Simulation of Global Terrestrial Carbon Cycle using the JRA-25 Reanalysis as Forcing Data

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Abstract

The quality of climate data is critical for reliable simulations of spatial and temporal variations in the carbon budget. To examine the quality of the new dataset produced by the JMA reanalysis project (JRA-25), we applied JRA-25 data as well as data from the established climate datasets NCEP-R1, NCEP-R2, and ERA40 to the terrestrial ecosystem model Sim-CYCLE and compared the result. Using each of the datasets, we conducted global simulations for the period 1979–2001 and investigated the spatial and temporal patterns of plant uptake and the net ecosystem budget of carbon. The JRA-25 dataset provided pertinent land surface conditions with respect to solar radiation, temperature, and precipitation, resulting in moderate simulation results of terrestrial productivity and the carbon budget. Unusual conditions of the JRA-25 resulted in different regional carbon budgets such as the Amazon basin and global budgets in a few anomalous years.

1. Introduction

The terrestrial carbon cycle is a vital component of advanced climate models and critical for simulating climatic change in relation to atmospheric carbon dioxide (CO$_2$). Thus, quality climate data are vital for achieving reliable simulations by terrestrial ecosystem carbon cycle models, which simulate spatial and temporal distributions of CO$_2$ exchange in response to environmental conditions. Reanalysis climate datasets have been increasingly used for such simulations because they provide the global, long-term, physically consistent conditions required to analyze the carbon budget over recent decades. Although data observation and assimilation methods have improved dramatically, different climatic datasets sometimes provide inconsistent conditions for carbon cycle models. Terrestrial ecosystem models are so sensitive to climatic conditions that differences among forcing climatic datasets can affect simulation results (e.g., Zhao et al. 2006). Ito and Sasai (in press) suggested that three existing reanalysis climate datasets used in two terrestrial carbon cycle models produced largely different results for plant productivity and the net carbon budget. They suggested that a standard, accurate climate dataset is required to conduct more reliable simulations of global atmospheric-land CO$_2$ exchanges. In this study, we examined the properties of a new dataset (JRA-25) as forcing data for a terrestrial ecosystem model based on the results obtained using existing climate datasets.

2. Model and methods

2.1 Climate datasets

Meteorological conditions at the land surface were derived from the following four climate datasets: the JRA-25 produced by the Japan Meteorological Agency (JMA) and the Central Research Institute of Electric Power Industry (CRIEPI), the ERA40 by the European Centre for Medium-range Weather Forecasts (ECMWF) 40-year Reanalysis Project (Uppala et al. 2005), the NCEP-R1 produced by the U.S. National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR) (Kistler et al. 2001), and the NCEP-R2 by the NCEP and the U.S. Department of Energy (DOE) for the Atmosphere Model Intercomparison Project Phase II (AMIP-II) (Kanamitsu et al. 2002). These datasets are all based on the three-dimensional variational method (3D-VAR) of data assimilation but differ in spatial resolution, parameterizations, and observational data. Note that we used the evaluation version of the JRA-25 dataset (as of June 2006) and land surface conditions for soil properties and topography were used.

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2.3 Simulation and analyses

First, to remove artificial trends from the initial condition, a stable carbon budget state was obtained using each of the four reanalysis datasets. The spin-up simulations were performed for 2300 years, assuming the climate conditions and atmospheric CO₂ level in 1979, repeatedly. Then, experimental simulations were performed using the time-series climate data and atmospheric CO₂ trend (Keeling and Whorf 2004) from 1979 to 2001. The simulations provided global maps and time-series of terrestrial carbon flows and carbon stocks. In this study, we chiefly analyzed the most important indices of the terrestrial carbon cycle, i.e., NPP and NEP. The four climate datasets and corresponding simulation results were compared, with special emphasis on the JRA-25 reanalysis.

3. Results and discussion

3.1 Land surface climate conditions

The characteristics of the JRA-25 reanalysis were assessed for representative climatic conditions over the land surface determined by the land-cover data. The global average land surface air temperature, which strongly affects vegetation activity, by the JRA-25 (13.2 °C; Table 1) was comparable with the other three reanalysis datasets and the CRU data. Regionally, the JRA-25 gave lower temperatures than the ERA40 for Australia and western North America, and higher temperatures than the NCEP-R1 and NCEP-R2 for central Eurasia and the Amazon. The JRA-25 data were reasonable for downward shortwave radiation, although large variability occurred among the datasets. The global average (212 W m⁻²) fell within the range of variability among the existing datasets including the ISCCP (179–228 W m⁻²). Regionally, the JRA-25 gave higher radiation than the ERA40 and NCEP-R2 in tropical areas and lower values than the NCEP-R1 in most land areas except the Amazon. For precipitation, the JRA-25 (751 mm yr⁻¹) provided comparable values with the CMAP (743 mm yr⁻¹) but lower over land surfaces than other reanalysis datasets, especially over tropical rainforest areas such as the Amazon, central Africa, and Southeast Asia. Locally, precipitation by the JRA-25 was higher than by the other datasets, i.e., for parts of southern China to western India and southern North America. Therefore, at least the present version of the JRA-25 reanalysis may provide relatively warmer and drier conditions in tropical regions, and intermediate conditions for temperate and boreal regions.

Interannual variability (IAV) of land surface climatic conditions by the JRA-25 reanalysis was mostly consistent with that by the other datasets but included several unique anomalies. The IAV in downward shortwave radiation (Fig. 1a) shows that JRA-25 gave larger anomalies in the 1980s. As shown in the difference from the ISCCP data, difficulties remain in reconstructing the solar radiation map due to the heterogeneity of clouds and aerosols and insufficient observations. The CRU and four reanalysis datasets agreed very well for IAV of air temperature (Fig. 1b); for example, the datasets reproduced the warming trend during the experimental

![Fig. 1](image1.png)

![Fig. 2](image2.png)

Table 1. Comparison of global average land surface climate conditions derived from the four reanalysis and observational datasets.

<table>
<thead>
<tr>
<th>Input data</th>
<th>Air temp (°C)</th>
<th>Precip (mm yr⁻¹)</th>
<th>D SW rad (W m⁻²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>JRA-25</td>
<td>13.2</td>
<td>751</td>
<td>212</td>
</tr>
<tr>
<td>ERA40</td>
<td>13.2</td>
<td>787</td>
<td>179</td>
</tr>
<tr>
<td>NCEP-R1</td>
<td>12.1</td>
<td>872</td>
<td>228</td>
</tr>
<tr>
<td>NCEP-R2</td>
<td>12.4</td>
<td>883</td>
<td>197</td>
</tr>
<tr>
<td>ISCCP</td>
<td>–</td>
<td>–</td>
<td>194</td>
</tr>
<tr>
<td>CRU CMAP</td>
<td>13.9</td>
<td>805</td>
<td>–</td>
</tr>
<tr>
<td>CMAP</td>
<td>–</td>
<td>743</td>
<td>–</td>
</tr>
</tbody>
</table>
period and the notable warmth in 1998. Among the four datasets, the IAV of precipitation (Fig. 1c) was not always consistent. The JRA-25 reanalysis showed a clearer increase in 1987–1988 and following decrease as found in the CMAP data. In the 1990s, the IAV of the JRA-25 dataset was smaller than those of the NCEP-R1 and -R2.

### 3.2 Spatial patterns of the terrestrial carbon budget

On average for the 1979–2001 period, global terrestrial NPP was estimated as 60.1 Pg C yr⁻¹ using the JRA-25 dataset (Table 2); this value is intermediate compared to those produced by the other climate datasets (53.9–63.1 Pg C yr⁻¹). These estimates fall within the range found by the previous studies, and the estimated global NPP using the JRA reanalysis is remarkably close to that by a recent synthesis (60 Pg C yr⁻¹; Intergovernmental Panel on Climate Change (IPCC) 2001). However, the differences among the climate datasets used may result from differences in model simulations. Ito and Sasai (in press) have noted that variations among the NPP estimations using different datasets may be largely attributable to differences in downward shortwave radiation. Solar radiation is the vital source of energy for plant photosynthesis, and therefore the highest (lowest) radiation by the NCEP-R1 (ERA40) resulted in the highest (lowest) NPP estimation. This implies that the accuracy of shortwave radiation data is critically important for terrestrial carbon cycle simulations. Figure 2a shows the spatial distribution of NPP using the JRA-25 reanalysis and suggests that high productivity in tropical ecosystems and low productivity in arctic and arid ecosystems were captured. However, due to low precipitation, tropical rainforests in the Amazon, Southeast Asia, Australia, and South Africa were not captured. However, due to low precipitation, tropical rainforests in the Amazon, Southeast Asia, Australia, and South Africa were not captured. However, due to low precipitation, tropical rainforests in the Amazon, Southeast Asia, Australia, and South Africa were not captured. However, due to low precipitation, tropical rainforests in the Amazon, Southeast Asia, Australia, and South Africa were not captured. However, due to low precipitation, tropical rainforests in the Amazon, Southeast Asia, Australia, and South Africa were not captured. 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Figure 3. (a) Latitudinal distribution and (b) seasonal change of the estimated terrestrial net primary productivity (NPP) simulated using the four climate datasets.

![Figure 3](image)

### Table 1. Comparison of the estimated terrestrial carbon budget using the four reanalysis datasets for the 1979–2001 period.

<table>
<thead>
<tr>
<th>Input data</th>
<th>NPP</th>
<th>NEP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean (Pg C yr⁻¹)</td>
<td>st.dev. (Pg C yr⁻¹)</td>
</tr>
<tr>
<td>JRA-25</td>
<td>60.1</td>
<td>1.83</td>
</tr>
<tr>
<td>ERA40</td>
<td>53.9</td>
<td>1.64</td>
</tr>
<tr>
<td>NCEP-R1</td>
<td>63.1</td>
<td>1.10</td>
</tr>
<tr>
<td>NCEP-R2</td>
<td>60.8</td>
<td>1.51</td>
</tr>
</tbody>
</table>
with those by Nemaini et al. (2003) derived from satellite data: 0.12 to 0.23 Pg C yr\(^{-1}\) in 1982–99. As shown in Fig. 2b, use of the JRA-25 reanalysis resulted in a NPP increase for the Amazon, South Africa, Australia, and arctic North America, and an NPP decrease in central Africa. However, NPP enhancement in northern Eurasia over the past decades, likely due to climatic warming (Nemaini et al. 2003), was not shown by the JRA-25 simulation. As indicated in Fig. 5a, the IAV of NPP estimated using the JRA-25 reanalysis had large year-by-year variability (standard deviation, ±1.83 Pg C yr\(^{-1}\)), especially from 1985 to 1994. Therefore, this IAV was analyzed in detail. Figure 2c shows the spatial distribution of the coefficient of variance (standard deviation divided by the average) for the estimated 23-year NPP. The JRA-25 resulted in remarkable interannual variability (as high as 100%) for the Amazon and subtropical Africa, where the carbon cycle of the terrestrial ecosystem is regulated by water conditions (note that the JRA-25 provides lower precipitation in the Amazon). Because the terrestrial ecosystem is sensitive to this environmental limiting factor, the NPP of the Amazon and subtropical Africa responds largely to interannual changes in precipitation. Moreover, these regions are influenced by evident climatic events such as El Niño/Southern Oscillation and Indian Ocean Dipole events. In contrast, in Southeast Asia, where tropical rainforests receive ample precipitation, the NPP is not as sensitive to changes in water availability. Importantly, the simulations based on the other climate datasets did not result in such large NPP variability for the Amazon (data not shown). In these simulations, subtropical areas in Africa, Australia, Central America, and South Asia showed relatively large interannual variability. These results suggest the necessity for careful interpretation of specific anomalies in the IAV of the terrestrial carbon budget. In most years, however, the simulation results for the JRA-25 reanalysis dataset were consistent with those by other climate datasets. This consistency should provide researchers with higher confidence in modeling results.

4. Conclusion

Terrestrial model simulations are important applications of reanalysis datasets; however, a careful insight of the dataset is indispensable for interpreting simulation results. For the first time, JRA-25 data are explored as forcing in a terrestrial carbon cycle model to retrieve the global carbon budget for recent decades. The JRA-25 and existing three climate datasets resulted in some simulation difference, but these variations could be largely reduced by improving solar radiation fields. The JRA-25 dataset produced global long-term plant and ecosystem productivity results that are consistent with results based on the other datasets. This reanalysis dataset can thus be used for various model analyses of the carbon budget. In this study, we used the evaluation version of the JRA-25 reanalysis dataset. Although the use of advanced data assimilation algorithms and observations data are expected to improve the precision of this dataset, several land surface conditions remain that are of concern, such as dryness in the Amazon. After revisions, the dataset should have higher accuracy and enable us to reduce the quantitative uncertainty in global carbon budget modeling.

Acknowledgments

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