Assessing the Feasibility of Economy-Scale Direct Air Capture Deployment by 2050

Nicoletta Brazzola

nicoletta.brazzola@usys.ethz.ch

ETH Zurich (Swiss Federal Institute of Technology) https://orcid.org/0000-0002-5041-9972

Tatjana Zurbriggen

ETH Zurich

Adrian Odenweller

Potsdam Institute for Climate Impact Research https://orcid.org/0000-0002-1123-8124

Falko Ueckerdt

PIK Potsdam

Joeri Rogelj

Imperial College London https://orcid.org/0000-0003-2056-9061

Brief Communication

Keywords:

Posted Date: July 30th, 2025

DOI: https://doi.org/10.21203/rs.3.rs-6165238/v1

Additional Declarations: There is **NO** Competing Interest.

Assessing the Feasibility of Economy-Scale Direct Air Capture Deployment by 2050

Tatjana Zurbriggen[1], Nicoletta Brazzola[1*], Adrian Odenweller[2], Falko Ueckerdt[2], Joeri Rogelj[3,4]

Author information

1. Institute for Environmental Decisions (IED), ETH Zürich, Zurich, Switzerland
2. Potsdam Institute for Climate Impact (PIK), Potsdam, Germany
3. Centre for Environmental Policy (CEP) and Grantham Institute – Climate Change and Environment, Imperial College London, UK
4. Energy, Climate and Environment Program, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria

* Corresponding author: nicoletta.brazzola@usys.ethz.ch

Abstract

Direct Air Capture (DAC) could play a key role in achieving net-zero emissions. Here, we use a probabilistic approach to explore its growth and therefore its contribution to climate change mitigation by 2050. We find that, based on its characteristics alone, DAC may only reach the megaton -scale by mid-century. However, with targeted policy support - especially to increase near-term capacity – a climate-relevant gigaton-scale could still be reached.

Main

Direct Air Capture (DAC) is a promising technology to tackle climate change. Combined with CO_2 storage (as Direct Air Carbon Capture and Storage, DACCS), DAC enables long-term carbon dioxide removal (CDR). Unlike other land-based CDR methods, DAC operates with fewer biophysical constraints and possibly lower sustainability trade-offs[1-3], while offering great flexibility in the choice of the location of its deployment[4]. DAC can also provide CO_2 feedstock to produce synthetic fuels, chemicals, and materials, broadening its application across sectors[5,6]. As such, DAC is rising as a promising solution to abate unavoidable residual emissions and achieve net-negative emissions both in modelling[7–10] and policymaking[11–13].

Despite its potential, current deployment of DAC remains critically low, with approximately 27 small-scale plants operational globally, primarily in Europe and North America[13]. If DAC is to make a climate-relevant contribution to net-zero emissions and reach the gigaton-scale by 2050, it will need to scale its capacity by 100,000 times from the 2024 annual capture rate of 0.01 $MtCO_2/a$[14,15]. This discrepancy underscores the urgent need for clarity on the scale-up potential of DAC. In particular, assessments of feasible DAC capacity by mid-century and the role of policy in scaling up this technology are essential to manage expectations and avoid over-reliance on infeasible DAC rates to achieve our net zero targets.

This brief communication aims to investigate possible growth pathways for DAC with an adapted technology diffusion model, highlighting the critical role of including different policy levers.

To explore this issue, we modelled probabilistic pathways for DAC deployment, using ammonia synthesis growth rates as our base case. This case represents DAC deployment in a situation where there is no additional enhanced technology policy. In addition, we modelled a set of scenarios that represent cases with enhanced technology policy, with the impact of three key policy levers explicitly explored: (i) short-term capacity pushes by 2030 through increasing initial capacity, (ii) long-term demand credibility through increased anticipation for DAC requirements, and (iii) minimum long-term demand security through long-term market size (Online Methods, 2.3).

Our study built on and extended findings from existing research on DAC diffusion (SI_Table *1*). Prior studies[16] emphasized the use of analogs like ammonia synthesis, liquid natural gas (LNG), and carbon capture and storage (CCS). We focused on ammonia synthesis as the most suitable analog, and therefore as our baseline, using LNG and wind energy as sensitivities to reflect pessimistic and optimistic growth scenarios. While previous studies[5] employed Integrated Assessment Model (IAM) - based approaches, we used an extended logistic diffusion model[17] that was initially used to study green hydrogen and incorporated probabilistic elements to capture uncertainties from policy impacts and market dynamics. The logistic diffusion model used in this study incorporated key uncertain parameters mentioned below (Table 1):

Table 1: Overview of the key uncertain parameters used in this study. For further explanations see Online Methods, 2.3.

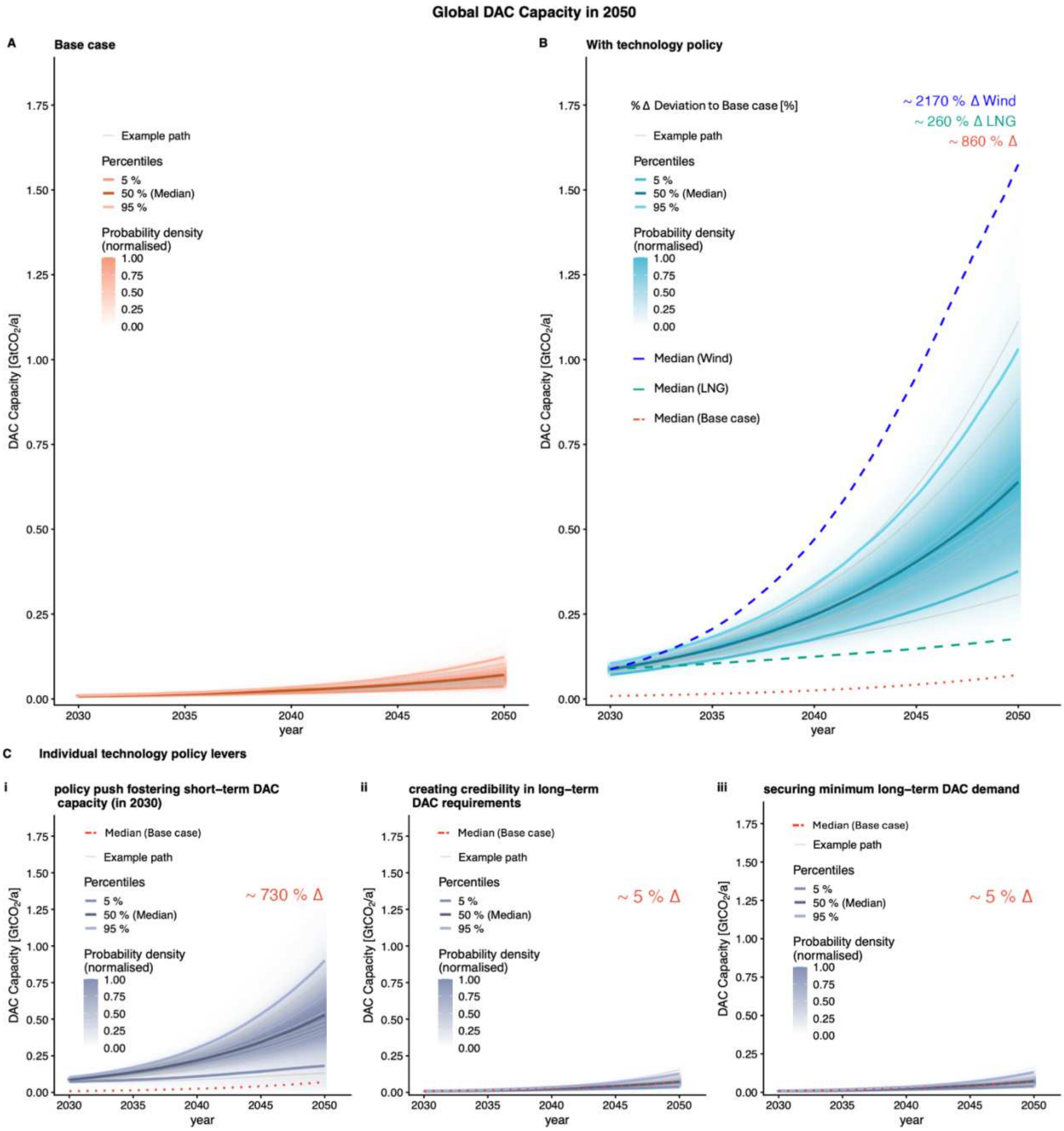
Nr.	Uncertain parameters	Definition
1	Initial capacity in 2030	Reflects the transition from formative to growth phase (SI_Visual 1). Our base case (Visual 1, A) used empirical DAC capacity data (SI_Table 2); our case with enhanced technology policy (Visual 1, B) modelled a significant capacity acceleration (10x increase) driven by political interventions (Visual 1, C (i)).
2	Emergence growth rate	Captures maximum annual growth in the post-formative phase (SI_Visual 1). We used ammonia synthesis (~11%/a) as the baseline scenario (Visual 1, A), wind energy (~20%/a) as optimistic, and LNG (~4%/a) as pessimistic sensitivity scenarios (Visual 1, B).
3	Credibility in long-term DAC requirements (demand pull)	Accounts for investor confidence in DAC's long-term market potential. Our base case (Visual 1, A) assumed an anticipation of 5 years; our case with technology policy (Visual 1, B) extended this to 15 years, reflecting enhanced regulatory certainty regarding long-term DAC requirements (Visual 1, C (ii)).
4	Long-term market size (demand pull)	Generated by uniform distributions of potential DAC capacity by 2050. Our base case (Visual 1, A) ranged from 0 to 5.1 $GtCO_2$/a; our case with technology policy (Visual 1, B) from 1.79 to 5.1 $GtCO_2$/a, reflecting improved market conditions driven by policy (Visual 1, C (iii)).

These parameters are inputs for the probabilistic simulation of scenarios for both the base case and the case with enhanced technology policy, revealing how interventions shape DAC's growth trajectories (Online Methods, 2.3).

Our findings indicated that global DAC capacity cannot reach gigaton-scale deployment by 2050, even with enhanced technology policy support, when following the median path of the base case where growth rates are driven by our defined baseline technology analog (Visual 1, A and B). If growth is only based on the characteristics of DAC and its announced capacity by 2030 (Visual 1, A), DAC capacity would grow only slowly, reaching ~50 $MtCO_2$/a by 2050 if following the median path, where the 95th percentile reaches a maximum of ~100 $MtCO_2$/a by mid-century.

With a mix of enhanced technology policy (Visual 1, B), DAC capacity improved, reaching ~600 $MtCO_2$/a for the median path and ~1 $GtCO_2$/a for the 95th percentile by 2050. If DAC proved to achieve more optimistic growth rates, modelled after wind energy, it could achieve ~1.6 $GtCO_2$/a. Conversely, pessimistic growth, modelled after LNG diffusion, resulted in ~130 $MtCO_2$/a, lower than the baseline growth rates of ammonia synthesis in the base case. Across all scenarios, in the case with enhanced technology policy, the DAC capacity resulted consistently higher compared to the base case.
We further explore the impact of different policy levers on DAC diffusion (Visual, C): Short-term policy pushes to boost 2030 DAC capacity (Visual 1, C (i)) prove to be the most impactful. This capacity push

increased the base case median path by more than ~700%, enabling DAC to reach ~500 $MtCO_2$/a by 2050. In contrast, measures to establish long-term demand credibility or secure minimum demand each yielded only modest improvements (~5%) (Visual 1, C (ii,iii)). Without the mentioned policy push, DAC could not exit its formative phase (SI_Visual 1) or achieve meaningful capacity by 2050. Regional findings for Europe and North America showed similar trends (SI_Visual 8-SI_Visual 9).



Visual 1: Probability feasibility space for achieving global DAC deployment by 2050, based on ammonia synthesis growth rates: (A) without enhanced policy support (base case) and (B) with enhanced policy support scenarios. Dashed lines compare optimistic (wind, blue) and pessimistic (LNG, green) analog growth rate sensitivities. Policy scenarios include (C): (i) a policy push to accelerate initial DAC capacity by 2030, (ii) measures to establish credible long-term DAC demand, and (iii) policies to secure minimum long-term demand. The colour shading indicates the annual probability density (determined from the uncertainty propagation of the initial capacity in 2030 and the emergence growth rate), with grey lines showing example growth paths, representing the broad spectrum of possible outcomes. The deviation to the base case (% Δ) was rounded to the nearest 5th or 10th for all plots in A, B and C.

Our analysis sheds light on the complex challenge of scaling up DAC to gigaton-scale by 2050, emphasizing the critical role of policy to yield high growth rates and boost short-term capacity. Even with policy support, baseline ammonia synthesis growth rates (~11%/a) remained insufficient, following the median path. Optimistic scenarios, such as wind energy (~20%/a), showed promise but require robust policy measures, while pessimistic trajectories, like LNG (~4%/a), fell far short of meeting mid-century targets.

These findings align with prior studies[5,15,18] emphasizing that DAC would need to follow the growth rates of fast-diffusing technologies, such as photovoltaics and nuclear power, to achieve gigaton-scale by mid-century. This challenge is not unique to DAC, as it was shown to apply also to other novel technologies such as green hydrogen[17]. However, our innovative probabilistic approach constitutes a methodological advance over previous studies[16] that based future capacity projections on linearly extrapolated growth rates of technological analogs. Our study also highlights the interplay between future DAC capacity and policy interventions, which in previous literature remained implicit[18]. Additionally, modellers can use this analysis to better assist policy makers by incorporating DAC diffusion constraints into scenario analyses.

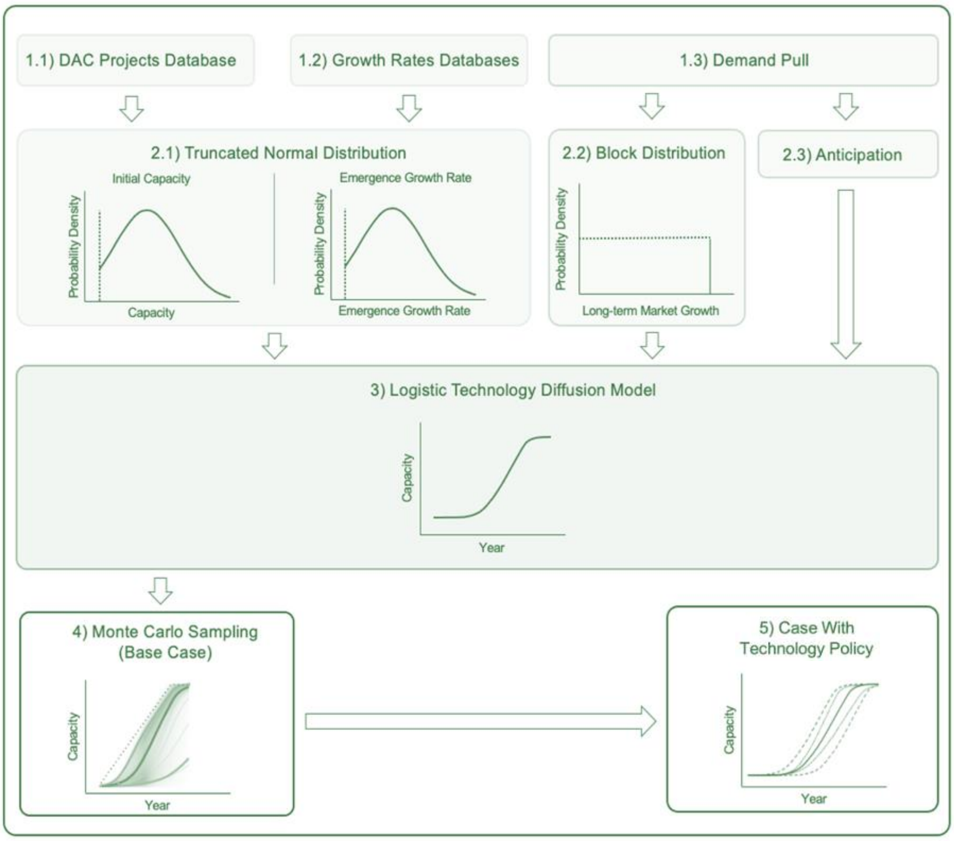
Furthermore, our research shows that policy pushes to boost short-term capacity are crucial. Instruments like public investments, subsidies, and tax credits (e.g., the U.S. 45Q tax credit) can stimulate early deployment and achieve a similar effect to what simulated in our analysis[19–22]. In addition, broad societal buy-in for this technology is also essential. Policymakers should engage communities, foster stakeholder dialogue, and implement transparent, inclusive policies to address public resistance and social challenges[20,23–25]. However, this study indicates that even all these policies mentioned may not be sufficient to achieve the gigaton scale by 2050. This means that, in absence of serious efforts to multiply the short-term DAC capacity, we should not over-rely on future large-scale DAC deployment to meet our climate targets, as this could lead to potential carbon lock-ins[26]. Given the potentially limited role of DAC in achieving net-zero emissions by 2050, policymakers should balance efforts to scale DAC with advancing other carbon removal technologies such as BECCS (Bioenergy with Carbon Capture and Storage) and afforestation, while prioritizing aggressive emissions reductions. This highlights also the urgency of proven and readily available solutions, such as renewable energy and end-use electrification, to reach the Paris Agreement's climate targets in time.

In summary, accelerating DAC deployment while managing its risks requires a careful balance. Policymakers must encourage fast growth to meet near-term capacity goals while preparing for limited availability by supporting complementary solutions. Our research highlights these considerations despite data and assumption limitations. Future work should refine uncertainties in DAC diffusion to guide realistic policy frameworks and strategies for meeting global climate goals.

Online Methods

1 Modelling Outline

Visual 2 conceptually illustrates the modelling of diffusion pathways for DAC deployment, depending on the influence of policy levers simulated using a logistic function. We defined the function by three uncertain and independent main parameters: initial capacity, emergence growth rate and demand pull.



Visual 2: Modelling outline of DAC deployment analysis: definition of uncertain parameters (initial capacity, growth rate, demand pull), creation of probabilistic feasibility spaces using an adjusted logistic diffusion model as well as Monte Carlo sampling (base case) and subsequent adjustment regarding different policy levers to analyse their influence (case with enhanced technology policy).

To estimate the initial capacity and emergence growth rates for analog technologies, we relied on the combination of existing databases and determined these parameters by applying truncated normal distributions (SI_Table *2*). Further, for the emergence growth rate parameters we used the same technology analogs regarding the base case and the case with enhanced technology policy. We parameterized the emergence growth rates using the distribution of exponential growth rates (SI_Visual 3, SI_Visual 4) of ammonia synthesis, LNG and wind energy, whereas the key focus was on ammonia synthesis as a baseline and the latter two technologies functioned as optimistic and pessimistic growth rate sensitivities (Table *2*).

We also defined a steadily increasing long-term demand pull for a growing market size using a uniform (block) distribution, and a demand pull anticipation to describe the credibility in long-term DAC requirements. These demand pulls represented the political, regulatory, and competitiveness-enhancing effects that expand market opportunities. Using the logistic diffusion model, the initial capacity determined the timing, the emergence growth rate influenced the slope, and the demand pulls defined the asymptote of the S-shaped diffusion curve (SI_Visual 1), reflecting the introduction of the CDR market by DAC.

Finally, with this approach we derived DAC capacities based on probability distributions over time. These different distributions and therefore the spread of the uncertain initial capacity and emergence growth rate defined probabilistic feasibility spaces under the condition of an increasing demand pull for the base case.

In a subsequent step, we extended this framework to include additional technology policy levers. This involved forming further probabilistic feasibility spaces under more optimistic conditions then in the base case, including (i) a policy push fostering short-term DAC capacity in 2030, (ii) the creation of credibility in long-term DAC requirements through an extended demand pull anticipation, and (iii) the introduction of a greater minimum long-term demand for DAC as in the base case.

These two cases—the base case and the case with enhanced technology policy—we then used to define and analyse different diffusion pathways for DAC deployment by 2050.

2 Theoretical Approach

2.1 Selected Methods

We explored diffusion pathways for DAC deployment and assessed the impact of enhanced technology policy by drawing on technology diffusion models, particularly those addressing CDR and green technologies due to the limited literature on DAC. We found the probabilistic diffusion model for green hydrogen, as described by Odenweller et al. (2022)[17], to be especially relevant. This model integrates two approaches: modifying growth models with historical asymptotic parameters[27,28] and using historical development to set ex-ante targets for wind and solar energy [29,30]. Odenweller et al. (2022)[17] synthesized these approaches to create probabilistic feasibility spaces for green hydrogen diffusion, which parallels the current stage of DAC technology. Therefore, their model built the basis for our further developed and optimized analysis.

For the growth rates chosen in our analysis (ammonia synthesis as a baseline, LNG and wind energy as sensitivities), we relied on the study of Roberts and Nemet (2024)[16]. This is because on the one hand, they developed specific criteria to identify suitable technological analogs, focusing on technologies with at least 20 years of history, significant scaling potential, and high complexity and moderate adaptability. On the other hand, they used the findings of Malhotra and Schmidt (2020)[31], which emphasized the role of complexity and customization in technology adoption, to assess the suitability of different technologies. Lastly, the analysis of Sievert et al. (2024)[32] confirmed the high complexity and moderate customization of liquid DAC, which further supported the selection of relevant technological analogs and provided a solid basis for the analysis of scaling potential.

In this regard, our study not only utilised the results of previous studies and applied the most similar technology analog[16], ammonia synthesis, for the main analysis, but it also differed from the current literature by expressing probabilistic pathways for DAC adoption with an S-shaped logistic diffusion model rather than relying on IAMs. These are widely used, but subject to limitations due to the lack of empirical data on DAC technology and the need to account for policies and market dynamics[5,17,18].

The SI_Table *1* gives an overview of the mentioned and additionally relevant studies and how we used them for our approach and therefore how it differs from other literature.

2.2 Modelling Technology Diffusion Pathways

We modelled the diffusion of DAC using an S-shaped curve (SI_Visual 1), which technologies typically follow when entering a finite market [17,33]. The logistic form of this curve, rooted in Rogers' (1962) concept of technology adoption [34], begins with rapid initial growth and flattens as saturation approaches. It

reflects how early adopters, familiar with a new technology, create niche markets, enabling wider adoption as conditions improve, such as better performance or lower costs.
Green, clean and CDR niche technologies can also be approximated by such an S-shaped curve to predict a so-called technology diffusion pathway [35–37]. Consequently, our analysis also assumed this approximation for DAC deployment.
The diffusion pathway progresses through three phases: formative, growth, and saturation. The formative phase involves gradual, uncertain growth as demonstration projects face technical challenges and high costs, often described as the "valley of death" [38]. The growth phase sees accelerated market adoption driven by cost-reducing learning effects [39,40]. Finally, the saturation phase occurs when growth slows due to techno-economic and social factors, reaching the market's final level[34]. Such paths, which are modelled with the help of a logistical function, captures the full technology adoption process accordingly (SI_Visual 1).

2.3 Uncertain Parameters

Since the scale-up and therefore the extent of the deployment of DAC is highly dependent on the political measures taken in the short and long term, it is critical to capture the effects of possible policy levers. This provides policymakers with a guideline on how and to what extent measures must be taken to align with global climate targets. Possible future policy levers that directly influence the diffusion pathway and therefore the deployment of DAC include the influence on the starting capacity in 2030, as well as the impact on the demand pull. The latter can be characterised on the one hand by a growing market size in the long term and on the other hand by anticipation through the creation of credibility regarding long-term DAC requirements (Table *2*).
The uncertain parameters described below relate to the base case and the case with enhanced technology policy and are differentiated in the respective sub-chapters regarding their underlying differences and assumptions.

Table 2: Overview of uncertain parameters for the base case and the case with enhanced technology policy regarding the baseline emergence growth rate of ammonia synthesis (see SI_Table 3 for wind energy and LNG).

	Uncertain parameters										
								Policy levers			
	Initial capacity (2030)			Emergence growth rate (ammonia synthesis)				i) Policy push: short-term capacity (factor)	ii) Demand pull: long-term credibility	iii) Demand pull: long-term market size	
	Min	Mean	Max	Min	Mean	Max	σ			Min. Value	Max. Value
	[$MtCO_2$/a]			[%/a]				[-]	[%/a]	[$GtCO_2$/a]	
A) Base case	4.8	8.8	76.0	0.0	11.0	25.5	5.0	1.0	5.0	0.0	5.1
B) With technology policy	48.0	88.0	760.0					10.0	15.0	1.79	5.1

a) Initial Capacity in 2030

The momentum driving DAC's removal capacity from the formative to the growth phase is uncertain, but potentially significant in the coming years. Since the initial capacity depends on this momentum, we treated it as an uncertain parameter in our analysis.
We compiled data for the initial capacity analysis from the IEA CCUS Project Database[41], the State of CDR Report[20,42] and other individual sources (SI_Table *1*). Using these, we created a comprehensive database of historical and future DAC projects, detailing their locations, development statuses,

technological characteristics, and removal capacities. We reclassified projects labeled "Proof of Technology" as "Operational" or "Decommissioned" depending on whether they are still in operation, resulting in a database of 78 entries (SI_Table *1*). This data was then used to describe the initial capacity of existing, planned, and announced projects and to parameterize the distribution of cumulative initial capacity based on project status (SI_Visual 2).
We selected 2030 as the initial year, assuming that it takes around five years to initiate the necessary political measures for the realization of the projects and thus to implement the corresponding projects from announcement to commissioning. This assumption accounts for the uncertainty of project implementation before a Final Investment Decision ("FID") and recognizes that even projects with a "FID" may face delays. Therefore, this approach balances short-term dynamics with the exclusion of uncertain long-term announcements. These considerations apply to the base case in our analysis, which excludes the application of targeted policy levers.

As mentioned above, the initial short-term capacity has a direct effect on the path of the diffusion curve and consequently on the long-term DAC capacity available in 2050. Therefore, by increasing this capacity by a certain factor, more capacity will be available in 2030, which results in a faster scale-up, a quicker emergence of the technology from its niche and ultimately a more probable saturation. For the case with enhanced technology policy, we therefore assumed the effect of a policy push on short-term capacity by 2030 to be 10 times the initial capacity. This assumption implies that such an increase in capacity is within the realms of possibility, provided that many projects that are currently in "FID" or "Under Construction" project development status transition to "Operational" status by 2030[43].

b) Emergence Growth Rate

Possible cost reductions, political and government support, and technological maturity influence the growth rate of new CDR technologies [19,20,22,44]. Given these uncertainties, we included the growth rate of DAC as an uncertain parameter in our analysis.
In this study, we focused on the maximum annual growth rate, known as the emergence growth rate[29], rather than the gradually declining rate due to market saturation. The emergence growth rate, realized after the formative phase, was parameterized using the slope parameter in the logistic function, following Odenweller et al. (2022)[17] (chapter 2.4).

To determine the different emergence growth rates, we used empirical data from the most suitable technology analogs for liquid and solid DAC (chapter 2.1), with having the goal to obtain different growth rates for DAC and therefore a range of possible deployment scenarios, defining a main baseline case and a pessimistic and an optimistic case as sensitivities for the analysis:

<u>Baseline and pessimistic scenario:</u> For the liquid DAC technology analogs, we followed the methodology of Roberts and Nemet (2024)[16](chapter 2.1). With their approach we identified ammonia synthesis and LNG for technology analogs of liquid DAC in our analysis. We focused on ammonia synthesis for our baseline scenario, since this analog is the most suitable analog for liquid DAC. For our pessimistic scenario we chose LNG, since this technology showed a similar but more pessimistic growth then ammonia synthesis[16].

<u>Optimistic scenario:</u> Since our methodology expand on solid DAC, we also included wind energy as a third analog technology. To determine wind energy as a third analog technology for solid DAC we used the same approach as Roberts and Nemet (2024)[16] and combined findings out of two studies (chapter 2.1). Besides that wind energy identifies as an analog for solid DAC specifically, the inclusion of it also allows us to determine diffusion pathways for DAC deployment with a highly optimistic growth rate and

therefore with a deployment example of one of the most established successful energy technologies besides solar PV (SI_Table *4*). For those reasons, we selected wind energy as our optimistic case.

Furthermore, instead of comparing the same technology across different regions, we considered different technologies within the same region, as historical growth rates for DAC and similar technologies, like green hydrogen, primarily reflect past political support rather than future potential [45]. This approach also simplified scenario construction by not requiring consideration of all factors influencing technology diffusion speed [17]. Lastly, since the uncertainties of these emergence growth rate parameters were also unstable and non-linear, as in Odenweller et al. (2022)[17], we expressed this scattering using a Monte Carlo simulation approach in the logistic diffusion model (chapter 2.4-2.5).

c) Demand pull

As the outcome of competition between different climate mitigation measures has not yet been determined for many end applications, the final CDR market volume is characterised by uncertainty [17,46]. In these applications, DAC is not only a new CDR technology in itself, but its supply, demand and infrastructure must be developed simultaneously [15,19,22,44,47]. This stands in contrast to for example solar and wind energy, which is already fully embedded in the electricity market and its infrastructure (SI_Table *4*). Therefore, the demand pull represented political, regulatory and competitiveness-enhancing effects that increase market opportunities. Due to the uncertainties mentioned above, we included the demand pull, which was differentiated in long-term market size and in credibility in long-term DAC requirements, as a third uncertainty parameter in the analysis.

<u>Long-term market size:</u> In contrast to Odenweller et al (2022)[17], we did not use a fixed market size until 2050 for DAC. Instead, we used a randomly selected uniform distribution per Monte Carlo Iteration (chapter 2.5) to draw a plausible range between a minimum and a maximum demand of the possible long-term DAC market size by 2050, reflecting the unpredictability of future demand and market dynamics for DAC. This range is based on a sector-specific assessment of global climate mitigation scenarios (Table 4). In the base case, we therefore assumed a range between a minimum demand of 0 $GtCO_2$/a and a maximum demand of 5.1 $GtCO_2$/a. In the case with enhanced technology policy, we assumed a more optimistic range with a minimum demand of 1.79 $GtCO_2$/a and the same maximum demand of 5.1 $GtCO_2$/a for long-term market growth, where political interventions and measures promote more favorable market conditions and therefore higher demand for DAC (Table *3*).

For the maximum potential demand, we included DAC-based carbon in the hard-to-abate sectors, aviation, maritime shipping, chemicals and cross-sectoral carbon dioxide removal (Table *3*). We then obtained the energy or carbon demand for 2050 for each sector. In terms of energy demand, we assumed a carbon intensity of fuels and feedstocks of 250 g/kWh. We assumed that up to 50% of the carbon demand associated with the largest hard-to-electrify fuels and feedstocks in the mentioned sectors, along with 50% of the novel carbon removal needs at the 75^{th} percentile of scenarios limiting warming to below 2°C by 2050, could be met by DAC or DAC-based e-fuels (Table *3*). This led to a maximum DAC market size of 5.1 GtCO2/a in total, which defined the upper limit of the uniform demand distribution (SI_Visual 3d).

For the minimum potential demand for DAC-based carbon and in the case with enhanced technology policy we multiplied the potential maximum demand of 5.1 $GtCO_2$/a by 35%, resulting in a value of 1.79 $GtCO_2$/a. The 35% reflects a general assumption that, by 2050, demand in each hard-to-abate sector will increase by at least this amount, inspired by the projected 35% rise in synthetic aviation fuel (SAF) demand across all EU airports by 2050[48]. For simplicity, we assumed that the minimum demand for CDR for cross-sectoral carbon capture covers only 17.5% of the total carbon required by 2050, rather than

50% as in the maximum potential demand. This also corresponds to a 35% increase in CDR demand compared to DAC's maximum carbon demand by mid-century (Table *3*).

Table 3: Summary Table of the minimum and maximum long-term DAC demand market size.

<table>
<tr><th>Case</th><th>Minimum Value [$GtCO_2/a$]</th><th>Maximum Value [$GtCO_2/a$]</th></tr>
<tr><td>A) Base case</td><td>0</td><td rowspan="2">5.1</td></tr>
<tr><td>B) Case with technology policy</td><td>1.79</td></tr>
</table>

Table 4: Maximum and minimum DAC demand pull values

Sector or application with potential DAC requirement	**2050 energy or carbon demand**	**Total carbon required**	**Maximum carbon required from DAC**	**Assumption on deriving the sector-specific DAC requirement from the total annual demands**	**Source**
Aviation	15.27 EJ/a	1.1 $GtCO_2/a$	0.5 $GtCO_2/a$	50% of carbon requirements met by DAC	IEA NZE 2050 [49]
Maritime	9.9 EJ/a	0.7 $GtCO_2/a$	0.3 $GtCO_2/a$	50% of carbon requirements met by DAC (this assumes large role of methanol compared to the carbon-free fuel ammonia)	IEA NZE 2050[49]
Chemicals carbonaceous feedstocks	55 EJ/a	3.8 $GtCO_2/a$	1.9 $GtCO_2/a$	50% of carbon requirements met by DAC (this maximum DAC scenario implicitly assumes little waste incineration CCS, less circularity such as mechanical/chemical recycling routes and less bioplastics)	Fritzeen et al. 2023[50] (GCAM), which shows 55-60 EJ/a only for chemical feedstocks (in 3 of 4 scenarios). In comparison, the IEA NZE[49] only has 28 EJ feedstock demand in 2050 (due to demand reductions in e.g. plastics compared to a baseline)
Carbon dioxide removal (CDR)	4.6 $GtCO_2/a$	4.6 $GtCO_2/a$	2.3 $GtCO_2/a$	50% of carbon requirements met by DAC (assuming limits in the availability of biogenic carbon for BECCS, which dominates novel CDR in many IAM scenarios)	Smith et al. 2023 (table 8.2) [20], 75th percentile from novel CDR (e.g. DACCS, BECCS) in C1-C3 scenarios
Sum across sectors		10.2 $GtCO_2/a$	**5.1 $GtCO_2/a$**		

Credibility in long-term DAC requirements: The demand pull regarding the credibility in long-term DAC requirements reflected investors' foresight and regulatory certainty, indicating their expectations for the duration of demand pull long-term market size projections and the competitiveness of CDR by DAC. For the base case we set the default assumption of this anticipation to five years. This assumption is based on Odenweller et al. (2022)[17] and data regarding the market expansion duration of other clean technologies [22,43]. For the case with enhanced technology policy, we scaled the default anticipation up to 15 years, based on the assumption that ambitious policy measures have been taken place.

2.4 Truncated Normal Distribution

The implementation of the stochastic uncertainty analysis was based on the Monte Carlo simulation approach. The parametric uncertainty underlying this approach was reflected by randomly selected samples extracted from probability distributions. For the initial capacity in 2030, as well as for the different emergence growth rates, we applied a normal distribution with a lower truncation (chapter 2.3). The lower truncation constrained the distribution to a certain lower bound[51]. We defined this lower bound "a" for the initial capacity distribution by all projects that were already "Operational" or "Under construction" and will start production in 2030. By defining the lower truncation, we were able to determine the truncation interval [a,]. In the next step, we set up suitable conditions for the remaining two degrees of freedom using the μ (mean) and s (standard deviation).

For the first condition, we assumed that the success rate of the projects with the development status "Feasibility Study" (FS) and "Design and Engineering Phase" (DEP) is 30% due to techno-economic and financial influences[52–54]. Therefore, we set the corresponding post-truncation expected value to this assumed capacity, which can be described as $C_{0.3\,(FSandDEP)}$. Since the probability density function can be expressed as ϕ and the cumulative density function of the normal distribution as Φ, the first condition relates to the expected value (E(X)):

$$E(X) = \mu + \sigma \frac{\phi\left(\frac{a-\mu}{\sigma}\right)}{1-\Phi\left(\frac{a-\mu}{\sigma}\right)} = C_{0.3(FSandDEP)} \tag{2.4.1}$$

The second condition we determined by assuming a further techno-economic and financial scenario, namely the probability of those projects that have already been confirmed by a "FID" and are therefore actually built is 15%. We labelled this capacity C_{FID}. Using the truncated cumulative distribution function, this condition can be described as follows:

$$F(C_{FID}) = P(X \leq C_{FID}) = \frac{\Phi\left(\frac{C_{FID}-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)}{1-\Phi\left(\frac{a-\mu}{\sigma}\right)} = 0.15 \tag{2.4.2}$$

Due to the scarcity of empirical data to determine these conditions regarding DAC, we adopted the two conditions 2.4.1 and 2.4.2 almost identically to those of Odenweller et al. (2022)[17]. However, for the capacity $C_{0.3\,(FSandDEP)}$ in the first condition, we orientated us not only on the success rate of 30% from the source of Odenweller et al. (2022)[17] in the case of hydrogen projects, but also on Abdulla et al. (2020)[52], which has shown a failure rate of 80% for CCS investments in the US, and on Kazlou et al. (2023)[53], which has predicted a failure rate of 76% for today's CCS plans. Furthermore, since we additionally included the DEP projects between the development stages of the FS and the "FID" and aimed for an optimistic and representative distribution, both capacity assumptions of 30% and 15% already made by Odenweller et al. (2022)[17] also proved to be valid for our analysis.
To obtain μ and σ, we numerically solved the non-linear system formed by the conditions 2.4.1 and 2.4.2, which allowed us to completely determine the truncated distribution by adding the previously determined truncation value "a". The changed initial capacity of the case with enhanced technology policy also passed through this truncated normal distribution, except that that capacity was multiplied by a factor of 10 (chapter 2.3).

For the distribution of baseline growth rates of the analog ammonia synthesis, we extracted the global ammonia synthesis production data from the dataset of Roberts and Nemet (2024)[16]. From this dataset, which contains data between 1924 and 2018, we used only the data from the period 1932 to 1959 to isolate exclusively the exponential growth phase of this technology. We obtained the data for wind energy, which reflected the optimistic sensitivity of the growth rates for DAC, by using the installed wind capacity from the BP Statistical Review of World Energy 2024[55]. This data was available and therefore used to examine the exponential growth phase of wind energy from 1997 to 2023 for Europe, North America and globally. Our database for LNG capacity, which represented the pessimistic sensitivity of growth rates for DAC, originated from the HATCH database[56], where we looked at a selected period from 1974 to 2020 to capture its exponential growth phase (SI_Visual 3, SI_Visual 4, SI_Table *2*).
We fitted exponential models to the data of each technology in 7-year moving intervals by calculating the mean and standard deviation of the 7-year growth rates of them (SI_Visual 4). We then subsequently used the intervals to parameterise the emergence growth rate distributions of each technology (SI_Visual 3). For the respective distributions, and therefore the different growth rate cases, we assumed a lower truncation of 0%/a for all the considered technologies, which we also defined as the lower limit of CDR market growth for DAC. By doing so, we accounted for the possible reality in which the growth of the CDR market for DAC and therefore its adoption has a non-ambitious outcome in the future. We then used the values from the truncated normal distributions for the respective initial capacities of the base case and the case with enhanced technology policy, as well as for the emergence growth rates, to further calculate the logistic diffusion model and finally to determine the resulting feasibility spaces.

2.5 Logistic Technology Diffusion Model

As already introduced in chapter 2.3 c) Demand pull, we elaborated the adapted logistic technology diffusion model provided by Odenweller et al. (2022)[17]. As with the scale-up of green hydrogen in the case of DAC deployment, the demand pull of the long-term market size must also simultaneously expand and harmonise the three definition areas of infrastructure, supply and demand. To realise this, we implemented the standard logistical technology diffusion model in such a way that a steadily growing demand pull was embedded, similar to Odenweller et al. (2022)[17]. In contrast to the referenced study, our demand pull approach did not assume a fixed end-market volume. Instead, we considered a range of potential end-market volumes and corresponding market growth trajectories, applying a randomized distribution with the following characteristics (equation 2.5.1):

$$f(x) = \begin{cases} \frac{1}{(g-c)}, & \text{for } c \leq x \leq g \\ 0, & \text{otherwise} \end{cases} \qquad (2.5.1)$$

Whereas "c" is the minimum potential demand and "g" the maximum potential demand that can occur in the distribution (chapter 2.3 c) Demand pull). Furthermore, all values between "c" and "g" have equal probability and the area under the probability density function is equal to 1, as it represents a probability distribution. This method enabled us to determine a randomly selected long-term DAC demand for each Monte Carlo iteration, resulting in varied end-market size outcomes. This range of possible end-market size scenarios we then defined differently between the base case and the case with enhanced technology policy, based on specific assumptions (chapter 2.3).
Additionally, since the CO_2 removal by DAC, like green hydrogen, cannot be described representatively by substituting technology shares, as Odenweller et al. (2022)[17], we modelled the directly growing market volume, expressed by the CDR capacity of DAC in our analysis, instead of its market shares. In this way, the implementation of the diffusion could be reconstructed as described below:

The standard logistic function for the DAC removal capacity C(t) is described per definition by the asymptote C_{max}, growth constant k, inflection point t_{inf} and Euler's number e = 2.718 (equation 2.5.2):

$$C(t) = \frac{C_{max}}{1 + e^{-k(t-t_{inf})}} \qquad (2.5.2)$$

By deriving this function, the solution of the logistic differential equation 2.5.3 could be obtained. As a result, $C(t_{inf})$ is subject to the condition $C(t_{inf}) = C_{max}/2$ due to the existing point symmetry of the S-shaped curve:

$$\frac{dC}{dt} = kC\left(1 - \frac{C}{C_{max}}\right) \qquad (2.5.3)$$

Whereas Odenweller et al. (2022)[17]'s model idea was based on this differential equation 2.5.4. The resulting adapted model converted C_{max} into a time-dependent demand pull $C_{max(t)}$ and discretised the differential equation, where t denotes the time in years and b the annual growth rate $b = e^{k} - 1$:

$$C_{t+1} = C_t + bC_t\left(1 - \frac{C_t}{C_{t,max}}\right) \qquad (2.5.4)$$

We then drew a sample (N = 1000) for the base case and the case with enhanced technology policy, in each case separately for the corresponding initial capacities in 2030, and for the annual growth rate b of the baseline and sensitivity growth rates using the Monte Carlo simulation. This allowed us to use the values obtained in the adjusted diffusion equation 2.5.2. Furthermore, the presented model improved numerical accuracy by using a quarterly time resolution with a quarterly growth rate. This growth rate was defined by $b_q = (1 + b)^{1/4} - 1$. Like Odenweller et al. (2022)[17], we found no noticeable influence on the results by further increasing the temporal resolution.

Data availability

All data analysed in the paper have been derived from previously published materials, which are included in the listed references and in the GitHub repository.

Code availability

All code necessary for replicating reported results is available in the GitHub repository.

References

1. Zickfeld, K. et al. Net-zero approaches must consider Earth system impacts to achieve climate goals. Nat Clim Chang **13**, 1298–1305 (2023).
2. Nolan, C. J., Field, C. B. & Mach, K. J. Constraints and enablers for increasing carbon storage in the terrestrial biosphere. Nat Rev Earth Environ **2**, 436–446 (2021).
3. Ho, D. T. et al. Monitoring, reporting, and verification for ocean alkalinity enhancement. State of the Planet **2-oae2023**, 12 (2023).
4. Terlouw, T., Pokras, D., Becattini, V. & Mazzotti, M. Assessment of Potential and Techno-Economic Performance of Solid Sorbent Direct Air Capture with CO2 Storage in Europe. Environ Sci Technol. (2024) doi:10.1021/acs.est.3c10041.
5. Edwards, M. R. et al. Modeling direct air carbon capture and storage in a 1.5 °C climate future using historical analogs. Proceedings of the National Academy of Sciences **121**, e2215679121 (2024).
6. Hepburn, C. et al. The technological and economic prospects for CO2 utilization and removal. Nature **575**, 87–97 (2019).

7. Fuhrman, J. et al. The role of direct air capture and negative emissions technologies in the shared socioeconomic pathways towards +1.5 °c and +2 °c futures. Environmental Research Letters **16**, (2021).
8. Realmonte, G. et al. An inter-model assessment of the role of direct air capture in deep mitigation pathways. Nat Commun 10, 3277 (2019).
9. IPCC. Summary for Policymakers. In: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change[P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA (2022).
10. Babiker, M. et al. Chapter 12: Cross-sectoral perspectives. https://www.ipcc.ch/report/ar6/wg3/chapter/chapter-12/ (2022) doi:10.1017/9781009157926.005.
11. The Federal Council. Carbon Capture and Storage (CCS) and Negative Emission Technologies (NETs). https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://www.bafu.admin.ch/dam/bafu/en/dokumente/klima/fachinfo-daten/br-bericht-zu-ccs-und-net.pdf.download.pdf/Carbon%2520capture%2520and%2520storage%2520(CCS)%2520and%2520negative%2520emission%2520technologies%2520(NETs).pdf&ved=2ahUKEwiJ_eGvk5aKAxUV0gIHHULWENIQFnoECB8QAQ&usg=AOvVaw0aGtiKunY99k5VdcTd1wsm (2022).
12. Tamme, E. & Beck, L. L. European Carbon Dioxide Removal Policy: Current Status and Future Opportunities. Frontiers in Climate **3**, (2021).
13. IEA. Tracking Direct Air Capture. Preprint at (2023).
14. IEA. Direct Air Capture 2022. Preprint at (2022).
15. McQueen, N. et al. A review of direct air capture (DAC): scaling up commercial technologies and innovating for the future. Progress in Energy **3**, 32001 (2021).
16. Roberts, C. & Nemet, G. Lessons for scaling direct air capture from the history of ammonia synthesis. Energy Res Soc Sci **117**, 103696 (2024).
17. Odenweller, A., Ueckerdt, F., Nemet, G. F., Jensterle, M. & Luderer, Gunnar. Probabilistic feasibility space of scaling up green hydrogen supply. Nat Energy **7**, 854–865 (2022).
18. Nemet, G. F. et al. Near-term deployment of novel carbon removal to facilitate longer-term deployment. Joule **7**, 2653–2659 (2023).
19. Ozkan, M., Nayak, S. P., Ruiz, A. D. & Jiang, W. Current status and pillars of direct air capture technologies. iScience **25**, 103990 (2022).
20. Smith, S. et al. The State of Carbon Dioxid Removal. (2023).
21. Honegger, M. Toward the effective and fair funding of CO2 removal technologies. Nat Commun **14**, 534 (2023).
22. IEA. International cooperation in clean energy research and innovation. Preprint at (2023).
23. Geels, F., Sovacool, B. K., Schwanen, T. & Sorrell, S. R. Sociotechnical Transitions for Deep Decarbonization. SSRN **357 (6357)**, 1242–1244 (2017).
24. Cox, E., Spence, E. & Pidgeon, N. Public perceptions of carbon dioxide removal in the United States and the United Kingdom. Nat. Clim. Chang. 10 744–749 (2020).
25. von Rothkirch, J., Ejderyan, O. & Stauffacher, M. Carbon dioxide removal: A source of ambition or of delays? Examining expectations for CDR in Swiss climate policy. Environ Sci Policy **153**, 103659 (2024).
26. Unruh, G. C. Understanding carbon lock-in. Energy Policy **28**, 817–830 (2000).
27. Hansen, J. P., Narbel, P. A. & Aksnes, D. L. Limits to growth in the renewable energy sector. Renewable and Sustainable Energy Reviews **70**, 769–774 (2017).

28. Cherp, A., Vinichenko, V., Tosun, J., Gordon, J. A. & Jewell, J. National growth dynamics of wind and solar power compared to the growth required for global climate targets. Nat Energy **6**, 742–754 (2021).
29. Grubb, M., Drummond, P. & Hughes, N. THE SHAPE AND PACE OF CHANGE IN THE ELECTRICITY TRANSITION: Sectoral dynamics and indicators of progress. UCL Institute for Sustainable Resources (2020).
30. Lowe, R. J. & Drummond, P. Solar, wind and logistic substitution in global energy supply to 2050 – Barriers and implications. Renewable and Sustainable Energy Reviews **153**, 111720 (2022).
31. Malhotra, A. & Schmidt, T. S. Accelerating Low-Carbon Innovation. Joule **4**, 2259–2267 (2020).
32. Sievert, K., Schmidt, T. S. & Steffen, B. Considering technology characteristics to project future costs of direct air capture. Joule **8**, 979–999 (2024).
33. Meade, N. & Islam, T. Modelling and forecasting the diffusion of innovation – A 25-year review. Int J Forecast **22**, 519–545 (2006).
34. Rogers, E. M. DIFFUSION OF INNOVATIONS. Free Press of Glencoe, A Division of Macmillan Publishing Co., Inc. (1962).
35. Schilling, M. A. & Esmundo, M. Technology S-curves in renewable energy alternatives: Analysis and implications for industry and government. Energy Policy **37**, 1767–1781 (2009).
36. Li, Y. & Qin, S. Comparative Study on the Developmental Stages of Global CCS Technology Based on the S-Curve Model. Energy RESEARCH LETTERS **2**, (2021).
37. Zielonka, N., Wen, X. & Trutnevyte, E. Probabilistic projections of granular energy technology diffusion at subnational level. PNAS Nexus **2**, pgad321 (2023).
38. Nemet, G., Zipperer, V. & Kraus, M. The valley of death, the technology pork barrel, and public support for large demonstration projects. Energy Policy **119**, 154–167 (2018).
39. Fasihi, M., Efimova, O. & Breyer, C. Techno-economic assessment of CO2 direct air capture plants. J Clean Prod **224**, 957–980 (2019).
40. Arthur, W. B. Increasing Returns and Path Dependence in the Economy. (University of Michigan Press, 1994).
41. IEA. CCUS Projects Database. Preprint at (2024).
42. Smith, S. M. et al. The State of Carbon Dioxide Removal - 2nd Edition. https://osf.io/f85qj/ (2024).
43. IEA. Rapid progress of key clean energy technologies shows the new energy economy is emerging faster than many think. Preprint at (2023).
44. Kazemifar, F. A review of technologies for carbon capture, sequestration, and utilization: Cost, capacity, and technology readiness. Greenhouse Gases: Science and Technology **12**, 200–230 (2022).
45. Beaumont, M. L. L. Making Direct Air Capture Affordable; Technology, Market and Regulatory Approaches. Front. Clim., Sec. Carbon Dioxide Removal **4**, (2022).
46. Coffman, D. & Lockley, A. Carbon dioxide removal and the futures market. Environmental Research Letters **12**, 15003 (2017).
47. Bisotti, F., Hoff, K. A., Mathisen, A. & Hovland, J. Direct Air capture (DAC) deployment: A review of the industrial deployment. Chem Eng Sci **283**, 119416 (2024).
48. European Union. REGULATION (EU) 2023/2405 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 18 October 2023 on ensuring a level playing field for sustainable air transport (ReFuelEU Aviation), ANNEX 1(f). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02023R2405-20231031 (2023).
49. International Energy Agency. Net Zero by 2050 - A Roadmap for the Global Energy Sector. www.iea.org/t&c/ (2021).
50. Fritzeen, W. E. et al. Integrated Assessment of the Leading Paths to Mitigate CO2 Emissions from the Organic Chemical and Plastics Industry. Environ Sci Technol **57**, 20571–20582 (2023).

51. Burkardt, J. The Truncated Normal Distribution. (2023).
52. Abdulla, A., Hanna, R., Schell, K. R., Babacan, O. & Victor, D. G. Explaining successful and failed investments in U.S. carbon capture and storage using empirical and expert assessments. Environmental Research Letters **16**, 14036 (2020).
53. Kazlou, T., Cherp, A. & Jewell, J. Feasible deployment trajectories of carbon capture and storage compared to the requirements of climate targets. (2023) doi:10.21203/rs.3.rs-3275673/v1.
54. Lambert, M. EU Hydrogen Strategy – A case for urgent action towards implementation. 4 (2020).

Acknowledgements

This work was supported by the Climate Policy Lab within the Institute for Environmental Decisions at ETH Zurich. The Climate Policy Lab conduct problem-driven research on the strategies to address climate change and related environmental problems. FU and AO gratefully acknowledge funding from the Kopernikus-Projekt Ariadne through the German Federal Ministry of Education and Research (grant nos. 03SFK5A and 03SFK5A0-2) and the HyValue project (grant no. 333151). NB was funded through a Doc.CH Grant No. P000PS_203884 and gratefully acknowledges support from the Swiss National Academy of Science.

Contributions

JR, NB and TZ initiated the study, with further inputs of AO and FU during the study design. TZ led the research, carried out the analysis, and created all figures, supervised by NB and JR. AO and FU contributed analysis tools and supported setting up the analysis. All authors contributed to analysing and interpreting the results. The first draft was developed by TZ with all authors contributing significantly to subsequent iterations and revisions.

Corresponding author

Correspondence to nicoletta.brazzola@usys.ethz.ch.

Ethics declarations

Competing interests

The authors declare no competing interests.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- FeasibilityofDACDeploymentby2050SupplementaryInformation.pdf