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CMIP6 models agree on similar carbon cycle feedbacks between
enhancing terrestrial and marine carbon sinks

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Supplementary material for this article is available [online](#)

Abstract

Carbon dioxide removal (CDR) is a crucial component of climate mitigation required to reach international climate targets. However, gaps exist in our understanding of the responses and feedbacks of the Earth system to the deployment of CDR. In this study, we compare two complementary approaches that enhance the terrestrial and marine carbon sinks with afforestation and reforestation (A/R) and ocean alkalinity enhancement (OAE), respectively, under the high emission scenario SSP5-8.5. Eight CMIP6 Earth system models are utilized, enabling a quantification of both inter-model and internal variability. By mid-century, simulated large-scale deployment of A/R and OAE individually reduces atmospheric CO₂ concentrations by up to 20 ppm. For both methods, while carbon removal from the atmosphere is robust, it is difficult to detect the effects on global mean temperature, posing challenges for monitoring, reporting and verification of mitigation efforts. To quantify the carbon cycle feedbacks, we define the carbon cycle feedback ratio of A/R (OAE) as the ratio of changes in the marine (terrestrial) sink to changes in the terrestrial (marine) sink. We show that the carbon cycle feedback ratios of A/R and OAE have similar magnitudes, which are −16% and −13%, respectively. Moreover, although inter-model differences of the simulated amounts of carbon removal due to A/R are large, the corresponding carbon cycle feedback ratios of A/R are similar.

1. Introduction

Alongside deep emission reductions, carbon dioxide removal (CDR) is an essential element of climate policy, as net-zero targets are only achievable with CDR balancing residual emissions (Luderer *et al* 2018, Möller *et al* 2024). Depending on the techniques, the removed carbon is stored as wood products, or in terrestrial, marine, and geological

carbon reservoirs for a time scale ranging from decades to thousands of years (Babiker *et al* 2022). For the more sustainable scenarios in line with the Paris Agreement, it is estimated that a total of 170 GtCO₂ must be removed between 2020 and the time of net zero (Smith *et al* 2024). One of the most conventional CDR options is afforestation and reforestation (A/R), which enhances the terrestrial carbon reservoir and accounts for almost all current CDR

deployment (Smith *et al* 2024). To enhance the marine carbon sink, CDR options such as ocean alkalinity enhancement (OAE) and ocean fertilization are also under consideration (National Academies of Sciences, Engineering, and Medicine 2022). The premise of OAE is to add alkaline substances to sea surface waters to reduce partial pressure of CO₂ in the surface waters and enhance the CO₂ uptake of the ocean from the atmosphere. With a theoretical CDR potential of 3–30 GtCO₂ yr^{−1} (Oschlies *et al* 2023), OAE has the highest theoretical potential among the marine-based CDR options.

Previous studies have used models to assess the carbon cycle response to idealized large-scale application of different CDR options, including A/R (e.g. Sonntag *et al* 2018, Koch *et al* 2021, Loughran *et al* 2023, Moustakis *et al* 2024), OAE (Ilyina *et al* 2013, González and Ilyina 2016, Lenton *et al* 2018, Fröb *et al* 2020, Burt *et al* 2021), ocean fertilization (Oschlies *et al* 2010), and open-ocean macroalgae cultivation with sinking (Wu *et al* 2023). However, few studies have investigated multiple CDR options with the same model (Keller *et al* 2014, Sonntag *et al* 2018), and in some studies, only the land or the ocean alone are considered, without being coupled to the atmosphere or without a fully-coupled land–ocean–atmosphere system (Burt *et al* 2021). Due to the interlinkage of carbon fluxes between land and ocean, an enhancement of the terrestrial carbon sink weakens the marine carbon sink, and vice versa (Keller *et al* 2018a, Schwinger *et al* 2024, Moustakis *et al* 2025). Studies with uncoupled models might thus result in an overestimate of the CDR potential. For example, Moustakis *et al* (2024) demonstrated that studies with uncoupled approaches showed overestimations of the carbon removal potential of A/R.

As uncertainties exist in model simulations, which affect the detectability of the CDR effects, it is important to quantify different sources of uncertainty in order to make reliable inferences about the impacts of different CDR approaches. At least two major uncertainties exist in simulating the carbon cycle of the earth system. The first is the uncertainty associated with the internal variability of the climate system, which originates from the chaotic nature of the Earth system. It can be estimated by running an ensemble of model simulations with slightly different initial conditions (called different realizations hereafter). The second is the model uncertainty, which results from the differences in model structure, parameterizations and parameters. The model uncertainty can be estimated by the inter-model variability across an ensemble of different models. Studies have shown that the internal variability contributes to an uncertainty of as large as 50 PgC (approximately 46%) for the remaining carbon budget from 2019 for limiting global warming to 1.5 degrees (Tokarska *et al* 2020). Depending on the geographical location, the uncertainty due to internal variability has been estimated to

be larger (Bonan *et al* 2019, 2021) or smaller (Padrón *et al* 2022) than the model uncertainty.

In this study, we compare Earth system model (ESM) simulations of two CDR options, A/R and OAE, which enhance the terrestrial and marine carbon sinks, respectively. The experiments were conducted with multiple CMIP6 ESMs. We quantify both the uncertainty associated with internal and inter-model variability, and analyze whether the achieved CDR and the mitigated warming robustly emerge.

To understand the carbon cycle feedbacks due to A/R and OAE, we define the carbon cycle feedback ratios $\lambda_{A/R}$ and λ_{OAE} as follows: $\lambda_{A/R}$ (λ_{OAE}) is the ratio between the changes in marine (terrestrial) carbon inventory and changes in terrestrial (marine) carbon inventory due to A/R (OAE). Finally, the regional responses to A/R and OAE are also analyzed.

2. Methods

2.1. Models

Of the CMIP6 models, we choose those having conducted the reference experiment and at least one of the A/R and OAE experiments for the respective model intercomparison projects (see section 2.2 for the experimental protocols) and are available from the Earth System Grid Federation (ESGF) website (<https://esgf-metagrid.cloud.dkrz.de>). However, BCC-CSM2-MR and GFDL-ESM4 are excluded despite having the A/R experiment, as there was a bug in the soil respiration in BCC-CSM2-MR (Loughran *et al* 2023), and the terrestrial and marine carbon fluxes were not available for GFDL-ESM4. We also include FOCI (Matthes *et al* 2020, Chien *et al* 2022), with which we have conducted all experiments used in this study. In total, eight ESMs are utilized in this study. Among them, seven models (ACCESS-ESM1-5 (Ziehn *et al* 2020), CESM2 (Danabasoglu *et al* 2020), CanESM5 (Swart *et al* 2019), FOCI, MIROC-ES2L (Hajima *et al* 2020), MPI-ESM1.2-LR (Mauritsen *et al* 2019), and UKESM1-0-LL (Sellar *et al* 2019)) have performed the A/R experiment. Four ESMs (FOCI, MPI-ESM1-2-LR, NorESM2-LM (Seland *et al* 2020), and UKESM1-0-LL) have performed the OAE experiment. A comparison of the earth system components used by the models is provided in table 1 (for details see text S1 in the supplementary material).

2.2. Experiments

Three sets of experiments are used. All three experiments start from the end of the historical simulation (*esm-hist*) in 2015 and run until 2099 under the high greenhouse gas emission shared socioeconomic pathway (SSP) 5–8.5 with the corresponding land use and land cover change (Kriegler *et al* 2017, Gidden *et al* 2019, Feng *et al* 2020), and are run in the CO₂ emission-driven mode, which enables the interactive carbon cycle between different earth system components. The *esm-hist*

Table 1. Comparison of the land, ocean, and atmosphere components of the Earth system models utilized, and number of realizations of the experiments used in this study.

Model	Land	Ocean	Atmosphere	A/R	OAE
ACCESS-ESM1-5	CABLE	GFDL MOM5	UKMO UM	10	
CanESM5	CLASS/CTEM	NEMO/CMOC	CanAM5	1	
CESM2	CLM5	POP2	CAM6	1	
FOCI	JSBACH3.2	NEMO3.6/MOPS	ECHAM6.3	3	3
MIROC-ES2L	MATSIRO/VISIT	COCO/OECO2	CCSR-AGCM	1	
MPI-ESM1-2-LR	JSBACH3.2	MPIOM1.6/HAMOCC6	ECHAM6.3	3	3
NorESM2-LM	CLM5	BLOM/iHAMOCC	CAM6-Nor		1
UKESM1-0-LL	JULES	NEMO/MEDUSA-2	UKMO UM	1	1

experiment is in turn started from *esm-piControl*, and *esm-piControl* is started from a spun-up state. As described in the Coupled Climate–Carbon Cycle Model Intercomparison Project (C4MIP) protocol (Jones *et al* 2016), the technique for reaching spun-up state is up to modeling groups. However, the land, ocean and atmosphere carbon inventories should each vary by less than 10 PgC/century, which is equivalent to less than 5 ppm/century in the atmosphere. The first experiment is the reference experiment (hereafter referred to as *REF*), which is the *esm-ssp585* experiment in the C4MIP (Jones *et al* 2016). The second experiment simulates a large-scale application of OAE (hereafter referred to as *OAE*), where a total of 0.14 Pmol of alkalinity is added per year to the ice-free global surface ocean between 70°N and 60°S from 2020. The OAE experiment is the *esm-ssp585-ocn-alk* experiment in the CDRMIP, and is described in more detail in the modeling protocol (Keller *et al* 2018b). The third experiment simulates the land use of the sustainable SSP1-2.6 pathway under the SSP5-8.5 scenario. As SSP1-2.6 is characterized by reduced deforestation and restoration of degraded forests (Doelman *et al* 2018, Hurtt *et al* 2020), this set of simulations is referred to as *A/R* hereafter. The land use change implemented in CMIP6 models is based on the Land-use Harmonization 2 (LUH2) dataset, which provides harmonized land use data for both historical period and different future scenarios (Hurtt *et al* 2020). This experiment is the *esm-ssp585-ssp126Lu* experiment in the Land Use Model Intercomparison Project (LUMIP) and is described in more detail in the protocol (Lawrence *et al* 2016).

An ensemble of ten realizations have been conducted for ACCESS-ESM1-5 for the experiments *REF* and *A/R*, and an ensemble of three realizations have been conducted for both FOCI and MPI-ESM1-2-LR for the experiments *REF*, *A/R* and *OAE*. The multi-realization ensembles can thus be used to quantify the uncertainty due to internal variability. The different realizations of all experiments start from the year 2015 of different historical simulations, which in turn start from different years of the pre-industrial spun-up

simulations. For all other models, only one realization is available for analysis. The numbers of realizations for the experiments *A/R* and *OAE* is shown in table 1.

2.3. Robustness against uncertainties

To determine whether the CDR effect on the annual mean of a climate variable emerges from internal or inter-model variability, we determine whether the signal $S(t)$ stands out from the noise $N(t)$ (where $N(t)$ is determined either from internal or inter-model variability). The signal is quantified as the ensemble mean of the difference between the CDR and the reference experiments (i.e. $A/R-REF$ and $OAE-REF$), and the noise is quantified as the standard deviation of the multi-model or the multi-realization ensembles.

In this study, a signal is considered to emerge from the noise when the signal exceeds two noise levels ($S(t) > 2 \cdot N(t)$) (see, e.g. Bonan *et al* 2021). If, after a specific year, the signal consistently emerges until the end of the experiment, then the specific year is called time of emergence (ToE). Additionally, to compare the two sources of uncertainty, the variance of the multi-model ensemble is compared against the variance of the multi-realization ensembles, and both are compared across the experiments. The differences of the variance are tested with the *F*-test to determine if the differences are significant (see, e.g. Deser *et al* 2012, Deser and Phillips 2023).

2.4. Efficiency metrics

Two metrics are used to quantify the efficiency of *A/R* and *OAE*, respectively.

For *A/R*, the *A/R* efficacy is used, which is modified from the forest carbon density (see, e.g. Baccini *et al* 2012, Panda *et al* 2014) and calculated as the ratio of the changes in total terrestrial carbon storage to the changes in global forest area between *A/R* and *REF* (see also Moustakis *et al* 2025):

$$\text{A/R Efficacy}(t) = \frac{\Delta C_{\text{land}}(t)}{\Delta \text{Forest area}(t)}.$$

For OAE, the OAE efficacy for year t is calculated as the difference in the cumulative sum of annual air-sea CO_2 fluxes (F_{CO_2}) from the start of the experiment to the year t between OAE and REF divided by the amount of added alkalinity to the ocean by year t (see, e.g. Schwinger *et al* 2024):

$$\text{OAE Efficacy}(t) = \frac{\Delta(\sum_0^t F_{\text{CO}_2})}{\Delta \text{Total Alkalinity}(t)}.$$

2.5. Carbon cycle feedback ratios of A/R and OAE

To quantify any change in the carbon sink due to OAE and A/R, we define the carbon cycle feedback ratios $\lambda_{\text{A/R}}$ and λ_{OAE} as follows:

$$\lambda_{\text{A/R}}(t) = \frac{\Delta C_{\text{ocean}}^{\text{A/R}}(t)}{\Delta C_{\text{land}}^{\text{A/R}}(t)} \times 100\%$$

and

$$\lambda_{\text{OAE}}(t) = \frac{\Delta C_{\text{land}}^{\text{OAE}}(t)}{\Delta C_{\text{ocean}}^{\text{OAE}}(t)} \times 100\%,$$

where $\Delta(\cdot)^{\text{A/R}}$ denotes the difference between A/R and REF, $\Delta(\cdot)^{\text{OAE}}$ is the difference between OAE and REF, C_{land} and C_{ocean} are the total terrestrial and marine carbon inventories, and ΔC_{ocean} is calculated as

$$\Delta C_{\text{ocean}}(t) = \Delta \left(\sum_0^t F_{\text{CO}_2} \right).$$

For comparison, an estimate of the theoretical values of the feedback ratios is calculated based on the carbon cycle feedback framework of Friedlingstein *et al* (2003) (see also Friedlingstein *et al* 2006, Arora *et al* 2013, 2020). In this framework, model-specific parameters for the carbon-concentration feedback (β_{land} and β_{ocean}) and the carbon-climate feedback (γ_{land} and γ_{ocean}) are used to quantify the changes in carbon storage on land and ocean due to changes in atmospheric CO_2 concentration and temperature. The parameter climate sensitivity (α) is used to quantify the temperature change due to the change in the atmospheric CO_2 concentration (hence hereafter also the α - β - γ framework). The estimated theoretical values from the parameters α , β , and γ are given as follows (see text S2 for the derivation):

$$\lambda_{\text{OAE}}^{\text{theo}} = \frac{-\beta_{\text{land}} - \alpha \cdot \gamma_{\text{land}}}{c \cdot \left(1 + \frac{\beta_{\text{land}}}{c} + \frac{\alpha \cdot \gamma_{\text{land}}}{c} \right)}$$

and

$$\lambda_{\text{A/R}}^{\text{theo}} = \frac{-\beta_{\text{ocean}} - \alpha \cdot \gamma_{\text{ocean}}}{c \cdot \left(1 + \frac{\beta_{\text{ocean}}}{c} + \frac{\alpha \cdot \gamma_{\text{ocean}}}{c} \right)},$$

where the superscript theo indicates the theoretical values, $c = 2.124 \text{ Pg ppm}^{-1}$ is the conversion factor from ppm to PgC, and the parameters α , β and γ are taken from Arora *et al* (2020) for each utilized model. The α - β - γ parameters are derived from the

C4MIP *1pctco2* experiment, which starts from pre-industrial CO_2 concentration and has an increase in atmospheric CO_2 at a rate of 1% per year until quadrupling. In the following we use two sets of parameters for calculating α , β , and γ , which are taken at the time of doubling and quadrupling of CO_2 in the *1pctco2* experiment.

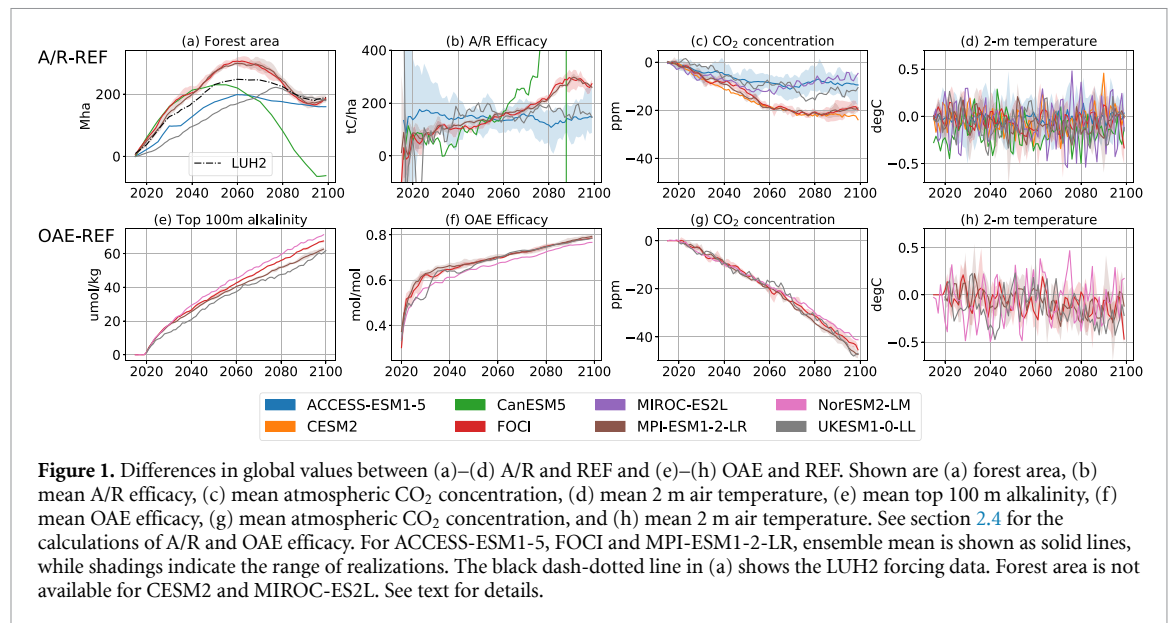
3. Results

3.1. CDR effects at global scale

The effects of A/R (A/R-REF; figures 1(a)-(d)) and OAE (OAE-REF; figures 1(e)-(h)) at global scale is shown in figure 1. For most models, global forested area increases during most of the period in both REF and A/R (see figure S1 in the supplementary material), with A/R increasing faster than REF (figure 1(a)). The difference in forest area between A/R and REF reaches a maximum after mid-century, and starts to decline afterwards, which is in line with the input data of LUH2. The simulated forest areas in REF, A/R as well as A/R-REF have a large inter-model variability. FOCI and MPI-ESM, sharing the same land surface model component, simulate the highest increase in forest area, reaching 300 Mha by 2060. For ACCESS-ESM1-5, CanESM5, and UKESM1-0-LL, the peak value is lower (200 Mha to 230 Mha), but also occurs during the second half of the century. The most extreme case is CanESM5, where the difference in forest area between A/R and REF decreases after 2060 and even becomes negative after 2088, since the dynamic land cover change implemented in CanESM5 is such that the changes in non-crop PFTs are only driven by the changes in crop area (Kou-Giesbrecht *et al* 2024). As in LUH2, the total crop area in SSP1-2.6 exceeds that in SSP5-8.5 near 2090 (figure S2), the difference in forest area between A/R and REF also becomes negative accordingly.

Figure 1(b) shows the A/R efficacy (see section 2.4 for the definition). For all models, by the time the increase in forest area reaches its peak value, the A/R efficacy lies between 100 to 200 tC ha^{-1} . For FOCI and MPI-ESM1-2-LR, the A/R efficacy increases afterwards and reaches $\sim 290 \text{ tC ha}^{-1}$ by 2090s, while ACCESS-ESM1-5 and UKESM1-0-LL do not simulate a further increase afterwards. For CanESM5, as the increase in forest area becomes negative after 2088, and ΔC_{land} is always positive, the A/R efficacy first reaches high values in the 2070s and becomes negative afterwards.

The atmospheric CO_2 concentration of all experiments exceeds 1000 ppm by 2100, which is more than 600 ppm higher than in 2015 (figure S3). In comparison, the reduction in atmospheric CO_2 concentration due to A/R lies between 5 to 20 ppm by 2100 (figure 1(c)). CESM2, FOCI, and MPI-ESM1-2-LR simulate a similar trajectory of the atmospheric CO_2 concentration, with the anomaly peaking at about 20 ppm near 2075 and plateauing afterwards. For



ACCESS-ESM1-5, MIROC-ES2L, and UKESM1-0-LL, the reduction reaches the peak value earlier (near 2050) and also plateaus afterwards. The signal of the CO₂ removal clearly emerges with respect to both the inter-model and the internal variability, as the ToE for CO₂ concentration is no later than 2031.

The effect of A/R on mitigating warming is shown in figure 1(d). During the period of 2040–2060 when the increase in simulated forest area peaks, the multi-model mean of warming mitigation is 0.08 ± 0.06 degrees (positive values indicate cooling compared to REF; multi-model-mean $\pm$ one standard deviation). However, in contrast to the robust reduction in atmospheric CO₂ concentration (figure 1(c)), the effect on near-surface temperature is difficult to detect, with much larger variability both within the same model and across the models, and the temperature signal does not emerge throughout the experiment.

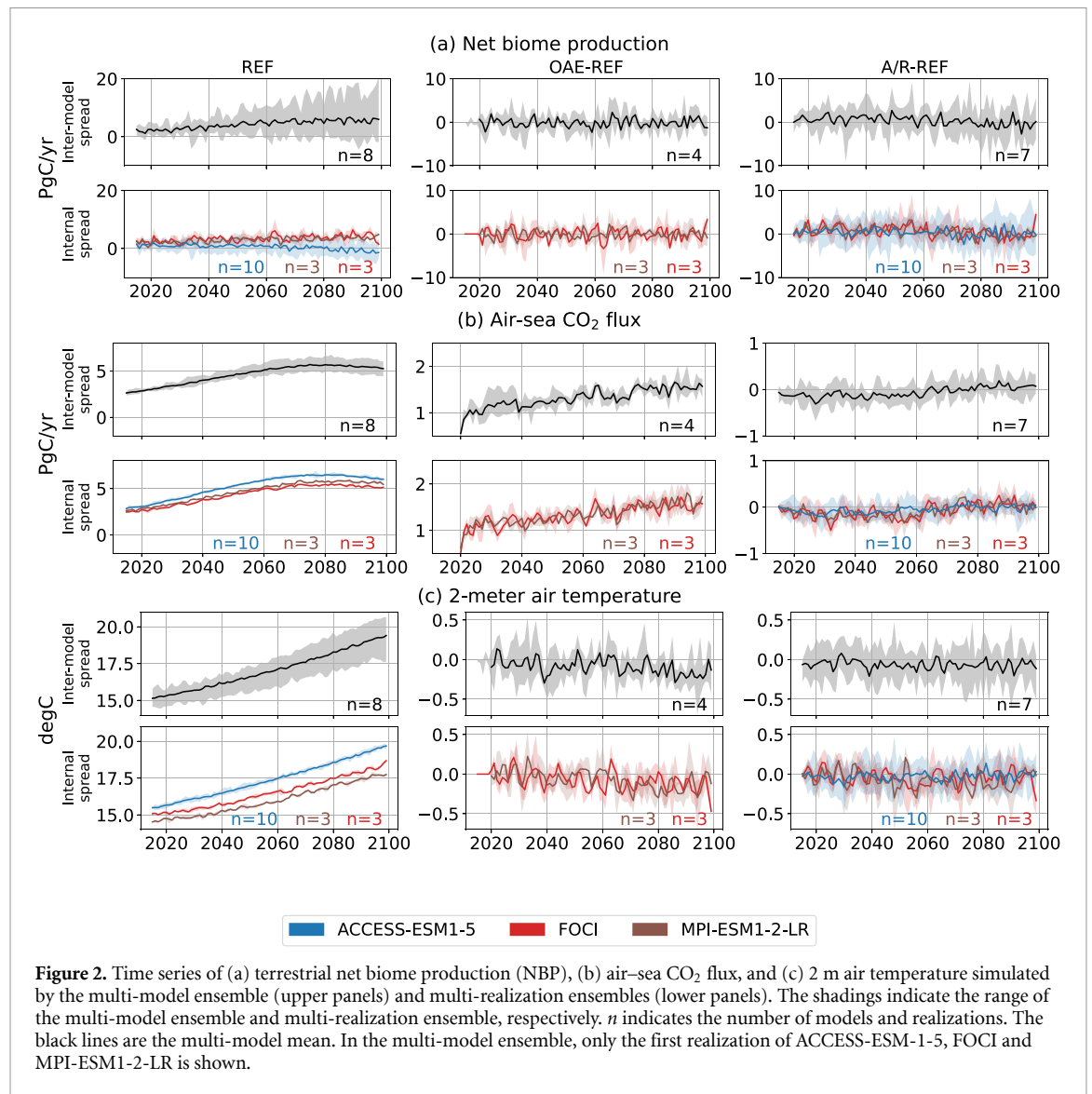
For all four models that conducted the OAE experiment, the global mean surface alkalinity of the top 100 m of the ocean steadily increases and reaches an anomaly of more than $60 \mu\text{mol kg}^{-1}$ by the end of the experiment (figure 1(e)). This behavior is in contrast to the forest area increase in the A/R experiment, which is halted already in the middle of the century (figure 1(a)).

Similar values of OAE efficacy are simulated across the models (figure 1(f)), where the efficacy is low initially and increases within a few years to ~ 0.65 in the 2030s. After the 2030s, the efficacy steadily increases at a slower rate and reaches ~ 0.8 at the end of the experiment. The increase in efficacy under strong emissions is consistent with the chemical mechanisms described in Schwinger *et al* (2024). CO₂ is continuously removed from the atmosphere until the end of the experiment

(figure 1(g)). The decrease in atmospheric CO₂ concentration is $18.5 \text{ ppm} \pm 0.86 \text{ ppm}$ in 2060, and $44.4 \text{ ppm} \pm 2.22 \text{ ppm}$ at the end of the century. The CO₂ removal by OAE also clearly emerges, as the ToE is no later than 2029 against both the inter-model and internal variability.

For better comparisons between the A/R and OAE experiments in this study, the analysis that follows is done for the period between 2040 to 2060, when both A/R and OAE are still removing CO₂ from the atmosphere. When averaged from 2040 to 2060, the multi-model-mean of warming mitigation due to OAE is 0.07 ± 0.02 degrees (figure 1(h)). Despite continuously removing CO₂ from the atmosphere, the effect on surface temperature does not emerge robustly from either the inter-model or internal variability.

Figure 2 shows the time series of simulated terrestrial net biome production (NBP; the land–atmosphere carbon flux), air–sea CO₂ flux (F_{CO_2}), and 2 m air temperature (T_{as}) in REF and the CDR effects (OAE–REF and A/R–REF). The comparison between figures 2(a) and (b) show that the inter-model variability of NBP is larger than that of F_{CO_2} . The difference is significant for both REF and the CDR effects. As for the comparison between inter-model and internal variability, for all three variables (NBP, F_{CO_2} and T_{as}) the inter-model variability is larger than the internal variability in REF, whereas for the CDR effects the two are of similar magnitude. We also compare the variability between REF and the CDR effects. For all three variables, inter-model variability is larger in REF than in the anomalies. Internal variability is less consistent: for F_{CO_2} it is greater in REF than in OAE–REF, for T_{as} it is larger in REF than the anomalies, and for NBP it is similar in REF to A/R–REF.



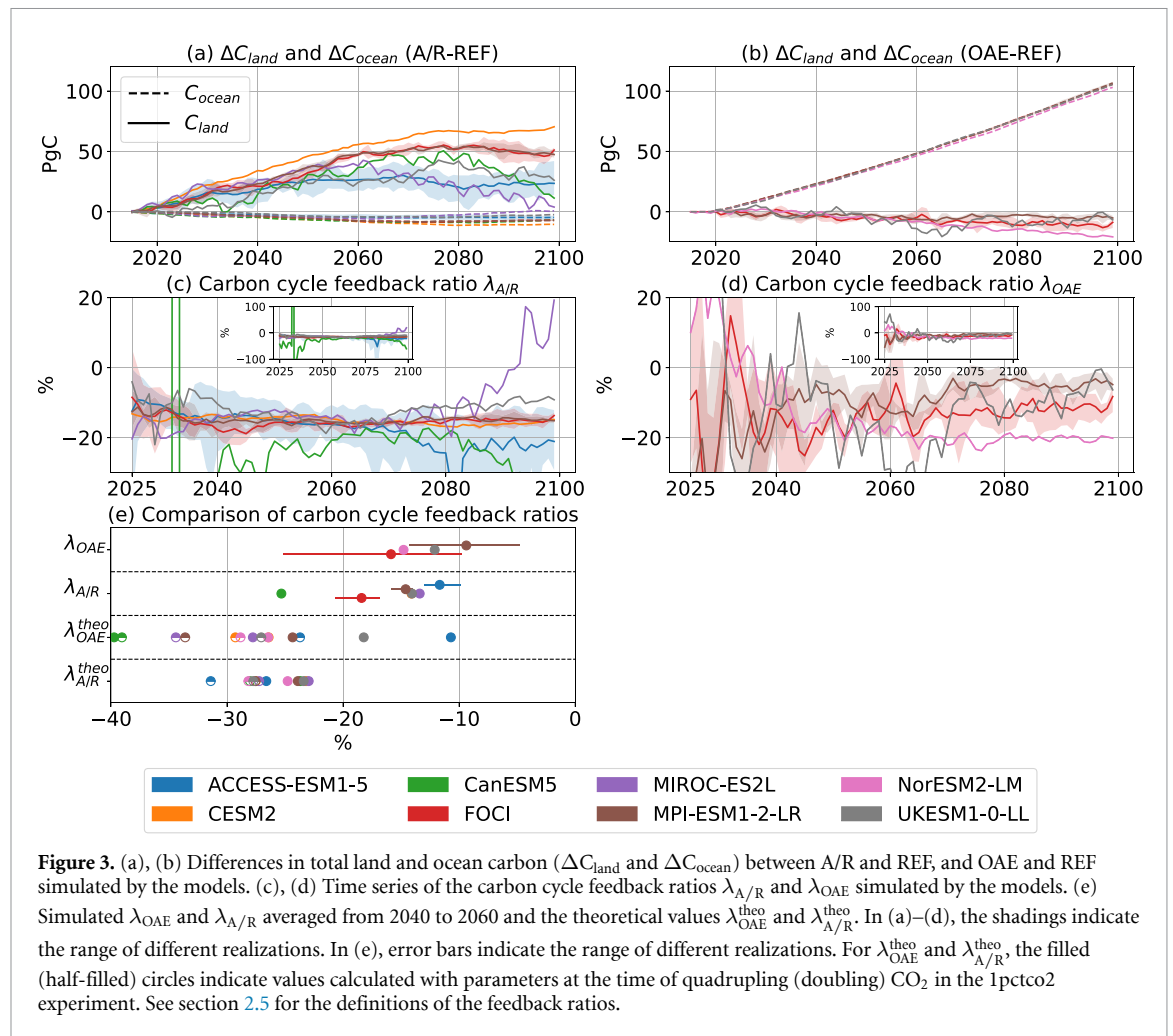
3.2. Carbon cycle feedback

From the differences in total land and ocean carbon between *A/R* and *REF* (figure 3(a)), and *OAE* and *REF* (figure 3(b)), it is clear that for *A/R* (*OAE*), the positive ΔC_{land} (ΔC_{ocean}) comes at the cost of a negative ΔC_{ocean} (ΔC_{land}). For *A/R*, ΔC_{land} is $30.9 \text{ Pg} \pm 8.3 \text{ Pg}$ (averaged from 2040 to 2060), while ΔC_{ocean} is $-4.8 \text{ Pg} \pm 1.5 \text{ Pg}$ (figure 3(a)). For *OAR*, ΔC_{ocean} is $34.8 \text{ Pg} \pm 0.6 \text{ Pg}$, while ΔC_{land} is $-4.7 \text{ Pg} \pm 2.0 \text{ Pg}$ (figure 3(b)). The time series of the feedback ratios $\lambda_{\text{A/R}}$ and λ_{OAE} is shown in figures 3(c) and (d) (see section 2.5 for the definitions). For all models except for CanESM5, $\lambda_{\text{A/R}}$ is stable during most of the time when the land carbon is still increasing (before 2080). In comparison, the interannual variability of λ_{OAE} is much larger than $\lambda_{\text{A/R}}$, which is due to the larger interannual variability of ΔC_{land} than ΔC_{ocean} . The internal variability of λ_{OAE} is also larger than that of $\lambda_{\text{A/R}}$. The multi-model mean of $\lambda_{\text{A/R}}$ averaged from 2040 to 2060 is $-15.9\% \pm 4.3\%$, and for λ_{OAE} it is $-13.0\% \pm 2.5\%$ (figure 3(e); see also table S1 in the supplementary material for details). In

comparison, the multi-model-mean of $\lambda_{\text{A/R}}^{\text{theo}}$ and $\lambda_{\text{OAE}}^{\text{theo}}$ is $-24.1\% \pm 1.2\%$ and $-24.8\% \pm 8.3\%$, respectively, when calculated with the $-\gamma$ parameters at the time of quadrupling CO₂. The values are more negative if calculated with the parameters at the time of doubling CO₂ ($-28.2\% \pm 1.3\%$ and $-30.8\% \pm 4.8\%$).

3.3. Spatial patterns of CDR effects

The spatial pattern of the changes in NBP and F_{CO_2} between *A/R* and *REF* as well as *OAE* and *REF* is shown in figure 4. For *A/R*, the variance of the spatial patterns of the change in NBP is larger than the increase in tree cover among models (figure S4). For example, for FOCI and MPI-ESM1-2-LR, the change in NBP matches well with the increase in forest cover, which occurs mostly over Europe, Brazilian Atlantic Forest, Congo Basin, Eastern North America and Eastern China. However, some models also simulate pronounced decreases in NBP over boreal high latitudes (CanESM5, MIROC-ES2L, UKESM1-0-LL) and central Amazonia (UKESM1-0-LL).



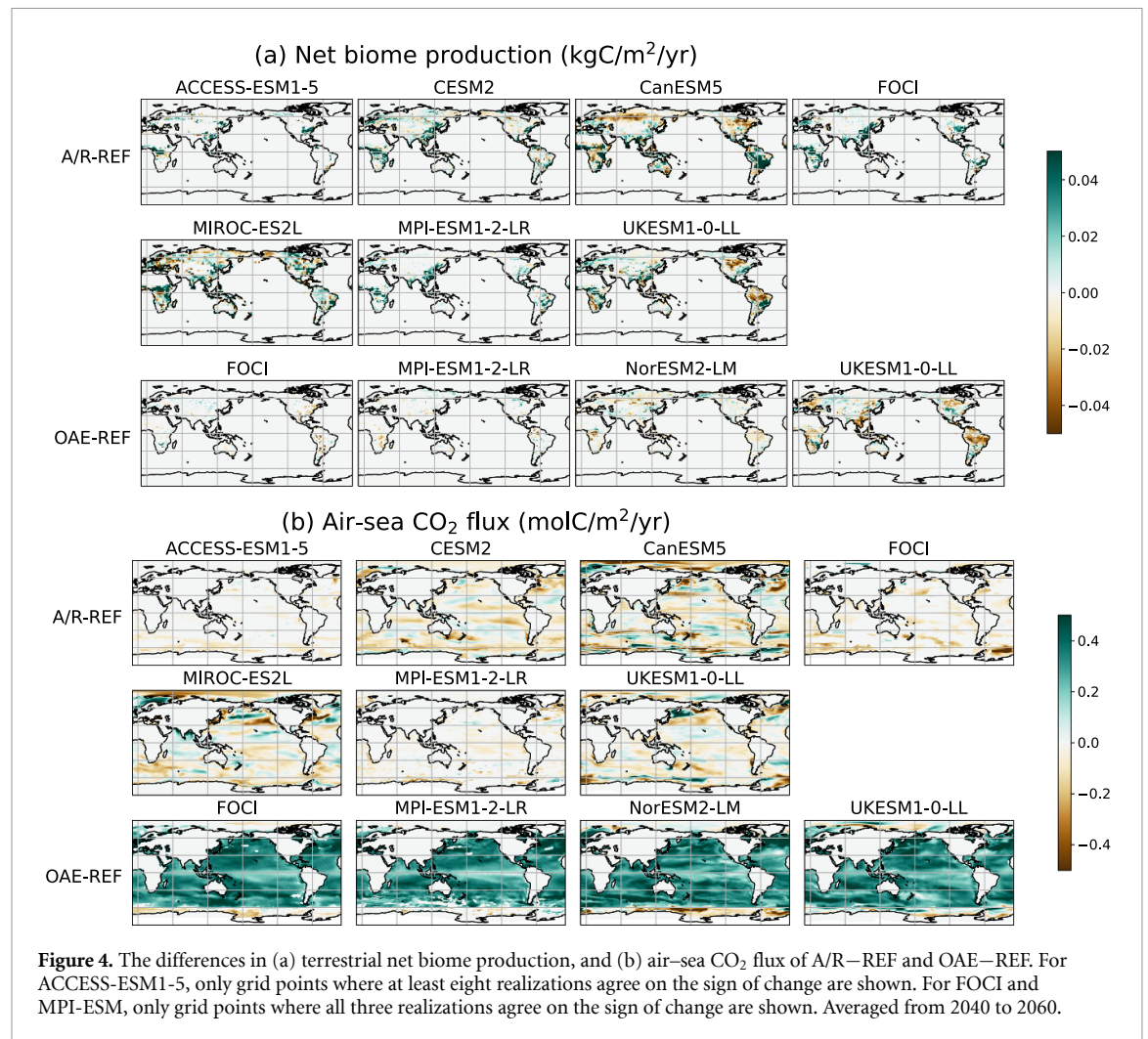
The responses of NBP to OAE is also shown in figure 4(a). Despite having the same land surface model component, FOCI and MPI-ESM1-2-LR are slightly different. For FOCI, NBP is decreased over the Amazon and North America, and increased over Eurasia in response to OAE. In contrast, MPI-ESM1-2-LR simulates an increase over North America. NorESM2-LM also simulates a decrease in Amazonia, and UKESM1-0-LL simulates strong decreases in regions including large parts of South America, East and Southeast Asia, Northern Australia, Eastern Europe, Central and Southern Africa.

The NBP responses are the sum of ecosystem production and ecosystem respiration, which in turn are affected by atmospheric CO_2 concentration, temperature and soil moisture. The sensitivities of NBP to these factors are also different across different models and regions. For example, the reduced NBP over Amazonia in the responses to both A/R and OAE simulated by UKESM1-0-LL suggest that the response is rooted in the reduced atmospheric CO_2 concentration by CDR, as the warming mitigation is different between A/R and OAE. For CanESM5 and MIROC-ES2L, the spatial patterns of NBP response at boreal regions resemble those of the changes in precipitation (figure S5), indicating the contribution of the

indirect effect of changes in precipitation. For models with multi-realization ensembles (ACCESS-ESM1-5, FOCI, and MPI-ESM1-2-LR), regions with robust changes are limited to regions with increased forest cover and their vicinity (figure S4), indicating the large internal variability in non-local effects.

Figure 4(b) shows the effects of CDR on F_{CO_2} . For A/R, all models simulate large differences over higher latitudes of both hemispheres, including the North Pacific, the North Atlantic, and the Southern Ocean, where F_{CO_2} is already large. For FOCI, the A/R-induced decrease in F_{CO_2} occurs mostly over the Southern Ocean. For MIROC-ES2L, and UKESM1-0-LL, a dipole pattern is simulated over the North Atlantic, which is an increase accompanied by a decrease. In contrast, for CanESM5, CESM2, and MPI-ESM1-2-LR, there is only a decrease without the dipole pattern over the North Atlantic.

The effects of OAE on F_{CO_2} are generally in line with the patterns of the changes in top 100 m alkalinity (figure S6), with increases in both alkalinity and F_{CO_2} over subtropical regions and limited effects over the eastern tropical Pacific. However, over the subarctic North Pacific, North Atlantic and south of 50°S , F_{CO_2} is increased prominently despite the relative small increase in top 100 m alkalinity, indicating the



importance of ventilation and circulation in determining favorable regions for OAE deployment. Over the Southern Ocean south to 60°S where OAE is not applied, F_{CO_2} is decreased as well. While the spatial pattern of increase in top 100 m alkalinity is smooth (figure S6), the spatial pattern of F_{CO_2} shows larger regional variations, indicating that the OAE efficacy is dependent on local physical and chemical characteristics. In contrast to the A/R effects on NBP, where large regional differences are simulated by the models, the regional differences of the changes in both the top 100-m alkalinity and F_{CO_2} are much smaller. For the temperature response, as is the case for the global mean value (figures 1(d) and (h)), the spatial patterns also have a high inter-model and internal variability (figure S7).

4. Discussion and summary

The current study is the first multi-model study analyzing and comparing the effects of enhancing the terrestrial (A/R) and marine carbon sink (OAE), respectively, under the high emission scenario SSP5-8.5.

In our set-up of A/R, the increase in tree cover peaks at mid-century and the effect of CO₂ removal stops before the end of the century. By 2075, the decrease in atmospheric CO₂ concentration relative to REF saturates at 15.4 ± 6 ppm. For OAE, the increase in upper-level alkalinity and the effect of atmospheric CO₂ removal is persistent until the end of the experiment. For both A/R and OAE, the effect of CO₂ removal emerges from both the inter-model and internal variability, but the warming mitigation is difficult to detect. Due to the large inter-model and internal variability, values reported from previous studies with only one model or one realization should therefore be interpreted with caution. As both the A/R and OAE simulations in this study represent the upper end of feasible future CDR deployment, a warming mitigation due to similar amounts of carbon removal is only detectable under scenarios with less emission than SSP5-8.5.

A comparison between the inter-model and internal variability is provided. The models agree more on the CO₂ flux between ocean and atmosphere (F_{CO_2}) than between land and atmosphere (NBP),

and this is the case not only in *REF*, but also for the responses to CDR. While NBP, F_{CO_2} and near surface temperature (T_{as}) all have larger inter-model variability than internal variability in *REF*, for the CDR effects (*A/R-REF* and *OAE-REF*), the uncertainty associated with the internal variability is similar to that of the inter-model variability.

We quantify the carbon cycle feedback of CDR with the carbon cycle feedback ratios $\lambda_{\text{A/R}}$ and λ_{OAE} . The models used in this study simulate similar magnitudes of $\lambda_{\text{A/R}}$ and λ_{OAE} , which are $-15.9\% \pm 4.3\%$ and $-13.0\% \pm 2.5\%$ (multi-model mean $\pm$ one standard deviation; averaged from 2040 to 2060). For *A/R*, although the models simulate a large spread in the magnitude of achieved CDR, the feedback ratios of different models are close to each other. Due to the uncertainty in the terrestrial carbon sink, both the interannual and internal variability of λ_{OAE} are much larger than those of $\lambda_{\text{A/R}}$.

A multi-model set of theoretical feedback ratios $\lambda_{\text{OAE}}^{\text{theo}}$ and $\lambda_{\text{A/R}}^{\text{theo}}$ is derived from the classical metrics for describing the carbon-concentration and carbon-climate feedback of climate models (the α - β - γ framework). The magnitudes of $\lambda_{\text{OAE}}^{\text{theo}}$ and $\lambda_{\text{A/R}}^{\text{theo}}$ are similar, which is in line with our results. Although the α - β - γ parameters are not directly applicable to this study, as SSP5-8.5 includes non- CO_2 forcing that *1pctco2* does not (Melnikova et al 2024), and it has been shown that both β and γ depend on the CO_2 growth rate in the atmosphere (Gregory et al 2009, Hajima et al 2014, Arora et al 2020), it is nevertheless insightful to explore the difference between the simulated and theoretical feedback ratios. When comparing the emission pathways SSP5-8.5 and *1pctco2*, the climate and carbon state during 2040–2060 under SSP5-8.5 lie between the time of doubling and quadrupling CO_2 of *1pctco2* (see text S3 for details). However, as $\lambda_{\text{OAE}}^{\text{theo}}$ and $\lambda_{\text{A/R}}^{\text{theo}}$ calculated with the two sets of parameters (at the time of doubling and quadrupling CO_2) are both more negative than the simulated λ_{OAE} and $\lambda_{\text{A/R}}$, further investigation is needed to understand the application of the α - β - γ framework for estimating the carbon cycle responses to CDR deployment under different emission scenarios. Recently, a generalized framework has been proposed, where the α - β - γ parameters are generalized to account for responses at different time-scales and are therefore independent of emission scenarios, which might be suitable for the purposes (Torres Mendonça et al 2021a, 2021b, 2024).

Several modeling studies have also conducted *A/R* or *OAE* experiments under the SSP5-8.5/RCP8.5 scenario, with $\lambda_{\text{A/R}}$ ranging from -16.7% to -19.8% and λ_{OAE} ranging from 2.8% to -14.7% (Keller et al 2014, Feng et al 2017, Lenton et al 2018, Sonntag et al 2018, Palmiéri and Yool 2024, Moustakis et al 2024; see text S4 and table S1 for a summary of the model configurations used in previous studies). The results from previous studies are in line with our findings.

The range of $\lambda_{\text{A/R}}$ among previous studies is smaller than the range of λ_{OAE} . The studies deploying different amounts of *OAE* with the same model showed large ranges of λ_{OAE} (Feng et al 2017, Palmiéri and Yool 2024). Except for Palmiéri and Yool (2024), values of λ_{OAE} are not larger than the multi-model range of this study. As the amount of *OAE* applied and hence the increase in total marine carbon in Palmiéri and Yool (2024) is smaller than in this study, it indicates that λ_{OAE} might be scale dependent.

In addition to the carbon and climate responses to CDR at global scale, we also show the spatial patterns of the responses simulated by different models. For *A/R*, the spatial patterns of terrestrial carbon sink enhancement are different among the models, with some models showing a strong reduction of the carbon sink over regions without forestation. For large-scale *OAE*, the spatial patterns of the increase in air-sea CO_2 flux are more consistent. For both *A/R* and *OAE*, the spatial pattern of decrease in marine (terrestrial) carbon sink due to *A/R* (*OAE*) is less consistent among the models, compared to the spatial pattern of carbon sink enhancement. The temperature responses to *A/R* and *OAE* are also subject to high inter-model and internal variability. The high inter-model and internal variability of CDR response poses challenges for understanding the non-local carbon cycle responses due to both biogeophysical and biogeochemical mechanisms. In terms of monitoring, reporting and verification, this suggests that more efforts should be put into enhancing our understanding of CDR-induced responses over the hotspots of responses, such as Amazonia, the North Atlantic, and the Southern Ocean. To incorporate CDR into future climate policy without carbon budget mismatch, a top-down approach such as atmospheric monitoring and global modeling will be necessary, in order to correctly determine the reduced natural terrestrial and marine carbon sink due to CDR, aside from the bottom-up approach of CDR crediting mechanisms.

The LUMIP experiment *esm-ssp585-ssp126Lu* has been used in this and previous studies for representing the CDR effect of *A/R* (Keller et al 2018b). However, it is not suitable for representing a continuous CDR effect of *A/R* throughout the century, as for all models the change in forest area between *A/R* and *REF* decreases for at least half of the time after mid-century. The change in forest area between *A/R* and *REF* are different from the sum of primary and secondary forest land from the LUH2 data, which is likely due to how the models translate the LUH2 forcing data into the different Plant Functional Types used by the models (Loughran et al 2023). Further studies are needed to bridge the gap in the simulations of land use and land cover change between the ESMs and the Integrated Assessment Models, which are used to produce projections of future land use. Moreover, the experimental setup is not ideal to isolate the *A/R* effects as a CDR option, as the land use in

both SSP5-8.5 and SSP1-2.6 changes over time and includes conversions between various types of land use and land cover, which makes it difficult to disentangle the effect of A/R and avoided deforestation. For example, for FOCI, about 20% of the increase in global NBP by 2060 is due to the reduced fluxes from land use and land cover change (figure S8), indicating that the avoided deforestation is mixed together with the increase in forest cover, and is therefore not suitable for isolating the effect of A/R as a CDR application. To fully isolate the effect of A/R on the Earth system, a reference scenario is thus needed, where no land use change occurs (e.g. Moustakis *et al* 2024).

Finally, based on our results, we provide some suggestions for future modeling studies aiming to understand how the carbon cycle responds to CDR deployment: (1) Multi-realization ensembles are necessary for representing the large internal variability of the temperature response as well as the land–atmosphere carbon flux. (2) The results for the high-emission scenario SSP5-8.5 might not be transferable to other scenarios, and experiments should be conducted for different emission scenarios. (3) A better protocol is needed for isolating the CDR effect of A/R from other land use and land cover changes.

Data availability statement

LUMIP and CDRMIP data for ACCESS-ESM1-5, CESM2, CanESM5, MIROC-ES2L, MPI-ESM1.2-LR, UKESM1-0-LL, NorESM2-LM are available from the Earth System Grid Federation (ESGF) website. The details of the utilized experiments and scripts necessary to reproduce the output for FOCI and MPI-ESM1.2-LR is available at <https://hdl.handle.net/20.500.12085/05bb4c13-f924-497e-8f15-701abf16eb0d>. Scripts for processing and analyzing data as well as generating the figures are provided at the same location. MPI-ESM-1-2-LR is made available under a version of the MPI-M software license agreement (the license and information on how to access the code is available at: <https://code.mpimet.mpg.de/projects/mpi-esm-license>). The code of the FOCI version used in this study is available at: <https://doi.org/10.5281/zenodo.6772175>. The LUH2 data is publicly accessible at: <https://luh.umd.edu/>.

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References

- Arora V K *et al* 2013 Carbon–concentration and carbon–climate feedbacks in CMIP5 earth system models *J. Clim.* **26** 5289–314
- Arora V K *et al* 2020 Carbon–concentration and carbon–climate feedbacks in CMIP6 models and their comparison to CMIP5 models *Biogeosciences* **17** 4173–222
- Babiker M *et al* 2022 Cross-sectoral perspectives *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* ed P R Shukla *et al* (available at: www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_Chapter12.pdf)
- Baccini A *et al* 2012 Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps *Nat. Clim. Change* **2** 182–5

- Bonan G B, Lombardozzi D L and Wieder W R 2021 The signature of internal variability in the terrestrial carbon cycle *Environ. Res. Lett.* **16** 034022
- Bonan G B, Lombardozzi D L, Wieder W R, Oleson K W, Lawrence D M, Hoffman F M and Collier N 2019 Model structure and climate data uncertainty in historical simulations of the terrestrial carbon cycle (1850–2014) *Glob. Biogeochem. Cycles* **33** 1310–26
- Burt D J, Fröb F and Ilyina T 2021 The sensitivity of the marine carbonate system to regional ocean alkalinity enhancement *Front. Clim.* **3** 624075
- Chien C-T et al 2022 FOCI-MOPS v1—integration of marine biogeochemistry within the flexible ocean and climate infrastructure version 1 (FOCI 1) Earth system model *Geosci. Model Dev.* **15** 5987–6024
- Danabasoglu G et al 2020 The community earth system model version 2 (CESM2) *J. Adv. Model. Earth Syst.* **12** e2019MS001916
- Deser C and Phillips A S 2023 A range of outcomes: the combined effects of internal variability and anthropogenic forcing on regional climate trends over Europe *Nonlinear Process. Geophys.* **30** 63–84
- Deser C, Phillips A, Bourdette V and Teng H 2012 Uncertainty in climate change projections: the role of internal variability *Clim. Dyn.* **38** 527–46
- Doelman J C et al 2018 Exploring SSP land-use dynamics using the IMAGE model: regional and gridded scenarios of land-use change and land-based climate change mitigation *Glob. Environ. Change* **48** 119–35
- Feng E Y, Koeve W, Keller D P and Oschlies A 2017 Model-based assessment of the CO₂ sequestration potential of coastal ocean alkalization *Earth's Future* **5** 1252–66
- Feng L, Smith S J, Braun C, Crippa M, Gidden M J, Hoesly R, Klimont Z, Van Marle M, Van Den Berg M and Van Der Werf G R 2020 The generation of gridded emissions data for CMIP6 *Geosci. Model Dev.* **13** 461–82
- Friedlingstein P et al 2006 Climate–carbon cycle feedback analysis: results from the C⁴MIP model intercomparison *J. Clim.* **19** 3337–53
- Friedlingstein P, Dufresne J-L, Cox P M and Rayner P 2003 How positive is the feedback between climate change and the carbon cycle? *Tellus B* **55** 692
- Fröb F, Sonntag S, Pongratz J, Schmidt H and Ilyina T 2020 Detectability of artificial ocean alkalization and stratospheric aerosol injection in MPI-ESM *Earth's Future* **8** e2020EF001634
- Gidden M J et al 2019 Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century *Geosci. Model Dev.* **12** 1443–75
- González M F and Ilyina T 2016 Impacts of artificial ocean alkalization on the carbon cycle and climate in Earth system simulations *Geophys. Res. Lett.* **43** 6493–502
- Gregory J M, Jones C D, Cadule P and Friedlingstein P 2009 Quantifying carbon cycle feedbacks *J. Clim.* **22** 5232–50
- Hajima T et al 2020 Development of the MIROC-ES2L Earth system model and the evaluation of biogeochemical processes and feedbacks *Geosci. Model Dev.* **13** 2197–244
- Hajima T, Tachiiri K, Ito A and Kawamiya M 2014 Uncertainty of concentration–terrestrial carbon feedback in Earth system models *J. Clim.* **27** 3425–45
- Hurt G C et al 2020 Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6 *Geosci. Model Dev.* **13** 5425–64
- Ilyina T, Wolf-Gladrow D, Munhoven G and Heinze C 2013 Assessing the potential of calcium-based artificial ocean alkalization to mitigate rising atmospheric CO₂ and ocean acidification *Geophys. Res. Lett.* **40** 5909–14
- Jones C D et al 2016 C4MIP—The coupled climate–carbon cycle model intercomparison Project: experimental protocol for CMIP6 *Geosci. Model Dev.* **9** 2853–80
- Keller D P, Feng E Y and Oschlies A 2014 Potential climate engineering effectiveness and side effects during a high carbon dioxide-emission scenario *Nat. Commun.* **5** 3304
- Keller D P, Lenton A, Littleton E W, Oschlies A, Scott V and Vaughan N E 2018a The effects of carbon dioxide removal on the carbon cycle *Curr. Clim. Change Rep.* **4** 250–65
- Keller D P, Lenton A, Scott V, Vaughan N E, Bauer N, Ji D, Jones C D, Kravitz B, Muri H and Zickfeld K 2018b The carbon dioxide removal model intercomparison project (CDRMIP): rationale and experimental protocol for CMIP6 *Geosci. Model Dev.* **11** 1133–60
- Koch A, Brierley C and Lewis S L 2021 Effects of Earth system feedbacks on the potential mitigation of large-scale tropical forest restoration *Biogeosciences* **18** 2627–47
- Kou-Giesbrecht S, Arora V K, Seiler C and Wang L 2024 The impacts of modelling prescribed vs. dynamic land cover in a high-CO₂ future scenario—greening of the Arctic and Amazonian dieback *Biogeosciences* **21** 3339–71
- Kriegler E et al 2017 Fossil-fueled development (SSP5): an energy and resource intensive scenario for the 21st century *Glob. Environ. Change* **42** 297–315
- Lawrence D M et al 2016 The land use model intercomparison project (LUMIP) contribution to CMIP6: rationale and experimental design *Geosci. Model Dev.* **9** 2973–98
- Lenton A, Matear R J, Keller D P, Scott V and Vaughan N E 2018 Assessing carbon dioxide removal through global and regional ocean alkalization under high and low emission pathways *Earth Syst. Dyn.* **9** 339–57
- Loughran T F, Ziehn T, Law R, Canadell J G, Pongratz J, Liddicoat S, Hajima T, Ito A, Lawrence D M and Arora V K 2023 Limited mitigation potential of forestation under a high emissions scenario: results from multi-model and single model ensembles *JGR Biogeosci.* **128** e2023JG007605
- Luderer G et al 2018 Residual fossil CO₂ emissions in 1.5 °C–2 °C pathways *Nat. Clim. Change* **8** 626–33
- Matthes K et al 2020 The flexible ocean and climate infrastructure version 1 (FOCI1): mean state and variability *Geosci. Model Dev.* **13** 2533–68
- Mauritsen T et al 2019 Developments in the MPI-M Earth system model version 1.2 (MPI-ESM1.2) and its response to increasing CO₂ *J. Adv. Model. Earth Syst.* **11** 998–1038
- Melnikova I, Ciais P, Tanaka K, Shiogama H, Tachiiri K, Yokohata T and Boucher O 2024 Carbon cycle and climate feedback under CO₂ and non-CO₂ overshoot pathways (available at: <https://egusphere.copernicus.org/preprints/2024/egusphere-2024-1553/>)
- Möller T, Högnér A E, Schleussner C-F, Bien S, Kitzmann N H, Lamboll R D, Rogelj J, Donges J F, Rockström J and Wunderling N 2024 Achieving net zero greenhouse gas emissions critical to limit climate tipping risks *Nat. Commun.* **15** 6192
- Moustakis Y, Nützel T, Wey H-W, Bao W and Pongratz J 2024 Temperature overshoot responses to ambitious forestation in an Earth system model *Nat. Commun.* **15** 8235
- Moustakis Y, Wey H-W, Nützel T, Oschlies A and Pongratz J 2025 No compromise in efficiency from the co-application of marine and terrestrial CDR *Nat. Commun.* submitted
- National Academies of Sciences, Engineering, and Medicine 2022 *A Research Strategy for Ocean-based Carbon Dioxide Removal and Sequestration* (National Academies Press) (available at: www.nap.edu/catalog/26278)
- Oschlies A, Bach L T, Rickaby R E M, Satterfield T, Webb R and Gattuso J-P 2023 Climate targets, carbon dioxide removal, and the potential role of ocean alkalinity enhancement *State Planet Discuss.* **2-oe2023** 1–9
- Oschlies A, Koeve W, Rickels W and Rehdanz K 2010 Side effects and accounting aspects of hypothetical large-scale Southern Ocean iron fertilization *Biogeosciences* **7** 4017–35
- Padrón R S, Gudmundsson L, Liu L, Humphrey V and Seneviratne S I 2022 Drivers of intermodel uncertainty in land carbon sink projections *Biogeosciences* **19** 5435–48

- Palmiéri J and Yool A 2024 Global-scale evaluation of coastal ocean alkalinity enhancement in a fully coupled earth system model *Earth's Future* **12** e2023EF004018
- Panda D K, Mishra A, Kumar A, Mandal K G, Thakur A K and Srivastava R C 2014 Spatiotemporal patterns in the mean and extreme temperature indices of India, 1971–2005 *Int. J. Climatol.* **34** 3585–603
- Schwinger J, Bourgeois T and Rickels W 2024 On the emission-path dependency of the efficiency of ocean alkalinity enhancement *Environ. Res. Lett.* **19** 074067
- Seland Ø et al 2020 Overview of the Norwegian Earth system model (NorESM2) and key climate response of CMIP6 DECK, historical, and scenario simulations *Geosci. Model Dev.* **13** 6165–200
- Sellar A A et al 2019 UKESM1: description and evaluation of the U.K. Earth System Model *J. Adv. Model. Earth Syst.* **11** 4513–58
- Smith S et al 2024 *The State of Carbon Dioxide Removal* 2nd edn (available at: <https://osf.io/f85qj/>)
- Sonntag S, González M F, Ilyina T, Kracher D, Nabel J E M S, Niemeier U, Pongratz J, Reick C H and Schmidt H 2018 Quantifying and Comparing Effects of Climate Engineering Methods on the Earth System *Earth's Future* **6** 149–68
- Swart N C et al 2019 The Canadian Earth system model version 5 (CanESM5.0.3) *Geosci. Model Dev.* **12** 4823–73
- Tokarska K B, Arora V K, Gillett N P, Lehner F, Rogelj J, Schleussner C F, Séférian R and Knutti R 2020 Uncertainty in carbon budget estimates due to internal climate variability *Environ. Res. Lett.* **15** 104064
- Torres Mendonça G L, Pongratz J and Reick C H 2021a Identification of linear response functions from arbitrary perturbation experiments in the presence of noise—part 1: method development and toy model demonstration *Nonlinear Process. Geophys.* **28** 501–32
- Torres Mendonça G L, Pongratz J and Reick C H 2021b Identification of linear response functions from arbitrary perturbation experiments in the presence of noise—part 2: application to the land carbon cycle in the MPI Earth system model *Nonlinear Process. Geophys.* **28** 533–64
- Torres Mendonça G L, Pongratz J and Reick C H 2024 Timescale dependence of airborne fraction and underlying climate–carbon-cycle feedbacks for weak perturbations in CMIP5 models *Biogeosciences* **21** 1923–60
- Wu J, Keller D P and Oschlies A 2023 Carbon dioxide removal via macroalgae open-ocean mariculture and sinking: an Earth system modeling study *Earth Syst. Dyn.* **14** 185–221
- Ziehn T, Chamberlain M A, Law R M, Lenton A, Bodman R W, Dix M, Stevens L, Wang Y-P and Srbinovsky J 2020 The Australian Earth system model: ACCESS-ESM1.5 J. *South. Hemisph. Earth Syst. Sci.* **70** 193–214