Canadian Journal of Forest Research
Revue canadienne de recherche forestière

Climate sensitive site index models for Norway

Journal:	<i>Canadian Journal of Forest Research</i>
Manuscript ID	cjfr-2015-0155.R3
Manuscript Type:	Article
Date Submitted by the Author:	02-Feb-2016
Complete List of Authors:	Antón-Fernández, Clara; Norwegian Institute of Bioeconomy Research Mola-Yudego, Blas; Norwegian Institute of Bioeconomy Research Dalsgaard, Lise; Norwegian Institute of Bioeconomy Research Astrup, Rasmus; Norwegian Institute of Bioeconomy Research
Keyword:	climate change, Picea abies, Pinus sylvestris, boreal forest, productivity

Climate sensitive site index models for Norway

Clara Antón-Fernández,¹ Blas Mola-Yudego, Lise Dalsgaard, and Rasmus Astrup

1

Draft

Clara Antón-Fernández,¹ Blas Mola-Yudego, Lise Dalsgaard, and Rasmus Astrup.
Norwegian Institute of Bioeconomy Research

¹Corresponding author (e-mail: caf@nibio.no).

Abstract: The present study aims to develop biologically sound and parsimonious site index models for Norway to predict changes in site index under different climatic conditions. The models are constructed using data from the Norwegian national forest inventory (NNFI) and climate data from the Norwegian meteorological institute. Site index was modeled using the potential modifier functional form, with a potential component (POT) depending on site quality classes, and two modifier components (MOD): temperature, and moisture. Each of these modifiers was based on a portfolio of candidate variables. The best model for spruce dominated stands included temperature as modifier ($R^2 = 0.56$). In the case of pine and deciduous dominated stands, the best models included both modifiers (R^2 of 0.40 and 0.54, for temperature and moisture respectively). We illustrate the use of the models by analyzing the possible shift in SI for year 2100 under one (RCP4.5) of the benchmark scenarios adopted by the IPCC for its fifth Assessment Report. The models presented can be valuable for evaluating the effect of climate change scenarios in Norwegian forest.

Key words: Climate change, *Picea abies*, *Pinus sylvestris*, Norway spruce, Scots pine, deciduous, boreal forest, productivity.

1. Introduction

Quantification and prediction of stand productivity is a key question in forest research, with evident implications in forest planning. The productivity of a given area has traditionally been estimated by measuring the height of dominant trees at a given age. This value, known as site index (SI), is assumed to be a valid surrogate for the potential productivity of a particular site. Site index is widely used as a measure of site quality as it can be estimated from direct measurements of height and age, and it is a good predictor of volume growth and yield (Weiskittel et al., 2011). Site index is also a prevalent key predictor in most traditional growth and yield models.

The site index reflects inherent site characteristics, such as soil and climate, which are directly related to forest productivity. Except in the case of intensively managed stands (e.g. plantations subject to irrigation or fertilization) site index is generally assumed to remain constant through time (Assmann, 1970), as average soil and climatic variables have been assumed to remain stable. Therefore, many approaches oriented towards the estimation of site index include topographic or locational variables (e.g. slope, latitude, altitude) that relate to climate and soil conditions, providing good accuracy in the estimates.

However, this static approach does no longer hold in the present context of future climatic changes, as it is reasonable to expect changes in site index in parallel to changes in climate conditions (e.g. Kauppi et al., 2014). This climatic uncertainty context urges for the development of adequate tools for a more dynamic estimation of site index. This is particularly relevant in high latitudes, where current climate change scenarios predict the largest temperature increases (Stocker et al., 2013). In these regions, temperature is the main variable driving forest productivity, and therefore the expected changes will strongly affect forest productivity (Peltola et al., 2010).

Climatic projections for Norway forecast a generally warmer and wetter climate (Stocker et al., 2013). The forecasted conditions for Norway are outside the range of conditions currently present in Norway, particularly in the southernmost part. Hence, the importance of having a site index model that gives biologically sound estimates outside the range of observed conditions. Several empirical approaches for predicting SI from biophysical predictors,

including climatic variables, have been developed. These approaches range from linear models (e.g., Nigh et al., 2004; Sharma et al., 2012) to nonparametric approaches (e.g., Sabatia and Burkhart, 2014; Weiskittel et al., 2011). Some nonparametric approaches seem to have gained some popularity, e.g. the random forest model (e.g., Crookston et al., 2010; Weiskittel et al., 2011), because of their high accuracy and lack of assumptions about how the independent variables relate to each other and the dependent variable. This approach has, however, an important drawback, that when used outside the range of the training data its predictions are unreliable (Sabatia and Burkhart, 2014). Linear regression models and similar approaches like generalized additive models, GAM, (e.g., Albert and Schmidt, 2010) or other semiparametric additive smoothing approaches (e.g., Nothdurft et al., 2012) share, somehow, a similar drawback: since SI has biological constraints that are not directly considered within the linear model, linear models could predict unrealistic values when used outside the range of the fitting data.

The present study aims to develop biologically sound and parsimonious models for predicting changes in site index under different climatic conditions for the three main species in Norway. The models are constructed using data from the Norwegian national forest inventory and climate data from the Norwegian meteorological institute. We illustrate how the SI models can be used by estimating the SI shift in 2100 under one of the IPCC climate change scenarios.

2. Material and methods

2.1. Data sources

The forest measurements for this study were based on data from the Norwegian National Forest Inventory (NNFI) measured during the period 2009-2013. The NNFI consists of permanent plots laid systematically on a 3x3 km grid, covering an extension from latitude 58.8N up to 70.8N. The grid covers the whole country except for the northernmost region (Finnmark). Plots with more than 20% of Sitka spruce (*Picea sitchensis* (Bong.) Carr.) were excluded, due to differences in measurement methods, and only plots located in productive forestland were considered, resulting in 8943 plots included in the calculations. The main species in Norway are, in this order, Norway spruce (*Picea abies* (L.) Karst.), Scots pine (*Pinus sylvestris* L.) and birch (*Betula pendula* Roth. and *Betula pubescens* Ehr.).

77 Site index (SI) was defined as the average height of the 100 thickest trees per hectare at
78 the reference age of 40 years, and it is estimated at each cycle of the NNFI. At each plot
79 the SI was assessed for the main species by selecting at least one dominant tree within a 0.1
80 ha circle. The selection of the dominant tree was done by visual assessment. The heights of
81 the selected trees were measured and their corresponding ages were estimated from increment
82 cores. The resulting data was used to estimate the SI according to Tveite and Braastad (1981),
83 which places SI in classes: 6 (5-6.5), 8 (6.5-9.5), 11 (9.5-12.5), 14 (12.5-15.5), 17 (15.5-18.5),
84 20 (18.55-21.5), 23(21.5-24.5), and 26 (>24.5) m.

85 In addition, records of soil depth and understory vegetation class were taken at each plot.
86 The understory vegetation classes were grouped into 9 categories (Astrup et al., 2010), accord-
87 ing to their position along a gradient in nutrients (poor, moderate, and rich) and moisture
88 (wet, moderate, and dry). The soil depth was classified in 4 categories: soil depth below 25
89 cm, between 25 and 50 cm, between 50 and 100 cm, and above 100 cm. The resulting com-
90 bination of soil richness, moisture, and depth form a total of 36 potential combinations, most
91 of which are only represented by a small number of plots. These combinations were the basis
92 of a categorical variable that organized richness, moisture and soil depth into five biologically
93 meaningful groups. The groups were defined to minimize the SI variability for each species
94 within each group. The new site quality variable (SQ) had a value of 1 to indicate the poorest
95 sites and 5 to indicate the best sites (Figure 1).

96 The location of spruce, pine and deciduous dominated stands in Norway is therefore re-
97 flected in their frequency in each of the SQ groups defined (Table 1). Pine dominated stands
98 are mostly located on poor sites (SQ1) while they are rare on the best sites (SQ5), whereas
99 spruce dominated and deciduous dominated stands were mostly distributed in SQ3 and SQ4.
100 The distribution of plots among SI classes is similar for deciduous and pine dominated stands
101 (Figure 2). The lower SI classes are most commonly dominated by pine and deciduous species,
102 while spruce dominated stands lead SI classes higher than 11m. The highest SI observed, 26m,
103 is only found in few (12) spruce dominated stands. With respect to soil wetness, deciduous
104 and spruce dominated stands are most common in moderate soils while pine are most common
105 in dry soils (Figure 2). Most of the plots classified as wet are dominated by deciduous species,
106 and only 18 of the plots classified as wet are dominated by pines.

Historical climate data (1900-2008) at the plot level were provided by the Norwegian meteorological institute. Monthly precipitation and temperature were geographically interpolated from about 400 weather stations throughout Norway. 30-years averages were calculated using data from 1979-2008 (MET7908). We used the multimodel (67) ensemble mean monthly temperature and precipitation outcomes from representative concentration pathway (RCPs) 4.5 (Thomson et al., 2011) from the CMIP5 21st century experiments (Royal Meteorological Institute of The Netherlands (KNMI), 2014), RCP4.5, for projecting SI changes in 2100 for NNFI plots currently on forestland. RCP4.5 is one of the benchmark scenarios adopted by the IPCC for its fifth Assessment Report (Moss et al., 2008).

2.2. Modeling approach

Since the aim of this study is to predict changes in site index under changing climatic conditions it is important that the selected modeling approach produces models that behave well beyond the range of current climatic conditions. We use a multiplicative potential (POT) modifier (MOD) functional form for the SI model ($SI = POT \times MOD$) where MOD is scaled to only have values between 0 and 1. This functional form has the advantage of being constrained and robust since the predicted SI will not exceed the potential even when approaching the limits of the empirical data used for model development. In this modelling approach both the potential and modifiers are estimated as parameters in a nonlinear regression model. The applied modelling approach is equivalent to that frequently applied in studies of tree diameter growth where an estimated potential maximum growth rate (estimated as part of a nonlinear regression model) is modified according to site factors or competition for light or belowground resources (e.g. Lilles and Astrup, 2012; Canham and Uriarte, 2006). The approach applied in this analysis is different than the more conventional potential modifier approach (as in Belcher and Brand, 1982) where the potential is estimated in a separate analysis, and often using a different data set, than the one used for fitting the modifier. It is similar to the conventional potential modifier approach in the sense that the modifiers vary between 0 and 1 and modify how close to realization of the potential the estimated SI is.

The SI was, therefore, modeled using the multiplicative potential modifier functional form. This functional form has two components: The potential component (POT), which can be

136 interpreted as the mean SI at a given SQ when neither temperature or moisture are limiting,
137 and a modifier component (MOD) which reduces the potential site index according to relevant
138 variables, in the form $SI = POT \times MOD$. The modifier component can consist of one or
139 several multiplicative modifiers, each of them taking values between 0 and 1, e.g. $MOD =$
140 $MOD_1 \cdot MOD_2$, which results in MOD varying between 0 and 1, and the model predicting
141 values between 0 and POT . The potential modifier functional form is commonly used to model
142 growth, where the lower limit of zero makes sense. However, when applied to SI modeling a
143 value of zero does not make biological sense. Therefore, to account for a lower SI limit of 6,
144 which is the minimum SI measured in the NNFI, we redefined the basic form of the model as:
145 $6 + (POT - 6) \times MOD$.

146 The candidate modifiers included a temperature effect, MOD_T , and a moisture surplus
147 effect MOD_M . For each modifier, a simple portfolio of candidate variables was considered.
148 The modifier MOD_T included variables related to temperature that may affect SI, namely the
149 number of growing days (GD, number of days with average temperature above 5°C), and com-
150 binations of the 30-year monthly average temperatures, for instance the temperature sum for
151 spring and summer months (TSUM). The modifier MOD_M included variables related to water
152 availability that may restrict the SI, and included several combinations of the 30-year monthly
153 average precipitation, the Palmer drought severity index (Palmer, 1965), PDSI, for the grow-
154 ing season months, the topographic wetness index (Beven and Kirkby, 1979), TWI, and the
155 monthly moisture surplus defined as the difference between 30-year monthly average precipita-
156 tion and the average monthly potential evapotranspiration (MSJ). We followed Thornthwaite
157 (1948) to calculate potential evapotranspiration (PET) using the 30-year monthly average
158 temperature:

$$PET = 16K \left(\frac{10T}{I} \right)^m$$
$$I = \sum_{i=1}^{12} \left(\frac{T}{5} \right)^{1.514} ; m = 6.75 \times 10^{-7} I^3 - 7.71 \times 10^{-5} I^2 + 1.79 \times 10^{-2} + 0.492$$

$$K = \left(\frac{N}{12}\right) \left(\frac{NDM}{30}\right); \quad N = \left(\frac{24}{\pi}\right) \bar{\omega}_s$$

$$\bar{\omega}_s = \arccos(-\tan \phi \tan \delta); \quad \delta = 0.4093 \sin\left(\frac{2\pi J}{365} - 1.405\right)$$

159

160 Where T is the monthly-mean temperature ($^{\circ}\text{C}$), I is a heat index, which is calculated as
 161 the sum of 12 monthly index values i , m is a coefficient depending on I , K is a correction
 162 coefficient computed as a function of the latitude and month, NDM is the number of days of
 163 the month, N is the maximum number of sun hours, $\bar{\omega}_s$ is the hourly angle of sun rising, ϕ is
 164 the latitude in radians, and δ is the solar declination in radians, J is the average Julian day of
 165 the month.

166 The plots were grouped according to dominant species (spruce, pine, and deciduous plots)
 167 and equations were fit to each of these categories separately. All the candidate variables were
 168 preliminarily explored by examining graphically and analytically their explanatory power for
 169 site index, for each modifier and for each species. To explore the strength and shape of the
 170 relationship between site index and the candidate variables we fitted linear tail-restricted
 171 cubic splines (5 knots) functions to each candidate variable and species (Harrell, 2001). When
 172 analyzing the strength of the association between site index and the candidate variables, cubic
 173 splines offer the advantage of allowing departures from the assumption of linearity in the
 174 association. In addition, correlation matrices were computed and examined, to determine the
 175 degree of intercorrelation among variables.

176 The criteria for including the candidate variables in the final version of the models were:
 177 they had to be significant at the 0.05 level, and they had to provide the highest explanatory
 178 power of the candidate variables.

179 Concerning the model shape of the modifiers, two basic forms were considered. Variables
 180 increasing with the value of the explanatory variable were modelled using the logistic functions
 181 $1/(1 + \exp(-\beta\mathbf{X}))$, where $\mathbf{X}$ is a vector of explanatory variables, and β is the vector of param-
 182 eters to be estimated. Relationships reaching a peak at certain point and decreasing afterwards
 183 were modelled using the Weibull function $\gamma/\alpha \cdot ((\mathbf{X} - \mu)/\alpha)^{\gamma-1} \exp(-((\mathbf{X} - \mu)/\alpha)^{\gamma})$, where
 184 $\mathbf{X} \geq \mu$, and $\alpha > 0$, scaled to be bounded between 0 and 1. The Weibull function is a widely used

©2016 NRC Canada

185 and flexible function that have a shape parameter (γ), a scale parameter(α), and a location
186 parameter (μ). To bound the Weibull function between 0 and 1, we added a scaling factor
187 ($1/\xi$) which multiplied the whole function and was calculated as the maximum value of the
188 function, and we redefined $\mathbf{X}$ as

$$\mathbf{X} = \begin{cases} \mathbf{X} & \mathbf{X} \geq \mu \\ \mu & \text{otherwise.} \end{cases}$$

189 Thus, $(\mathbf{X} - \mu)$ will never be negative, and values of $\mathbf{X}$ below μ will result in the modifier
190 taking a value of 0.

191 The basic form of the model was $6 + (POT - 6) \times MOD$, where $MOD = MOD_T \times MOD_M$,
192 resulting in two models, named md1 and md2. Model md1 includes the temperature modifier
193 MOD_T , and model md2 includes both the temperature and the moisture availability modifier
194 MOD_M .

Finally, the models were assessed in order to identify which modifiers, and in which combination, resulted in a better model. The assessment was based in the Akaike information criterion, AIC, (Akaike, 1974), and BIC (Schwarz, 1978), and the proportion of variance explained by the model relative to that explained by the simple mean of the data, adjusted by the sample size (n) and the number of regressors (p):

$$R_{adj}^2 = 1 - \left(\frac{n-1}{n-p-1} \right) (1 - R^2)$$
$$R^2 = 1 - \left(\frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \bar{y})^2} \right)$$

195 where $\bar{y}$ is the mean of the observed SI, f_i is the i th model predicted SI, and y_i is the i th
196 observed SI.

197 To avoid, as much as possible, problems with convergence we used a simulated annealing
198 algorithm (Goffe et al., 1994) implemented in the likelihood package (Murphy, 2015) in R
199 (R Core Team, 2015) to fit all models. The likelihood package allows to find the maximum
200 likelihood estimates of statistical models using simulated annealing, a global optimization

algorithm, with or without bounded searches.

2.3. Projections

The temperature and precipitation outcomes from the multimodel ensemble for RCP4.5 have a 0.5 degree spatial resolution. Since the source and resolution of these data are different from the ones used for fitting the models (MET7908), we estimated the 30-years monthly average temperature at each plot for the 2071-2100 period as the sum of MET7908 and the projected change according to RCP4.5. We calculated the projected change according to RCP4.5 as the difference between the average monthly temperature for the 1979-2008 period available from RCP4.5 and the 2071-2100 monthly average from RCP4.5. We used the estimates of the 30-years monthly averages for the 2071-2100 period, calculated as the sum of MET7908 and the projected change according to RCP4.5, to calculate the variables required by the models, TSUM and MSJ.

3. Results

3.1. Model fitting

Several candidate variables for MOD_T were available. The preliminary correlation matrices of the candidate variables showed that temperature and number of growing days were highly correlated and that the best temperature-based variable had higher correlation with SI than the number of growing days for all species. Among the best temperature variables there was little variation in their correlation with SI, and the correlation among them was high (>0.94). The graphical evaluation of the residuals of the linear tail-restricted cubic splines revealed that April, May, and June monthly temperatures performed best, but different months tended to perform better in different regions (e.g. northern region), while the sum of temperature in spring and early summer had a more consistent residual pattern. Therefore, we selected temperature in spring and early summer, defined as the sum of the 30-year average temperatures in April, May, and June (TSUM), for MOD_T . The range and distribution of these variables is shown in Figure 3.

For MOD_M the correlations among candidate variables and SI were smaller than for MOD_T , but stronger for deciduous than for spruce or pine. Measures of goodness-of-fit (resid-

ual standard error and coefficient of determination R^2) of the linear tail-restricted cubic splines revealed that water surplus in June outperformed all variables. Therefore, we selected moisture surplus in June (MSJ), defined as the difference between 30-year average precipitation in June and average potential evapotranspiration in June.

The preliminary analysis determined the parameters that varied with SQ and the most adequate functional form for each modifier and for each species. We assessed graphically the need to make each parameter dependent on the SQ group. Table 2 shows the two modifiers selected for each species. In general, the variability explained by the best models, as measured by R^2 , was highest for spruce dominated plots, followed by deciduous and pine dominated plots. For all species the largest variability was explained by temperature.

Consistently with the limiting factor theory, the sensitivity analyses revealed that the effect of temperature on SI was smaller for poorer sites and that this effect increases with site quality for all species (Figures 4, 5, and 6)

In the spruce dominated stands, a large part of the variability was already explained by the model including TSUM (md1) in addition to the SQ factor (Table 3). In pine dominated stands (Table 3), model md2, with two modifiers, performed best. The full model (md2) improved AIC and R^2 while keeping the estimates of the parameters within the expected range. A decrease in moisture surplus at the wetter sites results in an increase in SI, but once the optimum was reached, a drier climate (lower moisture surplus) results in a decrease in SI. The effect of temperature was greater at optimal moisture surplus, and it was very limited at the lowest and highest moisture surplus limits.

Thus, we regarded md2 (temperature as modifier), md2 (temperature and moisture surplus as modifiers) and md2 (temperature and moisture surplus as modifiers) as the best models for spruce, pine and deciduous dominated stands, respectively. The selected models show little apparent trend in plots of residual values against either predicted values (Figure 7) or any of the independent variables (data not shown).

3.2. Projections

Climatic projections for Norway forecast a generally warmer and wetter climate, which results in a similar range of MSJ values, but a generally higher TSUM (Figure 8). Projections

for SI in 2100 for the NNFI plots used for fitting the models were calculated by adding the expected change to the current SI. That is, we used the best models for each species to estimate SI for current conditions and for conditions in 2100, we then calculated the difference between these two and applied it to the current SI on each plot. For all species the patterns of SI remain similar to the current patterns of SI. The projections show that in most plots there will be an increase or no change in SI, with pine being the species less affected by climate change. The projections show constant or increasing SI, with very rare occurrences of decreasing SI (Figure 9). The largest changes in SI are for spruce dominated stands, where the projections show an increase in SI of at least 1 meter in most regions, with a higher increase in the central part of Norway and plots close to the tree line in the southern part of Norway. For pine dominated stands the increase in SI was more moderate, with most of the plots experiencing little change. For deciduous dominated stands the change in SI was below 3 meters in most plots, with little change in the northernmost regions, and only few plots experiencing increases of SI above 3 meters. The range of MSJ on the original data (-115, 134) does not differ much from the range of MSJ on RCP4.5 (-119, 118), being the average change in MSJ -6.5 mm. The average change in TSUM in RCP4.5 with respect to MET7908 was 6.5 °C. The range of TSUM change from (0, 32.5) in MET7908 to (1.6, 38.5) in RCP4.5.

4. Discussion

The present paper explains the variations of SI in Norway according to climatic and soil conditions by using an empirical approach. The models are fit using an extensive data pool resulting from the NNFI and environmental variables from the Norwegian meteorological institute. Thus, an application to recent climate conditions becomes straightforward. At the same time, the models are biologically sound, and efficiently represent the main limitations to forest growth in Norwegian conditions.

However, there are limitations in the data used for the estimation of the SI: in general, the overall estimation of site index based on a reference height is a difficult task subject to measurement error and the site classes in Norway are defined in intervals, which reduces the precision of the predictions. Despite these limitations, the NNFI is the largest data set available for the region and covers systematically a broad geographical region with diverse

287 climate conditions, thus providing a solid empirical basis for the models presented.

288 The models presented precision levels similar to other recent studies of SI prediction using
289 alternative statistical approaches (e.g. Seynave et al., 2005; Albert and Schmidt, 2010; Aertsen
290 et al., 2010). In Norway, Sharma et al. (2012) presented SI models for Norway spruce and Scots
291 pine with higher predictive power than the ones presented here. Sharma et al. (2012) used linear
292 regression models and the year of stand establishment, the temperature sum (degree days above
293 5°C), location, topography, soil, and understory vegetation variables as explanatory variables.
294 Although Sharma's et al. R^2 values may look promising (up to 0.85 for Norway spruce and
295 0.72 for Scots pine), their models present several limitations when used for prognoses under
296 climate change. They assume a linear relationship between temperature sum and SI, thus
297 higher temperatures will always, regardless of precipitation, result in higher SI. The inclusion of
298 the year of stand establishment results in a continuous trend of higher SI in newly established
299 stands, which may result in illogical SI when used for prediction of long-term prognoses.
300 Recent studies on SI prediction have focused on modeling the spatial SI trends. For example,
301 Albert and Schmidt (2010) used generalized additive regression models with a two-dimensional
302 location component to model the spatial SI trend. We chose not to include location components
303 in our models because, in our case, location is correlated with the main variables of interest
304 (the correlations between TSUM and latitude and longitude are 0.47, and 0.36 respectively,
305 and between MMS and latitude and longitude are 0.47, and 0.72, respectively) and that would
306 cause confounding of the effects of changes in the climatic variables. Other options to address
307 spatial correlation is that of Nothdurft et al. (2012), who applied a simplified universal kriging
308 method using B-spline basis functions to provide spatio-temporal predictions of site index
309 for an area of Southwest Germany. The Nothdurft et al. (2012) approach requires that the
310 mean function of the spatial site-index process, the one that depends on climatic variables, to
311 be linear. Since the relationship between SI and most of the climatic variables is non-linear,
312 the relationships are linearized through the B-spline functions. Nothdurft et al. (2012) chose
313 the number and location of the B-spline knots heuristically to avoid illogical behavior when
314 extrapolating beyond the range of the model data. The strength of the approach selected in the
315 present paper is that we ensure biologically sound results beyond the current range of climatic
316 conditions, and that behavior is defined by the data and the basic form of the models, avoiding

317 having to select heuristically some of the parameters. Other interesting approach to model the
318 effects of biophysical factors on tree growth is to model the effect of biophysical factors on the
319 potential tree height as it is done in SILVA (Pretzsch et al., 2002). This approach, however,
320 requires data on dominant height, which is neither currently recorded by the NNFI nor is
321 available from experimental plots in a representative scale for Norwegian conditions.

322 Our results show that SI increases with temperature. Due to interaction effects between
323 temperature and site quality, the increase becomes more pronounced with increasing site qual-
324 ity. This results are congruent with Sigurdsson et al. (2013), who found that the effect of
325 increase on temperature or CO₂ on mature Norway spruce in the boreal zone was not evident
326 unless nutrient availability was improved. Our results are also consistent with Pretzsch et al.
327 (2014) findings that growth acceleration, likely due to climate change, for Norway spruce since
328 1960 in Central Europe is stronger in more fertile sites.

329 The effects of the variables included in the final version of the models were logical and
330 in line with previous studies. In Norway, Andreassen et al. (2006) underlined the effect of
331 temperature and precipitation on Norway spruce growth based on tree-ring series. Andreassen
332 et al. (2006) concluded that, of the variables explored, June temperature and precipitation
333 had the largest influence on tree ring increments of the variables explored, which is consistent
334 with our results. For all three species, most of the variability was explained by MOD_T , which
335 is also consistent with previous studies on the relationship between climatic factors and tree
336 growth in Fennoscandia, which show that growth is mainly determined by summer temperature
337 (e.g. Ge et al., 2011; Andreassen et al., 2006). Ge et al. (2011) used a process-based growth
338 model to assess the impacts of climate change on stem wood growth. They found that most of
339 the variability of annual growth in Norway spruce in Finland was explained by temperature,
340 particularly June temperature, while the relationship between annual growth and monthly
341 precipitation was more subtle. Andreassen et al. (2006) also found stronger correlations of
342 growth with summer temperatures than with monthly precipitation for Norway spruce in
343 Norway. The fact that moisture surplus is not included in the final model for spruce is not
344 to say that that moisture surplus is not an important factor in spruce dominated stands
345 productivity. Rather, it indicates that moisture surplus is not a limiting factor within the
346 current range of spruce dominated stands.

347 For pine dominated stands the optimal MSJ is lower than for deciduous dominated stands.
348 This is not surprising, since pine dominated stands are already dominating the drier sites in
349 Norway (Figure 2).

350 One of our main objectives was to make the models biologically sound, which is a require-
351 ment when the aim of the models is to forecast the productivity of large non-homogeneous
352 areas. To achieve this objective we used empirical data and a modeling approach that bounds
353 the response of the model between a maximum, the potential, and a minimum, defined as the
354 minimum recorded SI (6m). As a result of this, even if the conditions on a plot for a certain
355 species become unsuitable for the survival of the species or the plot becomes unproductive, the
356 model will still give an estimate of the SI between the minimum and the maximum. Predict-
357 ing the suitability of a site for the survival or establishment of a species should be answered
358 separately, and it is not within the scope of this paper.

359 There are other considerations that should be taken into account when applying climate
360 sensitive SI models. One should be careful when applying these models to already established
361 stands, as the climate-growth response of the stands already established might depend on
362 the provenance of the trees, their age, and elevation, among other factors (Primicia et al.,
363 2015). Productivity might also be affected by other factors that might change with time and
364 that are not considered here, like CO₂, nitrogen deposition (Sigurdsson et al., 2013), nutrient
365 availability, and solar radiation.

366 The potential component (POT) is the mean SI index at a given site quality (SQ) when
367 neither temperature or moisture are limiting. Even under the best climatic conditions there
368 are other factors that limit the growth of trees, such as light and nutrient availability, or me-
369 chanical factors (e.g. wind, snow). Since the fit of a model is usually performed by minimizing
370 weighted errors, the model will predict the average SI found under certain site conditions,
371 temperature, and precipitation, which will never be the maximum SI observed because of the
372 imperfect correlation between SI and the variables of the models, and the error implicit in
373 the measurements of the variables. Thus, the models correctly predict trends due to a change
374 in temperature or precipitation, but they will predict expected SI under given conditions. In
375 order to predict future SI under climate change, we suggest that the models should be used
376 to predict SI change (predicted SI in future climate - predicted SI in current climate) which

377 then is added to the currently observed SI. If no information about the current site index is
378 available, the models can be used directly but with an expectation of a larger error than when
379 current site index information is available. If there is information about current SI and the
380 model is used to predict SI change, the predicted SI can exceed POT.

381 Thanks to the broad array of conditions currently present in Norway we have been able to
382 use the space-for-time substitution, an approach widely used in other fields such as biodiversity
383 modeling (Blois et al., 2013), to predict climate change effects on SI for Norway. The space-for-
384 time substitution assumes that spatial and temporal variation are equivalent. This approach is
385 commonly used accross fields when long-term time-series data are not available. However, this
386 approach has some drawbacks that should be considered. For example, as with any empirical
387 model, caution should be used when extrapolating beyond the original range. Also, although
388 SI is assessed at each cycle of the NNFI, the observed SI is the result of the stand history and
389 climate throughout the life of the trees currently in the stand, and as so, it is an imperfect
390 measurement of the current SI if a new stand were to be established. Since the observed SI is
391 the result of the compound response over the life span of the trees, we chose to use the average
392 of the climatic variables over the last 30-years, instead of using only more recent data, as the
393 explanatory variable for our SI models.

394 When the best models are applied using climate projections for 2100 (RCP4.5), the patterns
395 of change observed in Figure 9 reflect the behavior of the models. The general trend for all plots
396 considered and all species is an increase in SI for 2100. For more extreme climate scenarios (e.g.
397 RCP8.5) the results may be considerably different than under RCP4.5. The moisture indicator,
398 MSJ, does not change dramatically between MET7908 and RCP4.5, which is why there are only
399 very few plots with a decrease in SI greater than 1 meter (Figure 9). Contrary to the presented
400 results, studies from other parts of the boreal forest indicate reduced forest productivity. For
401 example, projections for Canada under climate change indicate a likely decrease in productivity
402 in areas with relative high water stress and low water-holding capacity, but an increase on forest
403 productivity on sites with high water-holding capacity during the 21st century (Johnston et al.,
404 2009). In northern Finland, where soil moisture seldom limits forest growth, stem wood growth
405 are expected to be higher under climate change, while in southern Finland stem wood growth
406 is, on average, lower under climate change due to limited water availability compared with the

current climate (Ge et al., 2011). Climatic projections for Norway forecast a generally warmer and wetter climate (Stocker et al., 2013), and at least for RCP4.5, it seems that the higher precipitation will, in general, compensate the higher water requirements and result in higher productivity for most areas in Norway and mainly for spruce and deciduous dominated stands.

Finally, despite the restrictions of the modelling approach and the obvious limitations in forest growth prognoses, the models presented in this paper present a robust and easily applicable basis for SI prediction in boreal conditions.

5. References

References

Aertsen, W., Kint, V., van Orshoven, J., Özkan, K., Muys, B., 2010. Comparison and ranking of different modelling techniques for prediction of site index in Mediterranean mountain forests. *Ecological Modelling* 221, 1119–1130.

Akaike, H., 1974. A new look at the statistical model identification. *IEEE transactions on automatic control* 19, 716–723.

Albert, M., Schmidt, M., 2010. Climate-sensitive modelling of site-productivity relationships for Norway spruce (*Picea abies* L. Karst.) and common beech (*Fagus sylvatica* L.). *Forest Ecology and Management* 259, 739–749.

Andreassen, K., Solberg, S., Tveito, O.E., Lystad, S.L., 2006. Regional differences in climatic responses of Norway spruce (*Picea Abies* L. Karst) growth in Norway. *Forest Ecology and Management* 222, 211–221.

Assmann, E., 1970. *Principles of forest yield study*. Pergamon Press Ltd., Oxford.

Astrup, R., Dalsgaard, L., Eriksen, R., Hysten, G., 2010. Utviklingsscenarioer for karbonbinding i Norges skoger [Development scenarios for carbon sequestration in Norwegian forest]. Oppdragsrapport fra Skog og landskap 16/10. Norwegian Forest and Landscape Institute. Ås, Norway. In Norwegian with English summary.

Belcher, D.M., Brand, G.J., 1982. A description of STEMS- the stand and tree evaluation and modeling system. Gen. Tech. Rep.

- Beven, K.J., Kirkby, M.J., 1979. A physically based, variable contributing area model of basin hydrology. *Hydrological Sciences Bulletin* 24, 43–69.
- Blois, J.L., Williams, J.W., Fitzpatrick, M.C., Jackson, S.T., Ferrier, S., 2013. Space can substitute for time in predicting climate-change effects on biodiversity. *Proc. Natl. Acad. Sci. U.S.A.* 110, 9374–9379.
- Canham, C.D., Uriarte, M., 2006. Analysis of neighborhood dynamics of forest ecosystems using likelihood methods and modeling. *Ecological Applications* 16, 62–73.
- Crookston, N.L., Rehfeldt, G.E., Dixon, G.E., Weiskittel, A.R., 2010. Addressing climate change in the forest vegetation simulator to assess impacts on landscape forest dynamics. *Forest Ecology and Management* 260, 1198–1211.
- Ge, Z.M., Kellomäki, S., Peltola, H., Zhou, X., Wang, K.Y., Väisänen, H., 2011. Impacts of changing climate on the productivity of Norway spruce dominant stands with a mixture of Scots pine and birch in relation to water availability in southern and northern Finland. *Tree Physiol.* .
- Goffe, W.L., Ferrier, G.D., Rogers, J., 1994. Global optimization of statistical functions with simulated annealing. *Journal of Econometrics* 60, 65–99.
- Harrell, F.E., 2001. Regression modelling strategies with applications to linear models, logistic regression, and survival analysis. Springer, New York, NY.
- Johnston, M.H., Campagna, M., Gray, P.A., Kope, H.H., Loo, J.A., Ogden, A.E., O'Neill, G., Price, D.T., Williamson, T.B., 2009. Vulnerability of Canada's tree species to climate change and management options for adaptation: an overview for policy makers and practitioners. Res. Coun. Pub. 12416-1E10. Canadian Council of Forest Ministers.
- Kauppi, P.E., Posch, M., Pirinen, P., 2014. Large Impacts of Climatic Warming on Growth of Boreal Forests since 1960. *PLoS ONE* 9, e111340.
- Lilles, E.B., Astrup, R., 2012. Multiple resource limitation and ontogeny combined: a growth rate comparison of three co-occurring conifers. *Can. J. For. Res.* 42, 99–110.

Antón-Fernández, Mola-Yudego, Dalsgaard, Astrup

19

- 460 Moss, R.H., Babiker, M., Brinkman, S., Calvo, E., Carter, T., Edmonds, J.A., Elgizouli, I.,
461 Emori, S., Lin, E., Hibbard, K., others, 2008. Towards new scenarios for analysis of emis-
462 sions, climate change, impacts, and response strategies. Technical Report. Pacific Northwest
463 National Laboratory (PNNL), Richland, WA (US).
- 464 Murphy, L., 2015. likelihood: Methods for maximum likelihood estimation, R package version
465 1.7.
- 466 Nigh, G., Ying, C.C., Qian, H., 2004. Climate and productivity of major conifer species in the
467 interior of British Columbia, Canada. *Forest Science* 50, 659–671.
- 468 Nothdurft, A., Wolf, T., Ringeler, A., Böhner, J., Saborowski, J., 2012. Spatio-temporal pre-
469 diction of site index based on forest inventories and climate change scenarios. *Forest Ecology*
470 *and Management* 279, 97–111.
- 471 Palmer, W., 1965. Meteorological drought. Res. Pap. 45 45. U.S. Weather Bureau.
- 472 Peltola, H., Ikonen, V.P., Gregow, H., Strandman, H., Kilpeläinen, A., Venäläinen, A., Kel-
473 lomäki, S., 2010. Impacts of climate change on timber production and regional risks of
474 wind-induced damage to forests in Finland. *Forest Ecology and Management* 260, 833–845.
- 475 Pretzsch, H., Biber, P., Schütze, G., Uhl, E., Rötzer, T., 2014. Forest stand growth dynamics
476 in Central Europe have accelerated since 1870. *Nature Communications* 5.
- 477 Pretzsch, H., Biber, P., Ďurský, J., 2002. The single tree-based stand simulator SILVA: con-
478 struction, application and evaluation. *Forest Ecology and Management* 162, 3–21.
- 479 Primicia, I., Camarero, J.J., Janda, P., Čada, V., Morrissey, R.C., Trotsiuk, V., Bače, R.,
480 Teodosiu, M., Svoboda, M., 2015. Age, competition, disturbance and elevation effects on
481 tree and stand growth response of primary *Picea abies* forest to climate. *Forest Ecology and*
482 *Management* 354, 77–86.
- 483 R Core Team, 2015. R: A language and environment for statistical computing. R Foundation
484 for Statistical Computing. Vienna, Austria.

©2016 NRC Canada

- 485 Royal Meteorological Institute of The Netherlands (KNMI), 2014. CMIP5 Scenario Runs
486 - Surface Variables [online]. [http://climexp.knmi.nl/selectfield_cmip5.cgi?id=](http://climexp.knmi.nl/selectfield_cmip5.cgi?id=someone@somewhere)
487 [someone@somewhere](http://climexp.knmi.nl/selectfield_cmip5.cgi?id=someone@somewhere). [accessed 14 jun 2014].
- 488 Sabatia, C.O., Burkhardt, H.E., 2014. Predicting site index of plantation loblolly pine from
489 biophysical variables. *Forest Ecology and Management* 326, 142–156.
- 490 Schwarz, G., 1978. Estimating the dimension of a model. *Ann. Stat.* 6, 461–464.
- 491 Seynave, I., Gégout, J.C., Hervé, J.C., Dhôte, J.F., Drapier, J., Bruno, E., Dumé, G., 2005.
492 *Picea abies* site index prediction by environmental factors and understorey vegetation: a
493 two-scale approach based on survey databases. *Canadian Journal of Forest Research* 35,
494 1669–1678.
- 495 Sharma, R.P., Brunner, A., Eid, T., 2012. Site index prediction from site and climate variables
496 for Norway spruce and Scots pine in Norway. *Scandinavian Journal of Forest Research* 27,
497 619–636.
- 498 Sigurdsson, B.D., Medhurst, J.L., Wallin, G., Eggertsson, O., Linder, S., 2013. Growth of
499 mature boreal Norway spruce was not affected by elevated [CO₂] and/or air temperature
500 unless nutrient availability was improved. *Tree Physiology* 33, 1192–1205.
- 501 Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia,
502 Y., Bex, V., Midgley, P.M. (Eds.), 2013. *Climate change 2013: The physical science basis.*
503 *Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental*
504 *Panel on Climate Change.* Cambridge University Press, Cambridge, United Kingdom and
505 New York, NY, USA.
- 506 Thomson, A.M., Calvin, K.V., Smith, S.J., Kyle, G.P., Volke, A., Patel, P., Delgado-Arias, S.,
507 Bond-Lamberty, B., Wise, M.A., Clarke, L.E., Edmonds, J.A., 2011. RCP4.5: a pathway for
508 stabilization of radiative forcing by 2100. *Climatic Change* 109, 77–94.
- 509 Thornthwaite, C.W., 1948. An approach toward a rational classification of climate. *Geograph-*
510 *ical review* 38, 55–94.
- 511 Tveite, B., Braastad, H., 1981. Bonitering for gran, furu og bjork. *Norsk Skogbruk* 27, 17–22.

Antón-Fernández, Mola-Yudego, Dalsgaard, Astrup 21

512 Weiskittel, A.R., Crookston, N.L., Radtke, P.J., 2011. Linking climate, gross primary produc-
513 tivity, and site index across forests of the western United States. Canadian Journal of Forest
514 Research 41, 1710–1721.

Draft

Fig. 1. Definition of the variable site quality (SQ). Missing squares represent combinations that did not exist in the data.

Fig. 2. Site index (left) and soil wetness (right) distribution by species dominating the stand.

Fig. 3. Maps of the distribution and range of the temperature and moisture variables included in the models. The maps are interpolations of the climatic data at the plots, masked to show only productive forest area in Norway. TSUM (in °C) is the sum of the 30-year average temperatures in April, May, and June. MSJ (in mm) is the moisture surplus in June, defined as the difference between 30-year average precipitation in June and average potential evapotranspiration in June.

Fig. 4. Sensitivity graphs for the spruce model (md2).

Fig. 5. Contour plots showing the behavior of md2 for pine dominated stands. Grey rectangles indicate combinations of MSJ, TSUM and SQ that existed in the fitting dataset.

Fig. 6. Contour plots showing the behavior of md2 for deciduous dominated stands. Grey rectangles indicate combinations of MSJ, TSUM and SQ that existed in the fitting dataset.

Fig. 7. Residuals of the best model for each species against the predicted SI. A loess smooth function with span smoothing parameter = $2/3$ and degree of local polynomial = 1 is shown in black.

Fig. 8. Distribution of TSUM and MSJ under current climate (C) and RCPs 4.5 projections (F).

Fig. 9. Maps of current SI (top), projected SI (middle), and projected SI change (bottom). Projections are made using the best models for spruce dominated stands (left), pine dominated stands (middle), and deciduous dominated stands (right), and climate data from the multimodel (67) ensemble mean monthly temperature and precipitation outcomes from representative concentration pathway (RCPs) 4.5 from the CMIP5 21st century experiments.

Table 1. Number of observations by site quality and species dominating the stand. The + indicates categories aggregated with the next closest category.

	Spruce	Pine	Deciduous
SQ1	+	1183	+
SQ2	712	927	433
SQ3	1697	540	1061
SQ4	915	110	928
SQ5	172	+	265
Total	3496	2760	2687

Draft

Table 2. Definition of the components for each species group. [SQ] indicates when the parameters vary with the site quality parameter.

spruce dominated	POT	$\pi_0[SQ]$
	MOD_T	$(1 + \exp(-\tau_1[SQ] \cdot TSUM + \tau_0[SQ]))^{-1}$
	MOD_M	$(1 + \exp(-\mu_1 \cdot MSJ + \mu_0))^{-1}$
pine dominated	POT	$\pi_0[SQ]$
	MOD_T	$(1 + \exp(-\tau_1 \cdot TSUM + \tau_0[SQ]))^{-1}$
	MOD_M	$\xi^{-1} \cdot \mu_1 / \alpha \cdot ((MSJ - \mu_0) / \alpha)^{\mu_1 - 1} \exp(-((MSJ - \mu_0) / \alpha)^{\mu_1})$
deciduous	POT	$\pi_0[SQ]$
	MOD_T	$(1 + \exp(-\tau_1 \cdot TSUM + \tau_0))^{-1}$
	MOD_M	$\xi^{-1} \cdot \mu_1 / \alpha \cdot ((MSJ - \mu_0) / \alpha)^{\mu_1 - 1} \exp(-((MSJ - \mu_0) / \alpha)^{\mu_1})$

Draft

Table 3. Parameter estimates and measures of goodness of fit for the two candidate models for the three species.

Parameters	spruce md1	pine md1	pine md2	deciduous md1	deciduous md2
$\pi_0[SQ1]$		9.0797	9.469		
$\pi_0[SQ2]$	15.4929	12.7145	13.3917	14.4688	13.041
$\pi_0[SQ3]$	21.7727	13.3343	14.7684	20.1651	18.0119
$\pi_0[SQ4]$	22.9493	16.7999	17.8809	25.3659	22.5634
$\pi_0[SQ5]$	26.1775			29.5949	25.9418
τ_1		0.1576	0.2068	0.1126	0.1125
τ_0				3.1924	2.7009
$\tau_0[SQ1]$		1.8948	2.4028		
$\tau_0[SQ2]$		2.3125	2.9211		
$\tau_0[SQ3]$		1.7933	2.4689		
$\tau_0[SQ4]$		2.5339	3.0053		
ξ			0.0076		0.0060
μ_1			1.5042		1.8939
μ_0			-103.5199		-115.2986
α			98.0557		137.4867
AIC	17427	13121	12844	12742	12539
BIC	17508	13180	12921	12784	12598
R^2_{adj}	0.56	0.33	0.40	0.50	0.54
RMSE	2.91	2.60	2.47	2.58	2.49