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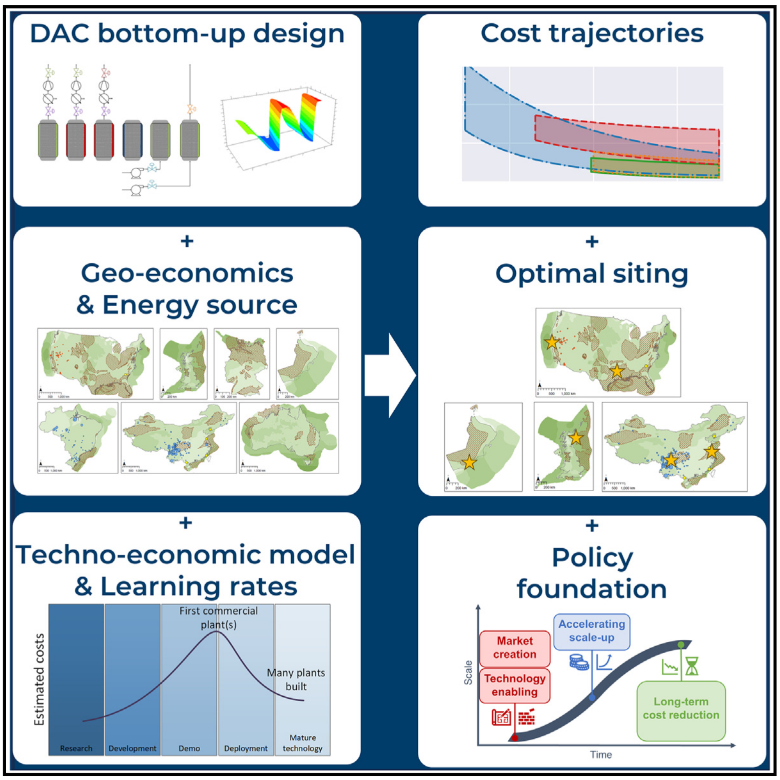
The cost of direct air capture and storage can be reduced via strategic deployment but is unlikely to fall below stated cost targets

Graphical abstract



Highlights

- Cost of direct air capture and storage (DACS) can fall to \$100–600 t-CO_2^{-1}
- Coupling DACS to intermittent renewables is typically not favorable for low costs
- Geoeconomic parameters have notable influence on cost
- Investment grants are best used to support small projects

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In brief

Direct air capture and storage (DACS) of CO_2 can enable negative emissions that we critically need to meet the Paris climate targets. The feasibility of DACS depends on its economic viability and costs further along the technological learning curve, which is presently underexplored. Here, we fill the knowledge gap via a top-down and bottom-up cost evaluation approach. We find that the long-term cost can fall substantially, but stronger policy support will be required to meet optimistic targets.

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The cost of direct air capture and storage can be reduced via strategic deployment but is unlikely to fall below stated cost targets

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SCIENCE FOR SOCIETY Scientists, policymakers, and businesses are scrambling to understand feasible pathways to meet the Paris climate goals, with a strong focus on carbon dioxide removal (CDR) that is essential for net-zero. As a prime, but currently costly, CDR technology, direct air capture and storage (DACS) technologies and deployment routes have been examined by many modelling studies, and governments are working to develop policy frameworks to steer favourable business conditions. Both efforts are striving to project when and how DACS will be cost-effective. Strategies such as site selection and choice of electricity sources are supposed as key cost decline drivers; what is yet unclear is whether such strategies can enable the optimistic cost targets, like those preferred by the US government (i.e., \$100 t-CO_2^{-1}), to be met. Via a plant-level bottom-up and top-down cost assessment, we find that costs could drop to \$100-600 t-CO_2^{-1} by 2050 thanks to strategic deployment that can bend the capital cost curve, but to reach economically viable cost levels, strong and tailor-made policies will almost certainly need to be put into place.

SUMMARY

Carbon dioxide removal (CDR) is necessary to minimize the impact of climate change by tackling hard-to-abate sectors and historical emissions. Direct air capture and storage (DACS) is an important CDR technology, but it remains unclear when and how DACS can be economically viable. Here, we use a bottom-up engineering-economic model together with top-down technological learning projections to calculate plant-level cost trajectories for four DACS technologies. Our analysis demonstrates that the costs of these technologies can plateau by 2050 at around \$100-600 t-CO_2^{-1} mainly via capital cost reduction through aggressive deployment, but still exceed the optimistic targets defined by countries such as the US (i.e., \$100 t-CO_2^{-1}). A further analysis of existing policy mechanisms indicates that strong, project-catered policy support will be required to create market opportunities, accelerate DACS scale-up and lower the costs further. Our work suggests that strategic DACS deployment and operation must be coupled with strong policies to minimise the cost of DACS and maximise the opportunity to make a planet-scale climate impact.

INTRODUCTION

Carbon dioxide removal (CDR) is a vital tool in the fight against climate change. The prevention of greenhouse gas (GHG) emissions should be a priority, but there is little doubt that CDR will be required to offset hard-to-abate emissions if we are to prevent the worst impacts of climate change and limit the planet's warming to 1.5°C or even 2°C.[1,2] Also, CDR is needed to achieve net-negative emissions once carbon neutrality of our economies has been reached. Bergman and Rinberg approximate that "hard-to-avoid" emissions may be between 1.5 and 3.1 Gt-$CO_{2,eq}$ year^{-1} (throughout this paper, *t* always refers to metric tonnes) by 2100,[3] while the economic-optimized integrated assessment modeling pathways that result in 1.5°C of warming suggest that net-negative CO_2 emissions are required from between 2040 and 2070.[4] Direct air capture (DAC) and direct air capture and storage (DACS) is a technological solution to CDR. DAC entails the extraction of CO_2 from air, in most cases, using a

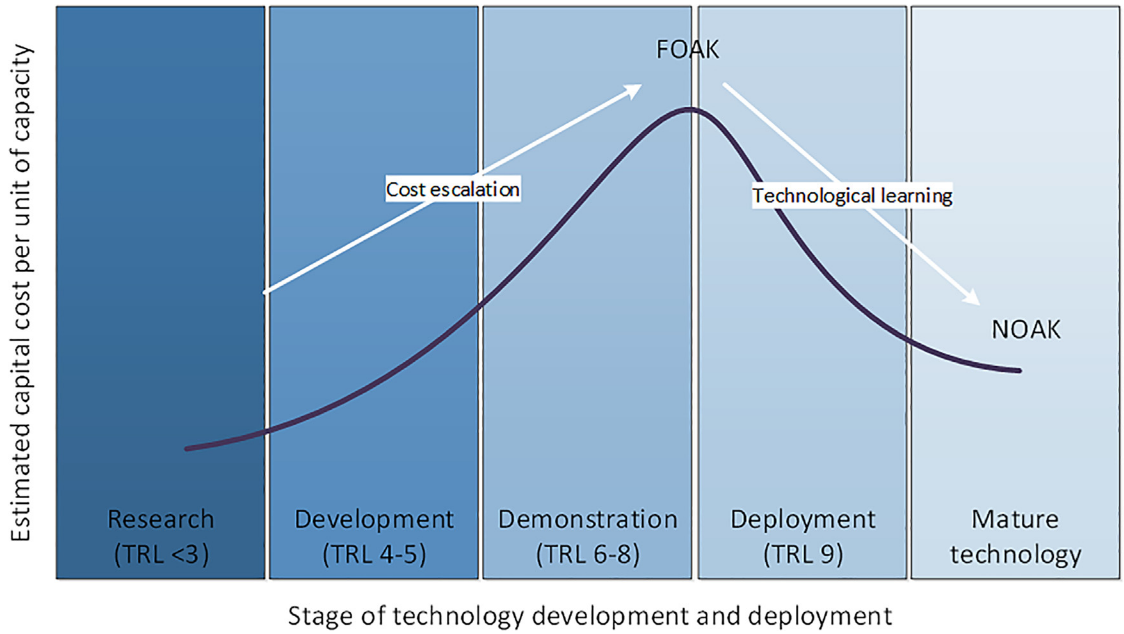


Figure 1. Graphical representation of typical cost trajectories for processing technologies

Cost estimates of the FOAK plant tend to increase from low to high TRL due to issues such as legal and safety requirements, incomplete process designs and understanding of the process, and the need to engineer out issues identified during upscaling. From the FOAK plant, the costs typically start to fall as a result of learning how to operate the plant optimally, learning where redundancies are in process design, mass manufacturing of plant components, profits being funneled back into innovation leading to process intensification and reduced energy penalties, etc. Adapted from van der Spek et al.[103]

chemical sorbent and subsequent release of that CO_2 from the sorbent. As an approach to CDR, DACS facilitates comparatively easy carbon accounting and fewer external impacts, such as competition for land, than other approaches for CDR.[5,6] However, it may also be costly and energy intensive, and, in some cases, water intensive.[7] In this context, it is important to understand that removing carbon dioxide from the atmosphere at \$100 t-CO_2^{-1} has widely been identified as a holy grail of economic viability for DACS and an ambitious target set by policymakers in the United States.[8] The importance of this specific value will not be analyzed in this work, although readers should be aware that estimates place the global social cost of carbon as high as \$417 t-CO_2^{-1}.[9]

This shows there is a critical need for DACS cost estimates to underpin policymaking, integrated assessment modeling, and investment decisions. These estimates must be produced independently (i.e., by organizations other than DAC technology developers). As a result, several studies have attempted to estimate the current cost of DACS[10–17] or project the cost of DACS into the future.[16,18–20] However, these studies all use methods inconsistent with the nature of the cost development of early-stage technologies, whose costs tend to rise during the research, development, and deployment (RD&D) phase up to the first deployed commercial scale plant, i.e., the first-of-a-kind (FOAK) plant, and then start falling as a function of deployment, as demonstrated in Figure 1. A recent method for the costing of advanced CO_2 capture technologies was postulated by Rubin and coworkers.[21] It is currently the only method consistent with the cost trajectory of early-stage, low-technology-readiness-level (TRL) technologies. The method is called the "hybrid method." It combines bottom-up engineering-economic studies to estimate the cost of a FOAK plant, with technological learning projections accounting for cost reductions with cumulative technology deployment as a result of innovation, learning by doing, learning by using, and economies of scale, among others.[21–28] Critical to this method is a sound FOAK cost estimate for the low-TRL technology, which should include the cost escalations from the current TRL to the FOAK plant, i.e., TRL 8 (demonstration) or 9 (deployment). In particular, the correct application of this cost escalation is missing in the existing literature. Consequently, the few academic studies that project the costs of DACS into the future using technological learning commence from a starting point that is too low (sometimes by a whole order of magnitude in the case of solid sorbent DAC), leading to unrealistically low estimates of the future cost of DACS.[18–20]

Furthermore, many cost figures of DAC that are quoted in the public domain are based on available information from the companies developing the technologies, and independent interpretation and corroboration are lacking. Additionally, existing academic studies and publicly presented cost figures differ in assumed boundary conditions, often omitting parts of the DACS value chain (e.g., CO_2 compression, transport, and storage), leading to further unjustified lowering of DACS costs. There is also high uncertainty on the current costs of DACS, which is often not sufficiently highlighted in cost modeling studies. Also, there is little to no information on how the economics of DACS will vary in locations outside the United States, and perhaps Europe, and on how government policy may support the deployment and cost development of DACS projects. Finally, the cost projections of

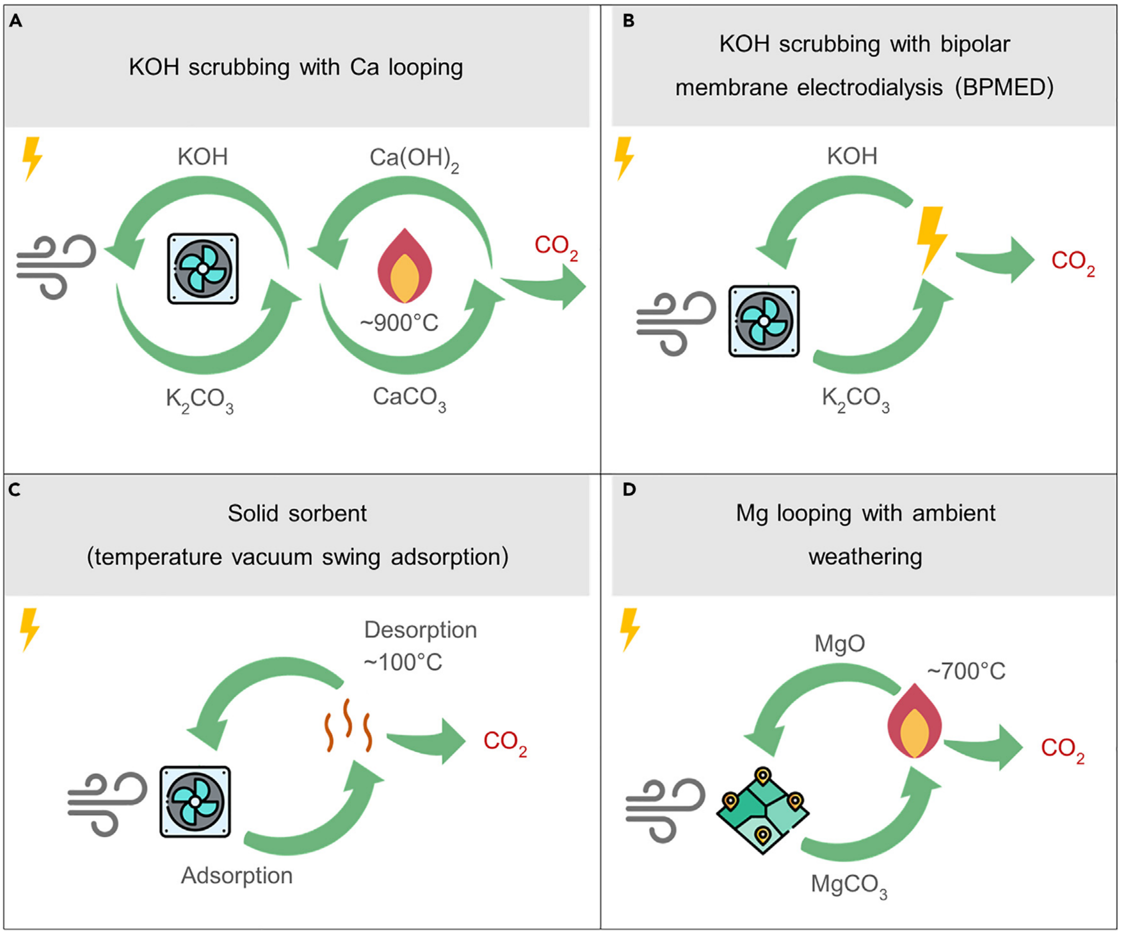


Figure 2. Summary of DACS technologies studied

The four technologies assessed as part of this study. (A) KOH absorption paired with regeneration via Ca looping, (B) KOH absorption paired with regeneration via bipolar membrane electrodialysis (BPMED), (C) solid sorbent DAC using temperature vacuum swing adsorption, and (D) MgO ambient weathering with regeneration via calcination. It is assumed in this study that the heat in both (A) and (D) is supplied by natural gas to oxy-fired calciners.

DACS typically include solid sorbent DAC (or low-temperature [LT] DAC), and liquid solvent DAC with Ca looping (or high-temperature [HT] DAC), but other technologies are often omitted. Hence, actually plausible current cost ranges and projections for a portfolio of DACS technologies across different geographies remain unavailable.

Here, we aim to address this caveat by providing a methodologically consistent answer to where the costs of DACS may occur due to large-scale deployment and the potential impact of deployment location and policy. We apply our costing approach to four DAC technologies to span a technology space wider than only solid sorbent and liquid solvent DAC: (1) KOH absorption paired with regeneration via calcium looping,[12] (2) KOH absorption paired with regeneration via bipolar membrane electrodialysis (BPMED),[29] (3) solid sorbent DAC using temperature vacuum swing adsorption,[30] and (4) MgO ambient weathering with regeneration via calcination,[31] presented in Figure 2. We identify that the cost of DACS will fall to \$100–600 t-CO_2^{-1} and, as a result, the long-term target of \$100 t-CO_2^{-1} will remain elusive, while policymakers must revisit the social cost of carbon to assess whether this target is even relevant. We also show that the costs of DACS can vary quite significantly between countries and energy supply strategies and rational siting may thus be critical to obtain cost-optimal solutions. We finally show that grant support is more suited for smaller than for larger projects and can rapidly lower the costs of the first implementations, while policies lowering the cost of capital are key for the feasibility of larger projects and long term.

RESULTS AND DISCUSSION

Learning curves and modularity

Figure 3 shows the learning-curve ranges obtained from the analysis for the United States paired with nuclear electricity. The insights drawn from this figure are generalizable, but the exact cost values vary by location and energy source, as discussed later.

The commonly cited cost goal is unlikely to be met

Figure 3 suggests that the common long-term target to remove CO_2 from the atmosphere under \$100 t-CO_2^{-1} will be very

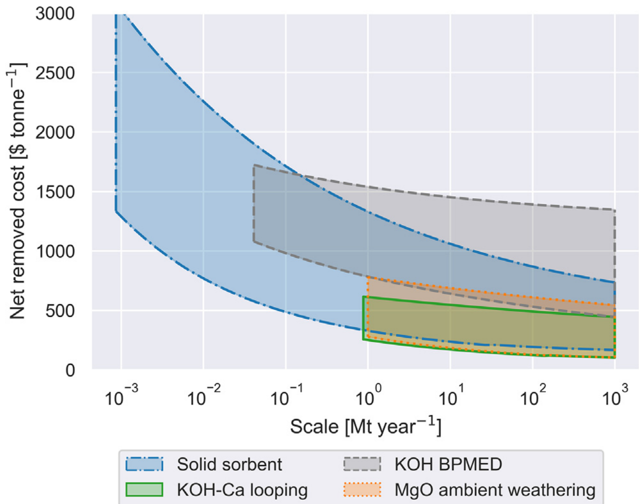


Figure 3. DACS cost learning curves paired to nuclear electricity

Cost development trajectories of the four technologies from the kilotonne to the gigatonne CO_2 net removed per annum scale. Note the log scale on the x axis. The cases studied are in the United States paired to nuclear electricity and using a heat pump for low-grade heat where applicable. The figure provides ranges instead of lines, highlighting a large amount of uncertainty and variability in the estimates. Trajectories for different locations paired with geothermal electricity can be found in Figure S13. Example cost breakdowns from this plot at the Mt-CO_2 year^{-1} and Gt-CO_2 year^{-1} scales are available in Table S19.

challenging to reach.[8,32] The figure shows that the Gt-CO_2 year^{-1} scale estimates range from \$100 t-$CO_2$$^{-1}$ to \$1,350 t-$CO_2$$^{-1}$, with three of the technologies being in a similar range, excluding KOH BPMED. Along the way, at the Mt-CO_2 year^{-1} scale, the costs range from \$250 to 1,500 t-$CO_2$$^{-1}$. The lowest estimate for three of the four technologies converges onto \$100–170 t-$CO_2$$^{-1}$, indicating the lower limit to the cost of DACS under our current assumptions and the four technologies studied here. The technology with the highest cost at scale is the electrochemical KOH BPMED due to its (current) high electricity requirement of 22.5 GJ t-$CO_2$$^{-1}$. However, alternative electrochemical technologies have the potential to reduce this requirement. For example, the recent work by the Hatton group demonstrates a technology that could use much less energy,[33,34] but there are not enough published data, and the TRL is too low to perform an accurate cost assessment, and hence this technology improvement was not considered for analysis in this work.

Modular technologies are only more expensive now

The solid sorbent and KOH BPMED FOAK scale is smaller than for the other two technologies, leading to higher FOAK costs yet similar costs at comparable scales. The smaller FOAK scale technologies incur a much higher FOAK cost as theycannot utilize economies of scale. However, these more modular technologies also exhibit more technological learning as there are greater opportunities to improve and reduce costs when producing such modules through mass production, and they undergo more doublings in installed capacity before a certain scale is reached.[35] This leads to overlapping costs at similar scales across all four technologies. The downstream processing units of all the technologies, such as compression and condensation, are not inherently modular. Hence, they have a greater impact on the FOAK cost of the modular technologies, as economies of scale are not utilized. This can be observed in Figure S14, where the FOAK net removed cost for the most modular process, solid sorbent, is sensitive to the compressor capital cost. Co-located DAC systems could alleviate this if multiple plants share downstream processing units, which could be an opportunity to reduce the FOAK costs of (modular) DAC technologies.

Due to the large dependence on the individual unit size, optimizing the module size could be an exciting problem for further investigation within each DACS technology. Figures S1–S4 present some preliminary analysis of the impact of FOAK plant size on the learning curves. Across the plant sizes studied, the initial size of the solid sorbent and KOH BPMED technologies has little impact on the Gt-CO_2 year^{-1} scale cost projections, but the solid sorbent FOAK costs are affected. For the MgO ambient weathering and KOH-Ca looping technologies, the 1 Mt-CO_2 year^{-1} and 0.5 Mt-CO_2 year^{-1} FOAK plant size learning curves overlap almost perfectly. However, decreasing the FOAK plant size further to 0.1 Mt-CO_2 year^{-1} dramatically affects both the FOAK and Gt-CO_2 year^{-1} scale costs negatively, indicating that the FOAK plants for these technologies should ideally be built at large scales.

Point estimates or targets should be avoided

There is a large potential range in the FOAK costs of each technology, given the accuracy of the capital cost estimate, the potential range of possible process contingencies, variation in energy prices, range of possible discount rates, and range of possible transport and storage costs. Due to this uncertainty, singular point estimates for the cost of DACS provide little value and should be avoided in the public discourse in future. The capital cost accuracy, and range of process contingencies in particular, reflects the immaturity and perhaps more the lack of publicly available technology design, performance, and cost data.

Capital cost reduction by deployment is critical

Cost breakdowns at the FOAK and Gt-CO_2 year^{-1} scale are available in Figure S15. For a FOAK plant, the capital costs are dominant for solid sorbent DACS, but they also make up a large proportion of the cost for KOH-Ca looping and MgO ambient weathering. The exception is KOH BPMED, which is dominated by operating costs through high energy demands. This begins to change as deployment progresses. Operating costs have much more influence when the technology has fully matured. Deployment will drive capital costs down at a higher rate than operating costs, therefore deployment is key to cost reductions.

Pairing DACS to intermittent renewables is expensive

Figure 4 shows the learning-curve ranges obtained from the analysis for the United States paired with intermittent renewable electricity for comparison to Figure 3 and provides a key insight. The ranges in Figure 4 are much larger than the ranges in Figure 3, essentially due to the large range of intermittent renewable capacity factors across the United States, indicating that pairing

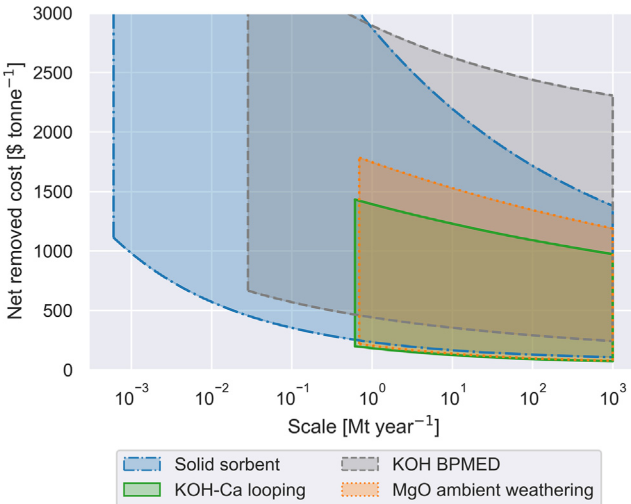


Figure 4. DACS cost learning curves paired to intermittent renewables

Cost development trajectories of the four technologies from the kilotonne to the gigatonne CO_2 net removed per annum scale. Note the log scale on the x axis. The cases studied are in the United States paired to intermittent renewable electricity and using a heat pump for low-grade heat where applicable. The figure provides ranges instead of lines, highlighting a large amount of uncertainty and variability in the estimates.

DACS to intermittent renewables is unlikely to be cost-effective unless the renewable electricity comes from installations with high-capacity factors, such as some offshore wind installations. This counters the argument that DACS could run on cheap curtailed renewable energy, for instance, as the sharing of the capital investment over the total amount of CO_2 removed would be insufficient. Ideally, DACS would run constantly on an almost completely decarbonized grid.

Results in context

Currently, the only commercial plants in the world are operated by Climeworks. They have quoted costs or prices of $500–600 t-$CO_2$$^{-1}$ in 2019 and €1,000 t-$CO_2$$^{-1}$, specifically from the Orca plant, in 2021.[36,37] However, our FOAK cost estimates are $1,300–3,100 t-$CO_2$$^{-1}$ for a case study in the USA paired to nuclear electricity. These costs are perhaps not entirely comparable, given the lack of information on cost breakdown and whether their quotes include compression, transport, and storage. For example, if we assume in our model that we have free waste heat with a 0% discount rate and no compression or storage costs, this value becomes $580–920 t-$CO_2$$^{-1}$, which is consistent with previous quotes from Climeworks. Then, if we extrapolate this using learning rates from the Hinwil to Orca scale, the range becomes $410–760 t-$CO_2$$^{-1}$. Previously, companies have paid up to $2,050 t-$CO_2$$^{-1}$ in voluntary CDR markets, suggesting there is a potential business case currently.[38] The opportunities for these early cost reductions, such as using waste heat, will likely be exploited first, leading to slightly lower costs than those predicted here for FOAK and early plants. However, when we reach large-scale deployment, these opportunities should have been fully utilized, leading to the scenarios predicted in our learning curves. Papapetrou et al. estimate that 100 TWh year^{-1} of recoverable LT waste heat (<200°C) is available in the European Union,[39] but this waste heat can also be utilized for space heating or efficiency gains if it is close to urban areas or other industries. If this waste heat could be utilized for solid sorbent DACS alone, this would only support ~37 Mt-CO_2 year^{-1} of deployment, which is an unrealistically optimistic best-case scenario.

For the KOH-Ca looping process, Keith et al. explicitly state that they do not do a cost evaluation for a FOAK plant.[12] Instead, they compare the cost of an "early plant" and Nth-of-a-kind (NOAK) plant. The early plant estimates from their study are $190–260 t-$CO_2$$^{-1}$ when we escalate Keith et al.'s capture cost to net removed cost using their figure of 0.1 tonnes of CO_2 emitted per tonne captured.[12] However, our FOAK cost estimate is larger and ranges from $260–620 t-$CO_2$$^{-1}$ in our harmonized framework for a case study in the USA paired to nuclear electricity. The main reason is that the contingencies that we apply are now reflective of the TRL and detail of the engineering study. These contingencies also cascade into higher fixed operating and maintenance costs, which here are a function of capital cost. Meanwhile, the literature cost estimates of the KOH BPMED and MgO ambient weathering processes are said to be for a NOAK plant and are not comparable to the FOAK cost estimates here.

Costs will plateau from 2050 to 2075

So far, we have investigated how costs develop with deployment. Now we will attempt to translate this into projected costs as a function of time. The rate of deployment depends on targeted maximum global temperature increases and other socio-economic, political, and technological variables. There are less than a handful studies that project DACS deployment into the future, and we used these to provide an indicative projection of the cost development of DACS in time.[2,40,41] Figure 5 shows the scenario analysis results for a United States location paired with nuclear electricity. The conclusions drawn from this figure are general to other locations and electricity sources, with only the exact values varying. This variation is discussed below using Figure 6.

Figure 5 shows that the initial high cost of a small modular FOAK plant for solid sorbent DACS may be mitigated by higher learning rates and more doublings by 2030 at the latest if deployment continues. Another critical observation from Figure 5 is that the difference in cost between the two uptake scenarios is greater than the difference between a 25% or 100% market share, indicating that we could scale four technologies simultaneously and still expect to bring down the cost through technological learning. We do not need to pick a winner up front. From Figure 5, we see that the long-term costs, toward the end of the century, are likely heading to around $100–600 t-$CO_2$$^{-1}$. When this is achieved depends on the scenario. For example, under the low-uptake scenario, the costs plateau by around 2075. Meanwhile, under the high-uptake scenario, this will happen by 2050.

Siting decisions must be rational

The colored matrices in Figure 6 show how the median costs, using our middle or most likely values for all parameters, vary across locations and electricity sources. Generally, higher

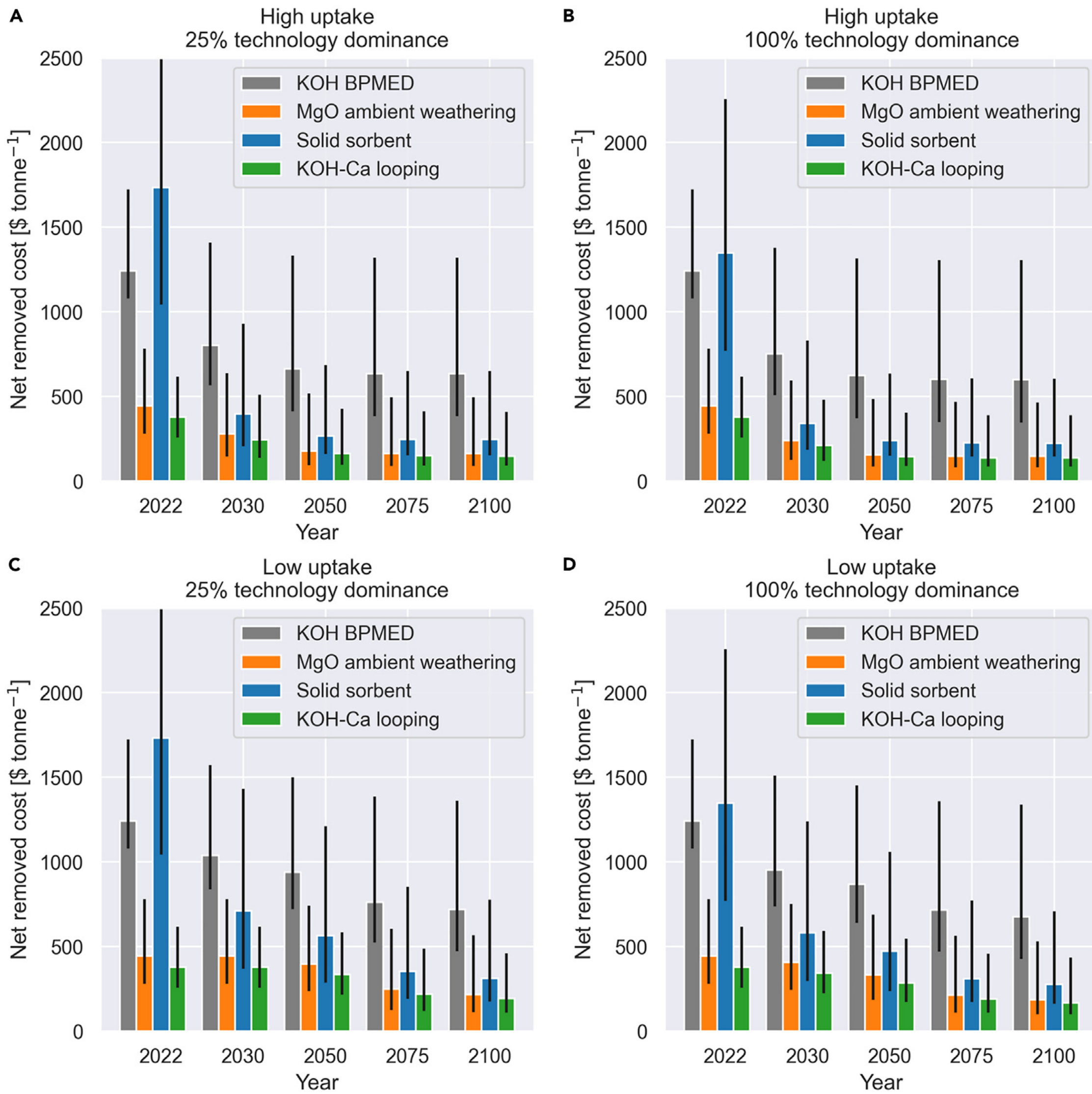
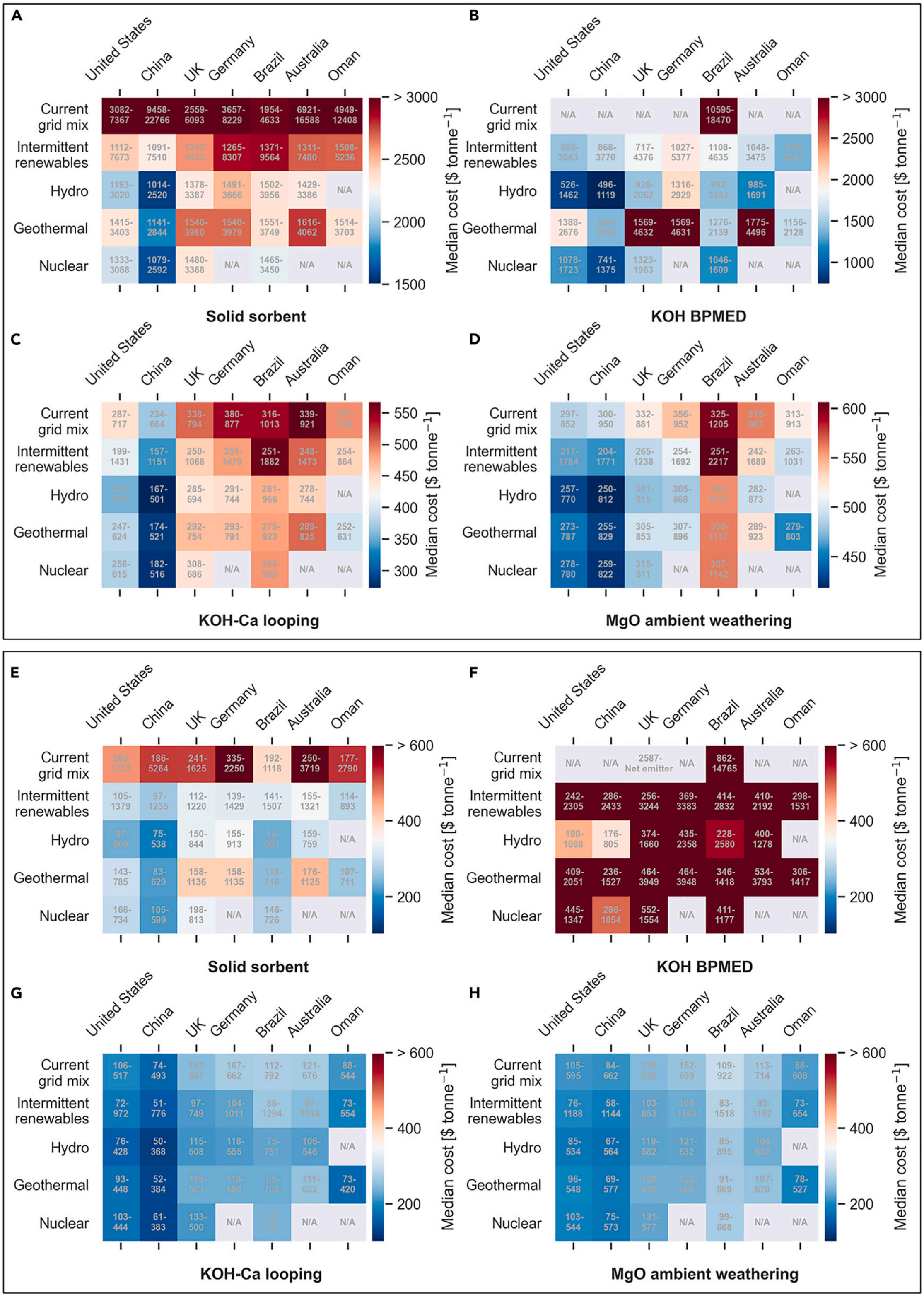


Figure 5. The net removed cost of each technology as time advances for four different scenarios

Extreme low and high uptake scenarios were identified that would still allow us to limit the planet's warming to 1.5°C or 2°C, based on integrated assessment modeling studies, while we also allowed for a 25% or 100% technology dominance.[2,40,41] This is for the United States paired with nuclear electricity and a heat pump for low-grade heat where appropriate. The error bars are defined by the lowest and highest costs using the assumption and parameter lower and upper bounds. In (A), the technologies account for 25% of the deployment in the high uptake scenario from Table S16. In (B), the technologies account for 100% of the deployment in the high-uptake scenario from Table S16. In (C), the technologies account for 25% of the deployment in the low-uptake scenario from Table S16. In (D), the technologies account for 100% of the deployment in the low-uptake scenario from Table S16.

savings from rational siting and electricity source selection are observed at the FOAK scale. The MgO ambient weathering process is the most location and electricity source agnostic economically, so technical performance and availability of $MgCO_3$ may be crucial to siting this technology. China is the cheapest location for the FOAK cost in Figure 6. The lower costs are primarily due to the decreased capital costs, as a result of the low cost of labor, which has a knock-on effect on the cost of raw materials. Location seems to be a more critical factor to cost than electricity source when considering a FOAK plant apart from the KOH BPMED process. As the capital costs decrease with deployment, the source of electricity becomes more critical at the Gt-CO_2 year^{-1} scale. Brazil has the highest natural gas price and highest natural gas carbon intensity, as shown in Table S9, which penalizes the two processes using natural gas, i.e., KOH-Ca looping and MgO ambient weathering, primarily due to the gas price but also affected by the carbon intensity, as seen in Figure 6. The methane leakage rate affects the two processes that rely on natural gas, and thorough assessments of the leakage rate associated with any local supply chain to be used are required to integrate these data with techno-economic analysis.

The non-intermittent sources of low-carbon electricity, geothermal, hydro, and nuclear consistently are among the



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cheapest electricity options because of their lower carbon intensity and constant supply. Meanwhile, Figure 6 shows that it is never logical to use the current grid mix of electricity generation to power solid sorbent or KOH BPMED DACS. The exception is if solar heat collectors or geothermal heat is available to supply solid sorbent DACS, as shown by Figure S12. The technologies that utilize natural gas for heat are not penalized as severely for using the current grid mix of electricity, allowing the deployment of these plants regardless of the grid mix. This is important as it is difficult to justify the opportunity cost of pairing low-carbon electricity to DACS currently, compared to using it to decarbonize the electricity grid.

Figure 7 presents a map showing low-carbon electricity availability and potential CO_2 storage sites. While the distance from CO_2 storage does not strongly affect the net removed cost (as shown in the sensitivity analysis in Figures S14 and S16), minimizing the distance between DAC and the associated storage will reduce the number of local stakeholders and decrease the legal complexity of deploying any pipelines required.[42,43] Figure 7 shows that sweet spots exist between the availability of CO_2 storage and low-carbon electricity. Some examples of these sweet spots may be the north-east of the United Kingdom, east China, or south-east Australia. However, it is essential to note that Figure 7 does not highlight all the critical geographical aspects. Socio-political aspects and variations in life cycle analysis factors, such as local natural gas leakage rates, are examples.

A key limitation of this study is that we do not consider the impact of climate on DAC technical performance. Some insightful studies have been published recently that address this for the solid sorbent and KOH-Ca looping technologies.[44–46] In our solid sorbent DAC process modeling, we assume a temperature of 15°C and relative humidity of 55%. Wiegner et al. find that, under the extreme conditions of 30°C and 100% relative humidity, solid sorbent capital costs increase by 40%, while energy consumption also increases by 40%.[44] However, at 5°C and 100% relative humidity, capital costs would be 30% less and energy consumption would be 55% less. Meanwhile, Sendi et al. show that, with a heat pump, solid sorbent electricity requirements vary by ± 25% across the globe due to climate, and process productivity varies by ±15% if temperatures below −15°C are avoided.[45] The Keith et al. study that our KOH-Ca looping techno-economic analysis is based on assumes conditions of 21°C and 40% relative humidity.[12] An et al. show that costs may increase by 25% under cool, dry conditions (5°C, 40% relative humidity) and decrease by 15% under warm, humid conditions (30°C 100% relative humidity) compared to this case.[46] An analogy can be drawn between the KOH-Ca looping and the KOH BPMED technologies as they use the same contactor design, and the variation in cost due to climate stems from water loss and the CO_2 capture rate in the contactor.[46] To the best of our knowledge, currently, no studies analyze the impact of climate on the MgO ambient weathering process.

Policy support should be project catered

Assessing the cost of DACS is an important step, and lower costs naturally provide a more robust business case. However, DACS requires a critical mass to reach the scale necessary to meet the cost constraints required to be self-sustaining. In this sense, DACS will need policy support. We analyze the available policy mechanisms, their purpose, and how they may affect the short and long-term cost. A summary of all the policies investigated is shown in Table S17, while the ones examined quantitatively can be found in Table S18.

Currently, the small market for removal credits generated by DACS is supported by companies pursuing voluntary offsets.[47] However, verification, including the storage and life cycle project emissions and future monitoring, is currently (to an extent) based on trust, and, although it is not concerning the voluntary market, it should at least be standardized going forward.[48,49] This agrees with the 10 key policy recommendations from an expert interview study by Sovacool et al., who suggested that ensuring net-negative emissions, alongside certification and compliance, is crucial.[50] The work from Sovacool et al. contains many other insightful recommendations and should be considered complementary to the quantitative work on policy and deployment presented here.[50] Another critical bottleneck for DACS deployment at scale is the availability of CO_2 transport and storage infrastructure. Developing transport infrastructure and storage sites is capitally intensive, and significant economic advantages can occur at larger scales.[51–53] Sovacool et al. recommend co-developing DACS with conventional capture, transportation, and storage and harnessing storage hubs.[50]

Once the infrastructure and policy are in place for a DACS plant to generate negative emission certificates, a large market is required to sell these certificates to promote further deployment and resulting cost reductions. So, we need to consider how to create a large market. Ways of doing this could be integrating carbon removal into a subsidy, tax, or trading scheme, or regulating companies to reduce or mitigate a proportion of their emissions or, in the long term, have net-negative emissions.[54] Beyond this, advanced market commitments (AMCs) and contracts for differences (CfDs) are potential mechanisms for a DACS plant developer to receive a specific price for generating negative emissions for a particular time, providing a guaranteed market for a plant.[55–57]

In addition to market creation, accelerating scale-up is essential to encourage technological learning and decrease costs. As discussed earlier and observed in Figure S15, capital costs dominate FOAK plant economics. Hence, supporting these initial investments is key to lowering early-scale deployment costs. Investment grants or grants via public competitions to pay for the capital expenditure can be used as policy instruments to help reduce the removal cost for a FOAK plant. These may pay for all of the capital costs, or there may be a cost-sharing structure. There may be mechanisms to further encourage the cost reductions of such technologies, such as decreasing the sizes of

Figure 6. Cost matrix comparing locations and electricity sources

Matrices show different location and electricity source combinations for each technology, colored by the median net removed cost, with the range of net removed cost in \$ t-CO_2^{-1} in text inside each square. (A–D) A FOAK plant paired to a heat pump for low-grade heat where appropriate. (E–H) A plant when a Gt-CO_2 year^{-1} scale has been reached paired to a heat pump for low-grade heat where appropriate. It should be highlighted that the FOAK panels have differing color scales, whereas the Gt-CO_2 year^{-1} scale panels all have the same color scale. Additionally, some KOH BPMED squares are gray when on the current grid mix row as they are net emitters of CO_2.

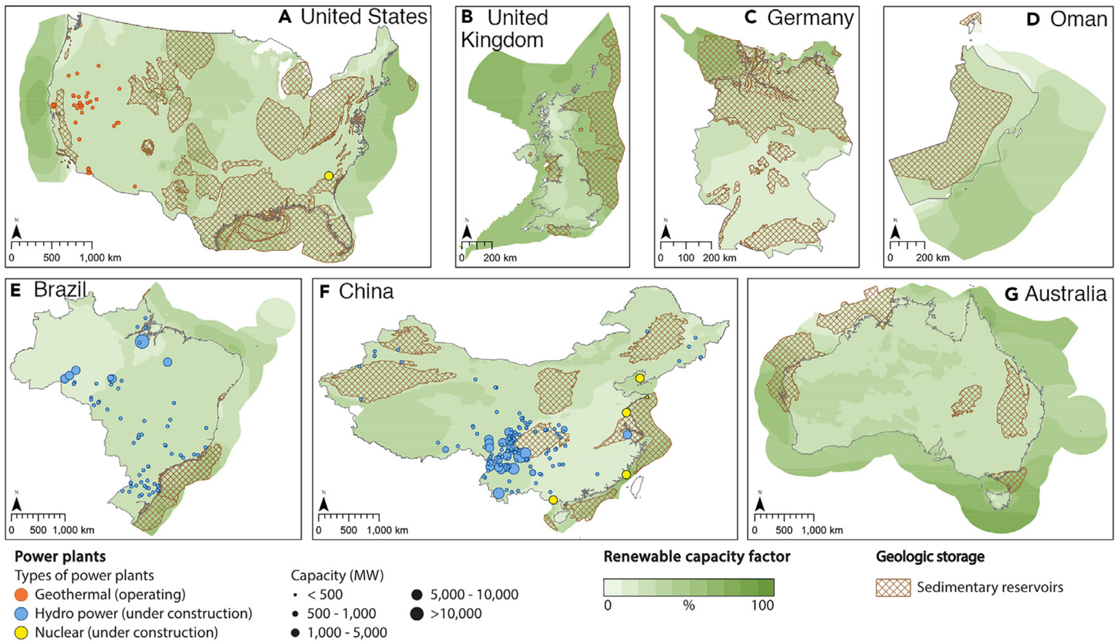

Figure 7. A map of the seven locations studied with low-carbon electricity and CO_2 storage potential highlighted
Each of (A)–(D) shows a different country, as labeled. Adapted from Pilorgé et al. 2021 with renewable capacity factors from the IEA.[42,88]

grants or specific cost-reduction targets that technologies must meet for the funder to fund further projects. This is analogous to the reduction in price cap enforced, for example, by the Dutch government as part of their annual request for offshore wind tenders.[58,59] An alternative (and equivalent) to grants could be investment tax credits, which returns a percentage of money spent on capital when a tax equity partner is available.[55]

Another option that reduces the capital burden of early-scale deployment would be to reduce the interest rates paid on the investment. For example, Tesla (formerly Tesla Motors) was heavily supported by a sizable low-interest government loan during its early years.[60] A similar loan could be provided to DACS companies. Other ways of reducing risk, and hence discount rate, could be the implementation of feed-in tariffs, carbon subsidies, or production tax credits, CfDs, or a regulated asset base (RAB) model. An even larger reduction in the discount rate and net removed cost could be achieved via a state-owned enterprise since the state has a higher risk tolerance than the private sector. However, the potential implementation of these is highly subject to the socio-political environment. A compromise could be a public-private partnership (PPP) where a certain amount of risk is transferred onto the state from the private sector depending on the exact PPP model chosen. However, there is debate over the actual effectiveness of PPPs.[61] Finally, tax-advantaged financing structures could make investment more attractive. Examples are Master Limited Partnerships, Real Estate Investment Trusts, or Private Activity Bonds.[62,63] A summary of the policies discussed and their categorization is displayed in Figure 8. It should be noted in Figure 8 there will be an overlap between accelerating scale-up and long-term cost reductions. For example, the RAB model could also prove useful for accelerating scale-up if a regulator and centralized market can be mobilized fast enough.

Figure 9 quantifies how a selection of such policy instruments might affect the costs of CO_2 removal via DACS. Meanwhile, Table 1 shows the percentage cost reduction at the start and end of the learning curves in Figure 9. The figure shows the median learning curves for net removed costs in the United States paired to nuclear electricity and a heat pump for low-grade heat where appropriate, while Figure S17 shows the full ranges for the same case. Figure 9 is demonstrative, and the exact values should be taken cautiously due to the uncertainty in the cost discussed previously.

The presented learning curve for grants in this figure represents a scenario where a government wants to spend \$3.5 billion on grants (equivalent to the sum made available by the US government in their Bipartisan Infrastructure Bill of 2021) to pay for the scale-up of a technology.[64] Grants have a high potential to reduce the FOAK costs, with a median reduction of 68% for the solid sorbent process and around 58% and 63% for the KOH-Ca looping and MgO ambient weathering processes, respectively. Long term, grants benefit technologies most when many small plants are built rather than one or two large plants. For example, in Figure 9, the median costs for the solid sorbent process will have come down from over \$2,000 t-CO_2 $^{-1}$ to below \$700 t-CO_2 $^{-1}$ once the grant runs out, a decrease of over 65%. The median costs for the KOH-Ca looping process can be brought down from approximately \$375 t-CO_2 $^{-1}$ to just under \$350 t-CO_2 $^{-1}$ with the same grant size, a reduction of less than 10%. This is because the assumed FOAK plant size of the KOH-Ca looping process is much larger than the assumed FOAK plant size of the solid sorbent process. A sensitivity analysis is available in Figure S18 that shows how the curves in Figure 9 would be different if the FOAK plant size is 36 kt-CO_2 year^{-1} for solid sorbent DAC and 100 kt-CO_2 year^{-1} for all other

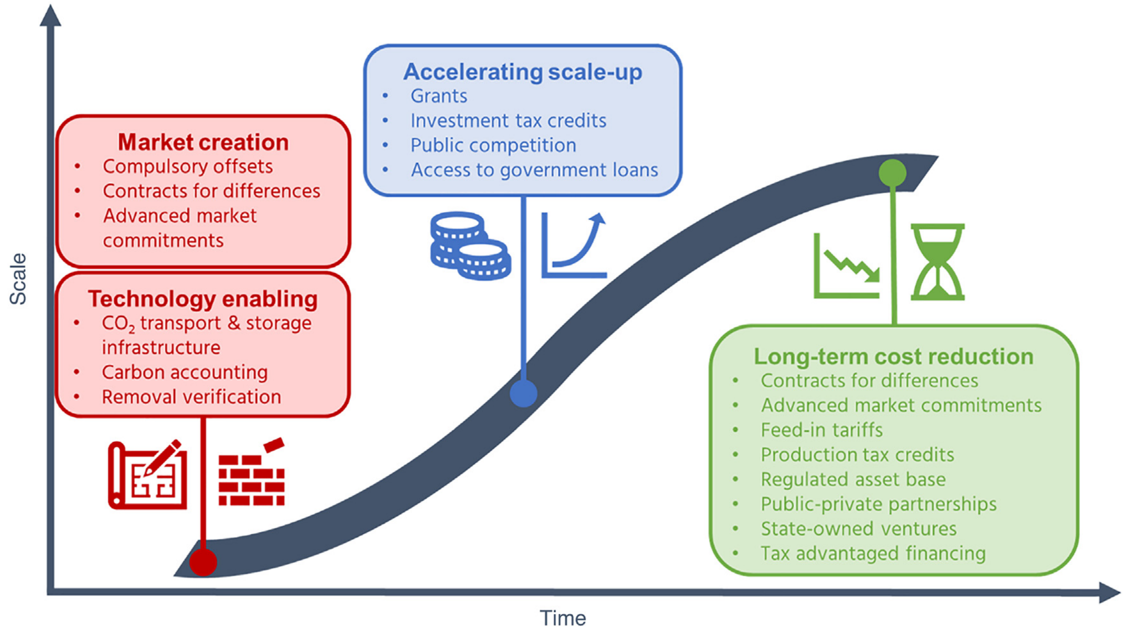

Figure 8. A selection of different policy levers available to support DACS
A complete list of policies considered and their relations to the cost reductions in Figure 9 is available in in Table S17.

technologies. In this scenario, the median costs for the solid sorbent process will decrease from over \$1,600 t-CO_2 $^{-1}$ to around \$950 t-CO_2 $^{-1}$ once the grant runs out, a decrease of 41%. Meanwhile, the median costs for the KOH-Ca looping process can be brought down from approximately \$575 t-CO_2 $^{-1}$ to around \$390 t-CO_2 $^{-1}$ with the same grant size, a reduction of about 30%. The long-term impact of grants is much reduced for solid sorbent DAC and increased for KOH-Ca looping DAC compared to the base case. In summary, for any technologies, grants are better spent on many smaller modular plants, as this allows learning to occur faster. Meanwhile, when grants end, it should be evaluated whether it is worth switching to an economies-of-scale approach for any given technology.

The "state" learning curve shows the potential impact of providing state-backed loans in Figure 9. They also have a considerable potential to reduce FOAK costs. For example, this reduction is 34% for the MgO looping ambient weathering process. These large initial reductions are another promising route to accelerating scale-up. In this case, the loan will likely be repaid, in contrast to grants, where the money is never repaid. This means the cost to the government will be lower and will be essentially the risk of the loan not being paid back. It is important to note that we leave this label simply as state, as the same curve could be relevant to a state-run enterprise. The impact of the lower discount rate is commensurate to the sensitivity analysis results in Figures S14 and S16, where the discount rate is the fourth most influential factor on FOAK costs for all technologies apart from KOH BPMED, where it is seventh.

In Table 1, we see that, at the Gt-CO_2 year^{-1} scale, the cost reductions achieved by the RAB model and CfDs for the MgO ambient weathering and KOH-Ca looping processes are more prominent than for the more modular technologies. This is because the technologies have lower learning rates and have undergone fewer doublings. Hence, they retain a higher proportion of their costs as capital costs, which are the costs affected by a reduction in the discount rate achieved by these policies. Nevertheless, for all technologies, these two policies have a considerable impact at the Gt-CO_2 year^{-1} scale, with median reductions of up to 3% and 17% for CfDs and an RAB model, respectively, in the case of the MgO with ambient weathering process. If we make an analogy with the electricity market, for example, a reduction of 17% in cost would have a significant and positive impact on the consumer. In the case of an RAB model, the extra cost is to organize the regulatory body to regulate a centralized market. So, this cost would need to be balanced against the cost reductions achieved.

There are promising approaches to encourage the scale-up and drive future cost reductions of DACS. State-backed loans, grants, and investment tax credits are all encouraging options to achieve this. The approach chosen will depend on the political and economic environment within the country of interest. There are also possibilities to reduce the long-term costs in the future using policies such as CfDs and an RAB model. Here, the benefits of these approaches should be weighed against their respective costs to make an informed decision on which path to pursue. It is also crucial not to neglect the impact of innovation and the feedback loop between deployment and innovation. As identified by Kittner et al. and Sovacool et al., research and development needs support alongside deployment to achieve the maximum technological learning rates and ensure the lowest long-term cost possible.[22,50]

Limitations

As previously discussed, *ex ante* costing studies contain much uncertainty, increasingly so for technologies further down the TRL ladder. Still, they are critical to inform the public and policy

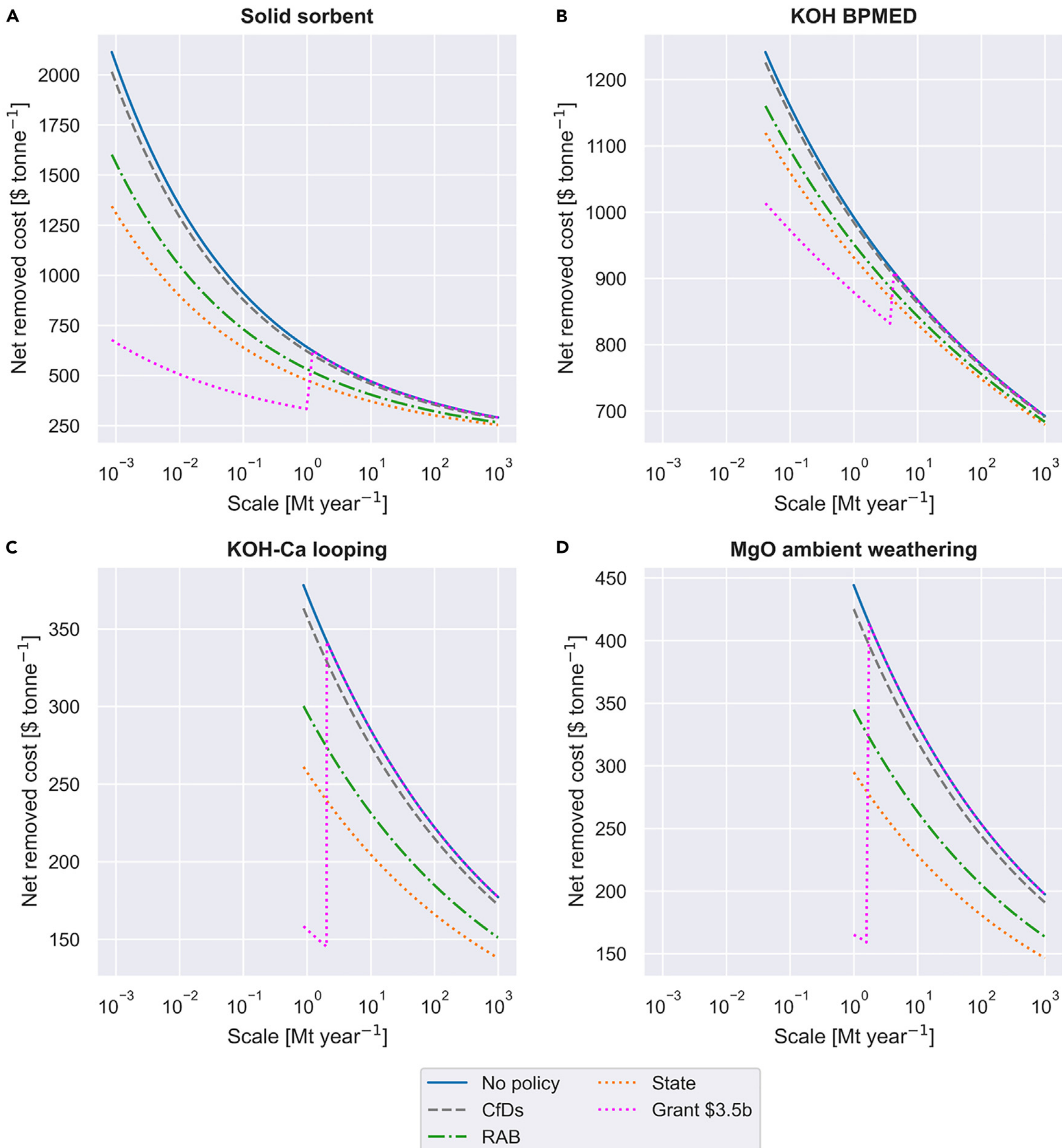

Figure 9. Median net removed costs of each DACS technology with different policies

This is for the United States paired with nuclear electricity and a heat pump for low-grade heat where appropriate. The full range of possible values is found in Figure S17. The variation in the discount rate by the policy is shown in Table S18.

domain. To ensure their utility, it is vital to understand how the results of techno-economic studies are produced, what can be inferred from them, and where the potential weaknesses of the study are. One method specifically developed to evaluate and communicate the strength of quantitative science for policymaking is the Numeral Unit Spread Assessment Pedigree (NUSAP) method, which includes pedigree analysis to provide a systematic qualitative assessment of the strength of quantitative information and models.[65–68] We here performed a rudimentary pedigree analysis (Table S20 and Figures S19–S30), which the reader can view as a reading guide and should be consulted when reproducing or using our results. The pedigree analysis highlighted some limitations to our work that are not immediately apparent. To summarize, the key limitations of our work are the independence of the source data and validation for the KOH-Ca looping process from Carbon Engineering and the lack of field validation of the MgO ambient weathering, KOH-Ca looping, and KOH BPMED processes. In addition, DAC deployment numbers used in the scenario analysis rely on integrated assessment modeling, which assumes certain costs. The cost results in this work will likely affect these deployment numbers. Furthermore, the impact of location on technical process performance is not assessed. This is discussed earlier, regarding recent literature that addresses this. Also, the locational data available for

Table 1. Median cost reductions achievable for each policy and technology combination

Technology	CfDs (%)		RAB (%)		State (%)		Grant \$3.5b (%)	
Scale	FOAK	Gt-CO_2 year^{-1}	FOAK	Gt-CO_2 year^{-1}	FOAK	Gt-CO_2 year^{-1}	FOAK	Gt-CO_2 year^{-1}
KOH-Ca looping	4.0	2.8	20.6	14.8	31.0	22.2	58.1	N/A
KOH BPMED	1.3	0.2	6.5	1.3	9.8	1.9	18.4	N/A
Solid sorbent	4.7	1.6	24.2	8.4	36.4	12.7	68.0	N/A
MgO ambient weathering	4.3	3.3	22.4	17.1	33.6	25.8	62.8	N/A

Median cost reductions from the original cost achieved for different technologies and policies at two scales, FOAK and Gt-CO_2 year^{-1} extracted from Figure 9. This is for the United States paired with nuclear electricity and a heat pump for low-grade heat where appropriate. N/A, not applicable.

Oman are limited, meaning proxies were often required instead of exact values for that location. Finally, the results generally have a large uncertainty margin, mainly caused by capital cost uncertainty, highlighting the detailed engineering work required to hone in on the capital costs of the different technologies at scale. This includes the detailed design and operation of pilot plants in the field alongside the distribution of the results publicly.

Conclusions

This work sought to answer the question, "Where are the costs of DACS heading, and what influence does siting and policy have on the costs?" by estimating ranges for the current and future costs of four case study DAC technologies paired with CO_2 transport and storage. Unlike previous studies, we utilized a hybrid costing approach that is consistent with the TRL of DACS. We performed this analysis across seven different countries, four sources of low-carbon electricity as well as the current grid mix, and a selection of policy interventions. From this analysis, we drew the following key insights that are relevant to a wide range of stakeholders across academia, industry, policymaking, and investment.

First, it is unlikely that the costs of DACS will reach the aspired \$100 t-$CO_2$$^{-1}$ target. Our study forecasted that the costs will reduce, at the Gt-CO_2 year^{-1} scale for a plant in the United States paired to nuclear electricity and a heat pump for low-grade heat where applicable, to (1) \$100–440 t-$CO_2$$^{-1}$ for KOH-Ca looping, (2) \$450–1,350 t-$CO_2$$^{-1}$ for KOH BPMED, (3) \$170–730 t-$CO_2$$^{-1}$ for solid sorbent, and (4) \$100–540 t-$CO_2$$^{-1}$ for MgO ambient weathering. The lower bounds of these ranges are only attainable if very high learning rates are achieved ($\sim$15%–19%), capital and energy are cheap ($\sim$\$0.09 kWh$^{-1}_{electricity}$ and $\sim$\$3 GJ$^{-1}_{natural\ gas}$), and there is a very strong reduction in energy requirements ($\sim$50%).

Second, pairing electricity-driven DACS to highly intermittent renewables is not a promising strategy as the net removed cost highly depends on the plant capacity factor. Instead, grid electricity needs to be decarbonized as a priority. The performance of larger-scale and predominantly natural-gas-powered processes does not strongly depend on the carbon intensity of grid electricity, but the natural gas supply chains should be thoroughly reviewed to avoid the negative effects of methane leakage, including an increase in net removed cost.

Third, strong and holistic government policy is paramount to drive down the cost of DACS and should include short-term market creation and technology-enabling instruments, as well as policy to support scale-up and long-term cost reductions. It is more beneficial to spend a capped pot of investment grants on several smaller plants to enhance learning, while policies that reduce the cost of capital may aid large-scale projects more. Policy support can target multiple technology types at the same time. We do not need to pick a winning technology now. Cost reductions via technological learning in a scenario with four competitors were similar to a scenario with only one dominant technology.

Key actions identified by this study are that (1) we should begin scaling DACS now alongside research and development in order to bring down costs long term, (2) policy support should aim to progress a suite of DACS technologies while (3) catering to the different needs of specific DACS technologies to achieve this. Also, (4) integrated assessment modeling should be reperformed with more realistic DACS costs than the ones previously used, to assist in understanding the role of DACS for preventing the worst impacts of climate change, which in turn should aid policy and investment decisions. Finally, (5) electricity grids need to be decarbonized faster to provide low-carbon-intensity electricity for DACS and, equally, methane leakage from natural gas supply chains should be targeted with greater ambition than the 30% reduction pledge agreed at the 26th Conference of Parties.[69]

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Requests and questions should be directed to Mijndert van der Spek at M.Van_der_Spek@hw.ac.uk.

Materials availability

No materials were used directly as part of this study.

Data and code availability

Data points of all learning curves across all technologies, locations, electricity sources, and heat sources along with the data from the policy learning curves in Figure 9 are contained in individual .csv files in the zip file available online at the following link: https://github.com/johnyoung1996/young_et_al_2023_DAC_TEA.

Methodology

The costing approach applied here uses the aforementioned hybrid costing method, which combines engineering-economic bottom-up calculations of the cost of a FOAK plant and technological learning-curve projections (a top-down method) to estimate how costs may develop as a result of mass deployment. The techno-economic assessment model is discussed first. The technical performance estimates are based on the existing literature for all but the solid sorbent technology, for which we used our own modeling,[30] briefly discussed later. Because the impact of location on the economics of DACS is largely missing from the literature, we estimated DACS costs for seven geographically and economically diverse case study countries (United States, China, the United Kingdom, Germany, Brazil, Australia, and Oman) by assessing the variation of different economic parameters across these locations, detailed after the section "techno-economic model." These case

Table 2. Rational FOAK plant size of each technology

Technology	FOAK scale [kt-CO_2 year^{-1}]	Reasoning
KOH-Ca looping	980	used the value provided by Keith et al., as this is used to assess an "early plant" cost estimate.[12] The study highlights that the minimum practical scale is 100 kt-CO_2 year^{-1}. However, there are significant cost advantages to operating at 1,000 kt-CO_2 year^{-1} due to the economies of scale of the calciner and the slaker.[12,84] It is important to note, however, that the contactors are a modular component
KOH BPMED	46	the original study from Sabatino et al. studied a plant at a 1,000 kt-CO_2 year^{-1} scale.[29] However, most of the system's components are modular, so very few economies of scale are utilized when they scale to this size for a first plant. For this reason, we scaled the process down to one electrodialysis stack. Information on this is available in the caption of Figure S4
Solid sorbent	0.96	the scale chosen here was the two units operated in Hinwil, Switzerland, by Climeworks.[102] This technology is inherently highly modular, particularly the contactors. The maximum size of systems operating under vacuum is limited by the mechanical stress, which increases linearly with unit size. This limits the scale that one module can reach, adding to our choice for this relatively small scale as a FOAK size
MgO ambient weathering	1,100	the size was chosen to remove 1,000 kt-CO_2 year^{-1} at a 90% plant capacity factor. This process uses the same type of calciner as the KOH-Ca looping process, so similar arguments can be made about the optimal scale being influenced by the calciner[12,84]

Assumed FOAK design scales for each technology and the corresponding justification for choosing this size. A sensitivity analysis on this parameter is available in Figures S1–S4.

studies allowed us to explore siting decisions based on the availability of low-carbon energy sources, cost of materials and labor, etc., while also acknowledging that complex factors beyond costs (e.g., political and geographic) exist. Finally, we investigated which policies are required to reduce the cost in the short and long term, further detailed last. Importantly, we provide all results as cost ranges instead of point estimates, given the very high uncertainties of *ex ante* projections of NOAK costs.

Techno-economic model

Bottom-up engineering-economic model

The bottom-up part of the framework produced the FOAK costs for the four technology archetypes. The techno-economic framework developed in this work is based on the International Energy Agency's Greenhouse Gas Research and Development Programme's (IEAGHG's) framework,[70] adapting it for consistency with recently published guidelines for the cost estimation of CO_2 capture and storage projects, published by IEAGHG, the United States Department of Energy National Energy Technology Laboratory (DOE/NETL), and the Electric Power Research Institute (EPRI).[21,71–74] First, rational FOAK scales were selected for each technology. These are available in Table 2, including the reasoning behind their selection. The FOAK scale differs for different types of technologies as a function of their design. The selection of the FOAK scale is important to technological learning, as it provides the starting point for cost reductions and determines how many doublings take place when deployment increases to a certain level; therefore, the impact of this choice is further discussed in the section "results and discussion." Then, the capital costs were built up from the installed equipment costs and are in 2019 US dollars. A critical element here was to differentiate between the different TRL levels of the four technologies. This was accounted for by varying the process contingencies as a function of TRL, as per guidelines by Rubin and a recent white paper published by, DOE/NETL, and IEAGHG.[21,71–75]

Note that the KOH BPMED and MgO ambient weathering installed equipment costs were scaled down as the details in literature were for plants larger than the here-assumed FOAK scale.[29,31] The scaling methodology is identical to that used in Figures S1–S4 and is detailed in the captions of these figures. The installed equipment costs are available in Table S1.

To calculate the capital costs, first, the costs of engineering, procurement, and construction (EPC) were calculated according to Table S2. Next, the EPC costs were escalated to those of a FOAK commercial project using the process and project contingencies, and owner's, spare parts, and start-up costs to arrive at the total overnight cost (TOC), as defined by Rubin et al. and detailed in Tables S3 and S4.[73] The inclusion of appropriate project and process contingencies, which are representative of the development stage of a technology and the level of detail in the project design, is lacking in all but a very few *ex ante* techno-economic studies of climate-change-mitigation process technologies.[71,74] The project contingencies take into account costs not considered in the analysis due to the preliminary level of project specification. Meanwhile, process contingencies account for any uncertainty surrounding capital costs on account of the technology maturity of a process and the cost of upscaling that accompanies this. Therefore, the process contingency is higher for low-TRL technologies as they are more likely to incur extra costs while developing through unforeseen issues that must be addressed with process adjustments or a change of operation. The process contingencies used for each technology (as function of their TRL) can be found in Table 3.

The resulting TOC was then annualized and levelized using the capital recovery factor calculated from the assumed location-dependent discount rates, a plant life of 25 years, and 90% capacity factor unless paired to intermittent renewables to arrive at a levelized capital cost. The accuracy of the FOAK capital cost calculation was assumed to be −30% to +50% of the calculated value, which the Association of the Advancement of Cost Engineering (AACE) expects for a class 4 estimate.[76]

Details of the fixed operating and maintenance and the variable operating costs are available in Tables S5 and S6. The sum of the levelized capital costs, fixed operating and maintenance, and the variable operating costs was then escalated to the net removed cost, as shown in Equation 1, using the calculated GHG emissions from the processes.

For this calculation, only energy-related emissions were considered as it has been shown that these dominate in life-cycle analysis of the greenhouse gas emissions of DAC technologies.[12,77,78] The carbon intensities of the electricity sources across different locations were calculated using SimaPro and the EcoInvent v3.8 database and are shown in Table S7.[79] Meanwhile, the

Table 3. Process contingencies and capital cost learning rates selected for this study and the justification

Parameter		KOH-Ca looping	KOH with BPMED	Solid sorbent	MgO ambient weathering
Process contingency	TRL	6	4	7	4
	minimum (% of EPC)	20	30	5	30
	middle (% of EPC)	30	50	20	50
	maximum (% of EPC)	35	70	20	70
Capital cost learning rates	minimum (%)	5	10	10	5
	middle (%)	10	14	14	10
	maximum (%)	15	19	18	15
	analogous technologies	flue gas desulfurization, coal power plant, integrated gasification combined cycle power, air separation units	electrolysis, fuel cells	modular technologies. Fuel cells, photovoltaic solar panels	flue gas desulfurization, coal power plant, integrated gasification combined cycle power, air separation units
	Malhotra and Schmidt type and corresponding learning rate in brackets[23]	2 (10%–15%)	2 (10%–15%)	2 (10%–15%)	2 (10%–15%)

This is the TRL for process contingency as suggested by the AACE and EPRI,[73,76] and the analogous technologies plus level of modularity for the learning rate. The white paper by Roussanaly et al. was used as a reference to select the analogies and corresponding learning rates, while the Malhotra and Schmidt typology allowed us to verify this further.[21,23]

associated values for grid electricity are shown in Table S8. Upstream natural gas emissions in different locations were calculated using a previous study on methane leakage rates across the world, and the carbon intensity values calculated are shown in Table S9.[80] Across our case studies, these leakage rates vary between 0.26% and 2.21%. The carbon intensity of gasoline was assumed to be a constant value of 66.97 $kg_{CO2,eq}$ GJ^{-1}.[81] The carbon intensity of dedicated geothermal heat and solar thermal energy were extracted and scaled from previous studies based on different locational factors. More details can be found in Table S9.[82,83]

The costs of net CO_2 removed are:

$$C_{NR} = \frac{C_{GC}}{1 - X} \quad \text{(Equation 1)}$$

In Equation 1, C_{NR} (\$ t-CO_2^{-1}) is the net removed cost, C_{GC} (\$ t-CO_2^{-1}) is the gross capture cost, and X (t-$CO_{2,eq}$ t-CO_2^{-1}) is the GHG emissions accounted to the process per tonne of CO_2 captured.[84] As a result, we obtained the FOAK net removed costs.

Top-down technological learning projections

The FOAK capital and variable operating costs were then extrapolated into the future using learning rates and Equations 2 and 3.

$$b = -\frac{\ln(1 - L_r)}{\ln 2} \quad \text{(Equation 2)}$$

$$y = ax^{-b} \quad \text{(Equation 3)}$$

Where b (–) is the learning exponent, L_r (–) is the learning rate, y (\$ t-CO_2^{-1}) is the current capital or operating cost, a (\$ t-CO_2^{-1}) is the FOAK capital or operating cost, and x (–) is the ratio of existing capacity to the initial capacity of the technology.[21]

Given that all DAC technologies are yet to fully commercialize and progress along the learning curve, capital cost learning rates must be selected as no observed values are available. This is inherent to *ex ante* technology assessment and relies to an extent on judgment, but guidance is available to structure the selection. IEAGHG guidelines propose breaking technologies down into subsections and use learning rates reported for technologies that are identical or similar to each of the subsections.[71] Given no identical technologies exist, they propose using learning rates from analogous technologies as a proxy. If this is not possible, they suggest using expert elicitation (recently applied to DACS by Sievert et al.[85]) or general heuristics on observed learning rates. For example, "the highest learning rates (e.g., 20–30%) are typically associated with smaller-scale technologies that are modular in nature and amenable to mass production" and "learning rates are significantly lower [e.g., 10–15%] for large-scale process systems and technologies that are typically field-erected and designed for a unique site or size."[71] Malhotra and Schmidt systematized such general heuristics into a matrix that compares the degree of design complexity of a technology with its need for customization to its use environment.[23] The high learning rates achieved by the modular technologies are analogous to the high learning rates achieved by wind and solar power, fuel cells, and electrolyzers, which are enabled by mass production, along with the ease and speed of implementing research and development breakthroughs into the system.[21] Another reason behind the higher learning rate is their potential to gain learning from other industries, such as CO_2 supply to niche markets in the case of DAC (i.e., via diversification).[86] However, large-scale plants may be better suited to supply CO_2 to large-scale utilization processes, such as a sustainable aviation fuel plant. We applied both analogies and Malhotra and Schmidt's typology to the four DAC technologies investigated here, and this is presented in Table 2. Note that the Malhotra and Schmidt typology leads to identical learning rate ranges (10%–15%) for each technology.[23] We captured the lowest and highest capital cost learning rates predicted by the analogous technology approach and the Malhotra and Schmidt approach to use as our final range of learning rates.

In the techno-economic model, the fixed operating and maintenance costs are highly coupled to the capital costs. Hence, these fixed operating and maintenance costs reduce with the reducing capital costs. The recently published guidelines on cost evaluations for carbon capture and storage explain in detail why fixed operating and maintenance costs will be higher for a FOAK plant compared to a NOAK plant.[21,71] However, the variable operating costs are not linked to the capital costs, so we selected separate learning rates for these costs. Assuming an equal proportion of this learning is applied to a reduction in energy consumption, we set a maximum second-law efficiency limit of 20%. This number is based on a previous study that suggested this could be an optimistic limit for solid sorbent DACS.[87] Using the same underlying assumption on the relationship between variable-operating-cost learning and learning on energy consumption, we also assumed the learning was reflected in a reduction of energy-based emissions of the process. The same variable-operating-cost learning rates were chosen for all technologies with a minimum of 0%, a maximum of 5%, and a median value of 2.5%. The 5% value is the same as the observed operating-cost learning rate for oxygen production.[21] We then calculated the NOAK net removed cost using the same approach used for a FOAK plant with the levelized capital costs, levelized fixed operating and maintenance costs, levelized variable operating costs, and process emissions.

Locational analysis

The economic parameters that were varied across locations are detailed in Tables S7–S11. These include the discount rate, materials and construction costs, CO_2 transportation costs, operator salary and productivity, and energy prices and carbon intensities. The sources of electricity considered were grid, intermittent renewables, hydroelectricity, geothermal, and nuclear. Meanwhile, solar heating and geothermal heating were considered as alternatives to a heat pump to supply low-grade heat.

Note that we assumed that a DACS plant can be paired to each electricity source without adjustment apart from intermittent renewables. In this case, the DACS plant capacity factor was assumed to be the minimum from the intermittent renewable capacity factor and the assumed maximum DACS plant capacity factor of 90%. The possible ranges of intermittent renewable capacity factors for each country were identified in an International Energy Agency (IEA) report on DAC, available in Table S11.[88] The IEA report provides global intermittent renewable energy capacities assuming the maximum capacity factor between solar photovoltaic and wind. The lowest capacity factors provided are generally found inland, and the highest in coastal regions or offshore. Therefore, we assumed the worst-case intermittent renewable capacity factor to have the electricity cost and carbon intensity associated with solar electricity, while the best-case intermittent renewable capacity factor was assumed to have the electricity cost and carbon intensity associated with wind electricity. The middle values of capacity factor, cost, and carbon intensity were assumed where median values were needed.

Solid sorbent process modeling

The basis for the solid sorbent temperature vacuum swing adsorption process was two units containing 18 contactors each, as is the set-up at the Climeworks plant in Hinwil, Switzerland.[89] The contactor design was based on a 2020 patent, and the sorbent used is Lewatit VP OC 1065 due to its commercial availability.[90] Note that the heating mechanism of the contactor in this patent is indirect via pipes inside the sorbent bed and not using steam stripping. We used a model and Lewatit VP OC 1065 data from previous work to calculate the energy and productivity values of a process optimized for maximum productivity as shown in Figure S5.[30] Here, we adjusted the sorbent volume based on one plate in the chosen contactor design and calculated a heat transfer coefficient using a one-dimensional radial approximation around a heat transfer pipe, as presented and discussed in Figure S2 and S3. The parameters used can be found in Tables S12–S14. Afterward, we built up a flow diagram of the process and assessed the equipment requirements and costs based on this. This flow diagram and the cycle design, as well as schematics of the column internals relevant to flow and heat transfer, can be found in Figures S6 and S8–S10. All the calculated costs and their sources can be found in Tables S1 and S15.

We considered natural gas only for the two processes powered by high-grade heat, i.e., KOH-Ca looping and MgO ambient weathering, since the process configurations reported both use natural gas in an oxy-fired calciner.[12,31] Nevertheless, we did investigate the impact of low-grade heat choice on the solid sorbent process. The three investigated low-grade heat sources are electricity with an air-source heat pump, dedicated geothermal heating, and solar heating. Figure S11 compares the effect of different heat sources on net removal cost, and we find that all of the options have the potential to be competitive, but, for simplicity, we selected a heat pump to use in the analysis for the rest of this study due to its lower median cost estimate. Here, we assumed a coefficient of performance (COP) of 2, which is consistent with an 85°C temperature rise, and we did not consider the effect of location.[91] There is also the option of using waste heat, especially for FOAK and pilot plants. This will reduce the early costs, supporting initial scale-up, but this is expected not to significantly affect cost at the scale of carbon removal we will require.[92] Figure S12 further compares the heat sources for solid sorbent DACS powered by grid electricity in the US. Due to the high carbon intensity of grid electricity, solar and geothermal heat becomes much more attractive compared to when low-carbon electricity is available.

Scenario illustration and policy investigation

As a thought experiment, we opted to illustrate how the learning curves may translate into costs in specific years and defined two extreme technology uptake scenarios (Table S16). In one scenario, we took the least-aggressive DACS uptake possible from integrated assessment modeling that still meets the 2°C or 1.5°C scenarios based on analysis from the IEA, Realmonte et al., and Fuhrman et al.[2,40,41] Meanwhile, the second scenario was based on the most aggressive possible DAC uptake to meet either the 1.5°C or 2°C scenarios using the analysis from the IEA and Fuhrman et al.[40,41] Within these scenarios, we allowed for a 25% technology dominance or a 100% technology dominance to understand the effect of future DAC market share. To demonstrate the scenarios, the total DACS scale in 2050 varies from 0.01–11.9 Gt-CO_2 year^{-1}, and in 2100 this increases to 1.8–31.6 Gt-CO_2 year^{-1}.

We also wanted to assess DACS policy needs and the potential impact of different policies on the DACS learning curves. As a result, we performed a comprehensive literature review on policy options. To examine the impact of different policies on DACS costs, four policies of interest that cover a wide range in the policy design space were identified and quantitatively examined. A comprehensive list of the policies investigated as part of the literature review and their relation to the four policies analyzed quantitatively can be found in Table S17. The four policies selected for quantitative investigation were (1) investment grants, (2) CfDs, (3) an RAB model, and (4) state-owned DACS facility or a DACS facility fully backed by a state loan. Investment grants are capital supplied to support projects without any expected return from the granter. CfDs allow a fixed price to be paid for a product for a particular duration. Any deviation from the market price from this fixed price is paid for by the CfD broker, which in this case is likely to be a government or consumer. We assumed the duration of the CfD was for the whole project. An RAB allows a project developer to start receiving payment for their product during the project's construction phase before operation begins. This is done through an agreement between the project developer and a regulatory body. In addition, the price charged during operation is also set by the regulator rather than an open market. Finally, a state-owned DAC facility or a DAC facility backed by state loans could take advantage of the low interest rates available to a government through their high-risk tolerance.

The location of the DACS plant for the policy analysis was the United States, whilst the electricity source was kept constant. This was utilizing nuclear electricity with a heat pump for low-grade heat where required. This was chosen as an example, and it is likely that the results would vary by location, especially for the policies where the government takes on risk from the project developer, as the risk tolerance, and hence bond yields, of governments across the world vary significantly.[93] The analysis of investment grants was based on a scenario where a government wanted to grant \$3.5 billion of cash to scale up DACS, equal to the grant size that the United States government is committing to developing "DAC hubs."[64] In our scenario, the money was then used to pay for the capital expenditure directly with no interest until the \$3.5 billion runs out. The same learning rates are assumed as in a scenario without grants. Then, the reduction of investment risk was found to be the main impact reducing the DACS cost directly in the case of CfDs, RABs, and state-owned facilities/state-backed loans. By drawing analogies with other markets and technologies, we assessed the potential decrease in the discount rate on account of each of these three policy options.[94–101] These reductions are found in Table S18. Finally, the impact of the reductions on the cost learning curves was analyzed.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2023.06.004.

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AUTHOR CONTRIBUTIONS

Conceptualization, J.Y., N.M., C.C., S.F., O.H., M.O., H.P., J.A., P.P., P.R., S.G., and M.v.d.S; formal analysis, J.Y., N.M., C.C., S.F., O.H., M.O., H.P., J.A., P.P., P.R., S.G., and M.v.d.S.; investigation, J.Y., N.M., C.C., S.F., O.H., M.O., H.P., J.A., P.P., P.R., S.G., and M.v.d.S.; methodology, J.Y., N.M., C.C., S.F., O.H., M.O., H.P., J.A., P.P., P.R., S.G., and M.v.d.S.; software, J.Y., N.M., S.F., M.O., P.P., and M.v.d.S.; visualization, J.Y., H.P., and M.v.d.S.; writing – original draft, J.Y.; writing – review & editing, N.M., C.C., S.F., O.H., M.O., H.P., J.A., P.P., P.R., S.G., and M.v.d.S.

DECLARATION OF INTERESTS

N.M. and P.R. are named inventors on Patent Application Systems and Methods for Enhanced Weathering and Calcining for CO_2 Removal from Air, no. 62/865,708, filed on June 2, 2019, based on the MgO ambient weathering technology discussed in this work and described in a previous paper by McQueen et al.[10] N.M. is also employed by Heirloom Carbon Technologies, Inc.

INCLUSION AND DIVERSITY

One or more of the authors of this paper self-identifies as a gender minority in their field of research. One or more of the authors of this paper self-identifies as a member of the LGBTQIA+ community. We support inclusive, diverse, and equitable conduct of research.

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