Carbon Dioxide Removal Supply Curves:

A Multi-Model Assessment

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Abstract

Carbon dioxide removal (CDR) is widely recognised as essential for pathways consistent with the Paris Climate Agreement. Yet the cost-dependent potential of CDR options, given resource competition, remains uncertain. Here we present CDR-supply curves assessing a range of CDR options across carbon price levels using five Integrated Assessment Models (IAMs) for 2035, 2050 and 2100. At 400 (200) $ tCO_2^{-1}, global CDR potential reaches 2.6-9.7 (2.1-6.0) $GtCO_2\ yr^{-1}$ in 2050 and 10.3-20.9 (5.9-12.4) $GtCO_2$ yr^{-1} in 2100, with higher prices enabling more diverse portfolios. Cross-model comparison shows that DACCS has the largest variability, while BECCS is consistently deployed; overall, options with geological storage dominate. CDR deployment drives resource demand, but with diversified portfolios these impacts are small compared to total energy and land use. These results indicate sufficient global technical CDR potential to meet long-term strategy (LTS) targets, though achieving this requires substantial policy and financial support.

Introduction

Carbon dioxide removal (CDR) plays a critical role in all model-based scenarios limiting global warming to levels consistent with the Paris Agreement[1–3]. As global greenhouse gas emissions continue to rise, meeting these temperature goals will be increasingly difficult without substantial CDR deployment. However, uncertainties remain regarding the scale and spatial distribution of CDR potential, competition among CDR options for limited resources, and alignment of CDR strategies with regional capabilities[4–6].

Assessing CDR potential is not straightforward. It depends on both demand and uncertainties in technological development, resource availability, and scalability[7,8]. Uncertainty also surrounds the evolution of CDR options and their markets. Many CDR options remain at early stages of commercial maturity and require significant capital investment, regulation, and infrastructure support[9]. Interactions between CDR options and broader mitigation strategies complicate estimates, limiting the insight from isolated technology-specific assessments.

Integrated Assessment Models (IAMs) provide a system-level framework to assess CDR potential and cost, capturing feedback in the energy and land systems, as well as competition between CDR options for limited land, energy, and geological storage resources[10,11]. IAM results differ from technical, bottom-up estimates, which typically reflect maximum feasible or sustainable deployment independent of costs and system constraints[6,12]. While IAMs use information from bottom-up studies, they additionally capture interactions across CDR options. When multiple CDR options are deployed simultaneously they compete for land, depending on total CDR demand and land-use intensity. Land availability is further influenced by agricultural production, dietary patterns, and protected areas, creating potential competition with food production and biodiversity protection[13]. IAMs also account for the energy requirements of CDR, essential for assessing energy system adaptation. They capture cumulative storage potential and dynamic constraints on the rate at which geological storage capacity can expand, which may lead to competition for storage between CDR options and with fossil CCS[14]. Linking CDR deployment to energy and land system dynamics, while accounting for resource competition, enables more targeted and regionally aligned CDR strategies.

We use five IAMs (IMAGE, MESSAGE, GCAM, REMIND-MAgPIE, WITCH) to derive CDR supply curves, representing the potential of different CDR options at given carbon prices, while accounting for system-wide responses in energy and land use. Each model includes a portfolio of CDR options: afforestation and reforestation (A/R), direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS), enhanced rock weathering (ERW), and biochar (BC). Models are run under stylized carbon price trajectories of 0-400 \$ tCO_2^{-1} to identify global cost-effective CDR portfolios and their associated deployment potentials for 2035, 2050, and 2100. Cross-IAM comparisons capture uncertainty in projected CDR deployment and its implications for energy systems, land use, and geological storage, reflecting differing model assumptions about CDR options and their interactions with energy and land systems.

CDR deployment over different carbon prices and time horizons

Across all five IAMs, higher carbon prices lead to greater global CDR deployment and more diverse CDR portfolios (Fig. 1), with the relative importance of individual technologies changing over time. In 2100, global CDR supply ranges from 0-21 $GtCO_2$ yr^{-1} depending on carbon price and model. Interestingly, BECCS is less price-sensitive than other technologies and is most consistently deployed across carbon prices. BECCS is used not only for CDR but also for energy production, meaning that its deployment depends on the energy system representation within the IAMs[15]. By contrast, the deployment of DACCS and ERW increase with carbon price. DACCS is the most price-sensitive CDR option, with high upfront capital costs limiting deployment to higher carbon prices. The composition of the CDR supply curve varies substantially between IAMs, and no single technology dominates across models. Differing structural and parametric assumptions across models lead to differences in supply curve shape and composition, revealing substantial uncertainty in overall CDR potential. Inter-model potentials align broadly with typical carbon capture fingerprints reported in literature ensembles, contextualising the models' relative positions[16].

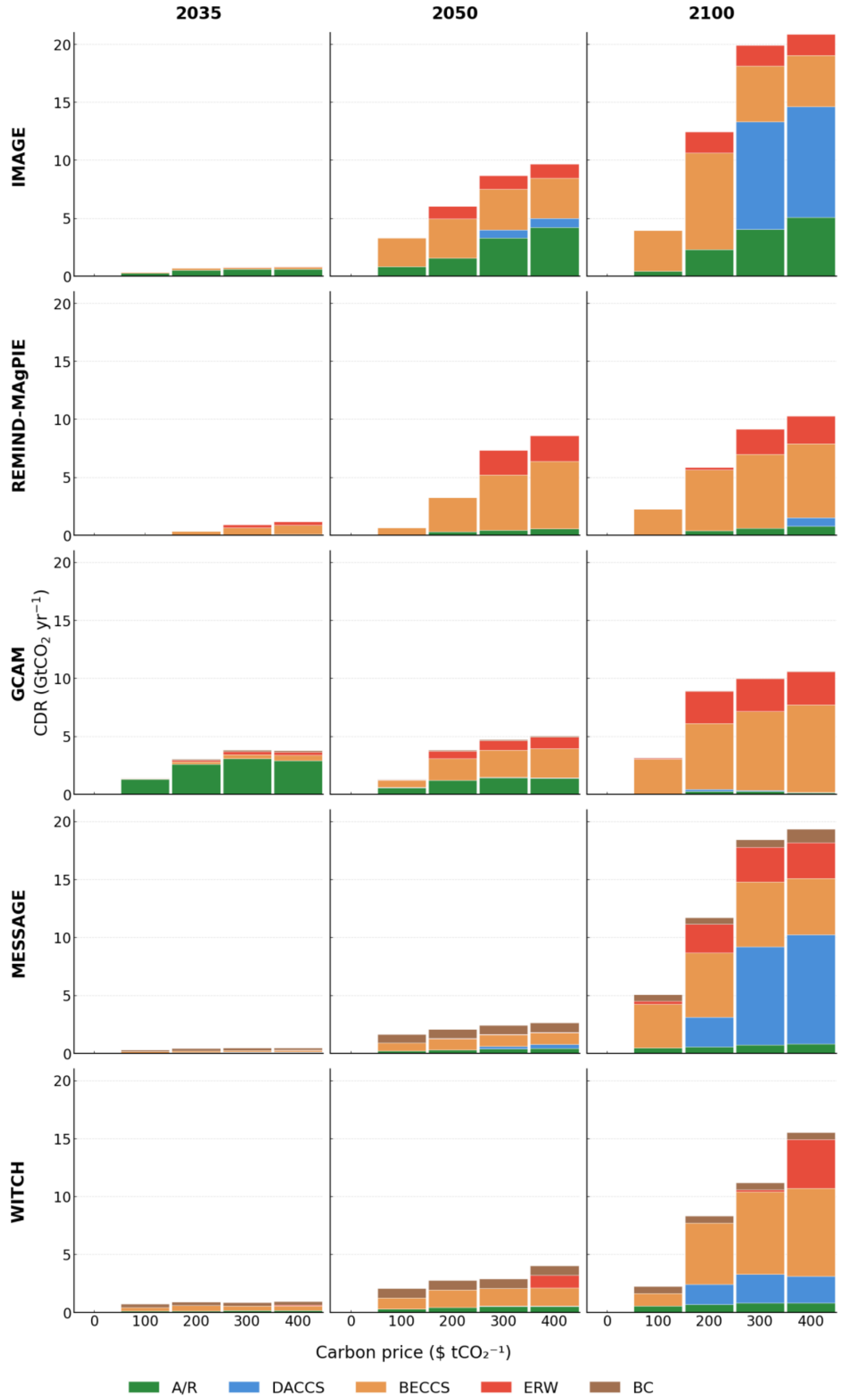

Figure 1: Annual global deployment of CDR options, with contributions from different options stacked, at different carbon prices in 2035, 2050, 2100 for the different IAMs.

CDR deployment increases over time as capacity expands, driven by modelled cost-reductions and by growth rates that limit early expansion. In the near term (2035), IAMs indicate limited CDR deployment even at higher carbon prices, with A/R contributing a relatively larger share of total CDR potential than in later periods. GCAM shows higher A/R deployment in 2035 than other models, although this declines over time as land sinks saturate and other CDR options become more cost competitive. From mid-century onwards, IMAGE deploys the largest A/R volumes, which increase over time and with carbon price as land dedicated to A/R expands due to relatively high land-sector carbon prices and low competition[17]. The A/R results align with global estimates of 0.5-3.6 $GtCO_2$ yr^{-1} sustainable removal by 2050[8], with higher technical potentials achievable only under strong economic incentives and optimistic land-use assumptions[17].

Across IAMs, technology-based CDR options deploy later due to capital requirements, reliance on modern energy systems, and expansion constraints. Global CDR deployment shows an inflection between 100-300 \$ tCO_2^{-1}, beyond which deployment saturates at 10.4-20.9 $GtCO_2$ yr^{-1} by 2100. Long-term BECCS deployment plateaus at 5-7 $GtCO_2$ yr^{-1}, constrained by biomass availability and reduced bioenergy demand in highly electrified and efficient energy systems under high carbon-price levels[18]. ERW reaches 2-4 $GtCO_2$ yr^{-1}, limited by basalt resource availability, weathering rates, and suitable agricultural land. Land availability and carbon saturation assumptions significantly impact A/R maximum potential (0.5-5 $GtCO_2$ yr^{-1}). DACCS shows the greatest uncertainty across models (0.1-10 $GtCO_2$ yr^{-1}), with a clear model-specific pattern - IMAGE and MESSAGE scale DACCS significantly (>8 $GtCO_2$ yr^{-1}) at high carbon prices, WITCH has modest deployment (< 2.5 $GtCO_2$ yr^{-1}), while REMIND and GCAM remain highly conservative (< 1 $GtCO_2$ yr^{-1}). These differences result largely from differing methods for determining competitiveness and deployment rates of DACCS. Despite its relative near-term importance, consistent with the large number of announced projects, BC remains comparatively limited (~ 1 $GtCO_2$ yr^{-1}). In the models, BC deployment is constrained by direct competition with BECCS, which is more economically competitive due to higher CDR efficiency and higher energy production per unit of biomass[19].

While global potential is the focus of this study, regional deployment patterns differ across IAMs in both total removal potential and sensitivity to carbon price, reflecting differences in regional CDR representation. Across models, Latin America and North America consistently emerge as the regions with the greatest CDR potential over the century (Supporting Information).

Cumulative removals by different CDR options

Cumulative removal volumes assess the long-term potential of CDR options over the century, highlighting their role in meeting climate targets. Across IAMs, approximately 300-600 $GtCO_2$ are projected to be removed by 2100 at a carbon price of 200 \$ tCO_2^{-1}. Depending on the model, cumulative CDR deployment increases from near zero at 0 \$ tCO_2^{-1}, when no climate policy is assumed, to over 1000 $GtCO_2$ at 400 \$ tCO_2^{-1}. The highest cumulative removals result from different combinations of CDR options across models, reflecting diverse assumptions and system dynamics.

The contribution of individual CDR options varies substantially across models and carbon prices. This reflects differences in the relative costs and deployment thresholds at which CDR becomes economically viable (Fig. 2). Despite this variation, BECCS consistently emerges as a major contributor, while DACCS projections show greater variation. IMAGE shows the highest cumulative removal potential, with a significant increase at 300 \$ tCO_2^{-1} due to substantial DACCS deployment, while MESSAGE also projects a significant role for DACCS at higher prices. A/R values fall within conservative literature estimates accounting for land competition and ecological constraints, estimating cumulative sequestration of 366 $GtCO_2$[20].

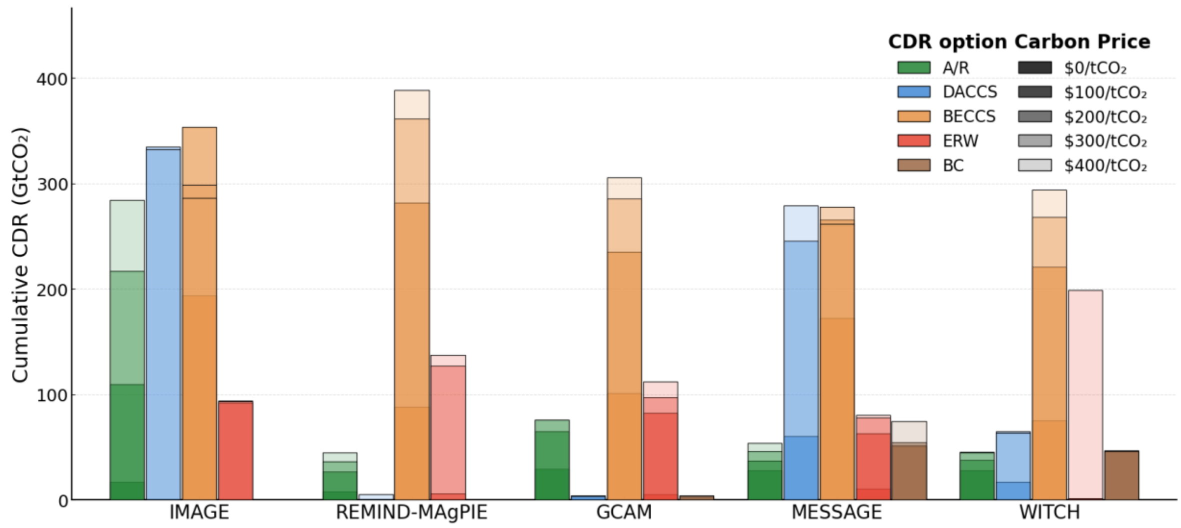

Figure 2: Cumulative global removal volume ($GtCO_2$) by the end of the century (2025-2100), by CDR option, at different carbon prices, for each IAM. (Note: IMAGE and REMIND-MAgPIE do not model BC).

Cumulative removal volumes indicate the total storage needed to meet demand at these carbon prices, highlighting constraints when considering land and geological storage as intergenerational resources. Within the uncertainty across models (Fig. 3), land-based storage options are consistently projected to play a smaller role than geological storage options due to limited land availability and carbon saturation. Geological storage offers greater permanence[21,22], and its dominance in CDR potential provides robust options for durable, large-scale storage.

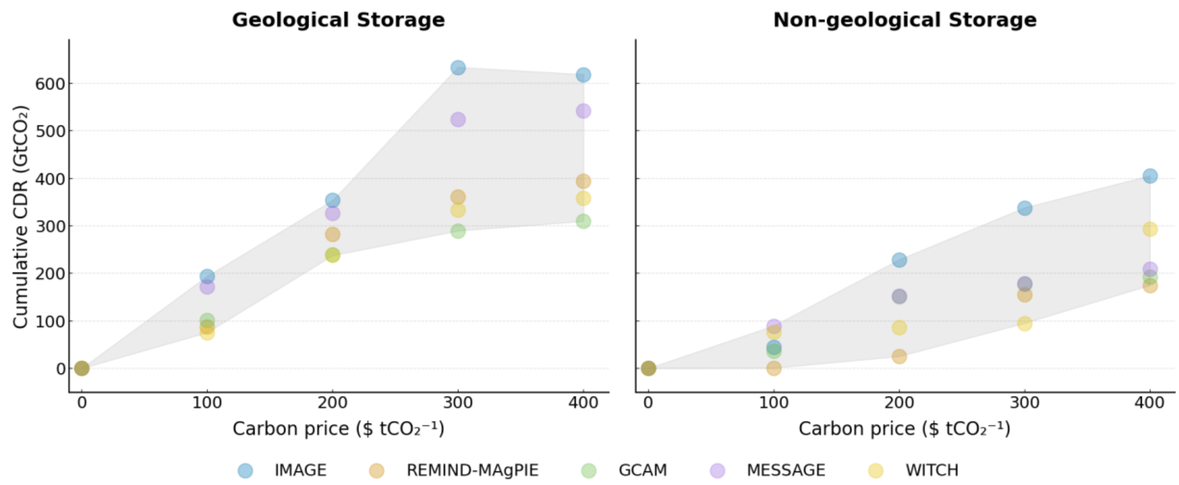

Figure 3: Cumulative global removal volume ($GtCO_2$) by the end of the century (2025-2100) at different carbon prices, split into geological (DACCS and BECCS) and non-geological (A/R, ERW, and BC) storage. IAM results are presented with the associated range.

Although geological storage options are sometimes considered too expensive[23], their technical potential is shown in the models to be cost competitive with non-geological alternatives. Cumulative geological storage exhibits higher carbon price elasticity than non-geological options, reflecting DACCS deployment at higher prices. At 400 \$ tCO_2^{-1}, models use 300-600 $GtCO_2$ geological storage for CDR, remaining below conservative global storage estimates[24,25]. Total geological storage requirements would be higher if fossil-based carbon capture and storage (fossil CCS) were included (see section (b) Geological Carbon Storage) . These estimates only extend to 2100, after which additional storage may be required, particularly in scenarios demanding net-negative emissions to reverse temperature overshoot.

Competition for limited resources

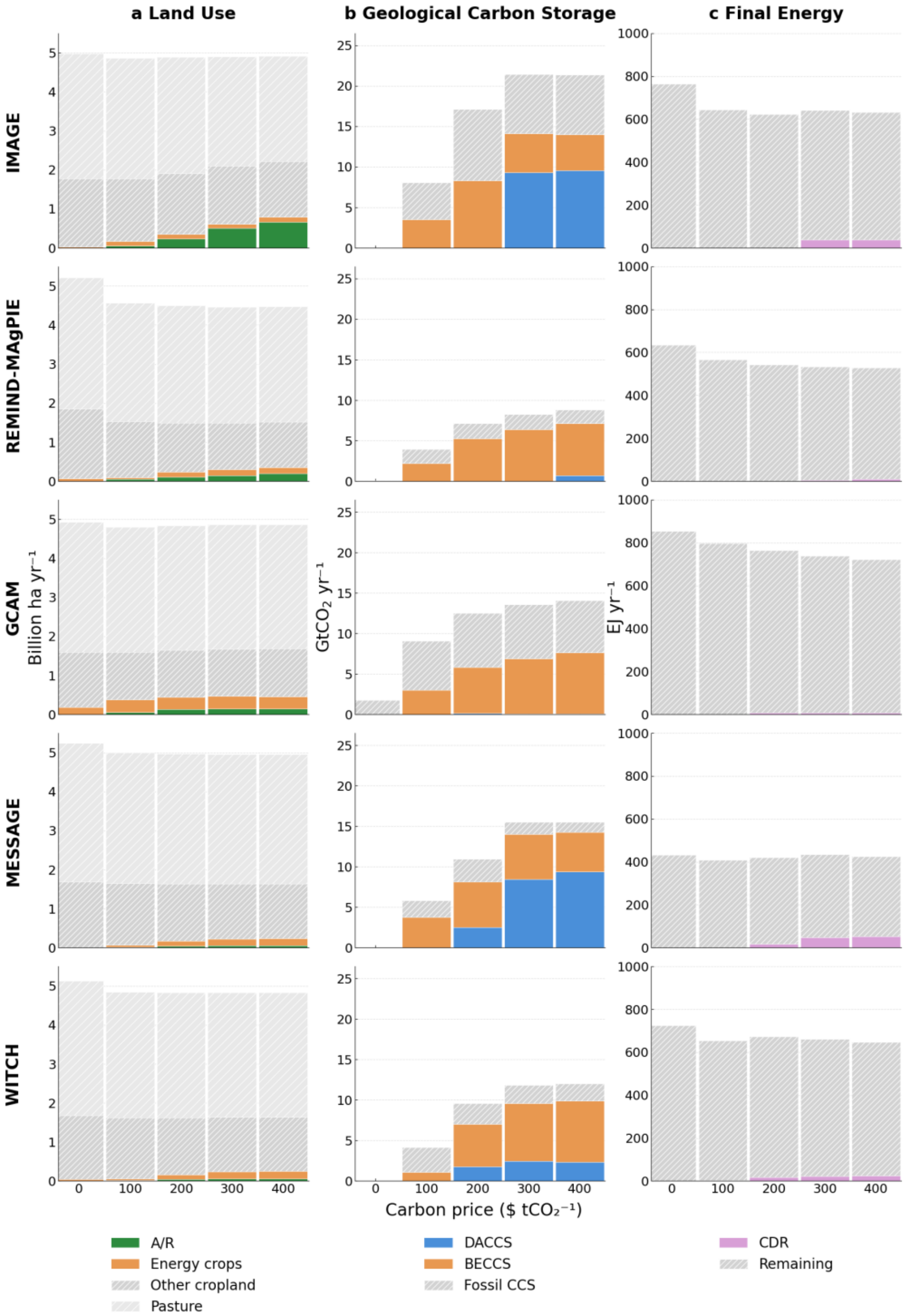

Figure 4: Annual CDR resource requirements in 2100 across IAMs, shown as stacked contributions at different carbon prices. (a) Land use for A/R, energy crops (bioenergy with and without CCS; model detail does not allow land use separation), other cropland and pasture. (b) Geological carbon storage for DACCS, BECCS and fossil CCS. (c) Final energy use for CDR deployment (DACCS and ERW) and remaining energy use.

When multiple CDR technologies are deployed, co-deployment challenges may result from competition for limited resources. In this study, the impact on (a) land use, (b) geological carbon storage, and (c) final energy are addressed.

(a) **Land use**

The share of land allocated to CDR varies across models (Fig. 4a). Biomass production and A/R (dedicated CDR land) directly compete with cropland and pasture. At higher carbon prices and later years, a greater proportion of agricultural land is dedicated to CDR, reaching 0.3-0.8 billion ha. By 2100, 4-15% of agricultural land is allocated to CDR at 200-400 \$ tCO_2^{-1}, with IMAGE as an upper bound, driven primarily by high A/R deployment. In 2035, a larger share of land is allocated to A/R due to its rapid near-term scalability. By 2050, bioenergy land use approaches A/R, and by 2100, bioenergy occupies a similar or greater share, except in IMAGE where A/R remains dominant. Inter-model differences in A/R deployment reflect variations in land opportunity costs, carbon saturation, and land sector carbon pricing accounting for impermanence and land carbon rental approaches.

Land use for energy crops includes dedicated bioenergy crops for BECCS and other (non-BECCS) bioenergy, overestimating the BECCS land footprint. By 2100, most models combine 55-65% of primary bioenergy with CCS at prices above 200 \$ tCO_2^{-1}, apart from REMIND-MAgPIE which exceeds 90% (Supporting Information). Up to 50% of BECCS biomass comes from agricultural and forestry residues, depending on demand and residue availability. Consequently, BECCS is more land-efficient per tCO_2 removed than energy crop estimates suggest. Over time, A/R becomes relatively more land-intensive per tCO_2 removed as carbon uptake saturates, so policies limiting CDR land use may prioritize bioenergy[26]. BC and ERW can operate more synergistically with cropland, particularly when BC is produced from second-generation biomass, offering potential fertilisation co-benefits if risks are managed[27,28,11]. Carbon pricing also drives broader land-use change: when introduced, cropland and pasture decrease, constrained by forest protection and taxes on agricultural non-CO_2 emissions.

(b) **Geological Carbon Storage**

Estimates of cumulative storage potential (Fig. 3) indicate sufficient static storage capacity to meet end of century demands[25,29], however, dynamic constraints remain. All models incorporate annual injection limits, which vary across models as outlined in the Online Methods. Across models, higher carbon prices drive higher annual geological storage rates (Fig. 4b), increasing over time as the technology matures. By 2100, annual storage reaches 4.2-9.3 $GtCO_2\ yr^{-1}$ at 100 \$ tCO_2^{-1}, increasing to 9.5-21.5 $GtCO_2\ yr^{-1}$ at 400 \$ tCO_2^{-1}. Fossil CCS accounts for a larger share of geological storage at lower carbon prices, while CDR dominates at higher prices. In most models, BECCS geological carbon storage requirements increase with carbon price, though IMAGE and MESSAGE deviate, as high overall geological storage demand constrains BECCS deployment due to competition with DACCS under storage rate limits. Storage distribution also shifts over time: early on, BECCS accounts for a larger share, while DACCS share increases with both carbon price and time.

Typical literature estimates of annual geological storage growth extend to 2050, ranging from 8.6-16 $GtCO_2\ yr^{-1}$[14,30]. In 2050, under the highest carbon price (400 \$ tCO_2^{-1}), models deploy 2.5-9.6 $GtCO_2\ yr^{-1}$ (Supporting Information), mostly within literature growth limits. IMAGE deploys the highest geological storage due to relatively high BECCS, DACCS, and fossil CCS deployment. Lower DACCS deployment in GCAM and REMIND-MAgPIE reflects higher techno-economic costs. DACCS competes with BECCS for storage space, with BECCS often favoured as energy co-production adds system value, whereas DACCS requires high energy inputs.

(c) **Final Energy**

While large-scale CDR expansion will increase total energy demand, even if the full potential is realised, it accounts for no more than 12% of global final energy demand across all models by the end of the century under high carbon prices (Fig. 4c). This suggests that only modest changes to the energy system may be needed to accommodate CDR, particularly because the additional demand occurs primarily late in the century. Final energy required for CDR is dominated by DACCS, and to a lesser extent ERW, while other CDR options use co-generation to offset energy demand. In models with substantial DACCS deployment (IMAGE, MESSAGE, WITCH), CDR represents a non-negligible share of final energy, with DACCS accounting for more than 80% of CDR-related energy use in 2100. Final energy for CDR varies across models and carbon prices, 0-52 EJ (0-12% of total final energy) in 2100, driven by DACCS sensitivities and model differences. As carbon prices rise, CDR energy demand increases, while overall final energy consumption declines through efficiency improvements, raising CDR's share. By comparison, final energy supplied by biomass (with and without CCS) is more consistent across models and carbon prices at 25-75 EJ (5-12% of total final energy) in 2100, and even high CDR energy demand remains below bioenergy supply (Supplementary Information).

CDR's role, along with the energy system itself, evolves over time. Early to mid-century, CDR's contribution to final energy is minimal, but late-century scaling increases requirements. Energy-intensive CDR technologies like DACCS require a lower-carbon energy system, expected in the second half of the century, to ensure effective CO_2 removal. Across models, overall final energy demand also rises with global energy growth, with absolute differences reflecting model structure and assumptions.

Drivers and barriers to CDR deployment potentials

At higher carbon prices, the models project larger CDR potential, particularly in the latter half of the century as technologies scale. By mid-century deployment is shaped more by IAM-specific techno-economic assumptions than by carbon price or technology type, with BECCS emerging as a major contributor. By 2100, the carbon price strongly influences both the magnitude and diversity of CDR options, with higher prices reflecting more ambitious climate policy. Ultimate potentials span 10.3-20.9 $GtCO_2\ yr^{-1}$, most becoming cost competitive at 300 \$ tCO_2^{-1}, with DACCS showing the strongest price sensitivity. However, $GtCO_2$-scale CDR will not occur without economic incentives. Here, globally consistent carbon prices are used as a proxy for policy support, but in reality deployment will depend on targeted incentives, infrastructure, and regulatory frameworks. The model-derived CDR supply curves assume political, social, and economic feasibility, which may underestimate real-world challenges. For example, political feasibility of land use for CDR, energy constraints, or emphasis on co-benefits and costs may influence which options are actually deployed[31]. Ultimately, these results should be interpreted primarily as technical potentials, illustrating how different CDR options could contribute under varying levels of ambition.

Increasing CDR deployment intensifies competition for land, geological storage, and energy; however, resource pressures appear manageable in aggregate. Utilizing full CDR potential could affect food security due to reduced agricultural land[17,32,33], depending on wider system conditions, as measures such as increased agricultural yields or dietary shifts may offset impacts[17,34,35]. CDR is also linked to biodiversity: it can provide benefits from avoided climate change[36], and A/R can restore forests and habitat connectivity, though converting natural forests to energy crops or monocultures may harm it. Overall biodiversity supports ecosystem resilience, lowering the risk of carbon storage reversal[37]. Therefore, while supply curves indicate technical potential, land-use constraints and social-environmental limits will shape future CDR portfolios, through competition with food production, conservation, and other land uses[17,26]. Further work should assess CDR potential under social and environmental limits, especially in regions sensitive to food security or biodiversity losses[26,38]. For example, high removal potentials in Latin America and Africa reflect favourable biophysical conditions and relatively low opportunity costs of land conversion. Realising this potential may shift burdens toward regions with weaker governance, higher investment risks, and biodiversity constraints[17,31,37].

Durability of CDR options should also be considered. Land-based CDR is less durable, with permanence sensitive to policy and climate change[21,22], while novel engineered CDR faces feasibility and scalability risks. Their complementary timing and risk profiles should therefore inform policy. IAM results are constrained by underlying assumptions, and given the novel nature of many CDR technologies, substantial deployment uncertainty remains. A precautionary approach using lower-bound estimates may reduce risk, while rapid investment supports technological learning and empirical understanding of constraints to large-scale deployment. The broader role of CDR in net-zero transitions, including impacts of temperature overshoot, is beyond this study's scope.

Under countries' long-term strategies (LTS), CDR deployment by 2050 is estimated at 1.9-2.3 $GtCO_2$ yr^{-1} (from a 2020 baseline)[9]. At the highest carbon prices assessed, this study finds a higher potential on average of 6 (2.6-9.7) $GtCO_2$ yr^{-1}, including 1.4 (0.4-4.2) $GtCO_2$ yr^{-1} from conventional and 4.6 (2.2-8.0) $GtCO_2$ yr^{-1} from novel CDR, suggesting sufficient potential to meet LTS. However, a CDR gap remains between current ambitions and Paris-consistent pathways[39], with IPCC AR6 scenarios requiring 5.3 (4.1-6.4) $GtCO_2$ yr^{-1} by 2050[9]. Whether CDR potential at these carbon prices is sufficient remains within model uncertainty. While higher carbon prices could increase total CDR supply, deployment is constrained by environmental and resource limits. Paris-consistent scenarios assume a substantial contribution from conventional CDR on land, however, A/R supply is limited at the assessed carbon prices, implying a larger role for novel CDR. Achieving Paris Agreement targets will depend on both mitigation and CDR deployment, highlighting the need for targeted policy and investment strategies, support for high carbon prices, and diversified portfolios aligned with capabilities.

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Online Methods

Modelling Protocol

We run all models using a range of global carbon prices to identify CDR option deployment at that carbon price level. These carbon prices are applied to both the energy and land systems, and thus take into account systemic effects which may affect the deployment of CDR. The socioeconomic development assumed in these scenarios is based on a standardised set of assumptions representing medium trends in socio-economic, demographic, and technological developments, referred to as the SSP2[40,41]. All models and scenarios imposed a 150 EJ yr^{-1} global constraint on bioenergy[42], to lessen risks to biodiversity, freshwater systems, and food prices and availability resulting from large-scale biomass cultivation.

We present four different carbon prices - 100, 200, 300, and 400 $ tCO_2^{-1} (2010$ USD) - to investigate how different options compete at these levels. These are compared against a pure baseline with no carbon price. We do not assume a specific climate target, but the higher level of carbon prices is roughly in line with carbon prices aligned with the Paris Agreement. CDR deployment is evaluated for three target years: 2035, representing a near-term milestone to inform investment; 2050, representing mid-century deployment; and 2100 representing long-term deployment. The global carbon price trajectory is modelled to increase linearly until 2035, then plateau at the set value through 2100. This approach isolates the effects of growth and technological learning, at a given carbon price, across the target years.

These scenarios do not reflect real world expected developments in carbon pricing. Instead, they represent stylized experiments in order to provide insights on the development of energy, land, and CDR systems at these carbon price levels. Deployment of CDR technologies, particularly A/R, at a zero carbon price results from current policy frameworks that some models cannot disaggregate, afforestation decisions based on profitability, and incidental CDR resulting from an evolving land-use market. Therefore, A/R is considered relative to baseline levels to account only for dedicated CDR consequence of the carbon price.

IAM CDR representation

The IAMs—IMAGE, MESSAGE, GCAM, REMIND-MAgPIE, WITCH —include representations of CDR technologies, with updated cost, performance, and growth constraints. Afforestation and reforestation (A/R), direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS), enhanced rock weathering (ERW), and biochar (BC), where modelled, are included. While this isn't exhaustive representation of all the CDR options, it is a representation of the most mature technologies, with the most certainty over future projection. CDR technology assumptions and parameterisation have been harmonised across the IAMs where possible, with key structural and parametric assumptions outlined. The following details outline how the different technologies are represented across the IAMs, with more details in relevant model publications[10,17,19,43–45]. Regional aggregation is reported at the R10 level, a standard IPCC classification that groups the world into 10 distinct geographical regions, enabling inter-model comparison[46].

A/R

IMAGE: A/R refers to carbon sequestered by tree growth on former agricultural land or degraded lands for the specific purpose of climate change mitigation. It does not include natural regrowth on abandoned land, restoration or demand for forest products. It takes place if profitable compared to use of land for agriculture. A maximum A/R rate is assumed. Non-permanence is excluded.

REMIND-MAgPIE: A/R are represented in the land-use model MAgPIE as natural forest planted for the purpose of climate mitigation. A/R is incentivised by the carbon price provided by REMIND and competes with other agricultural uses of land, such as food and bioenergy production. To account for the risk of carbon reversal, only 50% of sequestered carbon is credited for carbon price revenue, with the remainder held as a permanence risk buffer.

GCAM: A/R efforts are modelled as a subsidy to land-owners for holding carbon stocks, as opposed to a tax/subsidy on the change in carbon in land. Specifically, the subsidy is equal to the carbon price x the carbon density x a discount factor to account for the amount of time it takes carbon to accumulate x a discount factor to annualize the subsidy. Here, land-use CO_2 emissions are priced at a 0.1 multiplier of the fossil and industrial CO_2 price, following the convention in Fawcett et. al., (2015) and Ou et. al., (2021)[47,48].

MESSAGE: A/R in managed forests are estimated by the geographically explicit (0.5x0.5 degree) model, in which the activity on A/R occurs where it is more profitable than agriculture, and environmental conditions are suitable for forest growth. For example, when compared to the cost of producing fertilizer, A/R is selected to an extent that the reduced fertilizer demand could lead to cost savings larger than “revenue” generated from agricultural activities. Non-permanence is excluded.

WITCH: A/R is driven by the price of carbon in the land-use sector. Land allocated for A/R also compete with land used for bioenergy, through cost supply curves. These curves result from a LUT built from simulation of the GLOBIOM land-use model. Afforestation decisions (which rely on the G4M model-connected with GLOBIOM) choose afforestation levels depending on profitability, i.e. afforestation will occur where it is more profitable to have forests than agricultural land, considering wood prices. The land system is capped at a carbon price of $300\ \$\ tCO_2^{-1}$.

DACCS

IMAGE: Two technology options, using either solid sorbent or liquid solvent to capture CO_2 from the atmosphere. Captured CO_2 will be stored geologically. An annual geological carbon storage rate limit is defined to follow a logistic growth curve with a mid-century 16 $GtCO_2\ yr^{-1}$ limit[14]

REMIND-MAgPIE: One technology option representing the low-temperature solid sorbent capture process. The technology requires electricity for ventilation. The energy required for the regeneration can either be supplied by district heat or electricity. Captured CO_2 will either be stored geologically or used for the production of synthetic fuels but only stored CO_2 contributes to CDR. Annual geological carbon storage rates are limited to 0.5% of regional total storage potential, leading to global maximum storage rate of 20 $GtCO_2\ yr^{-1}$.

GCAM: Four technology options using various combinations of electricity, gas, and geothermal energy for sorbent or solvent regeneration to capture CO_2 from the atmosphere. Captured CO_2 will be stored geologically. Regionally explicit rate and growth limits on geologic carbon storage (affecting DACCS, BECCS, and fossil CCS) consistent with the “CCS breakthrough” scenario from Fuhrman et. al, (2025) are used here[44].

MESSAGE: Four technology options, each representing variations in capture and regeneration processes, energy sources for heat requirements, and availability of dedicated electricity storage. Captured CO_2 is then either stored in the geological storage or utilised in the industrial processes. Here, we assumed 50% of the prudent geological storage capacity from Gidden et al., (2025) is available to store the captured CO_2, shared between BECCS, DACCS, and fossil CCS[25]. Global CO_2 injection rate is limited to 16.5 $GtCO_2\ yr^{-1}$[30].

WITCH: Three technology options, using liquid sorbent, solid sorbent and calcium oxide. Heat is produced from gas and the CO_2 from the combustion is captured. Captured CO_2 will either be stored geologically or used for the production of synthetic fuels. Annual geological carbon storage is limited to 5 $GtCO_2$ yr^{-1} up to 2050, and after 2050 up to 20 $GtCO_2$ yr^{-1}.

BECCS

IMAGE: 11 technology options. Land not available for food production or A/R is available for bioenergy production. Captured CO_2 will be stored geologically.

REMIND-MAgPIE: Five technology options across electricity, refining, biogas, industrial heat and H_2 production. Biomass cost supply curves are provided according to different grades of biomass, differentiating residues and bioenergy crops. The cost curves for bioenergy from crops are provided by the MAgPIE land-use model. Captured CO_2 will either be stored geologically or used for the production of synthetic fuels but only stored CO_2 contributes to CDR. Annual geological carbon storage rates are limited to 0.5% of regional total storage potential, leading to global maximum storage rate of 20 $GtCO_2$ yr^{-1}.

GCAM: 16 technology options across electricity, refining, industry, and H_2 production sectors. Captured CO_2 will be stored geologically. Regionally explicit rate and growth limits on geologic carbon storage (affecting DACCS, BECCS, and fossil CCS) consistent with the “CCS breakthrough” scenario from Fuhrman et. al, (2025) are used here[44].

MESSAGE: Seven technology options across electricity, refining, industry, and H_2 production sectors. Captured CO_2 is then either stored in the geological storage or utilised in the industrial processes. Global CO_2 injection rate is limited to 16.5 $GtCO_2$ yr^{-1}, considering estimates by Grant et al., (2022)[30].

WITCH: One technology option. Biomass cost supply curves are provided according to different grades of biomass. These curves result from a LUT built from simulation of the GLOBIOM land-use model. Captured CO_2 is then either stored in the geological storage or utilised in the industrial processes. Annual geological carbon storage is limited to 5 $GtCO_2$ yr^{-1} up to 2050, and after 2050 up to 20 $GtCO_2$ yr^{-1}.

ERW

IMAGE: Crushed basalt application to croplands within a humid warm and temperate climate. Regional supply curves define economically attractive potential, with growth determined by a logistic substitution model. Limits are applied to global available basalt supply. Costs and associated emissions for the energy for grinding (electricity) and transportation are calculated endogenously.

REMIND-MAgPIE: Crushed basalt application to croplands within a humid warm and temperate climate. A maximum mass of un-weathered rock per hectare of cropland is limiting overall deployment and annual growth is limited to 20%. Transportation costs are given by regionalised cost supply curves estimating the distance between basalt reservoirs and cropland. Costs and associated emissions for the energy for grinding (electricity) and transportation and spreading (diesel) arise endogenously from the energy system modelling.

GCAM: Crushed basalt application to croplands, with regionalized, rate-based supply curves developed in Fuhrman et. al., (2023) and further calibrated to publicly available data on planned projects to constrain near-term growth[43]. Annual supply curves are scaled up over time following a logistic growth trajectory to each region's carrying capacity C(t) with initial growth rate of 20% (consistent with recent growth in cobalt mining from the HATCH database) is used here. The fuel mix, associated emissions, and costs for electricity (rock crushing) and transportation (rock hauling) are solved endogenously.

MESSAGE: Crushed basalt application to croplands. Key technology supply chain elements are represented: mining, transport, grinding facility and application on cropland. Site-specific removal rates are estimated using pH and T data from internal spatial analysis for all regions.

WITCH: Basalt is ground and deposed on croplands. Capture rates are computed based on the regional temperature, which is endogenous in the model. Emissions from transportation are taken into account using the average, endogenous emission factor of freight vehicles, thus considering electrification. Scale-up of the technology is constrained using as a proxy the cement industry, which is used as a plausible limit for the scale of mining operations.

BC

IMAGE: N/A. BC is not implemented in this model version of the IMAGE and REMIND-MAgPIE. At the carbon prices represented in this assessment, IAMs display limited BC deployment, suggesting addition of BC modelling is not a priority.

REMIND-MAgPIE: N/A.

GCAM: BC is produced from second-generation biomass (e.g. residual and cellulosic) rather than from dedicated food crops. Slow pyrolysis of lignocellulosic feedstocks, wherein approximately 50% of the biomass carbon is assumed stored in agricultural soils to which it is applied, with the remainder either being released during manufacture or mineralizing to CO_2 after distribution. BC is demanded as an input option to improve crop yields, similar to fertilizer and irrigation water[19].

MESSAGE: In addition to the implementation of BC for land use application in the GLOBIOM side of the MESSAGE-GLOBIOM framework, 8 BC technology configurations are incorporated in the MESSAGE side for non-land use applications, representing variation in the pyrolysis process (slow and fast-pyrolysis), CCS implementation in the pyrolysis plant, and energy by-product (electricity or heat). In GLOBIOM, biomass includes biomass from residues (crops, forest industry, logging), roundwood harvest, energy crops, and fuel wood, this commodity input from the GLOBIOM emulator is not differentiated by types and feedstock sources in MESSAGE.

WITCH: BC is provided by the GLOBIOM land-use model.