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# Calibration models for diameter and height growth of Norway spruce growing in uneven-aged stands in Finland

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ABSTRACT

The great interest in continuous cover forestry (CCF) in Finland has increased the need for tools to predict tree growth in uneven-aged stands. Growth predictions are commonly obtained with stand simulators like MOTTI, which is primarily targeted at even-aged stands for rotation forestry (RF) in Finland. The aims of this study were: 1) to test how the existing individual tree growth models of MOTTI worked for Norway spruce trees growing in uneven-aged stands in Finland; 2) to identify significant predictors if biases were detected; and 3) to compile calibration models in diameter or height growth. We used data based on 20 CCF Norway spruce permanent sample plots with a 20–25-year monitoring period measured in southern Finland. Simulation with MOTTI revealed obvious diameter and height growth biases in these stands. Growth was especially overpredicted for small trees. The current MOTTI predictions were unsuitable for CCF, and calibration models were therefore compiled using a linear mixed-effects regression approach. They were developed based on variables indicating tree size, tree- and stand-level competition, an uneven-aged stand structure, an asymmetrical competition variable, and dummy variables indicating the time since the last selection cutting in years. The resulting models predicted tree dbh and tree height more accurately than the existing MOTTI. The compiled calibration models will be incorporated into the MOTTI simulator to provide a more reliable prediction of tree diameter and height growth in uneven-aged stands. Moreover, the significant predictors reported in this study were considered as informative variables to develop calibration models for tree growth in CCF in a similar situation, where models are equipped only for RF.

## 1. Introduction

Norway spruce (*Picea abies* (L.) Karst.) is one of the most widely distributed and most important economic tree species in Finland. Before the advent of industrial-scale forestry in the late 19th century, management practices in Finnish forests varied greatly, depending on the prevailing needs, from slash and burn cultivation to tar burning (Mielikäinen and Hynynen, 2003; Siiskonen, 2007; Kuuluvainen et al., 2012). From the beginning of large-scale forest industry in Finland until the middle of the 20th century, single-tree selection cuttings or high-grading in which only the biggest trees were cut were commonly applied for logs and papermaking. However, such silviculture was found to result in decreased wood production and the poor technical quality of stands by the leading foresters and forestry authorities and was banned in Finland in 1948 (Appelroth et al., 1948; Siiskonen, 2007). Since the middle of the 20th century, rotation forestry (RF) has been the

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prevailing management method in production forests.

The management of RF involves a typical even-aged system which develops a single-storied stand and can be managed with clearcutting (Lundqvist, 2017). Meanwhile, sustainable forest management is of increasing interest due to the recent environmental challenges biodiversity loss and the climate crisis pose. Continuous cover forestry (CCF) is indicated as a potentially more sustainable management method than RF by delivering a wider range of ecosystem services (Mizunaga et al., 2010). CCF is one approach to forest management that avoids the use of large clearcutting and thus maintains a continuity of tree cover across the site (Mason et al., 1999). The CCF system does not follow a cyclical harvest-and-regeneration pattern and is characterised by selective harvesting, which leads to an uneven-aged stand structure (Gadow, 2001; Pommerening and Murphy, 2004). Reliance on small openings and natural regeneration leads to uneven-aged and more structurally diverse stands (cf. Kerr, 2008; Helliwell and Wilson, 2012; Lundqvist, 2017). However, the comparison between the RF and CCF management approaches is still not conclusive from an ecological, economic, or societal perspective, and various studies have produced contradictory results (see the extensive reviews by Kuuluvainen et al. (2012) and Lundqvist (2017)). To plug these gaps in Finnish forestry, a comparison of growth and yield between RF and CCF is essential through software equipped with adequate models.

In forest growth and yield models, growth factors are described with predictors based on site, stand, and tree characteristics, which can be measured in forest inventories (Wykoff, 1990; Repola et al., 2018). These variables depict tree size, competition, site productivity, stand structure, and the effect of silvicultural treatment such as thinning and fertilisation (Repola et al., 2018). In the models for even-aged RF stands, stand age and stand dominant height are commonly used to describe the stage of stand development. However, they cannot be applied in models for CCF stands because of heterogeneous size and age structure, and because the selection cuttings of CCF affect the values of these variables (Pukkala et al., 2013; Hynynen et al., 2019; Fagerberg et al., 2022). This characteristic also prevents the application of site index estimation based on dominant height at a given age, which is traditionally used for RF (Vuokila, 1956; Lee et al., 2021, 2023). Furthermore, it is demanding and inefficient to collect individual tree ages, meaning this is not applied as a predictor of a tree-level growth model. Tree age is known to be highly correlated with tree size (Assmann, 1970). Tree size variables such as tree diameter or height were therefore used as a main predictor of age-independent diameter and height growth models (Stage, 1973; Hynynen and Ojansuu, 2003; Eerikäinen et al., 2007; Pukkala et al., 2009; Repola et al., 2018; Bianchi et al., 2018, 2020a).

The differences between RF and CCF related to stand structure and harvesting methods result in differences in within-stand competition between trees. In even-aged RF stands, symmetric competition and overall stand density heavily control the growth rate of individual trees, as well as the growth response of trees to management practices. In heterogeneous CCF stands, the role of asymmetric competition is an important factor controlling the growth of individual trees, even in low stand density (Hynynen et al., 2019). For example, stand density can affect the height growth of an individual tree in CCF differently. This perspective is supported by Eerikäinen et al. (2014), who studied uneven-aged stands of Norway spruce in Finland. They reported that the height growth of small trees (0.1–9 m in height) was slow especially in the smallest size classes and mentioned the effect of stand density, along with site quality and selection cutting (Eerikäinen et al., 2014). Meanwhile, it has also been observed that the cutting method (thinning from below or above) and the combined effect of the cutting and stand density may substantially influence height growth (Nilson and Lundqvist, 2001). According to Bianchi et al. (2020a, 2020c), taller trees had longer live crowns in CCF than in RF. This can cause more competitive pressure for undergrowth trees on dominated trees in CCF. On the other hand, the live crown is related to growth potential. This means that hypothetically smaller trees should grow worse, but mid-size and larger trees may grow better in CCF than in RF.

One of the most widely used growth and yield simulators in Finland is MOTTI (Hynynen et al., 2002, 2014), developed formerly by the Finnish Forest Research Institute (METLA) and currently at Natural Resources Institute Finland (LUKE). MOTTI includes both stand-level and tree-level models for predicting stand dynamics (regeneration, growth, and mortality) and stand structure (Hynynen et al., 2015; Salminen et al., 2005; Siipilehto et al., 2014). It therefore provides a variety of outputs such as the predicted development of tree and stand characteristics, deadwood dynamics, yield by timber assortments, changes in stand biomass and carbon storage, economic profitability, etc., which can be reported as the results of scenario analysis or long-term simulations.

MOTTI is designed for RF, which means that most of its models have thus far been developed and tested mainly on data from even-aged single-species forests (Hynynen et al., 2002; Mäkinen et al., 2005). The growth models of MOTTI have also been validated for even-aged mixed-species stands, showing reliable performance within the original range of the modelling data (Aldea et al., 2023). However, MOTTI has yet to be tested in uneven-aged stands. Model validation is needed to assess their applicability for simulating CCF stands. Across Fennoscandia, the situation is similar to other forest growth simulators, namely HEUREKA in Sweden (Fahlvik et al., 2014) and SiTree in Norway (Antón-Fernández and Astrup, 2022). They are based on models for RF, but they can technically be used for CCF. However, HEUREKA has shown worse performance when applied to CCF stands than to RF (Fagerberg et al., 2022; Lämås et al., 2023). SiTree has not been properly tested for CCF and uses the site index (the dominant height at a given age), which can be a difficult and meaningless estimation in uneven-aged stands.

This study's aims were therefore 1) to test how the individual tree growth models of MOTTI performed for Norway spruce trees growing in uneven-aged stands in Finland for CCF, 2) to identify the most significant predictors that caused the biases in tree growth in CCF if biases were detected, and 3) to compile calibration models to improve the predictions for CCF considering the modelling data characteristics. We focused on growth prediction for all the trees that were measured at the beginning of the growth period. Mortality and ingrowth were beyond the scope of this study, although they also can differ between RF and CCF. Nevertheless, with this study's research findings, we aimed to provide informative predictors to calibrate the tree growth of uneven-aged stands based on general models for RF in the other stand simulators.

## 2. Materials and methods

### 2.1. Study materials

#### 2.1.1. Experimental sites

The study material consisted of 20 spruce-dominated stands on mineral soil in southern and central Finland (Fig. 1). Sixteen stands were on a submesic site (*Myrtillus* forests type), and four stands on a mesic site (*Oxalis-Myrtillus* herb-rich heath) according to Cajander (1949). The stands already had an irregular structure and were subject to a single-tree selection harvest (selection cutting) in the 1980s. The first measurement was carried out in 1991–1996 and was then repeated every five years. In 1996, sixteen stands were selectively harvested, while four stands were not harvested because they were deemed to have too low a growing stock. In 2011, all the stands were selectively harvested. According to the removed basal area, the cutting intensity was 26% on average, ranging from 13% to 59%.

One permanent square plot (40 m side, 1600 $m^2$ area) was established in the centre of the stand, surrounded by a large buffer zone of varying size that was similarly managed. In other words, there was no edge effect on the plot. All the trees higher than 1.3 m in the plots were measured for diameter at breast height, total height, location, and tree

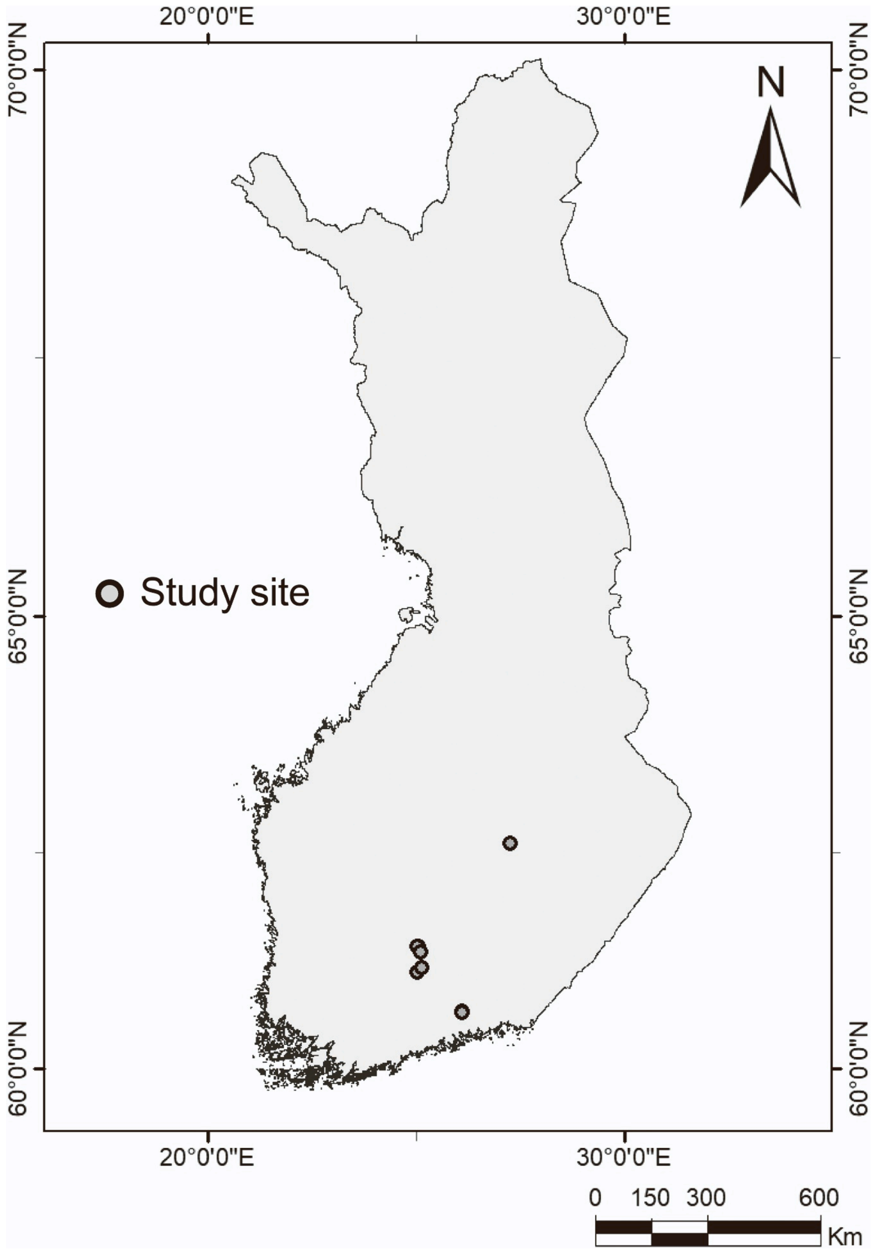



**Fig. 1.** The experimental sites used to develop the calibration models of Norway spruce for MOTTI in Finland.

species. Trees with a heavy sign of damage were excluded from modelling but were still used to calculate stand characteristics. The age of individual trees was unknown. Only general information about plot-level age was recorded based on the age measurement during the first inventory. More information is given in Valkonen et al. (2020).

### 2.1.2. Description of stand and tree characteristics

In addition to stand density such as *N* (the number of trees) and *BA* (stand basal area), the uneven-aged stand structure was confirmed by stand variables (Table 1). The difference between $D_a$ (arithmetic mean diameter) and $D_w$ (basal area-weighted mean diameter) and between $H_a$ (arithmetic mean height) and $H_w$ (basal area-weighted mean height) described the irregular diameter and height distributions. Additionally, the ratio of $D_a$ to $D_w$ ($D_a/D_w$) as an uneven-aged stand indicator was sufficiently low to imply irregular stand structures (Hynynen et al., 2019; Bianchi et al., 2020c). To further demonstrate the irregular stand structure, the supplementary figures illustrating the dbh and height distributions by stand are provided in Appendix A. The cutting quotients

**Table 1**
Stand characteristics at the time of establishment.

| Variable | Mean | Std Dev. | Minimum | Maximum |
|---|---|---|---|---|
| $N$, trees ha$^{-1}$ | 1376 | 643 | 500 | 3438 |
| $BA$, m$^2$ ha$^{-1}$ | 18.5 | 4.8 | 9.2 | 35.2 |
| $D_a$, cm | 9.8 | 2.3 | 5.3 | 17.7 |
| $D_w$, cm | 24.1 | 3.3 | 16.4 | 33.3 |
| $D_a/D_w$ | 0.41 | 0.08 | 0.24 | 0.68 |
| $H_a$, m | 9.2 | 1.9 | 5.3 | 15.8 |
| $H_w$, m | 19.9 | 2.1 | 16.3 | 25.5 |
| $CQ_{Da}$ | 1.60 | 0.77 | 0.48 | 3.73 |
| $CQ_{Dw}$ | 1.22 | 0.16 | 0.88 | 1.60 |

Abbreviations: *N*, Number of stems per hectare; *BA*, stand basal area; $D_a$, arithmetic mean diameter at breast height; $D_w$, basal area weighted mean diameter at breast height; $D_a/D_w$, the ratio of $D_a$ to $D_w$; $H_a$, arithmetic mean diameter height; $H_w$, basal area weighted mean height; $CQ_{Da}$, cutting quotient between the mean diameter of removed trees and the mean diameter of all trees before selection cutting based on $D_a$; $CQ_{Dw}$, cutting quotient based on $D_w$.

between the mean diameter of removed trees and the mean diameter of all trees before selection cutting based on $D_a$ ($CQ_{Da}$) and on $D_w$ ($CQ_{Dw}$) were greater than one on average, which demonstrated that the diameter of the harvested trees was mainly above the mean and indicated the selection cutting system.

The modelling data consisted of 4382 spruce trees. The trees showed high variation in terms of dimensions and growth (Table 2). The diameter growth at breast height ($i_{d5}$) and height growth ($i_{h5}$) of spruce for five years were obtained as the difference of the tree dimensions between successive measurements.

### 2.2. Modelling procedures

#### 2.2.1. General description of modelling steps

New increment models for CCF stands could not be directly developed because the data were collected only regionally by target stands, and the number of trees was relatively small compared to the models for RF stands in MOTTI (Hynynen et al., 2002; Salminen et al., 2005; Hynynen et al., 2014). The calibration models for trees growing in uneven-aged stands to be applied to MOTTI were therefore a reasonable approach to be developed, which contained several stages as follows:

1) Produce five-year growth predictions with MOTTI using the study material as input data.
2) Diagnose bias in the above predictions using all the candidate variables, calculated from the stand and tree characteristics that may explain the bias.
3) Develop calibration models for such a bias by applying the most significant predictors selected among the variables found in Step 2 above.
4) Examine the accuracy improvement by comparing calibrated predictions with observed values and the initial MOTTI predictions.

In the first stage, the current MOTTI produced the predicted growth of Norway spruce trees for RF based on site, stand, and tree characteristics, e.g. location (coordinates), altitude, temperature sum, site class, regeneration method, time from the last treatment/cutting, tree diameter and height at the start of each five-year timestep, and competition index (Hynynen et al., 2014). In the second stage, a wide range of variables was analysed to identify noticeable biases, including tree dbh and height, and mean diameter and height. In addition, competition can be considered an additional predictor of tree growth, which is generally divided into two categories depending on scope: stand- and tree-level. The stand-level competition variable includes absolute stand density like $N$, $BA$, or stand volume per unit area (Miina, 1994; Penner et al., 1995; Hökkä et al., 1997) and relative stand density like relative density in proportion to the stand density index or stocking percentage (Lee and Choi, 2019, 2020). In this study, $N$ and $BA$ were examined to find significant predictors. The basal area of trees larger than the target tree ($BAL$) was also analysed at tree-level competition (Wykoff, 1990). Moreover, the ratio of $D_a$ to $D_w$, the ratio of $H_a$ to $H_w$, and cutting dummy variables were analysed to find any significant indicators regarding the stand structure and management system. The tested cutting dummy variables were the time since the last selection cutting in years considering the measurement intervals on average. For example, $CUT_{0\text{–}4}$ was coded as 1 if time since the last selection cutting was < 5 years or coded as 0 if the time was ≥ 5 years. $CUT_{5\text{–}9}$ was coded as 1 if time since the last selection cutting was ≥ 5 years and < 10 years or coded as 0 if the time was < 5 years or ≥ 10 years. Similarly, other cutting dummy variables, such as $CUT_{10\text{–}14}$ and $CUT_{15\text{–}19}$, were tested in the analysis. The candidate variables were tested, including transformations such as logarithmic, reciprocal, squared, and/or square-root form, and a small constant from 0.1 to 10. In the third stage, consequently, it was attempted to develop the calibration models to correct the biases of basal area and height growth for Norway spruce as functions of tree size, stand density, an uneven-aged stand indicator, a competition-related variable, and cutting dummy variables.

**Table 2**
Tree characteristics of Norway spruce at the time of establishment.

| Variable | Mean | Std Dev. | Minimum | Maximum |
|---|---|---|---|---|
| *dbh*, cm | 6.7 | 7.8 | 0.1 | 42.3 |
| *h*, m | 6.3 | 6.5 | 1.3 | 31.3 |
| $t_{13}$, year | 65 | 14 | 39 | 110 |
| $i_{d5}$, cm | 1.02 | 0.73 | 0.05 | 5.95 |
| $i_{h5}$, m | 0.76 | 0.65 | 0.01 | 4.60 |

Abbreviations: *dbh*, diameter at breast heigh above 1.3 m from the ground; *h*, tree height; $t_{13}$, tree age at breast height; $i_{d5}$, 5-year diameter growth; $i_{h5}$, 5-year height growth. Note that $t_{13}$ was provided based on plot-level observation.

#### 2.2.2. Statistical approaches of the calibration models

MOTTI obtained the tree-level growth predictions of the uneven-aged stand material. Growth simulation for each stand was carried out in five-year steps using the site characteristics and measured trees as input data (Fig. 2). There were four to five simulation periods.

The five-year growth predictions for tree dbh ($i_{d5}$) and height ($i_{h5}$) were compared with observed values (Fig. 2), and the presence of biases was investigated. This examination process was carried out for every measurement period, e.g. 1–2, 2–3, 3–4, etc. The calibration models for the bias of basal area growth ($i_{g5}$) and height growth ($i_{h5}$) were then developed for spruce (Eq. 1). The $i_{d5}$ was replaced with $i_{g5}$ because there was a higher correlation between the basal area growth and initial diameter than between the diameter growth and initial diameter (West, 1980), and MOTTI is also based on $i_{g5}$ (Salminen et al., 2005). In the model specification, a logarithmic transformation of the response variable was used, adding a constant $z$ to the observed and predicted growth values, to obtain normally distributed residuals with homogenous variance and to transform the model to a linear form. The preliminary results showed that the best values for the constant $z$ were 5 for $i_{g5}$ and 3 for $i_{h5}$. To account for spatially and temporally correlated observations, we applied a linear mixed-effects model (Searle, 1987) with both fixed and random effects as follows:

$$\begin{aligned}\ln CAL_{ijk} &= \ln(y_{ijk}+z) - \ln(\hat{y}_{ijk}+z) \\ &= \beta_0 + \beta_1 \bullet X_{ijk,1} + \beta_2 \bullet X_{ijk,2} + \cdots + \beta_n \bullet X_{ijk,n} + u_i + v_{ij} + e_{ijkt} \end{aligned} \quad (1)$$

where $\ln CAL_{ijk}$ is the dependent variable, calibration effect for tree basal area $\left(\ln CAL.ig5_{ijk}\right)$ or height growth $\left(\ln CAL.ih5_{ijk}\right)$, $y_{ijk}$ is the observed ($i_{g5}$ or $i_{h5}$), and $\hat{y}_{ijk}$ the predicted ($\hat{i}_{g5}$ or $\hat{i}_{h5}$) value of the tree basal area or height growth based on the existing MOTTI, $z$ is a constant added to response variable, $\beta_0$–$\beta_n$ are fixed-effect parameters, $X_{ijk,1}$–$X_{ijk,n}$ are independent variables for tree $k$ in plot $j$ in stand $i$, $u_i$ is the random effect of stand $i$, $v_{ij}$ is the random effect of plot $j$ in stand $i$, and $e_{ijkt}$ is the residual error at period $t$ for tree $k$ in plot $j$ in stand $i$. The covariance structure of the successive five-year growth periods at tree level was assumed to follow the first-order autoregressive (AR-1) structure. The random parameters ($u_i$, $v_{ij}$) and residual errors ($e_{ijkt}$) were assumed to be uncorrelated and to be identically distributed Gaussian random variables with a mean of 0, and to follow constant variances at each level. Hereafter, the observed values of $\ln CAL_{ijk}$ in arithmetic scale are defined as $CAL_{obs}$ ($CAL_{obs} = \exp(\ln CAL_{ijk})$), and the fitted values of $\ln CAL_{ijk}$ in arithmetic scale as a calibration coefficient from calibration models are defined as $CAL_{pred}$ ($CAL_{pred} = \exp(\ln CAL_{ijk})$).

The model performance was assessed by comparing observed growth ($OBS$) with the predicted growth from the existing MOTTI values ($MOTTI_{pred}$), and the calibrated (or corrected) MOTTI predictions ($CORM_{CCF}$). $CORM_{CCF}$ were obtained by multiplying $CAL_{pred}$ by $MOTTI_{pred}$ as follows:

$$CORM_{CCF} = \left(emp \times CAL_{pred} \times \exp\left(\ln\left(MOTTI_{pred}+z\right)\right)\right) - z \quad (2)$$

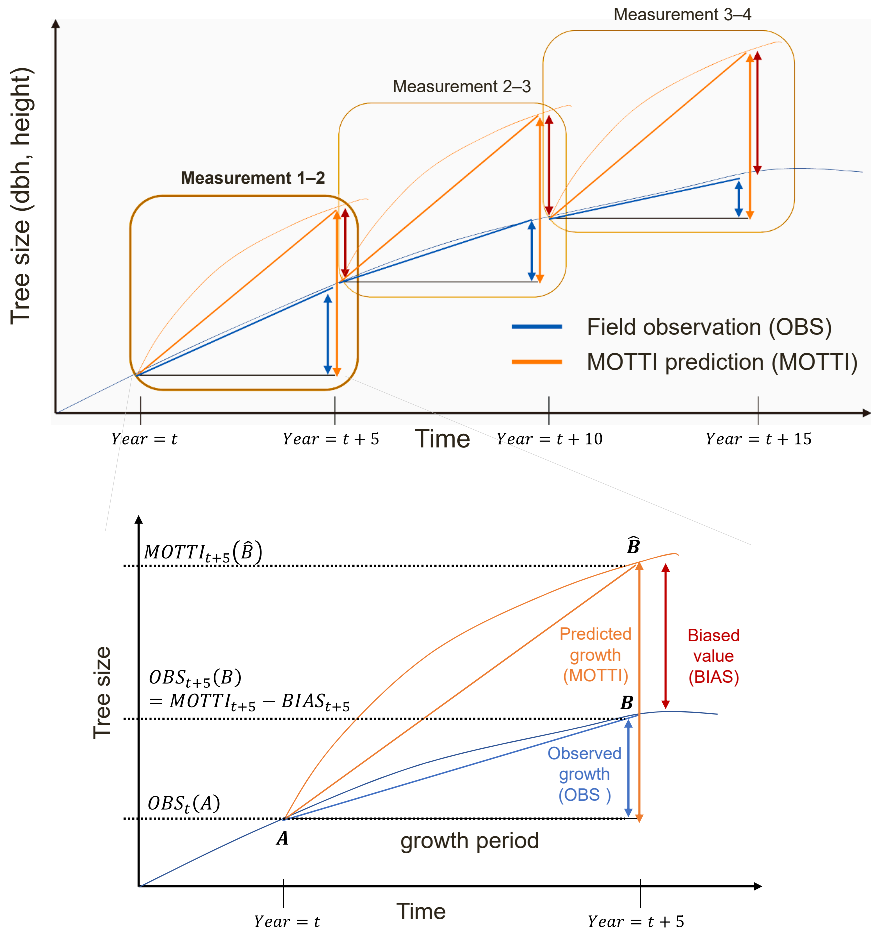



**Fig. 2.** An illustration of observed values from repeated field inventories, predicted values based on MOTTI, and biases between two values. The five-year growth prediction was simulated to match the growth period of the field measurements. Note that linear or curvilinear interpolation was supposed for graphic illustration. The biases from overprediction were described in the example, but biases from underprediction can also be viable in practice.

where $CORM_{CCF}$ is the predicted basal area or height growth applying calibration models in this study to provide the calibrated MOTTI predictions for CCF, $CAL_{pred}$ is the fitted values of $\ln\left(y_{ijk}+z\right)-\ln\left(\hat{y}_{ijk}+z\right)$ in arithmetic scale from the calibration models as previously defined, $MOTTI_{pred}$ is the predicted value of tree basal area or height growth based on the existing MOTTI as also previously defined as $\hat{y}_{ijk}$ in Eq. (1), *emp* is the empirical correction factor, $\sum(CAL_{obs})/\sum(CAL_{pred})$, and $z$ is the selected constant, with 5 and 3 for the $i_{g5}$ and $i_{h5}$ respectively in the modelling process. *emp* was used instead of a variance correction term, $(\mathrm{var}(u_i)+\mathrm{var}(v_{ij})+\mathrm{var}(e_{ijk}))/2$, to transform the prediction to an arithmetic scale as a solution for avoiding overestimates of $CORM_{CCF}$ caused by a large variance of random parameters in the compiled models (Repola et al., 2018).

The predicted growth of $MOTTI_{pred}$ and $CORM_{CCF}$ was compared with *OBS* by calculating the evaluation metrics: the mean difference (BIAS, Eq. 3); mean absolute error (MAE, Eq. 4); root mean squared error (RMSE, Eq. 5); and root mean squared relative error (RMSRE, Eq. 6).

$$\mathrm{BIAS}=\frac{\sum_{i=1}^{n}\left(y_{ijk}-\hat{y}_{ijk}\right)}{n}, \tag{3}$$

$$\mathrm{MAE}=\frac{\sum_{i=1}^{n}\left|y_{ijk}-\hat{y}_{ijk}\right|}{n}, \tag{4}$$

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}\left(y_{ijk}-\hat{y}_{ijk}\right)^2}{n}}, \tag{5}$$

$$\mathrm{RMSRE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left(y_{ijk}-\hat{y}_{ijk}\right)}{y_{ijk}}\right)^2}, \tag{6}$$

where $y_{ijk}$ is the observed (*OBS*), and $\hat{y}_{ijk}$ the predicted ($MOTTI_{pred}$, $CORM_{CCF}$) values of tree basal area or height growth ($i_{g5}$ or $i_{h5}$), and $n$ is the number of observations.

All the modelling processes were performed with R statistical software (R Core Team, 2023) to fit the parameters, including the *lme* function of the *nlme* packages in R (Pinheiro et al., 2020). Additionally, the residual variance for the calibration model of tree basal area growth was formulated with the power function: $v_\varepsilon = \mathrm{std}(\varepsilon)^2 \times e^{2P}$, where $v_\varepsilon$ is the residual variance, $\mathrm{std}(\varepsilon)$ is the standard deviation of the residuals $\varepsilon$, and P is the estimated power for the variance function. To describe the improvement of model accuracy in the last stage, e.g. Figs. 4 and 5, several line plots and point estimates with confidence intervals were examined and presented comparing the five-year growth of tree basal area and height between *OBS*, $MOTTI_{pred}$, and $CORM_{CCF}$ over major tree or stand characteristics such as tree dbh, tree height, *BA*, and *BAL*.

## 3. Results

### 3.1. Accuracy examination of MOTTI

In the examination of the existing MOTTI prediction, bias was detected in both $i_{d5}$ and $i_{h5}$. In general, the $MOTTI_{pred}$ bias for $i_{d5}$ was highest for small trees (Fig. 3). For trees with a diameter < 15 cm, the bias tended to decrease with an increasing tree diameter (Fig. 3a).

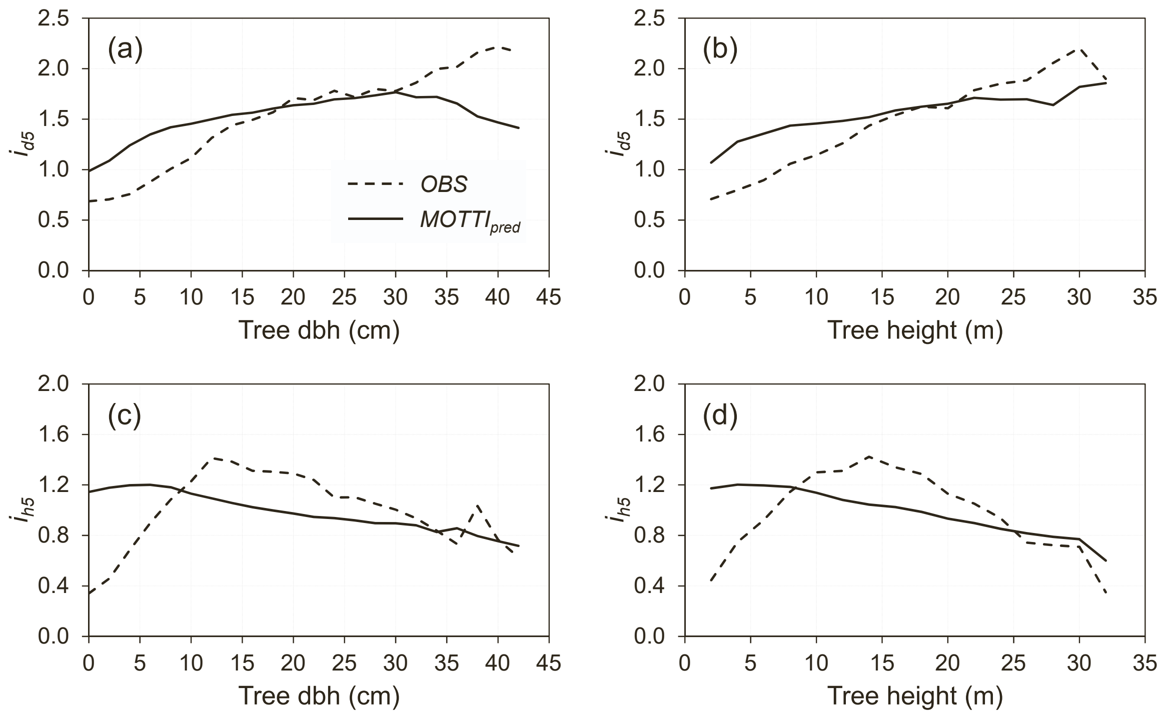



**Fig. 3.** The five-year tree diameter growth ($i_{d5}$, cm 5years$^{-1}$) (plots a and b) and tree height growth ($i_{h5}$, m 5years$^{-1}$) (plots c and d) of spruce trees growing in uneven-aged stands based on the average of observed values (*OBS*) by dbh and height class and predicted values (*MOTTI$_{pred}$*) from the existing MOTTI simulator.

*MOTTI$_{pred}$* was relatively unbiased in the middle of the diameter range (diameter between 15 and 30 cm). When the tree diameter was more than 30 cm in the dbh class, the bias trend was the opposite; *OBS* was increasingly higher than *MOTTI$_{pred}$*, with an increasing diameter. The bias for tree height appeared to be similar to that for tree dbh (Fig. 3b).

The bias trend of $i_{h5}$ differed according to the dbh class. *MOTTI$_{pred}$* produced overestimates of $i_{h5}$ for small trees. *MOTTI$_{pred}$* for $i_{h5}$ was higher only in small trees with a dbh $< 8$ cm, while for trees with a dbh $> 8$ cm, *OBS* was higher and then tended to be close to *MOTTI$_{pred}$* with an increasing tree diameter (Fig. 3c). The bias trend of $i_{h5}$ for the height class was similar to the bias for the dbh class. *MOTTI$_{pred}$* overestimated $i_{h5}$ for small trees (height $\leq 8$ m), while it underestimated $i_{h5}$ afterwards until a tree height of above 25 m (Fig. 3d). All the findings verified the need to develop calibration models of $i_{d5}$ and $i_{h5}$ for Norway spruce in CCF.

### 3.2. Calibration models

#### 3.2.1. Basal area growth

The calibration models for $i_{g5}$ were based on variables depicting tree size, tree competition status, stand structure, and cutting effect (Table 3). The selected predictors were all on an arithmetic scale and based mainly on tree dbh-related variables and cutting effect. Tree diameter at breast height was statistically the most significant predictor with a non-linear relationship and was expressed both with a linear (*dbh*) and squared term (*dbh$^2$*) (Fig. 3a). As an additional tree-level predictor, *BAL* was included. The variable represented asymmetric non-spatial competitions reasonably and was statistically significant.

The ratio of the arithmetic mean diameter to the basal area-weighted mean diameter ($D_a/D_w$) was included as a plot-level variable. According to the definition, $D_a/D_w$ is considerably higher in even-aged stands than in uneven-aged stands (Hynynen et al., 2019; Bianchi et al., 2020c). As the target stands of this study presented the stands for CCF and a diverse range of tree size in *dbh*, $D_a/D_w$ was found, as expected, to be a statistically significant predictor of the bias in $i_{g5}$. In addition, $CUT_{0–4}$ and $CUT_{5–9}$ were chosen indicating effects of the time since last selection cutting (Table 3).

The calibrated MOTTI $i_{g5}$ predictions (*CORM$_{CCF}$* $i_{g5}$) were more accurate than those obtained from *MOTTI$_{pred}$*, especially for small trees (Fig. 4). The *CORM$_{CCF}$* was quite accurate throughout the *dbh* and height range (Figs. 4a and 4b), where most data were from small trees, and less data were from large trees (Table 2). In an examination of the calibration results according to *BA*, the *CORM$_{CCF}$* $i_{g5}$ was more accurate than the *MOTTI$_{pred}$* $i_{g5}$, but in dense stands, there was a distinguishable $i_{g5}$ between *CORM$_{CCF}$* and *OBS* near 30 m$^2$ ha$^{-1}$, possibly because there were less data (Fig. 4c).

The *CORM$_{CCF}$* showed a higher accuracy than *MOTTI$_{pred}$* especially with $D_a/D_w$ values lower than 0.5 (Fig. 4d). The *CORM$_{CCF}$* also showed more accurate predictions throughout the range of *BAL* (Fig. 4e), and it revealed significantly improved performance in stands with high *BAL* than *MOTTI$_{pred}$* as *CORM$_{CCF}$* was closer to *OBS* (Fig. 4 f). The included cutting dummy variables of $CUT_{0–4}$ and $CUT_{5–9}$ (Table 3) showed improved predictions for *CORM$_{CCF}$* than *MOTTI$_{pred}$* (Fig. 4 g and 4 h). Table 4

#### 3.2.2. Height growth

Two types of $i_{h5}$ calibration models (ln*CAL.ih5*) were developed using different major predictors. The ln*CAL.ih5* model type 1 contained tree height and stand variables (Table 5). To be specific, due to non-linear bias, both the height ($h$) and square root of height ($\sqrt{h}$) were significant with opposite parameter signs and were included in the ln*CAL.ih5* model 1. At plot level, the additional predictors were *BA* and the selection cutting dummy variable. Only *BA* was relatively less significant ($p$=0.0028) than the other highly significant predictors ($p$<0.0001). Contrary to the calibration model for $i_{g5}$, only $CUT_{0–4}$ was statistically significant for $i_{h5}$ calibration in terms of cutting dummy variables.

The ln*CAL.ih5* model type 2 was based only on tree diameter and *BAL*. Both *dbh* and *dbh$^2$* were highly significant, and the parameter signs were the opposite to fit the non-linear bias. Additionally, *BAL* resulted as significant, with a positive parameter sign. Unlike the ln*CAL.ih5* model 1, plot-level predictors were nonsignificant: for example, $D_a/D_w$, *BA*,

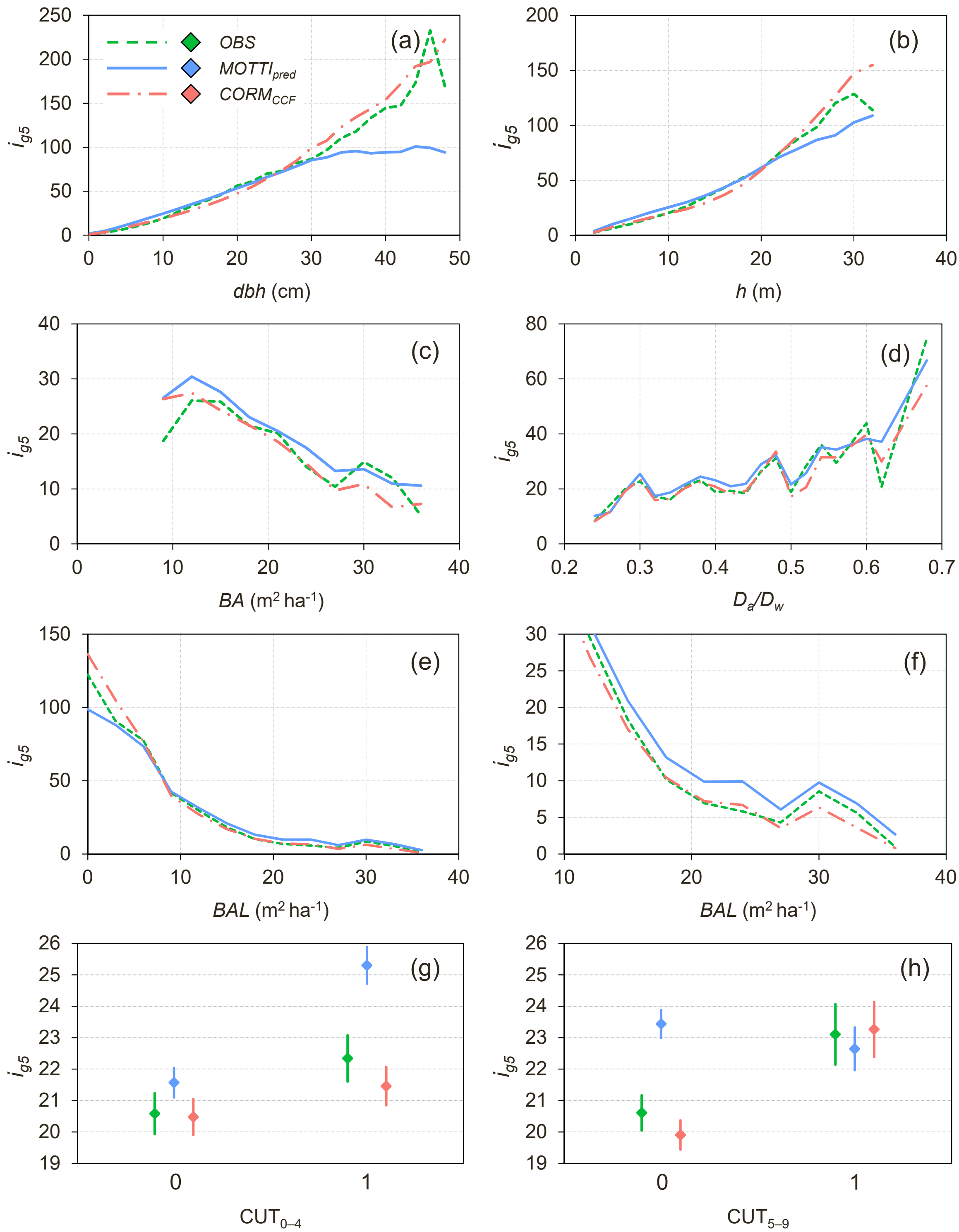
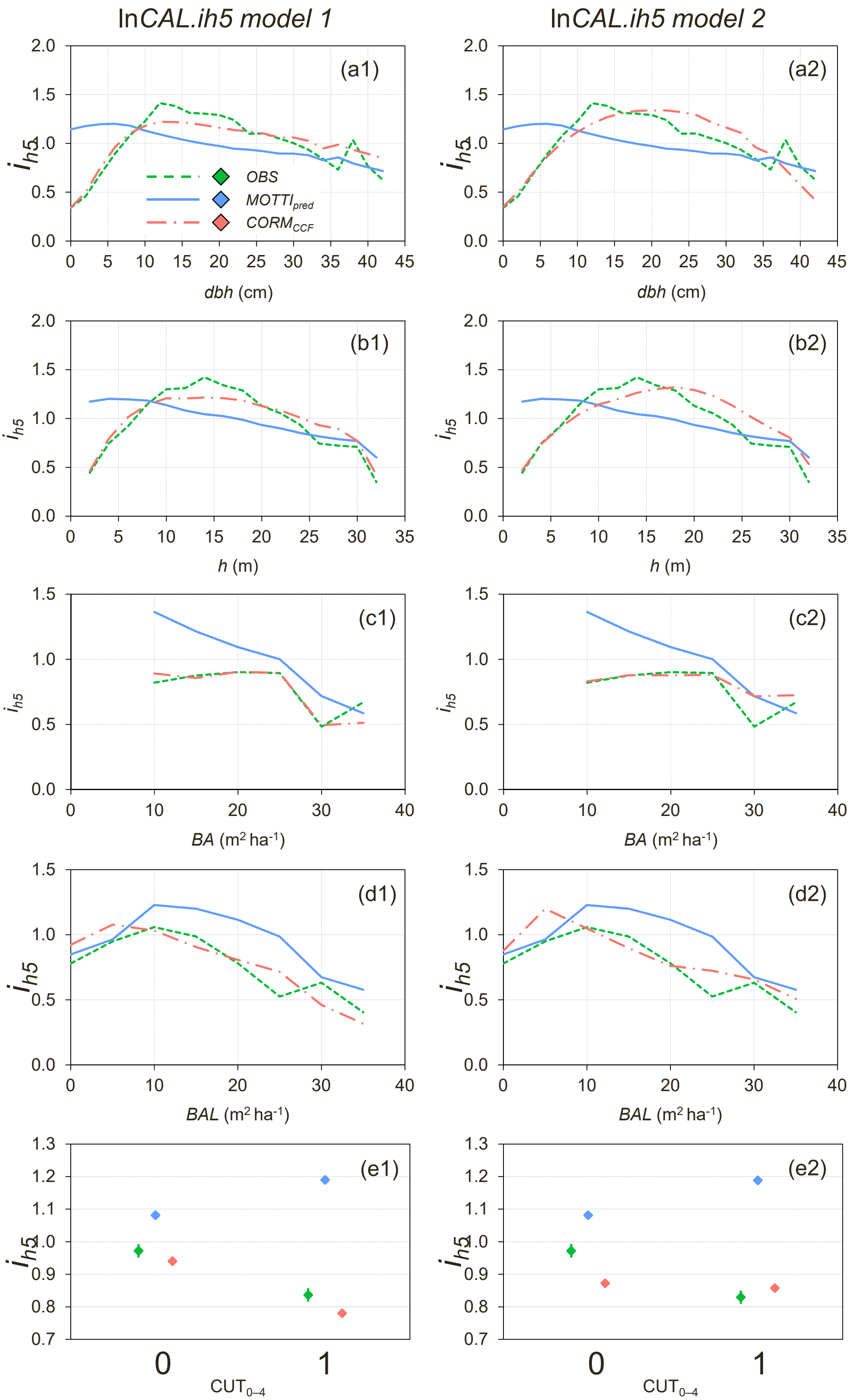



**Fig. 4.** Prediction comparison of basal area growth ($i_{g5}$, cm$^2$ 5years$^{-1}$) between observed values (*OBS*), the existing MOTTI prediction (*MOTTI$_{pred}$*), and the calibrated MOTTI prediction (*CORM$_{CCF}$*) using the developed calibration model (ln*CAL.ig5*). Each of the figure panels illustrates an overall prediction accuracy and bias over the selected predictors; *dbh* (plot a), diameter at breast height above 1.3 m from the ground; *h* (plot b), tree height; *BA* (plot c), stand basal area; $D_a/D_w$ (plot d), the ratio between $D_a$ (arithmetic mean diameter) and $D_w$ (basal area-weighted mean diameter); *BAL* (plots e and f), the basal area of trees larger than the target tree; $CUT_{0\text{–}4}$ (plot g) with code 1 if time since the last selection cutting is < 5 years, or code 0 if the time is ≥ 5 years; $CUT_{5\text{–}9}$ (plot h) with code 1 if time since the last selection cutting is ≥ 5 years and < 10 years, or code 0 if the time is < 5 years or ≥ 10 years. The figure plot (f) is a zoom-in view of the plot (e) to display the clear distinction of predicted values in large *BAL*. The figure plots (g and h) show the 95% confidence interval for the mean.




(caption on next page)

**Fig. 5.** Prediction comparison of height growth ($i_{h5}$, m 5years$^{-1}$) between observed values (*OBS*), the existing MOTTI predictions ($MOTTI_{pred}$), and the calibrated MOTTI prediction ($CORM_{CCF}$) using the developed calibration models (ln*CAL.ih5* type 1 and 2) for Norway spruce. Each of the figure panels illustrates an overall prediction accuracy and bias over the selected predictors, with model type 1 in the left-hand column and model type 2 in the right-hand column; *dbh* (plots a1 and a2), tree diameter at breast height above 1.3 m from the ground; *h* (plots b1 and b2), tree height; *BA* (plots c1 and c2), stand basal area; *BAL* (plots d1 and d2), basal area of trees larger than the target tree; $CUT_{0-4}$ (plots e1 and e2) with code 1 if time since the last selection cutting is < 5 years, or code 0 if the time is ≥ 5 years. The figure plots (e1 and e2) show the 95% confidence interval for the mean.

**Table 3**
Parameter estimates of calibration models for basal area growth ($\ln CAL.ig5_{ijk} = \ln\left(ig5_{ijk}+5\right) - \ln\left(\widehat{ig5}_{ijk}+5\right)$) of Norway spruce.

| Variable | Estimate | S.E. | D.F. | t-value | p-value |
|---|---|---|---|---|---|
| Fixed effects | | | | | |
| Intercept | 0.0301 | 0.0711 | 11445 | 0.42 | 0.6725 |
| *dbh* | -0.0129 | 0.0016 | 11445 | -7.90 | <0.0001 |
| $dbh^2$ | 0.0006 | 0.0001 | 11445 | 11.59 | <0.0001 |
| *BAL* | -0.0096 | 0.0012 | 11445 | -8.06 | <0.0001 |
| $D_a/D_w$ | -0.3372 | 0.0488 | 11445 | -6.92 | <0.0001 |
| $CUT_{0-4}$ | -0.0391 | 0.0104 | 11445 | -3.77 | 0.0002 |
| $CUT_{5-9}$ | 0.1169 | 0.0079 | 11445 | 14.74 | <0.0001 |
| Random effects | | | | | |
| std($u_i$) | 0.131 | | | | |
| std($v_{ij}$) | 0.085 | | | | |
| corr($e_{ijkt}$) | 0.306 | | | | |
| std($e_{ijk}$) | 0.265 | | | | |
| P | -0.530 | | | | |
| *emp* | 1.124 | | | | |

Note: $\ln CAL.ig5_{ijk}$, the calibrated effect of tree basal area growth (cm$^2$ 5years$^{-1}$) for tree *k* in plot *j* in stand *i*; $ig5_{ijk}$, the observed tree basal area growth (cm$^2$ 5years$^{-1}$) for tree *k* in plot *j* in stand *i*; $\widehat{ig5}_{ijk}$, the predicted tree basal area growth (cm$^2$ 5years$^{-1}$) based on the existing MOTTI for tree *k* in plot *j* in stand *i*; *ln*, natural logarithm; *dbh*, tree diameter at breast height (cm) above 1.3 m from the ground; *BA*, stand basal area (m$^2$ ha$^{-1}$); *BAL*, basal area of trees larger than the target tree (m$^2$ ha$^{-1}$); $D_a$, arithmetic mean diameter at breast height (cm); $D_w$, basal area weighted mean diameter at breast height (cm); $CUT_{0-4}$, cutting dummy variable with code 1 if time since the last selection cutting is < 5 years, or code 0 if the time is ≥ 5 years; $CUT_{5-9}$, cutting dummy variable with code 1 if time since the last selection cutting is ≥ 5 years and < 10 years, or code 0 if the time is < 5 years or ≥ 10 years; std($u_i$), standard deviation of random stand effect; std($v_{ij}$), standard deviation of random plot effects; corr($e_{ijkt}$), autocorrelation of the successive five-year growth periods; std($e_{ijk}$), random error; P, the estimated power of the exponential variance function; *emp*, empirical correction factor calculated from the data as $\Sigma(CAL.ig5_{obs})/\Sigma(CAL.ig5_{pred})$; $CAL.ig5_{obs}$, the observed value of $\ln CAL.ig5_{ijk}$ in arithmetic scale; $CAL.ig5_{pred}$, the predicted value of $\ln CAL.ig5_{ijk}$ in arithmetic scale as a calibration coefficient based on the model developed in this study.

**Table 4**
Evaluation metrics comparison of five-year basal area increment ($i_{g5}$, cm$^2$ 5years$^{-1}$) prediction between the existing MOTTI ($MOTTI_{pred}$) and the calibrated MOTTI prediction ($CORM_{CCF}$) using the developed calibration model (ln*CAL.ig5*). BIAS is mean error, MAE is mean absolute error, RMSE is root mean squared error, and RMSRE is root mean squared relative error.

| Class | BIAS | MAE | RMSE | RMSRE |
|---|---|---|---|---|
| $MOTTI_{pred}$ $i_{g5}$ | −1.969 | 9.854 | 17.092 | 5.626 |
| $CORM_{CCF}$ $i_{g5}$ | 0.312 | 9.072 | 16.608 | 4.030 |

$CUT_{0-4}$, and $CUT_{5-9}$. However, according to the standard deviations of the random and residual effects, the simpler ln*CAL.ih5* model 2 was nearly as accurate as the ln*CAL.ih5* model 1 (Table 5).

The calibrated results ($CORM_{CCF}$ $i_{h5}$ 1 and *2*) of $i_{h5}$ using the calibration models (ln*CAL.ih5* models 1 and 2) in Table 5 were considerably more accurate, especially for smaller trees, than $MOTTI_{pred}$ (Table 6, Fig. 5). Among the model types, $CORM_{CCF}$ $i_{h5}$ 1 with tree height predictors showed a slightly higher accuracy with lower BIAS, RMSE, and MAE (Table 6), as similarly shown in lower *std($e_{ijk}$)* in Table 5. However, these differences between model types were minor.

In the $i_{h5}$ comparison, $CORM_{CCF}$ provided better accuracy in height growth than $MOTTI_{pred}$, especially for small tree dbh and/or height (Fig. 5, plots a1, a2, b1, and b2). On the other hand, the errors of $CORM_{CCF}$ increased for predictions of large trees, as $CORM_{CCF}$ performed mainly for the growth of far small trees in CCF than *OBS* or $MOTTI_{pred}$ (Fig. 5, plot a2). However, for very tall trees such as those with a height > 30 m, $CORM_{CCF}$ did not show similar underestimation for both $CORM_{CCF}$ *1* and *2* (Fig. 5, plots b1 and b2). Simultaneously, $CORM_{CCF}$ *1* and *2* resulted in decreased height growth accuracy in dense stands (*BA* > 30 m$^2$ ha$^{-1}$). It should be noted that the number of large trees was less sufficient than for small trees (Table 2). Nevertheless, the $i_{h5}$ predictions over stand basal area showed that $CORM_{CCF}$ *1* and *2* were more appropriate than $MOTTI_{pred}$ throughout the range of *BA*, and $CORM_{CCF}$ *1* was more accurate than $CORM_{CCF}$ *2* when *BA* was lower than 30 m$^2$ ha$^{-1}$ (Fig. 5, plots c1 and c2).

$CORM_{CCF}$ was more accurate than $MOTTI_{pred}$ over most of the whole range in *BAL*, except for large trees, whose *BAL* was lower than 5 m$^2$ ha$^{-1}$ (Fig. 5, plot d1 and d2). Finally, the comparison by cutting effect indicated a well-calibrated prediction with $CORM_{CCF}$ (Fig. 5, plot e1 and e2). Note that, depending on the $CORM_{CCF}$ model type, some variables such as *BA*, *BAL*, or $CUT_{0-4}$ were not applied, but the calibrated values appeared closer to *OBS* as desired. Overall, the models were examined against the most evident variables, and there was no critical bias difference between $CORM_{CCF}$ $i_{h5}$ types 1 and 2 (Fig. 5).

## 4. Discussion

### 4.1. Evaluation of the materials and modelling rationale

Given that MOTTI was developed based on even-aged stand data, we tested the prediction accuracy using uneven-aged stand data. Calibration models were developed at tree level to decrease the bias of $MOTTI_{pred}$ $i_{d5}$ and $i_{h5}$ in such situations. The longitudinal tree growth data were obtained from repeated measurements with a monitoring period of 20–25 years, and more tree size classes were retained in the cuttings of CCF than in those of RF. Therefore, these experiments generally represented CCF stands of Norway spruce well with a selection cutting system and were considered as suitable for analysing tree growth dynamics in CCF. However, the calibration data only included a modest number of plots from within a limited geographical range, which may restrict the applicability of our model to the whole country.

A bias in diameter and height growth was obvious in the existing MOTTI before updating the calibration models. The bias trend was observed especially showing an overprediction for small trees (Fig. 3). This suggested that the current $MOTTI_{pred}$ is thus unsuitable for a CCF simulation. Similar results were found in a Swedish study which evaluated the HEUREKA simulator (Fagerberg et al., 2022). In our study, the bias probably occurred because the existing MOTTI was developed based mainly on even-aged stands for RF where growth conditions were relatively similar for all trees. On the other hand, trees in uneven-aged stands can be affected differently by variations in vertical structure, stand density, and live crown length (Bianchi et al., 2020a). After updating MOTTI with the compiled calibration models, the calibrated predictions were noticeably less biased when applied to CCF stands (Tables 4 and 6 and Figs. 4 and 5). MOTTI updated by calibration models is therefore expected to provide a more logical and less biased output of uneven-aged stands for CCF. Furthermore, beyond the MOTTI update,

**Table 5**
Parameter estimates of calibration models for height growth ($\ln CAL.ih5_{ijk} = \ln\left(ih5_{ijk}+3\right) - \ln\left(\widehat{ih5}_{ijk}+3\right)$) of Norway spruce.

| | $\ln CAL.ih5_{ijk}$ model type 1 | | | | | $\ln CAL.ih5_{ijk}$ model type 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Estimate | S.E. | D.F. | t-value | p-value | Estimate | S.E. | D.F. | t-value | p-value |
| Fixed effects | | | | | | | | | | |
| Intercept | -0.5065 | 0.0219 | 11226 | -23.14 | <0.0001 | -0.3995 | 0.0190 | 11227 | -21.08 | <0.0001 |
| *dbh* | | | | | | 0.0296 | 0.0007 | 11227 | 45.58 | <0.0001 |
| $dbh^2$ | | | | | | -0.00055 | 0.00002 | 11227 | -25.63 | <0.0001 |
| *h* | -0.0294 | 0.0015 | 11226 | -20.28 | <0.0001 | | | | | |
| $\sqrt{h}$ | 0.2498 | 0.0086 | 11226 | 29.21 | <0.0001 | | | | | |
| *BA* | 0.0014 | 0.0005 | 11226 | 2.99 | 0.0028 | | | | | |
| *BAL* | | | | | | 0.0073 | 0.0003 | 11227 | 21.18 | <0.0001 |
| $CUT_{0-4}$ | -0.0669 | 0.0033 | 11226 | -19.99 | <0.0001 | | | | | |
| Random effects | | | | | | | | | | |
| std($u_i$) | 0.036 | | | | | 0.036 | | | | |
| std($v_{ij}$) | 0.020 | | | | | 0.026 | | | | |
| corr($e_{ijkt}$) | 0.094 | | | | | 0.095 | | | | |
| std($e_{ijk}$) | 0.141 | | | | | 0.142 | | | | |
| *emp* | 1.029 | | | | | 1.030 | | | | |

Note: $\ln CAL.ih5_{ijk}$, the calibrated effect of tree height growth (m $5\text{years}^{-1}$) for tree *k* in plot *j* in stand *i*; $ih5_{ijk}$, the observed tree height growth (m $5\text{years}^{-1}$) for tree *k* in plot *j* in stand *i*; $\widehat{ih5}_{ijk}$, the predicted tree height growth (m $5\text{years}^{-1}$) based on the existing MOTTI for tree *k* in plot *j* in stand *i*; *ln*, natural logarithm; *dbh*, tree diameter at breast height (cm) above 1.3 m from the ground; *h*, tree height (m); *BA*, stand basal area ($m^2\ ha^{-1}$); *BAL*, basal area of trees larger than the target tree ($m^2\ ha^{-1}$); $CUT_{0-4}$, cutting dummy variable with code 1 if time since the last selection cutting is < 5 years, or code 0 if the time is ≥ 5 years; std($u_i$), standard deviation of random stand effect; std($v_{ij}$), standard deviation of random plot effects; corr($e_{ijkt}$), autocorrelation of the successive 5-year growth periods; std($e_{ijk}$), random error; *emp*, empirical correction factor calculated from the data as $\Sigma(CAL.ig5_{obs})/\Sigma(CAL.ig5_{pred})$; $CAL.ih5_{obs}$, the observed value of $\ln CAL.ih5_{ijk}$ in arithmetic scale; $CAL.ih5_{pred}$, the predicted value of $\ln CAL.ih5_{ijk}$ in arithmetic scale as a calibration coefficient based on the model developed in this study.

**Table 6**
Evaluation metrics comparison of 5-year height increment ($i_{h5}$, m $5\text{years}^{-1}$) prediction between the existing MOTTI ($MOTTI_{pred}$) and the calibrated MOTTI prediction ($CORM_{CCF}$) using the developed calibration models ($\ln CAL.ih5$). BIAS is mean error, MAE is mean absolute error, RMSE is root mean squared error, and RMSRE is root mean squared relative error.

| Class | BIAS | MAE | RMSE | RMSRE |
|---|---|---|---|---|
| $MOTTI_{pred}$ $i_{h5}$ | −0.252 | 0.731 | 0.869 | 8.307 |
| $CORM_{CCF}$ $i_{h5}$ *1* | 0.001 | 0.542 | 0.713 | 4.192 |
| $CORM_{CCF}$ $i_{h5}$ *2* | 0.004 | 0.546 | 0.722 | 4.070 |

the selected variables can be considered possible indicators of bias for CCF in any of the other similar growth simulators equipped only with RF models.

### 4.2. Significance and interpretation of the selected predictors

Using age predictors in the models for CCF was not valid, and *dbh* was applied instead in the calibration model of $i_{g5}$ (Table 3). In the calibration model of $i_{h5}$, *dbh* and/or *h* were used, primarily depending on $\ln CAL.ih5$ model types (Table 5). The use of such highly significant predictors indicated that the individual tree growth in uneven-aged stands differed from that in even-aged stands, as simulated by the current MOTTI software. *BA* proved a significant predictor of stand-level competition in the $\ln CAL.ih5$. As predictors of tree-level competition, asymmetrical variables are often used, such as *BAL*, $dbh/H_{dom}$, and $h/H_{tot}$ (Wykoff et al., 1982; Repola et al., 2018; Bianchi et al., 2020a). Generally, between-tree competition is known to influence tree dbh more than tree height (Repola et al., 2018). In the present study, a bias according to the between-tree competition was found in both $i_{d5}$ and $i_{h5}$ predictions with MOTTI, and it was therefore used as a predictor in the calibration models (Tables 3 and 5). The most significant predictor of between-tree competition was *BAL* for both $\ln CAL.ig5$ and $\ln CAL.ih5$ of Norway spruce. The predictor was considered reasonable because the variable, as a tree-level asymmetric variable, represented the poor status of a large number of suppressed trees in uneven-aged stands. The suggested variable was statistically significant in each of the calibration models (Tables 3 and 5). In particular, this implies that *BAL* suitably reflects the individual tree growth and shade tolerance of Norway spruce in uneven-aged stands.

Concerning between-tree competition at tree level, comparisons between spatial and non-spatial competition variables have sometimes been conducted to find a more accurate model (Martin and Ek, 1984; Biging and Dobbertin, 1992). In our study, the selected predictor was a non-spatial variable such as *BAL* (Tables 3 and 5). Although spatial, or distant-dependent, predictors were not examined in our study, our calibration models presented a better, unbiased prediction and were suitably validated with $CORM_{CCF}$ (Figs. 4 and 5). This result was supported by a previous study in which non-spatial models for uneven-aged stands of Norway spruce were sufficient, with a similar level of accuracy for the spatial models (Bianchi et al., 2020b). Moreover, Kuehne et al. (2019) found no clear indication of better performance by including distant-dependent variables, suggesting that spatial competition metrics should not be overrated for individual tree growth prediction (Kuehne et al., 2019). We therefore inferred that in uneven-aged stands, our distance-independent between-tree competition predictor such as *BAL* sufficiently reflected individual tree growth characteristics. Moreover, these are more desirable variables than spatial variables from a practical perspective for cost-effective data collection.

In our study, the height-based $\ln CAL.ih5$ model (type 1) for height growth performed better than the dbh-based $\ln CAL.ih5$ model (type 2), with a similar number of explanatory variables (Table 5). This finding may be related to the light availability in irregular multi-layered stands (Bianchi et al., 2020b). Furthermore, the height-based model is considered practical and more accurate, as remote sensing techniques such as unmanned aerial vehicles (UAV) and terrestrial LiDAR have progressed in the forest inventory field. It has been proved that such equipment is applicable, and the collected inputs can be used for growth and yield models (Bianchi et al., 2020b).

The selection cutting effect, described by a dummy variable, was significant in the calibration models of $i_{g5}$ and $i_{h5}$ (type 1) (Tables 3 and 5). Hynynen et al. (2019) inferred an analogous selection cutting effect, where stand basal area growth reacted slowly after tree removal. This result was consistent with another previous study of Norway spruce, which reported a faster response of the tree and stand basal area to thinning in even-aged stands (Jaakkola et al., 2005). The results from the previous studies and our study support the inclusion of the cutting effect as reasonable and appropriate because they demonstrated a disjunction of cutting effects between even-aged and uneven-aged stands. It can therefore be used as an explanatory variable in calibration models.

Fagerberg et al. (2022) found a consistent result for a late culmination in the growth response. They evaluated an individual growth model of HEUREKA software for Norway spruce in uneven-sized stands in Sweden. Similarly, the growth response was apparently found three years after release from competition and then peaked in 13 years for eastern white pine stands in Canada (Bevilacqua et al., 2005). Bianchi et al. (2020b) found that selection cutting in their analysis did not promote individual tree growth for more than 15 years in Finnish forest conditions. In line with the inferences from the previous studies, the interval and period of years in the applied selection cutting dummy variables, $CUT_{0-4}$ and/or $CUT_{5-9}$, were considered adequate for uneven-aged stands of Norway spruce. The different cutting effect on tree growth between even- and uneven-aged stands was therefore presented as a characteristic of CCF compared to RF (cf. Hynynen et al., 2019).

As a stand-level asymmetric variable, $D_a/D_w$ was useful for addressing the irregularity in tree size in a multi-storied stand. The predictor was highly significant for explaining the various tree sizes of Norway spruce and a decreasing reverse J-shaped and right-skewed diameter distribution in CCF (Table 3). As $D_a/D_w$ is close to one if the tree size is uniform in a forest, a $D_a/D_w$ of less than 0.7 implies a widely distributed stand in tree size, and the smallest values of less than 0.5 can be evaluated as a distinct indicator of an uneven-aged stand (Fig. 4d). The difference originates in the forest management system, by which single-tree selection cutting leads to a smaller ratio of $D_a/D_w$ for CCF (Hynynen et al., 2019). Based on the $D_a/D_w$ value as an uneven-aged stand indicator, our spruce material represented an uneven-aged stand structure with low values of $D_a/D_w$ (0.24–0.68) (Table 1). $D_a/D_w$ was a significant variable for spruce calibration models, indicating lower basal area growth with a decreasing $D_a/D_w$ value. In this study, MOTTI showed an evident bias for $D_a/D_w$, and ln*CAL.ig5* with $D_a/D_w$ significantly improved predictions in $CORM_{CCF}\ i_{g5}$ for Norway spruce (Tables 3 and 4).

Site productivity, soil, and topographical factors such as temperature sum and altitude were not included in this study's calibration models because there was an insufficient number of experimental sites to consider these variables, and/or because growth characteristics between even- and uneven-stands did not differ because of these factors (Bianchi et al., 2020a, 2020b). Note that this study was conducted entirely based on mineral soils, and fertilisation was not examined, as the sample plots were not designed for fertiliser treatments.

### 4.3. Applicability of the final models in practice

The compiled calibration models will be equipped in the MOTTI simulator to offer a more reliable prediction of tree diameter and height growth in Norway spruce stands in CCF. To apply our calibration models in a simulation with a practical purpose, some limitations should be noted regarding our data, variables, and model characteristics. First, the geographical range of the data was limited to southern Finland (Fig. 1), which may limit the calibration models' applicability to other regions. Second, the stand structural characteristics falling within the range of variables listed in Table 1 can be used as a reference to determine suitable target stands for the calibration models. Here, for example, it can be observed that $D_a$ and $H_a$ were distinctly smaller than $D_w$ and $H_w$ respectively (Table 1). Moreover, the ratio $D_a/D_w$ should be carefully checked, as it was revealed as a significant indicator of CCF stands (Table 3). These statistics may suggest applicable stand ranges for the models.

Regarding tree-level characteristics, most of the trees were distributed in relatively small dbh and heights, as shown by the mean, minimum, and maximum values in Table 2. This would be a representative characteristic in CCF stands, and it meant tree dbh and height distribution were skewed to the right (Appendix A). Accordingly, there were fewer trees in large dbh and height classes than in small dbh and height classes. Some caution therefore needs to be exercised with large trees, e.g. a tree close to the maximum value of dbh and/or height in the sample data, because $CORM_{CCF}$ may be less accurate than expected from our model validity.

## 5. Conclusion

To examine the MOTTI accuracy in CCF, the predicted individual tree growth of Norway spruce stands managed with a selection system was compared with the observed growth. The existing MOTTI predictions were found to be inaccurate for tree diameter and height growth in uneven-aged stands. The bias was more evident for both tree dbh and height especially for small trees. Calibration models were developed to update the existing MOTTI and provide better predictions. The biases of basal area and height growth were modelled as functions of tree size, stand density, the uneven-aged stand indicator, the competition-related variable, and cutting dummy variables. The calibration models of basal area and height growth presented better accuracy than the existing MOTTI for Norway spruce.

It was noticeable that the uneven-aged stand indicator, $D_a/D_w$, was significant for the basal area growth calibration model. Moreover, the asymmetrical competition, *BAL*, was significant in the basal area and height growth calibration models. This indicated that distant-independent competition variables significantly improved the model accuracy. However, it should be noted for practical use that the data were collected from several different Finnish regions. It is also recommended to consider the modelling data coverage of tree and stand characteristics, especially with $D_a/D_w$. Small trees could be calibrated more accurately, as they were more represented in the data. Overall, this study can be considered useful for calibrating the existing RF models to CCF and explaining the tree diameter and height growth of uneven-aged Norway spruce stands in CCF.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## CRediT authorship contribution statement

**Daesung Lee:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Jaakko Repola:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Simone Bianchi:** Writing – review & editing, Writing – original draft, Data curation. **Jouni Siipilehto:** Writing – review & editing, Validation. **Mika Lehtonen:** Software. **Hannu Salminen:** Software, Funding acquisition. **Jari Hynynen:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

## Declaration of Competing Interest

The authors declare that they have no conflict of interest.

## Data Availability

Data will be made available on request.


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## Appendix A. Illustration of dbh and height distributions

In addition to the summary statistics provided in Tables 1 and 2, the dbh and height distributions were illustrated here as supplementary figures to provide additional information about stand structure. The distributions of Norway spruce stands appeared similarly by year, so before and after selection cutting in 2011 was chosen to demonstrate the dbh and height distributions (Figs A1 and A3). Additionally, the comparisons between 2011 and 2016 displayed the transition of distributions over time (Figs A2 and A4). The figures showed the inversed J-shape curves in both dbh and height distribution, which is considered a representative stand type of uneven-aged stands (Figs A1–A4). Overall, all the supplementary figures supported the illustration of the stand type of continuous cover forestry (CCF) rather than rotation forestry (RF) for the data on Norway spruce.

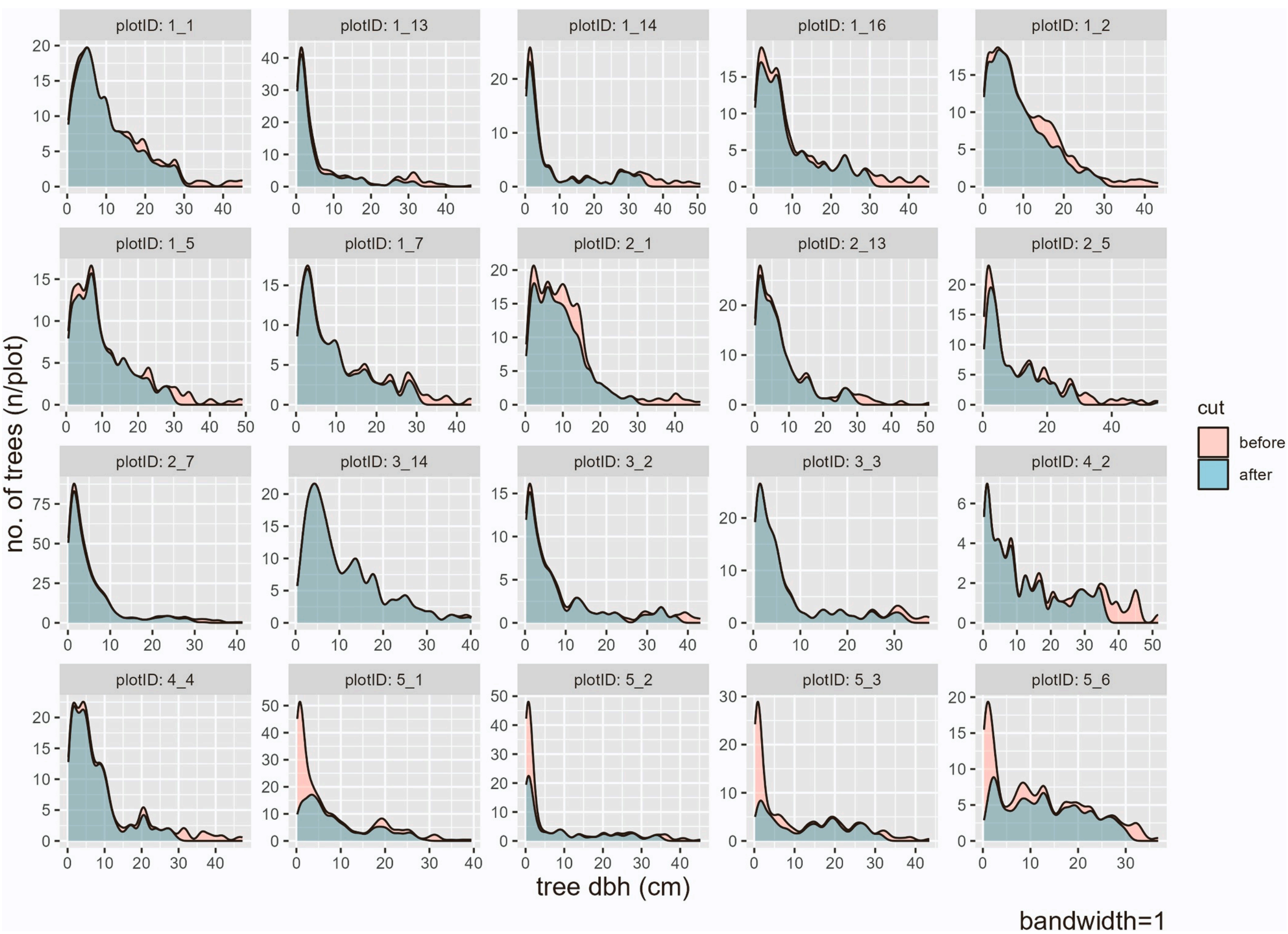


**Fig. A1.** Dbh distributions of uneven-aged Norway spruce stands in continuous cover forestry in 2011 before and after selection cutting.

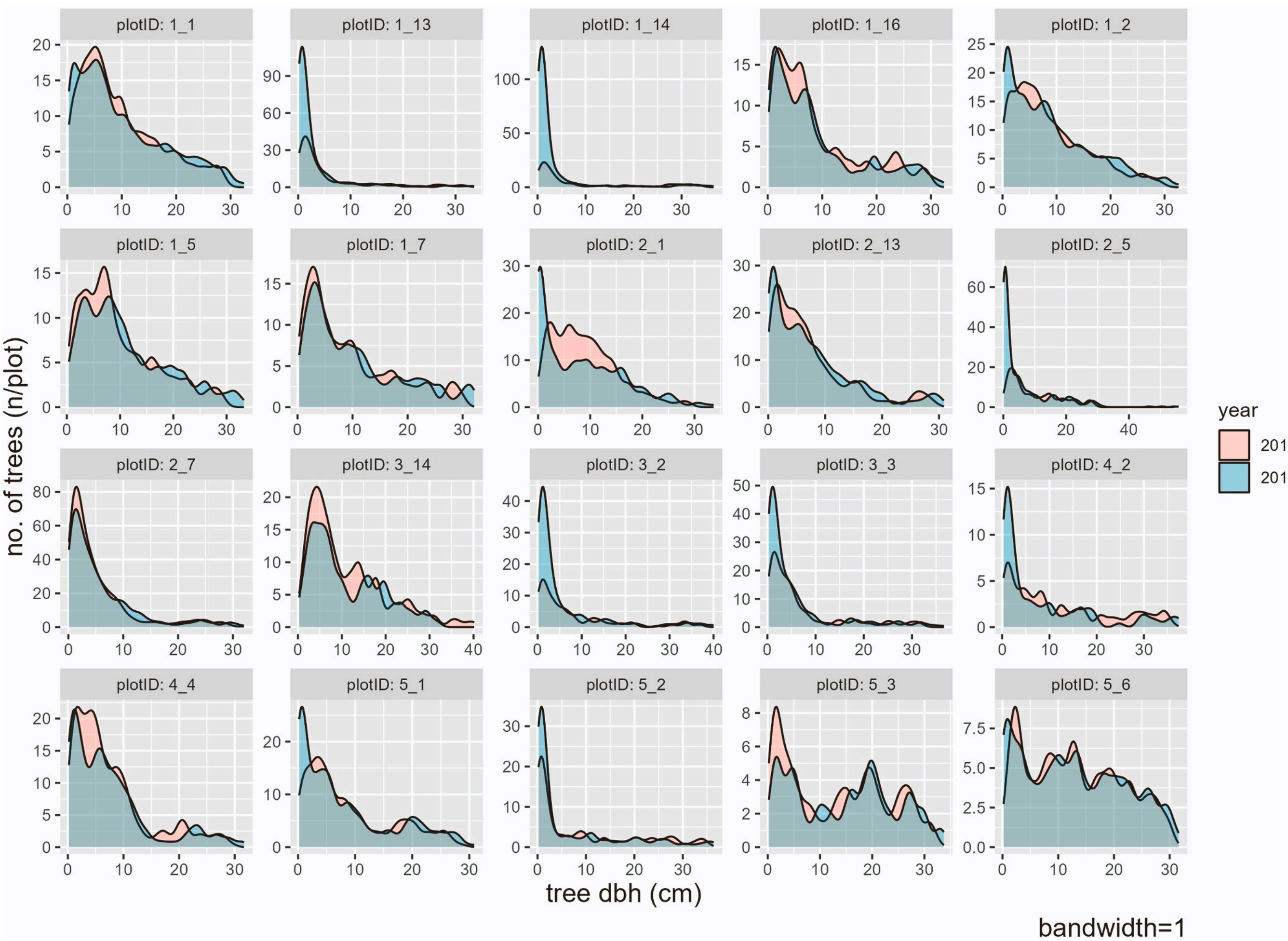


**Fig. A2.** Dbh distributions of uneven-aged Norway spruce stands in continuous cover forestry in 2011 and 2016.

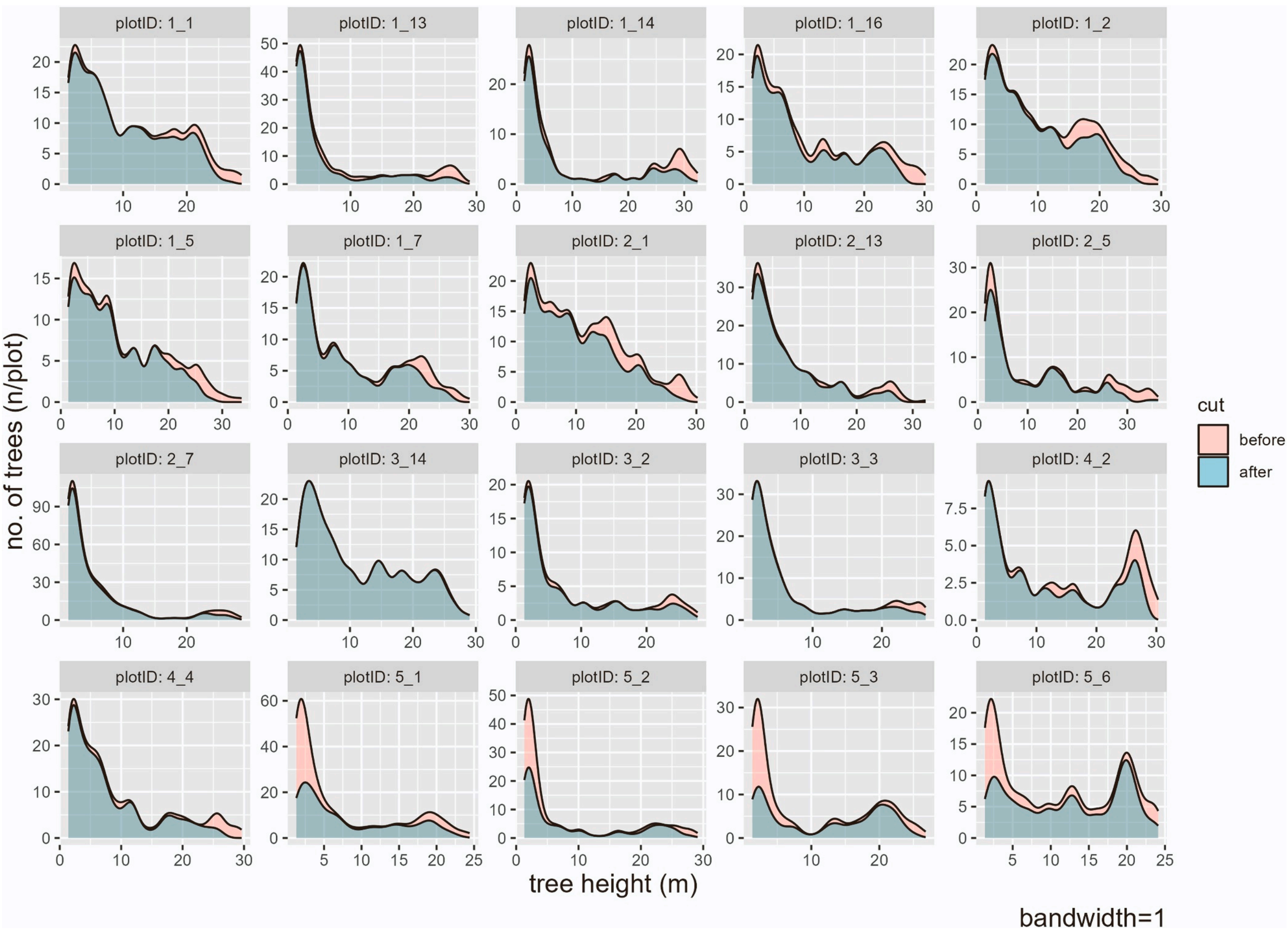


**Fig. A3.** Height distributions of uneven-aged Norway spruce stands in continuous cover forestry in 2011 before and after selection cutting.

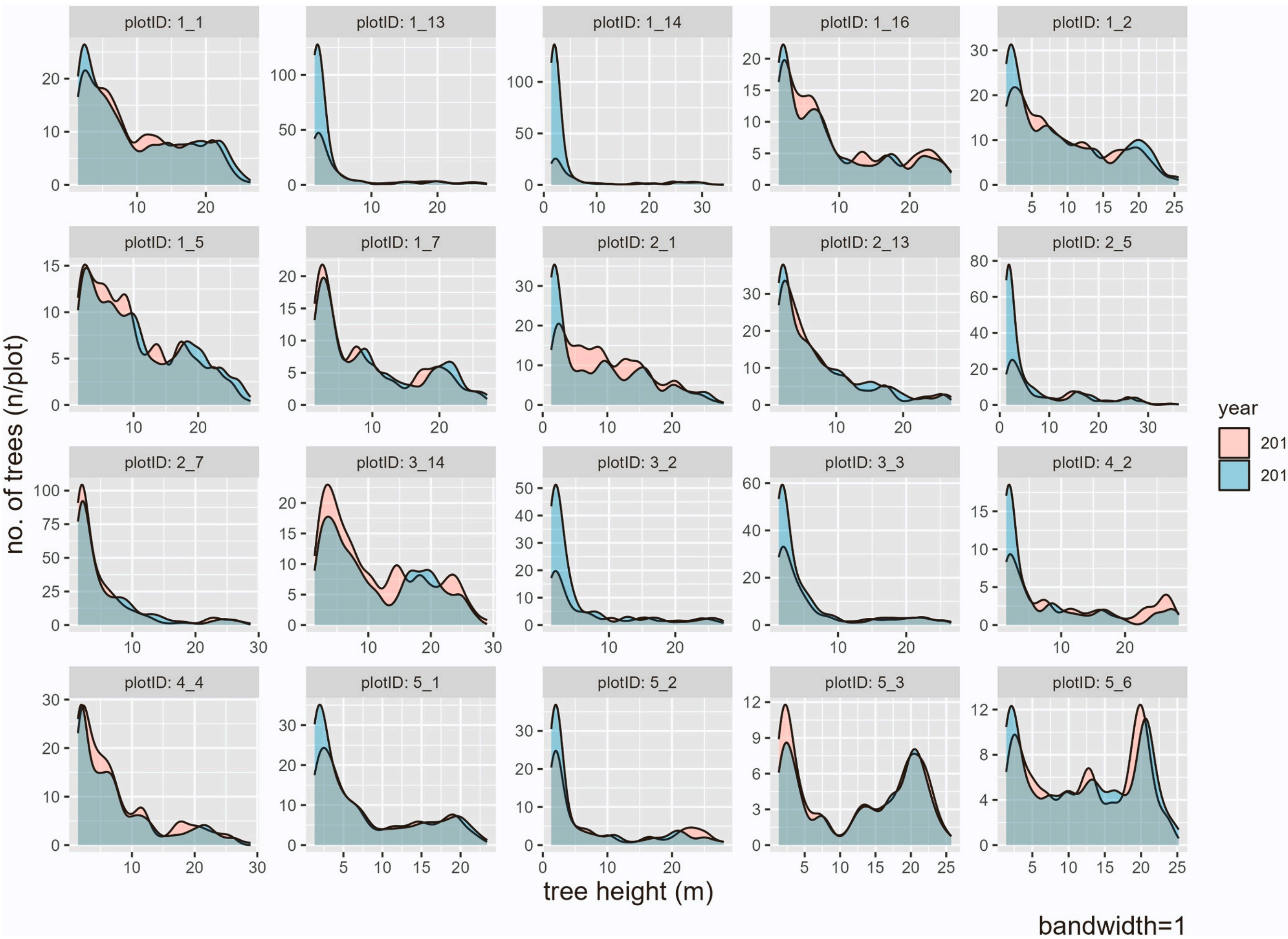


**Fig. A4.** Height distributions of uneven-aged Norway spruce stands in continuous cover forestry in 2011 and 2016.

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