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LETTER

Deep uncertainty in carbon dioxide removal portfolios

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Abstract

Deep uncertainty about the costs and resource limits of carbon dioxide removal (CDR) options challenges the design of robust portfolios. To address this, we here introduce the CDR sustainable portfolios with endogenous cost model, a mixed-integer linear optimization model for cost-optimal and time-dependent CDR portfolios including endogenous treatment of technology cost dynamics. We explore future uncertainty in three key dimensions: realisable mitigation potentials, cost dynamics, and resource constraints. Our results demonstrate that afforestation and reforestation, and soil carbon sequestration appear as robust options, deployed regardless of the removals required. Direct air carbon capture and storage emerges as the most deployed technology in 2100 at median value (6.7 GtCO2 yr^{-1}), but with the widest range of possible outcomes (interquartile range from 4 to 8.7 GtCO2 yr^{-1}) depending largely on future renewable energy capacity and annual geological storage injection rates. Bioenergy with CCS deployment remains severely constrained by available land, as the median falls from 1.8 to 0.3 GtCO2 yr^{-1} in land-constrained scenarios, but gains portfolio share when future energy availability is bounded. Our simulations also reveal that ocean alkalinisation could become a dominant solution in high removal scenarios. Evaluating the performance of portfolios beyond economic costs, we also provide a framework to explore trade-offs across different aspects relevant to planetary boundaries.

1. Introduction

Limiting global warming to well below 2 °C, following the Paris Agreement, requires rapid and deep greenhouse gas emission reductions as well as atmospheric carbon dioxide removal (CDR) [1–4]. CDR may play a key role to accelerate the timing at which net-zero emissions are reached, to counterbalance non-abated emissions that remain after deep decarbonisation efforts, and to provide net-negative emissions to compensate for overshooting of climate targets [5–7].

Removing atmospheric carbon dioxide (CO_2) and storing it from decades to millennia can be achieved through different methods that differ in their capture mechanism, storage medium and permanence. Often discussed CDR options also have different levels of readiness, achievable potential, social acceptance and impacts on ecosystems [8–10]. Competition for physical resources such as land [11], water, energy and nutrients, related sustainability constraints, but also diverse associated side effects [12], novelty, and patterns of deployment [13, 14] imply that meeting the cumulative amount of CDR required to limit global warming while hedging for risks will thus most likely be realised through a portfolio of CDR options rather than through a single silver-bullet solution.

The composition of an optimal CDR portfolio delivering required removals within sustainability

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limits will depend on available resources, technologies and preferences, and will change over time. However, uncertainty emerging from the nascence and system complexity of CDR pathways poses significant challenges to their integration in climate policy making processes [9, 15, 16]. A situation of *deep uncertainty* exists when experts or stakeholders do not know or cannot agree on: (i) appropriate conceptual models that describe relationships among key driving forces in a system, (ii) the probability distributions used to represent uncertainty about key variables and parameters, and/or (iii) how to weigh and value desirable alternative outcomes [17].

For the case of CDR pathways, the substantive multi-gigatonne scales and rates of diffusion of CDR implied in climate scenarios [18] have not been echoed neither by the climate change mitigation strategies of countries [19] nor in the private innovation sphere [20]. The upscaling of CDR is also contingent on a plethora of techno-economic, environmental, and socio-political, legal and ethical uncertainties, including but not limited to: the durability of the sequestered carbon under a changing climate [21, 22], the socio-political, legal and ethical challenges to CDR deployment arising due to overlapping systems [23, 24], or how to monitor, report and verify removals [25]. These pose substantial limitations on what can be known about policy-relevant questions regarding the deployment of CDR options, which thus represents a clear case of deep uncertainty.

CDR technologies and practices have been explored mostly in either technology-specific studies or integrated assessment modelling (IAM), which often rely on a limited set of CDR options [26, 27], with the notable exception of two recent studies that each use an IAM to evaluate the implications and trade-offs of deploying over 4 CDR methods [28, 29] (supplementary information (SI) table S1). Previous literature also has attempted to assess CDR portfolios through a multi-criteria decision analysis [30, 31] and through cost-optimisation methods [32–34], and only a few studies attempt to explicitly consider uncertainty in CDR deployment [35, 36]. What is missing is a systematic exploration of the uncertainty pervading CDR deployment and the extent to which it shapes the composition of an optimal CDR portfolio that sustainably meets climate targets.

Previous literature has also principally focused on the potential cost reductions achieved through technological learning [37–39], while increases in the cost of deploying CDR due to adverse sustainability consequences or societal factors such as public opposition have remained largely unexplored.

In this study, and drawing from tools for decision-making under deep uncertainty (DMDU), we address these issues by exploring how cost-optimal portfolios of CDR options vary when considering uncertainty about CDR cost dynamics, realisable mitigation potentials and the state of planetary boundaries [40] as a framework for identifying earth systems processes relevant to CDR. We do this by providing both a framework with which to characterise the variation of removal costs with deployment and a computational experimentation approach to characterise CDR deployment pathways under deep uncertainty. We developed the CDR sustainable portfolios with endogenous cost (CDR-SPEC) model to identify optimal CDR portfolios across a large set of plausible futures and compare their composition and performance to present the merits of different strategies. The resulting database contains detailed information about how varying combinations of uncertainty conditions trigger the implementation of different CDR portfolios, thus producing valuable data for identifying near-term trade-offs and developing long-term adaptive strategies.

2. Methods

2.1. Cost dynamics of CDR deployment

Experience curves relate the number of units produced or capacity installed of a given product (i.e. the gathered 'experience') to the efficiency of that production. They have been used to describe the dynamics of technological cost with deployment: salient examples are the cost reductions achieved with the deployment of renewable energy technologies [41], or the cost increases experienced by nuclear power plants [42–44]. We provide a first-of-a-kind conceptualisation of different drivers of both cost increases and reductions based on the literature focusing on cost dynamics (table S2).

Projecting future costs of CDR methods, a key metric for policy-making, is nevertheless challenging due to the early development phase of novel CDR technologies and the large scales of removals required, potentially leading to a new land-use paradigm with adverse sustainability consequences. Previously, the amount of capacity deployed for a CDR technology has been used to characterise the cost dynamics of CDR methods (e.g. see [37–39] for DACCS). We generalise this approach to evaluate both cost reductions and increases achieved from the deployment of CDR capacity. 'Experience' here refers to cumulative capacity installed and can therefore only increase with time, while 'installed capacity' can decrease at the end of its operational period.

Experience rates (ERs) and the shape of the experience curve vary between different technologies (refer to SI section 3). To characterise CDR cost dynamics, we here use the one-factor experience curve model to describe an exponential correlation between the unit cost of investing in CDR capacity SC ($\$/tCO_2 \cdot yr^{-1}$), and the cumulative experience achieved z ($tCO_2 \cdot yr^{-1}$). For each doubling of cumulative experience, investment unit costs reduce or increase by a factor ER for positive and negative ERs, respectively.

2.2. Uncertainty characterisation and data collection

Complexity inherent in dynamic, coupled social-ecological systems demands thinking about future uncertainty in terms of multiple plausible futures, rather than probability distributions [45, 46]. *Plausible* climate futures can be defined as 'occurable' under internally consistent assumptions[5] [47, 48], with *plausibility* being the guiding principle in the 'what-if' logic of climate scenarios [7, 49].

We identified parameters that represent key uncertainties in CDR pathways based on previous research that focuses on potential adverse sustainability and socio-economic consequences of CDR [9, 12, 50]. To define many future plausible states of the world (SOW), we use a Latin Hypercube to sample uniformly ($N = 3001$) across ranges within the 26 relevant uncertain parameters (supplementary table S15). These include the required cumulative (2020–2100) removals, the limits to land available and geological storage annual injection for CDR, the year from which energy becomes available for CDR (see supplementary table S3 and figure S4 for definition), the ER and maximum cumulative capacity of each of the 8 CDR options modelled, and the land and energy requirements of certain CDR options.

The eight CDR methods considered in this assessment include afforestation and reforestation (A/R), soil carbon sequestration (SCS), bioenergy with carbon capture and storage (BECCS), biochar (BC), direct air carbon capture and storage (DACCS), direct ocean carbon capture and storage (DOCCS), enhanced rock weathering (EW), ocean alkalinisation (OA). A summary of the parameterization of CDR methods is included in figure 1.

2.3. Model formulation

We here define the CDR-SPEC model, a mixed-integer linear optimization model for cost-optimal and time-dependent global CDR portfolios including endogenous treatment of technology cost dynamics. The model formulation is inspired by previous literature on energy system modelling that incorporates endogenous learning effects [52–54]. It minimises cumulative discounted costs for the entire time period (2020–2100) across all CDR methods. A discount rate of 3% was assumed [55]. Three categories of constraints define the model: system constraints (defining capacity balances), endogenous cost constraints (describe cost dynamics with cumulative deployed experience) and resource constraints (setting required removals and land, energy and geological storage limits)—see SI for detailed list of relevant assumptions and equations defining the model. Specifically on capacity balances, the model assumes that any capacity installed has a method-specific operational period during which it removes CO_2 that remains permanently stored (table S4). This strong assumption about storage durability neglects important permanence differences between CDR methods [56, 57] as well as the potential impacts of reversibility on tackling global warming and the amount of CDR required [58].

We designed the CDR-SPEC model to identify combinations of CDR methods that meet removal requirements within selected sustainability constraints under a set of assumptions regarding CDR deployment dynamics and views of the world. As such, it does not seek to represent complex interactions between the economy, society and the environment and cannot be compared with the results of a large-scale IAM. Despite their advantageous extensive coverage of physical and social systems, the large system complexity of IAMs challenges the traceability of implicit assumptions and the systematic evaluation of a plethora of plausible futures. The strength of our model is that it provides a framework which allows for the systematic exploration of a range of assumptions about future developments in a flexible and transparent fashion.

3. Results

Across the plausible future SOW evaluated, 8% were on average deemed infeasible by the model (see section 4 in SI). To better understand drivers of infeasibilities, machine learning techniques were used to explore the parameters that better explain whether a solution has been found for a future or not. These are, in order of relative importance: the amount of removals required, the maximum potential of BC, the limit to land available, and the starting year at which energy becomes available for CDR (figure S6 in SI).

3.1. Composition of CDR portfolios

Our results show that achieving high removals while respecting sustainability constraints requires a larger diversity of CDR options than currently explored (figure 1). This is especially true for very high removal requirements (>900 $GtCO_2$ by 2100), where all portfolios require on average the deployment of more than six different CDR options (see also figure 6(b).

Diversification is however not only required across technologies, but also across temporal scales: deploying A/R and SCS, followed by DACCS, BECCS and BC, is a robust short- to medium-term strategy (figure 2(a), see supplementary figure S8 for capacity installed by 2075). Despite being deployed in most SOW, the amount of CDR installed for these

[5] As pointed out by Jewell & Cherp [47], this diverges from a recent suggestion that defines *plausible futures* as those which empirical evidence about recent trends in key drivers and enabling conditions point to [68, 69]. While we acknowledge that assessing the social plausibility of climate futures is key for fostering climate action, we depart from this conceptualisation of *plausibility* because we aim to systematically explore the option space without ranking which future state of the world is more or less plausible to be realised.

	Afforestation & Reforestation	Soil Carbon Sequestration	BECCS	Biochar	DACCS	Direct Ocean CCS	Enhanced Weathering	Ocean Alkalinisation
Potential ($GtCO_2/yr$)	[2 6.3]	[0.6 2.5]	[0.7 12.6]	[0.5 6.6]	[5 20]	[1 10]	[2 4]	[1 15]
Initial Capacity (tCO_2/yr)	$1.98 \cdot 10^9$	1	$1.82 \cdot 10^6$	$0.5 \cdot 10^6$	$10 \cdot 10^3$	1	1	1
Experience Parameter	[-23% 2%]	[-23% -1%]	[-15% 15%]	[-5% 10%]	[5% 15%]	[5% 15%]	[-5% 5%]	[-5% 10%]
Initial Investment Cost ($/tCO_2 \cdot yr^{-1}$)	100	1	570	205	2000	2000 (at 10^4 tCO_2/yr)	215	465
Operational Costs ($/tCO_2$)	50	35	60	115	60	900	130	115
Land (ha/tCO_2)	[0.07 0.09]	0*	[0.04 0.17]	0*	$5.8 \cdot 10^{-5}$	$5.8 \cdot 10^{-5}$	0*	0*
Energy (GJ/tCO_2)	0**	0**	0**	0**	[4.7 10]	[2.5 8.3]	[0.07 12.5]	[0.7 6.8]
Lifetime (years)	55	20	20	25	25	25	10	10
Annual Max Deployment ($MtCO_2 \cdot yr^{-1}$)	80	1000	500	500	500	500	1000	1000

* Assumes no additional land requirements; ** Assumes no additional energy requirements

Figure 1. Overview of assessed CDR options, split into conventional and novel methods, as per characterisation in Smith *et al* [51]. Parameters with ranges rather than single values are shown in square brackets. Referenced information and descriptions of CDR options, as well as further details on the CDR selection criteria and the choice of parameters and values, can be found in supplementary information section 5 and tables S3–S14.

options greatly differs depending on future uncertainties. For instance, looking at BECCS deployment, it can be observed that the median capacity installed by 2100 is 1.8 $GtCO_2$ yr^{-1} despite the maximum available capacity being uniformly sampled from 0.7 to 12.6 $GtCO_2$ yr^{-1} (figure 1). This shows that even if this CDR option is deployed across many futures (figure S7), it is not often deployed to the large scales available in the modelling framework.

DACCS emerges as the dominant CDR option in 2100 (figure 2(b)), with a median of 6.7 $GtCO_2$ yr^{-1} maximum deployed capacity, but with a wide range of possible outcomes. It is followed, by large margin, by OA and by A/R, which is in turn a more robust option exhibiting a narrower interquartile range of deployed capacity. The most robust option is SCS.

Exploring the composition of portfolios that are repeated across futures for the two time periods shown in figure 2, we observe that the six most recurrent portfolios in 2050 rely on large amounts of BECCS and A/R and SCS, and to a lower extent on DACCS (figure S11). These recurrent short-term portfolios cover the whole range of possibly required removals (400–1100 $GtCO_2$ by 2100). This indicates that the short-term deployment of these four options would leave the door open to multiple possibilities and minimise the risk of not meeting future climate targets. However, this is not the case for long-term portfolios: the most recurrently repeated portfolios mainly cover the lower end of the removals range (400–900 $GtCO_2$), highlighting that optimal portfolios for 2100 highly depend on how key uncertainties unfold.

3.2. Drivers of adoption of CDR capacity

To better understand the drivers of adoption or barriers to deployment of each CDR option, we explore the uncertainty parameters that have the greatest impact on the maximum capacity installed per CDR option across futures (figure 3). In general, for most options, their own maximum available potential (i.e. the largest capacity that can be deployed in a future) is the key limiting constraint, with DACCS, EW and DOCCS being exceptions to this trend. The annual limit to geological injection dominates for DACCS, while for the case of EW, this can be explained by the narrow range of the sampled achievable potential (i.e. 2–4 $GtCO_2$ yr^{-1}, see figure 1), with variation in other factors having a larger relative importance. However, as DOCCS is only deployed in 2% of the futures (figure S7), several features score highly for this CDR option, resulting in no clear and reliable trend that can be identified for DOCCS.

In relative terms, the maximum available potential is more influential for some CDR than for others. For instance, modelled as requiring no additional energy or land, SCS deployment is almost exclusively driven by the maximum available capacity, with increasing costs with deployment (i.e. negative ER) not having a substantial effect in relative terms.

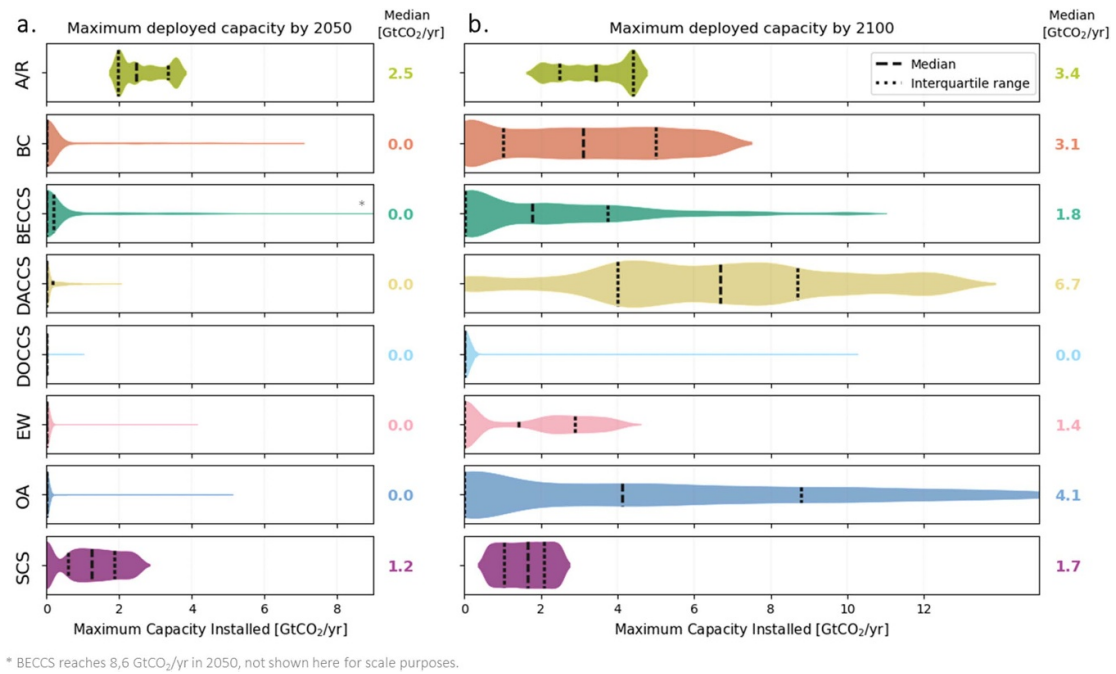

Figure 2. Distribution of maximum deployed capacity per CDR option for two different time periods, 2050 (a) and 2100 (b). *x*-axis: maximum $GtCO_2$ yr^{-1} installed per future in period of interest; *y*-axis: outcome distribution across $N = 2758$ solved futures. Vertical lines within distributions represent quartile ranges, *x*-axis scale is the same for both time periods. Abbreviations: afforestation and reforestation (A/R), soil carbon sequestration (SCS), bioenergy with carbon capture and storage (BECCS), biochar (BC), direct air carbon capture and storage (DACCS), direct ocean carbon capture and storage (DOCCS), enhanced rock weathering (EW), ocean alkalinisation (OA).

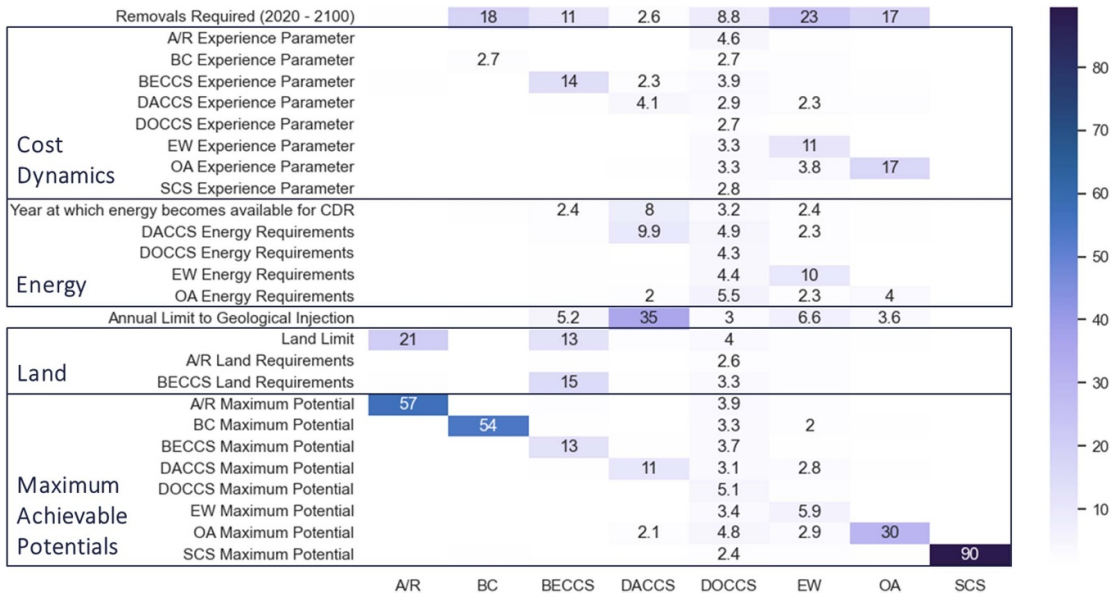

Figure 3. Feature scoring of maximum deployed capacity per CDR option. This machine learning technique identifies the uncertainty parameters (i.e. model inputs, in rows) that have the greatest impact on the maximum capacity deployed per CDR option (i.e. model outputs, in each column). Cells are coloured from white to dark blue, showing low-to-high importance. Values shown in percentages (%), only values above 2% are shown for better readability.

The amount of cumulative removals required across the entire time period is similarly a key driving factor of adoption. CDR options that are deployed in almost all futures (i.e. A/R, SCS, DACCS) are nevertheless relatively less affected by the amount of required removals, whereas EW, BC and OA are deployed at a greater extent depending on the removal target. The latter can be interpreted as these options being deployed to bridge the gap between the baseline removals delivered by robust near-term CDR options (figure 2(a)) and required removals. BECCS however does not follow the same trend, as

its deployment exhibits a strong relationship with required removals, despite being deployed in 75% of futures (see figure S7 in SI). This indicates that the magnitude of deployed capacity, and not whether BECCS is deployed or not, is sensitive to how much CDR is needed. Removals required is also the only distinctive feature scoring relatively high for DOCCS.

Regarding cost dynamics, ERs play a larger role in the deployment of certain CDR options (e.g. OA, BECCS, EW, and to a lesser extent DACCS) than for others. Similarly as observed for maximum achievable potential, EW's capacity is not only driven by its own ER but also how costly other technologies are, underlining the importance of a portfolio approach. It is worth noting that these results emphasise the *relative* importance of different parameters contingent on how CDR options are characterised and parameterized in our modelling framework.

In terms of resource use, land constraints more substantially impact A/R's and BECCS's capacity relative to their potential increasing costs with deployment. Geological injection appears more limiting for DACCS than for BECCS, for which land limits might play a larger role. Interestingly, stringent limits to geological storage also drive EW and OA deployment. Despite being energy-intensive CDR options, EW and OA deployment is not substantially related to the year (and hence the amount) at which energy becomes available for CDR. This might be a consequence of EW and OA being CDR options that are in general deployed later in the century, rather than in the short-term as for DACCS.

3.3. Scenarios on resource constraints and cost dynamics

The analysis of drivers of adoption and barriers to deployment of CDR options (figure 3 above) revealed that uncertain parameters have different effects on the deployment of individual CDR options, but does not provide insights into the direction of such effect, the portfolio composition, or portfolio costs and resources used. To address this, we explore the effect of high-scoring uncertainty parameters (figure 3) on portfolios by identifying futures that lie within a certain range of such parameters, and comparing the composition and performance of CDR portfolios between these futures of interest and all futures solved. To expand on the analysis of resource use, we compute water, nitrogen and phosphorus used by each portfolio from model outputs (see table S5 in the SI for values used).

Focusing on parameters that define model constraints (figure 4), it can be observed that in futures with low land available for CDR (figures 4(a) and (b)), A/R and BECCS are deployed to substantially lower capacity levels relative to the distribution across all futures. This however does not compromise the amount of removals delivered as there is a substantial increase in EW and OA deployment. A delay in the year at which energy becomes available for CDR (figures 4(c) and (d)) does however have an impact on the amount of land, as well as water, nitrogen and phosphorus used, translating into a higher median land demand relative to all futures. Under energy constraints, DACCS is the CDR option whose distribution is most skewed towards lower levels of installed capacity, as opposed to BECCS, which is more often deployed at greater scales. Futures in which the annual rate of geological storage injection is lowest (figures 4(e) and (f)) rely on substantially more OA, EW and A/R, while BECCS but more importantly DACCS capacity is constrained. Energy and land used for CDR are also reduced at median.

Cost dynamics are highly relevant. The ER affects the deployment of many CDR options. In particular, EW and BECCS are deployed to greater extents when OA becomes more costly with capacity installed (figures 5(a) and (b)). However, the effect of BECCS's ER is not as pervasive as OA's on other CDR options (figures 5(c) and (d)): only A/R, and to a lesser extent EW, are deployed to greater capacity levels. A negative ER for BECCS could represent a world where competition for land usage and negative environmental externalities result in increasing investment costs of BECCS with deployment. This is mirrored in the modelling results as futures in which BECCS's ER is between −7.5% and −15% effectively minimizing land for CDR.

Futures with a large cumulative removal target (i.e. above 825 $GtCO_2$, figures 6(a) and (b)) intuitively require more resources and are the most costly. Costs however do not increase linearly with removals, as the median across futures follows a convex curve with increasing removals (figure S9 in SI). High removals skew the distribution of all CDR options towards higher capacity deployed, except for SCS and DOCCS, for which the median remains unchanged, and for DACCS, where less capacity is deployed. The latter might be explained by the need to deploy CDR options alternative to DACCS to meet the extra removals required, which cannot exclusively be delivered by increasing DACCS due to resource constraints. This would reduce the energy and economic resources available for DACCS, while decreasing the costs of alternative technologies due to gaining of experience, making DACCS a less competitive option.

CDR portfolios' composition and performance can also be assessed for ranges of interest of output metrics. For instance, only <1% of the futures solved are within the upper 50% range of portfolio costs (i.e. from 36 to 67 billion USD—see figures 6(c) and (d)). These high cost portfolios deliver a high amount of cumulative removals and involve very large OA, EW and BECCS deployment, while levels of DACCS

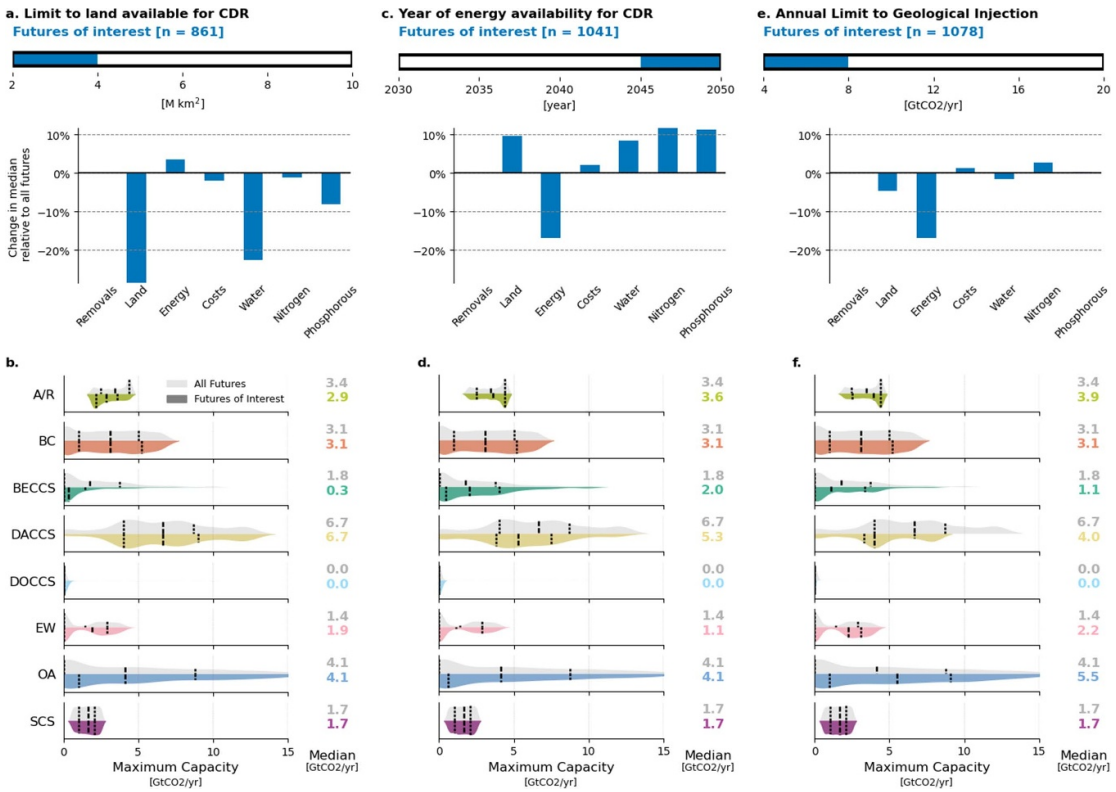

Figure 4. Variation of performance of key metrics (a), (c), (e) and portfolio composition (b), (d), (f) for futures of interest defined by model constraints. The parameters of interest explored are (a), (b), the limit to land available for CDR, (c), (d) the year at which energy becomes available for CDR, and (e), (f) the annual limit to geological storage injection. The ranges defining futures of interest are shown in blue the top corner of panels (a), (c), and (e), and the number of futures in each group (n) are indicated in square brackets. In panel (a), (c), (e), metrics are either model constraints (incl. removals, land, energy), model objective (costs) or post-modelling metrics (incl. water, nitrogen, phosphorous). For each metric, bars represent the change in median of futures of interest relative to the median of the entire ensemble ($N = 2758$)—refer to supplementary figure S12 for full statistics.

and SCS are reduced. It can also be observed that there's a more substantial DOCCS deployment: 70% of the futures where DOCCS deployment is above 1 $GtCO_2$ are within the most expensive (i.e. outliers in figure 6(d)) portfolios. Land used is not compromised, but these portfolios require significantly larger amounts of water, nitrogen and phosphorous.

4. Discussion

This study highlights the relevance of comprehensively considering uncertainty in decision-making contexts involving the deployment CDR where future cost dynamics and resource availability cannot be predicted with high confidence. Far from aiming to forecast future CDR developments, this analysis should be interpreted as a framework for considering how uncertainty impacts CDR deployment and policy-relevant performance metrics such as costs, resource use and delivery of CDR. It provides a transparent framework useful to devise robust net-zero and net-negative emissions strategies in the light of uncertainty and to assess trade-offs arising across them.

Data mining algorithms have been used to examine which (combinations of) uncertainties generate vulnerability in the system. The identified key uncertainties can then be used to develop policy-relevant narrative scenarios to inform implementation and monitoring efforts or new policy deliberations. This analysis can thus be expanded to monitor signposts and assumptions about future CDR developments: the actual values of key uncertain factors can be measured as the future unfolds, and the preferred strategy can be adapted depending on the arrival of new information. For instance, if uncertainty around the environmental effects or removal effectiveness of OA's deployment is high, and therefore OA costs are high (figures 5(a) and (b)), this analysis suggests that greater efforts could be directed towards EW, BECCS, and DACCS deployment.

Considering wide ranges in key uncertain parameters also allows to draw different narratives regarding cooperation on global commons. As an example, low land availability for CDR could represent a world where conflicts across countries challenge the large-scale deployment of land-intensive CDR. This process of characterising scenarios computationally through empirical data after the future option space has been evaluated—rather than defining them *a priori* in the first stages of the analysis—constitutes a fundamental

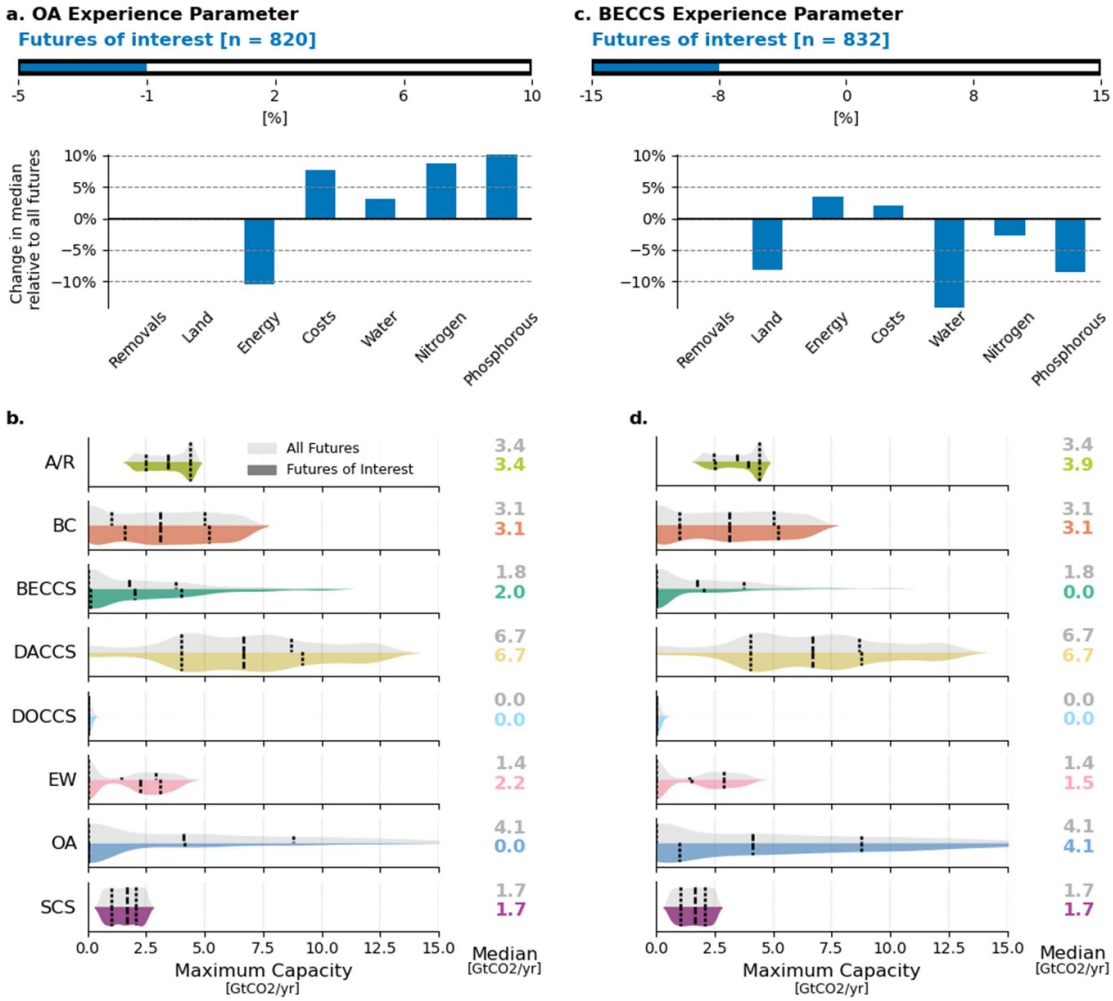

Figure 5. Variation of performance of key metrics (a), (c) and portfolio composition (b), (d) for futures of interest defined by experience rates. The parameters of interest explored are (a), (b) the experience rate of OA, (c), (d) the experience rate of BECCS—refer to supplementary figure S13 for full statistics.

difference between DMDU methods and traditional decision-making support tools [59].

However, despite this flexibility regarding narrative interpretations, a limitation of this analysis resides in the aggregation of resources and decision power in the modelling framework: a distinction is not made between different types of land, sources of funding, CO_2 markets or actors that will deploy CDR following each their own objectives. The modelling framework could also be extended to not only consider competition for resources across CDR options, but also capture the possible synergies arising between different CDR methods, such as the deployment of a CCS infrastructure simultaneously benefitting BECCS, DACCS and DOCCS, or the use of energy produced through BECCS or BC for energy-intensive CDR.

Additionally, 8 key parameters have been used to represent uncertainty in CDR deployment, but alternative parameters that could also be considered include the permanence of the sequestered CO_2 [58, 60], the sensitivity of C drawdown effectiveness to combat climate change [61–63], the operational costs of CDR [64], and the carbon price [65], among others. We also conducted a sensitivity analysis to evaluate the impacts of varying discount rate and operational period of capacity at the first time period (table S16, figures S15 and S16 in SI) on the composition of CDR portfolios. This reveals that the amount of capacity deployed of OA, EW and BC is highly sensitive to the assumed discount rate (figure S15), while only OA and EW's deployed capacity is substantially affected by varying assumptions regarding operational period (figure S16).

Beyond parametric uncertainty, which is exogenous to the modelling framework, alternative functional forms for experience curves (e.g. sigmoid rather than exponential [66]) or energy availability (e.g. exponential rather than logistic), as well as alternative objective functions such as minimising for CDR required or resources used for different regions, represent fundamental knowledge gaps that could, in future works, address structural uncertainty endogenous to the modelling process.

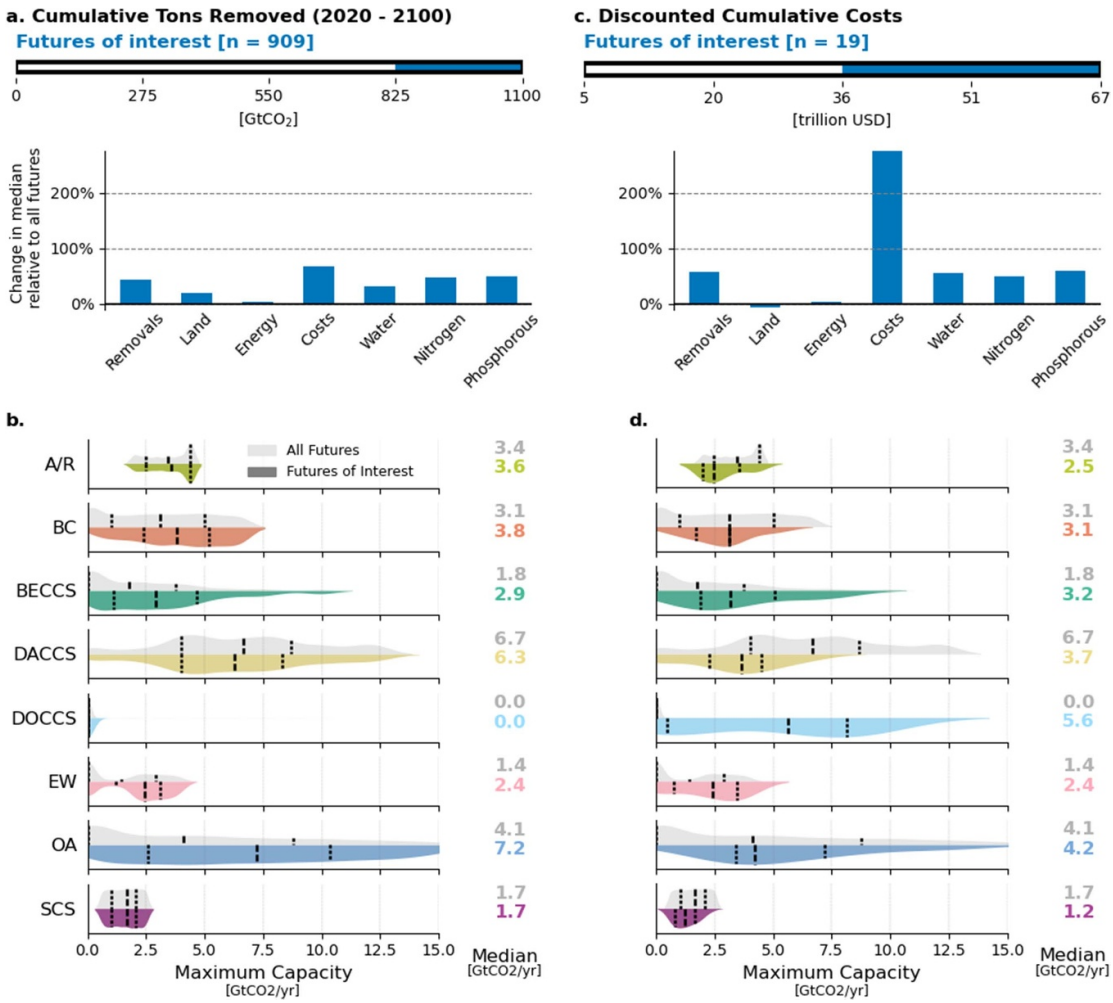

Figure 6. Variation of performance of key metrics (a), (c) and portfolio composition (b), (d) for futures of interest defined by removal requirements (a), (b) and portfolio costs (c), (d). The right-hand side panels look at portfolios with high cumulative discounted cost—refer to supplementary figure S14 for full statistics.

5. Concluding remarks

By developing a transparent computational experimentation approach to characterising CDR deployment pathways and cost dynamics, our work provides a methodology for exploring the effect of uncertainty on the composition and performance of CDR portfolios. Considering uncertainty in CDR deployment reveals that cost-minimal CDR portfolios are highly dependent on how the future unfolds. On a few occasions, no feasible solution can be found for meeting removal targets within environmental constraints.

For the futures where a cost-optimal strategy is identified, our findings suggest that a robust portfolio of climate change mitigation strategies should include a diversified set of, on average, over six different CDR options deployed throughout the century—with diversification benefits realised not only across technologies, but also time. Based on our modelling assumptions, robust short-term options include A/R and SCS, and are followed by DACCS, BECCS and BC. Despite BECCS being present in most SOW modelled, its distribution is skewed towards lower amounts of deployed capacity. Our results indicate that DACCS is deployed to substantially lower extents when geological storage is limited, and to lesser extent when removal requirements are high due to resource constraints reducing its competitiveness. DOCCS is principally scaled to giga-ton levels in futures with high removals and high cost portfolios.

We also show that assumptions about cost dynamics and resource constraints play distinct roles in the deployment of different CDR methods: ERs have a greater impact on the deployment of certain CDR options such as OA, BECCS, EW, and to a lesser extent DACCS. Low geological storage injection rates are associated with substantially lower energy requirements due to constrained DACCS deployment. Energy use is however not compromised under stringent land availability limits, while portfolios with low energy requirements need on average more land, water, nitrogen and phosphorus, and are associated with higher levels of BECCS deployment. Our study also highlights the potential complementarity or substitutability arising between CDR approaches, sometimes deployed as alternatives to other options when

these are relatively too costly or environmentally constrained. Key interactions include a greater deployment of EW, DACCS and BECCS when OA becomes more costly with experience, as well as an increase in EW in futures with low rates of geological storage injection.

Data availability statement

The data that support the findings of this study are openly available at the following DOI : https://doi.org/10.5281/zenodo.15114611 [67].

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