Natural Variability in a Stable, 1000 Year Global Coupled Climate-Carbon Cycle Simulation
Submitted to J. Climate
June 17th, 2005

Scott C. Doney
Marine Chemistry and Geochemistry
Woods Hole Oceanographic Institution
Woods Hole, MA 02543, USA
sdoney@whoi.edu
508-289-3776

Keith Lindsay
Climate and Global Dynamics
National Center for Atmospheric Research
Boulder, CO 80307, USA

Inez Fung and Jasmin John
Berkeley Atmospheric Sciences Center
University of California, Berkeley
Berkeley, CA 94720, USA
**Abstract**

A new three-dimensional global coupled carbon-climate model is presented in the framework of the Community Climate System Model (CSM-1.4). The biogeochemical module includes explicit land water-carbon coupling, dynamic carbon allocation to leaf, root and wood, prognostic leaf phenology, multiple soil and detrital carbon pools, oceanic iron limitation, a full ocean iron cycle, and 3-D atmospheric CO$_2$ transport. A sequential spin-up strategy is utilized to minimize the coupling shock and drifts in land and ocean carbon inventories. A stable, 1000-year control simulation—global annual mean surface temperature $\pm 0.10$ K and atmospheric CO$_2$ $\pm 1.2$ ppm (1$\sigma$)—is presented with no flux adjustment in either physics or biogeochemistry. The control simulation compares reasonably well against observations for key annual mean and seasonal carbon cycle metrics; regional biases in coupled model physics, however, propagate clearly into biogeochemical error patterns. Simulated interannual to centennial variability in atmospheric CO$_2$ is dominated by terrestrial carbon flux variability, $\pm 0.69$ Pg C y$^{-1}$ (1$\sigma$, global net annual mean), which in turn reflects primarily regional changes in net primary production modulated by moisture stress. Power spectra of global CO$_2$ fluxes are white on timescales beyond a few years, and thus most of the variance is concentrated at high frequencies (timescale $< 4$ years). Model variability in air-sea CO$_2$ fluxes, $\pm 0.10$ Pg C y$^{-1}$ (1$\sigma$, global annual mean), is generated by variability in sea surface temperature, wind speed, export production, and mixing/upwelling. At low frequencies (timescale $> 20$ years), global net ocean CO$_2$ flux is strongly anti-correlated (0.7 to 0.95) with the net CO$_2$ flux from land; the ocean tends to damp (20-25%) slow variations in atmospheric CO$_2$ generated by the terrestrial biosphere.
(1) Introduction

Over the last two centuries, the levels of atmospheric carbon dioxide CO$_2$, an important greenhouse gas that modulates Earth’s radiative balance and climate, have increased due to fossil-fuel combustion and land-use. Levels have risen from a preindustrial value of 280 ppm to about 380 ppm at present, equivalent to an increase of ~200 Pg of carbon (1 Pg = $10^{15}$ g) (Prentice et al., 2001). By comparison, atmospheric carbon dioxide levels for the preceding several millennia of the Holocene were essentially flat, within plus or minus 5 ppm of the preindustrial value. ‘Business as usual’ economic and climate scenarios project values as high as 700 to 1000 ppm by the end of the twenty-first century, levels not experienced on Earth for the past several million years (Pearson and Palmer, 2000). There is growing evidence that this increase in atmospheric CO$_2$ will have a significant, long-term impact on the planet’s climate and biota (IPCC, 2001).

Recent estimates suggest that only about half of the fossil fuel CO$_2$ released by human activity during the last two decades has remained in the atmosphere; on average, about equal amounts or roughly 2 Pg C/yr have been taken up by the ocean and land, respectively. As global climate models are improved, the future behavior of these land and ocean carbon sinks and the resulting atmospheric forcing are emerging as one of the main uncertainties associated with climate projections (Hansen et al., 1998; Prentice et al., 2001). In most previous anthropogenic climate change projections, the trajectory of atmospheric CO$_2$ concentration is prescribed and the resulting physical climate response computed. This approach, however, neglects the potential for substantial feedbacks between climate change and the carbon cycle that could either exacerbate or partially ameliorate global climate change.

Human perturbations to the Earth’s climate occur on top of a large natural carbon cycle, a complex system involving the ocean, atmosphere and land domains and the fluxes among them. Many of the underlying ecological and biogeochemical processes are sensitive to shifts in temperature, the hydrological cycle, and ocean dynamics, and the magnitude and, in some cases, the sign of specific carbon-climate feedbacks are unknown. Two recent studies by Cox et al. (2000) and Dufresne et al. (2002) present strikingly different pictures of carbon-climate feedbacks, differences that must arise because of the underlying formulations linking the physical climate and biogeochemistry. On geological time-scales, ice core and other paleo-proxy reconstructions suggest large contemporaneous variations in climate and atmospheric CO$_2$, ranging from glacial-interglacial cycles (Petit et al., 1999) to the high CO$_2$, warm periods of the Cretaceous and Permian; the exact interplay of climate forcing and carbon cycle dynamics on these scales also is not well resolved.

Numerical models provide one of the few direct and quantitative methods for assessing such questions. Here we present a new, fully coupled 3-D climate-carbon cycle model based on the framework of the Community Climate System Model (CCSM) project (Blackmon et al., 2001). Our overall objectives are to better understand: (1) what processes and feedbacks are most important in setting atmospheric CO$_2$, and (2) how do
CO₂ and climate co-evolve. We focus in this paper on the description of the land, ocean and atmosphere biogeochemical component models (Section 2), their integration within the CSM 1.4 physical model framework, and the analysis of a stable, 1000-year pre-industrial simulation. By introducing a sequential spin-up procedure, we minimize the drifts in land and ocean carbon inventories that can arise from biases in coupled model physical climate (Section 3). In Section 4, we assess the skill of the control simulation by comparing the annual mean and seasonal cycle of key simulated carbon metrics against observations. In contrast to previous coupled carbon-climate models, we fully resolve the 3-D structure of atmospheric CO₂, providing important constraints on model dynamics. We then use the control integration to quantify the magnitude and physical mechanisms of natural interannual, decadal, and centennial variability in carbon exchange within and among the reservoirs (Section 5). Experiments exploring the carbon-climate feedbacks arising from the anthropogenic fossil fuel CO₂ emissions for the 19th, 20th, and 21st centuries are presented in Fung et al. (2005).

(2) Model Description

The coupled carbon-climate model treats radiative CO₂ as a prognostic variable, with the atmospheric abundance as the residual after accounting for the climate-sensitive fluxes into and out of the land biosphere (\(F_{ab}\) and \(F_{ba}\), respectively), and into and out of the ocean (\(F_{ao}\) and \(F_{oa}\), respectively).

\[
\frac{\partial}{\partial t} \text{CO}_2 + \nabla (\text{CO}_2) = \text{ExternalSource} - F_{ab} + F_{ba} - F_{ao} + F_{oa} \tag{1}
\]

In Equation 1, \(\nabla (\text{CO}_2)\) is the 3-dimensional atmospheric transport of CO₂ due to large-scale advection and to turbulent mixing associated with dry and moist convection. We have added Equation 1 to the NCAR coupled atmosphere-land-ocean-ice physical climate model (CSM 1.4) and embedded new versions of a terrestrial carbon module to estimate \(F_{ab}\) and \(F_{ba}\), and oceanic carbon module to estimate \(F_{ao}\) and \(F_{oa}\). These are described below. In the control run described here, \(\text{ExternalSource}=0\).

(2.1) CSM 1.4 coupled physical model

The core of the coupled carbon-climate model is a modified version of NCAR CSM1.4, consisting of ocean, atmosphere, land, and sea-ice physical components integrated via a flux coupler (Boville and Gent, 1998; Boville et al., 2001). The simulations here are integrated with an atmospheric spectral truncation resolution of T31 (~3.75°) with 18 levels in the vertical, and an ocean resolution of 3.6° in longitude and 0.8° to 1.8° latitude and 25 levels in the vertical (referred to as T31x3). The sea ice component model runs at the same resolution as the ocean model, and the land surface model runs at the same resolution as the atmospheric model. Physical control simulations display stable surface temperatures and minimal deep ocean drift without requiring surface heat or freshwater flux adjustments. The water cycle is closed through a river runoff scheme, and modifications have been made to the ocean horizontal and vertical diffusivities and viscosities from the original version (CSM 1.0) to improve the equatorial
ocean circulation and interannual variability.

The 3-D atmospheric CO\textsubscript{2} distribution is advected and mixed as a dry-air mixing ratio using a semi-Lagrangian advection scheme; both dry and moist turbulent mixing schemes are used for the transport of water vapor mass fractions. The model CO\textsubscript{2} field affects the shortwave and longwave radiative fluxes through the column average CO\textsubscript{2} concentration.

\textbf{(2.2) Land carbon-cycle model}

The CSM1.4-carbon land carbon module (Figure 1) combines the NCAR Land Surface Model (LSM) biogeophysics package (Bonan, 1996) with the CASA biogeochemical model (see Randerson et al., 1997). The land surface is characterized by the fractional coverage of 14 plant functional types (PFTs) and 3 soil textures (Bonan 1996). LSM estimates leaf-level stomatal conductance of CO\textsubscript{2} and water to maximize carbon assimilation for sunlit and shady conditions (Collatz et al. 1990; Sellers et al. 1996). The carbon assimilation is integrated through the canopy using the fraction of sun-lit and shade leaves to yield gross primary productivity (GPP). A terrestrial CO\textsubscript{2} fertilization effect arises physiologically in the model because carbon assimilation via the Rubisco enzyme is limited by internal leaf CO\textsubscript{2} concentrations; GPP thus increases with external atmospheric CO\textsubscript{2} concentrations, eventually saturating at high CO\textsubscript{2} levels.

In this implementation, net primary productivity ($NPP = F_{ab}$) is assumed to be 50\% of GPP calculated by LSM (replacing NPP calculated by CASA). NPP is allocated to three live biomass pools $M$ (leaf, wood, root) following Friedlingstein et al. (1999), with preferred allocation to roots during water-limited conditions and to leaves during light-limited conditions:

$$\frac{\partial}{\partial t} M_k = \alpha_k NPP - \frac{M_k}{\tau_k} \quad k=1,2,3$$

In the CASA formulation, turnover times $\tau_k$ of the three live pools are PFT-specific but time-invariant, with constants ranging from 1.8 years for leaves in tropical broadleaved evergreen trees to 48 years for wood in broadleaf deciduous tress. The leaf mortality of deciduous trees is modified to include cold-drought stress to effect leaf-fall in 1-2 months, and leaf biomass (kgC/m\textsuperscript{2} land) is translated into prognostic leaf area indicies (LAI) using specific leaf areas (SLA, m\textsuperscript{2} leaf/kgC), following Dickinson et al. (1998), so that LAI varies with climate. We place limits on LAI, with a minimum of 0.6 to simulate the storage of carbon in photosynthates and a maximum of 6 to simulate light and nutrient limitation. The excess carbon above the maximum $M_{leaf}$ is added to litterfall $M_{leaf}/\tau_{leaf}$.

There are 9 dead carbon pools, with leaf mortality contributing to metabolic and structure surface litter ($k=4,5$), root mortality contributing to metabolic and structure soil litter ($k=6,7$), and wood mortality contributing to coarse woody debris (CWD, $k=8$). The subsequent decomposition of $M_k$, $k=4-8$ by microbes leads to transfer of carbon to the dead surface and soil microbial pools ($k=9,10$) and the slow and passive pools ($k=11,12$).
A fraction of each carbon transfer is released to the atmosphere via microbial or heterotrophic respiration. This is summarized in Equation 3:

\[
\frac{\partial}{\partial t} M_k = \sum_{j=1}^{12} \frac{M_j}{\tau_j} k - \sum_{n=4}^{12} \frac{M_k}{\tau_k} (1 - \sum_{n=4}^{12} \gamma_{kn}) M_k \quad k=4,\ldots,12
\]

The first term on the RHS of Equation 3 is the gain of \( M_k \) due to litterfall and the transfer from other dead carbon pools \( j \); the second term is the loss of \( M_k \) due to transfer from pool \( k \) to other pools \( n \); and third term is \( R_{bh} = F_{ba} \), the loss of carbon to the atmosphere via heterotrophic respiration. The transfer coefficients \( \gamma_{jk} \) are time-invariant constants following CASA.

The rates of transfer are climate sensitive, following CASA:

\[
\tau_k^{-1} = \tau_{k0}^{-1} f(T) g(w) \quad k=4,\ldots,12
\]

where \( \tau_{k0} \) is the turnover time of pool \( k \) at 10°C with no water limitation; \( \tau_{k0} \) ranges from 20 days for the metabolic soil pool to 500 years for the passive pool. The modulators \( f(T) \) and \( g(w) \) are functions of soil temperature \( T \) and an index of soil moisture saturation \( w \), respectively. Soil temperature and soil moisture are averaged over the top 30 cm (top 2 model soil layers) of the soil. \( f(T) \) is represented by a \( Q_{10} \) of 2, or a rate doubling for every 10°C increase in soil temperature referenced to 10°C. \( g(w) \) is a monotonic function of soil moisture saturation, and ranges linearly between 0 and 1 for \( w \) between 0.25 and 0.75.

Carbon fluxes and carbon pools are updated at LSM time-steps of 30 minutes so that the prognostic biogeochemistry is in step with the biogeophysics. The geographic distribution of the net atmosphere-land flux:

\[
\Delta F_{\text{land}} = F_{ab} - F_{ba} = \text{NEP} = \text{NPP} - R_h
\]

is passed to the atmosphere to update atmospheric CO\(_2\) concentration. In this way, changes in leaf areas calculated by CASA influence GPP, transpiration and albedo, and changes in temperature and soil moisture calculated by LSM alter NPP, allocation and decomposition rates. Thus there is full coupling of the energy, water and carbon cycles.

### (2.3) Ocean carbon-cycle model

The ocean carbon-cycle model is a derivative of the OCMIP-2 biotic carbon model, which is itself a derivative of the model of Najjar et al. (1992), and is described for instance in Doney et al. (2003). Air-sea fluxes of CO\(_2\) are estimated as:

\[
\Delta F_{\text{ocn}} = F_{ao} - F_{oa} = k_u \beta_T (p\text{CO}_2^{\text{atm}} - p\text{CO}_2^{\text{sw}})(1-f_{\text{ice}})
\]

where \( k_u \) is the wind-dependent gas-exchange coefficient across the air-sea interface, \( \beta_T \) is the temperature-dependent solubility of CO\(_2\), and \( p\text{CO}_2^{\text{atm}} \) and \( p\text{CO}_2^{\text{sw}} \) are the partial pressures of CO\(_2\) in the lowest two layers of the atmosphere (~60 mb) and in the top layer of the ocean, respectively, and \( f_{\text{ice}} \) is the fractional ice coverage. \( p\text{CO}_2^{\text{sw}} \) is calculated from model DIC, ALK, temperature and salinity according to carbonate chemistry.
The primary differences between the new model (Figure 2) and the OCMIP-2 BGC model are:

- nutrient uptake has been changed from a nutrient restoring formulation to a prognostic formulation,
- iron has been added as a limiting nutrient in addition to phosphate, and
- a parameterization for the iron cycle has been introduced.

The prognostic variables transported in the ocean model are phosphate $PO_4$, total dissolved inorganic Fe, dissolved organic phosphorus DOP, dissolved inorganic carbon DIC, alkalinity ALK, and oxygen $O_2$. We describe here only the differences with the OCMIP-2 biotic carbon model.

### (2.3.1) Nutrient Uptake

The parameterization of biological uptake is similar to that used in HAMOCC (Bacastow and Maier-Reimer, 1990; Maier-Reimer, 1993). Uptake of $PO_4$ is given by the turnover of biomass $B$, modulated by temperature, macro- and micronutrients, and surface solar irradiance:

$$J_{prod} = F_T \cdot F_N \cdot F_I \cdot B \cdot \max\{1, z_{ml}/z_c\} / \tau.$$  \hspace{1cm} (6)

Like the OCMIP-2 BGC model, biological uptake only occurs in the production zone ($z < z_c$), where $z_c$ is the compensation depth (75m). The temperature limitation function:

$$F_T = (T + 2) / (T + 10)$$  \hspace{1cm} (7)

is the same that is used in HAMOCC with $T$ in degrees Celsius. The nutrient limitation term is the minimum of Michaelis-Menten limiting terms for $PO_4$ and Fe:

$$F_N = \min\{\frac{PO_4}{PO_4 + \kappa_{PO4}}, \frac{Fe}{Fe + \kappa_{Fe}}\}$$  \hspace{1cm} (8)

where $\kappa_{PO4}$ is 0.05 $\mu$mol/L and $\kappa_{Fe}$ is 0.03 nmol/L. The light (irradiance) limitation term:

$$F_I = \frac{I}{I + \kappa_I},$$  \hspace{1cm} (9)

uses $I$, the solar short-wave irradiance, and a light limitation term $\kappa_I$ (20 W/m$^2$). Irradiance decays exponentially from the sea surface with a 20 m length-scale. If the cell is completely contained in the mixed layer, then $I$ is the average over the entire mixed layer. If the cell is completely below in the mixed layer, then $I$ is simply the average over the cell. For intermediate cases, $I$ is the appropriate weighted average. As a consequence, the light limitation term decays like $O(1/z_{ml})$ for $z_{ml} > z_c$. $B$ is a proxy for biomass ($\mu$mol/L):

$$B = \min\{PO_4, \frac{Fe}{r_{Fe,P}}\},$$  \hspace{1cm} (10)
where \( r_{Fe:P} \) is the ratio of Fe to PO\(_4\) uptake 5.85x10\(^{-4}\) (mol/mol) derived by assuming a Fe to C uptake ratio of 5.0x10\(^{-6}\) (mol/mol) and a C to PO\(_4\) uptake ratio of 117 (mol/mol). The term \( \max\{1, z_{ml}/z_c\} \) term scales the uptake by \( z_{ml} \) when it exceeds \( z_c \); this is meant to implicitly extend the production zone to the base of the mixed layer. Finally, \( \tau \) is the optimal uptake timescale (15 d).

(2.3.2) Iron Parameterization

There are three conceptual forms of iron in the model, Fe representing dissolved inorganic iron, DOFe the iron content of the dissolved organic matter, and POFe the iron content of the sinking particles. The following processes govern the iron cycle:

- surface deposition of Fe from the atmosphere,
- biological uptake of Fe, converting Fe into DOFe and POFe
- remineralization of DOFe into Fe,
- scavenging of Fe into POFe,
- and remineralization of POFe into Fe.

Surface deposition of Fe is derived from the monthly climatological dust flux estimated by Mahowald et al. (2003) The dust is assumed to be 3.5% Fe by weight with 2% of the Fe bioavailable. Biological uptake of Fe is equal to \( r_{Fe:P} \cdot J_{prod} \). It is routed to DOFe and POFe using the same partitioning that is used for P, where a fixed fraction \( \sigma = 0.67 \) goes to DOFe and the remainder goes to POFe. DOFe remineralizes into Fe following first-order kinetics with a rate constant \( \kappa = 2 \text{ y}^{-1} \). Since \( r_{Fe:P} \) is constant and \( \sigma \) and \( \kappa \) are the same for the Fe pools as they are for the P pools, DOFe is equal to \( r_{Fe:P} \cdot DOP \). Because of this relationship, DOFe is not explicitly tracked in the model.

The scavenging of Fe is similar to the single ligand model described in Archer and Johnson (2000). Conceptually there is a ligand that organically binds to Fe molecules, protecting them from scavenging. Fe that is not bound to ligands is denoted Fe\(_{\text{free}}\) and is the positive root of the quadratic equation

\[
Fe_{\text{free}}^2 + (L + 1/K_L - Fe) Fe_{\text{free}} - Fe/K_L = 0,
\]

where \( L \) is the concentration of ligand and \( K_L \) is the strength of the binding reaction. We assume a globally uniform ligand concentration of 1.0 nmol/L and a \( K_L \) equal to 300 L/nmol. The scavenging of Fe is given by:

\[
J_{Fe,scav} = Fe_{\text{free}} \cdot C_0 \cdot (1 + \alpha \exp(-z/z_{scav})),
\]

where \( C_0 = 0.2 \text{ y}^{-1}, \alpha = 200, \) and \( z_{scav} = 250 \text{ m} \).

Scavenged Fe is attached to the sinking particles to form POFe. A fraction (40%) of the scavenged Fe is assumed to be insoluble and is directly lost to the sediments. The remaining 60% can be remineralized back to dissolved form below \( z_c \). The OCMIP-II model used a single Martin power law curve (\( a=-0.9 \)) to describe the vertical POP flux profile overall the full water column. This scheme needs to be modified to a local power law because scavenged Fe is attached to the sinking organic matter throughout the water.
column. Consider a model cell with a flux $F_{POFe}$ through the top at $z_t$. The flux at the bottom ($z_b$) is then:

$$F_{POFe}(z_b) = F_{POFe}(z_t) \cdot \left(\frac{z_b}{z_t}\right)^a + (z_b - z_t) \cdot 0.6 \cdot J_{Fe\_scav}$$

where 0.6 represents the 60% of the scavenged Fe that is potentially soluble. Of the POFe that reaches the sea floor, that due to biological uptake is remineralized into the bottom cell. This is equivalent to setting the sea floor remineralization of POFe to $r_{Fe:P}$ times sea floor POP remineralization.

### (3) Coupled Carbon-Climate Spinup

In order to reduce the magnitude of the coupling shock and transient response when carbon is coupled to the climate of the coupled model, a sequential spin-up procedure is employed (Figure 3). The spin-up procedure involves categorizing atmospheric CO$_2$ into three flavors:

*Tracer CO$_2$ ($C_{Tracer}$): This flavor is transported by the atmospheric dynamics and responds to the geographically varying surface fluxes provided by the land and ocean components.*

*Biogeochemistry CO$_2$ ($C_{BGC}$): This flavor is passed to the land and ocean components for inclusion in photosynthesis and air-sea flux computations. It is either a specified constant, e.g. 280 ppm for pre-industrial conditions, or taken to be the model time/space varying $C_{Tracer}$ field averaged in the vertical over the bottom two model levels (~60 mb). The specification could be different for the land and the ocean.*

*Radiative CO$_2$ ($C_{Rad}$): This flavor is passed to the atmospheric component’s radiation parameterization. It is either a specified constant or is taken to be the (pressure-weighted) column average of $C_{Tracer}$. Note that in traditional climate models and some previous coupled carbon-climate studies (e.g., Cox et al., 2000), $C_{Rad}$ depends only on time. In this study, we additionally allow $C_{Rad}$ to vary with longitude and latitude. The CSM-1 atmospheric radiation parameterization makes numerous simplifications based on the assumption that $C_{Rad}$ is vertically homogeneous, making it impractical to include the vertical distribution of $C_{Tracer}$. However, independent computations indicate that the impact of including the vertical distribution of CO$_2$ in the radiation calculations is negligible (pers. comm. J. Kiehl).*

The land and ocean carbon components are first spun-up to an approximate steady-state and then incrementally coupled with each other and the physical climate. For the ocean circulation and carbon model spin-up, we use prescribed atmosphere physics and sea-ice observational datasets that correspond to modern conditions. Atmospheric CO$_2$ ($C_{BGC}$) is held at 278 ppm, representing pre-industrial conditions. Integrating the ocean model to steady-state would take thousands of model years. In order to avoid such a long integration, a depth dependent acceleration technique is used following Danabasoglu et al. (1996). Because this technique is not conservative, PO$_4$, DOP, and
ALK are multiplied by a scale factor at the beginning of each year to restore the global inventories of PO$_4$+DOP and ALK-TP DOP. The ocean model is run for 350 surface years, corresponding to 17500 deep-water years, at which point the annual air-sea CO$_2$ gas flux is 0.063 ± 0.011 Pg C y$^{-1}$, over the last 10 years of the integration.

The land carbon component is particularly sensitive to soil moisture, so it is expeditious for the hydrological cycle in the land spin-up to resemble that from a coupled simulation. The approach taken here is to start with M$_k$ produced by a 1000-year integration of the land carbon module forced by the CSM1.4 surface climate, and generate coupled carbon-climate model climatologies from a preliminary 100 year run with all active physical components and land carbon (C$_{BGC}$=C$_{Rad}$ = 280 ppm). This step yields approximate steady states for NPP and the live carbon pools under the coupled model climate. The detrital and soil carbon pools are spun up next in an off-line mode forced by the coupled carbon-climate model climatologies of litterfall, surface air and soil temperatures and soil moisture. The land spin-up is then continued with active atmospheric and land components (C$_{BGC}$=C$_{Rad}$ = 280 ppm) and data cycling of the model climatologies of SST and ice extent. Additional numerical acceleration techniques are applied during this phase to the Slow and Passive Soil carbon pools, which have turnover times in excess of 200 years and thus would require over 1000 years to fully equilibrate. The final net land CO2 flux over the last 10 years of the land spin-up is 0.072 ± 0.613 Pg C y$^{-1}$.

The end states of the land and ocean carbon spin-ups are inserted into a full physically-coupled atmosphere-ocean-land-ice configuration and are the carbon cycles are then incrementally coupled to the physics and each other. In a first 100 year segment (Figure 3), C$_{BGC}$ and C$_{Rad}$ are fixed at 280 ppm in order to allow the land and ocean carbon cycles to adjust to the climate of the coupled model. The land and ocean carbon components at this step are thus independent. In a second 50 year segment, C$_{Tracer}$ is reinitialized to 280 ppmv, C$_{BGC}$ for the land and ocean is the average of the lowest ~60 mb of C$_{Tracers}$ and C$_{Rad}$ remains set to 280 ppm. The purpose of this segment is to allow the land and ocean carbon cycles to adjust to each other via C$_{Tracer}$ prior to the introduction of radiative feedbacks. The end state of the second segment has net CO$_2$ fluxes of 0.17 ± 0.74 Pg C y$^{-1}$ and is used as the initial condition of the 1000 year control run, where C$_{Rad}$ varies with C$_{Tracer}$ providing full prognostic carbon-climate coupling. Note that C$_{Tracer}$ is not reset at the beginning of the control run. Because of this and the fact that the system conserves carbon, the total carbon inventory for the 1000 year control is determined by the initial conditions of second segment, and is in equilibrium with an atmospheric CO$_2$ of ~280 ppmv and the corresponding model climate.

In our standard 1000-year control, we do not consider CO$_2$ fertilization of the land biosphere; C$_{BGC}$ seen by the land is 280 ppmv. This is equivalent to assuming that terrestrial production is limited by other factors such a nitrogen. A companion 500 year experiment includes the full effects of CO$_2$ fertilization on terrestrial photosynthesis by setting C$_{BGC}$ to be the evolving CO$_2$ concentration in the lowest ~60 mb of the atmosphere. The mean state and variability of the two simulations are indistinguishable.
statistically in both physical and biogeochemical measures, reflecting the fact that the natural variations in atmospheric CO$_2$ in our control simulations are relatively small.

(4) Model Stability and Mean Physical/Biogeochemical Climate

(4.1) Global Climate and Carbon Cycle Time-Series

As shown in Figure 4, global integral properties such as the average surface temperature, atmospheric CO$_2$ concentration, and the ocean and land carbon inventories remain approximately stable over the entire 1000-year coupled carbon-climate control simulation. Global annual mean model surface temperature remains constant within ±0.10 K (1σ) over the integration, and other global integral physical climate metrics are similarly constant. The stability of the CSM-1 physical climate with fixed atmospheric composition and no flux corrections is documented in Boville and Gent (1998) and Boville et al. (2001). The global annual mean atmospheric CO$_2$ in the 1000-year control run displays no long-term trend, and the variations are ±1.2 ppmv (1σ), small enough that the concomitant alterations in the radiation budget are relatively minor. Thus the variability in Figure 4 arises from natural, internal dynamics of the climate system working on the carbon cycle.

The model carbon inventories vary on interannual to centennial time-scales, reflecting continuous repartitioning of carbon among the atmosphere, ocean and land reservoirs (Figure 4c). A dominant feature is the gradual increase in atmospheric CO$_2$ by ~4 ppmv in the first 350-400 years of the integration followed by a comparable decrease over the ensuing 200-250 years. These changes are tied to oscillations in both the land and ocean inventories and are related to slow adjustments in the physical climate (soil moisture, land and sea surface temperatures, ocean circulation) and, for the oceans, changes in atmospheric CO$_2$. The 500-year simulation with CO$_2$ fertilization also exhibits a stable, but somewhat different, atmospheric CO$_2$ trajectory (Figure 4b); in this case there is an initial transient uptake rather than release from the land biosphere. The magnitude of the interannual to centennial variability is quite comparable, however.

Superposed on the very low-frequency variations are centennial and shorter time-scale signals, which dominate the variability in the last 400 years of the 1000-year control simulation. Because it is difficult to separate the effects of model drift from natural variability on the millennial time-scale with only a 1000-year simulation, we focus our analysis to centennial and shorter timescales. These variations in atmospheric inventory appear to be driven primarily by changes in the land inventory, with net terrestrial carbon uptake and release events as large as 5-10 Pg C on decadal scales. On these same scales, the ocean carbon inventory is positively correlated with the atmosphere and anti-correlated with the land but with a smaller amplitude signal (~10-20%). The dynamics controlling this variability is discussed in more detail in Section 5.
(4.2) Physical Climate Drift and Biases

Similar to previous physics-only CSM-1 solutions, the carbon-climate control simulation is not completely stationary, exhibiting long-term drift in some physical properties. There is a vertical redistribution of salt in the ocean with the surface ocean freshening (~0.035 psu/century) and a corresponding increase of deep-water salinity. A small net heat flux imbalance leads to a weak ocean warming (~0.02K/century averaged over full water column). The surface warming and freshening would both contribute to a small ocean CO₂ outgassing, but the flux is small relative to internal variability of the model or the anthropogenic fluxes explored in Fung et al. (2005). The global storage of soil moisture and the biogeochemical moisture dependence term shows little or no long-term drift. Non-negligible patterns of regional climate drift occur but do not significantly impact our main findings.

There are also a number of biases in the spatial patterns of the physics in the CSM 1.4 coupled model that impact the biogeochemical solution. Model surface temperatures are too cold in the northern hemisphere continental interiors relative to observations (Figure 5a). Although some of the cooling may be ascribed to the fact that our control run has preindustrial atmospheric CO₂ concentrations, other simulations with greenhouse forcing equivalent to the late 20th century also show similar biases of ~2 to 6K (Boville et al., 2001; Dai et al., 2001). The CSM 1.4 solutions produce an unrealistic precipitation pattern in the equatorial Pacific pattern with a double Inter-Tropical Convergence Zone (ITCZ) and bands of excess rainfall north and south of the equator (Boville and Gent, 1998; Dai et al., 2001). Significant biases exist in tropical and temperate land precipitation with too wet conditions in central Africa, western South America, western North America, and parts of Indonesia and overly dry conditions in parts of Amazonia and eastern North America. In the model ocean, the double ITCZ leads to bands of too fresh and vertically stratified surface waters in the Pacific and to an off-equator shift in the maxima of interannual air-sea CO₂ flux variability (Section 5.2). On land, the temperature and precipitation biases result in corresponding anomalies in the simulated spatial patterns of NPP, LAI and carbon storage.

(4.3) Land Carbon Dynamics

The net terrestrial CO₂ flux ΔFLand or net ecosystem production (NEP) reflects the lag on seasonal, interannual to centennial timescale between net primary production NPP and heterotrophic respiration Rh. The global mean terrestrial NPP is 66.74±0.88 Pg C y⁻¹ in the 1000 year control run, and its geographic distribution (Figure 6a) compares reasonably well with in-situ measurements and satellite observations of the normalized difference vegetation index (NDVI). The latitudinal gradient of NPP is steeper than observed, with an underestimation at high latitudes due to the small area of boreal forests and high latitude cold bias, and an overestimation at low latitudes because of excessive stomatal conductance under diffuse radiation. Some obvious blemishes in the simulated NPP field, such as the relatively low simulated values along the coast of eastern South America or in Indochina, are a direct result of biases in the coupled model precipitation field (Figure 5b).
With the turnover times $\tau_k$ specified via the land carbon module (Equations 2-4), the simulated NPP field yields reasonable distributions of living biomass and detrital/soil carbon, 871±2.4 and 1086±2.0 PgC respectively (Figure 1 and 6b). Substantial terrestrial carbon storage occurs in the regions of high NPP in the tropics and subtropics, mostly in living biomass. Elevated carbon inventories are found as well along a band of boreal forests in the Northern Hemisphere associated with cooler temperatures and a larger fraction of storage in the detrital and soil pools. While the model inventories are reasonable to the lowest order, it is difficult to directly compare the model detrital and soil carbon distribution against the observations. The model soil carbon pools represent only the organic material in the upper 20 cm of the soil, and the model does not account for carbon storage in high latitude peats, for example.

(4.4) Ocean Carbon Dynamics

The geographic pattern of the average annual net air-sea flux (Figure 7a) from the control simulation broadly resembles that compiled by Takahashi et al. (2002) for the contemporary ocean, showing net outflux of CO$_2$ from the equatorial regions and Southern Ocean and net invasion of CO$_2$ into the temperate and subpolar North Pacific and North Atlantic. Some differences in the spatial distribution, such as the larger net CO$_2$ efflux from the model Southern Ocean, are expected since the model represents pre-industrial conditions. The patterns and integrated magnitude (8.94 ±0.10 Pg C y$^{-1}$) of the simulated sinking particulate organic matter export (Figure 7b) are also generally consistent with the more limited observational constraints on this quantity (Doney et al., 2003) except for the Equatorial Pacific problems already mentioned. So too are the water column DIC and nutrient distributions, which are governed by a combination of air-sea exchange, biological uptake and export, subsurface remineralization, and ocean circulation.

(4.5) Atmospheric CO$_2$ Distributions

The time/space distribution of atmospheric CO$_2$ integrates land and ocean fluxes on regional to global scales. Because our model tracks the 3-D atmospheric CO$_2$ tracer field, we can utilize the model atmospheric CO$_2$ field to assess the skill of simulated surface fluxes. Surface CO$_2$ fluxes are reflected in spatial patterns in the mean atmospheric surface CO$_2$ distribution (lowest ~60 mb) (Figure 8a). Over land, net long-term fluxes into/out of the land biosphere are approximately zero, and the elevated CO$_2$ levels found in the tropics and Northern Hemisphere temperate zone arises from the so-called “rectifier effect” associated with seasonal correlations between surface CO$_2$ fluxes and atmospheric convection and mixing (Denning et al., 1995). Over ocean, the model exhibits a peak due to equatorial CO$_2$ outgassing regions (Figure 7a). Atmospheric CO$_2$ is also slightly higher in the Southern than in the Northern hemisphere because of the large uptake of CO$_2$ in the North Pacific and North Atlantic formation sites and subsequent southward lateral transport and release in the Equatorial and Southern Oceans (Broecker and Peng, 1992). The simulated mean spatial patterns in the model cannot be directly compared to modern observations, which are strongly influenced by fossil fuel emissions and fluxes due to current and past land-use change.
The seasonal cycle of CO$_2$ at Mauna Loa, Hawaii provides a useful measure of the seasonal imbalances between NPP and $R_h$ of the northern hemisphere land biosphere (e.g., Fung et al., 1987; Randerson et al., 1997) and is thus an indirect constraint on the bulk turnover time of soil carbon. The 1000-year mean CO$_2$ seasonal cycle at the location of Mauna Loa, Hawaii, in the model resembles that observed (Figure 8b). Both the modeled and observed cycles peak in May and have a trough in September/October; the simulated peak-trough amplitude is $\sim$4 ppmv, somewhat smaller than the observed value of $\sim$6 ppmv, which also includes the small but non-negligible effects of seasonal transport of fossil fuel CO$_2$ (Randerson et al., 1997). The model underestimation of the CO$_2$ amplitude is also partially due to the underestimation of NPP at northern high latitudes. The agreement suggests that the seasonal dynamics of both photosynthesis and decomposition are reasonably well captured in the model, and that known deficiencies in the physical climate model have not impaired gross features of terrestrial carbon dynamics. The spatial patterns of the seasonal atmospheric CO$_2$ amplitude (not shown) are consistent with modern observations, increasing from <1-2 ppmv over the Southern Ocean to 5-15 ppmv over high terrestrial NPP regions in the tropics and Northern hemisphere temperate (Figure 6a).

(5) Natural Carbon-Climate Variability

(5.1) Global Surface CO$_2$ Flux Variability

Time-series of the global integrated, annual net CO$_2$ surface fluxes from the land $\Delta F_{land}$ and ocean $\Delta F_{ocean}$ (Figure 9) highlight the high frequency, interannual variability in surface atmosphere exchange. The rms variability (1σ) in the annual net global fluxes is $\pm$0.69 Pg C y$^{-1}$ and $\pm$0.10 Pg C y$^{-1}$, for $\Delta F_{land}$ and $\Delta F_{ocean}$ respectively. For monthly, deseasonalized anomalies, the corresponding rms variability increases to $\pm$1.40 Pg C y$^{-1}$ and $\pm$0.19 Pg C y$^{-1}$. As with the low-frequency signal, interannual variability in terrestrial exchange dominates over that of the ocean by almost an order of magnitude, in part because of the chemical buffering of the carbon dioxide system in seawater, with year-to-year shifts from the terrestrial biosphere as large as $\pm$2 Pg C.

The interannual variability in the simulated terrestrial flux is comparable to that estimated from the contemporary atmospheric CO$_2$ record (Bousquet et al., 2000). Note that the pentadal variability in $\Delta F_{land}$ is similar in magnitude to the inferred magnitude of the anthropogenic terrestrial carbon sink; thus the attribution of the contemporary carbon sink to processes other than climate variability remains a statistical challenge. The simulated ocean variability is considerably smaller than that inferred from atmospheric inversions but is consistent with estimates derived from historical reconstructions using ocean only biogeochemical models (monthly global anomalies: $\pm$0.20 Pg C y$^{-1}$, Le Quere et al., 2000; $\pm$0.23 Pg C y$^{-1}$, Obata and Kitamura, 2003).

(5.2) Spatial Patterns in CO$_2$ Flux Variability

The geographic distribution of the rms variability in the annual means of $\Delta F_{land}$ and $\Delta F_{ocean}$ (1σ standard deviation of the time-series at each individual grid point) is shown in Figure 10a. Variability in $\Delta F_{land}$ is largest in the tropics, peak values exceeding
100-200 gC m\(^{-2}\) y\(^{-1}\), and is elevated (20-100 gC m\(^{-2}\) y\(^{-1}\)) across temperate North America and Eurasia. The tropical variability maxima occur in bands of moderate NPP surrounding the terrestrial NPP maxima in Amazonia, Central Africa and Indonesia (Figure 6a). Locally, the air-sea CO\(_2\) flux variability of the annual means ranges from <1 to >10 gC m\(^{-2}\) y\(^{-1}\) in the coupled model, with maxima in the subpolar North Atlantic and North Pacific, Southern Ocean, and in two off-equatorial bands in the tropical Pacific. There is a general correspondence between the locations of the maxima in air-sea CO\(_2\) flux variability and the regions of strong CO\(_2\) uptake and degassing (Figure 7a).

The largest variability in our air-sea flux is in the Southern Ocean and North Atlantic. This is in contrast to most modeling and observational studies that show the highest air-sea CO\(_2\) flux variability associated with El Nino-Southern Oscillation (ENSO), accounting for the majority of the total global variability in ocean only simulations (70%, Le Quere et al., 2000; >50% Obata and Kitamura, 2003). This could be because these ocean-only models underestimate high-latitude ocean dynamics and biology. It could also be because of overly weak vertical gradients in DIC in upper thermocline in the model tropics, caused by overly strong iron limitation and therefore low surface biological uptake (Figure 7b). The variability in simulated monthly sea surface temperature anomalies (±0.72 K) in the central Equatorial Pacific in the 1000-year control agrees well with observations (±0.82 K) suggesting that our low tropical variability is not an issue of physical upwelling.

Not surprisingly, the model regions with high surface CO\(_2\) flux variability create corresponding areas of elevated variability in the overlying surface atmospheric CO\(_2\) field (Figure 10b). Rms variability (1σ) in the spatial anomalies in annual surface CO\(_2\) concentrations (after removal of global mean) range from < 0.2 ppmv over oceans to 0.2-0.5 ppmv over northern Eurasia and eastern North America to as high as 0.5-1.0 ppmv in the tropics. The spatial patterns in the annual mean and rms spatial variability in surface atmospheric CO\(_2\) are almost identical between the cases with and without land CO\(_2\) fertilization.

(5.3) Terrestrial Variability Mechanisms

Terrestrial photosynthesis and decomposition are enhanced by positive temperature and soil moisture anomalies (unless thresholds are exceeded), and the net effect on NPP and \(R_\text{h}\) depend on their synergistic or competing effects. Over land, the interannual variability of surface air temperature and soil moisture is positively correlated (warm-wet and cool-dry) when mean air temperature is low (e.g., temperate latitudes in winter and polar regions in the summer) and negatively correlated (warm-dry and cool-wet) when the mean air temperatures are high (tropics all year and temperate bands in the summer). These distinct regional/seasonal patterns are illustrated in Figure 11a, a spatial map of air temperature/soil moisture correlation for Northern Hemisphere summer. Interannual variations in simulated NEP tend to be controlled by summer moisture stress (annual mean stress in the case of the tropics) rather than temperature stress (Figure 11b). An exception is in the polar Northern Hemisphere, where temperature and moisture effects are synergistic and comparable in size.
Because the turnover time of vegetation carbon is shorter than that of soil carbon, NPP is slightly more sensitive to climate perturbations than \( R_h \), ±0.88 Pg C y\(^{-1}\) versus ±0.54 Pg C y\(^{-1}\) (1σ rms, global net annual mean), respectively. Thus NPP decreases faster than \( R_h \) with climate stress and increases faster than \( R_h \) under favorable climate conditions (Figure 12a). NPP and \( R_h \) co-vary on subannual timescales. Globally, however, the linkage of land photosynthesis to respiration is considerably weaker on interannual timescales because regional flux anomalies tend to cancel.

Variations in simulated terrestrial NEP can be driven by NPP, \( R_h \) or both. In our model formulation, the climate modulations are the same for all the dead carbon pools (cf Equation 4). The respiratory fluxes from the fast (\( \tau_k < 5 \) yr) pools are in step with NPP and cancel 50-60% of the NPP. It is the variation of wood biomass, coarse woody debris (CWD) and the “leakage” of dead carbon from the litter to the slow pool that determines NEP on decadal to centennial time scales. Unlike the fluxes, the variability of these pools is comparable on interannual and interdecadal time scales (Figure 4c), with 1-σ rms for global annual means of ±1.51, ±0.63, and ±0.95 PgC for wood, CWD, and the slow pool, respectively. Figure 12b shows that NEP, the non-cancellation between NPP and \( R_h \), is essentially uncorrelated with \( R_h \) on all timescales shorter than 10 years. \( R_h \) is coherent with both NPP and NEP on centennial timescales, lagging by about a decade (turnover time of coarse woody debris) and largely tracks the variations in net accumulation/loss of soil/detrital carbon (cf Equation 3).

### 5.4 Ocean Variability Mechanisms

Several competing mechanisms govern oceanic CO\(_2\) flux variability in the 1000-year control, and the relative magnitudes (and even the signs) of the interactions differ from region to region and by time-scale. The variability in net air-sea CO\(_2\) flux \( \Delta F_{ocn} \) (Figure 10a) can be analyzed in terms of the components contributing to the model air-sea flux parameterization (Equation 5). The transfer velocity \( k_u \) depends on the square of 10-m wind speed \( U^2 \). Wind driven variability contributes to high frequency flux variability everywhere, with the sign of the \( U^2 - \Delta F_{ocn} \) correlation depending on mean net air-sea flux patterns (Figure 7a). Sea-ice coverage plays a role at high latitude both in terms of capping gas exchange and altering stratification. The impact of low frequency variations in pCO\(_2\)\(_{atm}\) on \( \Delta F_{ocn} \) is discussed in Section 5.5; the high frequency atmospheric signal is small enough over the ocean (Figure 10b) to have little impact on air-sea flux.

Variability in surface water pCO\(_2\)\(_{sw}\) is governed by thermal solubility and freshwater inputs (cooling and freshening decrease pCO\(_2\)), biological uptake and particle export that draws down dissolved inorganic carbon (DIC) and alkalinity with the net effect of reducing pCO\(_2\), and mixing/circulation that can bring up subsurface waters with elevated DIC, alkalinity, nutrients, and pCO\(_2\) (metabolic CO\(_2\)) due to respiration of organic matter at depth. The interplay of these different factors is show in a set of \( \Delta F_{ocn} \) versus property covariance maps (Figure 13). Interannual variations in freshwater fluxes associated with the model ENSO lead to surface freshening, warming, stratification, and negative CO\(_2\) flux anomalies (uptake), driving the large off-Equator variability in the tropical Indo-Pacific (Figure 10a). The effects of particle export and circulation are often
opposed to each other because the same enhanced mixing or upwelling that brings nutrients to the surface to enhance production (lower pCO$_2$ and positive, downward ocean CO$_2$ uptake anomaly) also brings DIC that increases pCO$_2$. In the deep-mixing zones of the Southern Ocean and North Atlantic, upwelled DIC from deeper mixing overwhelms enhanced biological drawdown, leading to positive CO$_2$ flux anomalies (outgassing). In the Southern Ocean, deeper mixing is associated with colder SSTs while the pattern occurs in the subpolar North Atlantic, where mixing is governed by sea-ice distributions and surface salinity.

(5.5) Ocean Damping of Land-driven Atmospheric CO$_2$ Variability

The power spectral densities (Pg C y$^{-1}$)$^2$/cycles$^{-1}$) in the simulated global net land and ocean CO$_2$ fluxes are plotted in Figure 14a versus the log of frequency (cycles y$^{-1}$). The spectral analysis utilizes monthly, deseasonalized anomalies where a mean seasonal climatology has been removed from the global time-series of $\Delta F_{\text{land}}$ and $\Delta F_{\text{ocean}}$. Figure 14b displays the spectrum for the total flux (land+ocean) but plotted in a variance-preserving form where the area under any frequency band is proportional to variance in that band (Emery and Thomson, 1998). The spectral analysis illustrates several features: terrestrial variability dominates over ocean variability at all frequencies; the spectra are white on timescales beyond a few years and thus most of the variance is concentrated at high frequencies (frequency $>0.25$ cycles y$^{-1}$; timescale $<4$ y); on a relative basis, the ocean has more variability than the land at low frequencies (frequency $<0.1$ cycles y$^{-1}$; timescale $>10$ y).

A cross-spectral analysis of the model global net ocean and land CO$_2$ fluxes is presented in Figure 15. The first panel displays the squared coherence versus frequency; squared coherence varies from 0 (completely incoherent or uncorrelated at all phase lags) to 1 (fully coherent) and indicates the fraction of variance that can be accounted for between the two time-series with a linear model. The average coherence of $\Delta F_{\text{land}}$ and $\Delta F_{\text{ocean}}$ on subannual time-scale is low, essentially indistinguishable from zero at the 95% confidence level. The global time-series are strongly coherent on timescales of 2 to 100 years, and the land CO$_2$ fluxes can explain 40-90% of the variance in the ocean fluxes.

The mechanism and relationship between $\Delta F_{\text{land}}$ and $\Delta F_{\text{ocean}}$ varies with timescale. The second panel (Figure 15b) displays the phase difference (in degrees) between $\Delta F_{\text{land}}$ and $\Delta F_{\text{ocean}}$ on a linear model. Assuming that the pairs of time-series are coherent (Figure 15a), a phase of 0 degrees occurs when the time-series are perfectly correlated (peaks matching peaks) and +/-180 degrees when perfectly anti-correlated (peaks matching troughs). Negative phases mean the ocean lags either the land fluxes or atmosphere CO$_2$. On timescales of a few years (frequency 0.25 to 0.50 cycles y$^{-1}$), the ocean and land fluxes are approximately in phase (~+50 degrees) with the ocean somewhat leading the land by a few months. Although the land and ocean CO$_2$ fluxes amplify each other with respect to their impacts on atmospheric CO$_2$, the two carbon reservoirs are only indirectly coupled via the biogeochemical responses to regional and global physical climate modes (ENSO, NAO, etc.) (Wang and Schimel, 2003).
On decadal and longer time-scales, $\Delta F_{\text{land}}$ and $\Delta F_{\text{ocean}}$ are closer to being anti-correlated (Figure 15b), and the land-ocean carbon coupling occurs more directly through variations in atmospheric CO$_2$. At a phase of +180 degrees, the troughs in ocean CO$_2$ flux would exactly line up with the peaks in the land flux (and visa versa); since the land-ocean phase difference is $\sim$+150 degrees, the ocean troughs somewhat lag the land peaks by $\sim$1 to 10 years on decadal to centennial timescales, respectively. Correspondingly, the ocean troughs somewhat lead atmospheric CO$_2$ peaks by a roughly similar amount of time. The strong land-ocean coherence (Figure 15a) and phasing (Figure 15b) suggest that global low-frequency carbon cycle variability originates on the land and then propagates into the atmosphere and ocean. For example, a CO$_2$ release from the terrestrial biosphere results in the growth of atmospheric CO$_2$ that in turn drives a net air-sea CO$_2$ flux into the ocean; the maximum ocean uptake occurs prior to the peak in atmospheric concentrations when the temporal gradient is largest (Figure 16). The strength of this ocean damping of land induced atmospheric CO$_2$ variability is about 20-25% on multi-decadal scales.

(6) Discussion

This paper documents the development of and results from the first coupled carbon-climate model in the NCAR CCSM framework. The 1000-year integration is stable, and the simulated climatologies in carbon inventory and fluxes resemble, to the lowest order, those determined from available observations. Atmospheric CO$_2$ excursions are small, $\sim$4 ppm over several centuries, and no abrupt changes are found in this integration. Documentable discrepancies between simulations and observations can be traced to biases in the physical climate in the model, so that future development of the carbon modules must be accompanied by concomitant improvements in the climate models.

Analysis of the 1000-year integration shows that globally terrestrial fluxes are more variable than oceanic fluxes on all time scales; however different processes dominate the variability on different time scales. Variability of the land fluxes and ocean fluxes on interannual time scales is principally a response to interannual variability in surface climate, and so these fluxes are, to lowest order, independent of one another, even though they both have statistics similar to climate variability. Long time scale ($10^1$ - $10^2$ years) variability of land fluxes is modulated by the slowly decomposing coarse woody debris and soil carbon pools, while that of the ocean fluxes is modulated by variability of atmospheric CO$_2$. It is on decadal and longer time scales that the atmosphere-land-ocean coupling becomes evident. Climate variability drives changes in the land NEP. This in turn alters atmospheric CO$_2$ and drives changes in air-sea exchange of CO$_2$. The reverse does not happen in our 1000-year simulation, as the variability in the ocean fluxes is too small to drive an atmospheric CO$_2$ anomaly (and concomitant climate anomaly) that could impact stomatal conductance on land.

The variability of the land and ocean fluxes is the “noise” in the detection of anthropogenic carbon sinks. Short-term NEP is driven by changes in NPP, which is more sensitive than $R_h$ to climate perturbations. The detrital and soil carbon pools are minor
contributors to the instantaneous $R_h$, and their slow variations set the background for long-term NEP. Thus, not only is the variability in terrestrial NEP comparable in magnitude to the contemporary land sink for anthropogenic CO$_2$, but also inferences about NEP processes based on interannual variability may not hold on longer time scales.

**Acknowledgements**

The authors gratefully acknowledge the support of the Community Climate System Model (CCSM) project and the numerous scientists and programmers involved in its development. In particular, we would like to thank G. Bonan, W. Collins, J. Kiehl, S. Levis, P. Rasch and M. Vertenstein. This work was supported by NCAR, NSF ATM-9987457, NASA EOS-IDS grant NAG5-9514, NASA Carbon Cycle Program grant NAG5-11200, Lawrence Berkeley National Laboratory LDRD, and the WHOI Ocean and Climate Change Institute. Computational resources were supplied from the NSF Climate Simulation Laboratory and the DOE NERSC. NCAR is sponsored by the U.S. National Science Foundation. This is WHOI contribution #XXXXX.
References


Figure Captions

Figure 1: Schematic of land biogeochemistry module in CSM 1.4-Carbon based on modified versions of the NCAR Land Surface Model (LSM) and CASA biogeochemical parameterizations (Bonan, 1996; Randerson et al., 1997). Simulated net primary production (NPP) (Pg C/y) on land is computed as the difference between gross primary production (GPP), provided by LSM thus linking carbon uptake and stomatal water loss, and autotrophic respiration. NPP is allocated to three biomass pools (leaf, wood, root), and heterotrophic respiration and detrital material are incorporated through nine detrital and soil carbon pools. Prognostic leaf phenology and dynamic allocation are also incorporated. The land biogeochemical modules effects the physical climate water and energy cycles through varying leaf area index (LAI) and GPP. The mean carbon standing stocks (Pg C) for each of the living and detrial pools is shown for the 1000 year control integration.

Figure 2: Schematic of ocean biogeochemistry module in CSM 1.4-carbon based on a modification of the Ocean Carbon Model Intercomparison Project (OCMIP-II) biotic carbon parameterization (Doney et al., 2003). The model includes in simplified form the main processes for the solubility carbon pump, organic and inorganic biological carbon pumps, and air-sea CO$_2$ flux. Modifications from the original OCMIP-II version include prognostic computation of new/export production as a function of light, temperature, phosphate and iron concentrations and a dynamical iron cycle.

Figure 3: Schematic of sequential spin-up procedure used to reduce physical and biogeochemical drift for CSM 1.4-Carbon control simulation.

Figure 4: Time-series of annual mean global a) surface temperature (deg. C), b) surface atmospheric CO$_2$ concentration (ppmv-dry air), and c) atmosphere, land, and ocean carbon inventory anomalies (Pg C) from the CSM 1.4-Carbon 1000 year control simulation. The dashed line in b) is the surface atmosphere CO$_2$ concentration from a companion 500-year control simulation with land biosphere CO$_2$ fertilization.

Figure 5: Spatial maps of annual mean physical biases of the CSM 1.4-Carbon control simulation relative to modern climatological observations for a) temperature (K), model minus National Center for Environmental Prediction (NCEP) and b) precipitation (mm/day), model minus Global Precipitation Climatology Project (GPCP).

Figure 6: Spatial maps of terrestrial a) annual net primary production NPP (g C m$^{-2}$ y$^{-1}$), and b) total carbon storage (g C m$^{-2}$) averaged over the 1000 year CSM 1.4-Carbon control simulation.

Figure 7: Spatial maps of a) annual net air-sea CO$_2$ flux (mol C m$^{-2}$ y$^{-1}$) (positive out of the ocean) and b) particulate organic export at 75 m depth (mol C m$^{-2}$ y$^{-1}$) averaged over the 1000 year CSM 1.4-Carbon control simulation.
Figure 8: Atmospheric surface CO$_2$ fields (ppmv) from CSM 1.4-Carbon 1000 year control simulation. Panel a) shows the mean spatial distribution averaged over the bottom two model layers (~60 mb). Panel b) shows the mean seasonal cycle with rms interannual variability (shading) from the model and observations at the Mauna Loa Observatory, Hawaii. The model is sampled at the nearest sigma surface to the altitude of the Mauna Loa Observatory. Observed data are from NOAA/CMDL.

Figure 9: Time series of global integrated, annual net a) land and b) ocean CO$_2$ fluxes (Pg C/y) from the CSM 1.4-Carbon 1000 year control simulation, highlighting the magnitude of the interannual variability. Note the different vertical scales for the land and ocean panels.

Figure 10: Spatial maps of the rms variability (1σ rms variability) of a) annual net surface CO$_2$ fluxes (g C m$^{-2}$ y$^{-1}$) and b) annual surface atmospheric CO$_2$ spatial concentration anomalies (ppmv) over the 1000 year CSM 1.4-Carbon control simulation. Note the non-linear scale in panel a.

Figure 11: Spatial maps of the a) correlation between surface 2-m air temperature and soil moisture for June-July-August and b) covariance of net annual ecosystem production (NEP) and annual mean non-dimensional model soil moisture stress term g(w) (Equation 4) from the CSM 1.4-carbon 1000-year control run (grey regions are where the correlation is not significant).

Figure 12: Panel a) Time-series of low-pass filtered, global net land net primary production NPP, respiration $R_h$ and net ecosystem production NEP (Pg C y$^{-1}$) from the CSM 1.4-Carbon 1000 year control simulation. A 20 year Hanning filter is used to remove high-frequency variability. Panel b) shows the squared coherence (0-1) versus frequency (cycles y$^{-1}$) from cross-spectrum analyses of global land NEP versus NPP and $R_h$.

Figure 13: Spatial covariance maps of annual mean air-sea CO$_2$ flux (positive into ocean) and biological and physical forcing factors.

Figure 14: a) Power spectral density (Pg C y$^{-1}$)$^2$/cycles y$^{-1}$) versus frequency (cycles y$^{-1}$) for the global integrated land and ocean CO$_2$ fluxes from the CSM 1.4-Carbon 1000 year control simulation. The power spectra are for monthly anomalies generated by removing a mean seasonal cycle. Panel b) displays the spectrum for the total flux (land+ocean) in variance preserving form (frequency*power spectral density).

Figure 15: Cross-spectrum analysis for global integrated land and ocean CO$_2$ fluxes ($\Delta F_{\text{land}}$ vs. $\Delta F_{\text{ocean}}$) from CSM 1.4-Carbon 1000-year control simulation. Panel a) shows the squared coherence (0-1) versus frequency (cycles y$^{-1}$). Panel b) shows the phase difference (degrees; <0 ocean lags) between ocean and land CO$_2$ fluxes (solid line) and ocean CO$_2$ flux and atmospheric CO$_2$ (circles). A value of 0 degrees occurs when the time-series are perfectly correlated and +/-180 degrees when they are perfectly anti-correlated. Phase in degrees can be converted to lags/leads in years by dividing by 360.
(degree cycle$^{-1}$) * frequency (cycles y$^{-1}$). Phases are not displayed for frequencies > 0.5 cycles y$^{-1}$ because the $\Delta F_{\text{land}}$ vs. $\Delta F_{\text{ocean}}$ coherences (Panel a), on average, are equivalent to zero at the 95% confidence level.

Figure 16: Time-series of low-pass filtered, global net land and ocean CO$_2$ fluxes (Pg C y$^{-1}$) and atmospheric CO$_2$ inventory anomaly (Pg C; scaled by dividing by 20) from the CSM 1.4-Carbon 1000 year control simulation. A 20 year Hanning filter is used to remove high-frequency variability.
Figure 1: Schematic of land biogeochemistry module in CSM 1.4-Carbon based on modified versions of the NCAR Land Surface Model (LSM) and CASA biogeochemical parameterizations (Potter et al., 1993; Bonan, 1996). Simulated net primary production (NPP) (Pg C/y) on land is computed as the difference between gross primary production (GPP), provided by LSM thus linking carbon uptake and stomatal water loss, and autotrophic respiration. NPP is allocated to three biomass pools (leaf, wood, root), and heterotrophic respiration and detrital material are incorporated through nine detrital and soil carbon pools. Prognostic leaf phenology and dynamic allocation are also incorporated. The land biogeochemical modules effects the physical climate water and energy cycles through varying leaf area index (LAI) and GPP. The mean carbon standing stocks (Pg C) for each of the living and detrital pools is shown for the 1000 year control integration.
Figure 2: Schematic of ocean biogeochemistry module in CSM 1.4-carbon based on a modification of the Ocean Carbon Model Intercomparison Project (OCMIP-II) biotic carbon parameterization (Doney et al., 2003). The model includes in simplified form the main processes for the solubility carbon pump, organic and inorganic biological carbon pumps, and air-sea CO$_2$ flux. Modifications from the original OCMIP-II version include prognostic computation of new/export production as a function of light, temperature, phosphate and iron concentrations and a dynamical iron cycle.
Figure 3: Schematic of sequential spin-up procedure used to reduce physical and biogeochemical drift for CSM 1.4-Carbon control simulation.
Figure 4: Time-series of annual mean global a) surface temperature (deg. C), b) surface atmospheric CO$_2$ concentration (ppmv-dry air), and c) atmosphere, land, and ocean carbon inventory anomalies (Pg C) from the CSM 1.4-Carbon 1000 year control.
simulation. The dashed line in b) is the surface atmosphere CO\textsubscript{2} concentration from a companion 500-year control simulation with land biosphere CO2 fertilization.

Figure 5: Spatial maps of annual mean physical biases of the CSM 1.4-Carbon control simulation relative to modern climatological observations for a) temperature (K), model minus National Center for Environmental Prediction (NCEP) and b) precipitation (mm/day), model minus Global Precipitation Climatology Project (GPCP).
Figure 6: Spatial maps of terrestrial a) annual net primary production NPP (g C m$^{-2}$ y$^{-1}$), and b) total carbon storage (g C m$^{-2}$) averaged over the 1000 year CSM 1.4-Carbon control simulation.
Figure 7: Spatial maps of a) annual net air-sea CO$_2$ flux (mol C m$^{-2}$ y$^{-1}$) (positive out of the ocean) and b) particulate organic export at 75 m depth (mol C m$^{-2}$ y$^{-1}$) averaged over the 1000 year CSM 1.4-Carbon control simulation.
Figure 8: Atmospheric surface CO$_2$ fields (ppmv) from CSM 1.4-Carbon 1000 year control simulation. Panel a) shows the mean spatial distribution averaged over the bottom two model layers (~60 mb). Panel b) shows the mean seasonal cycle with rms interannual variability (shading) from the model and observations at the Mauna Loa Observatory, Hawaii. The model is sampled at the nearest sigma surface to the altitude of the Mauna Loa Observatory. Observed data are from NOAA/CMDL.
Figure 9: Time series of global integrated, annual net a) land and b) ocean CO₂ fluxes (Pg C/y) from the CSM 1.4-Carbon 1000 year control simulation, highlighting the magnitude of the interannual variability. Note the different vertical scales for the land and ocean panels.
Figure 10: Spatial maps of the rms variability (1σ rms variability) of a) annual net surface CO$_2$ fluxes (g C m$^{-2}$ y$^{-1}$) and b) annual surface atmospheric CO$_2$ spatial concentration anomalies (ppmv) over the 1000 year CSM 1.4-Carbon control simulation. Note the non-linear scale in panel a.
Figure 11: Spatial maps of the a) correlation between surface 2-m air temperature and soil moisture for June-July-August and b) covariance of net annual ecosystem production (NEP) and annual mean non-dimensional model soil moisture stress term $g(w)$ (Equation 4) from the CSM 1.4-carbon 1000-year control run (grey regions are where the correlation is not significant).
Figure 12: Panel a) time-series of low-pass filtered, global net land net primary production NPP, respiration $R_h$ and net ecosystem production NEP (Pg C yr$^{-1}$) from the CSM 1.4-Carbon 1000 year control simulation. A 20 year Hanning filter is used to remove high-frequency variability. Panel b) shows the squared coherence (0-1) versus frequency (cycles yr$^{-1}$) from cross-spectrum analyses of global land NEP versus NPP and $R_h$. 
Doney et al., Natural Climate-Carbon Cycle Variability, *J. Climate, submitted*. 

**Covariance of Air-Sea CO$_2$ Flux and NLD, (mol C/m$^2$/y)/(m)**

**Covariance of Air-Sea CO$_2$ Flux and SST, (mol C/m$^2$/y)/(C)**

**Covariance of Air-Sea CO$_2$ Flux and SSS, (mol C/m$^2$/y)/(psu)**
Figure 13: Spatial covariance maps of annual mean air-sea CO$_2$ flux (positive out of the ocean) and biological and physical forcing factors including a) mixed layer depth, b) sea surface temperature, c) sea surface salinity, and d) export production.
Figure 14: a) Power spectral density (Pg C y$^{-1}$)$^2$/cycles y$^{-1}$) versus frequency (cycles y$^{-1}$) for the global integrated land and ocean CO$_2$ fluxes from the CSM 1.4-Carbon 1000 year control simulation. The power spectra are for monthly anomalies generated by removing a mean seasonal cycle. Panel b) displays the spectrum for the total flux (land+ocean) in variance preserving form (frequency*power spectral density).
Figure 15: Cross-spectrum analysis for global integrated land and ocean CO$_2$ fluxes ($\Delta F_{\text{land}}$ vs. $\Delta F_{\text{ocean}}$) from CSM 1.4-Carbon 1000-year control simulation. Panel a) shows the squared coherence (0-1) versus frequency (cycles y$^{-1}$). Panel b) shows the phase difference (degrees; <0 ocean lags) between ocean and land CO$_2$ fluxes (solid line) and ocean CO$_2$ flux and atmospheric CO$_2$ (circles). A value of 0 degrees occurs when the time-series are perfectly correlated and +/-180 degrees when they are perfectly anti-
correlated. Phase in degrees can be converted to lags/leads in years by dividing by 360 (degree cycle\(^{-1}\)) \* frequency (cycles y\(^{-1}\)). Phases are not displayed for frequencies > 0.5 cycles y\(^{-1}\) because the \(\Delta F_{\text{land}} vs. \Delta F_{\text{ocean}}\) coherences (Panel a), on average, are equivalent to zero at the 95% confidence level.

Figure 16: Time-series of low-pass filtered, global net land and ocean CO\(_2\) fluxes (Pg C y\(^{-1}\)) and atmospheric CO\(_2\) inventory anomaly (Pg C; scaled by dividing by 20) from the CSM 1.4-Carbon 1000 year control simulation. A 20 year Hanning filter is used to remove high-frequency variability.