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The importance of climate and soils for estimates of net primary production: a sensitivity analysis with the terrestrial ecosystem model

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Abstract

We used the Terrestrial Ecosystem Model (TEM) to investigate how alternative input data sets of climate (temperature/precipitation), solar radiation, and soil texture affect estimates of net primary productivity (NPP) for the conterminous United States. At the continental resolution, the climates of Cramer and Leemans (C&L) and of the Vegetation/Ecosystem Modelling and Analysis Project (VEMAP) represent cooler and drier conditions for the United States in comparison to the Legates and Willmott (L&W) climate, and cause 5.2% and 2.3% lower estimates of NPP. Solar radiation derived from C&L and given in VEMAP is 32% and 60% higher than the solar radiation data derived from Hahn cloudiness. These differences cause ≈ 8% and 10% lower NPP because of radiation-induced water stress. In comparison to the FAO/CSRC soil texture, which represents most biomes with loam soils, the soil textures are finer (more silt and clay) in the Zobler and VEMAP data sets. The use of VEMAP soil textures instead of FAO/CSRC soil textures causes ≈ 3% higher NPP because enhanced volumetric soil moisture causes higher rates of nitrogen cycling, but use of the Zobler soil textures has little effect. In general, NPP estimates of TEM are more sensitive to alternative data sets at the biome and grid cell resolutions than at the continental resolution. At all spatial resolutions, the sensitivity of NPP estimates represents the impact of uncertainty among the alternative data sets we used in this study. The reduction of uncertainty in input data sets is required to improve the spatial resolution of NPP estimates by process-based ecosystem models, and is especially important for improving assessments of the regional impacts of global change.

Keywords: climate, geographically referenced data, net primary productivity, soil texture, solar radiation, terrestrial ecosystem model (TEM)

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Introduction

The atmospheric concentrations of the major long-lived greenhouse gases continue to increase as a direct result of human activity. Equilibrium simulations of general circulation models (GCMs) for a doubled CO_2 atmosphere project that the global mean surface temperature will rise between 1.5 °C and 4.5 °C, and that precipitation and cloud patterns will also be altered (Houghton *et al.*1995). Climate changes of this magnitude are expected to affect terrestrial ecosystems both functionally and structurally. Interest in the effects of global climate change has motivated the development of ecological analysis at large spatial scales. Process-based ecosystem models have become a common means to evaluate the potential consequences of climate change on terrestrial ecosystems.

In general, process-based ecosystem models have similar requirements for input data. Most of the models need geographically referenced data on temperature, precipitation, solar radiation, topography, soil characteristics, and vegetation as inputs. The availability of these data has been limited in the past, and the data requirements of ecosystem models have simultaneously stimulated the development of data sets organized within geographical information systems. Today there are several alternative data sets available and different modelling groups often use different data sets to run their models. However, it is not clear what differences exist among alternative data sets, and it is not known whether differ-

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ences among data sets affect results of process-based ecosystem models.

It is important to understand how differences among alternative data sets affect the results of ecosystem models for two reasons. First, it is relevant for reducing uncertainty of ecosystem model results for contemporary climate. This is especially relevant for model comparison activities (see VEMAP Members 1995). Second, when ecosystem models are used in a prognostic mode, climate changes inferred from general circulation models (GCMs) are applied to contemporary climate to generate future climatic scenarios (Adams *et al.* 1990; Melillo *et al.* 1993, 1995; McGuire *et al.* 1993, 1996a, 1996b; Dai & Fung 1994; Schimel *et al.* 1994; VEMAP Members 1995). Uncertainty in contemporary climate influences future climate scenarios and the results of ecosystem models.

We used the Terrestrial Ecosystem Model (TEM) to evaluate how different alternative data sets (temperature, precipitation, solar radiation and soil texture) affect estimates of annual net primary productivity (NPP) for the conterminous United States. Annual NPP is the net amount of carbon assimilated by vegetation through the process of photosynthesis over a year. We chose to evaluate the sensitivity of terrestrial NPP because it is an important integrative ecological measure. Also, NPP is a major component of the global carbon cycle and the sensitivity of NPP has important consequences for the global climate system.

Methodology

The Terrestrial Ecosystem Model

In this study we use version 4.0 of TEM (McGuire *et al.* 1996b). The TEM is a process-based ecosystem model (Fig. 1) that uses spatially referenced information on climate, elevation, soils, vegetation and water availability (Fig. 2) to make monthly estimates of important carbon and nitrogen fluxes and pool sizes (Raich *et al.* 1991; McGuire *et al.* 1992, 1993, 1996a, 1996b; Melillo *et al.* 1993, 1995).

In TEM, NPP is calculated as the difference between gross primary productivity (GPP) and plant respiration (R_A). The flux GPP is affected by several factors and is calculated at each time step as follows:

$$GPP = C_{max}\, f(PAR)\, f(LEAF)\, f(T)\, f(CO_2, H_2O)\, f(NA),$$

where C_{max} is the maximum rate of C assimilation, PAR is photosynthetically active radiation, LEAF is leaf area relative to maximum annual leaf area, T is monthly air temperature, CO_2 is the atmospheric concentration of carbon dioxide, H_2O is water availability, and NA is nitrogen availability. The calculation of R_A considers both maintenance respiration and construction respiration.

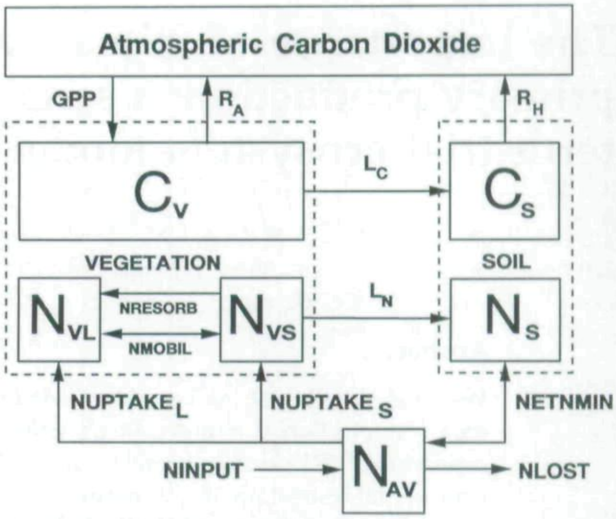

Fig. 1 The Terrestrial Ecosystem Model (TEM). The state variables are: carbon in the vegetation (C_V); structural nitrogen in the vegetation (N_{VS}); labile nitrogen in the vegetation (N_{VL}); organic carbon in soils and detritus (C_S); organic nitrogen in soils and detritus (N_S); and available soil inorganic N (N_{AV}). Arrows show carbon and nitrogen fluxes: GPP, gross primary productivity; R_A, autotrophic respiration; R_H, heterotrophic respiration; L_C, litterfall C; L_N, litterfall N; $NUPTAKE_S$, N uptake into the structural N pool of the vegetation; $NUPTAKE_L$, N uptake into the labile N pool of the vegetation; NRESORB, N resorption from dying tissue into the labile N pool of the vegetation; NMOBIL, N mobilized between the structural and labile N pools of the vegetation; NETNMIN, net N mineralization of soil organic N; NINPUT, N inputs from outside the ecosystem; and NLOST, N losses from the ecosystem (McGuire *et al.* 1993).

The functions in the GPP and R_A equations have been described in previous work (Raich *et al.* 1991; McGuire *et al.* 1992, 1993).

The application of TEM requires spatially explicit data for 10 input variables (Fig. 2); atmospheric CO_2 and nitrogen inputs are considered to be constant. Data on monthly temperature, monthly precipitation, monthly solar radiation (or cloudiness), soil texture, elevation, and vegetation are used either as direct inputs to TEM or inputs to intermediate models that are used to generate inputs for TEM (Fig. 2). For example, hydrological inputs for TEM are determined with a water balance model (WBM) that uses temperature, precipitation, solar radiation, elevation, soils and vegetation data (Vörösmarty *et al.* 1989). The temperature, precipitation and solar radiation data used by TEM represent long-term averages. The input data sets are gridded at a resolution of 0.5° latitude by 0.5° longitude.

To make estimates for a grid cell, TEM also needs the soil- and vegetation-specific parameters appropriate to the grid cell. Although many of the parameters in the model are defined from published information, some of the vegetation-specific parameters are determined by

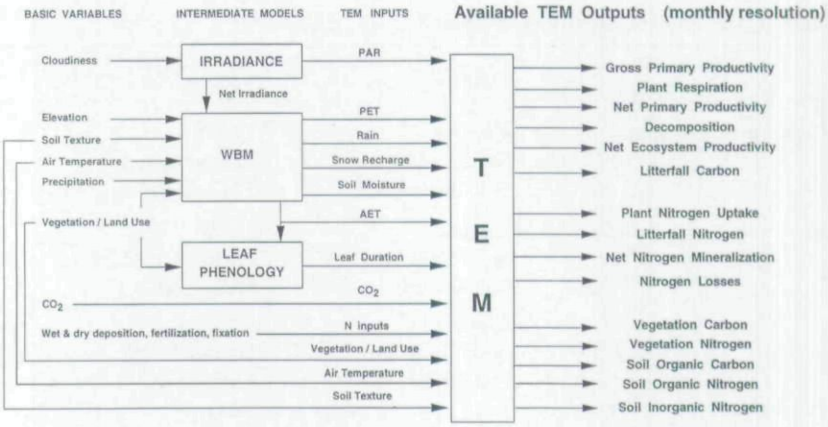

Fig. 2 The inputs and outputs of the Terrestrial Ecosystem Model (TEM). Some input variables are generated using intermediate models as described in the text. PAR is photosynthetically active radiation; PET is potential evapotranspiration; AET is actual evapotranspiration; and CO_2 is atmospheric CO_2 concentration.

calibrating the model to the fluxes and pool sizes of an intensively studied field site. The data used to calibrate the model for different vegetation types are documented in previous work (Raich *et al.* 1991; McGuire *et al.* 1992, 1996b). To calibrate the model for each vegetation type, we used the Legates & Willmott temperature and precipitation data (Legates & Willmott 1990a 1990b), the solar radiation data derived from Hahn *et al.* (1988) cloudiness, and the modified FAO soil texture data (FAO/CSRC 1974) for the grid cells containing the study sites.

Design of sensitivity experiments

For a simulation run, the system of models coupled with TEM (Fig. 2) requires six spatially explicit variables as inputs: vegetation, elevation, temperature, precipitation, solar radiation and soil texture. Several spatially explicit data sets exist for each of these variables, so a series of sensitivity experiments may be conducted. Because different vegetation data sets use different classification schemes, we used only one vegetation data set for all runs in the sensitivity experiments. Since elevation is used only as a switch to determine snowmelt dynamics of a grid cell (below 500 m, snowmelt occurs in one month; above 500 m snowmelt occurs in two months), variation in elevation has little effect on NPP estimates of TEM. Therefore, we used only one elevation data set for all runs in the sensitivity experiments. For the remaining variables, we set up a series of three sensitivity experiments to examine the effects of alternative data sets on NPP estimates by TEM: (i) alternative climates as defined by air temperature and precipitation; (ii) alternative solar radiation; and (iii) alternative soil textures. Because air temperature and precipitation data sets are usually available from the same source, we investigated the combined effects of these 'climate' data sets on NPP estimates in the first experiment (Table 1).

Experiment 1: sensitivity to alternative climate data sets. In TEM, mean monthly air temperature directly influences GPP, autotrophic and heterotrophic respiration rates (R_A and R_H), plant nitrogen uptake (NUPTAKE), and soil nitrogen mineralization (NETNMIN); and indirectly influences leaf phenology, GPP, R_H, NUPTAKE, and NETNMIN via WBM outputs (Fig. 1, Fig. 2). Monthly precipitation directly influences WBM, and indirectly, through the WBM, influences leaf phenology, GPP, R_H, NUPTAKE, and NETNMIN.

We used three climate data sets to investigate the sensitivity of TEM to different temperature and precipitation inputs: Legates and Willmott climate (L&W; Legates & Willmott 1990a 1990b), the climate developed for the Vegetation/Ecosystem Modelling and Analysis Project (VEMAP; Kittel *et al.* 1996; VEMAP Members 1995), and Cramer and Leemans climate (C&L; Cramer, personal communication). The C&L climate data set is a major update of the Leemans and Cramer (1991) data set, and is being widely used (Cramer, personal communication). We ran TEM for each of three alternative climate data sets to determine climate effects on NPP estimates (see experiment 1 in Table 1). For the baseline run we used the L&W climate, the Hahn-derived radiation and the FAO/CSRC soil texture data sets as inputs. For the runs with the C&L and VEMAP climate data sets, we used the same radiation and soil texture data sets.

Experiment 2: sensitivity to alternative solar radiation data sets. The solar radiation data sets used in this study represent short-wave irradiance at the top of the canopy. Solar radiation is used to calculate potential evapotranspiration (PET) based on the Jensen–Haise algorithm (Jensen & Haise 1963). Potential evapotranspiration influences the hydrological outputs of WBM. Solar radiation also influences the PAR output of the irradiance model. Through effects on hydrology and

Table 1. Design of sensitivity experiments[1]

	Data Sets	Baseline Run	Comparison	Comparison
Experiment 1 (climate)	Climate	L&W[2]	L&C[3]	VEMAP[4]
	Solar Radiation	Hahn-derived[5]	Hahn-derived	Hahn-derived
	Soil Texture	FAO/CSRC[8]	FAO/CSRC	FAO/CSRC
Experiment 2 (radiation)	Climate	L&W	L&W	L&W
	Solar Radiation	Hahn-derived	C&L-derived[6]	VEMAP[7]
	Soil Texture	FAO/CSRC	FAO/CSRC	FAO/CSRC
	Climate	C&L	C&L	C&L
	Solar Radiation	Hahn-derived	C&L-derived	VEMAP
	Soil Texture	FAO/CSRC	FAO/CSRC	FAO/CSRC
	Climate	VEMAP	VEMAP	VEMAP
	Solar Radiation	Hahn-derived	C&L-derived	Hahn-derived
	Soil Texture	FAO/CSRC	FAO/CSRC	FAO/CSRC
Experiment 3 (soil texture)	Climate	L&W	L&W	L&W
	Solar Radiation	Hahn-derived	Hahn-derived	Hahn-derived
	Soil Texture	FAO/CSRC	Zobler[9]	VEMAP[10]
	Climate	C&L	C&L	C&L
	Solar Radiation	Hahn-derived	Hahn-derived	Hahn-derived
	Solar Texture	FAO/CSRC	Zobler	VEMAP
	Climate	VEMAP	VEMAP	VEMAP
	Solar Radiation	Hahn-derived	Hahn-derived	Hahn-derived
	Soil Texture	FAO/CSRC	Zobler	VEMAP

[1]All model runs used the Vegetation/Ecosystem Modelling and Analysis Project (VEMAP) vegetation distribution (Kittel *et al.* 1996; VEMAP Members 1995) and NCAR/NAVY (1984) elevation data.
[2]Legates & Willmott (1990a, 1990b) monthly air temperature and precipitation data.
[3]Cramer and Leemans monthly air temperature and precipitation data (Cramer, personal communication).
[4]Monthly air temperature and precipitation data (NCDC, 1992) developed for VEMAP (Kittel *et al.* 1996; VEMAP Members 1995).
[5]Solar radiation data set derived from Hahn *et al.* (1988) cloudiness data using the irradiance equation of Black *et al.* (1954)
[6]Solar radiation data set derived from the Cramer and Leemans sunshine duration data set (Cramer, personal communication) using the irradiance equation of Black *et al.* (1954).
[7]VEMAP solar radiation data set, which were generated by CLMSIM (Running *et al.* 1987; Glassy and Running 1994) for VEMAP (Kittel *et al.* 1996; VEMAP Members 1995).
[8]FAO/CSRC soil texture data digitized at 0.5° resolution from FAO-UNESCO's (1971) 'Soil Map of the World 1:50,000,000' (FAO/CSRC 1974).
[9]Zobler soil texture data digitized at 1° resolution from FAO-UNESCO's (1971) 'Soil Map of the World 1:50,000,000' (Zobler 1986).
[10]VEMAP soil texture data, which were aggregated from Kern (1994) 10-km gridded Soil Conservation Service NATSGO data to 0.5° resolution for VEMAP (Kittel *et al.* 1996; VEMAP Members 1995).

PAR, solar radiation influences leaf phenology, GPP, R_H, NUPTAKE, and NETNMIN in TEM.

We used three solar radiation data sets to investigate the sensitivity of TEM to different radiation inputs: the solar radiation data set derived from Hahn *et al.* (1988) cloudiness, the solar radiation data set derived from C&L sunshine duration (Cramer, personal communication), and the VEMAP solar radiation data set (Kittel *et al.* 1996; VEMAP Members 1995). To determine the effects of alternative solar radiation on NPP while keeping climate constant, we ran TEM three times for each climate (see experiment 2 in Table 1). For each climate (L&W, C&L or VEMAP), all three runs used the same climate data set and the FAO/CSRC soil texture data. Among the three runs, the baseline run used the Hahn-derived radiation data set, and the other two runs used either the C&L-derived radiation data set or the VEMAP radiation data set.

Experiment 3: sensitivity to alternative soil texture data sets. Soil texture affects GPP, R_H, NUPTAKE, and NETNMIN because the equations describing these fluxes in TEM have parameters that depend on soil texture. In addition, soil texture affects the hydrological outputs of WBM because field capacity and wilting point depend on soil texture and rooting depth depends on both vegetation type and soil texture. Soil texture also indirectly affects leaf phenology, GPP, R_H, NUPTAKE, and NETNMIN through effects on WBM outputs.

Fig. 3 Potential vegetation distribution of the conterminous United States based on the VEMAP vegetation classification.

We used three soil texture data sets to investigate the sensitivity of TEM to different texture inputs: the FAO/CSRC (1974) soils data set, the Zobler soils data set (1986) and the VEMAP soils data set (Kittel *et al.* 1996; VEMAP Members 1995). To determine the effect of alternative soil texture data sets on NPP, we also ran TEM three times for each climate (see experiment 3 in Table 1). For each climate (L&W, C&L or VEMAP), all three runs used the same climate data set and the Hahn-derived radiation data set. Among the three runs, the baseline run used the FAO/CSRC soil texture data set, and the other two runs used either the Zobler soils data set or the VEMAP soils data set.

Description of the data sets

Data sets used for all simulations. The vegetation data set is required to define the vegetation-specific parameters for each grid cell in the spatial extrapolation of TEM. In this study, we used the VEMAP vegetation distribution (Kittel *et al.* 1996; VEMAP Members 1995) for the conterminous U.S. (Fig. 3), which is based on Küchler (1964, 1975). The vegetation types in the VEMAP data set are classified on the basis of the physiognomic characteristics of dominant lifeforms except for grassland vegetation types, which are distinguished by photosynthetic pathway (C_3 vs. C_4). Elevation data are used in the WBM to affect snowmelt and therefore affect soil moisture. The elevation data used in this study represent an aggregation to 0.5° resolution of the NCAR/NAVY global 10-minute elevation data set (NCAR/NAVY 1984).

Data sets used for sensitivity to climate. The L&W climate data for the conterminous United States are derived from the global database of Legates and Willmott (1990a, 1990b), which is based on long-term temperature records of 17 986 terrestrial stations and 6955 oceanic grid-points, and gauge-corrected precipitation records of 24 635 terrestrial stations and 2223 oceanic grid-points. Data were interpolated to 0.5° resolution globally using a spherical interpolation algorithm (Willmott *et al.* 1985).

The C&L data set was derived from the CLIMATE global database (Cramer, personal communication) which is a major update of the Leemans & Cramer (1991) database. The database was developed from 10 to 40 year records of 18 000 stations from across the globe, with about 4000 in the conterminous United States. Data were interpolated to 0.5° resolution globally using a 3-D smoothing spline technique for all variables. The smoothing spline surfaces are functions of latitude, longitude and elevation with the degree of data smoothing determined by minimizing the predictive error (Hutchinson & Bischof 1983). This interpolation method is different from the method used to develop the Leemans and Cramer (1991) data sets and greatly improves the topographic sensitivity of the interpolated data sets, especially in mountainous areas (Cramer, personal communication).

The VEMAP temperature data set (Kittel *et al.* 1996; VEMAP Members 1995) is based on 4613 station normals (NCDC 1992) within the conterminous United States. The data were adiabatically adjusted to sea-level (Marks 1990) before being interpolated to 0.5° resolution and were then adjusted for the elevation of each grid cell as defined by the elevation data set used in this study. Precipitation data were spatially aggregated to 0.5° resolution from the 10-km gridded data set for the U.S. developed by PRISM (Daly *et al.* 1994). The PRISM divides areas into topographic facets of similar aspect, then develops precipitation-elevation regressions for each facet based on the regional station data. The regressions are used to spatially interpolate precipitation data for cells with similar facets.

Data sets used for sensitivity to radiation. The Hahn-derived solar radiation data set used in this study was derived from the Hahn *et al.* (1988) cloudiness data set. The Hahn *et al.* (1988) cloudiness data set describes the long-term average global cloudiness for 3-month periods at 5° resolution. The data set was developed from surface observations between 1930 and 1979; but observations at different sites are not consistent in duration and measurement. For use by TEM, Hahn cloudiness data were temporally and spatially smoothed. The average 3-month cloudiness at 5° resolution was interpolated temporally into average monthly cloudiness & spatially to 0.5° resolution. The solar radiation data was estimated with the Black *et al.* (1954) solar radiation model:

$$R_{TOC} = R_{TOA}\,[0.23 + 0.48\,(S_D)],$$

where R_{TOC} is short-wave irradiance at the top of the canopy, R_{TOA} is short-wave irradiance at the top of the atmosphere and S_D is percentage sunshine duration. We used the algorithm of Turton (1986) to calculate R_{TOA} and the quantity $(1 - C)$ to represent S_D where C is percentage cloudiness from the cloudiness data set.

The C&L-derived solar radiation data set used in this study was derived from the C&L global monthly database of sunshine duration (Cramer, personal communication). Similar to the temperature and precipitation data sets, the C&L sunshine duration data set is a major update of the Leemans & Cramer (1991) sunshine duration data set which is based on observations from more stations and interpolated using a 3-D smoothing spline fuction. The C&L sunshine duration data set has been converted to the solar radiation data set using the model of Black *et al.* (1954).

The VEMAP daily solar radiation data were estimated by the CLIMSIM model (Running *et al.* 1987; Glassy & Running 1994), which uses latitude, elevation, the diurnal range of temperature, and the occurrence of precipitation. Monthly means were derived from the daily values (Kittel *et al.* 1996; VEMAP Members 1995). To generate solar radiation data, the CLIMSIM model used the elevation data set described earlier and daily temperature and precipitation data sets from VEMAP (Kittel *et al.* 1996; VEMAP Members 1995). The monthly means of the daily data match the long term monthly climatology of the VEMAP climate data sets.

Data sets used for sensitivity to soil texture. The FAO/CSRC soil data set (1974) represents a digitization to 0.5° resolution of the UNESCO/FAO World Soil Map (FAO-UNESCO 1971). The seven classes in the FAO/CSRC soil texture data set represent 'average' soil profiles based on three FAO texture classes (Table 2). Each FAO/CSRC soil texture class defines a combination of percentage sand, silt and clay (Table 2).

The Zobler soils data set (1986) represents a digitization to 1° resolution of the UNESCO/FAO World Soil Map (FAO-UNESCO 1971). Each one-degree grid cell represents the near-surface texture (upper 30 cm) of the dominant soil unit. Besides organic soils and land ice, there are seven texture classes which are identical to those in the FAO/CSRC soil texture data set (Table 2). For use by TEM, the Zobler soils data were converted from 1° resolution to 0.5° resolution by assigning the value of each 1° grid cell to its corresponding four 0.5° grid cells.

The VEMAP soils data set is based on the Kern (1994) 10-km gridded Soil Conservation Service National Soil database (NATSGO). The data were aggregated to 0.5° resolution and grouped by cluster analysis to a set of one to four modal soils. The first modal soil was used to represent soil properties for the grid cell. The soil texture is characterized by percentage of sand, silt and clay (Kittel *et al.* 1996; VEMAP Members 1995).

Results

Sensitivity to alternative climate data sets

The C&L and VEMAP data sets represent cooler and drier climates for the conterminous United States than is represented by the L&W climate, with VEMAP the coldest and C&L the driest (Table 3). In comparison to the L&W climate, mean annual temperature and annual precipitation of the conterminous U.S. are 0.4 °C and

Table 2. Percentage sand, silt and clay assigned to the FAO/CSRC soil textures

FAO/CSRC Code	Combination of FAO Code*	Class description	% Sand	% Silt	% Clay
1	1	Sand	80	10	10
2	2	Loam	45	40	15
3	3	Clay	25	30	45
4	1 and 2	Sandy loam	65	20	15
5	1 and 3	Loam	45	40	15
6	2 and 3	Clay loam	35	30	35
7	1, 2, and 3	Loam	45	40	15
8	none	Lithosols	45	40	15

*FAO codes: 1, coarse-textured; 2, medium-textured; and 3, fine-textured. No textures were assigned to lithosols.

Table 3. Mean climate data and effects on annual NPP (10^{12} g C y^{-1}) estimates for biomes of the conterminous United States

Biomes	Mean annual temperature (°C)			Annual precipitation (mm)			Annual NPP[1]		
	L&W[2]	C&L[3]	VEMAP[3]	L&W[2]	C&L[3]	VEMAP[3]	L&W[2]	C&L[4]	VEMAP[4]
Tundra	5.5	–3.4	–6.0	937.4	–602.9	–149.2	1.79	–26.91	–14.63
Boreal conifer forest	4.4	–1.4	–3.8	630.6	–238.4	+102.5	44.87	–18.07	–20.27
Maritime conifer forest	10.7	–2.5	–3.5	1402.0	–683.2	+103.9	87.98	–13.38	–9.65
Continental conifer forest	6.6	–1.4	–3.2	592.1	–246.5	+74.8	198.25	–16.31	–13.14
Cool temperate mixed forest	6.5	–0.1	–1.1	1183.4	–152.6	–167.0	221.49	–1.41	–5.29
Temperate conifer savanna	7.1	–1.2	–2.9	387.8	–136.8	+29.7	4.86	–25.63	–5.31
Temperate deciduous forest	11.8	–0.1	–0.8	1174.4	–104.8	–72.5	706.53	–0.62	–1.81
Temperate deciduous savanna	12.9	–0.1	–0.6	973.8	–105.5	–70.3	434.23	–1.71	–1.14
Warm temp/ subtrop mixed forest	17.2	–0.2	–0.7	1363.2	–92.6	–67.0	782.07	–0.92	–0.75
Warm temp/ subtrop mixed savanna	17.7	+0.2	–0.5	672.6	–54.9	+5.2	98.55	–4.49	+0.64
C_3 grasslands	6.9	+0.1	–0.3	471.7	–86.7	–21.6	221.64	–13.74	–4.55
C_4 grasslands	11.4	+0.3	–0.3	641.4	–94.0	–43.5	383.25	–4.06	–2.37
Temperate mixed xeromorphic forest	14.6	–1.2	–2.2	425.6	–161.8	+93.1	33.12	–23.74	+9.59
Temperate conifer xeromorphic forest	10.3	–0.8	–2.1	331.9	–129.8	+24.7	89.04	–25.35	+4.39
Mediterranean shrublands	15.2	–3.4	–3.4	561.4	–251.0	–32.6	11.23	–30.25	+2.21
Temperate arid shrublands	8.0	–0.6	–1.8	303.4	–49.6	+52.3	113.39	–13.26	+4.96
Subtropical arid shrublands	17.9	–1.0	–1.0	256.8	–42.1	+21.2	56.31	–12.81	+10.62
Mean/Total	11.2	–0.4	–1.2	782.7	–123.0	–22.7	3488.61	–5.24	–2.27

[1]Hahn-derived solar radiation and FAO/CSRC soil texture data sets were used for all simulations.
[2]Baseline values for the biome: mean annual temperature in °C, annual precipitation in mm, and annual NPP in 10^{12} g C y^{-1}.
[3]Absolute difference with respect to L&W data.
[4]Relative difference (%) with respect to NPP estimates for L&W climate data.

123 mm less in the C&L climate, and 1.2 °C and 23 mm less in the VEMAP climate. Cooler and drier climates cause NPP estimates for the conterminous U.S. to decrease (Table 3). In comparison to NPP estimates for the L&W climate, NPP estimates are 5.2% less for the C&L climate and 2.3% less for the VEMAP climate.

At the resolution of biomes, there is a greater range in temperature and precipitation differences among the three climates than at the continental resolution (Table 3). The VEMAP climate always has the lowest temperatures; the C&L climate generally has intermediate temperatures except in a few biomes where temperatures are slightly higher than in the L&W climate (warm temperate/ subtropical mixed savanna, C_3 and C_4 grasslands). For some biomes there are large temperature differences among data sets. For example, mean annual temperature in the C&L and VEMAP climates is 3.4 and 6.0 °C less in tundra, 2.5 and 3.5 °C less in maritime conifer forests, and 3.4 °C less in Mediterranean shrublands. Lower temperature in tundra, conifer forests and dry biomes in the C&L and VEMAP climates generally reflects the effects of elevation in the interpolated data sets, which have been ignored in the L&W data set. The VEMAP temperatures were adiabatically adjusted for high elevation, and the C&L temperatures were interpolated as functions of latitude, longitude and elevation with a 3-D smoothing spline technique. However, the C&L interpolation technique cannot adequately correct for elevation in high elevation areas that do not have weather stations (Cramer, personal communication).

Among the three climates, the C&L climate generally has the lowest precipitation in almost all biomes (Table 3). The C&L precipitation is substantially lower in tundra, conifer forests (boreal conifer forest, maritime conifer forest, continental conifer forest) and several dry biomes (temperate mixed xeromorphic forest, temperate conifer xeromorphic forest, Mediterranean shrublands); these biomes are located in the western United States. The VEMAP climate, in comparison to the L&W climate, has higher annual precipitation in several conifer forests (boreal conifer forest, maritime conifer forest, continental conifer forests, temperate conifer savanna) and dry biomes (temperate mixed xeromorphic forest, conifer xeromorphic forests, temperate arid shrubland and subtropical arid shrublands). Precipitation in the C&L climate is generally lower than the other climates because the interpolation method cannot adequately correct for elevation in high elevation areas. The L&W precipitation is generally higher in all biomes because gauge-induced biases from standard raingauge measurements, which have long been recognized as underestimates of actual precipitation, have been removed from the L&W climate. The VEMAP precipitation has been adjusted for elevation and aspect by the 'orographically smart' interpolation procedure of PRISM. Therefore, VEMAP precipitation is higher for conifer forests and dry biomes that are located in mountainous regions.

The NPP estimates of TEM are sensitive to differences among climates at the resolution of biomes. In comparison to estimates for the L&W climate, NPP estimates for the C&L and VEMAP climates are substantially lower in tundra (14.6% to 26.9% lower) and in conifer forests (9.7% to 20.3% lower). The VEMAP climate in those biomes is colder and generally moister. Colder temperatures are more likely to cause lower NPP estimates by TEM in those biomes where photosynthesis and decomposition are limited by low temperature (McGuire *et al.* 1992, 1993; Melillo *et al.* 1993, 1995). The C&L climate in those biomes is generally colder and drier. Both colder temperature and lower precipitation are responsible for lower NPP because of slower rates of photosynthesis and decomposition.

Greater precipitation in dry biomes generally causes higher NPP estimates. For several dry biomes (temperate mixed xeromorphic forest, temperate conifer xeromorphic forest, temperate arid shrublands, and subtropical arid shrublands), TEM estimates higher NPP with the VEMAP climate (4.4% to 10.6% higher) which indicates higher precipitation and lower temperature than the L&W climate (21–93 mm higher and 1.0–2.2 °C lower). In contrast, TEM estimates lower NPP (12.8% to 25.4% lower) with the C&L climate in the same biomes because precipitation and temperature are lower than the L&W climate (42–162 mm lower and 0.8–1.2 °C lower). Water stress is a critical factor that affects NPP estimates in dry biomes; both higher precipitation and lower temperature alleviate water stress. In Mediterranean shrublands, NPP is 2.2% higher for the VEMAP climate, which indicates 33 mm less precipitation and 3.4 °C lower temperature than the L&W climate. The lower temperature alleviates water stress to more than offset potential stress induced by lower precipitation. However, for the C&L climate, NPP is 30.3% lower in Mediterranean shrublands because the 3.4 C° lower temperature does not compensate for the 251 mm less precipitation. The lower temperature does not compensate for water stress induced by lower precipitation.

At the grid cell resolution, there are greater ranges of temperature and precipitation differences among the three alternative climate data sets than at the continental and biome resolutions (Fig. 4). In comparison to the L&W climate, mean annual temperature in the C&L climate ranges from ≈ 10 C° lower to 4 C° higher, with 90% of the differences between 3 C° lower and 1 C° higher; mean annual temperature in the VEMAP climate ranges from ≈ 15 C° lower to 6 C° higher, with 90% of difference between 5 C° lower and 1 C° higher. Annual precipitation in the C&L climate ranges from 1676 mm lower to 425 mm higher than in the L&W climate, with 90% of the variation between 397 mm lower and 54 mm higher. Similarly, annual precipitation in the VEMAP climate ranges from 904 mm lower to 1426 mm higher, with 90% of the variation between 214 mm lower and 223 mm higher. In comparison to NPP estimates for the L&W climate, the range of climate differences cause 10% of the NPP differences to be more than 33.2% lower or more than 6.4% higher for the C&L climate and more than 22.1% lower or more than 24.4% higher for the VEMAP climate (Fig. 4, Fig. 5). Clearly, NPP estimates are more sensitive to differences among alternative climate data sets at the grid cell resolution than at the continental and biome resolutions.

Sensitivity to alternative solar radiation data sets

At the continental resolution, the difference between the three solar radiation data sets is substantial and the effects of alternative radiation data on NPP estimates are large (Table 4). Mean solar radiation for the conterminous United States is 3.83 MJ m^{-2} d^{-1} higher (+ 32%) for the C&L-derived data set and 7.06 MJ $m^{-2}d^{-1}$ higher (+ 60%) for the VEMAP data set than for Hahn-derived solar radiation. The higher solar radiation in the C&L-derived and the VEMAP data sets causes lower NPP estimates. For any climate data set, TEM always estimates 8% to 9% lower NPP with the C&L-derived and 10% to 11%

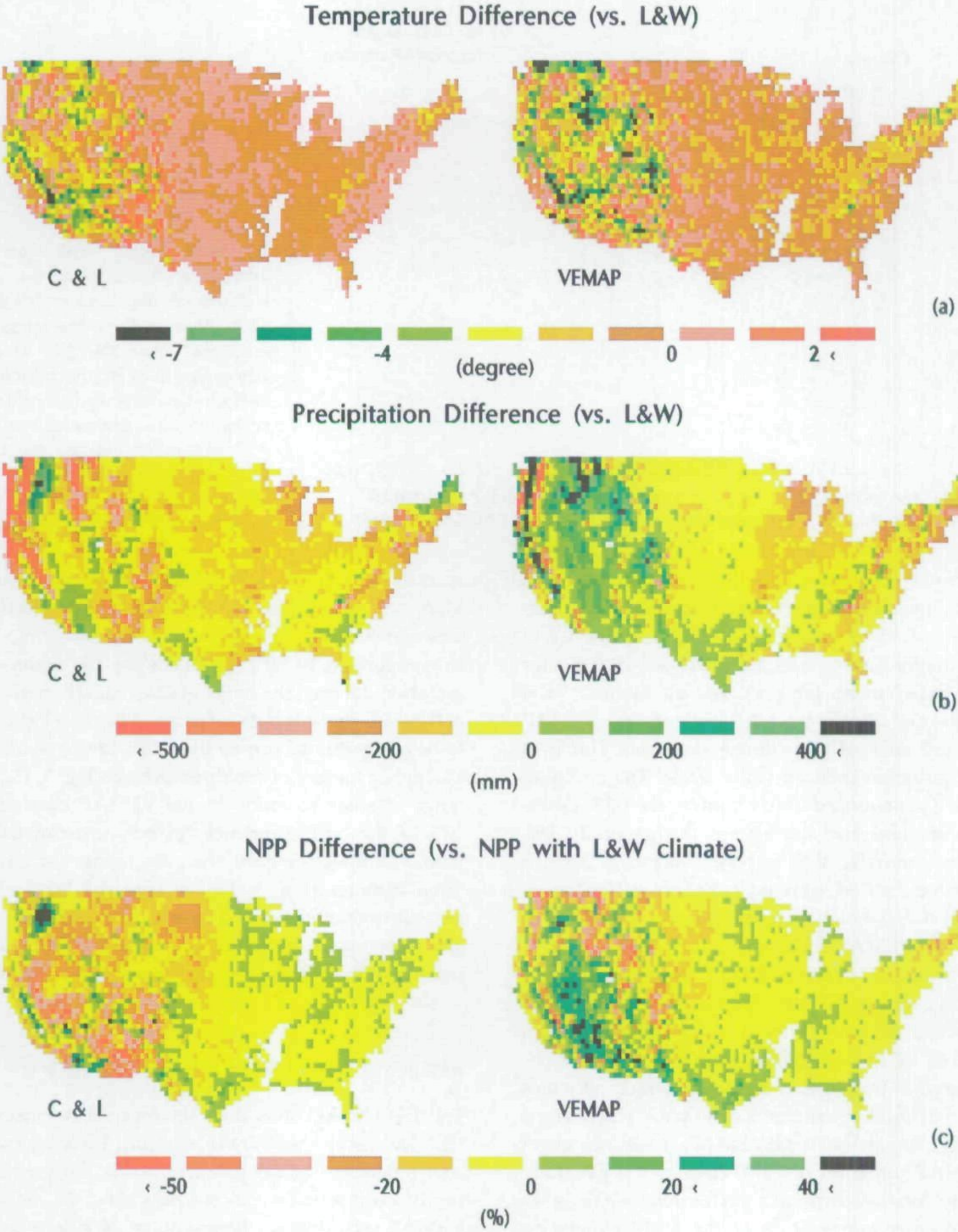

Fig. 4 Comparisons of climate data sets; and TEM estimated NPP using different climate data sets. (a) Temperature difference (°C) between the C&L and the L&W data sets; and between the VEMAP and the L&W data sets. (b) Precipitation difference (mm) between the C&L and the L&W data sets; and between the VEMAP and the L&W data sets. (c) Relative difference (%) between NPP estimates based on the C&L and the L&W climate data sets; and between NPP estimates based on the VEMAP and the L&W climate data sets. The Hahn-derived solar radiation data set and FAO/CSRC soil texture data set were used as other inputs for all simulations.

lower NPP with the VEMAP solar radiation (Table 4). In TEM, increased solar radiation may enhance PAR to potentially increase NPP, but enhanced PET may increase water stress to potentially decrease NPP. The lower NPP estimates with the C&L-derived and the VEMAP solar radiation data sets indicate that radiation-induced water stress is stronger than the potential enhancement of photosynthesis by higher PAR.

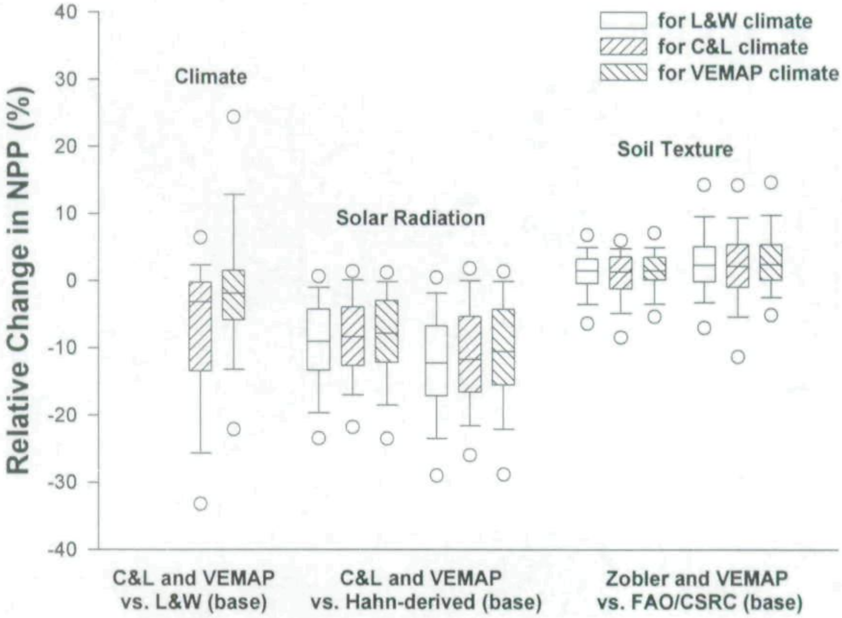

Fig. 5 The NPP sensitivities to the alternative climate, solar radiation and soil texture data sets at the grid cell scale. Boxes indicate the range of NPP sensitivity from the 25th to the 75th percentile; lines in the middle of the boxes indicate the median value of NPP sensitivity; lines extending from 25th and 75th percentiles indicate the range of NPP sensitivity from the 10th to the 90th percentiles; and the open symbols indicate the 5th and 95th percentiles.

At the biome resolution, the differences among solar radiation data sets are similar to the continental-resolution differences (+ 2.95 to + 4.78 MJ m^{-2} d^{-1} for the C&L-derived radiation and + 6.21 to + 8.19 MJ m^{-2} d^{-1} for the VEMAP radiation; Table 4). For all biomes, TEM estimates lower NPP for the C&L-derived and VEMAP radiation with any of the climate data sets (Table 4) because of radiation-induced water stress. The radiation effect is most pronounced in dry biomes; the NPP estimates of cooler and moister biomes are generally less affected. For example, NPP in boreal forests is 0.5% to 4.8% lower for the C&L-derived radiation, which estimates 3.50 MJ m^{-2} d^{-1} higher irradiance; and 1.2% to 8.7% lower for the VEMAP radiation, which estimates 7.71 MJ m^{-2} d^{-1} higher irradiance than the Hahn-derived radiation. In contrast, NPP of Mediterranean shrublands is 11.6–15.3% lower for the C&L-derived radiation, which estimates 3.64 MJ m^{-2} d^{-1} higher irradiance; NPP is 15.0–21.0% lower with the VEMAP radiation, which estimates 6.21 MJ m^{-2} d^{-1} higher irradiance than the Hahn-derived radiation. In comparison to the VEMAP climate, the effect of the VEMAP radiation on NPP estimates is generally more severe for the L&W and C&L climates (Table 4). Either the higher temperature of the L&W climate or lower precipitation of the C&L climate could be factors that enhance radiation-induced water stress.

At the grid cell resolution, there is a greater range of solar radiation differences among alternative solar radiation data sets than at the continental and biome resolutions (Fig. 6). In comparison to the Hahn-derived radiation data set, mean annual solar radiation in the C&L-derived data set ranges from 1.29 MJ m^{-2} d^{-1}–5.62 MJ m^{-2} d^{-1} higher, with 90% of difference between 2.62 MJ m^{-2} d^{-1} and 4.92 MJ m^{-2} d^{-1} higher; mean annual solar radiation in the VEMAP data set ranges from ≈ 4.37 MJ m^{-2} d^{-1}–8.33 MJ m^{-2} d^{-1} higher, with 90% of differences between 5.92 MJ m^{-2} d^{-1} and 7.84 MJ m^{-2} d^{-1} higher. In comparison to NPP estimates for the Hahn-derived radiation data set, the range of solar radiation differences in the C&L-derived data set cause 10% of NPP differences to be approximately more than 23% lower or more than 1% higher for any of the three climate (Fig. 5, Fig. 6); the range of solar radiation in the VEMAP data set cause 10% of the NPP differences to be approximately more than 30% lower or more than 1% higher for any of the three climates (Fig. 5, Fig. 6). Clearly, NPP estimates are substantially more sensitive to differences among alternative solar radiation data sets at the grid cell resolution than at the continental and biome resolutions.

Sensitivity to alternative soil texture data sets

The FAO/CSRC soils data set represents most biomes with loam soils (≈ 50% silt plus clay, Table 5), except for cool temperate mixed forest which is represented with sandy loam soils (≈ 35% silt plus clay). In contrast, the VEMAP soils data set represents most biomes with clay loam and clay soils (65–75% silt plus clay) except for cool temperate mixed forest which is represented with loam soils. The soil textures in the Zobler soils data are intermediate between those of the FAO/CSRC and the VEMAP soils; most biomes are represented with loam and clayloam soils except for cool temperate mixed forest which is represented with sandy loam soils. In comparison to the FAO/CSRC soils data set, these differences cause the average soil texture of the conterminous U.S. to contain 6.7% more silt plus clay in the Zobler

Table 4. Mean solar radiation data and effects on annual NPP (10^{12} g C y^{-1}) estimates for biomes of the conterminous United States

Biomes	Radiation (MJ m^{-2} d^{-1})			NPP (L&W climate)[1]			NPP (C&L climate)[1]			NPP (VEMAP climate)[1]		
	Hahn[2]	C&L[3]	VEMAP[4]	Hahn[5]	C&L[6]	VEMAP[7]	Hahn[5]	C&L[6]	VEMAP[7]	Hahn[5]	C&L[6]	VEMAP[7]
Tundra	11.74	+3.73	+8.19	1.79	–3.96	–1.28	1.31	–10.77	–11.61	1.53	–1.64	–5.76
Boreal conifer forest	11.06	+3.50	+7.71	44.87	–3.10	–5.99	36.76	–4.83	–8.75	35.77	–0.52	–1.15
Maritime conifer forest	11.11	+3.05	+6.46	87.98	–3.54	–6.51	76.21	–7.67	–13.63	79.49	–3.24	–5.71
Continental conifer forest	11.07	+3.65	+7.43	198.25	–6.55	–10.87	165.91	–8.88	–14.35	172.20	–3.56	–5.37
Cool temperate mixed forest	10.17	+2.95	+7.03	221.49	–4.83	–8.55	218.36	–5.23	–8.00	209.76	–5.09	–7.72
Temperate conifer savanna	11.11	+4.19	+7.96	4.86	–11.23	–15.20	3.62	–13.31	–20.97	4.60	–6.24	–7.97
Temperate deciduous forest	11.18	+3.74	+7.22	706.53	–9.03	–10.83	702.13	–9.41	–11.04	693.73	–8.28	–9.16
Temperate deciduous savanna	11.69	+3.76	+6.78	434.23	–10.15	–12.43	426.82	–10.71	–12.78	429.29	–10.62	–12.42
Warm temp/ subtrop mixed forest	12.49	+3.93	+7.15	782.07	–6.05	–7.72	774.84	–5.99	–7.95	776.24	–5.17	–6.88
Warm temp/ subtrop mixed savanna	13.68	+3.32	+6.58	98.55	–3.69	–5.66	94.13	–3.28	–5.45	99.19	–3.29	–4.93
C_3 grasslands	10.88	+3.47	+6.62	221.64	–19.66	–22.35	191.19	–9.54	–9.41	211.56	–17.45	–18.82
C_4 grasslands	12.29	+3.94	+6.89	383.25	–11.73	–15.00	367.67	–10.02	–12.73	374.17	–11.60	–14.89
Temperate mixed xeromorphic forest	13.60	+4.27	+6.67	33.12	–10.67	–13.91	25.26	–9.12	–12.48	36.30	–10.56	–13.70
Temperate conifer xeromorphic forest	13.01	+4.78	+7.81	89.04	–10.27	–15.78	66.47	–11.25	–16.34	92.95	–10.75	–15.50
Mediterranean shrublands	13.72	+3.64	+6.21	11.23	–15.34	–20.02	7.83	–11.57	–14.95	11.48	–12.81	–20.98
Temperate arid shrublands	11.70	+4.33	+7.67	113.39	–10.03	–13.79	98.35	–11.88	–16.81	119.01	–7.66	–11.10
Subtropical arid shrublands	14.12	+4.37	+6.57	56.31	–8.39	–12.57	49.10	–6.59	–10.54	62.29	–9.39	–13.26
Mean/Total	11.84	+3.83	+7.06	3488.61	–8.79	–11.37	3305.96	–8.36	–10.77	3409.56	–8.12	–10.11

[1]The simulations used same climate data set (e.g. L&W) and FAO/CSRC soil texture data set, but used different solar radiation data sets.
[2]Annual mean Hahn-derived solar radiation for biomes (MJ m^{-2} d^{-1}).
[3]Absolute difference of the C&L solar radiation with respect to the Hahn-derived solar radiation (MJ m^{-2} d^{-1}).
[4]Absolute difference of the VEMAP solar radiatin with respect to the Hahn-derived solar radiation (MJ m^{-2} d^{-1}).
[5]Annual NPP estimates of TEM for the biomes (10^{12} g C y^{-1}) using Hahn-derived the solar radiation data set.
[6]Relative difference (%) of annual NPP estimates using the C&L-derived solar radiation with respect to using the Hahn-derived solar radiation.
[7]Relative difference (%) of annual NPP estimates using the VEMAP solar radiation with respect to using the Hahn-derived solar radiation.

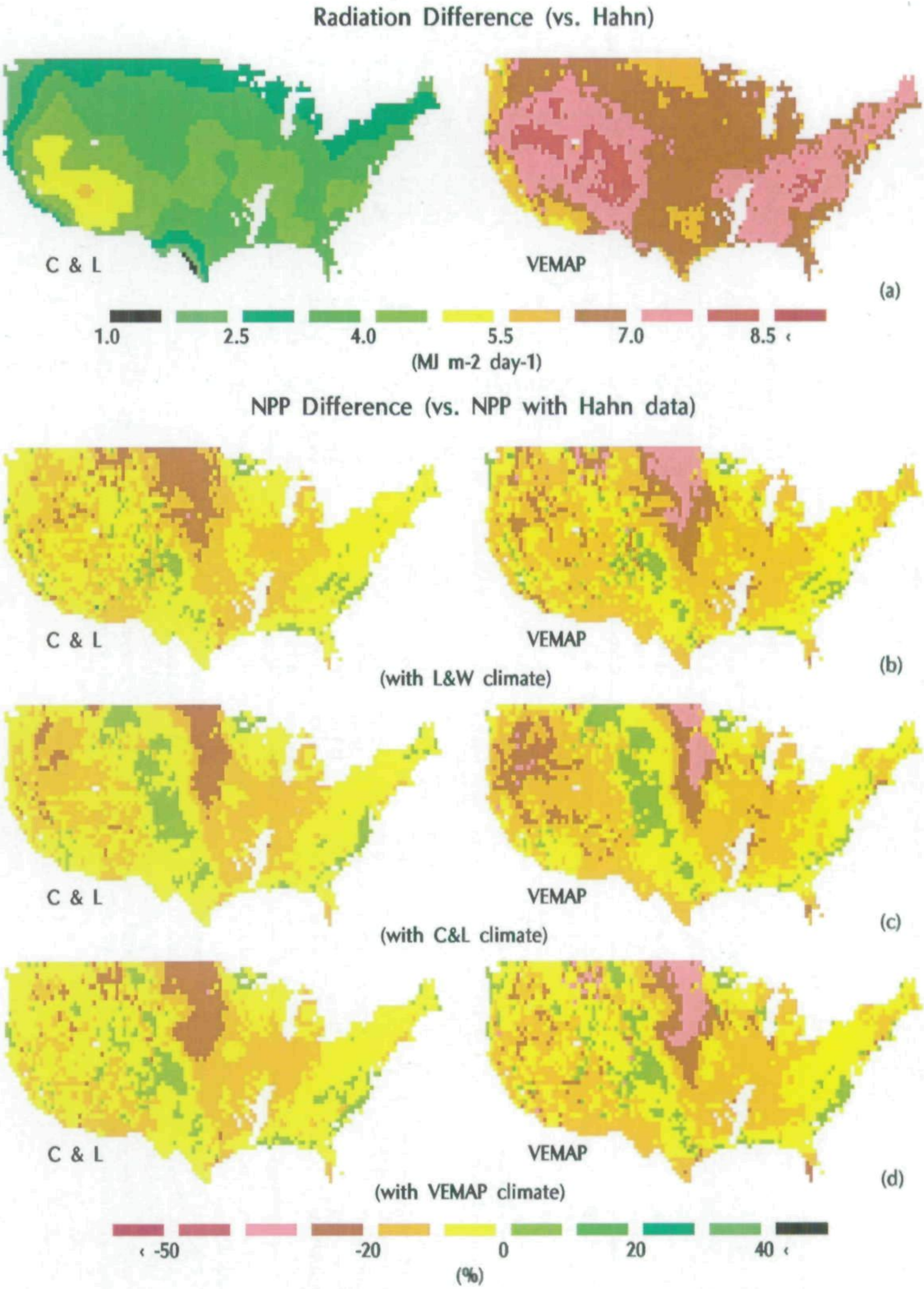

Fig. 6 Comparisons of solar radiation data sets; and TEM estimated NPP using different solar radiation data sets. (a) Solar radiation difference (MJ m^{-2} d^{-1}) between the C&L-derived and the Hahn-derived radiation data sets; and between the VEMAP and the Hahn-derived radiation data sets. (b, c, d) Relative difference (%) between NPP estimates based on the C&L-derived and the Hahn-derived radiation data sets; and between NPP estimates based on the VEMAP and the Hahn-derived radiation data sets. (b) The L&W climate data sets and FAO/CSRC soil texture data set were used as other inputs for all simulations. (c) The C&L climate data sets and FAO/CSRC soil texture data set were used as other inputs for all simulations. (d) The VEMAP climate data sets and FAO/CSRC soil texture data set were used as other inputs for all simulations.

Table 5. Soil texture data and effects on annual NPP (10^{12} g C y^{-1}) estimates for biomes of the conterminous United States

Biomes	Soil Texture (% silt+clay)			NPP (L&W climate)[1]			NPP (C&L climate)[1]			NPP (VEMAP climate)[1]		
	FAO[2]	Zobler[3]	VEMAP[4]	FAO[5]	Zobler[6]	VEMAP[7]	FAO[5]	Zobler[6]	VEMAP[7]	FAO[5]	Zobler[6]	VEMAP[7]
Tundra	55.0	+8.0	+11.5	1.79	+2.46	+4.02	1.31	−2.37	−2.67	1.53	+0.13	−0.52
Boreal conifer forest	52.2	+6.5	+12.8	44.87	+0.52	+3.15	36.76	−0.38	+1.38	35.77	−0.31	+2.98
Maritime conifer forest	54.3	+6.5	+16.7	87.98	−0.27	+1.13	76.21	−1.92	−0.45	79.49	−0.56	+0.47
Continental conifer forest	50.6	+7.0	+15.1	198.25	−0.01	+2.69	165.91	−0.80	+0.75	172.20	+0.16	+2.76
Cool temperate mixed forest	37.4	+0.7	+22.4	221.49	−1.72	+6.59	218.36	−1.71	+6.03	209.76	−1.91	+6.73
Temperate conifer savanna	55.0	+5.1	+15.3	4.86	+0.43	+2.47	3.62	−1.24	−2.85	4.60	+0.87	+3.39
Temperate deciduous forest	54.4	+7.6	+18.4	706.53	+1.44	+2.59	702.13	+1.42	+2.39	693.73	+1.35	+2.53
Temperate deciduous savanna	54.9	+7.9	+21.5	434.23	+2.48	+4.08	426.82	+2.34	+3.91	429.29	+2.29	+3.75
Warm temp/ subtrop mixed forest	49.5	+5.6	+2.7	782.07	+0.21	−0.53	774.84	+0.34	−0.60	776.24	+0.31	−0.55
Warm temp/ subtrop mixed savanna	62.5	+6.6	+11.3	98.55	+2.39	+4.17	94.13	+2.52	+4.80	99.19	+2.43	+4.08
C_3 grasslands	55.2	+8.4	+15.8	221.64	+2.83	+4.33	191.19	+3.95	+6.20	211.56	+3.18	+4.80
C_4 grasslands	52.1	+6.5	+15.3	383.25	+2.82	+6.32	367.67	+2.84	+6.39	374.17	+2.38	+5.57
Temperate mixed xeromorphic forest	54.8	+8.8	+12.2	33.12	+4.62	+5.98	25.26	+3.77	+5.08	36.30	+6.22	+8.75
Temperate conifer xeromorphic forest	54.4	+8.2	+9.3	89.04	+6.58	+6.93	66.47	−5.12	+4.87	92.95	+7.38	+8.69
Mediterranean shrublands	52.2	+7.6	+7.5	11.23	+1.11	+1.58	7.83	−0.50	−1.58	11.48	+2.36	+2.24
Temperate arid shrublands	54.6	+7.5	+12.4	113.39	−2.12	−2.30	98.35	−4.01	−5.75	119.01	−0.23	+1.89
Subtropical arid shrublands	46.5	+4.5	+14.4	56.31	−1.52	−0.93	49.10	−1.08	−1.66	62.29	−1.60	−1.15
Mean/Total	52.2	+6.7	+14.2	3488.61	+0.25	+2.80	3304.88	+0.11	+2.45	3409.56	+0.32	+2.87

[1]The simulations used same climate data set (e.g. L&W) and Hahn-derived solar radiation data set, but used different soil texture data set.
[2]The mean FAO/CSRC soil texture data for biomes: sum of percent silt and clay content.
[3]Absolute difference of Zobler soil texture with respect to FAO/CSRC soil texture (sum of percent silt and clay content).
[4]Absolute difference of VEMAP soil texture with respect to FAO/CSRC soil texture (sum of percent silt and clay content).
[5]Annual NPP estimates (10^{12} g C y^{-1}) of TEM using the FAO/CSRC soil data set.
[6]Relative difference (%) of annual NPP estimates using the Zobler soil data with respect to using the FAO/CSRC soil data.
[7]Relative difference (%) of annual NPP estimates using the VEMAP soil data with respect to using the FAO/CSRC soil data.

soils data set, and 14.2% more silt plus clay in the VEMAP soils data set.

Soil texture can affect NPP estimates of TEM by influencing GPP through effects on actual evapotranspiration (AET) and by influencing plant nitrogen uptake through effects on volumetric soil moisture (VSM), which is the percentage of the rooting zone occupied by water. Evapotranspiration depends on available water capacity, which is 15% of the rooting depth in WBM (based on Ratliff *et al.* 1983). In forests, rooting depth decreases for finer-textured soils (Thornthwaite & Mather 1957) and less water is available for transpiration in finer-textured soils. In grasslands and shrublands, rooting depth increases slightly from sandy to loam soils, and decreases substantially from loam to clay soils (Thornthwaite & Mather 1957). Therefore, in grasslands and shrublands more water is available for transpiration in loam soils than in sandy or clay soils. Because the ratio of AET to PET controls canopy conductance in TEM (Raich *et al.* 1991; McGuire *et al.* 1992) and because PET depends only on radiation and temperature in WBM, lower AET associated with finer-textured soils has the potential to cause lower NPP. Although there is generally less available soil water to transpire in clay loam and clay soils, VSM is generally higher in finer-textured soils because finer-textured soils have higher field capacity and wilting point as fractions of the rooting zone than coarser-textured soils (Ratliff *et al.* 1983). In TEM, both decomposition rates and the diffusion of inorganic nitrogen in the soil solution are enhanced by higher estimates of VSM (McGuire *et al.* 1996b). Because nitrogen availability to plants generally increases for higher rates of decomposition and nitrogen diffusion, finer-textured soils tend to enhance NPP via higher VSM.

In comparison to the FAO/CSRC soils, finer-textured soils in the VEMAP data set causes ≈ 2% less AET and 4% higher VSM for the conterminous U.S. for any of the climates. The continental NPP estimate is 3% higher for the finer-textured VEMAP soils (Table 5) because the effects of VSM enhancements are stronger than the effects of AET reductions. Similarly, finer-textured soils in the Zobler data set causes ≈ 1% less AET and 2% higher VSM for any of the climates. The continental NPP estimate is only slightly higher (0.1% to 0.3% higher).

Average soil texture is finer for all biomes in the Zobler and the VEMAP soils data. For the VEMAP soils data, soil texture ranges from 2.7% more silt plus clay in warm temperate/subtropical mixed forest to 22.4% more silt plus clay in cool temperate mixed forest. The NPP estimates of most biomes are generally higher for the finer-textured VEMAP soils, with ≈ 5–9% higher estimates in cool temperate mixed forest, C_4 grasslands, and temperate mixed and conifer xeromorphic forest (Table 5). For some climates, estimates of NPP are less in warm temperate/subtropical mixed forest, tundra, maritime conifer forest, Mediterranean shrublands and temperate and subtropical arid shrublands. As described above, finer-textured soils have simultaneously opposite effects on NPP, i.e. a tendency to reduce NPP because of lower AET and a tendency to enhance NPP because of higher VSM. The change of NPP depends on which effect is stronger in a particular biome. For example, in cool temperate mixed forest the 6.0–7.0% higher NPP estimates for the VEMAP soils are primarily caused by greater than 5% enhancement in VSM; estimates of annual AET are depressed less than 1% in this biome. In contrast, the 0.5–0.6% lower NPP in temperate/subtropical mixed forest for the VEMAP soils occurs because the 0.6–0.7% higher VSM does not compensate for the effects of lower AET on canopy conductance. The lower NPP estimates that occur for VEMAP soils in tundra and shrublands are associated with estimates of annual AET that are less than 300 mm; the effect of enhanced VSM on nitrogen availability cannot compensate for low canopy conductance in extremely dry environments.

The Zobler soils data set, which has soil textures that are intermediate between the FAO/CSRC and VEMAP soils data sets, causes higher NPP estimates in more than half of the biomes with the L&W and VEMAP climates, but in less than half of the biomes with the C&L climate. Decreases in NPP estimates occur when the effect of enhanced VSM on nitrogen availability cannot compensate for reduced canopy conductance. This occurs more frequently for the C&L climate, which is drier than other two climates.

At the grid cell resolution, there is a greater range of differences between the soil texture data sets than at the continental and biome resolutions (Fig. 7). In comparison to the FAO/CSRC soil textures, percentage silt plus clay in the Zobler soil texture data set ranges from 58% lower to 63% higher, with 90% of difference between 3% lower and 8% higher; percentage silt plus clay in the VEMAP soil texture data set ranges from 47.0% lower to 73.0% higher, with 90% of differences between 10.0% lower and 37.0% higher. In comparison to NPP estimates for the FAO/CSRC soil texture data set, the range of differences in the Zobler soil texture data set causes 10% of the NPP differences to be approximately more than 5% lower or more than 7% higher (Fig. 5, Fig. 7). Similarly, the range of differences in the VEMAP soil texture data set causes 10% of the NPP differences to be approximately more than 5% lower or more than 14% higher for any of the three climates (Fig. 5, Fig. 7). Clearly, NPP estimates are substantially more sensitive to differences among

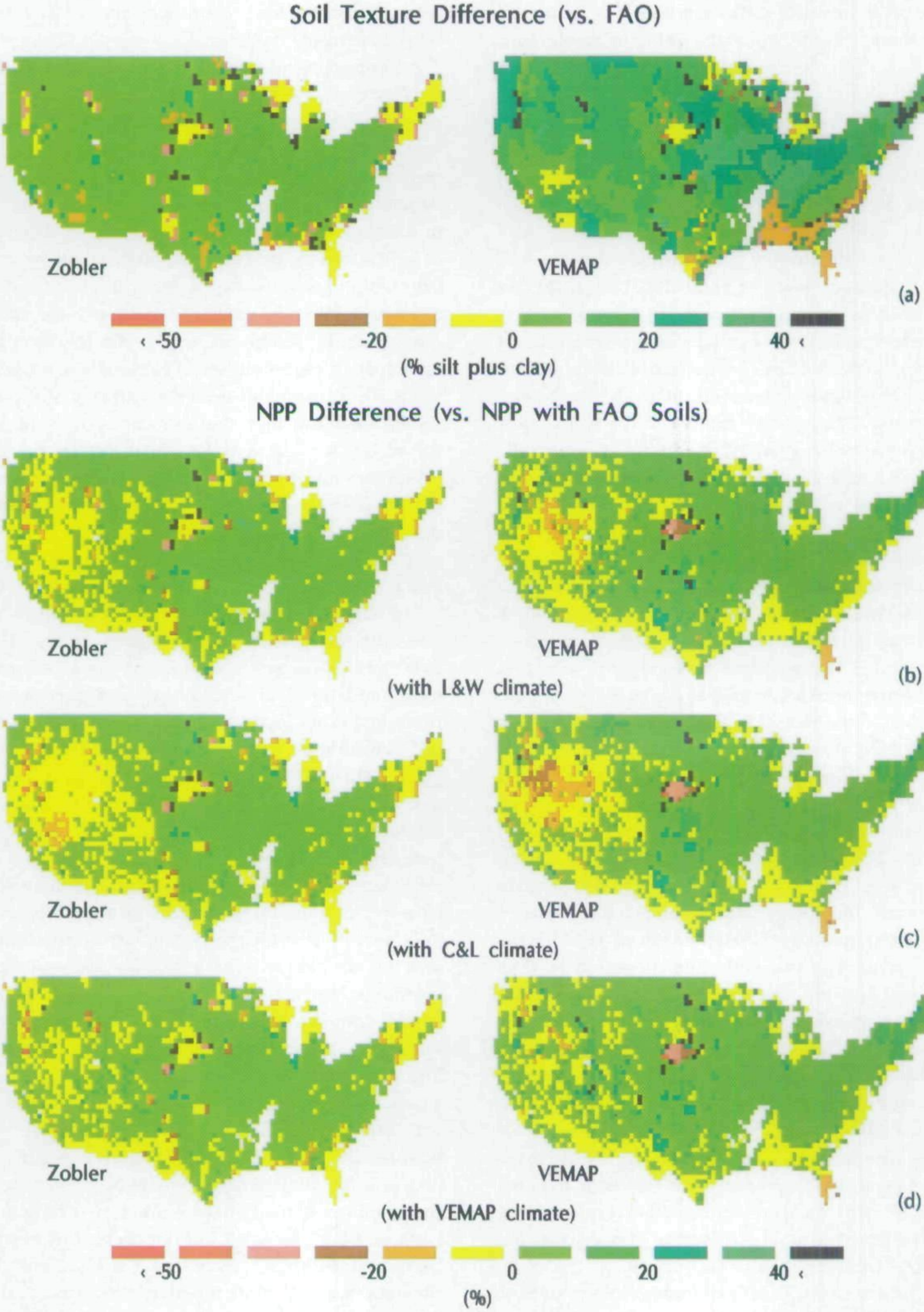

Fig. 7 Comparisons of soil texture data sets; and TEM estimated NPP using different soil texture data sets. (a) Soil texture difference (% silt plus clay) between the Zobler and the FAO/CSRC soil texture data sets; and between the VEMAP and the FAO/CSRC soil texture data sets. (b, c, d) Relative difference (%) between NPP estimates based on the Zobler and the FAO/CSRC soil texture data sets; and between NPP estimates based on the VEMAP and the FAO/CSRC soil texture data sets. (b) The L&W climate data sets and Hahn-derived solar radiation data set were used as other inputs for all simulations. (c) The C&L climate data sets and Hahn-derived solar radiation data set were used as other inputs for all simulations. (d) The VEMAP climate data sets and Hahn-derived solar radiation data set were used as other inputs for all simulations.

alternative soil texture data sets at the grid cell resolution than at the continental and biome resolutions.

Discussion

It has long been recognized that spatial patterns of NPP at large scales can be explained by spatial patterns in temperature and precipitation (Lieth 1973, 1975). Spatial patterns in NPP can also be explained by AET (Rosenzweig 1968), and the relationship between AET and solar radiation (Jensen & Haise 1963) suggests that NPP is related to solar radiation at large spatial scales. For mature temperate conifer and deciduous forest stands in the same climate, field measurements of above-ground and below-ground production indicate that NPP increases with increasing silt plus clay content of the soil (Pastor *et al.* 1984; Nadelhoffer *et al.* 1985). Studies in grasslands indicate that above-ground production increases with finer soil texture when annual precipitation is greater than 370 mm, but decreases when precipitation is less than 370 mm (Sala *et al.* 1988).

It logically follows that model estimates of NPP at large spatial scales should be sensitive to alternative input data sets of temperature, precipitation, radiation, and soil texture. The standard method for evaluating model performance at large spatial scales is to compare the estimates of the model to field measurements. For estimates of NPP at large spatial scales, the performance of TEM has been evaluated by Raich *et al.* (1991) and Melillo *et al.* (1993). One way to evaluate the efficacy of alternative input data sets might be to compare the NPP estimates of TEM to field measurements for each of the input data sets. However, this approach has several problems. First, the comparison requires an analysis of covariance to compare the NPP estimates of TEM for the alternative input data sets with field measured NPP as the covariate. Not enough site measurements of total NPP (above plus below ground) have been made for different sites within the conterminous United States to provide the statistical power necessary for evaluating the efficacy of different alternative input data sets. In addition, model estimates and site measurements of NPP are at different spatial resolutions. A truly robust comparison of model estimates with site data requires replication of field measurements within grid cells as well as a sufficient sample size across grid cells of the conterminous United States.

Finally, for this study TEM is calibrated to one suite of input data sets (L&W climate, Hahn-derived radiation, and FAO/CSRC soils). This single calibration means that we cannot compare model estimates to field measurements among simulations based on alternative data sets. However, the evaluation of the sensitivity of NPP estimates to alternative input data sets has important implications for both the calibration and extrapolation of biogeochemistry models.

An important question that arises is: what level of NPP sensitivity is meaningful? Field measurements of NPP are uncertain, and $\pm$ 20% is probably a conservative approximation of the error associated with the measurement of NPP. Uncertainty in NPP at the grid cell resolution depends on both quantitative uncertainty of field measurements within the grid cell and spatial heterogeneity of NPP across the grid cell. Although estimates of NPP for sites within grid cells are generally too few to adequately estimate NPP at the grid cell resolution, uncertainty at a coarser spatial resolution is generally less than that at a finer spatial resolution (see O'Neill 1979 & Rastetter *et al.* 1992). Thus, meaningful NPP sensitivity at the grid cell resolution is less than that at measurement sites, that at the biome resolution is less than that at the grid cell resolution, and that at the continental resolution is less than that at the biome resolution. Although we cannot quantitatively define the meaningful level of NPP sensitivity at these different spatial resolutions, we can assume that it is less than the measurement error of NPP.

The simulations in this study indicate that NPP estimates are less sensitive to differences among alternative data sets at coarser spatial resolutions. Although the meaningful level of sensitivity for a particular spatial resolution is not quantitively defined, in our opinion grid cell sensitivities greater than 20%, biome sensitivites greater than 10%, and continental sensitivities greater than 5% are meaningful differences. At the grid cell resolution, meaningful sensitivities are observed more frequently for alternative climate and solar radiation data sets than for alternative soil texture data sets. At the biome resolution, NPP estimates of most biomes appear to be sensitive to alternative climate and radiation data sets. It is not clear whether any of the biomes demonstrate meaningful sensitivity to alternative soil texture data sets. At the continental resolution, NPP estimates are most sensitive to differences between solar radiation data sets. The greatest differences, which are $\approx$ 10%, occur for alternative solar radiation data sets, and are associated with 60% differences in mean annual solar radiation between the VEMAP and Hahn-derived solar radiation data sets. Meaningful sensitivity of NPP estimates for the conterminous United States is also observed between the L&W and C&L climates, but not necessarily between the L&W and VEMAP climates or the C&L and VEMAP climates. It is not clear whether alternative soil texture data sets cause meaningful sensitivity in continental resolution estimates.

Among the three types of data sets used in this study, uncertainty may be greatest for solar radiation. Similar to the sensitivity of NPP estimates by TEM, the uncertainty in cloudiness and solar radiation at the earth's surface also has substantial effects on the projections of climate models (Cess *et al.* 1989, 1995; Ramanathan *et al.* 1989, 1995).

The Hahn-derived and C&L-derived solar radiation data sets are calculated from cloudiness or sunshine duration data that represent surface observations. In comparison to the Hahn cloudiness data set, the C&L sunshine duration data set has higher spatial resolution and finer temporal resolution and appears to be more accurate. Our comparison of the C&L-derived solar radiation data sets with the contour maps of Bennett (1965), which are based on ground-measured solar radiation, indicate good agreement for the C&L-derived radiation data throughout the year. In contrast, the Hahn-derived data set tends to underestimate solar radiation during the summer for whole U.S. (6.0 MJ m^{-2} d^{-1} lower). The coarse spatial and temporal resolution of the original data may affect data interpolation and cause lower estimates of solar radiation. The VEMAP solar radiation is based on the solar radiation estimates of the CLIMSIM model, which has been well-validated for estimates of daily solar radiation in the western U.S. (Running *et al.* 1987; Glassy & Running 1994). Our comparison of the VEMAP solar radiation data set with the contour maps of Bennett (1965) indicates that the VEMAP data set tends to overestimate solar radiation in much of the U.S. Thus, the Hahn-derived solar radiation and the VEMAP data sets appear to have biases. Removal of biases from solar radiation data sets is required to improve spatial patterns of NPP estimates.

Each of the climate data sets has its strengths in representing the spatial pattern of monthly temperature and precipitation. Both temperature and precipitation data in the C&L climate data sets were adjusted for elevation with a 3-D smoothing spline technique. The temperature data in the VEMAP climate data sets were adiabatically adjusted for elevation. One of the strengths of the L&W climate data set is that there has been an attempt to remove gauge-induced biases from the precipitation data, and a strength of the VEMAP climate data set is the orographically smart interpolation of precipitation data. The reduction of uncertainty requires that the strengths of the individual approaches be combined into a single approach. The TEM simulations suggest that the spatial resolution of NPP estimates in biomes located in mountainous areas would benefit most by the reduction of both precipitation and temperature uncertainties.

Our comparison of the FAO/CSRC, Zobler and VEMAP soils data sets indicates that the conterminous U.S. is primarily represented by loam soils in the FAO/CSRC data set, by loam and clay loam soils in the Zobler data set and by clay loam and clay soils in the VEMAP data set. The FAO/CSRC and Zobler data sets are both based on the Soil Map of the World (FAO-UNESCO 1971), which for the conterminous United States has better spatial resolution than the NATSGO database (Kern 1995) from which the VEMAP soils data set was derived. The FAO/CSRC data set was digitized at a finer resolution than the Zobler data set and represents soil textures for average soil profiles rather than the dominant soil profiles in the Zobler data set. Similar to the Zobler data set, the VEMAP soils data set represents soil texture with the first modal soil profile. The TEM simulations suggest that the spatial resolution of NPP estimates in cool temperate mixed forest, C_3 and C_4 grasslands, and temperate mixed and conifer xeromorphic forests would benefit most by the reductions of uncertainty in soil texture.

This study indicates that there is uncertainty in alternative data sets that characterize the long-term contemporary physical environment across large spatial scales. Estimates of process-based ecosystem models like TEM are sensitive to this uncertainty, and estimates at small spatial scales are generally more sensitive to uncertainty than estimates at large spatial scales. The reduction of uncertainty in input data sets is relevant for more than just improving the spatial resolution of NPP estimates for the contemporary condition; estimated impacts of global change that are based on the contemporary condition as a baseline are sensitive to both the accuracy of the contemporary physical environment and the changes applied to the contemporary physical environment. Assessments of the impacts of global change at large spatial scales will be improved by reducing uncertainty in data sets that characterize the physical environment. The reduction of uncertainty is especially important for improving assessments of the regional impacts of global change.

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