Nonlinearity of Carbon Cycle Feedbacks

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(Manuscript received 18 June 2010, in final form 18 February 2011)

ABSTRACT

Coupled climate–carbon models have shown the potential for large feedbacks between climate change, atmospheric CO2 concentrations, and global carbon sinks. Standard metrics of this feedback assume that the response of land and ocean carbon uptake to CO2 (concentration–carbon cycle feedback) and climate change (climate–carbon cycle feedback) combine linearly. This study explores the linearity in the carbon cycle response by analyzing simulations with an earth system model of intermediate complexity [the University of Victoria Earth System Climate Model (UVic ESCM)]. The results indicate that the concentration–carbon and climate–carbon cycle feedbacks do not combine linearly to the overall carbon cycle feedback. In this model, the carbon sinks on land and in the ocean are less efficient when exposed to the combined effect of elevated CO2 and climate change than to the linear combination of the two. The land accounts for about 80% of the nonlinearity, with the ocean accounting for the remaining 20%. On land, this nonlinearity is associated with the different response of vegetation and soil carbon uptake to climate in the presence or absence of the CO2 fertilization effect. In the ocean, the nonlinear response is caused by the interaction of changes in physical properties and anthropogenic CO2. These findings suggest that metrics of carbon cycle feedback that postulate linearity in the system’s response may not be adequate.

1. Introduction

Since preindustrial times, human activities have emitted large amounts of carbon dioxide (CO2) into the atmosphere (490 PgC from 1850 to 2006; Canadell et al. 2007). About half of these emissions have been taken up by sinks in the ocean and the terrestrial biosphere (Denman et al. 2007). On land, uptake of anthropogenic CO2 is driven by the stimulation of photosynthesis through elevated atmospheric CO2 (CO2 fertilization effect; Norby et al. 2005), warmer temperatures at high latitudes, anthropogenic nitrogen deposition (Lamarque et al. 2005), and regrowth of vegetation on abandoned agricultural lands (Caspersen et al. 2000). In the ocean, CO2 is dissolved in surface waters and is transported to depth by ocean circulation (solubility pump) and the formation and export of organic material by ocean biota (biological pump).

The future efficacy of these sinks in taking up anthropogenic CO2 is determined by two key processes:
the response to increasing atmospheric CO₂ and the response to climate change. The current generation of coupled climate–carbon cycle models simulates increases in carbon uptake in response to elevated CO₂ levels (Friedlingstein et al. 2006; Plattner et al. 2008; Gregory et al. 2009; Boer and Arora 2009). This response slows the rate of atmospheric CO₂ increase and hence results in a negative feedback. This feedback will in the following be referred to as the “concentration–carbon cycle” feedback (Boer and Arora 2009), in analogy to the more prominent climate–carbon cycle feedback discussed below. The magnitude of the concentration feedback remains highly uncertain, particularly with regard to the land biosphere. Key uncertainties are related to the rate of surface to deep ocean transport of carbon and nutrients, the effect of ocean acidification on marine biota, the response of terrestrial productivity to rising atmospheric CO₂, the concomitant availability of nitrogen and other nutrients, and vegetation dynamics.

Climate change affects the air–sea exchange of heat, freshwater, and momentum, which in turn modifies the physical (sea surface temperature, ocean circulation) and biogeochemical seawater properties and hence the oceanic sink of CO₂. It also affects temperature and precipitation over land, altering the distribution and functioning of terrestrial ecosystems and the associated CO₂ uptake. Coupled climate–carbon cycle models suggest that climate change could reduce CO₂ uptake and accelerate accumulation of CO₂ in the atmosphere, providing for a positive feedback (Cox et al. 2000; Friedlingstein et al. 2001; Fung et al. 2005; Gregory et al. 2009; Boer and Arora 2009). This climate–carbon cycle feedback varies widely among models (Friedlingstein et al. 2006; Plattner et al. 2008). Uncertainties arise from changes in the seawater solubility and surface to deep ocean transport of CO₂, the response of vegetation productivity and carbon overturning in soils under warmer temperatures, and vegetation shifts such as forest dieback in tropical regions.

To quantify the climate–carbon cycle feedback, earlier studies have generally performed two simulations: one fully coupled simulation in which climate change affects the carbon cycle and one “uncoupled” simulation in which fixed preindustrial CO₂ was prescribed to the model’s radiation scheme (so that the carbon cycle experiences the increasing atmospheric CO₂, but no CO₂-induced climate change). The climate–carbon cycle feedback was then computed as the difference in atmospheric CO₂ between the fully coupled and the uncoupled simulation. Implicitly, such a procedure assumes that the climate feedback is independent of the atmospheric CO₂ concentration. However, this is not necessarily the case; for example, model simulations have shown that the effect of climate change on land carbon uptake is significantly different in the absence or presence of CO₂ fertilization (Matthews 2007). Similarly, one would expect the effect of climate-induced changes in ocean properties, for example, in ocean circulation, on carbon uptake to be dependent on the atmospheric CO₂ level (Zickfeld et al. 2007).

Here, we use a coupled climate–carbon cycle model of intermediate complexity to systematically explore the response of land and ocean carbon uptake to the separate and combined effects of increasing CO₂ and climate change. We show that the concentration–carbon and climate–carbon cycle feedback do not combine linearly to the overall feedback and investigate the mechanisms responsible for this nonlinearity. Furthermore, we assess the implications of this nonlinearity for the estimation of proposed carbon cycle feedback metrics.

2. Methods

a. Model description

We use version 2.9 of the University of Victoria Earth System Climate Model (UVic ESCM). This version of the UVic ESCM consists of a 3D ocean general circulation model with isopycnal mixing and a Gent and McWilliams (1990) (GM) parameterization of the effect of eddy-induced tracer transport. For diapycnal mixing, a horizontally constant profile of diffusivity is applied, with a value of about 0.3 × 10⁻⁴ m² s⁻¹ in the pycnocline. The ocean model is coupled to a dynamic–thermodynamic sea ice model and an energy–moisture balance model of the atmosphere with dynamical feedbacks (Weaver et al. 2001).

The land surface and terrestrial vegetation are represented by a simplified version of the the Met Office Hadley Centre’s Surface Exchange Scheme (MOSES) coupled to the dynamic vegetation model the Top-Down Representation of Interactive Foliage and Flora Including Dynamics (TRIFFID). Land carbon fluxes are calculated within MOSES using a photosynthesis–stomatal conductance model based on a biochemical model for photosynthesis of C3 and C4 plants (Collatz et al. 1991, 1992). Carbon fluxes calculated in MOSES are allocated to vegetation and soil carbon pools of the five plant functional types represented by the vegetation model (Meissner et al. 2003). The land carbon cycle model does not consider nutrient limitation of photosynthesis. Ocean carbon is simulated by means of an Ocean Carbon Model Intercomparison Project (OCMIP)-type inorganic carbon cycle model (Orr et al. 1999) and a marine ecosystem–biogeochemistry model solving prognostic equations for nutrients, phytoplankton, zooplankton, and detritus (NPZD) with a parameterization of fast nutrient
recycling due to microbial activity (Schmittner et al. 2008). The ecosystem model includes two phytoplankton classes (nitrogen fixers and other phytoplankton), nitrate and phosphate as nutrients, as well as oxygen, dissolved inorganic carbon, and alkalinity. The version of the UVic ESCM used here includes a marine sediment component (Eby et al. 2009), which is based on Archer (1996).

b. Experimental design

The model was spun up with fixed preindustrial atmospheric CO₂ and run in the fully coupled mode for several thousand years. From 1800 to 2000, the model was forced with reconstructed historical CO₂ emissions. From 2001 to 2100, CO₂ emissions were prescribed according to the A2 scenario of the Special Report on Emission Scenarios (SRES) (Nakićenović and Swart 2000). After 2100, CO₂ emissions were assumed to decline linearly, reaching zero by 2300 (Fig. 1a). Non-CO₂ forcings were held fixed at their preindustrial values in all simulations. The spatial pattern of land use (cropland) was also held fixed at the preindustrial distribution, and CO₂ emissions from land use were prescribed externally rather than being simulated by the model.

The standard model configuration is represented by the fully coupled simulation (Table 1). To explore the effect of elevated CO₂ and climate change on the carbon sinks separately, we performed a set of model simulations whereby atmospheric CO₂ was fixed at preindustrial levels to either the physical climate model (more specifically, the radiation component) and/or the terrestrial carbon cycle and/or the ocean carbon cycle. We adopt a naming convention whereby we highlight the components of the earth system that are affected by...

![Fig. 1. Results for the simulations with specified CO₂ emissions: (a) CO₂ emissions, (b) atmospheric CO₂, (c) cumulative land carbon uptake, (d) cumulative ocean carbon uptake, and (e) global mean surface air temperature change relative to 1800.](image-url)
an increase in atmospheric CO2. Accordingly, the fully coupled experiment is referred to as CLOe, since all components, the climate (C), the land biosphere (L), and the ocean (O), respond to the increasing atmospheric CO2. The suffix “e” is used to characterize experiments with specified emissions, as opposed to experiments with specified concentrations which will be described below. The experiment LOe represents the “biogeochemically coupled” case and is equivalent to the “uncoupled” experiment of the Coupled Climate–Carbon Cycle Model Intercomparison Project (C4MIP) (Friedlingstein et al. 2006). Ce is an experiment whereby only the climate module is affected by increasing CO2, whereas the latter is held constant at preindustrial levels with respect to the terrestrial and oceanic carbon cycle components. In analogy to the above, this will be referred to as the “radiatively coupled” experiment (Gregory et al. 2009). In simulation COe (CLE) CO2 is fixed at preindustrial levels to the land (ocean). Finally, Le and Oe are simulations where only land and ocean, respectively, respond to elevated CO2. Ue is a fully uncoupled simulation, where neither the carbon sinks nor the climate are affected by the increasing CO2, implying that the atmospheric CO2 burden evolves according to the cumulative CO2 emissions. In the following this simulation will be referred to as the “control.”

In addition to the experiments with specified CO2 emissions described above, we performed a set of experiments with prescribed atmospheric CO2 concentrations and diagnosed emissions based on changes in terrestrial and oceanic carbon uptake that are consistent with the prescribed atmospheric CO2 increase (Hibbard et al. 2007; Plattner et al. 2008). The advantage compared to the simulations with prescribed emissions is that the carbon sinks respond to the same atmospheric CO2 concentration in all simulations, which allows for a more rigorous separation of feedback processes. We performed simulations with specified atmospheric CO2 for all model configurations described above (in the following referred to as CLO, LO, CL, CO, C, L, O, and U; see Table 1). In these simulations, atmospheric CO2 from the CLOe experiment was prescribed from 1800 to 2300, and non-CO2 forcings were held fixed at preindustrial levels as in the experiments with specified emissions.

To explain differences in ocean carbon uptake between the fully coupled (CLO) and radiatively coupled (C) experiments, we conducted four additional simulations isolating the effects of wind changes and marine biology on ocean uptake. Simulations CLOfwind and Cfwind are identical to CLO and C, respectively, but with winds fixed at the year-1800 pattern. Simulations CLOfnpzd and Cfnpzd are identical to CLO and C except with biological fluxes of dissolved inorganic carbon and alkalinity fixed at year-1800 values.

c. Carbon cycle feedback metrics

Following the standard C4MIP procedure (Friedlingstein et al. 2006), the climate–carbon cycle feedback is computed as the difference in simulated atmospheric CO2 between the fully coupled (CLOe) and the biogeochemically coupled (LOe) experiments with specified CO2 emissions. Alternatively, this feedback can be estimated from the atmospheric CO2 difference between the radiatively coupled (Ce) and the control simulation (Ue) (Gregory et al. 2009). Specifically, the former represents the effect of climate change on carbon uptake under elevated atmospheric CO2, whereas the latter quantifies the effect of climate change under preindustrial

<table>
<thead>
<tr>
<th>Expt</th>
<th>Simulation type</th>
<th>Model setup</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLOe</td>
<td>Prescribed emissions</td>
<td>Fully coupled model run</td>
</tr>
<tr>
<td>LOe</td>
<td>Prescribed emissions</td>
<td>CO2 fixed with respect to climate (biogeochemically coupled)</td>
</tr>
<tr>
<td>Ce</td>
<td>Prescribed emissions</td>
<td>CO2 fixed with respect to land and ocean (radiatively coupled)</td>
</tr>
<tr>
<td>Ue</td>
<td>Prescribed emissions</td>
<td>CO2 fixed with respect to climate, land and ocean (control)</td>
</tr>
<tr>
<td>COe</td>
<td>Prescribed emissions</td>
<td>CO2 fixed with respect to land</td>
</tr>
<tr>
<td>CLe</td>
<td>Prescribed emissions</td>
<td>CO2 fixed with respect to climate and land</td>
</tr>
<tr>
<td>Oe</td>
<td>Prescribed emissions</td>
<td>CO2 fixed with respect to climate and ocean</td>
</tr>
<tr>
<td>Le</td>
<td>Prescribed emissions</td>
<td>CO2 fixed with respect to climate and land</td>
</tr>
<tr>
<td>L</td>
<td>Prescribed concentrations</td>
<td>Fully coupled model run</td>
</tr>
<tr>
<td>CO</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to land and ocean (radiatively coupled)</td>
</tr>
<tr>
<td>C</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to land and ocean (radiatively coupled)</td>
</tr>
<tr>
<td>U</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to climate, land and ocean (control)</td>
</tr>
<tr>
<td>O</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to climate and land</td>
</tr>
<tr>
<td>L</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to climate and ocean</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>Expt</th>
<th>Simulation type</th>
<th>Model setup</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLO</td>
<td>Prescribed concentrations</td>
<td>Fully coupled model run</td>
</tr>
<tr>
<td>LO</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to climate (biogeochemically coupled)</td>
</tr>
<tr>
<td>C</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to land and ocean (radiatively coupled)</td>
</tr>
<tr>
<td>U</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to climate, land and ocean (control)</td>
</tr>
<tr>
<td>CO</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to land</td>
</tr>
<tr>
<td>CL</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to land</td>
</tr>
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<td>O</td>
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<tr>
<td>L</td>
<td>Prescribed concentrations</td>
<td>CO2 fixed with respect to climate and ocean</td>
</tr>
</tbody>
</table>
atmospheric CO₂. If the climate feedback were independent of the atmospheric CO₂ concentration, the two would be identical.

Given the availability of a set of extra simulations, where one or more components of the earth system are uncoupled with respect to atmospheric CO₂, we can also quantify a number of other feedbacks. For instance, the atmospheric CO₂ difference between the biogeochemically coupled (LOe) and control (Ue) experiments represents the direct effect of elevated atmospheric CO₂ concentration on the terrestrial and marine carbon sinks. This effect will be referred to as the “concentration–carbon feedback,” in analogy to the climate–carbon feedback. The concentration–carbon feedback can be further separated into the effect of elevated CO₂ on the terrestrial (marine) carbon cycle by taking the CO₂ difference between the fully coupled (CLOe) and control (Ue) experiments quantifies the total effect of elevated CO₂ and climate change on the carbon sinks (Table 2).

For the runs with specified atmospheric CO₂ (which is the same in all simulations), we compute the climate and concentration carbon feedbacks as differences in implied cumulative emissions. The designation of feedbacks and the runs used for their quantification are the same as for the runs with specified emissions (Table 2).

Table 2. Carbon cycle feedbacks for runs with specified CO₂ emissions (Spec. E) and specified CO₂ concentrations (Spec. CO₂) at 2100. Year-2300 values are given in parentheses. For the sake of comparison, diagnosed cumulative emissions in the runs with specified atmospheric CO₂ were multiplied by −1 and converted from PgC to ppm, using a conversion factor of 0.48. Negative values are indicative of a negative feedback. Differences between rows 1, 9, 10, and 11 give the nonlinearity in the total carbon feedback, and differences between rows 4 and 12 give the nonlinearity in the concentration-carbon feedback.

<table>
<thead>
<tr>
<th>No.</th>
<th>Model experiments</th>
<th>Feedback</th>
<th>Spec. E ΔC₄ (ppm)</th>
<th>Spec. CO₂ − ΔC₄ (ppm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CLO − U</td>
<td>Total carbon feedback</td>
<td>−440 (−710)</td>
<td>−440 (−720)</td>
</tr>
<tr>
<td>2</td>
<td>C − U</td>
<td>Climate feedback (preindustrial CO₂)</td>
<td>240 (400)</td>
<td>150 (330)</td>
</tr>
<tr>
<td>3</td>
<td>CLO − LO</td>
<td>Climate feedback (elevated CO₂)</td>
<td>110 (440)</td>
<td>170 (560)</td>
</tr>
<tr>
<td>4</td>
<td>LO − U</td>
<td>Concentration feedback</td>
<td>−540 (−1150)</td>
<td>−610 (−1280)</td>
</tr>
<tr>
<td>5</td>
<td>L − U</td>
<td>Land concentration feedback</td>
<td>−360 (−550)</td>
<td>−350 (−560)</td>
</tr>
<tr>
<td>6</td>
<td>O − U</td>
<td>Ocean concentration feedback</td>
<td>−300 (−730)</td>
<td>−270 (−730)</td>
</tr>
<tr>
<td>7</td>
<td>CL − U</td>
<td>Land total feedback, ocean climate feedback</td>
<td>−190 (40)</td>
<td>−190 (40)</td>
</tr>
<tr>
<td>8</td>
<td>CO − U</td>
<td>Ocean total feedback, land climate feedback</td>
<td>−140 (−390)</td>
<td>−110 (−350)</td>
</tr>
<tr>
<td>9</td>
<td>(C − U) + (LO − U)</td>
<td>Climate feedback + concentration feedback</td>
<td>−300 (−740)</td>
<td>−460 (−950)</td>
</tr>
<tr>
<td>10</td>
<td>(CL − U) + (O − U)</td>
<td>Land total feedback, ocean climate feedback + ocean concentration feedback</td>
<td>−490 (−690)</td>
<td>−450 (−760)</td>
</tr>
<tr>
<td>11</td>
<td>(CO − U) + (L − U)</td>
<td>Ocean total feedback, land climate feedback + land concentration feedback</td>
<td>−500 (−940)</td>
<td>−460 (−910)</td>
</tr>
<tr>
<td>12</td>
<td>(L − U) + (O − U)</td>
<td>Land concentration feedback + ocean concentration feedback</td>
<td>−660 (−1280)</td>
<td>−610 (−1280)</td>
</tr>
</tbody>
</table>

The feedback factors \( F \) are computed as the ratio in atmospheric CO₂ change between runs with a specific feedback on and off (Denman et al. 2007):

\[
F = \frac{\Delta C_A^{on}}{\Delta C_A^{off}}. \tag{1}
\]

For the concentration–carbon feedback, for instance, \( F \) is given as the \( \Delta C_A \) ratio between the biogeochemically coupled and the control simulation. The feedback parameter is greater than 1 for positive carbon cycle feedbacks and less than 1 for negative feedbacks.

Because the CO₂ concentration is identical in all simulations, the estimation of the feedback factor given by Eq. (1) is not meaningful in the case of specified atmospheric CO₂. Following Plattner et al. (2008) we estimate the feedback factor as the ratio in implied cumulative emissions (\( \Delta C_E \)) for simulations with a specific feedback on and off:

\[
F = \frac{\Delta C_E^{off}}{\Delta C_E^{on}}. \tag{2}
\]

Since a positive feedback is associated with lower implied emissions (i.e., \( \Delta C_E^{off} > \Delta C_E^{on} \)) and vice-versa, the ratio in Eq. (1) is inverted to preserve the magnitude of the feedback factor (greater than 1 for positive feedbacks and less than 1 for negative feedbacks).

Building on the formalism of Friedlingstein et al. (2006), we also compute the land and ocean carbon sensitivities to increasing atmospheric CO₂ and climate change. Assuming that the effects of elevated atmospheric CO₂ and climate change combine linearly, Friedlingstein et al. (2006) approximate changes in land and ocean carbon storage in the fully coupled simulation (CLOe) by
\[
\Delta C_L^{\text{LOe}} = \beta_L \Delta C_A^{\text{LOe}} + \gamma_L \Delta T^{\text{LOe}}, \quad \text{and (3)}
\]
\[
\Delta C_O^{\text{LOe}} = \beta_O \Delta C_A^{\text{LOe}} + \gamma_O \Delta T^{\text{LOe}},
\]
where \(\Delta C_L\) and \(\Delta C_O\) are the respective changes in land and ocean carbon storage since preindustrial times (in PgC), \(\Delta C_A\) is the change in atmospheric CO2 concentration (in ppm), and \(\Delta T\) is the change in global mean temperature (in K). Here, \(\beta_L\) (\(\beta_O\)) is the land (ocean) carbon sensitivity to atmospheric CO2 and \(\gamma_L\) (\(\gamma_O\)) the land (ocean) carbon sensitivity to temperature.

The land and ocean carbon sensitivity parameters to atmospheric CO2 can be estimated from the biogeochemically coupled simulation (LOe) as
\[
\beta_L = \frac{\Delta C_L^{\text{LOe}}}{\Delta C_A^{\text{LOe}}}, \quad \text{and (5)}
\]
\[
\beta_O = \frac{\Delta C_O^{\text{LOe}}}{\Delta C_A^{\text{LOe}}},
\]
Note that \(\beta_L\) (\(\beta_O\)) can also be determined from the simulation where only the land (ocean) is coupled with respect to CO2 (Le and Oe, respectively).

Similarly, the land and ocean carbon sensitivity parameters to temperature can be computed from the radiatively coupled simulation (Ce) as
\[
\gamma_L = \frac{\Delta C_L^{\text{Ce}}}{\Delta T^{\text{Ce}}}, \quad \text{and (7)}
\]
\[
\gamma_O = \frac{\Delta C_O^{\text{Ce}}}{\Delta T^{\text{Ce}}}
\]
Note that for the C4MIP project a radiatively coupled simulation was not available. Therefore, the carbon sensitivities to temperature change were estimated as
\[
\gamma_L = \left[ (\Delta C_L^{\text{LOe}} - \Delta C_L^{\text{LOe}}) - \beta_L (\Delta C_A^{\text{LOe}} - \Delta C_A^{\text{LOe}}) \right]/\Delta T^{\text{LOe}}, \quad \text{and (9)}
\]
\[
\gamma_O = \left[ (\Delta C_O^{\text{LOe}} - \Delta C_O^{\text{LOe}}) - \beta_O (\Delta C_A^{\text{LOe}} - \Delta C_A^{\text{LOe}}) \right]/\Delta T^{\text{LOe}}.
\]
As we will show in section 6, this procedure significantly overestimates the sensitivities \(\gamma_L\) and \(\gamma_O\), as it neglects nonlinearities in the response of the system to climate change and CO2.

Similar formulas as above [Eqs. (5)–(10)] are used to determine the carbon sensitivities for the runs with specified atmospheric CO2 concentration. The only difference is that \(\Delta C_A\) is identical in all simulations, which simplifies some of the equations. For instance, Eqs. (9)–(10) can be written as
\[
\gamma_L = (\Delta C_L^{\text{LOe}} - \Delta C_L^{\text{LOe}})/\Delta T^{\text{LOe}}, \quad \text{and (11)}
\]
\[
\gamma_O = (\Delta C_O^{\text{LOe}} - \Delta C_O^{\text{LOe}})/\Delta T^{\text{LOe}}.
\]

3. Carbon cycle feedbacks under specified CO2 emissions

In this section, we compare the results of the fully coupled (CLOe), biogeochemically coupled (LOe), radiatively coupled (Ce), and uncoupled or control (Ue) simulations driven by specified CO2 emissions.

a. Atmospheric CO2

Figure 1b displays the atmospheric CO2 concentration for the time period 1800–2300. The control simulation (Ue) represents the unperturbed case, where atmospheric CO2 is entirely uncoupled from the carbon sinks on land and in the ocean and hence evolves according to the cumulative CO2 emissions. If the carbon sinks are turned on but are affected by the rising atmospheric CO2 only, as in the biogeochemically coupled experiment (LOe), they act to significantly reduce the atmospheric CO2 perturbation relative to the control. This effect is driven by the CO2 fertilization of photosynthesis on land and the dissolution of CO2 in seawater. This negative feedback of carbon uptake on atmospheric CO2 (concentration–carbon feedback) amounts to −540 ppmv in 2100 and −1150 ppmv in 2300 (Table 2).

In contrast, if the sinks respond to the effects of climate change only (radiatively coupled simulation; Ce), they act to amplify the atmospheric CO2 perturbation relative to the control. The reason is that climate change leads to release of natural CO2 from the terrestrial biosphere and the ocean (Figs. 1c,d). This positive feedback of climate change on the natural carbon cycle amounts to 240 ppmv in 2100 and 400 ppmv in 2300.

The difference between the fully coupled simulation (CLOe) and the control (Ue) quantifies the total feedback of elevated CO2 and climate change on the carbon cycle. This feedback (~440 ppmv in 2100 and ~710 ppmv in 2300) is also negative, implying that the effect of elevated CO2 on the carbon sinks dominates over that of climate change.

An important question is to what extent the overall carbon cycle feedback (CLOe − Ue) is a linear combination of the climate–carbon (Ce − Ue) and the concentration–carbon (LOe − Ue) feedbacks. As indicated in Fig. 1b, the atmospheric CO2 in the linearly combined case (Ce + LOe − Ue) is higher than in the fully coupled simulation (CLOe), particularly during the period 2000–2200. This implies that the climate–carbon cycle feedback under elevated CO2 computed following the standard C4MIP procedure (i.e., as the
CO₂ difference between CLOe and LOe runs) differs significantly from the value reported above (110 ppm compared to 240 ppm in 2100; Table 2).¹

The nonlinearity in the carbon cycle feedbacks could be associated with the interactions between excess atmospheric CO₂ and climate change but may also be a simple consequence of the different CO₂ concentration levels seen by the sinks in the different experiments. To explore the nonlinearity in the carbon cycle feedbacks without the confounding effect of different CO₂ concentration levels, we performed a set of simulations whereby the same atmospheric CO₂ is specified in all experiments. The results of these simulations will be discussed in section 4.

b. Carbon budget changes

Figures 1c and 1d show the partitioning of CO₂ uptake between the land and the ocean. CO₂ uptake is strongest in the biogeochemically coupled simulation, where the sinks respond to the additional CO₂ but not to the changes in climate. In this simulation, land and ocean continue to take up CO₂, even though the land uptake declines around 2100. In the fully coupled simulation, the ocean takes up CO₂ throughout the simulated period, but uptake on land ceases around 2120 and becomes negative thereafter, implying that the land becomes a source of CO₂ to the atmosphere (Cox et al. 2000). In the radiatively coupled run (Ce) both the land and the ocean are sources of CO₂ throughout the simulation.

The negative effect of climate change on CO₂ uptake (Ce – Ue) is substantially larger on land than in the ocean (−650 PgC versus −205 PgC difference in cumulative uptake in 2300) (Friedlingstein et al. 2006). The nonlinearity in the response of the sinks to elevated CO₂ and climate change (Ce + LOe – Ue versus CLOe) is also more pronounced on land. Interestingly, the sign of the nonlinearity in land uptake flips around the year 2180; before this date, land uptake is stronger in the fully coupled simulation than in the linearly combined case but becomes weaker thereafter. This is also the reason why the nonlinearity in the CO₂ concentration is small during the last century of the simulation (Fig. 1b); before 2180, the nonlinearities in land and ocean uptake are of the same sign but are opposite thereafter.

c. Temperature changes

Global mean temperature change (relative to 1800) is largest in the Ce simulation (5.2°C in 2100 and 8.7°C in 2300; Fig. 1e). The temperature difference relative to the fully coupled simulation (CLOe) (7.5°C in 2300) is mostly due to the higher atmospheric CO₂ concentration. However, as will be demonstrated in section 4, the higher radiative forcing from CO₂ is partly compensated by a higher surface albedo in the Ce relative to the CLOe run associated with differences in spatial distribution of vegetation (Matthews 2007). Note also that global mean surface air temperature change is different from zero in the biogeochemically coupled experiment, although there is no radiative forcing from CO₂. This effect is also explained by surface albedo differences associated with vegetation shifts. The cause for these vegetation-induced albedo changes will be discussed in detail in section 4.

4. Carbon cycle feedbacks under specified CO₂ concentrations

a. Allowable CO₂ emissions

Figure 2a compares the allowable CO₂ emissions from the fully coupled (CLO), biogeochemically coupled (LO), radiatively coupled (C), and fully uncoupled (U) simulations. In these simulations, atmospheric CO₂ from the fully coupled run with specified CO₂ emissions (CLOe) is prescribed, and the allowable emissions are computed from the change in atmospheric carbon inventory plus the carbon uptake by land and ocean. Hence, the more efficient the carbon sinks, the higher the allowable emissions, and vice versa. Accordingly, the allowable emissions are largest in the biogeochemically coupled experiment (LO), where the sinks respond to the additional CO₂ but not the climate changes and lowest in the radiatively coupled experiment (C), where the sinks respond to the (negative) effects of climate change alone.

Similarly to the runs with specified emissions, the climate feedback on the natural carbon cycle is quantified as the difference in allowable emissions between the radiatively coupled (C) and the control (U) simulations. This feedback amounts to −310 PgC in 2100 and −690 PgC in 2300 (in Table 2 these values are given in ppm for easier comparison with the runs with specified emissions). It should be noted that in the case of specified atmospheric CO₂ a negative (positive) difference in allowable emissions implies a positive (negative) feedback, in contrast to the runs with specified emissions. The concentration–carbon feedback (LO – U) is negative and amounts to 1270 PgC in 2100 and 2670 PgC in 2300.

The allowable CO₂ emissions in the case where the concentration–carbon and the climate–carbon feedbacks are combined linearly (C + LO – U) are remarkably

¹ This value is slightly lower than that reported in the C4MIP intercomparison for an earlier version of the UVic ESCM (125 ppm; Friedlingstein et al. 2006).
similar to those in the fully coupled experiment (CLO) until about 2100, indicating that in the UVic ESCM the effects of CO$\textsubscript{2}$ and climate change on the carbon sinks combine almost linearly up to this date. Thereafter, the response becomes increasingly nonlinear, with the difference between the linearly combined and the coupled case reaching 480 PgC in 2300. Accordingly, the climate–carbon cycle feedback computed with the C$^4$MIP procedure (CLO$\textsuperscript{2}$LO) is very similar to that computed using the emissions difference between the C and U runs up to 2100 but differs markedly thereafter (21170 PgC versus 2690 PgC in 2300; see also Table 2). Interestingly, the C$^4$MIP climate feedback in 2100 is slightly larger than the climate feedback under preindustrial CO$\textsubscript{2}$ (C$-$U) for the runs with specified CO$\textsubscript{2}$ concentrations but is considerably smaller for the experiments with specified CO$\textsubscript{2}$ emissions (cf. the rows labeled 2 and 3 in Table 2). This opposite sign of the nonlinearity is associated with the different atmospheric CO$\textsubscript{2}$ and warming levels in the experiments with specified emissions. For instance, the carbon sinks in the Ce experiment are affected by significantly warmer temperatures (1.2$^\circ$C globally) owing to higher atmospheric CO$\textsubscript{2}$ levels than their counterparts in the C experiment. The stronger warming results in lower carbon uptake and hence a stronger climate feedback (C$-$U) in experiments with specified emissions. On the other hand, the difference in atmospheric CO$\textsubscript{2}$ between the CLOe and the LOe experiments is larger than in the corresponding experiments with specified CO$\textsubscript{2}$, while the temperature difference is similar. The additional CO$\textsubscript{2}$ fertilization in the experiments with specified emissions leads to stronger carbon uptake and hence a smaller C$^4$MIP-type feedback.
b. Carbon uptake changes

Qualitatively, carbon uptake changes by the land and the ocean are very similar to those in the experiments with specified emissions (Figs. 2c,d). The main difference is that because of specified atmospheric CO2, the ocean does not compensate for the reduced land uptake. The nonlinearity in the effects of elevated CO2 and climate change on the sinks (C + LO – U versus CLO) is smaller compared to the runs with specified emissions, particularly before 2100. Also, the sign of the nonlinearity is opposite: the simultaneous effect of elevated CO2 and climate change acts to reduce uptake, whereas it acts to increase uptake in the runs with specified emissions (except for the land uptake between 2180 and 2300), as discussed above. Similarly to the specified emissions runs, the nonlinearity in the land response (380 PgC in 2300) is larger than that in the ocean response (90 PgC in 2300). The reasons for these nonlinearities will be discussed in detail in section 5.

c. Temperature changes

Global mean surface air temperature is slightly higher in the fully coupled (CLO) compared to the radiatively coupled experiment (C) (by 0.2°C in 2100 and 0.5°C in 2300; Fig. 2e). Since atmospheric CO2 is the same in the two experiments, the temperature difference must be associated with differences in the distribution of vegetation and/or in the physiological response of vegetation to CO2. The top panel of Fig. 3 indicates that the temperature difference between the CLO and C simulations is largest over land, particularly in the tropics and over East Asia. We find that the temperature differences in these regions are caused mainly by differences in vegetation cover in the presence or absence of the CO2 fertilization effect. In the tropics, climate change alone (as in C) induces replacement of forest by grassland, whereas such a shift does not occur under the combined effect of climate change and elevated CO2 (as in CLO) (see Fig. 4 and discussion in section 5). Since grassland has a higher albedo and reflects more solar radiation than forest, the land surface is cooler in the radiatively coupled than in the fully coupled experiment. In East Asia at the southern edge of the boreal forest, climate change alone (as in C) induces replacement of shrubs with needle leaf trees, which also results in a higher surface albedo in the radiatively coupled compared to the fully coupled case.

As indicated in Fig. 2e, there is some global mean temperature change also in the biogeochemically coupled experiment relative to the control, although there is no radiative forcing from CO2. The global mean temperature difference amounts to 0.3°C by 2300. The warming is largest over Northeast Asia (Fig. 3, bottom), where shrubs (higher albedo) are replaced by trees (lower albedo). A decrease in albedo associated with vegetation shifts is also the main cause of the warming over the Americas and Africa.

The indirect effect of CO2 fertilization (or absence thereof) on global mean temperature via vegetation-related albedo changes was previously noted by Bala et al. (2006) and Matthews (2007). Using an earlier version of the UVic ESCM, Matthews (2007) attributed this to a general increase in spatial coverage of forest, and hence lower albedo, in the presence of CO2 fertilization. Elevated atmospheric CO2 can also affect climate through the physiological response of vegetation, specifically increased water use efficiency, which results in reduced evapotranspiration under elevated CO2 (Sellers et al. 1996; Doutriaux-Boucher et al. 2009; Cao et al. 2010).

5. Nonlinearity of climate–carbon cycle response

This section analyzes in detail the difference between the linear combination of the concentration-carbon and
the climate–carbon feedbacks \((C - U) + (LO - U)\) and the total carbon feedback \((CLO - U)\) for the runs with specified atmospheric CO\(_2\). For the sake of brevity we will in the following refer to differences relative to the uncoupled run \(U\) by using the subscript \(d\), that is, \(CLO_d = CLO - U\), \(C_d = C - U\), etc. Figure 5a illustrates the nonlinearity in the effect of elevated CO\(_2\) and climate change on the carbon sinks by displaying the difference in allowable emissions between the two cases. It is shown that after 2100 the allowable cumulative emissions in the linearly combined case are higher than in the fully coupled case. This indicates that overall the carbon sinks are less efficient if they are exposed to the combined effect of elevated CO\(_2\) and climate change than to the two effects separately. This is true for both the land and the ocean, which take up more CO\(_2\) in the linearly combined case (Figs. 5b,c).

Following a similar experimental design with the Hadley Centre Climate Model version 3, run at lower spatial resolution with a coupled climate–carbon cycle (HadCM3LC), Gregory et al. (2009) also found greater carbon uptake and hence allowable emissions in the linearly combined case are higher than in the fully coupled case. This indicates that overall the carbon sinks are less efficient if they are exposed to the combined effect of elevated CO\(_2\) and climate change than to the two effects separately. This is true for both the land and the ocean, which take up more CO\(_2\) in the linearly combined case (Figs. 5b,c).

To understand the mechanisms responsible for the nonlinearity in the land uptake, we further separate this quantity into the contributions from vegetation and soil (Fig. 5b). We find that globally the sign of the nonlinearity is opposite for vegetation and soil, with the former exhibiting reduced uptake in the linearly combined case, while the latter exhibits enhanced uptake relative to the fully coupled case. Initially, the nonlinearity in vegetation and soil uptake compensate each other. In the long term, however, the nonlinearity in the soil carbon uptake is dominant and total (i.e., vegetation + soil) land uptake becomes stronger in the linearly combined case.

The nonlinearity in the land uptake can be understood in terms of the different vegetation response to climate change in the presence or absence of CO\(_2\) fertilization simulated by the UVic ESCM (Matthews 2007). The difference is largest at low latitudes (cf. left and right panels in Fig. 6), where climate change (in particular higher temperature) without the beneficial effect of CO\(_2\) fertilization induces a dieback of forests and replacement by C4 grasses (Fig. 4). If, on the other hand, the vegetation is exposed to climate change and elevated CO\(_2\), forest remains the dominant vegetation type at low latitudes. Since grasslands store less carbon as biomass...
than forests, the UVic ESCM simulates a significantly larger negative vegetation carbon anomaly in the case where climate change acts alone, without the beneficial effect of CO2 fertilization. On the other hand, C4 grasses are more productive than forest (Fig. 6, bottom) and are associated with higher soil carbon (Pendall et al. 2011). As a consequence, the soil carbon anomaly in low latitudes is positive under the effect of climate change alone.

In the northern high latitudes, where vegetation productivity is limited by low temperatures, climate change leads to higher vegetation carbon both with and without CO2 fertilization (Fig. 6, top). Under the combined effect of climate change and CO2 fertilization, however, the increase in vegetation carbon is larger. Soil carbon uptake at these latitudes is determined by a subtle balance between enhanced productivity and stronger heterotrophic respiration in response to the higher temperatures. Under climate change alone, the stronger heterotrophic respiration dominates, leading to widespread reduction in soil carbon. Under the combined effect of climate change and CO2 the picture is more heterogeneous, with enhanced productivity dominating in some regions.

b. Nonlinearity in ocean uptake

In the ocean, the nonlinearity arises through the interaction of anthropogenic CO2 with the effects of climate change on physical ocean properties, such as ocean circulation and sea ice cover changes.

Figure 7 illustrates the effect of climate change on relevant physical ocean variables. Under climate change, sea surface temperature (SST) increases considerably, particularly at high latitudes. Sea surface salinity (SSS) decreases at high latitudes and in the equatorial region and increases in the subtropical gyres, reflecting changes in precipitation patterns. At high latitudes, strong warming leads to a significant decline in sea ice cover. Globally, the sea ice area decreases to 30% of its preindustrial extent by 2300.

Freshening and warming of surface waters in the northern high latitudes lead to a weakening and shoaling of the Atlantic meridional overturning circulation (AMOC). The maximum of the overturning circulation decreases by 30% in 2300. This weakening in response to global warming is in agreement with multimodel projections (Schmittner et al. 2005). Over the Southern Ocean, global warming induces a poleward shift and intensification of the westerlies (Fig. 7, bottom). This causes an acceleration of the Antarctic Circumpolar Current (ACC) and the meridional overturning circulation in the Southern Ocean (Deacon cell). Similar changes in the winds and ocean circulation in the Southern Hemisphere have been diagnosed in a suite of state-of-the-art coupled climate models (Fyfe and Saenko 2006).

The difference in the effect of climate change on cumulative ocean CO2 uptake between cases with elevated and preindustrial CO2 is most prominent in the North Atlantic, the Southern Ocean, and the tropics (Fig. 8, top panels). The North Atlantic is a region of strong CO2 uptake (Takahashi et al. 2009), which is associated with the deep convective mixing in winter. Under climate
change, the UVic ESCM projects a shoaling of the mixed layer (Fig. 7, middle right) and a weakening of the AMOC. This weakening has a different effect on cumulative CO$_2$ uptake depending on whether surface waters are exposed to elevated or preindustrial atmospheric CO$_2$ levels. The effect of AMOC weakening is twofold: it slows mixing of anthropogenic CO$_2$ into the deep ocean, but it also slows upward mixing of CO$_2$ that accumulates in the North Atlantic at depth of 500–3000 m owing to horizontal advection and isopycnal diffusion from low latitudes (Zickfeld et al. 2008a). Under elevated CO$_2$, the first effect dominates, and weakening of the AMOC leads to a reduction in CO$_2$ uptake (Obata 2007; Zickfeld et al. 2008a). In contrast, AMOC weakening under preindustrial CO$_2$ leads to a positive anomaly in CO$_2$ uptake due to reduced upward mixing of CO$_2$ into the surface layer.

In the Southern Ocean, the most notable difference in the climate change effect on cumulative CO$_2$ uptake between runs with preindustrial and elevated CO$_2$ occurs south of 60°S. In the present-day climate, this is a region of CO$_2$ outgassing (Takahashi et al. 2009; Gruber et al. 2009), where deep waters rich in dissolved inorganic carbon (DIC) are ventilated through wind-driven upwelling. As discussed earlier, climate change is associated with widespread loss of sea ice in this region, and acceleration of the meridional overturning circulation that, in turn, leads to stronger upwelling. The combined effect of stronger wind-driven upwelling and sea ice loss leads to opposite responses of CO$_2$ uptake south of 60°S, depending on whether surface waters are exposed to elevated or preindustrial atmospheric CO$_2$ levels (Zickfeld et al. 2007, 2008b; Lovenduski et al.)
In the preindustrial CO$_2$ case (C - U), melting of sea ice exposes upwelled carbon-rich water to the atmosphere, leading to anomalous outgassing of CO$_2$. This effect is amplified by stronger wind-induced upwelling, which brings even more carbon-rich water to the surface (Fig. 8, middle right). In contrast, if anthropogenic CO$_2$ builds up in the atmosphere (CLO - LO), melting of sea ice results in anomalous uptake of CO$_2$. The reason is that the deep, old upwelled water is exposed to higher atmospheric CO$_2$ than the level it is equilibrated with. Stronger wind-induced upwelling again acts to amplify this effect (Fig. 8, middle left).

In the tropics, most prominently in the eastern Pacific and the Atlantic, climate change leads to increased CO$_2$ outgassing along the equator and increased uptake north and south of the equator. As indicated in Fig. 8 (bottom panels) this pattern is largely a result of changes in ocean biology (Schmittner et al. 2008). Warmer ocean temperatures boost biological production, which results in increased export of carbon from the surface to the deep ocean and hence stronger CO$_2$ uptake. On the other hand, warmer waters also lead to faster remineralization of organic matter, which acts to increase DIC in subsurface waters. These DIC-rich waters feed the equatorial upwelling system, leading to anomalous outgassing in that region. This pattern (anomalous outgassing along the equator, anomalous uptake to the north and south of the equator) is evident both under preindustrial and elevated atmospheric CO$_2$, though being more pronounced in the second case. Since marine biological production is independent of the atmospheric CO$_2$ level, and the climate differences between the CLO and C runs are small,
we speculate that this difference in uptake is caused by nonlinearities in ocean carbonate chemistry (i.e., a different effect of similar biological fluxes of DIC and alkalinity on carbon uptake because of different surface ocean CO2 partial pressure under preindustrial and elevated CO2).

c. Further nonlinearities

So far, we have discussed the nonlinearity in carbon cycle feedbacks by exploring the difference between the total carbon cycle feedback ($C\text{LO}_U$) and the linear combination of the climate–carbon ($C\text{C}_U$) and concentration–carbon ($L\text{O}_U$) feedbacks. However, other combinations of runs can also be used to investigate the nonlinearities in the carbon cycle response. For example, if the climate–carbon cycle system responded linearly to increasing CO2 and climate change, one would expect the linear combination of the run that is fully coupled with respect to the land, but only radiatively coupled with respect to the ocean (CL), and the run that is biogeochemically coupled with respect to the ocean (O) to give similar allowable emissions as the fully coupled simulation ($C\text{LO}_U$).

Similarly, one would expect the linear combination of the
run which is fully coupled with respect to the ocean, but only radiatively coupled with respect to the land (CO), and the run which is biogeochemically coupled with respect to the land (L) to give similar allowable emissions as the fully coupled simulation (CLO).

Figure 9a displays the allowable cumulative emissions for the full set of simulations with prescribed atmospheric CO2. The emissions range is spanned by the radiatively coupled (C) and biogeochemically coupled (LO) simulations, as before (Fig. 2). The allowable emissions of the runs which are fully coupled with respect to either the land or the ocean, and radiatively coupled with respect to the other component (CL and CO) are higher than in the control simulation, indicating that either the land or the ocean act to take up CO2 from the atmosphere (in contrast to the radiatively coupled simulation, C, where both land and ocean are sources of CO2 to the atmosphere). The allowable emissions of runs which are biogeochemically coupled with respect to either the land or the ocean (L and O) lie in between the CL and CO runs, and the fully coupled simulation (CLO).

Figure 9b illustrates the nonlinearity in the total carbon cycle feedback for all possible linear combinations of runs. The cumulative emissions anomaly of the linear combinations \((C_d + L_d)_{\text{d}}\) and \((C_d + O_d)_{\text{d}}\) relative to \(CLO_d\) are very similar, indicating that the carbon-concentration feedback on land \((L_d)\) and in the ocean \((O_d)\) combine linearly to the total carbon concentration feedback \((L_d + O_d) = L_O_d\;\text{ (see also Table 2)}\). The small difference is due to the effect of vegetation-induced climate changes on the ocean carbon cycle (which is present in the \(L_O_d\) but not in the \(L_d + O_d\) case). The difference in allowable emissions between the linear combination \(C_d + L_d\) and \(CLO_d\) represents the nonlinearity in the land uptake associated with the combined effect of elevated CO2 and climate change (the ocean uptake of \(C_d + L_d\) is very similar to that of \(CLO_d\) (Fig. 9d), the small difference being again caused by the effect of vegetation...
Table 3. Model sensitivities to CO2 and climate change for runs with specified CO2 emissions and specified CO2 concentrations in the year 2100 (numbers in parentheses are year-2300 values). Feedback factors and model sensitivities were computed using Eqs. (1)–(12).

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<th>Feedback</th>
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<th>Specified concentrations</th>
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<td>Climate-carbon</td>
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6. Evaluation of feedback metrics

We analyze the sensitivities of carbon uptake to increasing CO2 and climate change, and the feedback factor using Eqs. (1)–(12) introduced in section 2c. Results for simulations with both prescribed CO2 emissions and prescribed concentrations are listed in Table 3.

As expected, the feedback factors \( F \) are indicative of a negative concentration–carbon \( (F < 1) \) and a positive climate–carbon feedback \( (F > 1) \). Differences in feedback factors between runs with prescribed emissions and prescribed atmospheric CO2 can be related to differences in the airborne fraction of cumulative emissions \( A = \Delta C_d/\Delta C_E \). In fact, Eqs. (1) and (2) can be rewritten as

\[
F = \frac{A^{on}}{A^{off}},
\]

for experiments with both prescribed CO2 emissions and prescribed CO2 concentrations. It should be mentioned that in contrast to the carbon sensitivities discussed below, the feedback factors are not additive (Gregory et al. 2009).

In all cases, land and ocean carbon sensitivities to CO2 \( (\beta_L \) and \( \beta_O \) ) are positive, implying increased carbon storage under enhanced atmospheric CO2. In contrast, the carbon sensitivities to temperature \( (\gamma_L \) and \( \gamma_O \) ) are negative, indicating reduced carbon storage in a warmer climate. The magnitude of \( \gamma_L \) is significantly larger than that of \( \gamma_O \), suggesting a larger sensitivity of land carbon storage to temperature. These results are qualitatively consistent with those reported in Friedlingstein et al. (2006) for a range of climate–carbon cycle models.

While the differences in \( \beta_L \) and \( \beta_O \) between runs with prescribed emissions and prescribed atmospheric CO2 are modest, the differences in carbon sensitivities to climate \( (\gamma_L \) and \( \gamma_O \) ) are considerable, with \( \gamma_L \) and \( \gamma_O \) being substantially smaller in simulations with prescribed CO2 (Table 3). These differences can be explained with the different methodology used to estimate \( \gamma \) in the two type of experiments. In the runs with specified atmospheric CO2, \( \gamma \) is determined directly from the difference in carbon storage between simulations with the climate–carbon feedback on and off [Eqs. (11)–(12)]. In the simulations with specified emissions, \( \beta \) is needed to separate the climate effect from the combined climate and CO2 effect on ocean and land carbon storage [Eqs. (9)–(10)]. This approach, which was used in the C4MIP analysis, assumes that \( \beta \) is constant and independent of the atmospheric CO2 concentration, which is not the case (see discussion below). As a result, nonlinearities in the response of the carbon sinks to CO2 are attributed to climate change, leading to an overestimation.
of $\gamma$ in the simulations with specified emissions. These results are consistent with those of Plattner et al. (2008), who also find substantially larger values for $\gamma_L$ and $\gamma_O$ for runs with specified emissions with the Bern2.5CC model.

The carbon sensitivities reflect the linearity in the response of the coupled climate–carbon cycle system to elevated CO$_2$ and climate change. For the runs with prescribed atmospheric CO$_2$, the values of $\beta_L$ and $\beta_O$ are the same, irrespective of whether they are computed from the biogeochemically coupled run (LO) or the run where only the land or the ocean is coupled with respect to CO$_2$ (L and O, respectively) (Table 2 and Fig. 10). The reason is that the carbon sinks respond to the same atmospheric CO$_2$ concentration in the L, O, and LO simulations, and the climate is very similar, except for the small vegetation-induced climate change (in L and LO) mentioned earlier. In contrast, $\beta_L$ and $\beta_O$ are sensitive to the choice of model simulation in runs with prescribed emissions owing to different atmospheric CO$_2$ levels.

In the prescribed atmospheric CO$_2$ case the sensitivities $\gamma_L$ and $\gamma_O$ at 2100 are only slightly affected by the choice of model runs used for their estimation (Table 3), indicating the linearity in the response of the climate–carbon cycle system up to 2100. Thereafter, the system behaves nonlinearly and the carbon sensitivities to temperature are larger if the sinks are exposed to the effect of CO$_2$ and climate change simultaneously. For example, $\gamma_L$ at 2300 amounts to $-124$ PgC K$^{-1}$ if derived from simulations where the land is affected by elevated CO$_2$ and climate change simultaneously (CLO and CL), and to $-78$ PgC K$^{-1}$ if the land is affected by climate change alone (C and CL). The same is true for $\gamma_O$, which is about 30% smaller at 2300 if determined from runs where the ocean responds to climate change alone (C and CL). This is consistent with findings of Gregory et al. (2009), who find a considerably smaller value for $\gamma$ estimated from a radiatively coupled simulation with prescribed atmospheric CO$_2$ compared to that estimated from the fully coupled simulation as in the C$^4$MIP formalism. For the runs with specified

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**FIG. 10.** Sensitivity of carbon storage on (left) land and in the (right) ocean as a function of (top) atmospheric CO$_2$ and (bottom) global mean temperature from simulations with prescribed emissions and prescribed concentrations. The sensitivities to CO$_2$ ($\beta_L$ and $\beta_O$) were computed following Eqs. (5)–(6) using the radiatively uncoupled (LO, L, and O) simulations. The sensitivities to temperature ($\gamma_L$ and $\gamma_O$) were computed following Eqs. (7)–(8) for the radiatively coupled (C) and Eqs. (9)–(12) for the fully coupled (CLO) simulations.
emissions, $\gamma_L$ and $\gamma_O$ are strongly affected by the choice of simulations, consistent with the nonlinear response of the climate–carbon cycle system under specified emissions discussed earlier.

Friedlingstein et al. (2006) found that the carbon sensitivities to neither CO$_2$ nor climate are constant: for most CMIP models, the carbon taken up by the sinks in response to increasing CO$_2$ rises less rapidly than linearly with CO$_2$ (their Figs. 2c,d), that is, $\beta_L$ and $\beta_O$ decrease. On the other hand, the carbon released from land and ocean in response to warmer temperatures rises more rapidly than linearly with temperature (see their Figs. 2e,f), which means that both $\gamma_L$ and $\gamma_O$ become increasingly negative. The inconstancy of $\beta$ is also evident in our simulations (Figs. 10a,b) and has been noted in previous studies (Plattner et al. 2008; Gregory et al. 2009). Interestingly, constancy of $\gamma$ hinges on the estimation method used; if estimated from the fully coupled (CLO) and biogeochemically coupled simulation (LO) [Eqs. (11)–(12)], $\gamma$ becomes increasingly negative with rising temperature, whereas it remains approximately constant if estimated from the radiatively coupled simulation [Eqs. (7)–(8)]. This result applies to both simulations with prescribed emissions and concentrations (Figs. 10c,d). The reason for the inconstancy of $\gamma$ in the first case is again that $\beta$ is needed to separate the climate from the combined climate and CO$_2$ effect. Since $\beta$ is neither constant, nor independent of the CO$_2$ concentration, $\gamma$ is not constant either. Constancy of $\gamma$ evaluated from the radiatively coupled simulation was also noted by Gregory et al. (2009).

The sensitivities $\beta$ and $\gamma$ relate the carbon storage at any given time to the change in temperature and CO$_2$ concentration at that time, which presumes instantaneous equilibration of the climate–carbon cycle system. Boer and Arora (2009) follow a different approach and derive a relationship between the rates of change of carbon storage on land and in the ocean, and the change in temperature and CO$_2$ concentration. In their formalism, Eqs. (3)–(4) are replaced by

$$\frac{d\Delta C_L^\text{on}}{dt} = B_L \Delta C_A^\text{on} + \Gamma_L \Delta T^\text{on}, \quad (14)$$

$$\frac{d\Delta C_O^\text{on}}{dt} = B_O \Delta C_A^\text{on} + \Gamma_O \Delta T^\text{on}. \quad (15)$$

Here $\Gamma_L$ and $\Gamma_O$ are the “carbon–temperature” feedback parameters, while $B_L$ and $B_O$ are the “carbon–concentration” feedback parameters for the land and the ocean, respectively. These parameters are not only different characterizations of carbon cycle feedbacks but are also of opposite sign to $\beta$ and $\gamma$.

We use our set of simulations to evaluate these alternative carbon cycle feedback metrics. Interestingly, both $\Gamma$ and $B$ are largely independent of the method of estimation (prescribed emissions versus prescribed concentrations, fully coupled versus radiatively coupled simulation) (not shown). However, in contrast to Boer and Arora (2009), who computed these parameters using output from the Canadian Earth System Model (CanESM1; Arora et al. 2009), we find $\Gamma$ to be strongly dependent on temperature, particularly for the land. This discrepancy could be explained by the fact that Boer and Arora (2009) restrict their analysis to scenario with a maximum temperature increase of 3°C but may also reflect intermodel differences.

7. Summary and conclusions

In this paper we systematically explored the linearity of the climate–carbon cycle system by analyzing a set of simulations with the UVic ESCM that allowed us to isolate individual feedbacks. These simulations were performed with scenarios of both prescribed CO$_2$ emissions and prescribed atmospheric CO$_2$ concentrations.

Consistent with previous studies (Friedlingstein et al. 2006; Plattner et al. 2008; Gregory et al. 2009), we find increased CO$_2$ uptake under elevated CO$_2$ (negative concentration-carbon cycle feedback) and reduced CO$_2$ uptake in a warmer climate (positive climate–carbon cycle feedback). The total carbon cycle feedback is also nonlinear, implying that the effect of elevated CO$_2$ on the carbon sinks dominates over that of climate change.

In our model, the concentration–carbon and the climate–carbon feedback do not add linearly to the overall carbon feedback. The sign of this nonlinearity differs between runs with prescribed CO$_2$ emissions and prescribed CO$_2$ concentrations: for the former, the combined effect of atmospheric CO$_2$ and climate change acts to increase carbon uptake, whereas it acts to decrease uptake for the latter relative to the case where the two effects acted separately. In the case of prescribed CO$_2$ emissions, the separation of carbon cycle feedbacks is confounded by different CO$_2$ concentration levels in the different simulations. It is therefore preferable to explore the mechanisms for the nonlinearity of carbon cycle feedbacks using runs with prescribed CO$_2$ concentrations (Hibbard et al. 2007).

In these simulations, CO$_2$ uptake both on land and in the ocean is weaker if the sinks are exposed to the combined effect of increasing CO$_2$ and climate change than if the sinks are exposed to the linear combination of the two. The land accounts for about 80% of the nonlinearity, with the ocean accounting for the remaining 20%. On land, this nonlinearity is associated
with the different response of the biosphere in the absence and presence of the CO2 fertilization effect. In our model, climate change without the beneficial effect of CO2 fertilization induces a widespread dieback of forest in the tropics and replacement by C4 grasses (Matthews 2007). If the vegetation is exposed to the combined effect of climate change and CO2, the tropical forest remains in place. Since C4 grasses are more productive than forest, this different response leads to a less negative effect of climate change on land carbon uptake in the absence of CO2 fertilization.

In the ocean, the nonlinearity in uptake arises from the interaction between anthropogenic CO2 and climate change–induced alterations in ocean circulation. We find that changes in ocean circulation have a different effect on CO2 uptake depending on whether surface waters are exposed to elevated or preindustrial CO2 levels. In the North Atlantic, weakening of the Atlantic meridional overturning circulation leads to reduced uptake of anthropogenic CO2 but also reduced outgassing of natural CO2. In the Southern Ocean, intensification of the Southern Hemisphere westerlies leads to a stronger meridional overturning circulation. In combination with sea ice melting, these circulation changes act to increase the uptake of anthropogenic CO2 but also increase outgassing of natural CO2. Overall, the effects in the North Atlantic dominate, with climate change leading to a stronger global decrease in CO2 uptake under elevated than under preindustrial CO2.

Given the availability of a large set of model simulations, whereby all components of the climate–carbon cycle system (climate, land, and ocean) see fixed preindustrial CO2 either alone or in combination, it is possible to explore the system’s linearity further. We find that under scenarios of prescribed atmospheric CO2, the concentration–carbon cycle feedbacks on land and in the ocean combine almost linearly to the overall concentration feedback. Our results also indicate that land carbon uptake is independent of the ocean response (i.e., is the same in all linear combinations of runs where the effect of climate change and elevated CO2 on land are decoupled). In contrast, ocean carbon uptake is to a small extent affected by the land response, since vegetation changes have an effect on climate through surface albedo and heat flux perturbations.

We used the simulations carried out for our analysis to evaluate proposed metrics of carbon cycle feedback. We find that the carbon storage sensitivities to CO2 (denoted by \( \beta \) in Friedlingstein et al. 2006) are largely unaffected by the estimation method used. In contrast, the carbon storage sensitivities to climate (\( \gamma \), Friedlingstein et al. 2006) are significantly smaller if estimated from runs with specified emissions as opposed to runs with specified concentrations, when computed from the fully coupled experiment following the C4MIP methodology. Also, the \( \gamma \)s are more negative if computed from the fully coupled experiment as opposed to the radiatively coupled experiment, particularly for the land, reflecting the nonlinearity in the climate–carbon cycle response discussed earlier. Our results also confirm the findings of earlier studies showing that \( \beta \) is not a constant function of atmospheric CO2. The same is true for the \( \gamma \), except if computed from the radiatively coupled run.

It should be noted that the nonlinear response in the UVic ESCM may be more pronounced than in other models owing to the strong response of the vegetation model in the radiatively coupled run (i.e., dieback of the Amazon rain forest in the absence of CO2 fertilization). Another model exhibiting strong nonlinearities is HadCM3LC (Gregory et al. 2009), which includes the same vegetation model (TRIFFID; Cox et al. 2000). Preliminary results obtained with the Canadian Earth System Model (CanESM1; Arora et al. 2009), which does not include dynamic vegetation, exhibit smaller nonlinearities (C. Curry 2010, personal communication). The set of experiments recommended for the next Intergovernmental Panel on Climate Change (IPCC) report [the Coupled Model Intercomparison Project, phase 5 (CMIP5); Taylor et al. (2008)] includes a radiatively coupled simulation along with the fully and biogeochemically coupled simulations, such that it will be possible to compare nonlinearities in carbon cycle feedbacks between different models.

We conclude that an experimental design with specified CO2 concentrations is preferable to a design with specified emissions for the quantification of carbon cycle feedbacks. The reason is that different atmospheric CO2 concentration levels in the atmosphere in runs with prescribed emissions confound the separation of carbon cycle feedbacks. Our results also suggest that approaches to quantifying carbon cycle feedbacks that postulate linearity in the carbon cycle response [e.g., the linear Eqs. (2) and (3) in Friedlingstein et al. (2006)] may be inadequate. Finally, we support the suggestion by Gregory et al. (2009) that modeling groups perform a radiatively coupled experiment in addition to the fully coupled and biogeochemically coupled experiments. Such an additional experiment would allow one to estimate standard climate–carbon cycle feedback metrics (e.g., the carbon storage sensitivities to climate) without having to rely on linearity assumptions.

Acknowledgments. We thank Nathan Gillett, Vivek Arora, Jonathan Gregory, and two anonymous reviewers...
for providing comments on the manuscript, and Alvaro Montenegro for fruitful discussions. Michael Eby was supported by the National Science and Engineering Research Council of Canada (NSERC) and the Canadian Foundation for Climate and Atmospheric Science (CFCAS).

REFERENCES


Takahashi, T., and Coauthors, 2009: Climatological mean and decadal changes in surface ocean pCO2 and net sea-air


——, J. C. Fyfe, M. Eby, and A. J. Weaver, 2008b: Comment on “Saturation of the Southern Ocean CO₂ sink due to recent climate change”. *Science*, 319, 570b.