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Modelling effects of climate on site productivity of white pine plantations

Responding to Climate Change Through Partnership

Ontario

Modelling effects of climate on site productivity of white pine plantations

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Summary

Site productivity depends on environmental factors such as biotic, edaphic, and climatic conditions and in forestry is represented by site index (SI) or height at a given base age. Traditional SI equations are built on the assumption that climate remains constant. As climate is not constant and its variability is predicted to increase, climate variables were incorporated into stand height/site index equations developed for white pine (*Pinus strobus*) plantations.

Three dominant or co-dominant white pine trees were sampled from 93 plots in even-aged monospecific plantations at 31 sites across Ontario, Canada. Stem analysis data collected from these trees was used to develop and evaluate SI equations. The effects of climate on site productivity were examined by regressing site index against climate variables. Results indicated that site specific attributes explained 52% of the variability in white pine site productivity estimates.

Significant in the regression were growing season total precipitation (GSTP), growing season mean temperature (GSMT), August mean monthly precipitation (AugMP), and total climatic moisture index (TCMI). Significant climate variables were incorporated into the stand height growth models but only GSTP and GSMT were significant. Including climate variables significantly improved the fit statistics of the stand height model for white pine trees. A covariance structure (AR(1)) was used to address autocorrelation in the data.

Using the stand height growth model with climate variables incorporated, stand heights were predicted for 4 areas (middle, easternmost, westernmost and southernmost parts of Ontario where white pine were sampled) for the period 2021 to 2080 under 2 emissions trajectories known as representative concentration pathways (RCPs), with each reflecting different levels of heat at the end of the century (i.e., 2.6 and 8.5 watts m^{-2}). At the end of the 2021 to 2080 growth period, projected heights were shorter under both climate change scenarios compared to those under a no change scenario for 3 areas (eastern, western, and southern Ontario). Under both climate change scenarios, the decrease in height growth was more pronounced in the south than in the east and west, and was negligible in the centre of the province.

The resulting height growth models can be used to estimate stand heights for white pine plantations in a changing climate. Using the same model, site index of a plot/stand can be estimated by calculating height at a given base (index) age. In the absence of climate data, the model fitted without climate variables can be used to estimate stand heights and site indices.

Sommaire

Modélisation des effets du climat sur la productivité des stations de plantations de pins blancs

La productivité d’une station dépend de facteurs environnementaux comme les conditions biotiques, édaphiques et climatiques; en foresterie, elle est représentée par l’indice de qualité de station (IQS) ou la hauteur à un âge de référence donné. Les équations traditionnelles de l’IQS reposent sur l’hypothèse d’un climat constant. Or, vu que le climat n’est pas constant et que sa variabilité tend à augmenter, des variables climatiques ont été intégrées aux équations hauteur dominante/indice de qualité de station formulées pour des plantations de pins blancs (*Pinus strobus*).

Trois pins blancs dominants ou codominants ont été échantillonnés à partir de 93 parcelles-échantillons dans des plantations monospécifiques équiennes situées dans 31 stations en Ontario, au Canada. Les données d’analyses de tiges recueillies avec ces arbres ont été utilisées pour établir et évaluer des équations d’IQS. Les effets du climat sur la productivité des stations ont été étudiés en fonction d’une régression de l’indice de qualité de station par rapport à des variables climatiques. Selon les résultats, 52 % de la variabilité liée aux estimations de la productivité des stations de pins blancs étaient attribuables à des caractéristiques propres aux stations.

Les précipitations totales pendant la saison de croissance (PTSC), la température moyenne pendant la saison de croissance (TMSC), les précipitations mensuelles moyennes en août (PMMA) et l’indice d’humidité climatique totale (IHCT) ont joué un rôle significatif dans la régression. Des variables climatiques importantes ont été introduites dans les modèles de croissance de la hauteur dominante, mais seules les PTSC et la TMSC étaient représentatives dans ces modèles. Notons que l’intégration de variables climatiques a amélioré considérablement les statistiques d’ajustement du modèle de hauteur dominante pour les pins blancs. Une structure de

covariance (AR(1)) a par ailleurs été utilisée pour aborder l’autocorrélation dans les données.

À l’aide du modèle de croissance de la hauteur dominante intégrant les variables climatiques, les hauteurs dominantes ont été prédites pour quatre régions (régions au milieu de la province et celles tout à l’est, tout à l’ouest et tout au sud, où des pins blancs ont été échantillonnés) pour la période s’échelonnant de 2021 à 2080 selon deux trajectoires d’émissions appelées « profils représentatifs d’évolution de concentration (RCP) ». Chacune reflétait des niveaux de chaleur différents à la fin du siècle (2,6 et 8,5 W/m²). À la fin de la période de croissance s’échelonnant de 2021 à 2080, les hauteurs prévues étaient moins élevées selon les deux scénarios de changement climatique que selon un scénario statique pour trois régions (Est, Ouest et Sud de l’Ontario). Selon les deux scénarios de changement climatique, la diminution de la croissance en hauteur était plus marquée au Sud de l’Ontario par rapport à l’Est et à l’Ouest, et elle était négligeable dans le centre de la province.

Les modèles de croissance en hauteur obtenus peuvent être utilisés pour estimer la hauteur dominante de plantations de pins blancs dans un climat en évolution. Le même modèle peut servir à l’évaluation de l’indice de qualité d’une parcelle ou d’un peuplement grâce au calcul de la hauteur à un âge de référence (indice) donné. En l’absence de données climatiques, le modèle ne recourant pas aux variables climatiques peut aider à estimer les hauteurs dominantes et les indices de qualité de station.

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Contents

1.0 Introduction

Site index (SI) is a measure of site productivity. It helps predict the pattern of stand height development over time. Therefore, it is a critical variable in most growth and yield models. It is also a key driver used in the prediction of stand and forest volume, biomass, and carbon content. Carbon budget models such as CBM-CFS3 (Kurz et al. 2009) and FORCARB2 (Heath et al. 2010) rely heavily on forest growth and yield forecasts making SI equations an integral component.

Site productivity is influenced by environmental factors such as biotic, edaphic, and climatic conditions (Clutter et al. 1983). However, most traditional SI equations assume that climate remains constant and are strictly a function of tree age. Growth and yield models based on these SI models are used to forecast rates and patterns of stand development over long periods.

The climate is changing and is predicted to be generally warmer and more variable, with more frequent and longer hot periods in summer and cold periods in winter. Similarly, precipitation extremes are projected to become more frequent. Anticipated changes in Ontario's climate repudiate reliance on static SI curves even further. Summer temperatures for 2071–2100 predicted using one of the scenarios approved by the Intergovernmental Panel on Climate Change that is based on projections of changes in human population and greenhouse gas concentrations in the atmosphere indicate Ontario summer temperatures may rise by 3 to 6 °C by the end of the 21st century, with more pronounced differences in the north. These changes are likely to significantly affect tree growth rates.

Including climate variables in SI models will not only make them more realistic but will add dynamic predictive abilities to the models in which they are used such as benchmark yield curves, density management diagrams, and tree-scale models such as FVS$^{\text{Ontario}}$. Sharma et al. (2015) analyzed climate effects on site productivity of jack pine (*Pinus banksiana*) and black spruce (*Picea mariana*) plantations and reported that projected changes in climate would reduce site productivity of both species, with greater effects on black spruce than jack pine. Similarly, Sharma and Parton (2018a, b) examined climate effects on site productivity of red pine (*Pinus resinosa*) and white spruce (*Picea glauca*) plantations. They found that warming climate would negatively affect the site productivity of both species, with effects more pronounced in southern than northern Ontario for red pine and more in eastern than western and southern Ontario for white spruce.

The objectives of this study were to investigate the effects of climate on the SI of white pine (*Pinus strobus*) plantations, and to develop base-age invariant stand height/SI models that directly incorporate site and climate variables to improve model predictions and explore the effect of a changing climate on stand height and associated SI.

2.0 Methods

2.1 Height and age data

Data used to develop the site index models were collected from plantation-grown white pine trees. Thirty-one even-aged monospecific plantations were sampled from across the species' range in Ontario (Figure 1). At each plantation, three 100 m^2 circular temporary sample plots were established. In each plot, 1 planted largest diameter (at breast height) non-veteran tree that did not exhibit visible deformities, such as forks, major stem injuries, dead or broken tops, was selected and sampled. From each sampled tree, disks were cut at 0.15, 0.5, 0.9, and 1.3 m from ground level. The remaining height of the tree (between breast height and tip) was then divided by 10 and disks were cut at the resulting interval to yield 13 disks per tree.

Each sampled tree and disk was assigned a unique code. All disks from a tree were placed in a large breathable bag, transported, and stored at -10 °C until 24 hours before they were prepared for analysis, which involved sanding the surface of the disk. At time of analysis, geometric mean radius (r) was calculated from the diameters obtained from the major (r_1) and minor (r_2) axes on each disk (i.e., $r = (r_1.r_2)^{0.5}$). On each section, 2 radii matching this geometric mean were located and marked. All measurements were to the inner bark. All disks were scanned and the resulting images saved at a minimum resolution of 720 dpi. Using WINDENDRO™ software, images were analyzed for diameter growth and ring number along the radii marked from the pith.

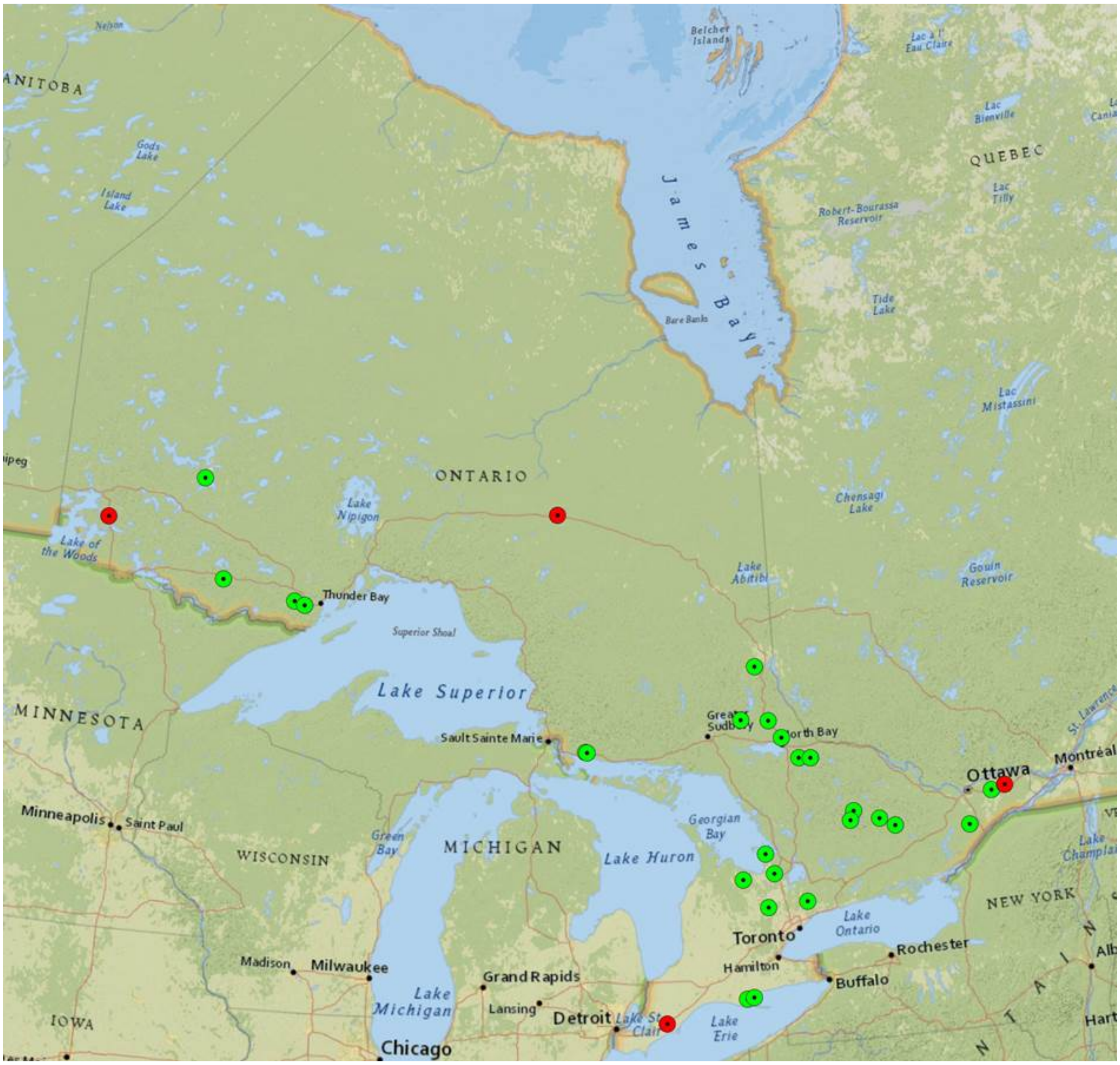

Figure 1. Distribution of white pine plantations sampled across Ontario, Canada. Models were developed using data from sites marked by all circles (green and red) and evaluated using that from sites marked by red circles.

Height of each tree at a given age along the bole was determined using Graves' (1906) method, which Subedi and Sharma (2010) reported as more accurate than other available methods for identifying where annual height growth ended. Annual height growth was then calculated for each tree. Observed stand heights and ages were plotted to form height-age curves for each tree. These curves were inspected for indications of early height growth suppression, top breakage, or dieback. None of the trees sampled showed any defects so data from all 93 trees was analyzed. To avoid the erratic height growth that often occurs before trees reach breast height, height above breast height and breast height age (BHA) were used in this study. Therefore, unless otherwise specified, reported heights and ages refer to stand heights from breast height and BHA, respectively.

To obtain site-scale observations of stand height, growth series from each plot were averaged to provide a mean plot growth curve. For plots that contained trees of different ages, series were truncated to the age of the youngest tree. This resulted in 31 total height-age series. For each series, average height was calculated at every 5-year non-overlapping interval starting at age 1 (from breast height) to minimize serial autocorrelation among observations and measurement errors in the ring data. Similarly, site index was calculated as the average height of 3 dominant/codominant trees sampled from a site at BHA 25 years. Summary statistics of sampled trees used in this study are presented in Table 1.

Table 1. Summary statistics (N = number of samples; SD = standard deviation) for total age, total height, breast height age (BHA), site index (SI), growing season total precipitation (GSTP), growing season mean temperature (GSMT), August mean monthly precipitation (AugMMP) and total climatic moisture index (TCMI) for white pine trees from Northern Ontario, Canada, used in this study.

Variable	N	Mean	SD	Min	Max
Total age (year)	93	61.37	17.18	26	90
Total height (m)	93	22.63	5.84	10.25	37.60
BHA (year)	93	56.45	17.30	21	87
SI (m)	29	10.50	2.29	6.85	15.85
GSTP	31	500.56	50.86	366.45	577.53
GSMT	31	13.78	0.54	12.62	15.13
AugMMP	31	78.45	4.05	69.92	84.68
TCMI	31	32.18	8.65	14.99	47.69

2.2 Climate data

None of the sample plots were near weather stations. Therefore, Canadian climate models (McKenney et al. 2011) were used to estimate a suite of climate variables for each plot location. These models were generated from continuous climate grids using ANUSPLINE based on corrected Canadian weather station data (Mekis and Vincent 2011, Vincent et al. 2012), which includes many stations in Ontario. Estimates of long-term average values of these variables at each plot location were calculated for the period of tree growth (from the year when the sampled trees reached breast height to 2015).

A total of 68 variables were calculated, including mean, minimum, and maximum air temperatures and total precipitation, estimated for each month of the year, for each quarter (consecutive 3-month periods), and annually. As well, climate data included estimates for start, end, and length of the growing season and the sum of growing degree days using a base temperature of 5 °C. Growing season was defined as the length of time between the day after March 1 when mean daily temperature was ≥5 °C for 5 consecutive days and the day after August 1 when minimum daily temperature was ≤-2 °C. The 68 variables also included 3 site related ones (longitude, latitude, and elevation).

In addition to the climate variables, climatic moisture index (CMI), obtained by subtracting monthly potential evapotranspiration (PET) from mean monthly precipitation (MMP) (see Hogg 1994), was estimated for each month for each year. Total climatic moisture index (TCMI) was then calculated by summing the 12 month values of CMI for each year for each site. Estimates for all climate variables were provided by Dan McKenney (Canadian Forest Service, 2018, pers. comm.).

2.3 Effects of climate on site productivity

Climatic effects on site productivity were determined by regressing SI against climate variables. The stepwise regression method was applied in SAS (SAS Institute Inc. 2004) using FORWARD, BACKWARD, and MAXR (maximum R^2) selection criteria to examine the importance of each site and climate variable in the regression. However, BACKWARD selection resulted in better fit statistics than other criteria. Given the limited number of SI values (29) as trees from 2 sites were younger than 25 BHA, climate data was grouped into site, periodic temperature, periodic precipitation, monthly temperature, and monthly precipitation related variables. Site index was regressed against the site and climate variables within a group and significant variables from each group were pooled. Finally, SI was regressed against pooled site and climate variables.

2.4 Stand height/site index models

The relationship between height and age is generally described using nonlinear mathematical models. Most often, these models are derived from single curve-based models that can be exponential or fractional functions (Cieszewski 2003). The most common exponential model used to describe height-age relationship is the Chapman-Richards growth function (see Burkhart and Tennent 1977, Carmean and Lenthall 1989, Goelz and Burk 1992, Garcia 2005). Similarly, the fractional function most appropriate to describe height development over time is Hossfeld IV (Cieszewski 2003).

Sharma et al. (2015) and Sharma and Parton (2018a, b) evaluated variants of these functions for several boreal tree species in Canada and found the following variant of the Hossfeld IV function (Eq. 1), also known as McDill-Amateis growth function (see Burkhart and Tome 2012, p. 126), provided the best fit statistics (R^2 and MSE) and produced the most consistent and biologically realistic height estimates across productivity classes:

$$H = \frac{\alpha_0}{1 - \left(1 - \frac{\alpha_0}{H_1}\right)\left(\frac{A_1}{A}\right)^{\alpha_1}} \quad (1)$$

where, H and H_1 are stand heights (from breast height) at BHAs A and A_1, respectively, and α_0 and α_1 are model parameters. In general, α_0 defines the asymptote of the curve and α_1 determines the shape. Therefore, this model form was adapted as the stand height growth model for this study. To model the effects of climate on stand height growth, the asymptote and rate parameter (α_0 and α_1, respectively) in Eq. (1) were expressed in terms of climate variables.

2.5 Model fitting and evaluation

Stem analysis was used to acquire the data used in this study. To obtain height-age series for a site, multiple measurements were made on individual sample trees, resulting in hierarchical data sets (i.e., height-age series within sites). This resulted in 2 sources of variation: among sites and within a site. Observations among sites are independent but observations within a site (height-age series) are dependent (correlated) as they originate from the same trees. Within a sampling unit, mixed-effects modelling (Meng et al. 2009; Subedi and Sharma 2011, 2013), correlation structure (Diéguez-Aranda et al*.* 2006), or a combination of both approaches (Trincado and Burkhart 2006, Subedi and Sharma 2013) can be used to address the autocorrelation problem.

NLINMIX macro in SAS was used to fit Eq. (1) to the data with 2 random effects parameters associated with the asymptote and the rate parameter first. To address problems associated with autocorrelation, the model was fitted using the covariance structure AR(1). Climate and site related variables were then introduced sequentially from each group. Initially, all precipitation-related variables were introduced into the model one by one. The variable that was significant (alpha=0.05) and resulted in the best fit was selected as the first climate (precipitation) variable to be included in the model.

All temperature-related variables were then introduced into the model one by one in the presence of the first climate (precipitation) variable. The one that was significant and resulted in the least AIC value was selected as the second climate (temperature) variable to be incorporated. All other climate and site variables, including quadratic transformations and 2-way interactions, were introduced one by one in the presence of the first 2 variables. The climate and site variables selected were those that were both significant and improved model fit.

Random effects parameters were added sequentially to the fixed-effects coefficients of climate variables as necessary. The model with random effects was evaluated based on goodness-of-fit criteria such as log-likelihood (twice the negative log-likelihood) ratio, assessment of model residuals, and Akaike's Information Criterion

(AIC) (Akaike 1978). The model with the smallest goodness-of-fit value was considered best. The structure that resulted in the smallest value of AIC was used in the final model. To check for possible heteroscedasticity, estimates of residuals (observed − predicted) from stand height growth were calculated (with the covariance structure in the model) for all 5-year growth periods for each growth series and plotted against predicted stand height growth.

Climatic effects on future stand height growth were evaluated by estimating stand heights of white pine trees using the model with climate variables for 4 areas (the middle (near Hearst) and the most eastern (near Ottawa), southern (near Chatham), and western (near Kenora) parts of Ontario where the trees were sampled (shown in Figure 1) under 2 emissions trajectories (2.6 and 8.5 Watts m^{-2}). These trajectories, known as representative concentration pathways (RCPs), produce different levels of warming at the end of the century using the Canadian model (McKenney et al. 2011, 2013). The projected values of climate variables (from McKenney et al. 2013) that were significant in expressing the asymptote and rate parameter in Eq. (1) were used in evaluating climate effects. Height growth curves were generated for the 60-year growth period (2021–2080).

3.0 Results

Parameter estimates for Eq. (1) fitted using NLINMIX macro in SAS are displayed in Table 2. Random effects parameters were not significant. Therefore, the model was fit only with AR(1) covariance structure. The model fit the data well but does not include climate variables.

To examine the effects of climate on site productivity, the site index (SI) was regressed against 35 site and climate variables along with their quadratic and exponential transformations and interactions using stepwise regression analysis in SAS. Four climate variables: wettest period mean temperature (WPMT), precipitation of wettest quarter (PWQ), August mean monthly precipitation (AugMMP), and total climatic moisture index (TCMI) explained 65% of variability in SI. However, PWQ and TCMI were highly correlated (correlation coefficient = 0.943) and the variance inflation factor

(VIF) associated with PWQ was 10.48. A variable with VIF greater than 10 is assumed to be highly influential in the regression. As a result, interpretation of the regression coefficients could be misleading. Therefore, climate variables that were not severely correlated but can explain the variation in SI were investigated.

Table 2. Parameter estimates, standard errors (SE), and fit statistics (MSE (σ_e^2), twice the negative log-likelihood (-2ln(L)), Akaike's Information Criterion (AIC), and autocorrelation (***ρ***) for the model without climate variables (Eq. 1) for white pine trees from Northern Ontario, Canada. (N/A = not applicable)

Parameters	Estimates	SE
α_0	89.0296	8.3753
α_1	1.0362	0.0243
σ_e^2	2.4807	N/A
-2Ln(L)	−11536.5	N/A
AIC	−11540.5	N/A
ρ	0.7354	N/A
R^2	0.9608	N/A

The best model found to express SI for white pine plantations in terms of climate variables that were not highly correlated was:

$$SI = a_0 + a_1\, GSTP + a_2\, GSMT + a_3\, AugMMP + a_4\, TCMI + \varepsilon \qquad (2)$$

where,

GSTP = growing season total precipitation,

GSMT = growing season mean temperature,

a_0 - a_4 are regression parameters, ε is the error term, and other variables are as defined earlier. All climate variables were significant ($p < 0.05$) in the regression and explained more than 52% of the variability in SI (Table 3). These variables were not highly correlated (highest value of the correlation coefficient was 0.68 between GSTP and TCMI and of VIF was 7.608 for GSTP).

These results indicated that the SI of white pine stands is significantly affected by climate. However, as adjacent sites in the same climate zone could have different site productivity, climate variables are not the only drivers of site productivity. Therefore, a model for stand height growth/site index with parameters expressed in terms of climate variables would be more appropriate to determine site productivity in a changing climate. As a result, the asymptote and rate parameter (α_0 and α_1, respectively) in Eq. (1) were expressed in terms of climatic variables.

Table 3. Parameter estimates, standard errors (SE), and fit statistics including mean square error (MSE), and variance inflation factor (VIF) for site index (SI) expressed in terms of climate variables (Eq. 2) for white pine trees from Northern Ontario, Canada. (N/A = not applicable)

Parameters	Estimates	SE	t-value	p-value	VIF
a_0	-22.3616	7.5242	-2.97	0.0039	0
a_1	0.0218	0.0098	2.22	0.0296	7.6080
a_2	0.9093	0.4114	2.21	0.0297	3.7215
a_3	0.1851	0.0385	4.80	<0.0001	2.1016
a_4	-0.1591	0.0391	-4.07	0.0001	4.2364
R^2	0.5276	N/A	N/A	N/A	N/A
Adj. R^2	0.5033	N/A	N/A	N/A	N/A
MSE	3.2016	N/A	N/A	N/A	N/A

Climate variables that explained significant (alpha=0.05) variation in height growth of dominant and co-dominant white pine trees were growing season total precipitation (GSTP) and growing season mean temperature (GSMT). Other climate variables that were significant in the SI regression were not significant in the presence of GSTP and GSMT. However, both parameters could not be expressed in terms of both climate variables. The asymptote and the rate parameter expressed as a linear function of GSTP and GSMT, respectively, resulted in the best model. Therefore, the model form that included climate variables was:

$$H = \frac{\beta_0+\beta_1 GSTP}{1-\left(1-\frac{\beta_0+\beta_1 GSTP}{H_1}\right)\left(\frac{A_1}{A}\right)^{\beta_2+\beta_3 GSMT}} + \varepsilon \tag{3}$$

where, $\beta_0 - \beta_3$ are parameters and other variables are as defined earlier. All other climatic variables that were significant in the stepwise regressions (Eq. 2) were not significant in the height growth models. Both intercepts of the linear expressions for the asymptote and rate parameter were positive but the coefficients of both climate variables were negative (Table 4). This indicates that an increase in GSTP and GSMT would reduce the asymptote (the maximum potential height) and the rate parameter.

Table 4. Parameter estimates, standard errors (SE) and fit statistics (MSE (σ_e^2)), twice the negative log-likelihood (-2ln(L)), and Akaike's Information Criterion (AIC) for the model with climate variables (Eq. 3) for white pine trees from Northern Ontario, Canada. (N/A = not applicable)

Parameters	Estimates	SE
β_0	177.91	32.4112
β_1	−0.1360	0.0587
β_2	1.2269	0.03784
β_3	−0.01498	0.00273
σ_e^2	2.3828	N/A
ρ	0.7286	N/A
-2Ln(L)	−11474.3	N/A
AIC	−11478.3	N/A

When climate variables were included in the model all fit statistics (MSE, log-likelihood, AIC) decreased (tables 2 and 4). Thus, Eq. (3) not only incorporated climate variables but also improved the fit statistics. As a result, Eq. (3) could be used to explain the effects of climate on stand height growth for white pine plantations. Random-effects parameters were added to the fixed-effects coefficients of climate variables sequentially. However, none of the random effects were significant in the regression.

Heteroscedasticity was not apparent from residual plots. Estimates of studentized residuals (observed − predicted) from stand height growth were calculated (with the AR(1) structure in the model) for all 5-year growth periods for each growth series and plotted against predicted stand height growth (not shown). Trends in error structure did not suggest autocorrelation or heteroscedasticity. The first order autoregressive autocorrelation structure (*ρ)* indicated that model error terms were positively correlated with the residual of the prediction from the previous period.

Equation (4) was further evaluated by calculating bias. For each height and age class, residuals (observed − predicted) from height predictions were obtained and bias (average residual) and its standard deviation were calculated (Table 5). Bias and its standard deviation in estimating stand height across both classes (height and age) depended on height and age classes; bias was slightly higher for small and young trees than for taller and older trees.

Table 5. Bias (observed – predicted) and its standard deviation (SD), and minimum and maximum of the residuals for height class and age class that resulted from fitting Eq. (3) for white pine trees in Northern Ontario, Canada.

Height class (m)	N	Bias	SD	Min	Max
0–5	55	−0.1484	0.3511	−1.2602	0.5645
5–10	73	0.1261	0.3771	−0.9616	1.3097
10–15	70	0.1205	0.3593	−0.9532	1.1539
15–20	60	0.0506	0.5372	−2.4535	0.9292
20–25	41	0.0575	0.4055	−0.7689	1.1079
>25	17	−0.0422	0.3031	−0.5270	0.8586
Age class (yr)	**N**	**Bias**	**SD**	**Min**	**Max**
<10	29	−0.2812	0.3928	−1.2602	0.5645
10–20	60	0.0483	0.3586	−0.9616	1.3097
20–30	59	0.1340	0.3177	−0.5529	0.8308
30–40	55	0.0662	0.4561	−0.9532	1.1539
40–50	46	−0.0002	0.5090	−2.4535	0.8463
50–60	30	0.0448	0.3743	−0.5365	0.6810
60–70	20	0.2487	0.4443	−0.3772	1.1079
>70	17	0.0911	0.2431	−0.1633	0.8433

To predict future stand height growth under a changing climate, white pine stand heights were estimated using Eq. (3) for 4 areas in Ontario under 2 emissions trajectories (Figure 2), using climate projections from a Canadian climate model

(McKenney 2013). These trajectories are known as representative concentration pathways (RCPs), referring to the level of heat produced at the end of the century (8.5 and 2.6 Watts m^{-2}). Average height at BHA 1 year (0.44 m) was used as the initial height for generating height-age curves. Average values of 2 climate variables (GSTP and GSMT) were calculated for the 60-year growth period (2021–2080) and used to estimate future stand heights for both climate scenarios. For the same period, stand heights were estimated using the model fitted without climate variables. As illustrated in the figure, for both climate scenarios, stand height growths at age 60 are slower relative to those for no climate change scenario except in the centre of Ontario.

Under RCP 2.6, height growth was not affected by climate change for plantations in the centre of Ontario and the difference in height growth between the no climate change and the RCP 8.5 scenario at the end of growth period was very small (3.4%). For other areas, height growth was reduced under both climate scenarios. The difference in height growth between the RCP scenarios was less pronounced than that between the no climate change and the RCP scenarios for all areas. Under the climate change scenarios, height growth decreased from the outset. The least and the most pronounced differences in height growth were in western and southern Ontario, respectively. At age 60, stand heights in the west were shorter by 8.3% and 13.3%, for RCP 2.6 and 8.5 scenarios, respectively, relative to those for the no climate change scenario. Similarly, stand heights in the south were shorter by 15.8% and 19.75% under the RCP 2.6 and 8.5 scenarios, respectively, relative to the no climate change scenario.

Finally, stand height over age curves were generated using Eq. (1) for the observed range of site productivity of white pine stands (Figure 3). To generate these curves, stand heights at the index age of 25 years were used as site indices. These curves were very consistent and realistic across all productivity classes.

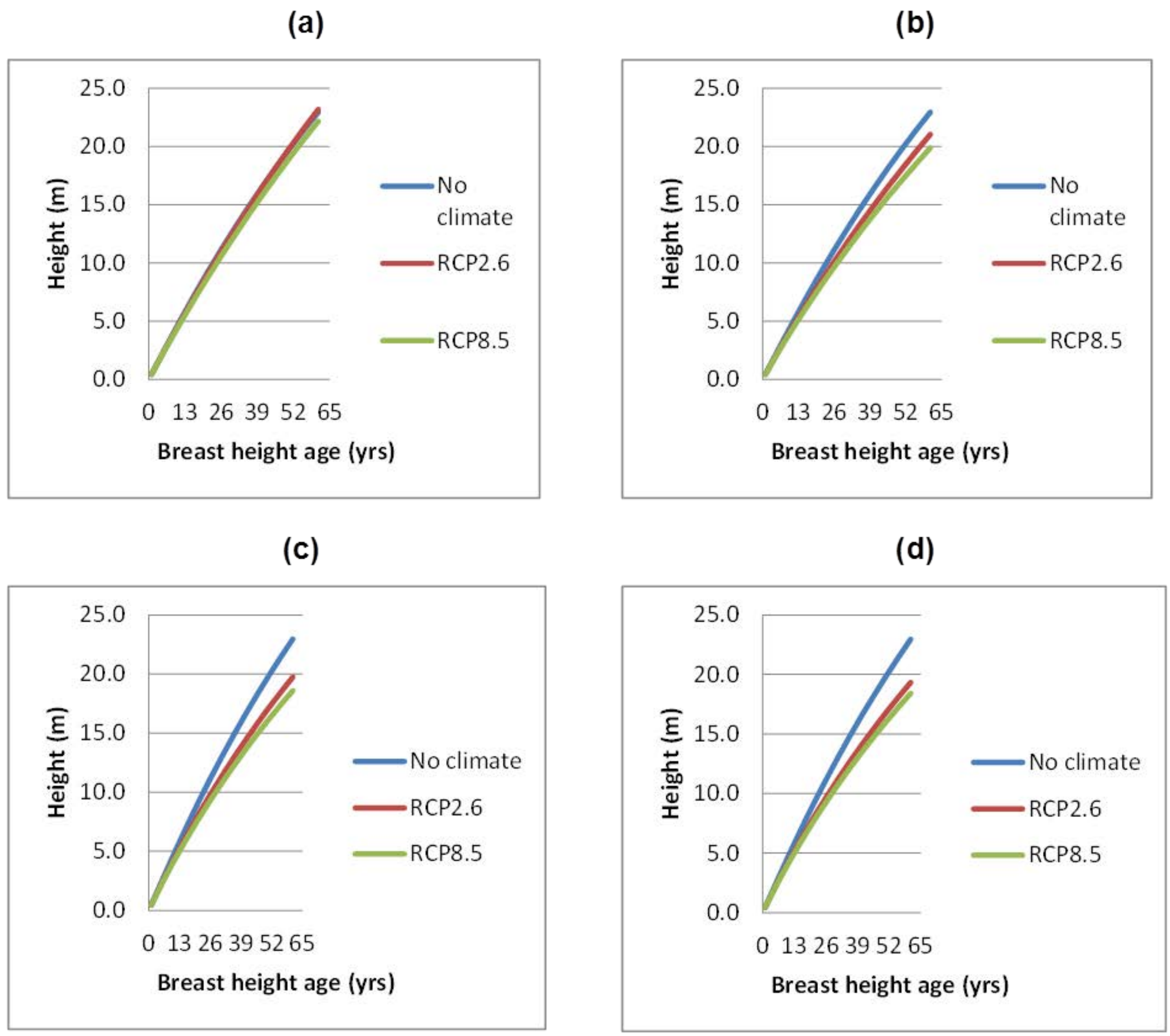

Figure 2. Stand height profiles for plantation-grown white pine trees generated using average values of climate variables for the period 2021 to 2080, assuming climate remains stable (no change) or warms (RCP 8.5 and 2.6), and Eq. (3) for central (near Hearst) (a), northwestern (near Kenora) (b), eastern (near Ottawa) (c), and southern (near Chatham) (d) Ontario, Canada. Climate variables were projected for locations close to sample sites using 3 emissions trajectories known as representative concentration pathways (RCPs).

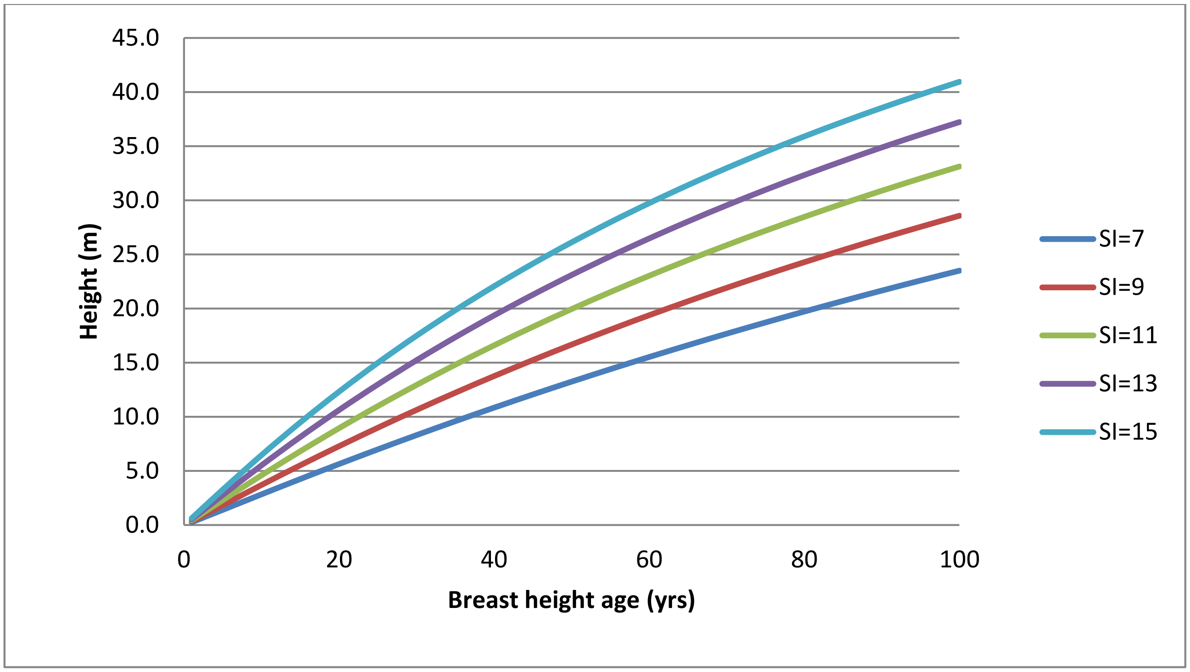

Figure 3. Stand height/site index (SI) profiles generated using Eq. (1) for the range of site productivity of plantation-grown white pine trees in Northern Ontario, Canada.

4.0 Discussion

As Clutter et al. (1983) stated, the productivity of a site depends on environmental conditions (biotic, edaphic, and climatic) at a particular location. Similarly, Latta et al. (2010) mentioned that forest productivity is directly influenced by changes in temperature and precipitation regimes. Results from this study indicated that climate variables (temperature and precipitation) are important in determining the productivity of a site. To make them climate sensitive, these variables could be incorporated in existing height growth models. This can be accomplished, at least in the McDill-Amateis growth function, by expressing the parameters (often referred to as the asymptote and rate parameter) in terms of climate variables.

The variation in stand height growth of white pine trees in this study could be explained using the climate variables GSTP and GSMT. These variables are very intuitive and can be easily interpreted when explaining the growth of any tree species.

Including climate variables significantly improved the fit statistics of the stand height growth model.

These results are consistent with findings of previous studies. For example, Wang et al. (2007) and Bravo-Oviedo et al. (2008) reported that including climate variables improved the fit and predictive accuracy of the model in their studies. Newton (2012) reported that jack pine yields on low-to-medium quality sites would largely be unaffected by climate change by the end of a 60-year growth period (2011–2070) but that, under the B1 and A2 scenarios, the mean dominant height growth on good-to-excellent quality sites would be reduced by 6.6% and 12%, respectively. Similarly, Sharma et al. (2015) found that stand height growth of jack pine and black spruce trees would be reduced under changing climate. They projected 16 and 28% reductions in height growth under the A2 scenario for jack pine and black spruce, respectively, at age 30. Under the B2 scenario, reductions were 2% and 16% for jack pine and black spruce, respectively, at age 30.

In other studies, Sharma and Parton (2018a, b) found that warming climate would negatively affect the site productivity of red pine and white spruce, with effects more pronounced in southern than northern Ontario for red pine, and in eastern more than western and southern Ontario for white spruce. For red pine, stand heights in the northeast were shorter by 10.8% and 12.5% under the 2.6 and 8.5 RCP scenarios, respectively, than under the no climate change scenario at the end of 2011–2040 growth period. Similarly, stand heights in the south were shorter by 25.1% and 30.5% under the 2.6 and 8.5 RCPs scenarios, respectively, than under the no climate change scenario at the end of the same growth period.

For white spruce, stand heights were shorter in the south, east, and west by 43.8%, 38.2%, and 27.8%, respectively, under the 2.6 RCP relative to the no climate change scenario at the end of 2041–2070 growth period. Similarly, stand heights were shorter in the east, west, and south by 74.4%, 72.1%, and 64.6%, respectively, under the 8.5 RCP relative to the no climate change scenario at the end of the same growth period.

Similarly, Way and Sage (2008) conducted an experiment in 2004 and 2005 in which black spruce was grown at low and high temperatures. They found that the dominant height of black spruce grown under high temperature was shorter by 20% compared to that of dominant trees grown under low temperature. Recently, more studies have been published that report the effects of changing climate on the growth of jack pine and black spruce trees (e.g., Huang et al. 2010, 2013; Subedi and Sharma 2013). However, since those studies were focused on radial rather than height growth, the results are not directly comparable with those of this study.

With models developed by expressing SI directly in terms of climate variables, Albert and Schmidt (2010) found that biophysical variables (latitude, longitude, soil, and climate) explained 39 and 34% of the variability in SI for Norway spruce (*Picea abies*) and common beech (*Fagus sylvatica*), respectively. Weiskittel et al. (2011) reported that 68% of the variability in SI was accounted for by variations in climate-related variables across western U.S. forests. In this study, the coefficient of determination (R^2) for the SI model with climate variables (Eq. 2) was 52%.

Some of the white pine trees sampled for this study were as old as 87 years from breast height. Even at this age, no trees showed any signs of senescence. Therefore, the estimate for the asymptote (89.02 m) for the model without climate variables (Eq. 1) seemed slightly higher than expected. In practice, the estimated asymptote, which is the maximum potential height a tree could achieve, is never achieved. However, the stand heights projected for a relatively poor and the best sites in this study (SI = 7 and 15 m, respectively, at BHA 25 years) using Eq. (1) were 23.51 and 40.96 m, respectively, at BHA 100 years. The projected heights at BHA 200 years at these sites were 37.75 and 56.63 m, respectively. According to Wikipedia, 57.55 m tall white pine trees have been measured in North America east of the Rocky Mountains. Therefore, these projected heights seemed to be reasonable estimates.

5.0 Conclusions

The models developed here can be used to estimate stand height at any age, given height at a point in time and relevant climate variables, and will support more informed forest management decisions. In addition, since height estimated at the base age will provide the site index value, the models can also serve as site index equations. As well, when climate variables are unavailable, the equation fitted to height-age pair data can be used as a stand height/site index equation for white pine plantations in temperate forests.

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