Simulating *Picea schrenkiana* forest productivity under climatic changes and atmospheric CO$_2$ increase in Tianshan Mountains, Xinjiang Autonomous Region, China

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Abstract

A process-based model, BIOME-BGC, was used to investigate the response of *Picea schrenkiana* forest to future climate changes and atmospheric carbon dioxide (CO$_2$) concentration increases in the Tianshan Mountains of northwestern China. The model was validated by comparing simulated net primary productivity (NPP) under current climatic conditions with independent field-measured data. Then the model was used to predict *P. schrenkiana* forest productivity response to the different climatic and CO$_2$ change scenarios. The results showed that NPP increased moderately (about 18.6%) for all sites when both temperature and precipitation changes were taken into account. The main factor contributing to NPP increase was an increase in precipitation, which tended to alleviate moisture stress for *P. schrenkiana* forest growth. NPP increase was relatively low (about 2.7%) when the physiological fertilizing effect of the doubled atmospheric CO$_2$ concentration was considered alone, in part because of nitrogen limitation and low temperatures. When both climatic changes and doubling of atmospheric CO$_2$ concentration were taken into account, NPP increased more dramatically (from 26.4% to 37.2%). The results also indicated that the interactive effects of climate and CO$_2$ changes were not a simple additive combination of the individual responses. The results provided support for the view that forest response to climatic change depends on local site conditions.

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Keywords: *Picea schrenkiana* forest; Global change; Net primary productivity (NPP); Tree ring width standard index (RWSI); BIOME-BGC

1. Introduction

Since the industrial revolution, atmospheric carbon dioxide (CO$_2$) concentration has increased markedly, from 280 parts per million by volume (ppmv) in preindustrial times to 368 ppmv in 2000 (Keeling and Whorf, 2002), and the global mean temperature increased by 0.6 ± 0.2 °C during the 20th century (Jones and Moberg, 2003). Those changes have had significant impacts on the structure and function of terrestrial ecosystems (Cao and Woodward, 1998; Alley et al., 2003). Now most climate models predict that during the 21st century, air temperature will rise by 1.5–4.5 °C and that major changes will occur in precipitation and cloud patterns (Cubasch et al., 2001).

Forests cover nearly one-third of the earth’s land area and contain up to 80% of the total above-ground terrestrial carbon and 40% of below-ground carbon (Dixon et al., 1994). Therefore, understanding how forest ecosystems will respond to global change in the future is imperative. Kirschbaum and Fischlin (1996) have suggested that the first response of forests to climate change and atmospheric CO$_2$ concentration increase will likely be an increase in productivity. Although there is a long history of forest net primary productivity (NPP) studies, it is not yet clear how forest NPP will respond to global changes at ecosystem scale.

In recent years, numerous models have been developed to estimate NPP. Regression-based models estimate NPP using only climate variables such as temperature, precipitation, and evaporation (Zhou and Zhang, 1996). However, the potential application of regression models for future projection is limited, because most of them do not consider the fertilizing effect of increased atmospheric CO$_2$ concentration and the possible limitations of nutrient availability (e.g., nitrogen) on...
productivity (Melillo et al., 1993). Unlike regression-based models, process-based models combine scaled-up representations of basic plant biology with ecosystem dynamics and functions to simulate ecosystem-scale processes, including canopy photosynthesis, transpiration, litter dynamics, changes in soil moisture regime, and carbon and nutrient dynamics (VEMAP Members, 1995). Process-based models coupled with field studies of single plants or of whole-ecosystem NPP can help quantify the impacts of global changes on forest ecosystem productivity at various scales (Thornton et al., 2002; Hanson et al., 2004; Law et al., 2004).

*P. schrenkiana* (*Picea schrenkiana* var. tianschanica) forest is the most dominant and widespread boreal forest type on the north slopes of the Tianshan Mountains. It is also one of the most important zonal forms of vegetation in the study region, representing 60.8% of the timber growing stock and 54.0% of forest land in the Xinjiang area (Zhang and Tang, 1989). The biomass and NPP of *P. schrenkiana* forest have been studied over the past two decades (Zhang et al., 1980; Luo, 1996; Wang and Zhao, 1999). The geographical patterns of the *P. schrenkiana* forest have also been analyzed using data from forest inventories and direct field measurements (Wang and Zhao, 2000; Ni, 2004). Until now, no work has been carried out to predict *P. schrenkiana* forest productivity under future scenarios of climatic change and CO2 increase.

In this study, a process-based model, BIOME-BGC (Thornton et al., 2002), was used to assess the effects of potential climatic changes and atmospheric CO2 concentration increases on the NPP of *P. schrenkiana* forest. First, the model was validated by comparing independent field observed data with simulated NPP values. Then the BGC model was used to predict the NPP of *P. schrenkiana* forests under the different scenarios of climatic change and atmospheric CO2 concentration increase in the future.

## 2. Materials and methods

### 2.1. Study sites

The forested zone in the Tianshan Mountains is limited to altitudes between 1500 and 2700 m where sufficient moisture and warmth exist. The thermal tree line lies at 2700 m, where the average temperature during the warmest month is about 10 °C, and the areas below 1500 m are generally too dry to support boreal forest (Zhang and Tang, 1989). The forest structure is multilayered, with different types of plants including trees, shrubs, ferns, grasses, and moss. The canopy is dominated by *P. schrenkiana*. Four sites representing different climatic conditions in the middle elevations on the northern slopes of the Tianshan Mountains were selected for this study: west Tianshan = Zhaosu (ZS), central Tianshan = Tianchi (TC) and Xiaoquzi (XQZ), and east Tianshan = Yiwu (YW) (Fig. 1). The forests are relatively undisturbed by either natural or anthropogenic factors and tend to be quite homogeneous within each site. General characteristics of the forests and sites are given in Table 1.

### 2.2. Field measurements

A total of 37 plots were surveyed in the four sites (Table 1), each of size 20 m × 20 m. Measurements were made of tree diameter at breast height (DBH, 1.30 m above the ground) and of height for all trees >4 cm DBH. Smaller trees were included in the survey as shrubs. Six *P. schrenkiana* trees in different diameter classes without visible signs of damage were randomly selected as sample trees to obtain increment cores for each plot. Two increment cores for each selected tree were sampled at 1.30 m above the ground with a Presler increment borer and stored in paper straws.

Fig. 1. Location of the four studied sites, and the corresponding meteorological stations in the Tianshan Mountains, Xinjiang Autonomous region, China.
2.3. Tree-ring chronology development

Tree cores were mounted on grooved boards and sanded to facilitate identification of the tree rings. Tree rings were then crossdated using a skeleton plot (Stokes and Smiley, 1968), and the ring widths were measured to the nearest 0.001 mm using the WinDENDRO™ 2001b apparatus (Université du Québec à Chicoutimi, Canada). Crossdating and measurement accuracies were checked and confirmed by correlating overlapping 50-year segments of all measured series using the COFECHA software developed by Holmes (1983), and the cores that could not be crossdated were discarded. Tree-ring chronologies were constructed using conventional analytical techniques (Fritts, 1976; Cook and Kairiukstis, 1990). To focus on the common growth variations associated with climate, growth trends were removed from individual series using conservative detrending (negative exponential curves or straight lines) (Fritts, 1976). Indices for each series were derived by taking the ratio of the measurement over the fitted value in each year. After standardizing series were derived by taking the ratio of the measurement over the fitted value in each year.

Table 1

General characteristic of the four study sites with current climate (mean annual temperature and total precipitation).

<table>
<thead>
<tr>
<th>Sites</th>
<th>No. of plots</th>
<th>Alt. range (m)</th>
<th>Soil type a</th>
<th>SOM b (%)</th>
<th>Total N b (%)</th>
<th>Density (trees ha⁻¹)</th>
<th>DBH c (cm)</th>
<th>Height (m)</th>
<th>Temperature (°C)</th>
<th>Precipitation (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZS</td>
<td>7</td>
<td>2130–2230</td>
<td>MLGS</td>
<td>25.31</td>
<td>0.81</td>
<td>1123(700–2200)</td>
<td>17.9 ± 1.5</td>
<td>11.0 ± 1.1</td>
<td>2.3 ± 0.1</td>
<td>657.7 ± 17.7</td>
</tr>
<tr>
<td>XQZ</td>
<td>9</td>
<td>1940–2090</td>
<td>MTGS</td>
<td>23.03</td>
<td>0.75</td>
<td>1269(825–1700)</td>
<td>17.1 ± 1.4</td>
<td>13.5 ± 1.0</td>
<td>2.3 ± 0.1</td>
<td>540.1 ± 16.0</td>
</tr>
<tr>
<td>TC</td>
<td>12</td>
<td>1900–2320</td>
<td>MTGS</td>
<td>23.03</td>
<td>0.75</td>
<td>1975(1050–3450)</td>
<td>15.6 ± 1.0</td>
<td>11.4 ± 0.7</td>
<td>2.1 ± 0.1</td>
<td>533.2 ± 18.9</td>
</tr>
<tr>
<td>YW</td>
<td>9</td>
<td>2310–2440</td>
<td>MCGS</td>
<td>14.34</td>
<td>0.46</td>
<td>1583(795–3250)</td>
<td>17.5 ± 1.4</td>
<td>11.9 ± 1.0</td>
<td>1.2 ± 0.1</td>
<td>417.0 ± 11.7</td>
</tr>
</tbody>
</table>

a MLGS: mountain leaching gray-cinnamon forest soil, MTGS: mountain typical gray-cinnamon forest soil, MCGS: mountain carbonate gray-cinnamon forest soil.
b SOM: soil organic matter, total N: total nitrogen. Only organic matter content and total nitrogen in the top 30 cm were analyzed by Wang and Zhao (2000).
c DBH: diameter at breast height. DBH, height, temperature and precipitation are all presented: mean ± S.E.

2.4. Field-based estimation of NPP

Using field survey data, biomass values for tree stems, branches, and needles were estimated from DBH (cm) and H (m) following the allometric relationship derived from P. schrenkiana forests adjacent to the central Tianshan study sites (Zhang et al., 1980). The allometric equations used were:

\[ W_{stem} = 0.047465712(D^2H)^{0.88217} \]  
\[ W_{branch} = 0.00189147(D^2H)^{1.03981} \]  
\[ W_{needle} = 0.01451443(D^2H)^{0.78914} \]

where \( W_{stem} \), \( W_{branch} \), and \( W_{needle} \) are the biomass values of tree stems, branches, and needles, respectively. Stem and branch NPP were estimated from the mean radial growth increment over 10 years (1991–2000), tree dimensions, and species (the last using specific allometric equations on a tree-by-tree basis) were summed to the plot level. The arithmetic average radial increment was estimated from all the increment cores for each site. The annual net increment of leaf was derived from leaf biomass divided by leaf age (residence time, which is 5 years for \( P. schrenkiana \)). The belowground biomass and NPP were not measured in the field in this study. Root biomass was assumed to account for 18.6% of total tree biomass and the root NPP to be 26.9% of total tree NPP, in accordance with the work of Wang and Zhao (2000).

Biomass of shrubs and grasses was estimated using ratios based on the biomass of trees. The average NPP of the shrub and grass layers was estimated by dividing their biomass by their average age (7 years for shrubs and 1 year for grasses in this study) (Luo, 1996). Litter and biomass losses to herbivores were not considered. Total forest NPP was estimated by summarizing annual net increments of tree stems, branches, leaves, and roots and the annual net increments of shrubs and grasses.

The field-based NPP data were converted to grams of carbon per square meter per year (g C m⁻² year⁻¹), where 1 g carbon is equivalent to 2.2 g oven-dry organic matter (Ni, 2003), for purposes of comparison with model-predicted NPP values.

2.5. Simulation of NPP using BIOME-BGC model

2.5.1. Model description

The BIOME-BGC (Version 4.1.1) model has been described in detail by Thornton et al. (2002), and therefore only a summary of important components of the model relating to the NPP and carbon-cycle processes is briefly presented here. NPP was computed as the difference between gross photosynthesis and autotrophic respiration. Gross photosynthesis on a unit projected leaf area basis for \( C_3 \) plants was estimated independently for the sunlit and shaded canopy fractions using...
a biochemical model (Farquhar et al., 1980), with kinetic parameters from Woodrow and Berry (1988) and de Pury and Farquhar (1997) and substitution from the CO₂ diffusion equation to eliminate the explicit dependency on intracellular CO₂ concentration. The maximum rate of carboxylation was calculated as a function of the specific activity of the Rubisco enzyme (itself a function of leaf temperature), the weight fraction of nitrogen in the Rubisco molecule, the fraction of total leaf nitrogen in the Rubisco enzyme, the specific leaf area, and the leaf C:N ratio. Autotrophic respiration was the sum of maintenance and growth respiration of the different parts of the plant (canopy, stem, and roots). Maintenance respiration of each plant component was calculated as a function of tissue mass, tissue nitrogen concentration, and tissue temperature. Growth respiration was a simple proportion of total new carbon allocated to growth. Thus, BIOME-BGC was able to simulate the effects of a number of abiotic and biotic controls on forest productivity.

### Table 2
Ecophysiological parameterization of *Picea schrenkiana* forest for BIOME-BGC model

<table>
<thead>
<tr>
<th>Value</th>
<th>Unit</th>
<th>Parameter description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
<td>DIM</td>
<td>Transfer growth period as fraction of growing season</td>
</tr>
<tr>
<td>0.3</td>
<td>DIM</td>
<td>Litterfall as fraction of growing season</td>
</tr>
<tr>
<td>0.25</td>
<td>1 year⁻¹</td>
<td>Annual leaf and fine root turnover fraction</td>
</tr>
<tr>
<td>0.70</td>
<td>1 year⁻¹</td>
<td>Annual live wood turnover fraction</td>
</tr>
<tr>
<td>0.005</td>
<td>1 year⁻¹</td>
<td>Annual whole-plant mortality fraction</td>
</tr>
<tr>
<td>1.0</td>
<td>Ratio</td>
<td>(Allocation) new fine root C: new leaf C</td>
</tr>
<tr>
<td>2.2</td>
<td>Ratio</td>
<td>(Allocation) new stem C: new leaf C</td>
</tr>
<tr>
<td>0.1</td>
<td>Ratio</td>
<td>(Allocation) new live wood C: new total wood C</td>
</tr>
<tr>
<td>0.3</td>
<td>DIM</td>
<td>(Allocation) new root C: new stem C</td>
</tr>
<tr>
<td>0.5</td>
<td>DIM</td>
<td>(Allocation) current growth proportion</td>
</tr>
<tr>
<td>42.0</td>
<td>kg C/kg N</td>
<td>C:N of leaves</td>
</tr>
<tr>
<td>93.0</td>
<td>kg C/kg N</td>
<td>C:N of leaf litter, after retranslocation</td>
</tr>
<tr>
<td>42.0</td>
<td>kg C/kg N</td>
<td>C:N of fine roots</td>
</tr>
<tr>
<td>50.0</td>
<td>kg C/kg N</td>
<td>C:N of live wood</td>
</tr>
<tr>
<td>729.0</td>
<td>kg C/kg N</td>
<td>C:N of dead wood</td>
</tr>
<tr>
<td>0.32</td>
<td>DIM</td>
<td>Leaf litter labile proportion</td>
</tr>
<tr>
<td>0.44</td>
<td>DIM</td>
<td>Leaf litter cellulose proportion</td>
</tr>
<tr>
<td>0.24</td>
<td>DIM</td>
<td>Leaf litter lignin proportion</td>
</tr>
<tr>
<td>0.30</td>
<td>DIM</td>
<td>Fine root labile proportion</td>
</tr>
<tr>
<td>0.45</td>
<td>DIM</td>
<td>Fine root cellulose proportion</td>
</tr>
<tr>
<td>0.25</td>
<td>DIM</td>
<td>Fine root lignin proportion</td>
</tr>
<tr>
<td>0.76</td>
<td>DIM</td>
<td>Dead wood cellulose proportion</td>
</tr>
<tr>
<td>0.24</td>
<td>DIM</td>
<td>Dead wood lignin proportion</td>
</tr>
<tr>
<td>0.041</td>
<td>1/LAI/d</td>
<td>Canopy water interception coefficient</td>
</tr>
<tr>
<td>0.5</td>
<td>DIM</td>
<td>Canopy light extinction coefficient</td>
</tr>
<tr>
<td>2.6</td>
<td>DIM</td>
<td>All-sided to projected leaf area ratio</td>
</tr>
<tr>
<td>12.0</td>
<td>m²/kg C</td>
<td>Canopy average specific leaf area (projected area basis)</td>
</tr>
<tr>
<td>2.0</td>
<td>DIM</td>
<td>Ratio of shaded SLA:sunlit SLA (specific leaf area)</td>
</tr>
<tr>
<td>0.04</td>
<td>DIM</td>
<td>Fraction of leaf N in Rubisco</td>
</tr>
<tr>
<td>0.003</td>
<td>m/s</td>
<td>Maximum stomatal conductance (projected area basis)</td>
</tr>
<tr>
<td>0.00001</td>
<td>m/s</td>
<td>Cuticular conductance (projected area basis)</td>
</tr>
<tr>
<td>0.08</td>
<td>m/s</td>
<td>Boundary layer conductance (projected area basis)</td>
</tr>
<tr>
<td>0.6</td>
<td>MPa</td>
<td>Leaf water potential: start of conductance reduction</td>
</tr>
<tr>
<td>2.3</td>
<td>MPa</td>
<td>Leaf water potential: complete conductance reduction</td>
</tr>
<tr>
<td>930.0</td>
<td>Pa</td>
<td>Vapor pressure deficit: start of conductance reduction</td>
</tr>
<tr>
<td>4100.0</td>
<td>Pa</td>
<td>Vapor pressure deficit: complete conductance reduction</td>
</tr>
</tbody>
</table>

* DIM: dimensionless.

### Table 3
Site-specific parameterization of the study sites for BIOME-BGC model

<table>
<thead>
<tr>
<th>Sites</th>
<th>Latitude (°)</th>
<th>Longitude (°)</th>
<th>Alt. (m)</th>
<th>Soil texture*</th>
<th>Soil depth (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Sand (%)</td>
<td>Silt (%)</td>
</tr>
<tr>
<td>ZS</td>
<td>43.23</td>
<td>81.11</td>
<td>2007.1</td>
<td>19.79</td>
<td>66.21</td>
</tr>
<tr>
<td>XQZ</td>
<td>43.49</td>
<td>87.11</td>
<td>2018.9</td>
<td>26.17</td>
<td>51.67</td>
</tr>
<tr>
<td>TC</td>
<td>43.88</td>
<td>88.12</td>
<td>1942.5</td>
<td>26.17</td>
<td>51.67</td>
</tr>
<tr>
<td>YW</td>
<td>43.40</td>
<td>93.87</td>
<td>2395.6</td>
<td>28.18</td>
<td>50.62</td>
</tr>
</tbody>
</table>

* Data from Sun (1995).
Consistency between model results and field measurements is essential for establishing the credibility of a model such as BIOME-BGC. Although the logic of the BIOME-BGC model has undergone widespread testing and validation (Hunt et al., 1991; Korol et al., 1991; Thornton et al., 2002; Churkina et al., 2003; Hanson et al., 2004; Law et al., 2004; Schmid et al., 2006), the performance of the model was further tested in this research for *P. schrenkiana* forests in the Tianshan Mountains by comparing modeled outputs to independent field observations.

### 2.5.2. Model parameterization

The BIOME-BGC model requires parameters relating to vegetation, site condition, and daily climate data to simulate the NPP of an ecosystem. The model was initialized for the four *P. schrenkiana* forest sites with a single set of ecophysiological parameters (Table 2) and with four site-specific sets of parameters (Table 3).

The standard daily meteorological input file, including maximum temperature, minimum temperature, precipitation, solar radiation, vapor pressure deficit, and day length, was generated by a computer program for microclimate simulation, MT-CLIM (Version 4.3, www.forestry.umt.edu/ntsg). Daily meteorological records (daily air temperature and precipitation for 1961–2000) were obtained from the China National Climatic Data Center (NCDC). The XQZ and TC stations are centrally located in the study region and fall within the elevation range of the plots under study, so the weather data could be used without interpolation. MT-CLIM initialized the flat surface conditions of the two sites to the same elevation as the original station data to compute the variables not present in standard weather station records for the BIOME-BGC model. However, the ZS and YW stations are some distance from the study sites (about 10 and 25 km, respectively), which may introduce some uncertainty into the climate data used for the simulations. Therefore, the daily data were adjusted for site conditions using MT-CLIM. In addition, the coefficient to adjust daylight average temperature (TEMCF), which was set to 0.45 in the original model program, was set to 0.07 for ZS, TC, XQZ, and YW, respectively, to help separate the relative importance of doubled CO2 concentration and precipitation +25%.

### 2.5.3. Climate and CO2 scenarios

The future climate scenario was obtained from a second-generation regional climate model (RegCM2) downscaled to the study sites (Gao et al., 2001, 2003). The grid resolution of this model was approximately 60 km × 60 km. A control run of the RegCM2 model was available which covered a 10-year period (January 1981 to December 1990), and the doubled CO2 scenario was simulated over 5 years. The simulated climatic changes for a doubled CO2 scenario were very similar at each of the four sites. The same climate change scenario was therefore used for all sites, taking the mean change for each variable (temperature +2.6 °C and precipitation +25%). To help separate out the relative importance of doubled CO2 concentration and climate change, the three primary driving variables, each at two levels, were used to define eight combinations as climatic scenarios (Table 4).

### 2.5.4. Model simulation

Unless initial values for the model’s state variables are available from measurements, model simulations (startup runs) are required to initialize them. In the startup run, the model is run to steady state to obtain the size of the ecosystem’s C and N pools under the assumption that the ecosystem is in

### Table 4

The future climatic scenarios obtained from a second-generation regional climate model (RegCM2) for the BIOME-BGC run

<table>
<thead>
<tr>
<th>Climatic scenarios</th>
<th>Ambient CO2 concentration</th>
<th>Temperature</th>
<th>Precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>C0T0P0</td>
<td>No change</td>
<td>No change</td>
<td>No change</td>
</tr>
<tr>
<td>C0T1P0</td>
<td>No change</td>
<td>No change</td>
<td>+25%</td>
</tr>
<tr>
<td>C1T0P0</td>
<td>No change</td>
<td>+2.6 °C</td>
<td>No change</td>
</tr>
<tr>
<td>C1T0P1</td>
<td>No change</td>
<td>+2.6 °C</td>
<td>+25%</td>
</tr>
<tr>
<td>C1T0P0</td>
<td>Doubled</td>
<td>No change</td>
<td>No change</td>
</tr>
<tr>
<td>C1T0P1</td>
<td>Doubled</td>
<td>No change</td>
<td>+25%</td>
</tr>
<tr>
<td>C1T1P0</td>
<td>Doubled</td>
<td>+2.6 °C</td>
<td>No change</td>
</tr>
<tr>
<td>C1T1P1</td>
<td>Doubled</td>
<td>+2.6 °C</td>
<td>+25%</td>
</tr>
</tbody>
</table>

*The first simulation (C0T0P0) was realized with the current meteorological data and an atmospheric CO2 concentration fixed at 355 ppmv.*

### Table 5

General statistics of the standardized chronology for four *P. schrenkiana* forest sites

<table>
<thead>
<tr>
<th>Sites</th>
<th>Samples/trees</th>
<th>Period</th>
<th>MS</th>
<th>S.D.</th>
<th>R1</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZS</td>
<td>33/33</td>
<td>1941–2002</td>
<td>0.16</td>
<td>0.15</td>
<td>0.23</td>
</tr>
<tr>
<td>XQZ</td>
<td>26/25</td>
<td>1929–2002</td>
<td>0.22</td>
<td>0.18</td>
<td>0.28</td>
</tr>
<tr>
<td>TC</td>
<td>61/32</td>
<td>1900–2000</td>
<td>0.19</td>
<td>0.20</td>
<td>0.07</td>
</tr>
<tr>
<td>YW</td>
<td>18/18</td>
<td>1851–2002</td>
<td>0.23</td>
<td>0.22</td>
<td>0.20</td>
</tr>
</tbody>
</table>

equilibrium; the 40-year climate record was also replicated as a requirement. Using the endpoint of the startup run as an initial condition, the model first reconstructed the NPP series for the last 40 years (using the observed climatic data and atmospheric CO₂ concentrations during the period from 1961 to 2000) to provide validation. Then, in order to assess the impact of climatic change and atmospheric CO₂ concentration increases, the model was run with each scenario in Table 4 for each site.

3. Results

3.1. Tree-ring standard chronologies and field-based NPP

Tree-ring chronologies were developed for *P. schrenkiana* forest in each site and the general statistics are shown in Table 5. The higher values of MS and S.D. are exceptional for arid site forest (e.g., plot YW). Based on field survey data, the mean
NPP of *P. schrenkiana* forests was 630.7 g C m$^{-2}$ year$^{-1}$ in ZS, 524.4 g C m$^{-2}$ year$^{-1}$ in XQZ, 446.0 g C m$^{-2}$ year$^{-1}$ in TC, and 342.4 g C m$^{-2}$ year$^{-1}$ in YW (Fig. 2).

3.2. Model validation

For the climate data and atmospheric CO$_2$ concentrations for 1991–2000, the BIOME-BGC estimations of mean NPP were close to the mean field-based estimates of NPP for the forests in ZS and XQZ, and 13.7% and 11.7% higher than the field estimates for the forests in TC and YW, respectively (Fig. 2). However, all the model-derived estimates were within the ranges of statistical validity established from field surveys at each site.

The NPP series produced by the model were significantly correlated ($R$ values ranging between 0.35 and 0.54) with the independent RWSI series, which was used as an index of long-term forest productivity variations under natural environmental conditions at the four sites (Fig. 3). Although the model showed some bias in the estimation of the RWSI series and predicted lower-than-observed values in some years (e.g., 1995 in ZS, 2000 in YW), the model matched quite well the year-to-year frequency component of productivity variation, which corresponds to interannual climatic variations.

3.3. Response of NPP to changes in climate and atmospheric CO$_2$ concentration

Using the simulated results with current values of 355 ppmv CO$_2$ (under the C$_0$T$_0$P$_0$ scenario) as the baseline for comparison, the predicted NPP of the *P. schrenkiana* forests increased by 14.5% when precipitation increases alone were taken into account (under the C$_1$T$_0$P$_1$ scenario). Nevertheless, some differences could be observed among the different sites: the

![Figure 4](image-url)
productivity increases ranged from 10.4% (for site ZS) to 17.8% (for site YW) (Fig. 4). The effects of temperature increases alone (under the $C_1T_1P_0$ scenario) were positive for all the studied sites, and the simulated increase was about 6.4%. The increase is not uniform and ranges between 1.8% (for site XQZ) to 12.1% (for site YW). With changes in both temperature and precipitation (under the $C_1T_1P_1$ scenario), NPP increased by about 18.6%, with a range from 13.3% (for site ZS) to 29.2% (for site YW). In contrast to the results for climate change, the simulated results indicated that NPP showed relatively little response to doubled atmospheric CO2 concentration alone (under the $C_1T_0P_0$ scenario); NPP increased by about 2.7%, and only the XQZ site showed a significant increase (8.6%). With changes in both temperature and atmospheric CO2 concentration (under the $C_1T_1P_0$ scenario), productivity increased by about 17.9% (with a range from 13.7% for site TC to 19.8% for site XQZ). Changes in both precipitation and atmospheric CO2 concentration (under the $C_1T_0P_1$ scenario) increased NPP by about 18.6% (with a range from 12.3% for site ZS to 23.4% for site XQZ). When all climatic changes and doubled atmospheric CO2 concentration were taken into account (under the $C_1T_1P_1$ scenario), NPP increased dramatically, with an average increase of about 30.4% and a range from 26.4% (for site ZS) to 37.2% (for site YW) (Fig. 4).

4. Discussion

4.1. Tree-ring standard chronologies

In a dendroclimatological study, it is necessary to select sites carefully to maximize the potential climate sensitivity within tree-ring samples, so most field work in this area has been done in extreme tree-growth environments such as timberlines. Such areas are near the biotic ecological limits of the tree species that occur there, where the trees may react more strongly to climatic changes (Graumlich, 1991). However, the dendrochronological variable RWSI was used in this study as an estimator of forest productivity, and all the samples were obtained within the center of the forest zone, where competition among trees may have had significant effects on growth. As a result, the MS (ranging from 0.16 to 0.23) and S.D. (ranging from 0.15 to 0.22) of the tree-ring standard chronologies were relatively low (Table 5). Nevertheless, these values agree with previously published tree-ring standard chronologies for the north slopes of the Tianshan Mountains (Li, 1989). $R_1$ values ranged from 0.07 to 0.28, suggesting some autocorrelation between the previous year’s and the current year’s growth rings, mostly because of tree biology (Berneiring et al., 2004; Table 5), MS, S.D., and $R_1$ for each chronology all suggested that the four chronologies constructed in this study are well suited for evaluating the impacts of climatic change and atmospheric CO2 concentration increases on forest productivity.

4.2. Field-based NPP estimates

Field-based NPP estimates obtained in this study agreed with previously published estimates of productivity in the north slopes of the Tianshan Mountains. Based on forest inventory data for 1991–1996, Wang and Zhao (2000) estimated that the NPP of $P. schrenkiana$ forests was 466.8 g C m$^{-2}$ year$^{-1}$ (with a range from 246.65 to 863.9 g C m$^{-2}$ year$^{-1}$) in west Tianshan, and 328.8 g C m$^{-2}$ year$^{-1}$ (with a range from 162.6 to 636.9 g C m$^{-2}$ year$^{-1}$) in central and east Tianshan. Ni (2004) found that the NPP of coniferous forests was 495.0 ± 215.0 g C m$^{-2}$ year$^{-1}$ (with a range from 110.0 to 915.0 g C m$^{-2}$ year$^{-1}$) using data derived from a national forest inventory for 1956–1970 at 56 plots in 14 forest sites in the Tianshan Mountains. Although much work has already been done, there are still some uncertainties in the NPP estimates derived from field measurements in this study. The problems relate to biomass measurements and the methodologies used for NPP estimation. Developing site-specific allometric equations for forest trees is laborious and expensive, sometimes impossible. Therefore, existing allometric equations were used in this study. Because of the potential for intersite variation in factors such as tree architecture and wood density (dependent on site conditions and climate variability), this decision may have caused some errors in the estimated forest biomass. For this reason, in any future work, it will be important to test the allometric equations used by measuring and harvesting some individual trees on each study site. The measured productivity was obtained by summing the increments from individual trees in a unit area. The 10-year radial growth increment was estimated from all the increment cores for each site. This approach may overrate the production from old trees. The magnitude of this error depends largely on the age structure of $P. schrenkiana$ forest and the composition of the tree-ring sample.

The results of the field survey also suggested that the productivity gradually decreased from west to east on the north slopes of the Tianshan Mountains (Fig. 2). This result agreed with the work of Sun (1994) and of Wang and Zhao (2000). These researchers all indicated that two main environmental gradients control the NPP of $P. schrenkiana$ at a regional scale: productivity decreased with annual temperature and with precipitation.

4.3. Model validation

Using site-specific parameters, the BIOME-BGC predictions showed good agreement with the independent field-based NPP values, being of similar magnitude and presenting similar temporal dynamic patterns to those of the RWSI at the four sites (Figs. 2 and 3). This demonstrated the ability of BIOME-BGC to simulate accurately the $P. schrenkiana$ forest in the Tianshan Mountains and provided the first step toward a future regional-scale analysis of $P. schrenkiana$ forest NPP or carbon budgets using this process-based model.

The main discrepancies between field-based NPP estimates and the simulated results may be associated with the effect of an inadequate representation of the impact of site age (or successional stage) on growth of $P. schrenkiana$ forests in the BIOME-BGC model. Based on the study by Zhang and Tang (1989), productivity of $P. schrenkiana$ forest rapidly increases initially with site age and reaches its maximum in
about 100 years. Productivity then gradually decreases with age until the trees are about 200 years old. This suggests that site age is a critical factor determining forest ecosystem productivity (Simith and Long, 2001). However, an accurate age structure of the *P. schrenkiana* forests in the study areas was not available, and the model simulations were performed for the same number of years, equal to the time span of climate records, with all C and N pools initialized from the steady-state condition (startup run representing a mature site) in this study. Because of this simplification, the actual simulated NPP values may not be representative, though they are comparable with observed values (Churkina et al., 2003). In any future work, the site age structure should be taken into consideration when simulating NPP using the BIOME-BGC model. At the same time, the *P. schrenkiana* forests in the four study sites were assumed in this study to have the same ecophysiological characteristics. However, this assumption is not necessary true, because tree physiology has been shown to be site-dependent, varying with water and nitrogen availability, stand density, and other environmental variables (White et al., 2000). This is one more possible reason for the observed discrepancies. With a view to future regional applications of the model, it would be important to test this assumption.

The dendrochronological variable RWSI is a good estimator of tree radial growth, which is related to the annual biomass increment of stem wood under natural environmental conditions. In this study, the correlations between the observed RWSI series and the simulated NPP series were not very high. However, this result is reasonable and acceptable, because it is difficult to estimate how much of the NPP should be allocated to stem wood, as this depends on a number of biotic and abiotic factors (Running and Coughlan, 1988). It is especially noteworthy that the trends in the simulated NPP were consistent with the annual fluctuations in the independently observed RWSI series at all sites. This confirmed that the process-based model is sensitive to the year-to-year variations in climate represented in the annual growth rings of trees. This study has also suggested that unless interannual variables for ecosystem productivity are available from long-term measurements, the RWSI can be used as a good estimator of interannual NPP variations under natural environmental conditions to validate process-based models for the temporal dynamics of productivity simulations (Korol et al., 1991; Rathgeber et al., 2003). The very large size of the existing tree-ring database for Xinjiang offers a wide scope for possible applications (Li et al., 2000).

### 4.4. Climatic change scenarios

For a doubled CO$_2$ scenario, the RegCM2 model simulates a significant increase in annual air temperature and precipitation for the *P. schrenkiana* forest ecosystems in the Tianshan Mountains. These simulations agreed well with other atmospheric general circulation model (AGCM) simulations, which suggested that the annual air temperature will increase by 2.2 °C and that precipitation will increase by 28.0% in Xinjiang under IPCC95 scenarios (Zhao et al., 2002). However, in this study, the climate change scenarios do not include seasonal changes. This simplification may cause some uncertainty in the climate data used for the simulations, but the climatic changes in most growth seasons and the overall annual changes remained comparable, and this variability does not alter the general trends.

### 4.5. Climate change versus NPP variations

The predicted NPP responses to the scenario with temperature increase alone (C0T1P0) are positive in this study (Fig. 4). In the BIOME-BGC model, the specific activity of the Rubisco enzyme depends on air temperature (Farquhar et al., 1980). Similarly, litter and soil organic matter (SOM) decomposition supplies most of the available soil mineral N for tree growth, which depends on the size of the litter and SOM pools and their decomposition rates. These rates depend on soil temperature and soil moisture. Therefore, increased temperature may increase NPP through metabolically enhanced photosynthesis as well as by increasing nutrient availability through higher rates of decomposition. Moreover, some nutrients can be stored to support growth during the following growing season, as represented by the phenology module in the BIOME-BGC model. In addition, the increased temperatures may increase NPP by increasing the length of the growing season, which strongly correlates with site mean annual temperature in mid- and high latitudes. On the other hand, evaporation and transpiration in the BIOME-BGC model are estimated using the Penman–Monteith equation, and a decrease in soil moisture is caused by increased evaporative demand because of higher temperatures. Thus increased temperatures may also decrease NPP by decreasing water availability and enhancing plant respiration (see the earlier description of the BIOME-BGC model). In this study, the results suggest that the positive effects of the temperature increase more than compensate for the negative effects on the NPP of the *P. schrenkiana* forest in the Tianshan Mountains region.

An increase in precipitation tends to alleviate the effects of moisture stress on *P. schrenkiana* forest growth and hence has positive effects on the NPP (Fig. 4). This result agreed with the studies of water-limited regions by Nemani et al. (2003) and Mohamed et al. (2004) and also showed that the direct effect of precipitation increase has a greater influence on forest productivity than do temperature changes (Fig. 4). This indicates that water availability may be the main limiting factor for NPP at the current atmospheric CO$_2$ concentration. This result agreed with the evidence from *P. schrenkiana* tree rings in this study region (Yuan and Li, 1995; Yuan et al., 2001; Zhu et al., 2004).

### 4.6. Atmospheric CO$_2$ concentration increase versus NPP variations

In the BIOME-BGC model, the responses of intercellular CO$_2$ and leaf nitrogen concentration to a doubling of CO$_2$ concentration are included. Intercellular CO$_2$ increases with a rise in atmospheric CO$_2$ because these two quantities are linearly related in the model. Similarly, the BIOME-BGC
model represents the observation that increased CO2 reduces leaf nitrogen concentration by prescribing a 40% reduction of leaf nitrogen in conifers for a doubling of atmospheric CO2. Thus, carbon assimilation increases with increasing intercellular CO2 and decreases with decreasing leaf nitrogen concentration. Except at the XQZ site, a doubling of atmospheric CO2 concentration had no significant effect on NPP (Fig. 4). This result agreed with the study by Melillo et al. (1993), which found that increasing simulated atmospheric CO2 levels from 312.5 to 625.0 ppmv did not change the NPP of the boreal woodland and boreal forest as predicted by the terrestrial ecosystem model (TEM) (Raich et al., 1991).

Compared with published CO2 enrichment experiments, the simulated NPP increase predicted by the BIOME-BGC model in this study was substantially low. Curtis and Wang (1998) carried out a meta-analysis on 102 measurements of tree biomass response to elevated CO2 and found a 29% increase. Similarly, Ainsworth and Long (2005) reported a 28% increase in aboveground dry matter production for trees grown under elevated CO2 concentration, based on the data collected from 120 primary, peer-reviewed articles describing tree physiology and production in the 12 large-scale free-air-CO2-enrichment (FACE) experiments (with simulated CO2 concentrations from 475 to 600 ppmv). So the question arises: are the representations of CO2 effects in the model used here reasonable, and why do they not agree with what is known from direct observations and experimentation? The response of forest productivity to CO2 enrichment is local, and there have been no contemporary experiments or observations on the P. schrenkiana forests, so it is difficult to provide a direct answer to this question. The large difference between the results of the two kinds of studies might be due, in part, to the BIOME-BGC model prediction that the P. schrenkiana forests, which are boreal ecosystems, have a low capacity to incorporate elevated CO2 concentrations into production because of nitrogen limitation and low temperatures (Melillo et al., 1993). Most of the experimental studies were performed under fertile and warm conditions, and trees are assumed to react more strongly in these environments. Furthermore, most of the experimental studies were short-term, and the reported responses of photosynthesis and growth to environmental factors do not fully predict the true responses of plant productivity (Lloyd and Farquhar, 1996) because the long-term changes in ecosystem properties in response to CO2 enrichment are largely regulated by indirect, interactive, and feedback effects (Luo et al., 2004).

4.7. Climate change and CO2 increase versus NPP variations

As productivity in boreal forest ecosystems is substantially limited by low temperatures and N availability, P. schrenkiana forest NPP in Tianshan region increased dramatically (by 26.4–37.2%) under the C1T1P1 scenario (Fig. 4). By comparison, Zhou and Zhang (1996) suggested that the NPP of the boreal coniferous forest zone in China would increase by 26.9% under conditions of doubled CO2 concentration and associated climate changes (temperature +2 °C and precipitation +20%). Using the TEM (Version 4.0) for climate change simulation at 519 ppmv CO2, Xiao et al. (1998) showed that the annual NPP of boreal forest in China would increase by 22.2% for the Goddard Institute for Space Studies (GISS) climate scenario, 21.0% for the Oregon State University (OSU) scenario, and 23.9% for the Geophysical Fluid Dynamic Laboratory (GFDL-q) scenario. These studies together with the present study all indicate that the projected global climate change would increase boreal forest NPP in China and that the forest region is likely to become a major potential carbon sink. However, a more detailed and accurate calculation of carbon storage and flux in these boreal forests has not been performed here.

Comparison of the results of various scenarios in this study indicated that the effects of precipitation and temperature change were simply additive, but that the synergy between the effects of climate change and doubled CO2 was important, since the feedback loops associated with the water and nitrogen cycles ultimately influence the carbon assimilation response. The simulated results presented here are consistent with the work of Shaw et al. (2002), which suggested that ecosystem responses to realistic combinations of global changes are not necessarily simple combinations of the responses to the individual factors.

4.8. Site location versus NPP variations

An important aspect of analyses of ecosystem responses to global climatic change is dependency on local conditions (Shaver et al., 2000). In this study, the effects of doubled atmospheric CO2 concentration on NPP were higher at the XQZ site than at the YW site, with intermediate values at the ZS and TC sites (Fig. 4). It is suggested that the effects of CO2 fertilization on productivity may be dependent on climate at the study site. Under the C0T1P1 scenario, the NPP response is lowest for the westernmost site and highest for the easternmost site (Fig. 4). It is noteworthy that the site with the lowest productivity increases, ZS, was the warmest and wettest site, and hence the least likely to benefit from climate change, while the site with the harshest conditions (YW) experienced the greatest productivity increases under the C0T1P1 scenario (Fig. 4). These results are in agreement with Xiao et al. (1998), who suggested that the NPP would show a large increase in dry and cool regions and only a slight increase in humid and warm regions, in their study of NPP change of various vegetation types in China under conditions of climate change using different AGCMs. A wider variety of sites and climate types should therefore be taken into account in future studies to make a proper assessment of how ecosystems respond to global changes at larger scales.

5. Conclusions

The predictions of the BIOME-BGC model are in reasonably close agreement with the magnitude and the temporal dynamics of the independent productivity variables in four P. schrenkiana forests on the north slopes of the Tianshan...
Mountains. Therefore, the model can be used in future studies as a diagnostic tool to explain changes in forest growth as a result of global changes.

For the study sites, the model simulations showed that the effects of climate change (increase in NPP from 13.3% to 29.1% under the C3T1P1 scenario) are more significant than the effect of doubled atmospheric CO2 concentration on the NPP of the P. schrenkiana forests in the Tianshan Mountains. Climatic changes and atmospheric CO2 concentration increase together led to a marked increase in NPP (from 26.4% to 37.2% under the C3T1P1 scenario), but with variations in magnitude from place to place. The simulations also indicated that climate change and elevated atmospheric CO2 concentration had strongly interactive effects on NPP. These model simulations of various scenarios provide valuable predictions that can be helpful in understanding how ecosystems respond to simultaneous increases in atmospheric CO2 concentration and climate changes.

Experimental investigations (Van Breemen et al., 1998) and model-based simulations (Ni, 2002) have strongly indicated that boreal forests would change significantly, both in geographical range and in their biogeochemical processes, under the influence of global warming and atmospheric CO2 concentration enrichment. Future studies using BIOME-BGC will evaluate the sensitivity of NPP to vegetation redistribution as a part of investigations into the long-term effects of elevated atmospheric CO2 concentrations and associated climate changes on forest ecosystems. In addition, given the focus of this study on the effects of climate change and atmospheric CO2 concentration on NPP, NPP variability associated with other environmental factors such as N, O2, and UVB was not investigated. These and similar topics should be the subject of further research.

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