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Integrated Assessment of Carbon Dioxide Removal

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Key Points:
- We analyze carbon dioxide removal (CDR) in DICE2016R under different climate objectives and with different carbon cycle models
- We analyze the substitution effect between emission reduction and CDR, and the extra CDR required to compensate for carbon cycle feedbacks
- The University of Victoria Earth system climate model is used to validate atmospheric carbon and temperature trajectories derived with DICE

Supporting Information:
- Supporting Information S1.
- Supporting Information S2.

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Abstract To maintain the chance of keeping the average global temperature increase below 2°C and to limit long-term climate change, removing carbon dioxide from the atmosphere (carbon dioxide removal, CDR) is becoming increasingly necessary. We analyze optimal and cost-effective climate policies in the dynamic integrated assessment model (IAM) of climate and the economy (DICE2016R) and investigate (1) the utilization of (ocean) CDR under different climate objectives, (2) the sensitivity of policies with respect to carbon cycle feedbacks, and (3) how well carbon cycle feedbacks are captured in the carbon cycle models used in state-of-the-art IAMs. Overall, the carbon cycle model in DICE2016R shows clear improvements compared to its predecessor, DICE2013R, capturing much better long-term dynamics and also oceanic carbon outgassing due to excess oceanic storage of carbon from CDR. However, this comes at the cost of a (too) tight short-term remaining emission budget, limiting the model suitability to analyze low-emission scenarios accurately. With DICE2016R, the compliance with the 2°C goal is no longer feasible without negative emissions via CDR. Overall, the optimal amount of CDR has to take into account (1) the emission substitution effect and (2) compensation for carbon cycle feedbacks.

1. Introduction

Achieving the 2°C and even more the 1.5°C goal is unrealistic without intentional atmospheric carbon dioxide removal (CDR) (Collins et al., 2013; Rockström et al., 2016; Rogelj et al., 2016). How effectively CDR could contribute to mitigate climate change is still very uncertain (Anderson & Peters, 2016; Field & Mach, 2017; Fuss et al., 2014; Smith et al., 2015; Tokarska & Zickfeld, 2015). One central issue is the storage of the carbon removed from the atmosphere. Especially given that carbon cycle feedbacks, saturation effects, and outgassing of carbon may limit the effectiveness of CDR (Fuss et al., 2014; Jones et al., 2016; Tokarska & Zickfeld, 2015; Vichi et al., 2013). For assessing the potential of CDR in economically efficient climate policies, the central methodological question thus is how well these feedbacks and effects are reflected in carbon cycle models used in integrated assessment models (IAMs).

A rigorous scientific assessment of these issues is lacking so far, in particular when taking the economic feedbacks and efficient choice of CDR patterns into account. Here, we analyze optimal climate policies (including CDR) in the dynamic IAM of climate and the economy DICE and investigate (1) the utilization of (ocean) CDR under different climate objectives, (2) the sensitivity of policies with respect to carbon cycle feedbacks, and (3) how well carbon cycle feedbacks are captured in the carbon cycle box models used in state-of-the-art IAMs.

We use DICE in its most recent version (Nordhaus, 2017) and analyze in addition how the results change if we replace the current carbon cycle model with the carbon cycle model from the previous version DICE2013R (Nordhaus & Sztorc, 2013) or with the carbon cycle model from the recent IAM by Gerlagh and Liski (2017). We focus on storage of carbon from CDR in the ocean, covering a broad range of specific CDR methods that are utilized incrementally according to their marginal deployment costs. To validate our integrated assessment of CDR we implement the optimal climate policies in the nonlinear Bolin and Eriksson adjusted model (BEAM) (Glotter et al. (2014) and the intermediate complexity University of Victoria Earth system climate model (UVic ESCM) (Eby et al., 2013; Weaver et al., 2001).

Simulations in Earth system models suggest that the extra amount of carbon added to the ocean or some other reservoir via CDR cannot be equated with the actual amount of carbon removed from the atmosphere (Jones et al., 2016; Tokarska & Zickfeld, 2015; Vichi et al., 2013). Removing carbon from the atmosphere results in reduced uptake of or even release of carbon from the terrestrial biosphere and the ocean for modest or strong removal scenarios, respectively. Enhancing oceanic carbon uptake (by, e.g., ocean alkalinity management) implies that not only atmospheric but also terrestrial carbon is added to the ocean and vice versa in case of terrestrial carbon uptake enhancement (by, e.g., afforestation; Keller et al., 2014). Without "extra" carbon removal to compensate for these carbon cycle feedbacks, desired atmospheric carbon reduction targets cannot be achieved (Jones et al., 2016).

The integrated assessment of CDR so far has focused on the role of terrestrial CDR (in particular bioenergy with carbon capture and storage, BECCS), analyzing how this sector would contribute to the required energy transition to achieve low-emission pathways (Azar et al., 2010; Kriegler et al., 2013; Rose et al., 2014; van Vuuren et al., 2013). IAMs and dynamic global vegetation models have been used to analyze implications of terrestrial CDR for land use, water consumption, and food production (e.g., Boysen et al., 2017, 2017; Smith et al., 2015). The influence of carbon cycle feedbacks on the efficiency of CDR has received less attention. One exception is the study of Chen and Tavoni (2013) who investigate CDR by direct air capture (DAC) as an additional mitigation option in the IAM WITCH (World Induced Technological Change Hybrid). Based on their standard DAC deployment scenario (without oceanic outgassing) they use information from Vichi et al. (2013) to estimate the average reduction in effective atmospheric carbon removal and correct the effectiveness of DAC for this outgassing. With this general correction, they find that instead of extra removal to compensate for this outgassing about 30% less DAC is deployed compared to their standard specification. This can be explained by the fact that in their specification the effectiveness of DAC is explicitly reduced and not implicitly determined by carbon cycle feedbacks as we do in our study.

Few studies investigate whether and under which conditions IAMs produce climate and carbon cycle outcomes which are consistent with outcomes of state-of-the-art Earth system models (Hof et al., 2012; van Vuuren et al., 2011; Warren et al., 2010). Warren et al. (2010) find that the selected IAMs show a significant variation in climate outcomes whereby some even result in inconsistent estimates for carbon concentrations and temperature response, compared to Intergovernmental Panel on Climate Change (IPCC) simulations. They suggest for example that the FUND (climate framework for uncertainty, negotiation, and distribution) model underestimates the temperature response and results therefore, in less ambitious mitigation strategies than are optimal. However, van Vuuren et al. (2011) find that the outcomes of the IAMs are within the range of more complex models. Still, they conclude that differences between carbon and climate outcomes across IAMs are significant and matter with respect to the derived policy advice. Hof et al. (2012) also find significant differences, but conclude that the implications on optimal policies are small, relative to other factors, and argue that for example a rather strong carbon cycle feedback found in the PAGE (policy analysis of the greenhouse effect) model (in its 2002 version) has only modest impacts on near-term mitigation due to discounting. In conclusion, the differences between carbon cycle models in IAMs matter in particular when considering exogenously given climate targets like the 2°C goal instead of endogenously derived optimal climate outcomes.

Furthermore, the carbon cycle models applied in the IAMs are continuously reviewed and updated with respect to new findings. For example, Glotter et al. (2014) show that the carbon cycle in DICE2013R fails to properly describe the long-term development of in particular oceanic carbon uptake. In response, the carbon cycle model in DICE2016R is calibrated to include improved long-run dynamics (up to 4000 years) (Nordhaus, 2017). Yet, DICE2016R has not yet been part of a comprehensive assessment with respect to the appropriateness of its carbon cycle model. Furthermore, the suitability of carbon cycle models applied in IAMs to capture carbon cycle feedbacks with respect to CDR has not yet been systematically assessed.

Only few carbon cycle models used in IAMs are capable of capturing these feedbacks with respect to (oceanic) CDR. For example, PAGE, MERGE (model for estimating the regional and global effects of greenhouse gas reduction), FUND, and REMIND (regional model of investments and development) rely on impulse-response representations of the (oceanic) carbon cycle (van Vuuren et al., 2011). This type of carbon cycle model does not allow tracking of the removed carbon, which is placed into the ocean, and in turn cannot account for outgassing of this carbon from the ocean. While impulse-response representations can capture very well nonlinarites in atmospheric carbon development, box-type representations become indispensable if options like (oceanic) CDR are considered when accounting for carbon cycle feedbacks (Rickels & Lontzek, 2012). In this article, we thus focus on the box-type carbon cycle models that are used in IAMs.

The article is structured as follows. Section 2 presents our methodical approach, explaining first the derivation of optimal mitigation policies (including CDR) in DICE and explaining secondly the comparison of the results obtained with linear carbon cycle models to nonlinear carbon cycle and Earth system models. Section 3 presents and discusses our results, Section 4 discusses potential limitations of our study, and Section 5 concludes.

2. Methods

2.1. Derivation of Optimal Climate Policies Including CDR

We derived optimal climate policies with the widely used IAM DICE in its most recent version (i.e., DICE2016R) (Nordhaus, 2017). We consider as optimization time horizon the DICE2016R planning period, starting in year 2015 and running until year 2500. We used three different carbon cycles models in combination with the economic and climate module from DICE2016R: (1) the carbon cycle model from DICE2016R itself (labeled *CC16* in the following), (2) the carbon cycle model from DICE2013R (Nordhaus & Sztorc, 2013) (labeled *CC13*), and (3) the carbon cycle model from Gerlagh and Liski (2017) (labeled *CCGL*). All three carbon cycles models are box models with linearized carbon fluxes between the boxes. Our research objective restricts the carbon cycle models we consider to those that allow the tracking of carbon removed from the atmosphere and added to nonatmospheric carbon reservoirs like the ocean. The box models we have chosen have this property. In both, *CC16* and *CC13*, the three boxes represent atmosphere, upper ocean, and lower ocean. *CCGL* is instead based on the assumption that atmosphere and upper ocean instantaneously equilibrate, implying that the atmospheric carbon stock is a constant fraction of the carbon stock in the first box, whereas the second and third box represent the terrestrial biosphere and deep ocean carbon stocks, respectively. *CC16* and *CC13* differ only in their calibration. While *CC13* is primarily calibrated to capture short-term dynamics of the global carbon cycle (until the first 100 years), *CC16* is calibrated to capture rather long-term dynamics (up to 4000 years) (Nordhaus, 2017). DICE2016R operates in 5 year time steps and the carbon cycle models are calibrated accordingly. In *CCGL* changing the time steps does not only imply an adjustment of the transition matrix between the boxes, but also the share of emissions (and CDR) entering the different boxes. While for 1 year time steps all emissions enter the upper box (atmosphere and upper ocean), for time steps larger than 1 year, a certain fraction enters directly the other two boxes. For all three carbon cycle model specifications we used the climate model (forcing and temperature specifications) from DICE2016R, its assumptions about the development of exogenous non-CO_2 forcing (resulting from other GHG emissions and aerosol emissions), its specification of economic dynamics, and its objective function (i.e., a social welfare function, which is the discounted sum of the population-weighted utility of per capita consumption). More details and the parametrization of the three carbon cycle models are presented in Supplementary information S1.

We analyze three different mitigation frameworks: (1) optimal mitigation where the costs of mitigation are weighted against the benefits of reduced climate damages (labeled *CBA* in the following), (2) cost-minimal mitigation under compliance with the 2°C goal throughout the optimization period (labeled *2C*), and (3) cost-minimal mitigation under compliance with the 2°C goal from the year 2100 onwards until the end of the optimization period (labeled *2C2100*). In *CBA* the optimal level of climate change is endogenously determined, in *2C* and *2C2100* the level of climate change is exogenously constrained. In the latter the level of overshooting of the temperature goal before the year 2100 is endogenously determined. We neglected the possibility to consider another overshooting framework where compliance with the 1.5°C goal would be achieved from 2100 onwards, as investigating such a tight climate target is only sensible with additional mitigation options for non-CO_2 emissions and land-use change emissions (Rogelj et al., 2016; Su et al., 2017). Here, we focused on the role of CDR and carbon cycle feedbacks and left therefore as many other components of the original DICE2016R model as possible unchanged (including its assumptions about exogenous forcing resulting, e.g., from non-CO_2 emissions).

In addition to abatement-only scenarios, we analyzed abatement with CDR within the three mitigation frameworks, distinguishing between three CDR options: (1) (hypothetical) perfect storage in some reservoir disconnected from the boxes of the carbon cycle model, (2) oceanic CDR, i.e. storage in the deep ocean box, and (3) and oceanic CDR under the (false) assumption of perfect storage. With the first option, carbon was actually removed from the carbon cycle. Such an option would correspond to geological storage under the unrealistic assumptions that there are no scarcity issues and no leakage. The first option was primarily used as benchmark for the second option to investigate how carbon cycle feedbacks in the simple carbon cycle models change the optimal CDR application. With the second option, carbon was removed from the atmosphere and added to the deep ocean. Here, we considered rather generic oceanic CDR and accordingly, such an option would correspond to a set of CDR methods that aim at sequestering carbon in the deep ocean. Probably the best analogy is achieved by considering deep ocean carbon injection (IPCC, 2005; Marchetti, 1977), however, also other CDR methods with significant deep ocean carbon sequestration are relevant. With the third option, carbon was removed from the atmosphere under the assumption of perfect storage; however, it is actually added to the deep ocean. Accordingly, the decision-maker observes in the next period that his expectations about carbon stocks and storage were wrong. Thus, after each time step a new optimal policy is derived, however with the actual values for the carbon stocks in the different boxes resulting from oceanic CDR. Consequently, here the mitigation policy was iteratively derived under constant updating with respect to the *true* values for the carbon stocks and corresponding forcing and temperature change. The optimization structure and objective function of DICE remained unchanged during the iterative optimization. Note that without different specification of CDR, the optimization from the first period until the planning horizon and the iterative optimization coincide. The third option provides insights regarding unforeseen leakage from submarine geological storage (here with the extreme assumption of full leakage into the deep ocean) under the condition that changes in carbon stocks are properly monitored. The third option also provides insights to which extend an inaccurate carbon cycle model results in less efficient climate policies under the condition of perfect monitoring.

The original specification of DICE2016R allows "net negative emissions" from the year 2165 onwards. There, negative emissions are simply abatement rates larger than one under the assumption of perfect storage as discussed above. However, the negative emissions in the original DICE2016R specification are constrained to not exceed 20% of the business-as-usual industrial emissions in each time step. In contrast, we introduced CDR as new variable into DICE2016R. We imposed no constraints on the amount or the timing of CDR except that atmospheric carbon concentration cannot be reduced below preindustrial levels (below we discuss the implication of relaxing this assumption).

There is a broad range of unit cost estimates for the various CDR measures in the literature, ranging for example for ocean alkalinity management from 40 up to 144 USD/tCO_2 (Harvey, 2008; Paquay & Zeebe, 2013, respectively). The differences arise from different assumptions regarding the implementation (e.g., scale and technology applied) and from the uncertainty about cost components. Furthermore, the studies neglect potential cost-savings via technological progress and economies of scale, but also neglect potential cost increases via (general equilibrium) price effects if the methods are applied on a larger-scale. We believe that the operational cost are best described by a convex cost function capturing increasing marginal costs, which holds (1) within a specific CDR method and (2) across CDR methods: because specific CDR methods are most likely applied to the most suitable locations first (e.g., close to an appropriate alkaline mineral deposit in case of alkalinity management) while increasing the amount of CDR requires more effort (e.g., larger transport distances to new mineral deposits and larger transport distance on sea) and because generic (oceanic) CDR implies that a set of CDR methods are considered which can be ordered according to their unit cost (like the McKinsey abatement cost curve; McKinsey&Company 2010). While almost certainly small-scale CDR (in the ton or even small megaton scale) can be carried out rather cheaply, the major uncertainty surrounds the operational cost of large-scale CDR application (in the gigaton scale). Accordingly, we assumed a simple linear-quadratic cost function for CDR operation:

$$CDRcost\,(\mathrm{CDR}) = c_1 * CDR + c_2 * \mathrm{CDR}^2. \tag{1}$$

CDR is measured in *GtC,* and c_1 in 10^{12} USD/GtC and c_2 in 10^{12} USD/GtC^2. Parameter c_1 was set to 0.29328×10^{12} USD/GtC, corresponding to 80 USD/tCO_2 for the initial amount of (oceanic) CDR (Klepper & Rickels, 2012). For parameter c_2 we considered a broad parameter range (to reflect the uncertainty about the scale of CDR), ranging from 0.01833×10^{12} USD/GtC^2 to 18.33×10^{12} USD/GtC^2, corresponding to a marginal CDR cost at the first GtC of 90 USD/tCO_2 and 10,080 USD/tCO_2, respectively. The marginal CDR cost curve is linear in the amount of CDR, and increasing with a slope c_2. In order to study the effect of CDR cost we vary this parameter c_2, that is, the slope of the marginal CDR cost curve, in our analysis.

An extra social cost of CDR arises in case of nonperfect storage from carbon cycle feedbacks and is determined by the carbon cycle models. Consequently, CDR allows saving the atmospheric social cost (i.e., the carbon price), but causes at the same time an oceanic social cost (arising from the carbon cycle feedbacks). Accordingly, for equal operational cost, the optimal amounts of CDR (and subsequently the optimal amount of emission via the substitution effect) differ for the three different carbon cycle models. Note that this approach is different to Chen and Tavoni (2013) who explicitly corrected the effectiveness of the CDR methods (i.e., increasing effectively its units costs.)

The DICE model with the different carbon cycles for the different mitigation frameworks has been solved with the constrained optimization package Knitro in AMPL. All model files are included in the supplementary information S2.

2.2. Assessment of Optimal Climate Policies with Respect to Carbon Cycle Feedbacks

For the assessment of the appropriateness of linear box models for the investigation of CDR in IAMs, we implemented the derived optimal policies in (1) the nonlinear BEAM model (Glotter et al., 2014) and the intermediate complexity UVic ESCM (Eby et al., 2013; Weaver et al., 2001). For this exercise, we followed Glotter et al. (2014) by extending the simulation time-horizon beyond the optimization time-horizon until the year 4000. Until the year 2500 we imposed the optimal climate policies derived by the IAM and beyond 2500 we assumed that both emissions and CDR were zero. This allowed us to investigate how well the linear box models simulate potential outgassing events and corresponding temperature responses of long-term CDR policies. Note that with a time-horizon beyond the year 2500 in the optimization exercise, the optimal policies would have suggested to sustain positive CDR in case of outgassing. We compare the distribution of carbon in the carbon cycle for the various mitigation scenarios in the year 4000 against a reference scenario (with zero emissions from 2015 onwards). In both models, BEAM and UVic ESCM, we imposed the same assumptions about the development of non-CO_2 exogenous forcing as in DICE2016R.

BEAM is also a three-box model, containing the atmosphere, upper ocean, and deep ocean carbon stocks. However, the carbon fluxes between atmosphere and upper ocean are influenced explicitly by nonlinear ocean carbonate chemistry and a temperature feedback (affecting carbon storage and CO_2 solubility) (Glotter et al., 2014). Oceanic CDR is implemented by simply adding carbon from the atmosphere to the carbon stock in the deep ocean. The application of BEAM is restricted to the carbon cycle that we combined with the climate model from DICE2016R.

UVic consists of three dynamically coupled main components: a three-dimensional general circulation ocean model based on the Modular Ocean Model (MOM2; Pacanowski, 1996) including a marine biogeochemical model (Keller et al., 2012) and a dynamic-thermodynamic sea-ice model (Bitz & Lipscomb, 1999), a terrestrial vegetation and carbon cycle model (Meissner et al., 2003) based on the Hadley Center model TRIFFID (top-down representation of interactive foliage and flora including dynamics) and the hydrological land component MOSES (Met Office surface exchange scheme), and a one-layer atmospheric energy-moisture balance model (based on Fanning & Weaver, 1996). All components have a common horizontal resolution of 3.6° longitude × 1.8° latitude. The oceanic component has 19 vertical levels with thicknesses ranging from 50 m near the surface to 500 m in the deep ocean. Formulations of the air-sea gas exchange and seawater carbonate chemistry are based on the OCMIP abiotic protocol (Orr et al., 2001).

CDR in UVic was simulated by injecting CO_2 at seven separate injections sites, which are located in individual grid boxes near the Bay of Biscay (42.3°N, 16.2°W), New York (36.9°N, 66.6°W), Rio de Janeiro (27.9°S, 37.8°W), San Francisco (31.5°N, 131.4°W), Tokyo (33.3°N, 142.2°E), Jakarta (11.7°S, 102.6°E), and Mumbai (13.5°N, 63°E) (Reith et al., 2016, Figure 1). Injections were simulated to be carried out at a 2900 m depth to minimize leakage and maximize retention time. At this depth, liquid CO_2 is denser than seawater, which has the additional advantage that any undissolved droplets would sink rather than rise to the surface (e.g., IPCC, 2005). The simulated injection were based on the OCMIP carbon sequestration protocols and carried out in an idealized manner by adding CO_2 directly to the dissolved inorganic carbon (DIC) pool (Orr et al., 2001). Thus, we neglected any gravitational effects and assumed that the injected CO_2 instantaneously dissolved into seawater and was transported quickly away from the injection point and distributed homogenously over the entire model grid box with lateral dimensions of a few hundred kilometers and many tens of meters in the vertical direction (Reith et al., 2016).

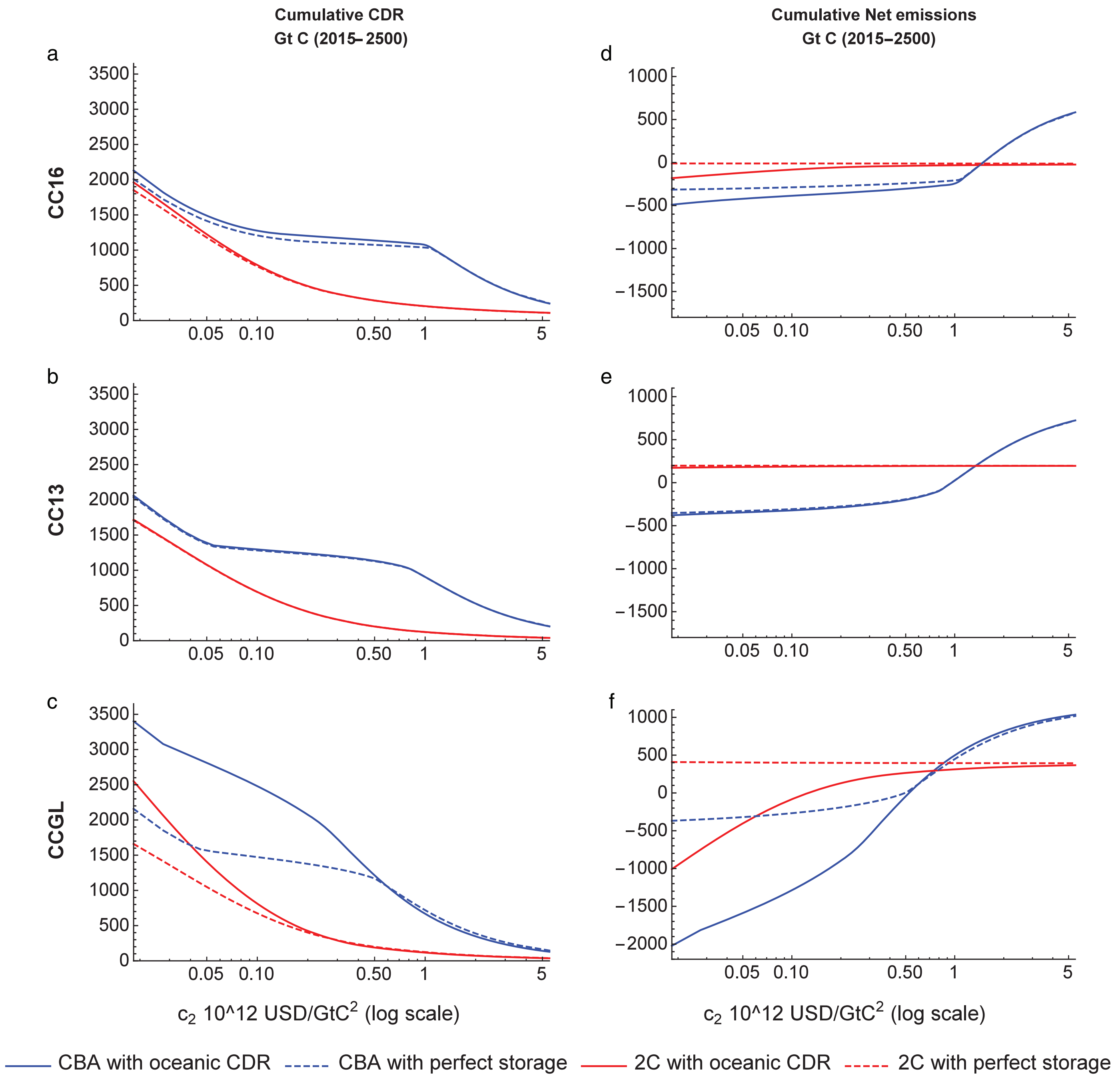

Figure 1. Cumulative CDR and net emissions as function of convexity of CDR cost. The figure shows the cumulative optimal amount of CDR (left panel) and cumulative optimal amounts of net emissions (right panel) as function of c_2, the slope of the marginal CDR cost curve. The upper panel corresponds to *CC16,* the middle panel corresponds to *CC13*, and the lower panel corresponds to *CCGL*. Each box displays the optimal amounts for *CBA* (blue lines) and *2C* (red lines) for two CDR options, oceanic CDR (solid lines) and perfect storage (dashed lines).

We also conducted sensitivity experiments for our CDR simulations that focus on the parameterization of vertical ocean mixing. Vertical ocean mixing plays a key role in (1) determining ocean circulation, (2) biogeochemical cycles, and (3) ocean to atmosphere heat and carbon fluxes. We varied this parameterization by increasing and decreasing it by 50% (hereafter, denoted by Kv_low and Kv_high), which is within the range of observational estimates (Duteil & Oschlies, 2011). Further details about the application of BEAM and UVic ESCM are presented in Supplementary Information SI.2.

3. Results

3.1. Cumulative CDR and Net Emissions for the Different Carbon Cycle Models

The carbon cycle model applied in integrated assessment has significant influence on the resulting optimal CDR policies. Figure 1 shows the cumulative amount of CDR (left panel) and cumulative amount of net emissions (right panel) in dependence of the convexity of the CDR cost function (i.e., the parameter c_2 corresponding to the quadratic term) for the time period 2015–2500. The figure displays for all three carbon cycle models two mitigation frameworks, *CBA* and *2C*, for two CDR options, oceanic CDR and perfect storage. In terms of the cumulative response of CDR and net emissions there is only a small difference between 2C and 2C2100 (see Figure SI.F1 in Supplementary Information).

Figure 1 shows that there is a significant difference between oceanic CDR and perfect CDR for the *CCGL* carbon cycle model and almost no difference for the *CC13* carbon cycle model, reflecting that *CCGL* has the fastest exchange between the boxes, whereas *CC13* has the lowest exchange, such that oceanic CDR is almost "perfect" in *CC13*. The CCGL box model assumes that atmospheric carbon is a constant fraction of the carbon stock in the upper box. Consequently, excess carbon in the deep ocean enters directly the atmosphere, while in the specification with *CC13* and *CC16* it needs to pass through the upper ocean box. However, with the updated calibration of *CC16* (in comparison to *CC13*), excess deep ocean carbon is more easily returned to the atmosphere, as becomes evident by the lower amount of CDR required with perfect storage in comparison to oceanic storage.

In contrast to Chen and Tavoni (2013) we find that the presence of carbon cycle feedbacks does not necessarily result in lower CDR deployment compared to the "perfect storage" case. While obviously higher operational cost result in less CDR deployment, the difference between oceanic CDR and perfect storage indicate that as long CDR is sufficiently cheap (from an operational cost perspective), extra CDR is carried out to compensate for leakage to the atmosphere and carbon cycle feedbacks (less ambient carbon uptake by the sinks). However, this holds only true until a certain value for the operational cost, as measured by the slope of the marginal cost curve: if the marginal cost function becomes too steep, it becomes too costly to carry out the extra CDR and in case of fast exchange between the boxes (*CCGL* carbon cycle model) less oceanic CDR is carried out compared to perfect storage.

The plots for the cumulative amount of CDR in the *CBA* framework show a few kinks. For all three carbon cycles we observe a kink towards the right end side of the plots, for *CC16* close to 1, for *CC13* around 0.8, and for *CCGL* (even though less pronounced) around 0.4. These kinks are explained because (1) we impose the constraint that atmospheric carbon concentration cannot be reduced below its preindustrial level and (2) we leave the other assumptions of DICE2016R with respect to exogenous forcing and land-use emissions unchanged. Due to increasing non-CO_2 exogenous forcing (up to 1 W/m^2 until the year 2100 and constant at this value thereafter) there is some non-CO_2 induced warming, causing damages. Accordingly, it would be optimal for a flat marginal CDR cost curve to decrease atmospheric carbon concentration below its preindustrial level to achieve negative CO_2 forcing (compared to the preindustrial level) to compensate for the non-CO_2 forcing. Accordingly, without that constraint we would observe more cumulative CDR to the left of this kink. The second kink which is only present for *CC13* and *CCGL* (in *CC16* the transition is smooth) coincides with a substitution effect becoming present: here the amount of emissions actually increases in response to the availability of CDR. We discuss this issue in more detail below.

Looking at the optimal amounts of net emissions for the *2C* framework indicates that *CC16* is most restrictive in terms of the (remaining) emission budget. While both, *CC13* and *CCGL*, still allow for positive cumulative net emissions for compliance with the 2°C goal, *CC16* requires already negative cumulative net emissions for this goal. The remaining carbon emission budgets for the period from 2015 until 2100 to comply with the 2°C goal are 195 and 392 GtC for *CC13* and *CCGL*, respectively. Assuming instead that non-CO_2 forcing follows RCP2.6 (i.e., increasing to 0.4 W/m^2 until 2100 and constant thereafter; van Vuuren et al., 2007), the remaining carbon emission budgets are calculated to increase to 161, 511, and 868 GtC for *CC16*, *CC13*, and *CCGL*, respectively. For comparison, the IPCC (2014) AR5 carbon emission budgets (adjusted with information from the global carbon budget (Le Quéré et al., 2016) to correspond to the time period from 2015 until 2100) are 230, 312, and 366 GtC for 66%, 50%, and 33% fraction of simulations meeting the 2°C goal. Accordingly, one could argue that *CC16* carbon budget comes closest to the IPCC estimates (given non-CO_2

forcing corresponds to RCP2.6), however, resulting in a temperature increase below 2°C in the majority of the models considered by the IPCC.

3.2. Time Profile, Emission Reduction Substitution, and Long-Term Impacts of CDR

For all three carbon cycle models, the optimal amounts of CDR and net emission are higher in the *CBA* frameworks than in the *2C* framework (Figure 1). This can be explained by the different time profile of CDR utilization and in turn different substitution effect. Figure 2 shows, in the left panel, similar information as Figure 1, but including the time profile of cumulative oceanic CDR (until 2500). The right panel shows the cumulative carbon emission as function of the cumulative amount of CDR, displaying in addition information on how the cumulative carbon emissions (the added carbon) are distributed among the different carbon reservoirs in the year 4000. Furthermore, the right panel contains information about peak and average temperature for the period 2015 until 2500 and for the period 2500 until 4000. Both panels provide the information for the *CBA* and *2C* mitigation framework in *CC16* from the top to the bottom, respectively. The information for the *2C2100* framework is provided by Figure SI.F2a. Figure SI.F2b and Figure SI.F2c display the information for all three mitigation frameworks (*CBA*, *2C*, and *2C2100*) for *CC13* and *CCGL*, respectively.

The time profile reveals the different utilization of CDR in DICE in the different mitigation frameworks. In the *CBA* framework the bulk of CDR is carried out beyond 2100 and CDR is used as long-term strategy to reduce the atmospheric carbon concentration (a). This becomes evident by looking at the corresponding distribution of emissions in the carbon cycle (c) as a function of cumulative CDR. First, there is almost no substitution effect with respect to emissions until cumulative CDR reaches 1200 GtC. Second, there is only a modest decline in peak temperature (purple line) compared to the situation without CDR. The reason is that the DICE model (also in the 2016R specification) has a rather modest estimate for climate impacts, suggesting that in a framework where the cost of abatement are weighted against the avoided damages of climate change a peak temperature increase of about 4°C is optimal. CDR is postponed into the future when the economy is very rich (due to continuous growth in the DICE economic model), making CDR cheaply affordable. This is indicated by the stronger decline in average temperature (orange line). While without CDR the decline in temperature is limited by the rather slow natural carbon uptake, with CDR this option is used to speed up this process.

Only for a rather flat marginal CDR cost function do we observe some substitution effect and some effect on atmospheric peak temperature. Turning to the long-term effects, we see that for CDR up to a cumulative amount of 1100 GtC, also peak and average temperature beyond 2500 are declining because CDR speeds up oceanic carbon uptake and storage compared to natural oceanic carbon uptake (without CDR) (dashed purple and dashed orange line, respectively). However, for larger CDR amounts, resulting in increasing cumulative emissions, we observe that peak and average temperature increase with the cumulative amount of CDR, indicating that carbon previously removed returns to the atmosphere (as indicated by the increasing blue atmospheric bar), causing peak and average temperature to rise again.

In the *2C* framework, CDR has a very different role compared to the *CBA* framework. A significant amount of CDR is deployed already before 2100 with an increasing share relative to the total amount of CDR with a steeper marginal CDR cost curve. In line with Anderson and Peters (2016) and Obersteiner et al. (2018) CDR is already deployed before 2050. Furthermore, we observe a significant emission substitution effect. As discussed above, *CC16* is most restrictive in terms of the (remaining) emission budget. Without CDR the 2°C target cannot be achieved under the DICE2016R specification of non-CO_2 forcing, however, already a cumulative amount of 100 GtC CDR is sufficient (here the solid purple line indicating peak temperature drops to 2°C) for compliance with 2°C. Increasing amounts of CDR result in increasing amounts of cumulative emissions, in turn with consequences for the temperature response beyond 2500. Without sustained CDR, carbon added to the oceanic reservoir in excess of the equilibrium values with respect to upper ocean and atmosphere (in the carbon cycle model) redistributes to these reservoirs and we observe both, a peak and average warming beyond 2500.

The utilization of CDR in the *2C2100* framework is only slightly different compared to the *2C* framework (Figure SI.F2a). The time profile in the left panel shows that less carbon is removed from the atmosphere before 2050, instead the majority of CDR is utilized in the period 2050 until 2100 because the 2°C goal has to be achieved by 2100. Accordingly, the right panel shows that peak temperature and therefore average

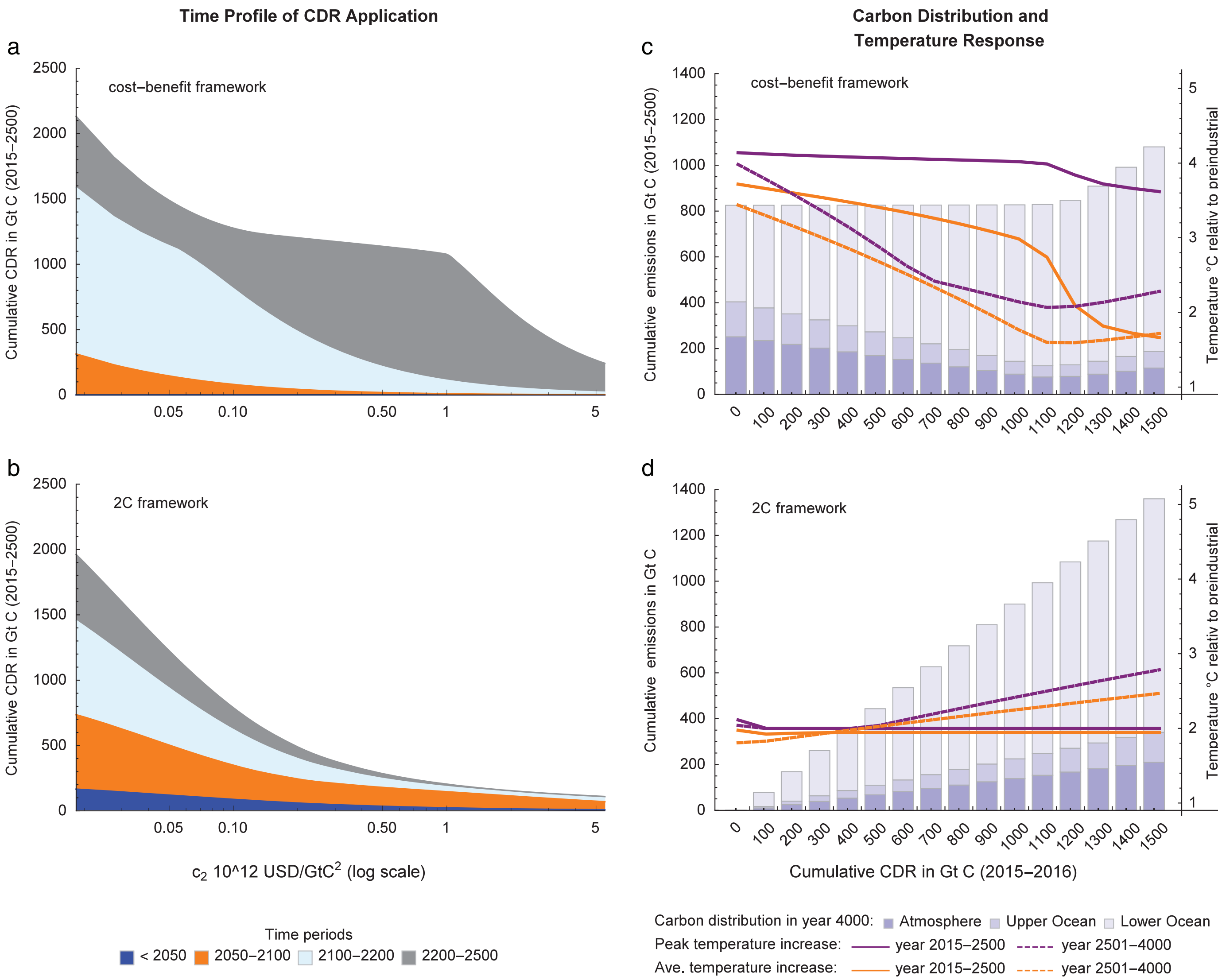

Figure 2. CDR time profile and cumulative emissions in *CC16*. The left panel shows the time profile of CDR utilization as function of c_2, the slope of the marginal CDR cost curve for the different mitigation frameworks (*CBA* and *2C* in (a) and (b), respectively). The right panel shows the cumulative emissions (from 2015 until 2500) as function of the cumulative amount of CDR for the different mitigation frameworks (*CBA* and *2C* in (c) and (d), respectively). The right panel also includes information about the distribution of the carbon emissions among the different carbon reservoirs in the year 4000 and about peak and average temperature for the period 2015–2500 and 2501 until 4000.

temperature overshooting increases with cumulative amount of CDR and with the same consequences for long-term warming (after switching CDR off) as in the *2C* framework.

The time profiles and distribution plots for *CC13* and *CCGL* look similar (Figures SI.F2b and SI.F2c in Supplementary Information, respectively), however there are two noticeable differences. First, due to the very slow exchange between carbon reservoirs in *CC13* all emissions end up in the deep ocean in the year 4000 for CDR application that cumulatively exceeds 1000 GtC in the *CBA* framework. Furthermore, we even observe that extra carbon, in excess of the cumulative emissions is removed from the atmosphere to the deep ocean, implying that atmospheric carbon content is lower than in the reference scenario without any emissions from the year 2015 to the year 4000. However, for *2C* and *2C2100* we do not observe this effect for *CC13* because here the substitution effect with respect to abatement results in a too strong emission increase. Still, the atmospheric carbon content in the year 4000 is significantly lower with *CC13* than with *CC16* or even *CCGL*. Accordingly, peak and average temperature do not increase beyond 2500 in *CC13*. Second, due to the fast exchange between carbon reservoirs in *CCGL* the substitution effect with respect to abatement is very low in the *CBA* framework, at least within the displayed scale of CDR (up 1500 GtC). Here, a significant increase in emissions can only be observed for cumulative CDR larger than 2500 GtC. In the *2C* and *2C2100* frameworks the substitution effect is present, however, resulting in a less step increase in cumulative emissions for increasing cumulative CDR compared to *CC13* and in particular *CC16*.

The influence of the different mitigation frameworks and the carbon cycle models becomes also apparent by looking at the social cost of carbon (SCC). The SCC measure the economic cost of an additional ton of carbon dioxide and are according to Nordhaus (2017) the “most important single economic concept in the economics of climate change (p. 1518).” Table SI.T5 displays the SCC (in 2010 USD) for the three mitigation frameworks and the three carbon cycles in the year 2015, 2020, 2025, 2030, and 2050 (to allow comparison with Nordhaus, 2017) for cumulative CDR in order of 0 (only abatement), 100, 500, 1000, and 1500 GtC. In line with the discussion of the remaining carbon emission budgets (Section 3.1), the SSC decrease when moving from *CC16* to *CC13* to *CCGL*. With CDR being used as long-term strategy to reduce the atmospheric carbon concentration in the CBA framework, the influence of CDR on the near-term SCC is almost negligible (up to the year 2030) and has a small decreasing effect in 2050 for amounts of CDR which result in an emission reduction substitution effect. In contrast, in both the *2C* and *2C2100* framework, the availability of CDR results in significant reductions in the SCC. For example, in *CC13* the SCC are 142 USD in year 2015 if as only option emission reductions are available to limit temperature increase to 2°C. With CDR available at an operational cost which results in a cumulative amount of 1500 GtC CDR, the SCC drop to 44 USD.

3.3. Oceanic Carbon Storage under the (False) Assumption of Perfect Storage

The faster exchange between reservoirs in *CCGL* also results in a stronger difference in the amount of CDR deployed between oceanic CDR and oceanic CDR under the (false) conjecture of perfect storage. Figure 3 shows the time profile of the difference between these two CDR options for all three carbon cycles in the *2C* framework. We have chosen a CDR cost scenario that corresponds to a cumulative amount of 1500 GtC CDR until the year 2500. For a smaller cumulative amount of CDR (i.e., steeper marginal CDR cost) the difference shrinks. As shown already in Figure 1, there is a significant difference between perfect storage and oceanic storage for *CCGL*. Because of the rather fast exchange, the substitution effect is smaller with oceanic CDR (and only present for very flat CDR cost that allow carrying out the extra CDR to compensate for the carbon cycle feedbacks) than with perfect storage. Accordingly, a social planner who falsely assumes perfect storage would set emission reductions too low (and in turn emissions are too high) such that more CDR is needed to compensate for carbon returning to atmosphere. In sum, the false assumption with respect to CDR results in an extra cumulative amount of CDR of about 180 GtC in comparison to the optimal amount of 1500 GtC under the correct assumption. With *CC13* there is almost no difference due to the effect that there is almost no difference between perfect and oceanic CDR in that model (cf. Figure 1). With *CC16* we observe a small difference, resulting from the same mechanism as for *CCGL* but the cumulative extra amount of CDR is below 10 GtC (in comparison to the optimal amount of 1500 GtC).

3.4. Implementation of Climate Policies without Ocean CDR in BEAM and UVic ESCM

We turn now to the question how well the atmospheric carbon and global mean temperatures trajectories obtained from optimal mitigation policies are reflected by corresponding simulations obtained in more sophisticated carbon cycle and Earth system models. We focus here on the optimal mitigation policies derived with *CC16* and implemented the obtained carbon emission and CDR paths in *CC13*, *CCGL*, BEAM, and UVic ESCM. The optimal polices were implemented until the year 2500, followed by zero emissions and zero CDR until the end of the simulation horizon in the year 4000. We look first at mitigation policies without CDR before we turn to selected CDR policies. Figure 4 shows the development of atmospheric carbon content and the increase in global mean temperature for business-as-usual emissions (as obtained in DICE2016R without climate policy), for carbon emissions in the *CBA* framework obtained with *CC16*, and for zero carbon emissions throughout the entire simulation period. The latter simulation serves the purpose to illustrate the degree of committed warming and the influence of the exogenously determined non-CO_2 forcing across the different carbon cycles.

The results indicate that *CC16* has significantly improved with respect to the long-term dynamics, in particular for high emission scenarios, as becomes evident by the much smaller gap to the simulated atmospheric carbon content and global mean temperature increase obtained with BEAM and UVic for

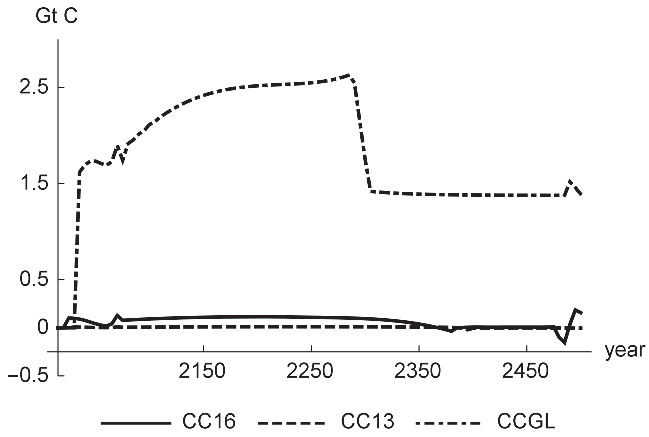

Figure 3. Implications of oceanic CDR under the (false) assumption of perfect storage. The figure shows the annual difference in the amount of CDR deployed between oceanic CDR and oceanic CDR under the (false) assumption of perfect storage in the *2C* framework for all three carbon cycles for the case of 1500 GtC cumulative oceanic CDR.

business-as-usual emissions compared to the gap with *CC13* and *CCGL*. For the cumulative business usual emissions of 5630 GtC (until the year 2500), peak atmospheric concentration (global mean temperature increase relative to preindustrial) increases to about 2330 and 2594 ppm (4.57°C and 4.97°C) in UVic ESCM and BEAM, respectively. In *CC16* the corresponding figures are 1884 ppm and 4.3°C, whereas in *CC13* peaks are only 1232 ppm and 3.42°C and in *CCGL* even lower with 953 ppm and 2.89°C. However, the improved long-term dynamics in *CC16* comes apparently at the cost of being too restrictive with respect to the short-term dynamics for mitigation scenarios (i.e., with less emission). In the *CBA* framework, the global mean temperature increase obtained with the UVic ESCM is more closely matched by *CC13* than by *CC16* (atmospheric carbon content obtained with UVic is between atmospheric carbon content of *CC13* and *CC16*) (see middle panel in Figure 4). Similarly, the decrease in atmospheric carbon content and global mean temperature is much slower in *CC16* for zero emissions than with the other carbon cycles (see lower panel in Figure 4).

Using *CC13* instead of *CC16* for the derivation of optimal carbon emissions in the *2C* framework (not shown in Figure 4), the implementation in UVic ECSM reveals that compliance with the 2°C goal is achieved up until the year 2500 (beyond that long-term warming increases up to 2.65°C). Using *CCGL* for the derivation of optimal carbon emissions in the 2C framework (not shown in Figure 4), the implementation in UVic ECSM reveals that the 2°C goal is already violated by the year 2165 (yet, the long-term peak increase is with 2.92°C degrees not that much higher than with the CC13 carbon emission path path).

Noteworthy is the high concordance between BEAM and UVic for business-as-usual emissions and also in parts for zero emissions, but BEAM overestimates the short-term atmospheric carbon concentration increase and accordingly temperature increase in the *CBA* framework. For the zero carbon emission simulations (lower panel in Figure 4) we observe that compliance with the 2°C goal can be achieved in *CC13*, *CCGL* and almost in BEAM (peak temperature increase is 2.03°C). Still, it needs to be kept in mind that we have left the DICE2016R assumptions with respect to exogenous land-use emissions and exogenous forcing unchanged. (Still, even with zero land-use emissions and linearly decreasing exogenous forcing from 0.5 W/m^2 in the year 2015 to 0 W/m^2 in the year 2100, application of *CC16* result for zero emissions from 2015 onwards in a committed warming increase of 1.43°C temperature relative to preindustrial after starting in 2015 with a temperature increase of 0.85°C). Noteworthy is that UVic ECSM allows for compliance up until the year 3500 (with the DICE2016R assumptions of exogenous forcing and land-use emissions), confirming that *CC16* can be considered too pessimistic with respect to its remaining emission budget. However, we observe for the UVic ECSM trajectory an irregularity in the temperature increase (which is also present as a small increase in the atmospheric carbon content via the temperature feedback) due to an ocean deep convection event. We discuss this issue in more detail below.

3.5. Implementation of Climate Policies with Ocean CDR in BEAM and UVic ESCM

Figure 5 shows the development of the atmospheric carbon content and the increase in global mean temperature for the *CBA* and *2C* framework until the year 4000 (in the upper and lower panel, respectively.) Figure SI.3 shows the corresponding information for the *2C2100* framework. The optimal emission and CDR paths in the three frameworks until the year 2500 were derived with *CC16*. We selected a cost scenario

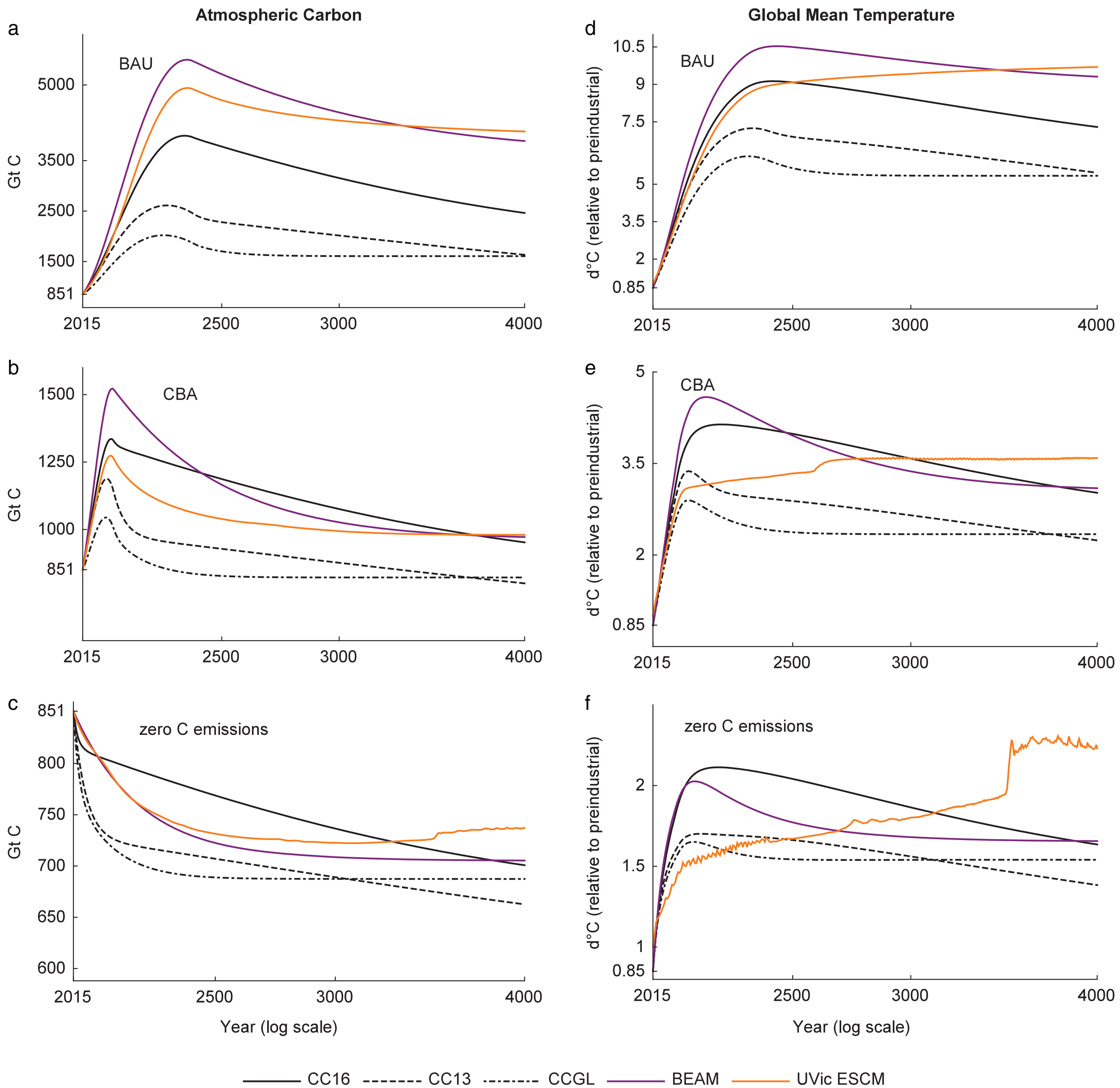

Figure 4. Comparison of carbon cycle models without CDR. The figure shows atmospheric carbon content (left panel) and global mean temperature increase (right panel) resulting from business-as-usual carbon emissions (a) and (d), respectively, for carbon emissions in the *CBA* framework derived with *CC16* (b) and (e), respectively), and for zero carbon emissions (c) and (f) respectively in *CC16*, *CC13*, *CCGL*, BEAM, and UVic ESCM.

corresponding to cumulative CDR of 1200 GtC as the amount that is large enough to result in sufficient carbon cycle feedbacks and also trigger a sufficient substitution effect, resulting in more emissions.

In general, the paths obtained with *CC16* appear reasonably close to the paths obtained with UVic ECSM, suggesting that integrated assessment of CDR in DICE2016R is sensible. In particular simulated atmospheric carbon content is rather similar in *CC16* and UVIC, at least until the year 2500, concurring therefore also for the short-term increase and decrease in the *2C2100* framework (see Figure SI.3). Beyond 2500 there is an

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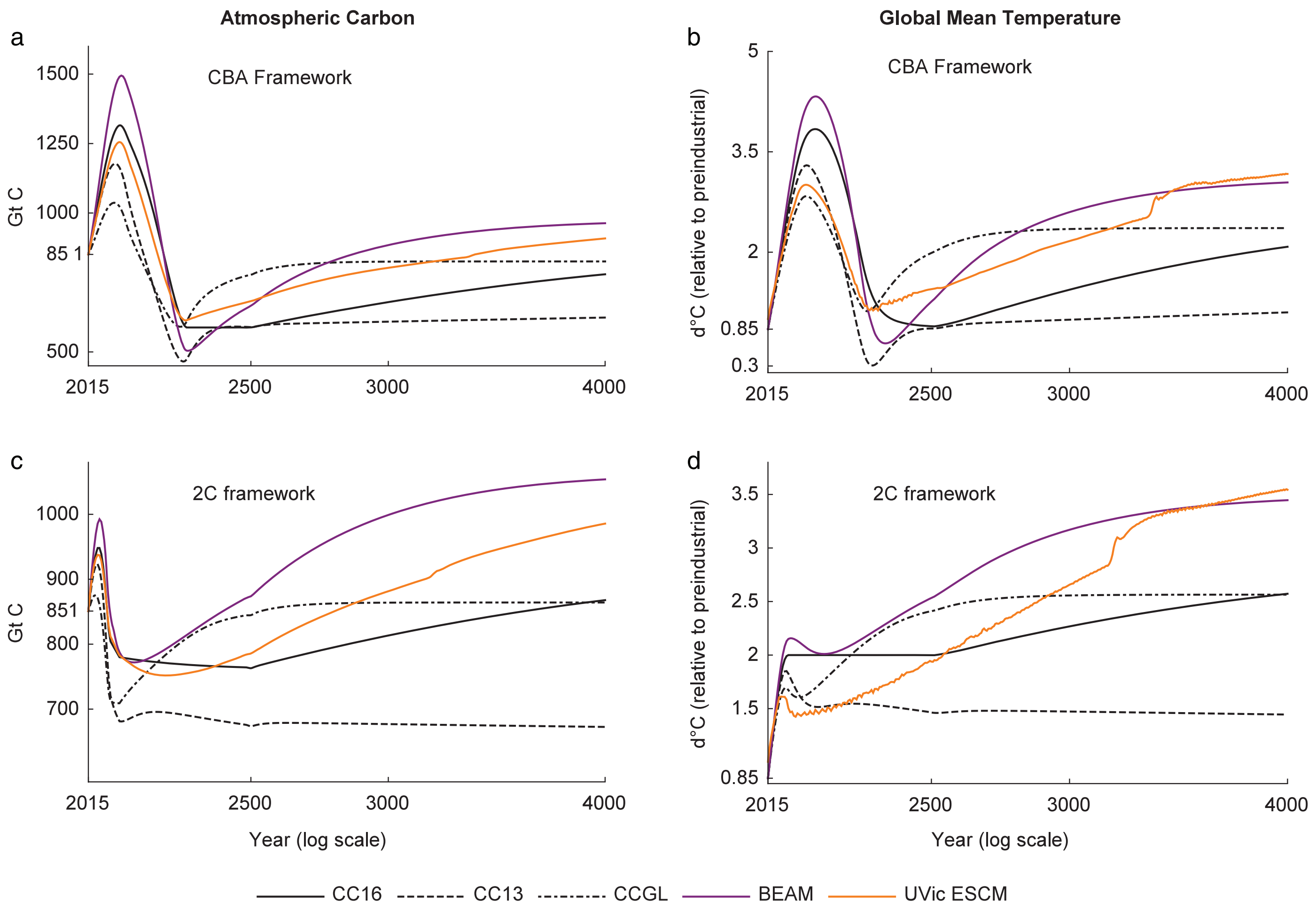

Figure 5. Comparison of carbon cycle models with CDR. The figure shows atmospheric carbon content (left panel) and the global mean temperature increase (right panel) resulting from carbon emissions and CDR in the *CBA* framework, (a) and (c), respectively and in the *2C* framework (b) and (d), respectively in *CC16*, *CC13*, *CCGL*, BEAM, and UVic ESCM. The optimal emission and CDR paths in the two frameworks until the year 2500 were derived with *CC16* for a CDR cost scenario which corresponds to cumulative 1200 GtC.

increasing gap between UVic and *CC16* because not all long-term saturation and carbon cycle feedbacks can be accounted for in *CC16*. However, as mentioned above, this gap is considerably smaller for *CC16* than for *CC13*. Given the close match of atmospheric carbon content it appears somewhat surprising that *CC16* overestimates the short-term increase in global mean temperature, suggesting that (1) the climate module of *CC16* requires further adjustments rather than the carbon cycle model and (2) the derived mitigation policies are probably too conservative, at least with respect to the short term. For all three mitigation frameworks, *CCGL* shows a stronger (short-term) increase in the atmospheric carbon content and consequently global mean temperature, than *CC16* or the UVic ECSM. While for scenarios without CDR is was close or even below the trajectories obtained with *CC13*. Again, the reason is the rather fast exchange between carbon reservoirs in *CCGL*, implying that the amount of CDR obtained with *CC16* is simply too small to compensate for the extra emissions resulting from the substitution effect. The increase in atmospheric carbon content and global mean temperature is only exceeded by BEAM which shows again a good match with the long-term dynamics, but appears to be too restrictive for the short-term dynamics, compared to UVic ESCM. Again, we observe for the UVic ESCM towards the end of the simulation horizon irregularities in the temperature response to which we turn next.

3.6. Sensitivity Analysis with Respect to Vertical Ocean Mixing

Global mean temperature shows a significant increase in the UVic ESCM simulations around the year 3300 which is at a point in time when emissions (and CDR) have been zero already for almost 1000 years. The increase is explained by an ocean deep convection event, resulting in a temporary carbon flux from the

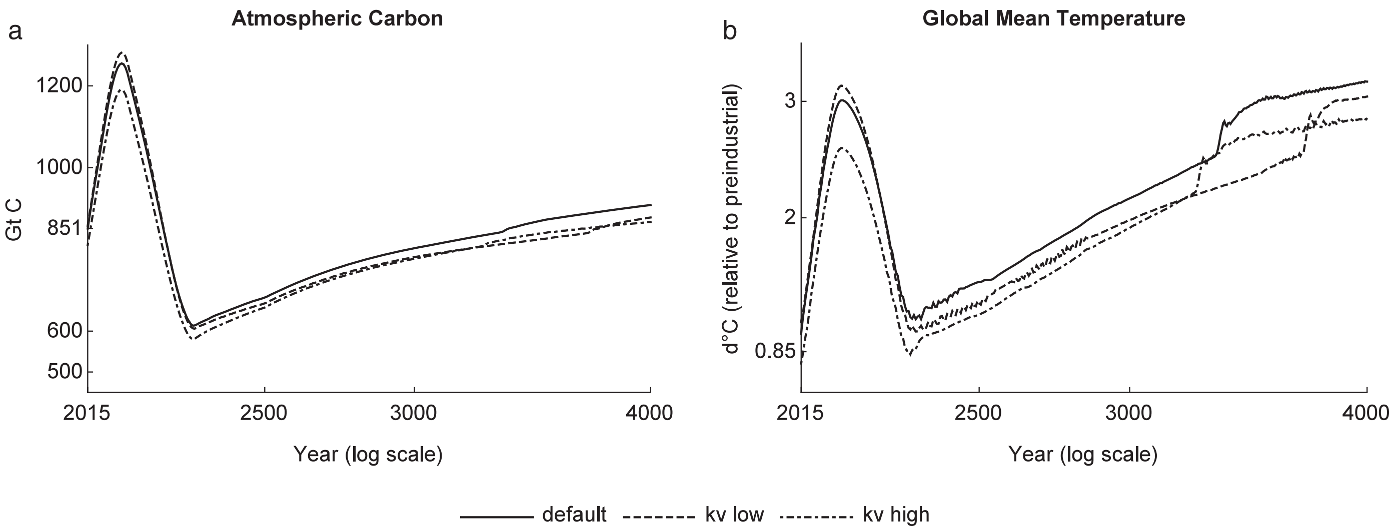

Figure 6. Sensitivity with respect to vertical ocean mixing. The figure shows atmospheric carbon content (left panel) and global mean temperature increase (right panel) for the *CBA* framework with CDR, (a) and (d), respectively. The optimal emission and CDR paths until the year 2500 were derived with *CC16*. The solid line shows the default parametrization, the dashed and dot-dashed line shows the results for 50% lower and higher parametrization for vertical ocean mixing, respectively.

ocean to the atmosphere with a total of about 8 GtC outgassing in a region of the Southern Ocean and in a substantial amount of heat loss from the ocean that adds to the warming triggered by the ongoing leakage of formerly injected carbon. This becomes also evident in the sensitivity experiments where we considered different parameterization of vertical mixing (Figure 6). A slower vertical ocean mixing (kv low) results in a slower air-sea gas exchange, postponing therefore the ocean deep convection event whereas faster vertical ocean mixing brings the event forward. These highly variable deep convection events appear in model runs with and without CDR and are influenced by several factors such as stratification strength and sea ice volume (Reintges et al., 2017).

Such open ocean deep convection in the Southern Ocean have been identified in many CMIP5 models (de Lavergne et al., 2014), the UVic model (Meissner et al., 2008; Reith et al., 2016) and also in the Kiel Climate Model, for which the cause could be linked to internal climate variability (Martin et al., 2013). An important model limitation in this respect is a coarse grid resolution, which for example prevents the correct representation of bottom water formation processes on the continental shelf and thus might favor such events (Bernardello et al., 2014). Clearly, capturing such effects is beyond the capability of simple carbon cycle and climate models used for integrated assessment.

4. Discussion

Obviously, our results are strongly affected by the general specifications of the DICE2016R model that we used in our analysis. Introducing abatement options for land-use emissions and non-CO_2 emissions (non-CO_2 forcing is assumed in DICE2016R to be linearly increasing from 0.5 W/m^2 in the year 2015 to 1 W/m^2 in the year 2100 and constant thereafter) allow simulations that comply with the 2°C or even 1.5°C goal without CDR (Su et al., 2017). Furthermore, the substitution effect is strongly dependent on the assumptions in DICE2016R with respect to the exogenous development of the carbon intensity and the backstop price. With less optimistic assumptions in this regard, we would observe a much stronger substitution effect also in the cost-benefit framework. While the magnitude of the substitution effect influences the magnitude of the outgassing and temperature increase beyond the year 2500, both are not inevitable outcomes of CDR policies obtained from the DICE2016R model. We have derived the optimal polices only until the year 2500 (the DICE2016R specification) and simulated the response of the carbon cycle model for the remaining 1500 years under the assumption of zero emissions and zero CDR. The purpose was to investigate to which extent the carbon cycle models used in integrated assessment capture stylized facts of the carbon cycle. Extending the optimization period would result in continuous CDR to remove carbon from the atmosphere and pump it into the deep ocean at the rate at which it leaks back to the atmosphere.

Due to discounting, such continuous long-term CDR application would, however, have negligible effects on near-term policies.

The carbon cycle models applied in the integrated assessment would require endless CDR application to prevent outgassing as aspects of the carbon cycle that would permanently sequester carbon, like for example chemical weathering are not included (Colbourn et al., 2015). Furthermore, many processes relevant for different CDR methods are not included, implying that our generic treatment of CDR may be too coarse to study details of specific CDR methods. For example, termination of alkalinity management is expect to result in smaller outgassing of removed carbon than termination of macro- or micronutrient fertilization and would rather correspond to the perfect storage scenario in our investigation than oceanic CDR (Keller et al., 2014; Paquay & Zeebe, 2013). However, if alkalinity increase would be achieved by spreading olivine (e.g., in the catchment area of large rivers) also nutrient cycles would be affected, resulting in additional fertilization effects, making the estimation of the actual net removal (after termination) more complex than suggested by the basic ocean chemistry (Köhler et al., 2013). Still, even under the assumption of perfect storage for alkalinity management, opposing carbon cycle feedbacks would be at play, resulting from the response of the terrestrial carbon reservoir (which is captured in our investigation by reduced ambient carbon uptake of the upper box for *CC13* and *CC16* and reduced uptake of the terrestrial biosphere in CCGL).

Finally, by choosing the deterministic DICE2016R model as point of reference we have neglected uncertainty in our analysis. Introducing uncertainty in the climate system would have allowed us to investigate to which extend CDR is used to increase the likelihood of compliance with the 2°C goal by for example a less pronounced substitution effect. Introducing uncertainty with respect to the carbon intensity and the development of the backstop price would also have implications for the application of CDR and the corresponding substitution effect. However, also the CDR methods themselves are uncertain with respect to their costs, their side-effects, and their carbon cycle implications (Field & Mach, 2017; Fuss et al., 2014). In particular CDR specific (uncertain) side-effects could limit their applications. The magnitude of the side-effects depends on the material cycles affected and the scale of application (Klepper & Rickels, 2014). Furthermore, the formation of CO_2 plumes or lakes and the potential risk of fast rising CO_2 bubbles (both potentially resulting from deep sea carbon injection) was neglected (Bigalke et al., 2008; IPCC, 2005). Despite no explicit treatment of uncertainty, our analysis of oceanic storage under the false assumption of perfect storage provides some insights. At least for *CC16* and *CC13* we can conclude that appropriate updating of the information on carbon stock levels reduces the misguidance from neglecting potential uncertainties about carbon cycle feedbacks.

5. Conclusion

Given the worlds shrinking carbon budget for ambitious climate change mitigation, achieving (net) negative carbon emissions appears to be inevitable. However, negative emissions would not linearly extend the carbon budget because in an interacting carbon cycle their net contribution is strongly influenced by feedbacks and saturation effects. So far, the investigation of these interactions and the net contribution of CDR has been mainly restricted to scenario analysis in Earth system models, which cannot answer how the presence of these feedbacks affects endogenously derived optimal or cost-effective mitigation policies. Consequently, the aim of our study was to investigate how well these feedbacks and effects are captured in IAMs, which are suitable to analyze a broad set of possible CDR scenarios. We have investigated (oceanic) CDR in the IAM DICE, in its most recent version (DICE2016R) and considered in addition two further carbon cycle models (DICE2013R and Gerlagh & Liski, 2017). We have considered three different mitigation frameworks, cost-benefit-analysis, compliance with the 2°C goal, and cost-effective compliance with the 2°C goal by the year 2100. In contrast to the literature, we did not imposed annual limits on the amount of CDR but considered a convex CDR cost function, as we believe that the operational cost are characterized by increasing marginal costs, both within any specific CDR method and across CDR methods.

We found that the role of CDR depends on the mitigation framework in our integrated assessment analysis. While cost-effective compliance with the 2°C target requires significant CDR application already before the year 2050, application of CDR in a cost-benefit framework (with an endogenous amount of climate change) is a long-term strategy to speed up the otherwise rather slow natural reduction of the atmospheric carbon concentration after the peak in atmospheric temperature. In turn, near-term application of CDR goes in line with a strong substitution effect, resulting in less emission reductions. For this mode of application, the main effect of CDR is to extend the near-term emission budget, as only a very small or even zero emission can still be emitted to the atmosphere without CDR. Using CDR to bring down the atmospheric carbon content in the long-term incurred only a moderate substitution effect. The magnitude of these effects is dependent on the carbon cycle feedbacks in the applied carbon cycle model. For a model that assumes a rather slow exchange between the carbon reservoirs, oceanic CDR is close to "perfect" storage. This makes CDR very effective and results in turn in a strong substitution effect. For a model that assumes a fast exchange between the carbon reservoirs, oceanic CDR becomes less effective, resulting in a weaker substitution effect. However, decreased effectiveness of CDR results in extra CDR efforts to compensate for the carbon leaking back to the atmosphere if the CDR cost function is sufficiently flat. Consequently, modeling the effectiveness of CDR in dependence of the carbon cycle explicitly, results in different results than obtained by adjusting simply the effectiveness of CDR as in Chen and Tavoni (2013).

The strongest carbon cycle feedbacks are observed in the carbon cycle model introduced by Gerlagh and Liski (2017), while with the DICE2013R carbon cycle model oceanic CDR was almost equivalent to perfect storage. Overall, the carbon cycle model in DICE2016R has significantly improved compared to DICE2013R, capturing very well long-term outgassing of carbon injected into the deep ocean and corresponding increases in the temperature beyond 2500 for large CDR scenarios. Comparing DICE2016R to UVIC ESCM simulations indicates that the improved long-term dynamics come at the cost of a (too) tight short-term remaining emission budget. Ignoring other abatement options with respect to land-use emissions and non-CO_2 greenhouse gases, compliance with the 2°C goal cannot be achieved in DICE2016R without CDR. Consequently, one could argue that short-term mitigation policies derived with DICE2016R are too restrictive, however, in a cost-benefit framework the rather restrictive carbon cycle model is overcompensated by the modest estimates for climate change impacts in DICE2016R. Furthermore, the match between DICE2016R and UVic ESCM is closer for the atmospheric carbon content than for the global mean temperature increase, suggesting that adjustments of the climate module could be a strategy for achieving better estimates for mitigation policies.

In conclusion, investigating (ocean) CDR in DICE2016R appears to be sensible and the derivation of endogenous mitigation policies provides relevant insights because the optimal amount of CDR is derived under (1) accounting for the emission substitution effect and (2) compensation for carbon cycle feedbacks. Clearly, simple carbon cycle box models cannot capture all relevant processes and feedbacks and further research is in particular required with respect to the temperature feedback impact on terrestrial carbon uptake in the context of the integrated assessment of CDR. However, for the DICE2016R carbon cycle model we find that appropriate updating of carbon stocks (based either on observations or more complex models) can provide a good workaround to correct for misspecifications of the carbon cycle model or unforeseen leakage events.

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