



Net0 Pathways through improved IAMs across Sectors, dimensions, and scales

Database of up-to-date probabilistic technology cost forecasts

*A report prepared by Sergey Kolesnikov, Rupert Way, and
Laura Diaz Anadon, University of Cambridge;
Bessie Noll, ETH Zurich*

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Prepared by: Sergey Kolesnikov, Rupert Way, and Laura Diaz Anadon (University of Cambridge); Bessie Noll (ETH Zurich)

Reviewed by: Bjarne Steffen (ETH Zurich), Johannes Emmerling (CMCC)

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Executive Summary

This report presents a database of up-to-date probabilistic technology cost forecasts for key low-carbon and clean energy technologies, developed as part of the Deliverable D3.2 of the PRISMA project. A few different technology cost forecasting methods are applied, and salient methodological issues are discussed, in order to stimulate progress on how energy system models (ESM) and integrated assessment models (IAM) represent technological change and its uncertainty.

The database includes:

- Up-to-date probabilistic technology cost forecasts for solar photovoltaics (PV), onshore and offshore wind energy, lithium-ion batteries, proton exchange membrane (PEM) electrolyzers, and LED lighting.
- Model forecasts for lithium-ion battery packs and fuel cell systems used in commercial road freight vehicles.
- Technology cost forecasts for three types of direct air carbon capture and storage (DACCS) constructed using a variation in inherent technology characteristics.
- New learning rate estimate for geothermal energy.

This report describes the database; outlines the key issues with the reliability of existing deterministic technology cost forecasts and forecasting methodologies; describes recent cost forecasting methodologies that address these issues from various perspectives and how these methodologies are applied to generate technology cost forecasts included in the database; visualizes these forecasts as data plots; and briefly describes key potential uses and limitations of these forecasts.

With up-to-date probabilistic cost forecasts provided for the key low-carbon and clean energy technologies, this deliverable contributes to advancing the global low-carbon transition by providing a robust foundation for improved representation of technological change and uncertainty in ESM and IAM modelling and analysis.

1. Introduction

Understanding the cost dynamics of key energy and low-carbon technologies is critically important for making informed policy and investment decisions related to climate change. Specifically, predicting how the costs of different technologies relevant to climate change and energy transition will behave in the future is essential for estimating the overall cost of transition and different technological pathways towards this transition.

Historical analysis of past trends in technology costs, typically called learning curves or experience curves, shows that while the vast majority of technologies do not undergo significant cost reductions due to technological progress, in a few rare cases, such as solar photovoltaics (PV), costs have declined rapidly and consistently with increasing cumulative production over extended periods of time, resulting in costs decreasing by many orders of magnitude (Way et al., 2022). In other technologies, observed cost improvements with experience (Wright, 1936) or over time (Moore, 1998) have been less rapid (e.g., in offshore wind), mostly absent (e.g., in the delivery of energy services via fossil fuels, see Way et al., 2022), or, in the case of nuclear energy, have reversed and become cost increases instead (Meng et al., 2021).

Traditional deterministic approaches to forecasting technology costs typically rely on extrapolating such trends into the future, with at best some scenario variation on future cost and technology deployment. However, technological progress is highly uncertain, as it is driven by a combination of various interacting innovation mechanisms such as learning-by-doing, R&D, economies of scale and scope, and knowledge spillovers, supported by public policy, and affected by a myriad of other socio-economic factors, such as fluctuations in the costs and accessibility of raw materials. As a result, there is no guarantee that past trends in technology costs will continue at similar rates in the future, yet deterministic cost forecasts based on past learning rates provide no insight into this uncertainty. Another major challenge for technology cost forecasting is that for many important climate-relevant technologies which are just emerging on the market, such as direct air carbon capture and storage (DACCS), there is not enough past data to make reliable future forecasts based on experience curves estimated from past cost data.

These challenges may partially explain why most energy system models (ESM) and integrated assessment models (IAM) of climate change have historically overestimated the costs of several critical low-carbon technologies, in particular solar PV, batteries and electric vehicles (EVs), and in doing so overestimated the cost of the transition to renewable energy and underestimated the rapid pace of scaling up in these technologies (Meng et al., 2021). Specifically, the issue of uncertainty in cost forecasts, which has been a major concern in energy modeling for over two decades (Wene, 2000), has led modelers to systematically “err on the side of caution” for many critical low-carbon technologies, but in doing so they failed to explore the continuation of current trends beyond just a few years into the future, instead assuming that technological progress trends abruptly stop. Our work also shows that many models represent technology cost dynamics as exogenous assumptions or do not represent these dynamics at all (Pasqualino et al., 2024). By endogenizing technological progress through modelling technology learning curves and by taking account of its inherent uncertainty through the adoption of probabilistic approaches to technology cost forecasting based on historical data and models, PRISMA project will help overcome these limitations and improve the technological granularity and explanatory power of IAMs.

In this deliverable, we present a database of up-to-date technology cost forecasts that can be integrated into the IAMs in PRISMA. We develop the database through the following three streams of work. First, for a set of existing clean energy technologies that have a significantly long history on the market (i.e., solar PV, onshore and offshore wind, lithium-ion batteries, PEM electrolyzers, and LED lighting), we use a probabilistic technology cost forecasting methodology (Farmer and Lafond, 2016; Lafond et al., 2018; Way et al., 2022) to create new up-to-date probabilistic technology cost forecasts that fully account for uncertainty in future technological progress in four deployment scenarios. For two additional technologies – lithium-ion battery packs and fuel cell systems used in commercial road freight transport – we construct future cost trajectories using system dynamics modelling (Noll et al., 2023). Finally, for technologies that are not yet deployed on the market at scale, we describe a new methodology originally introduced by Sievert et al. (2024) for forecasting technology costs based on an empirical analysis of technology-inherent characteristics that may explain the variation in technology-specific innovation rates. This methodology utilizes a framework that links cost reduction potential to two inherent technology characteristics (Malhotra and Schmidt, 2020): design complexity and the need for customization. In this deliverable, the framework is applied to estimate learning rates and generate cost forecasts in three direct air carbon capture and storage technologies (DACCS). In addition, we provide a new learning rate estimate for geothermal energy based on newly collected cost and deployment data.

The rest of the report is structured as follows. In the next subsection, we discuss in more detail the problem of technology cost forecast reliability to set the context for the need to use probabilistic cost forecasting methodologies. Section 2 describes the methods used to generate technology cost forecasts provided in the attached database, along with potential uses and limitations for the resulting cost forecasts. Section 3 provides visualisations for the cost forecasts in the database. Section 4 contains information about the structure of the database and the link to the data repository. A list of related peer-reviewed publications from the respective PRISMA task is provided in the appendix.

1.1 Forecast reliability

To address the issues with reliability of existing deterministic technology cost forecasting methods discussed above, the most scientific approach possible to forecasting is needed. In this subsection, we provide additional background leading to the development of probabilistic technology cost forecasting methodologies which we used to generate forecasts in this deliverable.

The complexity and granularity of energy system models (ESMs) and integrated assessment models (IAMs) has ballooned in the last two decades. However, during this time, too little attention has been paid to the question of how reliable the technology forecasting methods used therein are (i.e., the mechanisms by which technology costs and deployment are programmed by modelers to co-evolve as scenarios are generated), and consequently, how likely the different technology projections inherent to different scenarios are to occur in reality. Without careful, quantitative assessment of the likelihood of different technology cost trajectories, it is impossible to assess how likely various other scenario elements are to occur (in particular, technology deployment), nor how relevant any conclusions generated are for the real world if observed costs deviate far from forecasted costs.

To illustrate the importance of using empirically validated technology forecasting methods, observe in Figure 1 that during the AMPERE model comparison project conducted only around ten years ago, in 2014 (Riahi et al., 2015), all of the IAMs involved produced scenarios that overestimated the installed system cost of solar PV only six years ahead, in 2020, by factors of around 3 to 20 (i.e., the 2020 cost projections overestimated real world costs in 2020 by between around 100% and 2000%). No IAM produced any scenario in which PV costs were close to realistic, let alone lower than real-world costs. Similarly, a few years later, the IPCC's SR15 publication (IPCC, 2018) relied on IAM scenarios that included 2020 PV cost projections that were, without exception, higher than real-world 2020 costs, with most projections overestimating them by around 100% to 500%. In contrast, forecasts produced by methods whose performance has been tested and quantified using standard statistical techniques and real data (for example, like many forecasting methods employed in finance, banking, engineering, meteorology, etc.), should in hindsight be observed to have forecast errors scattered symmetrically both above and below realized values.

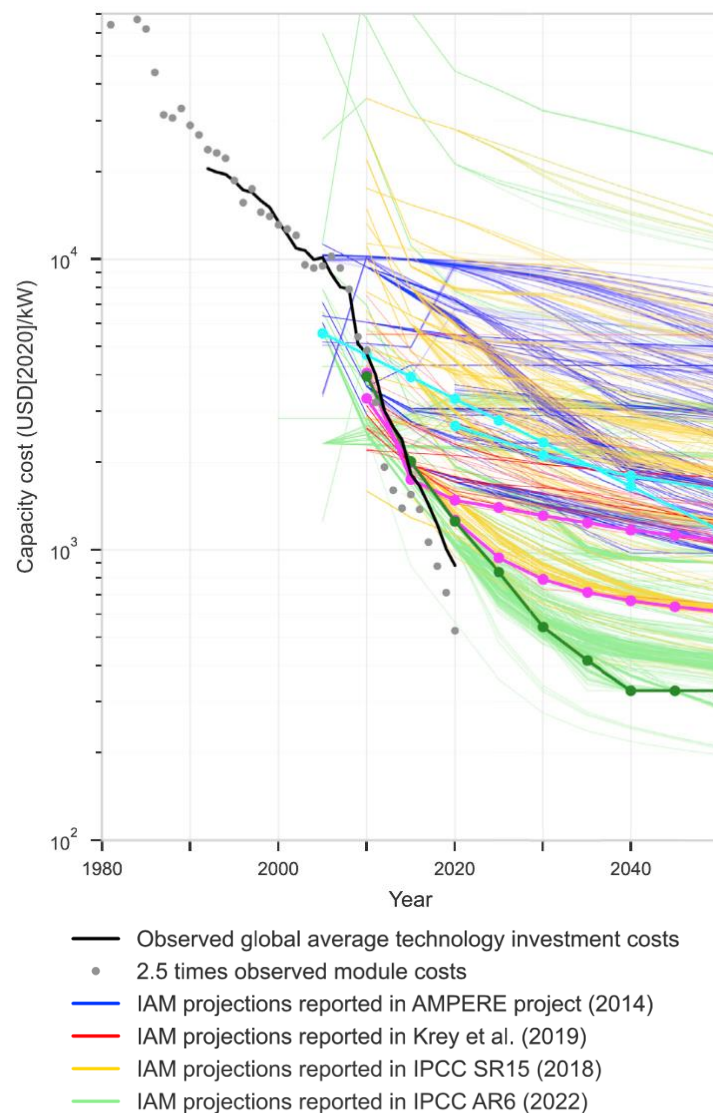


Figure 1 – Solar PV cost projections from a wide range of IAMs included in several modeling comparison exercises and IPCC reports in recent history. Reproduced from Figure 9A in Way et al. (2022), see there for full details.

To address this issue, Nagy et al. (2013) collected historical cost and production data for as many technologies as they could find (around 50) and applied a simple back-testing procedure to quantify the forecasting performance of six different cost forecasting methods. The forecasts generated were point forecasts, and the forecast errors were analyzed as a function of forecast horizon. The results demonstrated that in technology cost forecasting, it is essential to capture the intuitively obvious fact that cost trajectories gradually accumulate cost movements (whether positive or negative) due to various factors, rather than inexplicably revert to some long run trend lines such as those assumed by the use of historical learning rates.

This insight, plus the result that two of the simplest cost forecasting methods, Moore's law (Moore, 1998) and Wright's law (Wright, 1936; also known as the experience curve), were observed to produce the lowest forecast errors in general, led to the development of a more sophisticated probabilistic forecasting method using a stochastic first-difference model. This method, which we use in this work, was developed and applied in the generalized Moore's law case (Farmer and Lafond 2016), and in the experience curve case (Lafond et al. 2018).

2. Methods

2.1 Cost forecasts for solar PV, onshore wind, offshore wind, lithium-ion batteries, PEM electrolyzers, and LED lighting

In this deliverable, we develop probabilistic technology cost forecasts for key clean energy technologies using the stochastic first-difference method developed by Farmer and Lafond (2016) and Lafond et al. (2018). This method accounts for two fundamental sources of uncertainty: 1) uncertainty in our estimates of the learning or progress rate of a technology at any given time, since these can only ever be based on the data available at the time (which is itself subject to uncertainty), and 2) uncertainty caused by exogenous shocks in the world (such as changes in interest rates, supply chain constraints, or technological breakthroughs elsewhere in the economy). By generating probabilistic forecasts based on a model in differences rather than in levels, forecast confidence intervals are consistent with the idea that technology costs develop continuously over time as the result of accumulating technological progress and accumulating shocks. This method was extensively tested and validated on past data and forecasts (see Farmer and Lafond, 2016; Lafond et al., 2018), ensuring its reliability, which is typically missing in deterministic forecasting methods.

Further details of the probabilistic technology cost forecasting methodology used in this deliverable are provided in Way et al. (2022), along with cost forecasts generated from a 2020 baseline for solar PV, onshore wind, lithium-ion batteries, and PEM electrolyzers. In the time that passed since those forecasts were created, a substantial amount of new and updated cost and deployment data for key low-carbon technologies has been published. It allowed us to both update past forecasts using new data and generate entirely new probabilistic cost forecasts for technologies that were not previously explored with this forecasting methodology: offshore wind and LED lighting.

Limitations and use:

1. The cost forecasts provided are for global average technology costs up to 2050. Analysts should be aware of the large variations in technology costs locally and ensure they are consistent with the global values provided here.
2. For five technologies (solar PV, onshore wind, offshore wind, lithium-ion batteries and PEM electrolyzers) both cost and production data were available, and so we were able to make experience curve forecasts. For LED lighting technology at two levels of integration (white LED chips and LED lamps), production data were not available, and so we made generalized Moore's law forecasts.
3. For the experience curve forecasts, four different deployment scenarios were used for each technology, conditional upon which four different probabilistic forecasts were then generated. These deployment scenarios were constructed by assuming that the growth rate of deployment in each technology proceeds for a few years after 2024 at either 1) roughly the same growth rate as observed currently, or 2) a slightly higher rate, or 3) a slightly lower rate, or 4) a much lower rate. Following these different initial assumptions, the growth rate follows a decreasing S-curve path from the initial value to a value of 2% in 2060, so that deployment growth decreases smoothly over the next few decades.
4. It is essential when using the experience curve forecasts that modelers understand the conditionality of future costs upon future deployment – it would not be consistent to use the cost forecasts provided with deployment scenarios that differ greatly from those provided. In addition, for general consistency, modelers should always analyze technology cost and deployment trajectories produced as part of their scenarios and ensure they are consistent with the historically observed experience curve trend.
5. For both onshore and offshore wind, total wind deployment is used as the experience variable. This is because the onshore and offshore parts of the industry are so intertwined that it makes sense to assume they both contribute to innovation in both sub-fields. Similarly, for offshore wind, while cost data is only available from the year 2000, it makes sense to ensure that prior experience gained in the onshore industry also contributes to the experience curve for offshore installations. We therefore use the onshore wind cost series from 1984-1999, followed by offshore costs from 2000-2023, as we believe this best capture the long-run relationship between increments in experience and increments in technological progress.

2.2 Cost projections for lithium-ion battery pack and fuel cell system for commercial road freight vehicles

For both the lithium-ion battery pack and the fuel cell system, cost projections and relevant confidence intervals are obtained from a system dynamics technoeconomic model developed by Noll et al. (2023) that simulates technology competition over time and analyzes the effects of global innovation spillovers on clean technology deployment. The model was developed for the commercial road-freight sector, though it is generalizable and can also be applied in other sectors. Fundamentally, the model is well-suited to capture technology competition dynamics, incorporate global spillover effects, and project innovation diffusion for sustainability transitions. Crucially, the model endogenizes innovation by way of component-based experience curves, i.e. for lithium-ion battery packs or fuel cell systems, to derive a technology's future cost from its previous deployment. The model can also introduce policy

interventions to analyze spillover effects; however, cost projections presented here are a result of the baseline, business-as-usual modelling without policy intervention.

The basic model architecture follows an iterative procedure over a specified time period. In each time step, technologies compete in representative application segments and regions. Independent investors are simulated in a probabilistic Monte Carlo discrete choice selection mechanism. The selection decision is based on the least “cost” technology available—derived based on the total cost of ownership (TCO), a “hard-cost” metric, and the switching cost, a developed “soft-cost” metric. Aggregated investor selections generate technology market shares. These shares, when multiplied by forecasted deployment, both endogenous and exogenous, derive new technology component costs from the experience curves. New costs are then used in the TCO calculation and investor selection simulation in the subsequent time step.

An experience rate of 18% for the lithium-ion battery pack and 15% for the fuel cell system are assumed along with an initial cumulative capacity in the model base year 2020 (see Noll et al., 2023, for the details on this assumption). Yearly cost reductions are thus based on endogenously determined deployment from the road freight sector as well as exogenously calibrated deployment from relevant outside sectors.

For a full description of the methodology, please see the Materials and Methods section in Noll et al. (2023). Data plots for the resulting cost projections included in the database are provided in Figure 7.

Limitations and use:

1. The cost projections provided in the database are only applicable for commercial road vehicles. Particularly for the lithium-ion battery pack, projected pack costs are higher than what would be expected for pack costs in passenger road vehicles.
2. Projected cost values represent the “global” commodity cost. Region-specific costs may vary.
3. When applying these cost projections exogenously in a model, it is important to calibrate costs to expected yearly deployment as this will directly determine future costs based on the technology’s experience rate. See projected cumulative deployment assumed for both technologies in the accompanying dataset.

2.3 Cost projections for direct air carbon capture and storage (DACCS)

Traditional experience curve extrapolations, though widely used, are inapplicable to novel technologies without historical deployment data. To address this, Sievert et al. (2024) introduce a new methodology for forecasting technology costs based on an empirical analysis of technology-inherent characteristics that drive cost reduction potential.

The methodology utilizes a recently developed framework linking cost reduction potential to two inherent characteristics (Malhotra and Schmidt, 2020): design complexity and the need for customization. By comparing three direct air capture (DAC) technologies and their components to mature technologies along these dimensions, the methodology estimates cost reduction potential as expressed through experience rates. Following an ex-post validation,

Sievert et al. (2024) use multi-component experience curves to probabilistically project the cost of CO₂ net removed in a mature technology state.

The three DAC technologies considered comprise (1) a high-temperature liquid solvent process, (2) a low-temperature solid sorbent process, and (3) a calcium oxide (CaO) ambient weathering process (see the experimental procedures section of Sievert et al. (2024) for details). These DAC technologies each have distinct CO₂ capture processes but assumed identical transport and storage pathways. Liquid solvent DAC utilizes continuous absorption and regeneration stages for CO₂ capture, while solid sorbent DAC utilizes cyclic adsorption-desorption processes in CO₂ collectors. CaO ambient weathering DAC binds CO₂ to CaO in a carbonation phase and regenerates it in a calcination phase. The three technologies were selected for their comparatively high maturity, as demonstrated by existing pre-pilot, pilot, and commercial-scale plants.

Sievert et al. (2024) present a conceptual framework for estimating experience rates based on the inherent characteristics of technologies and their components. Innovation research has highlighted how cost reductions from innovation vary across technologies, suggesting that technology-specific characteristics can explain differences in experience rates. Key factors influencing these variations include the complexity of a technology's design and its need for customization, with simpler and more standardized technologies generally advancing along the experience curve more quickly. This approach builds on an established typology that categorizes technologies by their design complexity and need for customization, offering insights into whether their expected experience rates are higher or lower.

To apply this typology-based method to DACCS, the analysis involves four steps. First, DAC technology plants are qualitatively analyzed and decomposed into components using insights from academic literature and exploratory expert interviews. Second, additional expert interviews validate the component classification and evaluate the design complexity and customization needs of both the individual components and the overall system. A total of 33 interviews were conducted, with 22 experts rating the components and systems across two dimensions of complexity:

1. **Design complexity:** rated as "1: simple," "2: design-intensive," or "3: complex"
2. **Need for customization:** rated as "1: standardized," "2: mass-customized," or "3: customized"

Third, based on the interview results, components are arranged in a matrix according to their design complexity and need for customization. Fourth, the matrix position of each data point is compared with technology types outlined in innovation literature to select an experience rate that aligns with the technology type.

After determining multi-component experience curves for each DAC technology (details are available in the experimental procedures section in Sievert et al., 2024), future costs are projected using a probabilistic approach. This involves accounting for uncertainties in initial cost estimates and assigned experience rates. A Monte Carlo analysis is employed to examine the range of potential outcomes and their likelihoods. To address uncertainties in initial costs, the method applies uniform distributions for process contingencies and capacity factors across all DACCS systems, linking these uncertainties to the technology readiness level (TRL) of each system. Further, the same approach is applied to direct material costs for technical

components specific to liquid solvent and CaO ambient weathering DACCS technologies. This methodology reflects the high level of uncertainty due to the limited or nonexistent operational plants for these systems. The use of uniform distributions acknowledges the uncertainty in these costs, assigning equal probability to all potential outcomes.

For liquid solvent, solid sorbent, and CaO ambient weathering DACCS, from the initial capacity up to 10 Mt-CO₂/year cumulative capacity, the experience rates are 7%, 8%, and 10% respectively for the 50th percentile.

For a full description of the methodology, please see Sievert et al. (2024). Data plots for the resulting cost projections included in the database are provided in Figure 8.

Limitations and use

1. The cost of DACCS represents the average net cost of removing one ton of CO₂ for a given DAC technology including transport and storage.
2. Cost projections are based on cumulative deployment assumption of 1 Gt by 2050. Year intervals are therefore not given as this would require a yearly deployment assumption.
3. Also note that the initial cost years are different for each of the three DACCS technologies.
4. Costs are displayed in net removed cost at 2050 energy prices.
5. For proper use in projection models, directly use the specific experience rate and starting cost of each DACCS technology and a defined projection scenario for cumulative deployment for best estimation of future costs.

2.4 Learning rate estimation for geothermal energy

The learning rate in energy technologies refers to the percentage reduction in costs for each doubling of installed capacity, reflecting the improvements in efficiency and reduction in costs that typically accompany technological scaling and experience. In the database, we include preliminary results of the estimation of the installed project costs, global average learning rate, and country-specific learning rate range for geothermal energy. These estimates are a result of extensive data collection efforts, which included gathering cost and capacity data across multiple countries to capture regional variations in geothermal deployment.

3. Forecast visualizations

In Figure 22 - Figure 99 we plot the variables necessary to understand each set of forecasts included in the database.

3.1 Solar PV

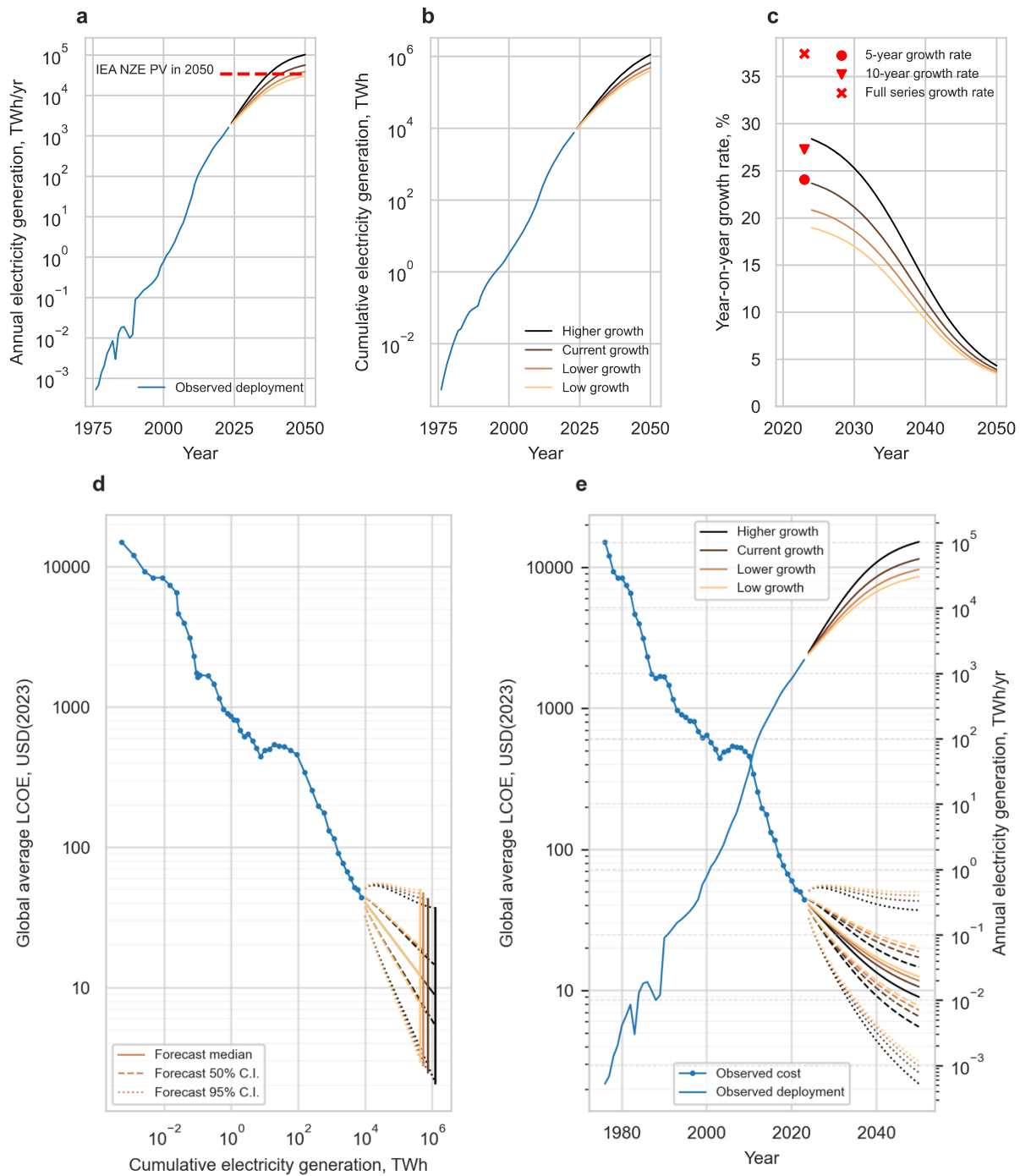


Figure 22 – Panels **a)** and **b)** show historical annual and cumulative electricity generation from solar PV (blue lines), plus four different hypothetical future deployment scenarios (yellow-through-black lines), based on different future growth rate decay assumptions. Annual PV generation in 2050 in the IEA's 2024 NZE scenario (IEA, 2024) is shown for comparison (red dashed line). Panel **c)** shows the four hypothetical growth rate decline scenarios in detail. The red symbols in the year 2023 show the 5- and 10-year-average annual deployment growth rates up to and including 2023, plus the average growth rate over the full data series. Panel **d)** shows the historical experience curve, plus four probabilistic cost forecasts, each conditional upon one of the four deployment scenarios. Forecast medians, 50% confidence intervals (C.I.s) and 95% C.I.s are shown. Panel **e)** shows historical costs (left axis) and deployment (right axis), plus the four future deployment scenarios and their associated probabilistic cost forecasts, but this time in the time domain rather than in the experience curve domain.

3.2 Onshore wind

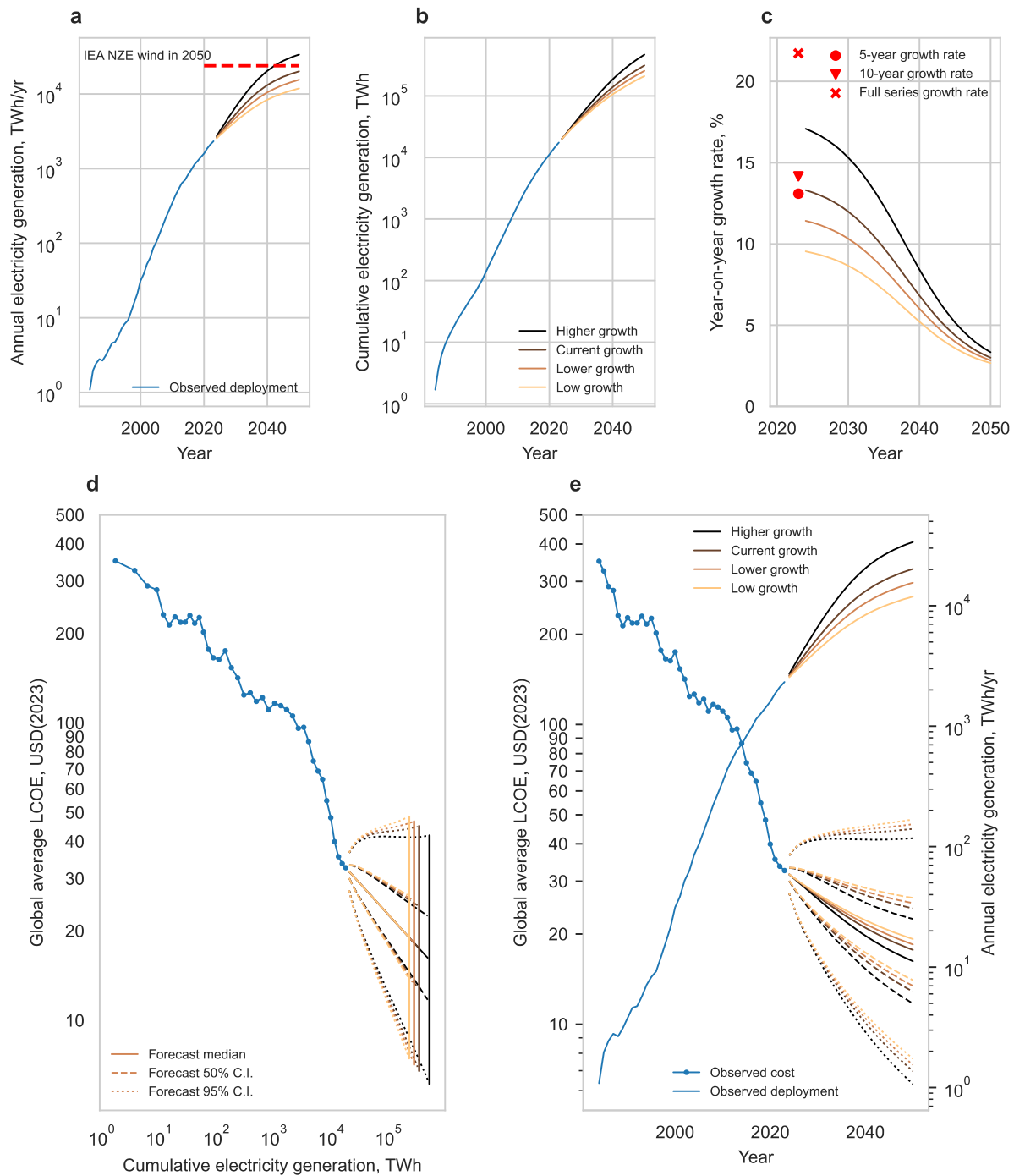


Figure 33 – Panels **a)** and **b)** show historical annual and cumulative electricity generation from wind (onshore and offshore combined) (blue lines), plus four different hypothetical future deployment scenarios (yellow-through-black lines), based on different future growth rate decay assumptions. Annual total wind generation in 2050 in the IEA's 2024 NZE scenario (IEA, 2024) is shown for comparison (red dashed line). Panel **c)** shows the four hypothetical growth rate decline scenarios in detail. The red symbols in the year 2023 show the 5- and 10-year-average hypothetical annual deployment growth rates up to and including 2023, plus the average growth rate over the full data series. Panel **d)** shows the historical experience curve, plus four probabilistic cost forecasts, each conditional upon one of the four deployment scenarios. Forecast medians, 50% confidence intervals (C.I.s) and 95% C.I.s are shown. Panel **e)** shows historical costs (left axis) and deployment (right axis), plus the four future deployment scenarios and their associated probabilistic cost forecasts, but this time in the time domain rather than in the experience curve domain.

3.3 Offshore wind

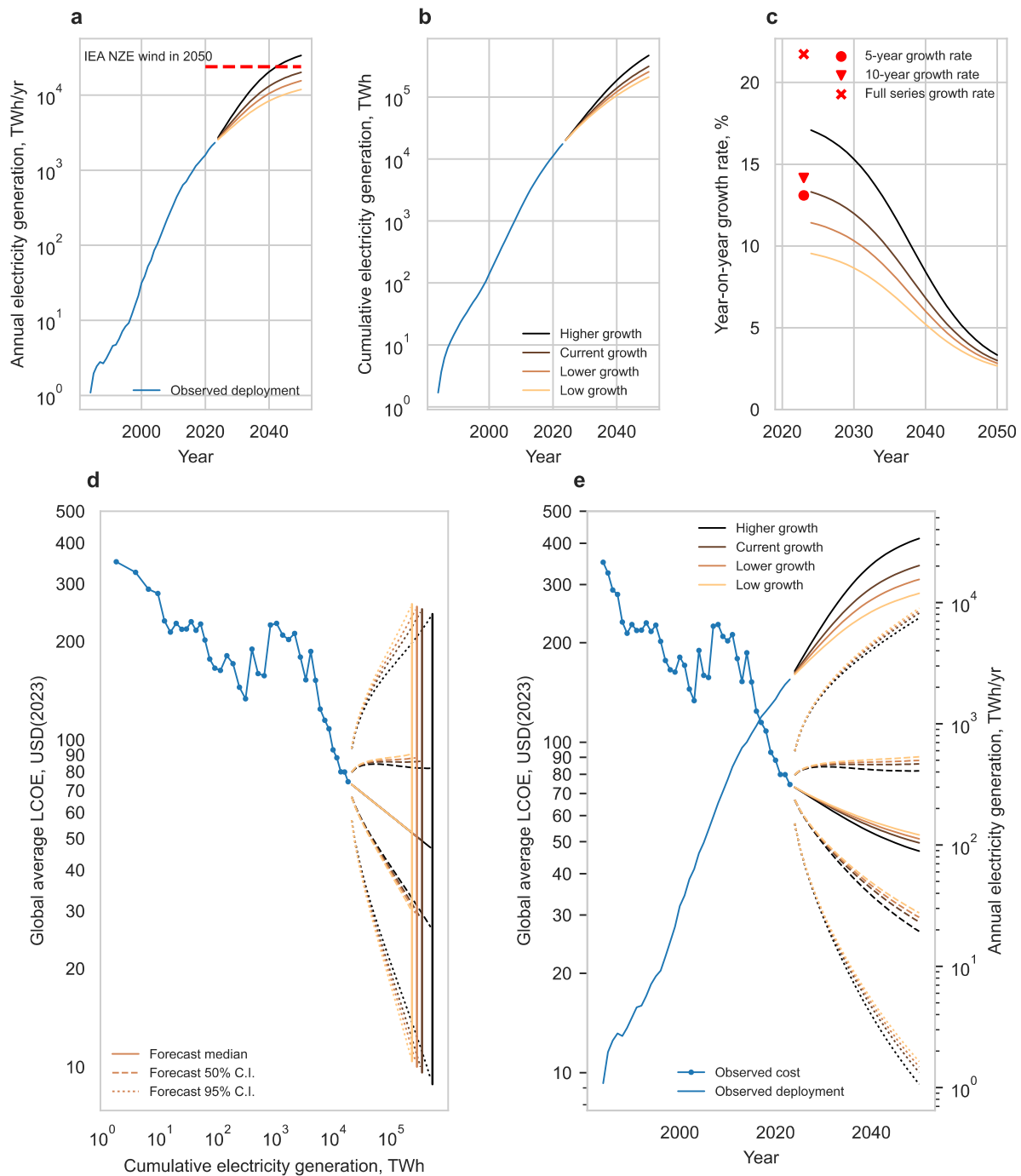


Figure 44 – Panels **a**) and **b**) show historical annual and cumulative electricity generation from wind (onshore and offshore combined) (blue lines), plus four different hypothetical future deployment scenarios (yellow-through-black lines), based on different future growth rate decay assumptions. Annual total wind generation in 2050 in the IEA's 2024 NZE scenario (IEA, 2024) is shown for comparison (red dashed line). Panel **c**) shows the four hypothetical growth rate decline scenarios in detail. The red symbols in the year 2023 show the 5- and 10-year-average annual deployment growth rates up to and including 2023, plus the full series average growth rate. Panel **d**) shows the historical experience curve, plus four probabilistic cost forecasts, each conditional upon one of the four deployment scenarios. Offshore wind LCOEs are only available for 2000-2023, so onshore wind LCOEs are used for 1984-1999 (see Methods above for further details). Forecast medians, 50% confidence intervals (C.I.s) and 95% C.I.s are shown. Panel **e**) shows historical costs (left axis) and deployment (right axis), plus the four future deployment scenarios and their associated probabilistic cost forecasts, but in the time domain rather than in the experience curve domain.

3.4 Li-ion batteries

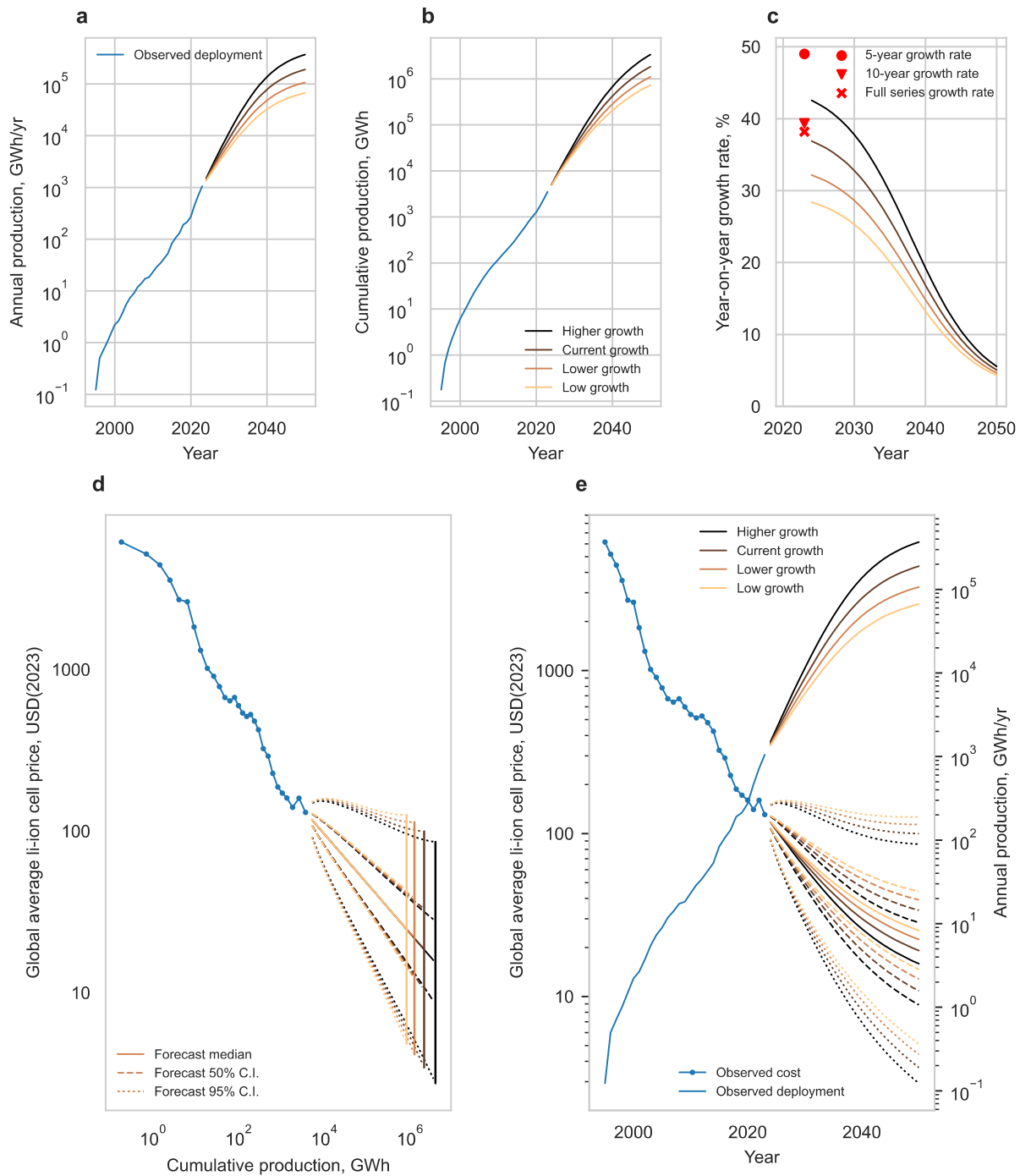


Figure 5 – 5 Panels **a)** and **b)** show historical annual and cumulative lithium-ion battery production (blue lines), plus four different hypothetical future deployment scenarios (yellow-through-black lines), based on different future growth rate decay assumptions. Panel **c)** shows the four hypothetical growth rate decline scenarios in detail. The red symbols in the year 2023 show the 5- and 10-year-average annual deployment growth rates up to and including 2023, plus the average growth rate over the full data series. Panel **d)** shows the historical experience curve, plus four probabilistic cost forecasts, each conditional upon one of the four deployment scenarios. Forecast medians, 50% confidence intervals (C.I.s) and 95% C.I.s are shown. Panel **e)** shows historical costs (left axis) and deployment (right axis), plus the four future deployment scenarios and their associated probabilistic cost forecasts, but this time in the time domain rather than in the experience curve domain.

3.5 PEM electrolyzers

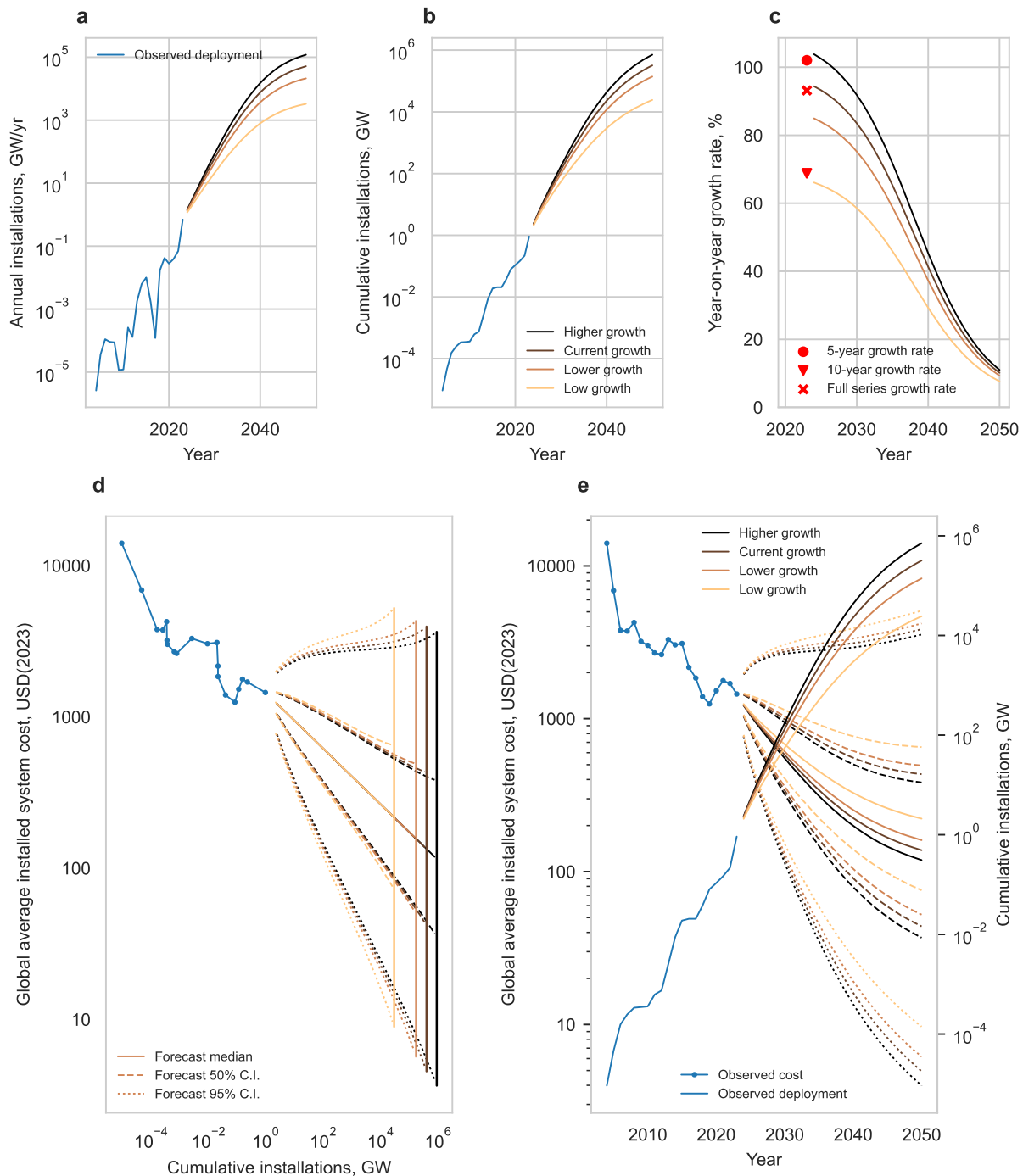


Figure 6 – Panels **a**) and **b**) show historical annual and cumulative PEM electrolyzer installations (blue lines), plus four different hypothetical future deployment scenarios (yellow-through-black lines), based on different future growth rate decay assumptions. Panel **c**) shows the four hypothetical growth rate decline scenarios in detail. The red symbols in the year 2023 show the 5- and 10-year-average annual deployment growth rates up to and including 2023, plus the average growth rate over the full data series. Panel **d**) shows the historical experience curve, plus four probabilistic cost forecasts, each conditional upon one of the four deployment scenarios. Forecast medians, 50% confidence intervals (C.I.s) and 95% C.I.s are shown. Panel **e**) shows historical costs (left axis) and deployment (right axis), plus the four future deployment scenarios and their associated probabilistic cost forecasts, but this time in the time domain rather than in the experience curve domain.

3.6 LED lighting

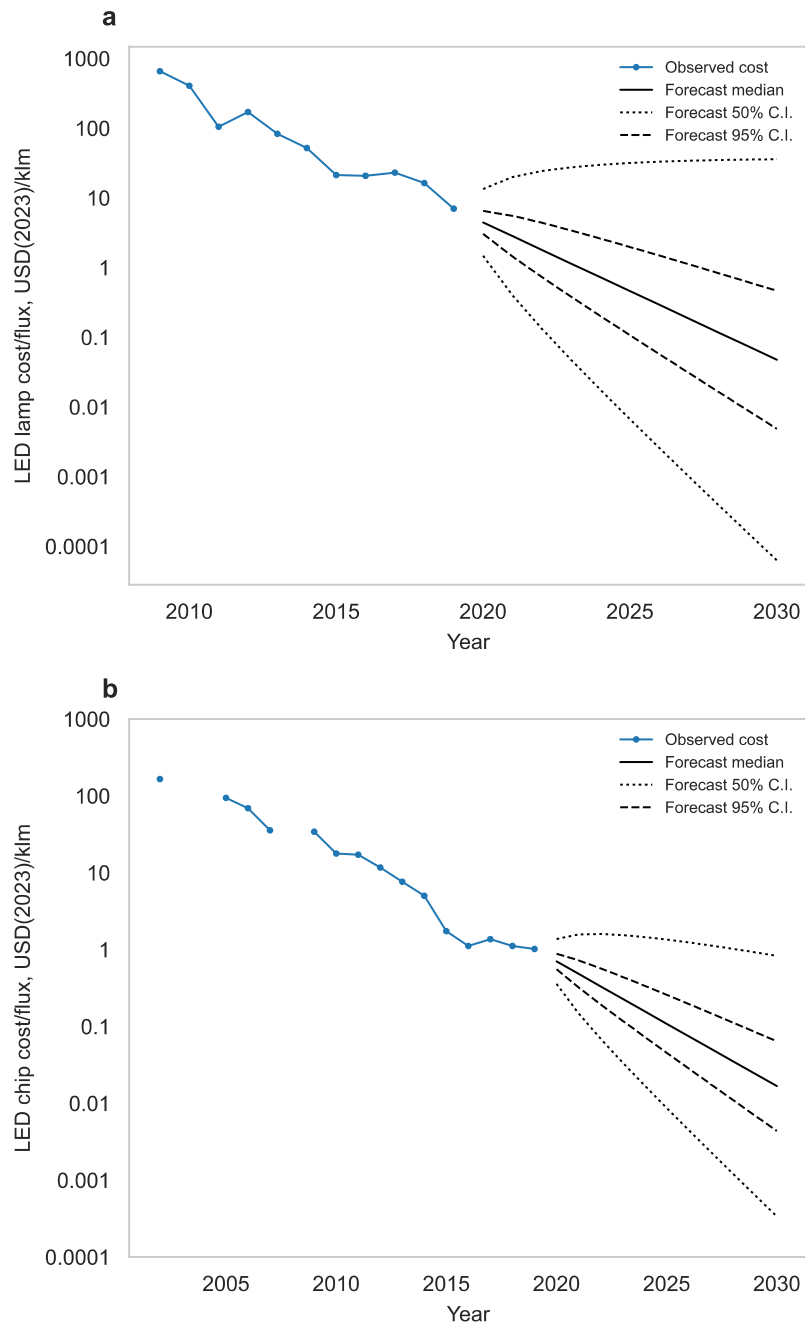


Figure 7 – Panels **a**) and **b**) show historical cost trends (blue lines) plus probabilistic cost forecasts for white LED lamps and white LED chips respectively. Forecast medians, 50% confidence intervals (C.I.s) and 95% C.I.s are shown.

3.7 Lithium-ion battery pack and fuel cell system for commercial road freight vehicles

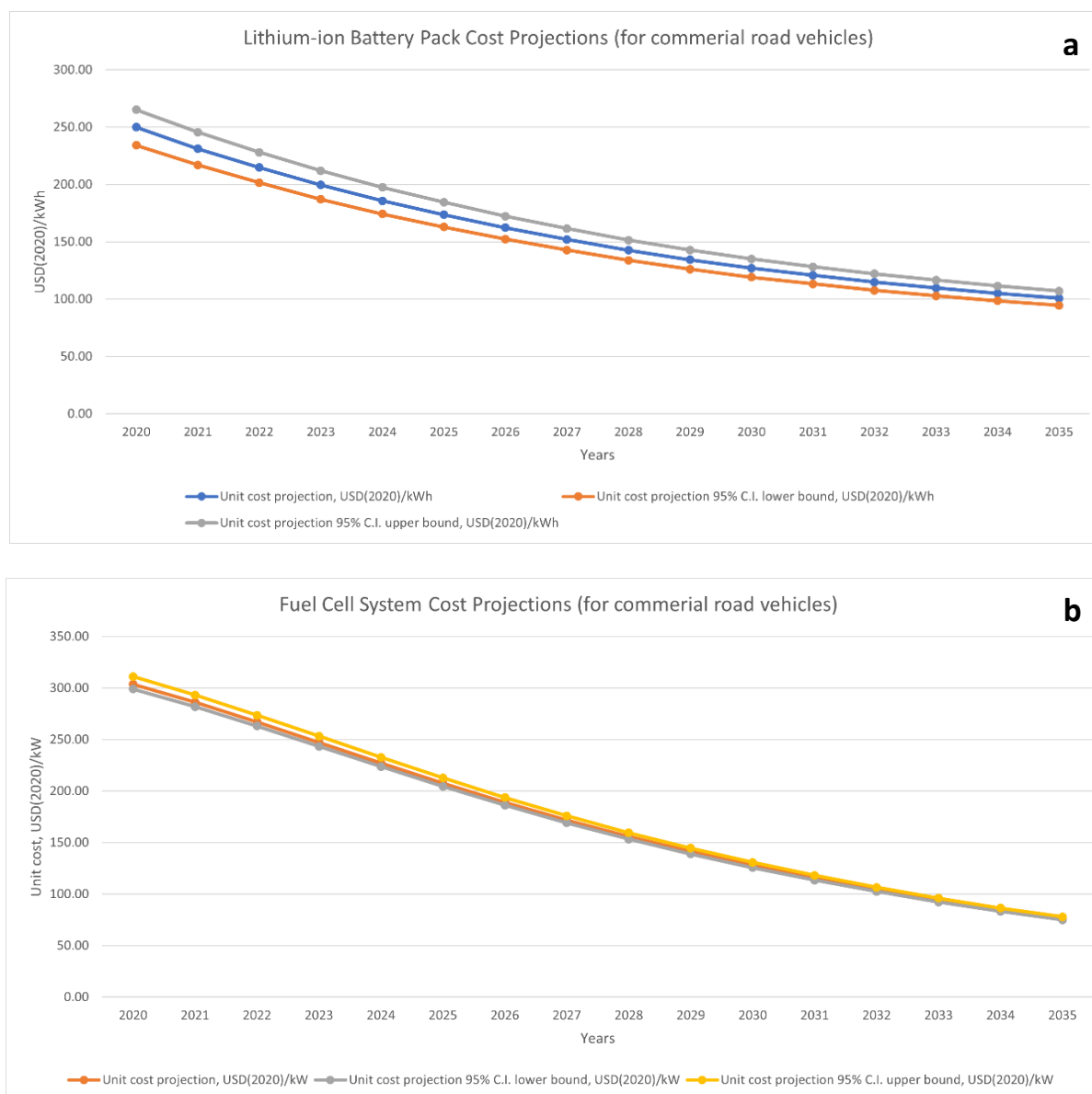


Figure 88 – Technology cost projections for lithium-ion battery packs (Panel a) and fuel cell systems (Panel b) used in commercial road freight vehicles. The data in the figure is reproduced directly from the accompanying dataset. Cost units are in 2020USD/kWh in Panel a, and 2020/USD/kW in Panel b.

3.8 DACCS

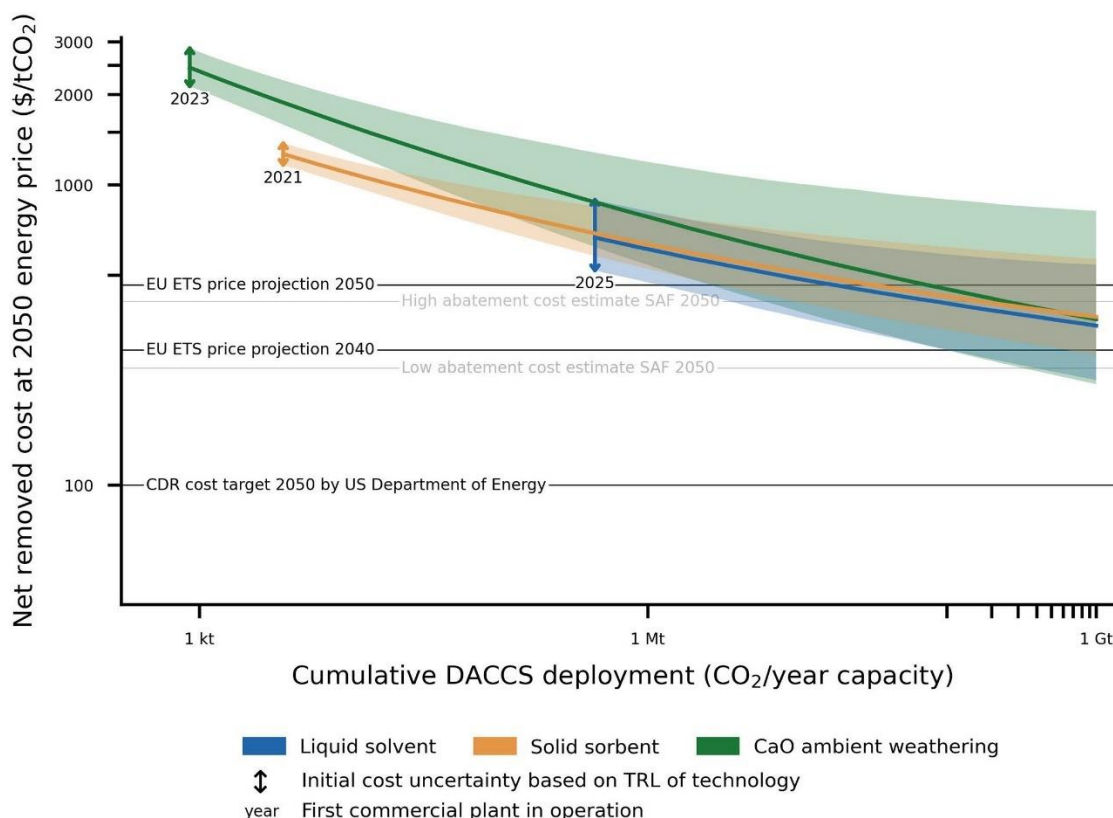


Figure 99 – Net removed cost trajectories for liquid solvent DACCS (blue), solid sorbent DACCS (orange), and CaO ambient weathering DACCS (green) at 2050 energy prices, on a log-log scale. Each technology's cost trajectory starts at the initial plant scale and increases to 1 Gt-CO₂/year cumulative design capacity. Each DACCS system starts its cost trajectory when the first commercial scale plant begins operation, with the start year varying and highlighted for each process. Thick lines represent the 50th percentile and colored areas the range between the 5th and 95th percentiles of cost projections. The dark grey lines represent the long-term US CDR policy target and two projected 2040 and 2050 EU ETS prices. The light grey lines highlight the abatement cost estimates projected for sustainable aviation fuel in 2050. Source: Sievert et al. (2024).

4. Database description

The deliverable D3.2, consisting of a database and this report, is published in a Zenodo repository at the following link:

<http://doi.org/10.5281/zenodo.14577628>

The database will be publicly accessible via this link from January 1, 2026. Before that date, it is embargoed. Preliminary access for project review purposes is available via a sharing link that can be provided by the PRISMA project coordinators.

The database provided in the deliverable consists of two Excel spreadsheets:

- **PRISMA_UCAM_TechCostForecasts.xlsx** – contains probabilistic cost forecasts for solar PV, onshore wind, offshore wind, lithium-ion batteries, PEM electrolyzers, and LED lighting, all produced by the UCAM team.
- **PRISMA_ETH_TechCostProjections.xlsx** – contains cost forecasts and data for lithium-battery packs and fuel cell systems for commercial road freight vehicles; DACCS; and geothermal energy, all produced by the ETH Zurich team.

The UCAM spreadsheet is structured as follows:

- There is one sheet per technology.
- For each technology with an experience curve-based forecast, data representing the four deployment scenarios are provided (year, annual production, cumulative production). The scenarios are labelled *Higher growth scenario*, *Current growth scenario*, *Lower growth scenario*, and *Lowest growth scenario*. For each deployment scenario, five percentiles of the conditional probabilistic cost forecast are provided (2.5th, 25th, 50th, 75th, 97.5th).
- For each technology with a forecast based on generalized Moore's law, no scenario data is given (as the forecasts are scenario-independent), only the five percentiles as above.

The ETH spreadsheet is structured as follows:

- There is one sheet per technology.
- Unit cost projections (in 2020 USD/kWh) for lithium-battery packs and fuel cell systems for commercial road freight vehicles are provided from 2020 to 2035, with 50% and 95% confidence intervals, calculated for a single baseline scenario for cumulative deployment (in GWh).
- Net removed cost of CO₂ at 2050 energy price (in 2022 USD/tCO₂) is provided for three types of DACCS technology, with 95% confidence intervals, at different cumulative DACCS deployment levels under cumulative deployment assumption of 1 Gt by 2050. Year intervals are not given as this would require yearly deployment assumptions.
- Installed project costs (in 2023 USD/W), calculated average global learning rate, and country-specific learning rate range are provided for geothermal energy.

5. References

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6. Appendix: Related PRISMA publications

List of peer-reviewed PRISMA publications linked to this deliverable published by December 2024.

- Pasqualino, R., Peñasco, C., Barbrook-Johnson, P., Senra de Moura, F., Kolesnikov, S., Hafner, S., Nijse, F.J., Lamperti, F., Hinder, B., Melekh, Y. and Sharpe, S., 2024. Modelling induced innovation for the low-carbon energy transition: a menu of options. *Environmental Research Letters*, 19, p. 073004. <https://doi.org/10.1088/1748-9326/ad4c79>.
- Noll, B., Steffen, B. and Schmidt, T.S., 2023. The effects of local interventions on global technological change through spillovers: A modeling framework and application to the road-freight sector. *Proceedings of the National Academy of Sciences*, 120(42), p.e2215684120. <https://doi.org/10.1073/pnas.2215684120>.