


## Dataset on the adoption of historical technologies informs the scale-up of emerging carbon dioxide removal measures

Gregory Nemet <sup>1</sup>✉, Jenna Greene <sup>1</sup>, Finn Müller-Hansen <sup>2</sup> & Jan C. Minx <sup>2,3</sup>

A variety of agricultural, industrial, and consumer technologies have been adopted over the past century and can provide insight into the scale-up of emerging technologies, such as carbon removal. Here we present the Historical Adoption of Technology dataset—a set of harmonized global annual time series from the early 20th century to present. We use three growth metrics to compare historical growth to that of carbon removal in emissions scenarios and future targets. We find heterogeneity in growth rates in the diffusion of historical technologies, ranging from 1.1 to 14.3% (median 6.2%) for our preferred growth metric based on a logistic function. Most emissions scenarios show growth within this range (median 5.9%, range 1 to >100%). Company announcements and policy targets imply faster growth than both historical technologies and carbon removal in emissions scenarios. Further work can explain the heterogeneity and facilitate more precise comparisons.

<sup>1</sup> La Follette School of Public Affairs, University of Wisconsin-Madison, 1225 Observatory Drive, Madison, WI 53706, USA. <sup>2</sup> Mercator Research Institute for Global Commons and Climate Change, Torgauer Strasse 12-15, 10829 Berlin, Germany. <sup>3</sup> Priestley International Centre for Climate Futures, University of Leeds, Leeds LS2 9JT, UK. ✉email: [nemet@wisc.edu](mailto:nemet@wisc.edu)

Over the past century, a wide variety of new technologies have been invented, passed through a formative phase, and grown to widespread adoption. Many have had profound effects on society. They span uses from medicine to agriculture to transportation, and exhibit diversity in function and adoption environments among other attributes. Amidst this heterogeneity, case studies of these technologies have generated stylized facts in the innovation literature that provide understanding, even in an environment inherently associated with discovery, novelty, and uncertainty. For example, we know that technology adoption is a process that takes time, even when attributes of a new technology surpass those of incumbent technologies<sup>1</sup>. And we know why; capital stock is long-lived, adopters are risk averse, early versions are imperfect, applications need to be found, and often complementary infrastructure needs to be developed<sup>2</sup>. Heterogeneity in attitudes towards these issues generates a sequence of adoption decisions, which in aggregate emerges as a classic s-curve pattern, defined by a logistic function<sup>3,4</sup>. Still, how quickly adoption occurs varies and is of high interest for novel technologies that could help address climate change because of the urgency of the required transition<sup>5</sup>. In this paper, we study a large set of these technologies to gain insight into the prospects for a class of emerging technologies to address climate change, carbon dioxide removal (CDR). This paper thus addresses the broad research questions: How quickly do CDR technologies need to grow to meet future CDR targets and climate scenarios? How realistic are those rates of growth compared to the historical empirical record on the scale up of analogous technologies?

The CDR scale up challenge is indeed daunting. The IPCC Sixth Assessment Report (AR6) finds that the world will need to remove hundreds of gigatons of CO<sub>2</sub> to meet the Paris Agreement targets<sup>5–7</sup>. Paris compatible scenarios include several gigatons of carbon dioxide removal annually by mid-century<sup>8</sup>, with a large range depending on the level of ambition for other mitigation options and long-term temperature goals<sup>7</sup>. A recent study of 507 AR6 scenarios found that “virtually all scenarios that limit warming to 1.5 °C or 2 °C require novel CDR, such as bioenergy with carbon capture and storage (BECCS), biochar, direct air capture (DAC), and enhanced rock weathering”<sup>9</sup>.

CDR involves a variety of capture methods and storage media, including afforestation, soil carbon management, bioenergy with carbon capture and storage, direct air capture, enhanced weathering, and ocean alkalization, among others. Many if not all of these could plausibly contribute >1 gigaton of CO<sub>2</sub> removal per year by 2050<sup>10</sup>. Given the challenges with build-out and sustainability risks at scale<sup>11</sup>, portfolios of multiple CDR methods are likely to provide the most robust solutions<sup>12</sup>. Aside from land-based CDR like afforestation, current adoption levels of novel CDR are trivial<sup>9</sup> and the implied scale up of nascent CDR technologies like DAC, BECCS, and biochar seems ambitious, and to some unrealistic.

Models of CDR scale up have thus imposed constraints citing historical benchmarks<sup>13</sup>. For example, in some cases they apply limits, such as limiting DAC growth to 20% per year<sup>14</sup> or assuming that growth rates decline once storage capacity reaches a threshold<sup>15</sup>. The sensitivity of results to these assumptions provides motivation for establishing an empirical basis for how scale up is modeled. Recent literature on this has progressed from measuring growth from an individual technology in one country<sup>14</sup> to two technologies (wind and solar) across multiple countries<sup>16</sup> to eleven technologies over 80 years<sup>17</sup>. The study of wind and solar made particular progress in also determining how best to measure growth using a variety of functional forms and metrics<sup>16</sup>, while the 11 technology study made an important distinction between growth in the early formative phase<sup>18</sup> and later growth<sup>17</sup>.

More broadly, case studies of previous technologies have proven helpful for arriving at insights for future technologies<sup>19</sup>. For example, a detailed history of the drivers of change in solar photovoltaics has been used to indicate how low-temperature direct air capture could grow<sup>20</sup>. In another study, a projected scale up of high-temperature direct air capture is based on the development of ammonia synthesis<sup>21</sup>. Useful technology analogues benefit from methodological development to structure the process of selecting historical case studies to strengthen their relevance to target innovations. This methodology depends on in-depth historical analysis to identify a set of relevant matching characteristics that can be used to identify the best analogue for comparisons<sup>22</sup>. Among the factors that affect how quickly technologies grow is the unit-scale of a technology; detailed empirical work has found that small unit scale, or granular, technologies are adopted more quickly and fall in costs more rapidly than large-scale technologies<sup>23–25</sup>. We thus assess growth in technologies with the awareness that some historical technologies will be better analogues for CDR than others, and that granularity, among other technology characteristics<sup>26</sup>, will be important in explaining the variation in historical growth. Our approach is thus to analyze a wide array of technologies to understand general trends in historic technology growth.

Using analogous technologies to inform CDR scale up requires developing metrics of technology adoption that are consistent across a diverse set of technologies. We need to assess: at what rates have historical technologies been adopted? how quickly do CDR technologies grow in Paris-compatible emissions scenarios? and what growth rates are implied in government, company, and industry targets for CDR? Answering these questions involves assembling consistent time series for a variety of data types such that they are comparable with each other. We assemble time series on four types of data, which we describe further in the Methods section: (1) an historical data set of the cumulative adoption of 148 unique technologies across 11 categories, (2) data on 1979 CDR technology time series in integrated assessment model scenarios from the IPCC 6th Assessment Report (AR6), (3) company announcements of CDR scale up plans, and (4) CDR targets in policy announcements and Nationally Determined Contributions (NDCs) under the Paris Agreement. We make all these data publicly available. The historical technologies are now available on-line as the Historical Adoption of TeCHnology (HATCH) dataset; the AR6 scenarios are available at the Scenario Explorer website<sup>27</sup>; and the company and government targets are available as part of recently launched State of CDR Report<sup>9</sup>. We then calculate multiple growth rates for each time series using nine measurements across multiple functional forms (see Methods section and Supplementary Fig. 4) and arrive at three metrics, on which we focus: (A) logistic coefficient, (B) linear around inflection point, (C) formative phase exponential (Fig. 1). We obtain these by fitting logistic curves to the historical data and extract relevant coefficients from the fitted curve as our growth rates. This allows us to use technologies from the second half of the twentieth century, rather than only earlier ones for which an inflection point has already been reached. We aim to include a broad set of technologies and observe a wide range of adoption rates, with the caveat that we do not observe technologies that are not commercially adopted<sup>28</sup>. A few CDR technologies have not yet seen commercial adoption and thus could fit into this non-deployment category.

Seminal studies of new techniques in agriculture found that adopters can be grouped by their propensity to use a new technology<sup>29</sup>. Their behavioral patterns follow a normal distribution of a small group of early adopters, a similarly small number of laggards, and in between, the majority<sup>3</sup>. In aggregate their behavior is characterized by rapid initial growth as early

adopters take on the risk of a new commercial technology, followed by a slower but larger population of majority adopters who act once the technology is de-risked, and finally laggards who eventually embrace the technology as growth slows and reaches market saturation<sup>4</sup>. This adoption behavior recurs across a variety of technology and adoption contexts<sup>30</sup> and when assessed cumulatively generates a logistic curve, with its signature s-curve shape<sup>31</sup>. A logistic function is defined by three parameters, which represent: the inflection point around which the curve is symmetrical, the asymptote, and the steepness of the curve, which we use as our first metric and interpret as indicative of a growth rate (Panel A in Fig. 1).

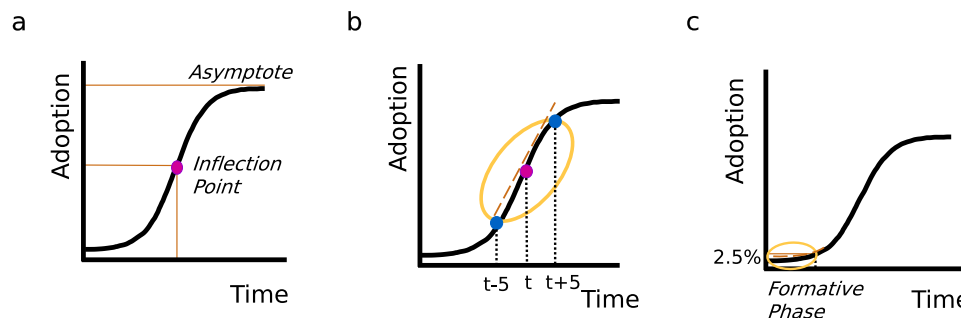
A second metric using the logistic function provides a more intuitive assessment of growth by focusing on the steepest section, the period when the most amount of adoption occurs. A recent paper on solar and wind growth assessed growth around the inflection point with the parameter  $G$ , the maximum amount of market share added annually, which in a logistic function occurs at the inflection point<sup>16</sup>. This metric works well for clearly defined markets such as those for electricity. But because we are using a much broader set of technologies, not all of which are straightforward substitutes for others, we need to arrive at a more general formulation of growth at the inflection point. For example, a clear market does not exist for road miles built, materials mined, or even e-bikes used. We thus normalize each technology to the inflection point and measure the linear growth over the five years before and five years after the inflection point. This provides a more generally applicable formulation than  $G$  and provides a more intuitive comparison to other growth rates than does simply using the coefficient defining the logistic function (Panel B in Fig. 1). For these reasons, we use this metric as our primary metric of technology adoption.

Third, because scale up of CDR in the early years of its development is of particular interest to policymakers, we include a separate look at each time series' formative phase<sup>18,32</sup>. Using the assumption that early adopters represent the 2-sigma left tail of a normal distribution of adopters, the formative phase includes the period from first commercialization to 2.5% of eventual saturation. Early growth is important to the eventual technology adoption levels for CDR, however this metric is sensitive to data at the beginning of the time series<sup>33</sup>, so we focus on it separately from later growth and include it as an additional metric (Panel C in Fig. 1).

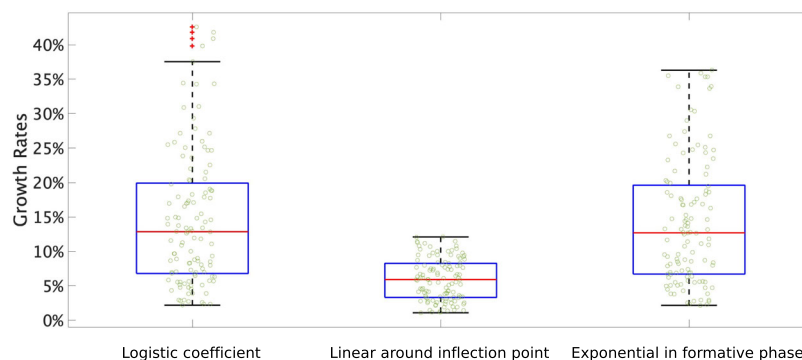
In summary, we found heterogeneity in growth rates for these data, ranging from 1.1 to 14.3% (median 6.2%) for our preferred growth metric based on a logistic function. Most emissions scenarios showed growth within this range (median 5.9%, range 1 to >100%). The growth of both historical technologies and carbon removal in emissions scenarios is lower than growth implied in company announcements and policy targets.

## Results

**Patterns of growth rates in the data.** The 148 unique technologies in the dataset exhibit a wide range of growth rates (Fig. 2 and Supplementary Table 8). Using the primary metric B. linear around inflection), we find a median growth rate of 6% and 1–14% for the min-max range. The logistic coefficient A provides a higher median (13%) as does C the formative phase exponential (13%). The min-max range of growth rates measured by linear around inflection is smaller than that of the logistic coefficient (0–69%) and the formative phase (1–36%). Beyond the min-max ranges, we observe plenty of dispersion across all three metrics prompting interest in what factors might be affecting rates. We provide an initial glimpse by assessing growth across technology



**Fig. 1 Metrics to assess the growth of technology adoption.** Panels show: (A) logistic coefficient, (B) linear around inflection point, (C) formative phase exponential. We use metric B as our primary metric of technology adoption.



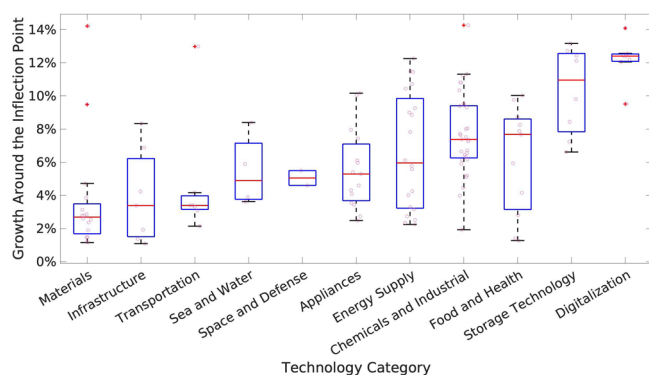
**Fig. 2 Historical technology adoption growth rates for 148 technologies across three metrics.** Box edges show the inter-quartile range, line in box indicates median, dashed lines extend from the interquartile range to the nonoutlier minimum or maximum, and plus signs indicate outliers. If errors occurred in function fitting to calculate the growth rate, the estimates were not included in this figure. All box plots in this paper use the same percentiles for display.

categories (Fig. 3 and Supplementary Table 9). Median and ranges vary by technology category. Storage technologies and digitalization technologies have the two highest median growth rates by category whereas infrastructure and materials have the lowest.

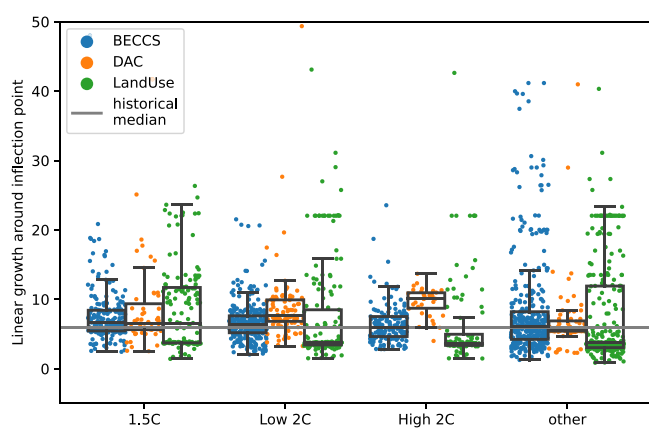
We also see large dispersion across scenario-technology pairs from the AR6 scenarios, again measuring growth across the three metrics, with a focus on B, linear around inflection (Fig. 4). Within these data, 1024 scenarios included BECCS, 248 included DAC, and 707 included land-use based CDR. The median growth rate B was highest for DAC at 7%, followed by BECCS at 6% and land use at 4%. DAC has the largest dispersion; for growth around the inflection point DAC has the largest range (120%), followed by land use (80%), and BECCS (47%). The policy category (as indicated by temperature target) only has a small impact on growth rates in scenarios, with more ambitious climate targets leading on average to higher scale up rates. Model specification has a much larger influence; the ranges and median values differ strongly across model families (Fig. 5) and we also observe that many model families have not yet implemented all

CDR options. While BECCS is available in all major IAMs, land-use options are not, and DAC is only available in a minority of models.

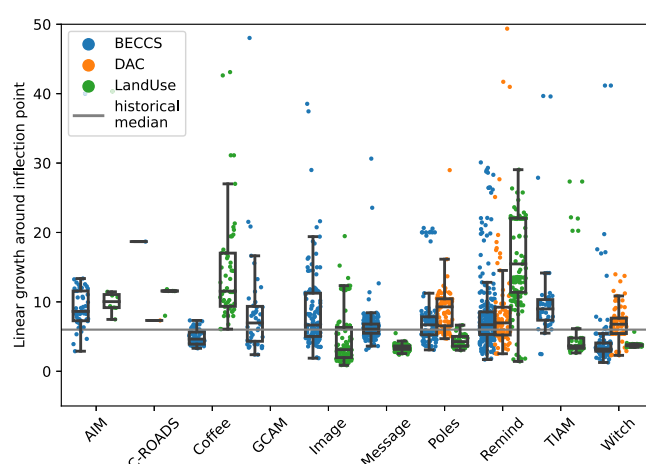
We combine announcements of CDR deployment targets by companies, with deployment potentials of each technology<sup>34</sup> to calculate the same growth rates, A, B, and C described above. We measure growth of company targets in three ways. The first way is dividing companies by technology type and then adding each company's targets to create a time series of cumulative targets (shown in Fig. 6). We then calculate each of the three growth metrics (A, B, and C) for each technology and find the growth around the inflection point of 13% for BECCS, 19% for biochar, and 17% for DAC. The second method is to measure each individual growth rate of the company targets using an exponential growth rate. We use the IEA 2020 levels as a base and the company announcements as the end point, resulting in a dataset of one growth rate per company. The last method is to create a time series of cumulative targets but not subdivided by technology type. We can then measure growth through the three growth metrics (A, B, and C). These data are sparser than the



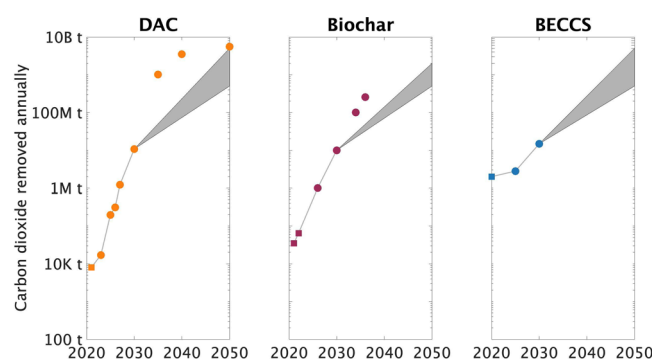
**Fig. 3 Historical technology adoption by technology categories. Growth metric is B: linear around inflection point.** Categories sorted by median growth rate (largest on right). Box edges show the inter-quartile range, line in box indicates median, dashed lines extend from the interquartile range to the nonoutlier minimum or maximum, and plus signs indicate outliers.



**Fig. 4 Growth rates from IAM scenarios for linear around inflection point for three CDR technologies and four categories of temperature targets.** Box plots are grouped by temperature targets and each point shows the growth rate around the inflection point for an integrated assessment model scenario. Blue points show estimates for BECCS, orange points show estimates for DAC, and green points show estimates for land use CDR. The horizontal gray line shows the median growth rate of historical technologies.



**Fig. 5 Growth rates from IAM scenarios for linear around inflection point for three CDR technologies and ten model families.** Each point shows the growth rate around the inflection point for a scenario in each integrated assessment model family. Blue points show estimates for BECCS, orange points show estimates for DAC, and green points show estimates for land use CDR. The horizontal gray line shows the median growth rate of historical technologies.



**Fig. 6 Company announcements for DAC, Biochar, and BECCS deployment.** Square points show built capacity, circle points show announced capacity from companies, and the line connecting each point extends from 2020 capacity to 2030 targets<sup>52</sup>. The shaded area represents the sociotechnical and economic potentials for these methods in 2050.

historical data and thus we would expect large uncertainty in fitting, although that the data are spread over multiple decades mitigates this concern and provides an implicit view on growth expectations from a company perspective. In doing this we are aligned with recent work<sup>35</sup>, although we are more cautious in avoiding imposing our own assumptions about future growth.

Countries and regions have set targets for carbon removal through policies, plans, and nationally determined contributions to the UNFCCC Paris Agreement. These goals include natural carbon removal solutions such as afforestation and soil carbon sequestration and to a lesser extent engineered carbon removal solutions such as direct air capture. As we did for companies, we calculate exponential growth rates from the starting capacity to the targeted amount and find a range from 0.2% to 152% with a median growth rate of 41%. The growth rates implied by country goals and NDCs vary by the carbon dioxide removal methods. Median growth rates for afforestation (11%) are much lower than for engineered carbon dioxide removal methods (66%), in part because of much higher existing base of removals for afforestation. In addition, afforestation targets mainly come from NDCs for the Paris Agreement, which could be interpreted as more binding than the small number of non-land-based CDR targets we found.

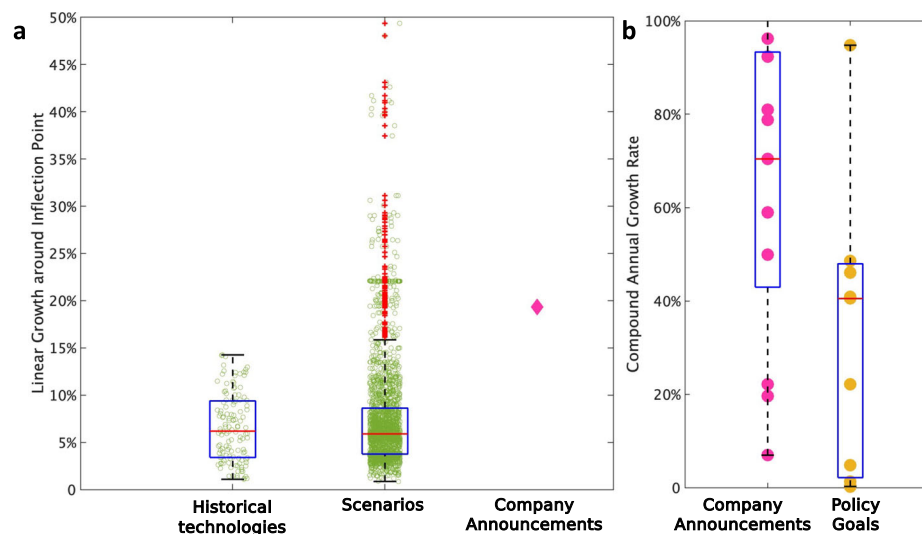
**Comparing growth rates across data types.** Using consistent definitions of growth that perform across diverse data types enables comparisons to address the question of how future growth compares to that of the past (Fig. 7). As a first comparison, we find that median growth for historical technology adoption is 6.2% and for AR6 scenarios is 5.9% using the linear growth around inflection. In aggregate, CDR growth in IAM scenarios modeling climate stabilization is similar to that averaged across a wide range of non-CDR technologies in HATCH. The interquartile ranges are also similar: 3–9% vs. 4–9%. Further, we find that companies when pooled have a higher growth (19%) rate than both historical and scenarios. Because they consist of individual data points and are not suitable to pooling, we do not calculate logistic growth for policies. The median exponential growth rate for policies is 40%, which is below that of company

announcements (70%). We note that the company and policy data are distinct from the historical and scenario data because the former pair are not globally aggregated as the latter are; it is not clear if national data would bias growth upwards. It is possible that the higher rates for companies and policies reflect leader actors.

To assess the robustness of findings to alternative growth metrics, we compare growth rates across several growth metrics. The order of the growth rate speed compared between historical technologies, IAM scenarios, and company announcements does not change by measuring growth through our three main metrics: measuring growth at the formative phase, inflection point, and logistic growth through the whole time series (Fig. 8 and Supplementary Table 10). Historical data and IAM scenarios are slowest; the fastest growth is from companies. Further growth rate comparisons are provided in Supplementary Table 11.

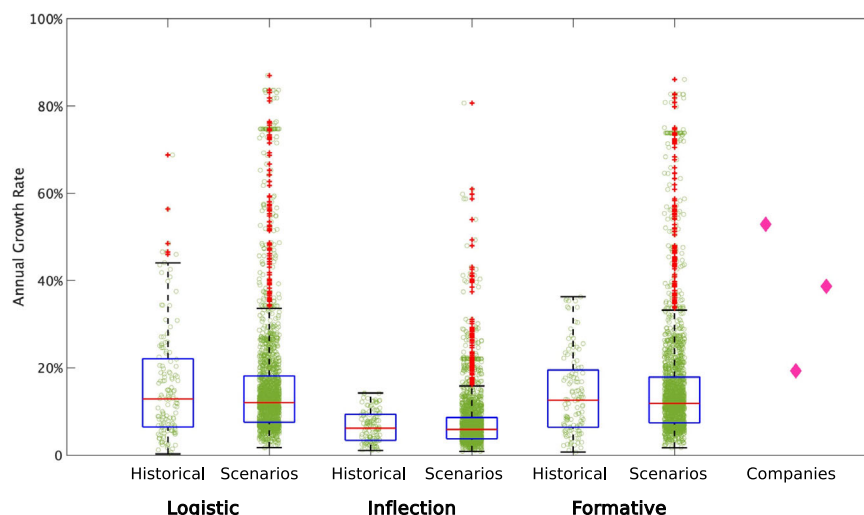
Understanding the drivers of this variation is crucial to being able to precisely use historical data to characterize scenarios, and targets. One can see already that the categorization of historical technologies explained above, shows quite distinct medians. Some of these categories are particularly valuable classifications because they display much lower dispersion than the pooled data. For example, infrastructure, materials, energy, and hardware all show narrower distributions than the pooled data. On the other hand, food, health, storage, and digitalization have wide distributions implying that other characteristics need to be accounted for to assess how they can be used to inform novel technologies. Variation of growth rates from IAM scenarios can also be partly attributed to model specification as shown by the stark difference in growth rates between model families and to some extent climate target stringency. However, they are potentially also influenced by other factors such as availability and cost of other mitigation technologies. Further analyses are needed to better understand how these factors influence variation in scale up rates, both using large datasets<sup>26</sup> as well as deep case studies<sup>36</sup>.

Our work to date in understanding this large observed heterogeneity in growth rates leads us to a few conclusions on promising directions identifying factors that explain dispersion in growth. First, the literature indicates that a broad set of possible



**Fig. 7 Comparison of growth around the inflection point of historical technologies, AR6 scenarios, CDR company announcements, and CDR policy goals.** Panel (A) compares growth around the inflection point across historical technologies and AR6 scenarios, with medians indicated for company announcements. Circle points show each growth metric for historical technologies and scenarios, and diamond point shows the linear growth around the inflection point for CDR companies, when combined. Panel (B) shows exponential growth rates for company and government targets. Box edges show the inter-quartile range, line in box indicates median, dashed lines extend from the interquartile range to the nonoutlier minimum or maximum, and plus signs indicate outliers.





**Fig. 8 Comparing historical technologies, AR6 scenarios, company announcements, and government targets to one another and across growth metrics.** Diamonds show the growth rates for companies: the point furthest to the left is the logistic growth rate, the middle is the linear growth around the inflection point, and the furthest right is the exponential growth in the formative phase. Box edges show the inter-quartile range, line in box indicates median, dashed lines extend from the interquartile range to the nonoutlier minimum or maximum, and plus signs indicate outliers.

explanatory factors might play a role, including granularity, policy, vintage, adoption phase, material intensity, design complexity, customization, lifetime, and types of adopters. Characterizing each of these factors for each technology is a substantial data collection project. Second, initial descriptive analyses can be helpful in assessing such factors, even if insufficient for attribution. As examples, we provide two illustrations in Supplementary Figure 5 and Supplementary Figure 6 showing how vintage and type of adopter correlate with growth rates. Third, a multiple regression framework will ultimately be needed to avoid omitted variable bias and spurious correlation. That depends on comprehensive data collection and dealing with collinearity. In practice, identification will likely require a variety of robustness checks to arrive at conclusions about causal factors. Large data sets will be helpful as will national rather than global data, both of which we aim to develop in a future iteration of the HATCH dataset. We are optimistic that a strong effort on data collection combined with an analytical framework that prioritizes robustness of results across specification can help identify the factors that contribute to the large heterogeneity in growth rates we observe.

## Discussion

These comparisons of large distinct data sets generated four main insights. First, median historical technology growth is similar to that in AR6 scenarios, albeit with wide dispersion. We see evidence from the scale up of over one hundred historical technologies in HATCH that the required scale up of carbon removal technologies fits within the historical range of previous efforts. Although there is large heterogeneity in the data requiring further assessment of drivers of variation to make dispositive comparisons. Clearly there are reasons, such as lack of policy support, that CDR technologies might grow more slowly than historical technologies.

Second, company announcements, as well as government targets imply much faster growth than the historical record and compared to AR6 scenarios. These data are sparse, so they are treated differently to enable comparisons; we pool them to use the same growth around inflection metric, and we use exponential growth to assess targets involving a single future value compared to the current level. Either way these targets imply much faster

growth. One explanation is that at least some of these targets are focused on novel CDR which will be growing from a very small base. A second explanation is that although these goals seem ambitious, they are consistent with gigatons of removal by mid-century for a 1.5 C net zero. Companies and governments are aiming well beyond the central tendency of the historical range.

Third, our main conclusion—that historical growth and scenarios are similar, but that company and policy targets are much higher—is robust across three distinct specifications of our growth metric. We find the same results when we assess growth in a variety of ways, using different functional forms and assessing different time periods of growth, which results in different growth estimates.

Fourth, there is wide dispersion across all data sets. For example, all interquartile ranges overlap. This spread of the data implies that understanding what drives the dispersion in growth rates will be important in determining how one can use the empirical record to calibrate the potential for growth in future oriented analyses like scenarios, literature, as well as company and policy goals. Further refining the comparison will include matching specific historical technologies to types of CDR using technology characteristics. This will illuminate technologies that may be analogous to different CDR methods<sup>22</sup>.

The number and diversity of technologies in the historical data set means there are a range of plausible analogues for each CDR technology. Our aim is that this historical technology data set provides a basis for further studies on technology adoption to inform the scale up of nascent technologies. This rich and expanding data set is now available on-line as the Historical Adoption of TeChnology (HATCH) dataset. Assembling and analyzing a large data set of technologies provides insight<sup>19</sup> that reliance on a smaller number of comparisons does not.

For the application of CDR, we see strong potential in work characterizing factors that affect dispersion in growth rates. For example, the technology categories seem to explain some of the variation in that their medians are different and there appears to be a rise in medians when ordered by decreasing unit scale. We also would consider granularity, which we presume is partially collinear with our technology categories, spatial scale, and material intensity, for which digitalization would be lowest. Model simulations of the effects of these factors as well as of the

dispersion in the data themselves can also provide indications of the importance (or potential the lack of importance) of how growth is calibrated and constrained in models to inform the role of CDR in climate change mitigation.

## Methods

**Data.** We assemble the Historical Adoption of TeCHnology (HATCH) dataset to assess growth rates of historical technologies. We build upon publicly available time series datasets as well as other public time series data such as the UN Food and Agriculture Organization. The dataset includes time series data of 148 unique technology time series measured in terms of cumulative adoption (cumulative capacity or annual production). For technologies that are measured as annual production, rather than in terms of cumulative capacity, authors include these data with the assumption that annual production is directly related to cumulative capacity, e.g., long-term growth in aluminum production reflects growth in capacity to produce aluminum. In gathering data, authors sought a variety of technology categories that range in terms of granularity (from household appliances to infrastructure technologies, for example) and in terms of technology type (from digitalization data to agriculture data, for example). Other technology types were chosen because of similarities to CDR, such as energy technologies and energy storage technologies. In assembling this dataset, authors prioritized gathering a large set of technologies to understand dispersion of growth rates across different technologies. We used publicly available data and prioritized gathering data from a broad set of technology types. To measure growth rates by fitting functional forms, we included technologies with at least ten data points. We did not select data based on speed of scale-up. In the data collection process, authors also collected technology time series data measured in terms of market data share and analyzed it separately to analyze the sensitivity of growth metrics to the data type; on average market share data are slightly higher (9% vs 8%) for growth around inflection (see Supplementary Fig. 3 and Supplementary Table 7). When possible, market share data were converted to cumulative capacity data to include in the overall dataset, if the size of the market and unit size were available. If technology adoption data were available on a global scale, authors used those time series data in favor of country-level data for this analysis. If only country level data were available, authors added adoption in each country per year to create as large of a market as possible for a more analogous comparison to global data.

To assess the AR6 Scenario data, we use the scenario database compiled for the sixth IPCC assessment report<sup>27,37</sup>. This database contains modeling results from integrated assessment models (IAMs) calculated for different baseline and policy scenarios. We focus our analysis on these because they were vetted for use in the IPCC publications, which were rigorously peer-reviewed. The IAM database includes modeled quantities of carbon removed from the atmosphere necessary for reaching climate goals such as the 1.5° and 2° Paris accord targets. Many models include BECCS and DAC as CDR options. Many models also include carbon removal in the land sector, even though only a few scenarios specify by which technology or management method this will be achieved, such as by afforestation/reforestation, enhanced weathering, biochar, soil carbon sequestration. Further analysis of growth rates by CDR method is included in Supplementary Fig. 2 and Supplementary Table 4. For handling the database, we use the open-source Python package *pyam*<sup>38</sup>.

Companies focused on carbon dioxide removal have long-term and interim goals for DAC, BECCS, biochar, and general CDR deployment. The authors use data from public company announcements to estimate growth rates for DAC companies

(Supplementary Tables 1 and 2). The authors searched the websites of all direct air capture companies listed in the Direct Air Capture Coalition for announced targets for DAC scale-up<sup>39</sup>. All companies with targets on their websites were included in the company announcement dataset. Biochar scale-up goals and current capacity come from the European Biochar Industry Consortium. Further analysis of company types can be found in Supplementary Note 1, Supplementary Table 3, and Supplementary Figure 1.

Assessing the level of carbon dioxide removal included in country policies and goals can also serve as a market signal for carbon dioxide removal. We assess policies and plans related to carbon dioxide removal in the United States, European Union, and United Kingdom as well as searching NDCs to the Paris Agreement for relevant carbon dioxide removal. More details about the growth rates within country policies and goals are included in Supplementary Tables 5 and 6. For regional and country policy targets, authors use starting values from the carbon removal purchases spreadsheet<sup>40</sup> divided by three between the United States, European Union and United Kingdom with each of these regions estimated to contribute to an equal third of carbon removal currently. For NDCs to be included, a starting number and goal number were needed to calculate a compound annual growth rate.

**Measurement.** None of the three main metrics we focus on tells the adoption story completely. Early years are of clear policy interest, but data quality can be low. Measuring growth at the inflection point using a linear fit and standardizing it to the asymptote level lessens this reliance on early data but can involve out-of-sample extrapolation through modeled data based on the logistic function. Other types of data, such as company targets, preclude curve fitting because they include fewer than three data points, typically including a starting year and capacity and an ending year and capacity. For those we calculate an exponential growth rate, the downside of which is that it is sensitive to the start year and the exponential is only an appropriate function for early years. Consequently, we test the robustness of our comparisons to these three distinct ways of measuring growth. We also consider a variety of other metrics including other functional forms such as Gompertz, exponential, and Softplus but, as we discuss in the Methods, we find that these three are the most appropriate for informing our research questions.

**Measuring growth in time series data.** The measurement of scale-up in the literature is mostly based on annual growth rates. However, growth rates have been estimated using a variety of techniques. In our analysis, we measure growth across technologies using four functional forms (logistic, exponential, Gompertz, and Softplus) and nine metrics. We measure growth in many ways to assess robustness of the growth rate comparisons depending on the type of growth metric we choose and to take an account of the many ways researchers have measured the growth of technology diffusion. More details on each measure are described in Supplementary Note 2 and Supplementary Table 13.

The speed of technology diffusion has been theorized as following a logistic curve, with its characteristic s-curve shape, beginning with an innovation that brings a technology to market, then growing with increased adoption that eventually slows upon reaching and plateauing at a saturation point<sup>4,41</sup>. Fitting an s-curve, particularly with a logistic function, to data is a common approach to measuring growth<sup>42,43</sup>. The logistic function has three free parameters and is defined as follows:

$$f(t) = \frac{L}{1 + e^{-k(t-t_0)}} \quad (1)$$

where the parameter  $L$  is the function's asymptote or upper bound for large  $t$ ,  $k$  is the growth rate parameter that corresponds to the growth rate for small  $t$ , and  $t_0$  is the position of the inflection point, i.e., the point of the curve of maximal absolute growth after which absolute growth decreases again. The growth rate parameter  $k$  is an estimate of the annual growth rate at the initial phase of the scaling. This metric,  $k$ , is one metric to measure growth across the whole time series period.

After fitting the logistic function to time series data, we use the modeled parameters to project data before and after the time series. Using these projected data based on the fitted logistic function, we measure growth in three periods within the time series. The first is in the formative (initial) phase of scale-up, the second is around the inflection point, and the third is the time it takes for a technology to grow from 10–90% of its eventual saturation point.

To measure the growth of the technology in its initial formative phase, we use the projected data to find the point at which the technology reaches 2.5% of its asymptote. We fit an exponential function onto the cut data to measure growth. This aligns with the shape of initial growth in the s-curve model.

Measuring growth around the inflection point is also of interest as a growth metric. We cut the projected data five years before and five years after the inflection point and fit a linear function onto these data. This gives us an absolute growth rate, which we standardize based on the value at the inflection point to reach a comparable growth rate around the inflection point of the s-curve.

The third metric is closely related to the main logistic growth metric. The time period  $\Delta t$ , defined as the time taken to increase from 10% to 90% of the market share, can equivalently be used to describe the function and is related to  $k$  in the following way:  $\Delta t = \ln(81)/k \approx 4.39/k$ . To calculate this growth rate, we use modeled data to find the years associated with reaching 10% and 90% of the market share, find the difference of these years, and find the inverse of this value which gives us a steepness metric that we consider a growth rate. This measure has been used to characterize the speed of scale up of energy technologies<sup>44</sup>.

Although measuring growth based on an s-curve shape is common in literature, the shape does not necessarily fit all data, for example those technologies without a clear asymptote (for example, some technologies do not have a natural market saturation level). Some authors use functional forms beyond a logistic function to measure growth<sup>16</sup>. We measure growth using two growth metrics based on an exponential functional form: an exponential growth rate fitted onto the whole time series and the maximum exponential growth rate of the dataset measured in ten-year increments. The exponential growth is measured with the following equation:

$$f(t) = a * e^{bt} \quad (2)$$

where  $b$  is the growth rate metric. We fit this exponential function onto each technology dataset to measure growth.

To measure the maximum exponential growth for each technology, we fit an exponential function to values of each 10-year time window in the time series. The exponential rate  $b$  of that function then gives the best estimate of the average exponential growth rate for each ten-year period. We choose the maximum of these ten-year exponential growth rates to represent the growth rate of the technology. This allows us to characterize the sustained maximal relative growth of a technology. For technologies that are measured by decade rather than yearly, we estimate the maximum 10-year exponential growth using a compound annual growth rate.

We also measure growth through two metrics based on a Gompertz function (Gompertz and  $G$ ) and one metric based on a

Softplus function. The Gompertz function is similar to a logistic function, but rather than a symmetrical function where initial growth and eventual slowdown are symmetrical around the inflection point, the Gompertz function estimates slower growth after the inflection point to reach the asymptote than in the initial period. The Gompertz equation is described as follows:

$$f(t) = Le^{-e^{-k(t-t_0)}} \quad (3)$$

where  $L$  measures the asymptote,  $k$  is the growth metric, and  $t_0$  is the initial year in the dataset.

The  $G$  metric measures the maximum growth rate at the inflection point normalized to the asymptote value. To find the  $G$  metric based on the Gompertz function, we use the following equation:

$$G = \frac{Lk}{e} \quad (4)$$

The Softplus function is a new way to measure technology diffusion. The Softplus function is similar to the logistic function, but with a linearly increasing asymptote, rather than a flat asymptote. This may account for technology diffusion measured by cumulative capacity, in which the capacity can continue to increase over time. The function is described as follows:

$$f(t) = \frac{L}{k} \log\left(1 + e^{k(t-t_0)}\right) \quad (5)$$

From the analysis of these nine growth metrics, we focus on three metrics of growth based on the logistic function: exponential growth measured in the formative phase, linear growth measured around the inflection point, and logistic growth measured through the whole dataset. A more thorough robustness analysis is included in Supplementary Fig. 4 and Supplementary Table 12 and throughout the rest of the study we include these three main growth types in comparisons.

For data with two points, a starting point and an ending point, we measure growth through a compound annual growth rate, which requires only a start and end year and values. The compound annual growth rate is measured with the following equation:

$$c = [v(t_2)/v(t_1)]^{1/(t_2 - t_1)}, \quad (6)$$

where  $v(t)$  are the values of the timeseries at time  $t$  and  $c$  is the compound annual growth rate. We use this metric to measure growth for policy goals and individual company announcements which are measured with two pairs of values, a start year and value as well as an end year and value.

**Analytical procedures and calculations for each data type.** For each data type below, we describe the specific method for data collection and analysis.

We assembled a dataset of historical analogue technologies (HATCH) that span a variety of categories, granularities, and vintage (see Supplementary Note 3 for details on data inclusion criteria). These data were compiled from a variety of sources, from government records on infrastructure buildout to publicly available datasets on energy technologies and hardware technologies, in the form of time series<sup>18</sup>. We fit a logistic function to estimate a growth rate parameter, an inflection point year, and an asymptote that estimates the time at which growth slows. We use this logistic fit to estimate a growth rate through the growth rate parameter, and we use the modeled data based on that logistic fit to measure growth around the inflection point and at the formative phase of growth.

We fit a logistic function to each integrated assessment model scenario for AR6 by the underlying technology for carbon removal (BECCS, DAC, land-use). This served as an estimate



about the scaling of the underlying technology. Before fitting the data to a logistic function, we removed data points from the start if there were drops (decreases) in the early data and removed data points from the end if there was a drop below more than 90% of the maximum technology level reached. For the logistic fitting on land use carbon dioxide removal methods, we added an offset to the fitted logistic curve as many of these CDR methods start at a non-zero level, so we only measure growth from that base level.

We fit a logistic function to 2350 scenario-technology pairs. From the logistic fit for each scenario-technology pair, we extracted the logistic growth rate parameters. For each of the fits, we excluded all pairs with an error for bad fit, another warning, or a runtime error (68 errors). Of the remaining 2282 pairs, 33 could not be properly trimmed as described in the pre-processing data and 270 had no growth, leaving us with 1979 scenario-technology pairs. The logistic function fit gives us a parameter we use as a growth rate of the whole function. We also use the modeled logistic fit data to measure growth around the inflection point and growth in the formative phase. We measure these growth rates for land use, BECCS, and DAC technologies in IAM scenarios.

Companies have made announcements about future carbon removal scale-up plans, including companies focused solely on one technology (BECCS and DAC, for example) and those focused more broadly on carbon dioxide removal<sup>45</sup>. To calculate a growth rate from each company announcement, authors used starting capacities listed by the companies (in reports from the International Energy Agency, or through the Marginal Carbon spreadsheet<sup>40</sup>), the announced capacity, and the timeline for the scale-up to calculate a compound annual growth rate.

To make the company announcement data comparable to scenario and historical technology data, we created a time series dataset of company announcements that added each company announcement to the market total to create a cumulative capacity time series dataset. With this time series data, we measured growth in the formative phase, around the inflection point, and logistic growth for the dataset in the same manner as historical technologies. Further, company announcements are coupled with global potentials of carbon removal by technology<sup>10</sup> as goal capacities for 2050 in Fig. 6. Authors use the average of the range of potentials for each technology (BECCS, biochar, DAC, and all CDR technologies).

The United States, United Kingdom, and the European Union have plans to reach net-zero emissions by 2050, which necessitates carbon dioxide removal. We reviewed the country and regional plans for net-zero carbon emissions<sup>9,46–48</sup>. To estimate growth rates of these technologies, we use the end points of carbon dioxide removal methods and the time period included in these goals (whether 2035 or 2050, for example) to estimate the exponential growth rate needed for this scale-up using a compound annual growth rate.

The CDR growth rates from policy goals includes one policy goal from the United States to scale up carbon dioxide removal—both engineered and natural solutions (land use changes) to 1 gigaton of carbon dioxide removal by 2050<sup>46</sup>. From the European Union, policy goals include 5 megaton of carbon dioxide removal from technological solutions by 2050<sup>48</sup>. The United Kingdom includes policy goals for 5 Mt of CO<sub>2</sub> removal by 2030 through BECCS and DAC deployment, 23 Mt of CO<sub>2</sub> removal by 2035 through BECCS and DAC deployment, and a range of removal of between 75 and 81 Mt of carbon dioxide annually by 2050 through engineered removal technologies<sup>47</sup>. Afforestation goals in NDCs include Pakistan, Bangladesh, Cabo Verde, Uganda, and Rwanda<sup>49</sup>.

To calculate the exponential growth rate, we use the starting estimates from the carbon removal purchase tracking spreadsheet<sup>40</sup>. We sum the carbon removal purchases across

technologies to come up with a CDR starting capacity and divide this amount by three, between the United States, United Kingdom, and European Union. In other words, we assume that the carbon dioxide removal purchases are equally distributed between entities, organizations, or companies within the United States, United Kingdom, and European Union.

For the national determined contributions that include carbon dioxide removal, authors search the NDC database with each technology name (e.g. “afforestation,” “direct air capture”) and broad carbon dioxide removal (e.g., “negative emission technologies,” “net-zero”)<sup>49</sup>. Authors capture both the inclusion of CDR terms in NDCs as well as any NDCs that include growth rate data.

### Data availability

The data that support the findings of this study are available in the Historical Adoption of TeCHnology (HATCH) dataset, available at <https://cdr.apps.ece.iiasa.ac.at/story/hatch/50>.

### Code availability

The code used to process the data in this study are available at <https://zenodo.org/record/832734751>.

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## Author contributions

Nemet designed research, analyzed data, and drafted text. Greene collected data, analyzed data, and drafted text. Mueller-Hansen analyzed data and drafted text. Minx designed research and drafted text.

## Competing interests

The authors declare no competing interests.

## Additional information

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**Correspondence** and requests for materials should be addressed to Gregory Nemet.

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