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Economic losses in forest management due to errors in inventory data

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Academic dissertation

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ABSTRACT

The performance of a forest inventory is typically evaluated using error indices, such as root mean square error (RMSE) and the difference between means of observed and predicted attributes (MD). However, error indices or errors as such, do not fully reveal the practical usefulness of forest inventory data. Using erroneous inventory data as a basis for management planning may have harmful effects on forestry decision-making. Errors in inventory data can lead to the selection of management prescriptions that differ from the optimal prescriptions based on error-free data. Eventually, differences in the selected prescriptions result in losses in regard to the objectives set for the management. The main aim of this thesis was to assess the effects of inventory errors on forest management where the objective is to maximize the net present value (NPV) of timber production and carbon payments. The studies considered different combinations and levels of errors in forest stand attributes and evaluated the effect of errors on the optimality of management prescriptions based on the expected economic losses, which were measured in NPV. The results showed that expected losses depend on the error rate of those forest stand attributes, which are used to describe the present state of the forest in the planning system. In particular, the results indicated that errors in mean diameter can be more harmful than errors in the basal area. Increasing the sample size in a remote sensing-based forest inventory increased the accuracy of predicted stand attributes and decreased the expected losses. The inclusion of carbon payments in the maximization of NPV showed that the effect of errors on expected losses decreases when the carbon price increases. The findings of this thesis indicate that it is very important that the effects of inventory errors are considered in forest management planning.

Keywords: forest management planning, net present value, prediction error, uncertainty, value of information

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Joensuu, May 2021

Roope Ruotsalainen

LIST OF ORIGINAL ARTICLES

This thesis consists of a summary and three articles, which are referred to by Roman numerals (**I–III**). The articles are reproduced with the kind permission of the publishers.

I Ruotsalainen R, Pukkala T, Kangas A, Packalen P (2021) Effects of errors in basal area and mean diameter on the optimality of forest management prescriptions. Ann For Sci 78: 18. https://doi.org/10.1007/s13595-021-01037-4

II Ruotsalainen R, Pukkala T, Kangas A, Vauhkonen J, Tuominen S, Packalen P (2019) The effects of sample plot selection strategy and the number of sample plots on inoptimality losses in forest management planning based on airborne laser scanning data. Can J Forest Res 49: 1135−1146. https://doi.org/10.1139/cjfr-2018-0345

III Ruotsalainen R, Pukkala T, Kangas A, Myllymäki M, Packalen P (2021) Economic losses in carbon forestry due to errors in inventory data. Can J Forest Res 51: 501−512. https://doi.org/10.1139/cjfr-2020-0251

Roope Ruotsalainen was the corresponding author in all articles. He carried out the analyses, interpreted the results and wrote the manuscripts under the supervision of Prof. Petteri Packalen and Prof. Timo Pukkala. Prof. Annika Kangas participated in the planning of the studies and commented on the manuscripts. Prof. Jari Vauhkonen and Dr. Sakari Tuominen commented on study **II**. Dr. Mari Myllymäki contributed to the error simulation part of study **III** and commented on the manuscript.

TABLE OF CONTENTS

ABBREVIATIONS

ALS	Airborne laser scanning
BA	Basal area (m^2 ha^{-1})
CPL	Cost-plus-loss
D	Basal area-weighted mean diameter (cm)
DBH	Diameter at breast height (at height of 1.3 m)
DM	Decision-maker
EVPI	Expected value of perfect information
EVII	Expected value of imperfect information
FPS	Forest planning system
H	Basal area-weighted mean height (m)
LiDAR	Light detection and ranging
LPM	Local Pivotal Method
MD	Mean difference
NN	Nearest neighbor
NPV	Net present value
RMSE	Root mean square error
VOI	Value of information

1 INTRODUCTION

1.1 Stand-level forest management inventories in Finland

Stand-level forest management inventory practices have developed significantly during the last 15 years, mainly due to practical applications of airborne laser scanning (ALS) (e.g., Nesset 2002; Maltamo et. al 2004; Packalén and Maltamo 2007). The traditional stand-wise field inventory method in Finland, which is based on subjective angle count sampling and partial visual assessment of stand attributes (e.g., Koivuniemi and Korhonen 2006), has been mostly replaced with an inventory method that utilizes a combination of local field sample plots, remote sensing data, and non-parametric estimation (Maltamo and Packalen 2014).

A nearest neighbor (NN) imputation method that utilizes independent variables calculated from the ALS and aerial image data, and stand attributes measured from the field sample plots as dependent variables, is often applied in Finnish stand-level management inventories. The species-specific stand attributes, namely mean diameter, mean height, basal area, number of stems and volume, are predicted simultaneously for Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) Karst.), and for all deciduous species considered as one species group (mostly birch, *Betula* spp.) (Packalén and Maltamo 2007). The method also allows the prediction of species-specific diameter distributions based on the field sample plot measurements (e.g., Packalén and Maltamo 2008; Peuhkurinen et al. 2008; Räty et al. 2018). However, in the current practice, theoretical diameter distribution models are still commonly used to predict the diameter distributions based on the species-specific values of basal area (or number of stems) and mean diameter (e.g., Kilkki et al. 1989; Maltamo 1997; Maltamo et al. 2002).

In the case of privately owned forests, the state-funded organization Finnish Forest Centre is responsible for conducting stand-level forest management inventories. Typically, the size of an inventory area varies between 100,000 and 500,000 ha, and 500–800 georeferenced circular sample plots are measured from each inventory area. While the Finnish Forest Centre collects the sample plot data by itself, acquisition of remotely sensed data (ALS and aerial image data), data processing, wall-to-wall mapping of stand attributes and stand delineation are conducted by private service providers. In wall-to-wall mapping, the stand attributes are predicted for 16 m × 16 m grid cells that cover the entire inventory area. The grid cells represent the smallest inventory units for which the stand attributes are predicted based on the sample plot and remotely sensed data. Stand boundaries are based on the existing information, or a new stand delineation can be carried out using aerial images and canopy height models derived from the ALS data (e.g., Mustonen et al. 2008). The Finnish Forest Centre produces stand-level predictions by aggregating the grid cells that are located within the stand boundaries. The inventory results are eventually made available to private forest owners via a web service called Metsaan.fi, which contains holding-specific information (e.g., stand delineation, current state of the forest, and suggested management prescriptions, which are simulated according to the silvicultural recommendations (Äijälä et al. 2014)).

1.2 Information requirements of forest management planning and error sources

Stand-level forest management inventories produce information that is used as a starting point for forest management planning. In general, forest management planning aims to assist the decision-maker (DM) to conduct such management actions that maximize the DM's utility with a given set of constraints (Pukkala 2002). The utility can be maximized by developing a management plan that fulfils the DM's forest management objectives.

Forest management planning is typically carried out using a forest planning system (FPS), which can be defined as a decision support tool that has two main parts: a simulator and a solver. The forest simulator forms a simplified model of the forest dynamics. It usually includes several sub-models that utilize information from the current state of the forest to predict structural changes that occur due to growth, mortality, and management activities. The solver is used to select the optimal combination of management alternatives among the simulated ones. Optimization can be carried out using exact solution methods, such as linear programming (e.g., Kangas et al. 2015), or heuristics (e.g., Bettinger et al. 2002; Pukkala and Kurttila 2005).

To describe the current state and the future development of the forest, FPS requires information on several stand characteristics. Information on the species-specific tree size distributions are typically provided based on the basal area (or number of stems) and mean diameter, which describe the density and the average tree size in a stand. Then, theoretical diameter distribution models are used to predict species-specific diameter distributions (e.g. Kilkki et al. 1989; Kangas and Maltamo 2003). The basic unit of the forest simulator is a so-called representative tree that represents several similar trees in the same diameter class. Heights and timber assortment volumes are predicted for the representative trees using height-diameter and taper curve models (e.g. Siipilehto and Kangas 2015; Laasasenaho 1982). In addition, tree-level sawlog defect models (e.g., Mehtätalo 2002) can be applied to predict the quality deductions for sawlog volumes. When the future development of the forest is simulated, distance-independent tree-level models (e.g., Hynynen et al. 2002; Pukkala et al. 2013) are commonly used together with survival and ingrowth models. Stand attributes (e.g., basal area, volume, mean diameter, and mean height) are then calculated based on the representative trees. In addition to tree size distributions, information on site characteristics is needed since it affects the model predictions.

In addition to the requirement for species-specific inventory information, information on the DM's objectives is needed. If there are several objectives, information on the relative importance of the objectives is also required. Usually, the economic profitability of forestry has been considered to be an important objective for the majority of DMs. In the case of timber production, information on the stands that can be soon harvested is important. The harvested volume and the quantity of timber assortments should also be known. However, non-timber forest products and services (e.g. carbon sequestration) may also be important. Moreover, DMs may have objectives that are not directly related to the economic aspects of forestry. For example, recreational and ecological aspects of forests may be more important than economic profitability. Information needs depend on the objectives set for the management planning.

There are many sources of errors in forest management planning that may affect the outcome of the planning process. Firstly, inventory information typically contains errors that affects the description of the current state of the forest stands and the appropriateness of the simulated management prescriptions. In Finland, prediction errors in stand attributes are often related to the identification of tree species in current remote sensing-based stand-level management inventories. For example, it may be difficult to identify the main tree species in mixed forests or recognize minor tree species located under the dominant canopy. The prediction errors can also result from unrepresentative sample plot data, i.e., the sample plot data do not sufficiently cover the variability of the forests. This can lead to the underestimation of the largest values and overestimation of the smallest values of stand attributes because extrapolation is not possible with the nearest neighbor methods (e.g., Maltamo and Packalen 2014). There might also be issues related to the acquisition of remotely sensed data, which can introduce additional errors. For example, the use of different flight parameters or ALS device or aerial camera in the same inventory area causes problems. Sample plot data can also contain errors.

In addition to the errors associated with the inventory information, predictions concerning the future development of forests contain errors. This is mainly because of the complexity and variability of forest stand dynamics (e.g., Porté and Bartelink 2002; Haara and Leskinen 2009). Inherently, the description of the current state of forest can also include errors, for example, when theoretical diameter distribution models are used (e.g., Palahi et al. 2008). Furthermore, the accuracy of planning calculations is also affected by several external factors, like markets (i.e., fluctuations in prices of forest products), natural hazards and climate change (e.g., Hanewinkel et al. 2011; Yousefpour et al. 2012). The errors in forest inventory data can be decreased by more accurate inventory methods, whereas the above-mentioned external error sources cannot be easily mitigated. This thesis focuses on the errors in forest inventory data and their effects on forest management planning.

1.3 Value of information in forest management planning

Errors in forest inventory data may have several undesirable implications for forestry decision-making. Errors (the differences between correct and incorrect values) are usually measured using error indices, such as root mean square error (RMSE) and mean difference (MD), that is often referred to as 'bias'. Even though these error indices can give a general impression of the accuracy of the forest inventory method, they do not provide information as to how a lack of accuracy will affect the outcome of forest management planning. Moreover, if accuracy of information is maximized with a given budget without considering the expected value of decisions, the increase in inventory costs may not be justified. In fact, increased costs associated with the acquisition of more accurate information should not be greater than the increase in the expected value of decisions.

The errors in forest inventory data can be approached using the concept of value of information (VOI), which can be defined as the expected improvement in the value of decisions: it is the difference in the expected value of decisions made with and without new information (Lawrence 1999; Bitcher and Bütler 2007; Kangas 2010). Information is considered valuable if it increases the expected benefit of the decisions compared to prior information. Therefore, the concept of VOI arises from the ability to conduct decisions that increase DM's utility. Furthermore, VOI can be distinguished as the expected value of perfect information (EVPI) and the expected value of imperfect information (EVII). The former refers to the value of error-free information, i.e., the maximum value of information that the DM would pay if such information were available. However, information usually contains errors, in which case VOI refers to EVII. One important aspect of VOI is that it is always analyzed before the actual decisions are carried out. This means that the effect of errors on decision-making is based on the expected VOI.

In forest management planning, VOI can be calculated based on the expected losses, which are commonly called inoptimality losses. Inoptimality losses are based on the premise that the use of erroneous data can lead to sub-optimal utilization of forests compared to the use of error-free data. Inoptimality losses are equal to the expected losses in the value of the objective function when forest management prescriptions that are optimal for the erroneous inventory data are followed, instead of management prescriptions that are optimal for error-free data. Therefore, erroneous and error-free information, as well as the optimal decisions based on both categories of information, are required for the calculation of expected losses. In research, field data are often used to represent perfect information and are assumed to be error-free. Inoptimality loss is calculated as the difference in the value of the objective function between optimal and sub-optimal management alternatives, both simulated with the error-free data. VOI is derived from decreased inoptimality losses compared to inoptimality losses of prior information. Moreover, VOI can also be evaluated using so-called pre-posterior analysis in Bayesian decision theory (e.g., Lawrence 1999).

The used objective function defines the unit of VOI. The objective function may consist of several objectives, but usually only the economic profitability of forestry is considered, and therefore, the net present value (NPV) is maximized without constraints. This means that VOI is commonly expressed in monetary units, although it can also be expressed in non-monetary units, for example, in utils (Kangas et al. 2010). However, constraints are common in practical forestry decision-making, and may be related, for example, to even-flow revenues, growing stock volume at the end of the planning period, or to the spatial aggregation of management activities. The constraints complicate the calculation of VOI because the effects of errors on the feasibility of constraints should also be considered (see Kangas et al. 2014). This means that inoptimality losses are larger if constraints are included in the analysis of VOI, and the results would be more limited to a particular planning case. In this thesis, constraints are not considered, i.e., it is assumed that the utility of the DM depends only on NPV.

Inoptimality losses can be used in a cost-plus-loss (CPL) analysis to compare the performance of alternative inventory methods. In CPL analysis, the total cost of the inventory is calculated as the sum of inoptimality losses and inventory costs, and the inventory method that results in the lowest total cost is considered as the best alternative (Burkhart et al. 1978; Hamilton 1978). To date, CPL analyses have been used in various forestry studies (e.g., Ståhl et al. 1994; Holmström et al. 2003; Eid et al. 2004; Duvemo et al. 2007; Mäkinen et al. 2012).

Inoptimality losses have been utilized to assess the effects of inventory errors on forest management planning. Errors are either observed errors from a specific inventory method, or simulated errors. The use of observed errors is straightforward since the error structure (i.e., joint distribution of errors) is realistic, but usually only one error realization (i.e., one set of predicted variables) per stand is available. For example, Eid et al. (2004) used observed errors from photo interpretation and ALS-based forest inventories. Bergseng et al. (2015) compared four different remote sensing-based inventory methods with different data combinations. Kangas et al. (2018) evaluated the expected losses when ALS and aerial image point cloud data were used in management planning. Recently, Haara et al. (2019) assessed the effect of errors in tree species proportions and site type classification on the expected losses. In general, simulated errors permit the evaluation of the effect of errors on individual stand attributes and the relative importance of these errors on expected losses. Several realizations of errors can be simulated to stand attributes of interest. Simulated errors can also provide information on the effects of errors on a more general level since they are not limited necessarily to a specific inventory method. Simulated errors have been used, for example, by Eid (2000), who simulated different levels of errors in stand attributes and assumed the errors to be normally distributed and non-correlated. The effects of errors in the basal area of minor tree species were assessed by Islam et al. (2009). Mäkinen et al. (2010) and Islam et al. (2010) simulated the joint distribution of errors, which were similar to the errors obtained in forest inventory based on ALS and aerial image data. More recently, Vauhkonen (2020) studied expected losses due to diameter distribution errors in simulated ALS-based tree-by-tree inventories.

The VOI depends on the use of inventory data and is always specific to the planning problem. This means that inoptimality losses are affected by the characteristics of the inventory area and inventory method (or simulated errors), the objectives of the DM, and the time that the data are used. Moreover, it should be noted that the differences between the FPSs (e.g., models used and simulation rules) used in different studies complicate comparison of the results. In general, VOI is low if errors in the inventory data have only a small effect on the timing and type of the selected management prescriptions. The timespan over which the data are used also affects VOI because more decisions can be carried out over a longer time period. In addition, discounting affects inoptimality losses, because the net incomes in the near future will affect NPV more than later net incomes (Kangas et al. 2014).

Nevertheless, an analysis of VOI based on the expected losses provides insights as to how inventory methods, or erroneous inventory data in general, can affect forestry decision-making. The development of inventory methods and the acquisition of information should be motivated not only by accuracy but also by the end-use of the information.

1.4 Objectives

The overall objective of this thesis was to assess the effect of erroneous forest inventory data on inoptimality losses in forest management planning. The specific objectives of studies **I**–**III** were to:

- **I** Assess how under- and over-estimates in stand basal area and mean diameter affect inoptimality losses when the NPV of timber production is maximized.
- **II** Evaluate the effects of sample plot selection strategy and the number of sample plots on inoptimality losses in forest management planning, which is based on ALS inventory data.
- **III** Study how errors similar to ALS-based inventory data affect inoptimality losses in forest management where the aim is to maximize the total NPV of timber and carbon benefits with various carbon prices.

2 MATERIALS

2.1 Study area

The study area is located in central Finland and covers around 580,000 ha (Figure 1). The elevation is mostly 100–200 m above sea level. According to the Finnish Multi-Source National Inventory data from 2013 (Natural Resources Institute Finland 2020; Tomppo and Halme 2004; Mäkisara et al. 2016), 81 % of the land area is classified into forestry land (incl. productive, poorly productive, and unproductive forests), most of which belongs to mesic (41.2 %) and sub-xeric (37.6 %) site fertility classes. Most of the forests are on mineral soils (72 %), whereas forested peatlands (26.2 %) and open mires (1.8 %) comprise smaller areas. The majority of the forests are dominated by Scots pine (73.8 %), whereas Norway spruce

(14 %) and deciduous species, mainly birch (12.2 %), are less common as dominant tree species. The forests are mainly owned by private landowners and are managed for timber production.

2.2 Sample plot data

The sample plots were measured between May and October 2013. In total, 2469 sample plots were established in the study area using systematic cluster sampling. The distance between clusters was 4.3 km and a full cluster contained eight sample plots, which were located 250 m apart. A total of 1956 sample plots were located on forestry land (Figure 1). Each circular plot had a fixed radius of 9 m. Information on the basic site characteristics was also recorded. All trees were measured for species, diameter at breast height (DBH: diameter at height 1.3 m) and tree class (living or dead, standing or fallen). The heights of basal area median trees were measured, separately for different species groups (Scots pine, Norway spruce and all deciduous trees as one species group). The mixed-effect models of Eerikäinen (2009) were used to predict tree heights for the remainder of the trees. Tree volumes were predicted with the models of Laasasenaho (1982) using DBH and height as predictor variables. Stand attributes, namely basal area per hectare (BA), basal area-weighted mean diameter (D), basal area-weighted mean height (H), number of stems per hectare, arithmetic mean diameter and arithmetic mean height were calculated for the above-mentioned species groups from trees with DBH $\geq$ 5 cm.

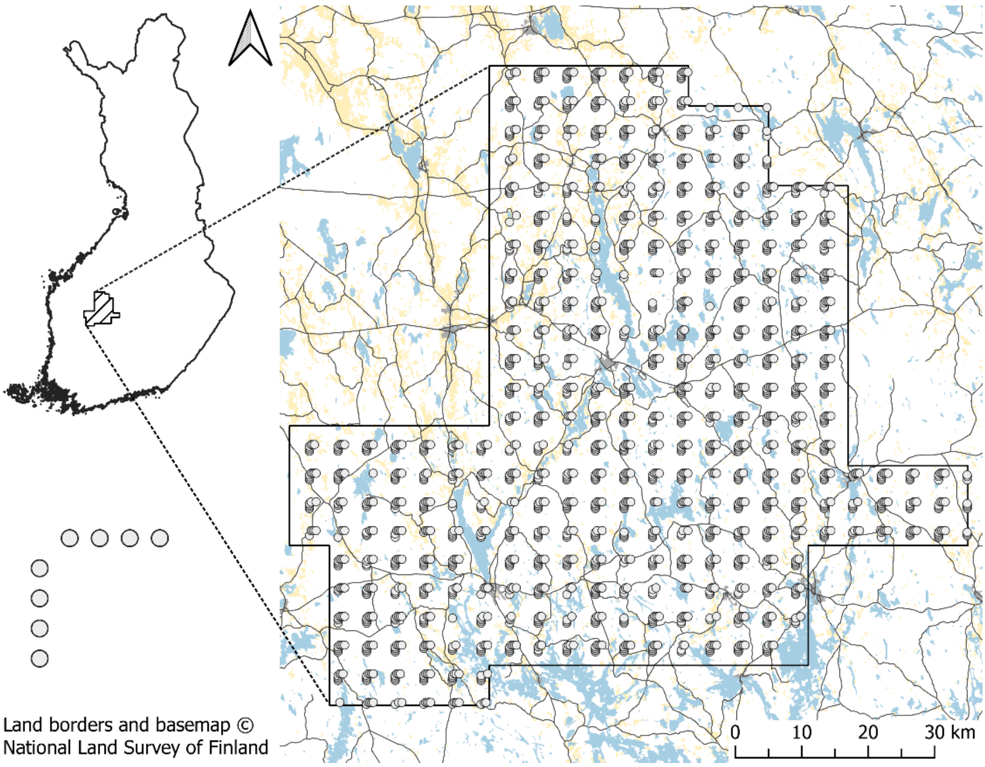

Figure 1. Study area and the locations of the sample plots.

Different subsets of sample plot data were utilized in studies **I**–**III**. In all three studies, sample plots located in the seedling stands were excluded from the data. In study **I**, sample plots where the main tree species was Scots pine were used (n = 1037). Study **II** utilized sample plots for which remotely sensed data were available (n = 1384). In study **II**, the validation data (n = 346) were selected from the 1384 sample plots by first assigning the data to main species groups (Scots pine, Norway spruce or deciduous). Species groups were further disaggregated into three equal-sized classes based on total tree volume. Then, 25 % of the plots in each species group and volume class were randomly selected. The remaining plots (n = 1038) were used as training data. In study **III**, 1501 sample plots were utilized (the plots from study **II** and some additional plots).

2.3 Remotely sensed data

The ALS data were collected between June and August 2013. A fixed-wing aircraft was equipped with an Optech Gemini ALTM laser scanner system and operated at a flying altitude of 1730 m. The half scanning angle was set at 20 degrees, pulse repetition frequency was 70 kHz and the lateral overlap was 20 %. These parameters resulted in a pulse density of about 0.7 observations per square meter. The used ALS device measured up to four returns per emitted pulse. The ALS echoes were separated into ground and non-ground echoes based on the method proposed by Axelsson (2000). The ground echoes were used to create a digital terrain model (DTM). Echo heights were normalized by subtracting the DTM from the original echo heights.

The aerial image data were acquired in July and August 2013. The aerial images were captured using a Microsoft UltraCam Eagle camera at an altitude of 4700 m. The orthorectified images had a spatial resolution of 0.3 m and included red, green, blue and near-infrared spectral bands. The ALS and aerial image data were used in study **II**.

3 METHODS

3.1 Simulation of under- and over-estimates and random prior information

In study **I**, systematic under- and over-estimates were simulated in BA and D to analyze the relative importance of errors in these attributes. Both BA and D have a significant effect on the description of the current state of a stand because diameter distribution is predicted using these attributes. The values of BA, D and H were calculated from all trees in the sample plot. All trees were assumed to be Scots pine, because most of the sample plots were located in pine-dominated forests. Error levels of -20 %, -15 %, -10 %, -5 %, 0 %, 5 %, 10 %, 15 % and 20 % were simulated in BA and D by multiplying the correct values in every sample plot with factors that ranged from 0.8 to 1.2. The other stand attributes were kept the same as the correct values in the sample plot data.

In addition to the simulation of inventory data with specific error levels, datasets that contained randomly selected stand attributes for each sample plot were generated in study **I**. It was assumed that the correct values of stand attributes (BA, D and H) were not known for a particular plot, but the distributions of these stand attributes in the generated datasets were equal to the distributions in the sample plot data. Ten datasets that describe random prior information were generated by replacing the correct values of stand attributes in a particular sample plot with attributes that belonged to another randomly selected sample plot in the sample plot data.

3.2 Sample plot selection strategies

In study **II**, four sample plot selection strategies for the selection of training data for the *k*-NN imputations were evaluated. The aim was to select 25, 50, 100, 200, 300, 400 and 500 sample plots from the training data (n = 1038). Each sample plot selection strategy was repeated ten times to capture the variation between the samples. The following strategies were tested: ALS-stratified sampling, Local Pivotal Method (LPM) sampling, spatially systematic sampling, and simple random sampling.

The ALS-stratified sampling utilized height and density variables calculated from the ALS data to stratify the training data into nine classes. The 90^{th} height percentile and the proportion of echoes ≤ 1 m above ground height were computed from the first and only ALS echoes (see section 3.3.1). Training data were first divided into three equal-sized classes based on the density variable and then, each class was further divided into three equal-sized classes based on the height variable. An equal number of sample plots were selected randomly from each class. Consequently, 27, 54, 99, 198, 297, 396, and 504 sample plots were selected from the training data.

The LPM proposed by Grafström et al. (2012) was used to select samples that cover the sample space defined by height and density variables. The height and density variables used were the same as in ALS-stratified sampling. The LPM aims to form samples that capture the original distributions of variables as much as possible. The LPM sampling was performed using the R package BalancedSampling (Grafström and Lisic 2016) and is explained in more detail in Grafström et al. (2012).

The geographical locations of the sample plots were used to select samples that covered the entire inventory area as systematically as possible. Sampling utilized the x and y coordinates of plot centers, principles of random sampling, and a distance criterion. Samples were formed by first randomly selecting an initial sample plot from the training data, and then, all plots within a defined Euclidean distance were removed from the sample space. The next sample plot included in the sample was selected randomly from the remaining plots in the training data. The selection process was terminated when no plots remained. The spatially systematic sampling was repeated ten times with different distance parameter values to form samples that differed by no more than 4 sample plots from the original sample sizes (25–500 sample plots).

Simple random sampling without replacement was repeated ten times with different sample sizes. Sampling was carried out without any auxiliary information, i.e., each sample plot included in the sample was chosen entirely by chance.

3.3 Prediction of stand attributes with the k-NN imputation method

3.3.1 Predictor variables

In study **II**, potential predictor variables were calculated from the remotely sensed data to be used in the prediction of species-specific stand attributes. The ALS predictor variables were calculated separately from three different echo categories: first ("first of many" and "only" echoes), last ("last" and "last of many" echoes), and all echoes. Height percentiles (h5, h10, h20, …, h80, h90, h95) correspond to the heights at which a specific proportion of the echo heights had accumulated. Percentiles were also calculated for LiDAR intensities (int5, int10, int20, …, int80, int90, int95). Density variables were calculated for the echo proportions less than or equal to 0.5, 1, 2, 5, 10, 15, and 20 m above ground. Mean, median, standard deviation, maximum, kurtosis, skewness and number of echoes were also calculated by echo categories. The predictor variables computed from the aerial images were the means and standard deviations of the spectral bands.

3.3.2 k-NN imputation method and variable selection

In study **II**, species-specific stand attributes were predicted using the *k*-NN imputation method. In *k*-NN imputation, *k* Nearest Neighbors are selected from the observations that are most similar to the object of prediction in terms of predictor variables. The distance to nearest neighbors was based on the most similar neighbor (MSN) distance metric (Moeur and Stage 1995), which is determined by canonical correlation analysis (for details, see Packalén and Maltamo (2007)). The stand attributes were predicted using equal weights for the three (k = 3) nearest neighbors.

Variable selection was performed by minimizing the mean relative RMSE value over all response variables using simulated annealing, as described in Packalen et al. (2012). Predictor variables were selected separately for 1) BA, D and H, and 2) number of stems per hectare, arithmetic mean diameter and arithmetic mean height using the training data (1038 sample plots). Ten predictor variables, which resulted in the lowest mean relative RMSE value among the species-specific stand attributes, were selected. The stand attributes were predicted for the validation data (346 sample plots) using the selected predictor variables and training datasets defined by alternative sample plot selection strategies (see section 3.2).

In study **II**, the errors between the observed and predicted sample plot-level stand attributes were decreased by 50 %, which was assumed to correspond approximately to the accuracy obtained in stand-level ALS-based predictions (Packalén and Maltamo 2007). Decreasing the level of errors is justified because the sample plot-level errors are not relevant in stand-level management planning.

3.4 Simulation of errors with vine copula and nearest neighbor approach

An error simulation method that considered the joint distribution of errors was developed in study **III**. The aim was to generate a similar distribution of errors to that obtained in the ALS-based predictions in study **II**. The errors were simulated for tree species-specific values of BA, D and H. The simulation method utilized a vine copula approach to model the dependency structure of observed and predicted stand attributes, and a nearest neighbor method to combine the simulated erroneous stand attributes with the observed values of stand attributes in the sample plot data.

Probability density functions were fitted to the observed and predicted values of the stand attributes of the sample plot data (validation data in study **II**) using logspline density estimation implemented in the R package logspline (Stone et al. 1997; Kooperberg 2019). The original values of stand attributes were converted to approximately follow the uniform distribution based on the cumulative probabilities of the fitted density distributions. The dependency structure of the multivariate uniform distribution was modeled using a vine copula approach (for further details, see Bedford and Cooke 2002; Aas et al. 2009; Joe 2014). In general, vine copulas are models that enable multivariate dependency modeling based on bivariate copulas (pair-copulas) that are organized in a nested tree structure. Vine copulas consist of three components: the tree structure, the bivariate copula families, and the parameters for bivariate copulas. In the case of d dimensions, vine copula includes $d(d–1)/2$ bivariate copulas in $d–1$ linked trees. The tree structure, bivariate copula families and their parameters were selected using the method proposed by Dißmann et al. (2013), available in the R package VineCopula (Nagler et al. 2019). The fitted vine copula model was used to generate 10 separate copula populations. The uniformly distributed values of the copula populations were transformed back to the original scale by calculating quantiles based on the fitted probability density distributions (Kooperberg 2019). Each copula population contained the observed and predicted values of stand attributes.

A nearest neighbor method was used to match the observed stand attributes in the sample plot data and the observed stand attributes in the copula populations. For each sample plot, a nearest neighbor was found from the copula population by calculating Euclidean distances between the standardized stand attributes (i.e., between the observed values in the sample plot data and the observed stand attributes in the copula population). The predicted stand attributes of nearest neighbors were assigned to the sample plots. The means of observed and predicted values of stand attributes were fixed as equal by multiplying the predicted values with the ratio of means. Then, the errors were calculated as the difference between the predicted and observed values of the stand attributes. Different error levels were generated by multiplying the errors with factors that ranged between 1.0 and 0.1. Stand attributes with different levels of random errors were obtained when errors were added to observed values of stand attributes. In total, 10 realizations of errors with 10 different levels were simulated.

3.5 The forest planning system

The Monsu forest planning software (Pukkala 2004) was used in all three studies. Forest data were imported into the planning system using tree species-specific stand attributes and site characteristics. In studies **I** and **III**, BA, D and H were used. In study **II**, number of stems was also imported together with BA and BA-weighted mean variables. In study **II**, number of stems per hectare, arithmetic mean diameter and arithmetic mean height were used if the species-specific BA was < 1 m^2 ha^{-1}. Site characteristics included variables that describe site fertility and productivity, drainage state, soil type, and effective temperature sum.

Species-specific diameter distributions were predicted based on the basal area (or number of trees) and mean diameter. A set of indicator trees were selected from the predicted diameter distributions and used in the simulation. Forest development was simulated using distance independent tree-level models for diameter increment and height (Pukkala et al. 2013; Pukkala et al. 2009), and models for survival and ingrowth (Pukkala et al. 2013).

Several treatment alternatives were simulated for each sample plot. Treatment alternatives included treatments that followed even-aged management (thinnings from below and final felling) and continuous cover forestry (thinnings from above without final felling), i.e., no prior decision was made concerning the silvicultural system. In the case of even-aged management, cuttings were simulated based on the thinning basal area and regeneration diameter limit recommendations (Äijälä et al. 2014), which were assumed to indicate the earliest possible timing of cutting. Alternative treatment schedules were generated by delaying cuttings by one or more sub-periods. Thinnings from above were simulated according to the instructions that were especially developed for continuous cover forestry. The instructions predict thinning basal area and thinning intensity based on discount rate, site fertility class, tree species, mean tree diameter, and effective temperature sum. Alternative schedules were simulated by applying the instructions with different discount rates. In addition, removal of the upper canopy was simulated if there were two separate canopy layers. A management schedule with no cuttings was also simulated for every sample plot.

Timber assortment volumes were predicted with taper curve models (Laasasenaho 1982). A proportion of sawlog volume was transferred to pulpwood volume due to quality issues. A decrease in sawlog volume was predicted using the models of Mehtätalo (2002) and the correction factors of Malinen et al. (2007). The time consumption models of Rummukainen et al. (1995) were used to estimate harvesting costs. The net incomes from cuttings were calculated for each simulated treatment alternative by subtracting the harvesting costs from the roadside value of the harvested trees. The NPV of timber production was calculated for each treatment alternative by discounting the net incomes within the planning period to the present. In addition, NPV after the planning period was predicted with the updated models of Pukkala (2005), and NPV of future net incomes was calculated as a BA-weighted mean of species-specific NPV estimates and discounted to the present (updated models are described in the appendix of study **I**).

The carbon dynamics of forestry were simulated in study **III**. The total carbon balance of forestry (sequestrated – released carbon) considered the changes in three carbon pools: 1) living biomass, 2) soil (dead organic matter, DOM), and 3) wood-based products. The quantity of living biomass was predicted using the models of Repola (2008; 2009) and its carbon content was calculated as a proportion of the predicted biomass (species-specific fractions, ~ 0.5 of the dry biomass). The carbon pool of living biomass increased due to growth and ingrowth, and decreased as a result of harvesting and mortality. The soil carbon pools were initialized using the models reported in Pukkala (2014). Dead trees, harvest residuals and litter production were the inputs to the soil carbon pool. Litter production was calculated from the biomass using the species-specific turnover rates reported in Pukkala (2014). Inputs to the soil carbon pool were divided into several sub-pools based on the tree species and the sizes of the biomass components. Carbon releases from DOM were simulated using the Yasso07 model (Liski et al. 2009; Tuomi et al. 2011a; 2011b). In the case of peatlands, the same model was also used to simulate the decomposition of the aerobic peat layer. The depth of the aerobic peat layer was calculated using the model reported in Sarkkola et al. (2010). The amount of peat in the aerobic layer was calculated based on the peat density and depth of the aerobic layer.

The carbon pools of wood-based products were initialized using the models of Pukkala (2014). Harvested sawlog and pulpwood were assigned to five different end-product categories. Each end-product category was parametrized with a defined production release rate, annual disposal rate, substitution rate (reduced carbon emissions from fossil-fuel-based materials) and recycling rate (proportion of product biomass used as bioenergy after the primary use). The parameters of the end-product categories and the proportions of manufactured end-products were the same as in Pukkala (2020). The carbon pool of wood-based products decreased when products were discarded and then decomposed, or when they were used as biofuel. The carbon balance of this pool also included the carbon emissions due to harvesting and transport.

The incomes and costs of carbon payments were calculated for each simulated treatment schedule. The carbon balance (sequestration – release) was calculated at the middle of each sub-period, multiplied by the carbon price, and discounted to the present. The forest owner was subsidized if the carbon balance was positive and was taxed if the carbon balance was negative.

The treatment schedule that maximized NPV with a 3 % discount rate was selected for each sample plot. In studies **I** and **II**, NPV of timber production was maximized. In study **III**, total NPV of timber production and carbon payments was maximized using several carbon prices. The simulation and selection of optimal management prescriptions were carried out similarly for the correct data (sample plot data) and the erroneous data (predicted or simulated data).

3.6 Economic losses

The effects of errors on the suitability of forest planning and management prescriptions were assessed based on economic losses, i.e., inoptimality losses. Inoptimality losses describe the EVPI. The management prescriptions that were selected based on the erroneous data were assumed to result in suboptimal management compared to prescriptions that are based on the correct data. The inoptimality losses were determined as the difference in the NPVs of the optimal (prescriptions based on the correct data) and suboptimal (prescriptions based on the erroneous data) management schedules.

Inoptimality losses considered the NPV of the selected treatments and the predicted NPV of timber production after the planning period. In studies **II** and **III**, the inoptimality loss for a particular sample plot was calculated directly as the difference in the NPVs of optimal and suboptimal management prescriptions selected for the entire planning period. In study **I**, subsets of 10 and 20 years were selected from the 50-year planning period. The erroneous management prescriptions during the 10- and 20-year periods were compared to prescriptions based on correct data. If the erroneous prescriptions were not the same as the prescriptions based on correct data during the selected period, it was assumed that the erroneous prescription was followed until the end of the 50-year period.

In some rare cases, the management prescription that was selected based on the erroneous data led to greater NPV in the correct data than the initial prescription selected based on the correct data, i.e., the difference in NPVs was negative. Inoptimality losses were set to zero in these situations.

In studies **I** and **III**, inoptimality losses were calculated relative to the sum of NPVs of optimal management prescriptions selected for the stands based on the correct data. In study **II**, inoptimality losses were calculated for each sample plot selection strategy with a given number of plots as the mean of 10 repetitions.

$$NPV_{relative\ loss} = \frac{\sum_{i=1}^{n}\left(NPV_{opt\ i} - NPV_{err\ i}\right)}{\sum_{i=1}^{n} NPV_{opt\ i}} \times 100 \tag{1}$$

$$NPV_{mean\ loss} = \frac{\sum_{j=1}^{10}\left(\frac{1}{n}\sum_{i=1}^{n}\left(NPV_{opt\ i} - NPV_{err\ i}\right)\right)}{10} \tag{2}$$

where $NPV_{opt\ i}$ is the NPV (€ ha^{-1}) of sample plot i when the management prescription is selected based on the correct data, $NPV_{err\ i}$ is the NPV (€ ha^{-1}) of the same sample plot i when the management prescription is selected based on the erroneous data and simulated with the correct data, j is the number of repetitions, and n is the number of observations.

In study **I**, the relative inoptimality losses due to errors in BA and D were compared to the relative inoptimality loss that resulted from the use of random information. The Better than Random Information (BRI) metric was introduced for this purpose:

$$BRI = \left(1 - \left(\frac{NPV_{relative\ loss}}{NPV_{relative\ loss\ RI}} \right) \right) \times 100 \tag{3}$$

where $NPV_{relative\ loss}$ is the inoptimality loss (calculated with equation 1) that results from error combination in BA and D, and $NPV_{relative\ loss\ RI}$ is the mean of relative inoptimality losses of random information over 10 iterations. The BRI metric describes how much better decisions, and consequently smaller (%) inoptimality losses, can be expected with a specific level of error in BA and D compared to a situation when randomly assigned stand attributes are used.

3.7 Statistical error indices

Errors associated with stand attributes were measured using RMSE and MD. The latter measures the difference between the means of observed and erroneous values, while the former is the square root of averaged squared errors, which is equal to the square root of the sum of variance of errors and squared MD. Relative error indices were calculated as follows:

$$Relative\ RMSE = \frac{\sqrt{\frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2}{n}}}{\bar{y}} \times 100 \tag{4}$$

$$Relative\ MD = \frac{\frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)}{n}}{\bar{y}} \times 100 \tag{5}$$

where y_i is the correct value of the attribute, $\hat{y}_i$ is the erroneous (predicted or simulated) value of the attribute, n is the number of observations, and $\bar{y}$ is the mean of correct values. The absolute error index can be obtained by multiplying the relative error index by $\bar{y}$.

4 RESULTS

4.1 Under- and over-estimates in basal area and mean diameter (I)

Error levels in BA and D resulted in inoptimality losses of 0.11–3.01 % during the 10-year period (Figure 2). Errors in D led to greater losses than similar relative errors in BA. In particular, errors in D affected the selected cutting type (i.e., thinning vs. final felling), whereas errors in BA mainly affected the timing and intensity of thinnings. Simultaneous underestimation of BA and D introduced greater losses than simultaneous overestimation of these attributes. The losses were greater when D was underestimated, and BA was overestimated compared to the opposite error combination. The greatest BRI value (98.7 %) and the smallest inoptimality loss were obtained when BA was underestimated by 10 % and D corresponded to the true value. The smallest BRI value (66 %) and greatest inoptimality loss was obtained when BA was overestimated by 20 % and D was underestimated by 20 %. The BRI values indicated that the inoptimality losses due to errors in BA and D were, on average, 82.7 % and 85.8 % smaller than the inoptimality losses of random information when BA and D were simultaneously underestimated or overestimated, respectively.

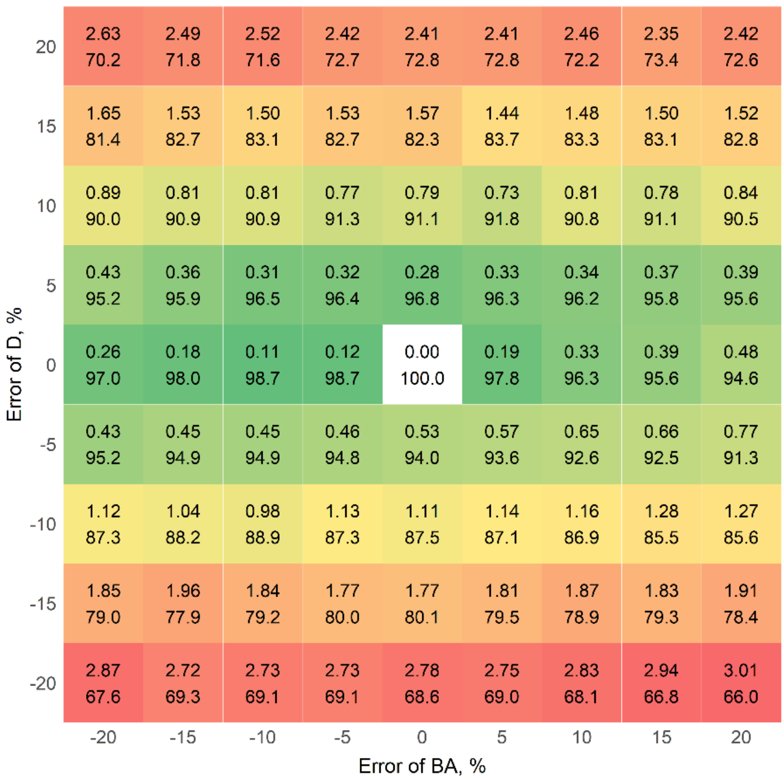

Figure 2. Relative inoptimality losses and Better than Random Information (BRI) values in different error combinations for the next 10 years. In each cell, the upper number indicates the relative inoptimality loss and the lower number is the BRI value. The green-yellow-red color scale corresponds to ascending losses.

On average, the relative inoptimality losses increased 0.37 percentage points (37.3 % increase), when a 20-year period was used instead of a 10-year period. This was because more errors in management prescriptions were done during the longer period. When the inoptimality losses (€ ha^{-1}) were illustrated using smoothing splines with BA or D as the predictor variable (Figure 3), the spline curves suggested that the inoptimality losses increased when the value of BA increased. The spline values also indicated that an increasing value of D increased the losses, but after D reaches a value of about 21–26 cm, the losses start to decrease. This was because the selected management prescriptions based on the correct and erroneous data were frequently identical for D > 25 cm, usually final felling.

The results reported in study **I** indicated that errors in D are more important than similar relative errors in BA when the NPV is maximized with a 3% discount rate. Large underestimation of D should be particularly avoided in stands where the next treatment is the final felling. The results also indicated that underestimation is more harmful than overestimation.

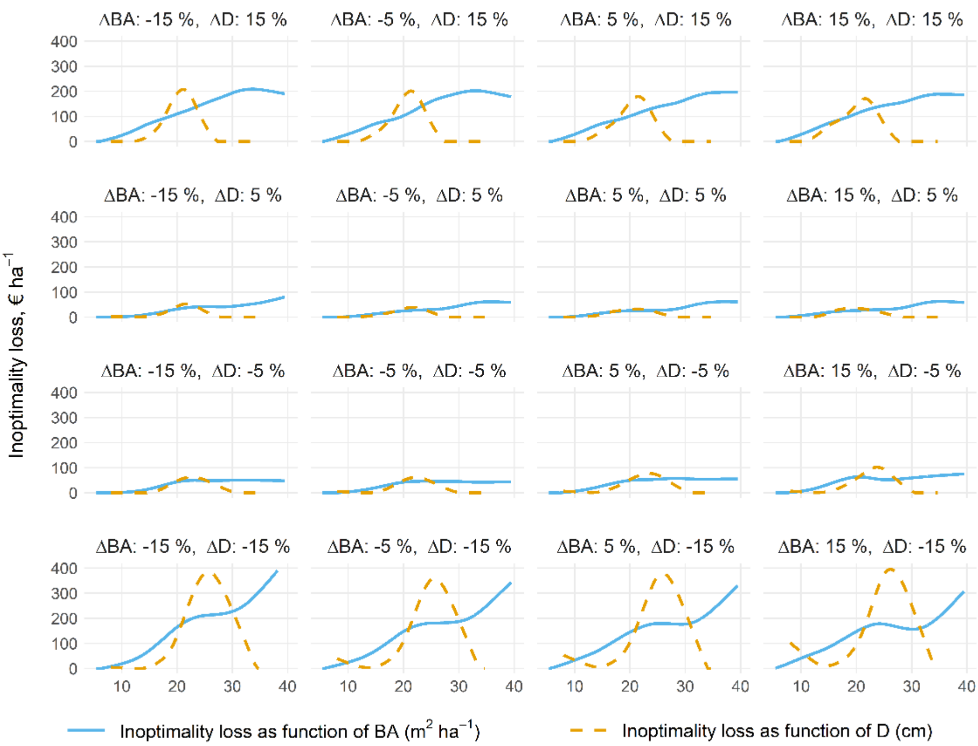

Figure 3. Inoptimality losses (€ ha^{-1}) illustrated in different error combinations using smoothing splines with correct values of BA or D as the predictor.

4.2 Sample plot selection strategies and number of sample plots (II)

The tested sample plot selection strategies and sample sizes resulted in mean inoptimality losses of €41.1–80.7 ha^{-1}, when the errors of the sample plot-level predictions were decreased by 50 % to approximately correspond to the accuracy of stand-level predictions (Figure 4). The sample plot selection strategies led in rather similar results in terms of mean inoptimality losses. The most important factor that affected the mean losses was the number of sample plots. Losses decreased most when the sample size increased from 25 to 100 sample plots, after which the decrease was slower, but continued until 500 sample plots. A clear decision to choose a sample plot selection strategy over the others could not be made based on the mean inoptimality losses obtained in study **II**.

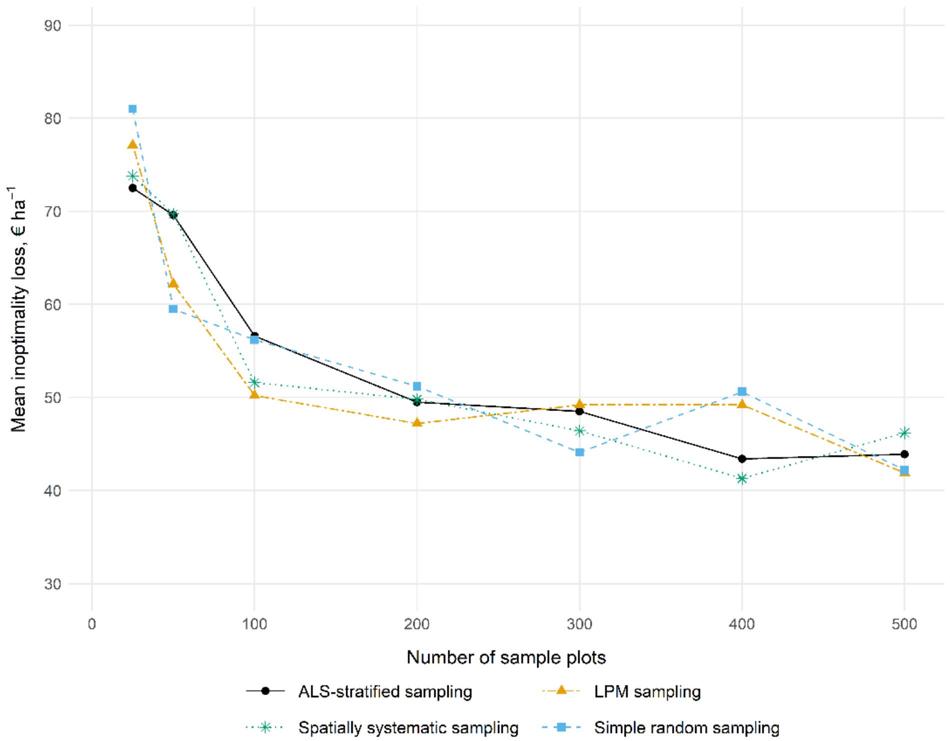

Figure 4. Mean inoptimality losses when alternative sample plot selection strategies were utilized to select 25–500 sample plots from the training data. The mean inoptimality losses are calculated as the mean of 10 repetitions.

The magnitude of mean inoptimality losses was associated with the error rates of stand attributes. Relative RMSE values and the absolute values of relative MD decreased as the sample size increased. All four strategies performed similarly in terms of error indices. The similarity between the selected management prescriptions (i.e., proportion of correct treatment types between the prescriptions based on correct and erroneous data) for the 10-year planning period increased as the sample size increased. When mean inoptimality losses were not averaged over 10 iterations, the results indicated that one unit increase in the relative RMSE value of merchantable volume (i.e., the total volume of log and pulpwood) and the mean of Hs, increased mean inoptimality losses by €3.9 ha^{-1} and €8.2 ha^{-1}, respectively.

Inoptimality losses were obtained in about 12.5 % of the validation sample plots. The majority of the losses were obtained in situations where no cutting had been prescribed during the planning period, even though cutting would have been optimal based on the correct data. A smaller proportion of inoptimality losses were obtained when the selected cutting types based on the correct and erroneous data differed, or in situations where a cutting was erroneously prescribed even though the optimal prescription was “no cutting”.

The results presented in study **II** suggest that measuring hundreds of sample plots from an inventory area is an economically justified decision. Measurement of more sample plots can be considered reasonable provided the costs of field measurements do not exceed the decrease in inoptimality losses.

4.3 Carbon prices and error levels (III)

Effects of carbon payments on inoptimality losses were evaluated using carbon prices of €0, 50, 75, 100, 125, and 150 t^{-1}. A wide range of carbon prices were used because the unit price in international carbon markets is highly variable. The results presented in study **III** showed that increasing the price of carbon decreased the relative inoptimality losses (Figure 5). The inclusion of carbon payments into the optimization of forest management led to lower relative inoptimality losses compared to the case where only the NPV of timber production was maximized (carbon price: €0 t^{-1}).

When the simulated data were divided into under- and over-estimates based on the sum of species-specific values of BA, the results indicated that underestimation in basal area results in greater inoptimality losses compared to overestimation. In particular, increasing the carbon price decreased the losses due to underestimation. Inoptimality losses due to overestimation also decreased as the carbon price increased, but the effect of carbon price was smaller than in the case when the basal area was underestimated.

In summary, study **III** indicated that increasing carbon price decreases the effect of errors on inoptimality losses, which means that an increasing value of carbon payments decreases the VOI in decision-making. This also implies that errors in forest inventory data have a smaller effect on the maximization of NPV when carbon payments are considered in addition to the NPV of timber production.

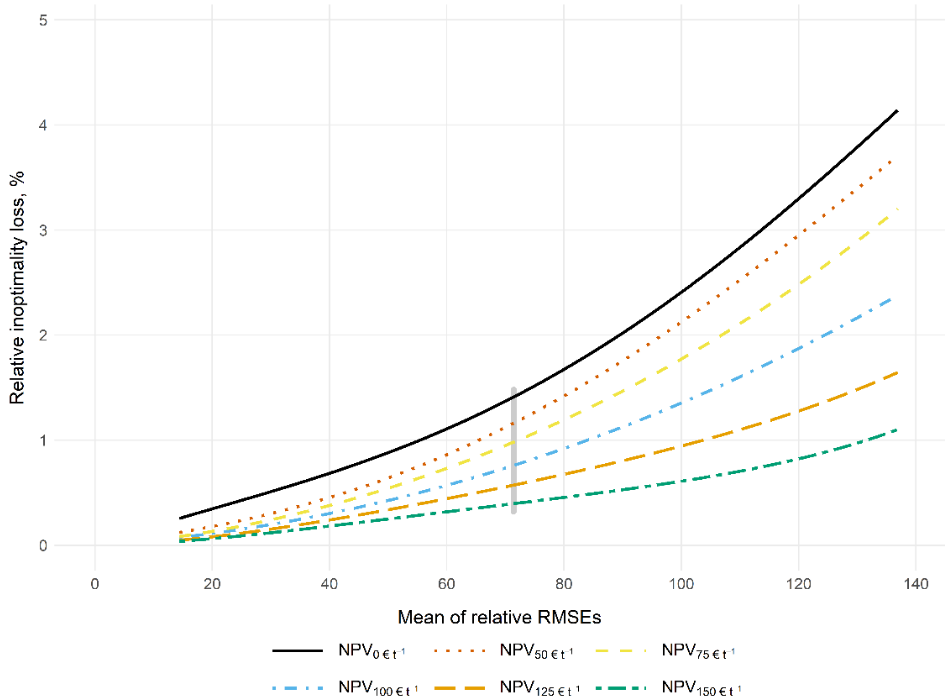

Figure 5. Relative inoptimality losses when the total net present value (NPV) of timber and carbon benefits is maximized with carbon prices of €0, 50, 75, 100, 125, and 150 t^{-1}. The horizontal axis is the mean of relative RMSE values associated with species-specific volumes. The vertical line denotes the point where errors are decreased by 50 % compared to the initial error level.

5 DISCUSSION

This thesis presents a decision-oriented approach to interpret forest inventory errors. The value of inventory data in forest management was evaluated based on the expected losses in NPV. Studies **I–III** showed that errors in inventory data can have a substantial effect on the optimality of forest management prescriptions.

In this thesis, both observed (**II**) and simulated (**I**, **III**) errors were used. Erroneous inventory data were imported in the FPS, and forest development and different treatment alternatives were simulated based on the erroneous and correct ('error-free') data for a given time period. It was assumed that the DM always chooses a management alternative that maximizes the economic profitability of forest management. In studies **I** and **II**, economic profitability consisted of the NPV of timber production. In study **III**, carbon payments were also considered.

In study **I**, the effects of relative errors in BA and D on inoptimality losses were assessed. This was a somewhat different approach to earlier studies, which used simulated errors, since errors were not assumed to follow a specific distribution or dependency structure but instead, the effect of a given error was evaluated. Errors between -20 % and 20 % were simulated in BA and D since those attributes are used to predict the diameter distribution. The sample plots were assumed to be located in pure pine forests, i.e., the effect of tree species was ignored. In reality, however, errors in minor tree species or in species proportions can introduce inoptimality losses (e.g. Islam et al. 2009; Haara et al. 2019). According to study **I**, simultaneous underestimation of BA and D lead to greater losses than simultaneous overestimation of these attributes. The results indicate that errors in D cause larger inoptimality losses than similar relative errors in BA. The main reason for this was that errors in D mainly altered the selected cutting type, whereas errors in BA mainly affected the timing and intensity of thinning. When D was overestimated, the losses frequently accrued from situations where the stand was erroneously prescribed for clear-felling or seed tree felling, although the prescription based on the correct data was to conduct several thinnings from above. In contrast, when D was underestimated, most of the losses accrued from situations where the selected management prescription (based on the erroneous data) was to conduct thinnings from above, although the optimal prescription would have been final felling. In other words, errors in D changed the selected management system from continuous cover forestry to even-aged management and vice versa.

In study **II**, inoptimality losses in ALS-based management planning were evaluated when the training data for the k-NN method were selected based on four different sample plot selection strategies. A decreasing trend in mean inoptimality losses was obtained when the number of sample plots was increased. The results reported in study **II** suggest that total inoptimality losses (i.e., mean inoptimality loss × size of inventory area) can decrease by about one million euro in an inventory area of 100,000 ha, when the number of sample plots used as training data for the k-NN method is increased from 100 to 500. This indicates that measuring several hundred sample plots is well-justified since the decrease in inoptimality losses is much larger than the increase in the costs of measuring more sample plots. Although these figures seem promising, some obvious limitations and simplifications remain. One factor that affected the similarity of mean losses between the different sample plot selection strategies was that the error rates of the stand attributes were similar regardless of the sampling strategy employed. On the other hand, a single 10-year planning period was used, i.e., there was only one time point where treatments were simulated. More substantial differences in the mean inoptimality losses between the sample plot selection strategies would probably have been obtained if the planning period had been divided into several sub-periods, and if a longer planning period had been used. This would have increased the number of simulated management prescriptions per sample plot. A longer planning period would have decreased the effect of the predicted NPV after the planning period on the results.

It can be argued that the results reported in study **II** depend considerably on the original sampling method used in the inventory area. While this might be true, the number of sample plots was, however, much larger than is usually measured in stand-level forest management inventories in Finland. Moreover, systematic sampling was used to provide a comprehensive sample of different forests in the inventory area. Systematic sampling is not usually utilized in Finland when sample plots are measured for a stand-level management inventory. Therefore, it can be assumed that the sample plot data used were suitable for the evaluation of sample plot selection strategies and for the assessment of the effect of inventory errors on inoptimality losses.

Earlier studies on VOI in forestry have usually assumed that inoptimality losses depend only on the NPV of timber production, even though forests can also produce other products and services that can be economically relevant. In study **III**, the total carbon balance of forestry (incl. trees, soil, and products) was included in the analysis of VOI by considering carbon payments in the maximization of NPV. The relative inoptimality losses were always smaller when carbon payments were included in the maximization of NPV compared to a situation where only the NPV of timber production was considered. A high carbon price meant that the “no cutting” prescription became the optimal alternative for most of the sample plots. In the case of cutting, thinning from above was usually selected, mainly due to its positive effect on the total carbon balance (e.g., Pukkala 2014; Díaz-Yáñez et al. 2020). The inclusion of carbon payments in the maximization of NPV showed that the selected management prescription based on the erroneous and correct data were often the same, regardless of the magnitude of the simulated errors, i.e., the value of more accurate inventory data decreased.

Estimation of the total carbon balance of forestry includes more uncertainties compared to a situation where only the carbon balance of the trees and forest soil are used as the basis for carbon payments. The carbon balance of wood-based products includes several assumptions related to product lifecycle, substitution effects, reuse rates and energy use in manufacturing, which are subject to change in the future. However, if the carbon balance of wood-based products had not been considered in study **III**, the effect of the carbon price on inoptimality losses would have been even greater. This is due to the compensatory effect of product carbon on the total carbon balance (Pukkala 2020).

Aside from the carbon payments that were investigated in study **III**, other non-timber products and services that have an economic value could also be included in the VOI analysis. If the non-timber product can be produced at the same time as the timber, the effects of inventory errors on timber production can be compensated for, at least to some extent, with the production of non-timber products. This applies at least to joint production of timber and carbon benefits. The products are also competitive, which means that reduction in timber production (due to errors in inventory data) can lead to an increase in carbon sequestration. However, the products manufactured from harvested wood also affect the calculated total carbon balance of the forestry. If non-timber products cannot benefit from the reduction in timber production, the value of more accurate inventory data may increase. Moreover, inventory data may also be utilized to select specific forests for the supply of timber and non-timber products. Erroneous data may lead to the incorrect assignment of stands for the production of timber and non-timber products. Moreover, VOI can be calculated based on the inoptimality losses in a situation that is not directly related to timber production. For instance, one could evaluate the effects of erroneous inventory data on the correct level of compensation received when part of the forest property is protected.

In study **III**, a technique was presented to simulate joint distribution of errors on stand attributes which were similar to errors in ALS-based inventory data. However, certain simplifications were made when the errors were simulated. For example, systematic errors were removed from the simulated erroneous stand attributes for the sake of simplicity. In addition, errors were decreased by multiplying them by factors that ranged between 1.0 and 0.1, and the dependencies between the errors were assumed to remain similar regardless of the error level. In study **II**, a similar simplification was employed by decreasing the prediction errors to half of the original sample plot-level errors.

In general, continuous cover forestry (i.e., thinnings from above without final felling) was chosen more frequently than even-aged management where thinnings are from below. This is mainly because, from an economic point of view, thinning from above often results in greater net incomes due to a greater proportion of sawlogs compared to thinning from below, which removes mainly pulpwood-sized trees. In other words, thinning from above mainly removes trees with a high opportunity cost and a low relative value increment (i.e., low profitability), while most of the remaining trees have a high relative value increment and a low opportunity cost (i.e., high profitability compared to the value of the stem) (Knoke 2012). In addition, the costs of artificial tree generation after clear-felling make management alternatives that use natural regeneration economically superior (e.g., Tahvonen 2010; Pukkala et al. 2014; Pukkala 2016). Simulating the thinning of even-aged management as uniform thinning or as thinning from above instead of thinning from below, would have likely increased the probability of selecting even-aged management instead of continuous cover forestry.

Simulation rules and the management system that is employed can affect the calculated inoptimality losses. The prescriptions selected based on erroneous data were simulated with the correct data by following the same rules that were initially used with correct data. Several different treatment alternatives representing even-aged management and continuous cover forestry were simulated in all studies. Loose simulation rules were used to make sure that most of the erroneous thinnings were eventually simulated in the correct data. However, some of the erroneous thinnings may still not have been simulated in the correct data due to the simulation rules used. The inoptimality losses can be interpreted as an indicator of how errors can affect the decision-making and whether it may be reasonable to invest in more accurate inventory data. However, they should be interpreted with caution, as simulation is always a simplification of reality and the true NPV of the forest cannot be known in advance.

It seems obvious that errors in inventory data can affect the optimality of forest management prescriptions. Eventually, erroneous inventory data can result in losses with regard to the set management objectives and in poor decisions compared to more accurate data. However, in reality, errors in inventory data are inevitable. When inoptimality losses are analyzed, errors in inventory data matter only if they result in different management prescriptions compared to more accurate or correct (‘error-free’) data. However, in practical decision-making, it is impossible to evaluate whether the errors are significant or not because error-free information is rarely available. It may be reasonable to pay attention to middle-aged forests that are likely to be harvested in the near future. In these forests, underestimation in stand attributes can cause inoptimality losses if the treatment is prescribed to take place too late, or if the treatment type is different compared to the optimal treatment. If the treatment is mistakenly conducted too late, it cannot be reversed. If the treatment is prescribed too early, then it can be mitigated provided the overestimation has been noted, and it is therefore less harmful from an economic point of view. However, a field visit by a forest expert will usually entail additional costs for the DM. On the other hand, new forest inventory data are usually collected during a field visit and at least part of the old data will be replaced with the new data. Treatments are prescribed based on the new inventory data and the old data are no longer utilized.

Inoptimality losses depend on the time span inventory data are used. In general, this means that the longer the planning period, the greater the losses that will be experienced. However, it is unlikely that the inventory data acquired today will be used in the long term. In Finland, the current practice in a stand-level forest management inventory is that new inventory data become available every ten years or even more often. New inventory data will eventually replace the old data, but the new data is not error-free either. The question is, however, what happens after the new data become available and how should this be considered in the calculation of expected losses? Performing analyzes for a time span longer than the data is actually intended to be used, together with the acquisition of new inventory data after ten years for example, may reveal that the acquisition of new information is not always profitable. If a similar management prescription can be proposed based on old but updated inventory data compared to new inventory data, then new data are not valuable (e.g., Kangas et al. 2019).

This research fills some of the gaps in this topic but makes a simplifying assumption that forest inventory data are the only source of uncertainty. As pointed out by previous authors, there are several other sources of uncertainty that could be considered. For instance, growth model errors (e.g., Pietilä et al. 2010), changes in the market prices of timber (e.g., Ståhl 1994; Pukkala 2015) and other forest products and natural hazards (e.g., Díaz-Yáñez et al. 2019) are some additional sources of uncertainty that can cause inoptimality losses. If the various sources of uncertainty are fully considered, the source of uncertainty with the greatest impact could be evaluated and its relative importance on expected losses could be considered. Holopainen et al. (2010a) concluded that inventory data and growth model errors affect the estimated stand-level NPV more than variation in timber prices. The relative importance of uncertainties depends on the time span they are analyzed (e.g., Holopainen et al. 2010b). The errors in inventory data can be more important than growth model errors if data are used only for a short time. Errors due to growth models become more and more important the longer the data are used. Different sources of uncertainty can also have interactions that further complicate the situation.

Inoptimality losses provide insights on how erroneous inventory data can affect the optimality of forest management. They are a practical and comprehensible measure for uncertainty. However, certain limitations and simplifications related to the planning set-up that was used remain, which should be kept in mind when interpreting the results. In conclusion, it is recommended that the value of forest inventory data is considered in order to improve decision-making in forest management.

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