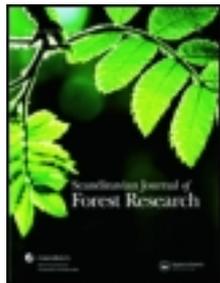


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Clara Antón-Fernández^a & Rasmus Astrup^a

^a National forest inventory, Norwegian Forest and Landscape Institute, Ås, Norway

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ORIGINAL ARTICLE

Empirical harvest models and their use in regional business-as-usual scenarios of timber supply and carbon stock development

CLARA ANTÓN-FERNÁNDEZ & RASMUS ASTRUP

National forest inventory, Norwegian Forest and Landscape Institute, Ås, Norway

Abstract

Harvest activity directly impacts timber supply, forest conditions, and carbon stock. Forecasts of the harvest activity have traditionally relied on the assumption that harvest is carried out according to forest management guidelines or to maximize forest value. However, these rules are, in practice, seldom applied systematically, which may result in large discrepancies between predicted and actual harvest in short-term forecasts. We present empirical harvest models that predict final felling and thinning based on forest attributes such as site index, stand age, volume, slope, and distance to road. The logistic regression models were developed and fit to Norwegian national forest inventory data and predict harvest with high discriminating power. The models were consistent with expected landowners behavior, that is, areas with high timber value and low harvest cost were more likely to be harvested. We illustrate how the harvest models can be used, in combination with a growth model, to develop a national business-as-usual scenario for forest carbon. The business-as-usual scenario shows a slight increase in national harvest levels and a decrease in carbon sequestration in living trees over the next decade.

Keywords: *Biomass, forecast, Norway, prediction, short-term, thinning.*

Introduction

The harvesting activity within a region has direct effects on timber production and economic activity within the forestry sector (e.g. Adamowicz et al., 2003). In boreal forests, harvesting and wildfires are the most common large scale disturbances (Andison & Kimmins, 1999; Cogbill, 1985) and impact most forest-related values such as biodiversity and wildlife (e.g. Bjørneraas et al., 2011), visual quality and recreational value (e.g. Pâquet & Bélanger, 1997), forest structure and species composition (e.g. Greene et al., 1999; Harvey, 2002), and the carbon sequestered in forest (e.g. Kellomäki et al., 2008; Nunery & Keeton, 2010; Scheller et al., 2011; Seely et al., 2002). Consequently, the ability to predict future harvest activity is central to predicting future forest conditions and forest attributes.

Forest models and scenario analysis are an integrated part of sustainable management of boreal forests (e.g. Messier et al., 2003). Given the importance of harvest activity on forest conditions and economic activity it is surprising that, to the authors knowledge, only two studies (Holm & Lundström,

2000; Sterba et al., 2000) have focused on data-driven models to predict future harvesting activity. In the case of Sterba et al. (2000), a set of equations were developed to predict timber harvest for Austria using forest stand condition variables such as basal area and mean height as predictor variables. Holm and Lundström (2000) used data from the Swedish national forest inventory to fit a set of equations to predict harvest using variables characterizing the stand such as age, species composition, volume, or previous treatments.

The majority of studies aimed at production of national or regional scenarios of forest development rely on the assumption that harvest activities are carried out according to a set of forest management guidelines (e.g. Kellomäki et al., 2008; Talkkari, 1998), a probability of harvest according to stand age (e.g. Nord-Larsen & Talbot, 2004) or optimize management regimes to maximize forest value (e.g. Hoen & Solberg, 1994; Raymer et al., 2009). Given the current focus on forest carbon sequestration, many studies focus on carbon forecasts at a regional or national level (e.g. Backéus et al., 2006). A common assumption in such studies is that forest

owners follow forest management guidelines (e.g. Alam et al., 2010; Ericsson, 2003; Kellomäki et al., 2008) even though it is acknowledged that in reality forest management practices deviate from the guidelines. For example, Kellomäki et al. (2008) and Alam et al. (2010) assumed that final felling was executed whenever the mean tree diameter on a plot exceeded a threshold indicating maturity, but randomly excluded 5% of the stands from harvest activity in each simulation cycle because the management rules are seldom applied systematically. Due to similar concerns, Ericsson (2003) assigned 20% of the harvesting volume randomly “to imitate the variations that exist in forest management.” For short-term predictions, deviations between management guidelines and actual management may cause large discrepancies between assumed harvest and observed harvest (Eid, 2000, 2004; Karjalainen et al., 1999). For example, forest scenarios in Norway commonly assume that all final fellings occur only in mature stands, and also that stand management includes one or two thinnings (Astrup et al., 2010; Eid, 2004). However, in practice, a large proportion of Norwegian forests are never thinned and a sizable proportion of the final fellings are carried out before maturity has been reached (Eid, 2004; Granhus et al., 2010).

In boreal forest, the time horizon for forest development is in the order of a century, while the planning for forestry-based industry development and carbon emissions often is one or two decades. For example, in the Kyoto protocol (UNFCCC, 2008) and in the current negotiations for a new climate agreement (UNFCCC, 2010), the focus is a decade rather than a century. To assess changes in carbon emissions, the reported emissions have to be compared to a reference level. The reference level can be a given year, such as 1990 in the Kyoto protocol (UNFCCC, 2008), or a forecasted business-as-usual development such as is suggested in both the REDD+ context (e.g. Angelsen, 2008; Santilli et al., 2005) and for Annex I countries in the current negotiations for a new climate agreement (UNFCCC, 2010). In this short-term context, the predictions of harvest levels are a central part of producing a business-as-usual scenario for forest carbon sequestration.

In this study, we develop data-driven models to forecast short-term harvest levels (<20 years) and illustrate how such harvest models can be used to predict business-as-usual forest development. The study has two main objectives: (1) To develop empirical models that predict probability of harvest based on forest attributes and (2) To illustrate how the probability of harvest models can be applied

in combination with a growth model to create a short-term business-as-usual scenario for forest carbon stock change at national scale.

Materials and methods

Data

The Norwegian forest is commonly divided in four regions with relatively similar topography, climate, forest structure, infrastructures, and forest management history within each region (Figure 1). In this study, we used data from all four regions but we accounted for differences between regions by including a dummy variable for each region. The data used for this study were from the 3×3 km grid of permanent plots in the Norwegian national forest inventory (NNFI) (see Landsskogtakseringen, 2008; Tomter et al., 2010). In the NNFI, one fifth of the permanent plots is measured every year, resulting in a complete remeasurement over a 5-year period. In the NNFI when a plot is located in a stand border and at least 15% of the plot lies in a stand that differs considerably from the rest of the plot in age, production capacity, or standing volume, the plot is split in two, and registrations are made separately for the two subplots. Data from the last three complete measurements of the NNFI were used in this study, that is, 1995–1999, 2000–2004, and 2005–2009. Hence, for most of the plots, two remeasurements were available. Due to incomplete time-series, data from Finnmark county and the mountain birch dominated forest were not included in this study (Figure 1).

At the tree level, diameter at breast height (dbh) is measured for all trees with dbh > 5 cm. On plots with 10 trees or less, all tree heights are measured, while for plots with more than 10 trees a relascope-selected subsample (sampling proportionally to basal area) with a target sample size of 10 trees per plot is measured. Current site index (SI) is estimated for the dominant species at each plot. SI is defined as the average height of the 100 largest trees per ha at age 40. At each remeasurement, treatments carried out in the past 5-year period are registered. Possible treatments include final fellings, thinnings, selective cuttings, regeneration treatments, early stand tending treatments, drainage, and pruning.

Total volume per plot was calculated as the sum of the individual volumes of all trees with dbh > 5 cm. Individual tree volumes were calculated with species-specific individual tree volume equations (Braastad, 1966; Brantseg, 1967; Vestjordet, 1967), with tree height and dbh as independent variables.

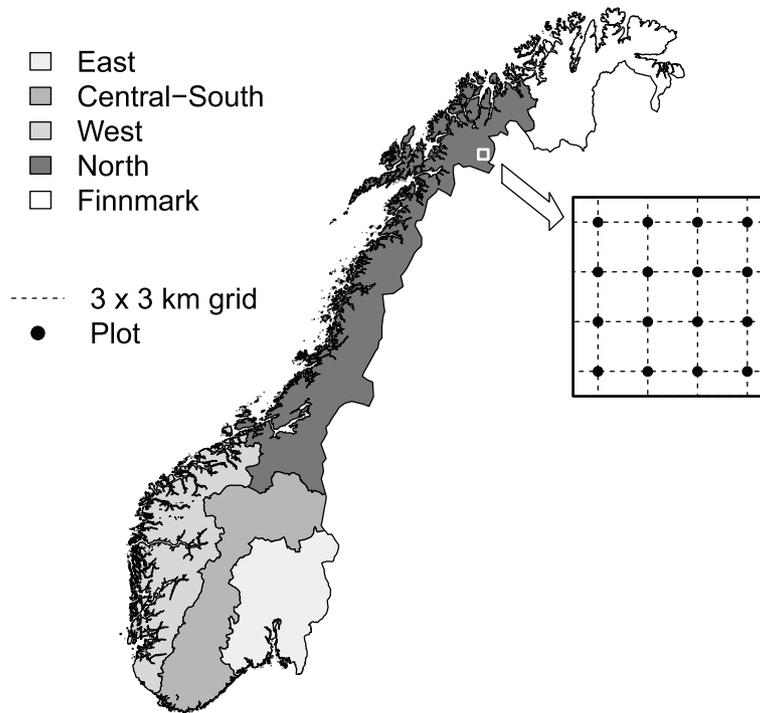


Figure 1. The four Norwegian forest regions.

Total biomass per plot was estimated as the sum of the individual biomass components (stump, roots, stem, bark, dead and living branches, and foliage) of all individual trees with $\text{dbh} > 5$ cm. Individual biomass was estimated using species-specific allometric equations (Marklund, 1988), with tree dbh and tree height as independent variables. Biomass was converted to carbon using the default factor 0.5 (Intergovernmental Panel on Climate Change, 2003), that is, $\text{carbon} = 0.5 \times \text{biomass}$.

Final felling and thinning models

For fitting the harvest and thinning models, data from the 1995–1999, 2000–2004, and 2005–2009 measurements were used but restricted to plots in *productive forest* and with land use classified as *forestry* in two consecutive measurements (Landsskogtakseringen, 2008). In this study, thinning is defined as commercial thinning, and final felling is defined as volunteer final felling. We use the term *harvest* to refer to both final fellings and thinnings. Plots in protected areas were excluded from the analysis due to their harvest and silvicultural treatments restrictions. Plots under regeneration, for example plots that have been recently harvested, were not included in the model fitting data-set, as commercial harvest is not possible. The data-set used to fit the thinning model also excluded plots that were final-felled in the 5-year period, since

final felling precludes the possibility of commercial thinning. A total of 8305 (277 final felled and 119 thinned plots) plots were available for the 1995–1999 to 2000–2004 remeasurement, and a total of 8087 (277 final felled and 114 thinned plots) for the 2000–2004 to 2005–2009 period. Summary statistics for the final felling fitting data-set are given in Table I.

We used logistic regression to model the probability of a final felling being carried out in a plot in the next five years (P_{FF}), and to model the probability of a plot being thinned in the next 5 years (P_{T}). A logistic regression model is commonly expressed as

$$P_i = \frac{1}{1 + e^{-\beta \mathbf{X}_i}} \quad (1)$$

where P_i is the probability of the i th plot to be thinned or felled in the next 5 years, $\beta \mathbf{X}$ is a linear combination of parameters β and explanatory variables \mathbf{X} . The candidate explanatory variables considered included: SC: a set of dummy variables

Table I. Summary statistics and description of data.

Variable	Mean	Range	SD
Site index (m)	11.28	6–26	4.00
Stand age (years)	72.32	2–349	42.97
Volume (m^3/ha)	94.44	0.08–1057.72	89.24
Distance to road (100 m)	6.92	0–99	8.90

Table II. Stand composition classification.

Type of stand	Code	Definition
Spruce dominated	1	Sp > 70%
Spruce dominated coniferous mixed forest	2	Sp 50–70%, De < 10%
Spruce dominated mixed forest	3	Sp 35–70%, De > 10%, Sp is the most frequent
Pine dominated	4	Pi > 70%
Pine dominated coniferous mixed forest	5	Pi 50–70%, De < 10%
Pine dominated mixed forest	6	Pi 35–70%, De > 10%, Pi is the most frequent
Birch forest	7	Birch > 70%
Other deciduous	8	De 70%, birch < 70%
Deciduous dominated mixed forest	9	De 35–70%, De is the most frequent

Sp = Spruce; De = Deciduous; Pi = Pine.

to distinguish among the different stand composition types defined in the NNFI (Table II); V : volume inside bark in m^3/ha ; D : distance to the closest road in 100 m; S : slope in %; Y_5 : time until development class 5 is reached, in years; SI : site index at a base age of 40 years; and R : a set of dummy variables to distinguish regions (Figure 1).

Development classes are defined according to the stand species composition, site quality (SI at base age 40), and age (Landsskogtakseringen, 2008). The NNFI defines five development classes that vary from class 1 (regenerating stands) to class 5 (mature forest). Y_5 is defined as the difference between stand age and the minimum age of development class 5 (for the given SI and species composition). Y_5 is, hence, negative when the stand has not reached yet the corresponding minimum age for class development 5, and positive when the stand is older than the corresponding minimum age for class development 5.

Each observation was weighted according to the proportion of the plot area represented by the observation. Thus, whole plots have a weight of 1, and subplots have a weight ranging from 0.2 to 0.8, corresponding to the proportion of the plot area represented by the observation.

The model fit was evaluated using a modified version of the Hosmer-Lemeshow test (HL_m) for differentially sample weighting logistic regression (Graubard et al., 1997). The Hosmer-Lemeshow test (Hosmer & Lemeshow, 1980) is based on grouping predicted probabilities into g groups of roughly similar size and performing a Pearson χ^2 test ($g-2$ d.f.) for the mean predicted probability against the observed fraction of events. In the modified version of the Hosmer-Lemeshow test the g groups are defined taking into account the weight of each observation (w_i), that is, the size of each group j (n_j) is such that $\sum_{i=1}^{n_j} w_i / \sum_{j=1}^g \sum_{i=1}^{n_j} w_{ji} = \frac{1}{g}$. Since the HL_m test does not have good power for detecting particular types of lack of fit (Hosmer et al., 1997), we also investigated lack of fit by plotting residuals

against the explanatory variables and by testing specific alternatives to the model (e.g. interaction terms). Model alternatives were compared using the likelihood ratio test, the Akaike information criterion (AIC; Akaike, 1974), and the deviance statistic.

We evaluated the predictive performance of the model in terms of discrimination and calibration (Harrell et al., 1984). Discrimination addresses how well the model can distinguish between harvested plots and the rest of the plots. Calibration measures the extent to which the predictive probabilities agree with the observed frequencies, calibration is a population-level metric of bias. The model's predictive discrimination was evaluated using the probability of concordance, c or c -index (Harrell et al., 1982, 1984). The c -index is identical to the area under a receiver operating characteristic curve (AUC) (Hanley & McNeil, 1982). The c -index takes values from 0.5 to 1, where a value of 0.5 indicates random predictions, and a value of 1 indicates perfect separation. A c -index larger than 0.8 indicates a model with excellent discrimination (Hosmer & Lemeshow, 2000, p. 162). We used the calibration slope (Cox, 1958) to evaluate the miscalibration. Ideally, for the model being evaluated the calibration equation would have an intercept of zero and a slope of one (Miller et al., 1991). Lack of calibration can be tested with a χ^2 -test with two degrees of freedom (H_0 : intercept = 0, slope = 1).

We assessed the linearity in the logit using linear tail-restricted cubic splines (rcs) (Harrell, 2001, p. 20). Plots of the residuals of the fitted models against the variables of interest, and plots of the estimated restricted cubic spline functions relating a single predictor to the response were used to suggest transformations of the variable that would result in linearity in the logit.

Since external validation data were not available, we performed an internal validation of the model using bootstrap resampling with 500 replications, which provide stable estimates with low bias (Steyerberg, 2001).

During model fitting it became obvious that keeping all nine stand types was not necessary and that similarly good models in terms of deviance, but more parsimonious could be achieved by grouping the stand composition types in three categories: spruce dominated forest (SC_S), pine dominated forest (SC_P), and deciduous forest (SC_D). Spruce dominated forests comprise spruce dominated and spruce dominated coniferous mixed forest; pine dominated forests comprise pine dominated and pine dominated coniferous mixed forest; and deciduous dominated forests comprise the rest of the categories defined in Table II.

For the final felling model, plots of the estimated rcs functions relating years to development class 5 (Y_5) to the logit of P_{FF} (Figure 2) indicated a nonlinear relationship between Y_5 and the logit of the response variable. Figure 2 suggests that below -50 Y_5 does not have an effect on P_{FF} , and that above -50 the effect of Y_5 on the logit of P_{FF} increases rapidly until about age 50 and starts to level off afterward. Thus, we created a modification of Y_5 where all values below -50 were collapsed into -50 . We called this modified variable Y'_5 . Several transformations were considered to make Y'_5 linear in the logit, and $(Y'_5 + 51)^{0.5}$ gave the best results in terms of deviance and AIC. The estimated rcs functions relating the slope with the logit of P_{FF} suggested that the effect of the slope on the probability of harvest between 0% and 30% was negligible. Hence, slopes between 0% and 30% were collapsed into 30%. This modification of the slope variable resulted in an improved model in terms of deviance and AIC.

For the thinning model, plots of the estimated rcs functions relating the main variables to the logit of P_T (Figure 2) indicated a nonlinear relationship between the logit of P_T and volume (V), SI, and Y_5 . For SI Figure 2 shows a moderate positive slope in the lower range of the variable that levels off after SI 15 m. For volume (V) Figure 2 shows a very sharp increase between 0–200 m^3/ha and a flat slope afterwards. Y_5 had a highly nonlinear relationship with the logit of P_T with a sharp initial increase, a pick around $Y_5 = -40$, and a sharp decrease until $Y_5 = 0$, where it reaches a relatively flat slope. This shape suggested to collapse all values of Y_5 above -1 to -1 (Y'_5) and then model the resulting inverted-v-shape curve. Several transformations were tested for each of the variables showing a nonlinear relationship with the logit of P_T . The transformations that resulted in the best fit in terms of deviance and AIC were the inverse for SI, the log for volume, and a combination of Y'_5 and $(Y'_5)^2$ for Y_5 .

Development of a national business-as-usual scenario for forest carbon stock change

In this section we describe how the probability of harvest models can be used to create a short-term business-as-usual scenario for forest carbon stock change development at the national scale. The business-as-usual scenario was developed for all Norwegian forest within the forest management category under the current Norwegian Kyoto reporting (Climate and Pollution Agency, 2010) and has as a goal (1) to be in accordance with the stock change method employed in the current Norwegian Kyoto

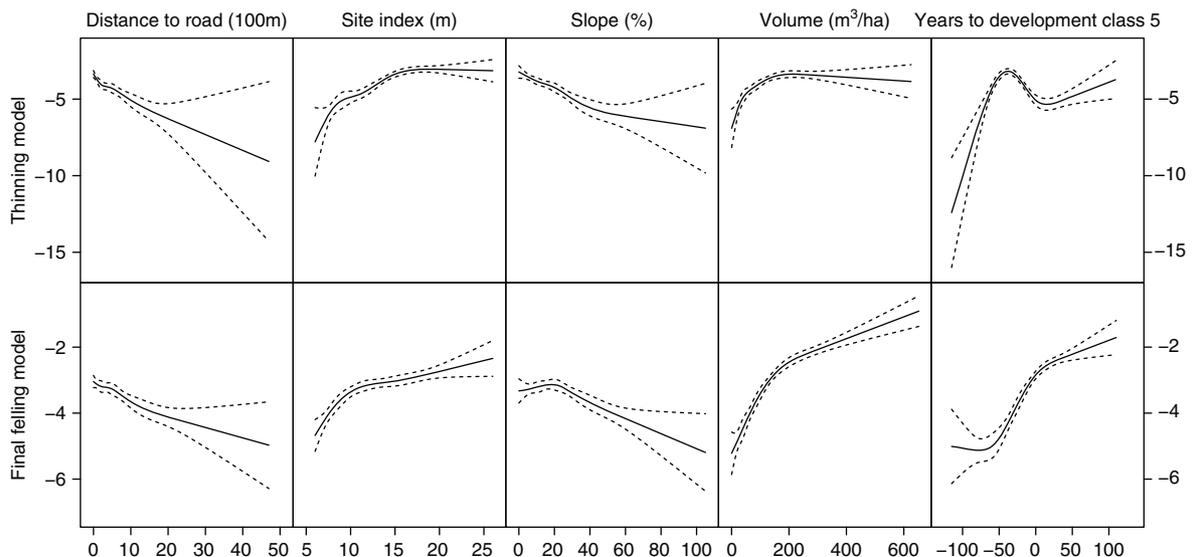


Figure 2. Estimated restricted cubic spline function (5 knots) relating the main variables to the logit of P_i . Confidence limits for the spline function are indicated by dashed lines.

reporting for forest management (Climate and Pollution Agency, 2010), (2) to be transparent and simple, and (3) to rely on a minimal number of assumptions. We used the developed final felling and thinning models in combination with simple volume and biomass increment models to develop the business-as-usual scenario. Using the ninth Norwegian forest inventory (2005–2009) as initial point, we forecasted the carbon change in living biomass for a 11-year period (2010–2020).

The core of the forecasting framework has two components, the developed harvest forecast models and a volume and biomass increment component (Figure 3). The volume and the biomass increment component is designed to be simple and transparent and consist of average annual biomass increase for different forest types stratified according to SI, age, and species composition. To represent the current growing conditions, data less than 10 years old were used to calculate the biomass and the volume increment component. In a given strata the volume and the biomass increments are estimated as the average observed changed on the NNFI plots with landuse class *forest* between the eighth (2000–2004) and ninth (2005–2009) NNFI. The volume and the biomass increment estimates include plots with noncommercial thinning and single tree removals (e.g. firewood cutting) but exclude the plots with commercial thinnings and final fellings that are included in the development of the harvest models. In effect, the volume and biomass increment models assume that growth rates are similar to the last 10 years, but take into account the change in age class structure over the prediction period (Figure 4).

To forecast the state of the Norwegian forest, each NNFI undivided plot and each subplot of the divided plots were forecasted individually. The harvest component was applied only to those plots/subplots in productive forest which had not been recently final felled and were in non-protected areas. The volume and biomass increment component was applied to all the plots/subplots. Harvest was

considered to occur in the middle of the 5-year period, and hence, the volume and biomass increments were applied only partially to harvested plots. When a final felling or thinning is carried out some part of the initial volume and biomass are left alive in the stand. We used data from the last measurement to estimate this percentage as the average portion of the volume left alive after harvest. We estimated the percentage of volume harvested in a similar way. To simulate the uncertainty originating from the randomness of the process, the forecasts were run 2000 times. In each period of each run the type of harvest allocated to a plot/subplot, if any, was determined by comparing random numbers (uniform [0, 1]) to the probabilities calculated for the plot/subplot. First, the final felling model was applied, and then the thinning model was applied to those plots/subplots that were not assigned final felling. We also accounted for models parameters uncertainty by varying in each run the model's parameters according to a multivariate normal distribution defined by the parameter estimates and their variance-covariance matrix. The results from the 2000 runs were used to estimate the mean harvest and carbon change and their 95% confidence intervals.

To compute the estimated carbon stock change in accordance with the current stock change method (Climate and Pollution Agency, 2010) for the forest management category, each NNFI plot/subplot was forecasted individually. Since only a fifth of the plots is measured every year, only information on a fifth of the country is updated every year. Following the current reporting practices in Norway, the total carbon pool for a particular year is calculated as the sum of the measured plots of the last 5 years. For example, the total carbon pool for the year 2010 ($C_{pool\ 2010}$) is estimated as the sum of the carbon estimates corresponding to plots measured in years 2006–2010, both inclusive. Carbon change from year to year is calculated as the difference between the total carbon pool for the current year and the total carbon pool for the previous year. For example, the carbon change between 2009 and 2010 is calculated as $C_{pool\ 2010} - C_{pool\ 2009}$.

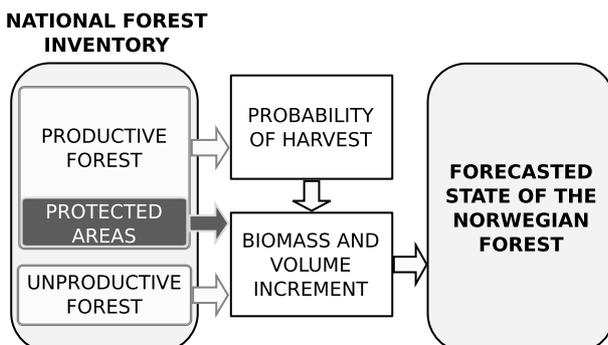


Figure 3. Outline chart of the forecast framework.

Results

Final felling model

The final felling model (Table III) included the volume (V), slope (S'), distance to road (D), a dummy variable to distinguish pine ($SC_P = 1$) from spruce and deciduous stands ($SC_P = 0$), a dummy variable to distinguish the west region ($R_R = 0$) from the rest ($R_R = 1$), the inverse of site index (SI^{-1}), and the

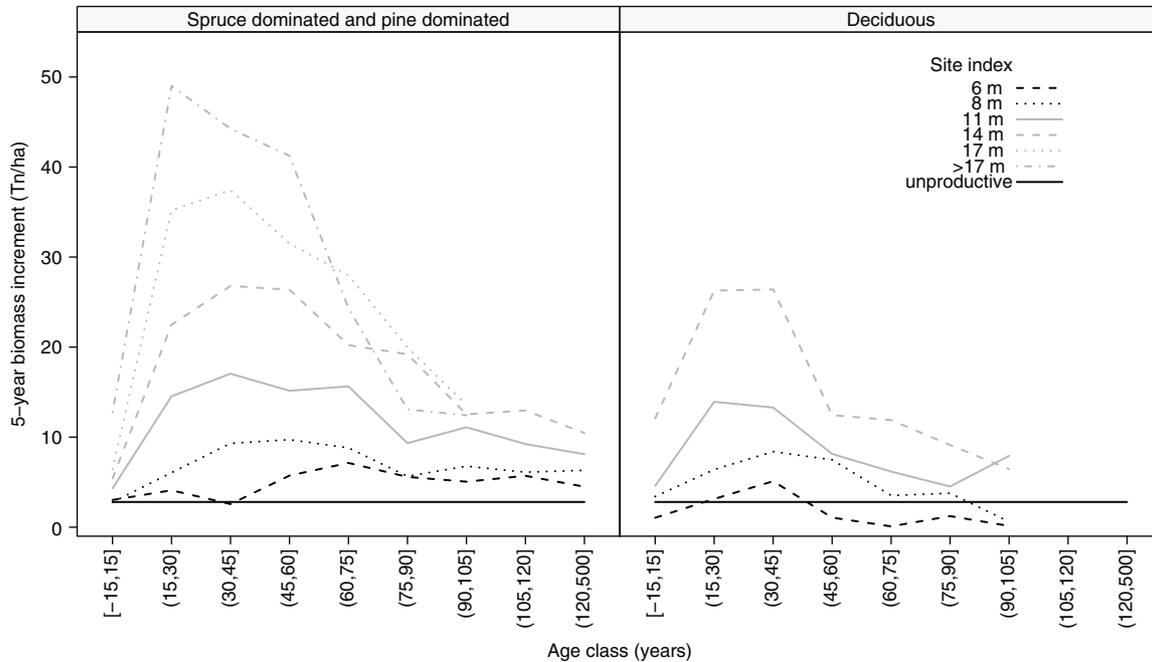


Figure 4. Biomass increment model.

transformed Y'_5 variable. The final model also included interactions between the transformed Y'_5 and a

Table III. Parameter estimates and standard errors for the final felling and thinning models. All parameters were statistically significant at 0.005 level.

	Variable	Estimate	Standard error
Final felling model	Intercept	-3.69040	0.39670
	V	0.00160	0.00060
	S'	-0.03450	0.00680
	D	-0.04040	0.00900
	SC_P	-0.59810	0.12240
	R_R	0.71940	0.23730
	SI^{-1}	-9.41430	2.71670
	$(Y'_5 + 51)^{0.5}$	0.24070	0.03590
	$SI^{-1} \cdot SC_C$	-7.99240	2.77320
Thinning model	$(Y'_5 + 51)^{0.5} \cdot SC_C$	0.19460	0.04010
	Intercept	-6.38970	1.01460
	$\text{Log}(V)$	0.56990	0.13850
	S	-0.03800	0.00650
	D	-0.06930	0.02060
	SC_P	0.82270	0.15080
	R_R	1.13540	0.38870
	SI^{-1}	-21.71000	3.97010
	Y''_5	-0.09550	0.01220
$(Y''_5)^2$	-0.00120	0.00020	

V = volume (m^3 /ha); S' = slope (%) where values below 30 have been collapsed to 30; D = distance to road (100 m); R_R = 0 for the west region and = 1 for the rest of Norway; SC_P indicates pines, and SC_C conifers; Y'_5 = years to development class 5 where values below -50 have been collapsed to -50; Y''_5 = years to development class 5 where all values above -1 have been collapsed to -1; and SI = site index (m) at a base age of 40.

dummy variable to distinguish coniferous stands ($SC_C = 1$) from deciduous stands ($SC_C = 0$), and an interaction term between the inverse of SI and SC_C .

In general, probability of final felling increased with increasing SI and volume and decreased with increasing slope, distance to road, and maturity [Y_5] (Figure 5). Under similar conditions, spruce dominated stands had the highest probability of being final felled, followed by pine dominated stands (Figure 5). Conifer dominated stands (spruce and pine dominated stands) were more sensitive to an increase in maturity (Y_5) and to an increase in SI than deciduous stands.

Thinning model

The thinning model included the same explanatory variables as the final felling model, although transformations and interactions differed. The final thinning model included the log-transformed volume, slope, distance to road, the dummy variables to differentiate pines (SC_P), and the west region (R_R), years to development class 5 where all values above -1 had been collapsed to -1 (Y''_5), the square of Y''_5 , and the inverse of SI . The behavior of the thinning model was consistent with the final felling model, expect for differences in the effect of stand composition and Y_5 (Figure 5). For the thinning model, the highest probability under similar conditions corresponds to pine dominated stands, and not spruce dominated stands as in the final felling model. While the final felling model predicts

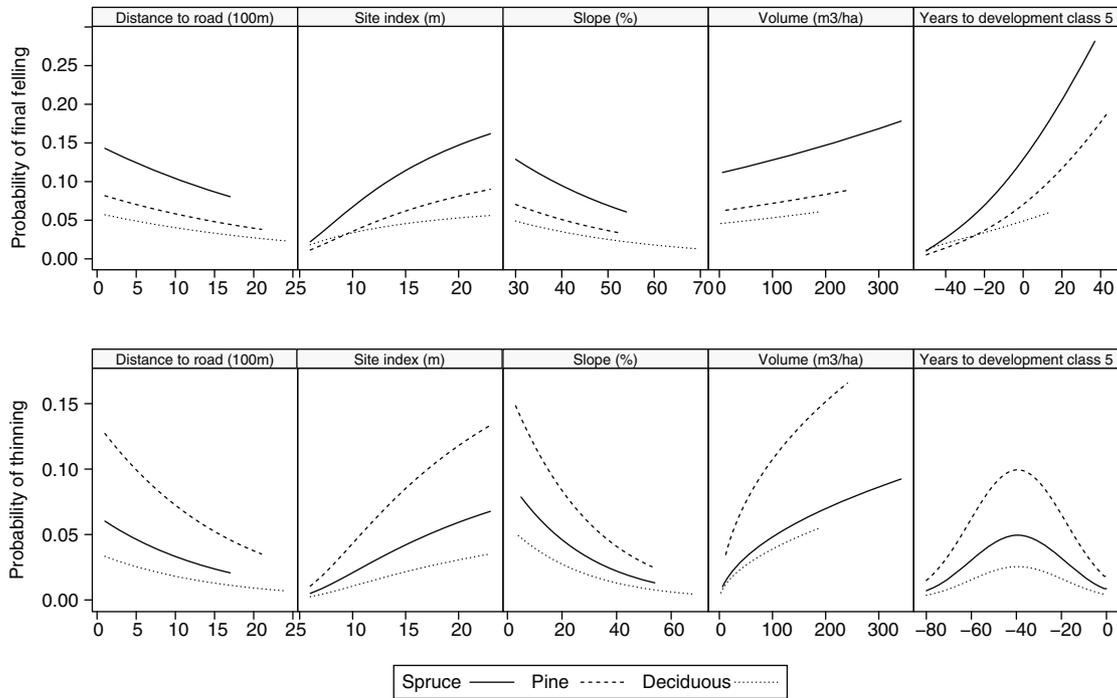


Figure 5. Sensitivity analysis for the main variables. Distance to road, slope and volume are set to the median of the values in the data for the species group; Y_5 is 0 for the harvest model and -40 for the thinning model; SI is set to 17, and R_R to 1. The range of the variables corresponds to the 5th and 95th percentiles of the data by species.

consistently higher probability of final felling with increasing maturity (Y_5), the probability of thinning peaks at around $Y_5 = -40$ and decreases afterwards.

Models evaluation

The final-felling and thinning models were a good fit to the data, had excellent discrimination and were well calibrated (Table IV). The differences between the models performance measures in the original data-set and in the internal bootstrap validation were small. The high p -values of the HL_m test in the fitting data-set and the internal validation indicate a good fit of both models to the data. The discrimination of the models, as measured by the c -index, was excellent (>0.8) for both the fitting data and the internal validation. The model was well calibrated, as shown by the lack of statistical significance in the

calibration test and by the values of the estimates for the calibration intercept and slope, which are very close to 0 and 1, respectively. The p -values for the lack of calibration test remain above 0.05 in the internal bootstrap validation.

To evaluate the models it is useful to investigate the performance of the models with respect to main variables such as region, SI, development class, and vegetation type (Figure 6). The models show a good fit to the data, with no systematic errors in the main variables explored.

Business-as-usual scenario for forest carbon stock change

The business-as-usual scenario for forest carbon stock change indicates a slow increase in average harvested volume (Figure 7), and a decrease in the uptake of carbon during the 11-year period (Figure 8). The

Table IV. Measures of goodness-of-fit and predictive discrimination for the fitting data-set and the bootstrap resampling internal validation (500 replications).

	Final felling		Thinning	
	Fitting data	Internal validation	Fitting data	Internal validation
HL_m (p -value)	8.649 (0.373)	4.751 (0.784)	8.885 (0.352)	4.983 (0.759)
c -index	0.820	0.822	0.870	0.871
Intercept	-0.045	-0.064	-0.059	-0.089
Slope	0.981	0.973	0.986	0.977
Lack of calibration	0.864	0.610	0.942	0.671

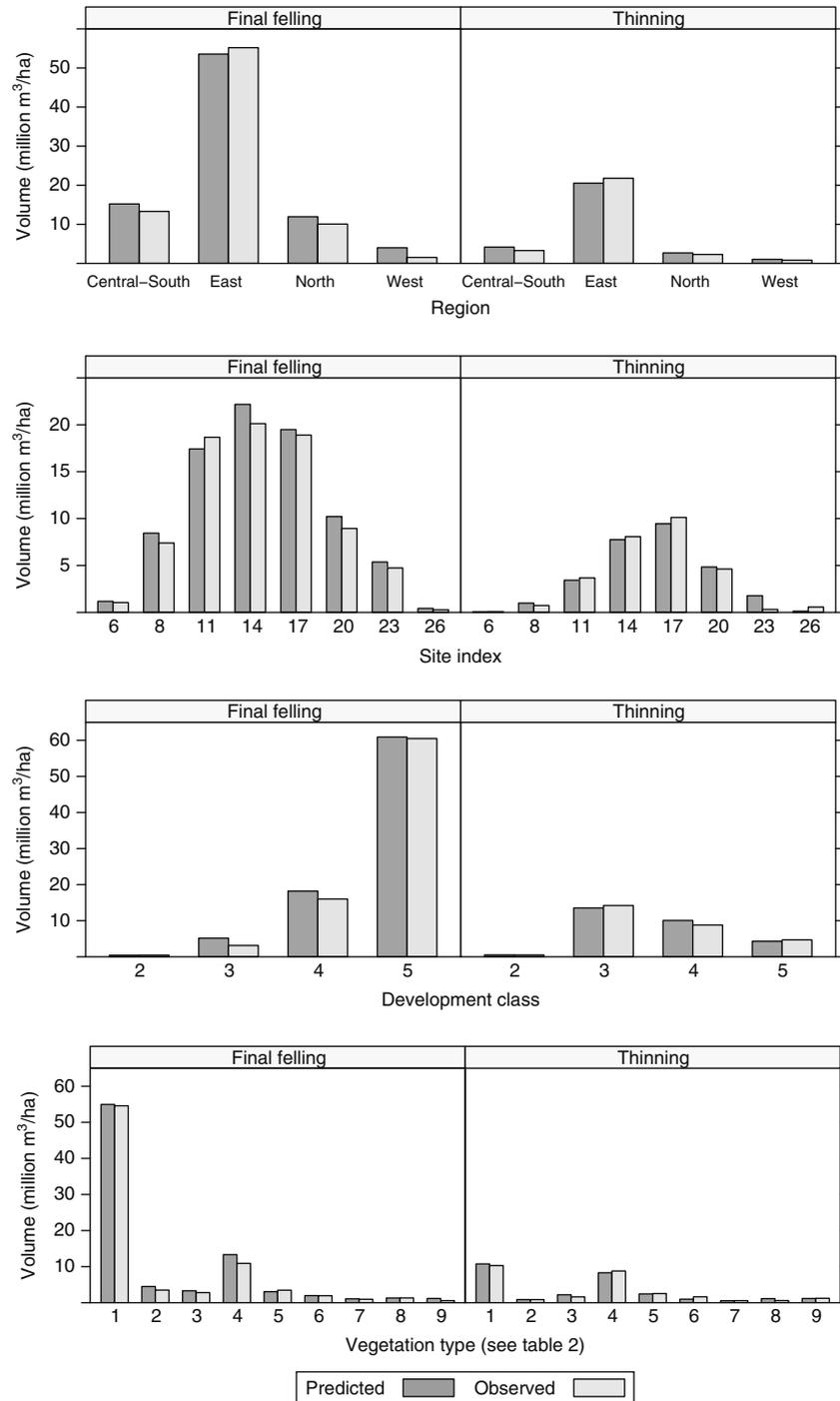


Figure 6. Observed and predicted volume for the fitting data-set.

increase in harvested volume was mostly driven by an increase in average stand age and an increase in volume. The largest increments in forecasted harvest, in absolute and relative (with respect to historical data) values, occurred in the west region, followed by the north region. Ninety-five percent confidence intervals on the harvest and carbon change estimates illustrate the relatively large variability of the annual

estimates from the NNFI. This variability is also displayed by the historical NNFI values in Figures 7 and 8. The uncertainty estimates of the forecasted values include uncertainty originating from the harvested model parameters and the uncertainty from the stochasticity of the processes, although the largest proportion of the uncertainty was due to the stochasticity of the process.

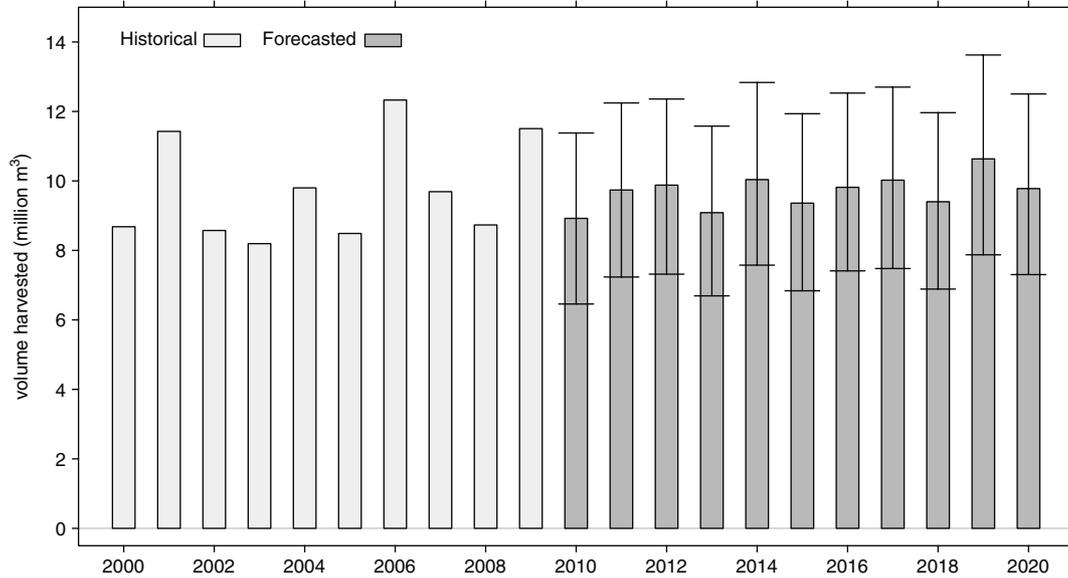


Figure 7. Historical and forecasted total harvest volume in Norway with uncertainties (95% confidence interval based on bootstrapping).

Discussion

When the objective is short-term forest development forecasts, data-driven approaches such as the one presented here offer a transparent and simple way to obtain congruent estimates in a business-as-usual scenario. Most studies dealing with large-scale modeling of forest development rely on deterministic rules to predict harvest levels (e.g. Kellomäki et al., 2008; Kurz et al., 2008; Nunery & Keeton, 2010). Some of these studies have recognized that harvest is not purely deterministic, and have developed ad hoc approaches to simulate randomness (e.g. Alam et al., 2010; Ericsson, 2003). Although this type of approaches might not have drastic consequences in long-term scenario analysis, for short-term predic-

tions, deviations of the predicted harvest from the actual management may be large. The data-driven harvest models presented here use logistic regression and data from the NNFI to model the behavior of forest owners in Norway and to obtain short-term business-as-usual harvest forecasts that conform to the expected behavior of forest owners and harvest levels in Norway. We believe that the presented approach to development of business-as-usual scenarios can be useful in instances with short-term focus (10–20 years) such as in the current climate discussions or in forestry-based industrial development. For future use of the developed approach and scenario it must be remembered that this is a purely empirical approach that does not account for future changes in economic conditions or legislation.

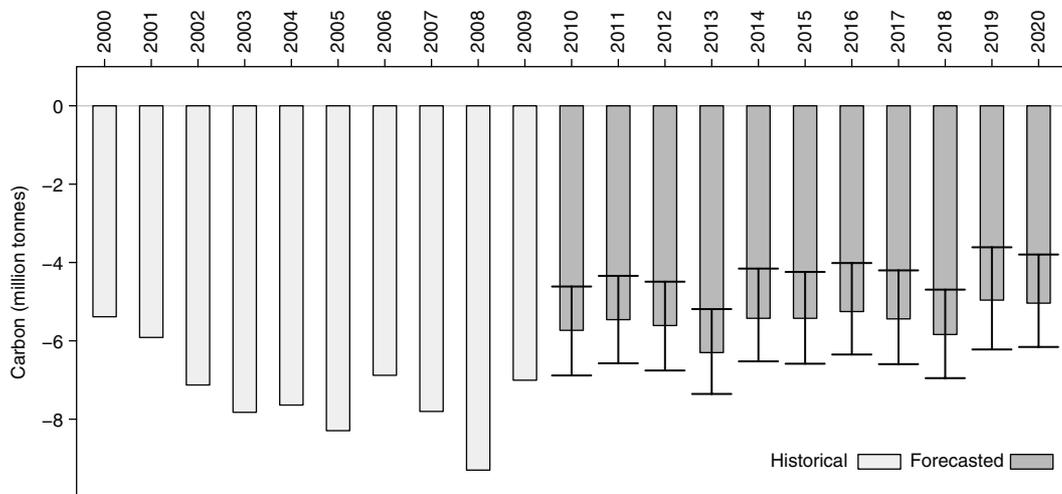


Figure 8. Historical and forecasted carbon change for forest remaining forest in Norway (95% confidence intervals for the forecasted period include stochastic and parameter uncertainties).

Harvest choices by private and public forest owners have been extensively studied (e.g., Andersson & Gong, 2010; Polyakov et al., 2010). This body of literature shows that forest owners' choices are generally consistent with economic theory and harvest is more frequent where a profit can be made. However, forest owner harvest decisions are not solely determined by profitability, and assuming that all forest owners operate exclusively to maximize profit results in low correlation to actual management decisions (Ericsson, 2003; Kellomäki et al., 2008). Not surprisingly, both the final felling model and the thinning model are consistent with economic theory. The final felling model predicts higher probability of final felling with the quantity and quality of the timber in the stands, that is, it increases with increasing SI, volume, and maturity (measured by Y_5), and decreases with increasing harvest cost, that is, with increasing slope, and distance to road. For thinnings, higher probabilities are assigned to stands with higher SI, close to the road, and with gentle slopes. Differences between stand composition types are in accordance with the commercial value of the different species, being spruce the most profitable followed by pine. In the case of the thinning model, the higher levels of thinning in pine dominated stands when compared to spruce dominated stands in similar conditions, is likely a reflection of the higher sensitivity of Scots pine growth to thinning (Mäkinen & Isomäki, 2004a, b; Nilsson et al., 2010) and potentially to the larger degree of wind stability of pine stands.

The predicted harvest patterns differ from the management assumptions made in existing national or regional Norwegian forest carbon simulation studies. The current Norwegian harvest levels are much lower than indicated by long-term sustainable yield calculations (Vennesland et al., 2006), and large areas of mature forests are not affected by harvest (Larsson & Hysten, 2007). For this reason, existing regional or national Norwegian carbon forecasts assumed a fixed overall harvest level, and then applied management guidelines or optimization to decide which stands are harvested to meet the harvest level. For example, Astrup et al. (2010) used a modified version of the decision support system AVVIRK-2000 (Eid & Hobbestad, 2000) to analyze the changes in the future carbon stocks in Norwegian forests under alternative climate and forest management scenarios. In Astrup et al. (2010), the simulation rules included a constant national harvest level with a set regional distribution, and silvicultural treatments included up to two thinnings, and final fellings only in mature stands. Raymer et al. (2009) used GAYA (Hoen & Eid, 1990), a forest simulator developed for long-term economic analysis of forest

production, to analyze alternative forest management scenarios with the objective to increase the carbon benefit for a county in Norway. For their 120 years long forecasts study, Raymer et al. (2009) restricted overall harvest from the region to the present level. Unlike in Raymer et al. (2009) and Astrup et al. (2010), the forecasted harvest levels presented here fluctuate over time and vary between regions. Compared to approaches that rely on management guidelines or maximization of forest value to estimate and assign harvest, our approach allocates harvest to differing forest structures, which affects both short and long term carbon sequestration. For example, many of the national and regional forest development scenarios only assign final felling to mature stands (e.g. Peltola et al., 2010; Raymer et al., 2009), while our approach assigns final felling based on standing volume, development class, and site characteristics, considering also the nondeterministic nature of the harvest activity. Although forest owners' behavior is in general consistent with economic theory, it is not deterministically driven by economic factors. We address the randomness of the decision-making process by fitting logistic regression models that predict probability of harvest. When the harvest models presented here are used to forecast harvest for the NNFI plots, this randomness translates into more or less wide confidence intervals. The magnitude of the variability is driven by the relatively low density of the NNFI grid and the low harvest levels and long rotation periods of the main commercial species. This variability in the forecasted national harvest levels based on the NNFI is also evident in the historical NNFI estimates (Figure 7), which present higher variability than similar estimates based on a census of forest owners such as carried out by Statistics Norway (Statistics Norway, 2010). The confidence intervals in Figures 7 and 8 include uncertainty originating from the randomness of the process and from the models' parameters; other relevant sources of uncertainty, such as sampling and measurement error, were not included in the analysis.

The lower rates of final felling in the west region, given similar age, stand composition, volume, and SI, are likely a reflection of regional differences in ownership structure, forest industry development, and forest management traditions. The west region is dominated by smaller forest owners and has a much less developed forest industry than, for example, the east region, where the harvest levels are highest (Vennesland et al., 2006).

During the 1950s–1970s, the west and north regions of Norway underwent an intense reforestation effort that resulted in highly productive spruce plantations. Those stands will be getting close to

maturity around the year 2020 (Larsson & Hysten, 2007; Øyen & Nygaard, 2008). The increase in harvestable areas in those two regions is the main source of the predicted increased harvested volume under the business-as-usual scenario for Norway during the 2010–2020 period (Figure 7). The business-as-usual scenario illustrates a decreasing trend in carbon uptake (Figure 8), which can be explained as a result of a slightly higher harvest level (Figure 7) combined with the age class structure of Norwegian forests (Larsson & Hysten, 2007), where a higher proportion of older forest will reduce the biomass increment in the coming decades.

We have illustrated that it is possible to create empirical models that predict harvest with high discriminating power at the national or regional level based on forest attributes, and believe that this approach has a place in development of short-term business-as-usual scenarios.

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