. 2008; 2009). They included radiometric and geometric correction, and pixel values were rescaled to 8-bit unsigned integers. Pre-processing of the imagery had been carried out by the MS-NFI team. It included rectification of the images to the national uniform coordinate system and resampling to a pixel size of 25 m × 25 m. The ETM+ panchromatic band (8) was first rectified with a pixel size of 12.5 m × 12.5 m and then averaged to the same spatial resolution as the other bands.

Table 1. Satellite imagery applied in studies I–IV.

Satellite image	WRS	Bands	Date of acquisition	Studies
Landsat 5 TM	188/16–17	1–5, 7	22.8.1996	I
Landsat 7 ETM+	186/16–17	1–8	10.7.2000	II, III
Landsat 5 TM	186/16	1–5, 7	2.7.2005	IV
Landsat 5 TM	186/16	1–5, 7	4.9.2005	IV
Landsat 5 TM	187/14	1–5, 7	9.7.2005	IV
Landsat 5 TM	188/15–17	1–5, 7	2.9.2005	IV
Landsat 5 TM	190/14–16	1–5, 7	31.8.2005	IV
Landsat 5 TM	190/17–18	1–5, 7	14.7.2005	IV
Landsat 5 TM	191/15–16	1–5, 7	5.7.2005	IV
Landsat 5 TM	190/16–18	1–5, 7	17.7.2006	IV
Landsat 5 TM	187/17	1–5, 7	4.6.2004	IV
Landsat 5 TM	188/18	1–5, 7	3.7.2006	IV

The aim was to obtain satellite image material from the same time point, that is, from the same summer as the NFI field measurements were carried out in the study area in question. In Study I, image material consisted of two Landsat TM scenes, Worldwide Reference System (WRS, path/row) 188/16–17 acquired on August 22, 1996. A subset image of 52 km × 60 km covering study area I was clipped, and the thermal band (TM 6) excluded from the analyses. The acquisition date matched well with the field inventory (1996) and the image over the study area was cloud free.

In studies II and III, the Landsat 7 ETM+ scenes 186/16–17 acquired on June 10, 2000 were used as image material. The image data were from the same year as the NFI9 measurements in the region. A subset image of 25 km × 30 km covering the Koli and Hattusaari study area was employed in the segmentation. The same subset was applied in the estimation, but the reference sample plots within the whole ETM+ 186/16–17 image were utilized. The ETM+ bands 6 and 8, that is, the thermal and panchromatic bands, were excluded from the segmentation, whereas in the estimation all bands were included. There were no clouds or cloud shadows in the images within study areas II–III.

The satellite images obtained to cover South Finland in the MS-NFI 2005 were employed in Study IV (Tomppo et al. 2009). These included ten Landsat 5 TM images, of which six were acquired in the target year 2005. Two images from 2006 and one from 2004 were used to fill the gaps where cloud free images from 2005 were not available (Tomppo et al. 2009). The TM bands 1–5 and 7 were used and the thermal band (TM 6) excluded both from the segmentation and estimation.

2.4 Other digital data

Other data employed in the estimation procedure included digital map data, a digital elevation model, the digital boundaries of protected forests and the digital boundaries of administrative units (Table 2). Study I differed from the others with regard to the software applied and, consequently, to ancillary data used in the estimation. In Study I, the estimation was carried out by algorithms implemented for research use, whereas in the others the operative MS-NFI procedure was applied (Tomppo et al. 2008; 2009).

The administrative borders of Forestry Centres and municipalities were used in the data preparation to delineate the study areas and estimation units. In Study IV, the municipality map was also used in defining two forest management regions, the Southern and Northern regions, where slightly different forest management rules were applied, for example, as regards rotation age. The digital map data of the Land Survey of Finland were used to separate forestry land from other land use classes, such as agricultural land, built-up and urban areas, roads and waterbodies. Some peatland production areas missing from the map data had been digitized from the satellite images (Tomppo et al. 2008; 2009). In Study I, the administrative borders and the map data determining land use areas were the only additional data sources used.

The map data also included peatlands classified to three categories: open bogs, woody peatlands and paludified peatlands. To improve the accuracy of the estimation results, stratification of forestry land area and NFI sample plots according to the peatland information was used. In studies II and III, the image and sample plots were divided into two strata, mineral soils and peatlands. In Study IV, three strata were applied: mineral soils, woody peatland, also including paludified peatlands, and open bogs. In addition to the map data, a threshold value of the near infrared band (4) was used to detect possibly missing waterbodies or seasonal changes in water level (Tomppo et al. 2008; 2009).

The digital elevation model was employed to correct the spectral values by removing the variation caused by different illumination conditions, that is, the slope and aspect of the terrain (Tomppo et al. 2008; 2009). The slope image generated from the digital elevation model was further applied in the constraining of waterbodies. A threshold for deviation from the flat terrain was given in the estimation. In Study III, the slope image created from the digital elevation model was used to delineate slopes steeper than 36%. They were considered as constraints for forest management, that is, too steep for fellings and other management practices, and consequently not available for timber production.

Digital maps of nature conservation areas were used to determine administrative land use constraints on timber production in studies II–IV. In Study II, the forest stand data from Koli National Park determined the area outside of wood production. In studies III and IV, three different spatial datasets from the Finnish Environment Institute were applied: nature protected areas, areas of nature conservation programmes and Natura 2000 areas. The nature protected areas included national parks and other protected nature reserves on state-owned land and nature reserves established on privately owned land. The areas of nature conservation programmes were included even though the data had not been updated. The nature conservation programmes are official resolutions given by the Finnish Government, and the areas defined in the conservation programmes are formed into nature reserves by law or decree. However, the map data were not updated after the site was declared as an official protection area. Consequently, there are areas overlapping with the nature protected areas and, on the other hand, areas that are outside of the declared protection area. The nature conservation programmes cover mires, bird wetlands, eskers, herb-rich woodland, shores, old-growth forests, nationally valuable landscape areas and areas for development of national parks and strict nature reserves.

In addition, the Natura 2000 areas were taken into account in delineating restriction areas in Study III. The Natura 2000 network aims to protect biodiversity, and protection of the sites is based on the EU Nature and Birds Directives. In Finland, most of the areas belonging to the Natura 2000 network are already nature protected areas or are included in the nature conservation programmes. Hence, the Natura 2000 areas are overlapping with the areas of the two other datasets. Further, management rules for the Natura 2000 sites are not ambiguous, while case-specific treatments can be allowed. Therefore, the Nature 2000 areas were not included in Study IV.

Table 2. Digital material applied in studies I–IV.

Data	Type	Date	Studies
Digital map data (land use, peatlands)	Raster	2002	I–IV
Administrative boundaries (Forestry centres, municipalities)	Vector, polygon	2002–2011	I–IV
Forest stand delineation	Vector, polygon	2000, 2005–2006	II
Digital elevation model	Raster	2004	II–IV
Nature conservation areas	Vector, polygon	2006	II–IV
Areas of nature conservation programmes	Vector, polygon	1999	III–IV
Natura 2000 areas	Vector, polygon	2006	III
Regional land-use plan	Vector, polygon	Unknown	III
Local master plans	Vector, polygon	1987–1992	III
Local detailed plans (shore plans)	Vector, polygon	1985–2007	III
Aerial photographs	Raster	2005	II–III

In Study III, constraints on timber production defined by the regional land use plan, local master plans and local detailed plans were taken into account. The land use plans comprised a map of different land use areas (polygons) with notations and regulations given in a description section. The regional land use plan for the province of North Karelia was from 2006. The areas in the regional plan that were considered as constraints on timber production were conservation areas, areas for the development of land use for shore areas and ground water areas. There were three master plans and 17 detailed plans for development (leisure housing) along shores, that is, detailed shore plans, valid in the Koli and Hattusaari study area prepared between 1985 and 2007. Map notations and regulations were used to formulate which forest management practices were allowed on different areas.

In studies II and III aerial photographs were used to update the estimated forest data in the private forests from 2000 to 2006, that is, from the time point of NFI field measurements and satellite image acquisition to the present time, when the local forestry programme for the Koli and Hattusaari villages was outlined. Forest stands treated by a regeneration or an intermediate felling during the intervening period were detected by means of visual interpretation and felling statistics. The aerial photographs were ortho-rectified colour-infrared images with a spatial resolution of 0.5 metres and acquired in 2005.

3 METHODS

3.1 Overview of the data generation process

The data generation for the scenario analyses comprised three main stages: 1) image segmentation, 2) pre-processing of the spatial data for the estimation and 3) estimation of sample plot weights. The main approach was to use image segments approximating forest stands as management units in the scenario analysis and to estimate new weights for the NFI sample plots representing each segment. The estimation was based on the spectral properties of the sample plots and, ultimately, on the correlation between spectral values recorded by the satellites and forest characteristics measured on the sample plots in the field. Technically, for each image pixel, spectrally nearest reference sample plots were searched to represent the pixel in question. In the estimation, different spectral features were tested (I and II).

In the image segmentation, spectral properties of the forest landscape were utilized to divide the study areas into homogenous units, which served both as estimation units and management units in the scenario analyses. As regards the size and shape, the segments were to correspond to forest stands as much as possible. A two-phase segmentation approach was applied in all studies. In this approach, the initial segments created in the first phase were further fine-tuned by a region-growing algorithm to remove segments smaller than a defined minimum size. In Study I, two different methods were tested both for initial segmentation and region merging (I). The methods found most feasible were further applied in studies II–IV.

The pre-processing of the spatial data before the actual estimation included the preparation of a map of spatially explicit constraints on forest management and assigning information about the constraints to the management units. Thereafter, spectral data of Landsat images were combined with the NFI sample plots. Selected image features for each sample plot were extracted either from the pixel where the sample plot located, that is, the pixel whose coordinates were closest to the sample plot centre, or from the immediate neighbourhood of the plot pixel. In Study I, the performance of features extracted from square-shaped windows of different sizes, and from those pixels within the fixed size windows that belonged to the same segment as the plot pixel was compared. Further, segments resulting from different segmentation algorithms were compared in terms of estimation accuracy. In Study II, two different features were tested, single pixel values and average pixel values within a segment, and their effects on the estimated forest data and scenario results were studied.

The non-parametric *k* nearest neighbour (*k*nn) method was applied for the estimation of sample plot weights and, further, forest variables of interest. In Study I, the variables of interest were the total volume of the growing stock and the volumes of pine (*Pinus sylvestris*), spruce (*Picea abies*) and broad-leaved species, mostly birch (*Betula pendula* and *Betula pubescens*) and aspen (*Populus tremula*). The accuracy of the estimated volumes was measured at the sample plot level by means of the cross-validation (leave-one-out) technique (I). In Study II, the estimated total volume and volumes by tree species' groups were evaluated by comparing them with the results of a stand-level field inventory. However, in the scenario analyses, the estimated sample plot weights and all corresponding sample plot data, including tree measurements, were utilized (II–IV).

The scenarios for the coming 50- or 60-year period were produced by the Finnish forestry dynamics model MELA (II–IV). The MELA model is composed of a forest simulator generating alternative stand-level management schedules, and an optimization package (Lappi 1992) simultaneously selecting both a production programme for the whole forest area and a management schedule for each forest management unit (Redsven et al. 2007).

3.2 Image segmentation

Two different methods were tested for initial segmentation in Study I. The first one was clustering of image pixels in the feature space followed by a connected component labelling (CCL) (Jain et al. 1995). The clustering was carried out by the ISODATA clustering algorithm of ERDAS Imagine software. The ISODATA clustering was iterative and controlled by two parameters, the number of clusters and the convergence threshold. The clustering started with setting arbitrary cluster centres and assigning each pixel to the nearest cluster in the feature space. Thereafter, new cluster centres were calculated and again, each pixel was assigned to the nearest recalculated cluster. The Euclidean distance measure and simple linkage were applied. The algorithm was run until the convergence threshold was reached. The convergence threshold was the proportion of those pixels which were assigned in the same cluster in two sequential iterations.

The second method used for initial segmentation (NG) was a modified implementation of the "Image segmentation with directed trees" method introduced by Narendra and Goldberg (1980) (Pekkarinen 2002a). In NG, an image was first divided to edge and plateau pixels by means of an edge and a gradient operator and a gradient threshold value. Next, the actual image segmentation was carried out by two sequential passes over the image. During the first pass, all edge pixels were marked as a root pixel or linked to the direction of the smallest edge gradient. During the second pass, all the plateau pixels were arbitrarily linked to the pixels of the same plateau in their eight-connected neighbourhood. Finally, all the root pixels were labelled and the pixels of each directed tree were given the label of the root pixel of that tree.

The initial segmentations were further processed by two region growing algorithms in order to remove segments of single or few pixels caused by image noise (Study I). The first algorithm (NN) was based on the Euclidean distance to the spectrally nearest neighbouring segment and a minimum size parameter. The second region growing algorithm (TR) was based on measuring distance with a *t*-ratio (Hagner 1990). The three first principal components of the original TM image (bands 1–6) were used, and the region-merging was controlled by a *t*-ratio threshold and minimum size parameters. If a segment was smaller than the minimum size, it was merged to its nearest neighbouring segment. If the segment was larger than the minimum size but the distance between it and its nearest neighbouring segment was smaller than the threshold value, the segments were merged. The minimum size parameter was set to 8 pixels, that is, 0.5 ha, with the both methods.

In studies II–IV, the NG method was applied for initial segmentation and the NN algorithm for region merging. In Study II, the NN region-merging was run separately for the areas of Koli national park and the private forests to avoid segments divided by the border line. The delineation of the study area in III was slightly different than in II, and therefore, a new segmentation was carried out for Study III. In Study IV, the segmentation was carried out by the Forestry Centres, by satellite images within the Centres and by forest management regions within the images, if there were areas of both regions covered.

3.3 Preparation of spatial data

The spatially explicit data on the restrictions for forest management practices were from different sources and in different geometry types, scales or pixel sizes and from different years. The restriction maps were first converted to a raster format using a cell size of 25 m × 25 m, as this was the type and resolution of the satellite imagery and map data applied in the estimation. The restriction areas were classified into different management categories according to the level of constraints set for forest management practices (Table 3). In Study II, Koli National Park was the only restriction area taken into account. Hence, the private forests in the Koli–Hattusaari study area were all classified as available for wood production. In Study III, six management categories and the management rules for each category were formulated. In Study IV, three management categories slightly modified from the Nuutinen et al. (2007a) and the respective rules were applied. In the category of restricted use in Study IV, the only restriction concerned regeneration method, that is, clear cutting was not allowed.

Some areas included in the nature conservation programmes were interpreted differently in studies III and IV. Shores were classified as available for wood production in III, whereas they were classified as restricted areas in IV. However, the shore areas defined in the nature conservation programme in the study area of III overlapped with either Natura 2000 areas or nature reserves and consequently were classified into a stricter management category, that is, outside of wood production. Bird wetlands were classified as not available for wood production in IV, though they covered mostly lakes and see, not land area. In the Study III, there were no bird wetlands defined in the study area. Eskers and valuable landscape areas were classified as available for wood production in both III and IV because fellings and other silvicultural measures are allowed in these areas.

After the classification of the restriction areas originating from different sources in III and IV, the raster maps were combined. If the areas overlapped and had different management categories, the stricter category and accordingly stricter management restrictions were applied. Next, the raster map of management categories was combined with the segmentation map (raster) to assign the category information for each segment (management unit). In cases where a segment included different management categories, it was divided into two or more separate units to apply the same management rules for the whole unit. Technically, the identification numbers of the segments were re-coded in a way that the identification number included the management category number.

Study IV covered the whole of South Finland, and though the data generation procedure was carried out image by image, and furthermore, by forest management regions within an image, the number of management units, that is, the segments combined with the restriction areas, was too high for feasible computation with the MELA model. Therefore, the first-level management units (segments) were clustered into spectrally homogenous groups which were then used as management units in the estimation. The clustering was run with an unsupervised ISODATA algorithm of the ERDAS Imagine software. The clustering was iterative and steered with three parameters: number of initial clusters, maximum iterations and convergence threshold. For the initial number of clusters, a value giving approximately 10,000 clusters per one million ha was applied. The size of the first-level management units was a little over 1 ha, and consequently the value was calculated by dividing the number of first-level management units within the image scene by 100. For the number of maximum iterations, such a high value (1000) was given that it did not affect the process. The convergence threshold was set as 0.95. After the clustering, clusters including different management categories were divided into separate units to apply same management rules for the whole unit. The resulting management units (clusters) were not spatially connected areas but consisted of first-level management units (segments) spread over the image in question.

Table 3. Management categories applied in studies II–IV.

Management category	Restriction level	Restriction area	Studies
0 No restrictions	Available for wood production	Areas not included in the other categories	II–IV
1 Clear cutting, soil preparation and ditching not allowed	Restricted use	Areas defined in the local master plan	III
2 Soil preparation and ditching not allowed	Restricted use	Ground water areas	III
3 Clear cutting not allowed	Restricted use	Areas of detailed shore plan	III
		Areas defined in the regional land-use plan for development of shore areas	III
		Areas defined in the local master plan	III
		Nature conservation programmes (shores)	IV
4 Clear cutting not allowed and in the case of natural regeneration, rotation period must be lengthened	Restricted use	Areas defined in the local master plan	III
5 No treatments allowed	Outside of wood production	Nature conservation areas	II–IV
		Nature conservation programmes (mires, herb-rich forests, old-growth forests, development areas)	III–IV
		Nature conservation programmes (bird wetlands)	IV
		Natura 2000 areas	III
		Slopes steeper than 36%	III

3.4 *K*nn estimation and feature selection

In a systematic sampling inventory each sample plot represents a certain proportion of the whole inventory area. Representativeness, that is, the weight of a sample plot can be calculated by dividing the inventory area by the number of sample plots. By means of satellite imagery, new weights (area of similar forest) for NFI sample plots in a new inventory unit were estimated with the non-parametric *k*nn estimator. The different estimation units applied in the studies were as follows: image pixels associated with a NFI sample plot (I), image segments corresponding to forest stands intersected with spatially explicit constraints approximating management units at the local level (II–III), and clusters of image segments intersected with spatially explicit constraints approximating management units at the regional (Forestry Centre) level (IV).

Technically, the estimation was carried out pixel by pixel, and for each image pixel, the k spectrally nearest pixels with a field plot were searched and for each of these neighbours, a weight according to spectral similarity was assigned. The similarity was measured with the Euclidean distance in the multi-dimensional space of satellite band intensities (Equation 1).

$$w_{i,p} = \frac{1}{d^2_{p_i,p}} / \sum_{j=1}^{k} \frac{1}{d^2_{p_j,p}} \tag{1}$$

where $w_{i,p}$ = the weight of the sample plot i ($i = 1,\ldots k$) for the image pixel p, $d^2_{p_i,p}$ = the Euclidean distance from sample plot i (plot pixel p_i) to the image pixel p, and k = the number of neighbours applied. Consequently, for one image pixel, the sum of the weights of the k nearest neighbours equalled the size of one image pixel.

The map data of the Land Survey of Finland were used to separate forestry land (forest land, poorly productive forest land, and unproductive land) from other land use areas. The sample plot weights were estimated only for pixels which were forestry land according to the map data. When stratification according to the peatland map was applied (II–IV), the neighbours for a pixel were searched among the sample plots belonging to the corresponding stratum. In studies I and IV, only original band values were used in calculating the distance metric. In studies II–III, in addition to the spectral data, large-scale forest data from the MS-NFI9 and transformations of spectral bands (their ratios) were applied in calculating the distance (d), and the selected variables were also weighted. The weights for the image features and additional variables were optimized using a genetic algorithm (Tomppo and Halme 2004; Tomppo et al. 2008).

For each image analysis unit, that is, the management unit in II–IV, the sum of the weights of the sample plots ($c_{i,u}$) was computed during the estimation procedure. The weight of the sample plot i of the analysis unit u was:

$$c_{i,u} = \sum_{p \in u} w_{i,p} \tag{2}$$

The Equation 2 denotes the basic situation where a sample plot consists of one forest stand. If a sample plot was divided into two or more forest stands, the estimated weight was divided between the sample plot stands according to their proportion of the plot area assessed in the field. Consequently, the sum of the weights for a management unit was technically computed by sample plot stands. That is, $c_{i,u}$ actually being the sum of the weights of a sample plot stand for the unit.

In studies II–IV, the operational MS-NFI algorithm required selection of some parameters to control the *k*nn estimation. These included the criteria defining the geographical reference area and the value of k separately for different strata. A maximum vertical distance (for example, 300 m in II–III) and maximum horizontal distance (900 km in II–III) were used to restrict the search of nearest neighbours. In studies II–III, the number of nearest neighbours (k) for both the peatland and mineral land strata was set as 5. In Study IV, the same parameter values as in the operational MS-NFI (Tomppo et al. 2009) were applied. In Study I, the parameter k was the only parameter to be selected, and values from 1 to 30 were tested.

The different spectral features used in the estimation are listed in Table 4. In the case of single pixel values, the spectral information was assigned to a sample plot from that image pixel which was geographically closest to the plot centre (plot pixel). The pixel value,

Table 4. Spectral features applied in studies I–IV.

Features	Neighbourhood	Size (ha)	Studies
Image pixel value	1 × 1 pixels	0.625	I–II
Average of fixed-size square window	2 × 2 to 11 × 11 pixels	2.5–75.625	I
Average of pixels within a segment in a fixed-size window	2 × 2 to 11 × 11 pixels ISOCCL-NN/TR NG-NN/TR	0.625–max 75.625	I
Average of pixels within a management unit (segment)	NG-NN	1.1–1.2	II
	NG-NN	1.0	III
Average of pixels within a management unit (cluster)	NG-NN and ISODATA	70.9	IV

the average etc. denote actually those values in different bands (see Table 1). Because the estimation procedure was run pixel by pixel, in the case of average pixel values, the average values were assigned to each pixel within a segment before the estimation.

In the analyses with the MELA model in II–IV, each management unit was represented by the NFI sample plot stands, each with the weight estimated by the *k*nn estimator. In the MELA system, there are two area variables in use: actual area weight and area weight for growing stock (see Redsven et al. 2005). The estimated weights of sample plot stands were used as actual area weights, and within a management unit the sum of the area weights equaled the total area of the unit. Furthermore, intersecting stands without tallied trees were omitted from the MELA data. In that case, the actual area weights of the remaining sample plot stands were calibrated within a management unit so that the total area of the unit remained unchanged. As the second MELA area variable, the area weight for growing stock, the total sample plot weight was used for all sample plot stands.

The forest characteristics of the management units were defined by the sample plots assigned to the unit in question. For example, the volume of the growing stock of a management unit was calculated as a weighted average of the sample plot volumes. In the scenario analyses, sample plot structure of the management units was preserved, that is, each unit was represented by sample plots.

3.5 Evaluation

In Study I, validation of the estimation results with the different spectral features was carried out by means of the cross-validation technique at the sample plot level. Each sample plot in turn was left out from the *k*nn estimation and its characteristics were estimated with the help of the other sample plots. The reliability of the volume estimates was measured by means of the root mean square error (RMSE), relative RMSE, bias and relative bias.

In Study II, the estimated initial forest data for scenario analyses were evaluated by comparing the estimation results with the forest data based on stand-level field inventories. The variables of interest were forestry land area by categories (forest land, poorly productive forest land and un-productive land) and the mean volume of the growing stock by tree species. The volume of the growing stock of a management unit was composed as a weighted average of the sample plot volumes representing the unit in question. The comparisons were done at the area level, separately for the national park and the private forests. For the comparison, the forest characteristics for these areas were summarized from the management units within the area.

3.6 Forest scenario analyses

The estimated datasets were applied in the scenario analyses using the Finnish forestry dynamics model MELA in studies II–IV. The MELA system consists of a stand simulator producing alternative management schedules for management units and an optimization package (Lappi 1992) selecting the set of management schedules which meet the objectives set for forest production and utilization. The simulation of stand dynamics was based on the development models designed for the Finnish conditions (Hynynen et al. 2002) and on the recommendations for forest management practice in Finland (Hyvän metsänhoidon suositukset 2006). Both natural processes, such as ingrowth, growth and mortality, and management activities were simulated by tree level models (Hynynen et al. 2002; Redsven et al. 2005). The management activities included intermediate and regeneration fellings, clearing of regeneration area, soil preparation, artificial regeneration, and tending of young stands. Feasible management schedules were simulated for each management unit, that is, for all sample plot stands representing the unit, on forest and poorly productive forest land. Feasibility of the fellings and other management activities was based on the mean characteristics of the management unit.

The same revenues and unit costs of logging and other management activities as in Nuutinen and Hirvelä (2006) were applied. The logging costs were based on time consumption and unit prices, and hence, were dependent on, for example, average size of logged stems and volume of the removal. The revenues were based on actualized stem prices by tree species and wood assortments. In studies II–III the simulation time was 50 years divided into five 10-year simulation periods, and the management activities were simulated in the middle of these periods. The results were presented only for the three first 10-year periods. The last 20 were used to ensure sustainability of the estimated cutting possibilities. In Study IV, the simulation time was 60 years, which of the last 10 years were to ensure sustainability of the solution. The results for the first 10-year period and after 50 years from the starting point were presented.

In Study II, the scenario corresponding to the maximum sustainable removal (MSUS) was used to evaluate feasibility of the two datasets estimated using different spectral features (segment averages and single pixel values) in the scenario analyses (Table 5). The dataset estimated using segment averages was found more applicable, and it was selected for the scenario analyses in Study III. In addition to MSUS, the scenario maximising the net present value of wood production (MAX) was formulated for optimisation in III (Table 5). In the MSUS scenario, the net present value of wood production was maximized by using a 4% interest rate subject to non-decreasing flow of removal, saw log removal and net income for each 10-year period. The net present value after the 50-year period (see Redsven et al. 2005) had to be equal to or greater than the value at the beginning of the simulation period. In the MAX scenario, the net present value was maximized without constraints using a 5% interest rate to emphasise the importance of earlier returns. In Study III, two different simulations were carried out. First, the restrictions for forestry were taken into account as formulated in Table 3. In the areas outside of wood production, only natural processes were simulated. In the second simulation it was assumed that all forest land was available for wood production, and fellings and other silvicultural treatments were simulated to all management units.

In Study IV, three different policy scenarios for each Forestry Centre were defined: MSUS, a “business as usual” (STAT) scenario and a scenario (PROG) formulated according to the Regional Forest Programmes for 2006–2010 (Maa- ja metsätalousministeriö 2006) (Table 5). The STAT scenario was based on the statistics of

Table 5. Scenarios applied in studies II–IV.

Scenario	Interest rate	Management activities	Studies
MSUS	4%	By spatially explicit constraints	II–IV
MSUS-N	4%	In all forests	III
MAX	5%	By spatially explicit constraints	III
MAX-N	5%	In all forests	III
STAT	4%	By spatially explicit constraints	IV
PROG	4%	By spatially explicit constraints	IV

the accomplished fellings in 2003–2007 (Natural Resources Institute… 2015) and it was assumed that the species and assortment structure of the removal would remain the same also in the future. In all scenarios, the net present value of wood production was maximised by using a 4% interest rate. The spatially explicit restrictions for forestry (Table 3) were taken into account in the simulations.

3.7 Applying habitat models in forest scenarios

In Study IV, two logistic regression models with forest variables on different spatial scales were applied to predict the presence of the flying squirrel in a forest stand, and the probability of presence was then taken as a measure of habitat suitability. The patch-scale model included only forest stand variables, whereas the landscape-scale model also included additional landscape-scale variables on the area of a 1 km circle around the stand centre. In addition, geographical location reflecting the distribution of the species was included in the models in the form of forest vegetation zones.

The prediction models were applied using the estimated forest data (from 2005) and the forest data for 2055 simulated according to the three different scenarios. The required stand variables (age and volume by tree species) in 2055 were assigned to each image segment and output as raster maps in order to calculate the landscape variables. The patch-scale model was applied to each image segment, whereas the landscape-scale model was applied to segments in a 1 km × 1 km grid only. The resulting probabilities were transformed to a binary scale with a chosen threshold, which was set as 0.3. If the predicted probability of presence was greater than or equal to 0.3, the segment was interpreted as suitable for the flying squirrel. The predicted suitable areas in the three policy scenarios were compared at the regional (Forestry Centre) level.

4 RESULTS

4.1 Segment-based features in the estimation (I)

The results of the two image segmentation methods tested in Study I differed in a way that the ISOCCL produced clearly more initial segments and of various shapes, whereas the number of NG segments was lower and they were more homogeneous in shape. The mean sizes of the initial segments were 0.39 and 0.97 ha, respectively. In fine-tuning of the ISOCCL segmentation, there was no big difference between the results of two region-merging algorithms tested. NN resulted in a mean size of 1.91 ha and TR in 1.83 ha. With the NG segmentation, the NN region merging led to a smaller mean size than the TR algorithm. The mean sizes of the resulting segments were 1.34 and 1.82 ha, respectively.

In Study I, the RMSEs of the volume estimates at the sample plot level decreased clearly when the number of nearest neighbours (parameter *k*) was increased from 1 to 10, but only slightly after that. Hence, volume estimates for the comparison of performance of different spectral features were computed using the 10 nearest sample plots. In general, the plot level RMSEs were high, the best relative RMSE for the total volume being 79.3% and for the volumes by tree species over 100%. Using the spectral features extracted from the neighbourhood around the sample plot pixel instead of the plot pixel only improved the estimation results. In the segment-based feature extraction, the window size of 3 × 3 pixels performed best for the total volume and the volumes of spruce and broad-leaved trees, and the window size of 7 × 7 for the pine volume. For example, the improvement of the RMSE of the total volume estimate was 3.5 m^3/ha (from 89.6 to 86.1 m^3/ha) when the average value of a ISOCCL-TR segment within the 3 × 3 window around the sample plot was applied instead of the plot pixel value only. Also in the fixed window approach, the best results were achieved with the features extracted from the 3 × 3 window for the other volumes except that of pine, for which the plot pixel values resulted in the lowest RMSE. The use of segment-based features improved the estimates compared to the use of fixed window features, 0.2–2.8 m^2/ha depending on the tree species. The improvement was most evident for the total volume and the volume of spruce. There were no big differences between the segmentation methods used in the feature extraction.

4.2 Estimation of segment-level forest data for scenario analyses (II – III)

In studies II and III, the two-phase NG-NN segmentation was applied. In Study II, the region-merging was run separately for the areas of Koli National Park and the private forests. The mean sizes of the resulting segments on forestry land and their standard deviations were 1.2 and 0.6 ha in the national park and 1.4 and 0.7 ha in the private forests, respectively. In Study III, the segments were intersected with the maps of restriction areas, and the mean size of the resulting management units was 1.0 ha and its standard deviation 0.7 ha. As regards the mean size, the management units corresponded well with the forest stands defined in the stand-level field assessments. However, the segmentation produced more homogenous units in size and shape compared to the forest stand delineation. The mean sizes of the forest stands and their standard deviations were 1.4 and 1.8 ha in the national park and 1.0 and 1.1 ha in the private forests, respectively.

The tested spectral features in Study II, single pixel values and segment averages, resulted in very similar area and volume estimates. The estimates for the mean volume of the growing stock were 159.9 and 161.1 m3/ha in the national park and 130.9 and 130.8 m3/ha in the private forests, respectively. Compared to the forest stand data, the volume estimates were clearly underestimated in the national park and overestimated in the private forests. The mean volumes according to the stand-level field assessment were 185.6 and 117.7 m^3/ha, respectively. However, the volume estimates in the private forests could be compared only after updating the estimated forest data from the year 2000 to 2006. The updating increased the mean volumes up to 140.8 and 138.3 m^3/ha in the data estimated with the single pixel values and the segment averages, respectively. In general, the *k*nn estimation resulted in a much narrower volume distribution than that of the stand-level field assessment. There were fewer segments with very low or high volumes; most had a volume near the average. This was clearly evident in the national park, where the distribution could be compared to that in the forest stand data.

The spectral features had some effect on the proportions of pine and spruce volume but hardly any on the proportion of broad-leaved trees. The single pixel values resulted in a higher proportion of spruce volume than the segment averages. In the national park, the proportions were 42% and 38%, and in the private forests 36% and 28%, respectively. The result with the segment averages was closer to the estimate based on the stand-level field assessment (35%) in the national park whereas the result based on the single pixel values (48%) in the private forests.

As regards the age of the growing stock, the *k*nn estimation resulted in a lower proportion of mature forests in the national park than in the stand-level forest assessment. According to the forest stand data, the proportion of forests older than 80 years was 42% of the forest land area. The single pixel values resulted in a proportion of 31% and the segment averages in 33%. The proportion of young forest in turn was overestimated with the *k*nn approach compared to the stand-level field assessment. In the private forests the *k*nn estimation resulted in an age distribution closer to the distribution in the forest stand data, but otherwise the results were in line with the results of the national park. Forests with an age of 81–100 years were underestimated, the proportions being 10% both with single pixels and segment averages compared to the proportion of 17% with the stand-level field assessment.

In Study II, the results of the scenario analyses with the two datasets estimated using different spectral features were compared in the area of the private forests. The forest data estimated with single pixel values resulted in a clearly lower felling potential in the first 10-year period, which then increased to the same level as the one based on segment averages. With the forest data based on the segment averages the felling potential was more stable during the whole 30-year period. The felling potential is the volume that could be cut according to management practice recommendations if the profitability and sustainability of the fellings are ignored. Since they were taken into account in the MSUS, the total felling potential could not be harvested. The maximum sustainable removals were stable and close the 30,000 m^3/year with both datasets for the whole 30-year period. The proportion of logs of the sustainable removal was also stable during the 30-year period, 43–44% for both datasets. The felling reserve was higher and more stable with segment averages than with single pixels.

In the first 10-year period, fellings were simulated to about 80% of the management units in both datasets, and they were mostly localized to the same units (72%). In the optimization, fellings were chosen for 60% and 54% of the management units in the datasets based on single pixel values and segment averages, respectively. There was no big difference between the estimated removals, but the total felling area (ha/year) and the proportion of intermediate fellings (m^3/year) were clearly higher with single pixels than with segment averages in the first 10-year period. During the second and third periods these differences levelled off. The felling area decreased, and the proportion of regeneration fellings increased with both datasets. With both feature sets, the mean volume of the growing stock decreased during the 30-year simulation period. There were minor differences between the datasets, 2–3 m^3/ha, but using segment averages produced more extreme values than did single pixels. The difference between the proportions of tree species in the beginning of the simulation levelled off during the 30-year period.

In Study III, the effects of spatially explicit constraints on wood production were analysed using the dataset estimated with segment averages. The proportion of forest not available for wood production was exceptionally high in the Koli and Hattusaari area. Conservation areas and steep slopes, where no treatments were allowed, covered 29%, and areas where management activities were somehow restricted covered 19% of the area of forest and poorly productive forest lands. When these spatially explicit constraints were taken into account in the scenarios, the felling potential in the first 10-year period was about 50% less than in the scenarios where all forest and poorly productive forest lands was assumed to be available for wood production. The maximum sustainable cutting removal (m^3/year) during the whole 30-year period was decreased by one-third because of the constraints. The constraints affected relatively more of the area of regeneration fellings (ha/year) than that of intermediate fellings, because the proportion of mature forests was high in the areas where the fellings were restricted. In the MAX scenario the effect of constraints on regeneration fellings was more evident than in the MSUS scenario, with a decrease of 60% in the regeneration felling area in the first 10-year period.

Due to the restrictions on the use of forest resources, the volume of the growing stock on the forest and poorly productive forest lands in the whole study area increased with both MAX and MSUS scenarios during the 30 years. However, the net present value was approximately 40% lower in the MSUS scenario when the restrictions were taken into account. Also the average logging costs were higher because of a smaller average volume of felling removal in the scenarios with the spatial constraints. Overall, the study showed that the effect of spatially explicit constraints can be remarkable in certain areas. The method applied in the estimation of spatial forest data enabled the analyses of detailed effects in two different felling scenarios, that is, a comparison between scenarios with and without spatial constraints.

4.3 Integration of habitat models to the scenario analyses (IV)

In Study IV, the mean size of the first-level management units (NG-NN segments intersected with restriction areas) on forestry land in the whole of South Finland was 1.35 ha with a standard deviation of 2.7 ha. The mean size varied between the Forestry Centres being smallest 1.04 ha in the south coast (in Forestry Centre Rannikko, Etelärannikko) and largest 1.67 ha in Central Finland (Forestry Centre Keski-Suomi). As a comparison, the mean size of forest stands in the database of private forests in South Finland was 1.34 ha in 2007. The mean size of the final management units (clusters intersected with restriction areas) on forestry land was 70.9 ha and its standard deviation 213.9 ha. Again, there was some variation between the regions, the smallest mean size being 55.2 ha in the south coast (Forestry Centre Rannikko, Etelärannikko) and the largest 81.7 ha in the north-eastern part of the study area (Forestry Centre Pohjois-Savo). The clusters were not spatially connected but consisted of segments scattered across an image in question.

The scenario analyses in Study IV confirmed that the intensity of fellings has impact on the predicted amount of suitable habitat for the flying squirrel. The comparison of the three alternative felling scenarios also indicated that there is variation in the impacts between the regions. In all Forestry Centres, the felling removal was lowest and consequently the volume of the growing stock highest in the STAT scenario, which was the “business as usual” scenario corresponding to the level of fellings accomplished in 2003–2007. This scenario also resulted in the highest amount of predicted suitable habitat in the end of the simulation period, 2055. The flying squirrel prefers spruce dominated forests and in the STAT scenario, the volume of spruce was highest. In most Forestry Centres the PROG scenario based on the Regional Forest Programmes for 2006–2010 was the second most favourable for the flying squirrel. Only in two Forestry Centres in Eastern Finland (Kaakkois-Suomi and Pohjois-Karjala) the MSUS scenario resulted in a higher amount of suitable habitat than the PROG scenario. In these Centres the spruce volume in 2055 was lowest in the PROG scenario. In general, MSUS demonstrated the most intensive alternative for the utilization of the felling potential. The Forest Programmes were regional development plans and they differed from each other depending, for example, on the importance of the forestry as a livelihood in the region. In Eastern Finland the PROG scenarios were more intensive, which supports the fact that the PROG scenario was the least favourable for the flying squirrel there. In Central Western Finland where the population of the flying squirrel was densest, there were no big differences between the scenarios. This indicated that the species has adapted to the prevailing conditions, namely fragmented landscapes and managed forests, as long as requirements for nesting and feeding are met.

The logistic models applied in Study IV could not predict the occurrence of the flying squirrel accurately. The aim in the selection of the threshold value (0.3) was to identify all potentially suitable habitats and predict correctly the actual proportion of occupied sites. However, only 12.9% from the "present" observations were correctly classified in the modelling data with the patch-scale model and 19.0% with the landscape-level model. One reason for this was that all suitable forests were not occupied by the flying squirrel. Obviously, there are other reasons than forest structure affecting the presence, such as distribution history and the presence of predators. However, the models enabled the comparison of the alternative felling strategies. The scenario analyses showed that the predicted amount of suitable habitat in 2055 was directly related to the intensity of fellings, especially in the spruce-dominated mature forests. The differences between the Forestry Centres showed that the impacts of alternative scenarios are case-specific and depend on the formulated felling strategy and the initial forest structure in the region in question.

5 DISCUSSION

5.1 Segment-based features in the estimation of forest data

The NG segmentation was found most feasible for forest inventory applications, because it was computationally less intensive than the iterative clustering algorithm (ISOCCL) and was controlled by fewer parameters that the user has to determine heuristically. Even the initial NG segments would have been applicable for further analyses, though the region merging improved the result. Further, the size and shape of NG segments were found to correspond better to those of forest stands.

The segment-based features improved the accuracy of volume estimates, but the gained reduction of the RMSE was small compared to that of the features extracted from fixed size windows. The type of field data employed in Study I is sensitive to locational errors and, consequently, may lead to the assigning of erroneous spectral features to the sample plots. The highest correlation between the volume of the growing stock and the intensities of Landsat TM bands 3 (red) and 4 (infrared) was found in the bottom-left corner of a 3 × 3 window around the sample plots, which indicated some errors in the image rectification or in the locations of sample plots in the field. However, extracting features from the neighbourhood instead of the plot pixel only did not improve the accuracy significantly for two reasons. First, the sample plots were relatively small in size, and the plot characteristics (volumes) may not be representative for the neighbourhood, that is, they did not necessarily match with the segment-based spectral features. Secondly, the combination of the small mean size of forest stands and the low spatial resolution of the Landsat TM images (25 m × 25 m) resulted in a large amount of mixed pixels, which confused the image analyses. Mixed pixels are pixels located on the border of two different forest stands and their intensity is a composite of responses from both sides. Due to the two sequential edge operators in the NG, the location of the edge of a segment may not be exact. In cases where a sample plot is located close to a forest stand border or where there is an error in the plot location, the plot may be linked with the spectral features of the segment representing an adjacent stand. This may be the reason why using the plot pixel only resulted in the lowest RSME for the spruce volume with the NG segmentation and also for the pine volume with the NG-NN method.

The NFI9 sample plots located via field measurement were applied in studies I–III. Since the beginning of NFI10 in 2004, the sample plots have been located with a GPS device, and thus the accuracy of sample plot locations has been improved. This reduces errors in assigning spectral information to the sample plots, especially in the cases where single pixels, that is, spectral features of plot pixels, are applied in the estimation. In the operational MS-NFI, the Landsat satellite images have been resampled to a pixel size of 20 m × 20 m in the rectification since 2007 (Tomppo et al. 2012), which in turn diminished the difference in the sizes of an image pixel and an NFI sample plot. The size of a relascope sample plot varies depending on the size of the trees growing on the plot, and the plot is not necessarily representative of the surrounding forest stand, whereas a Landsat image pixel contains information from an area that is larger than the plot size. The change from relascope plots to fixed size plots in the NFI12 since 2014 (Valtakunnan metsien 12… 2014) has further enhanced the coupling of spectral and field data.

The segment-based features provided a means to reduce the effects of locational errors in the image registration and sample plot positions on the estimation results (Study I). Because of the small size of the sample plots employed in the estimation, the feature extraction was restricted to the immediate neighbourhood of a sample plot. Due to the type of field data, it was found questionable whether image segments can be recommended for feature extraction. However, image segmentation provides a tool for analyses at the same level as the units of interest, namely forest stands. In Study II, this level was selected as the level of estimation, and the performance of single pixel values and segment averages was further explored.

5.2 Segment-level forest data in scenario analyses

The NG-NN image segmentation produced feasible units that could be employed as management units in the scenario analyses in studies II–IV. As regards the mean size, the segments corresponded well with the forest stands but were more homogenous in size and shape. Because of the relatively small size of forest stands and the low spatial resolution of Landsat images, the large amount of border pixels caused confusion in the analyses. Even though the aim was to produce spectrally homogenous units, there was variation in pixel values within segments. Consequently, using single pixel values in the estimation, the *k* nearest neighbours of each pixel, resulted in heterogeneous plot data representing a segment, that is, a management unit, in Study II. On the other hand, when using segment averages the border pixels affected the spectral average, which may have resulted in the *k* nearest sample plots that did not correspond to the forest characteristics of the segment.

Using single pixel values had the advantage that the full spectral variation of the Landsat images was utilized, whereas averaging by segments reduced this variation. Further, when using segment averages, the spectral information applied in the estimation was on a scale different from that extracted for sample plots. As a consequence, the averaging may have restricted the amount of sample plots employed in the estimation, in other words, sample plots with extreme spectral values were not necessarily among the *k* nearest neighbours of any segment average. Hence, the full range of variation in forest characteristics was better preserved when using single pixels. However, this variation represented by several sample plots was lost when calculating mean forest characteristics for the management units. However, the comparison of the estimation results in Study II indicated that the segment averages performed better than single pixel values as regards the age and volume distribution of management units.

Overall, the data estimated with segment averages were found more applicable for the simulation of forest activities and led to more stable wood production possibilities. Using single pixel values resulted in rather numerous and divergent sample plots representing a management unit, and this complicated both the deduction of feasible management activities for the unit and the simulation of these activities to all sample plots in question. The simulation of management activities was based on the mean forest characteristics of the management units. Using segment averages has the disadvantage of diminishing both spectral and forest variation and is, therefore, questionable. However, the use could be justified by the fact that even with segment averages, the management units were fairly small in size, and a management unit was still represented by several sample plots which brought variation within the unit.

The *k*nn estimates in the Koli and Hattusaari study area in Study II could not be validated properly, because there were no field data based on intensive field sampling available. Instead, the estimates and their distributions were compared to the summary results of two separate stand-level field assessments for which the accuracy was not known. The field inventory in the national park was regarded as more accurate than an operational one, but in general there may be an error of 5–20% in the stand parameters. However, with the help of the forest stand data, the performance of the two spectral features could be evaluated. Comparisons also assured that the estimated data were reasonable for scenario analyses. Unfortunately, scenario analyses based on stand-level field data could not be carried out, because stand-level forest attributes for the private forests were not available. To further develop the data generation method, the results of scenario analyses should be compared to the results based on field data.

According to previous studies, the error of the *k*nn estimate for the mean volume of the growing stock is about 5% for areas of 10,000 ha and 10–15% for areas of 100 ha (Reese et al. 2002; Katila 2006). For areas of 10,000 ha, the errors of mean volumes of pine, spruce and deciduous trees were 12%, 15% and 16%, and for areas of 100 ha, 37%, 27% and 40%, respectively (Katila 2006). The size of study area II was 7,900 ha, of which 5,500 ha were private forests. Consequently, the error of the volume estimate for the areas which were analysed separately, that is, private forests and the national park, would be between 5% and 10%, which can be regarded as acceptable. However, the estimation error of volumes by tree species would be at least 15%. In addition, the *k*nn estimates are potentially biased, especially if the estimation area is different than that of the reference area where the sample plots are from (e.g. Fazakas et al. 1999; Katila and Tomppo 2001). This was likely the case in Koli National Park, where the volume and age of the growing stock were clearly underestimated compared to the stand-level field data.

The *k*nn estimator has been widely used in forest inventory approaches; it is non-parametric, straight forward and easy to use. However, the method has a disadvantage, because there is no analytical estimator to assess the estimation errors for areas of interest of an arbitrary size (e.g. McRoberts et al. 2007; Magnussen et al. 2010). NFIs are designed to produce means and totals of forest attributes for large areas. Using satellite imagery as an ancillary data source, means and totals can be calculated for smaller areas. However, it should be noted that the satellite-based estimates are not adequate for stand-level analyses, and, therefore, the results should be analysed at a scale where the estimating errors are acceptable. Similarly, the *k*nn method can be used in estimating forest data for scenario analyses at the local level, that is, in areas smaller than is possible with the NFI sample plot data only and for which forest attributes can be estimated with an acceptable error.

The MELA system was developed for large-scale forest scenario modelling. In national and regional impact and scenario analyses based on NFI sample plots, the simulation of feasible management activities is based on stand-level forest characteristics recorded for the sample plots (Hirvelä et al. 1998, Nuutinen et al. 2000; Nuutinen and Hirvelä 2001; Nuutinen et al. 2007a). Because one NFI sample plot defined by a relascope is in general not large enough to represent a whole stand, a general procedure in the MELA model is to link the sample plots with 2–5 similar sample plots in terms of present stand characteristics (Hirvelä et al. 1998; Nuutinen et al. 2000; Nuutinen and Hirvelä 2001; Nuutinen et al. 2007a). Hence, the grouped sample plots represent variation within a forest stand and form a management unit. The mean characteristics of the grouped sample plots are used in defining feasible management activities for a management unit, but the target variables in the optimization and reporting are based on the actual NFI sample plots only (Hirvelä et al. 1998; Nuutinen et al. 2000; Nuutinen and Hirvelä 2001; Nuutinen et al. 2007a). This procedure was not needed in studies II–IV, because a management unit was already represented by several sample plots searched by means of the *k*nn-estimator.

The assessment of forest stand characteristics is generally included in the NFI field measurements. In Finland, approximately 100 variables describing, inter alia, land use, site and soil properties, growing stock by tree layers and species and accomplished and recommended management operations are recorded for the forest stand(s) intersecting the sample plot area. Previously the description was to cover the entire stand though auxiliary measurements, such as counting the number of stems in a seedling stand and measuring the basal area of the growing stock, were carried out in the neighbourhood of the plot. Since the beginning of the 12th NFI in 2014 the stand description has been formally changed to cover an area of a quarter of a hectare, that is, the part of the stand closest to the sample plot (Valtakunnan metsien 12… 2014). This should improve coherence between stand description and tree measurements on a sample plot.

5.3 Habitat models in regional scenario analyses

Study IV extended across the whole of South Finland, and the impacts of different policy scenarios were analysed at the regional level (by Forestry Centres). As regards the intensity of NFI sampling, the analyses could have been based on NFI sample plots. However, forest data at the segment (forest stand) level were a precondition for the use of patch- and landscape-level prediction models. Consequently, the huge number of low-level management units (segments) was reduced by clustering, and the spectral information for estimation was extracted from clusters, which were on average 70 ha in size. This was a clear weakening and a compromise between operability and accuracy. In the largest Forestry Centres, some of the satellite images covered an area over one million ha. The area was largest in Forestry Centre Etelä-Pohjanmaa (Southern Ostrobothnia), where the forestry land area to be estimated within one image was 1,418,473 ha. The segmentation resulted in 1,048,074 segments with an average size of 1.35 ha (22 pixels). If segment averages had been used in the estimation, 5–110 sample plots would have been assigned to one average segment. For the simulation of feasible management schedules over 50 years and for optimization, the number of units and the sample plots representing the units had to be somehow reduced. The clustering produced 13,100 clusters, and, after intersecting with the restriction areas, the number of management units in the example image in question was 21,894. Considering the forest structure and main forest characteristics, such as age class, dominance of tree species, volume and density of the growing stock, site potential and management history, this amount of different stands and spectral features could be, however, differentiated. The clustering was a technical solution for feasible computing, that is, simulation and optimization, and a compromise on the cost of accuracy. Clusters were employed as management units, and the estimated forest data both in the beginning and at the end of the simulation period could be derived for all segments pertaining to the cluster in question.

In studies II–IV, the operative MS-NFI procedure and software were applied in the estimation but not in the calibration method to reduce the errors due to confusion between land use classes in the field data and on the map (Katila et al. 2000; Tomppo et al. 2008; 2009). In Study IV, the employment of land use calibration would have improved the accuracy of the results. However, the objective was to compare the results of three different scenarios with respect to suitable habitats for the flying squirrel. Even though erroneous, all scenarios were based on the same data. Instead of absolute numbers, the differences between the scenarios were of interest, and the data estimation method enabled the comparison of the impacts of different forest policies. Generally in forest scenario modelling, the ultimate aim is not to predict the future but to analyse the dependencies between forest management policies and the development of the growing stock. Modelling forest dynamics under changing conditions is complicated and involves many assumptions as well as the acceptance of imperfect knowledge and uncertainties (Siitonen 1993).

The simulated management schedules were optimized at the Forestry Centre level, and only the summary results for the Forestry Centres were presented. The fact that the regional scenarios were based on NFI sample plot data, even though their weights were estimated by means of cluster features, may justify this compromise between accuracy and operability. However, the use of the average features of such large units is not recommended, because it reduces the variance of the spectral features and, consequently, leads to averaged and biased estimates. The segmentation approach is more suitable for impact analyses at the local level, where the number of management units remains reasonable.

5.4 Spatial data in scenario analyses

In studies II–IV, the management schedules for the management units were optimized at the area level, that is, at the village and Forestry Centre level, respectively. Consequently, the locations of allocated management activities are arbitrary and, for example, do not take forest ownership or adjacent management units into account. At the starting point, the selection of a feasible management schedule for each unit was based on the growing stock, soil properties, vegetation type and other site characteristics, and the management rules applied. Furthermore, the accuracy of forest variables estimated with Landsat satellite imagery is not sufficient at the forest stand level. For these reasons, the results should be looked at the level of optimization (village, region).

By means of image segmentation, the future forest resources could be presented in georeferenced form and combined with habitat predictions in Study IV. However, it should be pointed out that the aim was not to map potential habitats or future forest resources. The rational of mapping depends on the scope of analyses. For example, the species' presence may affect the management of the neighbouring forest stands in practice, but in the LP optimization, the management schedule for each unit was selected independently. Similarly, fellings and other management activities are often temporarily and spatially concentrated for reasons of cost-efficiency, which the result map of optimization at the Forestry Centre level cannot reflect. The optimization result is only one realization of many possible combinations at the level of analyses and does not take into account, for example, forest ownership. Moreover, the estimates of future forest resources describe only potential situations when following the current recommendations for forest management practice. The actual development of forest resources depend, for example, on forest policy measures and on the decisions of forest owners.

When incorporating spatial constraints into the impact analyses, segmentation is not necessarily needed. The spatially explicit constraints can be coupled with the map of administrative units, such as villages or municipalities for which the results are calculated. In this case, areas under different restrictions form separate management units where different management rules can be applied. Consequently, the management units are larger, and the weights of sample plots representing a management unit can be summed, which significantly reduces the needed computing resources. This is also a common procedure in the operational MS-NFI, where nature conservation areas are taken into account in the estimation (Tomppo et al. 2007; 2009). In local analyses, detailed restriction areas can be included within the data generation to assess their effects on wood production, for example, how a requirement for a felling permission determined in local master plans affects removals (Packalen et al. 2015).

Satellite image-based forest maps provide data applicable for many needs, because the maps enable spatial analyses, and the data can be aggregated for any area. However, pixel estimates typically contain large errors, and map users should be aware of uncertainties. In addition to small-area estimates, spatially aggregated products would require an assessment of bias and precision (McRoberts 2011). Instead of basing decision support on map products, the method introduced in the dissertation has the advantage that the simulation is based on exact sample plot measurements and tree-level models.

5.5 Further aspects of availability of forest data for scenario analyses

The operative MS-NFI produces up-to-date information on forest resources for municipalities, that is, for areas smaller than is possible with the NFI sample plots only. Studies II–IV and other recent studies (Packalen et al. 2015; Kärkkäinen et al. 2017a; 2017b) have shown that the same approach can be used in generating initial forest data for scenario analyses at different levels, from the regional to village levels. The MS-NFI has been continuously developed to provide results for small areas with increased accuracy, and in the form of raster maps. For these main purposes, the optical satellite imagery employed has been most advantageous because of its vast coverage and cost-efficiency. The low spatial resolution of satellite imagery, however, restricts the use of the method for areas that are smaller than for which forest variables can be estimated with an acceptable error. The results can be improved through imagery with higher spatial resolution and reducing the other known error sources (Tomppo et al. 2008), for example, location errors in sample plots and corresponding image pixels. In this sense, the new Sentinel-2 with a swath of 290 km, 12 spectral bands and a resolution of 10 m at the bands of visible light is promising.

The same MS-NFI method can be applied with other remote sensing material as well. Since 2015 the locations of all NFI sample plots on forest or unproductive forest lands have been recorded using a global navigation satellite system (GNSS) device with very high accuracy. This enables the use of NFI sample plot data as field reference data with the remote sensing material of high spatial resolution, such as aerial imagery and ALS data. Also the change from angle-count tree sampling to fixed size sample plots in 2012 improved the applicability of NFI plots as reference data for ALS, though the effect of plot configurations on the error of ALS-based estimates was found to be small (Maltamo et al.

2009; Tuominen et al. 2014; Tomppo et al. 2016). However, image acquisitions or ALS over large areas in various conditions, at different times of the growing season, or even under leaf-off conditions and with different devices complicate the use of NFI sample plots, because the field data should cover the entire variation of forest attributes in the area of interest, that is, within an image. There is ongoing research at the Finnish NFI aiming at improved cost-efficiency and providing information on forest resources at different levels, from local to national. This will be implemented by using different methods (field inventory and remote sensing) and applying different auxiliary data sources at different levels. Consequently, the accuracy of small area estimates can potentially be improved, and the MS-NFI method, that is, the estimation of sample plot weights, can be applied in data generation for scenario analyses in smaller areas than currently (approximately 5% error for volume in 10,000 ha).

The ALS-based inventory for forest planning purposes in Finland is aimed to be completed in 10 years (2010–2020). The inventory will cover all privately owned forests in Finland, and the collected forest data will be updated continuously with the help of felling notifications and growth models. A forest owner can decide which operators can have access and use the data concerning his or her forest. Further, a political consensus has been reached to open the raw data (forest data for grid cells of 16 m × 16 m) available for all operators. The applicability of these data for scenario analyses by means of MELA or another forestry dynamics model should be investigated. However, the problem with the timeliness and coverage of the data will remain. For example, the ALS-based inventory does not cover conservation areas, which may restrict the applicability of the data for comprehensive impact analyses.

Previously the NFI field measurements proceeded region by region, and it took 8–10 years to complete the measurements in the whole country. In 2004, the NFI method was changed to a continuous inventory where a part of the sample plots is measured in all regions each year. At the same time the inventory cycle was shortened to five years. Consequently, there are continuously up-to-date NFI field data available for all areas in Finland. Taking into account operative MS-NFI and the development work with new remote sensing materials, the NFI provides a good source for scenario analyses at the sub-regional and local levels.

6 CONCLUSIONS

Increased demand for analyses on forest production and utilization possibilities in different policy scenarios at different levels has encouraged the use of satellite imagery in the estimation of forest data for the analyses. NFI sample plot data are traditionally used in regional and national analyses carried out with the forestry dynamics model MELA in Finland. By means of satellite imagery, NFI sample plot data can be used as initial forest data for scenario analyses in areas smaller than is possible with the sample plot data only. The estimation of new weights for NFI sample plots, that is, representativeness in a new area of interest, proved to be a feasible method for data generation for the MELA model. The estimation method, a non-parametric *k*nn estimation, was the same as that applied in the operational MS-NFI to produce forest statistics for municipalities. The method enables the use of NFI sample plot data in scenario analyses at the local level (municipalities and villages). However, the medium resolution satellite imagery applied as well as requirements for accuracy restrict the use of the method for impact analyses in areas smaller than an area for which forest attributes can be estimated with an acceptable level of error.

The method has the advantage that spatially explicit constraints, even small set-a-sides or topographic restrictions, can be easily incorporated into the scenario analysis. In the present dissertation, image segmentation together with spatially explicit constraints was applied in the delineation of management units, and sample plot weights were estimated for these units. Segmentation, that is, small management units representing forest stands, enabled the use patch- and landscape-level habitat models in Study IV. The same approach could be used for other species with specific or spatially explicit habitat requirements. However, the use of segments intensified the computing required and complicated the deduction of feasible management operations if a unit was represented by heterogeneous sample plots. Using the segment averages as spectral features in the estimation also reduced variation and introduced bias, because, when averaging, small objects with extreme values are lost. Consequently, segments may be regarded as acceptable management units for limited areas where the optimization of management schedules for the units is still feasible, and segment level forest variables are required, for example, for predicting the presence of a valuable species. Spatially explicit restrictions can be included in the data generation without segmentation.

If image segmentation is applied, the results of scenario analyses, such as those of future forest resources, could be technically visualized as forest maps. The method is, however, not adequate for operational mapping, because the selection of management schedules for management units are optimized at the area level (region, municipality or village). The LP optimization result is only one realization of many possible combinations and do take into account, for example, forest ownership or adjacent management units. Consequently, the maps should be used with caution and the results rather presented as means and totals at the level of optimization.

The continuous development of the NFI in Finland has improved the applicability of the NFI sample plot data as reference data in image analyses. This together with the improved spectral and spatial resolution of optical satellite imagery contributes to a reduction of locational errors and, further, enables the coupling of pixel and plot data. High spatial resolution data such as digital imagery and ALS data provide accurate estimates on forest variables, but the high cost, limited coverage and technical properties of the materials due to acquisition in different conditions restrict their use in analyses with the NFI plot data over larger areas. Information needs for policy support, however, often concern administrative or otherwise continuous impact areas of interest for which the effects of alternative scenarios should be analysed. Satellite imagery together with continuous NFI field measurements provides cost-efficient and operational data sources for such analyses.

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