The uncertainty of forest management planning data in Finnish non-industrial private forestry

Arto Haara

Faculty of Forestry

University of Joensuu

Academic dissertation

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Author: Arto Haara

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Thesis supervisors:
Prof. Annika Kangas, University of Helsinki, Department of Forest Resource Management

Dr Kari T. Korhonen, Finnish Forest Research Institute

Prof. Matti Maltamo, University of Joensuu, Faculty of Forestry

Prof. Tuula Nuutinen, Finnish Forest Research Institute

Pre-examiners:
Prof. Jyrki Kangas, UPM-Kymmene Forest

Dr Jari Miina, Finnish Forest Research Institute

Opponent:
Prof. Jari Hynynen, Finnish Forest Research Institute

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ABSTRACT

Knowledge about the growing stock and the cutting potentials of stands, as well as predictions of growth and yield, are essential aspects of forest management planning. Growth predictions are obtained using complex simulation systems, whose accuracy and precision are difficult to predict. The uncertainty of growth and yield predictions, as well as the uncertainty of the stand-level inventory data behind the predictions, are not usually taken into account sufficiently in the planning process. Furthermore, the uncertainty resulting from the increasing use of updated inventory data as planning data should be studied in connection with current forest planning practices. However, the lack of suitable comprehensive re-measured study data sets with true planning data must also be noted. This dissertation provides new knowledge on the uncertainty related to forest management data. It also addresses the possibilities to use updated forest inventory data as forest management planning data and evaluates assessment methods for predicting the uncertainty of forest management data. Furthermore, four alternative simulation methods are evaluated as regards their ability to generate assessment errors in forest management planning data for further research. The usability of updated forest management planning data is evaluated also by looking at the suitability of the proposals for forest management operations as derived from the updated data.

The accuracy and precision of stand-level inventory were found to be moderate, although the costs and time spent in field work are considered to be fairly high. The variation between measurers was substantial. This variation in stand-level inventory data should be noted in forest management planning.

The assessment of uncertainty of updated forest management data was approached by means of two different methods, i.e. by modelling observed (past) errors and by applying the *k*-nearest neighbor method with multiobjective optimization. The uncertainty assessments of growth and yield predictions using these methods were found to be feasible with large stand data. The main advantage of the studied methods is in that both bias and accuracy can be assessed. However, the methods require independent contemporary data, which is their main drawback. Modelling observed (past) errors and *k*-nearest neighbor are quite easy to apply in forest simulation systems if only contemporary models and distance functions are estimated. The utilization of both methods does not considerably add the calculation time even when dealing with growth predictions for large areas. Stand-specific predictions of uncertainty were also found to be satisfactory.

According to the results of this study, updated stand inventory data can be used as a forest management planning data with respect to the accuracy of the updated stand characteristics. Updated stand inventory data were also found feasible with respect to treatment proposals when the mean stand characteristics and regulations and recommendations of current forest management practices were considered. However, tree-specific data are considered to be a slightly more suitable in this context.

Keywords: assessment error, forest planning, non-parametric methods, observed errors, stand-level inventory

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Joensuu, October 2005
Arto Haara

LIST OF ORIGINAL ARTICLES

This thesis includes the following articles, which are referred to in the text by means of Roman numerals.

I	Haara, A. and Korhonen, K.T. 2004. Kuvioittaisen arvioinnin luotettavuus. Metsätieteen aikakauskirja 4/2004: 489–508.
II	Haara, A. 2003. Comparing simulation methods for modelling the errors of the compartment inventory data. Silva Fennica 37(4): 477-491.
III	Haara, A. 2002. Kasvuennusteiden luotettavuuden selvittäminen knn-menetelmällä ja monitavoiteoptimoinnilla. Metsätieteen aikakauskirja 3/2002: 391-406.
IV	Haara, A. 2005. The assessment of the uncertainty of the updated stand-level inventory data. Manuscript.
V	Haara, A. and Korhonen, K.T. 2004. Toimenpide-ehdotusten tuottaminen laskennallisesti ajantasaistetusta kuvioaineistosta. Metsätieteen aikakauskirja 2/2004: 157-173.

Arto Haara is the corresponding author of studies I and V. The planning work was done by both authors. Arto Haara did the data processing and calculations, and he wrote the original manuscripts. The final texts of studies I and V were written by both authors.

CONTENTS

1. INTRODUCTION

Accurate and real-time forest inventory data are essential for forest management planning. In most Nordic countries, forest inventory data from non-industrial private forests have been collected by using subjective inventory methods, e.g. ocular inventory methods with supporting field measurements. The importance of these private forests is significant because of their extent and intensive management. In Finland, for example, the proportion of the privately-owned forests is substantial, covering about 60% of the total forest land and their proportion of the total cuttings is considerably larger. Field inventory and forest management planning in these forests are carried out at intervals of 10-20 years.

The main part of the costs of forest management planning accumulates in field inventory. The costs of traditional stand-level inventory are fairly high, but its accuracy is still considered to be fairly low (e.g. Poso 1983, Laasasenaho and Päivinen 1986, Ståhl 1992, Paananen and Uuttera 2003). Recently, there have been steps taken to reduce these by updating inventory data computationally (e.g. Anttila 2002a, Hyvönen and Korhonen 2003). In the updating process, stand growth and yield of stands are simulated using the old inventory data. Those stands, in which management operations (e.g. thinnings, clear cuttings, silvicultural operations) have been carried out after the initial inventory, might often have been re-measured after the operation. This updating process may reduce the precision of the inventory data.

Although stand-level inventory is widely applied in Finland, comprehensive research results on the accuracy of the current tree species-specific stand-level inventory are not available. Most of the associated research was done in the 1980s, when stand-level inventory data were not as detailed as they are nowadays (Poso 1983, Laasasenaho and Päivinen 1986). In addition to this, the further processing of inventory data and most of the models used in the calculation process have changed since those times. Cost-effective and less subjective inventory methods are also being studied constantly. Recent studies on the accuracy of the tree species-specific stand inventory data have been done with small stand data sets, and the main purpose of such studies has been to examine alternative inventory methods such as remote sensing applications (e.g. Pussinen 1992, Hyyppä et al. 1999, Anttila 2002a, Anttila 2002b, Hyvönen 2002). Thus, the usability of inventory data collected using new inventory methods must be studied with respect to traditional stand-level inventory data and noting the possibility to update old inventory data computationally.

There is currently a lack of comprehensive re-measured study data sets with true planning data. This being so, errors in stand-level inventory must be generated into study data. Moreover, knowledge about the uncertainty of stand-level inventory data is essential when generating errors.

In this dissertation, the uncertainty of forest management planning data is studied. The uncertainty of inventory data is studied both at stand level and at forest level. The methods of assessing uncertainty are also examined with respect to the empirical uncertainty of updated forest management data. The prediction methods used should be in reasonable compliance with current forest planning practices. The uncertainty associated with updating is assessed in terms of the validity of the updated stand characteristics and by the usability of the proposed forest management operations. Hence, the objectives of the study are as follows:

1. To examine the uncertainty of forest management planning data and the possibilities to generate this uncertainty into independent data for further research. The motivation in

Study I is to examine assessment errors of forest management planning data and to examine factors affecting the uncertainty of the planning data, e.g. variation between measurers, behavior of measurers, and effect of stand attributes. Study II compares four alternative simulation methods in regard to their ability to generate assessment errors in forest management planning data for further research.
2. To examine the uncertainty of updated forest management planning data and to examine different methods for assessing this uncertainty. Study III assesses the uncertainty of growth and yield predictions using the *k*–nearest neighbor method and multiobjective optimization, whereas Study IV uses the *k*–nearest neighbor method and modelling of observed errors and compares them in the assessment of the uncertainty of growth and yield predictions. Study V evaluates the usability of updated forest management planning data in terms of the suitability of the proposals for the forest management operations derived from the updated data.

2. THE UNCERTAINTY OF FOREST MANAGEMENT PLANNING DATA

2.1 Collected forest management planning data

Woodlot-level forest planning produces information to support forest-related decision making by forest owners. Forest planning is considered to be an important forest policy instrument in Finland (Paananen and Uuttera 2003). Therefore, special emphasis has been constantly attached to the high degree of coverage of forest areas with management plans. The area of non-industrial private forests covered by stand-level forest inventory in Finland has been about one million hectares per year. The country's thirteen regional forestry centres are the main producers of forest plans of non-industrial private forestry, including the collecting of field data. Although stand-level forest inventory covers all the non-industrial private forests in the particular planning area, only about half of the forest owners are willing to pay for and use their forest plans (Karppinen et al. 2002).

The main interest in stand-level inventory has been to find out the current growing stock, cutting potential, and the need for forest management and silvicultural operations in the stands, as well as determine the future predictions of these variables. In order to achieve this, some typical stand and tree characteristics are measured.

In Finland, as well as in the other Nordic countries, forest management planning data on non-industrial private forest woodlots are usually collected standwisely applying a subjective inventory method with supporting field measurements. A stand is the basic unit in this method; it is a homogeneous patch of forest about 0.5 – 20 hectares in size. The criteria for the delimitation of stands are based on relevant stand characteristics, e.g. site fertility, stand age, and tree species composition. A stand is also considered to be a feasible unit for forest operations, i.e. it is a compartment. One or more small stands can be combined in forest management planning to form a compartment in order to have a suitable stand size for forestry operations. Thus, stand and compartment are usually considered to be synonyms (Poso 1983).

Stand-level inventories of the non-industrial forests are mainly carried out using relascope (Bitterlich 1984) sample plots. The stand basal area is assessed as an average of subjectively located sample plots. Tree heights and diameters at breast height are not measured from sample plot trees. Instead, the trees are tallied using the Bitterlich relascope, and the basal area median diameter tree per tree species per stand is then assessed by the surveyor. The diameters, heights and ages of these median trees are recorded. In addition to these records, the special characteristics of the stand (biodiversity, landscape and recreational values, damage, etc.) are recorded and included in the plan. Perhaps the foremost issue is to define the current and future management needs and cutting possibilities of the stand depending on the forest owner's goals. In practice, one measurer assesses a contiguous planning area of composed of numerous woodlots. This helps to reduce costs of fieldwork and to utilize better up-to-date aerial images. The aim is for the planning areas to cover the forests of a particular village, thus facilitating concentrated timber marketing operations, common meetings with the local forest owners, and larger forest inventory areas.

This kind of a stand-level inventory is a subjective inventory method. The measurer uses his own judgment starting from the delimitation of the stand, i.e. determining its boundaries. The number and location of the relascope sample plots is, in practice, up to the measurer. Furthermore, the measurer divides the total basal area into tree strata while also noting the tree species distribution. The choice of the basal area median diameter tree in each tree stratum is also based on the measurer's own judgment. Because of the said subjectivity, there is considerable variation in the precision and the accuracy of stand-level inventory. For example, the standard error of the mean stand volume can vary from 15% to 45% (e.g. Poso 1983, Mähönen 1984, Laasasenaho and Päivinen 1986, Nersten and Næsset 1992, Ståhl 1992, Pigg 1994). The differences between different study data and different computation methods explain this variation only in part. The accuracy of the stand-level inventory is usually examined with checking inventory including standwise systematic sampling of relascope or fixed sample plots. The differences between checking inventory methods can also add the variation between the results of various studies (Kangas et al. 2002). The accuracy of stand-level inventory varies a lot from one measurer to the next (e.g. Laasasenaho and Päivinen 1986, Haara 2003, Kangas et al. 2004). Low precision and the diverse content of stand-level inventory data are problems to be encountered when making use of stand-level inventory data. Thus, exact measures of the precision of stand-level inventory data cannot be achieved.

Usually the measurement errors associated with forest inventories, as well as other measurement errors, are presented hypothetically (e.g. classical measurement error model, Carroll et al. 1995):

$$x_i = X_i + \varepsilon_i \tag{1}$$

where x_i is the measured value, X_i is the observed value, and ε_i is the error. The error is assumed to implicitly correlate with the measured value as opposed to the observed value. The deviation of the measured value is supposed to be larger than the deviation of the observed value:

$$\mathrm{var}(x_i) = \mathrm{var}(X_i) + \mathrm{var}(\varepsilon_i) \tag{2}$$

If the value of the considered variable is controlled by the surveyor, e.g. assessments of the variable are based on visual and subjective assessments more than the others, the classical model is no longer valid. Then the measured value is a fixed "readout", which is a typical value for the similar variables it represents (Lappi 1993, Kangas et al. 2002). This particular situation is referred to as Berkson's case:

$$X_i = x_i + \varepsilon_i \tag{3}$$

Now, the error is not dependent on the measured value. On the contrary, the error correlates with the observed value. Furthermore, the variance of the observed values is larger than the variance of the measured values:

$$\mathrm{var}(X_i) = \mathrm{var}(x_i) + \mathrm{var}(\varepsilon_i) \tag{4}$$

A measurement error can also be a combination of both of the introduced error models. If that is the case, both the measured value and the observed value include error. There is a common hidden variable in the background (Kangas et al. 2002). The error correlates with both the observed value and the measured value, and the variances of observed values and measured values are approximately the same.

Because there are a lot of options in stand-level inventory, assessments can become controlled by the measurer's own conceptions. The assessed value of the stand characteristics is typical for the similar stands it represents (Kangas et al. 2002). Observed values are then ranged around of this 'readout'. The measurement errors of the stand characteristics cannot always be illustrated using the classical error model. On the contrary, Berkson's case often complies with the errors of stand-level inventory (Kangas et al. 2002).

The collected stand and tree characteristics are used as independent variables in the models used to predict the growing stock of the stand and stand growth and yield. The errors associated with these variables occur in different ways (Gertner 1986, 1991):

1) *Measurement error.* In practice, measurements cannot be made accurately because of time and budget constraints.

2) *Sampling error.* Forest inventories usually involve the use of some sampling method. Therefore, the variable will be in error because only a subset of the total population is used to produce the estimate. The magnitude of the error depends on sample size, plot size, sampling method, etc.

3) *Prediction error.* In complex simulation systems, the regressor variables of one model are commonly predicted using other models. These prediction errors can become very large due to propagation of errors from one model to another model.

4) *Classification error.* Measurements may be grouped into classes (e.g. dbh classes), which can be noticeably larger than the presumed measurement accuracy. Classification errors can also cause bias (Päivinen et al. 1992). Even if the observations are distributed symmetrically, the use of grouping can cause bias (Loetch et al. 1973).

In addition to the measurement errors (1), the subjectivity of stand-level inventory causes variation in assessments between measurers, because the method leaves a lot room for measurer's judgments and the inventory practices applied.

The collected stand-level data are used to predict the current growing stock of the stand and the growth and yield of the stand for forest planning and decision-making purposes using simulation systems. These systems usually consist of very complex and interlinked parts containing models for predicting development of the stands, e.g. models for regeneration, growth and mortality, influence of different management schedules on predictions (e.g. Eid 1990, Jonsson et al. 1993, Siitonen 1993).

In Finland, forest management data from non-industrial private forests have been collected and these data have been treated using the SOLMU planning system since 1997 (SOLMU. Maastotyöopas. 2003). Forest management planning comprises the planning of forestry on individual woodlots as well as regional forest inventory. The content of the inventory data have been the same for both purposes. In SOLMU, stand boundaries are delimited on aerial photographs. Preliminary delimiting of stands is performed before field inventories are carried out. Old stand boundaries and topographical maps are used at this stage. The final stand boundaries are determined during field inventory, and indistinct stand boundaries are checked. The preliminary delimitation of stands can also be done semi-automatically using segmentation techniques (e.g. Pekkarinen 2002, Sell 2002), but the final delineation, nevertheless, has to be done manually because of the constraints of these techniques.

Before the adoption of the SOLMU system, the contents of inventory data collected from private forests were entered in the TASO planning system (Taso. Maastotyöopas …1993). The TASO data were also collected stand-specifically. The main difference between these inventory systems was the briefer description of the growing stock in the TASO system. Mean age, mean diameter, mean height and basal area were collected for the entire stand. The proportions of the tree species were derived from their proportion in the basal area or total stand volume. The tree species-specific stratum was recorded if its basal area or volume proportion amounted to at least 10% of the total basal area or total volume of the stand. Furthermore, the level of detail in TASO data varied a lot; sometimes only age, mean volume and proportions of the tree species were recorded. However, TASO data are still used in forest management planning, sometimes even in updating, as there may be no other more recent stand-specific field data available on the inventory area. In these cases, TASO data have to be first converted into SOLMU data format to enable them to be used in simulation systems (explained further in Chapter 3.2). In some cases, only available forest planning data can be predecessor of TASO-data, i.e. MTS-ALUE/Tapio-data (Ranta 1986), or a conversion from it. In MTS-ALUE/Tapio planning system, only stand age and volume, and proportions of pine, spruce and deciduous trees were recorded.

In Finnish private forestry, the collected stand-level data (SOLMU data) are applied, with an increasing tendency for notifying forest owner’s goals, in the forest plan preparation process. Stand development and optimization of management schedules for stands fitting the management goals are performed using the MELA system (Siitonen et al. 2001). MELA is a forestry model and an operational decision support tool for integrated forest production and management planning designed for Finnish conditions (Siitonen et al. 1996). SOLMU data and the MELA system are utilized in TFOREST geographical information system, which includes establishment of planning data from the inventory data, the management of planning data, and forest management planning facilitating multipurpose forest plans (TFOREST- metsätalouden … 2004).

Theoretical diameter distributions and individual tree growth models are used in forest management planning packages for predicting stand volume, timber volume and stand growth (Kangas and Maltamo 2000c). Theoretical diameter distributions are mainly predicted using species-specific basal area diameter distribution models with some assessed stand variables. The wide use of theoretical models, instead of measuring empirical diameter distributions, is based on cost restrictions impacting on field work. In TFOREST system, Weibull distributions have been applied (e.g. Kilkki and Päivinen 1986, Kilkki et al. 1989, Maltamo 1997). However, the use of percentile-based diameter distribution models, Johnson’s S_b distribution models, as well as calibration of the Weibull distributions with the number of stems, have been enabled in MELA planning package (Maltamo et al. 2002a, b).

2.2 Updated forest management planning data

2.2.1 The updating of forest management data

The Finnish forest management planning system for private forestry is currently under development. (e.g. Uuttera et al. 2002, Rakemaa 2003, Vierula 2003). In the course of this process, the alternatives for the currently applied inventory system will be developed and investigated. The main problem comes from the demand to decrease the costs of stand-level inventory, while at the same time striving to increase the accuracy of the inventory data gathered. One possible alternative is to utilize existing inventory data and information about management operations for computational updating of the inventory data. The said updating in regard to stand characteristics can be combined with the visual interpretation of aerial images (Anttila 2002a). Besides traditional stand-level inventory, also other possibilities and new inventory methods are being studied when updating forest management planning data (Paananen and Uuttera 2003). The use of sophisticated remote-sensing techniques offers one possible alternative (e.g. Næsset and Bjerknes 2001, Anttila 2002b, Hyvönen 2002, Maltamo et al. 2004, Korpela 2004, Korpela and Anttila 2004, Næsset 2004).

When the old inventory data are updated, the management operations performed during the updating time must be determined. Hyvönen and Korhonen (2003) studied the possibilities to utilize various registers of silvicultural operations and cuttings in forest management planning. These register data were used as *a priori* information of the management schedules of non-industrial private forests during the updating time. In addition to registers, the forest owners were also interviewed with the purpose of collecting management schedule data. The computational updating of the stand characteristics based on old inventory data with the management schedule data was found to be a promising alternative in the endeavor to obtain forest data for forest management planning. The updated forest stand data were found to be as reliable as the new inventory data. Over 90% of the operations implemented during the updating time were pinpointed without field checking. However, the updating time of the study was only 5-6 years. The costs and the time consumption were not studied.

2.2.2 The uncertainty of updated forest management planning data

Accurate predictions of forest growth and yield are required in forest management planning. The uncertainty of the predictions may include both random and systematic variation. The precision (variance) evaluates random variation, bias measures systematic variation, and accuracy (mean square error, MSE) measures both.

Prediction error in a statistical model has four main sources (Kangas 1999): (i) model misspecification, (ii) random estimation errors of model coefficients, (iii) residual variation of models, and (iv) errors in independent variables of models. Judgmental aspects in predictions can also cause some error (Alho 1990, Kangas 1999). In such a case, an outside observer may disagree with given judgments or prior beliefs about the parameters of the model, or the given weight of beliefs in predicting (Alho 1990). Planning packages can include some parameters under the judgmental aspects of the user (e.g. Redsven et al. 2004), and expert knowledge has been mobilized for growth models with prevailing planning systems (e.g. Hackett and Vanclay 1998).

The accuracy of growth and yield predictions is often unknown in decision-making or it is simply ignored. Predictions are usually made employing complex simulation systems consisting of network of models with fixed and estimated coefficients. The predictions of some models are used as predictor variables in other models. This use of model chains leads to propagation of errors. In addition to this, the length of the prediction period has an effect on the reliability of the predictions (Kangas 2001). It is a common practice to predict growth at 5-year intervals in forest management planning systems (e.g. Hynynen et al. 2002). The prediction errors of each period are propagated in further predictions (e.g. Salminen 1996, Kangas 2001). Because the separation of error sources and their interaction are very difficult to examine, the influence of different error sources in predictions is mainly studied via aggregated errors. Otherwise, the prediction of uncertainty can become very difficult. The errors from the different sources are not summarized in mean square error, because the opposite biases of different error sources can compensate each other (Lappi 1993).

In general, increased model complexity results in decreased predictive precision (Mowrer 1989). The relative importance of the error sources of the prediction errors can vary in time: in the short term, the residual variation of the models or the quality of the initial data set can be dominant, but in the long term, the model misspecifications can be the foremost source of error (Kangas 1999).

The growth models of the simulation systems are usually built to predict growth under average weather conditions (e.g. Kangas 1998, Hynynen et al. 2002). Kangas (1998) reported that simulation of annual variation in diameter growth markedly increased the coefficient of variation of stand volume growth. The annual variation of weather conditions affects the accuracy of growth predictions, especially in the case of short-term predictions (Kangas 1998). The annual variation of climatic conditions can also increase (e.g. Pan and Raynal 1995). Thus, the uncertainty of growth predictions can also increase.

2.2.3 The uncertainty assessment of growth and yield predictions

The uncertainty of growth and yield predictions is usually assessed using the mean square error method and with its two components, variance and bias. The assessment of the uncertainty of forest simulators includes either (i) the study of the misspecification of the models and its influence, or (ii) the study of the reasons causing the uncertainty. Misspecifications of the models are usually studied and analyzed by applying sensitivity analysis, which is used to study the influence of a certain detail of the model on model predictions and the sensitivity of the models to changing circumstances (Salminen 1996). The reasons for the uncertainty of predictions are usually studied by analyzing the errors.

The simplest way to assess the uncertainty of the growth and yield predictions is to apply confidence intervals. The observed errors of the predictions of the stand characteristics are sorted out and uncertainty of the predictions is then assessed using quartiles (e.g. 2.5% and 97.5% quartiles). The error of the predictions is the difference between estimated growth and observed growth in the light of empirical data, e.g. growth obtained via data from re-measured data plots.

The complexity of forest simulators leads to the propagation of the errors of the several models. Thus, it is difficult to assess the confidence intervals for the predictions.

Confidence intervals can be constructed if suitable checking inventory data are available. However, future growth cannot be measured. Therefore, the uncertainty of predictions must be assessed using accurately re-measured sample plots. Problems arise in that sample plots have been established for other purposes, and there are not enough of different kinds of stands for reliable estimates of the uncertainty of growth and yield predictions under different circumstances. The contents of the existing data can vary a lot between different data sets. In addition to this, there are only a few sets of data sets from long-term sample plots. Suitable existing data have been used most probably as modeling data in some parts of the planning systems.

There are some limitations to empirical assessments of uncertainty, and these must be taken into account. The assessments of uncertainty of growth predictions are calculated for certain past periods and limited areas. The extrapolation of assessments for future and for other areas should be considered carefully. The measurement errors in the empirical data should also be taken into account (Kangas and Kangas 1997, Ojansuu et al. 2002). The use of confidence intervals does not require the assumption of a normal distribution of errors. Thus, empirical confidence intervals can be used in the assessment of uncertainty, even if the distribution of the errors in periodical growth predictions does not follow normal distribution. In practice, there is a lack of available empirical re-measured data for the assessment of the precision of growth predictions for forest management planning purposes.

Uncertainty can also be assessed using estimation methods. The two most frequently used methods of assessing the precision of growth predictions have been Monte Carlo simulation and variance propagation methods, such as Taylor series approximations, in which the total prediction error is composed of several error sources (Kangas 1999).

Monte Carlo simulation has been widely used in assessing the uncertainty of growth predictions and the influence of initial data and predicted independent variables (e.g. Gertner and Dzialowy 1984, Mäkelä 1988, Mowrer 1991, McRoberts 1992, McRoberts et al. 1994, McRoberts 1996, Kangas 1997, 1998, 1999). Monte Carlo methods comprise the repeated sampling of the probability distribution for model parameters, driving variables, boundary conditions and initial conditions, and the use of re-iterated simulations (Rubinstein 1981). The probability distribution of model prediction is then derived from the combination of model predictions resulting from re-iterated simulations based on sampled inputs. The main advantages of Monte Carlo techniques include that precision can be assessed without an independent measurement data set and the effect of certain assumptions or models can be studied separately (Kangas 1999). Monte Carlo techniques are especially applicable for the assessment of the uncertainty of complex simulation systems in which non-linear growth models and propagated models are used. However, Monte Carlo simulations produce only a lower limit for the true variance because all the error sources may not be known and cannot therefore be taken into account (Kangas 1999). In addition to this, the dependencies of various error sources may not be known. Furthermore, Monte Carlo methods require massive computations when dealing with large areas.

Variance propagation methods, such as the Taylor series expansion (e.g. Mowrer and Frayer 1986, Gertner 1987, Mowrer 1991, Summers et al. 1993, Kangas 1996), require the computation of a deterministic output trajectory for the model, which is then followed by the quantification of the effects of various small in amplitude sources of input uncertainty or uncertainties about the reference trajectory (Burges and Lettenmaier 1975, Argantesi and Olivi 1976). The variance propagation methods can be used also for estimating the confidence intervals of the predictions (Ripley 1987). Although the use of variance propagation methods can be difficult in complex situations because of their highly restricted requirements, these methods can be more suitable than Monte Carlo methods when the simulation data are large (Gertner et al. 1995, Kangas 1996).

Forest growth and volume functions are quite often nonlinear with respect to independent variables. When this is the case, unbiased random errors in independent variables will result in biased predictions (Lappi 1993, Gertner 1996). This bias can be approximated by using Taylor series expansion (e.g. Gertner 1996, Kangas and Kangas 1997, Kangas 2001). The knowledge on how sensitive a certain function is to random errors helps to determine the allowable maximum errors. Furthermore, the sensitiveness of the corresponding models to the errors in the initial data can be evaluated.

A simple and effective way to assess the uncertainty of growth and yield predictions is to model observed (past) errors of the interesting variables (Kangas 1999). The observed errors are the differences between the predicted growth of the interesting variables and empirical growth. The use of an elementary model method offers also a simple way to assess the uncertainty of growth and yield predictions (Kangas 1999). In this method, an elementary model is formed to estimate the growth and yield of interesting variables. Model variance is used as a way of assessing the uncertainty of the simulation system giving an upper bound for the variance. The assumption behind the method is that the elementary model must be less precise than the simulation system.

The assumption that the uncertainties of growth predictions of similar stands are equivalent makes it possible to utilize the predictions of uncertainty of similar stands when forecasting the uncertainty of the growth predictions concerning the target stand. Non-parametric methods predict the value of present interest as the, mainly weighted, average of the values of most identical observations (Härdle 1989, Altman 1992). Thus, these models can be utilized in a manner similar to the least-square regression analysis models. In forestry, non-parametric methods have been used widely in many applications. Especially multi-source and multivariate forest inventories have been very popular applications (e.g. Kilkki and Päivinen 1987, Moeur 1987, Muinonen and Tokola 1990, Tomppo 1992, Moeur and Stage 1995, Holmström et al. 2001), but non-parametric methods have been used also for purposes such as generalizing sample tree information (Korhonen and Kangas 1997), estimating diameter distributions (e.g. Haara et al. 1997, Maltamo and Kangas 1998), estimating growth (Sironen et al. 2001) and yield (Maltamo and Eerikäinen 2001), modeling forest regeneration (e.g. Ek et al. 1997, Hassani et al. 2004), and for wood procurement planning (e.g. Malinen et al. 2001, Malinen 2003).

3. SUMMARY OF THE ARTICLES

3.1 Uncertainty of stand inventory data (I)

In study I, the purpose was to analyze the quality of the stand-level inventory data when dealing with large checking inventory data sets. The accuracy of the collected stand characteristics was studied in regard to entire data sets and in separate groups. The variation between measurers and the influence of different basal area diameter distribution models used in simulation system were also examined.

Main study data in the Study I consisted of 1304 stands locating in Eastern Finland. The data were divided into two groups, which were analyzed separately:

1) Older stands (1162) (see I, Table 2)
2) Seedling stands (142) (see I, Table 11)

The checking was carried out by measuring a systematic net of circular sample plots within each stand. The number and size of the plots within a stand depended on the size of the stand, the development class of the trees forming the stand, and the tree species composition of the stand. Tree species and diameter at breast height of each tree on the plots were measured. The tree heights were measured from the sample trees on every second plot. In seedling stands, the arithmetic mean diameter at breast height and the mean heights of each tree species were measured on each plot. The average stand size was 2.43 hectares in Group 1 and 2.66 hectares in Group 2. In Study I, the main interest focused on Group 1 because of the importance of older stands in deriving cutting potentials for forest management planning. The study data also included four smaller independent field checking data sets located in Eastern Finland (see I, Table 3). The data sets were used as reference data. The reliabilities of the four data sets were compared against large checking data generally and within some stand strata.

The accuracy of the main study data was also examined in separate groups; the study data were divided by site, stand development class, main tree species, and site fertility. The uncertainty of the stand data was examined with respect to the following tree and stand characteristics: Root Mean Square Error (RMSE) and bias. Relative errors were obtained by dividing the RMSEs and biases with the average of the examined variable.

The relative RMSE of the stand volume per hectare was 24.8%. When the sampling error of the checking inventory was notified, the RMSE of the stand volume was 21.4%. The stand basal area and the stand volume were slightly underestimated. The stand basal area and stand mean volume were underestimated in mature, closely-spaced stands (see I, Figures 1 and 2). On the other hand, these stand characteristics were slightly overestimated in younger stands (see I, Figures 1 and 2).

The variation between the measurers was analyzed by the comparison of the measurer's accuracies. The graphic representations and variance component analysis were utilized in this context. The variation between measures was noticeable. The relative RMSEs of the mean stand volume varied from 16.5% to 36.2% between the measurers (see I, Figure 4) and the biases of the mean volume of the stand varied from underestimating by 17.0% to overestimating by 16.2%. The relative RMSEs of the stand basal area also varied considerably between the measurers; from 13.0% to 27.7% (see I, Figure 3). Variance component analysis was also carried out in order to study the differences between the measurers. The measurement errors in regard to the stand characteristics (bias) and square roots of the measurement errors (precision) were explained using some stand characteristics. Some mixed models (see I, Table 12) showed that the influence of the measurers explained a substantial part from the residual variance.

The choice of diameter distribution model has a remarkable impact on inventory results with accurate data (e.g. Siipilehto 1999, Kangas and Maltamo 2000a,b, Maltamo et al. 2002a, b). In addition to this, calibration estimation has been found to be a promising way to utilize diameter models (e.g. Deville and Särndal 1992, Kangas and Maltamo 2000c). In calibration estimation, the predicted diameter distribution is calibrated using additional stand characteristics such as the number of stems per hectare. The use of additional measurements is impractical due to the extra cost unless there are simple rules for choosing an optimal measurement composition for certain types of stands. These rules can be produced by modelling the observed errors (e.g. Kangas and Maltamo 2002, Mehtätalo and Kangas 2005).

When different diameter distribution models were used with accurate data for predicting mean stand volume, the results were similar to those obtained in earlier studies (e.g. Kangas and Maltamo 2000a,b, Maltamo et al. 2002a,b). However, the choice of a diameter distribution model was found insignificant when the stand-level inventory data obtained using current forest inventory practices were used (see I, Table 13). Including the number of stems as a predictor did not improve volume and saw timber volume estimates. The use of number of stems as an independent variable in diameter distribution models is based on the possibility of including it to measured stand variables.

The uncertainty of stand-level inventory was found to be quite similar to the findings of earlier studies (e.g. Poso 1983, Laasasenaho and Päivinen 1986, Pussinen 1992, Ståhl 1992, Anttila 2002a). Stand basal area, along with mean stand volume, were clearly underestimated in closely-spaced mature stands. There are some possible reasons for the underestimates. Firstly, the measurers may be too cautious; the attitudes of the forest owners are considered to be more positive against underestimation of the growing stock than overestimation of the growing stock. Secondly, the basal area of dense stands is difficult to measure. Thirdly, most of the measured forest stand characteristics are Berkson's cases or combinations of it and the classical error model (Study I, Table 10). Measurers are having some kinds of endogenous 'readouts' for certain types of forests, and the spacing of the stands was not properly indicated. Saari and Kangas (2005) studied the factors affecting the underestimation of basal areas in closely-spaced stands and they found measurement errors to be the foremost factor, and recommended to use relascope factors higher than 1.

The assessment errors between the measurers varied widely. The differences between the checking stand groups per measurer explained only part of this variation. The systematic errors of the stand characteristics varied particularly widely between the measurers.

The accuracy and precision of the reference checking data sets were found to be the same as in the large checking data (see I, Tables 4, 14). This was also the case with stand strata (see I, Table 15).

3.2 Comparing simulation methods for modelling errors in stand inventory data (II)

The aim of Study II was to compare four different methods of generating errors into the stand-level inventory data and to study the effects of erroneous data on the calculation of species-specific and stand-specific inventory results. The considered methods of error generation in simulation experiments were the one nearest neighbor method (1nn-method), the empirical errors method, and the Monte Carlo method with log-normal and multivariate log-normal error distributions.

The study material of Study II consisted of two independent checking inventory data sets. A stand-level ocular inventory and checking inventory were carried out in all of the study stands by professional measurers. The first checking data consisted of 1842 stands (CC1) located in Northern Finland and the second data consisted of 41 stands (CC2) located in Eastern Finland (see II, Table 2). A small group of stands (CC1b) containing 90 stands was selected from the data set CC1 using random sampling. The remaining 1752 stands formed stand data CC1a. The checking of data set CC1 was carried out by measuring a systematic net of relascope sample plots in each stand while the checking of data set CC2 was done by measuring a systematic net of fixed sample plots in each stand. Data set CC1a was used to study the precision of the stand-level inventory and to study the relations between the stand characteristics within a stand. Data sets CC1b and CC2 were used for testing the examined error generation methods.

Accurate stand inventory data were established from the tree-specific checking data (Study II, Figure 1). The data including model and assessment errors were generated from the accurate data of CC1b and CC2.

In the nearest neighbor approach, the level and structure of the measurement errors were assumed to be the same in similar stands. The search for a similar reference stand was done by using standardized commonly measured stand characteristics as the variables of the distance function. Similarly, distance functions were applied species-specifically (see II, Function 1). When the empirical error method was applied, the reference data (CC1a) were first classified species-specifically into mean basal area diameter classes. The class to which the target stand belonged was accessed to choose a reference stand by applying random sampling. The measurement errors of the reference stand were added to the stand characteristics of the target stand.

Two Monte Carlo methods were also tested for error generation. The errors of the stand characteristics were simulated by using:

1) Log-normal distributions (see II, Chapter 2.5.1, Formula 5)
2) Multi-lognormal distributions (see II, Chapter 2.5.2, Formulas 6, 7)

Highly biased stand characteristics in the test data were noted by adding a bias term into the generated error (see II, Formula 3). The possibility of using a trend in error simulations was also utilized (see II, Formula 4). In models with trend, systematic errors were treated as varying depending on the size of the stand characteristics.

The observed errors of the basal area median tree characteristics were correlated. This dependency was also retained in estimates of variances when using multivariate distributions and the nearest neighbor approach for all tree species and the empirical error method for pine. The estimates of the relative biases and standard deviations of the differences of stand and basal area median tree characteristics showed that the Monte Carlo method with multivariate distributions was the most flexible method for describing the variation of the uncertainty of stand-level inventory data. The nearest neighbor method and the empirical error method were also potential methods for modelling the errors, if the reference data corresponded to target data. The use of trends in both Monte Carlo methods brought the estimates of the biases clearly closer to the observed biases.

3.3 Assessment of uncertainty of updated stand-level inventory data (III, IV)

Studies III and IV looked into the assessment of the uncertainty of the updated forest inventory data. Study III assessed uncertainty by utilizing the *k*-nearest neighbor method and multi-objective optimization, whereas Study IV considered the models of observed (past) errors besides the *k*-nearest neighbor method. The generation of study data, as well as the research methods applied, varied between these studies. Furthermore, the MELA planning system, which was used in the updating process, was under constant development (Siitonen et al. 2001 in Study III, Redsven et al. 2004 in Study IV).

The study data in Study III consisted of 754 stands modified from the permanent sample plots measured by the Finnish Forest Research Institute (FFRI) and established between the years 1976-1982 for growth modeling purposes on mineral soils (Gustavsen et al. 1988). The plots (INKA data) were re-measured twice at five-year intervals. Three fixed-radius circular plots were established in each stand. The size of the plots was determined by the total number of sample trees in each stand, which was at least 120 in Southern Finland and 100 in Northern Finland. The tree species were determined and diameter at breast height was measured from all the trees within the plots. More detailed measurements (e.g. sample tree ages and heights) were obtained from smaller plots located in the center of each plot. The trees within the plots were compounded to represent tree-specific stand data (INKA data, see III, Table 1).

Tree stratum data (SOLMU data) and stand-specific data (TASO data) were generated from the tree-specific stand plot data (INKA data). Measurement errors of the stand characteristics were generated into established correct stand-level inventory data using multivariate log-normal distributions (See Study II). The precision of the generated errors was obtained using the average precision of earlier studies (Purola 1983, Mähönen 1984, Laasasenaho and Päivinen 1986, Pussinen 1992, Pigg 1994).

Stand-specific TASO data had to be first converted into SOLMU data because of the demands of the used forest-management planning system MELA (Siitonen et al. 2001). This conversion was done by generalizing the mean tree characteristics of the stand (i.e. mean diameter, mean height and mean age) into the mean tree characteristics of the tree species within the stand. The basal area and the stem number of the tree species within the stand were obtained by dividing the total basal area and total stem number by the relative proportion of each tree species represented in the stand. The conversion method is similar to the method currently used in forest planning practices in Finland.

The growth of each stand was predicted using the MELA planning system. The basal area diameter distributions were estimated based on stand-level inventory data using species-specific Weibull distribution models (Kilkki and Päivinen 1986, Kilkki et al. 1989). The heights of the simulation trees in the predicted diameter distribution were predicted using regional tree height models (Veltheim 1987). The growth of the simulation trees was predicted using individual tree growth models for tree height and diameter at breast height developed per species in Finland (Hynynen et al. 2002). These predictions were produced at 5-year intervals. The total growth of the stand was achieved by summing up the growth of the simulation trees. The effects of forest management operations carried out during the updating time were also simulated using MELA.

The uncertainty of the growth predictions pertaining to the target stand was predicted from the uncertainty of the growth predictions of the neighbor stands. The *k*-nearest neighbor method was used to search the nearest neighbors to the target stand. Standardized stand characteristics were tested as the variables of the similarity distance functions. The search for the nearest neighbors was done per stand and per species. Multi-objective optimization was used to choose the decision variables of the distance functions (see III, $X_1,X_2,\ldots,X_n$ in Formula 1) and their weights (see III, $a_1,a_2,\ldots,a_n$ in Formula 1). The nonlinear programming algorithm presented by Hooke and Jeeves (1961) was used to find the combination of decision variables minimizing the objective function. The computer program developed by Osyczka (1984), and further modified by Pukkala and Miina (1997), was adapted into the *k*-nearest neighbor method to deal with the problem in Study III. The objective variable, which was minimized, was the difference between the predicted growth of the target stand and the predicted growth of the reference stands. Thus, the stand characteristics and the predicted growth of the target stand and of the neighbor stands were as similar as possible. The optimizations were done with and without measurement errors both with SOLMU data and with TASO data. The prediction interval of the simulations was 10 years.

The usability of the predictions of uncertainty was tested with the cross-validation method. Predictions of uncertainty were produced for every stand by using the rest of the stands as the reference data. Relative RMSEs and the biases of the updated stand characteristics for stand groups were achieved by summing up the stand-specific parameters and by dividing the sums thus obtained by the number of stands included in the group. The usability of stand-specific uncertainty predictions was examined by generating 95% confidence intervals from the prediction of uncertainty of the stand characteristics and by then calculating the proportion of the predictions of the stands located within these intervals.

The maximum basal area portion of a tree species within the stand, the site index, the basal area of the stand, the stand age and the basal area median tree diameter of the stand were chosen for the variables of the distance function of the stand. In species-specific distance functions, the maximum basal area proportion of a tree species within the stand was substituted by the relative proportion of the tree species represented in the total basal area of the stand. The predictions of the uncertainties of the updated stand characteristics followed very closely the empirical errors of the updated stand characteristics (see III, Table 3). In stands subjected to management operations the predictions of uncertainty were slight underestimates.

Multi-objective optimization was found to be a very effective method in searching for the variables and parameters of the similarity distance functions when comparing it with the trial-and-error method. The *k*-nearest neighbor method can be very useful in updating stand inventory data. The method can be used as a decision-support tool in situations where the choice between updating and re-measuring of stands has to be made. The lack of suitable reference data is most probably the main constraint to the wider use of the method. Reference data must be comprehensive enough and up-to-date for finding suitable neighbors for the assessment of uncertainty of a simulation system.

Study IV examined the models of the observed (past) errors and *k*-nearest neighbor method in order to assess the uncertainty of the updated forest inventory data. The study data consists of sample plot data (INKA data, see IV, Table 1) and two checking data sets (see IV, Table 2). The correct stand-level inventory data (SOLMU data) were generated from the tree-specific sample plot data. The assessment errors of the stand-level inventory were generated into the correct stand-level inventory using the 1nn-method, which is presented in Study II. Checking data sets were used as the reference stand data for the 1nn-method.

The considered stand characteristics were stand volume, basal area, median diameter, and median height of the stand. The predictions of uncertainty were also considered stand-specifically using the considered stand characteristics. Confidence intervals of 95% were obtained for each stand from their uncertainty predictions. The proportions of stands within these confidence intervals were examined.

The uncertainty assessments of the growth and yield predictions using these two methods were found to be feasible when dealing with large stand data. When the stand-specific predictions of uncertainty were examined applying confidence intervals, both methods proved to be effective in the case of correct stand-level inventory data, e.g. data with model errors. In case of the stand-level inventory data with assessment errors, the model of observed errors method gave slightly better stand-specific predictions of uncertainty when considering the proportions of the stands.

3.4 Usability of updated forest management planning data for suggestions and timing of forest management operations (V)

Various management schedules are applied in forest management planning to stands. The schedule of an individual stand may vary with respect to management treatments (e.g. thinning or clear-cutting), the timing of these treatments (years or periods), or both. The schedules are selected standwisely to achieve goals set by the forest owner. However, regeneration and thinning regulations and recommendations must also be taken into account in the timing of schedules. The purpose in Study V was to examine the usability of the updated stand-level data for defining the management schedules of stands. The considered error sources were as follows: (i) the errors due to the processing of the inventory data, (ii) assessment errors of stand-level inventory, and (iii) updating of inventory data.

The 'real' treatment suggestions for stands with respect to thinning models and regeneration limits were obtained from the tree-specific data. As soon as possible, treatments other than 'rest' were selected for the management operation of the stand. Thus, the goal was to maximize the area of the management operations. This criterion was chosen because had other goals been used, the treatment schedules and suggestions would have depended on these goals. The management planning period was 10 years.

The study data consisted of 274 forest stands from the INKA data (see V, Table 1). The stand-level inventory data were generated from the INKA sample plot data. The selection criteria for the stands were:

a) No treatments during the updating time and

b) The only allowed stand treatment suggestion is rest at the beginning of updating.

The study data also included the data of 988 stands from the checking inventory data set. The checking data includes the mineral-soil-based stands from Study I. These stands were used for generating assessment errors of the stand characteristics of stand-level inventory into the stand-specific INKA data. Error generation was done by using the *k*-nearest neighbor method. The assessment errors of each stand covered by the INKA data were achieved from similar stands providing the checking data. The similarity measures were normalized stand basal area diameter, stand basal area, and the tree species composition of the stand.

The tree-specific data and stand-specific data (stand-level inventory data) were first updated 10 years. Then the proposals of the management operations were made for the following 10-year period, which was divided into two 5-year periods.

When only the errors due to the processing of the inventory data were considered, 91.6-94.5% of the suggested management operations from the stand-level inventory data were the same as those obtained from true tree-specific data. When measurement errors along with processing errors were considered, the proportion of correctly classified management operations decreased by 11-15% units. When the errors of the updated stand characteristics were considered in addition to the two error sources above, the proportion of correctly classified management operations was 71.6-78.5%.

4. DISCUSSION

4.1 Analysis of main results

Forest management planning should provide accurate data and reliable predictions of forest growth and yield. Because of the complexity of forest simulator systems, especially the uncertainty of growth predictions is difficult to assess.

Stand-level inventory is a widely used method in Finland for collecting forest inventory data from all forests. Its accuracy and precision have been found to be fair, albeit that the costs and time consumed by field work are considered to be rather high. However, there are other benefits connected to a field inventory, e.g. timing of and suggestions for management operations, which must be considered when the evaluation of stand-level inventory is done.

Stand-level inventory is under development (e.g. new measurement equipment, new models, new measurement combinations, new approaches). In addition to this, compensatory and supplementary inventory methods (e.g. more effective utilization of existing inventory data, remote sensing) can be utilized. In changing situations, the reliability of the new method must be studied with respect to the conventional method. Thus, Study I provides valuable information on the usability of new methods and equipment for research and decision making.

According to the results of Studies I and II (also e.g. Kangas and Maltamo 2002, Saari and Kangas 2005), a substantial variation was noted between the accuracy of the measurers. The quality of the old inventory data should be always considered when old data are used for updating. If there are any questions about the accuracy of the updating data, sampling of a few stands for checking inventory data from the inventory area will provide information on the usefulness of the old data. The main problem with stand-level inventory is its subjectivity: typical points of the stand are measured while local extremities of the stand are often ignored. According to the results of Study I, most of the errors in the stand characteristics in stand-level inventory were Berkson’s cases or combinations of Berkson’s case and the classical error model. This refers to the measurer’s tendency to reject variation within stands. The differences between checking inventory data sets explained only part of the substantial variation between the measurers.

The variation between the measurers can be taken into account by reducing the bias by means of personal calibration models in stand-level inventory data. However, calibration should be based on real-time knowledge of the measurer’s accuracy. Finnish forest centers, regional forest authorities overseeing how non-industrial private forests are managed, have continuously paid attention to the training of their surveyors. Knowledge about the accuracy of measurers in different time periods can be utilized when selecting suitable areas for updating.

Checking inventory should be carried out in the areas chosen for potential updating. Stratified sampling is one effective method of implementing checking inventory. The accuracy of the updated data can then be examined covering the entire data and strata. The quality of the checking data, e.g. variation in stand age and volume, can then be taken into account.

Study I also looked into the different diameter distribution models in the calculation of inventory results. When the correct stand inventory data were used, the differences between the predictions of growing stock using the different models were found to be substantial.

But when using the stand inventory data with assessment errors, the differences between different models vanished.

Study II looked at the simulation methods for generating errors typical for stand-level inventory data because of the lack of suitable study data for assessing the uncertainty of growth and yield predictions. The Monte Carlo method was found to be the most flexible simulation method when dealing with multivariate error distributions. The method produced the required variation and relations between the errors of the basal area median tree characteristics. The use of Monte Carlo methods demands *a priori* information about the error variances of the stand characteristics. However, if the reference data are extensive, the 1nn-method, and in certain conditions also the empirical errors method, offer a useful tool for producing error structures reflecting reality. Systematic errors and possible trends can be taken into account also by using the Monte Carlo methods. However, the 1nn-method, and to a lesser extent the empirical errors method, include implicitly the trend.

The use of both non-parametric methods, the 1nn-method and empirical errors method, is quite simple. They do not require any assumptions about error distributions or relations between the errors of the stand characteristics. The correlations between the errors of the basal area median tree characteristics were found to be positive for all tree species. The errors of the species-specific basal areas within stands were also correlated.

The variation between the measurers was not simulated in Study II. However, the said variation can be taken into account, for example, by drawing up personal error models and by calibrating multivariate distributions with surveyor's error variances included. If the reference data are extensive, it is possible to estimate personal multivariate distributions. In the 1nn-method the variation between the measurers can be taken into account by weighting the measurer with distance functions. The use of surveyor classes, e.g. beginners and experienced, could also be advisable.

Studies III and IV looked into two methods for assessing the precision of growth predictions of stand inventory data using a forest simulator system. Study III revealed that the *k*-nearest neighbor method is a promising tool for assessing uncertainty. When the method was tested with erroneous data, the precision of the predictions was still on acceptable level. In addition, the species-specific predictions of uncertainty appeared to be on acceptable level (see III, Tables 5 & 6). However, the random variation in growth and yield predictions and in measurements errors makes it practically impossible to forecast individual large observed errors in growth estimates. Even with accurate measurers, significant errors are made even in stands appearing to be undemanding to measure and to update. One possible reason for this may be that surveyors employ less sample plots and measurements in homogeneous stands than in heterogeneous stands. However, large random errors in stand characteristics are typical also with new inventory data and they are simply ignored in the planning process.

In study IV, the *k*-nearest neighbor method with multi-objective optimization, and in addition, a model of observed errors, were found to be very effective and easily applicable methods for assessing the uncertainty of growth and yield predictions systems when contemporary models and distance functions were applied. The use of these methods requires comprehensive, and preferably independent, reference data, which is also the main drawback of both methods. The utilization of these methods does not considerably increase the calculation time even when dealing with growth predictions for large areas.

According to the results of Study V, updated stand inventory data could be used as forest management data with respect to treatment proposals. However, this argument is made subject to the reliability of stand data with thinning models and regeneration limits. The accuracy of updated stand characteristics was also found to be satisfactory for forest management data. The regulations could be adjusted to have lower limits, e.g. for finding potential stands for thinning. This is a far better way to deal with the uncertainty of suggestions for management operations than adjusting growth predictions as was considered in Study V. Treatment proposals, especially thinning proposals, were more reliable with updated tree-specific data than updated stand-specific data.

Assessment errors were found to be the foremost factor in regard to both the uncertainty of updating of stand characteristics data and the uncertainty of the prediction of treatment proposals. In Ojansuu et al. (2002), the assessment errors were also found to be the foremost factor affecting the uncertainty of the prediction of treatment proposals.

The effective temperature sum for the respective study area is not always available. However, these observations can be predicted from neighboring observations (e.g. Ojansuu and Henttonen 1988). The selection of the used effective temperature sum was found to be significant for the reliability of the treatment schedules. When the original effective temperature sums from the study data were selected, the results of the proposed treatment schedules were worse than if the temperature sums were predicted like as was done with the growth models used (Ojansuu and Henttonen 1988, Hynynen et al. 2002). Contrary to the original situation, stand growth was clearly overestimated when the predicted temperature sums were in use. The use of the predicted temperate sums, as well as the use of predicted altitudes, evolved into recommendations when using the MELA simulator following the completion of Study V. However, when the predicted temperature sums and predicted altitudes were used together, the results of the proposed treatment schedules were nearly same as in the situation in which the temperature sums and altitudes were obtained from the study data. The accuracy and precision of growth predictions were now equal as in the situation in which the temperature sums and altitudes were obtained from the study data.

The updating of stand data requires information on management operations made during the updating time. This can be done very accurately if the forest operations have been properly registered (e.g. Hyvönen and Korhonen 2003). However, borders/boundaries of the stand should be as little changed as possible. Obtaining the stand characteristics of new stands within new borders/boundaries from the updated stand characteristics of former stands can be difficult, especially if the former stands are heterogeneous. Unfortunately, the boundaries of the management units do not often correspond to stand boundaries. Had relascope sample plots been located, the stand characteristics for updating the new situation could have been obtained from stand plots located within the new modified stands (e.g. Koivuniemi 2003).

Sometimes it may be enough to arrange stand growth predictions using the estimate of uncertainty as the classifying measure; e.g. when searching for stands in which field inventory can be replaced with computational updating of the old forest inventory data more satisfactorily than in other stands. Then the updating of stands in which prediction of growth and yield is found to be more difficult, e.g. in younger stands, and also in those treated stands, which have not been re-measured after treatment, should be considered carefully.

The size of a stand did not affect the accuracy measurement of stand characteristics. The random errors of larger stands are far more important at the woodlot level than the random errors of smaller stands. If there are similar stands of varying sizes and updating concerns only some of the stands at the woodlot level, then the field inventory should be carried out in larger stands rather than in smaller stands. The updating of young stands must also be considered carefully. These forests are in that very development phase in which large variation in growth and yield, large transitions between timber assortment classes, and strict timing of management operations are typical. In practice, stands with imminent management operations and silvicultural operations should be inventoried with care.

The models used for prediction of growing stock, timber assortments and growth are typically national models, which can cause significant bias when applied in an individual stand or forest area (e.g. Korhonen 1993, Karlsson 1996, Gustavsen 1998, Sironen et al. 2001). Systematic errors of regional models can be reduced by calibrating the models, e.g. by modeling the observed biases (Hynynen et al. 2002). The coordinates of stands were considered to be the dependent variables in models of observed errors. However, the predictions of uncertainty were found to be very sensitive to coordinates. Therefore, the spatial dependence was taken into account mostly by using altitude and actual temperature sum as the dependent variables. When using the *k*-nearest neighbor method, the location of a stand is implicitly included slightly because the stand characteristics and predicted stand growth are similar in the neighborhood.

The updating time used in this thesis was at its longest 20 years, but time was mostly restricted to 10 years. The time horizon in forest management planning in non-industrial private forestry is typically approximately 10-15 years. However, when old inventory data are used in updating, the time horizon of the growth predictions is extended about 5-15 years. The uncertainty assessments of growth and yield predictions were made for the same period as represented by the reference data. This situation corresponds to the updating process of forest management planning data, because then there are similar possibilities to obtain reference data.

The use of the permanent data plots established to facilitate national forest inventory in Finland (NFI data) was also considered for the uncertainty analyses involving growth and yield predictions. The NFI data are the other of the two comprehensive re-measured data sets in Finland. The main reason why the NFI data were used only restrictedly was that the NFI plots are quite small in size. It is obvious that the development of the surrounding stand and its predictions can be very difficult to derive when dealing with small plots. However, the INKA data are a sample of the 7th national forest inventory data for Southern Finland and of the 6th national forest inventory in Northern Finland.

The use of INKA data was a little problematic, because the data have been used as modeling data in some models drawn up for the MELA simulation system (Hynynen et al. 2002). However, the INKA data are used as modeling data for single-tree growth models in MELA, and this dissertation deals with stand-level data. The variation of INKA data stands and the geographical variability of the data also reduce the dependence of the INKA data.

The growth and yield predictions of stand characteristics of the forest simulation system (MELA) used in this dissertation were underestimates. In Ojansuu et al. (2002), stand growth was also underestimated. Of course, this underestimation of growth affects the assessment of cutting potentials, but even more important is its effect on the timing of management operations. In particular, growth and yield predictions of stands in which management operation(s) had been implemented during the updating time were underestimates. This can be partly due to erroneous time assessments of the management operations in the study data. The growth models used were found to be very sensitive to the annual temperate sum and altitude values used.

There are studies in which the accuracy of the stand-level inventory data has increased when additional or varying measurements have been implemented (e.g. Kangas and Maltamo 2000c, Mehtätalo 2004a,b). However, in those studies the costs and time consumed have not been examined. Despite its low accuracy and problems encountered in assessing this uncertainty, stand-level inventory offers a good opportunity to learn to know the properties of stands within the planning area. This helps especially in case of multi-objective forest planning.

4.2 Conclusions

In this study, the variation between the measurers, in terms of the quality of the measurements, was found to be substantial. This variation in stand-level inventory data should be taken into account in forest management planning. One simple solution for that could be the use of confidence levels/intervals for growth and yield predictions, which could vary from unskilled measurer into precise measurer. If the measurer's working quality is known, only one confidence level/interval is needed. Confidence levels/intervals can be derived e.g. using models of the observed errors or k-nearest neighbor method. Sometimes the accuracies of the measurers are known, and even the measurement errors of the measurers are available. These can be used in estimating models of the observed errors or in generating reference data for k-nearest neighbor method.

Reliable estimates of the uncertainty of stand-level inventories can not be given without conducting objective checking inventories. At the woodlot level, systematic errors are more serious than random errors, because divergent random errors tend to cancel each other out. Random errors can be reduced by adding to the number of relascope plots and measurements conducted within an individual stand. Systematic bias can be reduced by training and controlling the work of the measurers, and by using higher relascope factors in dense mature forests (Saari and Kangas 2005). One possible solution for reducing the variation between the measurers and getting more reliable estimates of stand-level inventory could be the substitution of subjective decisions with objective measurements.

Updating old inventory data provides an opportunity to reduce the costs of forest management planning. However, the uncertainty of updated stand characteristics is difficult to predict. There can be noticeable errors even in stands considered to be relatively easy to measure and update.

Even if accurate values of the uncertainty of growth and yield predictions are not achieved, data on the uncertainty associated with the measurers can be very useful. If the classification of stands depending on the uncertainty of the measurers is reasonable, this can help in some decision situations, e.g. choice situation of re-measuring vs. computational updating. The predictions can also be calibrated if there is *a priori* knowledge of uncertainty.

According to the findings of this dissertation, updated stand inventory data can be used quite safely as forest management data with respect to treatment proposals. Because the treatment schedules were evaluated with respect to the recommendations and limitations of thinning models and regeneration rules, further study is still needed: treatment schedules from the updated data need to be compared with those obtained from field checking actions. Comparison with actual planning data can be problematic as suggestions for the management operations needed to be applied to the stands are often fairly subjective. The comparison data should consist of acceptable management operations conducted by many surveyors. However, the final treatment proposals are derived from forest owner's goals, with respect to current forest management practices, if he/she has participated in planning process.

The planning system MELA produced considerable underestimates of stand growth and yield in the study data. This underestimation should be examined using independent data in the event that the stand composition of the study data does not cause the underestimation, and perhaps then calibrate the growth models.

When the decision regarding the inventory method to be employed is of current importance, a cost-plus-loss analysis could help to find a suitable and cost-effective method (e.g. Holmström 2001, Holmström et al. 2003). The method's framework is such that the choice of method depends on the inventory costs and excepted losses due to non-optimal decisions at different levels of precision. This study provides some information for those kinds of analyses; the quality of forest inventory data as well as the quality of the updated data.

Cost-plus-loss analyses could be carried out at the woodlot level. One interesting approach would be to search for those stands within woodlots on which management schedules are not very sensitive to the quality of the forest management planning data and to changing conditions (e.g. timber prices, growth variation, rent) and those stands, which are sensitive. The latter stands are those to which attention should be focused during the planning and decision-making stage.

The contents of the collected stand-level inventory data of non-industrial forestry have changed along with the changes in the information needs of the forest owners and society. In the future, the information needs can further change and increase the contents of stand-level inventory data. For example, efficient management and optimization of wood-procurement needs more accurate planning data from marked stands. Adoption of new inventory methods (e.g. wider use of remote sensing techniques, new equipments and measurement combinations of field inventory and new sampling techniques containing e.g. located sample plots) can also cause changes in stand-level inventory. Furthermore, the increasing variation in stand structure caused by diversified applying of different forest management operations requires precise stand data. In addition, the prerequisite of instantly growing use of continuous inventory is accurate stand inventory data. Thus, from these viewpoints, the accuracy and precision of the stand-level inventory must be kept at least in its current level.

The assessment of uncertainty of growth predictions is 'continuously under construction'. The circumstances are far from permanent: e.g. new models, fluctuating growth factors (climate, forest damages, etc.), varying precision of the inventory data, changing management of forests, etc. Most of the changes in circumstances make old assessments unreliable. Changing circumstances make assessment of uncertainty a progressive task with no end to it.

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