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RESEARCH PAPER

Effects of errors in basal area and mean diameter on the optimality of forest management prescriptions

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Abstract

• ***Key message*** **Errors in forest stand attributes can lead to sub-optimal management prescriptions concerning the set management objectives. When the objective is net present value, errors in mean diameter result in greater losses than similar errors in basal area, and underestimation greater losses than overestimation.**

• ***Context*** Errors in forest inventory data can cause inoptimality losses in the objectives set to forest management. Losses occur when the forest is treated with management prescriptions that are optimal for erroneous data but not for correct data.

• ***Aims*** We evaluate the effect of varying levels of errors in basal area and mean diameter on the inoptimality losses.

• ***Methods*** Errors from 20% of overestimation to 20% of underestimation were simulated in basal area and mean diameter. For each stand, the management prescription that maximized the net present value was selected with and without errors. The inoptimality losses were calculated for different error levels.

• ***Results*** The tested error levels resulted in inoptimality losses of 0.11–3.01%. Errors in mean diameter increased inoptimality losses more than similar relative errors in basal area. Simultaneous underestimation of basal area and mean diameter led to greater inoptimality losses than simultaneous overestimation of these attributes.

• ***Conclusion*** If the forest is considered as an investment, using inventory data where basal area and mean diameter are underestimated causes greater losses compared with data where these attributes are overestimated. Errors in mean diameter are more important than similar errors in the basal area. Large errors in basal area and mean diameter should be avoided especially in stands where the basal area is high.

Keywords Forest management planning · Inoptimality loss · Inventory error · Net present value · Value of information

1 Introduction

Forest management planning aims to find the combination of management prescriptions for different stands that maximizes the utility of the decision-maker (Pukkala 2002). Plans are developed using forest planning systems where the current stand attributes are used as the starting point for the simulation of alternative treatment schedules for the stands or some other calculation units. Then, the optimal combination of the simulated treatment schedules is searched for. The decision-maker's utility function is maximized, possibly subject to a set of constraints. If the decision-maker considers the forest as an investment, the optimal management prescriptions are commonly selected based on the net present value (NPV).

Regardless of the inventory method, estimated stand attributes contain errors that affect the planning process. However, although accurate data are more valuable in decision-making than less accurate data, errors in stand attributes do not fully reveal the quality of the decisions that can be made with the data (e.g., Kangas 2010; Kangas et al. 2014). Errors in the stand attributes are relevant if they lead to management prescriptions different from those based on correct data. Therefore, errors should be analyzed from the viewpoint of the value of information in decision-making (Lawrence 1999).

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Contribution of the co-authors RR did all computations, analyzed the results, and wrote the original manuscript.
PP and TP supervised the research, commented, and revised the manuscript.
AK commented and revised the manuscript.

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Inoptimality losses describe the expected losses, in terms of the objectives set by the decision-maker, when sub-optimal management prescriptions that result from the use of erroneous data are followed instead of optimal management prescriptions based on correct data. In the case where the objective is to maximize NPV, the losses are expressed in monetary terms. Such economic losses are often used in cost-plus-loss (CPL) analysis to rank forest inventory methods. In CPL, the inventory method that leads to the lowest total cost, i.e., minimize (cost + loss), is ranked as the best alternative (Hamilton 1978; Burkhart et al. 1978). CPL analysis is related to the concept of the value of information (VOI) (Lawrence 1999, p. 45–94). In forest management planning, VOI can be defined based on inoptimality losses; the additional information has a value if the losses in NPV can be reduced compared with using existing (prior) information. The relationship between errors and losses can be analyzed to identify the stand attributes for which accurate inventory information is important (e.g., Eid 2000). VOI can be used as an indicator to evaluate whether reducing the magnitude of the error is worth the associated cost. Theoretically, VOI is defined based on Bayesian decision theory (e.g., Lawrence 1999, p. 65; Kangas 2010), but it can be calculated based on simulated stand-level inoptimality losses (Kangas et al. 2014).

Studies that assess the effects of errors on inoptimality losses can be divided into two groups. The first group includes studies that use data that contain the observed errors of a given forest inventory method. For instance, Eid et al. (2004) compared two different inventory methods based on photo interpretation and airborne laser scanning (ALS) and assessed how the errors associated with the inventory methods affected the timing of clear-fellings and the consequent losses. Alternative k-Nearest Neighbor (k-NN) predictions based on ALS and satellite image data were compared in terms of losses by Duvemo et al. (2007). Bergseng et al. (2015) assessed sub-optimal harvesting decisions and the corresponding losses using four different inventory methods. Kangas et al. (2018) analyzed errors and losses when ALS and aerial image point cloud data were used in forest planning.

The second category of studies uses simulated errors; i.e., errors are simulated for stand attributes, and those erroneous attributes are used in a forest planning system. The errors are generated from random distributions, which mimic an inventory method with a given accuracy. For instance, Eid (2000) generated normally distributed random errors with varying levels of variance for basal area, basal area-weighted mean height, stand age, and site quality index. Mäkinen et al. (2010) and Islam et al. (2010) simulated errors that are similar to errors in predictions based on ALS and aerial image data. Mäkinen et al. (2010) also compared several methods for simulating random errors and concluded that correlations between the errors and the shape of the error distribution had only a small effect on the expected losses.

A third possibility is to analyze the effect of a given error rather than an error distribution. For instance, Kangas et al. (2011) analyzed the effect of errors in stand attributes on the correctness of the timing of harvest decisions compared with silvicultural guidelines during a 10-year planning period. To consider different error combinations, they simulated, for all stands, errors ranging from − 30 to 30% for basal area, diameter or height of the basal area median tree, or a combination of them. No optimization was used, and hence, the effects of errors on expected losses caused by sub-optimal management prescriptions were not assessed.

In this study, we analyzed the effect of given errors in basal area and basal area-weighted mean diameter in the same way as Kangas et al. (2011) but, as a new element, we analyzed how different levels of errors affect the optimality of forest management prescriptions. The optimality of management prescriptions was assessed based on inoptimality losses calculated for the next 10 and 20 years. The results give insight into the effect of overestimation vs. underestimation, the importance of basal area vs. mean diameter, and the effect of the magnitude of the error. The inoptimality losses due to errors in basal area and mean diameter were compared with inoptimality losses arising from the use of randomly assigned forest information. Random information represents a benchmark case (i.e. population-level prior information).

2 Material and methods

2.1 Forest data

Sample plot data were collected from an inventory area located in central Finland (approx. 62° 27′ N, 24° 13′ E) between spring and autumn 2013. Systematic sampling with L-shaped clusters was used, and 2468 sample plots were originally placed in the inventory area. Exactly 1956 sample plots were located on forestry land. A full cluster comprised eight sample plots located 250 m apart along two perpendicular lines. The distance between clusters was 4.3 km.

Trees were measured in circular sample plots with radii of 9 m. Tree species and diameter at breast height (DBH, diameter at 1.3-m height) were measured for all tally trees. The heights of the tally trees were predicted with the species-specific mixed-effects models of Eerikäinen (2009). The observed heights of the basal area median trees of different tree species (Scots pine; *Pinus sylvestris* L., Norway spruce; *Picea abies* [L.] H. Karst., and deciduous trees; mainly birches, *Betula spp.* L.) were used to calibrate the species-specific mixed-effects models for each plot. The tree volumes were predicted using species-specific volume models described in Laasasenaho (1982) with DBH and height as independent variables. Basal area per hectare, basal area-weighted mean diameter (hereafter called mean diameter), and basal area-weighted mean height (hereafter called mean height) by tree species were determined from trees with a DBH of at least 5 cm.

Of the sample plots located on forestry land, we selected plots where the main tree species was Scots pine as we wanted to eliminate the effect of tree species. Since most of the plots were measured in pure or almost pure pine stands, we assumed that all the trees were pines in planning calculations. Sample plots located in seedling stands were omitted from the data. In total, 1037 sample plots remained for the analysis. Most of the selected sample plots were in forests that were classified as sub-xeric (55.2%) and mesic (29.8%) fertility classes. The main properties of the field data are shown in Table 1.

2.2 Simulating errors in basal area and mean diameter

A range of error levels were simulated for basal area and mean diameter within each stand. These variables were selected as they are used to predict the diameter distribution, and therefore, have a notable effect on the present state description of the stand. Other stand attributes were assumed error-free and were kept equal to the true values in the field data. Different combinations of errors were simulated using error levels of − 20%, − 15%, − 10%, − 5%, 0%, 5%, 10%, 15%, and 20%, resulting in a total of 81 error combinations for basal area and mean diameter for each stand. The errors were simulated by multiplying basal area and mean diameter in every sample plot with factors that ranged from 0.8 to 1.2.

Table 1 The main properties of the field data.

	Minimum	Maximum	Mean	SD
BA (m^2 ha^{-1})	2.4	39.5	17.6	6.7
D (cm)	8	34.7	18.4	4.6
H (m)	6.2	24.7	14.8	3.5
V (m^3 ha^{-1})	8.9	419.8	133.6	68.1

BA basal area, *D* mean diameter, *H* mean height, *V* total volume, and *SD* standard deviation

2.3 Forest planning computations and assessment of inoptimality losses

Forest planning computations were performed with the Monsu forest planning software (Pukkala 2004), in which the sample plots were treated as stands. Computations included a prediction of the present state, simulation of alternative treatment schedules, and selection of the optimal treatment schedule for each stand from the set of simulated schedules. The input variables were basal area per hectare, mean diameter, mean height, and variables that describe the basic site characteristics. Forest development was predicted, and several treatment alternatives were simulated for 50 years. The simulated treatments comprised different thinning alternatives (thinning from above and from below), clear-felling, seed tree felling, and removal of the upper canopy from two-storied stands. A schedule with no cuttings was also simulated for every stand. The regeneration rules of the simulator were modified so that after clear-felling the stand always regenerated to pine. The planning period was divided into 5-year sub-periods and possible treatments were simulated in the middle of a 5-year period.

The objective of the planning was to maximize NPV with a 3% discount rate. The NPV of each stand was calculated as the sum of discounted revenues and costs during the planning period. In addition, the net present value of the remaining growing stock at the end of the 50-year period was predicted with the updated models of Pukkala (2005), and the predicted NPV was discounted from the end of the planning period to the present. The updated prediction models for NPV are described in Appendix.

Since the objective of the planning was to maximize NPV and there were no global constraints, optimization was equal to selecting the management prescription that resulted in the greatest NPV for each stand.

Simulation and selection of optimal management prescriptions were carried out for correct data, data that contained simulated errors in basal area and mean diameter, and for random information. To determine the inoptimality losses due to the use of erroneous data, the management prescriptions selected for the stands based on erroneous data were simulated using the correct data. However, since it is unlikely that forest data acquired today is still used in decision-making in a very distant future, only the management prescriptions of the first two and four 5-year sub-periods were examined. In other words, it was assumed that the inventory data are used in decision-making for the next 10 or 20 years after which the new data will be acquired.

The inoptimality losses were defined as the difference in NPV between the management prescriptions that were based on correct and erroneous data. Inoptimality losses were calculated for the next 10 and 20 years. The simulations of the 50-year period were used in both cases. If the management prescription for the first two (10 years) or four (20 years) 5-year periods differed when based on correct or erroneous data, it was assumed that the erroneous management schedule was followed until the end of the 50-year period. If management prescriptions were the same for the 10 or 20 years, the management schedule based on the correct data was followed until the end of the 50-year period. Consequently, the NPV included the simulated net incomes during the 50-year period and the model predicted NPV at the end of this period. The inoptimality losses (%) were calculated relative to the sum of net present values of the management prescriptions selected for the stands based on correct data:

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

where $NPV_{\mathrm{opt}\ i}$ is the NPV (€ ha^{-1}) of stand i for the management prescription selected based on the correct data, $NPV_{\mathrm{err}\ i}$ is the NPV (€ ha^{-1}) of stand i for the management prescription selected using the erroneous data that is simulated with the correct data, and n is the number of stands.

The random information was determined based on random permutations of the observed data to preserve correct distributions at the population-level. For each stand, the correct values of basal area, mean diameter, and mean height were replaced with values that belonged to another randomly selected stand in the observed data. In other words, attributes were mixed between the stands so that none of the stands had the correct values of basal area, mean diameter, and mean height that originally belonged to it, but the values came from another stand in the observed data. Ten different datasets were generated this way to consider the variation between the permutations. The inoptimality loss of random information ($NPV_{\mathrm{loss\ RI}}$) was computed as the mean of NPV_{loss} over the ten iterations.

The inoptimality losses that resulted from different error combinations for basal area and mean diameter were compared with the $NPV_{\mathrm{loss\ RI}}$. This describes the value of the erroneous data with a given error level compared with the random information (i.e., population-level prior). We introduce a metric BRI (Better than Random Information) for this purpose. It indicates how much smaller (%) inoptimality losses can be expected from a certain combination of errors in basal area and mean diameter, compared with the inoptimality loss of random prior information. BRI equals 100 for the correct data. The BRI metric was calculated as follows:

$$BRI = \left(1 - \left(\frac{NPV_{loss}}{NPV_{loss\ RI}}\right)\right) \times 100 \tag{2}$$

3 Results

The inoptimality losses varied from 0.11 to 3.01% for the 10-year period (Fig. 1), depending on the error combination. In general, errors in mean diameter affected the inoptimality losses more than similar relative errors in basal area. Underestimation of mean diameter led to greater inoptimality losses than overestimation. When the management prescriptions were selected for the datasets that were based on random information, the mean of inoptimality losses ± standard error was 8.85 ± 0.09% for the 10-year period. When there was error in at least one of the variables, the greatest BRI value and smallest relative inoptimality loss were obtained when the basal area was underestimated by 10% and the mean diameter was correct. The greatest inoptimality loss and the smallest BRI value were obtained when the basal area was overestimated by 20% and the mean diameter was underestimated by 20%.

The increase in relative inoptimality losses between 10 and 20 years is presented in Fig. 2. Inoptimality losses were larger for the 20-year period in all error combinations. Relative inoptimality losses increased the most in error combinations where mean diameter was underestimated. Inoptimality losses also increased notably in situations where basal area was underestimated, and the mean diameter was overestimated. The increase was the smallest in situations where both attributes were overestimated.

The relationships between the inoptimality losses (€ ha^{-1}) and stand attributes at the beginning of a planning period are shown in Figs. 3 and 4, where inoptimality losses are presented as a function of basal area and mean diameter in different error combinations. The lines were fitted to inoptimality losses using smoothing splines with a smoothing parameter equivalent to 6 degrees of freedom (Green and Silverman 1993). A trend of increasing losses was apparent when the basal area increased (Fig. 3). When inoptimality losses were illustrated as a function of mean diameter, the greatest losses were obtained when the mean diameter was between 20 and 30 cm, forming hill-shaped like patterns (Fig. 4).

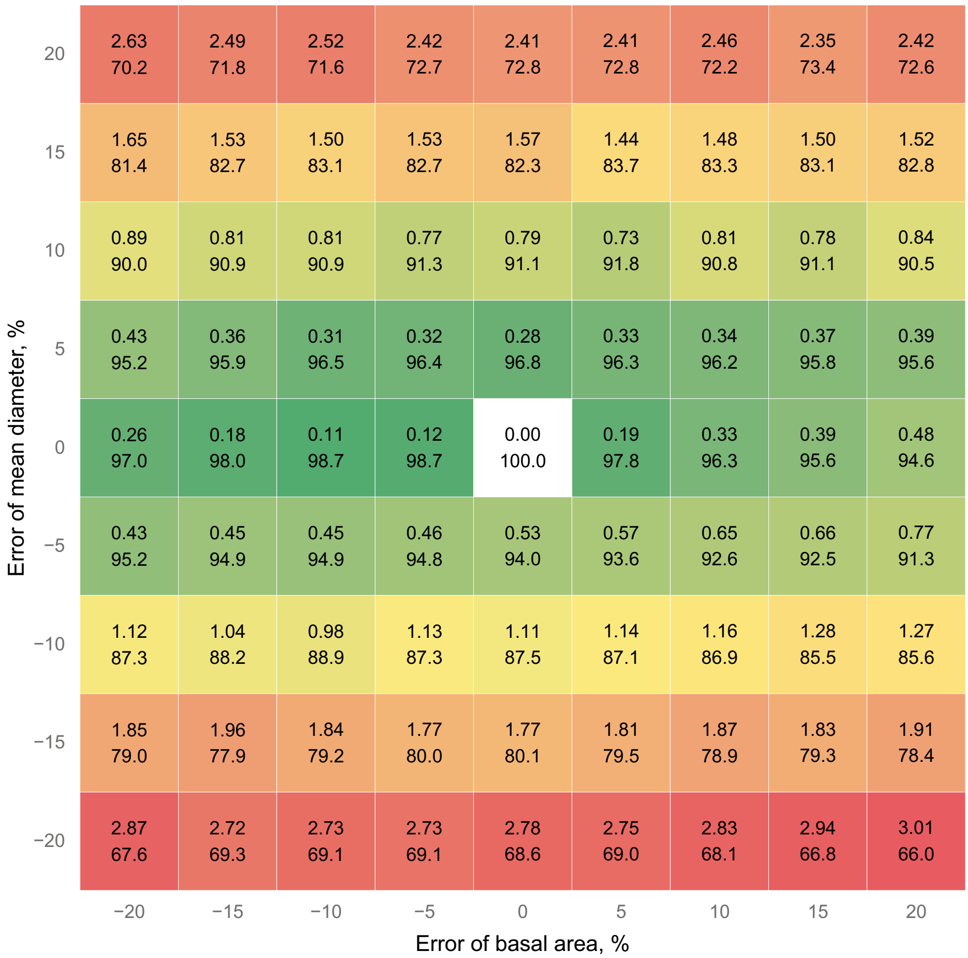

Fig. 1 Relative inoptimality losses (upper figures) and Better than Random Information (BRI) values (lower figures) in different error combinations for basal area and mean diameter during the next 10 years. The cells are colored in a green-yellow-red gradient according to ascending relative inoptimality losses

4 Discussion

Inoptimality losses occur when the management prescriptions optimal for the erroneous data result in lower NPV in the correct data than the truly optimal management prescriptions. Lower NPV originates from differences in management prescriptions due to errors in basal area and mean diameter.

Errors in mean diameter increased, on average, the inoptimality losses more than errors in basal area. Underestimation of mean diameter and basal area resulted in greater inoptimality losses than overestimation of these attributes (Fig. 1). On average, simultaneous underestimation of basal area and mean diameter resulted in inoptimality losses that were 1.3 times greater compared with simultaneous overestimation of these attributes. Inoptimality losses were 1.5–10.6 times greater when only the mean diameter contained error, compared with the situation where only the basal area was erroneous. The main reason for the stronger effect of mean diameter was the fact that error in mean diameter particularly affected the selected cutting type (thinning or final felling). The error associated with the basal area mainly affected the timing and intensity of thinning.

Inoptimality losses were also compared with the situation where the management prescriptions were based on random information (BRI). For example, when basal area and mean diameter were both underestimated by 15%, the inoptimality loss was 1.96% and the BRI value was 77.9% for the 10 years (Fig. 1). This means that the inoptimality loss was 77.9% lower than in the case where random stand attributes were used. On the contrary, when both stand attributes were overestimated by 15% at the beginning of the planning period, the inoptimality loss was 1.50% and the BRI value was 83.1%, which indicates that overestimates are less important than underestimates (Fig. 1).

Inoptimality losses increased when a 20-year period was used instead of a 10-year period (Fig. 2), since a 20-year period included more prescriptions, increasing the likelihood of prescription error. Losses increased particularly when the mean diameter was underestimated. The increase was mostly due to a large number of treatments (mainly thinning from above) that were

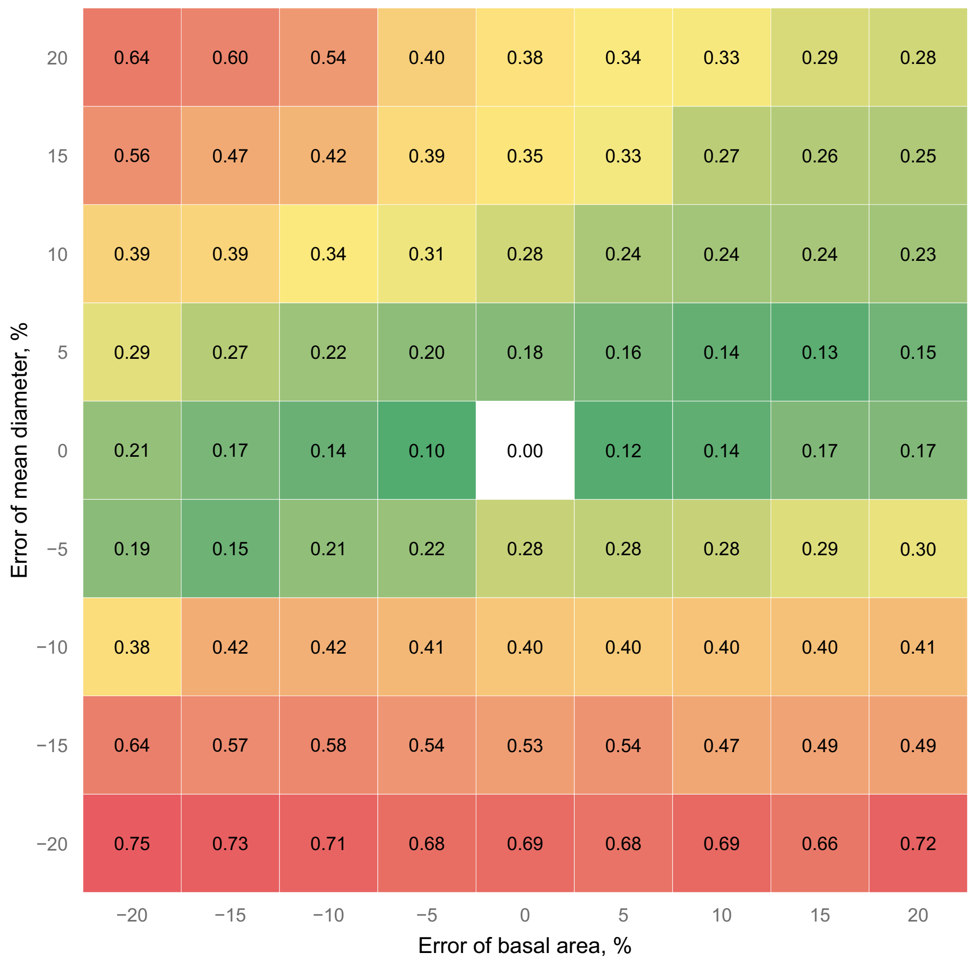

Fig. 2 Increase in relative inoptimality losses when the effects of 20-year prescription errors are calculated instead of 10 years. The cells are colored in a green-yellow-red gradient according to ascending difference

prescribed to take place later than optimal. Inoptimality losses increased also especially in error combinations where mean diameter was overestimated and basal area was underestimated.

Inoptimality losses increase when the basal area increases regardless of the error in the basal area and mean diameter (Fig. 3). This indicates that the errors of the basal area are the more important, the more valuable the stand is. The inoptimality losses also increased as a function of mean diameter, but after the mean diameter reached approximately 21–26 cm, the losses started to decrease (Fig. 4). The maximum losses reflect the time point where a selection between final felling (clear-felling or seed tree felling) and thinning is to be made.

The typical erroneous management prescriptions vary with different error combinations. For example, when the mean diameter was overestimated by 15% (Fig. 3a–d), most of the losses came from premature treatments (i.e., a treatment was prescribed to take place earlier than optimal), or from situations where clear-felling or seed tree felling was prescribed for the stand instead of thinning from above. On the contrary, when the mean diameter was underestimated by 15% (Fig. 3m–p), the losses resulted frequently from situations where the optimal treatment was final felling but the prescription was erroneously thinning from above, or treatments were prescribed to take place later than optimal.

In some cases, the errors can be large, but still, they do not cause losses. For instance, when the true value of mean diameter at the beginning of the planning period was larger than 25 cm and mean diameter was erroneously overestimated (Fig. 4a–h), the selected management prescriptions based on the correct data and erroneous data were often the same; i.e., clear-felling or seed tree felling was prescribed, and consequently, there were no losses. However, in this case, severe underestimation of mean diameter (15%) still cause losses (Fig. 4m–p), because clear-felling or seed tree felling was prescribed to take place later than optimal, or thinning was prescribed instead of clear-felling or seed tree felling. In summary, the results indicate that it is especially important to avoid large underestimation in mean diameter particularly in

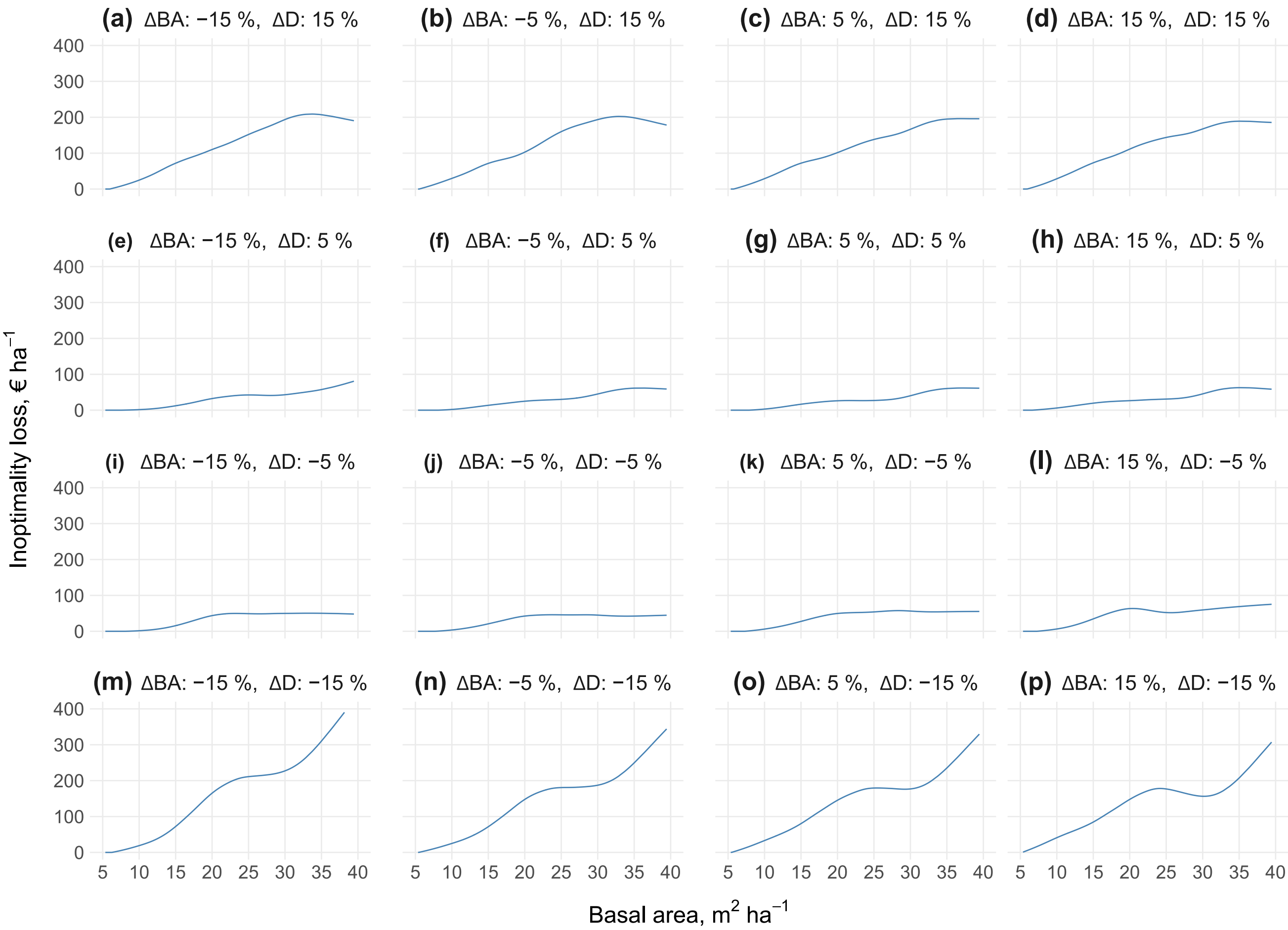

Fig. 3 Inoptimality losses (€ ha^{-1}) as a function of basal area when the errors in basal area (BA) and mean diameter (D) vary between − 15 and 15%. The basal area on the x-axis corresponds to the basal area of the stand in the correct data at the beginning of the planning period. Note that negative spline values are set to zero

stands in which the optimal treatment is clear-felling or seed tree felling in the near future.

In this study, different error levels were simulated for basal area and mean diameter by multiplying the values of stand attributes systematically with factors between 0.8 and 1.2. Error levels were simulated in this manner to evaluate the effect of underestimation and overestimation and the importance of errors in basal area and mean diameter. The errors do not mimic any specific inventory method, and neither do they follow any specific distributional or correlation assumptions. On the other hand, the stand-level results are valid for any inventory method, where a given error combination may occur. By using the Figs. 1 and 2 as lookup tables for observed error combinations, an expected loss for any given method could be calculated. In addition, information on the inventory costs may allow one to estimate which error combination would result in the lowest total inventory cost (i.e., inventory cost + inoptimality loss). The inventory efforts can be justified as long as the decrease in the inoptimality losses is greater than the additional costs associated with more accurate inventory information.

Some simplifications were made in this study. First, the effect of tree species was ignored. It has been found that errors in the attributes of the minor tree species affect the optimality of management prescriptions (e.g., Haara et al. 2019). Islam et al. (2009) pointed out that errors in the basal area of minor tree species can affect the correctness of holding-level forest plans. However, analyzing all tree species (pine, spruce, and deciduous trees) and their different error levels would have increased the number of error combinations substantially. Secondly, errors can also be present in other stand attributes. However, we decided to simulate errors only for the basal area and mean diameter, since in Finnish

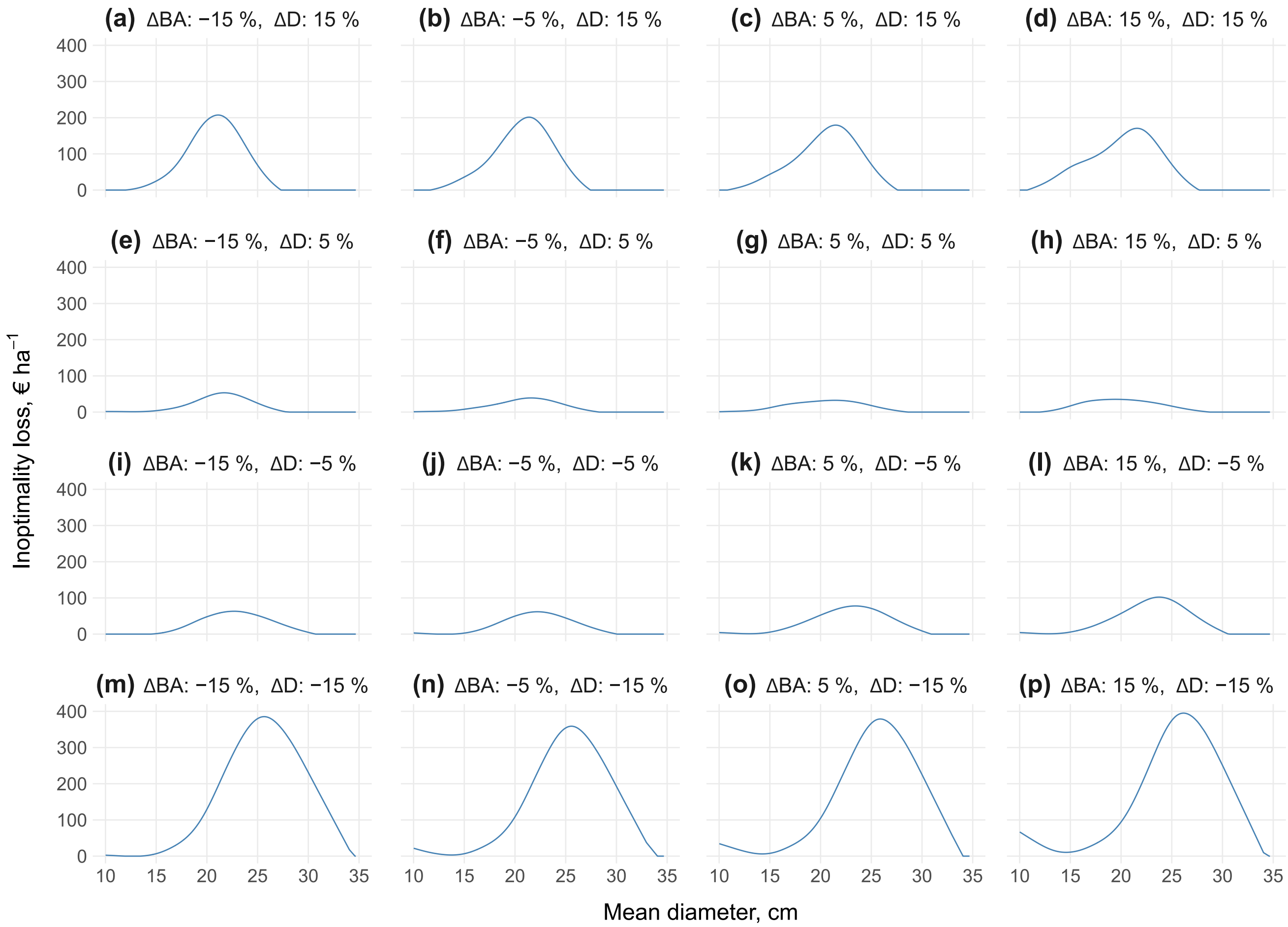

Fig. 4 Inoptimality losses (€ ha^{-1}) as a function of mean diameter when the errors in basal area (BA) and mean diameter (D) vary between − 15 and 15%. The mean diameter on the x-axis is the basal area-weighted mean diameter of the stand in the correct data at the beginning of the planning period. Note that negative spline values are set to zero

forestry practice these attributes are used to predict the present state of the stand (stand density and average tree size) and they also determine the financial maturity of the stand for cutting.

5 Conclusions

We evaluated the effect of errors in basal area and mean diameter on the optimality of management prescriptions based on inoptimality losses. When NPV was maximized with a 3% discount rate, simultaneous underestimation of basal area and mean diameter led to greater inoptimality losses than simultaneous overestimation of these attributes. Error in mean diameter increased inoptimality losses more than an equivalent error in basal area. Therefore, it is particularly important to avoid large errors in mean diameter when data are used in forest planning.

Appendix

The following linear models were used to predict the net present value of the growing stock at the end of the planning period (Table 2). The models predict the square root of net present value of timber production when rotations are expected to continue to infinity. The total net present value of the ending growing stock was calculated as the basal area-weighted mean of tree species–specific predictions. Stumpage prices of 50 € m^{-3} and 38 € m^{-3} were used for Pine/Spruce and Birch saw log, and price of 15 € m^{-3} for pulpwood.

Table 2 The models used to predict the net present value of the growing stock at the end of the planning period. The effective temperature sum was set to 1200 degree days in the current study. Mean diameter = basal area-weighted mean diameter. *Indicator variable. If the stand is classified into a specific site fertility class, the corresponding indicator variable is equal to 1; otherwise, it is equal to 0

Variable	Pine	Spruce	Birch
Constant	36.717	13.188	22.855
Effective temperature sum	0.0288	0.0667	0.0322
Effective temperature sum × mean diameter (cm)	−0.000313	−0.001540	−0.000277
sqrt(Interest rate (%))	−9.716	−9.520	−6.912
ln(Interest rate (%)) × mean diameter (cm)	0.377	0.664	0.305
Saw log stumpage price (€ m^{-3}) × effective temperature sum	0.000503	0.000670	0.000391
Pulpwood stumpage price (€ m^{-3})	1.840	1.712	1.965
Saw log stumpage price (€ m^{-3}) × ln(Interest rate (%))	−0.649	−0.822	−0.656
Pulpwood stumpage price (€ m^{-3}) × ln(Interest rate (%))	−0.387	−0.484	−0.367
Saw log stumpage price (€ m^{-3}) × mean diameter (cm)	0.0281	0.0371	0.0336
Pulpwood stumpage price (€ m^{-3}) × mean diameter (cm)	−0.00530	0.000	−0.00991
Basal area (m^2 ha^{-1})	3.126	3.086	3.421
sqrt(Basal area (m^2 ha^{-1}))	−19.876	−22.148	−20.982
ln(max(0.1, Basal area (m^2 ha^{-1})))	7.829	14.590	7.037
Mesic forest*	−7.077	−12.390	−4.072
Sub-xeric forest*	−11.977	−21.180	−4.872
Xeric forest*	−14.106	−25.000	−10.000
Barren forest*	−18.000	−28.000	−15.000

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Data availability The datasets analyzed during this study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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