Geosci. Model Dev., 7, 2545–2555, 2014
www.geosci-model-dev.net/7/2545/2014/
doi:10.5194/gmd-7-2545-2014

Geoscientific Model Development
Open Access

On linking an Earth system model to the equilibrium carbon representation of an economically optimizing land use model

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Received: 29 January 2014 – Published in Geosci. Model Dev. Discuss.: 27 February 2014
Revised: 21 September 2014 – Accepted: 29 September 2014 – Published: 6 November 2014

Abstract. Human activities are significantly altering biogeochemical cycles at the global scale, and the scope of these activities will change with both future climate and socioeconomic decisions. This poses a significant challenge for Earth system models (ESMs), which can incorporate land use change as prescribed inputs but do not actively simulate the policy or economic forces that drive land use change. One option to address this problem is to couple an ESM with an economically oriented integrated assessment model, but this is challenging because of the radically different goals and underpinnings of each type of model. This study describes the development and testing of a coupling between the terrestrial carbon cycle of an ESM (CESM) and an integrated assessment (GCAM) model, focusing on how CESM climate effects on the carbon cycle could be shared with GCAM. We examine the best proxy variables to share between the models, and we quantify how carbon flux changes driven by climate, CO_2 fertilization, and land use changes (e.g., deforestation) can be distinguished from each other by GCAM. The net primary production and heterotrophic respiration outputs of the Community Land Model (CLM), the land component of CESM, were found to be the most robust proxy variables by which to recalculate GCAM's assumptions of equilibrium ecosystem steady-state carbon. Carbon cycle effects of land use change are spatially limited relative to climate effects, and thus we were able to distinguish these effects successfully in the model coupling, passing only the latter to GCAM. This paper does not present results of a fully coupled simulation but shows, using a series of offline CLM simulations and an additional idealized Monte Carlo simulation, that our CESM–GCAM proxy variables reflect the phenomena that we intend and do not contain erroneous signals due to land use change. By allowing climate effects from a full ESM to dynamically modulate the economic and policy decisions of an integrated assessment model, this work will help link these models in a robust and flexible framework capable of examining two-way interactions between human and Earth system processes.

1 Introduction

Human activities are significantly altering biogeochemical cycles at the global scale, e.g., by appropriation of net primary production (Imhoff et al., 2004; Ito, 2011), modification of natural fire dynamics (Pechony and Shindell, 2010), and fossil fuel emissions raising atmospheric CO_2 levels (Le Queré et al., 2009). In addition, land use change (LUC) exerts strong effects on the global carbon cycle (Bonan, 2008; Caspersen et al., 2000; Arora and Boer, 2010; Laganière et al., 2009), as well as direct biophysical effects on albedo and water vapor fluxes, which in turn have significant regional to global consequences (Brovkin et al., 2013; Jones et al., 2013b). As a result, different policy choices vis-à-vis LUC and carbon may result in great differences in the future carbon cycle and global climate (Wise et al., 2009; Jones et al., 2013a), even though the direct LUC fluxes will likely be far smaller than in the past (Brovkin et al., 2013).

This poses a significant challenge for global Earth system models (ESMs), in which fully coupled climate models are used to draw inferences about Earth's past and future climate states and understand how changes to the radiative properties of Earth's atmosphere interact with its climate, biogeochemistry, and carbon cycle (Brovkin et al., 2013; Todd-Brown et al., 2014). Such models may incorporate LUC as prescribed inputs but do not simulate policy options or economic forces, a significant limitation given how strongly humans can perturb the Earth system (Hurtt et al., 2002; Randerson et al., 2009). Conversely, integrated assessment models (IAMs) are used to examine the human components of the Earth system, including greenhouse gas emission sources, and drivers of land use change. Their representation of the physical climate and Earth system is simplistic, however, with little spatial resolution or process fidelity compared to an ESM (Meinshausen et al., 2011a, b). These two modeling paradigms – ESMs with no economic or energy system modeling, and IAMs with only basic representations of natural processes – developed largely independently of each other, and their interactions have historically been limited.

ESMs and IAMs increasingly need each other's capabilities, however (van Vuuren et al., 2012; Houghton, 2013). One solution is to couple an ESM to an IAM, letting each model specialize in its specific domain while passing information on the natural and human systems, respectively, between them. This would provide a two-way coupling within a single integrated system, whereby economic decisions in the IAM translate directly into trace gas fluxes and land use changes in the ESM, and changes in the ESM climate feed back onto crop yields, heating and cooling demands, energy production, etc., in the IAM. Successfully linking such complex, large models would permit integrated and unprecedented analyses of the interactions between economic change, climate policy, and the physical Earth system, with fully coupled feedbacks between the economic and physical-science components (van Vuuren et al., 2012).

This paper describes the development and testing of a mechanism linking the terrestrial carbon components of an ESM (CESM, the Community Earth System Model) with an IAM (the Global Change Assessment Model, GCAM) (Fig. 1). The goals of the current study were to develop and test a robust but tractable coupling allowing GCAM LUC projections to respond to changes in the CESM climate and biogeochemical cycles. We focus here on the terrestrial aspect of the CESM-to-GCAM coupling, but this is only one component of a larger effort to create a more general integrated Earth system model (iESM) (Jones et al., 2013a) as described above.

2 Materials and methods

2.1 Model descriptions

Both CESM's Community Land Model (CLM) and GCAM have been extensively described, and here we note only their most relevant aspects (Gent et al., 2011). The terrestrial model in the CESM system, CLM simulates the cycling

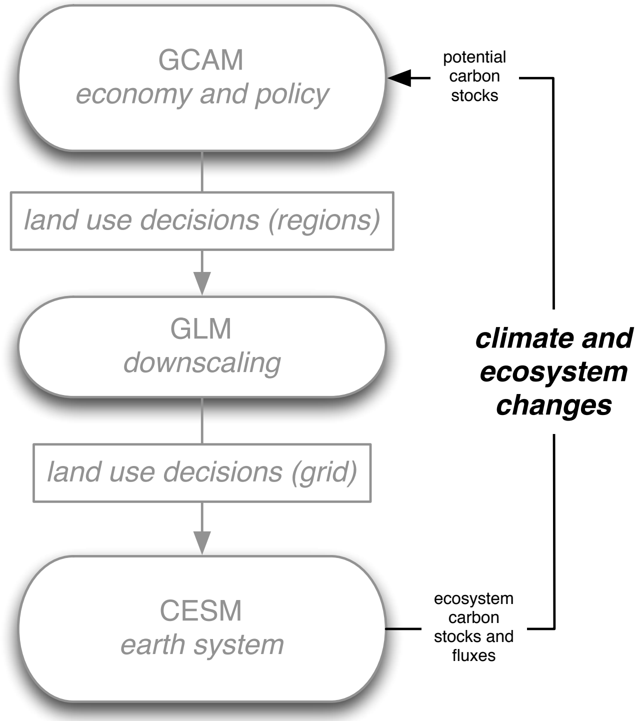

Figure 1. High-level overview of the iESM (integrated Earth system model) system; a more detailed schematic is presented by Di Vittorio et al. (2014). Oval boxes represent models, and arrows show data flows. This paper focuses on the information flow between CLM (part of CESM) and GCAM, in bold.

and land–atmosphere exchange of energy, water, carbon, and trace gases. CLM version 4, used in this study, resulted from merging the biophysical framework of CLM v3.5 (Oleson et al., 2008) with the carbon and nitrogen dynamics of the biogeochemistry model Biome-BGC (Thornton et al., 2002; Running and Hunt, 1993). The model incorporates biogeophysics, surface hydrology, biogeochemistry, and dynamic vegetation components (Bonan et al., 2002), whose dynamics have been extensively tested (Shi et al., 2011; Oleson et al., 2008; Lawrence et al., 2008; Mao et al., 2012a, b). Model vegetation is based on plant functional types (PFTs) occupying dynamic fractions of each grid cell (typically 0.25–2° resolution), with each PFT (one bare ground, eight tree, three shrub, three grass, one crop) characterized by distinct physiological parameters (Oleson et al., 2010). The model's carbon (C) and nitrogen (N) cycles are closely coupled and include canopy photosynthesis, plant growth and mortality, photosynthate allocation, and subsurface C and N cycling (Thornton et al., 2007); at any point in time, CLM tracks a wide suite of above- and belowground C pools resulting from the integrated effects of these and other (Kloster et al., 2010) processes.

The GCAM model, by contrast, is an economic model driven by assumptions about population size and labor productivity that determine potential gross domestic product in each of 14 regions; these regions are further divided by GCAM's agriculture and land use submodel into 18 agro-ecological zones, or AEZs (Monfreda et al., 2009). GCAM originated as the energy-economic MiniCAM model (Edmonds and Reilly, 1983) and currently integrates energy, agriculture, forestry, and land markets with a simple terrestrial carbon cycle (Thomson et al., 2010; Wise et al., 2009). The model operates on a 5-year time step, computing simultaneous market-clearing prices for all energy, agriculture, and land markets (Kim et al., 2006). The model is typically used to explore the effects of policy scenarios – for example, carbon pricing, emissions constraints, or capped limits on total radiative forcing (Calvin et al., 2009). Economic land use decisions are based on the relative inherent profitability of using land for competing purposes. GCAM does not use land use allocation constraints, but its calibration based on historical data means that history is reflected in future land allocation decisions (Wise and Calvin, 2010; Wise et al., 2014).

GCAM's terrestrial carbon model is fundamentally concerned with calculating LUC CO_2 emissions resulting from the model's economic decisions. It does this by determining the C stocks changes with every land use change, and allocating those as C fluxes over time. Specifically, each land use (i.e., the model's various crops, forest types, etc., in each AEZ of each political region) has above- (vegetation) and belowground (soil) steady-state C densities associated with it, values currently based on Houghton (1999). These values vary by AEZ and political region and do not change during the model run; i.e., land is assumed to be in C equilibrium with the atmosphere in the absence of LUC. When a particular land use category contracts in area, all the lost aboveground C (i.e., the land use's C density multiplied by the change in area) is emitted instantaneously, while its belowground C is emitted in an exponential decay pattern. When a land use category expands, the resulting C uptake depends on the length of time it takes for the vegetation to mature (from 1 year for crops to 30–100 years for forests), following a Bertalanffy–Richards growth function. Carbon emission and sequestration thus result only from changes in land use, with emission from shrinking land use categories set against uptake from growing ones. The model computes these fluxes across time but, importantly, does not track current C stocks in the manner of CLM or most land surface models. Further details on the agriculture, land use, and carbon cycle assumptions and algorithms of GCAM may be found in its online documentation (http://wiki.umd.edu/gcam) and several publications (Wise et al., 2014; Wise and Calvin, 2010).

In the iESM architecture a third model – the Global Land Model, or GLM – currently downscales GCAM's land use decisions (made on agro-ecological zones at the regional level) onto CLM's global grid (Fig. 1). This step uses algorithms and assumptions described by Di Vittorio et al. (2014) and Lawrence et al. (2012) and is not detailed further here, as this study focuses only on the coupling from CLM to GCAM.

2.2 Issues in linking the CLM and GCAM carbon cycles

The fundamental conceptual, as opposed to technical, problem in linking the CLM and GCAM carbon cycle models is that the former tracks time-varying C pools and fluxes, while the latter bases its economic optimization on long-term (equilibrium) C pools for large regions and only computes LUC fluxes. Replacing GCAM's entire internal carbon cycle (and its reliance on equilibrium C) may be possible in the long term, but it would require a fundamental rewriting of this complex model's agriculture and land use code. In this study a looser coupling between CLM and GCAM was deemed more tractable, while also sufficient for the experiments described here. Such an approach transmits relative changes between the models while allowing baseline data, against which the models have been calibrated and tested, to differ.

Such a "loose" coupling means that, when a CLM grid cell's carbon cycle changes, we need to (i) have a suitable proxy by which to change the values of GCAM's steady-state carbon assumptions and (ii) distinguish LUC effects on carbon fluxes from climate and other (CO_2, N deposition, etc.) effects, because only the latter should affect GCAM's assumptions of equilibrium C stocks. For example, if the land carbon pool size of a grid cell with forested fraction simulated by CLM changes from one time step to the next because of harvest, this should not affect GCAM's economic optimization – the forest will regrow to the same equilibrium state. If the same forest's carbon pool rises because of CO_2 fertilization, however, this information (i.e., there is more C sequestration potential available for this land use type) needs to be propagated to GCAM's assumptions about long-term pool potentials. Distinguishing these sources is thus critical (Gasser and Ciais, 2013).

2.3 Identifying the best proxy variables to link CLM to GCAM

Given the decision to adjust GCAM's equilibrium C assumptions based on relative changes in the CLM carbon cycle, one possible proxy variable to pass between the models was CLM's time-varying carbon pools, based on the assumption that short-term pool changes will translate to longer-term (i.e., equilibrium, as needed by GCAM) storage changes. These data may be more vulnerable to LUC effects than carbon flux data, however, as fluxes typically recover much faster from disturbance than do the slower pools (Amiro et al., 2010; Goetz et al., 2012). Short-term changes in C fluxes can be analytically related to steady-state C pools in models, even in the presence of ecosystem disturbances (Hurtt et al., 2010). This needed to be tested and demonstrated for CLM, however.

Table 1. Summary of simulations performed.

Name	Type	Purpose
S1	Uncoupled CLM, 1850–2010, constant (1901–1920) climate	Control for S2, S3, S4
S2	S1 + changing CO_2	Single-factor experiments quantifying how CO_2, N deposition, and LUC affect potential proxy variables
S3	S1 + changing N deposition	
S4	S1 + changing LUC	
E1	Uncoupled CLM, constant (2005–2009) climate	Equilibrium biomass simulations quantifying how initial NPP predicts final vegetation C
E2	Uncoupled CLM, constant (2090–2094) climate	Equilibrium biomass simulation quantifying how climate-driven changes in NPP predict changes in vegetation C
M1	Idealized Monte Carlo	Assess error that could be introduced to climate effects scalars by increasing amount of LUC.

We tested potential proxy variables in two ways. First, we ran a series of single-forcing-factor experiments in CLM, looking at how changes in each factor affected CLM carbon stocks and fluxes (specifically, gross primary production; net primary production, or NPP; heterotrophic respiration, or HR; soil organic matter; vegetation carbon; and total ecosystem carbon). The three forcing factors tested were atmospheric CO_2, as alleviating the CO_2 constraints on leaf-level photosynthesis may cascade up to ecosystem carbon storage (Gedalof and Berg, 2010; Lenton and Huntingford, 2003); nitrogen deposition, a potentially strong constraint on the current and future global carbon cycle (Galloway et al., 2005; Norby et al., 2010); and LUC, which affects both immediate and long-term land–atmosphere interactions (Caspersen et al., 2000; Pongratz et al., 2009). A "good" proxy variable would be strongly affected by the first two, CO_2 and N, but not by LUC (as only the former two will affect equilibrium C; see above), and would accurately reflect climate-driven changes to equilibrium C stocks in CLM.

In simulation S1 (the control), we used 1901–1920 climate drivers for the entire period 1850–2010 and kept atmospheric CO_2 concentration, nitrogen deposition, and land cover constant at their 1850 values. In transient 1850–2010 simulations S2–S4, we used the same looped 1902–1920 climate and varied one of the three factors in each while holding the other two factors constant (Table 1). The time-varying factors were based on transient data sets constructed to mimic as closely as possible the historical record over the period 1850–2010, as described by Shi et al. (2013). The effect of each individual factor was then calculated by subtracting S1 from simulations S2, S3, and S4. The CRUNCEP data used to drive these uncoupled simulations is a combination of the CRU TS.2.1 0.5° monthly 1901–2002 climatology (Mitchell and Jones, 2005) and the 2.5° NCEP2 reanalysis data beginning in 1948 and available in near real time (Kanamitsu et al., 2002; Mao et al., 2012b).

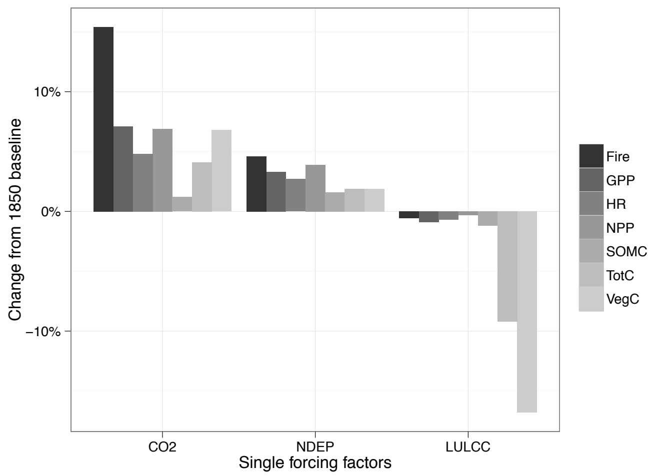

Figure 2. Response of Community Land Model outputs to changes in atmospheric CO_2 (simulation S2), nitrogen deposition (NDEP, simulation S3), and land use/land cover change (LULLC, simulation S4; cf. Table 1). Outputs shown are all relative to an 1850 baseline, as described in the text, and include fire emissions (Fire), terrestrial gross primary production (GPP), heterotrophic respiration (HR), net primary production (NPP), carbon in soil organic matter (SOMC), total ecosystem carbon (TotC), and total vegetation carbon (VegC).

Second, we examined how well NPP in particular was related to equilibrium C stocks in CLM only (i.e., before any coupling to GCAM). This involved two offline experiments (Table 1) with a repeating 5-year climate drawn either from the beginning (2005–2009, simulation E1) or end (2090–2094, simulation E2) of an Representative Concentration Pathways (RCP4.5) coupled simulation (Taylor et al., 2012). We quantified how well (i) NPP in the first 5 years of simulation E1 predicted total vegetation C in the final 5 years and how well (ii) the change in NPP resulting from an altered climate state (E2 minus E1) predicted the relative change in C pools over the final years of the two simulations.

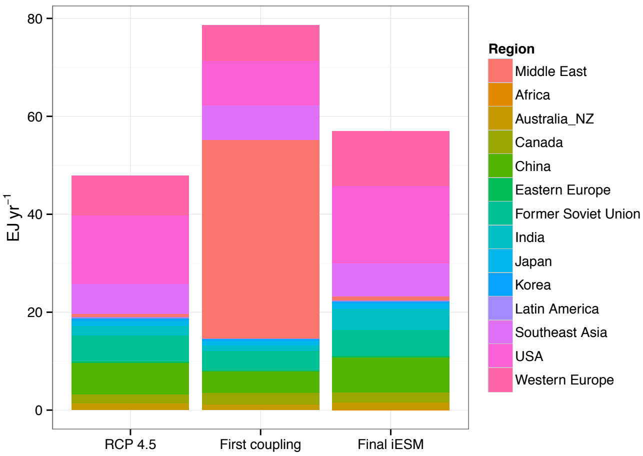

Figure 3. GCAM model output (energy derived from bioenergy by region of the world) in three model runs, the RCP4.5 control, a coupled CLM–GCAM run using carbon stocks as a coupling mechanism, and a run using the final coupling described in the text. In the second case the model diverged sharply and unrealistically from the RCP4.5 control because the vulnerability of C stock data to disturbance effects triggered a feedback loop in GCAM. The final run, incorporating the coupling and outlier-exclusion mechanisms described in the text, showed no such divergence. Data are from model year 2065, when the second run was stopped.

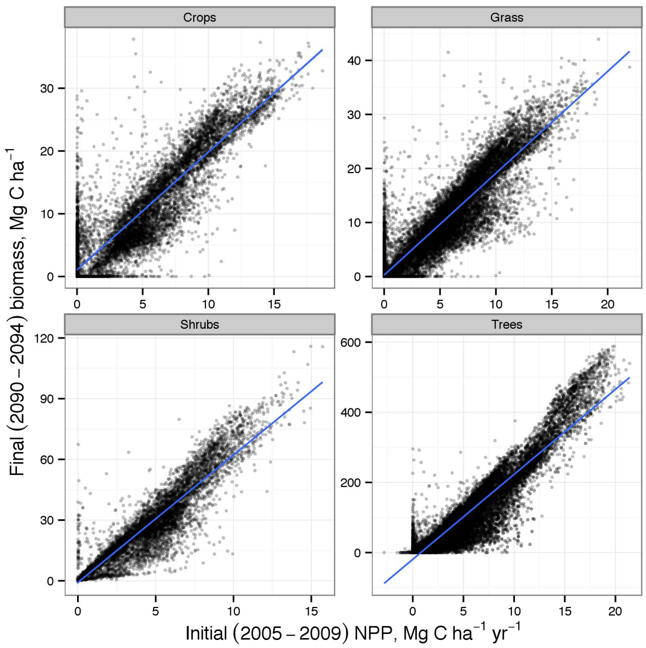

Figure 4. Relationship of net primary production (NPP, 2005–2009) to biomass (2090–2094) in CLM for crops, grasses, shrubs, and trees; cf. Table 2. Lines show best-fit linear regressions. Results are from the E1 and E2 simulations in Table 1.

Taken together, these experiments tested how well NPP could be used to predict equilibrium C under both constant and changing climate. The state of the terrestrial carbon system at the beginning of these simulations reflected the disturbance and climate histories of the 20th century, with various different non-equilibrium C states across different grid cells and PFTs. Land cover was fixed at 2000 values, and we ran the E1 and E2 simulations for 150 model years with no additional LUC in order to allow the carbon stocks to approach their equilibrium state. It is important to note that we did not disable the fire algorithms in CLM. Fire significantly influences model stocks and fluxes (Li et al., 2014), and thus, rather than converging to a single steady-state carbon stock, PFTs influenced by fire converged to a quasi-equilibrium characterized by periodic carbon losses due to fire followed by periods of recovery.

2.4 Distinguishing climate from land use signals

As noted above, it is important to distinguish carbon cycle changes caused by LUC from those caused by climate change. For the CLM-to-GCAM coupling, even a perfect proxy variable will be subject to climate and land use changes during a CESM run, both before the run starts (i.e., during spinup or initialization phases) and during a model run. For example, a cell in which a new PFT is established immediately prior to an iESM run would have very low C stocks and NPP in the first time step; as its vegetation regrows, the cell would appear, to GCAM, to be undergoing enormous productivity increases. Conversely, significant expansion of a PFT (e.g., agriculture reverting to forest) during the iESM run might appear to have drastically lowered productivity, leading GCAM to redirect land away from that PFT. Both of these cases cause problems for GCAM because productivity drives decision-making in the model, which bases its land use decisions on the relative inherent profitability of using land for competing purposes (Wise and Calvin, 2010). As a result apparent changes in productivity produce changes in profit (as measured in US dollars) and thus land use.

Thus in both cases, we need to exclude cells with anomalously large C changes, driven by LUC, from the final numeric scalars (i.e., the proxy variables signaling how much GCAM should adjust its assumptions of equilibrium C) computation. They will bias the computation of the scalars and lead GCAM into a possible feedback loop: if the model sees highly anomalous values, it may allocate more land to those PFTs, resulting in higher profits and further land use change in the region with the anomaly. (A negative feedback is also possible; both cases occur because the changed productivity alters the relative profitability of the different land uses, and profit maximization is the fundamental decision-making criterion in GCAM.)

To distinguish the effect of LUC (as opposed to climate effects) on primary CO2 fluxes and land carbon pools, we assumed that climate change will have a broad spatial distribution, either global or regional, while LUC will affect relatively small groups of cells in any particular time step; this obviously may not hold in particular regions and points in time (Arora and Boer, 2010) but should be broadly true across the millions of data points ($\sim 10^5$ grid cells $\times$ PFT combinations) being output by CLM. Thus a statistical outlier test, comparing how much any particular cell's carbon cycle has changed relative to the start of the run, should be able to exclude cells whose inferred change in long-term carbon density fall significantly outside of the norm. To do so we used a method based on median absolute deviation (Davies and Gather, 1993), a robust (insensitive to outliers) measure of central tendency. The scalars were then mapped from CLM's PFTs and grid cells to GCAM's land cover types and AEZ regions, weighted by PFT area, land area in each grid cell, and cell area in the AEZ.

This technique depends on the overall population mean not being overly perturbed and thus will not work in extreme scenarios of mass deforestation (e.g., Bonan et al., 1992). An important question is how soon, under increasing amounts of LUC, bias (i.e., LUC effects masquerading as climate change to GCAM) will be introduced into the iESM model system. We used a Monte Carlo simulation (M1 in Table 1), written in the statistical package R 2.15.1 (R Development Core Team, 2012), to examine how robust this outlier exclusion method would be to different levels of LUC and what, if any, bias it might introduce to the GCAM carbon density values. For this exercise, 10 000 cells (with normalized, unitless data) were simulated in which a constant +10 % climate change effect on equilibrium C was presumed to be occurring (Jain and Yang, 2005). A LUC effect, ranging from −500 to +500 % and affecting from 5 to 95 % of the cells, was then additionally applied. The outlier exclusion test defined above was then calculated on the cells, and a putative signal calculated on the remaining cells. This inferred climate change was then compared to the original known climate signal to estimate how much error (i.e., the difference between the two signals) would be introduced into iESM under such circumstances.

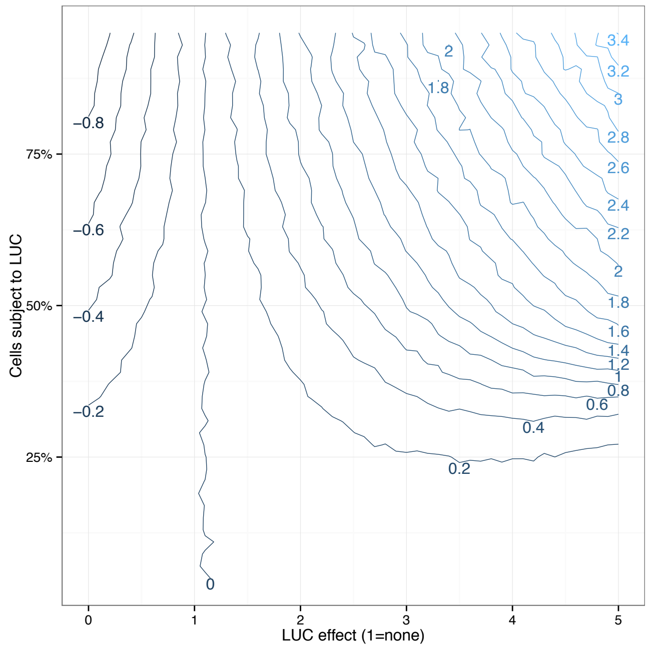

Figure 5. Monte Carlo simulation M1 (cf. Table 1) examining whether an outlier test can distinguish between artificial climate and land use change (LUC) signals. Contour lines (every 20 %) show error between the inferred climate change signal and the known signal as increasing numbers of cells (y axis) are perturbed by LUC with increasing effect (x axis). The effect (i.e., intensity) is shown as the ratio of perturbed cells' equilibrium C to that of unperturbed cells: a doubling (e.g., transitioning from crop to young forest) is an effect of 2.0, a halving as 0.5, etc.

3 Results and discussion

3.1 Single-forcing tests: identifying the best proxy variables

Clear differences emerged between the potential proxy variables tested in CLM in response to three different forcing factors (Fig. 2). Most notably, carbon stocks were much more sensitive to LUC than were carbon fluxes. This result matches both theory (Odum, 1969) and a wide variety of field studies (Amiro et al., 2010; Goetz et al., 2012): stocks are by their nature integrative and accumulate relatively slowly compared to C flux changes. In contrast, the C flux variables were highly sensitive to climate effects but exhibited low sensitivity to LUC.

A second, related problem arising from the use of carbon stocks as proxy variables can be seen in Fig. 3. In this case a test coupling between CLM and GCAM, using carbon stocks to pass climate change information, produced sharp and unrealistic changes from the GCAM RCP4.5 control run. (This occurred even when running the outlier-exclusion protocol described above.) Global LUC emissions climbed throughout the 21st century in a departure from the RCP4.5 control, because a few CLM grid cells, located in GCAM's "Middle East" region, were subject to LUC at the end of CLM's transient simulation phase. As a result, their C stocks (and GCAM's estimation of their long-term potential C) increased rapidly in the early years of the model run, leading GCAM to pour more resources into these cells (because these cells' productivity appeared extraordinarily high, as described in the methods section). Increasing the area of newly planted bioenergy crops created an even stronger signal of rapidly increasing carbon stocks, exacerbating the original problem and causing GCAM to put even more resources into the region. By the end of the century, GCAM was mistakenly growing a huge percentage of the world's bioenergy crops in the region, on a very small area of land (Fig. 3). Conversely, the use of NPP and HR caused no such problems, because

Table 2. Slope (yr), adjusted R^2 value, and number of grid cells for the relationship between change in NPP in response to a climate change signal and resulting change in equilibrium biomass (simulations E1 and E2 in Table 1). Excluding PFTs whose cumulative carbon loss from fires exceeds 8 Mg C ha^{-1} over 150 years generally improved the R^2 values and increased the slopes (data not shown).

PFT	Name	Slope	R^2	Count
1	needleleaf_evergreen_temperate_tree	20.4	0.52	3500
2	needleleaf_evergreen_boreal_tree	20.5	0.68	5136
3	needleleaf_deciduous_boreal_tree	24.9	0.92	1643
4	broadleaf_evergreen_tropical_tree	18.0	0.35	2609
5	broadleaf_evergreen_temperate_tree	20.9	0.40	1702
6	broadleaf_deciduous_tropical_tree	25.2	0.56	3909
7	broadleaf_deciduous_temperate_tree	21.9	0.49	3966
8	broadleaf_deciduous_boreal_tree	23.6	0.64	5311
	All trees	*21.5*	*0.51*	*27 776*
9	broadleaf_evergreen_shrub	1.9	0.06	299
10	broadleaf_deciduous_temperate_shrub	5.8	0.45	3336
11	broadleaf_deciduous_boreal_shrub	6.5	0.60	5979
	All shrubs	*6.0*	*0.50*	*9614*
12	c3_arctic_grass	1.8	0.30	6417
13	c3_non-arctic_grass	2.4	0.38	8061
14	c4_grass	1.1	0.19	5436
	All grasses	*1.6*	*0.28*	*19 914*
15	crop	1.7	0.19	9142

of their relatively fast recovery from LUC disturbance (cf. Fig. 2).

The two primary fluxes determining carbon balance (NPP and HR) were thus chosen as proxy variables linking CLM to GCAM, with CLM NPP changes used to scale GCAM's assumptions of aboveground equilibrium C, while a combination of NPP and HR provided a relative scaling for GCAM's belowground carbon, computed with a 5-year coupling step as

$$C_A = C_{A0}\frac{NPP}{NPP_0}, \quad (1)$$

$$C_B = C_{B0}\left[\frac{NPP}{NPP_0} + \frac{HR_0}{HR}\right]/2. \quad (2)$$

Here the ratio of NPP (at the current time step) to NPP at the beginning of the run (NPP_0) determines how aboveground equilibrium C in GCAM (C_A) will change relative to the beginning of the run (C_{A0}). CLM's NPP and HR together determine changes in GCAM equilibrium belowground carbon (C_B); note that as NPP and HR get larger/smaller and smaller/larger compared to their starting values, GCAM's equilibrium C rises/falls.

3.2 Correlation between NPP and equilibrium pools in CLM

Simulations E1 and E2 provided insight into the relationship between NPP and equilibrium C pools within CLM. NPP at the beginning of the E1 simulation was a good predictor of the equilibrium pool values at the end of the simulation (Fig. 4), although the slope of this relationship varied for different PFTs. It was also apparent that this relationship breaks down at very low NPP values for some PFTs. This result is consistent with ecological theory and observations, as freshly disturbed ecosystems require a period of initial growth before NPP stabilizes. These very low NPP values were reliably excluded by the outlier exclusion method discussed above and tested below.

We also found that the change in NPP resulting from an altered pattern of climate (comparing simulations E1 and E2) was a relatively good predictor of the subsequent change in equilibrium C stocks. Table 2 shows the slopes of the linear relationships between the change in initial NPP (simulation E2 minus E1) and change in equilibrium C for each PFT in CLM. The initial (2005–2009) change in NPP was able to explain 19–92 % of the variance in the C pool change over the 21st-century simulation with one exception (broadleaf evergreen shrubs, 6 %). In general, NPP was a better predictor for relatively high-carbon forest ecosystems, as compared to grasses, shrubs, and crops. This is good, as high-C systems are particularly important for GCAM: changes in their land areas exert disproportionate effects on atmospheric CO_2, which the model is frequently trying to minimize.

To determine whether fire dynamics were responsible for some of the unexplained variance in equilibrium C pools, we performed the same analysis a second time, excluding PFT–gridcell combinations in which the cumulative carbon loss from fire over the 150-year E1 simulation exceeded $800\,\mathrm{g\,C\,m^{-2}}$. This led to moderate (generally 5–10 %) improvements in the R^2 values in all PFTs except the two broadleaf evergreen PFTs and to moderate increases in the regression slopes, indicating that fire-influenced regions tend to have lower C values than others. This is consistent with both observations and CLM's general fire characteristics (Li et al., 2014), and it suggests that fire dynamics and fire regime changes in response to climate change are important to account for when constructing simple proxies that can predict changes in future terrestrial carbon stocks based on evolving climatic and ecological conditions.

3.3 Distinguishing the effects of LUC from climate

The initial experiments thus established the best available variables to loosely couple CESM and GCAM. But how well could the coupling – specifically, statistically excluding CLM grid cells whose carbon fluxes were changing "too fast" – separate LUC and climate signals? The M1 experiment results (Fig. 5) suggested that, as long as fewer than $\sim 25\,\%$ of the simulation cells were disturbed, the error (between the known climate signal and that inferred by the outlier test) remained relatively small ($< 20\,\%$). Even when larger numbers of cells were perturbed, the LUC effect had to be quite large to exceed this level. Because the outlier test is applied to the global population, and not sub-regions, this implies that only under extreme scenarios will this mechanism start to introduce substantial error. (In test iESM runs attempting to reproduce RCP 4.5, 4–8 % of the global grid cells were excluded – i.e., failed the outlier test – at each time step.)

3.4 Implications of the loose coupling between CLM and GCAM

For the initial construction of the iESM system, we chose a loose coupling between the ESM and IAM, in which GCAM's equilibrium C assumptions of various ecosystems tracked the *relative* changes in CLM's short-term C fluxes, after exclusion of LUC effects. This has the advantage of not requiring a fundamental rewriting of GCAM, as the mathematical formulae and economic principles underlying its land use decisions are based on equilibrium C (Wise and Calvin, 2010). In addition, it guarantees that, if climate change affects the carbon cycle, GCAM's equilibrium assumptions will change correspondingly for the same vegetation type and spatial location, feeding back into economic and land use decisions that propagate back to CLM (Di Vittorio et al., 2014).

This is a powerful improvement over the fixed assumptions of both IAMs and ESMs in these areas, sidestepping the lack of process fidelity and spatial resolution (for the IAM) and addressing the lack of human agency (for the ESM). The loose coupling does have disadvantages, however, requiring the statistical identification of outlier grid cells and inevitable mismatches between the models' definitions of PFTs, C pools, and time steps (Di Vittorio et al., 2014). In addition, the outlier-exclusion step will break down under extreme LUC scenarios, scenarios that while unrealistic can be a useful research tool (Bonan, 2008; Nobre et al., 1991; Thomson et al., 2010). This is a particular concern given that the current mechanism was only tested under the relatively moderate RCP 4.5. For these reasons, we anticipate that the long-term solution is a full incorporation of an IAM into an ESM, with a unified C cycle.

4 Conclusions

Here we have implemented and tested a coupling mechanism between the carbon cycles of an Earth system model (CLM) and an integrated assessment (GCAM) model. CLM's net primary production and heterotrophic respiration outputs were found to be the most robust proxy variables by which to manipulate GCAM's assumptions of long-term ecosystem steady-state carbon, with short-term forest NPP shifts strongly correlated with long-term biomass changes in particular. By assuming the carbon cycle effects of land use change are short-term and spatially limited relative to widely distributed climate effects, we were able to distinguish these effects successfully in the model coupling, passing only the latter to GCAM. Increasingly extreme LUC scenarios will eventually break down this mechanism, however.

This work is only one step to a full coupling of an ESM and IAM; the second is described by Di Vittorio et al. (2014), and it consists of land use and land cover harmonization steps that allow CLM to achieve higher afforestation and wood harvest rates than possible in the CMIP5 (Couple Model Intercomparison Project 5) process. By allowing climate effects on the CLM carbon cycle to modulate, in real time, the economic and policy decisions of an integrated assessment model, it provides a foundation for further development of the iESM project linking these models in a robust and flexible framework. Such a framework will, in turn, facilitate future modeling of the two-way interactions between human and Earth system processes.

Acknowledgements. We are grateful to the DOE Office of Science Integrated Assessment Research Program and Earth System Modeling Program for funding through the integrated Earth System Modeling Project. This research used resources of the National Energy Research Scientific Computing Center, which is supported by the Office of Science of the US Department of Energy under Contract DE-AC02-05CH11231. The CESM project is supported by the National Science Foundation and the Office of Science (Biological and Environmental Research) of the US Department of Energy. We thank S. Smith for his thoughtful comments on an early draft.

Edited by: P. Jöckel

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