

Testing for a CO₂ fertilization effect on growth of Canadian boreal forests

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29 **Abstract**

30 The CO₂ fertilization hypothesis stipulates that rising atmospheric CO₂ has a direct
31 positive effect on net primary productivity (NPP), with experimental evidence suggesting
32 a 23% growth enhancement with a doubling of CO₂. Here, we test this hypothesis by
33 comparing a bioclimatic model simulation of NPP over the 20th century against tree
34 growth increment (TGI) data of 192 *Pinus banksiana* trees from the Duck Mountain
35 Provincial Forest in Manitoba, Canada. We postulate that, if a CO₂ fertilization effect has
36 occurred, climatically driven simulations of NPP and TGI will diverge with increasing
37 CO₂. We use a two-level scaling approach to simulate NPP. A leaf-level model is first
38 used to simulate high-frequency responses to climate variability. A canopy-level model
39 of NPP is then adjusted to the aggregated leaf-level results and used to simulate yearly
40 plot-level NPP. Neither model accounts for CO₂ fertilization. The climatically driven
41 simulations of NPP for 1912–2000 are effective for tracking the measured year-to-year
42 variations in TGI, with 47.2% of the variance in TGI reproduced by the simulation. In
43 addition, the simulation reproduces without divergence the positive linear trend detected
44 in TGI over the same period. Our results therefore do not support the attribution of a
45 portion of the historical linear trend in TGI to CO₂ fertilization at the level suggested by
46 current experimental evidence. A sensitivity analysis done by adding an expected CO₂
47 fertilization effect to simulations suggests that the detection limit of the study is for a
48 14% growth increment with a doubling of atmospheric CO₂ concentration.

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50 *Key words* CO₂ enhancement, dendrochronology, process-based model, boreal forest,
51 jack pine

1. Introduction

The CO₂ fertilization hypothesis stipulates that rising atmospheric CO₂ has a positive effect on net primary productivity (NPP) due to increasing availability of carbon, a limiting factor for the photosynthesis of C₃ plants [Huang *et al.*, 2007]. The concept of CO₂ fertilization has a long experimental history and has been well demonstrated under laboratory or controlled conditions for a variety of C₃ vascular plants, including trees [see reviews by Norby *et al.*, 1999; Ainsworth and Long, 2005; Huang *et al.*, 2007; Körner *et al.*, 2007; Wang, 2007; Prentice and Harrison, 2009]. In a landmark paper, Norby *et al.* [2005] have reported on the most extensive experiments on this topic involving multi-year free-air CO₂ enrichment (FACE) in coniferous and deciduous plantations. In the four sites under study, they have found a 23% enhancement of NPP sustained over multiple years following a doubling of pre-industrial CO₂ concentrations. Given the current weight of experimental evidence, modellers have been including CO₂ fertilization effects in their simulations of past and future forest productivity [e.g. Rathgeber *et al.*, 2000, 2003; Chen *et al.*, 2000; Balshi *et al.*, 2007; Su *et al.*, 2007; Peng *et al.*, 2009], generally resulting in projected increases in forest growth under future atmospheric CO₂ concentrations. The impact of this type of inclusion is important as predictions of forest carbon sequestration dynamics are increasingly coupled to global circulation models and CO₂ emission scenarios [e.g. Notaro *et al.*, 2007; O'ishi *et al.*, 2009].

In spite of the current wealth of experimental evidence on CO₂ fertilization of tree growth, there is still some doubt as to the actual realization of this effect under natural conditions. Körner *et al.* [2005], in a FACE experiment in a mature deciduous forest, have found no lasting growth stimulation by CO₂ enrichment after 4 years of treatment.

Caspersen et al. [2000], in a study of long-term results from forest sample plots in the eastern United States, have found only a modest increase in tree growth over the past century. And recently, *Norby et al.* [2008, 2009] reported that nitrogen limitation was causing a dramatic reduction in growth enhancement in their hardwood FACE experiment from the 23% reported in *Norby et al.* [2005] to a current value of 9%. Evidences of site fertility restrain on carbon sequestration were also found by *Oren et al.* [2001] in their study of mature pine forests exposed to elevated atmospheric CO₂. In their global simulations of CO₂-enhancement on NPP, *Hickler et al.* [2008] concluded that current FACE results do not apply to boreal forest, because of the strong temperature dependence of the relative affinity of the carboxylation enzyme Rubisco for CO₂ and O₂. The predominantly colder temperatures of boreal forests compared with FACE experiments would limit the CO₂ effect, with a simulated increased of NPP of about 15% under a doubling of atmospheric CO₂ [*Hickler et al.*, 2008]. These reports raise the question of the importance of CO₂ fertilization in natural forest environments where tree growth is limited by other factors.

As mentioned above, CO₂ fertilization effects on growth have already been included in many process-based models. Such models serve as direct links between the climate and tree growth [*Hunt et al.*, 1991; *Landsberg and Waring*, 1997; *Rathgeber et al.*, 2000; 2003; *Misson et al.*, 2004] or ecosystem carbon dynamics [e.g. *Balshi et al.*, 2007; *Peng et al.*, 2009]. The challenge with any such inclusion, however, lies with the verification of the modeled change in growth against actual field measurements of realized growth. Because real-world CO₂ enhancement is not a step function, but rather a long-term monotonic increase, the signal it generates in tree growth is not easily

detectable. The signal is certainly far weaker than the large inter-annual variations caused by climate variability [D'Arrigo and Jacoby, 1993] and may be within the uncertainties related to forest inventory data [Joos *et al.*, 2002]. In addition, global temperatures have also been increasing, along with atmospheric nitrogen deposition in some parts of the globe, further confounding the effect of CO₂ fertilization. Finally, the response of plants to CO₂ is also affected by the possible down-regulation of photosynthesis [e.g. Eguchi, 2008; Crous *et al.*, 2008]. All these issues make the detection of CO₂ fertilization effects particularly challenging.

Here, we test the CO₂ fertilization hypothesis by comparing tree growth increment data from 1912 to 2000 with simulation results using a simulator that does not incorporate CO₂ fertilization effects, and is empirically adjusted to the current CO₂ growth environment through field measurements of photosynthesis. We postulate that, in the event that a CO₂ fertilization effect has occurred, climatically driven simulations of forest productivity will show increasing divergence with the measurement record over time as the atmospheric CO₂ increases [Graumlich, 1991; Jacoby and D'Arrigo, 1989; 1997; Rathgeber *et al.*, 2000]. For this purpose, we used tree-ring increments of 192 jack pine (*Pinus banksiana* Lamb.) trees from the closed-canopy boreal forest of Duck Mountain Provincial Forest (DMPF) in Manitoba, Canada. Growth increment data were transformed into a tree growth index (TGI) using the regional curve standardization technique, such that low-frequency signals were retained in the data. The final tree-ring chronology extends from 1717 to 2000. We used a two-level scaling approach to achieve estimates of forest productivity for the period of 1912 to 2000. At the finest scale, a leaf-level model of photosynthesis (FineLEAP) was used to simulate canopy properties and

their interaction with the variability in radiation, temperature and vapour pressure deficit. Then, the StandLEAP model, a top-down plot-level model of forest productivity, was used to simulate landscape-level productivity over the 20th century. The two levels of simulation are linked functionally as parameters of the coarser models are estimated from aggregated simulation results of the finer model, but neither model accounts for CO₂ fertilization. Finally, the detection limit of our approach was investigated through a sensitivity analysis in which an expected CO₂ fertilization was included in StandLEAP simulations via a response function.

2. Study area

The study took place in the DMPF (51°40'N; 100°55'W), which covers approximately 376,000 ha (Fig. 1). Duck Mountain is located within the Boreal Plains ecozone, a transition zone between the boreal forest to the north and the aspen parkland and prairie to the south, and is topographically part of the Manitoba Escarpment, which is characterized by a higher elevation compared with the surrounding plains (300–400 m above sea level, with highest point at 825 m). Pure to mixed deciduous and coniferous stands, primarily composed of trembling aspen (*Populus tremuloides* Michx.) and white spruce (*Picea glauca* [Moench] Voss), constitute about 80% of the DMPF. Stands dominated by black spruce (*Picea mariana* [Mill.] BSP) and jack pine constitute about 14% and 6% of the area, respectively, and occur most commonly in the central, higher elevation regions of the DMPF. The DMPF has a mid-boreal climate with predominantly short, cool summers and cold winters. At lower elevation Swan River (52°03'N; 101°13'W, elevation: 346.6 m asl), mean monthly temperatures ranged from –18.2°C in

January to 18.1°C in July for the reference period of 1971–2000. Average total annual precipitation was 530.3 mm, with most precipitation falling as rain between May and September.

3. Data

3.1. Tree-ring measurements

During the summers of 2000 and 2001, the DMPF was surveyed with the objective of reconstructing fire history [Tardif, 2004]. The DMPF was systematically divided into UTM grids (10 x 10 km) and sites were sampled within each grid based on accessibility. Detailed information on data collection is found in Tardif [2004]. For the current study, we analysed a subset of jack pine cores (2 radii/tree) and stem cross-sections consisting of 192 living and dead trees collected from 70 sampling sites located within 20 UTM grids. Only trees with complete ring measurements from pith to the last year of growth were included, which explains the lower sample replication compared to earlier studies [i.e., 291 trees in that of Girardin and Tardif, 2005]. The majority of samples were collected in the uplands in stands dominated by jack pine and black spruce. Each of the cores and sections were dried, sanded and cross-dated using the pointer-year method [Yamaguchi, 1991]. Annual growth increments were measured from the pith to the outermost ring at a precision of 0.001 mm using a Velmex measuring stage coupled with a computer, and both cross-dating and measurements were statistically validated using the COFECHA program [Holmes, 1983]. The final dataset consisted of 332 ring-width

measurement series. Ring-width measurements were recorded for a period extending from AD 1717 to AD 2000.

3.2 Meteorological data

Meteorological data used as input for the bioclimatic model were monthly means of daily maximum and minimum temperatures (from the Birtle [1905–1998] and Dauphin [1904–2003] meteorological stations; Fig. 1) and total monthly precipitation data (from the Birtle [1918–2000], Dauphin [1912–2003], and Russell [1916–1990] meteorological stations) from *Vincent and Gullett* [1999] and *Mekis and Hogg* [1999], respectively. Data were corrected by the authors for non-homogeneities associated with changes in instrumentation or weather station location. Regional climate data files were created by averaging data from all stations following the procedure described in *Fritts* [1976] (homogeneity testing, station adjustments for mean and standard deviation, and station averaging).

3.3 Forest inventories

Biometric information was obtained from DMPF temporary sample plots (TSP) of the Forest Lands Inventory initiated by Louisiana Pacific Canada Ltd.–Forest Resources Division and Manitoba Conservation–Forestry Branch. Necessary information for driving the StandLEAP bioclimatic model includes soil texture and forest stand properties (forest composition and biomass estimates). For simplicity, we only modelled forest stands classified as “pure” jack pine stands (i.e., where more than 75% of plot basal area was

contributed by jack pine). A total of ten plots (out of 1317) met the 75% criterion while also having all the necessary information for modelling purposes (auxiliary material Table S1). For each of these TSPs, aboveground biomass was estimated using the national biomass equations of *Lambert et al.* [2005]. These functions were applied to each tree, and the individual tree biomass values were summed to estimate stand-level biomass density (Mg ha^{-1}) in each TSP.

3.4 Atmospheric CO₂ data

We used annual average of the atmospheric concentrations of CO₂ reconstructed from ice cores [*Etheridge et al.*, 1996] and recorded at Mauna Loa observatory since 1953 [*Keeling et al.*, 1982]. The CO₂ concentration increased from 300 ppmv in 1910, to 317 ppmv in 1960, and to 370 ppmv in 2000.

4. Methods

4.1 Development of the tree growth index (TGI)

All ring-width measurements were detrended using the regional curve standardization technique [*Esper et al.*, 2003] in order to eliminate noise caused by site-related effects (e.g. competition and self-thinning) and biological effects (e.g. aging). This approach has the potential to preserve the evidence of long time scale forcing of tree growth [see reviews by *Esper et al.*, 2003 and *Briffa and Melvin*, in press] as it scales ring-width measurements against an expectation of growth for the appropriate age of each ring (Fig.

2). We first aligned the 332 measurement series by cambial age and calculated the arithmetic mean of ring width for each ring age. We then created a regional curve (RC) by applying a negative exponential smoothing [Cook and Kairiukstis, 1990] to the age series of arithmetic means (Fig. 2). It is assumed that this RC created from the means of ring width for each ring age describes the functional form of the age-related growth trend. Note that our conclusions were insensitive to the use of other types of smoothing [e.g. the ‘Hugershoff’ or spline smoothing; Cook and Kairiukstis, 1990] or to truncation of the measurement series by removal of the juvenile period (first 15 to 20 years of data) and downsampling of age cohorts (auxiliary material Figs. S1, S2 and S3). Next, we divided each one of the original 332 ring-width measurement series by the RC value for the appropriate ring age to create standardized series. These departures from the RC are interpreted as departures related to climate variability or some other induced forcing (e.g. insect herbivory). Finally, the 332 standardized series were realigned by calendar year and averaged using a bi-weight robust mean to create the jack pine tree growth index (TGI). TGI error was estimated by bootstrapping the standardized series and collecting the two-tailed 95% confidence interval from the distribution of the bootstrapped means. Robustness of the final jack pine chronology was assessed using a 30-year ‘moving window’ approach of the inter-series correlation, and of the expressed population signal (EPS) [Wigley *et al.*, 1984]. The EPS is a measure of the degree to which the mean chronology represents the hypothetical perfect, noise-free, chronology. The EPS ranges from zero to one. A value of 0.85 has been tentatively suggested as desirable [Wigley *et al.*, 1984]. Program ARSTAN (version 40c) was used for processing of tree-ring measurement series and for computation of statistics [Cook and Krusic, 2006].

4.2 Modelling of forest productivity

The bioclimatic model StandLEAP version 2.1 [Raulier *et al.*, 2000; Girardin *et al.*, 2008] was used to simulate past forest productivity. StandLEAP is based on the 3PG model [Landsberg and Waring, 1997], and is a generalized stand model applicable to even-aged, relatively homogeneous forests. It is parameterized for individual species. Application of StandLEAP to any particular stand does not involve the use of error reduction techniques. We conducted monthly simulations of forest productivity (described below) for each of the ten temporary sample plots of the DMPF Lands Inventory (auxiliary material Table S1). Monthly simulation outputs were summed to seasonal and annual values, and plots were averaged to a regional level. Sampling error was estimated by bootstrapping the simulations and collecting the two-tailed 95% confidence interval from the distribution of the bootstrapped means.

In StandLEAP, absorbed photosynthetically active radiation (APAR, mol m⁻² month⁻¹) is related to gross primary productivity (GPP, gC m⁻² month⁻¹) using a radiation use efficiency coefficient (RUE; gC/mol⁻¹ APAR):

$$[eq. 1] \quad GPP = APAR \times RUE,$$

where

$$[eq. 2] \quad RUE = \overline{RUE} \times f_1 f_2 \dots f_n.$$

$\overline{\text{RUE}}$ represents a species-specific mean value of RUE. The value of RUE differs among locations and through time because of the occurrence of environmental constraints on the capacity of trees to use APAR to fix carbon. Each constraint takes on the form of a species-specific multiplier ($f_1 \dots f_n$) with a value usually close to unity under average conditions, but which can decrease towards zero to represent increasing limitations (e.g. soil water deficit), or increase above 1.0 as conditions improve towards optimum (e.g. temperature). Constraints related to mean maximum and minimum daily soil and air temperatures, vapour pressure deficit (VPD), monthly radiation, and leaf area index are expressed using a quadratic function:

$$[\text{eq. 3}] \quad f_x = 1 + \beta_{lx} \left(\frac{x - \bar{x}}{\bar{x}} \right) + \beta_{qx} \left(\frac{x - \bar{x}}{\bar{x}} \right)^2.$$

where parameters β_{lx} and β_{qx} represent the linear and quadratic effects of the variable x on RUE and \bar{x} is the mean value of the variable over the period of calibration. The multipliers ($f_1 \dots f_n$) account for non-linearity in time and space that cannot be accounted for by a constant value of RUE.

Parameter values of eq. 3 for the f_x multipliers are derived from prior finer-scale simulation results of canopy-level GPP and transpiration carried out using FineLEAP, a species-specific multi-layer hourly canopy gas exchange model [Raulier *et al.*, 2000; Bernier *et al.*, 2001, 2002]. In FineLEAP, the representation of photosynthesis is based on the equations of Farquhar *et al.* [1980] parameterized from leaf-level instantaneous gas exchange measurements, including the sensitivity of shoot photosynthesis to PAR,

temperature and VPD, and the characterization of the shoot physiological and light-capturing properties with shoot age and surrounding average diffuse and direct light environment. Transpiration was computed using the energy balance approach of *Leuning et al.* [1995]. Sixty leaf angular classes were considered (five for the zenith and 12 for the azimuth).

The FineLEAP model simulates canopies aspatially as layers of foliage of equal properties by using the frequency distribution of the leaf area by classes of shoot age. This aspatial approach rests on the strong relationship between leaf area per unit mass, and both the photosynthetic properties of the foliage and the average light climate impinging upon it [*Bernier et al.*, 2001]. Ecophysiological and canopy structure data for jack pine were drawn mostly from the 1994 to 1996 BOREAS [*Sellers et al.*, 1997] datasets for northern and southern study areas in old jack pine stands (98°37'19"W, 55°55'41"N and 104°41'20"W, 53°54'58" respectively). These data are archived at the ORNL-DAAC [*Newcomer et al.*, 2000]. FineLEAP simulations were repeated for each climate sequence and for a range of leaf area indices (2 to 8 m²/m²). Hourly values of transpiration, of GPP, and of environmental variables derived from or used in FineLEAP simulations were then rolled up into a monthly dataset. This new synthetic dataset was used to fit simultaneously eqs. 1 and 2, in which modifier variables were expressed as in eq. 3. The fit was performed in an iterative procedure with the gradual inclusion of modifier variables in a declining order of significance. Only variables that reduced the residual mean square error by more than 5% were retained [*Raulier et al.*, 2000]. The atmospheric CO₂ concentration was assumed to be constant at 350 ppmv.

Other basic climate influences on productivity are encapsulated in StandLEAP within the following functions. The multipliers used to represent the effect of soil water content (f_θ) is as in *Landsberg and Waring* [1997], and that of frost (f_F) is as in *Aber et al.* [1995]; both are limited to a maximum of 1.0. Bud burst and growth resumption in spring takes place after the accumulation of a certain heat sum above a specific base temperature [Hänninen, 1990]. Monthly APAR is adjusted throughout the growing season for changes in leaf area due to phenological development, as in the PnET model [Aber and Federer, 1992].

Computation of NPP and respiration fluxes by the StandLEAP model is done as follows. NPP ($\text{gC m}^{-2} \text{ month}^{-1}$) is computed monthly after partitioning respiration into growth (R_g , a fixed proportion of GPP) and maintenance (R_m) quantities and subtracting these from GPP:

$$[\text{eq. 4}] \quad NPP = GPP - (R_g + R_m).$$

R_m ($\text{gC m}^{-2} \text{ month}^{-1}$) is computed as a function of temperature using a Q_{10} relationship [Agren and Axelsson, 1980; Ryan, 1991; Lavigne and Ryan, 1997]:

$$[\text{eq. 5}] \quad R_m = \sum (M \cdot r_{m10} Q_{10rm}^{(T_m - 10)/10})$$

where M is the living biomass of each plant component and r_{m10} is their respective respiration rate per gN at 10°C and Q_{10rm} is the temperature sensitivity of R_m , defined as the relative increase in respiration for a 10°C increase in temperature. This function is

derived from the strong correlation between tissue nitrogen concentrations and plant maintenance respiration [Ryan, 1991]. R_m is calculated separately for stem sapwood, root sapwood, fine roots, and foliage. Similarly, net ecosystem productivity (NEP) is obtained from

$$[eq. 6] \quad NEP = NPP - R_h$$

where heterotrophic respiration (R_h) ($\text{gC m}^{-2} \text{ month}^{-1}$) is computed as

$$[eq. 7] \quad R_h = y_0 + ae^{bT}$$

where T represents monthly mean temperature. Values of parameters y_0 , a and b were obtained from a least-squares adjustment to monthly synthetic R_h data obtained by summing up simulations of half-hourly R_h computed as in *Lloyd and Taylor* [1994] and using the 10-year temperature records of the old jack pine stand obtained from the Fluxnet-Canada / Canadian Carbon Program Data Information System.

The strength of this modelling approach is supported by the good performance of StandLEAP in a comparison of its simulation results with measurements by eddy-flux towers of GPP [data from Fluxnet-Canada, *Margolis et al.*, 2006], ecosystem respiration (R_e) and NEP from 2000 to 2006 in a 95-year-old stand in Saskatchewan, Canada (Fig. 3). The model captured reasonably well the month-to-month variability in these variables ($GPP-R^2 = 0.92$; $R_e-R^2 = 0.92$; $NEP-R^2 = 0.63$; $n = 84$ months). The capacity of FineLEAP to simulate canopy-level gas exchanges has also been verified by comparing

hourly [Bernier *et al.*, 2001] and daily [Raulier *et al.*, 2002] measurements of plot-level transpiration to simulated values for two different stands of sugar maple (*Acer saccharum* Marsh.).

4.3 Statistical analyses

Tree-ring width measurements in boreal forests have an autocorrelation structure that can be expressed as an auto-regressive (AR) process of order p :

$$[eq. 8] \quad I_t = \phi I_{t-p} + \dots + \phi_1 I_{t-1} + e_t,$$

where I_t are the tree-ring width measurements for year t , e_t are serially random inputs, and ϕ_i are the p autoregressive (AR) coefficients that produce the characteristic persistence seen in the tree rings [Monserud, 1986; Biondi and Swetnam, 1987; Cook and Kairiukstis, 1990; Berninger *et al.*, 2004]. A strong AR process will cause the tree-ring width measurements to be excessively smoothed, and vice versa. The AR process in tree rings reflects, amongst other things, how stored photosynthates are made available for growth in the following years. While this process can be mathematically described [Misson, 2004], its process basis remains difficult to express quantitatively so that one could predict empirically how much carbon produced a given month or year should be allocated to the growth in the following years [i.e. Kagawa *et al.*, 2006]. The autocorrelation function in TGI can indeed go beyond an AR1 process [Monserud, 1986].

In contrast, there is no such year-to-year carry-over in yearly totals of simulated NPP by StandLEAP. In order to correct for this deficit and make the comparison of NPP

and TGI possible, the two series must be brought to a similar AR process. In this study, we estimated the AR process of the jack pine TGI and applied the AR equation parameters [Cook and Kariukstis, 1990] to the standardized yearly totals of simulated NPP, which were obtained by dividing annual NPP values by the long-term mean of NPP over 1912–2000. We hereafter refer to this new NPP series as the NPP^{AR} series. The application of this transformation to NPP does not violate the assumption of independence between the two datasets, but allows them to have a similar time-dependent (or ‘smoothing’) behaviour. Another approach would have been to remove the AR process in TGI through auto-regressive modeling (i.e. prewhitening). This, however, would have resulted in a significant loss of low-frequency changes in the TGI [for analyses of ‘prewhitened’ data, refer to Girardin and Tardif, 2005 and Girardin *et al.*, 2008]. The order of the autocorrelation process was determined using the Akaike Information Criterion (AIC) implemented in the program ARSTAN (version 40c) [Cook and Krusic, 2006].

Long-term linear changes in TGI, climatic, and simulated data were detected using least-squares linear regressions [von Storch and Zwiers, 1999]. Goodness of fit was described by the coefficient of determination (R^2). Significance of the slope was tested against the null hypothesis that the trend is different from zero, using a variant of the t test with an estimate of the effective sample size that takes into account the presence of serial persistence (red noise bias) in data [von Storch and Zwiers, 1999; their sections 8.2.3 and 6.6.8]. For those time-series having an autocorrelation structure expressed as an AR process of order greater than one ($\text{AR} > 1$), the significance of trends was evaluated using Monte Carlo simulations. In this analysis, 1000 random time series with similar

autocorrelation structure as the original data were tested for the presence of trends and 99%, 95% and 90% percentiles of the coefficient of determination were collected and used as a criterion for testing against the null hypothesis. When necessary, data were ranked prior to analysis to satisfy the normality distribution requirement in model residuals [von Storch and Zwiers, 1999]. The period of analysis for this study was 1912–2000 (e.g. limited to the earliest year of meteorological data and the latest year covered by tree-ring data).

As mentioned earlier, the StandLEAP simulator does not incorporate CO₂ enhancement effects. In the event that a CO₂ fertilization effect has occurred during the 20th century, climatically driven simulations of NPP and TGI should show increasing divergence with increasing or decreasing atmospheric CO₂ [Graumlich, 1991; Jacoby and D'Arrigo, 1989; 1997; Rathgeber *et al.*, 2000]. To test this fertilization hypothesis, residuals of the difference between TGI and NPP^{AR} were related to atmospheric CO₂ data using correlation analysis and piecewise regression [Friedman, 1991]. In the regression analysis, the relationship between residuals and [CO₂] was described by a series of linear segments of differing slopes, each of which was fitted using a basis function. Breaks between segments were defined by a knot in a model that initially over-fitted the data, and was then simplified using a backward/forward stepwise cross-validation procedure. This approach was preferred over a linear trend analysis because CO₂ increases non-linearly through time. The null hypothesis H₀ of 'no fertilization effect' was to be rejected in the presence of a basis function with a positive slope post-1970 (i.e. when the rate of CO₂ increase was most important). The R package 'earth' was used [R Development Core Team, 2007]. The Generalized Cross Validation (GCV) penalty per knot was set to four

and the minimum amount of observations between knots was set to 25 to ensure numerical stability. Other parameters were kept as in the ‘earth’ default settings.

4.4 Sensitivity analysis to atmospheric CO₂

Empirical evidence indicating CO₂ fertilization effects has often resulted from laboratory or controlled experiments following a doubling of pre-industrial CO₂ concentrations from approximately 300 ppmv to 700 ppmv [e.g. *Norby et al.*, 2005]. The CO₂ forcing acting on natural environments is much lower (from 300 ppmv in 1910 to 370 ppmv in 2000) and, hence, the response of forests cannot be expected to be as large as the one seen in experimental conditions [*Joos et al.*, 2002]. The fertilization effect in natural environments could simply be under the limit of statistical detection [*D’Arrigo and Jacoby*, 1993]. We investigated this potential source of error through a sensitivity analysis in which an ‘expected’ effect of CO₂ fertilization was added to simulations of NPP^{AR}. The ‘expected’ effect of CO₂ fertilization on forest growth is often quantified using a logarithmic response function that takes the form of

$$[eq. 9] \quad NPP_E = NPP_O \cdot (1 + \beta \ln(CO_{2E} / CO_{2O}))$$

where NPP_E and NPP_O refer to net primary productivity (eq. 4) in enriched (CO_{2E}) and control (CO_{2O}) CO₂ environments, respectively [e.g. *Friedlingstein et al.*, 1995; *Rathgeber et al.*, 2000; *Peng et al.*, 2009]. In this equation, β is an empirical parameter that ranges between 0.0 and 0.7, and is adjusted so that NPP under a doubled atmospheric CO₂ concentration (from 350 to 700 ppmv) increases by approximately 23% (eq. 9)

[based on experimental evidence from *Norby et al.*, 2005]. We used a value of 0.34 for β , as in *Peng et al.*, [2009]. Under the hypothesis that a fertilization effect in TGI has not occurred, residuals of the difference between TGI and ‘CO₂-enriched NPP^{AR}’ simulations should show a significant bias toward decreasing values with increasing atmospheric CO₂ (i.e. negative slope). On the other hand, a slope that is not significantly different from zero would imply that the fertilization effect in TGI is possible but too small to be statistically detected by our modelling procedure. In such an eventuality, the CO₂ fertilization effect could simply be masked by the high inter-annual variability in the TGI time-series.

5. Results

5.1 Temporal changes in tree growth index

Most sampled jack pine trees originated from post-fire recruitment episodes, as for example in the 1890s (~60% of trees) and 1750s to 1770s (~20%) (Fig. 4b). The only information available on growth conditions prior to the 1890s was from dead trees. That being said, a close relationship between average ring width of dead and living trees and tree age (Fig. 5) ($R^2 = 0.49$; $n = 332$) suggested the existence of relatively homogeneous behaviour in the tree population under study with regard to growth rates. Also, the age-related growth trend of trees originating from prior to 1880 was reasonably similar in level and slope to a curve obtained from trees originating after 1880 (Figs. 2b). We also found little difference in the age-related growth trends under different classes of jack pine dominance (auxiliary material Fig. S4). Therefore, one can assume that the trees belonged

to the same population, a prerequisite for application of the regional curve standardization [Esper *et al.*, 2003].

First-order autocorrelation (AR1) of the jack pine record was 0.83 over 1717–2000, reflecting high biological memory (i.e. persistence of previous year growth conditions). The best AR model fit was obtained using an AR(5) process. However, an AR(2) model (described in Table 1) was considered the best for a sub-period covering 1880–2000.

Expressed population signal (EPS) values meet signal strength acceptance for the full period covered by tree-ring data (Fig. 4d). Replication of ring-width measurements may thus be considered sufficiently high to approximate a signal representative of a theoretical population of an infinite number of trees, i.e. an entire forest stand [Wigley *et al.*, 1984]. However, the low correlation obtained during the 30-year ‘moving window’ analysis of the inter-series correlation ($Rbar < 0.32$ over much of the 19th and 20th centuries; Fig. 4d) demonstrates the high variability among measurement series, and suggests the action of diverse biological and non-biological forcing agents on the growth of the jack pine trees. This was further highlighted by a wide bootstrap confidence interval around the mean throughout much of the 19th century, when sampling replication was low (Fig. 4a). As opposed to any previous time periods, the period submitted to our modelling experiment (i.e. 1912–2000) appeared minimally biased, as can be assessed from high EPS, relatively stable $Rbar$, and a narrow confidence interval around the mean. The final TGI chronology suggested marked variations in the growth of jack pine trees, with low growth from the 1910s to 1940 and around 1960, and highs in the 1950s and post 1970 (Fig. 4a). Least-squares linear regression applied to the TGI indicated a

positive trend over 1912–2000 (Table 2). The trend explained 34.4% of the variance in data (Table 2).

5.2 Simulated forest productivity

Simulated annual GPP over 1912–2000 averaged $857 \text{ gC m}^{-2} \text{ yr}^{-1}$, and simulated respiration losses were about 52% of this amount (Fig. 6). Annual simulated NPP averaged $460 \text{ gC m}^{-2} \text{ yr}^{-1}$, with a minimum of $212 \text{ gC m}^{-2} \text{ yr}^{-1}$ in 1961 and a maximum of $556 \text{ gC m}^{-2} \text{ yr}^{-1}$ in 1977 (Fig. 7). About 60% of annual NPP was produced during the June to August period (average equals $270 \text{ gC m}^{-2} \text{ yr}^{-1}$). Summer NPP also showed a higher departure from the mean (standard deviation of $45 \text{ gC m}^{-2} \text{ yr}^{-1}$) than spring or fall (respectively 21 and $15 \text{ gC m}^{-2} \text{ yr}^{-1}$). Indeed, except perhaps in the 1970-80s, most of the highs and lows in annual NPP (Fig. 7) were found within the productivity during summer months. These variations were driven in the model by the climate modifiers affecting RUE (eq. 2) and, hence, GPP. The temperature constraints on respiration (eq. 4) were likely not sufficiently important to induce in NPP the large departures from the mean seen in Fig. 7.

The simulation suggested an increase in forest productivity over the century, with an increase of annual GPP estimated at $0.780 \text{ gC m}^{-2} \text{ yr}^{-1}$ and a linear trend explaining 9.7% of the variance in data (Table 2; Fig. 6). Nevertheless, carbon losses due to respiration have also significantly increased, but such losses were more than compensated by increased GPP, resulting in a significant rise in NPP of $0.502 \text{ gC m}^{-2} \text{ yr}^{-1}$. This rise in NPP explained 7.8% of the variance in data (Table 2; Fig. 7). Most of the increase was simulated to have taken place in the spring (by $0.233 \text{ gC m}^{-2} \text{ yr}^{-1}$).

Climate factors encapsulated in the bioclimatic model were also tested for the presence of linear trends. Amongst factors that could explain the simulated upward trend in forest productivity were increases in the length of the growing seasons, as inferred from the annual sums of growing degree days above 5°C, and increased availability of soil moisture in the first meter of soil (Table 2 and Fig. 8). Both variables had a significant positive trend over 1912–2000 ($P < 0.05$), explaining 6.0% and 6.8% of the variance in data, respectively.

5.3 Comparing empirical data with simulations

The AR process dominating the jack pine TGI (Table 1) was applied to the yearly totals of simulated NPP so that both series could share similar time-dependent behaviour (see Methods). The two records, illustrated in Fig. 9a, shared 47.2% of common variance over their common period of analysis, i.e. 1912 to 2000 ($P < 0.01$ according to Monte Carlo simulations). The amount of shared variance equalled 28.5% ($P < 0.05$) when both series were detrended prior to analysis. Most often, the simulation of NPP^{AR} propagated well within the uncertainty band of the TGI data (Fig. 9). Nevertheless, the simulation did not do well in 1921–1925 (overestimation), 1936–1937 (underestimation), 1975–1976 (underestimation), and 1992 (overestimation). These years were not found to be systematically related to a climatic factor (as investigated with Student-t tests on monthly climatic data) or to a biological agent acting on growth, such as outbreaks of the jack pine budworm (*Choristoneura pinus* Freeman) [McCullough, 2000; Volney, 1988] recorded in the DMPF from 1938 to 1942 and in 1985 [Canadian Forestry Service, 1986]. These years might reflect the influence of climatic extremes not taken into account by the

simulator or of magnitudes outside the domain of calibration of the modifiers affecting RUE (see Methods). If we eliminate the ‘disconnected’ years 1936 and 1976 (with Studentized residuals > 3.0) from the data comparison, the amount of shared variance between data rises to 59.0% (39.5% after detrending).

A positive trend in productivity over the past century is clearly distinguishable in the NPP^{AR} simulations and in TGI (Table 2 and Fig. 9), indicating long-term changes in growing conditions. Both TGI and NPP^{AR} shared similar regression slopes (i.e. no statistical difference) and amount of variance explained by the trend line (Table 2). Also clearly distinguishable in the jack pine TGI series were growth declines in the 1920s to 1930s and early 1960s (Fig. 9a). Coincident with these episodes are notable drought events that are reflected in the index of available soil water at a depth of 1 m (Fig. 8b). The influence of moisture availability on jack pine growth was readily apparent when correlating the TGI data over 1912–2000 with the smoothed version of available soil water (Fig. 8b): the two records shared 42.7% of variance.

5.4 Testing for a CO₂ fertilization effect

Climatically driven simulations of NPP^{AR} and TGI did not show evidence of increasing divergence with increasing atmospheric [CO₂] as residuals of the difference between TGI and NPP^{AR} (Fig. 10a) were uncorrelated to long-term changes in the atmospheric [CO₂] ($R^2 = 0.017$, $P > 0.30$). In addition, the piecewise regression model did not detect a linear segment or a long-term trend in residuals capturing a missing effect of increasing atmospheric [CO₂] on NPP (Fig. 10a). When the effect of CO₂ fertilization was added to NPP through the use of eq. 9 and $\beta = 0.34$, the residuals of the difference between TGI

and CO₂-enriched NPP^{AR} were negatively correlated to long-term changes in the atmospheric CO₂ ($R^2 = 0.067$, $P < 0.05$), and presented a significant bias according to the piecewise regression analysis (Fig. 10b). Our results therefore suggest that long-term changes in the TGI were adequately reproduced by the climatically driven simulation of NPP^{AR} without inclusion of a CO₂ factor.

We also conducted a sensitivity analysis in order to evaluate the statistical detection limit of our approach. Our analysis involved re-doing the simulation of NPP^{AR} with values of β varying between 0 and 0.7. Results of this analysis revealed that values of β greater than 0.20 generated an overestimation of the slope of the linear trend between NPP^{AR} and TGI data (period 1912–2000) (Fig. 11a). Residuals between NPP^{AR} and TGI also increased with values of β greater than 0.20 (Fig. 11b) and were increasingly correlated to CO₂ (Fig. 11c). A cut-off value of $\beta = 0.20$ corresponded to a growth enhancement of 14% with a doubling of CO₂. We also found a slight improvement of model fit between TGI and NPP^{AR} with the addition of a weak CO₂ factor between 0.10 and 0.15, but this effect was non-significant (see minimum value in Fig. 11b and auxiliary material Figs. S5 and S6).

6. Discussion

It is of increasingly common practice for modellers to include CO₂ fertilization effects when assessing the current and future impacts of global climate change (see Introduction). This practice, which is done using empirical evidence from laboratory or controlled conditions, is often applied to large territories (e.g. continental scale) and over a range of habitats and species. Within the detection limit of the data-model approach

used in this work, we find nothing to support the idea of a FACE-level CO₂ growth enhancement (23% for a doubling of CO₂) in jack pine trees of the DMPF during the 20th century ($\beta = 0.34$). In addition, comparison between recent growth and growth prior to the 1890s in our jack pine TGI series of the DMPF fails to show the multicentury increase in growth that should be expected as a result of the CO₂ fertilization effect [Jacoby and D'Arrigo, 1989, 1997; Huang *et al.*, 2007]. As seen in Fig. 2, the age-related growth trend of trees originating after 1880 is reasonably similar in level and slope to a curve obtained from trees originating prior to 1880 in spite of significant increases in atmospheric CO₂ over the past century [Keeling *et al.*, 1982; Etheridge *et al.*, 1996]. Because of the detection limit of our approach, evaluated at 14% growth enhancement for a doubling of CO₂ (maximum $\beta = 0.20$), our results do not invalidate suggestions for a lower CO₂ fertilization effect, such as the value of 15% proposed by Hickler *et al.* [2008]. Our results do suggest the need to use caution when including CO₂ fertilization effects in models.

Empirical observations provide support to the correctness of our modelling results with respect to the factors driving the simulated 20th century increase in NPP. Net ecosystem productivity of coniferous forests is increased by early spring warming [Arain *et al.*, 2002; Grant *et al.*, 2009] but reduced by hot summers and soil moisture depletion [Griffis *et al.*, 2003; Dunn *et al.*, 2007]. The pattern of year-to-year changes in tree growth reflects the underlying influences of variability in the climate and occurrence rate of weather episodes favourable or not to photosynthesis (eq. 1) and respiration (eq. 4). Our observed trends toward greater length of the growing season and greater available soil water are consistent with these short-term observations. Notably, springtime

increases in simulated NPP suggest that growth conditions in the second half of the century have benefited from increasing growing season degree-days, particularly through an earlier onset of spring (Fig. 7). Extension of the growing season by up to 2 weeks in mid- and high northern latitudes since the early 1970s is apparent in remotely-sensed vegetation indices (NDVI) [Myneni *et al.*, 1997; Zhou *et al.*, 2001] and in seasonal trends of atmospheric CO₂ drawdown [Keeling *et al.*, 1996]. The positive influence of global warming on plant growth and establishment in high-latitude, cold-limited systems has widely been reported [e.g. Jacoby and D'Arrigo, 1989, 1997; Gamache and Payette, 2004; Briffa *et al.*, 2008].

Also clearly distinguishable in the jack pine TGI series of the DMPF were growth declines in the 1920s to 1930s and early 1960s coherent with intense or frequent drought years. These well-documented droughts [e.g. Girardin and Wotton, 2009] may have been relatively mild when examined in the context of past centuries [e.g. Cook *et al.*, 2004], but the 'Dust Bowl' drought nevertheless severely affected almost two-thirds of the United States and parts of Mexico and Canada during the 1930s [Schubert *et al.*, 2004]. It is apparent from our NPP simulations and empirical data that carbon uptake by the jack pine population of the DMPF was severely limited for much of the early 20th century as a consequence of this extreme climatic anomaly. The year 1961, which was referred to by Girardin and Wotton [2009] as the driest summer over the period 1901–2002 for Canada as a whole, also stands out as the year with the lowest simulated NPP (and measured TGI) for the entire simulated period.

So why has CO₂ fertilization of jack pine trees in the DMPF failed to be detected? It is apparent that constraints other than atmospheric CO₂ concentration have been and

are still limiting the growth of this forest. Temperature effects on growth are strongly mediated by nutrient availability and capture [*Jarvis and Linder, 2000*]. Although the drop in forest productivity with increasing latitude highlights the primary controlling role of climate across the spatial domain (e.g. temperature dependence of the CO₂-enhancement effect as discussed in the Introduction), secondary factors, such as soil fertility and stand age, that operate on a longer time lag may be attenuating the immediate impact of climate warming and CO₂ fertilization in these forests [e.g. *Körner et al., 2005*]. One constraint would be the insufficient availability of nitrogen in soils to meet the increasing demand under elevated CO₂ [*Oren et al., 2001; Johnson et al., 2004; Norby et al., 2008, 2009*], particularly on sites with low to moderate soil nitrogen availability [*Reich et al., 2006*]. In general, coniferous forests are believed to have lower availability of nitrogen due to slower nutrient turnover than deciduous forests [*Jerabkova et al., 2005; Ste-Marie et al., 2007*].

An additional constraint on the detection of the CO₂ fertilization effect is the expected size of this effect in comparison to the detection limit. The effect may not yet be detectable in natural forest environment, in part because it may be much smaller than what is found in controlled experiments, and in part because the CO₂ increases during the studied interval were relatively modest, again in comparison to controlled experiments. These findings concur with those of *Joos et al. [2002]*. The results of the sensitivity analysis revealed that our analysis cannot detect a fertilization effect of up to $\beta = 0.20$, which corresponds to a growth enhancement of 14% with a doubling of CO₂. However, this value of β as a detection cut-off results in part from our choice of pre-treatment method for the TGI measurement series that retained the most amount of trend possible

(auxiliary material Fig. S1). This choice enhances the probability of generating false positive or Type 1 errors at lower values of β (i.e. accept the fertilization hypothesis when in fact there is none). The use of other detrending methods would have resulted in a detection cut-off value of β lower than 0.20 (auxiliary material Fig. S6).

Other uncertainties may also weaken our inference. In particular, the method relies on the use of a dataset with a uniform distribution of tree establishment and mortality dates over time in order to allow common climate/CO₂ signals to be cancelled and averaged out when the series are aligned by cambial age (Fig. 3a). In our experimentation this condition is not necessarily met as a large proportion of trees germinated within a short period in the 1890s. Nonetheless, results of a sensitivity analysis (auxiliary material Fig. S2) that involved a downsampling of the number of trees established during that interval suggest that our inference is robust against this source of error. Finally, the instrumental weather data used as input for the simulator were subject to homogenization and this could induce some uncertainty in the measurement trend, which might also be carried over into the modeled estimates. In our estimation, however, none of these sources of uncertainty weaken the basic inference from this study that, in our boreal forest environment, we could not detect the level of CO₂ fertilization effect that has been reported in controlled FACE experiments [Norby *et al.*, 2005] and that is often included in simulations of future forest productivity [e.g. Chen *et al.*, 2000; Peng *et al.*, 2009].

7. Concluding remarks

This study suggests that empirical evidence from controlled experiments on CO₂ fertilization cannot be directly extrapolated to large forested areas without a good understanding of local constraints on forest growth. Inclusion of such additional constraints on growth in the models remains a daunting task when they are to be applied to large heterogeneous landscapes such as the boreal forest. Adding complexity to models without empirical supporting evidence as to the applicability of the additional relationships may in the end become counter-productive and generate unrealistic projections of future forest states. In spite of all their shortcomings, field-based studies such as this one remain one of the best guarantees that we indeed understand forest growth and can adequately predict its future.

We currently do not know if our inference with respect to the absence of long-term CO₂ fertilization applies to all of Canada's closed-canopy boreal region but widespread replication of this type of study is currently challenging. The technique employed in the processing of our jack pine tree-ring data (regional curve standardization) has high capabilities for preserving long-term growth changes [e.g. *D'Arrigo et al.*, 2006]. Nevertheless, the technique can only be applied in specific circumstances [*Esper et al.*, 2003] and requires high within-site replication (*D'Arrigo et al.*, 2006). Many tree-ring datasets across closed-canopy forests of boreal Canada have been developed in the past [*Girardin et al.*, 2006; *St. George et al.*, 2009]. However, few of these data have been collected from productive forests following a dense sampling scheme that includes sampling of multiple age cohorts. Expansion of this work is further limited by the absence of plot-level data necessary to run process-based models on stands in which growth increment data were collected. While the applicability of species-

specific process-based models may be fairly narrow in scale owing to the complexity of input data, they are of valuable help in answering specific questions that are relevant to modellers of carbon exchanges of broad spatial scales. Estimates of stand attributes, such as biomass and soil types, through remote sensing could help address some of these issues in the future. There is, however, clearly a need for additional tree-ring sampling campaigns coupled with complete plot-level information if we are to successfully document and attribute long-term growth trends in the circumboreal forests.

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References

Aber, J. D., and C. A. Federer (1992), A generalized, lumped-parameter model of photosynthesis, evapotranspiration and net primary production in temperate and boreal forest ecosystems, *Oecologia*, 92, 463–474.

- Aber, J. D., S. V. Ollinger, C. A. Federer, P. B. Reich, M. L. Goulden, D. W. Kicklighter, J. M. Melillo, and R. G. Lathrop Jr. (1995), Predicting the effects of climate change on water yield and forest production in the northeastern United States, *Clim. Res.*, 5, 207–222.
- Agren, G. I., and B. Axelsson (1980), Population respiration: a theoretical approach, *Ecol. Model.*, 11, 39–54
- Ainsworth, E. A., and S. P. Long (2005), What have we learned from 15 years of free-air CO₂ enrichment (FACE)? A meta-analytic review of the responses of photosynthesis, canopy properties and plant production to rising CO₂, *New Phytol.*, 165, 351–372.
- Arain, M. A., T. A. Black, A. G. Barr, P. G. Jarvis, J. M. Massheder, D. L. Versegny, and Z. Nesic (2002), Effects of seasonal and interannual climate variability on net ecosystem productivity of boreal deciduous and conifer forests, *Can. J. For. Res.*, 32, 878–891.
- Baldocchi, D. D. (2003), Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: past, present and future, *Glob. Change Biol.*, 9, 479–492.
- Baldocchi, D., et al. (2001), FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities, *Bull. Am. Meteorol. Soc.*, 82, 2415–2435.
- Balshi, M. S., et al. (2007), The role of historical fire disturbance in the carbon dynamics of the pan-boreal region: A process-based analysis, *J. Geophys. Res.*, 112, G02029, doi:10.1029/2006JG000380.

- Bernier, P. Y., F. Raulier, P. Stenberg, and C.-H. Ung (2001), Importance of needle age and shoot structure on canopy net photosynthesis of balsam fir (*Abies balsamea*): a spatially inexplicit modeling analysis, *Tree Physiol.*, *21*, 815–830.
- Bernier, P. Y., N. Bréda, A. Granier, F. Raulier, and F. Mathieu (2002), Validation of a canopy gas exchange model and derivation of a soil water modifier for transpiration for sugar maple (*Acer saccharum* Marsh.) using sap flow density measurements, *For. Ecol. Manag.*, *163*, 185–196.
- Berninger, F., P. Hari, E. Nikinmaa, M. Lindholm, and J. Meriläinen (2004), Use of modeled photosynthesis and decomposition to describe tree growth at the northern tree line, *Tree Physiol.*, *24*, 193–204.
- Biondi, F., and T. W. Swetnam (1987), Box-Jenkins models of forest interior tree-ring chronologies, *Tree-Ring Bull.*, *47*, 71–96.
- Briffa, K. R., and T. M. Melvin (in press), A closer look at Regional Curve Standardisation of tree-ring records: justification of the need, a warning of some pitfalls, and suggested improvements in its application, *Dendroclimatology: Progress and Prospects*, Series: Developments in Paleoenvironmental Research, edited by M. K. Hughes, H. F. Diaz, and T. W. Swetnam, Springer Verlag.
- Briffa, K. R., V. V. Shishov, T. M. Melvin, E. A. Vaganov, H. Grudd, R. M. Hantemirov, M. Eronen, and M. M. Naurzbaev (2008), Trends in recent temperature and radial tree growth spanning 2000 years across northwest Eurasia, *Philos. Trans. R. Soc. Lond. B. Biol. Sci.*, *363*, 2271–2284.
- Canadian Forestry Service (1986), Forest insect and disease survey reports, Edmonton, Alberta.

- Caspersen, J. P., S. W. Pacala, J. C. Jenkins, G. C. Hurtt, P. R. Moorcroft, and R. A. Birdsey (2000), Contributions of land-use history to carbon accumulation in U.S. forests, *Science*, 290, 1148–1151.
- Chen, J. M., W. Chen, J. Liu, and J. Cihlar (2000), Annual carbon balance of Canada's forests during 1895–1996, *Global Biogeochem. Cycles*, 14, 839–850.
- Cook, E. R., and L. A. Kairiukstis (1990), *Methods of dendrochronology: applications in the environmental sciences*, 408 pp., Kluwer Academic Publishers, Boston, MA, USA.
- Cook, E. R., C. A. Woodhouse, C. M. Eakin, D. M. Meko, and D. W. Stahle (2004), Long-term aridity changes in the western United States, *Science*, 306, 1015–1018.
- Cook, E. D., and P. J. Krusic (2006), Program ARSTAN 40c. Tree-ring Laboratory, Lamont-Doherty Earth Observatory, Palisades, NY.
- Crous, K. Y., M. B. Walters, and D. S. Ellsworth (2008), Elevated CO₂ concentration affects leaf photosynthesis-nitrogen relationships in *Pinus taeda* over nine years in FACE. *Tree Physiol.*, 28, 607–614.
- D'Arrigo, R., and G. C. Jacoby (1993), Tree growth-climate relationships at the northern boreal forest tree line of North America: evaluation of potential response to increasing carbon dioxide, *Glob. Biogeochem. Cycles*, 7, 525–535.
- D'Arrigo, R., R. Wilson, and G. Jacoby (2006), On the long-term context for late twentieth century warming, *J. Geophys. Res.*, 111, D03103, doi:10.1029/2005JD006352.

- Dunn, A. L., C. C. Barford, S. C. Wofsy, M. L. Goulden, and B. C. Daube (2007), A long term record of carbon exchange in a boreal black spruce forest: means, responses to interannual variability, and decadal trends, *Glob. Change Biol.*, *13*, 577–590.
- Eguchi, N., K. Karatsu, T. Ueda, R. Funada, K. Takagi, T. Hiura, K. Sasa, and T. Koike (2008), Photosynthetic responses of birch and alder saplings grown in a free air CO₂ enrichment system in northern Japan. *Trees*, *22*, 437–447.
- Esper, J., E. R. Cook, P. J. Krusic, K. Peters, and F. H. Schweingruber (2003), Tests of the RCS method for preserving low-frequency variability in long tree-ring chronologies, *Tree-Ring Res.*, *59*, 81–98.
- Etheridge, D. M., L. P. Steele, R. L. Langenfelds, R. J. Francey, J.-M. Barnola, and V. I. Morgan (1996), Natural and anthropogenic changes in atmospheric CO₂ over the last 1000 years from air in Antarctic ice and firn, *J. Geophys. Res.*, *101*, 4115–4128.
- Farquhar, G. D., S. von Caemmerer, and J. A. Berry (1980), A biochemical model of photosynthetic CO₂ assimilation in leaves of C₃ species, *Planta*, *149*, 78–90.
- Friedlingstein, P., I. Fung, E. Holland, J. John, G. Brasseur, D. Erickson, D. Schimel (1995), On the contribution of CO₂ fertilization to the missing biospheric sink, *Global Biogeochem. Cycles*, *9*, 541–556.
- Friedman, J. H. (1991), Multivariate adaptive regression splines, *Ann. Stat.*, *19*, 1–67.
- Fritts, H. C. (1976), Tree rings and climate. The Blackburn Press. Caldwell, NJ. 567 pp.
- Gamache, I., and S. Payette (2004) Height growth response of tree line black spruce to recent climate warming across the forest-tundra of eastern Canada, *J. Ecol.*, *92*, 835–845.

- Girardin, M.-P., and J. Tardif (2005), Sensitivity of tree growth to the atmospheric vertical profile in the Boreal Plains of Manitoba, Canada, *Can. J. For. Res.*, 35, 48–64.
- Girardin, M. P., and B. M. Wotton (2009), Summer moisture and wildfire risks across Canada. *J. Appl. Meteorol. Climatol.*, 48, 517–533.
- Girardin, M. P., F. Raulier, P. Y. Bernier, and J. C. Tardif (2008), Response of tree growth to a changing climate in boreal central Canada: a comparison of empirical, process-based, and hybrid modelling approaches, *Ecol. Model.*, 213, 209–228.
- Girardin, M.-P., J. C. Tardif, M. D. Flannigan, and Y. Bergeron (2006), Synoptic-scale atmospheric circulation and boreal Canada summer drought variability of the past three centuries. *J. Climate*, 19, 1922–1947.
- Gower, S. T., J. G. Vogel, J. M. Norman, C. J. Kucharik, S. J. Steele, and T. K. Stow (1997), Carbon distribution and aboveground net primary production in aspen, jack pine, and black spruce stands in Saskatchewan and Manitoba, Canada. *J. Geophys. Res.*, 102, 29029–29041.
- Grant, R. F., H. A. Margolis, A. G. Barr, T. A. Black, A. L. Dunn, P. Y. Bernier, and O. Bergeron (2009), Changes in net ecosystem productivity of boreal black spruce stands in response to changes in temperature at diurnal and seasonal time scales, *Tree Physiol.*, 29, 1–17.
- Graumlich, L. J. (1991), Subalpine tree growth, climate, and increasing CO₂: an assessment of recent growth trends, *Ecology*, 72, 1–11.

- Griffis, T. J., T. A. Black, K. Morgenstern, A. G. Barr, Z. Nesic, G. B. Drewitt, D. Gaumont-Guay, and J. H. McCaughey (2003), Ecophysiological controls on the carbon balances of three southern boreal forests, *Agric. For. Meteorol.*, *117*, 53–71.
- Hänninen, H. (1990), Modelling bud dormancy release in trees from cool and temperate regions. *Acta For. Fenn.*, *213*, 1–47.
- Hickler T., B. Smith, I. C. Prentice, K. Mjöfors, P. Miller, A. Arneth, and M. T. Sykes (2008), CO₂ fertilization in temperate FACE experiments not representative of boreal and tropical forests, *Glob. Change Biol.*, *14*, 1531–1542 doi: 10.1111/j.1365-2486.2008.01598.x
- Holmes, R. L. (1983), Computer-assisted quality control in tree-ring dating and measurement, *Tree-Ring Bull.*, *43*, 69–78.
- Huang, J.-G., Y. Bergeron, B. Denneker, F. Berninger, and J. Tardif (2007), Response of forest trees to increased atmospheric CO₂. *Crit. Rev. Plant Sci.*, *26*, 265–283.
- Hunt Jr., E. R., F. C. Martin, and S. W. Running (1991), Simulating the effects of climate variation on stem carbon accumulation of a ponderosa pine stand: comparison with annual growth increment data. *Tree Physiol.*, *9*, 161–171.
- Jacoby, G. C., and R. D'Arrigo (1989), Reconstructed Northern Hemisphere annual temperature since 1671 based on high-latitude tree-ring data from North America, *Clim. Change*, *14*, 39–59.
- Jacoby, G. C., and R. D. D'Arrigo (1997), Tree rings, carbon dioxide, and climatic change, *Proc. Natl. Acad. Sci. USA*, *94*, 8350–8353.
- Jarvis, P., and S. Linder (2000), Constraints to growth of boreal forests, *Nature*, *405*, 904–905.

- Jerabkova, L., C. E. Prescott, and B. E. Kishchuk (2005), Nitrogen availability in soil and forest floor of contrasting types of boreal mixedwood forests, *Can. J. For. Res.*, 36, 112–122.
- Johnson, D. W., W. Cheng, J. D. Joslin, R. J. Norby, N. T. Edwards, and D. E. Todd (2004), Effects of elevated CO₂ on nutrient cycling in a sweetgum plantation. *Biogeochemistry*, 69, 379–403.
- Joos, F., I. C. Prentice, and J. I. House (2002), Growth enhancement due to global atmospheric change as predicted by terrestrial ecosystem models: consistent with US forest inventory data, *Glob. Change Biol.*, 8, 299–303.
- Kagawa, A., A. Sugimoto, and T. C. Maximov (2006), ¹³CO₂ pulse-labelling of photoassimilates reveals carbon allocation within and between tree rings, *Plant Cell Environ.*, 29, 1571–1584.
- Keeling, C. D., R. B. Bacastow, and T. P. Whorf (1982), Measurements of the concentration of carbon dioxide at Mauna Loa Observatory, Hawaii, Carbon Dioxide Review: 1982, edited by W. C. Clarke, Oxford University Press, New York.
- Keeling, C. D., J. F. S. Chin, and T. P. Whorf (1996), Increased activity of northern vegetation inferred from atmospheric CO₂ measurements, *Nature*, 382, 146–149.
- Körner C. H., J. Morgan, and R. Norby (2007), CO₂ fertilization: when, where, how much? *Terrestrial ecosystems in a changing world series: Global change – The IGBP series*, edited by J. G. Canadell, D. Pataki, and L. Pitelka, pp 9–21, Springer, Berlin.

- Körner, C., R. Asshoff, O. Bignucolo, H. Hättenschwiler, S. G. Keel, S. Peláez-Riedl, S. Pepin, R. T. W. Siegwolf, and G. Zotz (2005) Carbon flux and growth in mature deciduous forest trees exposed to elevated CO₂, *Science*, 309, 1360–1362.
- Lambert, M.-C., C.-H. Ung, and F. Raulier (2005), Canadian national tree aboveground biomass equations, *Can. J. For. Res.*, 35, 1996–2018.
- Landsberg, J. J., and R. H. Waring (1997), A generalised model of forest productivity using simplified concepts of radiation-use efficiency, carbon balance and partitioning, *For. Ecol. Manag.*, 95, 209–228.
- Lavigne, M. B., and M. G. Ryan (1997), Growth and maintenance respiration rates of aspen, black spruce and jack pine stems at northern and southern BOREAS sites, *Tree Physiol.*, 17, 543–551.
- Leuning R., F. M. Kelliher, D. G. G. De Pury, and E. D. Schulze (1995), Leaf nitrogen, photosynthesis, conductance and transpiration: scaling from leaves to canopies, *Plant Cell Environ.*, 18, 1183–1200.
- Lloyd, J., and J. A. Taylor (1994), On the temperature dependence of soil respiration, *Funct. Ecol.*, 8, 315–323.
- Margolis, H. A., L. B. Flanagan, and B. D. Amiro (2006), The Fluxnet-Canada Research Network: Influence of climate and disturbance on carbon cycling in forests and peatlands, *Agric. For. Meteorol.*, 140, 1–5.
- McCullough, D. G. (2000), A review of factors affecting the population dynamics of jack pine budworm (*Choristoneura pinus pinus* Freeman), *Popul. Ecol.*, 42, 243–256.
- Mekis, E., and W. D. Hogg (1999), Rehabilitation and analysis of Canadian daily precipitation time series. *Atmosphere-Ocean*, 37, 53–85.

- 888 Misson, L. (2004), MAIDEN: a model for analyzing ecosystem processes in
889 dendroecology. *Can. J. For. Res.*, 34, 874–887.
- 890 Misson, L., C. Rathgeber, and J. Guiot (2004) Dendroecological analysis of climatic
891 effects on *Quercus petraea* and *Pinus halepensis* radial growth using the process-
892 based MAIDEN model. *Can. J. For. Res.*, 34, 888–898.
- 893 Monserud, R. A. (1986), Time-series analyses of tree-ring chronologies. *For. Sci.*, 32,
894 349–372.
- 895 Myneni, R. B., C. D. Keeling, C. J. Tucker, G. Asrar, and R. R. Nemani (1997), Increased
896 plant growth in the northern high latitudes from 1981 to 1991, *Nature*, 386, 698–
897 702.
- 898 Newcomer, J., et al. (2000), Collected data of the boreal ecosystem-atmosphere study.
899 CD-ROM. NASA, Goddard Space Flight Center, Greenbelt, MD.
- 900 Norby, R. J., S. D. Wullschleger, C. A. Gunderson, D. W. Johnson, and R. Ceulemans
901 (1999), Tree responses to rising CO₂ in field experiments: implications for the
902 future forest. *Plant Cell Environ.*, 22, 683–714.
- 903 Norby, R. J., J. M. Warren, C. M. Iversen, B. E. Medlyn, R. E. McMurtrie, and F. M.
904 Hoffman (2008), Nitrogen limitation is reducing the enhancement of NPP by
905 elevated CO₂ in a deciduous forest. *Eos Trans. AGU*, 89(53), Fall Meet. Suppl.,
906 B32B–05.
- 907 Norby, R. J., et al. (2005), Forest response to elevated CO₂ is conserved across a broad
908 range of productivity. *Proc. Natl. Acad. Sci. USA*, 102, 18052–18056.
- 909 Norby R. J., J. M. Warren, C. M. Iversen, C. T. Garten, B. E. Medlyn, and R. E.
910 McMurtrie (2009), CO₂ enhancement of forest productivity constrained by limited

nitrogen availability. *Nature Precedings*,
<http://precedings.nature.com/documents/3747/version/1> (last consulted on 2010-06-21).

Notaro, M., S. Vavrus, and Z. Liu (2007), Global vegetation and climate change due to future increases in CO₂ as projected by a fully coupled model with dynamic vegetation. *J. Climate*, 20, 70–90.

O'ishi, R., A. Abe-Ouchi, I. C. Prentice, and S. Sitch (2009), Vegetation dynamics and plant CO₂ responses as positive feedbacks in a greenhouse world, *Geophys. Res. Lett.*, 36, L11706, doi:10.1029/2009GL038217.

Oren R., et al. (2001), Soil fertility limits carbon sequestration by forest ecosystems in a CO₂-enriched atmosphere, *Nature*, 411, 469–472

Peng, C., X. Zhou, S. Zhao, X. Wang, B. Zhu, S. Piao, and J. Fang (2009), Quantifying the response of forest carbon balance to future climate change in Northeastern China: Model validation and prediction, *Global Planet. Change*, 66, 179–194.

Prentice, I. C., and S. P. Harrison (2009), Ecosystem effects of CO₂ concentration: evidence from past climates, *Clim. Past*, 5, 297–307.

R Development Core Team (2007), 'R: a language and environment for statistical computing', R Foundation for Statistical Computing. Vienna, Austria,
<http://www.R-project.org>.

Rathgeber, C., A. Nicault, J. Guiot, T. Keller, F. Guibal, and P. Roche (2000), Simulated responses of *Pinus halepensis* forest productivity to climatic change and CO₂ increase using a statistical model, *Glob. Planet. Change*, 26, 405–421.

- Rathgeber, C., A. Nicault, J. O. Kaplan, and J. Guiot (2003), Using a biogeochemistry model in simulating forests productivity responses to climatic change and [CO₂] increase: example of *Pinus halepensis* in Provence (south-east France), *Ecol. Model.*, 166, 239–255.
- Raulier, F., P. Y. Bernier, and C. H. Ung (2000), Modeling the influence of temperature on monthly gross primary productivity of sugar maple stands, *Tree Physiol.*, 20, 333–345.
- Raulier, F., P. Y. Bernier, C.-H. Ung, and R. Boutin (2002), Structural differences and functional similarities between two sugar maple (*Acer saccharum*) stands, *Tree Physiol.*, 22, 1147–1156.
- Reich, P. B., S. E. Hobbie, T. Lee, D. S. Ellsworth, J. B. West, D. Tilman, J. M. H. Knops, S. Naeem, and J. Trost (2006), Nitrogen limitation constrains sustainability of ecosystem response to CO₂, *Nature*, 440, 922–925.
- Ryan, M. G. (1991), A simple method for estimating gross carbon budgets for vegetation in forest ecosystems, *Tree Physiol.*, 9, 255–266.
- Schubert, S. D., M. J. Suarez, P. J. Pegion, R. D. Koster, and J. T. Bacmeister (2004), On the cause of the 1930s Dust Bowl, *Science*, 303, 1855–1859.
- Sellers, P.J., et al. (1997), BOREAS in 1997: experiment overview, scientific results, and future directions. *J. Geophys. Res.*, 102, 28731–28769.
- Ste-Marie, C., D. Paré, and D. Gagnon (2007), The contrasting effects of aspen and jack pine on soil nutritional properties depend on parent material, *Ecosystems*, 10, 1299–1310.

- 955 St. George, S., D. M. Meko, M. P. Girardin, G. M. MacDonald, E. Nielsen, G. T.
 956 Pederson, D. J. Sauchyn, J. C. Tardif, and E. Watson (2009), The tree-ring record of
 957 drought on the Canadian Prairies. *J. Climate*, 22, 689–710.
- 958 Su, H., W. Sang, Y. Wang, and K. Ma (2007), Simulating *Picea schrenkiana* forest
 959 productivity under climatic changes and atmospheric CO₂ increase in Tianshan
 960 Mountains, Xinjiang Autonomous Region, China. *For. Ecol. Manag.*, 246, 273–
 961 284.
- 962 Tardif, J. (2004), Fire history in the Duck Mountain Provincial Forest, Western Manitoba,
 963 Sustainable Forest Management Network. Project Reports 2003/2004 Series, 30 pp.,
 964 University of Alberta, Edmonton, Alberta.
 965 (www.sfmnetwork.ca/docs/e/PR_200304tardifjfire6fire.pdf)
- 966 Vincent, L.A., and D. W. Gullett (1999), Canadian historical and homogeneous
 967 temperature datasets for climate change analyses, *Int. J. Climatol.*, 19, 1375–1388.
- 968 Volney, W.J.A. (1988), Analysis of historic jack pine budworm outbreaks in the Prairie
 969 provinces of Canada, *Can. J. For. Res.*, 18, 1152–1158.
- 970 von Storch, H., and F. W. Zwiers (1999), *Statistical Analysis in Climate Research*, 484
 971 pp., Cambridge University Press, Cambridge, UK.
- 972 Wang, X. Z. (2007), Effects of species richness and elevated carbon dioxide on biomass
 973 accumulation: a synthesis using meta-analysis. *Oecologia*, 152, 595–605.
- 974 Wigley, T. M. L., K. R. Briffa, and P. D. Jones (1984), On the average value of correlated
 975 time series, with applications in dendroclimatology and hydrometeorology. *J.*
 976 *Climate Appl. Meteor.*, 23, 201–213.

- 977 Yamaguchi, D. K. (1991), A simple method for cross-dating increment cores from living
978 trees, *Can. J. For. Res.*, *21*, 414–416.
- 979 Zhou, L., C. J. Tucker, R. K. Kaufmann, D. Slayback, N. V. Shabanov, and R. B. Myneni
980 (2001), Variations in northern vegetation activity inferred from satellite data of
981 vegetation index during 1981–1999, *J. Geophys. Res.*, *106*, 20069–20083.
- 982

Figures

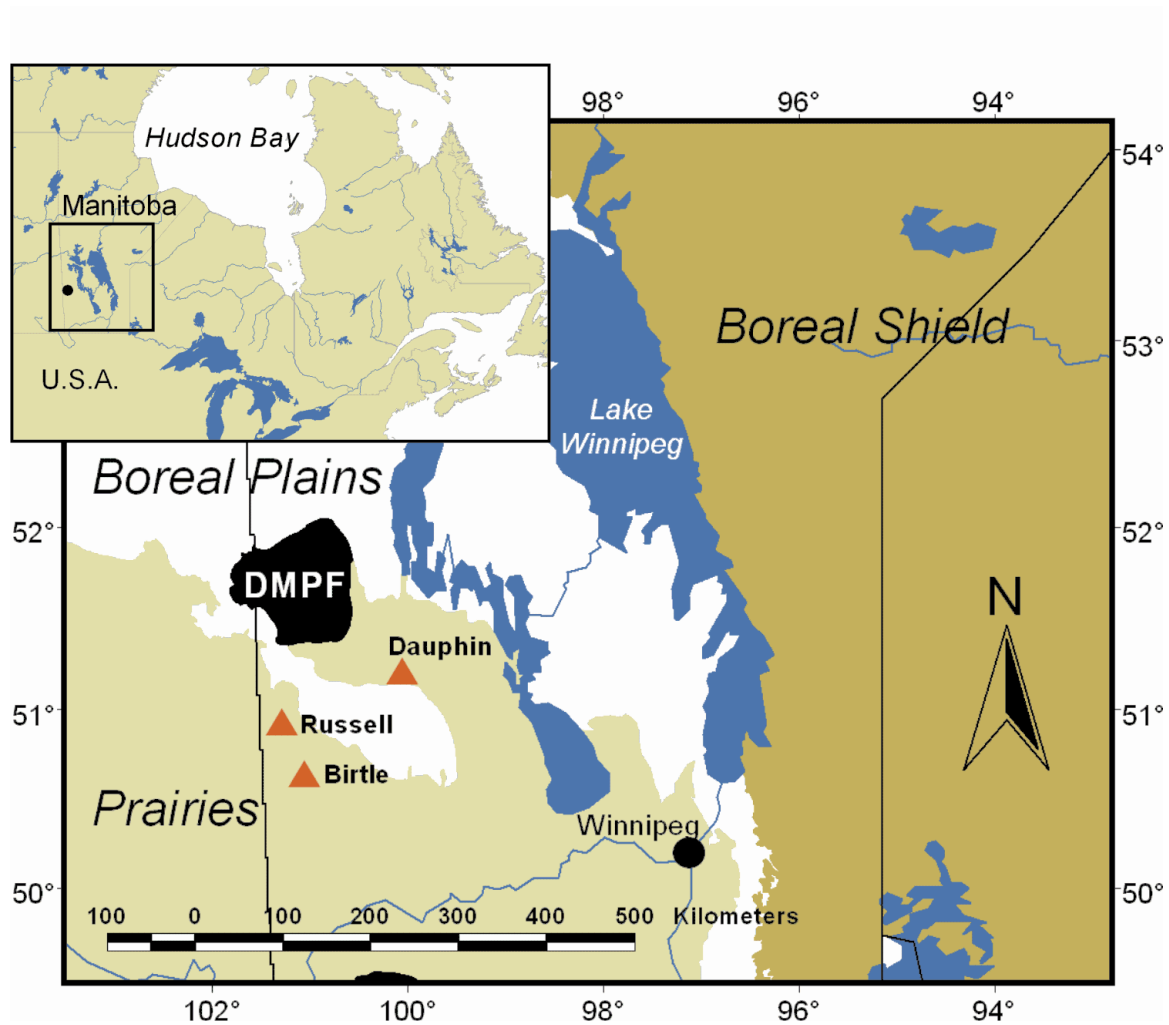


Fig. 1 Map showing the geographical location of Duck Mountain Provincial Forest (DMPF) in Manitoba, Canada. Meteorological stations are indicated by filled triangles.

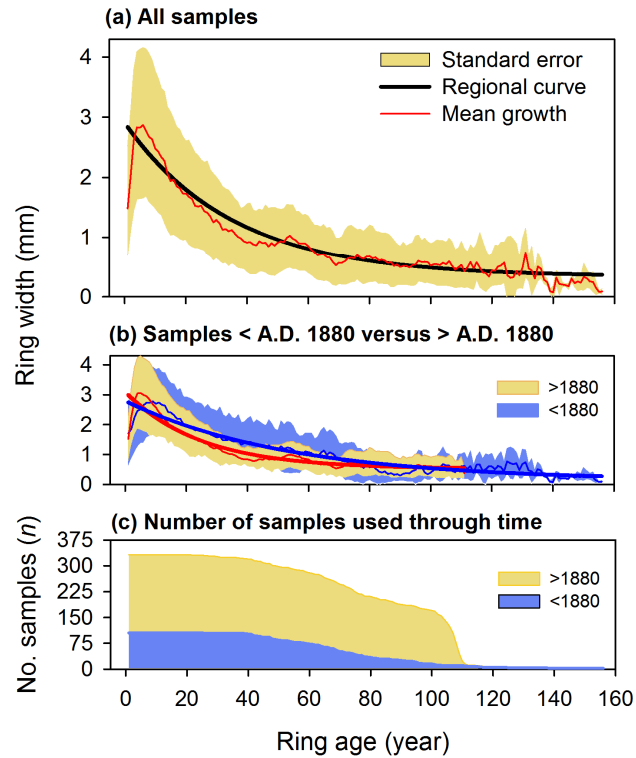


Fig. 2 a) The regional curve used in the detrending of the 332 jack pine ring-width measurement series (thick black line). Gray shaded area shows standard error associated with the mean growth of trees (red line) for each ring age. b) Regional and mean growth curves for trees established prior to and after A.D. 1880. c) Total number of samples (n) used through time (colors refer to dates of tree establishment). Refer to auxiliary materials Figs. S1 and S2 for sensitivity analyses of these curves.

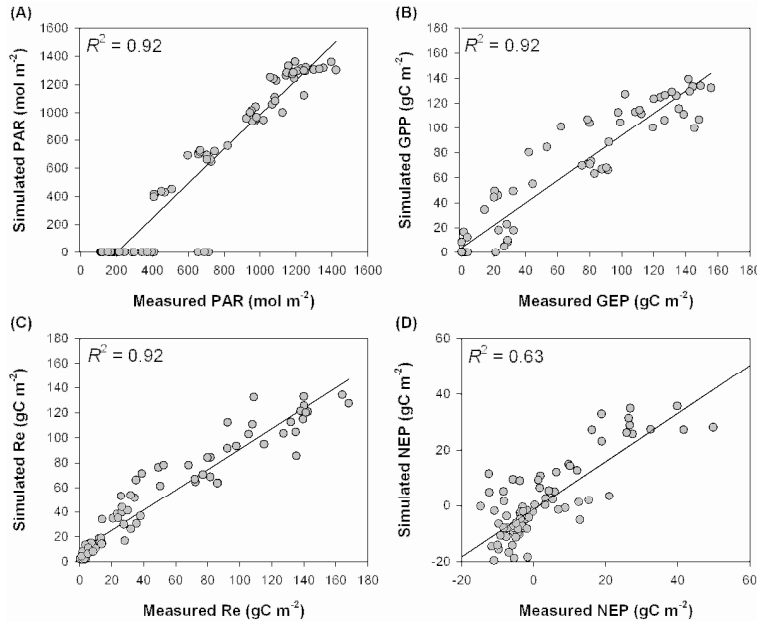


Fig. 3 Comparison of monthly simulated fluxes by StandLEAP with those measured by eddy covariance technique over 2000–2006 in a 95-year-old stand in Saskatchewan, Canada (53.92°N, 104.69°W) [Gower *et al.*, 1997; Griffis *et al.*, 2003]. Data shown are a) photosynthetically active radiation (PAR), b) gross primary productivity (GPP) versus gross ecosystem productivity (GEP), c) ecosystem respiration (Re), and d) net ecosystem productivity (NEP). Linear regression lines with model R-squared are shown. The eddy covariance technique is a well-established method to directly measure fluxes and net ecosystem productivity over a fetch larger than typical plot level measurements (Baldocchi, 2003). The methods used for flux measurements follow the methodology described in Baldocchi *et al.* [2001]. All fluxes were corrected for storage changes in the canopy atmosphere. Stand attributes for StandLEAP simulation were: stem density = 1190 stems ha⁻¹; aboveground biomass = 69.0 Mg ha⁻¹; depth of available soil water = 1.0 m; elevation 579.27 m [Gower *et al.*, 1997].

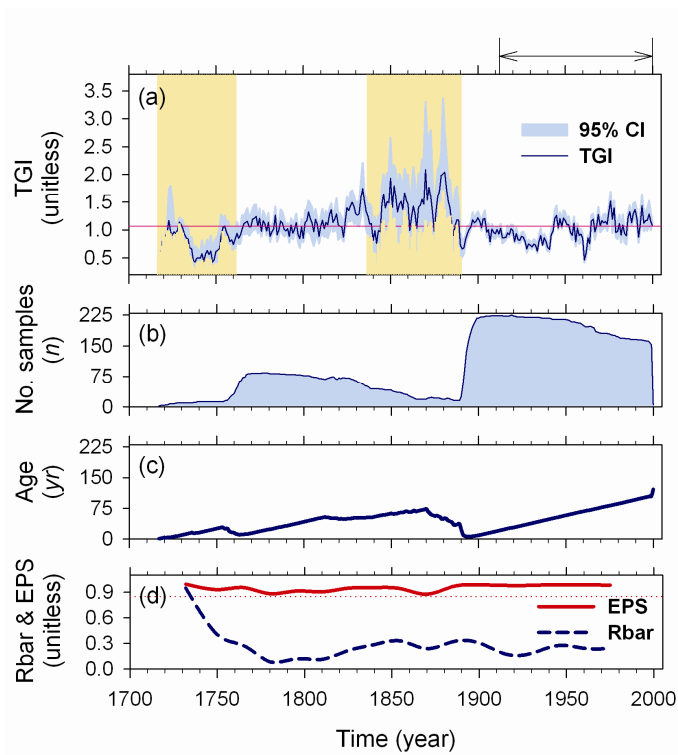


Fig. 4 a) Jack pine tree growth index (TGI) (AD 1717–2000) with 95% bootstrap confidence interval (95% CI; blue shading). A solid line (red) shows the long-term mean; a double arrow (dark grey) delineates the period of analysis 1912–2000 used in the bioclimatic modelling experiment. The vertical shading (yellow) denotes periods with low sample sizes and large error (larger confidence intervals). b) Number of tree rings used through time (divide by 2 for an approximate number of trees). c) Mean cambial age of each calendar year. d) EPS and $Rbar$ statistics (calculated over 30 years lagged by 15 years). The dotted line denotes the 0.85 EPS criterion for signal strength acceptance [Wigley *et al.*, 1984].

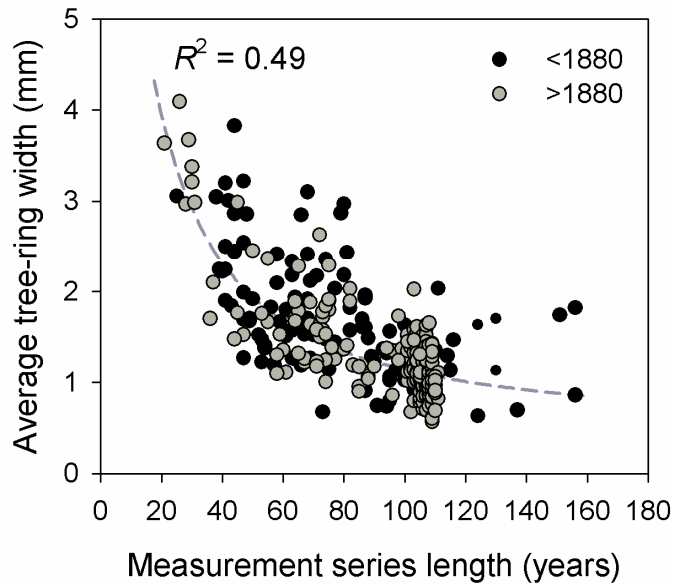
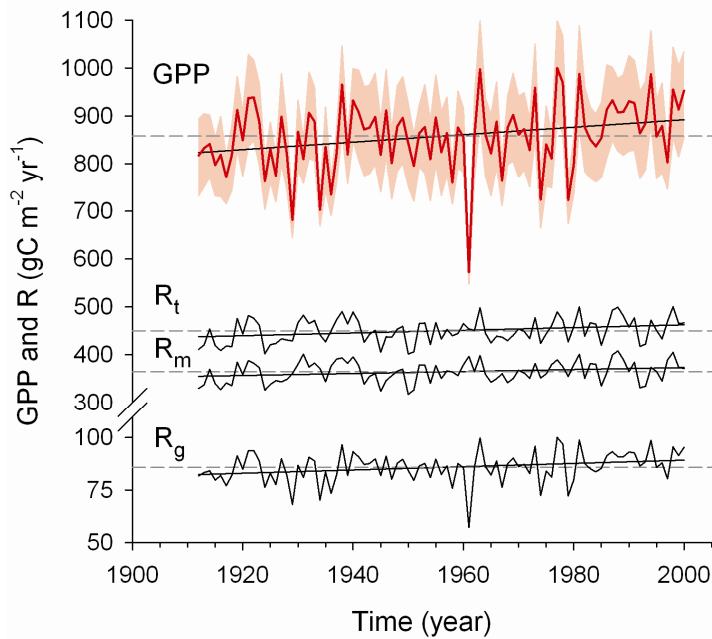
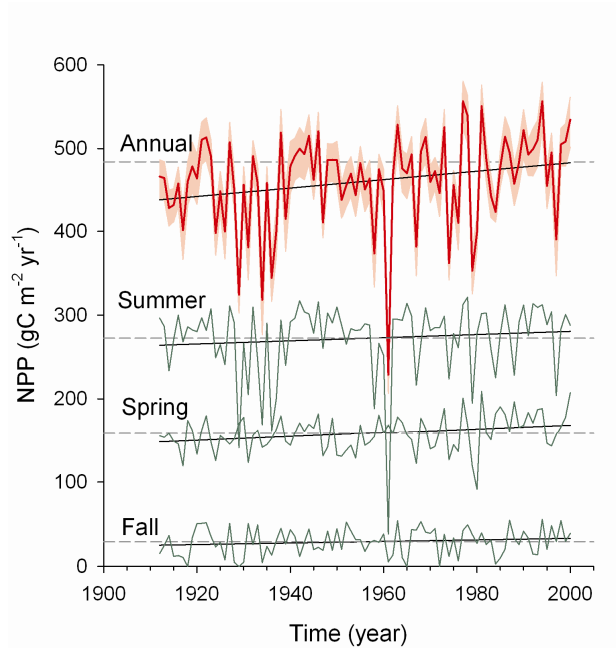


Fig. 5 Relationship between average ring width and length of measurement series for each jack pine series. The diagram differentiates between pre- and post-1880 age cohorts. An exponential fitting is shown along with model fit. The presence of an age-dependent, decreasing relationship between average tree-ring width and measurement series length suggests the existence of a relatively homogeneous behaviour in the growth rates of trees, a necessary condition for application of the regional curve standardization method (*Esper et al.*, 2003).

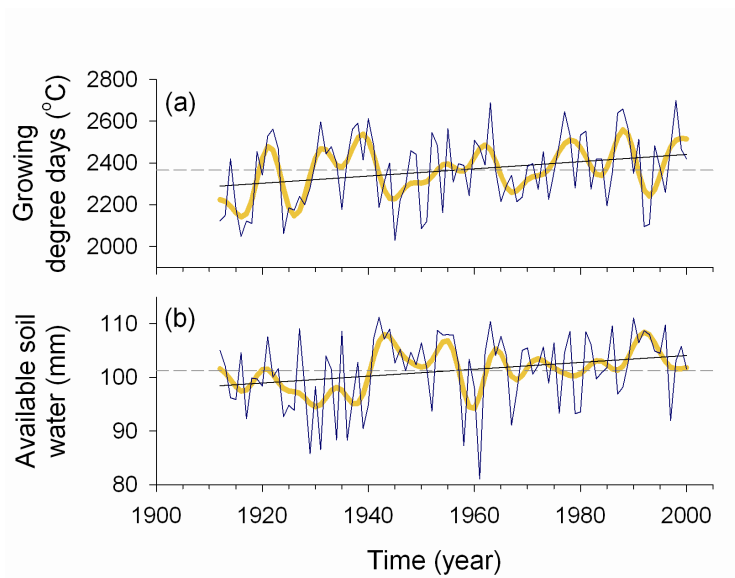


1

2 **Fig. 6** Simulated annual (January to December) gross primary productivity (GPP) and
3 respiration (growth R_g , maintenance R_m and total R_t) over 1912–2000. Shaded area
4 delineates the 95% confidence interval for uncertainty in the mean GPP. Trend lines
5 applied on data are shown; see Table 2 for model statistics.



1
2 **Fig. 7** Simulated net primary productivity (NPP) for spring (March to May), summer
3 (June to August), fall (September to November), and annually (January to December;
4 shaded area delineates the 95% confidence interval for uncertainty in the mean) over
5 1912–2000. Trend lines applied to data are shown; see Table 2 for model statistics. First-
6 order autocorrelation (AR1) values are 0.02, 0.03, 0.11 and 0.02, respectively.



1
2 **Fig. 8** Trend line applied to a) annual sums of growing degree days above 5°C and b)
3 seasonal average (April-September) of available soil water at depth of 1 m. See Table 2
4 for model statistics. Thick lines are 5-year polynomial smoothing across data.

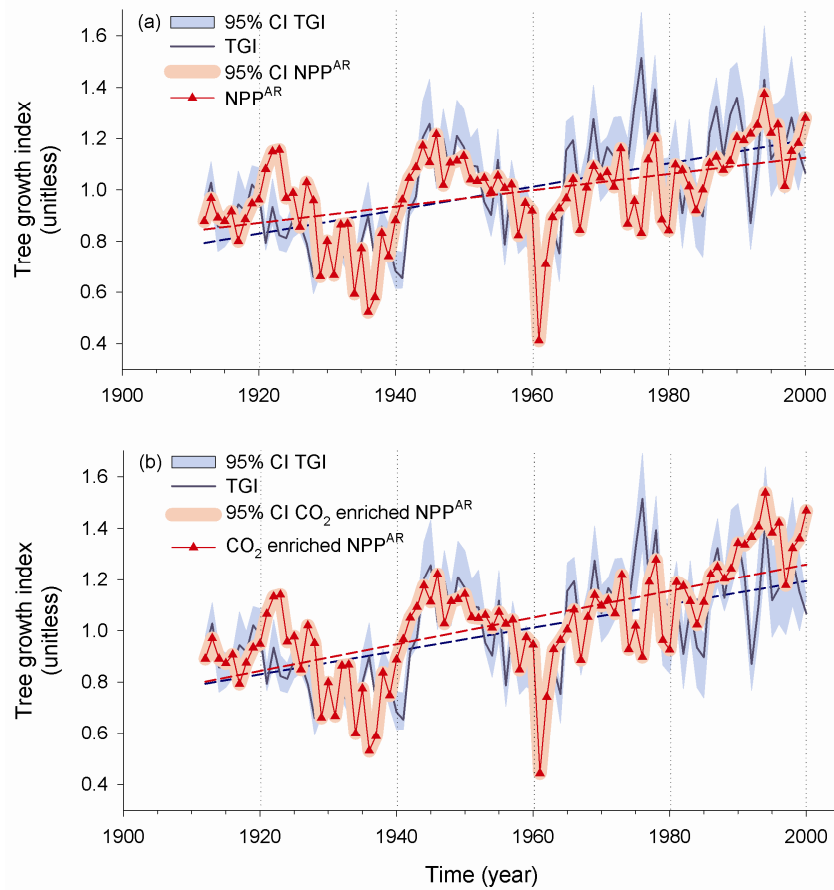


Fig. 9 a) Tree growth index (TGI) versus the AR simulated net primary productivity (NPP^{AR}) over 1912–2000 (both are unitless indices), with linear trend lines across the data (dashed lines; see Table 2 for model statistics). Shaded area: 95% bootstrap confidence interval for uncertainty in the mean TGI and NPP^{AR} (as in Figures 4a and 7). b) Tree growth index (TGI) versus AR simulated net primary productivity (NPP^{AR}) in a CO₂ enriched scenario. The CO₂ enriched simulation is incremented using a logarithmic response function so that NPP achieves an increase of 23% in a doubled CO₂ world (specified parameter $\beta = 0.34$; see text, eq. 9). The CO₂ enriched simulation was achieved using annual averages of atmospheric concentrations of CO₂ reconstructed from ice cores and recorded at Mauna Loa Observatory since 1953.

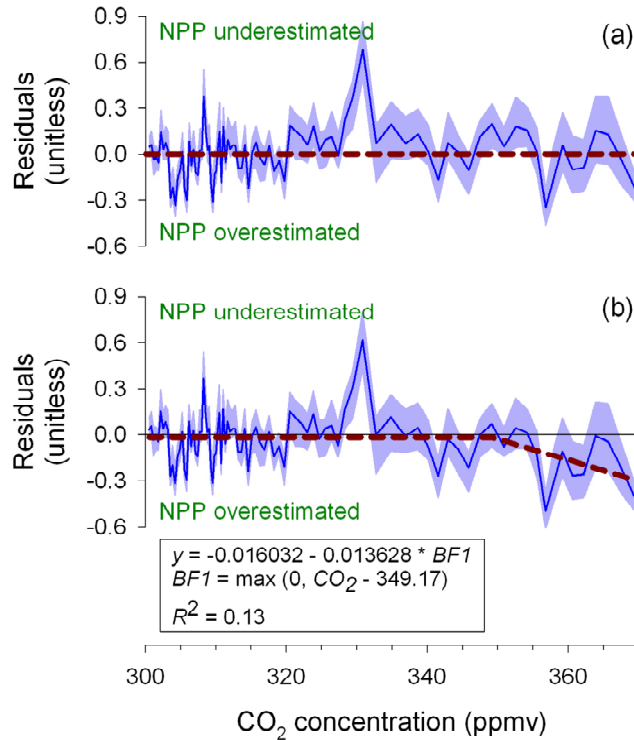


Fig. 10 Residuals of the difference between a) TGI and NPP^{AR} and b) TGI and CO₂ enriched NPP^{AR} (specified parameter $\beta = 0.34$) plotted against annual averages of atmospheric concentrations of CO₂ reconstructed from ice cores and recorded at Mauna Loa Observatory since 1953. Shaded area delineates the 95% confidence interval computed from the square root of the sum of squared errors for TGI and NPP^{AR}. The dashed line shows the relationship between the residuals and atmospheric concentrations of CO₂ modeled using piecewise regression. In (a) the model is suggested to be an intercept-only model; in (b) the relationship takes an inflection point at 349.17 ppmv, suggesting an overestimation of the rate of increase in forest productivity in the last decades of our simulation.

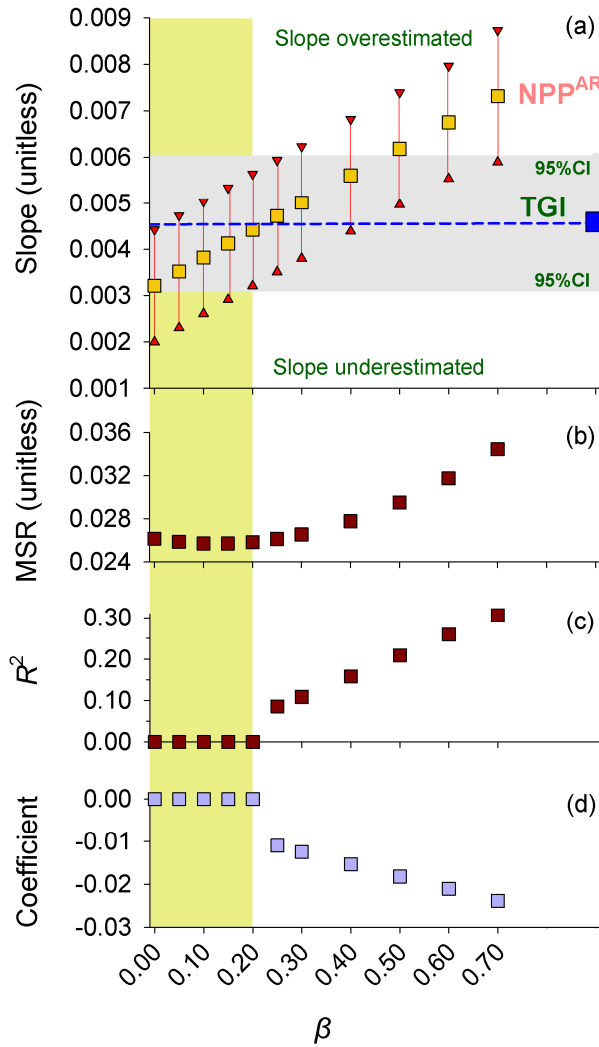


Fig. 11 Sensitivity analysis of the addition of an expected fertilization effect to NPP simulation under a parameter β ranging from 0 to 0.70 (see Methods). a) Slope of the linear trend lines across NPP^{AR} and TGI data (period 1912–2000) with 95% confidence interval (95% CI) (*errors bars* for NPP^{AR} and *horizontal shading* for TGI; adjusted for autocorrelation). b) Mean of squares of the residuals (MSR) of the difference between TGI and NPP^{AR} . c) R -squared of the modelled relationship between the residuals of the difference between TGI and NPP^{AR} and atmospheric concentrations of CO_2 as tested using piecewise regression (refer to Fig. 10). d) Coefficients applied to the basis functions that define the slopes of the non-zero sections. Modelled relationships at $\beta > 0.20$ all took

1 an inflection point at 349.17 ppmv; other models were suggested to be intercept-only
2 models. Results in b), c) and d) suggest an absence of bias in residuals attributed to an
3 over-estimated fertilization effect for values of β ranging from 0 to 0.20 (*vertical*
4 *shading*).

1 Tables

2 Table 1. Summary of the estimated autoregressive (AR) model

Parameter estimates	
Akaike information criterion (AIC) for each AR order	
AR(0)	1402.31
AR(1)	1349.69
AR(2)	1347.60
AR(3)	1348.18
Selected autoregression order	2
Autoregression coefficients	
p_1	0.495
p_2	0.184
R ² due to pooled autoregression	0.39

3 p : autoregressive (AR) coefficients (see eq. 8 in text)

4 Period of analysis: 1880–2000

1 Table 2. Summary of linear trend models on tree growth index (TGI), gross primary
 2 productivity (GPP), net primary productivity (NPP and NPP after application of the AR
 3 model, Table 2), respiration (growth R_g , maintenance R_m and total R_t), growing degree
 4 days above 5°C (GDD), vapour pressure deficit (VPD), and soil water content at a depth
 5 of 1 m (SWC) over the period 1912–2000.

Variable	R^2	Slope	Effective n	t -value	Probability
Annual GPP ^A	0.097	+0.780 (gC m ⁻² yr ⁻¹)	102	3.285	***
Annual R_m ^A	0.051	+0.078 (gC m ⁻² yr ⁻¹)	64	1.835	*
Annual R_g ^A	0.097	+0.204 (gC m ⁻² yr ⁻¹)	102	3.285	***
Annual R_t ^A	0.078	+0.282 (gC m ⁻² yr ⁻¹)	71	2.421	**
Annual NPP ^A	0.078	+0.502 (gC m ⁻² yr ⁻¹)	98	2.838	**
Spring NPP (March-May) ^A	0.083	+0.233 (gC m ⁻² yr ⁻¹)	90	2.830	**
Summer NPP (June-August) ^A	0.021	+0.188 (gC m ⁻² yr ⁻¹)	98	1.442	N.S.
Fall NPP (September-November) ^A	0.023	+0.092 (gC m ⁻² yr ⁻¹)	102	1.533	N.S.
Annual NPP ^{AR}	0.258	+0.0032 (unitless) 95% CI [0.0020, 0.0044]	N.A.	N.A.	**
Annual CO ₂ -enriched NPP ^{AR} ($\beta = 0.34$)	0.386	+0.0044 (unitless) 95% CI [0.0032, 0.0056]	N.A.	N.A.	***
Annual TGI ^B	0.344	+0.0046 (unitless) 95% CI [0.0032, 0.0060]	N.A.	N.A.	**
Residuals (TGI – NPP ^{AR})	0.045	+0.001 (unitless)	N.A.	N.A.	N.S.

Annual sums of GDD	0.060	+0.073 (°C)	68	2.055	**
Annual average of VPD	0.000	-0.023 (Pascal)	61	0.082	N.S.
Seasonal average (April-September) of SWC	0.068	+0.064 (mm)	93	2.058	**

1

2 *** Significant at $P \leq 0.01$ 3 ** Significant at $P \leq 0.05$ 4 * Significant at $P \leq 0.10$

5 N.S.: Not significant

6 N.A.: Not available

7 ^A Significance of the linear trend was examined using least-squares linear regressions

8 [von Storch and Zwiers, 1999]. Goodness of fit is described by the coefficient of

9 determination (R^2). Significance was tested against the null hypothesis that the trend is

10 different from zero, using a variant of the t test with an estimate of the effective sample

11 size (effective n) that takes into account the presence of serial persistence in data.12 ^B Significance of trends was evaluated using Monte Carlo simulations (see Methods).

13

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