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Benefit-cost ratios of carbon dioxide removal strategies

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Abstract

All pathways to achieving the Paris Agreement target of limiting global warming to 1.5 °C or 2 °C require the large-scale removal of carbon dioxide (CO_2) from the atmosphere. Many CO_2 removal (CDR) strategies have been proposed, which vary widely in both price per ton of CO_2 removed and storage timescale of this removed CO_2, as well as mechanism, maturity, scalability, and other factors. However, it has not yet been thoroughly assessed whether the benefits, in terms of climate change-related damages avoided, of CDR deployment exceeds their cost at current reported prices and storage timescales, or what cost is required for CDR strategies with a given storage timescale to provide net benefits and how these depend on socioeconomic assumptions. For CDR strategies that have long storage (>500 year) timescales, these questions reduce to whether its price is lower than the social cost of carbon, but here we show for CDR strategies that operate over shorter timescales they also depend on the duration of storage. We demonstrate that for CDR strategies with reported storage timescales of decades to centuries, the benefits of their deployment outweigh their reported costs under middle-of-the-road socioeconomic assumptions, and in some cases their benefits still outweigh their costs under optimistic socioeconomic assumptions. Overall, the benefit-cost ratios of the evaluated CDR strategies vary by more than an order of magnitude, and are strongly influenced by both price and storage timescale. Our results provide a framework that can be used to assess and compare different CDR strategies quantitatively to help guide future research, development, and policy efforts.

In order to avoid the more catastrophic consequences of climate change, the world has committed to 'holding the increase in the global average temperature to well below 2 °C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 °C above pre-industrial levels' through the Paris Agreement [1]. Achieving this goal will require both a significant and rapid reduction in greenhouse gas (GHG) emissions and substantial atmospheric carbon dioxide removal (CDR, also commonly referred to as negative emissions technology or GHG removal) [2–5]. The implementation of CDR strategies does not negate or reduce the need for deep GHG emissions reductions, but is required to help reduce net CO2 emissions in the near-term and to counteract hard-to-transition sectors such as some industrial activities and long-distance transport [6].

CDR strategies seek to remove CO_2 from the atmosphere and store it in geological, terrestrial or oceanic reservoirs or products. This is achieved via the implementation of biological or chemical techniques that artificially enhance the rate of natural carbon burial processes or provide new 'engineered' pathways for facilitating carbon removal [1–8]. Each of these archetypal approaches can be realised in a number of ways. For example: biological CDR strategies typically focus on enhancing the production and storage of organic carbon, and include changes in land-use practise that increase soil carbon sequestration (e.g. reforestation and application of regenerative farming practises), the production and burial of biochar (pyrolysed biomass), and growing and sinking macroalgae (seaweed) in deep marine environments [4, 5, 7–11]. Chemical CDR strategies primarily focus on the inorganic carbon pool, thus include approaches such as the enhanced weathering of rocks and minerals in agricultural environments, increasing ocean alkalinity, and accelerating carbonate mineralisation within mafic or ultramafic reservoirs [4, 5, 7, 8, 12–14]. Engineered pathways include methods such as direct air carbon capture and storage (DACCS) and bioenergy with carbon capture and storage (BECCS), both of which involve the injection of captured CO_2 into a geological reservoir, as well as processes that create building materials or other products as part of the carbon capture process [4, 5, 15–17].

All of these CDR strategies, as well as the many other methods that have been proposed [2–8], have different states of maturity and scalability [4, 5]. They also vary significantly in terms of their price per ton of CO_2 removed (P [USD, or $]) and the storage timescale (T [years]) over which that carbon stays removed from the climate system [18]. These differences, coupled with current uncertainties in the environmental and ecosystem impacts, co-benefits and feedbacks of each approach, make it hard to quantitatively and consistently compare between CDR strategies. As such, it has not yet been thoroughly quantitatively assessed whether the benefits in terms of climate change-related damages avoided of CDR strategies exceeds their cost at current reported prices and storage timescales, or what cost is required for CDR strategies with a given storage timescale to provide net benefits and how these depend on socioeconomic assumptions.

One of the simplest ways to achieve this is to assess the benefit-cost ratio (R, dimensionless) of different CDR strategies, where the benefit is the climate change damages avoided by deployment of that technique and the cost is P. The benefit-cost ratio can then be determined through integrated assessment modelling, factoring in both P and T. Other factors, such as the cost required to develop the CDR strategy to maturity, and the potential for environmental co-benefits, can also be incorporated in these evaluations and may be highly influential in determining their ability to be applied at climatically significant scales, though here we primarily focus on P and T.

In this study we first estimate and evaluate the benefit-cost ratios of the 58 CDR strategies that have reported prices and storage timescales within the open-access Carbon Plan CDR database [19]. We then establish the dependency of the benefit-cost ratio on each of these quantities, and determine at what price a given CDR strategy must be to provide net benefits (i.e. $R > 1$) under various socioeconomic assumptions (i.e. different levels of investment into the CDR strategy, discount rates, emissions scenarios, and damage functions). We use a simple climate model widely used in integrated assessment modelling [20] with parameters calibrated to mimic the response of more complex Earth system models (see methods), using a large ensemble of parameter combinations to quantify uncertainty related to the climate system's response to anthropogenic forcing. Under different Shared Socioeconomic Pathways (SSPs), we input a trillion dollars towards different CDR strategies with reported prices and storage timescales, and calculate the associated reduction in global average temperature over time. We then translate this to benefits, i.e. climate change damages avoided, under different assumptions of damages per degree of global warming and discount rates downweighting future damages relative to the present day. R is specified in terms of trillions of dollars of benefits per trillion of input cost, but is insensitive to the cost input (methods). For our first analysis, we do this for the 58 CDR strategies reported in the carbonplan database [19]; four our second analysis we do the same for a suite of hypothetical T-P pairs (with each variable ranging from 3–300) to determine the price at which $R > 1$ for different T values under different socioeconomic assumptions. The Carbon Plan CDR database attempts to be a fairly representative sample cataloguing a diverse range of CDR strategies, including geological, terrestrial and oceanic reservoirs such as DACCS, BECCS, reforestation, ocean alkalinity enhancement, and ocean biomass burial. However, our analysis is intentionally completely agnostic to the mechanism or type of CDR; we do not favour any particular CDR strategy over another or attempt to determine which approaches are most promising, because all CDR strategies are the subject of active research whose price and storage timescales are expected to improve in future, and because their implementation potential ultimately depends on many other factors outside of P and T. We also take the price and storage timescale values reported in the Carbon Plan CDR database at the time of access at face value; in all instances these may be optimistically estimated and must be rigorously and independently evaluated.

CDR strategies can be separated into two categories based on their storage timescale. For CDR strategies with long storage times (roughly >500 years, or much longer than the inverse of the discount rate one uses), the benefit-cost ratio effectively becomes a question of the social cost of carbon (SCC [$]) [21], with $R \approx SCC/P$ (note R is specified as the benefit per unit cost). We specifically define the social cost of carbon here as the additional (or avoided) climate change damages over time associated with the emission (or removal) of a ton of CO_2 from the atmosphere in the present day (methods). We find that for these CDR strategies, storage timescale is not quantitatively important. As expected the dependency of R on T is sufficiently weak

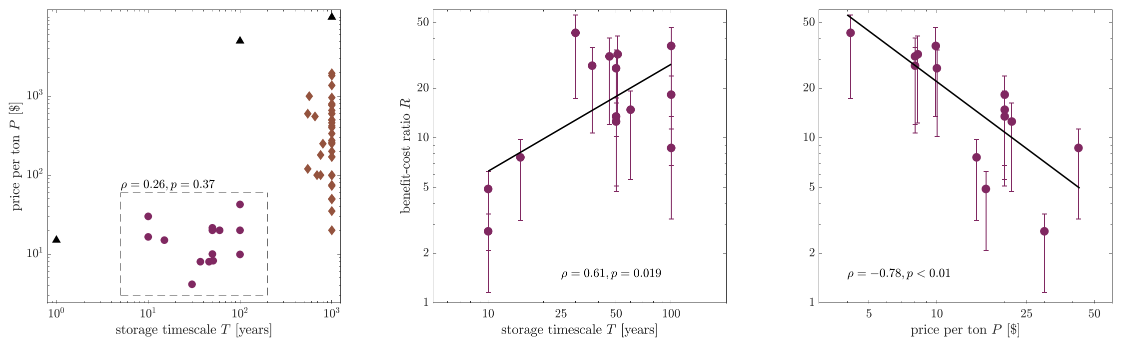

Figure 1. Left: Price [P, USD, \$] per ton of CO_2 sequestered versus storage timescale [T, years] for 58 CDR strategies [19] with high-T (orange diamonds), low-T or high-P (black triangles), or low-P and intermediate-T (purple circles). Rank correlation and p-value for purple points is given. Center/Right: Benefit-cost ratio R [dimensionless] for each CDR strategy, with 66% confidence intervals, versus T/P (center/right). Rank correlation and p-value are given; regression line is superimposed. R values are for baseline case: SSP2-4.5, \$1 Trn input, 2% discount rate, and median damage function.

that the benefit-cost ratio for these CDR strategies only depends on their price and the factors that one uses to estimate the SCC; one can simply consider $R = SCC/P$, and ignore any influence of T. In contrast, for CDR strategies with short or intermediate storage times (roughly $T < 500$ years, or on the same order as or shorter than the inverse of the discount rate one uses) the question is more complicated and requires consideration of the storage timescale. This is intuitive; for two equally-priced CDR strategies, one with $T = 10$ years and the other with $T = 100$ years, one would expect greater benefits from the latter for the same input cost. For different CDR strategies, these two quantities are not simply related; for instance, for 14 CDR strategies with $2 < T < 500$ years and $P <$\$1000 in figure 1 (left panel), P and T are not significantly correlated.

On the whole we find that in our baseline scenario (SSP2-4.5 control with a middle-of-the-road 2% discount rate [21] and damage function [22]), all of the CDR strategies in the dashed box in figure 1 (left panel) have an R significantly greater than one with 95% confidence. (For the black points in the left panel of figure 1, $R < 1$, and for the orange points, $R > 1$ if and only if $P < SCC$, as expected.) Though as noted above here we are intentionally agnostic to CDR strategy, the CDR strategies within the dashed box in figure 1 are predominantly land-use- and biomass-manufacturing-based.) Note that SSP2-4.5 and other SSPs incorporate significant emissions reductions; throughout this manuscript evaluated CDR impacts are imposed on top of these emissions reductions and thus CDR strategies are evaluated in terms of their benefits in addition to emissions reductions, rather than in place of emissions reductions. For all but two of the CDR strategies in the dashed box in figure 1, that R is significantly greater than one is robust to modest variations in the discount rate and different damage function assumptions, as well as SSP scenario. However, figure 1 shows there is a wide range in R across these CDR strategies. Unsurprisingly, R is inversely and significantly related to P, but we also find that R increases significantly with T, largely due to decadal-storage-timescale CDR strategies having R values in the single digits and centennial-storage-timescale CDR strategies having R values by and large in the double digits. We also find substantial uncertainty in R related to uncertainty in the parameters of the equations used to calculate the climate system's response to anthropogenic forcing. On the whole, these results suggest that even at current reported values of price and storage timescale, these CDR strategies likely provide net benefit to society. This underscores the potential of CDR to mitigate climate change damages, especially as prices are expected to decrease in the future due to technological advances. At the same time, the huge variation in benefit-cost ratios between strategies, and the dependence of this ratio on storage timescale as well as cost, underscores the importance of considering different CDR strategies carefully.

We perform the same analysis on a grid of price–storage timescale pairs for hypothetical CDR strategies, and identify the price for each storage timescale where $R = 1$ under various socioeconomic assumptions (figure 2, top). For storage timescales below roughly 50 years, the price where $R = 1$ varies strongly with storage timescale, e.g. corresponding to $P =$ \$11 for $T = 5$ years but $P =$ \$21 for $T = 10$ years for the baseline case. Even above 50 years, the price where $R = 1$ varies appreciably with storage timescale, asymptoting to the social cost of carbon for infinite storage times. This $R = 1$ curve also depends intuitively on socioeconomic assumptions. A more optimistic damage function, higher discount rate, lower confidence level, or lower emissions scenario all reduce the price at which $R = 1$ for a given storage timescale, with the opposite changes to assumptions correspondingly increasing the price. The variations in the location of this $R = 1$ curve, however,

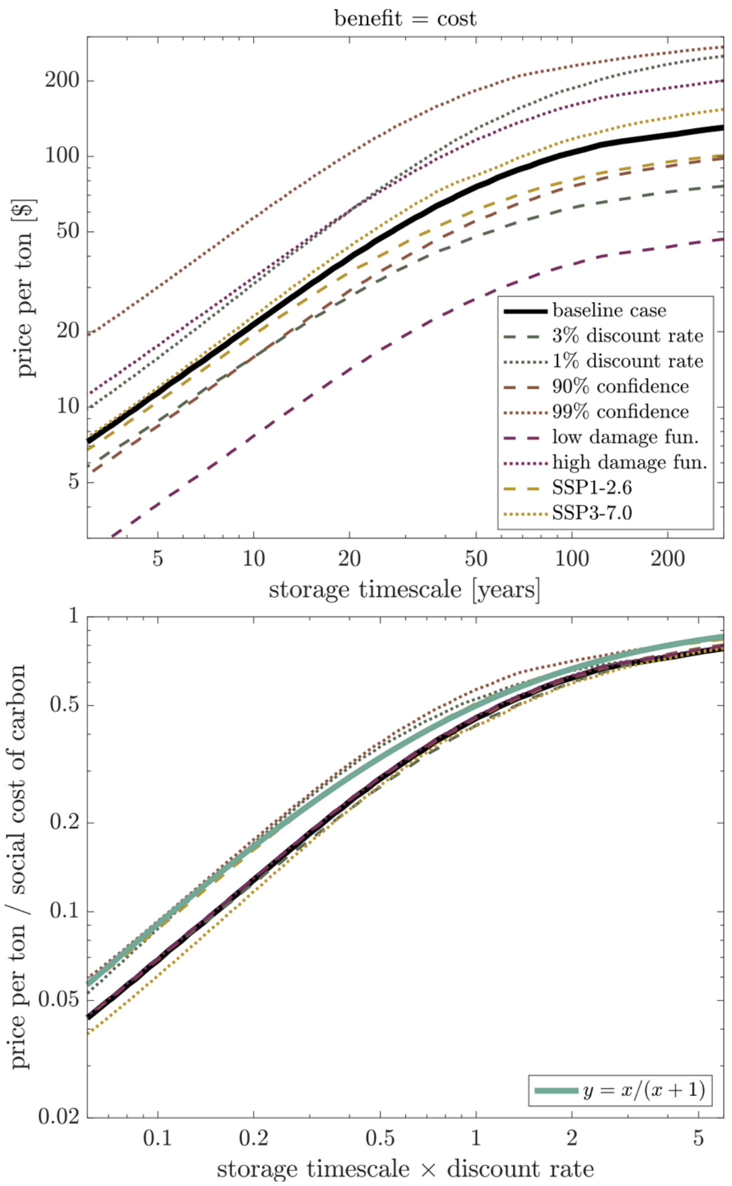

Figure 2. Top: Contour in storage timescale–price ($T-P$) space where benefit-cost ratio (R) equals one with 95% confidence. Black line is for baseline case; coloured and dashed/dotted lines indicate effect of changing assumptions. Changing input size from \$1 Trn to \$10 Trn or \$100 Bn results in a change smaller than the black line thickness. Bottom: Same but for price normalised by the social cost of carbon (P/SCC) and the storage timescale normalised by the discount rate, and with an approximate equation superimposed (solid teal line).

are determined to a large extent by how the different assumptions affect the social cost of carbon *SCC*, and to some extent by the discount rate (outside of its influence on *SCC*). When these curves are normalised to their respective *SCC* percentiles and discount rates (figure 2, bottom—e.g. in the baseline case P is divided by the 95th percentile of *SCC* calculated under SSP2–4.5 with a 2% discount rate and middle-of-the-road damage function [22], and T is multiplied by the 2% discount rate), they roughly collapse onto a single curve, which is well-approximated by the function $y = x/(x+1)$. This ensures $P/SCC \to 1$ for $T \to \infty$. This suggests that regardless of the assumptions one makes to calculate the *SCC*, the minimum price for a CDR strategy to have $R \geqslant 1$ can be well-approximated as a simple function of that CDR strategy's storage timescale and the *SCC* and discount rate. Note that this result is robust to larger variations in the discount rate—scenarios using a 0.1% or 5% discount rates, or a damage function equal to half of the lower damage function or twice the high damage function we use, all collapse along the same curve in the bottom panel of figure 2. This makes the result in the bottom panel of figure 2 particularly significant because there is substantial uncertainty in and argument over both the damage function and discount rate in the literature, and figure 2 shows that one can account for the effect of storage timescale on the benefit-cost ratio of a CDR strategy independently of one's socioeconomic assumptions.

Our analysis provides a coherent and consistent way to assess and compare CDR strategies quantitatively. This approach can be modified to match different socioeconomic assumptions, to evaluate portfolios of multiple CDR strategies, and can be made more sophisticated to capture other effects of CDR strategies such as their environmental co-benefits or impacts. Our calculations support assertions that the storage timescale of CDR strategies is an important aspect to consider alongside their prices, and moreover that these two aspects do not have to be considered in isolation from one another. We have also found indicative prices corresponding to conditions under which CDR strategies with different storage timescales are economically viable, which can help guide and support future CDR research and policy development. It is particularly important to note there are other important aspects to consider in evaluating CDR. Many other aspects also need to be considered when evaluating CDR strategies, such as environmental co-benefits, geospatial constraints, and other sociopolitical factors. Our analysis could beneficially be expanded to include such factors, for instance by adding the estimated monetary value of an environmental co-benefit of a given CDR strategy and adding it to the climate change damages avoided in that CDR strategy's benefit-cost ratio. Other factors that are harder to quantify economically such as governance and public perception will also affect implementation potential, but are still being investigated for most CDR strategies so have not been included into our analyses here. Including such factors in a quantitative analysis like we have presented here will be particularly important in identifying an optimal mixture of CDR strategies that balances costs, co-benefits, and constraints, e.g. by placing an additional cost or cap on reforestation above a realistic limit to areal coverage. Future work should incorporate these additional factors into CDR evaluation to identify the trade-offs and recommended distribution of CDR investment to produce sufficient overall atmospheric CO_2 removal with minimal costs—financial and otherwise—and maximal co-benefits.

Methods

We rely on the widely-used two-layer model [23–25] to simulate the climate system response to anthropogenic forcing:

$$c\,\mathrm{d}T/\mathrm{d}t = F + \lambda T - \gamma\,(T - T_D)\,,$$
$$c_D\,\mathrm{d}T_D/\mathrm{d}t = \gamma\,(T - T_D) \quad (1)$$

where T [K] is the Earth's global mean surface temperature, F (W m^{-2}) is anthropogenic radiative forcing, c J(m^{2}K)$^{-1}$ is the heat capacity of the surface layer represented by T, λ W(m^{2}K)$^{-1}$ is the climate feedback, and T_D [K] is the temperature of a deep ocean layer with heat capacity c_D J(m^{2}K)$^{-1}$ and with which the surface layer mixes heat diffusively at a rate determined by the mixing coefficient γ W(m^{2}K)$^{-1}$. This physical model is widely used in integrated assessment modelling [20]. Note that the inclusion or exclusion of an 'efficacy' term ϵ [26] does not affect our results and is only a question of parameter definitions. To quantify uncertainty in the response of the climate system to different forcing scenarios, we generate an ensemble of 10 000 parameter quadruplets $(c, c_D, \lambda, \gamma)$ by taking the parameter estimates of this model tuned to match the response of 30 CMIP6 Earth system models (https://github.com/mark-ringer/cmip6, accessed 14 November 2022), estimating the mean and covariance properties of the parameters from the mean and covariance of these 30 parameter combinations, and sampling 10 000 parameter combinations from a multivariate Gaussian distribution with the same mean and covariance. Using the CMIP5 model parameter estimates in [27] did not change our conclusions. Note either CMIP ensemble is a limited representation of climatic uncertainty, especially given that the likelihood of high-risk low-probability events disproportionately affects climate-economic calculations [28]; structural uncertainty may also be an appreciable factor in total economic uncertainty [29]. These uncertainty estimates are thus conservative, but are reflective of the usual sources of climate system uncertainty included in such calculations.

We take our control F and CO_2 emissions and concentration time-series from the Reduced Complexity Model Intercomparison Project [30]. We use SSP2-4.5 as our baseline scenario, but perform the same calculations for SSP1-2.6 and SSP3-7.0 to explore the sensitivity of our results to SSP scenario. We find non-CO_2 radiative forcing in each case by subtracting the CO_2 forcing from the total F, and add these forcings to all CO_2 forcing in all cases without further alteration. We relate CO_2 concentrations to forcing by fitting the forcing ϕ vs. concentration κ values from all scenarios and years with functions of the form $\phi = p_1\kappa^{p_2} - p_3$, which results for CO_2 in an $r^2 > 0.9999$ and a root-mean-square-error of <0.0025 W m^{-2}. We then generate CO_2 concentration time-series based on different emissions pathways, and translate these into total F. For all CO_2-reduction scenarios, from these emission and concentration time-series we compute the fraction of cumulative emitted CO_2 that remains in the atmosphere as a function of time $f(t)$ under each SSP, and assume that this does not change with adjustments to total CO_2 emissions. In other words, if 50% of cumulative emitted CO_2 is in the atmosphere at a certain year for a certain SSP, reducing the CO_2 emissions in that year by 1PgCO_2 will result in 0.5PgCO_2 less CO_2 in the atmosphere. This assumption is justified by the fact that we are interested in perturbations to total overall emissions small enough not to appreciably change the air-sea-land-balance of anthropogenic carbon.

For each CO_2 concentration time-series, we use either a control or an input of $1 Trn [USD] to each CDR strategy. We assess sensitivity to this input size by performing the same calculations with $10 Trn and $100 Bn. While some diminishing returns effects occur in the $10 Trn case for long-storage-timescale-low-cost CDR strategy due to the nonlinearity of the damage function, on the whole changes to the input size result in a negligible difference to the calculated benefit-cost ratios in the parameter range of interest and are not discussed further. For figure 1(a) we plot 58 CDR strategy price per ton P [$] and storage timescale T [years] from https://carbonplan.org/research/cdr-database (accessed 14 November 2022). CDR strategies with T from 3–300 years and $P < 300$$ are considered further here; others are too expensive or short-lived to be considered comparatively economically viable, or have storage timescales $T \geqslant 500$ years, such that their economic viability is effectively just a question of whether P is less than the social cost of carbon. We also generate an artificial grid of CDR strategies for figure 2, by generating a 32-by-32 grid of P–T values logarithmically spaced from 3 to 300 in both dollars and years. For each reported or artificial CDR strategy and each SSP, we (i) subtract $1 Trn/$P$ from CO_2 emissions in 2021, (ii) release this CO_2 to the climate system thereafter according to simple exponential decay of the reservoir of stored CO_2 with timescale T, (iii) partition $f(t)$ of this previously stored CO_2 into the atmosphere, (iv) determine the difference in CO_2 in the atmosphere each year in this case versus the baseline SSP scenario, and (v) subtract this difference from the baseline SSP scenario's atmospheric CO_2 concentration. These concentrations are then converted into F time-series, and equation (1) is then forced with these F time-series to determine $T(t)$. F time-series start at 1750 and we initialise equation (1) with $T(1750) = T_D(1750) = 0$.

For the economic calculations, we use a 2020 global purchasing-power-parity-adjusted global domestic product of 85 trillion USD as reported by the World Bank [31]. We use a baseline discount rate $r = 2\%$ as in [21]; we also assess sensitivity to discount rate by performing the same calculations with $r = 1\%$ and $r = 3\%$. We use the damage function that the percentage of global gross domestic product lost as damages to climate change D [%] is equal to $D = 0.7438T^2$ [22], which was identified as the preferred model for non-catastrophic damages via meta-analysis; it is also the median damage function, over 0 °C–6 °C, of the damage functions considered in said meta-analysis [22]. We also assess sensitivity to damage function by performing the same calculations with higher and lower damage functions of $D = 1.145T^2$ and $D = 0.267T^2$ [22] from the same meta-analysis, which correspond respectively to including catastrophic damages and productivity loss or to more optimistic assumptions about the nature of climate change impacts on the global economy. In each scenario the period used to calculated the social cost of carbon is from present day to 2500. For a given damage function, discount rate, and emissions scenario, the social cost of carbon is calculated by first estimating the cumulative, discount-rate-weighted climate change damages over this time period, then calculating the same for an emission scenario with a permanent and instantaneous removal of 1 billion tons of CO_2 from the atmosphere in the present day superimposed, then taking the difference between these two scenarios' damage calculations and dividing this difference by 1 billion tons. This calculation is not meaningfully affected by the magnitude or sign of the perturbation imposed on the present day.

Data availability statements

No new data were created or analysed in this study.

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Author contributions

Cael led all aspects of the study; Goodwin and Stainforth contributed guidance on modeling and supported writing; Pearce contributed guidance on CDR approaches and supported writing.

Conflict of interest

The authors have no competing interests to declare.

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