Probabilistic feasibility space of scaling up green hydrogen supply

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Abstract

Green hydrogen from renewable electricity and derived e-fuels can replace fossil fuels in applications where direct electrification is infeasible, making them very valuable for climate neutrality. However, here we show that even if electrolysis capacity grows as fast as wind and solar power have, green hydrogen supply remains scarce in the short-term and uncertain in the long-term. Using probabilistic technology diffusion modelling, we find that, despite initial exponential growth, green hydrogen likely (≥75%) supplies <1 % of final energy until 2030 (2035) in the EU (globally). By 2040, a breakthrough is more likely, but large uncertainties prevail with an interquartile range of 4.4-10.5% (EU) and 1.1-4.3% (globally). Both short-term scarcity and long-term uncertainty impede investment in hydrogen end-uses and infrastructure, reducing green hydrogen's potential and jeopardising climate targets. However, historic analogues suggest that emergency-like policy measures could foster substantially higher growth rates, expediting the breakthrough and increasing the likelihood of future hydrogen availability.

Introduction

Green hydrogen, defined as hydrogen produced from renewable electricity via electrolysis, and derived e-fuels[1] are critical components of the energy transition[2], enabling emissions reductions in sectors where direct electrification is infeasible[3,4] and avoiding sustainability concerns associated with biofuels[5,6]. These features, plus its versatility, have spurred a recent surge of enthusiasm[7], policy targets[8], and investment[3]. Hydrogen now plays a central role in facilitating many net-zero emissions scenarios[9,10]. Of all ways to produce hydrogen, green hydrogen offers the lowest life-cycle emissions[11] and likely lowest long-term mitigation costs[12], making it most suitable for climate neutrality[8].

While much of the debate and research around hydrogen has revolved around demand-related questions of suitable applications, markets, and sectors[1,13], the question of supply availability is equally critical. Because hydrogen is very valuable for achieving increasingly pressing and legally binding emissions reduction targets[14,15], particularly in hard-to-abate sectors of substantial size[1,16], ramping-up supply is urgent[17]. Growing awareness that scalability is a critical success factor for climate mitigation technologies has stimulated recent research to apply insights about the pattern[18–20] and pace[21–24] of energy technology diffusion to specific feasibility analyses[25–27] of ramping-up renewable[28–38] and phasing-out fossil technologies[26,39,40] fast enough. However, so far no study has analysed possible expansion pathways of green hydrogen from electrolysis, a technology in its infancy that needs to experience rapid innovation[17] and deployment[41] to unleash its potential for climate change mitigation.

Electrolysers are a centerpiece of future green hydrogen supply chains, and their deployment is thus an indicator of the systemic challenges of concurrently ramping-up additional renewable energy capacity, transport infrastructure, and hydrogen end-use applications. In addition, the ramp-up of electrolysers is a key bottleneck in itself. Starting at an estimated 600 MW globally in 2021 (Figure 1)[42] in mostly small and individually manufactured plants (<10 MW), global capacity needs to grow 6,000-8,000-fold from

2021-2050 to meet climate neutrality scenarios compatible with the Paris Agreement[9,10]. This dwarfs the simultaneously required 10-fold increase of renewable power[9,10], which is readily available and cost competitive[43–45]. While electrolysis project announcements indicate an exponential buildup of momentum in the upcoming years with triple-digit annual growth rates, 80% of additional capacity announced to come online in 2023 is not yet backed by a final investment decision (FID) (Figure 1c-d). It thus remains unclear how many electrolysis projects will materialise in the short term and whether overall electrolysis capacity can expand fast enough to meet mid- to long-term hydrogen demands.

Here we analyse the potential deployment of electrolysis capacity for green hydrogen production by combining an S-shaped logistic technology diffusion model[18] with a probabilistic parameterisation based on data from established successful energy technologies: wind and solar power[46–48]. Despite such high growth rates, we find strong evidence of short-term scarcity and long-term uncertainty of green hydrogen supply. This bears a high risk of a substantial gap between likely supply and potential demand, threatening the outlook of green hydrogen for urgent climate change mitigation. In contrast, if electrolysis capacity were to grow at unconventional growth rates, experienced for some non-energy technologies under special circumstances in the past, it could quickly overcome supply scarcity and secure future green hydrogen availability.

Three Uncertain Parameters That Define The Feasibility Space

In a finite market, technology adoption does not continue exponentially forever, but instead follows an S-shaped curve (Figure 2). In the formative phase, policy-backed demonstration projects face technical uncertainty and high costs during the proverbial valley of death[49], leading to slow and unsteady growth[50]. In the growth phase, increasing returns to scale[51] and cost-decreasing learning effects[52] accelerate market adoption. After attaining the maximum rate of expansion at the inflection point, growth starts to slow down as a result of technological, economic and social constraints[53]. This marks the beginning of the saturation phase when the final market level is approached. The resulting trajectory characterises all stages of the technology adoption process and is mathematically described by the three-parameter logistic function (see Methods). Considering the electrolysis market ramp-up, the three parameters initial capacity (timing), emergence growth rate (steepness) and saturation (asymptote) relating to these three stages are all uncertain and independent.

First, the initial capacity is an uncertain parameter as it depends on the possibly strong yet uncertain momentum in the upcoming years, which could propel electrolysis capacity from the formative phase to the beginning of the growth phase and therefore must be included in the analysis. Beyond the evidently speculative nature of projects pending an FID, there are further mutually opposing uncertainties. On the one hand, even projects that have secured an FID might fall behind schedule. On the other hand, data gaps due to additional future projects or missing projects might introduce downward biases. Striking a balance between including near-term momentum and excluding uncertain long-term announcements, we focus on the year 2023 as the “initial year”, as we do not expect any potential new projects to proceed from announcement to operation in less than two years. Figure 3a-b shows the probability distributions of the initial capacity in 2023, which spans the full range of project announcements, centred around an expected value of realising 30% of projects in the feasibility study category[54] and assuming that all projects under construction are built on time (see Methods).

Second, the growth rate is an inherently uncertain function of policy support[55,56], technological characteristics[57] and possible cost reductions[58], of which the latter are notoriously difficult to predict[59,60]. As the annual growth rate gradually decreases due to market saturation, we parameterise the emergence growth rate[30], which is the maximum annual growth rate that is realised after the formative phase, related to the steepness parameter in the logistic function (see Methods). Unlike previous research, which constructed feasibility spaces by looking at historical precedents of the same technology in different regions[32,40], we instead turn to historical precedents of different technologies in the same region. This comparison is necessary because, as long as green hydrogen is uncompetitive[58], historical growth rates are primarily proxies of past policy support and not necessarily indicative of future potential. In this way, we also abstract from a more granular analysis of factors that influence the pace of technology diffusion. In the conventional growth scenario, we compare electrolysis with wind and solar power, the historically fastest-growing energy technologies[61], which now comprise nearly 10 % of global electricity generation[62], during their periods of fastest relative growth, 1995-2010 (Extended Data Figure 1). Figure 3c-d shows the corresponding distributions, revealing that solar power grew faster than wind during all 7-year intervals, both in the EU and globally. The distributions are robust to the interval length (Extended Data Figure 2). Later, in the unconventional growth scenario, we compare these growth rates to a broader set of predominantly non-energy technologies.

Third, the final market volume is uncertain as the outcome of the competition among different climate change mitigation technologies remains undecided in many end-use applications[63]. In these applications, hydrogen constitutes a new energy carrier, which implies that not just its supply, but also its demand and infrastructure have to be ramped-up in parallel. In contrast, wind and solar power produced an economic good with existing demand and pre-installed infrastructure, namely electricity. We capture this property by a steadily-increasing demand pull and distinguish between its magnitude and the anticipation thereof (Figure 2). We opt for a simple piecewise linear demand pull function, parameterised on policy targets and pledges in the short- to mid-term and on demand from climate neutrality scenarios in the long-term (see Methods). The demand pull therefore comprises all factors that increase market opportunities through policies, regulation, and increasing competitiveness[64,65].

The propagation of the uncertain initial capacity and emergence growth rate (Figure 3) defines a probabilistic feasibility space, under the condition of an increasing policy-backed demand pull, spurring investment and mitigating financial risks. Table 1 summarises the key model parameters for the electrolysis market ramp up in the EU and globally.

Table 1: Key values of the three uncertain parameters of the electrolysis market ramp-up.

Parameters			EU	Global	Source
1. Initial capacity 2023		Min	0.26 GW	1.02 GW	IEA Hydrogen Projects Database[42], own market research
		Mean	0.92 GW	3.51 GW	
		IQR	0.65 – 1.17 GW	2.47 – 4.42 GW	
2. Emergence growth rate		Min	15 %/yr	15 %/yr	Historical growth of solar and wind capacity[66]
		Mean	50 %/yr	39 %/yr	
		IQR	35 – 63 %/yr	31 – 47 %/yr	
3. Demand pull	Magnitude	2024	6 GW	-	EU: Hydrogen strategy[8], Global: IEA Hydrogen Projects Database[42] and NZE scenario[3]
		2030	40 GW	154 GW	
		2050	500 GW	3600 GW	
	Anticipation	Default: 5 years (Sensitivity analysis: 0 years, 10 years, full anticipation)			Assumptions

Reconciling Different Approaches To Long-term Projections

Our model steers a middle course between two approaches in the recent literature that have analysed growth trajectories of wind and solar power, but arrived at different conclusions regarding their outlook. The first approach relies on fitting growth models with the final market share as a free parameter that is estimated from historical data if possible[28,32]. While this often yields a good fit to data, it comes at the expense of high sensitivity to random fluctuations in the last few data points[67]. A slowdown, which might in hindsight turn out to be just a temporary artefact, for example due to discontinuous policy[68] or economic crises[69] (see e.g. Extended Data Figure 1a), can easily be misinterpreted as terminal saturation. This approach risks constraining future conditions to policy-driven historical deployment[31], which can negatively bias the long-term outlook.

In contrast, the second approach in the literature applies an ex ante target towards which solar and wind power diffuse from their historical trajectory[30,31]. While this enables an inter-decadal feasibility analysis under the presupposition that a stated market volume will be attained, it implicitly assumes an existing market with sufficient demand, which technologies can penetrate. This may not be the case for hydrogen because demand-side transformations and infrastructure requirements mean it cannot immediately tap into new markets that are just emerging. In our approach these coordination challenges are summarised by the steadily-increasing demand pull, which contributes to reconciling the debate on long-term projections of energy technologies, especially for hydrogen, but potentially also for wind and solar power.

Electrolysis Capacity Using Growth Rates From Wind And Solar

Figure 4 shows the probabilistic feasibility space of electrolysis capacity in the EU and globally using a distribution of growth rates assembled from the historical growth of wind and solar power and applying demand pull anticipation of five years (sensitivity analysis in Extended Data Figure 3). Three key insights emerge from the simulations.

First, in the upcoming 1-2 decades electrolysis capacity is likely to remain relatively small compared to both intermediate and final targets as well as to total energy demand. Green hydrogen will thus remain scarce, leading to a large gap between likely supply and potential demand. The EU target of 40 GW by 2030 is only met at the 95th percentile of the probability distribution, whereas the 6 GW by 2024 target is entirely infeasible under conventional growth rates. The global target of 154 GW by 2030, which ensues from ambitious project announcements[42] (Figure 1d), lies well beyond the 95th percentile, illustrating the short-term challenges of ramping-up green hydrogen production especially on a global level.

Second, a breakthrough to high capacities is possible, but both timing and magnitude are subject to large uncertainties. The results reveal a threshold above which the probability distribution flips towards larger values and then follows the linear demand pull with a few years of delay. For the EU this occurs around 2038, and globally around 2045, which approximately coincides with the years of largest annual electrolysis capacity additions. This tipping behaviour is a property of the probability space, which combines the information of the pathway ensemble and is thus more relevant to decision makers than individual pathways, which are more continuous and span a larger range. The interquartile range (IQR) of probabilistic electrolysis capacity in 2040 is 90 – 308 GW in the EU (253 – 1138 GW globally), and 409 – 496 GW in the EU (1936 – 3440 GW globally) in 2050. Substantial uncertainty thus prevails for several decades, especially globally.

Third, the propagation of uncertainties not only leads to a tipping point but also to a pronounced bimodal distribution near the tipping point, which has adverse consequences for risk management. This pattern is a direct outcome of the superposition of many S-shaped diffusion curves and occurs despite input parameters that follow a well-defined normal distribution with a clear maximum (Figure 3). This is because for most of the period, the logistic curve produces low and later high capacities (small annual additions); because of high growth rates the transition phase occurs quickly (large annual additions), and thus the probability of being at an intermediate capacity is low. The bimodal distribution is thus not a methodological artefact, but an actual property of future uncertainty, which aggravates the risk of the supply-demand gap.

Both short-term scarcity and mid- to long-term uncertainty create challenges for policy makers, system planners, industry, and consumers. Relying on the large-scale availability of green hydrogen could lead to expensive path dependencies or even fossil lock-ins[70], if supply expansion falls short of expectations. Accounting for these risks likely discourages investments in hydrogen supply, infrastructure and end-use technologies, thus exacerbating short-term scarcity and mid- to long-term uncertainty. In addition, scarce and uncertain supply complicate and delay required end-use transformation and infrastructure investments. As a consequence, green hydrogen could fail to realise its potential.

There are good arguments both in favour and against the hypothesis that electrolysis could grow even faster than wind and solar power did. On the one hand, in contrast to the early years of solar and wind expansion, large and established companies have expressed their willingness to invest into hydrogen[71]. Industries could see hydrogen as a new business opportunity that also allows them to retain parts of their fossil fuel infrastructure, avoiding asset stranding[72]. Furthermore, the large-scale import of hydrogen and e-fuels from sparsely populated areas[73] could help bypass social acceptance issues of renewable electricity[74,75]. On the other hand, infrastructure bottlenecks could substantially hamper the adoption of hydrogen end-uses, whereas wind and solar power were able to connect directly to the electricity system and markets with pre-existing infrastructure. In addition, setting up international cooperation agreements in order to make hydrogen a globally traded commodity involves long lead times. Nevertheless, under a pressing sense of urgency to mitigate climate change mitigation, positive coordination between decision makers in industry and policy could reduce these risks. This could foster investments into green hydrogen supply chains such that growth rates are achieved that go beyond what has been experienced with energy analogues.

Emergency Deployment: Growth Beyond That Of Wind And Solar

To explore what might be possible with special dedication, coordination and funding, we now parameterise our electrolysis diffusion model with unconventionally high growth rates that have been achieved under specific circumstances in the past (Figure 5). These include mostly non-energy products in situations of wartime mobilisation (e.g. US aircraft or liberty ships in World War II), of massive public investments and central coordination (e.g. nuclear power in France or high-speed rail in China), or of market-driven deployment of highly modular IT innovations with low coordination requirements (e.g internet hosts or smartphones).

Figure 5a shows the normalised historical trajectories of these technologies. In order to cover the full spectrum of associated growth rates, we fit logistic curves and extract the respective annual emergence growth rates. The resulting distribution of unconventional growth rates has a mean value of 126 %/yr, substantially larger than in the conventional growth case (Table 1), and stretches beyond 300 %/yr (Figure 5b). Within the analysed data, only US production during World War II (WWII) achieved growth rates above 100 %/yr – except for the number of COVID-19 vaccinations, which far surpass all other technologies such that we exclude it as an outlier with very different circumstances and product characteristics.

The resulting probabilistic feasibility spaces show that unconventional growth rates substantially mitigate both the issue of short-term scarcity as well as mid- to long-term uncertainty (Figure 5c-d, sensitivity analysis in Extended Data Figure 4). In both regions, EU and global, the probability distribution already tips around 2030, after which the demand pull acts as the main constraint. In 2030 an even more pronounced bimodal distribution emerges from the simulations, which however also subsides more quickly thereafter. After 2035, the demand pull, median and 95th percentile are only separated by a small margin, effectively closing the gap between supply and demand with a high probability. While smaller than before, the 90 % confidence interval still indicates a significant spread as small growth rates cannot be ruled out. However, towards 2050 the spread swiftly decreases for the 80 % confidence interval, indicating a high probability of mid- to long-term availability.

The differences between conventional growth (like wind and solar power) and unconventional growth (emergency-like deployment) become even more apparent in the direct comparison of Figure 6. In the conventional growth case, the breakthrough year, defined as the year of largest annual capacity additions, in the median occurs shortly after 2040 in the EU and around 2045 globally. However, this is again subject to substantial uncertainty with an IQR of 2037 - 2045 in the EU and 2043 – 2049 globally. In contrast, unconventional growth hastens the median breakthrough to before 2035 in both regions, even though uncertainty remains with an IQR of 2029 - 2036 in the EU and 2030 – 2037 globally.

These marked differences in the breakthrough year are also reflected in the electrolysis capacity distributions (Figure 6c-f and Extended Data Figure 5). In the conventional growth case, it is likely (≥75 % probability) that in 2030 less than 1 % of final energy in the EU (less than 0.3 % globally) can be supplied with domestic green hydrogen. Even under unconventional growth, supply in 2030 is likely to remain below 2 % in the EU (0.5 % globally). Nevertheless, unconventional growth rates strongly increase the probability of achieving the EU 2030 target of 40 GW to 66 %, as opposed to 7 % under conventional growth. However, even under unconventional growth rates, ramping-up global electrolysis capacity to 850 GW by 2030 as required by the IEA Net Zero Emissions (NZE) scenario[9] is at the very edge of the distribution (8 % probability), which is also a result of the limited demand pull at that time (compare Extended Data Figure 4f).

In the long run, by 2040, large uncertainties dominate in the conventional growth case, illustrated by an IQR of 3.0 – 10.7 % in the EU (0.8 – 3.4 % globally), which stands in stark contrast to the narrow 10.7 – 12.3 % in the EU (6.3 – 7.7 % globally) under unconventional growth. The global probability distribution under conventional growth in 2040 is skewed to low capacities, while it is wide and slightly bimodal in the EU. Under unconventional growth, by 2040 the probability distribution is focussed at the upper end of the range in both regions and primarily determined by the demand pull.

Discussion And Conclusion

Despite strong momentum and enthusiasm around green hydrogen, the market ramp-up of electrolysis is a decisive bottleneck on the pathway to climate neutrality. We show that despite exponentially increasing project announcements for the upcoming years, green hydrogen likely (≥75%) remains scarce (<1% of final energy demand) until 2030 in the EU and until 2035 globally if electrolysis capacity grows similarly to wind and solar power, which have been the biggest success stories of the energy transition so far. This can be explained by the nature of exponential expansion, which includes a flat beginning such that even high annual growth rates take time to translate into noteworthy market shares. However, once the breakthrough occurs it may happen quickly – as was the case for solar power.

For the electrolysis market ramp-up, however, the timing of this breakthrough in terms of largest annual capacity additions is uncertain, but unlikely (≤25 %) to occur before 2037 in the EU and 2043 globally. We show that the propagation of inevitable uncertainties associated with both near-term deployment and feasible growth rates leads to uncertain availability of green hydrogen in the mid- to long-term. This is illustrated by the widespread IQR of 3.0 – 10.7 % of final energy in the EU (0.8 – 3.4 % globally) in 2040, which implies a substantial risk of a long-term gap between likely supply and potential demand. It is important to note that the probability distributions presented here are conditional on the continuous policy support assumed as part of the demand pull. Even under such policies, uncertainties prevail for decades.

In addition, future short-term scarcity and long-term uncertainty of electrolysis capacity might create additional barriers to electrolysis deployment already today. First, short-term scarcity creates problems due to the threefold coordination challenge of ramping-up hydrogen supply, demand and infrastructure simultaneously, which has been described as a "three-sided chicken-and-egg problem"[76]. The lack of sufficient hydrogen volumes delays both the end-use transformation on the demand side as well as required infrastructure development such as the repurposing of existing gas pipelines. Second, long-term uncertainty might deter investors, who could choose to wait for the market to consolidate and for costs to drop (second-mover advantage)[77]. From a policy perspective, relying on the large-scale availability of green hydrogen is therefore a risky bet that, if hydrogen abundance and affordability fail to materialise, may lead to a fossil lock-in due to remaining fossil fuel infrastructure and end-use equipment. As a consequence, under conventional growth like wind and solar power, uncertainties may translate into risks that discourage policy makers and investors such that green hydrogen might fall short of its potential and thus endanger climate targets.

By contrast, policy makers and industry could minimise these risks by fostering rapid investments into green hydrogen supply chains that enable unconventionally high growth rates of electrolysis. In this way the feasibility space would broaden beyond what has been experienced for energy analogues such as wind and solar. This could break the vicious cycle of uncertain supply, insufficient demand and incomplete infrastructure, and turn it into a positive feedback mechanism. Short-term scarcity and long-term uncertainty are two sides of the same coin and could be resolved together. Policies that kick-start a rapid deployment of Gigawatt-scale electrolysers in the upcoming few years could help to unlock substantial innovation and scaling effects, prompting industries to switch from manual to automated production and thus driving down costs, which would secure expectations and further accelerate growth.

Such unconventional growth could not only allow green hydrogen to meet demands in sectors inaccessible to direct electrification, but in conjunction with expanding renewable electricity, it could keep the window open to reaching a broader and more prominent role of hydrogen in a climate-neutral energy system. However, policy makers should be aware that there remains a risk of overestimating green hydrogen's potential. While it will be possible to expand the use cases of hydrogen if supply surpasses expectations, in the opposite case, if supply falls short of expectations, it might simply be too late to switch to alternatives. Under these asymmetrically distributed risks policy makers face a twofold problem. On the one hand, they need to accelerate the development of green hydrogen throughout the entire supply chain to foster unconventional growth; on the other hand, they need to safeguard against the inevitable risk of limited availability. Policy makers therefore need to strike a sensible balance between providing regulatory certainty in order to spur green hydrogen investment, while maintaining a realistic judgment on its long-term prospects as well as fostering available and more efficient alternatives such as direct electrification and energy efficiency. Future research should further develop probabilistic decision frameworks[78] that help enabling urgent technological deployment, while navigating the uncertain feasibility space and associated risks.

Methods

Approach and key input data

We conduct an uncertainty analysis of the market ramp-up and further expansion of electrolysis capacity, in the EU and globally, using a stochastic adaptation of the logistic technology diffusion model. The model accounts for inevitable uncertainties of two main parameters: the initial electrolysis capacity in 2023, and the annual growth rate, which we parameterise using up-to-date electrolyser capacity data from built, planned and announced projects as well as from empirical data on the growth of successful technologies from the past. We capture the nonlinear propagation of these uncertainties within the logistic diffusion model by a Monte Carlo simulation approach. We further assume a steadily-increasing electrolysis demand pull driven by continuous policy support and expanding competitiveness of hydrogen applications (Figure 2). This approach enables us to derive probability distributions of electrolysis capacity deployment over time, which we then interpret as a probabilistic feasibility space of scaling up green hydrogen supply. By design and by necessity, the results do not represent absolute probabilities, but conditional probabilities that are contingent on the assumed demand pull from policies and markets.

Our analysis relies on global electrolysis projects from the IEA Hydrogen Projects Database[42], complemented by our own market research, which we use to parameterise the initial capacity distribution, depending on the project status as explained below.

In order to parameterise the growth rate distribution, we draw on data of historical analogues and distinguish two cases. In the conventional growth case, we assume that electrolysis grows as fast as wind and solar power have during their period of fastest relative growth from 1995 – 2010 (Figure 3). In the unconventional growth case, we explore the electrolysis market ramp-up under historical growth rates of a wide set of primarily non-energy technologies that grew even faster than wind and solar power (Figure 5).

For the demand pull (from policies, regulation, and markets) that drives the technology diffusion, we parameterise its magnitude in time as well as its anticipation by investors. For the EU, in the short term the magnitude is parameterised to the political 2024 target of 6 GW, and the 2030 target of 40 GW. The long-term demand pull is set to 500 GW by 2050 as mentioned in the EU Hydrogen Strategy[8]. Globally, the short-term demand pull magnitude is aligned with cumulative project announcements of 154 GW by 2030. In the long run, we use scenario data of the IEA NZE scenario, which is 3600 GW by 2050[9]. The demand pull anticipation states by how many years these targets, associated policies, and hydrogen competitiveness are anticipated by potential investors, which thus constitutes a measure of both regulatory certainty and investor foresight. Our default assumption is 5 years, while we conduct sensitivity analyses for 0 years, 10 years, as well as a hypothetical case of full anticipation of the long-term market size (Extended Data Figure 3, Extended Data Figure 4).

Data handling

We use the IEA Hydrogen Projects Database, which lists 984 global hydrogen projects, of which 886 are based on electrolysis. The database includes the project's development status, technology characteristics, designated end-use applications, and most importantly size as electrical capacity in MW for electrolysis projects. In addition, to ensure the model's initial capacity in 2023 is accurately parameterised, we review all projects with an announced starting year in 2022 or 2023 and an announced size of at least 50 MW. This applies to 49 projects, which we track and include in the GitHub repository (see below). Electrolysis projects with a "DEMO" development status are allocated to the "Operational" and "Decommissioned" status, depending on whether they are still in operation or not. The IEA Hydrogen Projects Database also contains several entries for confidential projects between 2000-2020. We distribute these projects to all regions in proportion to the share of total capacity from other non-confidential projects within that time window, and equally over time.

For the conventional growth case, we use data of installed wind and solar capacity from the BP Statistical Review of World Energy 2021[66]. Solar capacity is available from 1997 onwards in the EU, and from 1996 globally. Wind capacity is available from 1997 in the EU, and from 1995 globally. We fit exponential models to this data in sliding 7-year intervals until 2010, which we use to parameterise the emergence growth rate distribution. This corresponds to the period in which both technologies grew the fastest (Extended Data Figure 1). The distribution is robust to the choice of the slice length (Extended Data Figure 2). The emergence growth rate is related to the steepness parameter in the logistic function (see below) and describes the growth rate that is approximately attained in the emergence phase of the technology diffusion when the asymptote is not yet constraining.

Truncated normal distributions

The stochastic uncertainty analysis rests on a Monte Carlo-based simulation approach to randomly sample from probability distributions that reflect the underlying parametric uncertainty. We use normal distributions with lower truncation for both the initial capacity in 2023 and the emergence growth rate.

For the initial capacity distribution, we define the lower truncation a by the capacity of all projects that are already operational or under construction and due to start production in 2023. Given the truncation interval $[a, \infty]$, we thus need to determine the pre-truncation parameters μ (mean) and σ (standard deviation). This leaves two degrees of freedom, for which we impose two conditions. First, we set the post-truncation expected value to the capacity that is equivalent to realising 30% of feasibility study projects, $C_{0.3FS}$. Given ϕ as the probability density function and Φ as the cumulative density function of the normal distribution, the first condition is related to the expected value and reads:

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

Second, we assign a 15 % probability to the option that only those projects that are already backed by an FID, with capacity C_{FID}, are built. Following the truncated cumulative distribution function, the second condition is:

$$F(C_{FID}) = P(X \leq C_{FID}) = \frac{\Phi\left(\frac{C_{FID}-\sigma}{\mu}\right) - \Phi\left(\frac{a-\sigma}{\mu}\right)}{1-\Phi\left(\frac{a-\sigma}{\mu}\right)} = 0.15 \qquad (2)$$

The two equations (1) and (2) form a system of nonlinear equations that we solve numerically to obtain μ and σ. Jointly with the lower truncation value a, this defines the truncated distribution (Figure 3a-b).

For the emergence growth rate distribution, we first calculate the mean and standard deviation of the 7-year growth rates of wind and solar power in the EU and globally. Subsequently, we apply a lower truncation of 15 %/yr, which thus constitutes the lower boundary of the electrolysis market ramp-up (Figure 3c-d).

Adapted logistic technology diffusion model

In order to account for the threefold coordination challenge of concurrently ramping-up green hydrogen supply, demand, and infrastructure, we propose an adaptation of the standard logistic technology diffusion model by including a steadily-increasing demand pull that replaces the fixed final market volume. This accounts for the observation that the market for green hydrogen is just emerging, which stands in contrast to energy technologies such as wind and solar power that were able to tap into the existing electricity market (also see main text). We deliberately do not model market shares, but instead directly describe the growing market volume because the emerging green hydrogen market is not well-described by a substitution of technology shares.

The standard logistic function for the electrolysis capacity $C(t)$ reads

$$C(t) = \frac{C_{max}}{1+e^{-k(t-t_0)}} \qquad (3)$$

where C_{max} is the asymptote, k is the growth constant, t_0 is the inflection point and e is Euler's number of approximately 2.718. This is the solution of the logistic differential equation

$$\frac{dC}{dt} = kC\left(1 - \frac{C}{C_{max}}\right) \quad (4)$$

under the condition that $C(t_0) = C_{max}/2$. Our model idea rests on an adaptation of this differential equation. We turn C_{max} into a time-dependent demand pull $C_{max}(t)$ and discretise the differential equation, which yields

$$C_{t+1} = C_t + bC_t\left(1 - \frac{C_t}{C_{t,max}}\right) \quad (5)$$

where t denotes time in yearly units, and $b = e^k - 1$ is the annual growth rate. In the Monte Carlo simulation we independently draw a sample (N = 10,000) for both the initial capacity C_{2023} and the annual growth rate b, and subsequently feed both into the diffusion equation (5). In order to improve numerical accuracy, we use a quarterly time resolution in the model with a quarterly growth rate of $b_q = (1+b)^{1/4} - 1$. Further increasing the temporal resolution did not noticeably affect results.

Emergency deployment

To extend the probabilistic feasibility space of electrolysis capacity to emergency deployment, we use a wide dataset of primarily non-energy technologies to parameterise a distribution of unconventional growth rates. This encompasses technologies on both regional and global level, measured in different units, which we normalise by the respective maximum value. In the case of global smartphone shipments and e-bike sales, we calculate cumulative numbers in order to represent the stock, not the flow. In contrast to the conventional growth case, where we used exponential growth rates of wind and solar power to parameterise the emergence growth rate distribution, for the unconventional growth case we fit logistic models (Equation 3), because many technologies have already passed through the entire S-curve (Figure 5a). After converting the growth constant k to the annual growth rate b, via $b = e^k - 1$, we re-parameterise the distribution of emergence growth rates (Figure 5b), draw another sample (N = 10,000) and run the Monte Carlo simulation again to obtain the probabilistic feasibility space of Figure 5c-d.

Final energy shares

We translate electrolysis capacity into corresponding shares of final energy demand that can be supplied under this capacity. This requires assumptions on the electrolysis efficiency, its full-load hours, and final energy demand.

We assume an overall efficiency of 60 %, which results from a 60-81 % efficiency of electrolyser systems[79] and additional losses due to further processing of some hydrogen into e-fuels[1] as well as losses incurred during transportation, storage and conversion[3].

Additionally, we assume that electrolysis runs at 5,000 full-load hours, equivalent to a capacity factor of 57%. Such full-load hours could be realised for example by hybrid solar-wind power plants in several world regions[80]. Furthermore, this assumption is in harmony with the range of 3,000-6,000 full-load hours regarded as cost-minimising using grid electricity[79].

Final energy demand over time is obtained from scenarios that reach climate neutrality by 2050. For the EU, due to the lack of published official modelling results beyond 2030, we use scenarios results of the INNOPATHS project, a recent EU-specific model intercomparison study[81]. Specifically, we calculate the median of a total of nine scenarios, which originate from three different models (ETM-UCL, PRIMES, REMIND-EU) under three different transformation narratives (New Players 1.5, Incumbents 1.5, Efficiency 1.5). As the results are only available for the EU28, not EU27, and all British Isles (the United Kingdom and the Republic of Ireland) are aggregated into one region (UKI), we approximate the EU27 final energy demand by subtracting the UKI values from the EU28 values. This leads to a slight underestimation of the EU27 value because only the United Kingdom has left the EU. However, as Ireland's final energy demand only accounts for around 1% of that of the EU27, the error is negligible compared to the modelling uncertainty. Global final energy demand is given by the IEA NZE scenario[9] (variable "total final consumption"), and linearly interpolated if necessary (for 2025, 2035, 2045 in Extended Data Figure 5).

Limitations

We focus on the upscaling of electrolysis capacity. However, there are other elements in the supply chain of green hydrogen that could also constitute critical bottlenecks. Of particular concern is the upscaling of technologies to capture atmospheric carbon[34], especially direct air capture[35], for the synthesis of climate-neutral e-fuels, which was however out of scope for this article.

The capacity data of wind and solar power does not include very early upscaling prior to 1995. To parameterise the growth rate distribution, we are therefore limited to the interval 1995-2010, after which growth starts to slow down again. The power of prediction could possibly be improved by including a longer dataset. However, we view 1995-2010 as a valid interval in order to explore the feasibility space of green hydrogen under the assumption that the growth rates observed for wind and solar power in this 15-year time period can be sustained at least as long for electrolysis.

The calculation of final energy shares in the EU leaves out imports from other world regions, which could become substantial in the longer term. An analysis of hydrogen trade was out of scope of this article and final energy shares must be interpreted accordingly.

Finally, all stated probability distributions are contingent on the demand pull, which assumes continuous policy support, in particular in the next decade, and an expanding competitiveness of hydrogen due to cost reductions as well as direct and indirect carbon pricing. While we regard this as a necessary assumption because green hydrogen is still at the very beginning of the market diffusion, future research could examine appropriate policy instruments that are capable of realising this demand.

Data availability

We used data from the IEA Hydrogen Projects Database[42] for electrolysis project capacity, complemented by our own market research. Data on wind and solar power capacity is taken from the BP Statiscial Review of World Energy 2021[66]. Data for the unconventional growth case is from refs[82–93]. Final energy data over time is taken from the IEA NZE[9] on the global level, and from the INNOPATHS project[81] for the EU. Source data is provided in the GitHub repository.

Code availability

The R model code, including all input data, is available on GitHub: https://github.com/aodenweller/green-h2-upscaling/

Pre-run simulation results to reproduce all figures are available on Zenodo: https://doi.org/10.5281/zenodo.5933122

References

1. Ueckerdt, F. *et al.* Potential and risks of hydrogen-based e-fuels in climate change mitigation. *Nat. Clim. Chang.* **11**, 384–393 (2021).

2. Bloomberg Finance L.P. *Hydrogen Economy Outlook - Key messages*. (2020).

3. IEA. *Global Hydrogen Review 2021*. (2021).

4. IRENA. *Green Hydrogen Supply: A Guide to Policy Making*. (2021).

5. Creutzig, F. *et al.* Bioenergy and climate change mitigation: an assessment. *GCB Bioenergy* **7**, 916–944 (2015).

6. Luderer, G. *et al.* Environmental co-benefits and adverse side-effects of alternative power sector decarbonization strategies. *Nat Commun* **10**, 5229 (2019).

7. van Renssen, S. The hydrogen solution? *Nature Climate Change* **10**, 799–801 (2020).

8. European Commission. *A hydrogen strategy for a climate-neutral Europe. COM(2020) 301 final* (2020).

9. IEA. *Net Zero by 2050*. https://www.iea.org/reports/net-zero-by-2050 (2021).

10. IRENA. *World Energy Transitions Outlook: 1.5°C Pathway*. (2021).

11. Bauer, C. *et al.* On the climate impacts of blue hydrogen production. *Sustainable Energy & Fuels* **6**, 66–75 (2022).

12. Ueckerdt, F. *et al.* On the cost competitiveness of blue and green hydrogen (submitted).

13. Liebreich, M. The Clean Hydrogen Ladder. https://www.linkedin.com/pulse/clean-hydrogen-ladder-v40-michael-liebreich/ (2021).

14. UNFCCC. *Adoption of the Paris Agreement*. (2015).

15. European Commission. *A Clean Planet for all - A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy*. *COM(2018) 773* (2018).

16. Davis, S. J. *et al.* Net-zero emissions energy systems. *Science* (2018) doi:10.1126/science.aas9793.

17. IRENA. *Green hydrogen cost reduction*. https://www.irena.org/publications/2020/Dec/Green-hydrogen-cost-reduction (2020).

18. Marchetti, C. & Nakicenovic, N. *The Dynamics of Energy Systems and the Logistic Substitution Model*. http://pure.iiasa.ac.at/id/eprint/1024/ (1979).

19. Grübler, A., Nakićenović, N. & Victor, D. G. Dynamics of energy technologies and global change. *Energy Policy* **27**, 247–280 (1999).

20. Wilson, C. Up-scaling, formative phases, and learning in the historical diffusion of energy technologies. *Energy Policy* **50**, 81–94 (2012).

21. Sovacool, B. K. How long will it take? Conceptualizing the temporal dynamics of energy transitions. *Energy Research & Social Science* **13**, 202–215 (2016).

22. Grubler, A., Wilson, C. & Nemet, G. Apples, oranges, and consistent comparisons of the temporal dynamics of energy transitions. *Energy Research & Social Science* **22**, 18–25 (2016).

23. Sovacool, B. K. & Geels, F. W. Further reflections on the temporality of energy transitions: A response to critics. *Energy Research & Social Science* **22**, 232–237 (2016).

24. Kern, F. & Rogge, K. S. The pace of governed energy transitions: Agency, international dynamics and the global Paris agreement accelerating decarbonisation processes? *Energy Research & Social Science* **22**, 13–17 (2016).

25. Jewell, J. & Cherp, A. On the political feasibility of climate change mitigation pathways: Is it too late to keep warming below 1.5°C? *WIREs Climate Change* **11**, e621 (2020).

26. Bi, S., Bauer, N. & Jewell, J. Dynamic Evaluation of Policy Feasibility, Feedbacks and the Ambitions of COALitions. (2022) doi:10.21203/rs.3.rs-827021/v1.

27. Cherp, A., Vinichenko, V., Jewell, J., Brutschin, E. & Sovacool, B. Integrating techno-economic, socio-technical and political perspectives on national energy transitions: A meta-theoretical framework. *Energy Research & Social Science* **37**, 175–190 (2018).

28. Hansen, J. P., Narbel, P. A. & Aksnes, D. L. Limits to growth in the renewable energy sector. *Renewable and Sustainable Energy Reviews* **70**, 769–774 (2017).

29. Madsen, D. N. & Hansen, J. P. Outlook of solar energy in Europe based on economic growth characteristics. *Renewable and Sustainable Energy Reviews* **114**, 109306 (2019).

30. Grubb, M., Drummond, P. & Hughes, N. *The shape and pace of change in the electricity transition: Sectoral dynamics and indicators of progress*. https://www.wemeanbusinesscoalition.org/blog/shape-and-pace-of-change-in-the-electricity-transition/ (2020).

31. Lowe, R. J. & Drummond, P. Solar, wind and logistic substitution in global energy supply to 2050 – Barriers and implications. *Renewable and Sustainable Energy Reviews* **153**, 111720 (2022).

32. Cherp, A., Vinichenko, V., Tosun, J., Gordon, J. A. & Jewell, J. National growth dynamics of wind and solar power compared to the growth required for global climate targets. *Nat Energy* **6**, 742–754 (2021).

33. Wilson, C., Grubler, A., Bauer, N., Krey, V. & Riahi, K. Future capacity growth of energy technologies: are scenarios consistent with historical evidence? *Climatic Change* **118**, 381–395 (2013).

34. Nemet, G. F. *et al.* Negative emissions—Part 3: Innovation and upscaling. *Environ. Res. Lett.* **13**, 063003 (2018).

35. Hanna, R., Abdulla, A., Xu, Y. & Victor, D. G. Emergency deployment of direct air capture as a response to the climate crisis. *Nature Communications* **12**, 368 (2021).

36. van Sluisveld, M. A. E. *et al.* Comparing future patterns of energy system change in 2°C scenarios with historically observed rates of change. *Global Environmental Change* **35**, 436–449 (2015).

37. Napp, T. *et al.* Exploring the Feasibility of Low-Carbon Scenarios Using Historical Energy Transitions Analysis. *Energies* **10**, 116 (2017).

38. Iyer, G. *et al.* Diffusion of low-carbon technologies and the feasibility of long-term climate targets. *Technological Forecasting and Social Change* **90**, 103–118 (2015).

39. Jewell, J., Vinichenko, V., Nacke, L. & Cherp, A. Prospects for powering past coal. *Nat. Clim. Chang.* **9**, 592–597 (2019).

40. Vinichenko, V., Cherp, A. & Jewell, J. Historical precedents and feasibility of rapid coal and gas decline required for the 1.5°C target. *One Earth* **4**, 1477–1490 (2021).

41. Vartiainen, E. *et al.* True Cost of Solar Hydrogen. *Solar RRL* 2100487 (2021) doi:10.1002/solr.202100487.

42. IEA. Hydrogen Projects Database. (2021).

43. Luderer, G. *et al.* Impact of declining renewable energy costs on electrification in low-emission scenarios. *Nat Energy* 1–11 (2021) doi:10.1038/s41560-021-00937-z.

44. Creutzig, F. *et al.* The underestimated potential of solar energy to mitigate climate change. *Nature Energy* **2**, 1–9 (2017).

45. Bogdanov, D. *et al.* Low-cost renewable electricity as the key driver of the global energy transition towards sustainability. *Energy* **227**, 120467 (2021).

46. Luderer, G. *et al.* Assessment of wind and solar power in global low-carbon energy scenarios: An introduction. *Energy Economics* **64**, 542–551 (2017).

47. Nemet, G. F. *How Solar Energy Became Cheap: A Model for Low-Carbon Innovation*. (Routledge, 2019). doi:10.4324/9780367136604.

48. Wiser, R. *et al.* Expert elicitation survey predicts 37% to 49% declines in wind energy costs by 2050. *Nat Energy* **6**, 555–565 (2021).

49. Nemet, G. F., Zipperer, V. & Kraus, M. The valley of death, the technology pork barrel, and public support for large demonstration projects. *Energy Policy* **119**, 154–167 (2018).

50. Bento, N., Wilson, C. & Anadon, L. D. Time to get ready: Conceptualizing the temporal and spatial dynamics of formative phases for energy technologies. *Energy Policy* **119**, 282–293 (2018).

51. Arthur, W. B. *Increasing Returns and Path Dependence in the Economy*. (University of Michigan Press, 1994).

52. McDonald, A. & Schrattenholzer, L. Learning rates for energy technologies. *Energy Policy* **29**, 255–261 (2001).

53. Rogers, E. M. *Diffusion of Innovations, 5th Edition*. (Free Press, 2003).

54. Lambert, M. *EU Hydrogen Strategy - A case for urgent action towards implementation*. https://www.oxfordenergy.org/publications/eu-hydrogen-strategy-a-case-for-urgent-action-towards-implementation/ (2020).

55. Trancik, J. E. Renewable energy: Back the renewables boom. *Nature* **507**, 300–302 (2014).

56. Chan, G., Goldstein, A. P., Bin-Nun, A., Diaz Anadon, L. & Narayanamurti, V. Six principles for energy innovation. *Nature* **552**, 25–27 (2017).

57. Wilson, C. *et al.* Granular technologies to accelerate decarbonization. *Science* **368**, 36–39 (2020).

58. Brändle, G., Schönfisch, M. & Schulte, S. Estimating long-term global supply costs for low-carbon hydrogen. *Applied Energy* **302**, 117481 (2021).

59. Meng, J., Way, R., Verdolini, E. & Anadon, L. D. Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition. *PNAS* **118**, (2021).

60. Trancik, J. E. Testing and improving technology forecasts for better climate policy. *PNAS* **118**, (2021).

61. IEA. *Renewables 2021*. https://www.iea.org/reports/renewables-2021 (2021).

62. IEA. *World Energy Outlook 2021*. (2021).

63. Quarton, C. J. *et al.* The curious case of the conflicting roles of hydrogen in global energy scenarios. *Sustainable Energy Fuels* **4**, 80–95 (2019).

64. Mowery, D. & Rosenberg, N. The influence of market demand upon innovation: a critical review of some recent empirical studies. *Research Policy* **8**, 102–153 (1979).

65. Nemet, G. F. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. *Research Policy* **38**, 700–709 (2009).

66. BP. *Statistical Review of World Energy 2021*. https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html (2021).

67. Rypdal, K. Empirical growth models for the renewable energy sector. in *Advances in Geosciences* vol. 45 35–44 (Copernicus GmbH, 2018).

68. Aguirre, M. & Ibikunle, G. Determinants of renewable energy growth: A global sample analysis. *Energy Policy* **69**, 374–384 (2014).

69. Hosseini, S. E. An outlook on the global development of renewable and sustainable energy at the time of COVID-19. *Energy Research & Social Science* **68**, 101633 (2020).

70. Unruh, G. C. Understanding carbon lock-in. *Energy Policy* **28**, 817–830 (2000).

71. Hydrogen Council & McKinsey & Company. *Hydrogen Insights: A Perspective on Hydrogen Investment, Deployment and Cost Competitiveness*. (2021).

72. Mercure, J.-F. *et al.* Macroeconomic impact of stranded fossil fuel assets. *Nature Climate Change* **8**, 588–593 (2018).

73. Fasihi, M., Bogdanov, D. & Breyer, C. Long-Term Hydrocarbon Trade Options for the Maghreb Region and Europe—Renewable Energy Based Synthetic Fuels for a Net Zero Emissions World. *Sustainability* **9**, 306 (2017).

74. Wüstenhagen, R., Wolsink, M. & Bürer, M. J. Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy* **35**, 2683–2691 (2007).

75. Batel, S. Research on the social acceptance of renewable energy technologies: Past, present and future. *Energy Research & Social Science* **68**, 101544 (2020).

76. Schlund, D., Schulte, S. & Sprenger, T. The who's who of a hydrogen market ramp-up: A stakeholder analysis for Germany. *Renewable and Sustainable Energy Reviews* **154**, 111810 (2022).

77. Biggins, F., Kataria, M., Roberts, D. & Brown, D. S. Green hydrogen investments: Investigating the option to wait. *Energy* **241**, 122842 (2022).

78. Anadón, L. D., Baker, E. & Bosetti, V. Integrating uncertainty into public energy research and development decisions. *Nat Energy* **2**, 1–14 (2017).

79. IEA. *The Future of Hydrogen: Seizing today's opportunities*. (OECD, 2019). doi:10.1787/1e0514c4-en.

80. Fasihi, M., Bogdanov, D. & Breyer, C. Techno-Economic Assessment of Power-to-Liquids (PtL) Fuels Production and Global Trading Based on Hybrid PV-Wind Power Plants. *Energy Procedia* **99**, 243–268 (2016).

81. Rodrigues, R. *et al.* Narrative-driven alternative roads to achieve mid-century CO2 net neutrality in Europe. *Energy* **239**, 121908 (2022).

82. Everall, J. & Ueckerdt, F. Electrolyser CAPEX and efficiency data for: Potential and risks of hydrogen-based e-fuels in climate change mitigation. (2021) doi:10.5281/zenodo.4619892.

83. Modley, R. *Aviation facts and figures*. (McGraw-Hill Book Company, 1945).

84. Fischer, G. J. *A Statistical Summary of Shipbuilding Under the US Maritime Commission During World War II*. (US Government Printing Office, 1949).

85. Norris, R. S. & Kristensen, H. M. Global nuclear weapons inventories, 1945–2010. *Bulletin of the Atomic Scientists* **66**, 77–83 (2010).

86. Internet Systems Consortium. Internet Domain Survey. https://www.isc.org/survey/ (2019).

87. International union of railways. *High speed lines in the world*. https://uic.org/passenger/highspeed/article/high-speed-database-maps (2021).

88. EIA. U.S. Shale Production. (2021).

89. statista. Global smartphone shipments from 2007 to 2020, by vendor. https://www.statista.com/statistics/271539/worldwide-shipments-of-leading-smartphone-vendors-since-2007/ (2021).

90. Kenney, M. & Pon, B. Structuring the Smartphone Industry: Is the Mobile Internet OS Platform the Key? *J Ind Compet Trade* **11**, 239–261 (2011).

91. statista. Number of e-bikes sold in Europe from 2009 to 2019. (2021).

92. Zweirad-Industrie-Verband (ZIV). Zahlen, Daten, Fakten zum Fahrradmarkt in Deutschland 2020. (2021).

93. Mathieu, E. *et al.* A global database of COVID-19 vaccinations. *Nat Hum Behav* **5**, 947–953 (2021).

Declarations

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Author contributions

FU and GL suggested the research question. AO and FU jointly conceived and designed the study in consultation with GFN and GL. AO implemented the model and created the visualisations. AO and FU interpreted the results and AO wrote the manuscript with contributions from GFN, MJ and GL. AO and MJ verified and updated relevant electrolysis project announcements. AO collected data for the unconventional growth case.

Competing interests

The authors declare no competing interests.

Figures

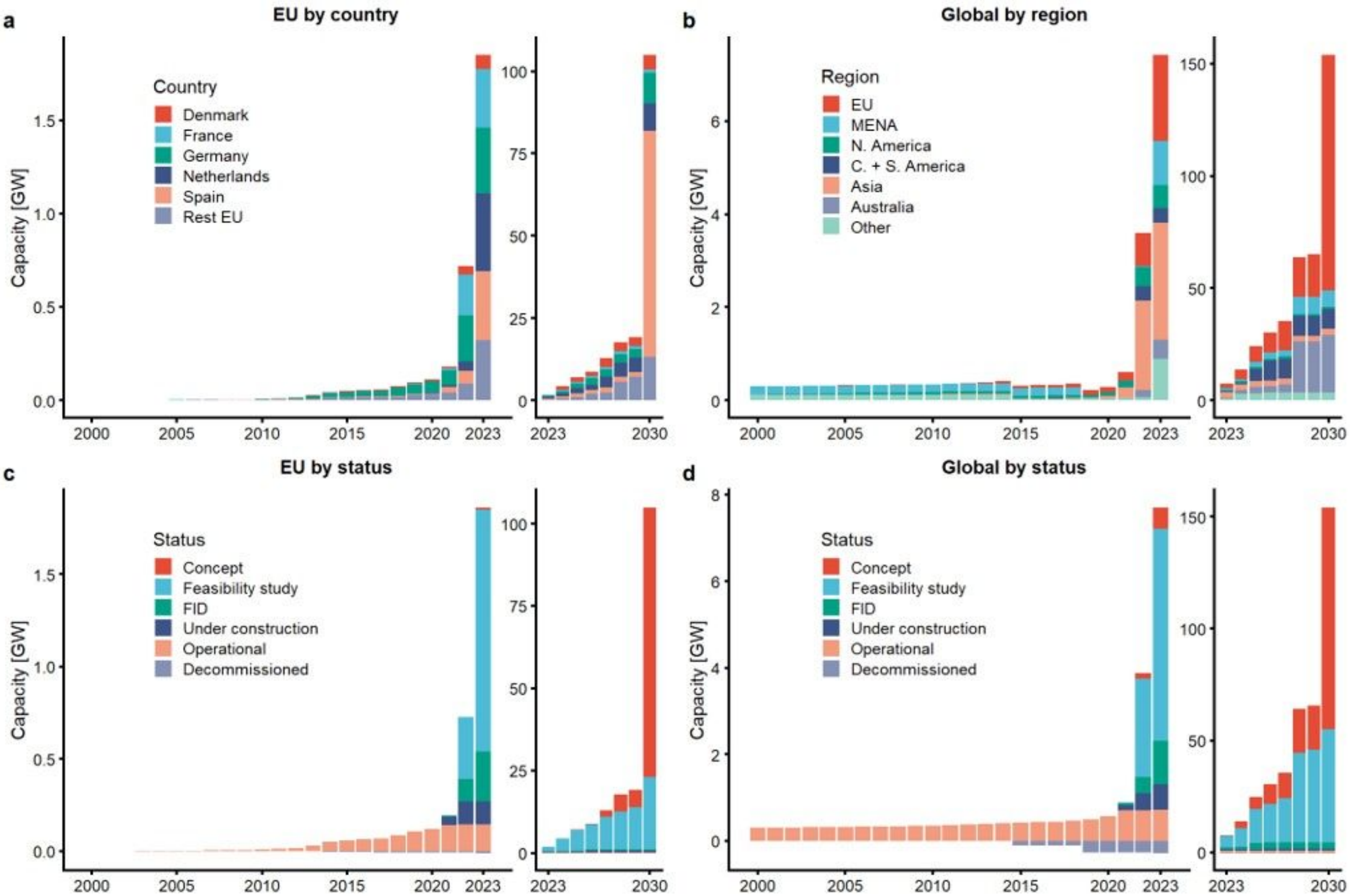

Figure 1

Historical development and future announcements of electrolysis projects. a,**c**, Projects in the EU by country (**a**) and by project development status (**c**). **b**,**d**, Global projects by aggregated region (**b**) and project development status (**d**). Each panel is split into two, showing data from 2000-2023 in the main left-hand part and 2023-2030 in the smaller right-hand part with a separate axis. Projects without a specified starting date are omitted, which affects 21 GW in the EU and 127 GW globally. In (a) and (b), decommissioned projects have been subtracted.

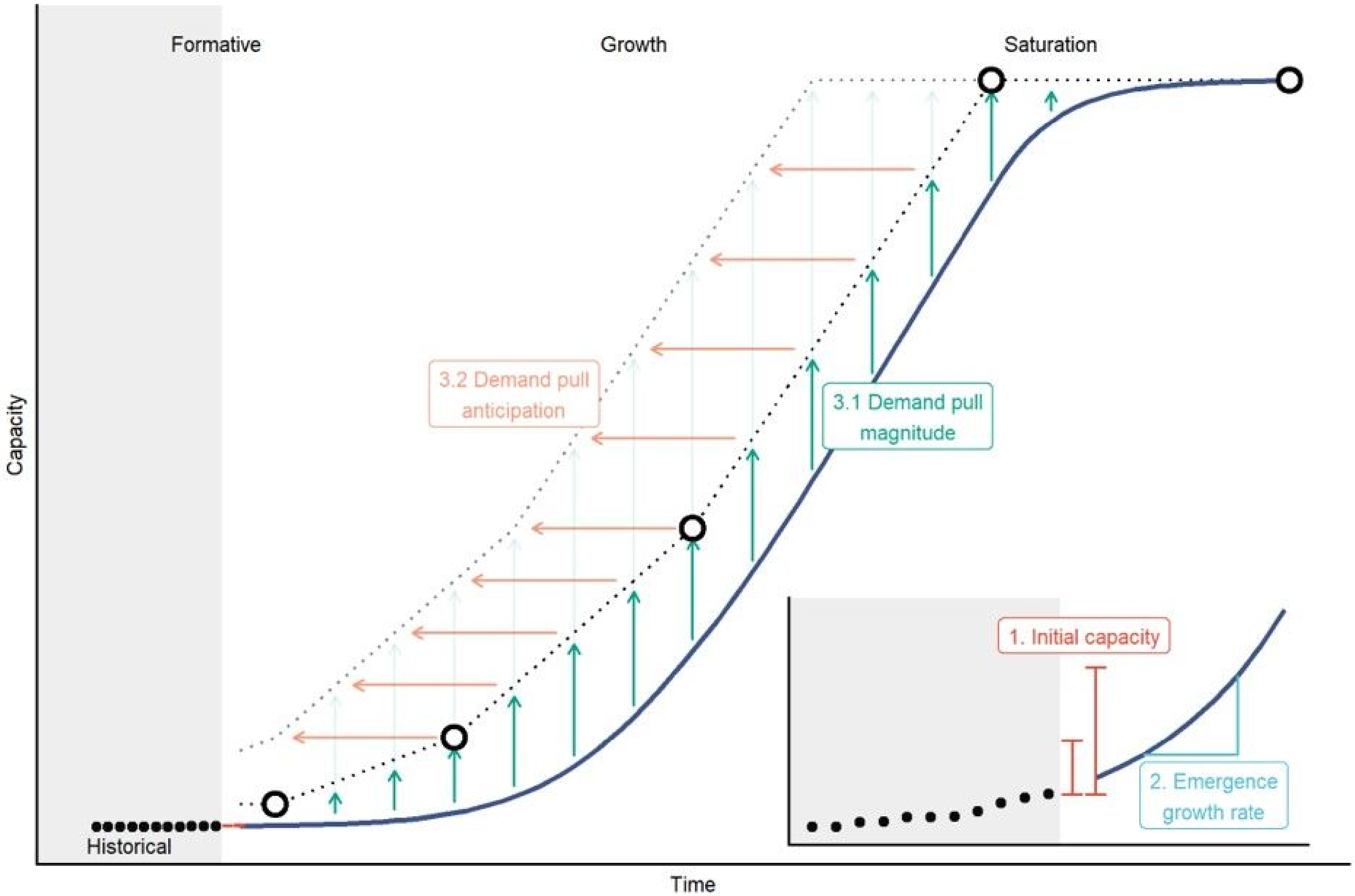

Figure 2

Illustration of the three uncertain parameters of the market ramp-up. In order these are initial capacity, the emergence growth rate, and the demand pull, for which we distinguish magnitude and anticipation.

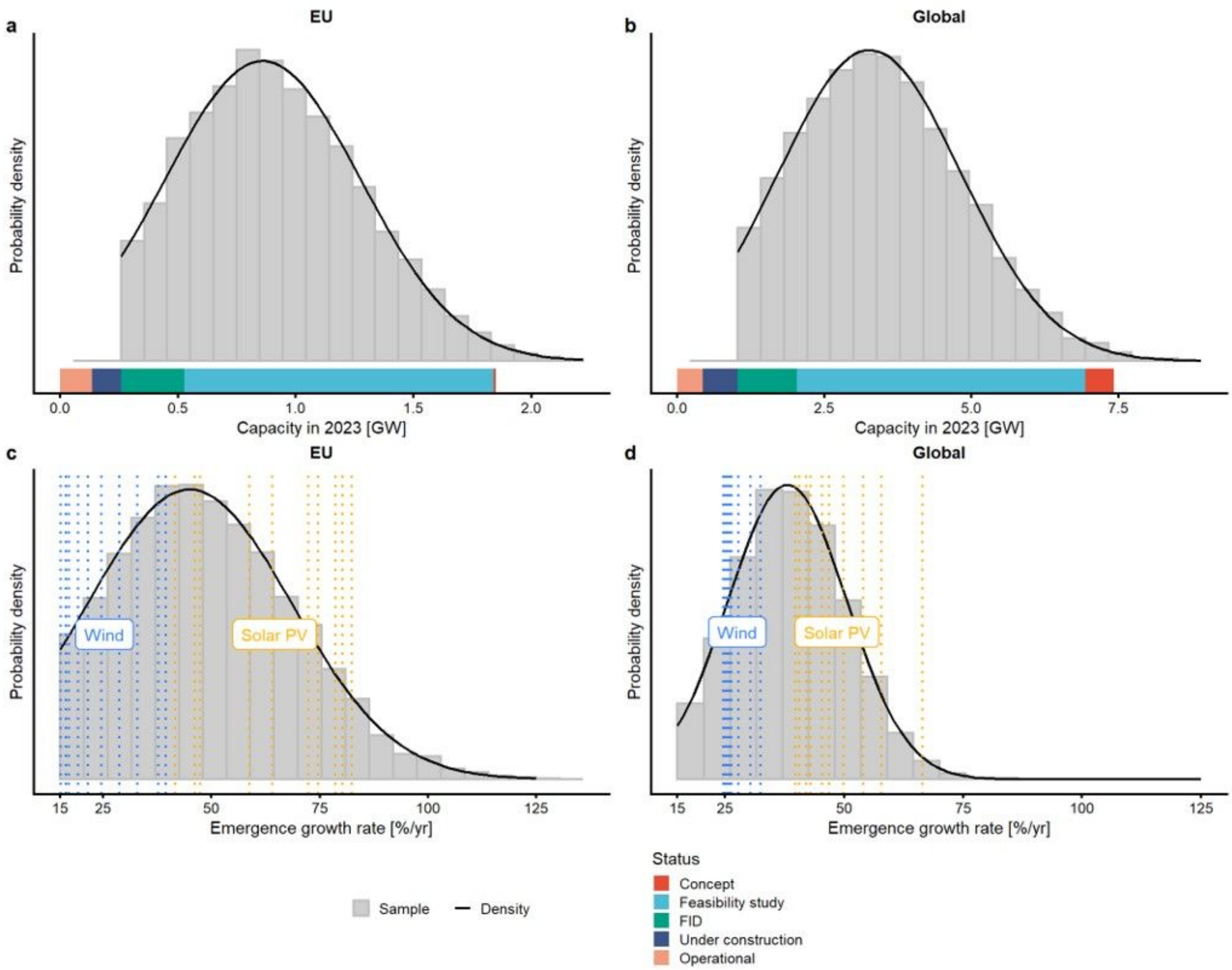

Figure 3

Truncated normal probability distributions of initial capacity in 2023 and emergence growth rates in the conventional growth case. a, b, Initial capacity distributions in the EU (**a**) and globally (**b**). The horizontal bars correspond to the 2023 bar in Figure 1c,d, where decommissioned projects have been subtracted from operational projects. **c,d,** Emergence growth rate distributions in the EU (**c**) and globally (**d**) based on wind and solar PV in 7-year time slices in the interval 1995-2010 (also see Extended Data Figure 1).

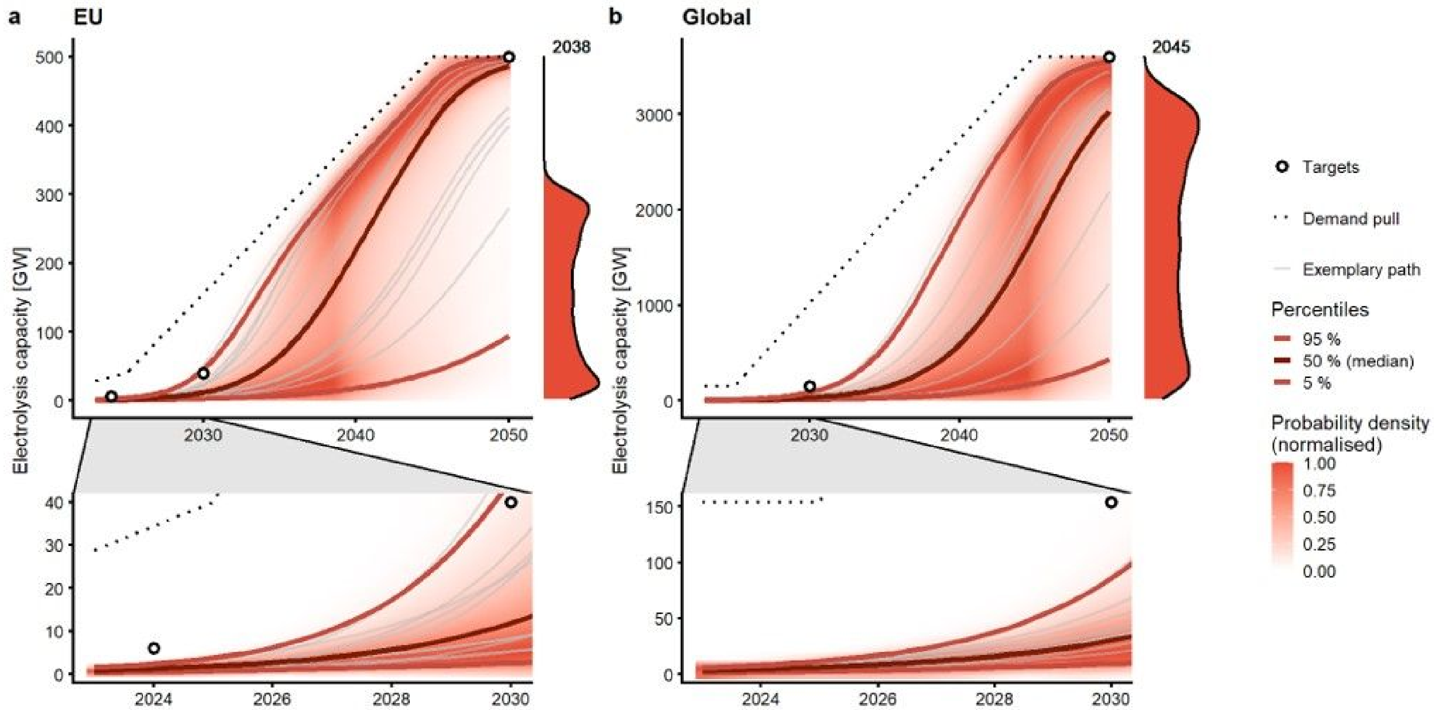

Figure 4

Probabilistic feasibility space of electrolysis growth in the conventional growth case. a, in the EU. **b,** globally. The colour shade indicates the yearly probability density that results from the uncertainty propagation of the initial capacity in 2023 and the emergence growth rate. Grey lines display random exemplary pathways, illustrating the vast range of plausible outcomes under growth rates similar to wind and solar power. The vertical diagram shows the probability density at the intersection year 2038 in the EU (**a**) and 2045 globally (**b**). The results reveal short-term scarcity, with little electrolysis capacity until 2030 (2035) in the EU (globally) and substantial long-term uncertainty, with a huge bandwidth of possible electrolysis capacity until 2050.

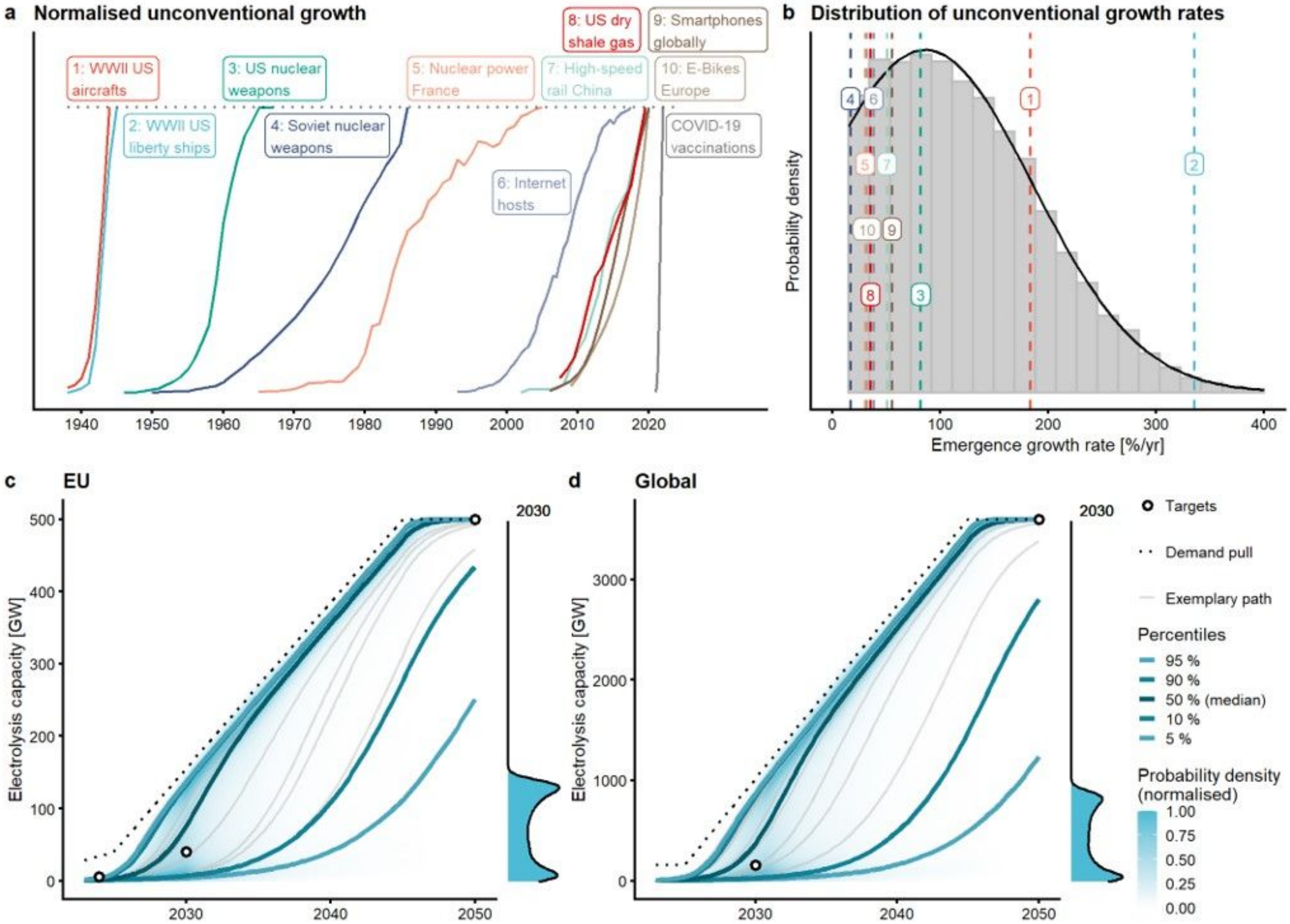

Figure 5

Historical examples of technologies with unconventional growth and probabilistic feasibility space of electrolysis under such growth rates. a, Growth pathways of 11 exemplary technologies in different regions from 1938 until today, normalised to their resepective maximum level measured in different units (see Methods). **b**, Distribution of emergence growth rates in the unconventional growth case, obtained from fitting logistic curves to the technology pathways in (a). **c-d,** Probabilistic feasibility spaces under unconventional growth rates for the EU (**c**) and globally (**d**). The results demonstrate that the ramp-up is substantially expedited compared to the conventional growth case, strongly reducing long-term uncertainty. COVID vaccinations are a case of extremely fast adoption and hence had to be excluded from the distribution.

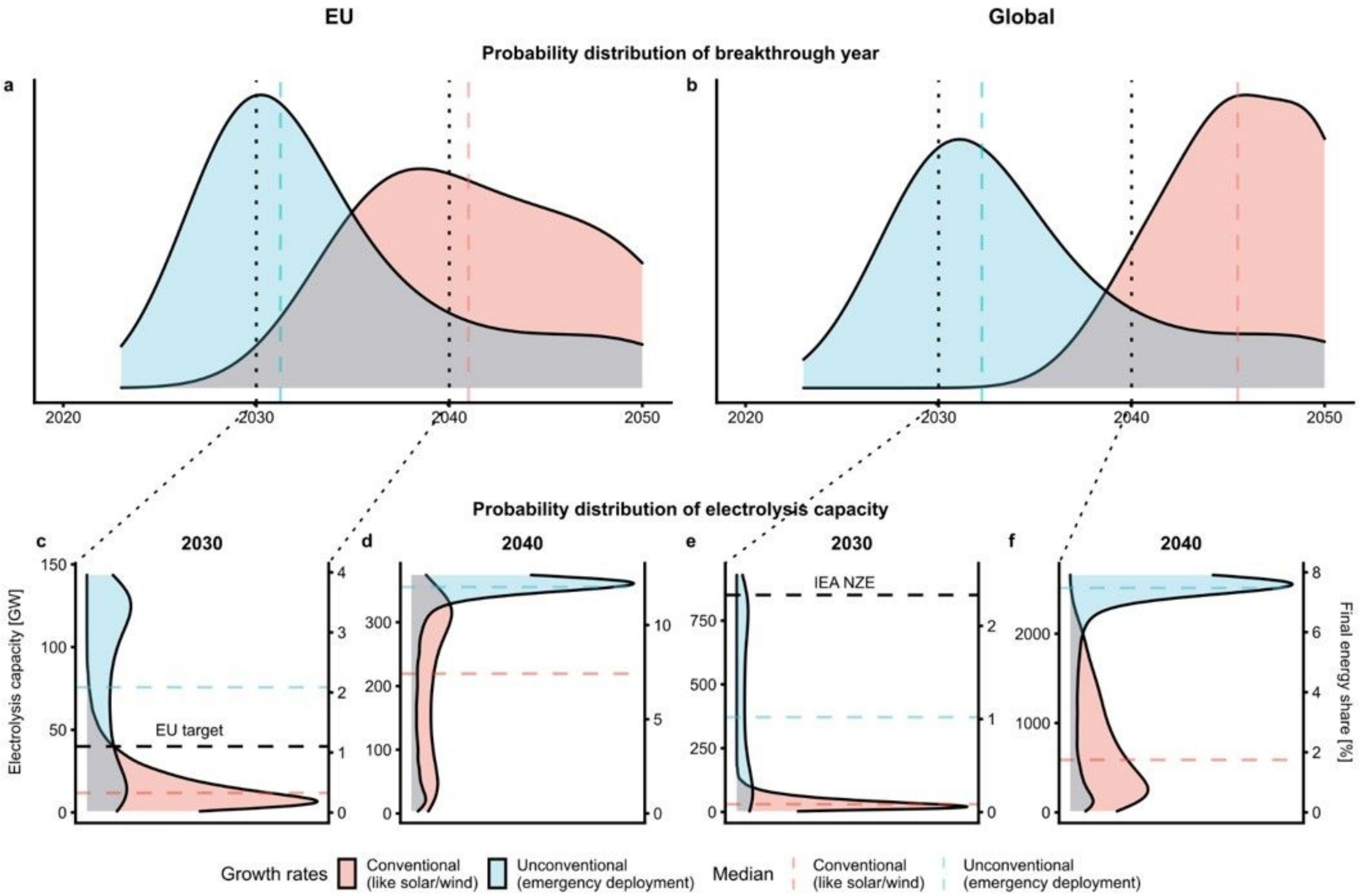

Figure 6

Uncertainty of breakthrough year and electrolysis capacity over time. a, Breakthrough year distribution in the EU. **b,** Breakthrough year distribution globally. **c,d,** Electrolysis capacity distribution in the EU. **e,f,** Electrolysis capacity distribution globally. In **c-f** the left axis shows electrolysis capacity (in GW), and the right y-axis shows the approximate final energy shares this capacity (in percent) could supply domestically given total final energy consumption of scenarios that reach net-zero emissions by 2050.

Supplementary Files

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

- ExtendedDataFigures.docx