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Estimation of local forest attributes, utilizing two-phase sampling and auxiliary data

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Finnish Forest Research Institute (Metla)

Academic dissertation

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ABSTRACT

This thesis examines the feasibility of a forest inventory method based on two-phase sampling in estimating forest attributes at the stand or substand levels for forest management purposes. The method is based on multi-source forest inventory combining auxiliary data consisting of remote sensing imagery or other geographic information and field measurements. Auxiliary data are utilized as first-phase data for covering all inventory units. Various methods were examined for improving the accuracy of the forest estimates. Pre-processing of auxiliary data in the form of correcting the spectral properties of aerial imagery was examined (I), as was the selection of aerial image features for estimating forest attributes (II). Various spatial units were compared for extracting image features in a remote sensing aided forest inventory utilizing very high resolution imagery (III). A number of data sources were combined and different weighting procedures were tested in estimating forest attributes (IV, V).

Correction of the spectral properties of aerial images proved to be a straightforward and advantageous method for improving the correlation between the image features and the measured forest attributes. Testing different image features that can be extracted from aerial photographs (and other very high resolution images) showed that the images contain a wealth of relevant information that can be extracted only by utilizing the spatial organization of the image pixel values. Furthermore, careful selection of image features for the inventory task generally gives better results than inputting all extractable features to the estimation procedure. When the spatial units for extracting very high resolution image features were examined, an approach based on image segmentation generally showed advantages compared with a traditional sample plot-based approach. Combining several data sources resulted in more accurate estimates than any of the individual data sources alone. The best combined estimate can be derived by weighting the estimates produced by the individual data sources by the inverse values of their mean square errors. Despite the fact that the plot-level estimation accuracy in two-phase sampling inventory can be improved in many ways, the accuracy of forest estimates based mainly on single-view satellite and aerial imagery is a relatively poor basis for making stand-level management decisions.

Keywords: multi-source forest inventory, two-phase sampling

ACKNOWLEDGEMENTS

The research work for this study was mainly carried out during 1999-2005 and the manuscript of this thesis was composed mainly during 2005-2006. I started my work while working in the Department of Forest Resource Management in the University of Helsinki. In 2000, I moved to the Finnish Forest Research Institute, where I continued this project after a while.

Simo Poso, the supervisor of my thesis and the professor of forest mensuration and management until 2000, was in many ways the prime mover in this thesis project, encouraging me to go ahead with my postgraduate studies as well as arranging the acquisition of most of the material used in this research work. He was succeeded in the professor's office by Annika Kangas and Markus Holopainen, who both have advanced this work by providing me encouragement as well as valuable advice on my study. I was fortunate to have excellent co-workers and co-authors during this research work: Simo Poso and Stuart Fish at the University of Helsinki and later at the Finnish Forest Research Institute, my friend and colleague Anssi Pekkarinen, whose contribution was essential in this work. I also wish to thank my friend and colleague Reija Haapanen, who has critically reviewed my text several times. I have learnt to trust her judgement in scientific as well as other matters.

The official pre-examiners of my thesis, prof. Håkan Olsson from SLU and prof. Petri Pellikka from the University of Helsinki gave valuable comments and suggestions for improving my thesis, of which I am grateful. I also wish to thank Dr. Kari T. Korhonen for the mental and material support for this research work as well as for his professional support in doing my official duties at the Finnish Forest Research Institute.

Additionally, I wish to thank M.Sc. Mark-Leo Waite for his technical support in tailoring the SMI software to my use, M.Sc. Soili Kojola for her contribution in measuring the field data, and the forestry students in forest mensuration field courses during 1999 and 2000 who participated in collecting the field data used in this study

LIST OF ORIGINAL ARTICLES

This thesis is a summary of the following substudies, which are referred to in the text by their Roman numerals. The articles are reprinted with permission of the publishers.

I. Tuominen, S. & Pekkarinen, A. 2004. Local radiometric correction of digital aerial photographs for multi source forest inventory. Remote Sensing of Environment 89: 72-82.

II. Tuominen, S. & Pekkarinen, A. 2005. Performance of different spectral and textural aerial photograph features in multi-source forest inventory. Remote Sensing of Environment 94(2): 256-268.

III. Pekkarinen, A. & Tuominen, S. 2003. Stratification of a forest area for multisource forest inventory by means of aerial photographs and image segmentation. In: Corona, P., Köhl, M. & Marchetti, M. (eds.). Advances in forest inventory for sustainable forest management and biodiversity monitoring. Forestry Sciences 76. Kluwer Academic Publishers. pp. 111-123.

IV. Tuominen, S. & Poso, S. 2001. Improving multi-source forest inventory by weighting auxiliary data sources. Silva Fennica 35(2).

V. Tuominen, S., Fish, S. & Poso S. 2003. Combining remote sensing, data from earlier inventories and geostatistical interpolation in multi source forest inventory. Canadian Journal of Forest Research 33, 624-634.

FIELDS OF RESPONSIBILITY

In substudy I, the image correction method was designed by Pekkarinen and Tuominen. Tuominen carried out the analysis of the study material. The scientific article was written together by Tuominen and Pekkarinen. In substudy II, Tuominen carried out the processing and analysis of the study material. The scientific article was written together by Tuominen and Pekkarinen. In substudy III, Pekkarinen was responsible for developing and implementing of image segmentation and clustering algorithms. Testing of the image features was carried out together by Tuominen and Pekkarinen. The scientific article was written together by Pekkarinen and Tuominen. In substudy IV, the analysis was designed by Poso and Tuominen. Tuominen carried out the processing and analysis of the study material. The scientific article was written together by Tuominen and Poso. In substudy V, the study was designed by Tuominen and Poso. Tuominen carried out the processing and analysis of the study material, excluding the geostatistical interpolation, which was carried out by Fish. The scientific article was written mainly by Tuominen and Poso, Fish contributed to the geostatistical part. The sampling and measurement of the field data was designed by Tuominen and Poso (excluding study area 2 of substudy I). Tuominen supervised the measurement of the field data (excluding study area 2 of substudy I and study area 2 of III).

TABLE OF CONTENTS

ABBREVIATIONS

3D	3-dimensional
AISA	Airborne Imaging Spectrometer for Applications
ALS	airborne laser scanner
BRDF	bidirectional reflectance distribution function
CIR	colour-infrared
ETM	enhanced thematic mapper
G	green
GPS	global positioning system
k-nn	k nearest neighbours
MSE	mean square error
MSFI	multi-source forest inventory
MSNFI	multi-source national forest inventory
MSS	multispectral scanner
NIR	near infra-red
NDVI	normalized difference vegetation
NFI	national forest inventory
PAN	panchromatic
R	red
RMSE	root mean square error
RS	remote sensing
SAR	synthetic aperture radars
TM	thematic mapper
VHR	very high resolution

INTRODUCTION

In Finland, data acquisition for forest management planning has traditionally been based on stand-level field inventories. Forest inventory by compartments is another term used for the same method (e.g. Poso 1983, Koivuniemi & Korhonen 2006). The method is associated with forest management based on stands, which was originally developed in Germany in the 19th century. Forest management by stands is based on the idea of a geographically contiguous parcel of forest whose site type and growing stock characteristics are homogeneous, i.e. a stand (Poso 1983, Koivuniemi & Korhonen 2006). The optimal management of a forested area is based on the optimal management of the forest stands in accordance with their site and growing stock characteristics (e.g. Poso 1983). Forest inventory by stands is a prerequisite for forest management by stands (e.g. Koivuniemi 2003).

In the form as is currently applied in Finland, the inventory method comprises the following phases: initial delineation of the inventory units (i.e. stands), field inventory, processing of inventory data and compilation of a forest management plan. Delineation of the inventory units is based on visual interpretation of aerial photographs and is typically done in the office before the fieldwork season. In the fieldwork phase every stand in the inventory area is visited and the stand characteristics are assessed ocularly with the aid of subjectively placed measurements of growing stock. Additionally, delineation of the stand borders is checked and revised, if necessary.

The subjectivity of the method is an apparent drawback. Delineation of the stands and selection of measurement points within the stands are dependent on the person carrying out the inventory, and the delineations carried out by different interpreters are seldom similar (Poso 1983). Second, the forest stand is usually delineated as an appropriate unit for silvicultural treatment or logging, and not as an ecologically homogeneous unit. This results in heterogeneity in stand properties and, since the stands are not homogeneous, the stand variables are typically defined as average values within the stand (Poso 1983). Therefore, the stand measurement is exposed to subjective selection of measurement points and the reliability of the field data may be poor. Additionally, the stand borders often tend to change between consecutive inventories, due to silvicultural operations and natural disturbances that do not follow the stand delineation. This makes the delineated stands unsuitable for forest monitoring.

Since all stands in the inventory area need to be visited in the field, the method requires extensive fieldwork and skilled professional staff. Currently, the main problem to be solved in the Finnish forest management planning system is the disparity between the required amount of fieldwork and the resources allocated for the work. Thus, new inventory methods must be introduced to increase the efficiency of forest management planning. One option that has been suggested for rationalizing the forest management planning system is reducing the fieldwork through the increased use of remote sensing (RS) imagery.

Other types of forest inventory are the large-scale inventories that typically aim at producing unbiased estimates of forest attributes at the national or regional levels. These inventories are typically based on plot sampling. However, it is also possible to utilize this type of inventory for estimating local forest attributes (e.g. at the level of a stand or a sample plot). One example of this is the Finnish multi-source national forest inventory (MSNFI) (e.g. Tomppo 1990, 1993). A method based on two-phase plot sampling has been suggested as an alternative to stand-level inventory for forest management planning (e.g. Holmgren & Thuresson 1995, Poso & Waite 1996).

TWO-PHASE SAMPLING IN FOREST INVENTORY

Two-phase sampling is based on the idea of a sampling design in which units of the same size are used at each phase of sampling, but fewer units are selected at the later phase (Schreuder et al. 1993). Sampling units of various types and sizes, such as circular sample plots or sample plots with variable radii, can be utilized in two-phase sampling. However, the sample unit should be small enough to be measured as a homogeneous unit in relation to its forest characteristics. Very large units often cover an area that is larger than a single forest stand and they are also expensive to measure in the field.

In a sampling-based forest inventory, it is often appropriate to consider the forest as a population of sample plots. The size of the first-phase sample is dependent on the objective of the inventory. For forest management purposes, information on local forest characteristics at the stand or substand level is required. This is likely to lead to a fairly dense grid of first-phase sample units.

Two-phase sampling-based forest inventory applications aiming at producing map form information on local forest attributes are typically based on the idea of estimating forest attributes by combining field measurements and auxiliary data, which usually includes at least some RS imagery. Auxiliary data are those that as such may not be appropriate or sufficiently accurate for the specific forest inventory task (such as satellite image pixel values or visually interpreted forest attributes), but are correlated with the true values of the forest attributes of interest and can thus be used for the estimation of forest attributes. RS images are the main source of auxiliary data for forest inventories, but other data have also been utilized, such as data from previous stand inventories or digital map data of land use, soil or topography (e.g. Hutchinson 1982, Poso et al. 1987, Bolstad & Lillesand 1992, Tomppo 1992, Tomppo 1993, Thuresson 1995, Tokola & Heikkilä 1997). Additionally, information on the geophysical properties of the terrain and maps of climatological zones have been studied as auxiliary data (e.g. Cibula & Nyquist 1987, Häme et al. 1991).

Applying two-phase sampling is appropriate when the following conditions are fulfilled:

1. The unit cost of the first-phase data is significantly lower than the unit cost of the second-phase data.
2. The accuracy of the second-phase data is significantly higher than the accuracy of the first-phase data.
3. The first-phase data are well correlated with the second-phase data.

Two-phase sampling with stratification can be applied to improve the efficiency of estimating population parameters. Stratification of first-phase units into strata as homogeneous as possible based on first-phase data makes it possible to allocate the field units efficiently. The main alternative stratification procedures that can be employed with two-phase sampling are:

A. Stratification of the first-phase units before drawing of the second-phase sample (i.e. pre-stratification). This makes it possible to draw the field sample in a desirable way.
B. Stratification of the first-phase units after drawing of the field sample (i.e. post-stratification). This means that stratification is used only for applying the two-phase sampling estimators.

A two-phase sampling-based forest inventory application aiming at estimation of the population and local characteristics can be divided into the following steps (e.g. Poso & Waite 1996, Tuominen et al. 2006).

1. Delineation of the inventory area.

2. Generation of the first-phase sample for the inventory area. The size of the first-phase sample is dependent on the objective of the inventory. Usually, the number of first-phase sample units can be high. The first-phase sample can be defined as an equidistant grid of points, in which each point defines the location of the sample plot centre.

3. Acquisition of the auxiliary data to the first-phase sample units. Auxiliary data should be highly correlated with the forest variables of interest and their acquisition cost should be low (compared to field data)

4. Stratification of the first-phase sample units. This step is optional but often worthwhile. Stratification before drawing the field sample is often advisable. The objective is to divide the first-phase sample into strata that are as homogeneous as possible with respect to the forest variables of interest.

5. Determining the number of second-phase sample units, i.e. field plots and drawing the field sample. Allocation of the field sample is important for the efficiency of inventory; if some type of forest is not present among the second-phase sample units, it will likewise not be present in the inventory results. If two-phase sampling with stratification is applied, proportional or optimal allocation of the field sample can be applied. In proportional allocation the field sample is allocated in proportion to the stratum area. In optimal allocation the field sample is allocated to the strata, while observing the variation within the strata, the field measurement cost in each stratum and the importance of each stratum. Proportional allocation is recommended if the field variables in each stratum are regarded as equally important for inventory purposes and the inter-stratum variances and the unit cost of the second-phase sample units are similar in the different strata. Optimal allocation is recommended if it is required that those strata that *a)* are regarded as most important, *b)* have the highest variances or *c)* have the lowest unit costs are allocated more field plots than suggested by proportional allocation. This usually requires a priori knowledge of the properties of the strata. The second-phase sample can also be drawn without stratification, e.g. based on systematic or cluster sampling. The formulas for proportional (Eq. 1) and optimal allocation (Eq. 2) of the field plots to strata are (Cochran 1977):

$$m_h = w_h m, \qquad \text{(Eq. 1)}$$

$$m_h = m \frac{\frac{w_h s_h}{\sqrt{c_h}}}{\sum \frac{w_h s_h}{\sqrt{c_h}}}, \qquad \text{(Eq. 2)}$$

where
$w_h = n_h/n =$ proportion of the total area represented by stratum h
n = total number of first-phase sample units
n_h = number of first-phase units in stratum h
m = total number of second-phase sample units
m_h = number of second-phase units in stratum h
c_h = measurement cost of an second-phase unit in stratum h
s_h = standard deviation within stratum h

6. Measurement of the field plots. Field data (i.e. ground truth) are considered as the most accurate data. As a general rule, all inventory variables are measured for all field plots. Errors in location decrease the correlation between auxiliary and field data, thus degrading the inventory accuracy.

7. Estimation of local (first-phase sample unit) and population characteristics and their accuracy. The forest parameters of the first-phase sample plots are estimated using an appropriate estimator. The forest estimates can be derived for the desired geographic units, e.g. for forest stands delineated on the basis of RS images.

The phases of a forest inventory application utilizing two-phase plot sampling and various auxiliary data sources are illustrated in Figure 1.

A method similar to two-phase sampling with stratification is two-phase sampling with regression. This method is based on modelling the forest attributes (i.e. second-phase data) using the first-phase (auxiliary) data as independent variables. The regression model can be presented as: $y = a+bx$ (where y refers to the second-phase data, a to a constant for the regression line, b to the coefficient of regression and x to the first-phase data). The main problem associated with this method in forest inventory applications is that each inventory variable basically requires a separate regression model. Thus, the method was not applied in this study.

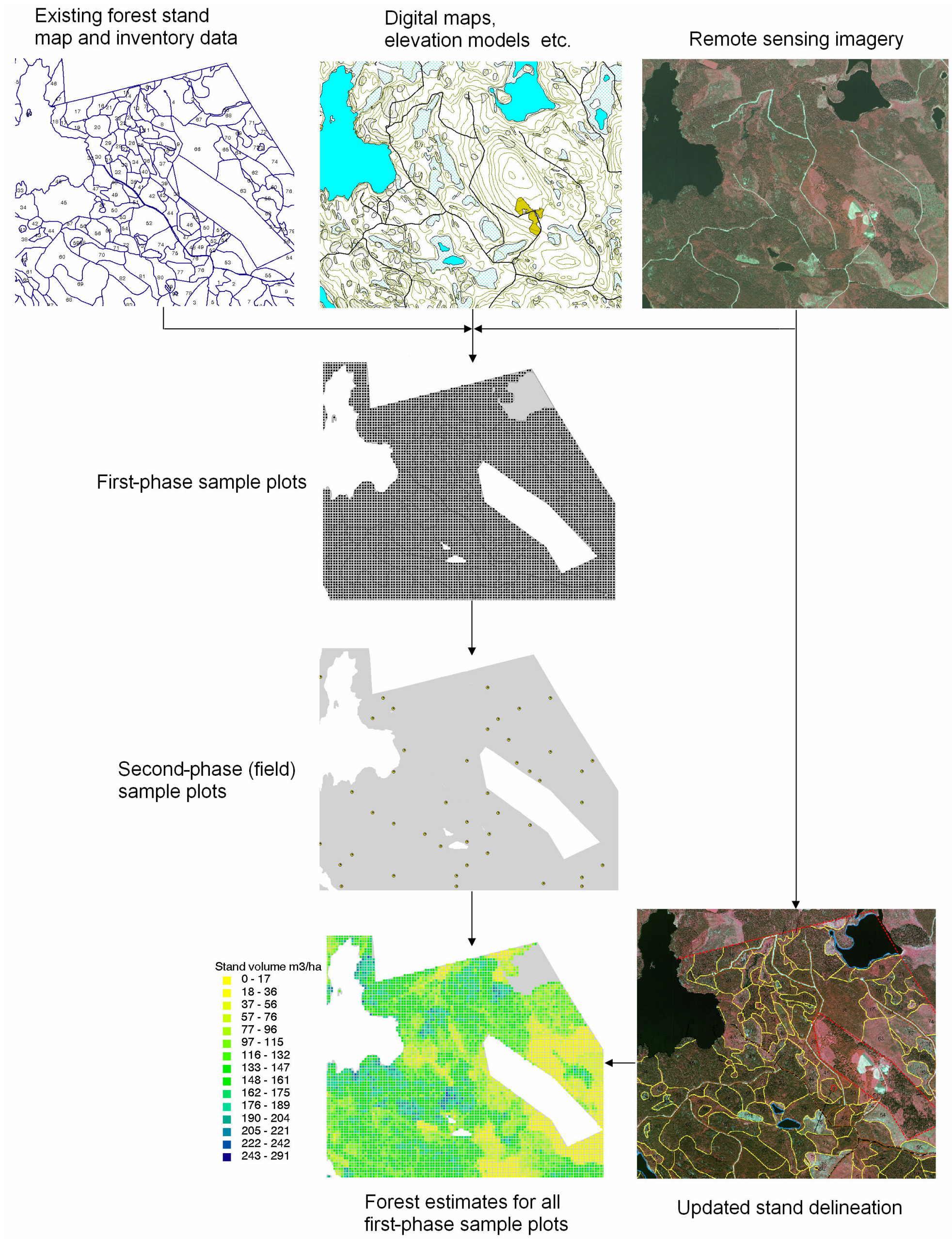

Figure 1. An example of the two-phase sampling procedure for estimating stand-level forest characteristics (input and output data and phases)

REMOTE SENSING IN FOREST INVENTORY

The use of RS imagery as auxiliary data for forest inventory and monitoring has been studied in the context of various applications. Aerial photographs were for long the only available RS data source for forestry. The first forestry applications of aerial photography were carried out in Germany in the late 19th century, where aerial photographs were acquired for mapping of forest stands, using an anchored aerial balloon (Hildebrandt 1996). Principally, the aerial photography technique was introduced into more widespread use along with the development of aeroplanes. During 1919-1930 there were a large number of aerial photography applications in fields of forest inventory, vegetation mapping and forest fire monitoring in Europe, North America and the British colonies in Africa and Asia (Hildebrandt 1996). In Finland the use of aerial photography in forest management planning was begun after the Second World War, although the applicability of aerial photographs in forestry and especially for mapping of forest stands was studied earlier by Sarvas (1938). At first, the aerial photographs were mainly used for the mapping and delineation of forest stands, replacing the line measurement method used for that purpose until then. Visual interpretation of aerial photographs for the estimation of forest characteristics was studied by Nyyssönen (1955). Poso and Kujala (1971) applied a two-phase forest inventory method based on aerial photograph and field plot sampling in the fifth national forest inventory (NFI 5) in northern Finland. The first-phase sample plots were stratified into fairly small strata based on interpretation of aerial photograph stereo pairs. One plot from each stratum was drawn for field measurement and the field data of the plot were transferred to all first-phase sample plots belonging to the same stratum. This method was also used in NFI 6 and NFI 7 with some modifications (Mattila 1985), until satellite images replaced aerial photographic interpretation.

The use of satellite imagery in forest inventory in Finland was first studied by Kuusela and Poso (1970), who tested the estimation of growing stock volume of large forest areas by regression modelling utilizing the spectral values of Environmental Science Services Administration (ESSA) 8 meteorological satellite. Later the same authors studied National Aeronautics and Space Administration (NASA) Earth Resources Technology Satellite (ERTS) multispectral scanner (MSS) imagery (Kuusela & Poso 1975). In this study the field material was stratified based on field measurements, and the variation of the spectral properties of the satellite data within the strata was examined. A forest inventory and monitoring application based on stratified two-phase sampling utilizing Landsat Thematic Mapper (TM) satellite imagery was presented by Poso et al. (1987). In this method, map data were used for differentiating forestry land from other land-use classes and RS imagery for stratifying the forestry land into strata representing different forest classes. The estimates of forest attributes for each first-phase plot were calculated as mean values of the field sample plots within each stratum.

Kilkki and Päivinen (1987) presented the reference sample plot method, in which the estimates for each first-phase sample plot were taken from the field plot that was nearest to it in the auxiliary data space. This method is closely related to the method applied earlier in northern Finland. In NFI 8 and consecutive inventories, Tomppo (1990, 1993) applied a method called the *k* nearest neighbours (*k*-nn) method, which differs from the reference sample plot method in that the estimates are derived from the *k* nearest field plots in the feature space. A similar method was also applied by Muinonen and Tokola (1990) for estimating communal level forest parameters in southern Finland.

The present NFI system in Finland is a multi-source forest inventory (MSFI) utilizing information from several data sources, including RS imagery, maps, elevation data and field measurements. This makes it possible to produce geo-referenced information in digital map format for all the attributes measured in the field (e.g. Tomppo 1990, Tomppo & Halme 2004). The accuracy of the map is then dependent on the correlation between the auxiliary and field data.

At the time of writing, currently developing areas in RS of forests include, among others, very high resolution (VHR) optical satellite image sensors, such as IKONOS and Quickbird, that are capable of producing image material with resolution similar to aerial photographs, active sensors such as satellite or airborne synthetic aperture radars (SAR), such as CARABAS, and airborne laser scanners (ALS), which probably are the most significant of these in Finnish forestry. Among other developments in digital aerial photograph interpretation is 3-dimensional (3D) tree measurement by means of digital aerial photogrammetry, which allows measurement of the location and dimension of individual trees (e.g. Korpela 2004).

OBJECTIVES OF THE THESIS AND SUBSTUDIES

The objective of this thesis was to examine the feasibility of inventory methods based on the two-phase sampling technique, utilizing RS images and other auxiliary data for estimating forest attributes for the purpose of forest management planning. The specific objectives of the individual substudies are defined as follows:

I. The objective was to develop and test a method for enhancing the usability of aerial photographs in MSFI by correcting the spectral properties of the aerial photographs, utilizing an image-fusion technique and satellite images as reference imagery.
II. The objective was to test the applicability of different types of image features in estimating forest characteristics and to introduce an appropriate combination of image features for the purposes of MSFI.
III. The objective was to determine the appropriate unit for extracting image features from very high resolution RS images for estimating forest characteristics.
IV. The objective was to examine methods for combining different auxiliary data sources and to examine different weighting procedures in combining several auxiliary data sources to improve the MSFI estimates.
V. The objective was to determine the proper combination of RS data, old inventory data and geostatistical interpolation of field measurements in estimating forest attributes.

MATERIALS

Study areas and field data

The substudies were carried out utilizing five study areas located in southern Finland. These five areas (A-E) were:

A. Längelmäki: IV
B. Kuru: I, IV
C. Leivonmäki: II, III, V
D. Kirkkonummi: III
E. Kontiolahti: I

A map of the study areas is presented in Figure 2.

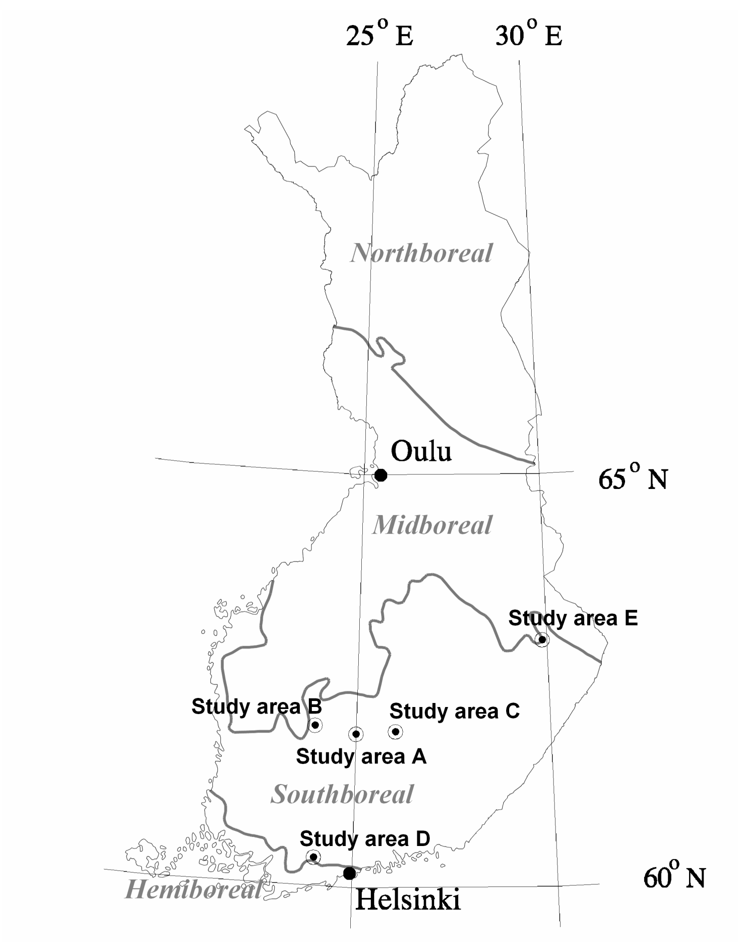

Figure 2. Map of the study areas and vegetation zones in Finland.

The field measurements in the study areas were carried out using relascope sample plots and concentric circular sample plots. In study areas A, B, C and D the field sampling was based on pre-stratification. The strata were derived, based on RS imagery, and the field sample was allocated proportionally to the strata. In study area E the field sample was drawn without pre-stratification. A minimum distance of 100 m was applied between the field plots in study areas A, B, C (for the set of 388 plots) and D to avoid spatial autocorrelation between the field sample plots. The set of 289 plots in C was drawn with closer distances to test the geostatistical interpolation of the forest attributes. Due to the small size of study area E, no minimum distance between the field plots was applied. The main characteristics of the field and auxiliary data for study areas A-E are presented in Tables 1 and 2.

Table 1. Study areas and materials.

	Approx. area, ha	Number of field plots (year when measured)	RS imagery (date)	Other auxiliary data (date)
A	1800	300 (1997)	▪ Landsat 5 TM 190/17 (1995) ▪ Landsat 5 TM 189/17 (1989) ▪ IRS-1C PAN 33/23 (1996) ▪ CIR aerial photographs* (1997)	Stand inventory data (1991-95)
B	4500	380 (1997)	▪ Landsat 5 TM 190/17 (1995) ▪ Landsat 5 TM 189/17 (1989) ▪ IRS-1C PAN 33/23 (1996) ▪ CIR aerial photographs* (1995)	Stand inventory data (1996)
C	1800	388 + 289 (1999)	▪ CIR aerial photographs* (1999)	Stand inventory data (1992)
D	1000	233 (2000)	▪ CIR aerial photographs* (1999)	-
E	60	707 (2002)	▪ Landsat 7 ETM+ 186/16 (2000) ▪ CIR aerial photographs* (2001)	-

*The scale of CIR aerial photographs was approx. 1:30 000

Table 2. Characteristics of the study areas (forest attributes are presented as average and maximum values of the field plots).

Study area	A	B	C	D	E
Min and max elevation, m a.s.l.	110 223	95 190	123 198	27 85	100 235
Total volume, m^3/ha	145 676	118 499	94 469	157 548	145 581
Volume of pine, m^3/ha	43 280	58 297	43 292	50 364	55 386
Volume of spruce, m^3/ha	87 676	48 441	34 419	68 484	73 449
Volume of broad-leaved trees, m^3/ha	15 214	12 292	17 258	39 336	18 191
Diameter at breast height, cm	18 45	15 52	13 44	25 47	17 56
Height, m	14 35	13 33	11 29	19 32	13 27
Basal area, m^2/ha	16 50	15 52	13 45	17 63	17 42

Remote sensing imagery

Satellite images were utilized in this study, because they provide auxiliary data with some indisputable advantages. Using satellite imagery it is possible to cover large areas with reasonably up-to-date image material. Furthermore, the unit cost of the satellite imagery (especially Landsat TM/ETM+) per covered area is low in comparison to other auxiliary data sources, which also makes their application in forest inventory economically feasible. Landsat TM/ETM+ images cover a wide spectral range and the spectral resolution of the sensor is favourable, which are clear advantages in forest or vegetation inventories, compared to RS images that have very high spatial resolution and narrow spectral range (e.g. Tuominen & Haakana 2005). Satellite images are typically used in large-area forest inventories, such as the Finnish NFI. Although the use of satellite images has accomplished successful results in large-area inventories, the general accuracy of satellite image-based estimates has been poor at the level of single field plots or forest stands (e.g. Tokola et al. 1996, Katila & Tomppo 2001, Mäkelä & Pekkarinen 2001). Therefore, their value for forest management planning has been considered low (e.g. Holmgren & Thuresson 1998). One reason suggested for the high stand- and plot-level estimation errors is the low spatial resolution of the satellite image material employed. Under conditions prevailing in Finland the average stand size is small, e.g. 1.5-2 ha in southern Finland. Due to the small size of the stands, a considerable proportion of the satellite image pixels are mixed, i.e. they also carry spectral information from adjacent stands and they may represent poorly the spectral properties of a stand. There are currently available a number of satellite sensors producing VHR imagery, but so far they have shown few advantages over aerial photographs with similar resolution.

Colour-infrared (CIR) aerial photographs are a common data source in management-oriented forest inventories. This type of aerial photograph has a spectral range from near infrared to green, which is reasonably well suited to forestry applications (e.g. for separating tree species). Furthermore, they have superior spatial resolution compared with Landsat TM (or similar) satellite images, which enables the utilization of image features that are based on the spatial organization of spectral values of the neighbouring pixels, i.e. image texture. Until recently, aerial photographs have been acquired mainly using the traditional camera and film-based analogue photography technique and converted to digital image products by scanning the film negatives. Currently, digital cameras are increasingly used in the acquisition of aerial images. For example, the National Land Survey of Sweden is aiming at entirely digital aerial imagery production, i.e. only digital cameras will be used (e.g. Bohlin et al. 2006).

Digital interpretation of aerial photographs and other VHR images has some shortcomings in forestry applications, mainly due to the fact that the spectral properties of a single pixel in a VHR image do not properly represent a forest stand or a tree. Thus, the stand or substand spectral information needed for the image analysis must be extracted from the local neighbourhood of each pixel. Additionally, the sun-object-sensor geometry of aerial photography causes radiometric distortions that are often larger than in satellite imagery. They have a particularly strong effect when the traditional film camera-based image acquisition technique is applied, since every point in the image is viewed with different zenith and azimuth angles. The magnitude of these phenomena is dependent on the sensor, illumination conditions, forest characteristics, and topography and they are more obvious at large viewing angles (e.g. Holopainen & Wang 1998, Leblanc et al. 1999, Pellikka et al. 2000). These phenomena cause spectral heterogeneity in aerial photographs, which complicates automatic image interpretation, since similar objects (e.g. forest stands) may have different spectral properties in different parts of the aerial photograph. For the same reason, the spectral properties of aerial photographs acquired from different areas or from the same area at different times are not commensurate. Thus, the similarity or dissimilarity of forest attributes cannot be judged directly based on these properties.

The CIR aerial photographs record the green (G), red (R) and part (700-900 nm region) of the near infra-red (NIR) radiation. The dyes applied to the film layers that are sensitive to these colours are yellow, magenta and cyan. In practice, the spectral sensitivity areas of the film layers are not exact, but greatly overlap each other (Figure 3). The colour of the dye in a film layer does not necessarily correspond to the colour of the light to which the layer is sensitive. Thus, the CIR images are also known as "false colour" images. (Lillesand et al. 2004) The spectral sensitivity of KODAK AEROCHROME III CIR film (utilized in the acquisition of most of the aerial photography used in this study) is illustrated in Figure 3. Anti-vignetting filters were used in acquiring the photography for this study to reduce the exposure falloff effect.

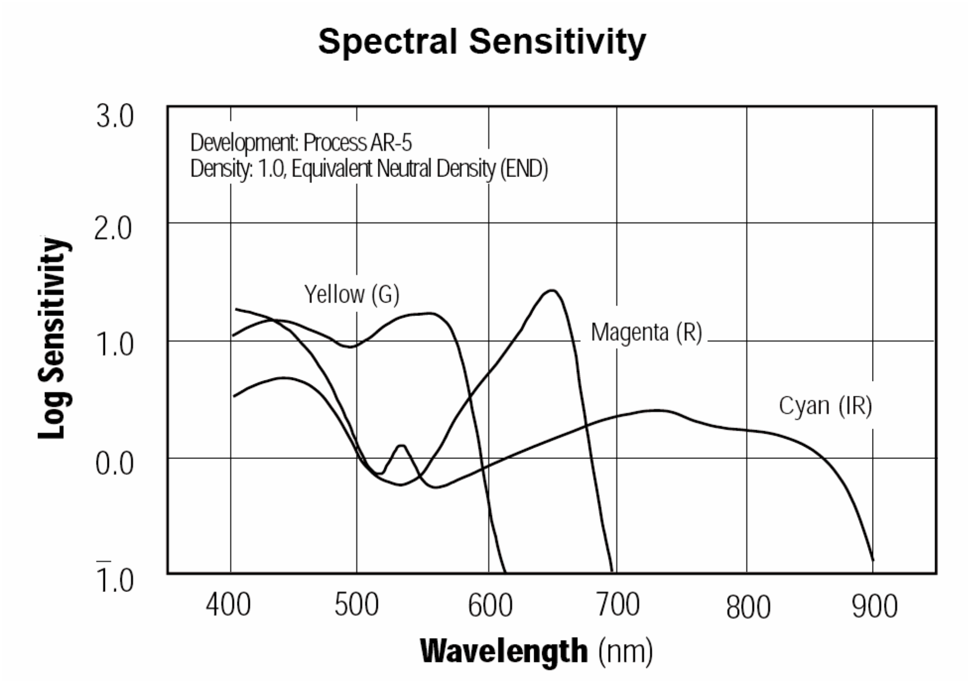

Figure 3. The spectral sensitivity of KODAK AEROCHROME III infrared film. (KODAK 2006). Sensitivity = reciprocal of exposure (erg/cm) required to produce specified density (presented in logarithmic scale), film density is a measure of the darkness/lightness of the film at a given area (Lillesand et al. 2004).

In addition to aerial photography, very high spatial resolution aerial image data have been acquired using airborne imaging spectrometers, e.g. Airborne Imaging Spectrometer for Applications, AISA. Their use in operational forestry has been rare in Finland, and they have not been included as auxiliary data sources in this study, although extensive tests have been carried out using the AISA imagery in association with the Finnish NFI (Mäkisara et al. 1997). In the future the use of digital aerial imaging sensors will likely substitute for film based photographs and the digital imagery will offer a solution to some of the problems associated with traditional camera and film-based photography, such as the radiometric resolution described in the previous paragraph (Bohlin et al. 2006). However, film-based photographs will likely remain as part of the available aerial image material for some time and also as a source of archived image material, e.g. for multitemporal image analysis. Some spectral and spatial properties of the RS image data used in this study are presented in Table 3.

Table 3. Properties of RS image data.

Image	Channel	Wavelength, µm	Pixel size, m
Landsat 5 TM	1	0.45-0.52	30
	2	0.52-0.60	30
	3	0.63-0.69	30
	4	0.75-0.90	30
	5	1.55-1.75	30
	6	10.40-12.50	120
	7	2.09-2.35	30
Landsat 7 ETM+	1	0.45-0.52	30
	2	0.52-0.60	30
	3	0.63-0.69	30
	4	0.75-0.90	30
	5	1.55-1.75	30
	6	10.40-12.50	60
	7	2.09-2.35	30
	Panchromatic	0.52-0.90	15
IRS-1C PAN	Panchromatic	0.50-0.75	5.8
Aerial photographs	NIR	Refer to	0.5-1.0**
	R	Figure 3.*	0.5-1.0
	G		0.5-1.0

*Spectral areas of the different channels are not exact and overlap each other in film-based aerial photography (e.g. Lillesand et al. 2004).
**Spatial resolution varies in digital image material available for different study areas

In two-phase sampling the size of the first-phase sample plots should approximate to the size of the second-phase sample plots (Schreuder et al. 1993) and extracting the image data for the sample plots was carried out accordingly. The size of the unit used in extracting the image features was set to approximately correspond to the size of the field measurement plot. The image features were extracted from Landsat TM satellite images as the spectral values of the available image channels from the nearest pixel to each sample plot. The image features from Indian Remote Sensing Satellite-1C panchromatic (IRS–1C PAN) satellite images were extracted as spectral averages and standard deviations from square-shaped windows (size 5 x 5 pixels) surrounding the sample plots. The image features were extracted from aerial photographs as spectral averages and various textural features from square-shaped windows, as well as image segments surrounding the sample plots. The window size used in extraction varied from approximately 20 to 30 m, depending on the image pixel size. The use of the single nearest pixel in the case of Landsat TM imagery was appropriate, concerning the relation between the pixel and field plot sizes, although this risked reducing the correlation between the image and field data in the event of image rectification errors.

When visual interpretation of aerial photographs was used as an auxiliary data source (IV, V), the auxiliary data variables consisted of visually interpreted variables, such as site type variables, development class, main tree species, stand height etc. The variables were interpreted either per sample plot or per stand. When the variables were interpreted per stand, a stereoscope and paper copies of each aerial photograph were utilized. The sample plot forest variables were interpreted utilizing a digital stereoscopic workstation.

Data from previous inventories

Data from previous inventories was available in some of the study areas (Table 1). The stand-level inventory data were measured for forest management planning. In this context the term stand refers to a forest inventory unit (i.e. a spatially continuous unit created for the purpose of logging or silvicultural treatment). Thus, there was a certain amount of internal heterogeneity within the stands, while very small stands were typically merged into adjacent stands. The stand inventory data, when utilized as auxiliary data, were either measured temporally close to the field (sample plot) material of this study or updated with growth models and records of cuttings and silvicultural treatments to the date of field plot measurement. The per stand (average) attributes of the old inventory data were transferred as such for the sample plot or plots located within the stand borders.

METHODS APPLIED FOR ESTIMATING FOREST ATTRIBUTES

Estimation methods

K-nearest neighbour estimation method (I, II, IV, V)

The estimation of forest attributes was carried out applying the k nearest neighbour (k-nn) method (I, II, IV and V). The method is based on the assumption that sample plots having similar forest characteristics also have similar auxiliary data features, i.e. are located near each other in the n-dimensional feature space, where n represents the number of auxiliary data variables. The k nearest neighbours were determined by the Euclidean distances between the observations in the feature space. Different weighting schemes can be applied within the k-nn method. The stand variable estimates for the sample plots can be calculated as arithmetical averages of the stand variables (with or without weighting) of the k nearest neighbours (Eqs. 3a & 3b).

Several studies have shown that when a large number of field plots are available for k-nn estimation, increasing the number of nearest neighbours (value of k) from 1 to approximately 10 in general clearly improves the accuracy of the (plot-level) estimates, after which the accuracy stabilizes and increasing the value of k does not lead to any significant improvement (e.g. Tokola et al. 1996, Nilsson 1997, Franco-Lopez et al. 2001). This effect is not independent of the total number of field plots. Thus, when relatively small numbers of field plots are used, the value of k at which the accuracy stabilizes is also likely to be smaller. On the other hand, the value of k is a trade-off between the accuracy of the estimates and the variation in the original field material that is retained in the estimates. The greater the value of k, the more averaging occurs in the estimates. Thus, Franco-Lopez et al. (2001) have suggested $k = 1$ for map production for retaining the full variation of the field data in the estimates.

Weighting by inverse squared Euclidean distance in the feature space was applied in substudies II and IV (Eq. 3b). This method reduces the bias of the estimates (e.g. Altman 1992). On the other hand, giving higher weights to the nearest neighbours has an effect similar to that caused by reducing the number of nearest neighbours. Thus, results showing no improvement in estimation accuracy when inverse distance weighting is applied in *k*-nn have also been reported (Franco-Lopez et al. 2001).

$$\hat{y} = \sum_{i=1}^{k} y_i / k \qquad \text{(Eq. 3a)}$$

$$\hat{y} = \left(\sum_{i=1}^{k} w_i y_i\right) / k \qquad \text{(Eq. 3b)}$$

where

$w_i = \dfrac{1}{d_i^{\,2}} / \sum \dfrac{1}{d_i^{\,2}}$ = weight for plot *i*

$\hat{y}$ = estimate for variable y

y_i = measured value of variable y in nearest field plot *i*

d = Euclidean distance to the *i*th nearest neighbour plot

k = number of nearest neighbours

For ordinal scale (categorical) forest attributes, the medians of the nearest neighbours can be applied in the estimation, and for nominal scale attributes (e.g. dominant tree species) the modes of the nearest neighbours can be applied. For binary type attributes, which receive only values 0 or 1 (indicating the presence or absence of a certain attribute in a sample plot), the *k*-nn estimates can be calculated as probabilities (Eq. 4).

$$P = \frac{\sum_{i=1}^{k} y_i}{k} \qquad \text{(Eq. 4)}$$

where P is the probability of the presence of variable y and y_i = measured value of variable y in the i^{th} nearest neighbour plot (0 or 1).

K-means stratification

In this study stratification was applied for two main purposes. First, stratification was used for allocation of the field sample plots in study areas A, B, C and D. Second, to determine the intra-stratum variation in timber volume, the first-phase plots and segments were stratified based on the extracted image features (III). Stratification was carried out using the k-means clustering algorithm (MacQueen 1967), which functions as follows. First, the initial stratum centres for a user-defined number of strata are selected as the set of observations that maximizes the distance between the stratum centres. Each observation (i.e. first-phase sample plot) of the feature set is then assigned to the spectrally nearest stratum centre employing Euclidean distance measure. Finally, the centroid vector of each stratum is recalculated as a mean vector of the observations assigned to that stratum. The process is iterated until the stratum centres remain unchanged. The number of strata are dependent on the purpose of the stratification.

The efficiency of stratification is closely linked to the variance within strata versus the total variance. The smaller the ratio of intra-stratum variance to total variance, the more efficient the forest inventory based on stratified two-phase sampling will be. The more sample plots per stratum that are measured in the field, the more accurate are the estimates, but as in k-nn estimation, more plots per stratum lead to increased averaging in the estimates. Thus, the optimum number of field plots per stratum cannot be determined exactly. The average number in this study varied from 5 to 10. If the desired total number of field plots (second-phase units) has been determined, the desired number of field plots per stratum can be obtained by regulating the number of strata (e.g. Tuominen et al. 2006). When stratification is utilized for estimating local forest variables (of the first-phase sample units), mean vector estimation is typically applied as with the *k*-nn.

Geostatistical interpolation (V)

Geostatistical methods are used for estimating continuous surfaces from point data measurements. The application of geostatistical methods is based on the assumption that the variables are spatially continuous. In other words, there is autocorrelation between two points as a function of the geographical distance between the two points. A common method of interpolation with geostatistics is kriging (Matheron 1963). Kriging has been applied in estimating forest variables in forest management planning, e.g. by Holmgren and Thuresson (1997) and Gunnarsson et al. (1998). The use of geostatistical methods begins by studying the spatial variation of the variables to be estimated. In kriging experimental variograms are calculated for the attributes to be estimated to determine their spatial dependencies. The kriging model used for estimating the forest attributes is based on the observed variograms. Ordinary kriging was applied in the estimation of forest attributes along with the *k*-nn method for utilizing aerial photographs and old stand inventory data (V).

In calculating the variograms, directional effects were not taken into account, which means that isotropic variograms were used. The calculation of variograms was based on the field plot material in the study area. The experimental variograms provided an insight into spatial dependencies within the data. Kriging was employed to establish the utility of these observable spatial patterns in the estimation of forest variables at unknown locations. Each attribute was modelled independently, using a spherical model. Once the kriging system was built, the sample data were cross-validated, using the leave-one-out method. The result of cross-validation was an estimate for each original sample point, based upon its neighbours, using weights obtained from the kriging.

Processing and extracting of auxiliary data

Correction of the aerial image spectral values for k-nn estimation (I)

Aerial photographs provide data that have superior spatial resolution compared with satellite imagery and their availability is generally good. However, the digital interpretation of aerial photographs is not without its shortcomings. The radiance observed by an aerial camera is affected by bidirectional effects and the properties of the sensor. Some of the factors affecting the observed radiances, such as variation in the viewing geometry, typically predominate in data acquired from low altitudes and using wide-angle lenses (Pellikka et al. 2000, Lillesand et al. 2004) and are therefore typical of aerial photographs. Due to bidirectional reflectance, the spectral characteristics of objects are not independent of their location in the image. Therefore similar objects are prone to have different spectral characteristics in different parts of the image. Tree crowns on the solar side of the image appear darker because the aerial sensor records radiation reflected by the shadowed parts of the tree crowns, whereas on the opposite side of the image the camera records radiation reflected from the illuminated parts of the tree crowns. The magnitude of the bidirectional reflectance is dependent on the forest or vegetation characteristics and topography (Holopainen & Wang 1998).

Another factor causing spectral variations in aerial photographs is exposure falloff. The effect is associated with the distance from the image centre, the exposure being maximum at the centre of the film and decreasing with the radial distance from the centre. The effect of exposure falloff is usually compensated for with anti-vignetting filters. As in exposure falloff, relief displacement is associated with the distance from the image centre and causes any object standing above the terrain to lean away from the principal point of a photograph radially (Lillesand et al. 2004). The relief displacement increases with the radial distance from the image nadir point.

The radiometric and geometric complexities of the digital aerial photographs make their use in MSFI applications problematic. The use of spectral features extracted from the uncorrected digitized image may result in errors in the estimation, because pixels of one informative class can belong to several spectral classes. Thus, some type of radiometric correction is required.

Various methods have been applied in correcting the spectral properties of aerial photographs. One approach aims at theoretical modelling of the mechanism of the bidirectional reflectance distribution function (BRDF) (e.g. Nilson & Kuusk 1989, Li & Strahler 1992, Chen & Leblanc 1997, Leblanc et al. 1999). Physical modelling of the BRDF requires radiometrically calibrated sensors (Pellikka et al. 2000). Forestry applications using BRDF models have been relatively rare, because modelling the BRDF of forests is a complex task. Empirical radiometric calibration models have been developed and tested for forest inventory applications (e.g. King 1991, Holopainen & Lukkarinen 1994, Holopainen & Wang 1998). The strengths of the empirical models are their simplicity and the fact that the effect of several factors affecting the spectral values can be dealt with by a single correction. However, since BRDF is dependent on the vegetation type, they often require a priori knowledge of the inventory area (e.g. Li & Strahler 1992, Holopainen & Wang 1998, Leblanc et al. 1999, Pellikka et al. 2000).

A common empirical approach has been the application of image channel ratios or normalized difference vegetation index (NDVI) instead of the original image channels (e.g. Jackson et al. 1990, King 1991, Holopainen & Wang 1998, Hyppänen 1999). The weak point of this method is that the effect of the BRDF is different in different parts of the electromagnetic spectrum and the BRDF also affects the channel transformations (Jackson et al. 1990, Sandmeier & Itten 1999). Furthermore, the effect of atmospheric scattering on the image properties varies in different image channels. The atmosphere scatters the shorter wavelengths more than the other visible wavelengths, which in turn, reduces the contrast in the shorter wavelength bands (Lillesand et al. 2004). This affects multiple channel transformations such as channel ratios or NDVI.

The substudy I presents a different empirical approach for radiometrical correction of aerial photographs. The recorded pixel values that are affected by the aforementioned phenomena are corrected utilizing reference imagery in which the effects of these phenomena are less significant. Satellite images having higher imaging altitudes and narrower fields of view generally fulfil this requirement. Image correction was carried out as a local adjustment of the aerial photograph spectral values using correction units that are larger than a single aerial photograph pixel. The correction was carried out separately for each aerial photograph channel. The satellite image channels with the approximately corresponding wavelength areas were used as the reference levels to which spectral values of the aerial photographs were adjusted at the correction unit level. The correction spatial units employed in this study were:

1. Landsat TM image pixel (size 25 m * 25 m)
2. Moving circle centred around a single pixel with a radius of 40 m (approx. 5000 m^2)
3. Image segments produced by automatic segmentation of the aerial photographs (min. size of segments 1500 m^2).

The advantages of the method presented are that the correction parameters can be determined empirically, and consequently the method requires no a priori knowledge of the forest characteristics in the study area, nor any information on the location of the pixels in relation to the solar coordinate axes of the aerial image. The method can be used in correcting the spectral values within an aerial image as well as between images.

Selection of an appropriate set of image features for MSFI (II)

The basic characteristics that can be utilized in interpreting aerial photographs are listed as: shape, size, pattern, tone, texture, shadows, site and association (Lillesand et al. 2004). In digital interpretation applications, spectral features (tone) have been most commonly utilized. However, digital interpretation based on the spectral properties of aerial photographs is complicated by the fact that the spectral properties of the pixels are not independent of the location of the pixel in the image. Therefore, as noted previously, similar forests may have different spectral characteristics in different parts of the image. Other image features such as texture, which has been defined as the spatial organization of the gray-levels of the image pixels (Haralick et al. 1973), are less affected by their location in the images. Typically, pattern and texture are the most important characteristics used in visual interpretation of aerial photographs, but it is difficult to automatize the recognition of objects based on these characteristics.

In substudy II a number of spectral and textural image features were extracted from three original aerial photograph channels (NIR, R and G), NDVI channel and three ratio channels (NIR/R, NIR/G, R/G). The extracted features were:

1. Spectral averages
2. Standard deviations
3. Variety of spectral values
4. Range of spectral values
5. Standard texture calculated from a 32 x 32 pixel window as the standard deviation of the spectral values of blocks into which the window was divided. The block sizes corresponded to 1 x 1, 2 x 2, 4 x 4 and 8 x 8 pixels. Furthermore, the standard deviation of the four standard deviations derived was computed (Wang et al. 1997).

Additionally, five texture features based on the image gray-level co-occurrence matrices (Haralick et al. 1973, Haralick 1979) were computed using horizontal (0°), vertical (90°) and diagonal (45° and 135°) directions:

6. Angular second moment
7. Contrast
8. Correlation
9. Entropy
10. Local homogeneity

The image features were extracted from the original resolution (0.5 m) images and from images resampled to 1.0-m and 2.0-m spatial resolutions. The feature extraction window was in most cases 20 m x 20 m, which has been stated generally to be the near-optimal window size for extracting aerial photograph features in forest inventory (Holopainen & Wang 1998). Prior to their use in the estimation of forest attributes, the image features were normalized to a mean equal to 0 and standard deviation equal to 1. The original image features had very diverse scales of variation. Since at this point there was no knowledge of their applicability in estimating forest attributes, similar scales were used. Without normalization, the variables with large variation would have had higher weights in the estimation, regardless of their correlation with the estimated forest attributes.

Not all image features have similar value in estimating forest attributes; e.g. in forest inventories based on the use of optical satellite imagery, different weights have been applied for the image features for enhancing the estimation (e.g. Franco-Lopez et al. 2001). In the present study the applicability of the extracted image features was evaluated by examining their correlation with the forest attributes and by testing them in the estimation of forest attributes for the field sample plots. The following stand variables were estimated: diameter at breast height, mean height, basal area and volume of total growing stock. The *k*-nn estimation method was applied and the estimates were tested using the leave-one-out cross-validation technique.

Utilizing a large number of image features may be beneficial in some estimation tasks, but this is not the case in general. If the performance of each of the features is not known a priori, they cannot be weighted in an optimal way. In that case the estimation errors may actually increase when the number of features employed is increased (e.g. McRoberts et al. 2002). This phenomenon is often referred to as the curse of dimensionality, in which *k*-nn is easily misled by the exponential growth of the feature space, because the number of ways of dividing the space increases rapidly as the dimensions increase. Often, the image features are also highly correlated. Utilizing a high number of image features with high mutual correlation does not benefit the estimation of forest attributes, since the additional features contain little further information. These problems can be avoided using techniques that can generate optimal weights for the features and/or are able to select the best-performing subset of the features for the actual analysis. In the present study the latter option was applied by analyzing which features significantly contributed to the estimation accuracy and what was the appropriate number of features needed for robust estimation results.

Feature selection was carried out as a sequential forward selection. In the first-phase of the process, the feature giving the lowest root mean square error (RMSE) in cross-validation was selected. Later the process was iterated and during each iteration the feature giving the best RMSE with the already selected features was added to the set of selected features. The effect of the number of selected features on the estimation accuracy was examined for all variables that were used in the estimation.

Examining the suitability of different spatial units for extracting image features from VHR imagery (III)

Pixel-based image interpretation has traditionally been used in forest inventory applications, which utilize field measurements and RS data. This is an easy option with medium and high resolution satellite imagery whose pixel size corresponds to a unit for which the forest attributes can be estimated. When VHR imagery is used in a forest inventory application, a single pixel does not represent the spectral characteristics of a forest stand or even an individual tree. Thus the stand or substand spectral information needed for the image analysis must be somehow generalized in the local neighbourhood of each pixel; e.g. square-shaped pixel windows have been applied for this task (e.g. Holopainen & Wang 1998). The window size should correspond to a unit that is adequate for estimating forest attributes. Another option for image interpretation units are polygons produced by automatic image segmentation of VHR imagery.

In substudy III, the effect of the selected image features extraction unit is examined on the estimation accuracy. Two alternative inventory approaches were examined. The first approach was based on two-phase plot sampling in which quadratic raster windows centred around the sample plots were utilized in extracting image features for the sample plots. The size of the raster windows was 20 x 20 m. The second approach was based on automatic image segmentation. The image segments having a relatively small size compared with the average stand size were employed as the inventory units. Two image segmentations were carried out, applying minimum sizes of 380 m^2 and 675 m^2 for the segments. Correspondingly, these segments were utilized in extracting the image features. Thus, three different image feature sets were utilized in the study: one sample plot-based set and two segment-based sets.

The test was carried out in two study areas. The inventory units (sample plots or segments) in the study areas were stratified, based on the image feature sets (with different extraction units). The k-means clustering algorithm was applied in the stratification (MacQueen 1967). Strata numbers from 20 to 50 were tested. After stratification, the field sample plots were assigned to the strata. In the sample plot-based approach, each plot was assigned to the spectrally nearest stratum. The Euclidean distance measure was employed. In the segment-based approach, the field plots were assigned to the stratum of the segment on which the plot centre was located. The homogeneity of the strata in relation to their forest attributes was examined. Standard deviations of the forest attributes within the strata were used here as the measure of their homogeneity.

Principal component analysis (IV, V)

The number of auxiliary data sources, and especially the number of auxiliary data variables (image features etc.), may become very high. The high number of auxiliary data variables often has an undesirable effect on the estimation procedure (also known as the curse of dimensionality). In high-dimensional space all pairs of points are almost equidistant from each other. In other words, as dimensionality increases the distance to the nearest neighbour approaches the distance to the farthest neighbour. In such cases, a nearest neighbour query becomes unstable (Beyer et al. 1999). Additionally, the data are usually sparse in high-dimensional space (Hinneburg et al. 2000).

Principal component transformation is a useful method for reducing the number of input variables, while simultaneously retaining most of the variation of the original variables. The method is effective when the original variables are correlated with each other. In principal component transformation, the original input variables are transformed into new variables, i.e. principal components, which do not correlate with each other, thus allowing retention of a large part of the original variation in a smaller number of principal components.

In substudies IV - V the auxiliary data variables were processed with principal component transformation. The standardized principal component transformation method (i.e. based on a correlation matrix) was used for normalizing the variation of the input variables to a similar scale. The original auxiliary data variables had different data scales and when the estimation procedures based on the distances in the feature space were used, those variables showing wide variation would have received more weight in the estimation. The auxiliary data sources were treated separately with principal component transformation in order to test them individually in the estimation. Here, the number of principal components that contained 95% of the original variation in each data source were used in the estimation.

Combining and weighting data sources in *k*-nn estimation (IV, V)

There are a number of ways to combine several auxiliary data sources within the *k*-nn estimation method. One alternative is to combine all auxiliary data sources into a single *n*-dimensional feature space, where *n* represents the total number of all auxiliary data variables (e.g. channels of different RS images). The nearest neighbours are then calculated within this feature space in a single operation. Another alternative is to deal with the different auxiliary data sources separately by creating several *n*-dimensional feature spaces, where *n* stands for the number of features within one auxiliary data source. Cochran (1977) showed that in the case of repeated samples from the same population, the best combined estimate is found by weighting the independent estimates inversely with their variances. In the substudy IV, the nearest neighbours were calculated separately in each feature space, resulting in a number of nearest neighbours equal to *k* multiplied by the number of auxiliary data sources. This procedure makes it possible to give different weights to separate auxiliary data sources based on their correlation with the attribute estimated. The auxiliary data sources were weighted by the inverse values of the mean square errors (MSE) of the estimates produced by each auxiliary data in *k*-nn estimation. This procedure resulted in a single weighted estimate (Eq. 5).

$$\hat{y}_{combined} = \frac{\sum_{i=1}^{z}(1/MSE_i)\hat{y}_i}{\sum_{i=1}^{z}1/MSE_i} \qquad \text{(Eq. 5)}$$

where

$\hat{y}_{combined}$ = estimate for variable y combining data sources weighted with their MSEs

MSE_i = mean square error of estimate derived using data source i

$\hat{y}$ = estimate for variable y derived using data source *i*

z = number of auxiliary data sources

Similar weighting was applied in substudy V when the *k*-nn estimates derived on the basis of aerial photograph features and data from previous stand inventories were combined. Another weighting system was applied in substudy IV to improve the accuracy of the estimates. The spectral difference values of two satellite images (Landsat 5 TM and IRS-1C PAN) that were acquired at one year intervals were used for picking out sample plots that were likely to have undergone changes (e.g. cuttings or natural disturbances) between the acquisition dates of the images. In these sample plots, those auxiliary data sources that were considered as outdated were given zero weights in the estimation.

RESULTS

Summary of the results of individual papers

Local radiometric correction of aerial photographs (I)

An image correction method based on the use of a reference image was used for correcting the radiometric problems (such as bidirectional reflectance) of aerial photographs. The correction method employed altered the spectral characteristics of the aerial images in several ways. First, the spectral values of the corrected images followed the satellite image channels used in the correction. Furthermore, the distribution of the spectral values became more peaked following the correction. Additionally, the correction appeared to reduce the correlation between the spectral values of different channels of the aerial photograph.

The choice of correction unit seemed to affect the output image. When a Landsat TM image pixel was used as the correction unit, the TM image pixel structure was clearly visible in the output image. Using image segments as correction units emphasized the segment or polygon structure in the output image: the segments used as correction units were visible in the output image. Correction based on the moving window or moving circle approach had a smoothing effect on the output image, but an evident drawback in this approach was the tendency to cause transition artifacts around objects that are clearly distinguishable from neighbouring objects (i.e. roads in the forest, boundaries between forest and water etc.). These transition artifacts were also found on the edges of images of noticeably differing brightness, when a moving circle or window was used as the correction unit.

When the correlation coefficients between the forest attributes and the image spectral features extracted from the original and the corrected images were examined, all correction methods improved the correlations. The TM pixel-based correction resulted in the smallest improvement. When the image correction was based on moving circles and segments, the correlation between most forest attributes and the image spectral values was notably improved by the correction. The improvement was particularly clear for the green channel.

Cross-validating the estimates based on the original and corrected images showed that image correction improved the accuracy of the forest variable estimates. Improvement after correction was consistent with improvement in the correlations between the forest variables and extracted image features. The TM pixel-based correction again did not result in significant improvement over the original image. The image segment and moving window or moving circle-based correction methods resulted in the highest estimation accuracy, especially for stand volume.

Selection of aerial photograph features (II)

Based on testing of the extracted image features and the parameters guiding the extraction, a high number of image features extracted from aerial photographs appear to be relatively well correlated with the forest attributes. The correlations between most image features and plot mean height or basal area were typically better than correlations between image features and volume. The original image resolution of 0.5 m resulted in consistently better correlations with forest attributes than images resampled to 1.0- and 2.0-m resolutions.

The number of requantification classes and pixel lag (i.e. spatial interval between pixels) that were applied in extracting the image features based on gray-level co-occurrence matrices had relatively little effect on the correlation coefficients between the image features and forest attributes. Generally, the number of requantification classes applied for these image features was not significant for the correlations. The pixel lag had slightly more effect on the correlations. In features contrast, correlation and local homogeneity, an evident peak was observed and the differences were clear, whereas in angular second moment and entropy, lag had no clear effect on the correlations. The values for the lag that resulted in the best correlation with stand volume were applied in extracting the Haralick features for the *k*-nn estimation.

The estimation based exclusively on the average spectral values of the three original image channels resulted in a volume RMSE of 73.5 m^3/ha, whereas the corresponding result with the best-performing individual image feature was 83.7 m^3/ha. Furthermore, the two best image features picked in the feature selection process resulted in better estimation accuracies for all forest attributes compared with the spectral features of the three original image channels. Adding further image features clearly improved the accuracy of the estimates until the number of selected features was approximately 10, after which adding further features to the estimation process produced little gain in estimation accuracy. Increasing the number of image features from 10 to 20 brought no significant improvement, while beyond 20 resulted in practically no improvement at all. The image features based on gray-level co-occurrence matrices generally were well represented among the selected features. Since these were often highly correlated with each other, it is natural that the estimation accuracy quickly reaches its saturation point when further features were added.

Examining the extraction unit for image features (III)

The distributions of the mean values of segment-based spectral features were wider than those extracted from square raster windows surrounding the plots in both study areas. Thus, it can be assumed that the segment-based approach retains more of the original spectral variation present in the image than the square window-based extraction. Furthermore, the spectral variation in the feature set extracted from larger segments was larger than in the feature set extracted from square windows, even though the area of the segments was larger than that of square windows. In general, the use of larger feature extraction should result in more averaged features. Using segments in feature extraction seems to avoid this drawback, at least to some extent.

In study area C, square window-based stratification gave clearly better results than the segment-based approach if the stratification utilized only the spectral averages of the three channels employed. In segment-based approaches, smaller segment size resulted in more homogeneous strata and more stable results than larger sizes. The introduction of spectral standard deviations of the three channels to the analysis clearly decreased the intra-stratum variation of total volume in the segment-based approaches. However, the square window-based strata were still more homogeneous when a relatively small number of strata was employed. With increasing numbers of strata, however, the variation within both segment-based and square window-based strata was comparable.

In study area D the segment-based strata derived only from the use of spectral averages only produced more homogeneous strata than the square window-based approach. The difference between the window-based and segment-based approaches increased with increasing numbers of strata. In most of the examined numbers of strata, the spectral averages extracted from larger segments produced also more homogeneous strata than averages extracted from smaller segments. Inclusion of the spectral standard deviation with the stratification significantly increased the homogeneity of the square window-based strata in study area D. Comparison of the results obtained with different numbers of strata revealed that the plot-based strata were more homogeneous than any of the segment-based strata in most cases.

The results were contradictory. Use of the segment-based spectral features retained more of the original spectral variation in the images than the features extracted from square windows. The intra-stratum variation in timber volume was generally larger in segment-based strata in both study areas. The introduction of spectral standard deviation features to the stratification diminished the intra-stratum variation in timber volume in the square window-based approach only slightly in study area C, but the improvement was more obvious in study area D. In segment-based strata, the effect was evident in study area C when larger segments were employed. In study area D, the inclusion of the standard deviation features did not have a clearly positive effect on the results. In fact, the combination of segment-based average and standard deviation features tended to produce more heterogeneous strata than spectral averages only in study area D.

The results indicate that the segment-based approach has some advantages over square window-based feature extraction utilizing VHR images. However, when segment-based image features are used in MSFI the field data should also be representative at the segment level.

Combining and weighting auxiliary data sources in *k*-nn estimation (IV)

Satellite images, aerial photographs (digital and visually interpreted) and stand data from previous inventories were examined as auxiliary data sources. Of those examined, the visual interpretation of aerial photographs and old stand inventory data generally proved to be the best data sources in estimating the stand characteristics. Digital interpretation of aerial photographs (using spectral averages and standard deviations of 20 m raster windows as image features) gave slightly inferior results in the estimation and satellite imagery gave clearly inferior results compared with the two best data sources. A clear exception to the aforementioned was the favourable performance of the IRS-1C PAN satellite imagery in estimating the growing stock basal area. Furthermore, combining several data sources gave significantly better estimation results than those obtained using any auxiliary data source individually.

Applying different weighting schemes in the *k*-nn estimation gave diverging results. Weighting the estimates derived from individual auxiliary data sources with the inverse values of their MSEs clearly improved the combined estimates of all forest attributes tested here. Weighting the reference plots with the inverse values of their distances in the feature space did not improve the estimation. Instead, the results of this method were markedly inferior compared with estimation without inverse distance weighting.

When the difference of two satellite images was used in finding the sample plots likely to have undergone changes and the outdated auxiliary data sources were discarded, improvement was shown in the estimates from one area but not from the other. When those sample plots located nearer than 20 m from the stand borders (i.e. mixed plots) were excluded from the estimation, the estimates for most stand variables were improved, resulting in the highest accuracy of the methods tested.

Combining remote sensing, data from previous inventories and geostatistical interpolation in multi-source forest inventory (V)

Several values (3-5) were tested for *k* in the *k*-nn estimation using different numbers of field plots (100-194-388). The results showed that increasing the value of *k* from 3 to 5 consistently improved the estimates, even when the lowest number (100) of field plots was applied. This trend was similar for all auxiliary data sources that were utilized, including digitally and visually interpreted aerial photograph features and stand data from previous inventories. The number of field plots followed the same trend: the greater the number, the better the estimates. When the number of field plots was increased from 100 to 194 and from 194 to 388, the difference in accuracy of the estimates was, however, quite small for most stand variables. The updated stand inventory data were the best auxiliary data source for the estimation of stand age. For estimation of stand mean diameter, age, basal area and growing stock volume, the visually interpreted aerial photograph gave the best estimation accuracy. The digital aerial photograph features were ranked as the worst performing auxiliary data source in the estimation of all stand variables.

When auxiliary data sources were combined in the *k*-nn estimation, the estimation accuracy was significantly improved in comparison with any individual auxiliary data source used separately, which was consistent with the results of substudy IV. There was also a modest improvement in the accuracy of the estimates when the number of field plots was increased, so that the trend was the same as when auxiliary data sources were used separately.

When the updated stand inventory data were used as estimates for sample plots, they were distinctly inferior to the *k*-nn estimates for all stand variables studied. When the *k*-nn estimate and the updated stand inventory estimate were combined and weighted with the inverse values of their MSEs, the estimates produced by this procedure were significantly better than those of the other estimators. When the estimation was carried out per stand, the results of the *k*-nn estimation and previous inventory data showed contrasting trends. The updated stand inventory data as such offered better estimates at the stand level than the *k*-nn estimates. At the plot level, they displayed notable negative bias, which makes it probable that stand-level estimates are biased as well (the bias was not calculated at the stand level due to the relatively small number of accurately measured stands). This suggests that the original stand inventory data were biased from the beginning or that the applied growth models were not entirely accurate. However, when the *k*-nn estimates and the updated stand inventory data estimates were combined with weighting, the results showed even more significant improvement in the estimation accuracy than in the estimation per sample plot. The general rule is that the accuracy of estimation improves when the area of the estimation unit increases. Thus, the accuracy of estimation per stand should be clearly superior to the estimation per sample plot.

Geostatistical interpolation applying Ordinary Kriging performed poorly in the estimation of forest attributes. Weighting procedures based on spatial autocorrelation do not generally perform very well when (growing stock-related) stand variables are estimated in managed forests (Gunnarsson et al. 1998). The main reason for this is that cutting operations produce abrupt changes in the forest, whereas geostatistical methods are best suited for data in which the value of the measured attribute changes gradually with smooth stages. In addition, the field sample design of two-phase sampling-based inventory is often not suitable for calculating the semivariances for the Kriging procedure, because the field sample plots are often distributed across the study area at relatively wide distances. Thus, Ordinary Kriging is not well suited for estimating growing stock-related variables when estimation methods combining field plot measurements and auxiliary data are used.

DISCUSSION

Based on the results of the substudies of this thesis and other studies, the estimation accuracy of forest characteristics in most RS-based forest inventories is generally poor at the levels of single sample plots or satellite image pixels. Table 4 compares the results of a number of studies in which forest attributes were estimated, using RS and other auxiliary data. The comparison shows that the estimation results of this study are generally similar to those of other studies utilizing similar auxiliary data. The results in Table 4 are presented as relative RMSEs of the estimates of mean/dominant height, basal area and volume.

Table 4. Estimation accuracy (corresponding plot level) of some forest attributes in a number of studies.

	Auxiliary data	relative RMSE, %		
		height	basal area	volume
Poso et al. 1999	Landsat TM satellite image	46-51	52-62	73 - 81
	IRS-1C PAN satellite image	48-49	51-54	71 - 74
	Digital aerial photograph	46	55	74
	Visual aerial photograph interpretation	44-46	49-53	66 - 68
	Old stand inventory data	47-54	52-59	68 - 76
Franco-Lopez et al. 2001	Landsat TM satellite image		46	65
Holmström & Fransson 2003	SPOT-4 XS (HRVIR) satellite data			64
	SPOT-4 XS (HRVIR) + CARABAS II radar data			53
Naesset & Bjerknes 2001	Airborne laser scanner	13		
Suvanto et al. 2005	Airborne laser scanner	8	17	20
	Airborne laser scanner + old stand inventory data	8	15	17
Tuominen & Poso 2001 (IV)	Weighted combination of satellite & aerial images and old stand inventory data	40	45	59 - 61
Tuominen et al. 2003 (V)	Combination of aerial photograph and old stand inventory data	43	42	54
Tuominen & Pekkarinen 2005 (II)	Selected digital aerial photograph features	47	44	58

It can be assumed that the accuracy of estimation improves when the size of the estimation unit increases (e.g. Tomppo et al. 1998). Thus, the accuracy of estimation per stand should be better than the estimation per sample plot. This assumption is based on the fact that the measure of accuracy, RMSE, consists of two components: 1) the systematic component, i.e. bias, that cannot be reduced by increasing the number of inventory units, and 2) the unsystematic component of random errors in the estimation process, which partly cancel out each other when the number of inventory units is increased. Based on the results of the substudies, the bias component is much less significant than the random error component. Thus, it is logical that the RMSE decreases when the size of the inventory unit is increased by adding the number of estimation units. On the other hand, it has been suggested that the accuracy is better for larger areas because the variation, e.g. in volume, is greater for small forest blocks than for large forest blocks (Päivinen & Anttila 2001). Figure 4 presents the estimation accuracy of stand volume as a function of inventory area, based on the results of Tomppo et al. (1998) in NFI 8 of Finland. It can be assumed that while the RMSE varies with different RS data, the general trend in relation to the area is similar. Thus, it is questionable whether the stand-level estimates are accurate enough that cutting operations and silvicultural treatments could be based on them. At the forest estate level the RMSE of RS-based forest estimates can be considered acceptable (~10-20%), but this is not as significant since the unit for silvicultural operations is a stand. Furthermore, even if the stand estimates produced by two-phase sampling inventory were considered accurate enough in general, the situation would not be satisfactory from the forest management point of view, since the stand estimates should be the basis for choosing the correct silvicultural treatments. Although the stand-level inventory method has several shortcomings, as discussed earlier, it is not likely to result in such gross errors in the estimation that would lead to utterly incorrect or economically unsound silvicultural treatments, since all stands are generally visited in the field. Additionally, forestry legislation sets constraints on forest management, e.g. by setting minimum age or diameter limits to stands destined for final cutting. Applying a two-phase sampling inventory method may result in stand estimates whose values are so far from the correct ones that making cutting decisions based on them may lead to unintentional violation of forestry law. Thus, when two-phase sampling is applied for acquiring inventory data for forest management proposes, all stands should always be checked in the field when carrying out silvicultural or logging operations.

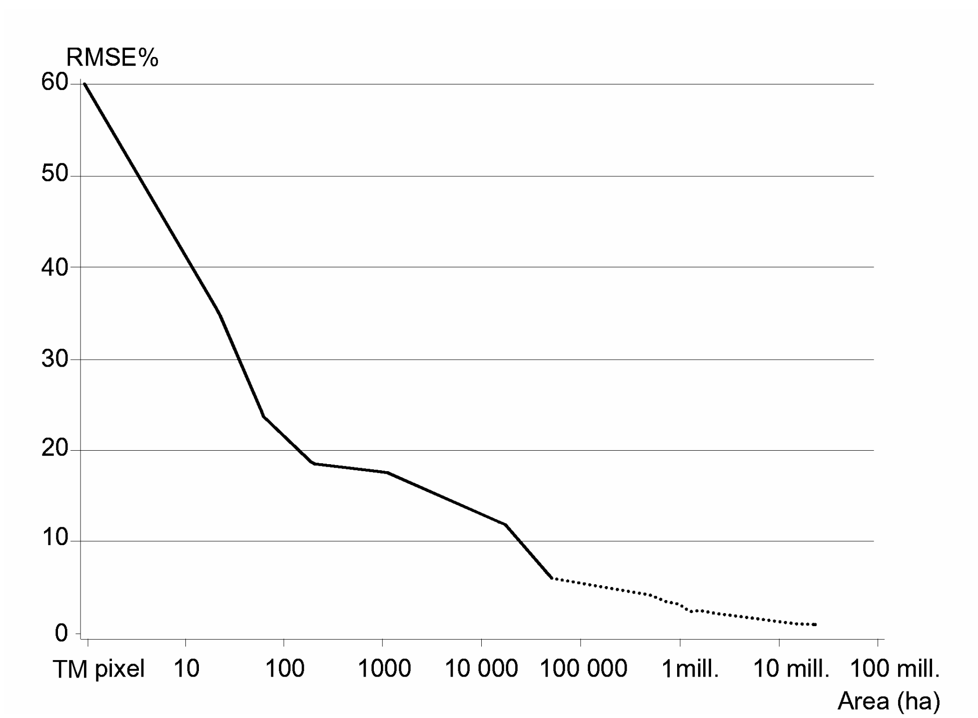

Figure 4. RMSE of stand volume estimates for different sizes of inventory units (Tomppo et al. 1998).

In addition to the estimation accuracy, another factor that should be taken into account is the proportion of the original variation (of the field material) that can be retained in the estimates. Typically, when the forest attributes of a point are estimated on the basis of several field plots, averaging occurs in the estimates; i.e. the higher the value of *k* the more that averaging occurs. As a result, the variation in the estimates is typically smaller than the variation in numerical variables of the original field data. In the case of categorical variables, rare classes may totally disappear in the estimation. Thus, in *k*-nn estimation the optimal value of *k* is a trade-off between the accuracy of the estimates and the variation retained in the estimates.

The *k*-nn estimation often produces more or less biased estimates. When forest data for forest management are estimated at the sample plot or stand level, the aim of inventory is the maximal local accuracy of the estimates for determining the (locally) correct silvicultural treatments, and at this level the bias is not a factor of high importance. When forest statistics are estimated for large inventory areas, the inventory result is the basis for a different type of decision-making, and here the bias must be avoided. Thus, it is not appropriate to produce large area estimates by summing the estimated sample plot or stand values. Instead, the original field plot data weighted with the areas that they represent should be used.

As alternatives to the *k*-nn method, stratification and regression analysis have been applied for estimating forest variables with the aid of auxiliary data (Tomppo 1987 & 1988, Poso et al. 1987 & 1999). When regression analysis is used, the variables must be estimated separately or in groups. This procedure may lead to estimates whose covariance structure is different from that of the original field variables (e.g. Tomppo & Halme 2004). Another problem of regression analysis in forest inventory applications is the high number of variables to be estimated. This leads to a laborious estimation procedure and estimates that may not be compatible with each other (Tomppo 1987, 1988). The problems of regression analysis can be avoided using *k*-nn or stratification-based estimation. Poso et al. (1999) have tested *k*-nn and stratification as alternative estimation methods with the same auxiliary data and their results showed that the accuracy of *k*-nn and stratification was similar for the estimation of plot variables. As far as similar auxiliary data are used, the estimation results of *k*-nn and stratification should be similar, since both methods are based on calculating distances in the feature space. The advantage of stratification is that it is capable of producing unbiased estimates for means on a population level.

As noted, the number of image features that can be extracted from RS images is high, and the number of auxiliary data variables can be expanded even higher by utilizing several auxiliary data sources. Thus, the problem of high dimensionality in the feature space must be controlled to avoid the detrimental effect of the curse of dimensionality in the estimation procedure (e.g. Beyer et al. 1999, Hinneburg et al. 2000, Aggarwal et al. 2001). The principal component transformation applied in some of the substudies is a means for reducing the number of auxiliary data sources while retaining most of the information contained in the original auxiliary data variables, when there is high mutual correlation between the auxiliary data variables. Nevertheless, the capability of the principal components for estimating the forest attributes is not necessarily any better than that of the original variables. In substudy II sequential forward selection was applied for analyzing which features significantly contributed to the estimation accuracy and what was the appropriate number of features needed for robust estimation results. This resulted in clear improvement in the accuracy of the forest estimates. A hierarchical combination of satellite and aerial image data utilizing k-means stratification and k-nn estimation within the strata has also been tested, but the results in improving the accuracy of the estimates were not promising (Tuominen 2005). The use of genetic algorithms in feature selection has been studied by Kudo and Sklansky (2000). Their results indicate that the genetic algorithm works well in problems with a large number of dimensions. Tomppo & Halme (2004) also have studied the genetic algorithm to find optimal weights for variables used in k-nn estimation. The genetic algorithms appear to have significant potential for solving the problem of feature selection in high-dimensional feature space.

The geostatistical interpolation methods applied in this study did not perform well in estimating forest attributes. In a managed forest, silvicultural operations generally determine the spatial structure of the forest, virtually eliminating spatial autocorrelation at relatively short distances. For example, Wallerman et al. (2002) have enhanced geostatistical interpolation by applying a kriging procedure adapted to forest edges detected in satellite images. To a certain extent, the applicability of geostatistical interpolation may also be a question of the geographic scale in which the geostatistical methods are applied. To improve the stand-level estimates, the density of field data should be significantly higher than applied in this study, but the cost of the field data would make the method economically infeasible. At the level of a country or a province, where geographic and climatic variation may significantly affect the forest characteristics (e.g. main tree species), the variation must be somehow taken into account. For example, the coarse-scale variation in forest data (present in field data or previous inventory data) can be used as an auxiliary data source (e.g. Tomppo & Halme 2004).

As mentioned earlier, it is often appropriate to define a forest as a population of sample plots in sampling-based forest inventories. Since the silvicultural treatment unit is a stand, the sampling unit applied (i.e. inventory unit) should enable estimation of forest attributes at the stand or, preferably, substand level. Thus, one stand should cover several sampling units. In principle, the same sampling unit size is used at each sampling phase (Schreuder et al. 1993), but often it is adequate for forest inventories that correlation exists between the field data and auxiliary data (i.e. the areas of field measurement and extraction of the auxiliary data need not be exactly the same). In some applications image pixels have been utilized as first-phase sample units. However, the pixel size in various RS materials varies greatly, and it is not necessarily appropriate to fix the first-phase sample units to the spatial resolution of a certain RS image. When the first-phase sample is defined independently of a pixel size, the image features can be extracted using a suitable unit. Generally, square windows centred around the sample plots have been utilized in extracting image features, particularly from VHR imagery. On the other hand, based on substudy III, image segments also have some advantages and could be used as sampling/inventory units as well, assuming that the field data can be measured in a representative way for a segment.

In forest inventory methods, in which the inventory unit can be monitored over consecutive inventories, it is possible to accumulate information throughout the monitoring period. Since the stand delineations of the consecutive stand inventories do not remain unaltered, i.e. the forest stand can be considered a throwaway inventory unit, the method provides a poor basis for accumulating information over time. In a two-phase point inventory it is possible to accumulate information during subsequent inventories, since the location of the inventory unit does not change. This option is advantageous in particular with forest characteristics related to the forest site, such as soil type, moistness/wetness etc. These characteristics change relatively slowly compared with growing stock-related characteristics and need not necessarily be surveyed in each inventory. However, data from previous stand-level inventories provide a poor basis for utilizing the site information, since the stands are usually delineated as treatment units and do not follow the borders of ecologically homogeneous areas. An accurate inventory of the site-related characteristics would in any case lead to smaller stand size than that currently utilized in forest management planning.

The information contained in RS imagery is limited with regard to its capability for predicting the forest characteristics. The fundamental reason for this is the fact that not all forest characteristics can be distinguished or recognized by a space- or airborne sensor. This holds true in digital image interpretation, irrespective of any improvements in methods of analyzing RS data, as well as in visual image interpretation regardless of the skills of an interpreter.

Currently, maximum accuracy of RS-based forest estimates is likely to be achieved by combining the information of aerial imagery and active sensors such as airborne SAR (e.g. Holmström & Fransson 2003, Folkesson et al. 2005), profiling radar (e.g. Hyyppä et al. 2000) or airborne laser scanning (ALS). Forest inventory experiments with profiling radar and ALS have proven that they are valuable data sources for stand-level forest inventories (e.g. Naesset 1997, Hyyppä et al. 2000). ALS is an especially accurate method for forest inventory, particularly in relation to forest attributes based on tree size and crown dimensions (e.g. Nilsson 1997, Naesset & Bjerknes 2001, Suvanto et al. 2005). CIR aerial photographs can be used to complement ALS in estimation of attributes, for which ALS is not well suited, such as tree species and forest health. Naesset (2004) has tested a practical two-phase stand inventory method based on the use of laser scanning and field plot measurements, achieving a higher accuracy of inventory data than conventional inventory methods currently in practice.

When the prospects of the two-phase sampling-based forest inventory method and traditional stand inventory method are examined, it can be noted that the traditional stand inventory method has already reached most of its developmental potential. It is conceivable that the efficiency of the stand inventory method can be slightly improved by utilizing advanced technology in field measurement, such as data-recording measuring instruments and field computers with digital maps attached to a GPS receiver. On the other hand, the same technology can be utilized as well in field measurement of other inventory methods. Apart from this, the productivity of the stand inventory method can be increased by lowering the accuracy requirements of the inventory data and spending less time per stand or area unit. The two-phase sampling-based inventory method still has a wealth of developmental potential. It is possible, for example, to increase the estimation accuracy (or cover larger areas with less cost) by using RS data from more advanced sensors, such as laser scanners. Another way of improving the estimation accuracy is to develop automatic data-processing methods for extracting more information from existing and future data sources.

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