The Effects of Different Climate Input Datasets on Simulated Carbon Dynamics in the Western Arctic

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ABSTRACT: As part of the Western Arctic Linkage Experiment (WALE), simulations of carbon dynamics in the western Arctic (WALE region) were conducted during two recent decades by driving the Terrestrial Ecosystem Model (TEM) with three alternative climate datasets. Among the three TEM

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simulations, we compared the mean monthly and interannual variability of three carbon fluxes: 1) net primary production (NPP), 2) heterotrophic respiration ($R_h$), and 3) net ecosystem production (NEP). Cumulative changes in vegetation, soil, and total carbon storage among the simulations were also compared. This study supports the conclusion that the terrestrial carbon cycle is accelerating in the WALE region, with more rapid turnover of carbon for simulations driven by two of the three climates. The temperature differences among the climate datasets resulted in annual estimates of NPP and $R_h$ that varied by a factor of 2.5 among the simulations. There is much spatial variability in the temporal trends of NPP and $R_h$ across the region in the simulations driven by different climates, and the spatial pattern of trends is quite different among simulations. Thus, this study indicates that the overall response of NEP in simulations with TEM across the WALE region depends substantially on the temporal trends in the climate dataset used to drive the model. Similar to the recommendations of other studies in the WALE project, this study indicates that coupling methodologies should use anomalies of future climate model simulations to alter the climate of more trusted datasets for purposes of driving ecosystem models of carbon dynamics.

**KEYWORDS:** Arctic; Boreal; Carbon; Ecosystem model; GPP; NEP; NPP; WALE

1. Introduction

High-latitude terrestrial ecosystems contain approximately 30% of the world’s vegetation carbon (McGuire et al. 1995) and about 40% of the world’s soil carbon (Melillo et al. 1995). Much of the soil carbon in these ecosystems is highly labile and has accumulated simply because of cold and/or anaerobic soil conditions (McGuire et al. 2006). This labile carbon pool is highly vulnerable to warming (Goulden et al. 1996), and a large release of carbon from high-latitude soils could substantially affect atmospheric concentrations of CO$_2$ (McGuire et al. 2006). However, increased vegetation growth in response to warming has the potential to mitigate the release of carbon from high-latitude soils (McGuire et al. 1992; Shaver et al. 1992). Analyses based on remote sensing approaches that use a 20-yr record of satellite data indicate that the tundra is greening in the Arctic, suggesting an increase in photosynthetic activity and net primary production (Sitch et al. 2007). In contrast, a recent remote sensing study has found that photosynthetic activity in the boreal forest of North America unaffected by fire has declined in the last two decades (Goetz et al. 2005). While process-based biogeochemical models generally simulate a small net carbon sink in the recent past for the distribution of Arctic tundra (Sitch et al. 2007), there is much spatial variability in estimated net carbon balance by these models (e.g., see McGuire et al. 2000a; Euskirchen et al. 2006; Thompson et al. 2006).

The Western Arctic Linkage Experiment (WALE) was set up to evaluate uncertainties in regional hydrology and carbon estimates in Alaska and the adjacent Yukon Territory associated with 1) alternative driving datasets and 2) alternative simulation models. As part of the WALE, Kimball et al. (Kimball et al. 2007) conducted a study of carbon balance in the WALE region that compared the simulations of remote sensing and process-based models during recent decades.
These simulations indicate that plant production and the ratio of vegetation to soil carbon are increasing throughout the region. These results suggest that the regional carbon cycle in the western Arctic is accelerating under a warming climate. The climate data used to drive the simulations presented in Kimball et al. (Kimball et al. 2007), which were drawn from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (Kistler et al. 2001), were just one of several alternative climate datasets that could have been used in the study. Because there is much uncertainty among the alternative climate datasets in the western Arctic (Drobot et al. 2006; Rawlins et al. 2006; Rupp et al. 2007), it is not clear the degree to which the findings of Kimball et al. (Kimball et al. 2007) depend on the alternative climate datasets. In this study, we assessed the sensitivity of carbon dynamics by the Terrestrial Ecosystem Model (TEM; Euskirchen et al. 2006) in recent decades to alternative driving datasets.

2. Methods
2.1. Overview

In this study, we conducted simulations of carbon dynamics in the WALE region during two recent decades by driving TEM with three alternative climate datasets: 1) NCEP–NCAR reanalysis (Kistler et al. 2001; referred to as NCEP1 in this study); 2) the Climate Research Unit (CRU; Mitchell and Jones 2005); and 3) the fifth-generation Penn State–NCAR Mesoscale Model (MM5; Wu et al. 2007). Among the three simulations, we compared the mean monthly and interannual variability of three carbon fluxes simulated by TEM: 1) net primary production (NPP), 2) heterotrophic respiration (R_h), and 3) net ecosystem production (NEP). We also compared cumulative changes in vegetation, soil, and total carbon storage among the three simulations. To evaluate one of the conclusions of Kimball et al. (Kimball et al. 2007), we compared how the ratio of vegetation to soil carbon is changing through time among the three simulations.

2.2. The Terrestrial Ecosystem Model

The TEM is a monthly, process-based, global-scale ecosystem model that uses spatially referenced information of climate, elevation, soils, and vegetation to simulate monthly estimates of terrestrial carbon, nitrogen, and water dynamics at different spatial scales. The TEM has been used to investigate several issues influencing carbon dynamics in high latitudes including studies focusing on boreal forests (Amthor et al. 2001; Potter et al. 2001; Clein et al. 2002; Zhuang et al. 2002), tundra ecosystems (Clein et al. 2000; McGuire et al. 2000a), and high-latitude ecosystems in general (McGuire et al. 2000b; Zhuang et al. 2003; Zhuang et al. 2004; Zhuang et al. 2006; Euskirchen et al. 2006). In this study, we used the version of the model described in Euskirchen et al. (Euskirchen et al. 2006), which is an update from the version used by Zhuang et al. (Zhuang et al. 2003). This version of the model has an integrated soil thermal model (with an updated soil freeze–thaw algorithm) and considers the effects of freeze–thaw dynamics on gross primary production. The most detailed descriptions can be found in Raich et
al. (Raich et al. 1991), McGuire et al. (McGuire et al. 1992), and Tian et al. (Tian et al. 1999). The following is a short summary of model components related to the simulated fluxes analyzed in this study.

The flux NPP, which represents the net amount of CO₂ taken up by vegetation, is calculated as the difference between gross primary production (GPP, the CO₂ fixed by vegetation in photosynthesis) and autotrophic respiration ($R_A$, the respiration of CO₂ by vegetation). Monthly GPP considers the effects of several factors and is calculated as follows:

\[
\text{GPP} = C_{\text{max}} f(\text{PAR}) f(\text{PHENOLOGY}) f(\text{FOLIAGE}) f(T) (C_a, G_e) f(\text{NA}) f(\text{FT}),
\]

where $C_{\text{max}}$ is the maximum rate of C assimilation, PAR is photosynthetically active radiation, and $f(\text{PHENOLOGY})$ is monthly leaf area relative to maximum monthly leaf area (Raich et al. 1991). The function $f(\text{FOLIAGE})$ is a scalar function that ranges from 0.0 to 1.0 and represents the ratio of canopy leaf biomass relative to maximum leaf biomass (Zhuang et al. 2002), $T$ is monthly air temperature, $C_a$ is atmospheric CO₂ concentration, $G_e$ is relative canopy conductance, and NA is nitrogen availability. The effects of elevated atmospheric CO₂ directly affect $f(C_a, G_e)$ by altering the intercellular CO₂ of the canopy (McGuire et al. 1997; Pan et al. 1998). The function $f(\text{NA})$ models the limiting effects of plant nitrogen status on GPP (McGuire et al. 1992; Pan et al. 1998). The function $f(\text{FT})$ is an index of submonthly freeze–thaw, which represents the proportion of a specific month in which the ground is thawed. This index is based on simulated soil temperatures at 10-cm depth, varies from 0.0 to 1.0, and influences the ability of the vegetation to take up atmospheric CO₂ (Zhuang et al. 2003).

The flux $R_A$ represents total respiration (excluding photorespiration) of living vegetation, including all CO₂ production from various processes including plant respiration, nutrient uptake, and biomass construction. It is the sum of growth respiration ($R_g$), which is prescribed to be 20% of the difference between GPP and maintenance respiration. The flux $R_m$ is a direct function of plant biomass as follows:

\[
R_m = K_r C_v e^{rT},
\]

where $K_r$ is the per-gram-biomass respiration rate of the vegetation at 0°C, $C_v$ is the vegetation carbon pool, $T$ is the mean monthly air temperature, and $r$ is the instantaneous rate of change in respiration with the change in temperature.

The flux NEP, which represents the net exchange of CO₂ by both plants and soils in an ecosystem with the atmosphere, is calculated on a monthly basis as the difference between NPP and $R_h$. The flux $R_h$ represents the decomposition of all organic matter and is calculated as follows:

\[
R_h = K_d C_s e^{rsT} f(M),
\]

where $K_d$ is the per-gram-biomass respiration rate of soil organic matter at 0°C, $C_s$ is soil carbon pool, $T$ is the mean monthly air temperature, $r_s$ is the instantaneous rate of change in decomposition with the change in temperature, and $f(M)$ is a scalar between 0 and 1 of volumetric soil moisture ($M$) effects on decomposition. The per-gram-biomass respiration rate of the soil is affected by the nitrogen concentration of litter that enters the soil.
The change in vegetation carbon is calculated as the difference between NPP and the litterfall flux of carbon ($L_c$), while the change in soil carbon is calculated as the difference between $L_c$ and $R_h$. The flux $L_c$ represents litter inputs from all forms of plant senescence and mortality entering the soil carbon pool in TEM and is calculated as follows:

$$L_c = \text{CFALL} \ C_{w}$$

where CFALL represents the mean monthly proportion of vegetation carbon ($C_{w}$) that senesces or dies.

### 2.3. Model parameterization

Although many of the parameters in the model are defined from published information (Raich et al. 1991; McGuire et al. 1992), some are determined by calibrating the model to fluxes and pools of an intensely studied field site. For the application of TEM to the WALE region, we created vegetation-specific parameterizations for wet boreal coniferous forest, dry boreal coniferous forest, boreal deciduous forest, moist tundra, and coastal maritime coniferous forest. The pools and fluxes used to develop these parameterizations (Table 1) are based on intensive field studies at the Bonanza Creek, Toolik Lake, and H. J. Andrews Long Term Ecological Research sites in Alaska and Oregon, and at the Boreal Ecosystem Atmosphere Study in Canada (Tables 1 and 2). We used the estimates of pools and fluxes in Table 1 to calibrate the rate limiting parameters in the flux equations for gross primary production, autotrophic respiration, heterotrophic respiration, litterfall carbon, litterfall nitrogen, plant nitrogen uptake, and soil nitrogen immo-

<table>
<thead>
<tr>
<th>Variable*</th>
<th>Wet boreal coniferous forest</th>
<th>Dry boreal coniferous forest</th>
<th>Boreal deciduous forest</th>
<th>Moist tundra</th>
<th>Coastal maritime forest</th>
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<td>3250</td>
<td>10 356</td>
<td>6544</td>
<td>750</td>
<td>43 500</td>
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<tr>
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<td>7700</td>
<td>6530</td>
<td>12 000</td>
<td>10 000</td>
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<td>314</td>
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<td>2.19</td>
<td>6.65</td>
<td>0.8</td>
<td>4.2</td>
</tr>
</tbody>
</table>

* Units for vegetation carbon ($C_v$) and soil carbon ($C_s$) are g C m$^{-2}$. Units for vegetation nitrogen ($N_v$), soil N ($N_s$), and available inorganic N ($N_{AV}$) are g N m$^{-2}$. Units for annual gross primary production (GPP), NPP, and annual N uptake by vegetation (Nup) are g C m$^{-2}$ yr$^{-1}$ and g N m$^{-2}$ yr$^{-1}$, respectively. Source of estimates for wet boreal coniferous is black spruce in Table 1 of Clein et al. (Clein et al. 2002). Source of estimates for moist tundra is Table A2 of McGuire et al. (McGuire et al. 1992), except that 1) GPP is estimated to be twice NPP and 2) $C_v$ and $N_v$ are from McGuire et al. (McGuire et al. 1995). Source of estimates for coastal maritime forest is Table A5 of McGuire et al. (McGuire et al. 1992), except that 1) GPP is rounded up after multiplying NPP by 2 and 2) $C_v$ and $N_v$ are estimated similar to the methods of McGuire et al. (McGuire et al. 1995).
bilization. Calibration of these parameters in TEM requires the use of climate data, and we used the mean climate averaged over the period from 1961 to 1990 from the CRU climate dataset for the parameterizations as this is the dataset that is generally used to calibrate TEM. We held atmospheric CO$_2$ at 280 ppmv during the calibration procedure as this is approximately the concentration of CO$_2$ that is used to initialize the model simulations in this study.

2.4. Alternative climate datasets

In this study, we drove TEM to estimate carbon dynamics of the WALE region with temperature, precipitation, and net irradiance (NIRR; downwelling shortwave radiation) from three different input climate datasets. One of the datasets we used is from the NCEP–NCAR reanalysis project (Kistler et al. 2001) and is the same NCEP1 dataset from 1980–2000 that was used to drive the TEM simulations reported in Kimball et al. (Kimball et al. 2007). These data, which were generated using an assimilation scheme to ingest data into a climate model in order to fill in data gaps in both space and time, were sampled using Geographical Information System techniques to develop datasets at 25 km × 25 km resolution for use in the WALE simulation (see McGuire et al. 2007a, manuscript submitted to Earth Interactions, hereafter M07). We also drove TEM over the WALE region from 1980 to 2000 with data from the CRU (Jones et al. 2001; Mitchell and Jones 2005). The global CRU dataset is a monthly 0.5° × 0.5° (latitude by longitude) climate dataset that has been developed based on the use of station anomalies in a variance-adjusted interpolation scheme to damp overestimates of variance in regions where data are sparse (Jones et al. 2001). For use in this study, we sampled the CRU datasets at the 0.5° latitude × 0.5° longitude grid cell and disaggregated them based on their areas of intersection to develop datasets at 25 km × 25 km resolution for use in the WALE simulation. Our CRU estimates of NIRR were developed
from the CRU mean monthly cloudiness data fields similar to the algorithm used in Pan et al. (Pan et al. 1996). Finally, we drove TEM with data from the MM5 simulation of Wu et al. (Wu et al. 2007), which produced estimates of surface climate over the WALE region at a spatial resolution of 50 km from 1990 to 2000. Thus, in this study, we only drove TEM with data from the MM5 simulation from 1990 to 2000. See Drobot et al. (Drobot et al. 2006) and Herzfeld et al. (Herzfeld et al. 2007) for more information on these datasets.

2.5. Other input datasets

Besides climate datasets, the TEM simulations required data on soil texture, elevation, vegetation, and atmospheric CO$_2$. The soil texture data are based on the Food and Agriculture Organization/United Nations Educational, Scientific and Cultural Organization (FAO/UNESCO 1974) soil map of the world. The input elevation map is based on 10-min digital elevation data (NCAR/Navy 1984). The input vegetation map (see M07), which is an extension of the dataset described in Calef et al. (Calef et al. 2005), is composed of moist tundra (63%), wet coniferous boreal forest (16%), dry coniferous boreal forest (10%), boreal deciduous forest (10%), and temperate maritime coniferous forest (1%). This 1-km-resolution land cover classification was developed by aggregating the 23 land cover classes in the commonly used Advanced Very High Resolution Radiometer (AVHRR)-based classification for Alaska (Fleming 1997) using topography, climate, and geographic location. In Fleming (Fleming 1997), land cover classes corresponding to tundra were delineated from classes corresponding to forest based on growing season temperature and geographic location. Classes corresponding to deciduous forest were delineated from classes corresponding to conifer forest based on summer spectral signatures. The conifer forest class derived from Fleming (Fleming 1997) was separated into black and white spruce classes based on aspect and slope, with black spruce located primarily on northern aspects or low slope angles (Calef et al. 2005; Rupp et al. 2007). We used inputs of atmospheric CO$_2$ from observations averaged from the Mauna Loa and South Pole monitoring stations (Keeling et al. 1995, updated).

2.6. Simulation protocol

The TEM simulations were initialized by running the model to equilibrium (NEP = 0 ± 1 g C m$^{-2}$ yr$^{-1}$) using the mean monthly climate for each climate driver dataset (e.g., mean monthly NCEP1 temperature data for 1980–2000), and then running through five cycles of the climate dataset (i.e., five cycles of 1980–2000 for the simulation driven by NCEP1 data) before encountering the final transient period of simulation. We simulated C and N pools and fluxes for each vegetation type for all 25 km x 25 km grid cells in the WALE region. Model outputs were then spatially aggregated according to the relative proportions of individual land cover classes identified within each 25-km grid cell. Spatial aggregation of model outputs within each grid cell was based on linear weighting of dominant and subdominant land cover classes, with no lateral transfers of mass or energy within a specified grid cell or between adjacent grid cells.
3. Results

3.1. Differences in input climate data

Our analysis of absolute differences in mean annual temperature over the entire WALE region indicates that CRU is warmer than NCEP1 on the order of about 1°C (Figure 1a). During the 1990s, mean annual temperature from the MM5 simulations is approximately 3°C cooler than CRU and 2°C cooler than NCEP1. In agreement with Drobot et al. (Drobot et al. 2006), comparison of mean monthly temperature indicates that CRU is warmest in summer and coolest in winter, MM5 is coolest in summer and warmest in winter, and NCEP1 is intermediate (Figure 1b).

Our analysis of absolute differences in annual precipitation indicates that both NCEP1 and MM5 estimate approximately 300 mm more precipitation than CRU, with MM5 being slightly higher than NCEP1 during the 1990s (Figure 1c). In the summer, NCEP1 has the highest estimates of precipitation, a pattern that in the
Arctic is generally considered an overestimation because of excessive convective precipitation in the model (Serreze and Hurst 2000), while CRU and MM5 have similar estimates from June to August (Figure 1d). In the winter, MM5 has the highest estimates of precipitation, CRU the lowest, and NCEP1 is intermediate (Figure 1d).

Our comparison of absolute differences in annual NIRR indicates that CRU and MM5 have similar estimates in the 1990s, but that NCEP1 is approximately 80 W m⁻² higher than CRU and MM5 (Figure 1e). The higher NIRR estimates of NCEP1, which occur in all months of the year (Figure 1f), are known to be too high because of insufficient cloud cover (Serreze et al. 1998; Serreze et al. 2003). The NIRR estimates of CRU are higher than those of MM5 in the summer, but this pattern is reversed in the winter (Figure 1f).

3.2. Differences in simulated annual and seasonal carbon fluxes

The annual carbon fluxes of NPP estimated by TEM were quite different in magnitude among the three simulations, with the highest fluxes for the CRU simulation and the lowest for the MM5 simulation (Figures 2a). The differences in NPP among simulations are primarily caused by differences that occurred in the growing season (Figures 3a) and are the result of the temperature differences among the simulations driven by CRU, NCEP1, and MM5. The differences in temperature can be seen to affect the seasonality of carbon uptake in the spring, as NPP in June is much higher in the CRU simulation in comparison with the other two simulations. This pattern is likely associated with differences in soil thaw during May as photosynthetic carbon uptake in TEM depends on the freeze–thaw status of the soil (Zhuang et al. 2003); mean May air temperature over the WALE region is 3°C in the CRU dataset, while it is −0.3°C in the NCEP1 and −1.6°C in the MM5 datasets. The earlier start to the growing season and the warmer temperatures leads to high carbon uptake in both June and July in the CRU simulation, while the NCEP1 and MM5 do not achieve peak uptake until July.

The annual carbon fluxes of $R_h$ estimated by TEM were also quite different in magnitude among the simulations and showed a similar pattern to NPP with the highest fluxes for the CRU simulation and the lowest for the MM5 simulation (Figure 2b). In contrast to NPP, the differences in $R_h$ are maintained throughout the year (Figure 3b) and are the result of differences in summer temperature as well as differences in soil carbon among the simulations as $R_h$ depends on both temperature and the size of the soil carbon pool; estimated soil carbon over the entire WALE region at the beginning of 1990 is $1.4 \times 10^{15}$ g C higher in the CRU simulation than in the NCEP1 simulation, which is $2.7 \times 10^{15}$ g C higher than in the MM5 simulation.

The annual fluxes of NEP, which is the difference between annual fluxes of NPP and $R_h$, are generally correlated and similar in magnitude from 1980 to the mid-1990s, but the correlation appears to be breaking down in the late 1990s (Figure 2c) primarily because of different interannual variability in NPP responses among the simulations (Figure 2a). The generally similar magnitudes throughout most of the simulation period are caused by net carbon uptake patterns in summer playing...
Figure 2. Comparison of annual carbon fluxes (a) NPP, (b) $R_h$, and (c) NEP over the WALE region in simulations with different climates.
off against net carbon release patterns in winter (Figure 3c). For example, CRU has the highest uptake in the summer and the greatest release in winter while MM5 has the lowest uptake in summer and the lowest release in winter (Figure 3c); the NCEP1 simulation has intermediate uptake in summer and intermediate release in winter.
3.3. Differences in temporal trends and sensitivities of annual carbon fluxes

Spatially averaged annual NPP does not significantly increase or decrease at the 0.05 level in any of the simulations (Figures 4a and 4b; Table 3), but it is marginally significant for the time period 1980–2000 in the simulation driven by NCEP1 climate ($P = 0.08$). The trend of increasing NPP from 1980 to 2000 in the NCEP1 simulation of TEM is associated with increases in summer air temperature and potential evapotranspiration and decreases in summer radiation. Annual NPP from 1980 to 2000 is significantly positively related to summer air temperature and summer potential evapotranspiration in both the NCEP1 and CRU simulations (Table 4) but is significantly negatively related to summer radiation in only the NCEP1 simulation (Table 4). Across all simulations, the variable that seems to be most strongly related to annual NPP is summer air temperature (Table 4). The spatial pattern of trends in NPP during the 1990s is quite different among the three simulations (Figure 5). For example, at the U.S.–Canada border in the WALE region, the NCEP1 simulation (Figure 5a) indicates large increases in NPP, the
Table 3. Spatially averaged temporal trends (g C m\(^{-2}\) yr\(^{-1}\) yr\(^{-1}\)) in annual NPP, \(R_h\), and NEP estimated for the WALE region in simulations driven by different climate datasets (NCEP1, CRU, and MM5); trends for variables are reported for mean annual and mean summer air temperature (TAIR; °C yr\(^{-1}\)), annual and summer precipitation (PREC; mm yr\(^{-1}\)), mean annual and mean summer downwelling shortwave radiation at the top of the canopy (NIRR; W m\(^{-2}\) yr\(^{-1}\)), annual and summer potential evapotranspiration (PET; mm yr\(^{-1}\)), and annual and summer precipitation minus potential evapotranspiration (P-PET; mm yr\(^{-1}\)). Probability that no trend exists is reported in parentheses. Bolded values are significant at \(p < 0.05\).

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<tbody>
<tr>
<td>NPP</td>
<td>0.425 (0.08)</td>
<td>0.368 (0.62)</td>
<td>0.277 (0.27)</td>
<td>0.368 (0.62)</td>
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</tr>
<tr>
<td>(R_h)</td>
<td>0.010 (0.90)</td>
<td>−0.238 (0.36)</td>
<td>−0.386 (0.00)</td>
<td>−0.830 (0.01)</td>
<td>−0.717 (0.47)</td>
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<tr>
<td>NEP</td>
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<td>0.606 (0.33)</td>
<td>0.663 (0.01)</td>
<td>0.592 (0.38)</td>
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<td>TAIR annual</td>
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<td>0.014 (0.65)</td>
<td>0.042 (0.66)</td>
<td>0.090 (0.43)</td>
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<td>0.047 (0.02)</td>
<td>−0.035 (0.49)</td>
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<td>PREC annual</td>
<td>−0.132 (0.93)</td>
<td>−8.864 (0.01)</td>
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<td>PREC summer</td>
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</tbody>
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Table 4. Spatially averaged sensitivity in annual NPP to different climate variables from simulations for the WALE region driven by climate variables from different climate datasets (NCEP1, CRU, and MM5); sensitivity to variables are reported for mean annual and mean summer air temperature (TAIR; °C), annual and summer precipitation (PREC; mm), mean annual and mean summer downwelling shortwave radiation at the top of the canopy (NIRR; W m\(^{-2}\)), annual and summer potential evapotranspiration (PET; mm), and annual and summer precipitation minus potential evapotranspiration (P-PET; mm). Probability that no trend exists is reported in parentheses. Bolded values are significant at \(p < 0.05\).

<table>
<thead>
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<tbody>
<tr>
<td>TAIR annual</td>
<td>2.147 (0.28)</td>
<td>3.237 (0.20)</td>
<td>1.472 (0.45)</td>
<td>−0.203 (0.93)</td>
<td>−3.876 (0.17)</td>
</tr>
<tr>
<td>TAIR summer</td>
<td>6.634 (0.00)</td>
<td>7.807 (0.00)</td>
<td>3.848 (0.14)</td>
<td>2.793 (0.51)</td>
<td>7.508 (0.07)</td>
</tr>
<tr>
<td>PREC annual</td>
<td>0.004 (0.92)</td>
<td>−0.011 (0.86)</td>
<td>0.023 (0.57)</td>
<td>0.019 (0.70)</td>
<td>−0.001 (0.98)</td>
</tr>
<tr>
<td>PREC summer</td>
<td>0.128 (0.09)</td>
<td>0.122 (0.21)</td>
<td>0.112 (0.24)</td>
<td>0.132 (0.23)</td>
<td>−0.186 (0.40)</td>
</tr>
<tr>
<td>NIRR annual</td>
<td>−2.359 (0.01)</td>
<td>−2.451 (0.07)</td>
<td>−0.971 (0.08)</td>
<td>−2.954 (0.06)</td>
<td>1.425 (0.24)</td>
</tr>
<tr>
<td>NIRR summer</td>
<td>−1.049 (0.01)</td>
<td>−0.938 (0.12)</td>
<td>−0.541 (0.19)</td>
<td>−0.934 (0.07)</td>
<td>0.678 (0.11)</td>
</tr>
<tr>
<td>PET annual</td>
<td>0.260 (0.00)</td>
<td>0.276 (0.00)</td>
<td>0.131 (0.24)</td>
<td>0.034 (0.82)</td>
<td>0.351 (0.08)</td>
</tr>
<tr>
<td>PET summer</td>
<td>0.335 (0.00)</td>
<td>0.411 (0.01)</td>
<td>0.070 (0.67)</td>
<td>−0.102 (0.68)</td>
<td>0.530 (0.05)</td>
</tr>
<tr>
<td>P-PET annual</td>
<td>−0.057 (0.10)</td>
<td>−0.075 (0.12)</td>
<td>0.005 (0.89)</td>
<td>0.015 (0.76)</td>
<td>−0.032 (0.62)</td>
</tr>
<tr>
<td>P-PET summer</td>
<td>−0.029 (0.74)</td>
<td>0.000 (1.00)</td>
<td>0.053 (0.47)</td>
<td>0.121 (0.22)</td>
<td>−0.240 (0.10)</td>
</tr>
</tbody>
</table>
CRU simulation (Figure 5b) indicates large decreases in NPP, and the MM5 simulation (Figure 5c) indicates moderate decreases in NPP. Spatially averaged annual $R_h$ does not increase or decrease in the NCEP1 and MM5 simulations, but it decreases significantly in the CRU simulations (Figures 4c and 4d; Table 3). The $R_h$ decreases in the CRU simulations are associated with significant decreases in annual precipitation (Table 3). From 1980 to 2000, the $R_h$ decreases in the CRU simulation are also associated with increases in summer air

Figure 5. Linear trends in NPP and $R_h$ from 1990 to 2000 over the western Arctic for simulations with TEM driven by different climates: (a) NCEP1 NPP, (b) CRU NPP, (c) MM5 NPP, (d) NCEP1 $R_h$, (e) CRU $R_h$, and (f) MM5 $R_h$. 

CRU simulation (Figure 5b) indicates large decreases in NPP, and the MM5 simulation (Figure 5c) indicates moderate decreases in NPP. Spatially averaged annual $R_h$ does not increase or decrease in the NCEP1 and MM5 simulations, but it decreases significantly in the CRU simulations (Figures 4c and 4d; Table 3). The $R_h$ decreases in the CRU simulations are associated with significant decreases in annual precipitation (Table 3). From 1980 to 2000, the $R_h$ decreases in the CRU simulation are also associated with increases in summer air.
temperature and summer potential evapotranspiration, and decreases in annual precipitation minus potential evapotranspiration (Table 3). However, of these variables, annual $R_h$ from 1980 to 2000 in the CRU simulation is only significantly positively related to annual precipitation and annual precipitation minus potential evapotranspiration (Table 5), which suggests that interannual variability in $R_h$ of the CRU simulation is primarily controlled by variability in simulated soil moisture. However, temperature is also an important control as annual $R_h$ across all simulations is strongly related to annual air temperature in addition to annual precipitation (Table 5). As with NPP, the spatial pattern of trends in $R_h$ during the 1990s is quite different among the three simulations (Figure 5). For example, at the U.S.–Canada border in the WALE region, the NCEP1 simulation (Figure 5d) indicates large increases in $R_h$, the CRU simulation (Figure 5e) indicates large decreases in $R_h$, and the MM5 simulation (Figure 5f) indicates moderate increases for the northern part of the border and moderate decreases for the southern part of the border.

Spatially averaged annual NEP from 1980 to 2000 increases significantly in the CRU simulation, and the increase in the NCEP1 simulation is marginally significant (Figure 4e; Table 3). The increases in NEP in the CRU simulation is associated with a nonsignificant increase in NPP coupled with a significant decrease in simulated $R_h$ over the time period (Table 3). In contrast, the increase in NEP in the NCEP1 simulation is associated with a marginally significant increase in NPP that is much stronger than the nonsignificant increase in $R_h$.

### 3.4. Comparison of changes in carbon stocks

Vegetation carbon accumulates in the NCEP1 and the CRU simulation but increases most rapidly in the CRU simulation (Figures 6a and 6b); changes in vegetation carbon are negligible in the MM5 simulation (Figure 6b). Changes in vegetation carbon storage depend on both the input of carbon to the vegetation (NPP) and the loss of carbon from the vegetation to the soil (i.e., litterfall carbon, $L_c$). The accumulation of vegetation carbon in the CRU simulation is greater because NPP is substantially higher than $L_c$ throughout the simulation period.
In contrast to vegetation carbon, soil carbon increases substantially only in the CRU simulation during the 1990s (Figures 6c and 6d). Changes in soil carbon storage depend on both the input of carbon to the soil ($L_c$) and losses of carbon from the soil ($R_h$). In the CRU simulation, soil carbon in the 1980s decreases because $R_h$ is greater than $L_c$, while in the 1990s CRU soil carbon increases because $R_h$ is less than $L_c$ (Figure 7b). The loss and accumulation of soil carbon in the CRU simulation from 1980 to 2000 is largely driven by the decrease in $R_h$ over the time period (Figure 4c; Table 3).

The increase in total carbon storage is greater in the CRU simulations than in the NCEP1 simulation (Figures 6e and 6f), and the increase in both simulations is primarily driven by changes in vegetation carbon compared to changes in soil carbon. The increase in ratio of vegetation to soil carbon is most prominent in the CRU simulation during the 1980s (Figure 8a), with very modest increases in the
Figure 7. Comparison of NPP, \( R_h \), and litterfall carbon (\( L_c \)) for TEM simulations driven by (a) NCEP1, (b) CRU, and (c) MM5 climate inputs.
ratio of vegetation to soil carbon for the NCEP1 simulation in the 1980s (Figure 8a) and in the CRU and NCEP1 simulations in the 1990s (Figure 8b). The substantial increase in the ratio of vegetation to soil carbon storage of the CRU simulation in the 1980s is driven by both increases in vegetation carbon and decreases in soil carbon during the 1980s. In contrast to the NCEP1 and CRU
4. Discussion

One of the objectives of the WALE project was to assess the ability of process-based ecosystem models to simulate CO\textsubscript{2} exchange of terrestrial ecosystems in the western Arctic during the 1980s and 1990s. Uncertainty in the estimates made by process-based models has many sources and includes uncertainties in parameters, formulations of processes, conceptual issues about the interaction of processes, and driving datasets. We have conducted numerous studies to explore uncertainties in parameters, formulations of processes, and conceptual issues of TEM, the ecosystem model used in this study (e.g., McGuire et al. 1992; McGuire et al. 1993; McGuire et al. 1995; McGuire et al. 1997; Clein et al. 2000; McGuire et al. 2000b; Clein et al. 2002; Zhuang et al. 2003; Zhuang et al. 2006). A companion paper by Kimball et al. (Kimball et al. 2007) reports on a study that evaluated conceptual issues among two process-based ecosystem models used in the WALE project, TEM and Biome–Biogeochemical Cycles (BIOME–BGC), in simulating terrestrial CO\textsubscript{2} exchange in the western Arctic during the 1980s and 1990s. That study used the NCEP1 to drive both models. Other studies in the WALE project have documented substantial differences among alternative climate datasets for the WALE region (e.g., Drobot et al. 2006; Herzfeld et al. 2007; Wu et al. 2007) and that these differences have consequences for estimating the dynamics of hydrology (Rawlins et al. 2006) and fire (Rupp et al. 2007) in the WALE region. Similar to the analyses of Rawlins et al. (Rawlins et al. 2006) and Rupp et al. (Rupp et al. 2007), this study extends the study of Kimball et al. (Kimball et al. 2007) to evaluate the consequences of alternative climate datasets for estimating the dynamics of terrestrial CO\textsubscript{2} exchange in the WALE region. First, we discuss the consequences of alternative climate datasets for estimating carbon exchange and then we discuss the consequences for estimating changes in carbon storage.

Our simulations revealed the magnitude of estimates of NPP and \( R_h \) varied by a factor of 2.5 among the different climate datasets (Figure 2), with the estimates of NPP and \( R_h \) of the NCEP1 simulation intermediate between the lowest estimates of the MM5 simulation and the highest estimates of the CRU simulation. It appears that these differences are primarily associated with differences in nonwinter air temperature among the datasets (Figures 1a and 1b), as the differences in magnitude among the simulations are not consistent with the differences in precipitation and radiation among the different climate datasets (Figures 1c–f). For example, the low NPP of the MM5 simulation appears to be associated with a later thaw, earlier freeze up, and lower growing season temperature in comparison with the CRU and NCEP1 climates. Because \( R_h \) depends on both soil carbon storage, which is lowest in the MM5 simulation, and annual air temperature (Table 5), which is lowest in the MM5 climate, it is lowest in the simulation driven by MM5 climate.

Our evaluation suggests that differences in temperature can affect seasonality of photosynthetic carbon uptake in the spring, a result that is consistent with the analysis by Kimball et al. (Kimball et al. 2006) that shows that annual anomalies
in NPP of the WALE region are highly correlated with the timing in spring thaw. Other studies (e.g., see Euskirchen et al. 2006) have also identified that the timing of spring thaw is an important factor in the uptake of carbon by vegetation across the pan-arctic/pan-boreal region. In contrast to the effects of different datasets on the magnitude of annual vegetation and soil CO$_2$ exchange, the general magnitude of annual net CO$_2$ exchange (i.e., NEP, NPP – $R_h$) was similar among the simulations driven by different climate sets. However, there were substantial differences in monthly net CO$_2$ exchange among the datasets. The seasonal differences are important in that they can affect evaluations of how well the models are able to reproduce seasonal anomalies in atmospheric concentration of CO$_2$ at high-latitude CO$_2$ monitoring stations (e.g., see McGuire et al. 2000b; Dargaville et al. 2002a; Dargaville et al. 2002b; Zhuang et al. 2003).

Kimball et al. (Kimball et al. 2007) reported a small positive trend in NPP for the region from 1982 to 2000 for simulations of BIOME–BGC and TEM driven by the NCEP1 climate dataset. The results of this study indicate that the trend of NPP from 1980 to 2000 is stronger in the TEM simulation driven by NCEP1 (marginally significant) than in CRU (not significant). These trends appear to be caused by increases in summer air temperature (Table 3) in addition to changes in the timing of thaw (Kimball et al. 2007). Our simulations with TEM from 1980 to 2000 indicated that $R_h$ did not vary substantially in the NCEP1 simulation because of a weak nonsignificant trend in mean annual air temperature and annual precipitation, but that substantial decreases in the CRU simulation were largely associated with decreasing precipitation, which may have resulted in decreasing summer soil moisture to reduce $R_h$ across the two decades.

Trends in NEP of the WALE region from 1980 to 2000 in the CRU simulation were associated with increases in NPP coupled with decreases in $R_h$. In contrast, in the NCEP1 simulation the marginally significant increase in NEP was primarily associated with an increase in regional NPP. There is much spatial variability in the trends of NPP and $R_h$ across the region in both the NCEP1 and the CRU simulations, and the spatial pattern of trends is quite different between the simulations. Thompson et al. (Thompson et al. 2006) applied TEM in the tundra–forest transition area of northern Alaska between 1981 and 2000 and found that trends in NEP depended on differential responses of NPP and $R_h$ to spatial variability in whether the climate is getting warmer or colder and wetter or drier. Thus, our study and that of Thompson et al. (Thompson et al. 2006) indicate that the overall response of NEP in simulations with TEM across the WALE region depends substantially on the accuracy of temperature and precipitation temporal trends in the climate dataset used to drive the model.

Kimball et al. (Kimball et al. 2007) documented that vegetation and soil carbon storage increased in both TEM and BIOME–BGC simulations that were driven by NCEP1 climate from 1981 to 2000 such that the ratio of vegetation to soil carbon storage increased. We found that this pattern was even stronger for the CRU climate because of stronger increases in vegetation carbon across the two decades and a decline in soil carbon in the 1980s. In contrast, the MM5 simulation showed little change in carbon storage and little change in the ratio of vegetation to soil carbon during the 1990s. Kimball et al. (Kimball et al. 2007) concluded that the simulations of TEM and BIOME–BGC both indicate that the terrestrial carbon cycle is accelerating in the WALE region with a more rapid turnover of carbon.
Our study supports this conclusion for simulations driven by both NCEP1 and CRU climates, but not for simulations driven by the MM5 climate.

5. Conclusions

The response of carbon dynamics of high-latitude ecosystems to climate change is of concern because it has the potential to act as a positive feedback to warming if large stores of soil carbon are released in response to warming (McGuire and Chapin 2006; McGuire et al. 2006; McGuire et al. 2007b). Ecological models of carbon dynamics are tools that can be used to evaluate the potential for high-latitude ecosystems to act as a positive or negative feedback to climate (e.g., Zhuang et al. 2006). Our retrospective study identified that simulated exchanges of \( \text{CO}_2 \) and changes in carbon storage over the WALE region from 1980 to 2000 are very sensitive to alternative climate datasets used to drive the simulations. Rawlins et al. (Rawlins et al. 2006) found that simulated water fluxes over the WALE region were substantially different among simulations driven by alternative climate datasets. Similarly, Rupp et al. (Rupp et al. 2007) found that simulated fire dynamics over the WALE region were substantially different among simulations driven by alternative datasets. All of these results have similar implications for coupling models of terrestrial dynamics with prognostic climate models. Both Drobot et al. (Drobot et al. 2006) and Wu et al. (Wu et al. 2007) have noted that while the mean state of climate variables often differ among alternative climate datasets for the WALE region, the temporal anomalies are often highly correlated. We agree with the recommendation of Rupp et al. (Rupp et al. 2007) that coupling methodologies should use anomalies of future climate model simulations to alter the climate of more trusted datasets. This approach has the potential to properly represent the sensitivity of carbon dynamics simulated by ecosystem models to alternate scenarios of future climatic change.

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References


Kimball, J. S., K. C. McDonald, and M. Zhao, 2006: Spring thaw and its effect on terrestrial vegetation productivity in the western Arctic observed from satellite microwave and optical remote sensing. *Earth Interactions*, **10**. [Available online at http://EarthInteractions.org; see WALE Special Theme.]


---, and Coauthors, 2007a: The Western Arctic Linkage Experiment: Overview and synthesis. *Earth Interactions*, submitted; see WALE Special Theme.


Serreze, M. C., and C. M. Hurst, 2000: Representation of mean Arctic precipitation from NCEP–

——, J. R. Key, J. C. Box, and J. A. Maslanik, 1998: A new monthly climatology of global
radiation for the Arctic and comparisons with NCEP–NCAR reanalysis and ISCCP-C2 fields.

——, M. P. Clark, and D. H. Bromwich, 2003: Monitoring precipitation over the Arctic terrestrial
drainage system: Data requirements, shortcomings, and applications of atmospheric reanaly-

Shaver, G. R., W. D. Billings, F. S. Chapin, A. E. Giblin, K. J. Nadlerhofer, W. C. Oechel, and
42, 433–441.

Sitch, S., and Coauthors, 2007: Assessing the carbon balance of circumpolar arctic tundra using


of terrestrial carbon storage to historical climate variability and atmospheric CO2 in the


analysis of the Western Arctic surface climate among observations and model simulations.
*Earth Interactions*, 11. [Available online at http://EarthInteractions.org; see WALE Special
Theme.]