Controlling the estimation errors in the Finnish multisource National Forest Inventory

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Academic dissertation

To be presented, with the permission of the Faculty of Agriculture and
Forestry of the University of Helsinki, for public examination in
Auditorium 2 (sali 2), Viikki Infocentre, Viikinkaari 11, on 6 February 2004,
at 12 o'clock noon.

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Abstract

This study concentrates on the assessment of the error in the estimates of Finnish multisource National Forest Inventory (MS-NFI) and its minimisation, as well as for the k–nearest neighbour method (k–NN). The MS-NFI utilises optical area satellite images, mainly Landsat TM and ETM+, and digital maps, in addition to field plot data, to produce geo-referenced information, thematic maps and small-area statistics. The non-parametric k–NN estimation method is used in the estimation of forest variables for single pixels and to define weights of field plots to a particular computation unit, e.g. a municipality. First, the estimation parameters that are optimal for the objectives of MS-NFI were achieved by examining the prediction error at the pixel level. Secondly, potential variables, covariates or other exogenous variables, what might explain the residual variation in the k–NN estimates were studied. Finally, two methods were presented aimed at reducing the effect of map errors on MS-NFI small-area estimates.

The selection of the estimation parameters was examined for four study areas that covered a greater part of the variation found in the Finnish forests. The error estimates were obtained by leave-one-out cross-validation. The most important parameters for minimising the estimation error of the total volume and volume by tree species at pixel level were the value of k, the geographical horizontal reference area (HRA) radius used to select the training data and the stratification of the field plot pixels, and training data employing the site class map. With the sampling intensity in the 8th and 9th Finnish National Forest Inventory, a geographical HRA with a radius of 40–50 km was found to be optimal for the total volume estimates and for volumes by tree species on the mineral land map stratum. For the peatland stratum, a wider reference area, 60–90 km, was required.

The main sources of error in the Finnish MS-NFI are considered to be the representativeness of the field sample with respect to the estimation problem, the low dynamic range of spectral channel values on forestry land (FRYL) on high resolution optical satellite data, the small size of the NFI field plots compared to the pixel size in image data and the locational errors in the image and field plot data. The first principal component (PC1) of the Landsat TM or ETM+ channel values of the field plot pixel was strongly related to the residual variation in the volume and basal area estimates. The residual variances of field plot volume were regressed against PC1 and the model was used to remove the trend component of PC1 from

the residuals, but the random error component still remained high in the residuals.

A calibration method was introduced to reduce the map errors on MS-NFI small-area estimates. The method was based on large-area estimates of map errors; i.e. the confusion matrix between land use classes of the field sample plots and corresponding map information. A method to compute the calibrated field plot weights was also presented. These weights were in turn used to calculate the small-area estimates. In the second method, the k-NN estimation was carried out separately within each map strata employing all the field plots from all the land use classes within each stratum.

Comparisons were made between the aggregates of MS-NFI small-area estimates from the two methods and field inventory estimates at the region level in order to determine the total amount of correction, and for the subregions (groups of municipalities) to detect the possible bias in the small-area estimates. Although quite different in nature, both methods corrected the bias in the FRYL area estimates. The FRYL estimates of the calibrated MS-NFI are consistent with post-stratified estimates at the region level. When compared to the field inventory based estimates of tree species volumes for subgroups of municipalities (1738–4238 km^2), the stratified MS-NFI performed better than the original MS-NFI and calibrated MS-NFI. Some of the estimates from the two latter methods differed by more than two standard errors from the field inventory estimates in the subregions of the test data.

The parameter selection methods and the small-area estimation map error correction methods, together with the field inventory estimates and their standard errors, provide a method for reducing the estimation error and a reference of the accuracy of the MS-NFI results. However, if there is a significant systematic error in the small-area estimates of a certain subregion, it may not be possible to remove the error by varying the estimation parameters. Other methods or auxiliar data is needed to do this.

Preface

After working several years with the operative multisource National Forest Inventory, I got the opportunity to concentrate on studying the estimation problems in the multisource method, after admission to the graduate school "Forests in Geographical Information Systems" in the University of Helsinki, in 1998. This work was mainly funded by the Finnish Foresters Foundation and the Finnish Forest Research Institute. I am grateful for their financial support.

I am also grateful for being able to work in the NFI-team led by my supervisor and co-author, Prof. Erkki Tomppo. His personal example of commitment to research work and experienced advice has been invaluable. I am also particularly indebted to my second supervisor and co-author, Dr. Juha Heikkinen for his guidance in the statistical problems, as well as in all practical problems but, most of all, for inspiring discussions of research problems. I would like to thank my pre-examiners, Prof. Michael Köhl and Dr. Ronald McRoberts for their valuable comments.

I would like to acknowledge Prof. Jouko Laasasenaho and Dr. Markus Holopainen for their support and management of the graduate school. I have enjoyed their company and that of the fellow students in the graduate school during these years. I also wish to thank Emeritus Prof. Simo Poso and Prof. Annika Kangas from the Department of Forest Resource Management for their support and valuable comments to my studies.

I have enjoyed discussions with Dr. Helena Henttonen, my first employer in scientific work, concerning statistical problems in forest inventories. Mr. Kai Mäkisara gave me advice on remote sensing and computer science matters, and provided valuable comments on the articles. I also wish to thank Dr. Jari Varjo for encouraging me to apply to the GIS school membership and support as a member of the executive board of the graduate school. With Mr. Jouni Peräsaari, with whom I shared the room during this work, I have had useful discussions on problems in the operative multisource inventory. Mr. Arto Ahola and Mr. Antti Ihalainen have helped me in the application of NFI field data. I am grateful to Dr. Ashley Selby for editing the English language both in compilation and in the articles and Ms. Anna-Kaisu Korhonen for her technical assistance. I wish to extend my gratitude for the whole NFI-team for their support and good working spirit. I also wish to thank the numerous persons not mentioned so far who have contributed to the completion of the work.

Finally, I wish to express my gratitude to my father Hannu, and my mother Eeva for supporting my work.

Helsinki, January 2004   Matti Katila

Contents

List of separate studies

This dissertation includes the following separate studies, which are referred to by roman numerals in the text as follows:

I Katila M., and Tomppo E. 2001. Selecting estimation parameters for the Finnish multisource National Forest Inventory. Remote Sens. Environ. 76: 16–32.

II Katila M. 2004. Error variatons at the pixel level in the k–nearest neighbour estimates of the Finnish multisource National Forest Inventory. Manuscript.

III Katila M., Heikkinen J., and Tomppo E. 2000. Calibration of small-area estimates for map errors in multisource forest inventory. Can. J. For. Res. 30: 1329–1339.

IV Katila, M., and Tomppo, E. 2002 Stratification by ancillary data in multisource forest inventories employing k–nearest neighbour estimation. Can. J. For. Res. 32:1548–1561.

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Fields of responsibility

In substudy I, Katila designed most of the tests, carried out the programming and drew the conclusions. Tomppo proposed some of the tests concerning the variation in the training data. He also participated in the writing of the manuscript and drawing the conclusions. In substudy IV, Katila designed the stratification in the MS-NFI method, carried out the analysis and wrote the article together with Tomppo. Tomppo carried out the necessary changes in the k–NN estimation program. In substudy III, Katila planned the realisation of calibration in the multisource method, carried out the analysis, drew the conclusions and wrote the manuscript together with Heikkinen and Tomppo. Heikkinen formulated the calibration method to be applied in the multisource inventory and wrote the statistical background of the estimation of standard errors (Appendix A). Tomppo carried out the necessary changes in the k–NN estimation program.

1. Introduction

1.1. The objectives of national forest inventories

There are three main types of forest inventories: the operational, the management and the national forest inventories (Cunia 1978). The objective of national forest inventories is to produce statistically unbiased, reliable forest resource information for large areas for strategic planning, primarily by decision makers. Estimates of both current values and rates of changes of forest resources are required (Cunia 1978). Periodic national forest inventories can provide information on trends in the state of forests (Lund 1993). The estimates are required, e.g. of the forest resources, growing stock, growth, health of forests and, increasingly, of the biodiversity in the forests. The national forest inventory methods should be statistically valid, cost-efficient and flexible (Cunia 1978).

In recent years, there has been a growing interest in obtaining national forest inventory results for smaller areas than had previously been possible based on field samples only, e.g. for municipalities and even for single forest stands, for forest planning, timber procurement and biodiversity assessment purposes (Tomppo 1987, 1991, Schreuder et al. 1993, Kangas 1996, Tokola & Heikkilä 1997, Nilsson 1997, Tomppo et al. 1998, Franco-Lopez et al. 2001). The remote sensing data from airborne and spaceborne sensors has been the key to a more efficient use of forest inventory data. Some of the advantages of remote sensing data are that they offer a synoptic view of the study area, the data can be obtained rapidly for large areas and they can be processed digitally (Schreuder et al. 1993). Traditionally, the remote sensing data has been used as a part of the sampling design, in order to decrease the cost of field work rather than to try to obtain results for significantly smaller areas than normally used in strategic forest inventories (Loetsch & Haller 1973). The classification based on remote sensing data has been used in stratified sampling (Tomppo et al. 2001), multistage-sampling (Schreuder et al. 1993) and multiphase-sampling (Poso 1972, Schreuder et al. 1995). The post-stratification may also provide an effective means to decrease the variance in the estimates after the actual sampling (McRoberts et al. 2002). The concept of multisource forest inventory employing remote sensing data and digital map data has been introduced to forest inventories. One prerequisite for a multisource inventory method is that it should be possible to estimate all the variables measured in the field (Kilkki & Päivinen 1987).

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1.2. Multisource national forest inventory

Multisource national forest inventories employ various sources of geo-referenced data, in addition to field inventory data, to obtain more reliable estimates or estimates for smaller areas than when employing the pure field plot data only. Holmgren & Thuresson (1998) list the following types of forest inventory applications employing remote sensing data: land cover classification of timber types, estimation of the forest variables for forest management planning purposes, segmentation to determine stand and other boundaries, landscape ecology analysis and large-scale forest inventories. Continuous variables, such as stand volume, volume by tree species, age and mean breast height diameters have been estimated for forest management planning purposes employing optical area remote sensing data and field plot data. Sampling based methods, parametric and non-parametric regression methods and neural networks have been used, occasionally in conjunction with segmentation techniques (Poso et al. 1987, Tomppo 1987, 1991, Tokola et al. 1996, Hagner 1997, Mäkelä & Pekkarinen 2001). In small-area estimations, indirect estimation methods are used and support is obtained from similar computation units by applying methods to link the field plot data and the auxiliary data (Schreuder et al. 1993). Non-parametric regression has been used for small-area estimation in the Scandinavian countries and the United States (Tomppo 1991, Tokola et al. 1996, Nilsson 1997, Gjertsen et al. 2000, Franco-Lopez et al. 2001). The non-parametric regression methods are relatively easy to use and require no assumptions about the shape of the model.

In multisource forest inventories, both airborne and spaceborne imagery from active or passive sensors may be employed, although optical area remote sensing data has mainly been employed. Aerial photography has demonstrated its applicability for both large area and management inventories (Poso 1972, Loetsch & Haller 1973, Schreuder et al. 1993). Airborne laser instrument and radar data applications in the mapping of forests are still at the development stage (Hyyppä et al. 1997, Naesset 2002).

The earth observation satellites provide continuous image data for large areas (Campbell 1996) and the increase in the number of satellites may help to overcome the problem of cloudiness in the image data. The high resolution image data from Landsat and SPOT satellite programs have been used frequently in large-area land-use or land-cover classification, as well as for multisource forest inventories (Campbell 1996, Eisele 1997, Nilsson 1997, Tomppo et al. 1998, Franco-Lopez et al. 2001). The medium resolution satellites have shown potential in estimating

volume and biomass, by covering large areas at low cost (Tomppo et al. 2002). The radar satellite imagery (SAR) has yielded less accurate forest parameter estimates than high resolution optical satellite data (Tomppo et al. 1996). The spectral and spatial resolution of the remote sensing data has been enhanced in multisource forest inventories by employing multitemporal or multiple instrument image data (Poso et al. 1999, McRoberts et al. 2002). New, very high resolution satellite data with 1–5 m pixel size is now available, but it is costly and requires new estimation methods due to the scale of the target, i.e. forest stands and trees (Woodcock & Strahler 1987, Hyppänen 1996, Pekkarinen 2002).

Topographic databases, digital elevation models and other map data are readily available in digital format (National Land Survey of Finland 1996). However, the map data may include location errors, it may be out-of-date and the attributes may not correspond to the ones used in the multisource forest inventory. Despite the possible inconsistencies between map data and remote sensing data, the map data can be used to improve an estimation either as ancillary information or together with remote sensing data in the analysis (Wilkinson 1996).

The Finnish multisource National Forest Inventory (MS-NFI) utilises optical area satellite images and digital maps, in addition to field plot data, to produce geo-referenced information, thematic maps and small-area statistics. A non-parametric k–nearest neighbour method (k–NN) is used in the estimation of forest variables for single pixels and to define weights of field plots to a particular computation unit, e.g. a municipality (Tomppo 1991). One advantage of the k–NN method is that all the inventory variables can be estimated simultaneously. Field data from surrounding computation units (municipalities), in addition to the unit itself, are utilised when estimating results for the particular unit. It is therefore possible to obtain estimates for smaller areas than would be the case when employing sparse field data only (Kilkki & Päivinen 1987, Tomppo 1991).

1.3. Aim of the study

This study concentrates on the assessment and minimising of the error in the Finnish MS-NFI and the k–NN estimation method. The errors are studied at the pixel level, for small areas, i.e. municipalities and at the region level. First, the different sources of error and their significance in the MS-NFI estimation are studied. The general outlines of small-area estimation and the non-parametric regression methods are discussed and the application of these methods in the MS-NFI is in-

troduced.

In the k–NN estimation, the overall error is minimised by tuning the estimation parameters. Leave-one-out cross-validation, a resampling technique, is used to guide the parameter selection at the pixel level. These techniques are applied to choose the parameters for the Finnish MS-NFI. The remaining variation in the error is studied and potential explanatory variables are sought to model the prediction error.

Two methods are developed to decrease the error in the small-area estimates caused by the forestry land (FRYL) area delineation based on erroneous map data. FRYL consists of forest land, other wooded land and waste land. A statistical calibration method posterior to the k–NN estimation is compared to the k–NN estimation applied by map strata. The MS-NFI small-area estimates are validated by groups of municipalities –subregions– and at the region level against the field inventory based key forest variable estimates and their standard errors.

2. Error sources in multisource national forest inventory

In multisource forest inventories, the number of errors increase with the number of data sources. Explanatory models or standardised rules must be applied at various phases of data production (Freden & Gordon 1983, Tomppo et al. 1997, Burrough & McDonnell 1998), e.g. a definition of land use classes, volume models for sample trees and calibration equations for the satellite imagery exo-atmospheric radiances. Various types of error taxonomies can be used to describe the error structure of the MS-NFI. The error components of a forest inventory are measurement errors, sampling errors and model estimation errors (Cunia 1965). The accuracy of the spatial data can be grouped into thematic, positional and temporal accuracy (Burrough & McDonnell 1998) or thematic and non-thematic errors (Foody 2002). The measurement errors in remote sensing procedures can be divided into errors in the measurement of field data, errors in the measurement of remote sensing data, and the misregistration in space or time between field variables and remote sensing variables (Curran & Hay 1986). The main sources of error in the Finnish MS-NFI are considered to be the representativeness of the field sample with respect to the estimation problem, the low dynamic range of spectral channel values on FRYL on high resolution optical satellite data, the small size of the NFI field plots compared to the pixel size in image data and the locational errors in the image and field plot data (II; Halme & Tomppo 2001). In the Table 1, several sources of error in the MS-NFI data are presented. They are grouped according to spatial data and forest inventory error types. Some estimates of error magnitudes are given, based on the literature and practical experiences in the Finnish MS-NFI.

Table 1. Sources of error in the data for Finnish MS-NFI employing Landsat Thematic Mapper image data

Data source	Error source	Thematic			Positional	Temporal
		Sampling	Measurement	Model		
Field plot	Intensity of sample and size of field plot	Does not cover the variation in the field and in the image	Field plot size (max. 492 m^2) < Instant Field of view of instrument (IFOV) (900 m^2) < Effective IFOV		Location error, RMSE 20 m (Halme & Tomppo 2001)	Field plot measurement and image acquisition date
	Tally trees		diameter at breast height measurement	Generalising sample tree variables for tally trees		
	Sample trees		Variables measured for volume models	Volume equations		
RS instrument	Spatial		Sensor sampling function causing spatial bias within pixels (Bastin et al. 2000)		Landsat 5 TM interband location error 0.2-0.5 pixels	
	Spectral Radiometric		Signal to noise ratio	Precalibration equations		
	Viewing		Varying irradiance due to latitude Varying irradiance due to instrument viewing angle			
	Atmosphere Target		Scattering Varying irradiance due to topography	Reflection model for topographic correction	Ground altitude variation	Varying irradiance due to seasonal effects (multitemporal images)
	Processing				Image system correction 90 % of errors less than 15 m (Landsat 5 TM) (Freden & Gordon 1983), repeated image lines (Bastin et al. 2000), geo-coordinate rectification model RMSE 15–20 m (Landsat 5 TM) (Tomppo 1996)	
Topographic map data	(Burrough & McDonnell 1998)		Correspondence of map attributes to field plot data	Map conversions, generalisation	Accuracy and precision	Field work date
Digital elevation model	(Burrough & McDonnell 1998)		Elevation curve density in the topographic map	Triangulation method accuracy		

3. Small-area estimation and k–nearest neighbour estimation in multisource national forest inventory

3.1. Small-area estimation

Small-area estimation refers to the calculation of statistics for a small subpopulation (domain) within a large geographical area. Sample sizes are often too small to provide reliable direct estimators for a small area (Rao 1998). Small-area estimates gain support from related areas that are nearby or similar according to auxiliary information (Schreuder et al. 1993). The indirect estimation methods are grouped into estimators based on implicit models and model-based estimators (Rao 1998). The former group contains a synthetic estimator, for which it is assumed that the small areas have the same characteristics as the large areas (Gonzalez 1973). A reliable direct estimator for a large area is used to derive an estimator for a small area (Rao 1998). In the model based methods, either non-parametric or parametric methods are applied to the auxiliary information in order to derive the small-area estimates. Because the small-area estimators are, at least partially, model-based, the estimates obtained are usually biased. However, the biased estimator can still be useful if the mean square error (MSE) of the estimator is smaller than that of the unbiased estimator (Kangas 1996).

Kangas (1996) employed several parametric and non-parametric models in a small-area estimation of municipality level volume estimates using NFI field plot data and their coordinates as auxiliary data. The mixed model estimator was found to be the most reliable of the tested models. In general, models that can be corrected for their observed residuals were recommended: mixed models, the Mandallaz estimator and kriging estimator (Kangas 1996). The area interpretation of weights for field plots used in a small-area estimation for a particular computation unit is useful, e.g. for management planning systems. To obtain this interpretation, all the weights must be positive, the weights must be same for all the target variables and add up to the total area of the calculation unit (Tomppo 1996, Lappi 2001). The weighting approach retains the natural covariation between the field plot variables within each field plot.

In the multisource inventories, non-parametric regression methods have been widely used to estimate the forest variables by associating the field plots directly to the pixels of satellite image data in order to produce thematic maps (Kilkki & Päivinen 1987, Tomppo 1991, Nilsson 1997, Franco-Lopez et al. 2001). Area inter-

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pretation is used at least in the reference sample plot method (Kilkki & Päivinen 1987) and Finnish MS-NFI (Tomppo 1991). Lappi (2001) argues that the chosen nearest neighbour field plots may not add up to statistically unbiased or statistically optimal estimates for the region to be estimated. He presented a small-area calibration estimator that minimises the sum of distances between prior and posterior weights of field plots for a distance function while respecting the calibration equation based on spectral values of satellite image. A spatial variogram model was applied for calculating the variances of the calibration estimator.

The bias in the Finnish MS-NFI small-area estimators has been assessed by applying the standard error estimates of the field inventory estimates at the region and subregion level (III), because an explicit error variance estimate is not available. Some small-area estimation methods have estimators for variances. The resampling methods are useful in the estimation of the error for small areas, but unlike in the kriging methods, it is difficult to take into account the possible autocorrelations in the data (Davison & Hinkley 1997).

3.2. k–nearest neighbour estimation method

Nonparametric regression methods are a collection of techniques for fitting a curve when there is little a priori knowledge about the shape of the true function, and the form of the function is not restricted. These methods are applied in exploratory analysis and, increasingly, as stand-alone techniques (Altman 1992, Linton & Härdle 1998). Nonparametric regression methods can be considered to belong to the group of generalised additive models (Hastie & Tibshirani 1997). The general formula for nonparametric regression for a simple bivariate dataset $(X_i, Y_i)_{i=1}^n$ is

$$Y_i = m(X_i) + \epsilon_i, \qquad i = 1, \ldots, n, \tag{1}$$

where ϵ_i is a random error independent over observations, $\mathrm{E}(\epsilon_i | X_i = x) = 0$ and $\mathrm{Var}(\epsilon_i | X_i = x) = \sigma^2(x)$. $m(\cdot)$ is the regression function of Y on X and m is estimated at the group of observations covering some subset $\mathcal{X}$ in support of X. It is a linear smoother of the form $\sum_{i=1}^n W_{ni}(x)Y_i$ for the weights $W_{ni}(x)_{i=1}^n$ depending only on $X_1, \ldots, X_n$ (Linton & Härdle 1998). The kernel and the k–nearest-neighbour estimators are among the most common smoothers in forestry applications.

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The kernel estimate is a weighted average of the response variable in a fixed neighbourhood, bandwidth h, of x; the Nadaraya-Watson kernel estimate is

$$\hat{m}_h(x) = \frac{\sum_{i=1}^n K_h(x - X_i)Y_i}{\sum_{i=1}^n K_h(x - X_i)}, \tag{2}$$

where $K(\cdot)$ is any kernel function. The k–NN estimate is a weighted average of the response variables in a varying neighbourhood, defined by those X that are among the k–NNs of a point x

$$\hat{m}_k(x) = \frac{\sum_{i \in \mathcal{N}(x)} Y_i}{k}, \tag{3}$$

where $\mathcal{N}(x)$ is the set of indices of the k–NNs of x. Eq. 3 is comparable to a kernel smoother applying a uniform kernel and a variable bandwidth h (Linton & Härdle 1998).

The NN algorithms have been extensively used in the statistical pattern recognition since the paper by Fix & Hodges (1951) in which they presented the simple nearest neighbour classifier. The pattern recognition system typically consists of a feature extraction and classification phase. Dasarathy (1991) reviews several studies concerning the classifier risks for finite and infinite samples, the asymptotic performance of the classifiers, selecting the training data, choice of k and metrics. The nearest neighbour distances are also used in geostatistics (Bailey & Gatrell 1995). Apart from the multisource inventories, the k–NN method and kernel methods have been used in other fields of forest inventory, such as basal area diameter distribution estimation (Haara et al. 1997, Maltamo & Kangas 1998), generalising sample tree data (Korhonen & Kangas 1997) and generalising detailed stand characteristics from stand databases employing less accurate stand information (Moeur & Stage 1995, Malinen 2003).

The choice of k affects the shape of the regression function; when k increases a smoother fit is obtained with a smaller variance but larger local bias for $\hat{m}_k(x)$ with given x and a fixed sample size (Altman 1992). The mean squared error (MSE) is a commonly applied optimality criterion for error minimisation. The quadratic loss by MSE can be studied at a single point x or globally (Linton & Härdle 1998), which may alter the selected smoothing parameter k.

The question may arise, how to select k as the sample size n increases? In pattern recognition, the k–NN classifier has the asymptotic property that when a sequence of k_n satisfies $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$, the classification error approaches the optimal rate of Bayes decision rule for discrete variables (Stone 1977,

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Keller et al. 1985). However, in practical problems with moderate n, the optimal selection depends largely on the distributions of the variables (X, Y) (Kulkarni et al. 1998).

The k–NN estimates are potentially biased if the true function has substantial curvature (Altman 1992); e.g. the convex relationship between satellite digital numbers (DN) and field plot volume should yield a positive bias in the estimates (Nilsson 1997). The weighting of the neighbours can be used to decrease the bias (Altman 1992).

Resampling techniques, the most popular of them being cross-validation, are frequently applied to the error quantification and parameter selection for classification and estimation problems. Bootstrap methods can be used to estimate the generalisation error and also confidence limits. Efron & Tibshirani (1997) introduced the .632 bootstrap method and improved .632+ bootstrap method for classification problems. These are smoothed versions of cross-validation, partially correcting the bias in the bootstrap variance estimates.

McRoberts et al. (2002) pointed out several weaknesses in the k–NN estimator compared to parametric linear regression: the small k value may result in RMSE values larger than the standard deviation of the observations, and unrelated predictor variables included in the subset of covariates may increase the MSE. The latter case is related to the 'curse of dimensionality'; the rate of convergence for optimal solutions to non-parametric regression is slower in multidimensional cases (Linton & Härdle 1998). In the k–NN estimation, the observations from large feature space distances may be negatively correlated, whereas observations separated by large geographic distances are expected to be uncorrelated (Tokola et al. 1996, McRoberts et al. 2002). The k–NN estimates may be biased near the boundaries of the feature space, because the nearest neighbour distances tend to be greater and the neighbours may be concentrated in one direction only. The spatial distribution of the neighbours in the feature space can be taken into account in the estimation. Local adaptation of non-parametric methods models may help to overcome the edge effect problem as well as the bias caused by strong curvature in the true regression function (Malinen 2003).

The standard techniques for bandwidth selection may fail in a situation where the ϵ_i satisfy $E(\epsilon_i | X_i = x) = 0$ but are autocorrelated. Altman (1990) studied the selection of bandwidth for the kernel estimator employing data with correlated errors. Cross-validation produces parameters favouring undersmoothing in this kind

of situations (Altman 1990). A simple way to correct the effect of autocorrelation in cross-validation is to leave out more than one observation. Altman (1990) suggested either adjusting of the selection criteria or the transformation of residuals. The correlation function should be estimated from the data. However, when the form of the function is not known, the wrong choice of smoothing parameter can induce false serial correlation in the residuals (Opsomer et al. 2001).

3.3. Parameter selection in the MS-NFI k–NN estimation (I)

In the k–NN estimation, the overall error (or other selected criterion) is minimised by tuning the estimation parameters. The selected parameters are the features of interest and their weighting; the distance metric and the smoothing parameter, value of k (Malinen 2003). The MS-NFI also has parameters related to the selection of training data: stratification of the image and field plots on the basis of digital map data; and the geographical reference area from which the nearest neighbours are selected (Tomppo 1996, Tokola 2000).

The aim in (I) is to examine the selection of the estimation parameters employing the error estimates obtained from leave-one-out cross-validation. There were two objectives in the selection of parameters: to minimise the MSE of the key variable estimates and at the same time to retain some of the variation of the original field plot data in the spatial variation of the estimates. The statistical significance of the global bias in the k–NN estimates was also examined in (I). Only one set of parameters per satellite image is preferred to maintain the covariation between the field plot variables in the estimates, consequently a weighting (Tomppo & Halme 2004) or other compromise is required in the operative MS-NFI between the set of parameters obtained for different variables.

The original features of the Landsat TM spectral channel values and Euclidean distance measure were used. The weighting of the Euclidean distance had only a slight effect on the global MSE in (I), (c.f. Tokola et al. 1996). A mild topographic correction was carried out for the DN values of satellite image spectral channels using a modification of the Lambertian surface reflectance assumption employing digital elevation model. Outside of northern Finland, the topographic correction had only local significance.

The two somewhat contradictory objectives –minimising the MSE and retaining variation– have led to heuristic rules or subjective selection of k in MS-NFI ap-

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plications employing Landsat TM or ETM+ image data. Several values of k have been applied: one (Franco-Lopez et al. 2001), 5–10 (Tomppo 1996), 10–15 (Tokola et al. 1996, Nilsson 1997), a minimum relative decrease RMSE k in (I) and an 'objective criteria' (minimum MSE) k_{opt} (McRoberts et al. 2002). In (I), the objectives defined earlier were met under the condition of minimum decrease of 0.5 % between k and $k+1$ sought from a window ranging from $k+1$ to $k+5$. This criterion was needed when different geographical reference areas were used to select the training data. It yielded k values 7–11 for the total volume estimates.

Landsat images cover geographically large areas that may contain edafic and climatic variation both horizontally and vertically. The atmospheric conditions and the radiometric properties of the image data may also vary within the image (Helder et al. 1992, Tomppo et al. 1998). The MS-NFI estimates will be biased for a forest area if there is locational dependency in the spectral values of pixels within the training data (Kilkki & Päivinen 1987). Kilkki & Päivinen (1987) proposed the use of the same training data (locationally uncorrelated) covering the particular surveyed forest area. On the other hand, the training data should be large enough to cover the true range and variation in the inventory area. A fixed size moving geographical horizontal (and vertical) reference area windows (HRA and VRA) have been used in the Finnish MS-NFI (Tomppo 1996). Because the locational dependencies are difficult to model explicitly, the global unbiasedness is checked using the cross-validation method.

The RMSE of the total volume and volume by tree species were studied against the geographical HRA radii. The mineral and peatland strata were analysed separately because there is high moisture content and moisture variation in the peatland soils compared to mineral soils. A near minimum MSE for volume estimates was obtained for mineral land already with a 20 km radius and for peatland with a 30 km radius, or employing 150–300 field plots. The maximum radius was sought by estimations based on field plots outside different geographical HRA. Significantly biased estimates were obtained for spruce and pine volume in some subregions that employed field plots from 40–60 km and larger radii. On mineral stratum, the 40–50 km geographical HRA radius yielded, on average, 400–600 field plots to the training data and did not increase the RMSE or decreased the bias in some cases. Nilsson (1997) in a simulation study recommended the same number of field plots for the estimation of total volume.

The area of peatlands is smaller than for mineral soils and their proportion varies across the country; generally larger geographical HRA radii, 60–90 km, are re-

quired to obtain a sufficient number of field plots. However, if the average number of field plots in the peatland stratum falls below 300, an estimation in two strata may not be justified. This map-based stratification is not very accurate and there are also differences within the peatland forests (Tomppo 1996). However, it was demonstrated in (I) that the stratification significantly decreased the global bias of the volume estimates within both strata.

Tokola (2000) found a 20 km geographical HRA radius to be optimal for total volume and pine and a 30 km radius for spruce and deciduous volume estimates in a study with NFI data in Eastern Finland applying cross-validation for error estimation. However, the decrease in the degree of determination was slow and the study material enabled radii only up to 40 km. Lappi (2001) in a small-area estimation study that used a calibration estimator and NFI field plots, concluded that 500 field plots outside the county to which the timber volume was to be estimated was reasonable in addition to the field plots of the county itself. To an average size county in the particular study area this would yield an approximately 35 km geographical HRA radius fixed to the centre of the county, assuming circular counties. However, the field plots outside the county obtained less weight in the estimation.

The parameters obtained are generally suitable for the MS-NFI, but a significant global bias in the results may still remain. Local bias may occur in the small-area estimates, especially in the edges of satellite image data or inventory area, when trend-like large-scale changes occur in the forest. The NFI sample is too small for reliable error estimation in small areas. The bias in the key field plot variables can be studied in the parameter selection phase or posterior to the k–NN estimation by comparing the MS-NFI estimates in the subregions (groups of municipalities) to the NFI field inventory estimates.

3.4. Error variations at the pixel level in the k–NN estimates of the MS-NFI (II)

There are several sources of error in the multisource forest inventories because they employ measurement data and models of different natures and scales. These errors contribute to the uncertainty in the k–NN estimates. At the pixel level, the prediction errors measured with relative RMSE are usually high, e.g. 50–80 % for field plot volume (I; Tokola et al. 1996). These error estimates are obtained by cross-validation.

The aim in (II) has been to study the variation in the error (residuals of the k–NN estimation by cross-validation) and to see whether there is a functional dependency between observable covariates and the prediction error. The potential explanatory variables for which the values could be obtained for every pixel were tested: i.e. estimated values of forest variables, variables of the selected nearest neighbour field plots and the spectral channel or digital map data values of pixels. The field plots in the training data were studied as an independent sample, ignoring the possible spatial autocorrelation between the field plots within the same cluster. The focus was on pixel-level prediction error of field plot volume and weighted mean of basal area (BA) observations in the k–NN estimation. The possible cumulation of systematic error in small areas was beyond the scope of the study.

The effect of locational error, which is quite significant in the MS-NFI training data, was minimised by employing a procedure to reassign the satellite image information to the field plot data (Halme & Tomppo 2001), or by restricting the number of mixed pixel field plots in the training data. The weighted mean of BA observations in and near the field plot was used instead of pure field plot BA to decrease the sampling error in the dependent variable. The use of weighted BA decreased the random variation (coefficient of variation) in the training data, as well as the MSE in the cross-validation. These results suggest that the optimum field plot size for MS-NFI purposes is larger than that currently applied when high resolution optical satellite data is used.

The standard deviation of the k neighbours' field plot variable was found to be a good measure of uncertainty. The estimated volume and BA correlated with the standard deviation and can be potentially employed in the analyses of uncertainty.

The residuals were studied against the spatial neighbourhood spectral variables, numerical map data (3×3 window) values and variables describing the spatial distribution, direction and clustering of neighbours in the Euclidean feature space. The first principal component of the field plot pixels, the spectral brightness feature (Horler & Ahern 1986), strongly correlated with the volume and BA estimates, and with their residuals from the k–NN estimation. Concerning the spatial neighbourhood, the bias in the estimates increased close to the non-FRYL map mask. This result supports the use of map data to stratify the MS-NFI in (IV). At the edges of the feature space, there should be more error in the k–NN estimates, but the variables describing the spatial distribution of the k neighbours did not correlate with the volume or BA residuals. The distances in DN for the majority of field plot pixels in the feature space are quite small compared to the possible magnitude

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of error in the Landsat TM data (Curran & Hay 1986).

The effect of the first principal component was removed from the residuals by using a model of field plot volume residual variances. The remaining variation was weakly correlated with the other potential explanatory variables. The random error component remained considerable in the k–NN residuals. At single field plot level, the cause of the error seemed to be case sensitive: mislocation of the field plot, the radiation from the surrounding land use classes or stands, the deviation of the target field plot from the surrounding forest and extreme field plot variable values.

3.5. Correction of map errors in the MS-NFI small-area estimates (III,IV)

The delineation of the inventory area is one of basic steps in planning and executing a forest inventory. The forest area estimate can be based on the sample and the remote sensing and map data can be employed as auxiliary data, e.g. in stratification (Loetsch & Haller 1973). The error component of the estimate of the area of FRYL is included in the total error of the estimate. In the Finnish NFI, the land area is assumed to be known, and the estimates, both for mean and total values, are based on ratio estimators of field sample plots (Tomppo et al. 1997). The standard errors are estimated using local quadratic forms (Matérn 1960). In the MS-NFI, the FRYL area has been delineated based on the numerical map data and in some cases from satellite image data (Tomppo 1991). More precisely, other land use has been estimated from the map data and the rest has been considered to be FRYL consisting of the forest land, other wooded land and waste land. The problem with the current MS-NFI map data is that it is not necessarily up-to-date, there are locational errors and it does not correspond exactly to the NFI land use classes. The aim in (III) and (IV) has been to reduce the map error in the MS-NFI small-area estimates: to obtain better FRYL area estimates and to correct the effect of map error in the forest resource estimates.

The error probabilities from the cross-tabulation (confusion) matrix of a classification can be used to correct or calibrate for misclassification bias in (remote sensing based) statistical estimates of class proportions (Hay 1988, Czaplewski & Catts 1992). The confusion matrix must be based on a statistical sampling scheme (Card 1982). In (III), a calibration method is introduced to reduce the map errors in MS-NFI small-area estimates. The method is based on the confusion matrix

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between land use classes of the field sample plots and corresponding map information, estimated from a large region. If the map strata can be expected to be reasonably homogeneous with respect to the map errors and land use class distribution, the proportions estimated for large region can be used for small areas (synthetic estimation) (Gonzalez 1973). In the calibration literature, the method is identified as "inverse calibration for classification error" (Brown 1982), introduced by Tenenbein (1972). In (III), the aggregates of the estimated land use class areas over the large region agree with unbiased post-stratification estimators (Holt & Smith 1979).

In (III), a method is found to calibrate the field plot weights $c_{i,U}$ for computation unit U in such a way that the sum of the calibrated weights over all training data plots is equal to the calibrated FRYL area estimates when applying the confusion matrix and the above method. The calibration of the weights is not straightforward because there are only FRYL field plots in the training data and there is a lack of correspondence between the NFI land use classes and the map strata. In addition, the calibrated MS-NFI may produce negative weights $c_{i,U}$ for some field plots.

In (IV), the k–NN estimation was employed by map strata. All the field plots within each map stratum, irrespective of the field measurement based land use class, were used for estimating the areas of land use classes and forest variables of the particular stratum. The applied strata were formed so as to be as homogeneous as possible with respect to the NFI based land use classes. However, the number of strata was restricted by the fact that there should be a sufficient number of field plots for the k–NN estimation (IV). The aim of the method was to obtain simultaneously the FRYL area estimate and accurate forest variable estimates within each stratum. A compromise was made in the parameter selection between the high overall accuracy of FRYL classification and minimising the MSE of the key forest variables. The stratified MS-NFI resembles the field inventory estimation in the sense that all the field plots within a stratum are retained in the training data. The final estimates are obtained by combining the stratum-wise estimates.

In (III) and (IV), the stratified and calibrated MS-NFI reduced the error in the FRYL area estimates caused by errors in the map data. Comparisons were made between the aggregates of MS-NFI small-area estimates and field inventory estimates at the region level in order to determine the total amount of correction, and at the subregions (groups of municipalities), to detect the possible bias in the small-area estimates. At the region level, the calibrated FRYL area estimates were by construction, equal to the post-stratified FRYL area estimates, and the

post-stratification efficiently reduced the standard error of the estimate in land use classes that were homogeneous with the map strata (III). For the stratified MS-NFI, FRYL area correction remained between the original MS-NFI and the calibrated estimates. The calibration typically increased the volume estimates at both the region and subregion levels. The original MS-NFI estimates were calibrated upwards or downwards more or less systematically. The stratified MS-NFI small-area estimates, especially for volume and volume by tree species, varied more compared to the original MS-NFI estimates. The calibrated and stratified MS-NFI estimates of FRYL and total volume did not differ significantly from the field inventory estimates in subregions of size ranging from 1728 to 4238 km^2. However, only the stratified MS-NFI estimates of tree species volumes were within two standard errors of the field inventory estimates in the subregions of the test data. If the original MS-NFI estimates are clearly biased in the subregions, the calibration method alone can not correct the bias.

In the calibration method, the confusion matrices were calculated for large regions, where several thousands of field plots were available. The assumption of constant misclassification probabilities within the strata may not have held. The confusion matrices could be formed for subregions: according to Czaplewski & Catts (1992) improvement in the estimation precision of the classes starts to diminish after 500–1000 sample plots in a simple random or systematic sample. However, in (III) the smallest strata had less than 50 field plots.

Formation of the strata is more simple in the stratified MS-NFI, but the estimation parameters must be sought for all the strata applying cross-validation. The FRYL area estimates for each stratum were not very sensitive to the values of k or geographical HRA in (IV). The field plot weights w_{i,p_h} to pixel p_h in stratum h, i.e. the fuzzy membership values of field plot i, retain the variation in the training data in the estimates. The classification accuracy for FRYL and non-FRYL was not very high in (IV); the number of field plots within minor strata may be too small for efficient classification.

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4. Discussion

In (I), the most important parameters for minimising the estimation error of the total volume and volume by tree species at pixel level were the value of k, the geographical HRA radius to select the training data and the stratification of the field plot pixels, and training data employing the site class map. With the parameter selection criteria employed, the parameters obtained were quite similar in the four different study areas that represented different geographical areas of Finland. This indicates a consistency in the quality of Landsat TM image data and in the NFI field plot data. The selection of k was based on the the condition of minimum decrease of 0.5 % between k and $k + 1$ on a smoothed prediction error curve in (I). According to McRoberts et al. (2002), the threshold percentage should be taken from the minimum RMSE. In general, if there is more than one criterion for selecting the estimation parameters, e.g. minimising the MSE and retaining some of the original variation in the field plot data in the estimates, it would be more objective to state and apply them in an analytical way. The use of a small value of k may be appealing because it retains the original variation of the field plot data in the produced map data (Franco-Lopez et al. 2001). However, a consequence may be that k–NN yields a MSE larger than the variance in the observations (McRoberts et al. 2002). Secondly, there is less variation in the forest variables for units the size of a Landsat TM pixel (30×30 m^2) than in the NFI field plots, c.f. Nyyssönen et al. (1967).

In (I), the geographical HRA radii for mineral land and peatland strata were determined using the following criteria: to minimise the MSE of the key variables, to exclude from the training data field plots that would introduce bias into the estimates (maximum HRA radius) as well as to obtain a sufficient number of field plots on average in the training data (minimum HRA radius). Tokola (2000) found a smaller HRA radius to be optimal when the criterion was to minimise the MSE of volume and volume by tree species from the cross-validation estimates. However, Nilsson (1997) recommended that the same number of field plots should be employed in the training data as were found to be suitable in (I) on mineral stratum. In northern Finland, there is more variation in the altitude and, according to experiences in the operative MS-NFI, the use of geographical VRA will decrease the bias in the vertical subsets of the training data (Tomppo et al. 1998).

Stratifying the image and field plots for mineral strata and peatland strata significantly decreased the bias of the volume estimates within those strata in (I). In gen-

eral, stratifying the low radiometric resolution satellite data employing auxiliary data that reduces the within strata variation, e.g. a forest site quality map (Tokola & Heikkilä 1997) or stand characteristics data (Nilsson 1997, Tomppo et al. 1999) will reduce the bias within strata and possibly the global MSE in the k–NN estimation. The k–NN estimates of forest stand border pixels have a larger bias than those inside the stand and a separate estimation of stand boundaries would decrease this error (Tokola & Kilpeläinen 1999). The bias in the estimates also increases close to non-FRYL map strata in (II). In (IV), The MS-NFI by strata was employed. The relatively large amount of training data required limits the number of strata to be formed. Combining remote sensing data and map data will propagate different types of error in the output data (Wilkinson 1996). The stratified remote sensing classification may produce artificial boundaries on the output thematic maps (Hutchinson 1982).

In (I and II), the cross-validation has been applied assuming independent sampling, despite the fact that the key forest variables between neighbouring field plots within clusters are spatially correlated. E.g. the volume for forest and other wooded land had a correlation coefficient greater than 0.3 up to a distance of approximately 500 m within the same cluster in Central and Northern Finland in the 7th NFI (Tomppo et al. 2001). Spatial autocorrelation also occurs in the satellite image spectral channel values. This derives from both the sensor spatial properties and the spatial structure of the scene (Collins & Woodcock 1999). However, in the cross-validation it has not been detected in practice that the nearest neighbours would be more often from the same cluster as the target field plot. Nevertheless, the spatial autocorrelation range from the left-out pixel in cross-validation should be taken into account either by modifying the cross-validation (Altman 1990) or simply by the 'leave-some-out' method (Linton & Härdle 1998).

It is inevitable that the prediction error at the pixel level will be considerable in an MS-NFI that employs high resolution satellite data. The size of the field plot is small compared to the instant field of view of the satellite, the amount of mixed pixels is large and the image spectral channel values contain little variation for well-stocked stands (Ripple et al. 1991, Ardö 1992). However, reducing the main sources of error in the MS-NFI, e.g. in the field plot data, should decrease the prediction error in the k–NN estimates. Reducing the field plot locational error in the training data not only decreases the RMSE of mean volume estimates obtained from the cross-validation, but also retains more of the correct variation in the estimates (Halme & Tomppo 2001). It also corrects the typical shrinkage towards the mean in the k–NN estimates rather more than when a small value of k is used. The

sampling error in the training data is decreased by the use of weighted mean of BA observations from a larger area than a field plot (II).

These results lead to the larger question of the optimal field sampling design for MS-NFI purposes. This will include the questions concerning the size of the field plot, the distance between field plots, the representativeness of the sample. When the field sample is used in a remote sensing application, an optimal spatial resolution of the remote sensing data may be selected for the estimation (Hyppänen 1996) or the resolution –and the sensor– may be fixed. Under budget constraints, a balance should be found between the need for a large enough field plot size to provide a good covariation between the remote sensing data and the key variables, and the need for the training data to cover the variation of field variables within the satellite image cover (I). The spatial autocorrelation in the forest variables and in the remote sensing data should be taken into account in this optimisation process, cf. Wang et al. (2001).

Further refinement of the estimation parameters could increase the accuracy of the forest variable estimates. The predictive power of the feature space variables employed can be summarised by applying canonical correlation analysis (Moeur & Stage 1995) or weighting the features based on optimisation rules (Tomppo & Halme 2004). This is useful when only one set of parameters is used for all the forest variables. The local adaptation of the k–NN method could be used, based on the selected nearest neighbours or on the spectral features. The larger k–NN estimates also had a larger residual variation and variation in the selected nearest neighbours in (II) and it might be possible to decrease the prediction error by applying a stronger smoothing for the pixels where high volume estimates will be produced. On the other hand, the spatial distribution of the k neighbours varies at the edges of the feature space and the Euclidean distances in DN are small between the field plot pixels of high stand volume, whereas in open land and in young forests the distances can be quite high.

The confusion matrices used for the calibration in (III) were estimated for entire forestry centres. If the error probabilities in the confusion matrix vary significantly within such large regions, the calibration could be split into subregions. *A priori* information of the map accuracies, efficient stratification to subregions and the evaluation of standard errors of the misclassification probabilities, c.f. (Card 1982), could be used to determine the optimal size and distribution of the subregions for calibration. In general, the stratified MS-NFI was a more simple method than calibration and provided, on average, more accurate estimates of the volume

by tree species for small areas.

The field inventory estimates and their standard errors for large regions and subregions (groups of municipalities) are useful in assessing the systematic error of the MS-NFI estimates within a satellite image or some subarea of it (III; Tomppo & Katila 1992). The errors for field inventory estimates are large for areas less than 150 000 ha of FRYL, and other methods could be tested to evaluate the accuracy of the MS-NFI results, e.g. post-stratified field inventory estimates or resampling methods at the municipality level. There is both map error and forest variable estimation error in the aggregates of MS-NFI small-area estimates and this makes comparison with the field inventory estimates more difficult than in the cross-validation at pixel level, where only FRYL field plot pixels are employed. The parameter selection methods studied in (I) and the small-area estimation map error correction methods in (III and IV), together with the field inventory estimates, provide a method to reduce the estimation error and a reference of the accuracy of the MS-NFI results. However, if there is a significant systematic error in the small-area estimates of a certain subregion, it may not be possible to remove the error by varying the parameters studied in (I). In practice, the small-area estimates are dependent upon where the small area is located with respect to the employed satellite image and the training data. The satellite images and the large regions covered by the field inventory data form a mosaic of 'estimation images' that are analysed separately. Consequently, neighbouring pixels and small areas may employ training data from different geographical reference areas. This may cause bias in the results. It has been found necessary to take the tree species composition of the reference area into greater account , i.e. large scale trend-like changes of forest variables (Tomppo & Halme 2004). This indicates that the correlation between covariates and the volumes by tree species may not be strong enough to define the field plot weights $c_{i,U}$ for the small areas, and the use of averages of variables from a window defined by large scale trends around a municipality, decreases the error in the small-area estimates. The bias in the small-area estimator could be therefore corrected, e.g. by applying a combination of k–NN estimator and a direct sample estimator, a composite estimator, weighted by some criteria (Schreuder et al. 1993).

The parameter selection in the cross-validation is based on the global MSE and bias criteria. The systematic error in the aggregates of small-area estimates at the region and subregion levels are assessed by applying field inventory estimates. The aim in the MS-NFI is to obtain unbiased estimates for the small areas as well. The question is open as to, how much the optimal parameters for small areas or

subregions would differ from the global optimum.

A spatial presentation of the estimation of uncertainty would be useful for the data analyst. Building an error estimation method based on sources of error is a complex problem (Bastin et al. 2000). The measures of uncertainty studied in (II) may be far from the true prediction of error and more information of the target pixels, especially mixed pixels, are needed. The finer resolution PAN images could help to assess the representativeness of the field plots and to decrease the estimation error. Also, the fact that pixel-level estimation errors can be spatially autocorrelated must be taken into account in the error estimation method (Congalton 1988, Flack 1995). Wallerman (2003) in a study employing Landsat TM and an intensive field sample, found the spatial dependence of the residuals from a spatial regression model to be lower than the residuals from ordinary least squares regression, but only with field plot data sampled by distances of less than 300 m.

Although a reliable method for estimating pixel-by-pixel error could be produced, such a method would not be suitable for deriving the error estimates for larger computation units such as forest stands and municipalities. The error estimates for larger areas cannot be obtained directly by combining the error estimates for single pixels due to spatial autocorrelation both in the satellite image and field data and, in the case of cross-validation error estimates, due to locational errors in the field plot data. The error variance of the MS-NFI for small areas could be estimated employing models describing the second order properties of the MS-NFI error estimates for pixels, obtained from cross-validation (Lappi 2001). However, the field plot volume prediction error of the MS-NFI estimates depends not only on distance between pixels but, e.g. on the true volume. In addition, the k–NN prediction errors may not be treated as the residuals of a trend surface of a spatial model. The several sources of error in the MS-NFI, both in the field plot data and the remote sensing data, can reduce the reliability of the spatial modelling of errors.

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