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Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) Terrestrial Primary Production to the Accuracy of Meteorological Reanalyses

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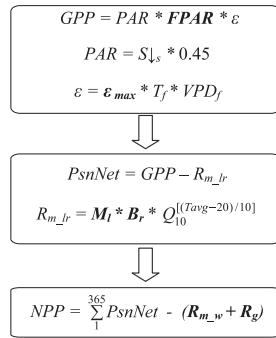NASA Ames Research Center, Moffett Field, California, USA

[1] The Moderate Resolution Imaging Spectroradiometer (MODIS) on board NASA's satellites, Terra and Aqua, dramatically improves our ability to accurately and continuously monitor the terrestrial biosphere. MODIS information is used to estimate global terrestrial primary production weekly and annually in near-real time at a 1-km resolution. MODIS terrestrial primary production requires daily gridded assimilation meteorological data as inputs, and the accuracy of the existing meteorological reanalysis data sets show marked differences both spatially and temporally. This study compares surface meteorological data sets from three well-documented global reanalyses, NASA Data Assimilation Office (DAO), European Centre for Medium-Range Weather Forecasts (ECMWF) (ERA-40) and National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis 1, with observed weather station data and other gridded data interpolated from the observations, to evaluate the sensitivity of MODIS global terrestrial gross and net primary production (GPP and NPP) to the uncertainties of meteorological inputs both in the United States and the global vegetated areas. NCEP tends to overestimate surface solar radiation, and underestimate both temperature and vapor pressure deficit (VPD). ECMWF has the highest accuracy but its radiation is lower in tropical regions, and the accuracy of DAO lies between NCEP and ECMWF. Biases in temperature are mainly responsible for large VPD biases in reanalyses. MODIS NPP contains more uncertainties than GPP. Global total MODIS GPP and NPP driven by DAO, ECMWF, and NCEP show notable differences (>20 Pg C/yr) with the highest estimates from NCEP and the lowest from ECMWF. Again, the DAO results lie somewhere between NCEP and ECMWF estimates. Spatially, the larger discrepancies among reanalyses and their derived MODIS GPP and NPP occur in the tropics. These results reveal that the biases in meteorological reanalyses can introduce substantial error into GPP and NPP estimations, and emphasize the need to minimize these biases to improve the quality of MODIS GPP and NPP products.

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1. Introduction

[2] Terrestrial Net Primary Production (NPP) is the net carbon fixed by vegetation from the atmosphere and equals the difference between gross primary production (GPP) and plant respiration (hereafter R_{plant}). Net ecosystem exchange (NEE) is the difference between NPP and heterotrophic respiration, and thus accurate estimates of NPP can increase confidence in estimations of NEE. NPP has received more attention not only because it is related to the global carbon cycle, but also because it is greatly influenced by the associated effects of a changing climate on that carbon cycle [*Prentice et al.*, 2001]. At the regional or global scale, NPP can be estimated by process-based ecosystem models, which are based on the fundamental mechanisms controlling NPP, such as moisture, temperature, solar radiation and nutrition [*Running and Coughlan*, 1988; *Parton et al.*, 1992; *Melillo et al.*, 1993]. These ecosystem models, however, generally estimate potential NPP, primarily because of the difficulty in obtaining existing and detailed land cover and soil information. Satellite remote sensing

$$GPP = PAR * FPAR * \varepsilon$$

$$PAR = S\downarrow_s * 0.45$$

$$\varepsilon = \varepsilon_{max} * T_f * VPD_f$$

$$PsnNet = GPP - R_{m\_lr}$$

$$R_{m\_lr} = M_l * B_r * Q_{10}^{[(Tavg-20)/10]}$$

$$NPP = \sum_{1}^{365} PsnNet - (R_{m\_w} + R_g)$$

The variables in bold font are determined by MODIS inputs; including MODIS land cover and 8-day MODIS **FPAR/LAI**. Where:

GPP	=	gross primary production (g C/m^2/d)
PAR	=	downward photosynthetically active radiation (MJ/m^2/d)
FPAR	=	fraction of PAR absorbed by the plant canopy
ε	=	light use efficiency parameter (g C /MJ)
$S\downarrow_s$	=	downward surface solar shortwave radiation (MJ/m^2/d)
$\boldsymbol{\varepsilon_{max}}$	=	maximum ε under optimal conditions (g C /MJ), determined by land cover
T_f	=	daily minimum temperature (T_{min}, ºC) scalar
VPD_f	=	vapor pressure deficits (VPD) scalar
PsnNet	=	net photosynthesis (g C/m^2/d)
R_{m_lr}	=	maintenance respiration from living leaves and fine roots (g C/m^2/d)
$\boldsymbol{M_l}$	=	living biomass for leaves and fine roots (g C/m^2), derived from **LAI**
$\boldsymbol{B_r}$	=	base respiration value (g C/g C/d), determined by land cover
Q_{10}	=	respiration quotient, equal to 2.0
T_{avg}	=	daily average air temperature (ºC)
NPP	=	annual net primary production (g C/m^2/y)
$\boldsymbol{R_{m\_w}}$	=	annual maintenance respiration from living wood (g C/m^2/y)
$\boldsymbol{R_g}$	=	annual growth respiration (g C/m^2/y)

Figure 1. Flowchart and acronyms of the MODIS global 1-km GPP and NPP algorithm.

data can provide near-real time information regarding vegetation cover, biome type, and disturbances, including wildfires, insect outbreaks and logging. As a result, models using satellite data make NPP estimation simpler and possibly more accurate [*Prince*, 1991; *Potter et al.*, 1993; *Running and Hunt*, 1993; *Ruimy et al.*, 1994; *Field et al.*, 1995]. In December 1999, the first Earth Observing System (EOS) satellite Terra was launched, and in February 2000, the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard began to provide information used to estimate global primary production at a 1-km resolution at 8-day intervals, which is known as MOD17 in MODIS land products [*Justice et al.*, 2002]. This consistent data set will benefit our understanding of the global carbon cycle and will be useful in natural resource management [*Running et al.*, 2004].

[3] Surface meteorological data are critical drivers for remotely sensed NPP estimates. Regular gridded reanalysis data sets, such as ECMWF and NCEP/NCAR, have been widely used to estimate regional or global NPP [*Knorr and Heimann*, 1995; *Behrenfeld et al.*, 2001; *Hicke et al.*, 2002a, 2002b; *Nemani et al.*, 2003; *Potter et al.*, 2003, 2004; *Hashimoto et al.*, 2004]. The NPP model driven by a long-term reanalysis data set and remotely sensed data has enabled us to gain a better understanding of recent global NPP variability under a changing climate [*Nemani et al.*, 2003]. Similarly, MOD17 uses a daily surface meteorolog-

ical data set from NASA's Data Assimilation Office (DAO). Reanalysis data sets have been generated by many different analysis systems, and their accuracies are temporally and spatially dependent on changing observing systems and unevenly distributed observation sites [*Kistler et al.*, 2001]. Moreover, even for the same reanalysis data set, the reliability of the variables differs [*Kalnay et al.*, 1996]. As a result, different choices of reanalysis data sets may generate different NPP estimates. Although there has been some work done on validation or inter-comparison of reanalyses with observations [*World Meteorological Organization* (WMO), 1998], most of the work is for earlier versions of the reanalyses (e.g., ERA-15 of ECMWF, GEOS 1 of DAO), or concentrates on only a few variables. None relates reanalysis accuracy to uncertainty in NPP estimates. There is still little known about the surface variable accuracies of reanalysis data sets and their impacts on NPP estimates.

[4] The objectives of this paper are (1) to evaluate the accuracy of three well-documented reanalyses, DAO, ECMWF, and NCEP, by comparing them to observed weather station data and other gridded data interpolated from the observations such as the Climatic Research Unit (CRU at the University of East Anglia) data set, and surface downward full-sky shortwave solar radiation from the latest International Satellite Cloud Climatology Project (ISCCP) data set developed at NASA Goddard Institute for Space Studies (GISS); (2) to compare MODIS GPP/NPP driven by the observed meteorological data to those driven by the three reanalysis data sets at the site level over the United States; and (3) to assess the global impacts of the uncertainties in meteorological inputs on the terrestrial productivity estimations by intercomparison of global 1-km MODIS GPP/NPP driven by the three reanalyses. We focus on MOD17 annual GPP and NPP, and surface meteorology inputs, including solar radiation, temperature, and vapor pressure.

2. Description of MODIS GPP and NPP

[5] MOD17 is the first continuous satellite-driven data set monitoring global vegetation productivity at 1-km resolution over 109,782,756 km^2 of vegetated land surface, providing 8-day composite GPP, net photosynthesis (PsnNet), and annual total GPP and NPP. The algorithm is based on the original logic of *Monteith* [1972] suggesting that the NPP of well watered and fertilized annual crops is linearly related to the amount of solar energy absorbed by the plants over a growing season. Combined with climatic controls on NPP [*Churkina and Running*, 1998] and lessons learned from a general process-based ecosystem model, BIOME-BGC [*Running and Hunt*, 1993], the algorithm was developed using satellite-derived land cover, fractional photosynthetically active radiation (FPAR), and leaf area index (LAI) as input surface vegetation information [*Running et al.*, 2000].

[6] Figure 1 provides a flowchart for the MOD17 algorithm and the acronyms for related variables. R$_{plant}$ is functionally divided into both maintenance and growth respiration. The biome-dependent parameters involved in the algorithm are stored in a Biome Properties Look-Up Table (BPLUT). The required meteorological variables for driving MOD17 are derived from DAO, including daily

surface shortwave solar radiation ($S{\downarrow}_s$), minimum air temperature (T_{min}), average air temperature (T_{avg}) and vapor pressure deficit (VPD). The VPD is the difference between saturated air vapor pressure (e_s) determined by air temperature [*Murray*, 1967] and actual air vapor pressure (e_a). Remotely sensed data for MOD17 inputs include MODIS global 1-km land cover [*Friedl et al.*, 2002], and the 8-day MODIS 1-km FPAR and LAI product[*Myneni et al.*, 2002]. MODIS land cover is converted into a biome type for each pixel to ascertain the corresponding parameters in the BPLUT. LAI is used to estimate the biomass of living organs, including leaves, fine roots, and live wood, on the basis of allometric relationships. The resulting estimate of living biomass is used for calculation of R_{plant}. More details regarding the algorithm and BPLUT can be found elsewhere [*Running et al.*, 2000; *Heinsch et al.*, 2005; *Running et al.*, 2004; *Zhao et al.*, 2005] (see also F. A. Heinsch et al., User's guide, GPP and NPP (MOD 17A2/A3) products, NASA MODIS land algorithm, version 2.0, December 2, 2003, available at http://www.ntsg.umt.edu/modis/MOD17Users-Guide.pdf).

[7] Recent validation work on improved MOD17 has shown that there is no consistent overestimation or underestimation compared to GPP derived from flux tower measurements and field observed NPP, and MOD17 can spatially and temporally capture GPP and NPP across a diverse range of biomes and climate regimes [*Turner et al.*, 2003; *Heinsch et al.*, 2005; *Zhao et al.*, 2005]. The direct comparison of MODIS annual GPP (MOD17A3) with observations for 38 site years has resulted in a high correlation and lower bias (r = 0.859 ± 0.173, relative error = 24%) [*Heinsch et al.*, 2005]. However, uncertainties from land cover, FPAR/LAI, and especially, daily meteorological inputs, can render substantial inaccuracies to MOD17 GPP and NPP estimates [*Heinsch et al.*, 2005].

3. Data Sets and Methods

[8] While there are only 4 years of MODIS GPP and NPP data, beginning in early 2000, the evaluation of uncertainties of meteorological reanalysis data related to the observations can begin in 1961.

3.1. Global Reanalysis Meteorological Data Sets

[9] DAO data for 2000 to 2003 (data are not available prior to 2000) are used in the study, and the assimilation system for DAO generation is GEOS402. The primary DAO data set is a 3-hour global product with $1° \times 1.25°$ (latitude $\times$ longitude) spatial resolution. It provides surface downward shortwave radiation, surface air pressure, 10-m air temperature and specific humidity. Detailed information on the GEOS analysis system and DAO data set can be found elsewhere [*DAO*, 2002; *Global Modeling and Assimilation Office* (*GMAO*), 2004]. Temperature and humidity in the other data sets are reported at a height of 2 m above the surface whereas DAO is reported at 10 m. Admittedly there are differences in temperature and humidity between 10 m and 2 m, but these differences should be negligible at kilometer scales. DAO atmospheric e_a was calculated using specific humidity and surface pressure.

[10] Daily ECMWF (latest ERA-40) data from 1961 to 2001 are also used in this study. The data are produced four times per day with a $2.5° \times 2.5°$ spatial resolution (http://www.ecmwf.int). Surface downward solar radiation and 2-m air and dewpoint temperatures were extracted for the study. Further information on this ECMWF reanalysis project can be found elsewhere [*European Centre for Medium-Range Weather Forecasts* (*ECMWF*), 2000]. ECMWF e_a was calculated from dewpoint temperature.

[11] Daily NCEP data from 1961 to 2003 are included in this analysis. NCEP data are provided four times per day in global Gaussian grid (T62, 192×94 points), with approximately a $1.9° \times 1.875°$ spatial resolution (http://www.cdc.noaa.gov). The variables used include surface downward solar radiation, surface air pressure, 2-m specific humidity, average temperature and extreme temperatures. More details on NCEP reanalysis are available elsewhere [*Kalnay et al.*, 1996; *Kistler et al.*, 2001]. The e_a was calculated using specific humidity and surface pressure.

3.2. Observed Meteorological Data Sets

[12] We used two types of observed data: (1) gridded data, such as CRU and ISCCP, and (2) point-source weather station data, including data collected over the United States and from World Meteorology Organization (WMO) stations.

3.2.1. Gridded Data Sets

[13] Monthly CRU climatology (1961–1990 mean) was used to evaluate the quality of T_{avg}, e_a and VPD for the three reanalysis data sets. The CRU at the University of East Anglia collected data from as many stations as possible to develop both monthly mean climatology (1961 to 1990) and time series (1901–2002) of various climate variables [*New et al.*, 1999, 2000], using a thin-spline interpolation [*Hutchinson*, 1995] with consideration of elevation effects. This data set has a spatial resolution of $0.5° \times 0.5°$. Strictly speaking, CRU is not an observed data set. However, we treat it as the observed as it is solely dependent on the observations from weather station with some uncertainties arising from the spatial interpolation scheme.

[14] The surface downward full-sky shortwave radiation from the latest ISCCP data set [*Zhang et al.*, 2004] was used to assess the accuracy of $S{\downarrow}_s$ from the three reanalysis data sets. The ISCCP was generated from GISS/NASA at 280-km intervals for an 18-year period from July 1983 to June 2001. To simplify the data process, only 17 years of ISCCP data (1984–2000) were used in this study. The equal-area ISCCP was first mapped to geographic projection at a $2.5° \times 2.5°$ resolution, and then resampled to $0.5°$ using spatial nonlinear interpolation (discussed in section 3.5) for further use. Although ISCCP $S{\downarrow}_s$ was derived from satellite and model data, it had been validated by ground observations and been proven highly accurate with a mean (RMSE) difference of 2.0 (18.5) W m^{-2} and a correlation coefficient 0.98 [*Zhang et al.*, 2004]. $S{\downarrow}_s$ from monthly mean ISCCP and from reanalyses for the same period were averaged for further comparison.

3.2.2. Weather Station Data From United States

[15] United States observation data (hereafter USA-OBS) were collected from agricultural or automated weather stations (n = 323, Figure 2a) over 21 states for 2001 and 2002. However, similar data were not available for remaining states. These valuable 323 weather stations' observed daily meteorological data, including solar radiation, were obtained from 19 different websites (not listed here) with
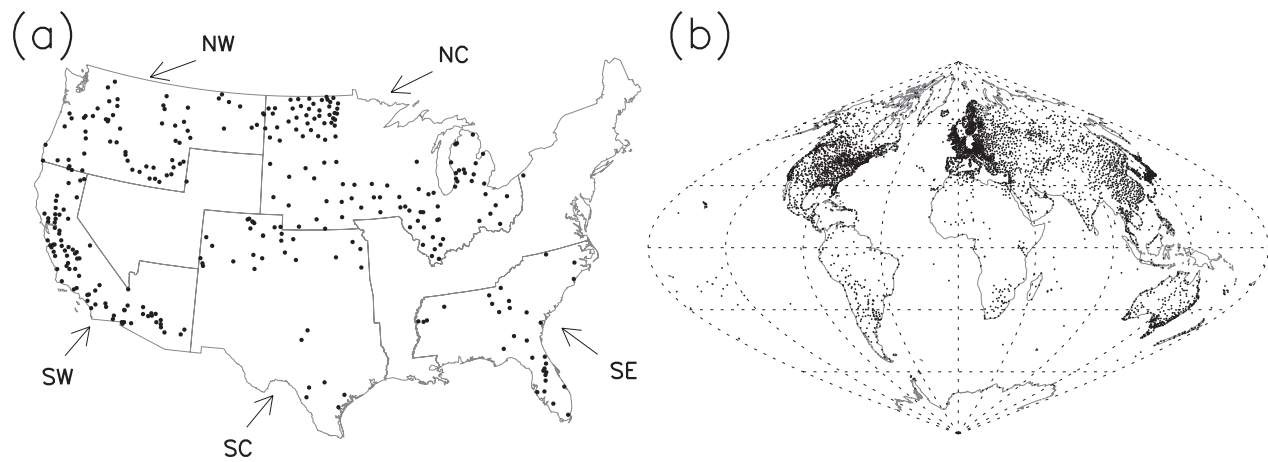
Figure 2. (a) Distribution of weather stations with daily solar radiation observations collected from 21 states in the United States (n = 323). These states are grouped into five regions, including northwest (NW), southwest (SW), north-central (NC), south-central (SC), and southeast (SE). (b) Distribution of WMO weather stations (n > 5000) without observed solar radiation.

different data formats. After these data were downloaded, they were cleaned so that they have the same format. The major difference between USA-OBS and the data from WMO discussed below is that the former have daily solar radiation observation, while the latter have no radiation record. Therefore the USA-OBS enables us not only to evaluate the accuracy of all the meteorological variables required by MOD17 at the local level, but also to directly test the impacts of uncertainties in reanalyses on MOD17. However, further information on the absolute accuracies of USA-OBS data from these agricultural or automated weather stations is not available. USA-OBS e_a was calculated from observed relative humidity and temperature, or directly computed from observed dew point owing to different observed variable to represent air humidity for different stations.

3.2.3. Weather Station Data From WMO

[16] The data for WMO stations (n > 5,000, Figure 2b) are from 2000–2003 (hereafter WMO-OBS) and can be downloaded from the National Climatic Data Center (NCDC) website (http://www.ncdc.noaa.gov). WMO-OBS was used to evaluate uncertainties of daily T_{avg}, e_a and VPD but not $S{\downarrow}_s$. Its e_a was derived from daily dewpoint temperature.

[17] We acknowledge there are some uncertainties involved in a direct comparison of coarse resolution gridded reanalyses with USA-OBS and WMO-OBS from weather stations. The observed data from weather stations are influenced by local environmental conditions such as topography and land cover. Reanalyses data, on the other hand, provide predictions for relative large scales. However, observed data are the only data we can use as a baseline, and the comparison of reanalyses with observations from a large number of weather stations can give us general information on the uncertainties of reanalysis data sets.

3.3. Additional Ancillary Data Sets

[18] Collection 3 MODIS global 1-km land cover [*Friedl et al.*, 2002], and Collection 4 MODIS global 1-km 8-day FPAR/LAI from 2000 to 2003 [*Myneni et al.*, 2002] were

used as remotely sensed data to drive the MOD17 algorithm as shown in Figure 1. MOD17 only generates GPP/NPP for vegetated areas, excluding areas with sparse or no vegetation cover such as barren areas, urban areas, and water bodies. To rule out data on nonvegetated areas for gridded meteorological data sets, we generated 0.5° global vegetation mask files based on MODIS land cover for further use with all analyses. To validate global MODIS NPP driven by different reanalysis data sets, the class C 0.5° EMDI (Ecosystem Model-Data Intercomparison) NPP data set [*Olson et al.*, 2001] was used as a baseline.

3.4. MODIS GPP/NPP

[19] Prior to late February 2000, FPAR/LAI are not available, and these missing periods were filled by averaging the corresponding 8-day FPAR/LAI from 2001 to 2003 that met the criteria for good quality assessment (i.e., without snow and cloud contamination, more details are available from *Zhao et al.* [2005]), in order to calculate a complete annual MODIS GPP and NPP data set for the year 2000.

3.4.1. United States 5 km by 5 km Subsets

[20] For each USA-OBS site, we used the MOD17 algorithm to calculate annual GPP and NPP. The algorithm was run for a 5 km by 5 km subset centered on the site using the correspondingly averaged 8-day MODIS FPAR/LAI of the dominant MODIS land cover. We then replaced the daily observed meteorological data with DAO, ECMWF and NCEP data to assess how uncertainties propagate from these reanalyses to annual GPP and NPP at the site level.

3.4.2. Global 1-km Data

[21] To evaluate the uncertainties in global 1-km MODIS GPP and NPP due to different reanalysis inputs, MOD17 was driven by ECMWF for 2000 and 2001, and by NCEP from 2000 to 2003. Improved MOD17 products driven by DAO from 2000 to 2003 are directly available at http://ntsg.umt.edu/. The major difference between the improved MOD17 used here and Collection 4 MOD17 located at the EOS data gateway (http://edcimswww.cr.usgs.gov) is that the improved MOD17 data have temporally filled the
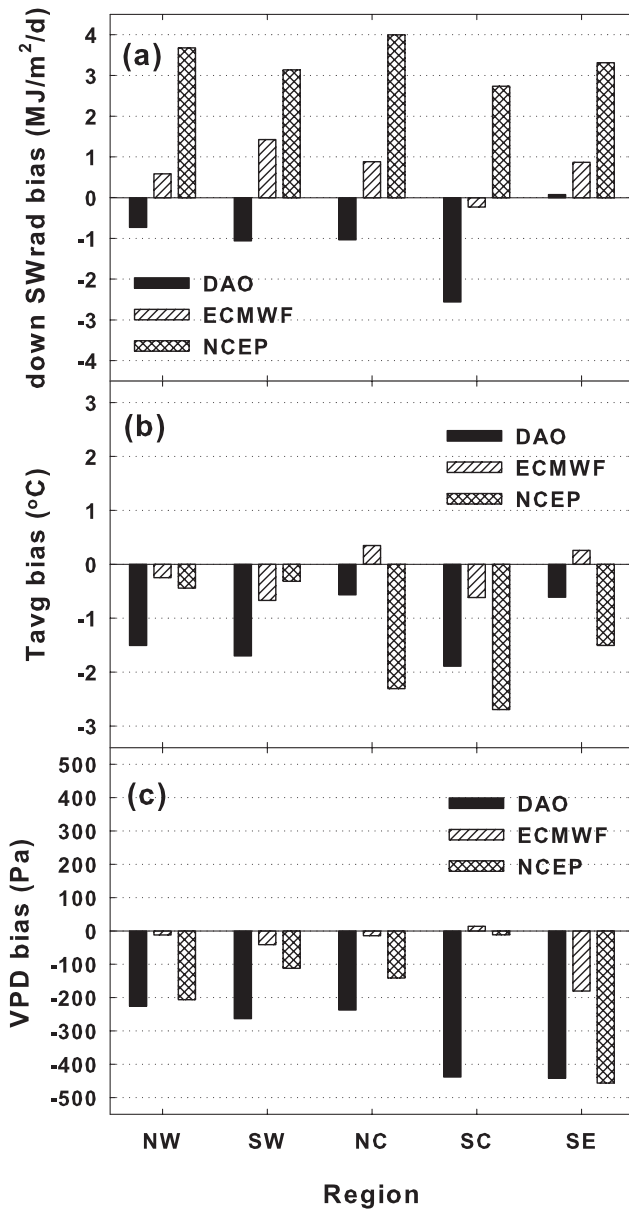
Figure 3. Bias of (a) daily solar radiation ($S\downarrow_s$), (b) average temperature (T_{avg}), and (c) vapor pressure deficit (VPD) for the three reanalyses compared to the observations from the stations (n = 323) in the five regions of the United States (see Figure 2a) from 2001 to 2002 (only 2001 for ECMWF).

missing or cloud contaminated FPAR/LAI, and spatially interpolated coarse resolution DAO data to the 1-km MODIS pixel level [*Zhao et al.*, 2005]. The calculation of GPP/NPP for the USA-OBS subsets and global 1-km data driven by ECMWF and NCEP uses the same approach to handle contaminated FPAR/LAI and the spatial resolution mismatch between reanalyses and MODIS data as those used to improve MOD17 driven by DAO [*Zhao et al.*, 2005].

3.5. Methods

[22] Bias, correlation and RMSE were used to evaluate accuracy and uncertainty. A relative error term (RE) is used to evaluate uncertainties in GPP and NPP for the USA subsets, such that

$$RE(\%) = \frac{\sum\limits_{i=1}^{n} \frac{P_r - P_o}{P_o}}{n} \times 100, \qquad (1)$$

where P_r is GPP or NPP driven by the reanalyses, P_o is the corresponding value driven by observed meteorological data, and n is the number of samples used in the analysis.

[23] To investigate spatial differences in the accuracy of reanalysis data over the United States, the 21 states with weather stations in USA-OBS were roughly grouped into five regions: northwest (NW), southwest (SW), north-central (NC), south-central (SC) and southeast (SE), while the remaining states were omitted from the study (Figure 2a). Spatial nonlinear interpolation was employed to interpolate the reanalyses to USA-OBS or WMO weather station locations. The spatial nonlinear function is the fourth power of cosine with the spherical distances of a given point (lat/lon) to the surrounding four coarse-resolution cells as independent variables, providing weighting values for the interpolation of coarse-resolution data into fine resolution. The method has been proven effective to smooth coarse-resolution data and enhance the accuracy of meteorological data at the local level as compared to the nearest neighbor method; further details on the method are given by *Zhao et al.* [2005].

[24] For the comparison of surface variables from reanalysis with 0.5°CRU and ISCCP, reanalysis data sets were nonlinearly interpolated to 0.5° as discussed above. For the global data comparison, we compared the annual zonal mean or total, to get a general distribution of uncertainties. Prior to 2000, DAO data were not available, and after 2001, no complete annual ECMWF data sets were available. Therefore we compared the ECMWF and NCEP climatology with 30-year CRU and 17-year ISCCP first, and then compared the ECMWF and NCEP data with the DAO data from 2000 to 2001 to indirectly infer the accuracy of DAO. We acknowledge such indirect comparison may bias our conclusions on DAO accuracy.

4. Results and Discussion

4.1. Comparison of Meteorological Data Sets

4.1.1. Comparisons Over the United States

[25] Figure 3 shows that the biases of annual mean $S\downarrow_s$, T_{avg} and VPD from the three reanalyses against the USA-OBS are regionally dependent. For these three variables, ECMWF tends to have the lowest absolute bias among reanalyses. Both DAO and NCEP tend to underestimate T_{avg} and VPD, and NCEP has the highest positive bias in $S\downarrow_s$ (approximately 3 MJ/m²/d).

4.1.2. Global Comparisons

[26] For the $S\downarrow_s$ comparison below, we have accounted for the overestimation $S\downarrow_s$ of ISCCP from 15°S to 15°N with a bias of 21.318 W/m² (equivalent to 1.84 MJ/m²/d) relative to the surface observations [*Zhang et al.*, 2004]. NCEP always overestimates $S\downarrow_s$ when compared to 17-year ISCCP annual mean by latitude (Figure 4a), and its bias relative to ISCCP ranges from 1.41 to 5.15 MJ/m²/d (+6.8% to +73% of ISCCP). The NCEP area-weighted average bias
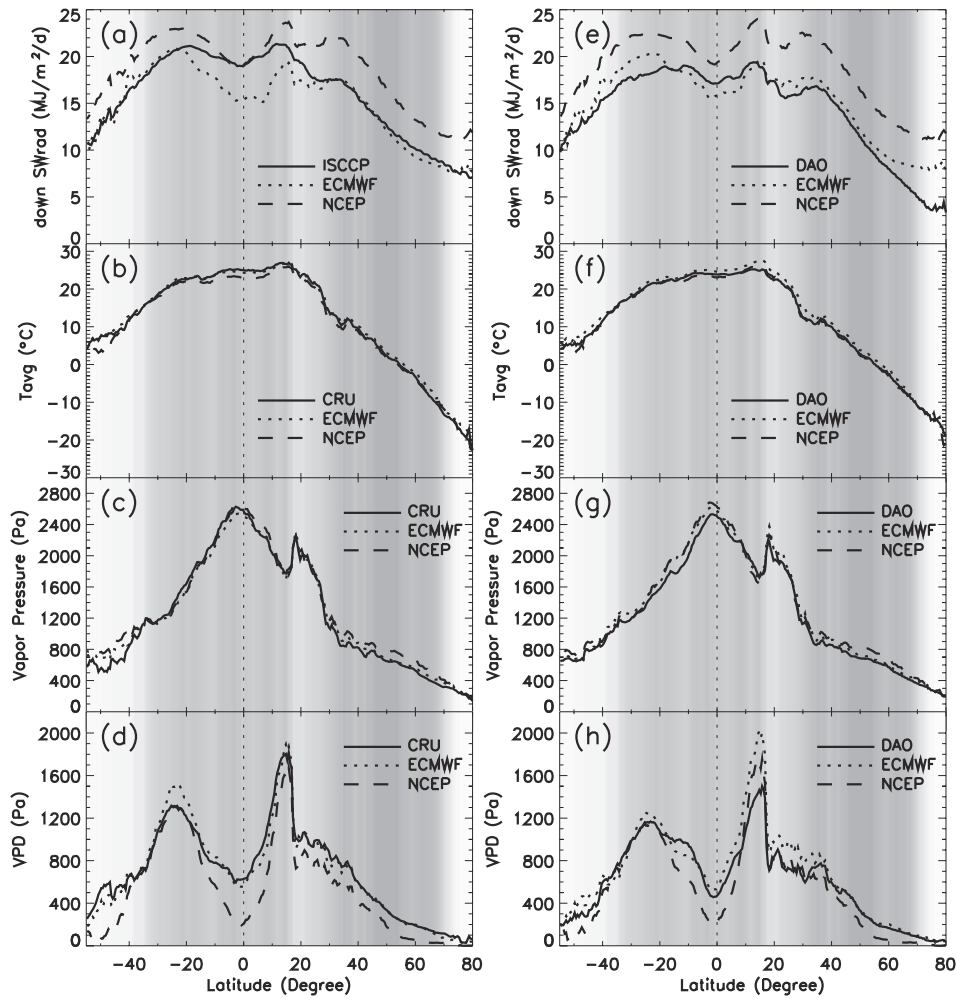
Figure 4. Comparison of the climatological zonal mean of (a) surface downward solar radiation ($S\downarrow_s$), (b) average temperature (T_{avg}), (c) vapor pressure (e_a), and (d) vapor pressure deficit (VPD) from NCEP and ECMWF, with ISCCP (1984–2000) and CRU (1961–1990) data sets. (e–hσ) Intercomparison of the three reanalyses for 2000 and 2001. Overestimated surface short wave radiation by ISCCP from 15°S to 15°N with bias of 21.318 W/m² (equivalent to 1.84 MJ/m²/d) relative to the surface observations [*Zhang et al.*, 2004] has been accounted for in this comparison (see text). These comparisons are only for vegetated land surfaces. The vegetated land area is shown as a gray scale, where darker shades represent more vegetated areas. Vertical dotted lines denote the location of the equator.

is +20% of ISCCP $S\downarrow_s$. This higher $S\downarrow_s$ will produce overestimated global GPP and NPP if other surface variables are accurate. Generally ECMWF $S\downarrow_s$ agrees well with ISCCP, but in the tropics from 20°S to 20°N, ECMWF $S\downarrow_s$ tends to be lower, with an area-weighted average bias of −1.58 MJ/m²/d, or nearly −8.4% of ISCCP. The lower ECMWF $S\downarrow_s$ will eventually generate underestimated GPP and NPP owing to the large vegetated areas and high productivity in the tropics, if other surface variables are accurate. Compared with ECMWF and NCEP zonal mean $S\downarrow_s$ from 2000 and 2001 (Figure 4e), DAO $S\downarrow_s$ is relatively more accurate, except for much lower values in high latitudes of the Northern Hemisphere.

[27] As compared to 30-year annual mean T_{avg} in CRU (Figure 4b), NCEP tends to have lower values for almost all latitudes, with particularly large negative biases (area-weighted bias of −1.43°C) from 20°S to 20°N. ECMWF

generally agrees well with CRU, but is somewhat higher in middle high latitudes and a little lower in the tropics. For the 2000 to 2001 intercomparison (Figure 4f), NCEP tends to have the lowest T_{avg}, ECMWF has the highest; and DAO is in the middle for most latitudes. Although the bias in T_{avg} is small, a small bias in temperature can introduce relatively large errors in VPD and R_{plant} and, consequently, in global GPP and NPP because of the nonlinear relationship between T_{avg} and both VPD and maintenance respiration (Figure 1).

[28] A comparison of e_a shows that NCEP has higher values than CRU in tropical and boreal latitudes, while ECMWF agrees well with CRU (Figure 4c). The area-weighted average biases at any given latitude are relatively small, with values of 2.92 Pa (0.22%) and 64.04 Pa (4.89%) for CMWF and NCEP, respectively. The 2000 and 2001 reanalyses intercomparison (Figure 4g) shows that DAO e_a is generally good in the middle and high latitudes of the
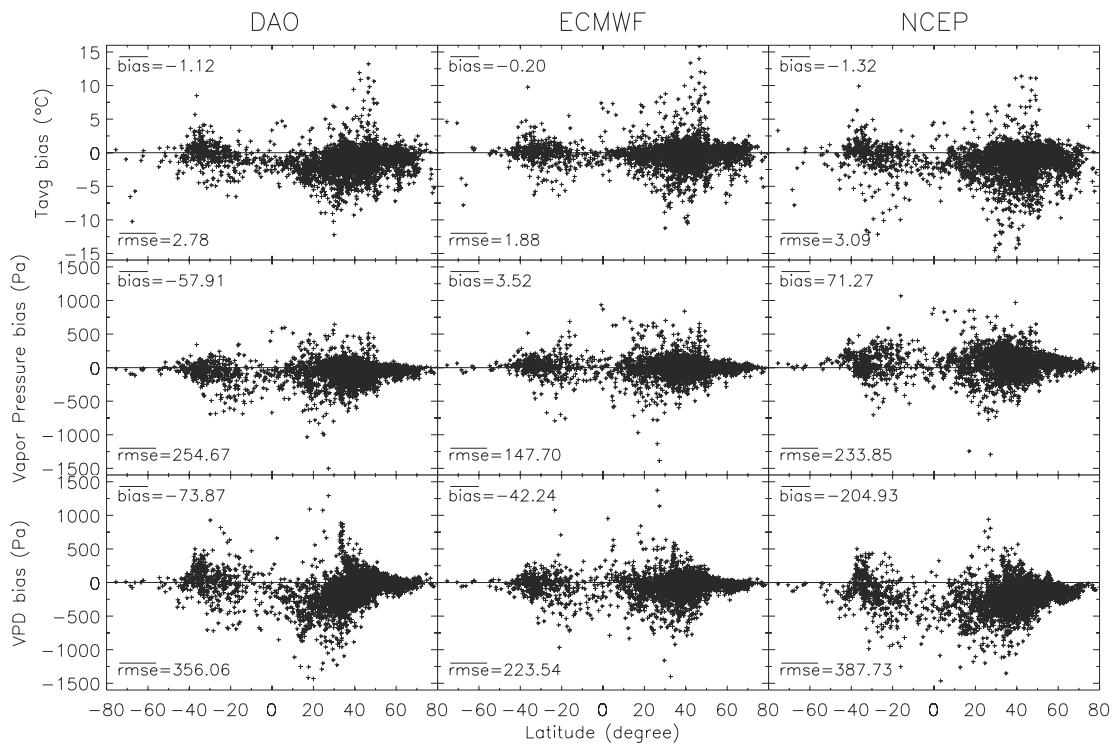
Figure 5. Latitudinal comparison of the bias of daily average temperature (T_{avg}), vapor pressure (e_a), and vapor pressure deficit (VPD) from the three reanalyses relative to observations from WMO (see Figure 2b) for 2000 to 2004 (2000 and 2001 for ECMWF).

Northern Hemisphere relative to ECMWF. DAO underestimates e_a in the tropics and Southern Hemisphere (54.75°S to 8°N), with an area-weighted bias of 102.93 Pa (5.57%) with respect to ECMWF e_a.

[29] NCEP has considerably lower VPD than both CRU and ECMWF (Figure 4d). The area-weighted mean bias along latitude reaches −185 Pa (−25.66%) as compared to CRU. The relaxed control (higher VPD$_f$) from the lower VPD will generate a higher global GPP and NPP as described by the equations in Figure 1. ECMWF generally agrees well with CRU with an area-weighted average bias of 2.55 Pa (0.35%), resulting in a negligible impact on light use efficiency (ε) and GPP. Comparison of reanalyses from 2000 and 2001 (Figure 4h) shows that DAO is closer to ECMWF than NCEP, although DAO VPD tends to be lower from approximately 5°S to 40°N, and there are some discrepancies between DAO and ECMWF at other latitudes. Both Figures 4d and 4h show that NCEP has lower VPD overall, and it is much lower in tropical areas.

[30] Bias in e_s will result in biases in VPD even if e_a bias is relatively small or negligible because VPD is calculated as e_s minus e_a [*Jolly et al.*, 2005]. In this case, the temperature bias will be the major source of bias in VPD because e_s is determined solely by temperature. Since there is a nonlinear exponential relationship between temperature and e_s, we conclude that the relatively small range of T_{avg} biases in Figures 4b and 4f are primarily responsible for the large range of VPD biases in Figures 4d and 4h. VPD is widely used as a measure of environmental water stress in ecosystem and hydrologic models, and our study highlights the need to use caution because large discrepancies in VPD could be introduced by small biases in temperature, espe-

cially for the tropics or for summer seasons in the middle and high latitudes when temperature is high.

[31] Figure 5 shows comparison of the three reanalyses with WMO-OBS from 2000 to 2003 by latitude. Generally the biases for all variables in the reanalyses increase from high to low latitudes. ECMWF has the lowest absolute mean bias and mean RMSE for all three surface variables (Figure 5), indicating that it has the highest accuracy. NCEP has the largest negative biases in T_{avg} and VPD, which is consistent with the results shown in Figures 4b and 4d. Figure 5 also indicates that a small temperature bias induces a large VPD bias as discussed previously. For example, since DAO e_a has a negative bias, VPD would have a positive bias if temperature were extremely accurate. The negative mean bias in DAO VPD, however, is caused by the reduced e_s induced by the underestimation of temperature. This explanation can also be applied to the negative ECMWF and NCEP VPD biases shown in Figure 5.

4.2. Comparison of MODIS GPP/NPP
4.2.1. United States Subsets
[32] The comparison between annual GPP/NPP values driven by USA-OBS and those driven by the three reanalyses shows that all of them tend to overestimate GPP and NPP, with NCEP having the largest bias and lowest correlation (Figure 6). DAO and ECMWF have similar accuracies in predicted GPP. ECMWF has the highest accuracy for NPP estimates with respect to NPP calculated using USA-OBS, although there is only 1 year of available data for cross comparison. It should be noted that GPP driven by reanalyses generally has higher correlations and lower biases than does NPP. Moreover, the RE values for GPP
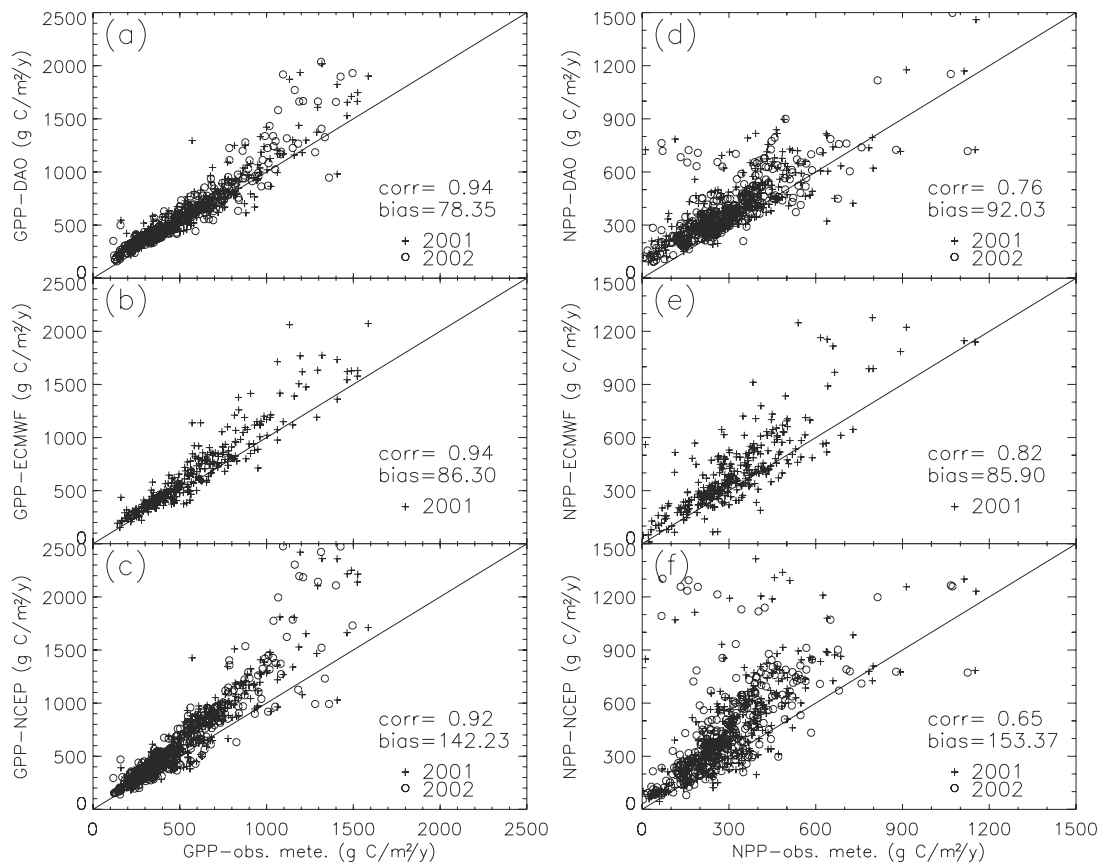
Figure 6. Comparison of MODIS GPP, and NPP driven by the three reanalyses with those driven by the observations from weather stations in the United States (n = 323) for 2001 (cross) and 2002 (circle) (2001 for ECMWF).

(DAO: 17.78%, ECMWF: 15.63%, NCEP: 23.91%) driven by the reanalyses are mush lower than that of NPP (DAO: 64.00%, ECMWF: 45.05%, NCEP: 72.87%). Consequently, the results indicate that MODIS GPP is more reliable than NPP.

[33] On the basis of the equations in Figure 1 and the reanalysis biases in Figure 3, the high GPP from NCEP results from the fact that NCEP has the highest $S\downarrow_s$ and the lowest VPD among the reanalyses. The underestimated T_{avg} results in underestimated respiration (Figure 1). High GPP together with low R_{plant} results in an overestimation of NCEP NPP. The overestimated NCEP $S\downarrow_s$ over the United States contradicts the conclusion drawn by *Hicke et al.* [2002a], in which they tend to trust NCEP with its higher $S\downarrow_s$ more than the *Bishop and Rossow* [1991] data set with lower $S\downarrow_s$ across North America. The slightly higher GPP estimate from the ECMWF data set as compared with that from USA-OBS is attributed to the slightly higher $S\downarrow_s$ of the ECMWF. This results in higher NPP because the reduced bias in ECMWF T_{avg} leads to relatively accurate estimates of R_{plant}. The results from the DAO data set are more complicated since the biases from different meteorological variables offset each other. DAO $S\downarrow_s$ tends to be low for four out of five regions and, consequently, DAO GPP should be underestimated according to the GPP equation in Figure 1. However, lower DAO VPD produces a higher ε, compensating for the effect of lower radiation and, hence,

overestimates GPP. The higher GPP combined with the lower R_{plant} from lower T_{avg}, produces a much higher bias in NPP (Figures 6a and 6d). NPP is the difference between GPP and R_{plant} and, as a result, NPP will inherit the uncertainties from meteorology on GPP and those related to R_{plant}. Ultimately, NPP contains more uncertainties than GPP.

[34] The continental United States has a denser weather station network than most other land areas in the world (Figure 2b). In theory, reanalyses should have higher quality in the United States and should generate more accurate GPP and NPP. However, our study shows that both reanalyses and the subsequent GPP and NPP estimates contain considerable uncertainties over the United States.

4.2.2. Global 1 km

[35] The global 1-km MODIS NPP results driven by the three reanalyses are shown in Figure 7, and the spatial patterns are generally similar. Tropical forests have the highest NPP values, while temperate and boreal forests are the second most productive areas. Dry areas and areas with short growing seasons have low NPP. However, differences in the magnitude of NPP among the three images can be found in most vegetated areas. The largest differences occurs in areas covered by tropical forests. ECMWF has the lowest NPP for most tropical forests, while NCEP has the highest NPP, and DAO NPP lies in between. Globally, except for very dry areas, NCEP consistently has the highest
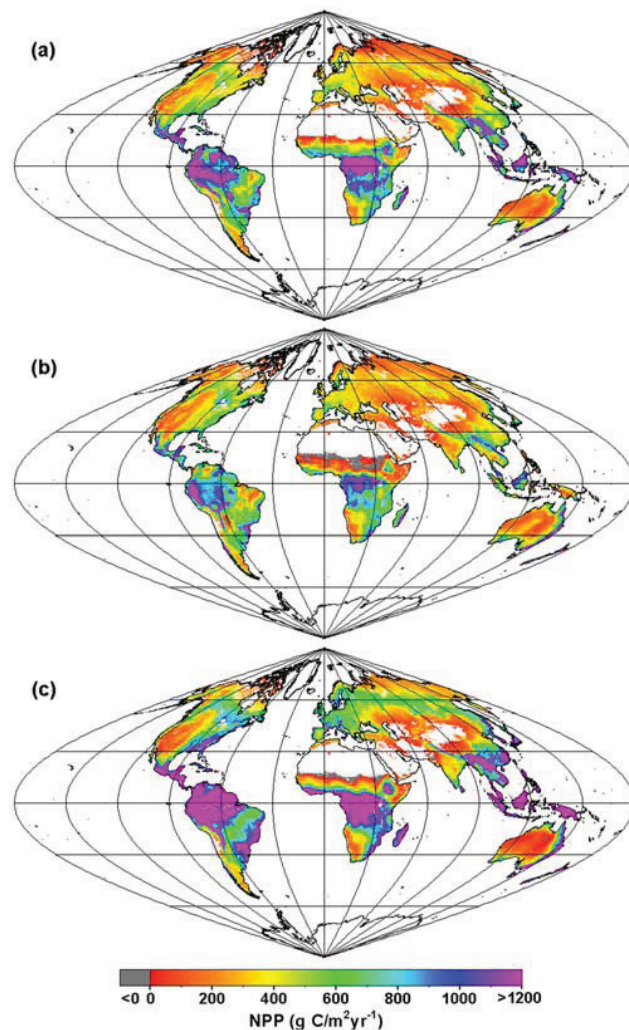
Figure 7. Results of annual averaged 4-year (2000–2003) 1-km MODIS NPP derived using (a) DAO, (b) ECMWF, and (c) NCEP. Only 2 years of data (2000–2001) are used in the ECMWF-derived NPP. Vegetated regions are shown in color, and the regions in white are nonvegetated areas, including water bodies, barren land, and built-up areas.

NPP, and ECMWF and DAO have similar NPP predictions for boreal areas. DAO and ECMWF may give relatively more reliable GPP and NPP estimates in the middle to high latitudes, since they have relatively more accurate surface meteorological data as discussed above.

[36] To remove the noise from local level data, global 1-km MODIS GPP, R_{plant} and NPP are aggregated to 0.5°, then averaged, and summarized into zonal means and totals, respectively (Figure 8). The patterns of zonal means and totals are reasonable. GPP, R_{plant} and NPP in the tropics are generally higher than those in the middle and high latitudes. The noticeable difference between them is that the zonal mean has several peaks, while the zonal total generally has two peaks, corresponding to the latitudes with large areas of tropical forests and boreal forests.

[37] Figure 8 suggests that significant differences in NPP are largely caused by the differences in GPP and not R_{plant}, although differences in R_{plant} do reinforce the differences in

NPP. Since T_{min} only constrains GPP in the early growing season in the MOD17 algorithm, VPD and $S\downarrow_s$ are the two primary factors controlling GPP during most of the growing season (Figure 1), and consequently annual total GPP is overwhelmingly determined by $S\downarrow_s$ and VPD. Because the high $S\downarrow_s$ and the low VPD in NCEP indicate the most favorable environment for plant growth, the highest GPP and the highest NPP are generated by NCEP combined with the lowest R_{plant} as NCEP has. The low ECMWF GPP estimates arise from underestimated $S\downarrow_s$ from 20°S to 20°N relative to ISCCP as discussed previously, resulting in underestimation of NPP according to the highly accurate R_{plant} generated by the extremely reliable ECMWF T_{avg}. DAO GPP may be somewhat overestimated in this area relative to ECMWF because the DAO underestimates VPD from 5°S to 30°N when compared to the more accurate ECMWF VPD. Ultimately, the real values of global GPP and NPP may lie somewhere between the estimations from the DAO and ECMWF data sets.

[38] Global total GPP and NPP are meaningful for global carbon cycle study because carbon sinks result from an increase in global terrestrial NPP [*Friedlingstein et al.*, 1995; *Thompson et al.*, 1996; *Nemani et al.*, 2003]. The 4-year values driven by the reanalyses are listed in Table 1, revealing the extraordinary differences in global total values for GPP and NPP induced by differences in the reanalyses inputs. The differences between GPP and NPP driven by NCEP and ECMWF are more than 20 Pg C per year, indicating the importance of accurate meteorological inputs to the model. Additionally, the table shows that the differences among the NPP values are always greater than those of GPP, suggesting again that NPP contains more uncertainty than GPP. The results also show that both DAO and NCEP capture the global GPP and NPP interannual variability induced by the global-scale weather patterns known as the El Niño–Southern Oscillation (ENSO) [*Hashimoto et al.*, 2004]; 2000 and 2001 are La Niña years, and 2002 and 2003 are weak El Niño years (http://www.cdc.noaa.gov). However, within the two La Niña or El Niño years, the signs for interannual anomalies among the three data sets are not consistent, especially for global NPP, further implying NPP has more uncertainties than GPP. The relatively short 4-year MODIS data set and the limited 2-year ECMWF restrict further study of the interannual variability, and more long-term data sets need to be created to determine if there are large differences in interannual variability driven by different reanalyses.

[39] Mean NPP driven by reanalyses for 2000 and 2001 are compared against the class C EMDI NPP (Figure 9). NCEP greatly overestimates NPP, but its correlation is also the highest. ECMWF and DAO NPP tend to be close to EMDI NPP but both have relatively low correlations. EMDI NPP values fall between ECMWF and DAO NPP estimations, which is consistent with the finding discussed above. It should be noted that there are uncertainties involved in these comparisons. First, the EMDI NPP data contain some uncertainties. EMDI NPP seems to be truncated at approximately 1100 g C/m²/yr, and the methods used to build EMDI NPP data sets from sparsely distributed observed NPP have uncertainties. The observed NPP data sets were measured using different approaches, and most of them only reported aboveground NPP [*Gower et al.*, 1999; *Clark et*
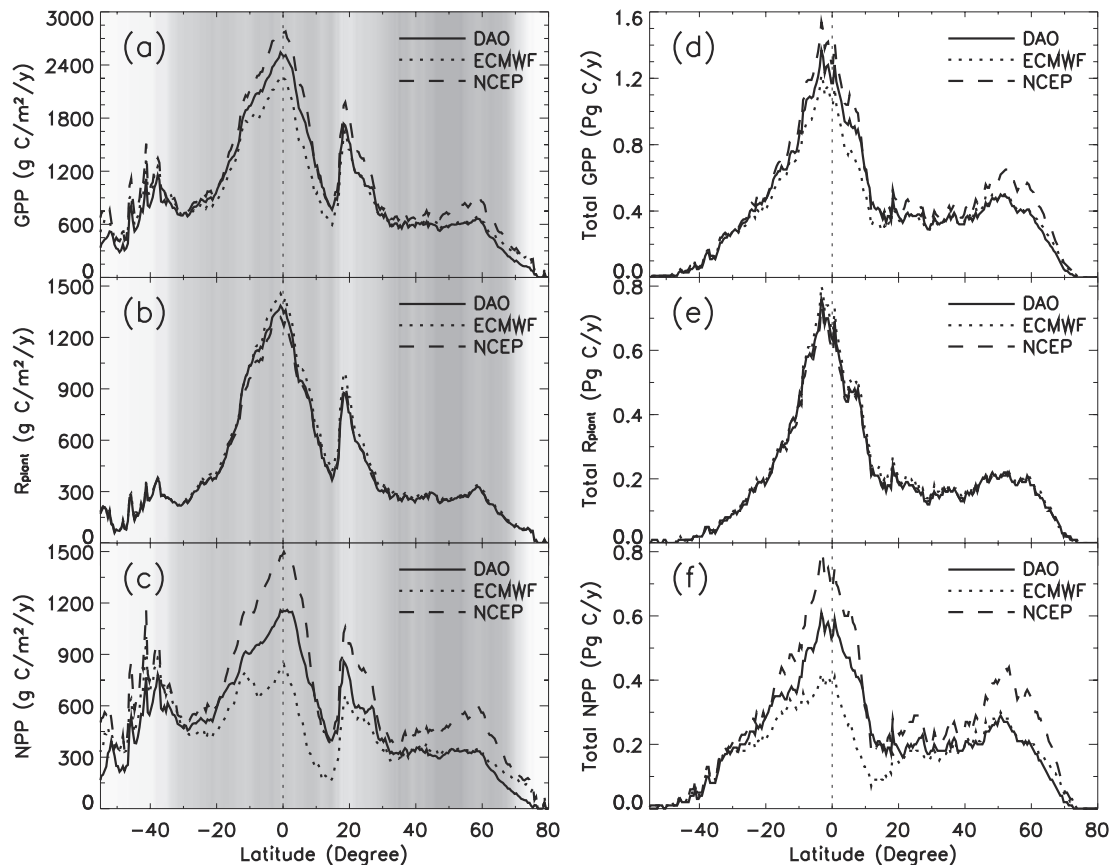
Figure 8. Comparison of the zonal mean of annual (a) GPP, (b) R_{plant}, and (c) NPP, and corresponding zonal totals (d−f) driven by the three reanalyses for 2000 and 2001 after aggregation into 0.5° intervals. The vegetated land area is shown as a gray scale, where darker shades represent more vegetation. Vertical dotted lines denote the equator.

al., 2001]. Second, NPP has interannual variability, and 2 years of MODIS NPP are insufficient for direct comparison with EMDI NPP. For consistency in comparison, we show only 2-year averaged MODIS data sets driven by reanalyses since limited ECMWF data are available after 2001. We found that 3-year mean NPP driven by DAO has a higher correlation ($r^2 = 0.77$) with EMDI NPP than the 2-year average in Figure 9a [Zhao et al., 2005]. Figure 9d shows that overall, the ensemble mean (mean of three estimations) may give better NPP estimations.

[40] Given the fact that meteorological reanalyses contain large biases, which introduce relatively large uncertainties to GPP and NPP estimations, there is a need to reduce these biases in the reanalyses to get relatively accurate GPP/NPP estimations. There are two possible approaches to reducing these biases. One approach is direct adjustment of these reanalyses on each grid at monthly step with the station records [Qian et al., 2005], and the other is to indirectly counteract biases from reanalyses by modification of parameters in the BPLUT of the MOD17 algorithm. With the first method, variations in the reanalyses meteorology will be retained on the submonthly level (hourly or daily), but the magnitude of the data will be adjusted to be equivalent to that of the monthly observations. Consequently, this method forces the reanalyses to have the same seasonal and inter-

annual variability and long-term trend as station records. More importantly, the adjusted reanalyses enable us to relatively accurately calculate historical GPP/NPP and their trends at the regional or the global scale. However, monthly gridded station records, such as CRU, are only available approximately 2 years after the date of acquisition (http://www.cru.uea.ac.uk). For the near-real time requirement of MODIS products, therefore, it is impractical to adopt the first method. The second method, modifying parameters within the BPLUT, has been partly applied during the calibration of the algorithm [Zhao et al., 2005]. However,

Table 1. Comparison of Global Total MODIS GPP and NPP Driven by Different Meteorological Data Sets From 2000 to 2003[a]

		2000	2001	2002	2003
DAO	GPP	108.42	110.76	107.82	107.50
	NPP	56.06	57.74	55.53	54.80
ECMWF	GPP	101.79	102.71	N/A[b]	N/A[b]
	NPP	46.71	46.59	N/A[b]	N/A[b]
NCEP	GPP	124.82	125.75	123.40	123.72
	NPP	73.80	73.73	72.22	72.29

[a]Units are Pg C.
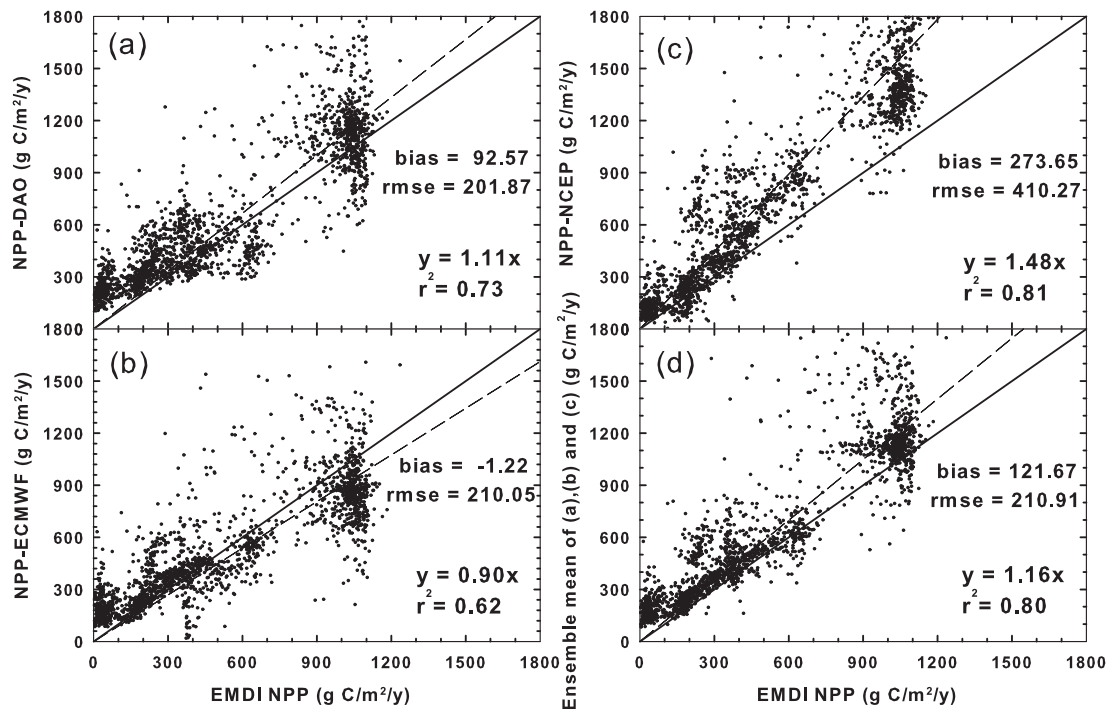[b]ECMWF reanalysis data (ERA-40) are not available after 31 August 2002.

Figure 9. (a–c) Comparison of average NPP for 2000 and 2001 driven by the three reanalyses with class C EMDI NPP, and (d) the mean NPP from averaged NPP by three reanalyses against EMDI NPP.

there are some problems with the second method. First, the modification of parameters in BPLUT to offset biases from reanalyses may result in the departure of some parameters from their theoretically optimum values. Thus, in some cases, MODIS GPP driven by DAO may contain less error than that calculated with local observed meteorology when both are compared to the GPP estimated from flux tower measurements [*Heinsch et al.*, 2005]. Second, if the reanalyses fail to accurately predict interannual variations and the long-term trends in climate, the method will give incorrect predictions of interannual variations and long-term trend in GPP and NPP as well. Regardless of these limitations, the second approach seems the only option for providing near-real time global standard MODIS GPP/ NPP products.

[41] Compared to general process-based ecosystem models, the remotely sensed global NPP model is relatively simple. The MOD17 algorithm captures the dominant environmental controls on NPP at the global scale [*Nemani et al.*, 2003], and it uses a reduced number of input meteorological variables as compared with other models, which need precipitation as an additional input. Precipitation generated by reanalyses is highly model-dependent and contains more problems than temperature, which is assimilated directly into the reanalysis system [*Janowiak et al.*, 1998]. Therefore a relative simple model with a reduced number of meteorological inputs should contain small uncertainties. However, our study shows that large uncertainties are introduced by using even minimal global meteorological variables as inputs. Reanalysis data sets, such as NCEP and ECMWF, have much higher accuracy than general circulation model (GCM) outputs [*Covey et al.*, 2000]. Therefore the complex regional NPP model driven

directly by GCM outputs may contain many more uncertainties than simplified model approaches.

5. Conclusions

[42] This study compares three reanalysis meteorological data sets with a variety of observed data, and compares remotely sensed GPP and NPP driven by these different reanalyses at both the conterminous United States and global scales. It reveals that differences in reanalyses can introduce considerable uncertainties in GPP and NPP estimates. Overestimated NCEP $S\downarrow_s$ and underestimated NCEP VPD are the dominant factors responsible for the high GPP and NPP estimates by NCEP. Underestimation of the ECMWF $S\downarrow_s$ in the tropics is the main reason for the low GPP and NPP by ECMWF for tropical forests, although ECMWF has the most accurate temperature and VPD. Underestimated VPD from DAO leads to overestimates of GPP and NPP from 5°S to 30°N. The large VPD uncertainties in the reanalyses are mainly caused by relatively small uncertainties in temperature, and not by e_a, owing to the magnification effect of the nonlinear relationship between temperature and e_s, implying the importance of some nonlinear processes in the model.

[43] Given that the reanalyses contain biases and that NPP contains more uncertainties than GPP, we propose two approaches to reduce biases from meteorological inputs, such as adjustment of reanalyses based on station observations and modification of parameters in the MOD17 BPLUT to compensate for the biases from different meteorological reanalyses. The modification of the BPLUT is the more practical option owing to the near-real time requirement of the MODIS standard products, but it may not capture the

interannual variability and trend in GPP/NPP as well as the direct adjustment of reanalyses.

[44] The tropics contain the largest uncertainties in GPP and NPP owing to the large uncertainties in the meteorological reanalyses of the region combined with the high productivity and the large vegetated areas. Given the important role of tropical forests to global carbon cycle science, and hence to global climate change, we need to expand the climate monitoring stations throughout the tropics as suggested by *Clark* [2004], to improve the accuracy of the reanalysis results resulting from a lack of observations. In addition, the reanalysis systems need to be improved to enhance the quality and accuracy of tropical surface reanalyses.

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