Tellus (2006), 58B, 513–522

TELLUS

A comparison of simulation results from two terrestrial carbon cycle models using three climate data sets

By AKIHIKO ITO[1,2]* and TAKAHIRO SASAI[3], [1]*Ecosystem Change Research Program, Frontier Research Center for Global Change, Japan Agency for Marine-Earth Science and Technology, 3173-25 Showa-machi, Kanazawa-ku, Yokohama 236-0001, Japan;* [2]*Center for Global Environmental Research, National Institute for Environmental Studies, 16-2 Onogawa, Tsukuba, Ibaraki 305-8506, Japan;* [3]*Geologic Remote Sensing research group, Institute of Geology and Geoinformation, Advanced Industrial Science and Technology, Central 7 1-1-1, Higashi, Tsukuba, Ibaraki 305-8567, Japan*

(Manuscript received 29 November 2005; in final form 19 June 2006)

ABSTRACT

This study addressed how different climate data sets influence simulations of the global terrestrial carbon cycle. For the period 1982–2001, we compared the results of simulations based on three climate data sets (NCEP/NCAR, NCEP/DOE AMIP-II and ERA40) employed in meteorological, ecological and biogeochemical studies and two different models (BEAMS and Sim-CYCLE). The models differed in their parameterizations of photosynthetic and phenological processes but used the same surface climate (e.g. shortwave radiation, temperature and precipitation), vegetation, soil and topography data. The three data sets give different climatic conditions, especially for shortwave radiation, in terms of long-term means, linear trends and interannual variability. Consequently, the simulation results for global net primary productivity varied by 16%–43% only from differences in the climate data sets, especially in these regions where the shortwave radiation data differed markedly: differences in the climate data set can strongly influence simulation results. The differences among the climate data set and between the two models resulted in slightly different spatial distribution and interannual variability in the net ecosystem carbon budget. To minimize uncertainty, we should pay attention to the specific climate data used. We recommend developing an accurate standard climate data set for simulation studies.

1. Introduction

The terrestrial ecosystem is a source of uncertainty in our understanding of the global carbon cycle, including atmospheric carbon dioxide (CO_2) change, which is strongly coupled with climatic change. This uncertainty is attributable to both the sparseness of observational data and the inadequacies of the simulation models used to analyse and predict the terrestrial carbon cycle. For example, one model comparison study (Cramer et al., 1999) found that different models produced estimate of global terrestrial net primary productivity (NPP) ranging from 40 to 70 Pg C yr^{-1}, even though each model used the same simulation configuration. The variability likely resulted from differences in the parameterizations of phenological and biogeochemical processes, which cause the models to respond to environmental conditions in different ways.

Unfortunately, current model estimations show even wider variability owing to differences in the simulation configuration and input data sets. Different configurations of the simulation period, spin-up method, spatial resolution and calculation time step may lead to artifacts in model estimation. Differences in the input data sets can also result in considerable interstudy variation, but such differences have not been addressed in detail. Since the 1980s, many global data sets containing information on topography, vegetation, soil, climatic conditions and remotely sensed vegetation indices have become available for statistical analyses and model simulations. Historically, several climate data sets have been used to drive carbon cycle models. Most terrestrial carbon cycle modelling studies in the 1990s employed the long-term average data on temperature, precipitation and cloud cover produced by Leemans and Cramer (1991), whose data set was based on the geometric interpolation of observatory data. An improved interpolation study (Mitchell and Jones, 2005) provided a century-long climate data set, which is quite useful for modelling studies simulating the carbon cycle in the 20th century. Recently, reanalysis climate data sets, which include variables such as soil temperature, wind velocity and surface radiation irradiance, have become available as forcing data. Since they satisfy meteorological laws and have fair spatial and high temporal resolutions, these data sets allow model simulations

*Corresponding author.
e-mail: itoh@nies.go.jp
DOI: 10.1111/j.1600-0889.2006.00208.x

with higher accuracy. Many meteorological studies have compared the spatial patterns and temporal trends in climate data sets with respect to temperature, precipitation and solar radiation (e.g. Trenberth et al., 2002; Simmons et al., 2004; Hicke, 2005). For example, Hicke (2005) pointed out that the surface solar radiation regime differed between two independent data sets, one from the U.S. National Centers for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR) and the other from the International Satellite Cloud Climatology Project (ISCCP). This difference potentially influences estimations of energy, water and carbon exchanges at the land surface.

Most terrestrial carbon cycle modellers select a climate data set arbitrarily, except in intermodel comparison studies (e.g. Cramer et al., 1999). Differences in the basic data, however, might yield different results, even when the same data-handling protocol is used. For example, Pan et al. (1996) compared the simulation results of the Terrestrial Ecosystem Model (TEM) for North America using two climate data sets: that of Leemans and Cramer (1991) and another produced by the Vegetation Ecosystem Modelling and Analysis Project (VEMAP). Their results show that differences in the climate data can lead to substantial differences in the simulation result. Nemani et al. (2003) and Zhao et al. (2006) showed that different estimations of primary productivity are obtained by the same method but using different satellite data products and climate data sets. Nevertheless, few studies have systematically addressed how such differences in climate data sets affect simulation results. In fact, many modelling studies have examined variability of the terrestrial carbon cycle (e.g. Kaduk and Heimann, 1994; Potter et al., 1999; Ito and Oikawa, 2000; Cao et al., 2004; Ichii et al., 2005; Zeng et al., 2005), on the basis of a single climate data set selected arbitrarily. Therefore, it is important to assess the output of terrestrial carbon cycle simulations in response to different climatic data input.

This study evaluated the range of variability in simulation results using the same simulation configuration but with three different climate data sets. Two terrestrial carbon cycle models, which adopt different approaches, were used to examine differences in data dependency between models. In this study, we focused on the differences in average patterns and the interannual variability of primary productivity and the net carbon budget. Finally, we discuss the importance of an accurate climate data set for use in terrestrial carbon cycle model studies.

2. Methods

2.1. Climate data sets

Three climate data sets covering a sufficiently long-time period and containing the physical variables necessary for terrestrial model simulations were selected: (1) a reanalysis product from NCEP/NCAR (Kistler et al., 2001); (2) a reanalysis product from the U.S. NCEP and the Department of Energy for the Atmospheric Model Intercomparison II (NCEP/DOE AMIP-II; Kanamitsu et al., 2002) and (3) data from the European Centre for Medium-Range Weather Forecast 40-yr reanalysis product (ERA40; Simmons and Gibson, 2000; Uppala et al., 2005). These three data sets are widely used in meteorological, ecological and biogeochemical studies. Since they were synthesized by the same fundamental data-assimilation method using at least in part common observational records, they are not entirely independent of each other. However, they employ different grid systems: T62 spectral resolution and 28 sigma levels in the NCEP/NCAR and NCEP/DOE AMIP-II and T159 resolution and 60 levels in the ERA40. In particular, the NCEP/DOE AMIP-II and ERA40 use an updated observational data set (Kanamitsu et al., 2002). In addition, they use different land surface schemes to obtain the boundary condition for atmospheric models, resulting in differences in the near-surface conditions (e.g. Betts et al., 1998; Dirmeyer et al., 2004). In this study, eight land-surface variables for the period 1982–2001 were extracted from each data set for forcing the TEMs: downward shortwave radiation, total cloudiness, 2-m air temperature, air humidity (specific humidity or dew point temperature), precipitation, soil temperatures in the surface and subsurface horizons and 10 m zonal and meridional winds.

2.2. Terrestrial carbon cycle models

2.2.1. BEAMS. Sasai et al. (2005) developed a remote sensing-based carbon cycle model called Biosphere model integrating eco-physiological And Mechanistic approaches using Satellite data (BEAMS). This model is driven primarily by the remotely sensed leaf area index (LAI) and fraction of absorbed photosynthetically active radiation (fAPAR) obtained using the Advanced Very High-Resolution Radiometer (AVHRR) of the Global Inventory Monitoring and Modelling Studies (GIMMS; Myneni et al., 1997; Nemani et al., 2003), and is regarded as a diagnostic model for interpreting the present state of the carbon cycle. Incident radiation, temperature and moisture conditions are used to estimate gross primary production (GPP), based on the light-use efficiency (LUE) concept (Kumar and Monteith, 1981; Field et al., 1995). The BEAMS model employs the stress-limited LUE derived from a biochemical photosynthesis model to obtain more realistic spatial and temporal patterns of photosynthetic carbon assimilation by terrestrial plants. Sasai et al. (2005) validated BEAMS with observational data on net primary production compiled by Zheng et al. (2003) and CO_2 Flux data from AmeriFlux and EuroFlux (e.g. Valentini et al., 2000), and used it to interpret the interannual variability in the global terrestrial carbon budget.

2.2.2. Sim-CYCLE. Ito and Oikawa (2000, 2002) developed a plant ecophysiology-based carbon cycle model called

Simulation model of Carbon cYCle in Land Ecosystems (Sim-CYCLE). This model is driven solely by climatic variables and is regarded as a prognostic model for simulating carbon budgets from the past (using records) to the future (using scenarios). GPP is estimated using a canopy production model based on the dry-matter production theory (Monsi and Saeki, 2005), which takes into account the exponential light attenuation within the canopy using the model-estimated LAI and fAPAR. Sim-CYCLE simulates C_3 and C_4 species separately, leading to different behaviours in tropical and temperate grasslands (Still et al., 2003). Sim-CYCLE was validated using plot-scale ecological surveys of biomass, NPP, and soil organic carbon, and global NPP data (Hazarika et al., 2005). Although few flux measurement data were used for validation, the estimated large-scale pattern of net ecosystem CO_2 exchange was examined by comparison with atmospheric CO_2 data (Fujita et al., 2003). This prognostic model has been used to investigate the effect of global warming on the terrestrial carbon cycle given several climate projection scenarios (Ito, 2005).

2.2.3. Points of similarity and difference. Both BEAMS and Sim-CYCLE estimate major components of the terrestrial carbon cycle such as GPP, NPP, ecosystem respiration (ER), net ecosystem production (NEP = GPP − ER) and plant and soil carbon pools. Both models use a two-component plant respiration scheme (construction and maintenance), and parameterizations of soil decomposition as functions of soil temperature and water content, after Parton et al., (1993) in BEAMS and after Ito and Oikawa (2002) in Sim-CYCLE. The two models use ecological and physiological parameters similar to those calibrated in the original versions (Ito and Oikawa, 2002; Sasai et al., 2005); note that simulations by both models agreed well with observed data. In both models, local radiation and water conditions (e.g. photosynthetically active radiation (PAR), net radiation, evapotranspiration, and soil water content) are estimated using hydrological schemes (see Ito and Oikawa, 2002; Sasai et al., 2005). Both models consider total (i.e. direct + diffuse) PAR absorption only. In this study, both models were operated using monthly climate data sets.

The two models differ in several aspects, allowing us to reduce model-specific biases. BEAMS is a diagnostic model, whereas Sim-CYCLE is a prognostic model. BEAMS determines leaf phenology exclusively from remotely sensed LAI and fAPAR, but Sim-CYCLE parameterizes leaf emergence and shedding in deciduous forests and grasslands as functions of cumulative temperature and precipitation. As a result, leaf phenology responds to different climate conditions only in Sim-CYCLE simulations. Both models incorporate stomatal regulation to simulate leaf gas exchange (Ball et al., 1987), which responds to the ambient CO_2 concentration, incident PAR irradiance, temperature and soil water availability, but they use different photosynthetic schemes. BEAMS uses a LUE scheme based on remotely sensed data, whereas Sim-CYCLE uses a plant ecophysiological scheme. Accordingly, BEAMS assumes that GPP responds more sensitively (i.e. an incremental response) to PAR absorption than does Sim-CYCLE, which assumes a saturation response. The two models simulate similar photosynthetic responses to temperature, but in different manners; Sim-CYCLE assumes an empirical optimal response curve of gross photosynthetic rate, whereas BEAMS takes into account the responses of the carbon assimilation enzyme, rubisco. Both models use exponential response curves to simulate the responses of plant maintenance respiration and soil decomposition to temperature. Finally, both models incorporate a reduction of the maximum photosynthetic rate in response to soil dryness, but using different parameterization functions.

2.3. Simulations and analyses

Before performing model simulations, we compared the characteristics of the three data sets (NCEP/NCAR, NCEP/DOE AMIP-II and ERA40) with those of several ancillary data sets compiled from observational data. From each data set, the 20-yr mean; standard deviation (*SD*), which reflects interannual variability; and the trend (slope of the linear regression against time) of each parameter were obtained. We used a time-series data set from the Climate Research Unit version 2.1 (CRU TS2.1; Mitchell and Jones, 2005) as air temperature and precipitation references. This data set, which was obtained by interpolating thousands of data observations, has a monthly time step and a spatial resolution of 0.5° in longitude and latitude. For precipitation references, we also used two additional data sets: the Global Precipitation Climatology Project (GPCP; Huffman et al., 1997) and the CPC Merged Analysis of Precipitation (CMAP; Xie and Arkin, 1997). These precipitation data sets are compilations of data from rain gauge and satellite observations. For the downward shortwave radiation reference, we used a data set from the International Satellite Cloud Climatology Project version D2 (ISCCP-D2; Rossow and Dueñas, 2004). Here, note that it is difficult to determine which data set is most reliable based solely on such comparison because uncertainties, including model-specific biases and artificial trends due to shifts in the data source and observational system (e.g. Bengtsson et al., 2004), are inherent in the observational data.

A series of simulations were conducted to clarify the variability across model simulations that were attributable to the differences in climate data sets from January 1982 to December 2001, a period covered by all of the climatic and remote sensing data sets. The simulations were conducted at a spatial resolution of 1° × 1°, so that climate data were obtained by resampling. The two models employ the same vegetation map (11 vegetation types; DeFries and Townshend, 1994), soil-type map (Zobler, 1986), topography map (ETOPO5; NOAA, 1988), and soil hydraulic parameterization (Saxton et al., 1986). Having these data in common facilitates comparison of the models and highlights the intersimulation differences caused by different climate data. A model simulation using either model has two phases: spin-up and experiment. In the spin-up phase of each model, the initial state of the terrestrial carbon pools was obtained by repeating more than 1000 yr using the climate data atmospheric CO_2 concentration (Keeling and Whorf, 2004) for 1982 until an equilibrium state of the carbon cycle, including that of soil carbon pool, was obtained. This method simplifies the spin-up phase, especially for the satellite-based model BEAMS, but is sufficient for examining the variability after 1982. During the experimental period, time-series climate and atmospheric CO_2 data were used sequentially. Using the two models (BEAMS and Sim-CYCLE) and the three climate data sets (NCEP/NCAR, NCEP/DOE AMIP-II and ERA40), we conducted six baseline simulations and compared the results in terms of the average state and interannual variability of parameters of the terrestrial carbon budget, namely, GPP, NPP and NEP. Then, to interpret the influence of the climatic data set, we correlated variability in the estimated carbon budgets with those in the climatic conditions. In addition, as a sensitivity analysis, we performed ancillary simulations, in each of which, based on a simulation using the NCEP/NCAR data set, one of the eight climatic variables was replaced with the corresponding variable from either the NCEP/DOE AMIP-II or ERA40 data set. By this means, we assessed which climatic variables accounted for the major differences between the model simulations.

Table 1. Summary of the terrestrial climatic conditions over the land surface (excluding ice sheets) derived from data sets for the period 1982–2001

Climatic variables	Mean	*SD*	Trend[a] (yr^{-1})
Downward shortwave radiation ($W\ m^{-2}$)			
NCEP/NCAR	228.0	0.6	+0.01
NCEP/DOE AMIP-II	197.1	0.6	+0.01
ERA40	179.7	1.1	+0.13
ISCCP (1984–2000)	193.8	1.2	−0.10
2-m air temperature (°C)			
NCEP/NCAR	12.1	0.2	+0.02
NCEP/DOE AMIP-II	12.4	0.3	+0.02
ERA40	13.2	0.3	+0.04
CRU TS2.1	14.0	0.3	+0.04
Precipitation ($mm\ yr^{-1}$)			
NCEP/NCAR	873	18.8	−1.33
NCEP/DOE AMIP-II	880	23.3	+0.29
ERA40	788	20.9	−2.70
CRU TS2.1	805	20.7	+1.76
GPCP	800	23.6	+0.06
CMAP	738	23.7	+0.64

[a] This represents the slope of a linear regression against time.

3. Results and discussion

3.1. *Comparison of the climate data sets*

A comparison of the three climate data sets and the observationally derived reference data sets (Table 1 and Fig. 1) shows that the average downward shortwave radiation is apparently higher in the NCEP/NCAR data set, as suggested by other studies (e.g. Hicke, 2005). The NCEP/DOE AMIP-II data set has mean values closer to those of the ISCCP-D2 data set, but the interannual variability (Fig. 1a) is obviously inconsistent between them. The global dimming trend in solar radiation, observed up to approximately 1990 at many sites (Wild et al., 2005), is not clearly seen in these global data sets, and the long-term linear trends from 1982 to 2001 (Table 1) differ markedly among them. With regard to temperature, the variability of the long-term average and interannual change is small among the data sets. In each data set, the same patterns of interannual temperature change are consistently found: for example, the highest temperature in each occurred in 1998 (a strong El Niño year) (Fig. 1b). However, the ERA40 data set shows slightly greater variability. The long-term warming trend is captured in all data sets, but inconsistencies are evident among them with regard to precipitation. The average annual precipitation in the NCEP/NCAR and NCEP/DOE AMIP-II data sets is more than 10% higher than that in the ERA40 data set. The patterns of interannual variability in precipitation (Fig. 1c) are reasonably similar among the climate data sets, and comparable to those of the observation-based data sets (CRU TS2.1, CMAP and GPCP) for many of the years, with some disagreements. In particular, long-term linear trends in precipitation are inconsistent, ranging from a clear decrease in the ERA40 data set to a slight increase in the NCEP/DOE AMIP-II data set.

3.2. *Comparison of the average carbon budget patterns*

We compared the average state (1982–2001) of the terrestrial carbon cycle among climate data sets and between model simulations. With both models, global GPP and NPP differed among the simulations: the highest values were obtained with the NCEP/NCAR and the lowest with the ERA40 data set (range, 43% in BEAMS and 16% in Sim-CYCLE; Table 2). The data-induced differences occurred heterogeneously over the global land surface (Fig. 2): evident differences occurred near the equator, in areas dominated by tropical rain forests. The distributions of the net ecosystem carbon budget estimated for the experimental period (Fig. 3) clarify this data dependency. In each of the six simulations, net climate-induced carbon sequestration was consistently simulated in the central Amazon, South Asia (particularly southern India), and eastern Australia, and net carbon release was consistently simulated in central and east Siberia and eastern Africa. In contrast, net carbon gain or loss was not consistently obtained (i.e. the results were data-dependent) in central Africa, eastern South America, East Asia, and Europe.

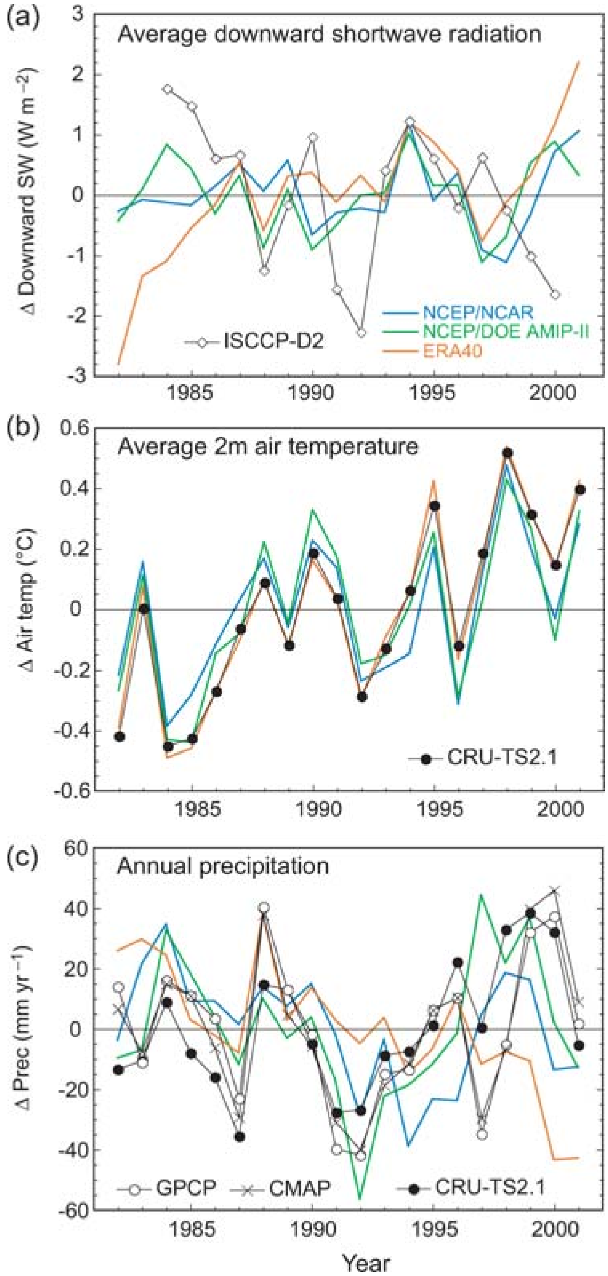

Fig. 1. Interannual variability in terrestrial climatic conditions derived from three climate data sets (NCEP/NCAR, NCEP/DOE AMIP-II and ERA40) and observational data. Anomalies (i.e. departures from the average) in (a) annual average downward shortwave radiation, compared with ISCCP-D2 data, (b) annual average 2-m air temperature, compared with CRU TS2.1 data and (c) annual precipitation, compared with CRU TS2.1, GPCP and CMAP data. See Table 1 for the average values.

The greater NPP values in the NCEP/NCAR-based simulations were ascribable to the higher shortwave radiation, especially in the BEAMS simulation (shown by the sensitivity analysis described below). In contrast, the Sim-CYCLE simulation gave a lower NPP in several subtropical regions (e.g. in Africa and South America) in the NCEP/NCAR-based simulation, which resulted from the lower precipitation numbers (i.e. more severe water limitation). In the ERA40-based simulations, considerably lower NPP was simulated in subtropical (e.g. in Southeast Asia and South America) and temperate (e.g. Europe and part of North America) regions than in the NCEP/DOE AMIP-II-based simulations, although the equatorial NPP values were comparable. The correlation and sensitivity analyses (described below) implied that the lower NPP values in the ERA40-based simulations in these regions were attributable to the lower shortwave radiation and precipitation values in that data set. These different carbon assimilation rates resulted in proportional differences in the ecosystem carbon storage because the same parameters were used to estimate carbon turnover rates.

3.3. *Comparison of the interannual variability in carbon budgets*

Differences in the interannual variability of climatic conditions resulted in corresponding differences in the terrestrial carbon budgets estimated by the two models. During the simulation period, global terrestrial GPP and NPP increased at rates of $+0.16$ to $+0.40$ Pg C yr^{-1} and $+0.08$ to $+0.21$ Pg C yr^{-1}, respectively (Table 2 and Fig. 4a). Since the fertilization effect of the atmospheric CO_2 rise is assumed in the simulations of both models, the differences in the increases in GPP and NPP resulted from differences in the climate data sets; that is, the NCEP/NCAR data set, which shows a small increment in shortwave radiation and a decrement in precipitation against time (Table 1), resulted in a lower increment in estimated plant productivity. In contrast, because both models assume a strong dependence of the respiration rate on temperature, the estimated ecosystem respiration rates (ER in Fig. 4b and Table 2) showed similar interannual variability in relation to temperature (Fig. 1b). However, the ERA40 data set, which shows a stronger warming trend, yielded a higher increment in the estimated ER (Table 2). We also compared regional patterns in linear trends in NPP. In the six simulations, greater increases occurred consistently in South Asia (India), central Africa and southwestern Siberia. However, opposite trends were found in some parts of South Africa and central South America among the input climate data sets. Finally, NEP, which combines ecosystem productivity and respiration, showed complex interannual variability in the six simulations. Most simulations showed consistently negative NEP anomalies (i.e. more release or less uptake) in 1983, 1988 and 1994. In contrast, in 1984, 1992 and 1999, the simulations showed qualitatively inconsistent anomalies in NEP. Interannual variability (as indicated by *SD* value; Table 2) was more evident in the simulations using the NCEP/DOE AMIP-II data set by both models. Finally, it is noteworthy that different patterns of interannual variability were obtained among climate data sets, models and time periods.

Table 2. Summary of the simulation results in terms of average, standard deviation and linear trend of interannual variability during 1982–2001

Estimations (Pg C yr^{-1})	BEAMS			Sim-CYCLE		
	Average	*SD*	Linear trend (yr^{-1})	Average	*SD*	Linear trend (yr^{-1})
Gross primary production (GPP)						
NCEP/NCAR	123.4	1.5	+0.16	122.2	1.8	+0.22
NCEP/DOE AMIP-II	109.9	2.3	+0.30	120.6	2.7	+0.37
ERA40	89.3	1.9	+0.28	107.4	2.6	+0.40
Net primary production (NPP)						
NCEP/NCAR	56.7	0.8	+0.08	63.0	1.0	+0.11
NCEP/DOE AMIP-II	49.9	1.4	+0.17	61.4	1.5	+0.19
ERA40	39.7	1.1	+0.14	54.2	1.4	+0.21
Ecosystem respiration (ER)						
NCEP/NCAR	123.2	1.3	+0.14	121.2	1.6	+0.19
NCEP/DOE AMIP-II	109.3	1.6	+0.21	119.8	2.1	+0.31
ERA40	88.5	1.4	+0.23	106.6	2.2	+0.33
Net ecosystem production (NET)						
NCEP/NCAR	0.2	0.9	+0.02	1.0	0.8	+0.03
NCEP/DOE AMIP-II	0.5	1.3	+0.09	0.8	1.3	+0.06
ERA40	0.8	0.9	+0.05	0.8	1.0	+0.07

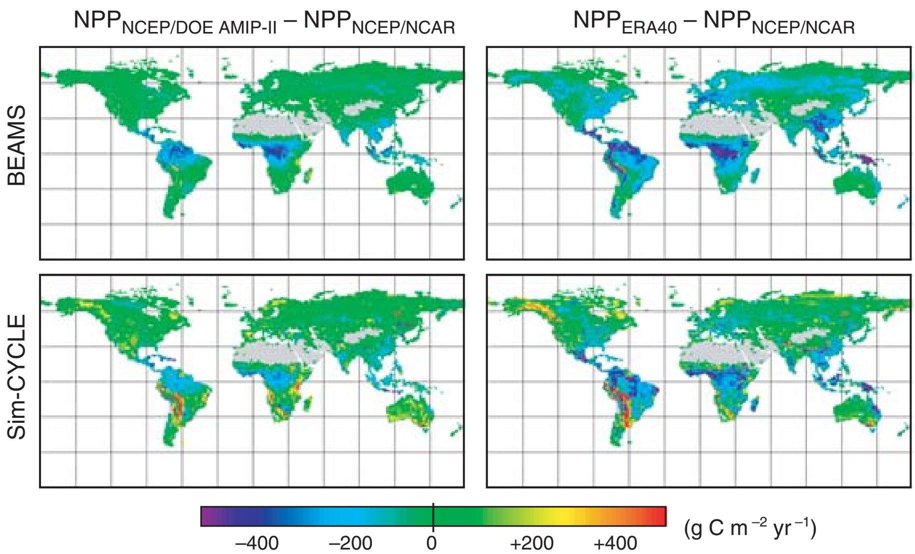

Fig. 2. Spatial distribution of the inter-data set differences of net primary production (NPP, averaged over 1982–2001) estimated by BEAMS and Sim-CYCLE. Deviations of the NCEP/DOE AMIP-II and ERA40 results relative to the NCEP/NCAR results are shown.

For example, anomalies in ER by Sim-CYCLE were more consistent among data sets for 1990–1998 than for other time periods.

3.4. Correlation and sensitivity analyses

Through a grid-by-grid correlation analysis, we found that 19%–25% of the differences in NPP by BEAMS using different climate data sets (Fig. 2) were attributable to differences in downward shortwave radiation among the data sets. On the other hand, the differences in NPP by Sim-CYCLE were more closely related to the inter-data set difference in precipitation, explaining 20%–35% of the variability. At the global scale, the relationships between average annual downward shortwave radiation and GPP obtained from the BEAMS- and Sim-CYCLE-based simulations with the three climate data sets show that the data-induced difference in the GPP was much greater than the interannual variability, but the magnitudes of the difference differed between

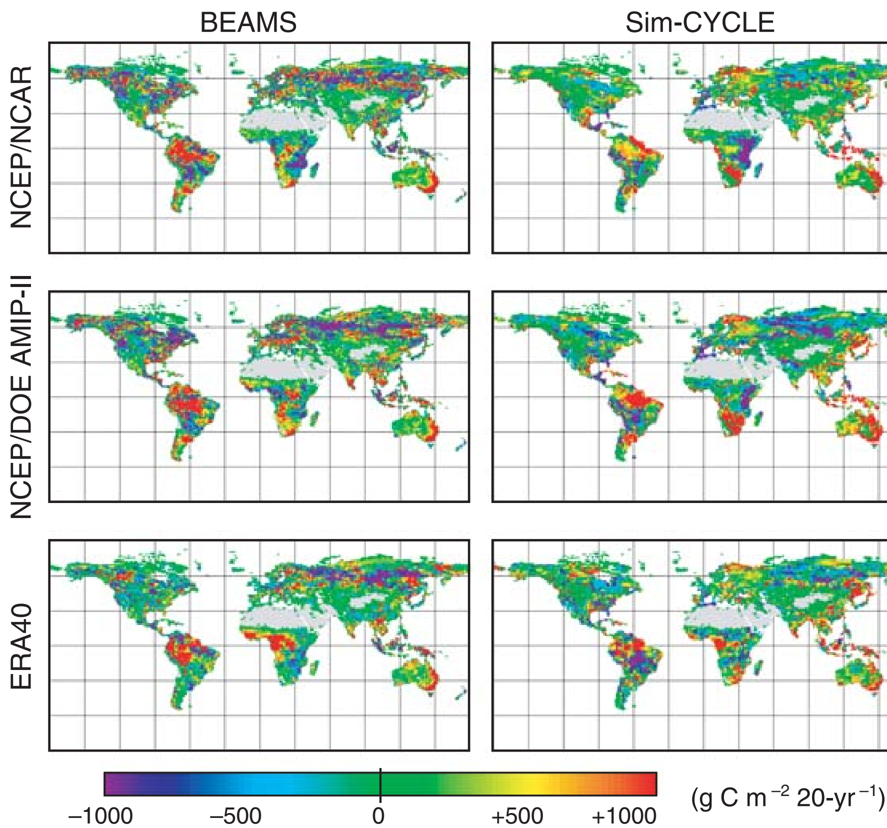

Fig. 3. Distribution of cumulative net ecosystem production (NEP) estimated by BEAMS and Sim-CYCLE using the three climate data sets, 1982–2001.

the two models (Fig. 5). BEAMS, which assumes a linear relationship between PAR absorption and the carbon assimilation rate, was quite sensitive to differences in shortwave radiation. In contrast, the NCEP/NCAR- and NCEP/DOE AMIP-II-based simulations by Sim-CYCLE seemed to reach radiation saturation.

We used a sensitivity analysis to assess which climatic variables most influenced the simulation differences resulting from the use of the three climate data sets (Fig. 6). The difference in downward shortwave radiation (cf. Table 1 and Fig. 1) exerted the strongest influence on the simulation results, as shown by the differences, 6–10 Pg C yr^{-1}, respectively, between the result obtained with the NCEP/NCAR data set and the values obtained using the NCEP/DOE AMIP-II and ERA40 data sets for the annual global GPP. This led to higher estimates for GPP by both models with the NCEP/NCAR data set (Table 2). Precipitation was the next most important factor leading to the intersimulation differences. As expected from the mean annual precipitation values of the data sets (Table 1), simulations using the NCEP/DOE AMIP-II precipitation data resulted in higher vegetation productivity than simulations with the other data sets. In addition, differences in air temperature among data sets exerted a moderate influence on simulation results, although the interdata set differences in air temperature were relatively small.

3.5. *Concluding remarks: requirement of a precise data set*

This study evaluated how much the climate data sets used to force terrestrial carbon cycle models affect the simulation outcomes. First, data dependency may partly explain differences among modelling studies of the terrestrial carbon cycle; thus, the climate data set used should be considered when simulation results are interpreted and compared. Furthermore, the results of this study suggest that a single accurate standard data set of climatic conditions should be produced and used for all terrestrial modelling studies to better elucidate the terrestrial carbon budget. However, since it is difficult to determine which of the existing data sets is most reliable for various simulations, compiling an appropriate climate data set may require the development of new observational and data assimilation methods. The same requirement applies to land-cover, land-use, soil and other input data sets used in simulations.

An interesting next step is to compare simulation results with independent observations (not used in model calibration) of

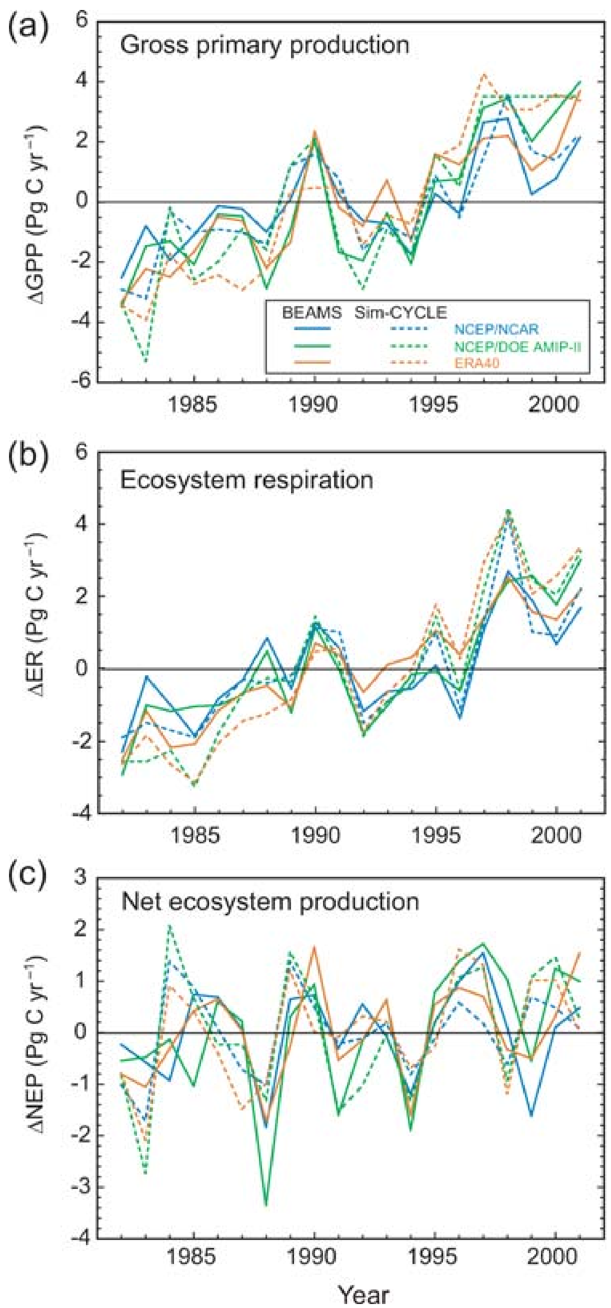

Fig. 4. Interannual variability in the terrestrial ecosystem carbon budgets estimated by BEAMS and Sim-CYCLE using the three climate data sets. Anomalies in the (a) annual gross primary production, (b) ecosystem respiration by plants and soil microbes and (c) net ecosystem production. Note that average values differ among simulation results (see Table 2).

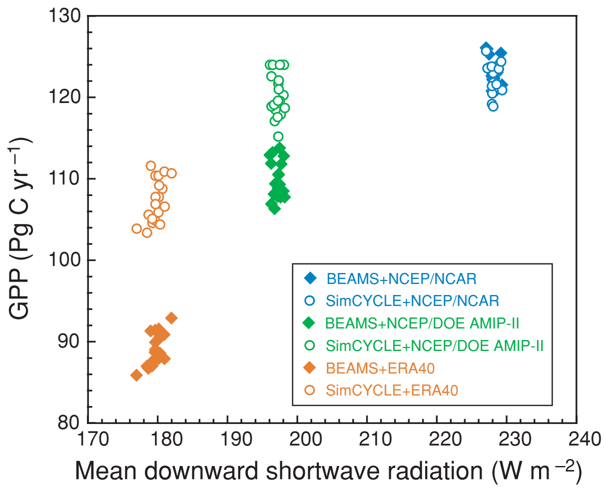

Fig. 5. Relationships between downward shortwave radiation among the three climate data sets and annual GPP estimated using the data sets, 1982–2001.

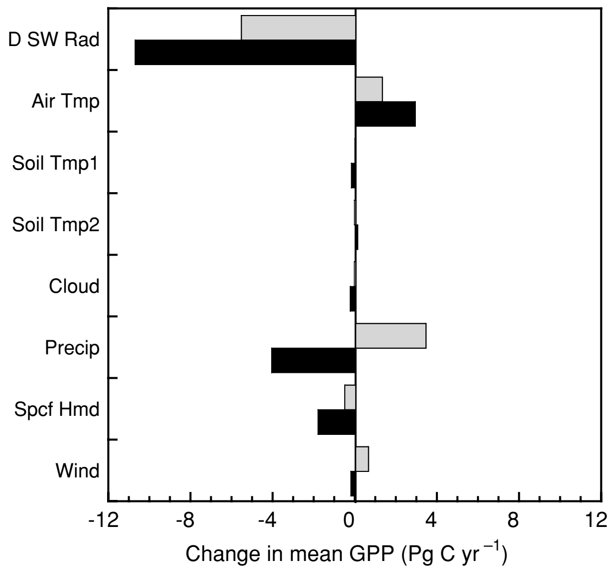

Fig. 6. Sensitivity analysis of the individual climatic variables, in which each NCEP/NCAR variable (used in the baseline simulation) was replaced by the corresponding variable from NCEP/DOE AMIP-II (gray bar) or ERA40 (black bar). The baseline is the average GPP obtained with Sim-CYCLE using the NCEP/NCAR data set.

seasonal change and interannual variability in ecosystem carbon cycles and atmospheric CO_2 concentrations. Our results (Fig. 3 and Table 2) showed that different net ecosystem carbon budgets were obtained with different climate data sets, even when the same model was used for the simulation. The sensitivity analysis (Fig. 6) implied that improving the accuracy of the downward shortwave radiation (including PAR) data, which primarily determines photosynthetic carbon assimilation by terrestrial plants, would have the greatest effect in improving simulation results. Moreover, several studies have suggested the importance of specifying the direct and diffuse components of radiation data in addition to total irradiance (e.g. Gu et al., 2002); recent canopy models have been developed that handle these components separately. Improvements in the accuracy of temperature and precipitation data would also improve simulation results. We are planning to assess the quality of the newer data as forcing data for terrestrial carbon cycle models; for example, a new climate data set has been developed by the Japan Meteorological Agency.

Our simulations showed that the degree of data dependency differed between terrestrial carbon cycle models; for example, BEAMS was more sensitive to the difference in the shortwave radiation, especially for equatorial regions, and Sim-CYCLE was more sensitive to the difference in precipitation in subtropical regions. Intermodel differences will be assessed in our forthcoming study (a cross-comparison of data and models), which will make detailed comparisons between parameterizations of the ecophysiological simulated in the models. In summary, further studies are required to investigate the variability caused by using different climate data sets and models, and thus to better understand the global terrestrial carbon cycle.

4. Acknowledgements

This study was partly supported by a Grant-in-Aid for Scientific Research from the Japan Society for the Promotion of Science (no. 16510016) and a grant from the Global Environmental Research Fund (S-1: Integrated Study for Terrestrial Carbon Management of Asia in the 21st Century based on Scientific Advancements) of the Japan Ministry of the Environment.

References

Ball, J. T., Woodrow, I. E. and Berry, J. A. 1987. A model predicting stomatal conductance and its contribution to the control of photosynthesis under different environmental conditions. In: *Progress in Photosynthesis Research* (ed. J. Biggens). Martinus Nijhoff, Dordrecht, 221–224.

Bengtsson, L., Hodges, K. I. and Hagemann, S. 2004. Sensitivity of the ERA40 reanalysis to the observing system: determination of the global atmospheric circulation from reduced observations. *Tellus* **56A**, 456–471.

Betts, A. K., Viterbo, P., Beljaars, A., Pan, H.-L., Hong, S.-Y. and co-authors. 1998. Evaluation of land-surface interaction in ECMWF and NCEP/NCAR reanalysis models over grassland (FIFE) and boreal forest (BOREAS). *J. Geophys. Res.* **103**, 23 079–23 085.

Cao, M., Prince, S. D., Small, J. and Goetz, S. J. 2004. Remotely sensed interannual variations and trends in terrestrial net primary productivity 1981-2000. *Ecosystems* **7**, 233–242.

Cramer, W., Kicklighter, D. W., Bondeau, A., Moore, B. I., Churkina, G., and co-authors. and the participants of the Potsdam NPP Model Intercomparison. 1999. Comparing global NPP models of terrestrial net primary productivity (NPP): overview and key results. *Global Change Biol.* **5**(suppl.1), 1–15.

DeFries, R. S. and Townshend, J. R. G. 1994. NDVI-derived land cover classifications at a global scale. *Int. J. Rem. Sens.* **15**, 3567–3586.

Dirmeyer, P. A., Guo, Z. and Gao, X. 2004. Comparison, validation, and transferability of eight multiyear global soil wetness products. *J. Hydrometeorol.* **5**, 1011–1033.

Field, C. B., Randerson, J. T. and Malmstrom, C. M. 1995. Global net primary production: combining ecology and remote sensing. *Rem. Sens. Environ.* **51**, 74–88.

Fujita, D., Ishizawa, M., Maksyutov, S., Thornton, P. E., Saeki, T. and co-authors. 2003. Inter-annual variability of the atmospheric carbon dioxide concentrations as simulated with global terrestrial biosphere models and an atmospheric transport model. *Tellus* **55B**, 530–546.

Gu, L., Baldocchi, D., Verma, S. B., Black, T. A., Vesala, T. and co-authors. 2002. Advantages of diffuse radiation for terrestrial ecosystem productivity. *J. Geophys. Res.* **107**, 4050, doi: 10.1029/2001JD001242.

Hazarika, M., Yasuoka, Y., Ito, A. and Dye, D. G. 2005. Estimation of net primary productivity by integrating remote sensing with an ecosystem model. *Rem. Sens. Environ.* **94**, 298–310.

Hicke, J. A. 2005. NCEP and GISS solar radiation data sets available for ecosystem modeling: description, difference, and impacts on net primary production. *Global Biogeochem. Cycles* **19**, GB2006, doi:10.1029/2004GB002391.

Huffman, G. J., Adler, R. F., Arkin, P., Chang, A., Ferraro, R. and co-authors. 1997. The Global Precipitation Climatology Project (GPCP) combined precipitation data set. *Bull. Am. Meteorol. Soc.* **78**, 5–20.

Ichii, K., Hashimoto, H., Nemani, R. and White, M. 2005. Modeling the interannual variability and trends in gross and net primary productivity of tropical forests from 1982 to 1999. *Global Planet. Change* **48**, 274–286.

Ito, A. 2005. Climate-related uncertainties in projections of the 21st century terrestrial carbon budget: off-line model experiments using IPCC greenhouse gas scenarios and AOGCM climate projections. *Clim. Dyn.* **24**, 435–448.

Ito, A. and Oikawa, T. 2000. A model analysis of the relationship between climate perturbations and carbon budget anomalies in global terrestrial ecosystems: 1970–1997. *Climate Res.* **15**, 161–183.

Ito, A. and Oikawa, T. 2002. A simulation model of the carbon cycle in land ecosystems (Sim-CYCLE): a description based on dry-matter production theory and plot-scale validation. *Ecol. Model.* **151**, 147–179.

Kaduk, J. and Heimann, M. 1994. The climate sensitivity of the Osnabrück Biosphere Model on the ENSO time scale. *Ecol. Model.* **75**, 239–256.

Kanamitsu, M., Ebisuzaki, W., Woollen, J., Yang, S.-K., Hnilo, J. J., Fiorino, M. and co-authors. 2002. NCEP-DOE AMIP-II reanalysis (R-2). *Bull. Am. Meteorol. Soc.* **83**, 1631–1643.

Keeling, C. D. and Whorf, T. P. 2004. Atmospheric CO_2 concentrations - Mauna Loa Observatory, Hawaii, 1958–2003. NDP001, Oak Ridge National Laboratory, Oak Ridge, TN.

Kistler, R., Kalnay, E., Collins, W., Saha, S., White, G. and co-authors. 2001. The NCEP-NCAR 50-year reanalysis: monthly means CD-ROM and documentation. *Bull. Am. Meteorol. Soc.* **82**, 247–267.

Kumar, M., and Monteith, J. L. 1981. Remote sensing of crop growth. In: *Plants and Daylight Spectrum* (ed.H. Smith). Academic Press, New York, 133–144.

Leemans, R. and Cramer, W. P. 1991. The IIASA database for mean monthly values of temperature, precipitation and cloudiness of a global terrestrial grid. RR-91-18, IIASA, Luxemburg.

Mitchell, T. D. and Jones, P. D. 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *Int. J. Climatol.* **25**, 693–712.

Monsi, M. and Saeki, T. 2005. On the factor light in plant communities and its importance for matter production. *Ann. Bot.* **95**, 549–567.

Myneni, R. B., Nemani, R. and Running, S. W. 1997. Estimation of global leaf area index and absorbed PAR using radiative transfer models. *IEEE Trans. Geosci. Rem. Sens.* **35**, 1380–1393.

Nemani, R. R., Keeling, C. D., Hashimoto, H., Jolly, W. M., Piper, S. C. and co-authors. 2003. Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science* **300**, 1560–1563.

NOAA (National Oceanic and Atmospheric Administration). 1988. Data Announcement 88-MGG-02: Digital Relief of the Surface of the Earth. National Geophysical Data Center, Boulder, CO.

Pan, Y., McGuire, A. D., Kicklighter, D. W. and Melillo, J. M. 1996. The importance of climate and soils for estimates of net primary production: a sensitivity analysis with the terrestrial ecosystem model. *Global Change Biol.* **2**, 5–23.

Parton, W. J., Scurlock, J. M. O., Ojima, D. S., Gilmanov, T. G., Scholes, R. J., and co-authors. 1993. Observations and modeling of biomass and soil organic matter dynamics for the grassland biome worldwide. *Global Biogeochem. Cycles* **7**, 785–809.

Potter, C. S., Klooster, S. and Brooks, V. 1999. Interannual variability in terrestrial net primary production: exploration of trends and controls on regional to global scales. *Ecosystems* **2**, 36–48.

Rossow, W. B. and Dueñas, E. N. 2004. The International Satellite Cloud Climatology Project (ISCCP) Web site. *Bull. Am. Meteorol. Soc.* **85**, 167–172.

Sasai, T., Ichii, K., Yamaguchi, Y. and Nemani, R. 2005. Simulating terrestrial carbon fluxes using the new biosphere model BEAMS: Biosphere model integrating Eco-physiological And Mechanistic approaches using Satellite data. *J. Geophys. Res.* **110**, G02014, doi: 10.1029/2005JG000045.

Saxton, K. E., Rawls, W. J., Romberger, J. S. and Papendick, R. I. 1986. Estimating generalized soil-water characteristics from texture. *Soil Sci. Soc. Am. J.* **50**, 1031–1036.

Simmons, A. J. and Gibson, J. K. 2000. The ERA-40 Project Plan. ERA-40 Project Report Series ECMWF, Reading, UK.

Simmons, A. J., Jones, P. D., da Costa Bechtold, V., Beljaars, A. C. M., Kallberg, P. W. and co-authors. 2004. Comparison of trends and low-frequency variability in CRU, ERA-40, and NCEP/NCAR analyses of surface air temperature. *J. Geophys. Res.* **109**, D24115, doi: 10.1029/2004JD005306.

Still, C. J., Berry, J. A., Collatz, G. J. and DeFries, R. S. 2003. Global distribution of C_3 and C_4 vegetation: carbon cycle implications. *Global Biogeochem. Cycles* **17**, 1006, doi: 10.1029/2001GB001807.

Trenberth, K. E., Stepaniak, D. P. and Caron, J. M. 2002. Accuracy of atmospheric energy budgets from analyses. *J. Clim.* **15**, 3343–3360.

Uppala, S. M., Kållberg, P. W., Simmons, A. J., Andrae, U., da Costa Bechtold, V. and co-authors. 2005. The ERA-40 re-analysis. *Quart. J. R. Meteorol. Soc.* **131**, 2961–3012.

Valentini, R., Matteucci, G., Dolman, A. J., Schulze, E.-D., Redmann, C., and co-authors. 2000. Respiration as the main determinant of carbon balance in European forests. *Nature* **404**, 861–865.

Wild, M., Gilgen, H., Roesch, A., Ohmura, A., Long, C. N. and co-authors.2005. From dimming to brightening: decadal changes in solar radiation at Earth's surface. *Science* **308**, 847–850.

Xie, P. and Arkin, P. A. 1997. Global precipitation: a 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. *Bull. Am. Meteorol. Soc.* **78**, 2539–2558.

Zeng, N., Mariotti, A. and Wetzel, P. 2005. Terrestrial mechanisms of interannual CO_2 variability. *Global Biogeochem. Cycles* **19**, GB1016, doi: 10.1029/2004GB002273.

Zhao, M., Running, S. W. and Nemani, R. R. 2006. Sensitivity of moderate resolution Imaging Spectrometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalysis. *J. Geophys. Res.* **111**, G01002, doi: 10.1029/2004JG000004.

Zheng, D., Prince, S. and Wright, R. 2003. Terrestrial net primary production estimates for 0.5° grid cells from field observations – a contribution to global biogeochemical modeling. *Global Change Biol.* **9**, 46–64.

Zobler, L. 1986. A world soil file for global climate modeling. NASA Technical Memorandum 87802, NASA Goddard Institute for Space Studies, New York.