Incorporation of a permafrost model into a large-scale ecosystem model: Evaluation of temporal and spatial scaling issues in simulating soil thermal dynamics

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Abstract. This study evaluated whether a model of permafrost dynamics with a 0.5-day resolution internal time step that is driven by monthly climate inputs is adequate for representing the soil thermal dynamics in a large-scale ecosystem model. An extant version of the Goodrich model was modified to develop a soil thermal model (STM) with the capability to operate with either 0.5-hour or 0.5-day internal time steps and to be driven with either daily or monthly input data. The choice of internal time step had little effect on the simulation of soil thermal dynamics of a black spruce site in Alaska. The use of monthly climate inputs to drive the model resulted in an error of less than 1oC in the upper organic soil layer and in an accurate simulation of seasonal active layer dynamics. Uncertainty analyses of the STM driven with monthly climate inputs identified that soil temperature estimates of the upper organic layer were most sensitive to variability in parameters that described snow thermal conductivity, moss thickness, and moss thermal conductivity. The STM was coupled to the Terrestrial Ecosystem Model (TEM), and the performance of the coupled model was verified for the simulation of soil temperatures in applications to a black spruce site in Canada and to white spruce, aspen, and tundra sites in Alaska. A 1oC error in the temperature of the upper organic soil layer had little influence on the carbon dynamics simulated for the black spruce site in Canada. Application of the model across the range of black spruce ecosystems in North America demonstrated that the STM-TEM has the capability to operate over temporal and spatial domains that consider substantial variation in surface climate given that spatial variability in key structural characteristics and physical properties of the soil thermal regime are described.

1. Introduction

There is evidence that warming is occurring in some high-latitude areas [*Beltrami and Mareschal*, 1991; *Chapman and Walsh*, 1993; *Osterkamp and Romanovsky*, 1999; *Serreze et al.*, 2000]. Ground temperature records for North America reconstructed from borehole temperature logs support the notion that large-scale warming has been occurring since the 19th century [*Lachenbruch et al.*, 1982; *Lachenbruch and Marshall*, 1986]. Over the last few hundred years, permafrost conditions in the Arctic have changed and are likely to continue changing [*Overpeck et al.*, 1997]. In the western boreal forest of Canada, permafrost has responded dynamically to climatic changes that have been occurring since the little ice

age [*Vitt et al.*, 2000]. The soil thermal regime and the distribution of permafrost in regions with discontinuous permafrost are especially sensitive to climate changes [*Osterkamp and Romanovsky*, 1999; *Brown*, 1960; *Halsey et al.*, 1995].

Although warming is occurring in high latitudes, some high-latitude regions are warming, other regions are cooling, and there is substantial interannual variability in climate across high latitudes [*Everett and Fitzharris*, 1998]. Projections of climate trends for high-latitude regions exhibit substantial temporal and spatial heterogeneity [*McGuire et al.*, 2000a], and this variability is expected to influence the structure and function of high-latitude ecosystems [*McGuire and Hobbie*, 1997; *Epstein et al.*, 2000; *McGuire et al.*, 2000a]. The response of carbon dynamics in high-latitude ecosystems, which contain approximately 40% of the reactive soil carbon in the terrestrial biosphere [*McGuire et al.*, 1995], to spatial and temporal variability in climate is of concern because the response has the potential to influence CO_2 concentrations in the atmosphere [*Oechel et al.*, 1993; *McGuire and Hobbie*, 1997; *McGuire et al.*, 2000a].

A number of studies have indicated that permafrost dynamics may substantially influence carbon storage [*Vitt et al.*, 2000] and carbon dynamics [*Hillman*, 1992; *Waelbroeck et al.*, 1997; *Goulden et al.*, 1998] of high-latitude ecosystems. *Goulden et al.* [1998] suggested that the stability of the soil carbon pool at a black spruce site in Canada appears sensitive to the depth and duration of thaw, and climatic changes that promote thaw are likely to cause a net efflux of carbon dioxide from the site. On the other hand, warming may not always lead to C losses [*Shaver et al.*, 1992; *McGuire et al.*, 1992, 2000a, 2001; *Oechel et al.*, 2000; *Clein et al.*, 2000, in press], and it is not clear if high-latitude ecosystems are presently storing or releasing carbon or if there is interannual variability in the source-sink activity of high latitudes [*Chapin et al.*, 2000].

Large-scale ecosystem models have been developed to simulate the carbon dynamics of the terrestrial biosphere [*McGuire et al.*, 2001]. Given that permafrost dynamics are currently changing in high latitudes and are likely to continue changing as the climate warms, it is important for these models to consider how changes in the soil thermal regime influence ecosystem structure and function. Although it has been demonstrated that representing the insulative effects of snowpack on the soil thermal regime improves the ability of large-scale ecosystem models to reproduce seasonal features of atmospheric CO_2 concentrations at high-latitude monitoring stations [*McGuire et al.*, 2000b], these models have been slow to integrate a consideration of permafrost into their dynamics.

Site-specific models of permafrost dynamics often simulate soil thermal dynamics based on a two-dimensional finite element or finite difference formulation [*Osterkamp and Gosink*, 1991; *Guymon and Hromadka*, 1977; *Guymon et al.*, 1984; *Romanovsky et al.*, 1991a, 1991b; *Garagulya et al.*, 1995]. These models typically use a fine-resolution internal time step (e.g., 0.5 hours) and fine resolution depth steps in the soil (e.g., 1 cm to 5 cm resolution depending on depth), and are driven by daily or subdaily resolution climate data. In contrast, large-scale ecosystem models are generally driven by monthly climate inputs [*Heimann et al.*, 1998; *Cramer et al.*, 1999; *Kicklighter et al.*, 1999; *McGuire et al.*, 2000a, 2000b, 2001]. Although a permafrost model with a fine internal time step driven by fine resolution climate data has obvious numerical advantages in comparison to a model with coarser resolution, it imposes a substantial computational time cost on the coupled model.

In this study we address the question whether a model of permafrost dynamics with a coarse resolution internal time step (0.5 days) that is driven by monthly climate inputs is adequate for representing soil thermal dynamics in large-scale ecosystem models that are driven by monthly climate inputs.

2. Methods

2.1. Overview

In this study we modified an extant version of the Goodrich model [*Goodrich*, 1976, 1978a, 1978b] for Alaskan ecosystems [*Romanovsky et al.*, 1997] to develop a soil thermal model (STM) with the capability to operate with either 0.5-hour or 0.5-day internal time steps and to be driven by either daily or monthly input data. On the basis of empirical data, calibration, and review of the scientific literature, we specified parameters of the model for a black spruce forest stand located in the Bonanza Creek Experimental Forest near Fairbanks, Alaska, where soil and air temperatures were measured from May 1996 to April 1997. We applied the model in a factorial fashion to this site with respect to the temporal resolutions of internal time step (0.5 hours and 0.5 days) and input data (daily and monthly). To provide monthly inputs to the model, we aggregated air temperature and snow depth to monthly resolution. We evaluated the performance of the factorial applications of the model by comparing simulated daily and monthly soil temperature to measurements of soil temperature at different depths. To evaluate issues of temporal scaling, we also analyzed differences among the factorial applications to determine the relative importance of internal time step and climate inputs to the differences. To evaluate spatial scaling issues, we conducted uncertainty analyses that allowed us to determine which parameters need to be described in a spatially explicit fashion for spatial application of the model. For application of the model to larger spatial scales, we coupled the STM with the Terrestrial Ecosystem Model (TEM) [*Xiao et al.*, 1998; *Tian et al.*, 1998, 1999, 2000; *Kicklighter et al.*, 1999; *Schimel et al.*, 2000; *McGuire et al.*, 2000a, 2000b, 2001; *Clein et al.*, 2000, in press; *Amthor et al.*, this issue], which provides the STM with monthly estimates of snowpack dynamics. To evaluate the performance of the coupled model for different vegetation types in high latitudes, we verified simulations of soil temperature by the model for white spruce, aspen, and tundra sites in Alaska in addition to a black spruce site in Canada. To determine whether it is appropriate to use simulated soil temperatures to drive ecosystem processes, we compared field-based and simulated estimates of carbon fluxes for the black spruce site in Canada. Finally, to evaluate the ability of the model to operate across a substantial spatial and temporal domain, we applied the black spruce parameterization of the coupled STM-TEM model to the range of black spruce forest ecosystems across North America.

2.2. Model Development

The Goodrich model is a one-dimensional finite difference model of heat flow in soils which considers phase changes between water and ice and includes the thermal effects of changes in snow depth and snow characteristics during the winter [*Goodrich* 1976, 1978a, 1978b]. The model simulates the thermal dynamics of a system that includes snow cover, thawed soil, and frozen soil in which the upper and lower boundaries of the system are specified. Soil thermal dynamics of the system are determined through finite difference calculations between specified depth steps within each of the major layers of the system.

In our modification of the Goodrich model, which we refer to as the soil thermal model (STM) in this study, the vertical profile is divided into snow cover, moss, upper organic soil, lower organic soil, and mineral soil layers (Figure 1a). Application of the model for a site requires specification of the thickness of each layer and simulation depth steps within each layer. The thermal properties of each layer also need to be prescribed. In addition, the dynamics of phase changes in the soils depend on the phase temperature, which we set to 0°C for applications of the model in this study. Specification of the upper boundary condition includes the temperature at the top of the moss layer during the summer and at the sur-
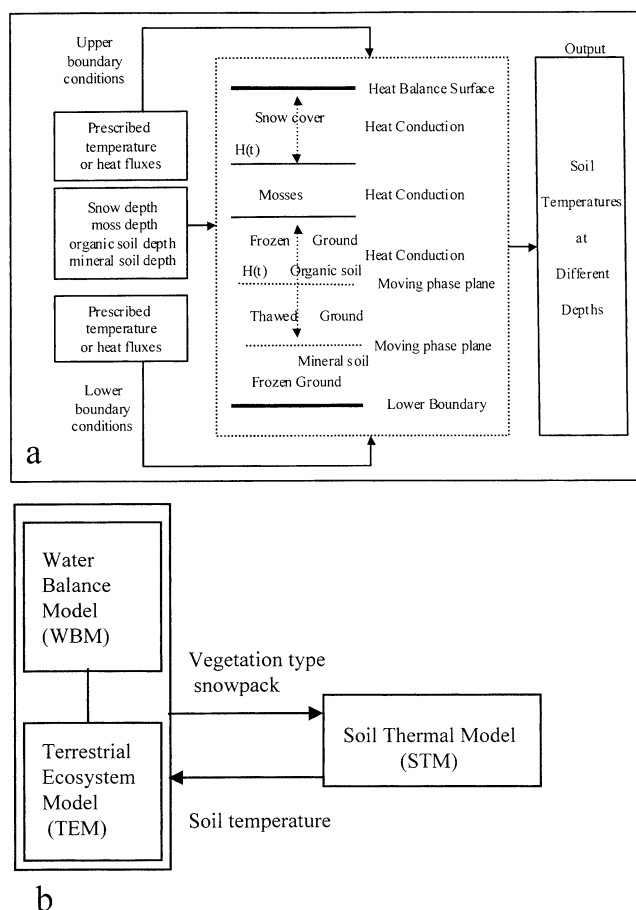
Figure 1. (a) Structure of the soil thermal model (STM) in the study. Heat conduction, H(t), is modeled as a function of time (t) within the snow, moss, organic soil, and mineral soil layers. The frozen and thawed phase boundaries move up and down during the simulation. Input data for driving the model include temporal variability in temperature or heat fluxes for upper and lower boundaries and in the depth of snow. The model simulates soil temperature at each depth with daily resolution. (b) Flow of data in the coupled model (STM-TEM), in which the STM receives information on vegetation and the depth of snowpack from the water balance model (WBM) of the terrestrial ecosystem model (TEM), and TEM receives information on soil temperature for driving soil biogeochemical processes.

face of snow during the winter. In this study we prescribed the depth, density, and thermal properties of snow cover. For the lower boundary condition we assumed a constant heat flux. Alternatively, the lower boundary condition can be specified as a temporally varying function of temperature or heat flux. Application of the model requires the prescription of initial conditions, which include specifying the initial soil temperatures of the system and the presence or absence of permafrost.

To drive the model with daily inputs the model linearly interpolates to 0.5-hour or 0.5-day resolution with three sequential days of data on daily air temperature and snow depth for the current day, the previous day, and the next day. Similarly, to drive the model with monthly inputs, the model linearly interpolates data on monthly air temperature and snow depth for the current month, the previous month, and

the next month. For example, to determine air temperature data for the model's internal 0.5-day time step in November, approximately 60 points are linearly interpolated between mean monthly October and November air temperature to determine the 30 points for the first half of November, and approximately 60 points are interpolated between mean monthly November and December air temperature to determine the 30 points for the second half of November.

2.3. Evaluation of STM Performance

2.3.1. Parameterization. We specified the parameters of the STM for a black spruce stand in the Bonanza Creek Experimental Forest near Fairbanks, Alaska, based on empirical data, calibration, and review of the scientific literature. The ground layer of this stand is covered by a nearly continuous layer of feather moss (*Hylocomium Splendens and Pleurozium Shreberi*). The distribution of permafrost and the active layer thickness is consistently uniform across the stand. Observed data for the stand include measurements of daily air temperature and daily soil temperatures at different depths (0, 23, 32, 42, and 52 cm, where 0 cm is the top of the moss layer) from May 1996 to April 1997.

In the STM we set the lower-boundary condition for this stand to a constant geothermal heat flux of 0.05 W m^{-2} [*Osterkamp and Romanovsky*, 1999]. Within each layer, we calculated the soil thermal dynamics for 10 depth steps within the snow layer, for 3.5 cm depth steps within the 12 cm of living and dead moss layer, for 2.5 cm depth steps within the 28 cm of upper organic soil layer, for 2 cm depth steps within the 64 cm of the lower organic soil layer, for 10 cm depth steps within the first 40 cm of the mineral soil layer, and for 50 cm depth steps down to the lower boundary of the mineral soil layer, which in our simulations was located at the 10 m depth from the top of the moss layer. We set the snow thermal conductivity to 0.2 W m^{-1} K^{-1}. The thawed soil thermal conductivity, frozen soil thermal conductivity, and water content and heat capacity for the moss, organic soil, and mineral soil layers are documented in Table 1.

2.3.2. Model Simulations. To evaluate the performance of the STM with either 0.5-hour or 0.5-day internal time steps and with either daily or monthly climate inputs, we conducted simulations of the soil thermal regime for the black spruce stand at Bonanza Creek between May 1996 and April 1997 in a two-factor design that considered different combinations for the temporal resolutions of internal time step and input data (Figure 2): (Simulation I) 0.5-hour internal time step and daily inputs; (II) 0.5-day internal time step and daily inputs; (III) 0.5-hour internal time step and monthly inputs; and (IV) 0.5-day internal time step and monthly inputs. The inputs of daily air temperature (Figure 3a) and snow depth (Figure 3b) for simulations I and II were obtained from measurements made at the Fairbanks International Airport weather station. To provide monthly inputs for simulations III and IV, we calculated monthly means from the daily air temperature and snow depth data used in simulations I and II. Soil temperatures can be output by the STM at the resolution of the internal time step. For each of the simulations we calculated mean daily and mean monthly soil temperature at several depths in the system profile (0, 23, 32, 42, and 52 cm, where 0 cm is the top of the moss layer) for comparison with observed mean daily and monthly soil temperature at corresponding depths in the correlation and regression analyses. In addition to evalu-

Table 1. Parameters Used for Simulations of the Soil Thermal Model (STM) for a Black Spruce Stand at the Bonanza Creek Experimental Forest (BNZ) Near Fairbanks, Alaska and the Coupling of the STM with the Terrestrial Ecosystem Model (STM-TEM) for a Black Spruce Stand in Canada (NSA-OBS), and White Spruce (WS), Aspen (AS), and Tussock Tundra (TT) sites in Alaska[a]

Parameter Code	Description	Normal					Value		
		BNZ	NSA-OBS	WS	AS	TT	Minimum	Maximum	Unit
V1	Moss thickness	0.12 (0.035)[b]	0.10 (0.05)	0.15 (0.15)	0.15(0.15)	0.20 (0.10)	0.05	0.35	Meter (m)
V2	Upper organic soil thickness	0.28 (0.025)	0.20 (0.05)	0.15 (0.15)	0.15 (0.15)	0.20 (0.15)	0.15	0.50	Meter (m)
V3	Lower organic soil thickness	0.64 (0.020)	0.15 (0.10)	0.30 (0.30)	0.30 (0.30)	0.40 (0.15)	0.20	0.65	Meter (m)
V4	Upper mineral soil thickness	0.40 (0.100)	0.85 (0.10)	0.60 (0.30)	0.30 (0.30)	0.90 (0.30)	0.40	2.00	Meter (m)
V5	Moss thawed thermal conductivity	0.10	0.20	0.45	0.50	0.15	0.10	0.50	W m^{-1} K^{-1}
V6	Moss frozen thermal conductivity	0.12	0.31	0.56	1.20	0.26	0.12	1.20	W m^{-1} K^{-1}
V7	Upper organic soil thawed thermal conductivity	0.30	0.20	1.20	1.00	0.70	0.20	1.20	W m^{-1} K^{-1}
V8	Upper organic soil frozen thermal conductivity	0.68	0.31	1.50	1.50	1.50	0.30	1.50	W m^{-1} K^{-1}
V9	Lower organic soil thawed thermal conductivity	0.50	0.50	1.40	1.20	0.70	0.40	1.40	W m^{-1} K^{-1}
V10	Lower organic soil frozen thermal conductivity	1.60	1.0	2.10	2.10	1.50	0.60	2.20	W m^{-1} K^{-1}
V11	Upper mineral soil thawed thermal conductivity	0.75	0.50	1.40	1.20	1.20	0.50	1.60	W m^{-1} K^{-1}
V12	Upper mineral soil frozen thermal conductivity	1.60	1.00	2.10	2.10	2.10	1.00	2.50	W m^{-1} K^{-1}
V13	Moss water content	0.04	0.08	0.44	0.10	0.65	0.03	0.60	Volumetric %
V14	Upper organic soil water content	0.65	0.20	0.10	0.10	0.10	0.10	0.70	Volumetric %
V15	Lower organic soil water content	0.65	0.08	0.33	0.19	0.10	0.08	0.65	Volumetric %

Table 1. Continued

Parameter Code	Description	BNZ	NSA-OBS	Normal			Value		
				WS	AS	TT	Minimum	Maximum	Unit
V16	Upper mineral soil water content	0.45	0.20	0.33	0.23	0.43	0.10	0.45	Volumetric %
V17	Moss thawed volumetric heat capacity	1.70	1.70	1.20	1.50	1.50	1.20	3.50	MJ m^{-1} K^{-1}
V18	Moss frozen volumetric heat capacity	1.50	1.50	1.00	1.20	1.20	1.00	3.50	MJ m^{-1} K^{-1}
V19	Upper organic soil thawed heat capacity	1.70	1.70	2.40	2.30	1.30	1.30	2.50	MJ m^{-1} K^{-1}
V20	Upper organic soil frozen heat capacity	1.60	1.50	2.20	2.20	1.20	1.20	3.50	MJ m^{-1} K^{-1}
V21	Lower organic soil thawed heat capacity	2.60	1.70	2.80	2.10	1.30	1.50	3.50	MJ m^{-1} K^{-1}
V22	Lower organic soil frozen heat capacity	1.60	1.50	1.70	1.70	1.20	1.50	3.50	MJ m^{-1} K^{-1}
V23	Upper mineral soil thawed heat capacity	2.60	2.60	2.80	3.10	3.10	1.50	3.50	MJ m^{-1} K^{-1}
V24	Upper mineral soil frozen heat capacity	1.60	2.40	1.70	1.70	1.70	1.50	3.50	MJ m^{-1} K^{-1}
V25	Snow thermal conductivity	0.20	0.20	0.15	0.17	0.20	0.10	0.30	MJ m^{-1} K^{-1}

[a]The uncertainty analyses were conducted for the BNZ black spruce site. In uncertainty analyses, parameters were varied within the minimum and maximum values shown here under the assumption of a uniform random distribution.

[b]The numerical value following the thickness of each layer was the depth step of the simulation.

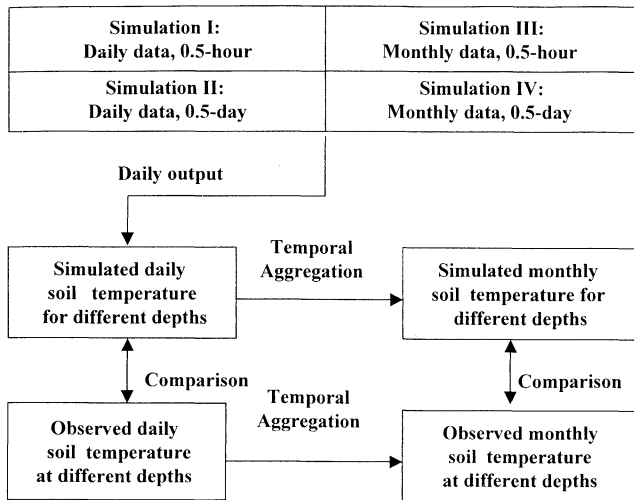| Simulation I: Daily data, 0.5-hour	Simulation III: Monthly data, 0.5-hour
Simulation II: Daily data, 0.5-day	Simulation IV: Monthly data, 0.5-day

Figure 2. Research design for evaluating performance of the STM with respect to the temporal resolutions of internal time step and climate inputs. The performance was evaluated for a black spruce ecosystem in Bonanza Creek site (BNZ) of Long-Term Ecological Research (LTER). Monthly input climate data for simulations III and IV were temporally aggregated from daily air temperature and snow depth. For comparisons between observed and simulated monthly soil temperatures, daily observed and simulated soil temperatures were aggregated. All simulations use the same parameters and initialization protocol.

ating performance at various depths of the system, we also evaluated the performance of the model to simulate the aggregated temperature within the upper organic layer, which is an important region for biological activity in the soil. The soil temperature in the upper organic layer $(T_{UO}^{(m)})$ at time m is obtained by linearly aggregating soil temperatures simulated at 2.5 cm depth steps throughout the 28 cm of the upper organic layer:

$$T_{UO}^{(m)} = \sum_{j=0}^{j=k} (T(m,j)*(X(j)))/ \sum_{j=0}^{j=k} X(j) \qquad (1)$$

Where $T(m,j)$ is the soil temperature at time m and node j, $X(n)$ is soil depth at node n, and k is the number of nodes within the upper organic layer with the zero node located at the boundary between the moss and the upper organic layer and the k node located at the boundary between the upper and the lower organic layers. We also calculated the root-mean-square deviation (D_{RMS}) of each soil depth and for the upper organic layer as well as active layer depths between each combination of the four simulations so that we could assess whether simulated soil temperature and active layer depth were more influenced by changing the resolution of the internal time step or by changing the resolution of the input data. We calculated D_{RMS} as

$$D_{RMS} = \sqrt{\sum_{i=1}^{i=n} (T_i - TT_i)^2 / n} \qquad (2)$$

Where T_i and TT_i are daily or monthly soil temperatures for each pair of simulations, i is simulation day or month, and n is number of days or months.

2.4. Uncertainty Analyses

Uncertainty analysis relates the variability in model predictions to uncertainty in the parameters of the model [*Turner et. al.*, 1994]. In this study we conducted uncertainty analyses for the version of the model that used 0.5-day internal time step and monthly inputs to identify which parameters need to be specified for spatial application of the model. Our analysis focused on evaluating the parameter uncertainty of the simulated mean monthly temperatures aggregated for the upper organic layer between May 1996 and April 1997. Simple Pearson correlation coefficients (R) were calculated between each of the parameters and the model predictions. We used the squared Pearson correlation coefficient (R^2), which is the percentage of the total variance in an output variable of the model that was explained by variability in a particular parameter, as our index of uncertainty. If the parameters considered in the uncertainty analysis are independent of each other, then the squared Pearson correlation coefficient can be used as a sensitivity measure [*Rose et al.*, 1991]. The sum of the sensitivity measures quantifies the proportion of the total variance of the model prediction that relates linearly to variation in the parameter [*Bartell et al.*, 1988].

To examine how the uncertainty relationships between output variables and parameters potentially depend on climate, we evaluated another eight climate scenarios in addition to the normal climate scenario defined by the observed air temperature and snow depth at the site (Table 2). For scenarios that considered higher or lower air temperature and which considered shallower and deeper snow depths, we manipulated air temperature and snow depth by increasing or decreasing by 20% the monthly mean air temperature and snow depth derived from the data measured at Fairbanks International Airport between May 1996 and April 1997. For each uncertainty analysis we obtained the 100 values of each parameter for the analysis by randomly drawing from a uniform random distribution over the possible range for each parameter (see Table 1). In the uncertainty analyses we considered all parameters in Table 1 except for the parameters that de-

Table 2. Combinations of Different Air Temperature and Snow Depth Scenarios for the Study of the Uncertainty Analyses for Simulations of Soil Temperature by the Soil Thermal Model (STM) for the Black Spruce Ecosystem at Bonanza Creek Experimental Forest near Fairbanks, Alaska

| Code	Description
LT-SS	Lower temperature and shallower snow depth
LT-NS	Lower temperature and normal snow depth
LT-DS	Lower temperature and deeper snow depth
NT-SS	Normal temperature and shallower snow depth
NT-NS	Normal temperature and normal snow depth
NT-DS	Normal temperature and deeper snow depth
HT-SS	Higher temperature and shallower snow depth
HT-NS	Higher temperature and normal snow depth
HT-DS	Higher temperature and deeper snow depth
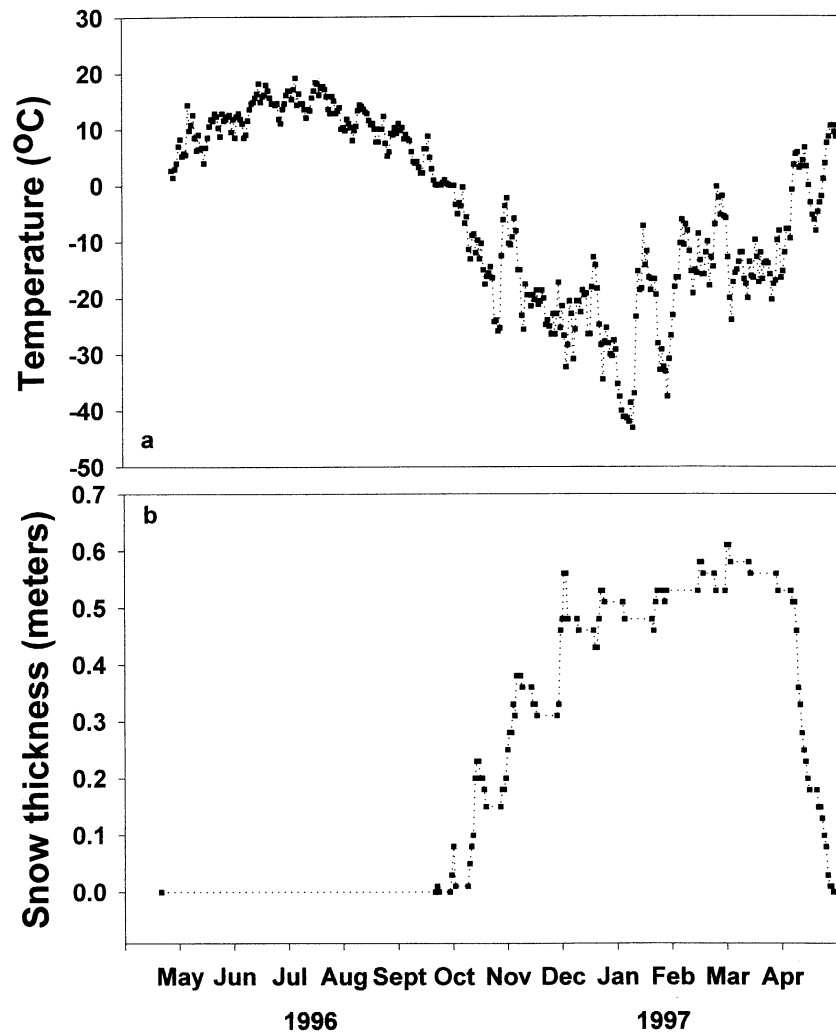
Figure 3. (a) Air temperature and (b) snow depth for the black spruce ecosystem at Bonanza Creek Experimental Forest from May 1996 to April 1997.

fined the water content of the lower organic and mineral soil layers because we were interested in evaluating the sensitivity to water content in the moss and upper organic layers. Correlation analysis among the parameters indicated that the parameters were statistically independent, as all R^2 values were less than 0.094 between pairs of parameters.

2.5. Evaluation of STM-TEM Performance for Different Ecosystem Types

We coupled the STM with version 4.2 of the Terrestrial Ecosystem Model (TEM) [*McGuire et al.*, 2001], which includes hydrology derived from the water balance model of *Vorosmarty et al.* [1989] and provides spatially distributed snow depth estimates based on precipitation inputs. In the coupled model (STM-TEM), the STM operates with an internal 0.5-day time step and monthly inputs of air temperature and snow depth. The snow depth is calculated by a specified snow density and snow water equivalent, which is provided from the simulation of hydrology by TEM (Figure 1b). We verified soil temperatures simulated by STM-TEM for four sites that represent the structural diversity of ecosystems that occur throughout high latitudes. These sites include a black spruce site in Canada and white spruce (*Picea glauca*), aspen

(*Populus tremuloides*), and tussock tundra (*Eriophorum Vaginatum*) sites in Alaska (Table 3).

The black spruce site in Canada is the old black spruce (OBS) site of the northern study area (NSA) of the Boreal Ecosystem-Atmosphere Study [*Sellers et al.*, 1997]. The white spruce ecosystem is a 100-year old forest located on a south-facing slope in the Bonanza Creek Experimental Forest with a silt-loam soil that contains permafrost. The aspen ecosystem is a 100-year old forest in the Bonanza Creek Experimental Forest with a silt-loam soil that contains no permafrost. The tussock tundra site is located near the Toolik Lake field station on a site with an organic soil that contains permafrost. We defined the profile of the system and parameters of STM-TEM for each of these sites based on physical properties of soils for each site (Table 1). The presence or absence of permafrost is prescribed through the initial temperature profile at each site. For application of the STM-TEM to these sites, we conducted simulations from 1975 to 1997 and compared the simulated and observed monthly soil temperatures at different depths for a period of time near the end of the simulations. The monthly climate data for driving the STM-TEM were determined from data measured at local weather stations or study sites (Table 3).

Table 3. Applications of the Coupled Model (STM-TEM) in Which the Soil Thermal Model (STM) Was Coupled to the Terrestrial Ecosystem Model (TEM), to Simulate Soil Temperature for Four Different Representative Ecosystem Types in High-Latitude Regions of North America

Vegetation Type	Stand Location	Driving Data	Depths of Soil Temperatures Simulated and Observed	Reference
Black spruce	Northern study area (NSA) near Manitoba, Canada	Thompson airport weather station, data from 1975 to 1997	5, 20, 20, 50, and 100 cm, depths relative to the surface of moss	*Sellers et al.*, [1997]
White spruce	333 mile Parks Highway, Fairbanks, Alaska	Field-based air temperature from 1994 to 1997, precipitation data from the Fairbanks International Airport weather station in period 1994 to 1997	Soil surface, 15, and 30 cm, depths are relative to the surface of moss and lichen	R. E. Erickson, personal communication, 1999
Aspen	20 mile Chena Hot Springs Rd., Fairbanks, Alaska	Field-based air temperature from 1994 to 1997, precipitation data from the Fairbanks International Airport weather station in period 1974 to 1997	Same as white spruce site	R. E. Erickson, personal communication, 1999
Tussock tundra	Toolik Lake tussock tundra site of Arctic Long-Term Ecological Research (LTER), Alaska	For period of 1995 to 1997, measured air temperature at the site, measured precipitation at Bettles FAA Airport	10, 20, 35, and 40 cm, depths are relative to the surface of moss layer	G. Shaver, personal communication, 1999

2.6. Evaluation of Carbon Fluxes for a Black Spruce Forest

In the STM-TEM, monthly soil temperature of the upper organic layer is used to drive the processes of decomposition and gross nitrogen mineralization in the simulation by the model (Figure 1b). To evaluate the performance of the model in simulating ecosystem carbon fluxes, we parameterized the STM-TEM for a black spruce forest site at the Bonanza Creek Experimental Forest, Alaska similar to the procedures described by *Clein et al.* [in press; see also *Amthor et al.*, this issue] and applied the model to simulate carbon dynamics for the black spruce site in Canada. To evaluate how uncertainty in simulated soil temperatures might influence estimates of carbon dynamics by the STM-TEM, we simulated carbon fluxes for two additional soil temperature scenarios. We manipulated the baseline simulated soil temperature of the upper soil organic layer (scenario B) by increasing (scenario I) or decreasing (scenario D) monthly temperatures of the layer by 1°C and compared simulated carbon fluxes among these soil thermal scenarios. The carbon fluxes we evaluated include monthly gross primary production (GPP), which is the amount of carbon taken up by the vegetation through the process of photosynthesis, and monthly ecosystem respiration (RESP), which is the amount of carbon released to the atmosphere through respiration by the vegetation and through decomposition of soil organic matter. Net ecosystem production (NEP), which represents the net exchange of carbon with

the atmosphere is calculated as the difference between GPP and RESP. Increases in ecosystem carbon storage are indicated by positive values of NEP, while decreases in carbon storage are indicated by negative values of NEP.

2.7. Application to the Range of Black Spruce Ecosystems across North America

To evaluate the ability of the STM-TEM to operate at large temporal and spatial scales, we applied the black spruce parameterization of the model for the NSA-OBS black spruce site to simulate soil thermal dynamics for the range of black spruce forest ecosystems across North America north of 50°N from 1900 to 2100. The climate data for the historical period (1900 to 1994) were developed at 0.5° spatial resolution by the Max Planck Institute for Meteorology (M. Heimann, unpublished data, 2000) by interpolating the monthly temperature anomalies of *Jones* [1994] and the monthly precipitation anomalies of *Hulme* [1995] to 0.5° resolution and then adding them to the long-term monthly air temperature and precipitation in the Cramer-Leemans CLIMATE database, which is an update of *Leemans and Cramer* [1991] database. The climate data for the projected period (1995 to 2100) were based on monthly temperature and precipitation ramps defined from a transient simulation of the Hadley Center CM2 model. The CM2 simulation we used considered the radiative forcing associated with the combined effects of changes in greenhouse gases and sulphate aerosols [*Mitchell et al.*, 1995]. The meth-

Table 4. Slope, Intercept, and Proportion of Variation (R^2) Explained by Linear Regressions Between Field-Based and Simulated Daily and Monthly Soil Temperatures at Various Depths and Active Layer Depths for Simulations I, II, III, and IV of the Black Spruce Stand at Bonanza Creek Experimental Forest from May 1996 to April 1997[a]

	0 cm	23 cm	32 cm	42 cm	52 cm	Upper Organic
			Daily Soil Temperature[b]			
			Simulation I			
R^2	0.91	0.85	0.74	0.61	0.66	0.77
Slope	0.97*	0.95	0.87	0.88	1.09	0.94
Intercept	-0.03	0.43	0.19	0.05[&]	-0.12	0.11
			Simulation II			
R^2	0.91	0.85	0.74	0.61	0.66	0.77
Slope	0.97*	0.93	0.83	0.84	1.10	0.92
Intercept	-0.08[&]	0.35	0.07[&]	-0.06[&]	-0.13	0.03[&]
			Simulation III			
R^2	0.85	0.82	0.76	0.68	0.67	0.78
Slope	0.98*	0.94	0.88	0.91	0.99*	0.89
Intercept	0.35	0.59	0.33	0.19	-0.18	0.14
			Simulation VI			
R^2	0.85	0.82	0.76	0.68	0.66	0.79
Slope	0.98*	0.93	0.84	0.88	1.08	0.80
Intercept	0.32	0.52	0.22	0.09[&]	-0.05[&]	-0.06[&]

ods for creating the projected monthly climate (air temperature and precipitation) are described in *McGuire et al.* [2000a].

3. Results

3.1. Evaluation of STM Performance

3.1.1. Simulated daily soil temperature. For the black spruce site at the Bonanza Creek Experimental Forest, the daily soil temperatures estimated by the four simulations at various depths (0, 23, 32, 42, and 52 cm and upper organic soil layer) generally fit the observed data well (Table 4 (top)). For linear regression analyses between simulated and observed soil temperatures, the proportion of variance explained (R^2) ranged from 0.61 to 0.91, slopes of the analyses ranged 0.80 to 1.10, and intercepts were less than 0.60°C. In general,

simulated soil temperatures near the surface were more accurate than simulated soil temperatures deeper in the profile. For the soil temperature aggregated across the upper organic layer, which is the temperature that is used to drive soil biogeochemical processes in the coupled model, R^2 values (0.77 to 0.79), slopes (0.80 to 0.94), and intercepts (-0.06 to 0.14 °C) across the four simulations were similar.

Although these comparisons indicate that the temporal resolution of internal time step and of input data did not substantially influence the overall accuracy of daily soil temperature simulated by the STM for the year of observed soil temperature, there are some seasonal differences among the simulations. For surface temperature (Figure 4a), simulations III and IV tended to underestimate from April to July and tended to overestimate from August to October and in March. Except for March the surface temperature estimated by simulations I and II did not show these biases. For the soil tem-

perature of the upper organic layer (Figure 4b), simulations III and IV tended to underestimate during April, May, December, and January and tended to overestimate from July to September and during March. Simulations I and II also tended to underestimate soil temperature in December and January and overestimate soil temperature in March.

These patterns suggest that differences among the simulations are related more to the temporal resolution of the input data than to resolution of the internal time step. To formally evaluate how differences in daily soil temperature among the simulations were influenced by differences in the temporal resolution of internal time step and input data, we calculated D_{RMS} for various soil depths between pairs of simulations (Table 5 (top)). At each depth in the profile, D_{RMS} was greater for pairs I-III, I-IV, II-III, and II-IV than for pairs I-II and III-IV. This result indicates that the simulations were more influenced by the temporal resolution of input data than by the temporal resolution of internal time step. Because D_{RMS} for pairs I-III, I-IV, II-III, and II-IV were greater for depths nearer the surface of the profile with values near 4oC at the surface, it appears that the temporal resolution of input data primarily influences estimates of soil temperature close to the surface. For the upper organic layer, D_{RMS} between simulations I-IV and II-IV was less than 1oC. Thus the ver-

Table 4. Continued

| | | | Monthly Soil Temperature[c] | | | | |
	0 cm	23 cm	32 cm	42 cm	52 cm	Upper Organic	Active Layer Depth
				Simulation I			
R^2	0.95	0.88	0.77	0.65	0.82	0.82	0.95
Slope	0.99	0.96	0.89	0.89	1.10	0.95	1.08
Intercept	-0.08&	0.43	0.21	0.07&	-0.10&	0.11	0.03&
				Simulation II			
R^2	0.95	0.87	0.77	0.66	0.82	0.82	0.90
Slope	0.99	0.94	0.84	0.86	1.12	0.93	1.43*
Intercept	-0.12&	0.35	0.08&	-0.05&	-0.11&	0.03&	0.06&
				Simulation III			
R^2	0.92	0.85	0.79	0.74	0.84	0.86	0.85
Slope	0.98	0.94	0.89	0.94	1.03	0.90	0.99
Intercept	0.44	0.62	0.37	0.26	-0.11&	0.50	0.02&
				Simulation VI			
R^2	0.92	0.85	0.80	0.74	0.84	0.86	0.94
Slope	0.99	0.93	0.85	0.91	1.12	0.80	1.00
Intercept	0.42	0.56	0.25	0.15&	0.04&	-0.06&	-0.01&

[a]Field-based estimates are the dependent variables, and the simulated estimates are the independent variables. Tests for significance were performed with a two sided t-test atα=0.05 level. The four simulations that varied with respect to the temporal resolutions of internal time step and of climate data used to drive simulations. (See Figure 2 and section 2 for more information).

[b]All linear regressions were significant atα=0.05 level with p < 0.001. An asterisk indicates slopes that were not significantly different from 1.0 and an ampersand indicates intercepts that were not significantly different from 0.0.

[c]All linear regressions were significant atα=0.05 level with p < 0.001. None of the slopes were significantly different from 1.0 except for the slope indicated with asterisk. An ampersand indicates intercepts that were not significantly different from 0.0.
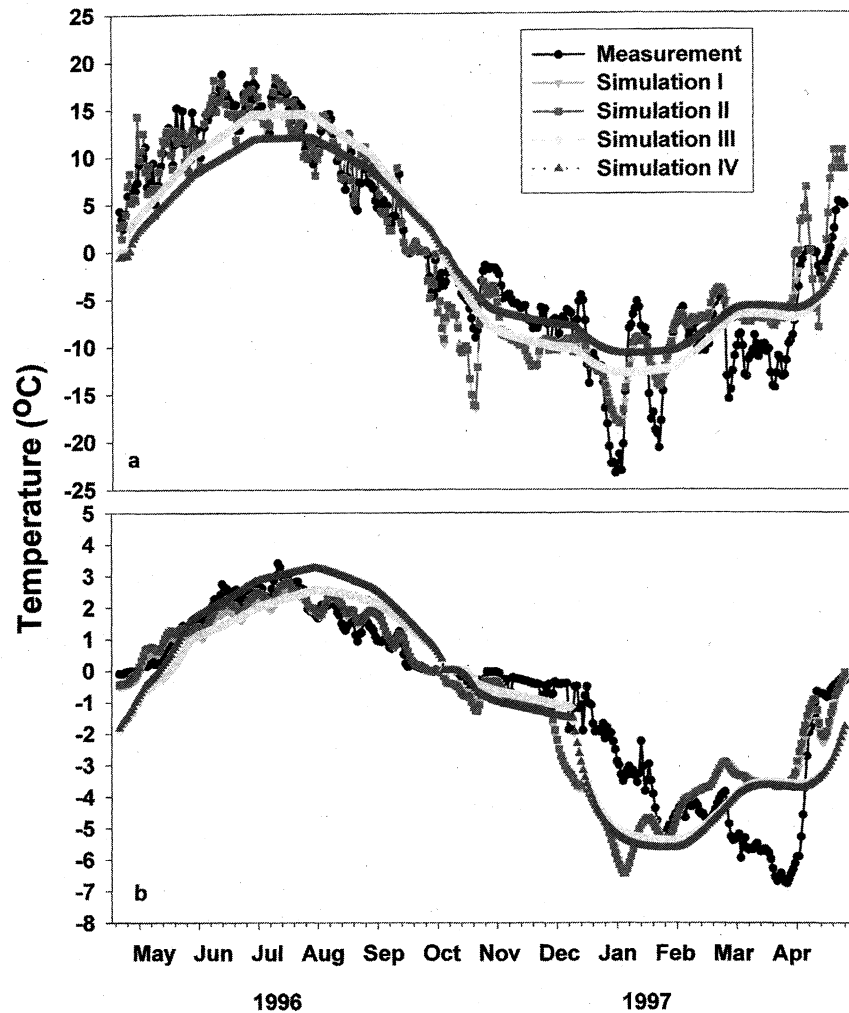
Figure 4. Observed and simulated daily soil temperatures for (a) the surface of the soil and (b) the upper organic soil layer.

sion of the model that uses 0.5-day internal time step and monthly input data may be acceptable if a root-mean-square error of 1°C in daily soil temperature is acceptable for driving soil processes in a daily biogeochemical model.

3.1.2. Simulated monthly soil temperature and active layer depth. The monthly soil temperature at the various depths and the active layer depth estimated by the four simulations generally fit the observed data well (Table 4(bottom)). For linear regression analyses between simulated and observed soil temperatures, the proportion of variance explained (R^2) ranged from 0.65 to 0.95, slopes ranged from 0.80 to 1.12, and the intercepts were less than 0.63°C. In contrast to the analysis for simulated daily soil temperatures, the accuracy of simulated monthly soil temperatures did not deteriorate with increasing depth, although the simulations were most accurate at the surface. For the soil temperature aggregated across the upper organic soil layer, R^2 values (0.82 to 0.86), slopes (0.80 to 0.95), and intercepts (-0.06 to 0.50°C) across the four simulations were similar. For the regression analysis between observed and simulated active layer depths, R^2 values (0.85 to 0.95), slopes (0.99 to 1.43), and intercepts (-0.01 to 0.06 m) across the four simulations were comparable. The seasonal differences noted in the analysis of simulated daily soil temperatures is reflected in the comparison

between observed and simulated monthly soil temperatures (Figure 5). For monthly surface temperature (Figure 5a), simulations I and II matched the observed data from May to September, tended to underestimate from October to December, and tended to overestimate from February to April. Simulations III and IV slightly underestimated monthly soil temperature from May to July and in November, December, and February and slightly overestimated soil temperature from August to October. For monthly temperature of the upper organic soil layer (Figure 5b), simulations I and II performed well from May to September, but underestimated from October to January. Except for August, September, and March, simulations III and IV tended to underestimate monthly temperature in the upper organic soil layer.

These patterns suggest that differences among the simulations were related more to temporal resolution of the input data than to resolution of the internal time step, which is a conclusion from the analysis of daily soil temperatures. Conclusions from the results of the monthly D_{RMS} analyses (Table 5(bottom)) are also similar to those of the daily analyses as they indicate that (1) the simulations were more influenced by the temporal resolution of input data than by the temporal resolution of internal time step, (2) the temporal resolution of the input data primarily influences estimates of temperature

coupled model reproduced the observed data well at various depths in the profile for white spruce (Figure 10), aspen (Figure 11), and tussock tundra (Figure 12) ecosystems in Alaska. For regressions between simulated and observed temperatures close the soil surface, and (3) D_{RMS} for all pairs of simulations was less than 1°C for the upper organic soil layer. For active layer depth, D_{RMS} was less than 0.06 m for all pairs of simulations. Thus the version of the model that uses 0.5-day internal time step and monthly input data accurately estimates the depth of the active layer and may be acceptable if a root-mean-square error of 1°C in monthly soil temperature is acceptable for driving soil processes in a monthly biogeochemical model.

3.2. Uncertainty Analyses

For the uncertainty analysis under the normal climate scenario, 30 to 80% of the variance in monthly soil temperature of the upper organic soil layer was explained by uncertainty in a subset of the parameters (Table 1, Figure 6), including the moss thickness (V1), moss thermal conductivity (V5 and V6), and snow thermal conductivity (V25). From January to April, uncertainty in moss thickness (Figure 6, V1) explained less variability than from June to October. Soil temperature was sensitive to uncertainty in the parameters describing the thermal conductivity of thawed and frozen moss (Figure 6), but was more sensitive to uncertainty in thermal conductivity

of thawed moss (V6) during summer than to the uncertainty of thermal conductivity of frozen moss (V5) during winter (Figure 6). Although uncertainty in snow thermal conductivity (V25) explained almost 30% of the variability in soil temperature from January to April, it only explained 2% and 11% of the variability in November and December, respectively (Figure 6).

The sensitivity of soil temperature in the upper organic layer to uncertainty in each of the parameters varied among the nine climate scenarios. The pattern of sensitivity among climate scenarios to uncertainty in the thermal conductivity of snow (Figure 7) and in moss thickness (Figure 8) illustrates that the pattern varies among parameters. For snow thermal conductivity, the sensitivity of soil temperature of the upper organic layer to uncertainty in this parameter ranged from approximately 10 to 30% from December to April under the normal and low temperature scenarios (Figure 7a and 7b), but soil temperature was insensitive during other months of the year and under the high temperature scenarios (Figure 7c). For moss thickness, the sensitivity of soil temperature to uncertainty in this parameter ranged from approximately 20 to 30% from May to October under all temperature scenarios (Figure 8). From December to April, uncertainty in moss thickness explains less than 10% of the variability in soil temperature across scenarios because snow thermal conductivity is a more important parameter in these months. The uncertainty analyses suggest that the accuracy to which pa-

Table 5. Root Mean Square (RMS) Deviations of Simulated Daily and Monthly Soil Temperature Between Pairwise Combinations of Simulations I, II, III, and IV of Soil Temperature and Active Layer Depths for the Black Spruce Stand at Bonanza Creek Experimental Forest from May 1996 to April 1997[a]

Daily Soil Temperature

	0 cm	23 cm	32 cm	42 cm	52 cm	Upper Organic
I, II	0.43	0.17	0.71	0.18	0.09	0.14
I, III	3.85	1.16	0.85	0.67	0.62	1.52
I, IV	3.85	1.14	0.84	0.67	0.63	0.88
II, III	3.90	1.25	0.98	0.75	0.65	1.49
II, IV	3.90	1.23	0.93	0.72	0.64	0.90
III, IV	0.05	0.11	0.20	0.15	0.22	0.86

Monthly Soil Temperature

	0 cm	23 cm	32 cm	42 cm	52 cm	Upper Organic	Active Layer Depth (m)
I, II	0.13	0.14	0.21	0.17	0.08	0.13	0.03
I, III	3.11	1.07	0.78	0.60	0.56	0.67	0.01
I, IV	3.10	1.05	0.78	0.60	0.57	0.79	0.01
II, III	3.13	1.16	0.92	0.70	0.60	0.74	0.04
II, IV	3.13	1.14	0.87	0.67	0.59	0.81	0.06
III, IV	0.05	0.10	0.19	0.14	0.21	0.40	0.02

[a]Four simulations that varied with respect to the temporal resolutions of internal time step and of climate data used to drive the simulations (see Figure 2 and section 2 for more information). The daily RMS deviation values were calculated one the basis of 365 daily estimates of soil temperature, and the monthly RMS deviations were calculated on the basis of 12 monthly estimates of soil temperature.
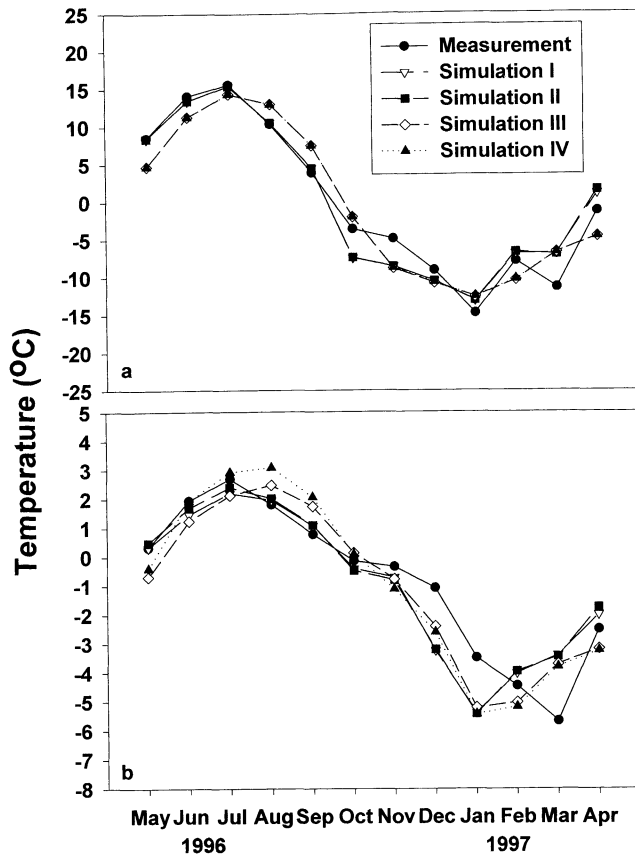
Figure 5. Observed and simulated monthly soil temperatures for (a) the surface of the soil and (b) the upper organic soil layer.
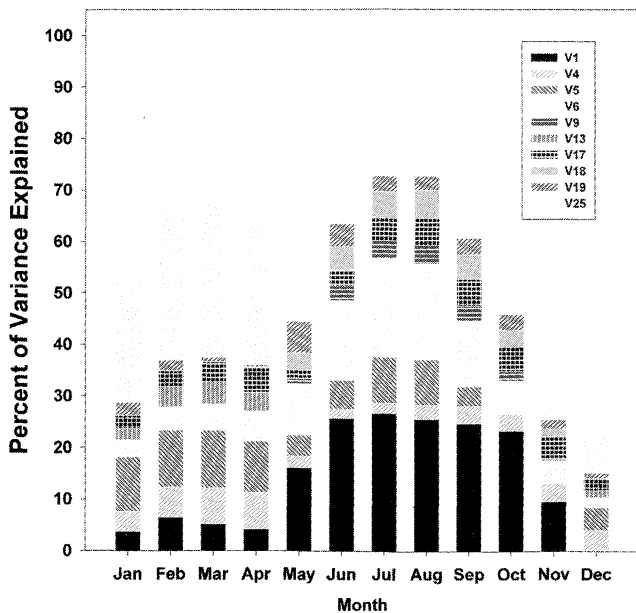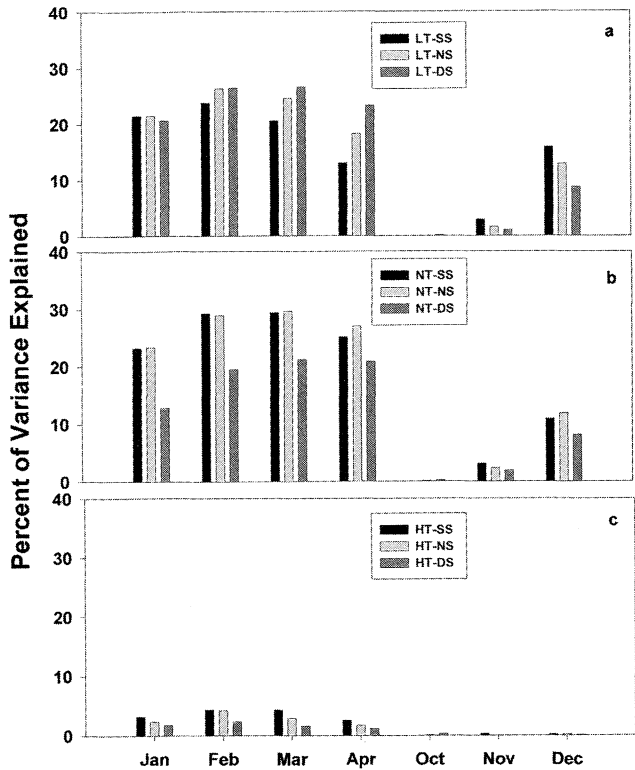

Figure 7. Proportion of variation in simulated soil temperature of the upper organic layer to variation in snow thermal conductivity in uncertainty analyses conducted for nine different climate scenarios: (a) low-temperature scenarios, (b) normal temperature scenarios, and (c) high-temperature scenarios. See Table 2 for additional information on the climate scenarios.

Figure 6. Proportion of variation in simulated soil temperature of the upper organic layer explained by variability in parameters in the uncertainty analyses conducted in this study. See Table 1 for additional information on parameters in these analyses.

rameters should be determined depends on the parameter and for some parameters depends on the climate space to which the model is applied.

3.3. Applications to Different Ecosystem Types

To evaluate the performance of the coupled model for different ecosystem types, in which the STM receives snow depth data from the hydrology model of TEM, we parameterized the model for a black spruce ecosystem in Canada and for white spruce, aspen, and tussock tundra ecosystems in Alaska (Table 1; see section 2). For the black spruce ecosystem, soil temperatures simulated by the coupled model reproduced the observed data well at various depths in the profile (Figure 9). For regressions between simulated and observed at different depths, R^2 ranged from 0.96 to 0.98, slopes ranged from 0.88 to 1.04, and intercepts ranged from 0.72 to 1.56°C (Table 6 (top)). These results indicate that the model can be applied to black spruce ecosystems with different structural characteristics and different soil thermal regimes when the model has information on structural characteristics relevant to the dynamics of the soil thermal regime.

For application to other ecosystems in high-latitude regions of North America, soil temperatures simulated by the coupled model reproduced the observed data well at various depths in the profile for white spruce (Figure 10), aspen (Figure 11), and tussock tundra (Figure 12) ecosystems in Alaska. For regressions between simulated and observed temperatures at different depths in these ecosystems, R^2 ranged from 0.72
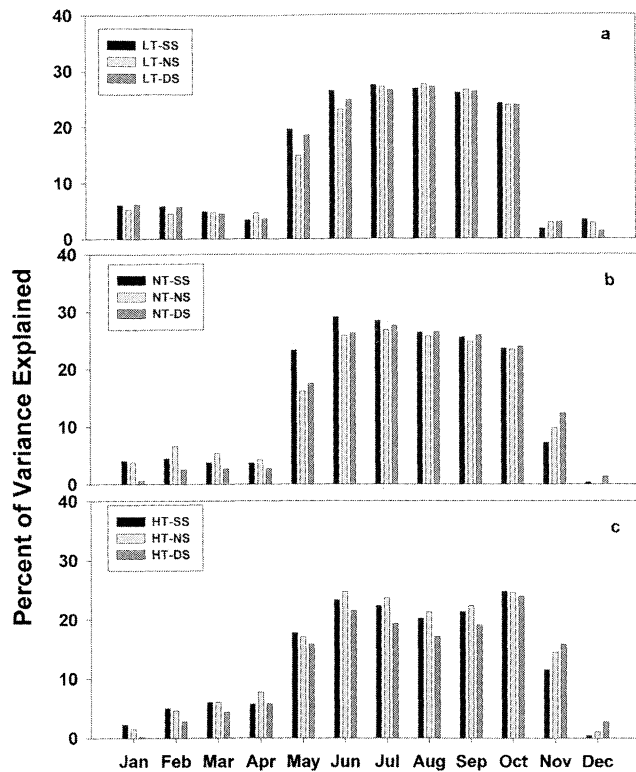
Figure 8. Proportion of variation in simulated soil temperature of the upper organic layer to variation in moss thickness in uncertainty analyses conducted for nine different climate scenarios: (a) low-temperature scenarios, (b) normal temperature scenarios, and (c) high-temperature scenarios. See Table 2 for additional information on the climate scenarios.

to 0.96, slopes ranged from 0.71 to 1.04, and intercepts ranged from -0.64 to 0.60°C (Table 6 (middle-bottom)). These results indicate that the model can be applied to different high-latitude ecosystems when the model has information on structural characteristics, physical properties, and boundary conditions relevant to the dynamics of the soil thermal regime.

3.4. Evaluation of Carbon Fluxes Simulated for a Black Spruce Forest

The estimates of monthly GPP and RESP simulated by the STM-TEM for the simulated soil temperature of the upper organic soil layer in the baseline scenario were highly correlated with tower-based estimates for the black spruce site in Canada (Figure 13; R^2 = 0.93 for GPP and 0.94 for RESP). While the slopes of regression between observed and simulated were not significantly different from 1 for both GPP and RESP (slopes = 1.01 for GPP and 1.06 for RESP), the intercepts were significantly different from 0 (intercept = -7.5 g C m^{-2} month^{-1} for GPP and -10.6 g C m^{-2} month^{-1} for RESP). Simulated monthly NEP generally fit the seasonal trends of the field-based estimates, although the correlation between field-based and simulated estimates of NEP (R^2 = 0.60) was lower than for estimates of GPP and RESP. Similar to the relationships between observed and simulated GPP and RESP, the slope between simulated and observed NEP (0.82) was not significantly different from 1, while the intercept (-2.21 g C m^{-2} month^{-1}) was statistically different from 0. The estimates of GPP, RESP, and NEP of scenario B were highly correlated with estimates simulated for scenarios I and D (R^2

= 0.99 for all B-I and B-D comparisons) with slopes that were not significantly different from 1 (slopes ranged from 0.96 to 1.02 for B-I comparisons and from 0.97 to 1.02 for B-D comparisons) and intercepts (less than 0.50 g C m^{-2} month^{-1} for all B-I and B-D comparisons) that were not significantly different from 0. These analyses indicate that differences of less than 1°C in simulated temperatures for the upper organic soil layer do not significantly affect the short-term carbon dynamics simulated by the STM-TEM.

3.5. Application to the Range of Black Spruce Ecosystems across North America

We applied the parameterization of the STM-TEM for the black spruce forest in Canada to simulate soil thermal dynamics for the range of black spruce forest ecosystems across North America north of 50°N from 1900 to 2100 at a spatial resolution of 0.5° latitude x longitude. This simulation maintained constant structural characteristics of the simulated soil profile, as defined by the black spruce site used to parameterize the model, but was driven by air temperature and snow depth that varied both spatially and temporally. The simulation of mean annual soil temperature within the upper organic soil layer for four different decades (1930s, 1980s, 2030s, and 2080s) responded to the spatial and temporal climatic variability that was used to drive the simulation (Plate 1). For all decades a north-south gradient in soil temperatures for this layer was maintained across the range of black spruce in North America north of 50°N. Across decades, the soil temperature at this depth increased from the 1930s to the 2080s in a fashion consistent with the scenario of climatic warming that was used to drive the simulation. These results indicate
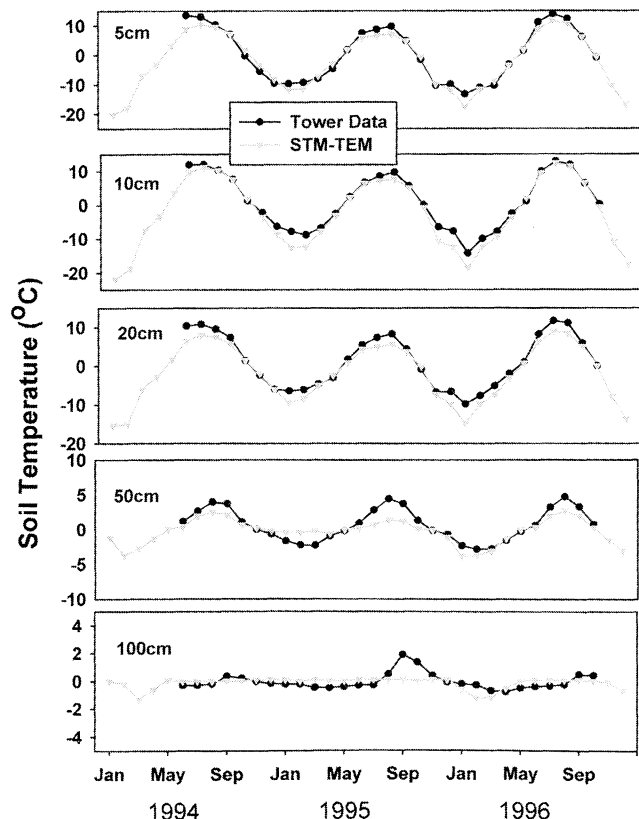

Figure 9. Monthly observed and simulated soil temperatures for an old black spruce ecosystem in northern Manitoba, Canada, from 1994 to 1996.

Table 6. Slope, Intercept, and Proportion of Variation Explained by Regression Analyses Between Observed and Simulated Soil Temperature at Various Depths in the Soil Profile for an Old Black Spruce Forest in Canada, a White Spruce Forest in Alaska, an Aspen Forest in Alaska, and a Tussock Tundra Site in Alaska[a,b]

Old Black Spruce

	5 cm	10 cm	20 cm
R[2]	0.96	0.98	0.96
Slope	1.04*	0.88	0.98*
Intercept	0.72	1.40	1.56

White Spruce

	0 cm	15 cm	30 cm
R[2]	0.96	0.81	0.78
Slope	0.95*	0.93*	0.94*
Intercept	-0.54	-0.17&	-0.18&

Aspen

	0 cm	15 cm	30 cm
R[2]	0.95	0.84	0.72
Slope	0.99*	0.85	0.71
Intercept	-0.64	0.46	0.60

Tussock Tundra

	10 cm	20 cm	35 cm	40 cm
R[2]	0.96	0.82	0.82	0.74
Slope	1.02*	1.04*	1.04*	0.95*
Intercept	-0.28	-0.51	-0.22	-0.50

[a]Field-based soil temperatures are the dependent variables, and the simulated soil temperatures are the independent variables. Tests for significance were performed with a two-sided t-test at α=0.05 level. Simulations were conducted with the coupled version of the model (STM-TEM), in which the soil Thermal model (STM) was coupled to the terrestrial ecosystem model (TEM). For more information see Table 3 and section 2.

[b]All linear regressions were significant at α=0.05 level with p < 0.001. An asterisk indicates slopes that were not significantly different from 1.0 and an ampersand indicates intercepts that were not significantly different from 0.0.

that the model has the potential to be used at large spatial scales to simulate the response of the soil thermal regime to climate change and variability.

4. Discussion

In this study we modified an extant model of permafrost dynamics for incorporation into a large-scale biogeochemical model that is driven by monthly climate data. Our incorporation of permafrost dynamics was based on an extant version

of the Goodrich model, which uses a numerical approach to simulate soil temperatures throughout the soil profile. Although analytical approaches to heat conduction represent an alternative to the numerical approach we have implemented in this study, they have a number of limitations for applications to ecosystems affected by permafrost [*Goodrich*, 1976; *Romanovsky et al.*,1997]. *Williams* and *Smith* [1989] point out that analytical solutions to the heat conduction are only applicable when transient effects of phase change are not important. The numerical solution of the Goodrich model is able to consider how phase changes are influenced by the effects of latent heat, which dominate the thermal dynamics of a freezing and thawing soil. In contrast, analytic approaches are only capable of predicting monotonic thaw penetration and tend to overestimate thaw depth because the approach fails to properly account for heat storage effects [see *Goodrich*, 1976]. Possible disadvantages of the Goodrich approach include computational costs and the number of parameters that need to be specified for implementing the approach. Therefore, we evaluated both temporal and spatial scaling issues to determine suitability of this approach for incorporation into a large-scale ecosystem model.

4.1. Temporal Scaling Issues

Romanovsky et al. [1997] conducted a comprehensive evaluation of three numerical models used in simulations of the active layer and permafrost temperature regimes with respect to internal time step and with respect to the depth step
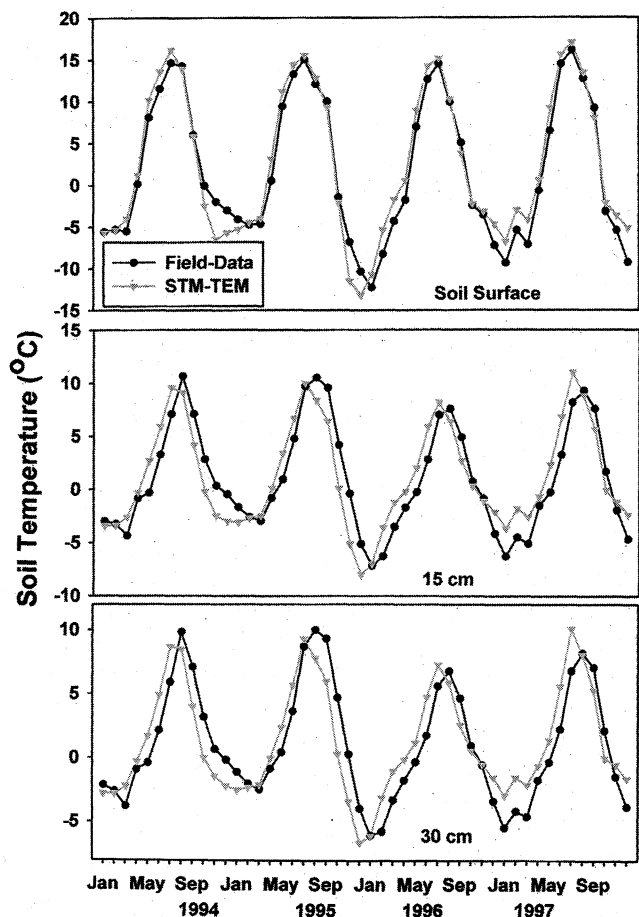

Figure 10. Monthly observed and simulated soil temperatures for a white spruce ecosystem in Alaska from 1994 to 1997.
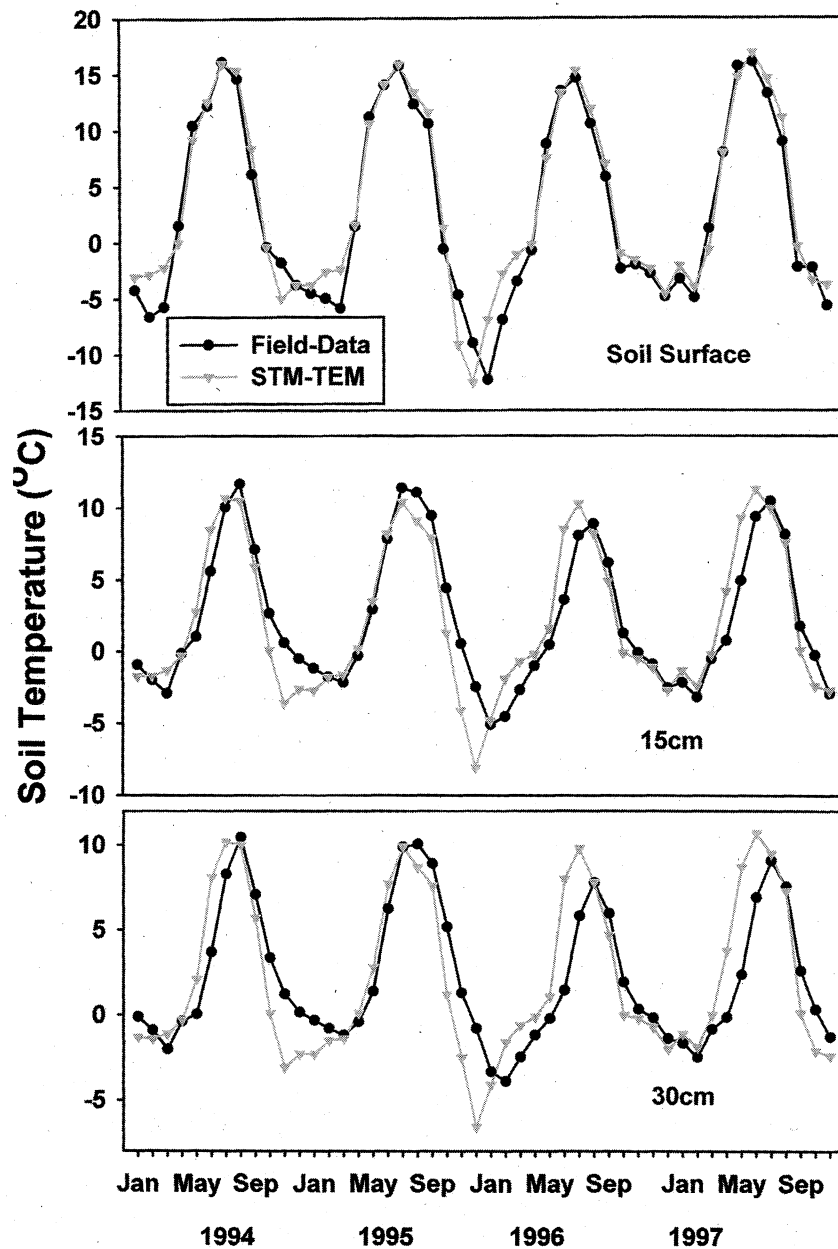
Figure 11. Monthly observed and simulated soil temperatures for an aspen ecosystem in Alaska from 1994 to 1997.

of different layers, and concluded that the choice of optimum time and depth steps appears to be specific to the application. The choices we made for depth steps in this study were based on what we considered to be an acceptable compromise between computational efficiency and simulation accuracy. Our evaluation of model performance indicated that there was little difference between simulations of daily or monthly soil temperature that used different internal time steps considered in this study (0.5 hours and 0.5 days), and all applications of the model accurately simulated the depth of the active layer. Between simulations that used input climate data at different temporal resolutions (daily versus monthly), we did find some differences in simulated daily and monthly soil temperature. Our evaluation of these differences indicated that monthly resolution climate data could be used to drive simu-

lations if an error of less than 1°C is acceptable for driving soil biogeochemical processes. Results of a sensitivity analysis indicate that an error of less than 1°C in the temperature of the upper organic soil layer does not significantly affect the carbon dynamics simulated by the STM-TEM. Furthermore, simulations with the STM-TEM indicate that annual carbon balance across the boreal region of North America is sensitive to the timing of spring thaw [Zhuang et al., unpublished, 1999], which is a conclusion reached in a site-specific analysis of this issue by Frolking et al. [1996]. The ongoing development of data sets that describe the freezing and thawing of the land surface at large spatial scales [e.g., Running et al., 1999; Frolking et al., 1999] represent important information for evaluating the timing of soil thermal dynamics simulated by the STM-TEM at large spatial scales.

4.2. Spatial Scaling Issues

The application of the model to the range of black spruce ecosystems across North America north of 50°N from 1900 to 2100 demonstrated to us that the soil thermal model has the capability to operate over spatial and temporal domains that consider substantial variation in surface climate. It is important to recognize that this application did not consider spatial variation in vegetation distribution. It also did not consider spatial variation in structural characteristics, physical properties, and lower boundary conditions of the soil thermal regime. The application also did not consider temporal changes in vegetation, structural characteristics, and physical proper-

ties associated with disturbance and gradual vegetation dynamics, e.g., changes in tree line. Our evaluation of model performance for different representative ecosystem types of high-latitude regions in North America indicated that the model can be applied to different vegetation types when it has information on structural characteristics, physical properties, and lower boundary conditions relevant to the soil thermal regime. Although a number of vegetation classifications are available at the global scale, classifications that can be linked to structural characteristics, physical properties, and lower-boundary conditions of the soil thermal regime in high latitudes will be most useful in the context of simulating soil thermal dynamics at large spatial scales. The development of
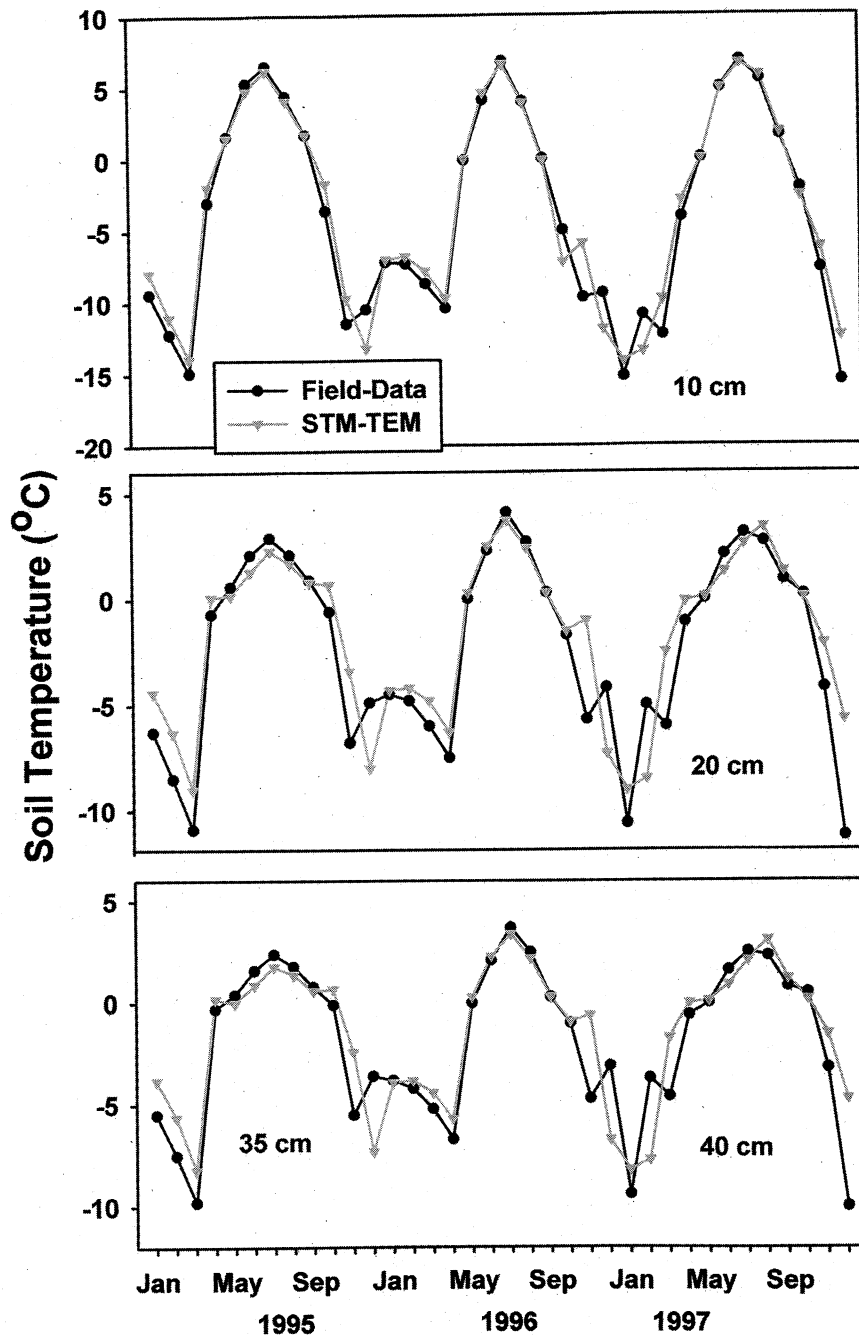

Figure 12. Monthly observed and simulated soil temperatures for a tundra ecosystem in Alaska from 1995 to 1997.
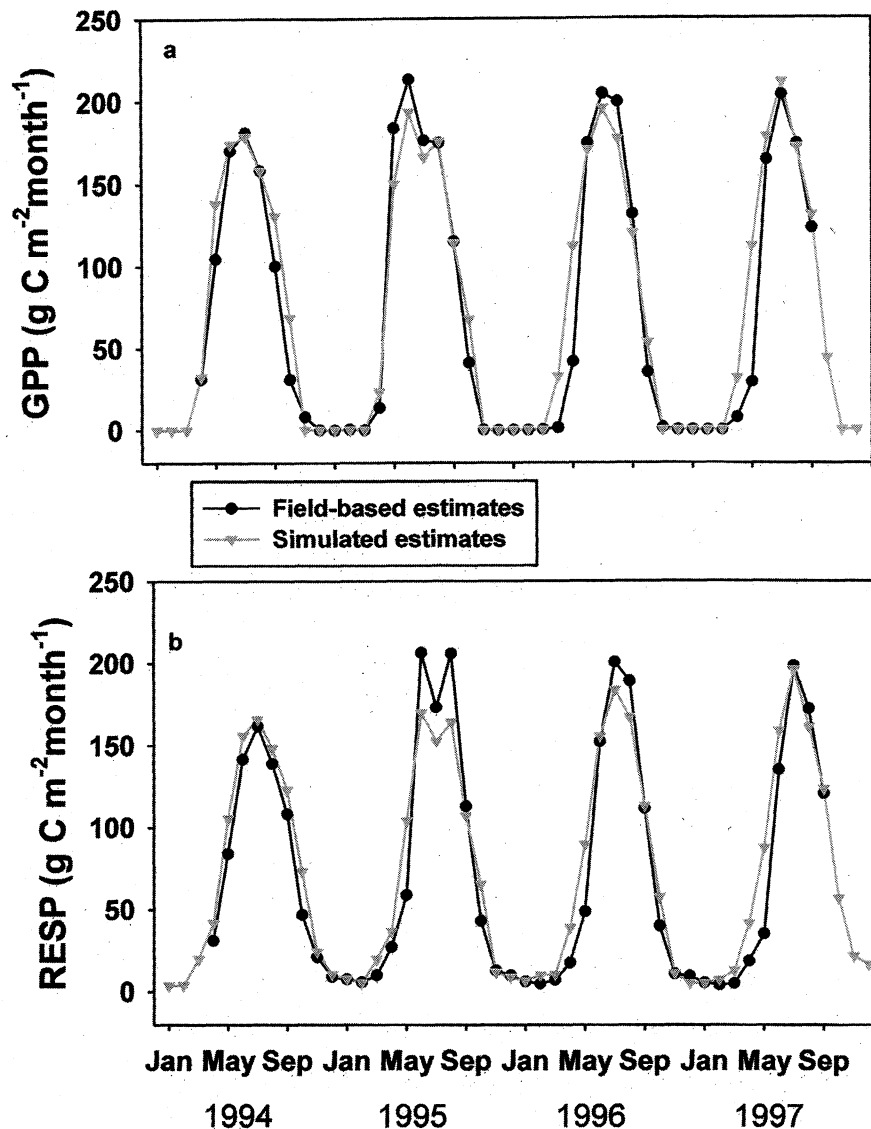
Figure 13. Field-based and simulated estimates of (a) monthly gross primary production (GPP) and (b) ecosystem respiration (RESP) for an old black spruce ecosystem in northern Manitoba, Canada from 1994 to 1997. Simulated soil temperatures were used to drive some of the biogeochemical processes in the coupled STM-TEM. Field-based estimates are from *Clein et al.* [in press].

spatially resolved data sets that describe structural characteristics, physical properties, and lower-boundary conditions of the soil thermal regime are necessary to facilitate progress in modeling the soil thermal regime at large spatial scales.

Our uncertainty analyses are relevant to the development of spatially resolved data sets in that they provide insight on which structural characteristics and physical properties of the soil thermal regime need to be determined for improving spatial applications of the STM-TEM. These analyses were primarily focused on soil temperature of the upper organic layer, which is the temperature used to drive soil biogeochemical processes in the coupled model. The uncertainty analyses identified that soil temperature estimates of the model for the organic layer were sensitive to variability in moss thickness and thermal conductivity under "normal" conditions of air temperature and snow depth, which is consistent with the field studies of *Dyrness* [1982]. Other modeling studies, for example, *Frolking and Crill* [1994] who adopted the method of *Clymo* [1984], highlight the need to consider how the physical properties of moss influence soil thermal dynamics.

In addition, soil temperature was sensitive to uncertainty in snow thermal conductivity, a result that has been highlighted in other modeling studies [*Zhang et al.*, 1996, 1997]. The uncertainty analyses of the study also revealed that the accuracy to which these parameters should be determined depends on the climate, a result that has been reported for other parameters in land surface schemes [*Pitman*, 1994]. With respect to the development of spatial data sets that describe the structural and physical properties of the soil thermal regime, our study indicates that effort should be prioritized on developing data sets that describe spatial variability of snow and moss thickness and of snow and moss thermal conductivity. Besides the development of data sets for "best" estimates of the parameters, it is also important to develop data sets for uncertainty in the parameter estimates.

4.3. Additional Issues and Future Directions

The dynamics of snow influence the soil thermal regime in cold regions because the low thermal conductivity of snow

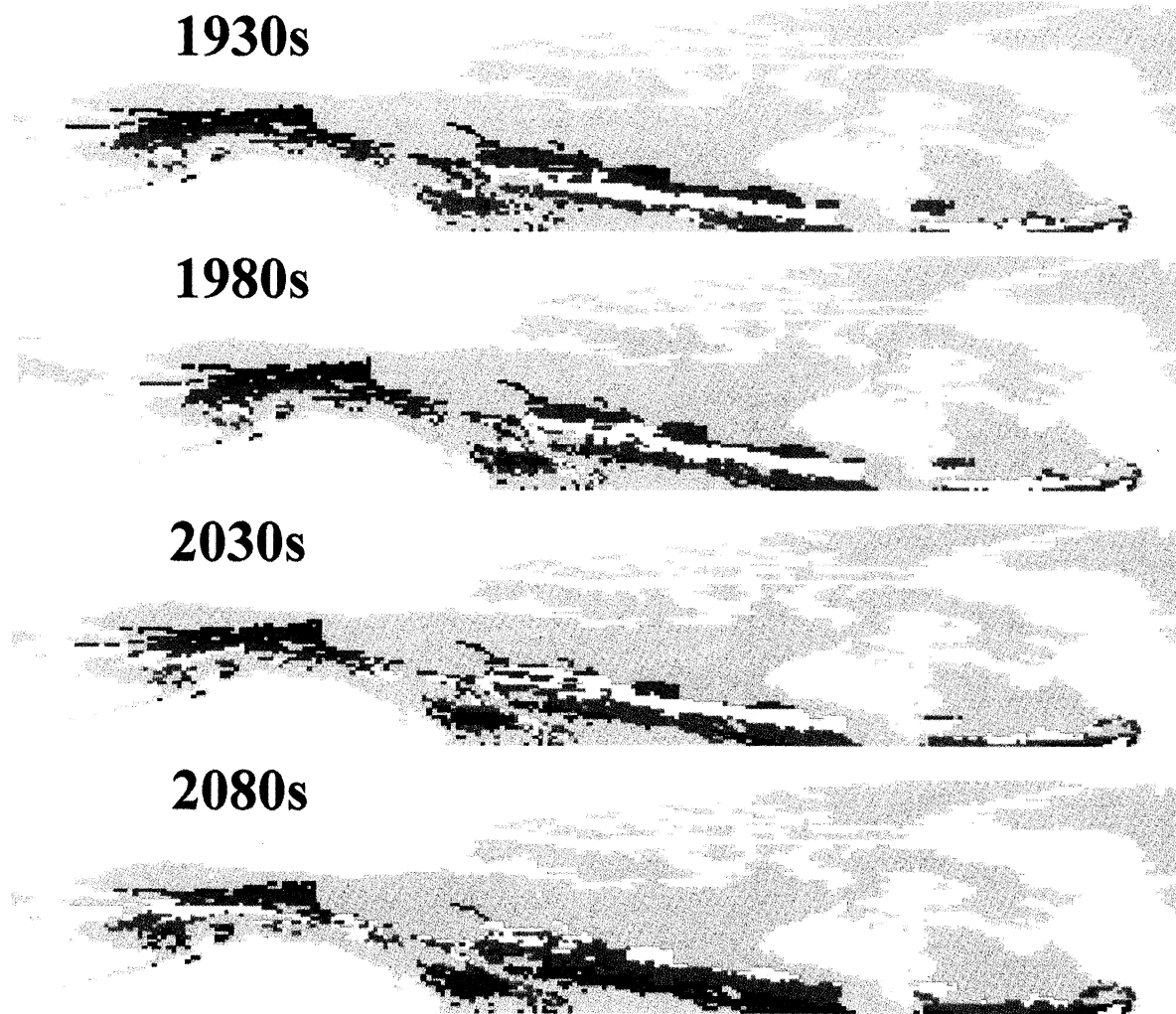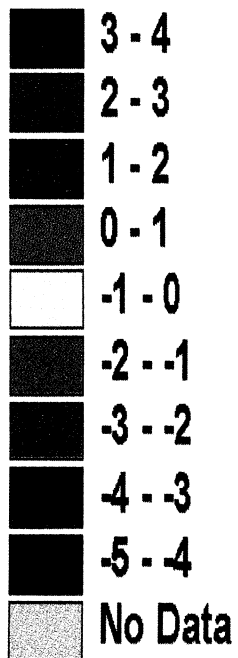**Mean annual soil temperature (°C) of the upper organic soil layer**

■	3 - 4
■	2 - 3
■	1 - 2
■	0 - 1
□	-1 - 0
■	-2 - -1
■	-3 - -2
■	-4 - -3
■	-5 - -4
▨	No Data

1930s

1980s

2030s

2080s

Plate 1. Spatial distribution of mean annual soil temperature for the upper soil organic layer simulated by the application of the STM-TEM across the range of black spruce ecosystems in North America north of 50°N during four decades separated by 50 years during the simulation period (1900-2100): (a) 1930-1939, (b) 1980-1989, (c) 2030-2039, and (d) 2080-2089.

makes it a good insulator [*Goodrich*, 1976, 1978a, 1978b; *Zhang et al.*, 1996; *Sturm et al.*, 2001]. Data sets for the timing, spatial distribution, and properties of snow represent a major uncertainty because the density of weather stations in high-latitude regions is low, and the reliability of precipitation data from these stations is low [*McGuire et al.*, 2000a]. The thermal properties of snow may also need to be considered in more detail than in the version of the STM in this study, in which snow cover is homogeneous with respect to thermal conductivity. Some studies have shown that separation of snow cover into wind slab and depth hoar fractions influences permafrost dynamics [*Zhang et al.*, 1996; *Loth and Graf*, 1998]. Microrelief and vegetation may interact with wind and snow seasonal cover to influence the physical and thermal properties of snow to affect the soil thermal regime in permafrost dominated regions [*Sturm et al.*, 2001]. As it is not clear whether data sets that describe the spatial and temporal variability of thermal properties for multiple layers of snow can be developed, the current version of the STM does not consider this variability.

Several studies have demonstrated that soil drainage in high-latitude ecosystems influences carbon dynamics and storage by affecting decomposition [*Oechel et al.*, 1995; *Harden et al.*, 2000; *Christensen et al.*, 1998]. The current version of the STM-TEM primarily uses the hydrology of a freely draining large-scale hydrological model [*Vorosmarty et al.*, 1989] to provide the STM with snow water equivalent, but the STM-TEM does consider how the active layer affects hydrology to influence soil thermal dynamics. As the STM-TEM accurately simulates active layer depth, it should be able to better consider spatial variability in carbon dynamics if it is modified so that active layer dynamics influence the hydrology of the moss, organic, and mineral layers in the soil and so that the hydrology of these layers influence both the soil thermal regime and the carbon dynamics. This is especially important in ecosystems recovering from disturbance events, which may substantially affect active layer depth and alter the thickness and properties of the moss and organic layers in the soil. We are currently developing a version of the STM-TEM that has been modified to consider these issues. Data sets that describe the spatial and temporal variability in the moisture of soil layers and ecosystem carbon dynamics with respect to soil drainage and disturbance history are needed to evaluate the performance of coupled models of soil thermal and ecosystem dynamics.

References

Amthor, J. S., et al., Boreal forest CO_2 exchange andevapotranspiration predicted by nine ecosystem process models: Intermodel comparisons and relationships to field measurements,*J. Geophys. Res.*, this issue.

Bartell, S. M., A. L. Brenkert, R. V. O'Neill, and R. H. Gardener, Temporal variation in regulation of production in a pelagic food web model, in *Complex interactions in lake communities,* edited by S. R. Carpenter, pp. 101-118, Springer-Verlag, New York, New York, USA, 1988.

Beltrami, H., and J. C. Mareschal, Recent warming in eastern Canada inferred from geothermal measurements, *Geophys. Res. Let., 18*, 605-608, 1991.

Brown, R. J. E., The distribution of permafrost and its reaction to air temperature in Canada and the U.S.S.R, *Arctic, 13*, 163-177, 1960.

Chapin, F. S., III, et al., Feedbacks from arctic and boreal ecosystems to climate, *Global Change Biol., 6,* S211-S223, 2000.

Chapman, W. L., and J. E. Walsh, Recent variations of sea ice and air temperatures in high latitudes, *Bull. Am. Meteorol. Soc., 74*, 33-47, 1993.

Christensen, T. R., S. Jonasson, A. Michelsen, T. V. Callaghan, M. Hastrom, Environmental controls on soil respiration in Eurasian and Greenlandic Arctic, *J. Geophys. Res., 103*, 29,015-29,021, 1998.

Clein J. S., B. L. Kwiatkowski, A. D. McGuire, J. E. Hobbie, E. B. Rastetter, J. M. Melillo and D. W. Kicklighter, Modeling carbon responses of tundra ecosystems to historical and projected climate: A comparison of a fine- and coarse-scale ecosystem model for identification of process-based uncertainties,*Global Change Biol., 6,* S127-S140, 2000.

Clein, J. S., A. D. McGuire, X. Zhang, D.W. Kicklighter, J. M. Melillo, S. C. Wofsy, and P. G. Jarvis. The role of nitrogen dynamics in modeling historical and projected carbon balance of mature black spruce ecosystems across North America: Comparisons with CO_2 fluxes measured in the Boreal Ecosystem Atmosphere Study (BOREAS), *Plant and Soil*, In press.

Clymo, R., The limits of peat bog growth, *Philos. Trans. R. Soc. London*, Ser. B, *303*, 605-654, 1984.

Cramer, W., D. W. Kicklighter, A. Bondeau, B. Moore III, G. Churkina, B. Nemry, A. Ruimy, A. L. Schloss, and the participates of the postdam NPP model intercomparison, Comparing global models of terrestrial net primary productivity (NPP) overview and key results, *Global Change Biol., 5* (Suppl. 1), 1-15, 1999.

Dyrness, C. T., Control of depth to permafrost and soil temperatures by the forest floor in black spruce/feathermoss communities,*U.S. For. Serv. Res. Note PNW-396*, Dept. of Agric., Washington, D.C., 1982.

Epstein, H. E., M. D. Walker, F. S. Chapin III, and A. M.Starfield, A transient, nutrient-based model of arctic plant community response to climate warming,*Ecol. Appl., 10 (3)*, 2000, 824-841, 2000.

Everett, J. T., and B. B. Fitzharris, The Arctic and the Antarctic, in *The Regional Impacts of Climate Change: An Assessment of Vulnerability*, edited by R. T. Watson, M. C.Zinyowera, R. H. Moss, and D. J. Dokken, pp. 85-103, Cambridge Univ. Press, New York, 1998.

Frolking, S., and P. Crill, Climate controls on temporal variability of methane flux from a poor fen in southeastern New Hampshire: Measurement and modeling, *Global Biogeochem. Cycles, 8(4)*, 385-397, 1994.

Frolking, S., et al., Modelling temporal variability in the carbon balance of a spruce/moss boreal forest,*Global Change Biol., 2*, 343-366, 1996.

Frolking, S., K. C. McDonald, J. S. Kimball, J. B. Way, R.Zimmermann, and S. W. Running, Using the space-borne NASA scatterometer (NSCAT) to determine the frozen and thawed seasons, *J. Geophys. Res., 104*, 27,895-27,907, 1999.

Garagulya, L. S., V. E. Romanovsky, and N. V. Seregina, Modeling temperature fields during nonhomogeneous rock freezing and thawing, *Russian Geocryological Research*, vol.1, pp. 34-42, Russ. Acad. of Science, Moscow, Russia, 1995.

Goodrich, L. E., A numerical model for assessing the influence of snow cover on the ground thermal regime, Ph.D. thesis, 410 pp., McGill Univ., Montreal, Quebec, 1976.

Goodrich, L. E., Some results of a numerical study of ground thermal regimes, in *Proceedings of 3rd international Conf. On Permafrost*, vol.1, pp. 29-34, Nat. Res. Counc. of Canada, Ottawa, 1978a.

Goodrich, L. E., Efficient numerical technique for one-dimensional thermal problems with phase change,*Int. J. Heat Mass Transfer, 21*, 615-621, 1978b.

Goulden, M. L., et al., Sensitivity of boreal forest carbon balance to soil thaw, *Science 279*, 214-217, 1998.

Guymon, G. L., and T. V. Hromadka II, Finite element model of transient heat conduction with isothermal phase change (two and

three dimensional), *CRREL Spec. Rep.* 77-38, 163 pp., Corps of Eng., U.S. Army, Hanover, N. H., 1977.

Guymon, G. L., T. V. Hromadka II, and R. L. Berg, Two-dimensional model of coupled heat and moisture transport in frost-heaving soils, *J. of Energy Resour. Technol.*, *106*, 336-343, 1984.

Halsey, L.A., D. H. Vitt, and S. C. Zoltai, Disequilibrium response of permafrost in boreal continental western Canada to climatic change, *Clim. Change, 30*, 57-73, 1995.

Harden, J. W., S. E. Trumbore, B. J. Stocks, A. Hirsch, S. T. Gower, K. P. O'Neill, and E. S. Kasischke, The role of fire in the boreal carbon budget, *Global Change Biol., 6* (Suppl. 1), 174-184, 2000.

Heimann, M., et al., Evaluation of terrestrial carbon cycle models through simulations of the seasonal cycle of atmospheric CO_2: First results of a model intercomparison study, *Global Biogeochem. Cycycles, 12*, 1-24, 1998.

Hillman, G. R., Some hydrological effects of peatland drainage in Alberta's boreal forest, *Can. J. For. Res., 22*, 1588-1596, 1992.

Hulme, M., A historical monthly precipitation data for global land areas from 1900 to 1994, gridded at 3.75 x 2.5 resolution, Clim. Res. Unit, Univ. of East Anglia, Norwich, United Kingdom, 1995.

Jones, P. D., Hemispheric surface air temperature variations: a reanalysis and update to 1993, *J. Clim., 7*, 1794-1802, 1994.

Kicklighter, D. W., et al., A first-order analysis of the potential role of CO_2 fertilization to affect the global carbon budget: A comparison of four terrestrial biosphere models, *Tellus, Ser. B*, 343-366, 1999.

Lachenbruch, A. H., J. H. Sass, B. V. Marshall, and T. H. Moses Jr., Permafrost, heat flow, and the geothermal regime at Prudoe Bay, Alaska, *J. Geophys. Res., 87*, 9301-9316, 1982.

Lachenbruch, A. H. and B. V. Marshall, Changing climate: Geothermal evidence from permafrost in the Alaskan Arctic, *Science, 234*, 689-697, 1986.

Leemans, R. and W. P. Cramer, The IIASA database for mean monthly values of temperature, precipitation, and cloudiness on an terrestrial grid, *IIASA RR-91-18*, International Institute for Applied Systems Analysis, Laxenburg, Austria, 1991.

Loth, B., and H. Graf, Modeling the snow cover in climate studies, 1. Long-term integrations under different climatic conditions using a multilayered snow-cover model, *J. Geophy. Res., 103*, 11,313-11,327, 1998.

McGuire, A. D., and J. Hobbie, Global climate change and the equilibrium responses of carbon storage in arctic and subarctic regions, pp. 53-54, in *Modeling the arctic system*: A workshop report of the Arctic System Science Program, Arct. Res. Consort. of the U. S., Fairbanks, Alaska, 1997.

McGuire, A. D., J. M. Melillo, L. A. Joyce, D. W. Kicklighter, A. L. Grace, B. Moore III, and C. J. Vorosmarty, Interactions between carbon and nitrogen dynamics in estimating net primary productivity for potential vegetation in North America, *Global Biogeoch. Cycles, 6*, 101-124, 1992.

McGuire, A. D., J. M. Melillo, D. W. Kicklighter, and L. A. Joyce, Equilibrium responses of soil carbon to climate change: Empirical and process-based estimates, *J. of Biogeogr., 22*, 785-796, 1995.

McGuire, A. D., J. Clein, J. M. Melillo, D. W. Kicklighter, R. A. Meier, C. J. Vorosmarty, and M. C. Serreze, Modeling carbon responses of tundra ecosystems to historical and projected climate: The sensitivity of pan-arctic carbon storage to temporal and spatial variation in climate, *Global Change Biol., 6*, 141-159, 2000a.

McGuire, A. D., J. M. Melillo, J. T. Randerson, W. J. Parton, M. Heimann, R. A. Meier, J. S. Clein, D. W. Kicklighter, and W. Sauf, Modeling the effects of snowpack on heterotrophic respiration across northern temperate and high latitude regions: Comparison with measurements of atmospheric carbon dioxide in high latitudes, *Biogeochemistry, 48*, 91-114, 2000b.

McGuire, A. D., et al., CO_2, climate and land-use effects on the terrestrial carbon balance, 1920-1992: An analysis with four process-based ecosystem models, *Global Biogeoch. Cycles, 15*, 1,183-206, 2001.

Mitchell, J. F. B., T. C. Johns, J. M. Gregory, and S. F. B.Tett, Climate response to increasing levels of greenhouse gases and sulphate aerosols, *Nature, 376*, 501-504, 1995.

Oechel, W. C., S. J. Hastings, G. L. Vourlitis, M. Jenkins, G. Reichers, and N. Grulke, Recent change of arctic tundra ecosystems from a net carbon dioxide sink to a source, *Nature, 361*, 520-523, 1993.

Oechel, W. C., G. L. Vourlitis, S. J. Hastings, and S. A. Bocharev, Change in arctic CO_2 flux over two decades: Effects of climate change at Barrow, Alaska, *Ecol. Appl., 5*, 846-855, 1995.

Oechel, W. C., G. L. Vourlitis, S. J. Hastings, R. C. Zulueta, L. Hinzman, and D. Kane, Acclimation of ecosystem CO_2 exchange in the Alaskan Arctic in response to decadal climate warming, *Nature, 406*, 978-981, 2000.

Osterkamp, T. E., and J. P. Gosink, Variations in permafrost thickness in response to changes in paleoclimate, *J. Geophys. Res., 94*, 4423-4434, 1991.

Osterkamp, T. E., and V. E. Romanovsky, Evidence for warming and thawing of discontinuous permafrost in Alaska, *Permafrost Periglacial process., 10*, 17-37, 1999.

Overpeck, J., et al., Arctic environmental change of the last four centuries, *Science, 278*, 1251-1256, 1997.

Pitman, A. J., Assessing the sensitivity of a Land-Surface Scheme to the parameter values using a single column model, *J. of Clim., 7*, 1856-1869, 1994.

Romanovsky, V. E., L. N. Maximova, and N. V. Seregina, Paleotemperature reconstruction for freeze-thaw processes during the Late Pleistocene through the Holocene, in *Proceedings International Conference, Role of Polar Regions in Global Change*, vol. 2, pp. 537-542, Geophys. Inst., Univ. of Alaska, Fairbanks, 1991a.

Romanovsky, V. E., L. S. Garagula, and N. V. Seregina, Freezing and thawing of soils under the influence of 300- and 90-year periods of temperature fluctuation, in *Proceedings of International Conference, Role of Polar Regions in Global Change*, vol. 2, pp. 543-548, Univ. of Alaska, Fairbanks, 1991b.

Romanovsky, V. E., T. E. Osterkamp, and N. S. Duxbury, An evaluation of three numerical models used in simulation of the active layer and permafrost temperature regimes, *Cold Reg. Sci. Technol., 26*, 195-203, 1997.

Rose, K. A., E. P. Smith, R. H. Gardner, A. L. Brenkert, and S. M. Bartell, Parameter sensitivities, Monte Carlo filtering, and model forecasting under uncertainty, *J. of Forecasting, 10*, 117-133, 1991.

Running S. W., J. B. Way, K. C. McDonald, J. S. Kimball, S. Frolking, A. R. Keyser, and R. Zimmermann, Radar remote sensing proposed for monitoring freeze-thaw transitions in boreal regions, *Eos Trans. AGU, 80*(19), 213, 220-221, 1999.

Schimel, D., et al., Carbon storage by the natural and agricultural ecosystems of the US (1980-1993), *Science, 287*, 2004-2006, 2000.

Sellers, P. J., et al., BOREAS in 1997: Experiment overview, scientific results, and future directions, *J. Geophys. Res., 102*, 28,731-28,769, 1997.

Serreze, M. C., J. E. Walsh, F. S. Chapin III, T. Osterkamp, M. Dyurgerov, V. Romanovsky, W. C. Oechel, J. Morison, T. Zhang, and R, G. Barry, Observational evidence of recent change in the northern high-latitude environment, *Clim. Change, 46*, 159-207, 2000.

Shaver, G. R., W. D. Billings, F. S. Chapin III, A. E. Giblin, K. J. Nadelhoffer, W. C. Oechel, and E. B. Rastetter, Global change and the carbon balance of arctic ecosystems, *BioScience, 42*, 433-441, 1992.

Sturm, M, J. P. McFadden, G. E. Liston, F. S. Chapin III, C. H. Racine, and J. Holmgren, Snow-shrub interactions in Arctic tundra: a hypothesis with climate implications, *J. of Clim., 14*, 336-344, 2001.

Tian, H, J. M. Melillo, D. W. Kicklighter, A. D. McGuire, J. Helfrich, B. Moore III, and C. J. Vörösmarty, Effect of interannual climate variability on carbon storage in Amazonian ecosystems, *Nature, 396*, 664-667, 1998.

Tian, H., J. M. Melillo, D. W. Kicklighter, A. D. McGuire, and J. Helfrich, The sensitivity of terrestrial carbon storage to historical climate variability and atmospheric CO_2 in the United States, *Tellus, Ser. B*, 414-452, 1999.

Tian, H., J. M. Melillo, D. W. Kicklighter, A. D. McGuire, B. Moore III and C. J. Vörösmarty, Climatic and biotic controls on interannual variations of carbon storage in undisturbed ecosystems of the Amazon Basin, *Global Ecol. and Biogeogr., 9*, 315-335, 2000.

Turner, M. G., Y. Wu, L. L. Wallace, W. H. Romme, and A. Brenkert, Simulation winter interactions among ungulates, vegetation, and fire in northern Yellowstone park, *Ecol. Appl., 4*(3), 472-496, 1994.

Vitt, H. D., L. A. Halsey, and S. C. Zoltai, The changing landscape of

Canada's western boreal forest: The current dynamics of permafrost, *Can. J. For. Res.*, *30*, 283-287, 2000.

Vorosmarty, C. J., B. J. Peterson, E. B. Rastetter, and P. A. Steudler, Continental scale models of water balance and fluvial transport: An application to south America, *Global Biogeochem. Cycles*, *3*, 241-265, 1989.

Waelbroeck C., P. Monfray, W. C. Oechel, S. Hastings and G. Vourlitis, The impact of permafrost thawing on the carbon dynamics of tundra, *Geophys. Res. Lett.*, *24*(3), 229-232, 1997.

Williams, P. J. and M. W. Smith, *The frozen Earth, fundamentals of geocryology*, 306pp, Cambridge University Press, 1989.

Xiao, X., J. M. Melillo, D. W. Kicklighter, A. D. McGuire, R. G. Prinn, C. Wang, P. H. Stone, and A. P. Sokolov, Transient climate change and net ecosystem production of the terrestrial biosphere, *Global Biogeochem. Cycles*, *12*, 345-360, 1998.

Zhang, T., T. E. Osterkamp, and K. Stamnes, Influence of the depth hoar layer of the seasonal snow cover on the ground thermal regime, *Water Resour. Res.*, *32*(7), 2075-2086, 1996.

Zhang, T., T. E. Osterkamp, and K. Stamnes, Effects of climate on the active layer and permafrost on the North Slope of Alaska, U.S.A., *Permafrost Periglacial Process.*, *8*, 45-67, 1997.

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