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Key Points:
- Changes in atmospheric carbon and climate drive changes in land management that can be characterized as carbon cycle feedbacks
- Land management changes alter the estimation of both the concentration-carbon and climate-carbon feedbacks
- Quantifying human-mediated carbon cycle feedbacks provides a framework for diagnosing cross-model uncertainty

Supporting Information:
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Quantifying Human-Mediated Carbon Cycle Feedbacks

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Abstract Changes in land and ocean carbon storage in response to elevated atmospheric carbon dioxide concentrations and associated climate change, known as the concentration-carbon and climate-carbon feedbacks, are principal controls on the response of the climate system to anthropogenic greenhouse gas emissions. Such feedbacks have typically been quantified in the context of natural ecosystems, but land management activities are also responsive to future atmospheric carbon and climate changes. Here we show that inclusion of such human-driven responses within an Earth system model shifts both the terrestrial concentration-carbon and climate-carbon feedbacks toward increased carbon storage. We introduce a conceptual framework for decomposing these changes into separate concentration-land cover, climate-land cover, and land cover-carbon effects, providing a parsimonious means to diagnose sources of variation across numerical models capable of estimating such feedbacks.

Plain Language Summary Estimating future changes to the Earth's climate requires an understanding of how carbon stored in vegetation and soils will respond to higher carbon dioxide in the atmosphere and changes in climate such as warmer temperatures and changes in precipitation. For instance, if plants and soils release more carbon, this will accelerate human-driven climate change, which is known as a positive feedback. Because climate change and higher atmospheric carbon dioxide will affect crop and forestry yields, we expect humans to alter their land management activities in the future, leading to greater or lesser storage of carbon in soils and vegetation. Higher crop yields could lead to less crop area globally and greater storage of carbon in forests and other natural vegetation. In this study, we introduce a method for quantifying such human influences on carbon storage, combining a model of land management with a model of atmospheric, land, and ecosystem processes. We find that both higher atmospheric carbon dioxide and climate change tend to reduce the footprint of human agriculture and therefore increase carbon storage on the land. Our method for quantifying such feedbacks provides a simple means to compare across models and identify areas of agreement or disagreement.

1. Introduction

Changes in land and ocean carbon storage in response to elevated atmospheric carbon dioxide concentrations and associated climate change, known as the concentration-carbon and climate-carbon feedbacks respectively, are principal controls on the response of the climate system to anthropogenic greenhouse gas emissions (Arora et al., 2013; Eby et al., 2013; Friedlingstein et al., 2003, 2006, 2014; Gregory et al., 2009; Hewitt et al., 2016; Randerson et al., 2015; Sitch et al., 2008). Carbon cycle feedbacks are estimated to be on the same order of magnitude as noncarbon climate feedbacks, yet their representation across numerical models varies widely (Arora et al., 2013; Friedlingstein et al., 2006, 2014). Coordinated efforts to quantify the concentration-carbon and climate-carbon feedbacks across models have typically done so using idealized simulations that do not consider anthropogenic land use and land cover change (LULCC) or treat LULCC as a static component of a net anthropogenic carbon dioxide emissions scenario (Gregory et al., 2009). However, recent work using a coupled Earth system and integrated assessment model framework demonstrates that LULCC responds dynamically to future biospheric change, which in turn alters future terrestrial carbon storage (Thornton et al., 2017).

A growing number of coupled model experiments have linked climate and Earth system models with models of human energy and land use (Calvin & Bond-Lamberty, 2018; Monier et al., 2018; Thornton et al., 2017; Voldoire et al., 2007), enabling quantitative examination of potential feedbacks and interactions among human and Earth system processes. Notably, Thornton et al. (2017) show that future changes in crop yields and ecosystem productivity in response to climate and associated atmospheric carbon changes could lead to a contraction of global crop area coupled with an expansion of forests and enhanced terrestrial carbon storage. This implies that the human LULCC response to biospheric change generates a negative climate feedback.

The primary cause of this negative feedback was not quantified. However, several studies based on a variety of models have found that accounting for the CO_2 fertilization effect can produce increases in yield projections in various regions of the world (Deryng et al., 2016; Rosenzweig et al., 2014; Verhage et al., 2017; Wing et al., 2015). This supports the hypothesis that the negative feedback found by Thornton et al. may be dominated by a concentration-driven effect on plant productivity rather than a climate-driven effect. The Coupled Climate-Carbon Cycle Model Intercomparison Project (C4MIP) framework for estimating carbon cycle feedback parameters provides a useful means of identifying and quantifying key differences across numerical models (Arora et al., 2013; Friedlingstein et al., 2006; Jones et al., 2016). To date, this framework has not been expanded to separately quantify human- and nonhuman-driven components of these feedbacks. In this study, we extend and apply this framework to test the hypothesis that human-driven carbon cycle feedbacks are driven by a concentration-carbon feedback. In doing so, we provide a parsimonious means to diagnose sources of model variation across numerical models capable of estimating such feedbacks.

2. Methods

We adapt the experimental paradigm of the C4MIP (Friedlingstein et al., 2006; Jones et al., 2016) for use with the Integrated Earth System Model (iESM; Collins et al., 2015) employed by Thornton et al. (2017). The C4MIP protocol calls for simulations that isolate the separate biogeochemical and radiative effects of atmospheric CO_2 on land and ocean carbon storage. These simulations are then used to estimate linear coefficients that describe the magnitude of these effects, including β_L, which quantifies the terrestrial CO_2 concentration-carbon feedback in units of petagrams of carbon per parts per million of atmospheric carbon dioxide, and γ_L, which quantifies the terrestrial climate-carbon feedback in units of petagrams of carbon per degree Celsius. Hereafter we refer to simulations that isolate the biogeochemical and radiative effects of atmospheric CO_2 as *Carbon Only* and *Climate-Only* simulations, respectively. Control simulations with both effects are referred to as *Carbon and Climate* simulations. All simulations are based on a variant of the Representative Concentration Pathway 8.5 (RCP8.5) emissions scenario (spanning 75 years from 2005 to 2089 Common Era [CE]) and include other climate forcers such as non-CO_2 greenhouse gases, anthropogenic aerosols, and a baseline scenario of LULCC. The effect of these additional forcing agents must be accounted for when calculating the feedback coefficients described above.

2.1. The iESM

The global change research community frequently uses integrated assessment models to generate scenarios of human energy and agricultural activities and associated climate forcing (e.g., greenhouse emissions and land cover change), which are then fed to Earth system models to examine their implications for climate and carbon cycle processes.The iESM (Collins et al., 2015; Thornton et al., 2017) couples two such models together in order to examine their bidirectional feedbacks: the Global Change Assessment Model (GCAM; Wise et al., 2014), an integrated assessment model, and the Community Earth System Model (CESM; Hurrell et al., 2013), a global Earth system model. The version of iESM used for this study focuses on biospheric feedbacks to LULCC, for example, changes in ecosystem carbon densities and crop model changes resulting from atmospheric, hydrologic, and nutrient dynamics over time. These terrestrial changes are fed to GCAM using linear scalars derived from net primary productivity (NPP) and heterotrophic respiration changes within CESM. These scalars modify carbon storage and crop yield values within GCAM (Bond-Lamberty et al., 2014). Changes in land use within GCAM are in turn translated into land cover changes at the plant functional type level, which are fed back to CESM (Di Vittorio et al., 2014).

2.2. Experimental Design

Following the experimental protocol for the fifth Coupled Model Intercomparison Project (CMIP5; Taylor et al., 2012), each of the simulations used in this study begins from a common preindustrial spin-up condition for the year 1850 CE and proceeds following prescribed atmospheric greenhouse gas and aerosol concentrations and land cover for the years 1850–2005 CE. We conduct three such historical simulations, which are designed to aid in the isolation of the concentration-carbon and climate-carbon feedbacks. These include a Carbon and Climate simulation with all climate forcings and carbon cycle processes enabled, a Carbon-Only simulation in which the radiative effect of atmospheric CO_2 is disabled, and a Climate-Only simulation in which the biogeochemical effect of atmospheric CO_2 on plant physiological processes is disabled. We note that non-CO_2 greenhouse gases, aerosols, and land cover change exert a forcing effect on climate in all cases; there is thus some moderate global warming even in the Carbon-Only simulation, which we account for below in our parameter estimation paradigm.

From 2005 to 2089 CE, the GCAM model is used to generate future forcing conditions that meet the criteria for the RCP8.5. We use the same population and income in GCAM as the original RCP8.5 to mimic that scenario as closely as possible. However, we note that while global forcing levels match the RCP8.5 trajectory, GCAM's particular mix of greenhouse gas, aerosol, and land cover changes differs slightly from the RCP8.5 forcing scenario adopted for CMIP5 (Riahi et al., 2011). Future simulations are conducted both with and without human-mediated LULCC feedbacks enabled via the iESM framework for all three forcing conditions: Climate and Carbon, Carbon Only, and Climate Only. This results in a total of six future simulations. In order to isolate human-mediated LULCC feedbacks, future simulations all use the same atmospheric concentrations for greenhouse gases and aerosols. They differ only in their LULCC trajectories.

2.3. Parameter Estimation Paradigm

Here we show how the C4MIP framework for estimating C cycle feedback parameters (Arora et al., 2013; Friedlingstein et al., 2006; Jones et al., 2016) can be extended to separately quantify human and nonhuman contributions to C cycle feedbacks. We begin by describing our framework for estimating the concentration-carbon (β_L) and climate-carbon (γ_L) parameters inclusive of both human- and nonhuman-mediated processes. The framework can be applied over a many time frames. However, except where noted, all results reported focus on the final two decades of our simulations (2070–2089) relative to pre-industrial conditions. According to the C4MIP framework, we approximate the change in terrestrial carbon (ΔC_L) within the Climate and Carbon simulation with human-mediated LULCC feedbacks as the linear combination of the concentration-carbon feedback and the climate-carbon feedback (Friedlingstein et al., 2006):

$$\Delta C_L = \beta_L \Delta C_A + \gamma_L \Delta T \tag{1}$$

where β_L and γ_L are the concentration-carbon and climate-carbon feedback coefficients respectively, ΔC_A is the change in atmospheric carbon, measured in parts per million of carbon dioxide, and ΔT is global mean temperature change measured in degrees Celsius. We obtain similar equations for the Carbon Only and Climate-Only simulations:

$$\Delta \widehat{C_L} = \beta_L \Delta \widehat{C_A} + \gamma_L \Delta \widehat{T} \tag{2}$$

$$\Delta \widetilde{C_L} = \beta_L \Delta \widetilde{C_A} + \gamma_L \Delta \widetilde{T} \tag{3}$$

where $\Delta \widehat{C_L}$, $\Delta \widehat{C_A}$, and $\Delta \widehat{T}$ are the change in terrestrial carbon, atmospheric carbon, and global mean temperature for the Carbon-Only simulation and $\Delta \widetilde{C_L}$, $\Delta \widetilde{C_A}$, and $\Delta \widetilde{T}$ are the changes in terrestrial carbon, atmospheric carbon, and global mean temperature for the Climate-Only simulation.

By design, the change in atmospheric carbon is identical in the Climate and Carbon compared to the Carbon-Only simulations. Likewise, the change in global mean temperature is equivalent in the Climate and Carbon compared to the Climate-Only simulations, although it is not identical due to both internal climate variability and the effect of enhanced terrestrial carbon storage on biogeophysical climate forcing. For instance, we estimate $\Delta \widetilde{T}$ to be 4.08 °C and ΔT to be 4.26 °C by comparing the final 20 simulation years (2070–2089 CE) from the Climate-Only simulation and Carbon and Climate simulation to the first 20 historical simulation years (1850–1869 CE). Thus,

$$\Delta\widehat{C_A} = \Delta C_A \tag{4}$$

$$\Delta\widetilde{T} \cong \Delta T \tag{5}$$

By combining equations (1) and (2) with (4) and equations (1) and (3) with (5), we can solve for β_L and γ_L as follows:

$$\gamma_L = \frac{\Delta C_L - \Delta\widehat{C_L}}{\Delta T - \Delta\widehat{T}} \tag{6}$$

$$\beta_L = \frac{\Delta C_L - \Delta\widetilde{C_L}}{\Delta C_A - \Delta\widetilde{C_A}} \tag{7}$$

We note that the effect of $\Delta\widetilde{C_A}$ on terrestrial carbon is disabled by design, so the denominator of equation (7) simplifies to ΔC_A. However, since the Carbon-Only simulation contains non-CO_2 climate forcing agents, $\Delta\widehat{T}$ is nonzero.

Next, we decompose the concentration-carbon and climate-carbon feedbacks into nonhuman- and human-mediated components. Consistent with the C4MIP parameter estimation paradigm that treats the concentration-carbon and climate-carbon feedbacks as independent and additive (Friedlingstein et al., 2006), we assume that the nonhuman- and human-mediated aspects of these feedbacks are independent and additive. In practice, these assumptions have been shown to be imperfect (Gregory et al., 2009), which introduces concentration-carbon and climate-carbon parameter sensitivity to the experimental and analytic estimation method. However, if applied in a consistent fashion, the approach has still provided a useful means to diagnose sources of cross-model variation (Arora et al., 2013; Eby et al., 2013). We decompose the concentration-carbon and climate-carbon feedbacks as follows:

$$\Delta C_L = \Delta C_{L,N} + \Delta C_{L,H} \tag{8}$$

$$\Delta C_{L,N} = \beta_{L,N}\Delta C_A + \gamma_{L,N}\Delta T \tag{9}$$

$$\Delta C_{L,H} = \beta_{L,H}\Delta C_A + \gamma_{L,H}\Delta T \tag{10}$$

where $\Delta C_{L,\ N}$ and $\Delta C_{L,\ H}$ are the nonhuman- and human-mediated changes in terrestrial carbon respectively, $\beta_{L,\ N}$ and $\beta_{L,\ H}$ are the nonhuman- and human-mediated components of the cocnentration carbon feedback respectively, and $\gamma_{L,\ N}$ and $\gamma_{L,\ H}$ are the nonhuman- and human-mediated components of the climate-carbon feedback. We note that $\Delta C_{L,\ H}$ represents change in terrestrial carbon that is above and beyond that associated with any baseline LULCC that would take place in the absence of human responses to biospheric changes.

It follows from equations (1), (8), (9), and (10) that feedback parameters can be written as the sum of their components as follows:

$$\beta_L = \beta_{L,N} + \beta_{L,H} \tag{11}$$

$$\gamma_L = \gamma_{L,N} + \gamma_{L,H} \tag{12}$$

Our Climate and Carbon, Carbon Only, and Climate Only in which the human-mediated LULCC feedback has been disabled provide a means to estimate the nonhuman components of feedbacks using the same logic behind equations (6) and (7):

$$\gamma_{L,N} = \frac{\Delta C_{L,N} - \Delta\widehat{C_{L,N}}}{\Delta T - \Delta\widehat{T}} \tag{13}$$

$$\beta_{L,N} = \frac{\Delta C_{L,N} - \Delta\widetilde{C_{L,N}}}{\Delta C_A - \Delta\widetilde{C_A}} \tag{14}$$

where $\Delta C_{L,\ N}$ is obtained from the Climate and Carbon simulation with human-mediated feedbacks disabled, $\Delta\widehat{C_{L,N}}$ is obtained from the Carbon-Only simulation with human-mediated feedbacks disabled, and $\Delta\widetilde{C_{L,N}}$ is obtained from the Climate-Only simulation with human-mediated feedbacks disabled. The human-mediated feedback components can then be calculated as the difference between the fully coupled feedback parameters and the nonhuman components using equations (11) and (12).

The relatively linear relationship between changes in global crop area and global terrestrial C storage found in our simulations (see Figure 2) suggests that we can further decompose the human-mediated C cycle feedbacks into land cover change and consequent carbon storage changes. We define the concentration-land cover effect (ε), climate land cover effect (η), and land cover-carbon effect (μ) as follows:

$$\beta_{L,H} = \varepsilon\mu \tag{15}$$

$$\gamma_{L,H} = \eta\mu \tag{16}$$

where ε is the concentration-land cover change effect in units of million square kilometers of cropland per part per million atmospheric carbon dioxide, η is the climate-land cover effect in units of million square kilometers of cropland per degree Celsius and μ is the land cover-carbon effect in units of Petagrams carbon per million square kilometers of cropland cropland. Moreover, we can write the human-mediated change in terrestrial carbon as a change in land cover due to feedbacks (ΔL_H) times the land cover-carbon effect:

$$\Delta C_{L,H} = \Delta L_H \mu \tag{17}$$

By substituting equations (15), (16), and (17) into (10), we obtain the following:

$$\Delta L_H \mu = \varepsilon\mu\, \Delta C_A + \eta\mu\, \Delta T \tag{18}$$

The μ terms cancel from this equation, yielding the following:

$$\Delta L_H = \varepsilon\, \Delta C_A + \eta \Delta T \tag{19}$$

We can now again repeat the logic behind equations (6) and (7) to solve for ε and η as follows:

$$\varepsilon = \frac{\Delta L_H - \Delta \widehat{L_H}}{\Delta T - \Delta \widehat{T}} \tag{20}$$

$$\eta = \frac{\Delta L_H - \Delta \widetilde{L_H}}{\Delta C_A - \Delta \widetilde{C_A}} \tag{21}$$

where ΔL_H can be obtained by examining the land cover difference between the Climate and Carbon simulations with and without human-mediated LULCC feedbacks, $\Delta \widehat{L_H}$ can be obtained by examining the land cover difference between the Carbon-Only simulations with and without human-mediated LULCC feedbacks, and $\Delta \widetilde{L_H}$ can be obtained by examining the landover difference between the Climate-Only simulations with and without human-mediated LULCC feedbacks.

Finally, we can estimate the land cover-carbon effect (μ) using equation (15) or (16). In practice, we obtain slightly different values if we use equation (15) or (16), which is not surprising given the assumptions underlying the parameter estimation paradigm, that is, that the various feedback effects are independent, linear, instantaneous, etc. (Gregory et al., 2009). To account for this discrepancy, we report the mean of the two values obtained using equations (15) and (16). For instance, for the final two decades of our simulations (2070–2089 CE), we estimate μ to be -15.5 PgC/Mkm^2 using equation (15) and -16.4 PgC/Mkm^2 using equation (16). We report a value of -16 in Table 1.

3. Results

Without human-mediated LULCC feedbacks, we find a positive value for β_L and a negative value for γ_L (Figure 1), implying that elevated atmospheric CO_2 enhances terrestrial carbon storage, but climate change associated with atmospheric CO_2 decreases terrestrial carbon storage. The sign of these effects is consistent with previous studies across a range of models (Arora et al., 2013; Eby et al., 2013; Friedlingstein et al., 2006),

Table 1
Estimated Terrestrial Carbon Cycle Feedback Parameters and Associated Units for Each Parameter

β_L PgC/ppmCO$_2$	$\beta_{L,N}$ PgC/ppmCO$_2$	$\beta_{L,H}$ PgC/ppmCO$_2$	ε Mkm^2/ppmCO$_2$	γ_L PgC/°C	$\gamma_{L,N}$ PgC/°C	$\gamma_{L,H}$ PgC/°C	η Mkm^2/°C	μ PgC/Mkm^2
0.28	0.26	0.02	−0.0014	−6.6	−8.9	2.3	−0.15	−16

Note. The concentration-carbon feedback (β_L) is decomposed into nonhuman-mediated ($\beta_{L,N}$) and human-mediated components ($\beta_{L,H}$), which in turn is decomposed into a concentration-land cover effect (ε) and land cover carbon effect (μ). Similarly, the climate-carbon feedback (γ_L) is decomposed into nonhuman-mediated ($\gamma_{L,N}$) and human-mediated components ($\gamma_{L,H}$), which in turn is decomposed into a climate-land cover effect (η) and the same land cover-carbon effect (μ) as above.

but their magnitudes are not directly comparable to other studies due to differences in the underlying emissions scenario (Gregory et al., 2009).

Inclusion of human-mediated LULCC feedbacks alters both the concentration-carbon feedback and the climate-carbon feedback (Figure 1). The CO_2 concentration-carbon feedback (β_L) becomes more positive (from a mean estimate of 0.26 to 0.28 PgC/ppmCO$_2$), and the climate-carbon feedback (γ_L) becomes less negative (from a mean estimate of −8.9 to −6.6 PgC/°C). Thus, for both effects, inclusion of human-mediated feedbacks enhances terrestrial carbon storage relative to the control simulations without such feedbacks. We compute individual model year estimates of the feedback parameters in Figure 1 in order to show the role of model internal variability and quantify the change in the parameter values relative to this internal variability.

Enhanced terrestrial carbon storage from the inclusion of human-mediated LULCC feedbacks is associated with reduced global crop area across all of the simulations examined (Figure 2). These changes are in turn associated with positive changes in globally averaged crop yields in all cases. While the direction of this effect is to be expected for the Carbon-Only case due to the productivity enhancing effect of atmospheric CO_2, it is less clear a priori what drives this effect in the Climate-Only simulations, as climate impacts crop productivity in both positive and negative ways, including changes in precipitation regimes, growing season length, drought stress, and heat stress. Many mechanistic crop models predict future declines in crop yields due to climate change, particularly in tropical regions, and particularly when the productivity enhancing effect of atmospheric CO_2 is disabled in models (Rosenzweig et al., 2014) as in our Climate-Only simulations.

To investigate the drivers of crop yield change in our simulations, we examine spatial patterns of the simulated change in NPP (the net accumulation of C due to photosynthesis minus C losses due to plant respiration) and a measure of water sufficiency change for the Carbon Only, Climate Only, and Carbon and Climate simulations (Figure 3). The current version of the iESM uses C3 crop NPP change as a proxy for crop yield change (Bond-Lamberty et al., 2014; Collins et al., 2015) so changes in NPP are a direct measure of changes in yield in this model. Water sufficiency is estimated using the BTRAN variable from the Community Land Model (Oleson et al., 2010). This unitless variable ranges from 0 to 1 and reflects the degree to which photosynthesis is enabled by adequate soil moisture. A value of 1 means fully adequate soil moisture with no limitations on photosynthesis, whereas a decrease in this value indicates additional soil moisture stress.

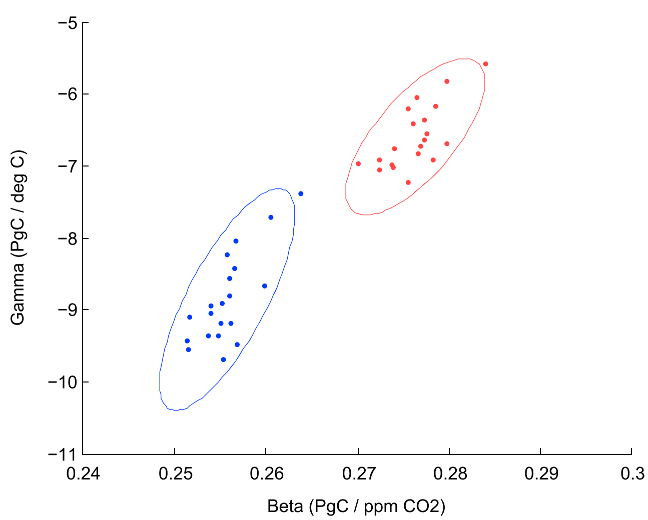

Figure 1. Estimates for the terrestrial concentration-carbon feedback parameter (β_L) and climate-carbon feedback parameter (γ_L) with (red circles) and without (blue circles) the inclusion of human-mediated land use and land cover change (LULCC) feedbacks. Twenty estimates for each parameter combination are shown, one calculated using each of the final 20 years (2070–2089 CE) of a 21st century forcing scenario based on the Representative Concentration Pathway 8.5. Blue (without human-mediated LULCC feedbacks) and red ovals (with human-mediated LULCC feedbacks) indicate the 95% confidence interval surrounding the joint distribution of parameter estimates.

In the Carbon-Only case, we see widespread NPP enhancements over regions of the planet with croplands (Figure 3b). However, in the Climate-Only case, there is a mix of regions with positive and negative changes in NPP (Figure 3c). Negative changes are seen in Equatorial regions of South America and Asia, as well as Southern Africa, Western Europe, the Southwest United States, and Australia. These regions correspond in general to regions where increased soil moisture stress is seen in the Climate-Only case (Figure 3f), but regions of reduced water stress do not universally correspond to regions of enhanced NPP, particularly

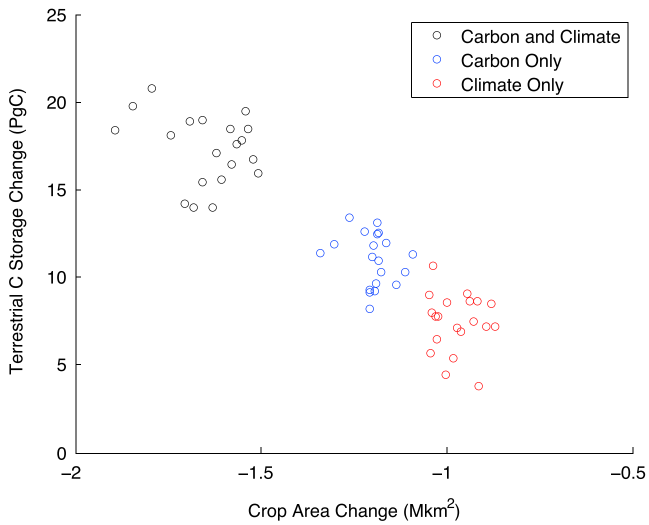

Figure 2. Global changes in crop area and associated changes in global terrestrial C storage due to inclusion of human-mediated land use and land cover change feedbacks. Individual circles represents the change in these quantities for the final 20 years (2070–2089 CE) of a 21st century forcing scenario based on the Representative Concentration Pathway 8.5 driven by both the biogeochemical and radiative effects of atmospheric CO_2 (black circles) the biogeochemical effect alone (blue circles), and the radiative effect alone (red circles).

at higher latitudes where light may be a limiting factor on annual photosynthesis. While a similar pattern of water stress is seen in the Carbon and Climate case (Figure 3d), the NPP changes in the combined case reflect the Carbon-Only pattern more so than the Climate-Only pattern (Figure 3a).

NPP changes in the Climate-Only case are broadly consistent with the expectation that climate change will have mixed effects on crop productivity. However, the large range of crop yield responses seen across mechanistic crop models (Müller et al., 2015; Rosenzweig et al., 2014) suggests that if a different crop model were used in the iESM or similar coupled model, we might find a very different estimate for the human contribution to the climate-carbon feedback (γ_L). Moreover, while the sign of the human contribution to the concentration-carbon feedback (β_L) is to be expected, the magnitude could vary widely across alternative plausible models.

Table 1 summarizes our estimated values for the human and nonhuman carbon cycle feedback parameters described above using the iESM model. We see that for this model, the human-mediated share of the total climate-carbon feedback (2.3 vs. −6.6 PgC/°C is larger than the human-mediated share of the total concentration-carbon feedback (0.02 vs. 0.28 PgC/ppm CO_2). We note, however, that in our simulations, these values are scaled by different quantities. For instance, in the fully coupled case, global atmospheric CO_2 rises by 480 ppm and global mean temperature rises by 4.26 °C for the final two decades of the simulation (2070–2089 CE) compared to preindustrial. As a result, the two human-mediated feedbacks have a similar magnitude effect on terrestrial carbon storage, 9.8 PgC for the human-mediated climate-carbon feedback and 9.6 PgC for the human-mediated concentration-carbon feedback. This indicates that negative atmospheric carbon feedbacks due to the LULCC response to biospheric change are not dominated by CO_2 concentration effects.

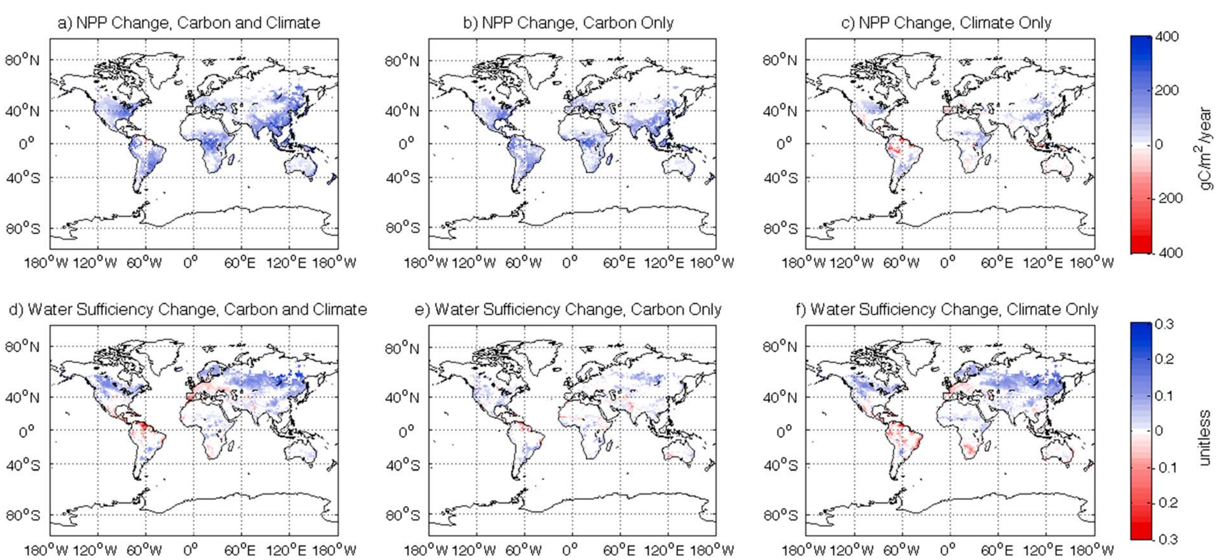

Figure 3. Simulated changes (2070–2089 CE minus 2005–2024 CE) in grid cell mean Net Primary Productivity (NPP; panels a–c) and water sufficiency (panels d–f) without the inclusion of human-mediated land use and land cover change feedbacks for model runs driven by both the radiative and biogeochemical effects of atmospheric CO_2 (panels a and d), the biogeochemical effect alone (panels b and e), and the radiative effect alone (panels c and f). Simulations are based on an adapted version of the Representative Concentration Pathway 8.5 forcing scenario. Water sufficiency is measured using the unitless BTRAN variable from the Community Land Model, which reflects soil moisture limitations on photosynthesis. Negative values of this quantity indicate greater limitations on photosynthesis due to lack of soil moisture and vice versa. NPP and water sufficiency values are shown only for those grid cells that contain cropland and for which a Student's *t* test indicates that the cell differences are significant at the 95% level.

4. Discussion

Our analysis demonstrates that human-mediated LULCC feedbacks can be quantified in a similar fashion as nonhuman concentration-carbon and climate-carbon feedbacks. Figure 1 indicates that the introduction of human-mediated feedbacks leads to a statistically significant change in the feedback parameters relative to model internal variability. Caution should be taken when comparing feedback parameters across studies because results are sensitive to the particular experiments used as a basis for calculating them (Gregory et al., 2009). However, the magnitude of the human-mediated feedbacks found in this study is small relative to the range of nonhuman feedbacks reported in the literature; for example, a recent study using Earth system models of intermediate complexity found the non-human concentration-carbon feedback to range from 0.22 to 1.09 PgC/ppm CO_2 and the nonhuman climate-carbon feedbacks to range from -96.6 to -6.9 PgC/°C (Eby et al., 2013). Similar ranges have been found among more process-rich Earth system models as well (Arora et al., 2013; Friedlingstein et al., 2006). The iESM model's nonhuman feedbacks are at the low end of this literature range, and the Community Land Model version 4 used within the iESM modeling framework has a low terrestrial carbon sink relative to their models (Anav et al., 2013; Keppel-Aleks et al., 2013), which further highlights the importance of examining such feedbacks within a multimodel context.

Just as there are significant uncertainties arising from model bias across a range of plausible terrestrial biogeochemical models (Arora et al., 2013; Eby et al., 2013; Friedlingstein et al., 2006, 2014), human-mediated LULCC are likely to vary significantly across alternative plausible models. In addition to terrestrial vegetation and soil carbon dynamics, there is significant model uncertainty associated with the estimation of future crop yield changes (Rosenzweig et al., 2014), the resulting economic response (Nelson et al., 2014), and the translation of land use change to land cover change (Di Vittorio et al., 2014; Jain & Yang, 2005; Meiyappan & Jain, 2012; Peng et al., 2017; Prestele et al., 2017). Thus, our decomposition of the human-mediated concentration-carbon and climate-carbon feedbacks into separate concentration-land cover, climate-land cover, and land cover-carbon effects is useful because it distinguishes two broad categories of processes that contribute to the human-mediated LULCC feedbacks: ε and η reflect model assumptions about the relative value of cropland compared to other land uses including crop and forestry yield changes and subsequent economically driven changes in LULCC, whereas μ reflects the process of land conversion itself, including which categories of land are converted to and from agricultural use as well as the amount of C associated with those conversions.

In this study, we found that it was sufficient to describe the effect of land cover change on carbon in a parsimonious fashion that focuses on changes in global cropland area and associated carbon changes, which is supported by the relatively linear relationship between global cropland and global carbon storage with the addition of human-mediated feedbacks (Figure 2). We note, however, that climate-driven changes in land productivity may induce changes in agricultural and forestry intensification (higher yields on existing lands) or extensification (expansion of agricultural lands). To the extent that intensification alters carbon storage within a particular land category, this would be reflected in the μ parameter. Alternative model formulations will likely show differences in the degree of agricultural and forestry intensification versus extensification induced by climate change, with implications for carbon storage and land cover conversions across multiple land cover types and regions. The feedback parameters that we describe will reflect such changes and can point to broad categories of processes that differ among models. However, additional decomposition and analysis may be required to further identify the specific processes and regions most responsible for model differences.

Currently only a handful of models have coupled each of the relevant processes into a consistent framework capable of estimating human-mediated LULCC contributions to carbon cycle feedbacks (Calvin & Bond-Lamberty, 2018; Monier et al., 2018; Robinson et al., 2018; Thornton et al., 2017; Voldoire et al., 2007). As the technical capability and scientific interest in this phenomenon grows, the feedback parameter framework illustrated above provides a parsimonious means to quantitatively differentiate first-order feedback drivers across models and identify the greatest source of cross-model uncertainty. While this study focuses on climate change feedbacks to terrestrial carbon storage through changes in land management, climate change is expected to affect many sectors of society including public health, water, energy, urban, and transportation systems (IPCC, 2014). Adaptive responses to these impacts all have the potential to generate feedbacks to the climate system, particularly if they affect activities that produce climate forcing such as the use of energy. Our framework demonstrates that such feedbacks can be formally quantified and compared with nonhuman feedbacks.

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References

Anav, A., Friedlingstein, P., Kidston, M., Bopp, L., Ciais, P., Cox, P., et al. (2013). Evaluating the land and ocean components of the global carbon cycle in the CMIP5 earth system models. *Journal of Climate*, *26*(18), 6801–6843. https://doi.org/10.1175/JCLI-D-12-00417.1

Arora, V. K., Boer, G. J., Friedlingstein, P., Eby, M., Jones, C. D., Christian, J. R., et al. (2013). Carbon–concentration and carbon–climate feedbacks in CMIP5 Earth system models. *Journal of Climate*, *26*(15), 5289–5314. https://doi.org/10.1175/JCLI-D-12-00494.1

Bond-Lamberty, B., Calvin, K., Jones, A. D., Mao, J., Patel, P., Shi, X. Y., et al. (2014). On linking an Earth system model to the equilibrium carbon representation of an economically optimizing land use model. *Geoscientific Model Development*, *7*(6), 2545–2555. https://doi.org/10.5194/gmd-7-2545-2014

Calvin, K., & Bond-Lamberty, B. (2018). Integrated human-Earth system modeling—State of the science and future directions. *Environmental Research Letters*, *13*(6), 063006. https://doi.org/10.1088/1748-9326/aac642

Collins, W. D., Craig, A. P., Truesdale, J. E., Di Vittorio, A. V., Jones, A. D., Bond-Lamberty, B., et al. (2015). The integrated Earth system model version 1: Formulation and functionality. *Geoscientific Model Development*, *8*(7), 2203–2219. https://doi.org/10.5194/gmd-8-2203-2015

Deryng, D., Elliott, J., Folberth, C., Müller, C., Pugh, T. A. M., Boote, K. J., et al. (2016). Regional disparities in the beneficial effects of rising CO_2 concentrations on crop water productivity. *Nature Climate Change*, *6*(8), 786–790. https://doi.org/10.1038/nclimate2995

Di Vittorio, A. V., Chini, L. P., Bond-Lamberty, B., Mao, J., Shi, X., Truesdale, J., et al. (2014). From land use to land cover: Restoring the afforestation signal in a coupled integrated assessment-earth system model and the implications for CMIP5 RCP simulations. *Biogeosciences*, *11*(22), 6435–6450. https://doi.org/10.5194/bg-11-6435-2014

Eby, M., Weaver, A. J., Alexander, K., Zickfeld, K., Abe-Ouchi, A., Cimatoribus, A. A., et al. (2013). Historical and idealized climate model experiments: An intercomparison of Earth system models of intermediate complexity. *Climate of the Past*, *9*(3), 1111–1140. https://doi.org/10.5194/cp-9-1111-2013

Friedlingstein, P., Cox, P., Betts, R., Bopp, L., von Bloh, W., Brovkin, V., et al. (2006). Climate-carbon cycle feedback analysis: Results from the C4MIP Model Intercomparison. *Journal of Climate*, *19*(14), 3337–3353. https://doi.org/10.1175/JCLI3800.1

Friedlingstein, P., Dufresne, J.-L., Cox, P. M., & Rayner, P. (2003). How positive is the feedback between climate change and the carbon cycle? *Tellus B*, *55*(2), 692–700. https://doi.org/10.1034/j.1600-0889.2003.01461.x

Friedlingstein, P., Meinshausen, M., Arora, V. K., Jones, C. D., Anav, A., Liddicoat, S. K., & Knutti, R. (2014). Uncertainties in CMIP5 climate projections due to carbon cycle feedbacks. *Journal of Climate*, *27*(2), 511–526. https://doi.org/10.1175/JCLI-D-12-00579.1

Gregory, J. M., Jones, C. D., Cadule, P., & Friedlingstein, P. (2009). Quantifying carbon cycle feedbacks. *Journal of Climate*, *22*(19), 5232–5250. https://doi.org/10.1175/2009JCLI2949.1

Hewitt, A. J., Booth, B. B. B., Jones, C. D., Robertson, E. S., Wiltshire, A. J., Sansom, P. G., et al. (2016). Sources of uncertainty in future projections of the carbon cycle. *Journal of Climate*, *29*(20), 7203–7213. https://doi.org/10.1175/JCLI-D-16-0161.1

Hurrell, J. W., Holland, M. M., Gent, P. R., Ghan, S., Kay, J. E., Kushner, P. J., et al. (2013). The Community Earth System Model: A framework for collaborative research. *Bulletin of the American Meteorological Society*, *94*(9), 1339–1360. https://doi.org/10.1175/BAMS-D-12-00121.1

IPCC. (2014). Climate change 2014: Impacts, adaptation, and vulnerability. Assessment Report 5. https://doi.org/10.1017/CBO9781107415379

Jain, A. K., & Yang, X. (2005). Modeling the effects of two different land cover change data sets on the carbon stocks of plants and soils in concert with CO_2 and climate change. *Global Biogeochemical Cycles*, *19*, GB2015. https://doi.org/10.1029/2004GB002349

Jones, C. D., Arora, V., Friedlingstein, P., Bopp, L., Brovkin, V., Dunne, J., et al. (2016). The C4MIP experimental protocol for CMIP6. *Geoscientific Model Development Discussion*, 1–52. https://doi.org/10.5194/gmd-2016-36

Keppel-Aleks, G., Randerson, J. T., Lindsay, K., Stephens, B. B., Keith Moore, J., Doney, S. C., et al. (2013). Atmospheric carbon dioxide variability in the Community Earth System Model: Evaluation and transient dynamics during the twentieth and twenty-first centuries. *Journal of Climate*, *26*(13), 4447–4475. https://doi.org/10.1175/JCLI-D-12-00589.1

Meiyappan, P., & Jain, A. K. (2012). Three distinct global estimates of historical land-cover change and land-use conversions for over 200 years. *Frontiers of Earth Science*, *6*(2), 122–139. https://doi.org/10.1007/s11707-012-0314-2

Monier, E., Paltsev, S., Sokolov, A., Chen, Y.-H. H., Gao, X., Ejaz, Q., et al. (2018). Toward a consistent modeling framework to assess multi-sectoral climate impacts. *Nature Communications*, *9*(1), 660. https://doi.org/10.1038/s41467-018-02984-9

Müller, C., Elliott, J., Chryssanthacopoulos, J., Deryng, D., Folberth, C., Pugh, T. A. M., & Schmid, E. (2015). Implications of climate mitigation for future agricultural production. *Environmental Research Letters*, *10*, 125004. https://doi.org/10.1088/1748-9326/10/12/125004

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., et al. (2014). Climate change effects on agriculture: Economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3274–3279. https://doi.org/10.1073/pnas.1222465110

Oleson, K. W., Lawrence, D. M., Bonan, G. B., Flanner, M. G., Kluzek, E., Lawrence, P. J., et al. (2010). Technical description of version 4.0 of the Community Land Model (CLM). https://doi.org/10.5065/D6FB50WZ

Peng, S., Ciais, P., Maignan, F., Li, W., Chang, J., Wang, T., & Yue, C. (2017). Sensitivity of land use change emission estimates to historical land use and land cover mapping. *Global Biogeochemical Cycles*, *31*, 626–643. https://doi.org/10.1002/2015GB005360

Prestele, R., Arneth, A., Bondeau, A., de Noblet-Ducoudré, N., Pugh, T. A. M., Sitch, S., et al. (2017). Current challenges of implementing anthropogenic land-use and land-cover change in models contributing to climate change assessments. *Earth System Dynamics*, *8*(2), 369–386. https://doi.org/10.5194/esd-8-369-2017

Randerson, J. T., Lindsay, K., Munoz, E., Fu, W., Moore, J. K., Hoffman, F. M., et al. (2015). Multicentury changes in ocean and land contributions to the climate-carbon feedback. *Global Biogeochemical Cycles*, *29*, 744–759. https://doi.org/10.1002/2014GB005079

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., et al. (2011). RCP 8.5—A scenario of comparatively high greenhouse gas emissions. *Climatic Change*, *109*(1-2), 33–57. https://doi.org/10.1007/s10584-011-0149-y

Robinson, D. T., Di Vittorio, A., Alexander, P., Arneth, A., Barton, C. M., Brown, D. G., et al. (2018). Modelling feedbacks between human and natural processes in the land system. *Earth System Dynamics*, *9*(2), 895–914. https://doi.org/10.5194/esd-9-895-2018

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., et al. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3268–3273. https://doi.org/10.1073/pnas.1222463110

Sitch, S., Huntingford, C., Gedney, N., Levy, P. E., Lomas, M., Piao, S. L., et al. (2008). Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five Dynamic Global Vegetation Models (DGVMs). *Global Change Biology*, *14*, 2015–2039. https://doi.org/10.1111/j.1365-2486.2008.01626.x

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

Thornton, P. E., Calvin, K., Jones, A. D., Di Vittorio, A. V., Bond-Lamberty, B., Chini, L., et al. (2017). Biospheric feedback effects in a synchronously coupled model of human and Earth systems. *Nature Climate Change*, *7*(7), 496–500. https://doi.org/10.1038/nclimate3310

Verhage, F. Y. F., Anten, N. P. R., & Sentelhas, P. C. (2017). Carbon dioxide fertilization offsets negative impacts of climate change on Arabica coffee yield in Brazil. *Climatic Change*, *144*(4), 671–685. https://doi.org/10.1007/s10584-017-2068-z

Voldoire, A., Eickhout, B., Schaeffer, M., Royer, J.-F., & Chauvin, F. (2007). Climate simulation of the twenty-first century with interactive land-use changes. *Climate Dynamics*, *29*(2–3), 177–193. https://doi.org/10.1007/s00382-007-0228-y

Wing, I. S., Monier, E., Stern, A., & Mundra, A. (2015). US major crops' uncertain climate change risks and greenhouse gas mitigation benefits. *Environmental Research Letters*, *10*(11). https://doi.org/10.1088/1748-9326/10/11/115002

Wise, M., Calvin, K., Kyle, P., Luckow, P., & Edmonds, J. (2014). Economic and physial modeling of land use in GCAM 3.0 and an application to agricultural productivity, land, and terrestrial carbon. *Climate Change Economics*, *5*(2), 1450003. https://doi.org/10.1142/S2010007814500031