Benefit-cost ratios of CO_2 removal strategies

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Keywords: Climate change | Negative emissions technologies | Carbon dioxide removal | Net zero

This paper is a non-peer reviewed preprint submitted to EarthArXiv.

Abstract

Limiting global warming to 1.5°C will very likely require, or to 2°C may require, large-scale removal of carbon dioxide (CO_2) from the atmosphere. Many CO_2 removal strategies (CDRSs), or negative emissions technologies, 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. It has not yet been assessed whether the benefits, in terms of climate change-related damages avoided, of CDRSs' deployment exceed their costs at current reported prices and storage timescales, nor what cost is required for a CDRS with a given storage timescale to provide net benefits, nor how these depend on socioeconomic assumptions. For a long-storage-timescale CDRS, these questions reduce to whether its price is lower than the social cost of carbon, but for CDRSs with shorter storage timescales, they may also depend on its storage timescale. We show that for CDRSs with reported storage timescales from decades to centuries, the benefits of their deployment outweigh their reported costs under middle-of-the-road socioeconomic assumptions. For some, their benefits still outweigh their costs under optimistic socioeconomic assumptions. These CDRSs' associated benefit-cost ratios vary by more than an order of magnitude, and are strongly influenced by both price and storage timescale. The price threshold where a CDRS yields net benefits depends strongly on storage timescale, particularly for storage timescales ≤50 years. Our results provide a framework to assess and compare different CDRSs quantitatively for future CDRSs research, development, and policy.

Under the Paris agreement, in order to avoid some of the more catastrophic consequences of climate change [1], 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" [2]. It is increasingly recognised that achieving this goal given current temperatures and greenhouse gas emissions will require substantial carbon dioxide (CO_2) removal from the atmosphere [3, 4]. (Solar radiation management is an alternative approach,

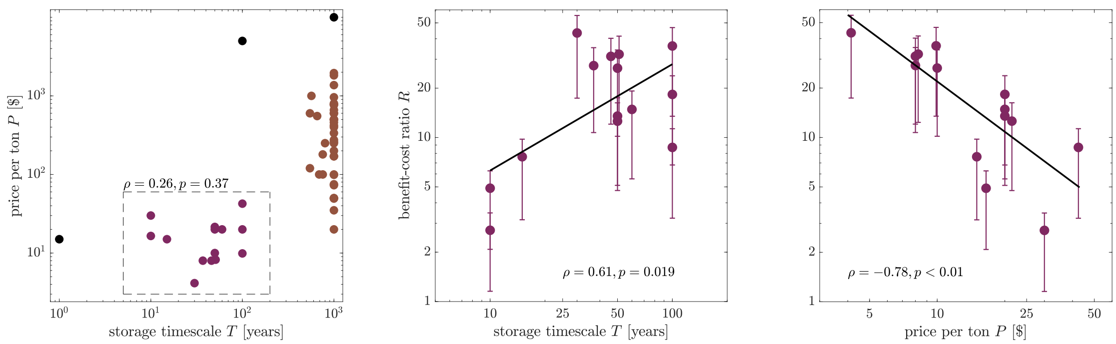

Figure 1: Left: Price [P, USD, $] per ton of CO_2 sequestered versus storage timescale [T, years] for 58 CDRSs (`https://carbonplan.org/research/cdr-database`, accessed 14.11.2022) with high-T (orange), low-T or high-P (black), or low-P and intermediate-T (purple). Rank correlation and p-value for purple points is given. Center/Right: Benefit-cost ratio R [dimensionless] for each CDRS, 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, $1Trn input, 2% discount rate, and median damage function.

which will not be discussed further here.) This has lead to an explosion of research and development of CO_2 removal strategies (CDRSs), with the hope of reducing corporations' carbon tax burden, offsetting other activities which are difficult to decarbonise, or removing previously emitted CO_2. These CDRSs employ a wide variety of mechanisms, such as habitat restoration, ocean alkalinity enhancement or fertilization, enhanced weathering, or direct air capture and storage, to name a few; they also vary greatly in terms of scalability and maturity [3, 4]. Crucially, they also vary a great deal in terms of their price per ton of CO_2 removed (P [USD, or $]) and in the storage timescale (T [years]) over which that carbon stays removed from the climate system. There is a general consensus that a mixture of different approaches will be necessary, with no one approach being far and above preferable to the rest [3, 4]. Therefore, in order to generate optimal climate mitigation policies and to spur CDRS research and development, there is a need for a way in which different CDRS can be evaluated and compared quantitatively and consistently.

A natural way in which to do so is in terms of a CDRS' benefit-cost ratio (R, dimensionless), with its benefit being the climate change damages avoided by its deployment and its cost being P. This ratio can be determined through integrated assessment modelling, factoring in both P and T. Other factors such as the cost required to scale up or to develop a CDRS to maturity, or the co-benefits of a given CDRS, can also be incorporated, though the primary aspects to consider will be P and T, which we focus on here. For CDRS with long storage times (i.e. much longer than the inverse of the discount rate), the benefit-cost ratio effectively becomes a question of the social cost of carbon (SCC [$]) [5], with $R \approx SCC/P$. (Here R is specified as the benefit per unit cost.) For CDRSs with short or intermediate storage times (roughly $T < 500$ years), however, the question is more complicated and requires consideration of the storage timescale. For example, for two equally-priced CDRSs, 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 CDRSs, these two quantities are not simply related; for instance, for 14 CDRSs with $2 < T < 500$ years and $P <$ $1000 in Figure 1 (left panel), P and T are not significantly correlated.

Here we estimate the benefit-cost ratios of CDRSs with reported prices and storage timescales, estimate the dependency of the benefit-cost ratio on each of these quantities, and at what price a CDRS must be to provide net benefits (i.e. $R > 1$) under various socioeconomic assumptions. We use a simple climate model widely used in integrated assessment modelling [6] with parameters calibrated to mimic the response of more complex Earth System Models (see Methods in Supporting Information, SI), 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 CDRSs 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 down-weighting 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 (SI). We do this both for reported CDRSs – specifically 58 CDRSs' reported price per ton P [\$] and storage timescale T [years] from `https://carbonplan.org/research/cdr-database` – to evaluate these, and 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. Note that our analysis is intentionally completely agnostic to the mechanism or type of CDRS; we do not favor any particular CDRS over another or attempt to determine which CDRS are most promising, because all CDRS are subjects of active research whose price and storage timescales are expected to improve in future. Note also that we take reported values for price and storage timescale at face value; in all instances these may be optimistically estimated and must be rigorously and independently evaluated.

On the whole we find that in our baseline scenario (SSP2-4.5 control with a middle-of-the-road 2% discount rate [5] and damage function [7]), all of the CDRSs 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.) Note that SSP2-4.5 and other SSPs incorporate significant emissions reductions; throughout this manuscript evaluated CDRSs' impacts are imposed on top of these emissions reductions and thus CDRSs are 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 CDRSs in the dashed box in Figure 1, that R is significantly greater than one is robust to different damage function and discount rate assumptions, as well as SSP scenario. However, across these CDRSs, Figure 1 shows there is a wide range in R. 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 CDRSs having R values in the single digits and centennial-storage-timescale CDRSs 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 CDRSs likely provide net benefit to society. This underscores the potential of CDRSs 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 CDRSs carefully.

We perform the same analysis on a grid of price–storage timescale pairs for hypothetical CDRSs, 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, 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 normalized 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 [7], 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 CDRS to have $R \geq 1$ can be well-approximated as a simple function of that CDRS' storage timescale and the SCC and discount rate.

Altogether our analysis provides a coherent and consistent way to assess and compare carbon dioxide removal strategies and mixtures thereof quantitatively. This approach can be modified to match different socioeconomic assumptions, and can be made more sophisticated to capture the more holistic effects of such strategies such as their co-benefits. Our calculations suggest that the storage timescale of such 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 found indicative prices corresponding to conditions under which carbon dioxide removal strategies with different storage timescales are economically viable, with potential uses in carbon dioxide removal research, development, and policy.

For Materials and Methods, see SI.

Author Contributions: Cael lead and Goodwin and Stainforth assisted with all aspects of this study.

Conflicts: The authors have no competing interests to declare.

Acknowledgments: Cael acknowledges support from the National Environmental Research Council through Enhancing Climate Observations, Models and Data, and the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No. 820989 (project COMFORT). The work reflects only the authors' view; the European Commission and their executive agency are not responsible for any use that may be made of the information the work contains. Stainforth acknowledges support from the Grantham Research Institute on Climate Change and the

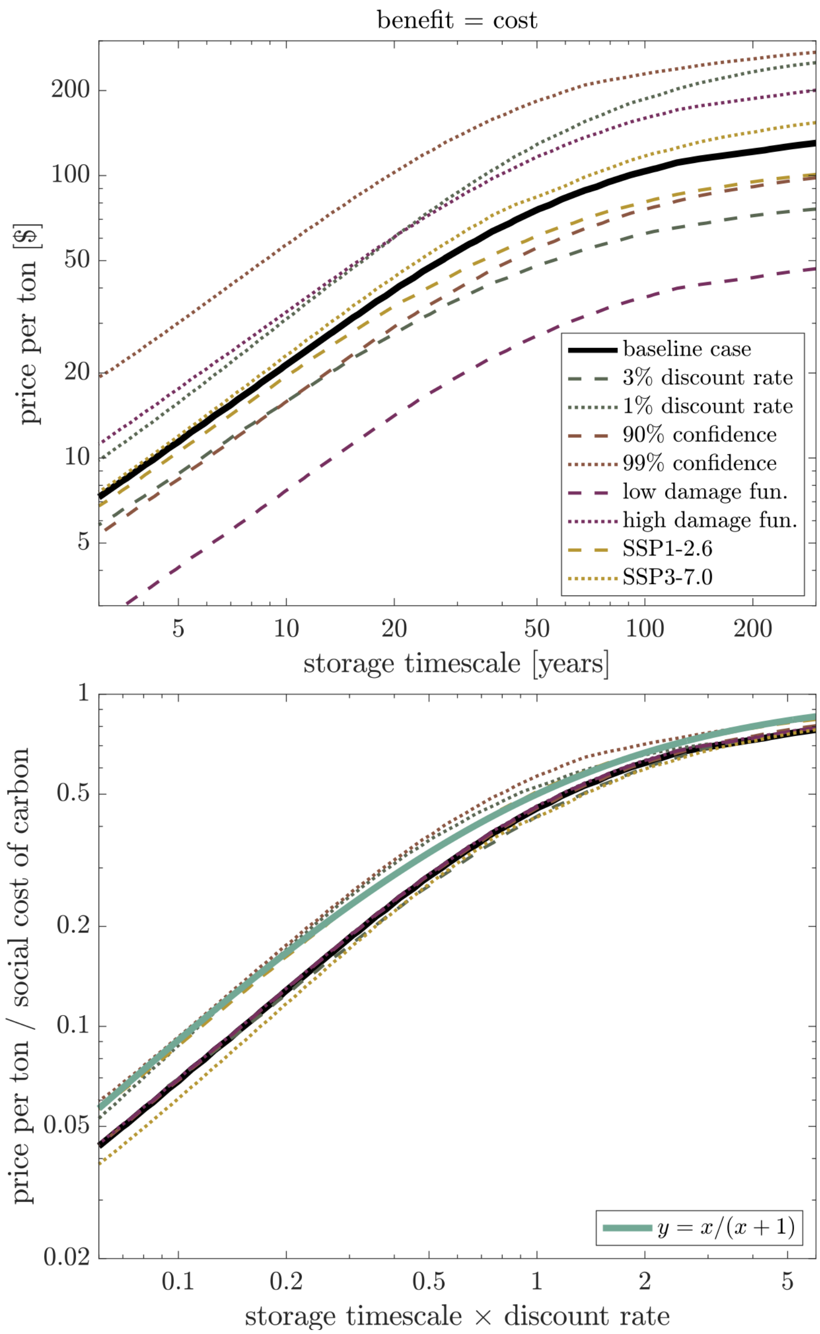

Figure 2: Top: Contour in storage timescale–price ($T - P$) space where benefit-cost ratio (R) equals one with 95% confidence. Black line is for baseline case; colored and dashed/dotted lines indicate effect of changing assumptions. Changing input size from \$1Trn to \$10Trn or \$100Bn results in a change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

Environment at the London School of Economics, and the Natural Environment Research Council through Optimising the Design of Ensembles to Support Science and Society (ODESSS; ref NE/V011790/1). Data are available from sources cited in the text.

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Supporting Information Text

Materials and Methods

We rely on the widely-used two-layer model (1–3) to simulate the climate system response to anthropogenic forcing:

$$c\ dT/dt = F + \lambda T - \gamma(T - T_D), \qquad c_D\ dT_D/dt = \gamma(T - T_D) \tag{1}$$

where T [K] is the Earth's global mean surface temperature, F [W/m^2] is anthropogenic radiative forcing, c [J/m^{2}K] is the heat capacity of the surface layer represented by T, λ [W/m^{2}K] 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] and with which the surface layer mixes heat diffusively at a rate determined by the mixing coefficient γ [W/m^{2}K]. This physical model is widely used in integrated assessment modelling (4). Note that the inclusion or exclusion of an 'efficacy' term ϵ (5) 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 14.11.2022), 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 (6) 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 (7); structural uncertainty may also be an appreciable factor in total economic uncertainty (8). 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 (9). 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 \$1Trn [USD] to each CDRS. We assess sensitivity to this input size by performing the same calculations with \$10Trn and \$100Bn. While some diminishing returns effects occur in the \$10Trn case for long-storage-timescale-low-cost CDRSs 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 1a we plot 58 CDRSs' price per ton P [\$] and storage timescale T [years] from https://carbonplan.org/research/cdr-database (accessed 14.11.2022). CDRSs 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 $T \geq 500$ 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 CDRSs 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 CDRS and each SSP, we i) subtract \$1Trn/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 Eq. 1 is then forced with these F time-series to determine $T(t)$. F time-series start at 1750 and we initialize Eq. 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 (https://data.worldbank.org/indicator/NY.GDP.MKTP.CD, accessed 14.11.2022). We use a baseline discount rate $r = 2\%$ as in (10); 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 $D = 0.7438T^2$. This was identified as the preferred model for non-catastrophic damages in a meta-analysis (11); it is also the median damage function, over 0-6°C, of the damage functions considered therein. We also assess sensitivity to damage function by performing the same calculations with higher and lower damage functions of $D = 1.145T^2$ and $D = 0.267T^2$ 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.

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