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Diverse decarbonization pathways under near cost-optimal futures

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Aditya Sinha [1] ✉, Aranya Venkatesh [2,5], Katherine Jordan [2], Cameron Wade [3], Hadi Eshraghi [1], Anderson R. de Queiroz [1,4], Paulina Jaramillo [2,6] & Jeremiah X. Johnson [1,6]

Energy system optimization models offer insights into energy and emissions futures through least-cost optimization. However, real-world energy systems often deviate from deterministic scenarios, necessitating rigorous uncertainty exploration in macro-energy system modeling. This study uses modeling techniques to generate diverse near cost-optimal net-zero CO_2 pathways for the United States' energy system. Our findings reveal consistent trends across these pathways, including rapid expansion of solar and wind power generation, substantial petroleum use reductions, near elimination of coal combustion, and increased end-use electrification. We also observe varying deployment levels for natural gas, hydrogen, direct air capture of CO_2, and synthetic fuels. Notably, carbon-captured coal and synthetic fuels exhibit high adoption rates but only in select decarbonization pathways. By analyzing technology adoption correlations, we uncover interconnected technologies. These results demonstrate that diverse pathways for decarbonization exist at comparable system-level costs and provide insights into technology portfolios that enable near cost-optimal net-zero CO_2 futures.

To limit global temperature rise to below 1.5 °C and mitigate the worst impacts of climate change, it is imperative to transition to a net-zero CO_2 emissions energy system by the middle of the century[1]. In net-zero systems, the amount of CO_2 emissions released into the atmosphere is balanced by the amount removed through various mechanisms such as carbon capture and storage, reforestation, or technological innovations. However, this transformation poses significant challenges and uncertainties in determining the configuration of the energy system to meet these targets[2,3]. Key decisions regarding capital-intensive and long-term energy system investments must be made today, with far-reaching consequences for future social, economic, and environmental systems. Promoting energy efficiency, electrifying end-use technologies, and transitioning to a carbon-free electricity grid are crucial components of this transition[4–6]. Nevertheless, there are unresolved questions surrounding the implementation of these solutions and coordinating efforts across different energy sectors.

Energy system optimization models (ESOMs) enable the study of energy transitions[7]. These models typically rely on least-cost optimization to inform decision-making, with investment and operational decisions achieving the lowest net present cost. ESOMs can determine the optimal deployment of resources, considering existing and new technologies, within a specified time horizon and subject to various constraints. Model designs can vary based on their sectoral representation and assumptions on technology advancements, policy measures, or economic factors. ESOMs can provide insight into crucial decision-making in interlinked systems where analyzing only a single technology or sector in isolation may be insufficient. These models are emerging as the standard in studying macro scale energy systems spanning over multi-decadal time periods[8]. For example, previous

[1]Department of Civil and Environmental Engineering, North Carolina State University, Raleigh, NC, USA. [2]Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA, USA. [3]Sutubra Research Inc., Halifax, Nova Scotia, Canada. [4]Department of Decision Sciences, North Carolina Central University, Durham, NC, USA. [5]Present address: EPRI, Palo Alto, CA, USA. [6]These authors jointly supervised this work: Paulina Jaramillo, Jeremiah X. Johnson. ✉e-mail: asinha2@ncsu.edu

studies have used capacity expansion models, a type of ESOM, and explored ranges of fuel and technology options for achieving net-zero CO_2 emissions in the United States by 2050[9–11], yielding valuable insights into the need for technological flexibility[10] and identifying key challenges and opportunities for decarbonization[11,12]. However, these studies have often relied on deterministic simulations of a small number of scenarios, with limited exploration of uncertainties in input parameters (parametric) or model architecture (structural)[13,14]. As a result, model projections may fail to anticipate future events[15]. Additionally, the detailed narratives often associated with these scenarios can introduce cognitive bias in interpreting results[16].

Recent research has proposed expanding the modeling frameworks to support feasibility assessment and robust strategy development to address these limitations[17,18]. For example, Lempert and Trujillo suggest that modelers should seek robust strategies for decarbonization, as this encourages more expansive thinking over potential futures and an iterative stress-testing process[19]. More recently, Jewell et al. proposed developing feasibility spaces through which modelers can add boundaries to the solution spaces (i.e., all possible decarbonization pathways) based on a multi-dimensional evaluation that accounts for parameters not included in the ESOMs (e.g., technology acceptability)[17]. Thus, identifying robust decarbonization pathways for the U.S. energy system warrants a systematic treatment of the deep uncertainty under which these models are formulated[20].

Approaches to address the uncertainty in input parameters include Monte Carlo analysis, stochastic programming, and robust optimization. Monte Carlo analysis involves propagating the uncertainty of one or more input parameters, represented by probability distributions, through the ESOM[21]. Stochastic programming considers numerous uncertain factors in the future and seeks to offer an optimal hedging strategy that informs a single best course of action[21,22]. However, these methods suffer from high computational burdens and require reliable probability distributions for model inputs[14,22], limiting their effectiveness in ESOMs, particularly when used alongside capacity expansion problems[22–26]. Robust optimization integrates elements from sensitivity analysis, multi-objective optimization, and stochastic programming to produce a set of solutions that gradually become less influenced by the uncertainties associated with input variables. These solutions remain stable and resilient even when facing modeled uncertainties[14]. Unlike stochastic programming, robust optimization cannot provide a unified hedging strategy yet still requires quantification of uncertain model parameters. Further, if knowledge of probability distributions of uncertain inputs is available, this uncertainty can potentially be better captured by other methods[14].

Structural uncertainties in ESOMs have been shown to lead to dramatic differences in the cost-optimal pathway and real-world energy transitions[27]. Modeling to generate alternatives (MGA) has emerged as a method to mitigate this uncertainty by exploring the near-optimal region to account for unmodelled considerations[28]. MGA produces near-cost-optimal solutions that can be maximally different to allow for more complete consideration of a wide range of alternatives. The solutions from this approach can represent outcomes beyond cost-optimal technology choices, illustrating the potential influence of non-monetary factors such as public acceptance, consumer preferences, and equity on decision-making. Further, MGA alleviates the cognitive biases of the energy modeler and also allows for the inspection of "knife-edge" effects, where small perturbations in the input assumptions can lead to drastically different outcomes[14,16]. The solutions from MGA can be assembled into a portfolio of options and presented to policymakers, giving them insight into making decisions while keeping in mind the interests of multiple stakeholders. These options may be able to capture non-monetary factors without any cognitive biases in a way that deterministic scenario modeling cannot. The applicability of MGA in the context of energy system modeling has been previously demonstrated[27,29–39].

In applying MGA, we modify the original optimization problem by converting the objective function into a constraint and allowing system costs to exceed the original optimal value by a specified threshold or slack. This addition of slack permits the exploration of near-optimal solutions within the decision space, even if there is a slight increase in the total system cost. As a result, alternative solutions that capture a broader range of possibilities beyond traditional least-cost formulations are extracted. MGA can identify correlations and trade-offs among technology choices, as well as options that are consistently favored or excluded across multiple pathways. By generating hundreds of pathways that cover a large solution space, this approach enables stress-testing of different system representations to assess robustness or the performance of multi-dimensional evaluations to establish a feasibility space. Given the inevitable presence of structural uncertainties and unmodeled objectives in ESOMs, near-optimal model solutions may prove more desirable when factoring in decision-makers' preferences. Furthermore, MGA results may also be interpreted as perturbations in the objective function coefficients, reflecting parametric uncertainty[40]. In this work, we use the Tools for Energy Model Optimization and Analysis (Temoa), an open-source energy system optimization model[41,42], in conjunction with an open-source database of the U.S. energy system[42]. Temoa represents the energy system as a process-based network, linking technologies through the flow of energy commodities. The database incorporates various exogenous engineering-economic parameters to describe each process in the network, including capital costs, operations and maintenance costs, technology lifetimes, conversion efficiencies, and emissions factors.

In this study, we introduce an application and design of MGA, applied to a comprehensive U.S. energy system model to assess near cost-optimal net-zero CO_2 futures. In the context of this study, near-cost-optimal net-zero CO_2 futures refer to pathways to achieve net-zero CO_2 emissions by 2050 that are close to the lowest possible system cost. These pathways allow for consideration of factors that may be desirable to include but difficult to explicitly model. The model endogenizes technology adoption, allowing for an extensive exploration of technology choices across diverse decarbonization pathways. By incorporating explicit descriptions of the transportation, buildings, power, and industrial sectors, the model accounts for the complex interactions between the major energy sectors. Furthermore, our work extends beyond previous studies in that it accounts for path dependencies resulting from past investments in energy system infrastructure, providing insights into the dynamics of the energy system in later years of the simulations. These features of the modeling effort enable us to better address the questions: What are the characteristics of a wide range of near cost-optimal pathways that achieve a net-zero energy system in the United States? Are there common themes amongst these pathways, including favored and disfavored technologies, from which we can extract robust insights? Are there correlated decisions in technology adoption that may be particularly informative for policy-making? Through our modeling, we find several consistent trends across the near cost-optimal pathways, including the rapid expansion of solar and wind power generation, substantial reductions in petroleum use, near elimination of coal combustion, and increased end-use electrification. We also observed varying levels of deployment for natural gas, hydrogen, direct air capture of CO_2, and synthetic fuels, with important correlations in adoption across some technologies.

Results

This section presents the findings from analyzing 1100 near-cost-optimal energy system pathways designed to achieve net-zero CO_2 emissions by 2050. These pathways were developed using MGA and exhibit variations in fossil fuel use, levels of electrification in end-use, as well as the incorporation of other net-zero enabling technologies, such as hydrogen production and direct air capture.

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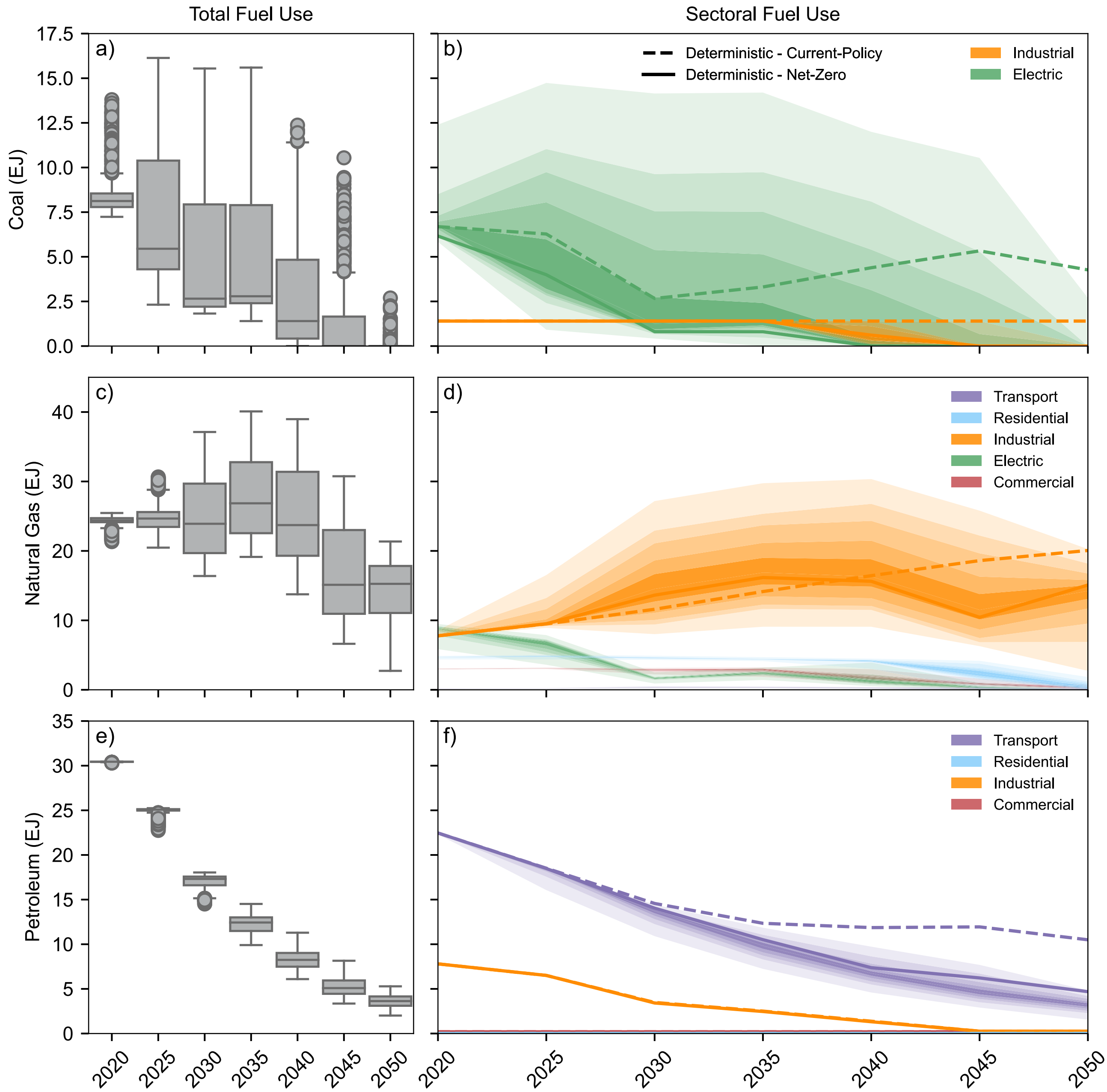

Fig. 1 | Fossil fuel use in near cost-optimal net-zero CO_2 pathways. Near cost-optimal pathways for coal (**a**, **b**), natural gas (**c**, **d**), and petroleum (**e**, **f**) in net-zero CO_2 pathways. The box plots (**a**, **c** and **e**) show the distribution of the total energy use by fossil fuel type across all 1100 net-zero pathways in exajoules (EJ). The pathway plots in (**b**, **d** and **f**) show the range of fossil fuel use by sector, with the shading representing each decile of results across the 1100 model runs (darkest shades around the median, lightest shades around the 10th and 90th percentiles). The solid lines show the deterministic least-cost net-zero pathway, while the dashed lines depict the least-cost current-policy pathway. Box plots indicate median (middle line), 25th, 75th percentile (box) and 1.5 times the inter-quartile range from the first and third quartiles (whiskers) as well as outliers (single points). Source data are provided as a Source Data file.

Fossil fuel use in near cost-optimal net-zero pathways

Figure 1 illustrates the range of primary fossil fuel use, specifically coal, natural gas, and petroleum, within the near cost-optimal net-zero CO_2 pathways along with the least-cost (deterministic) net-zero pathway for the U.S. energy system. The figure also shows the least-cost (deterministic) current-policy pathway, which includes the Inflation Reduction Act (IRA) provisions but excludes any other carbon constraints after the IRA provisions expire. Figure 1a shows that by 2050, most near cost-optimal pathways result in the near elimination of coal use by 2050, consistent with previous work[11,43,44]. Although achieving net-zero targets while maintaining higher levels of coal use is theoretically possible, nearly 99% of the decarbonization pathways rely on less than 0.1 exajoule (EJ) of coal in 2050, representing a 98% reduction from current levels. In 2020, the U.S. electric sector accounted for approximately 90% of the coal use in the energy system, with the remainder attributed to the industrial sector[45]. Consequently, Fig. 1a highlights that the pursuit of net-zero futures necessitates a rapid reduction in coal use in the electric sector, with the median pathway achieving a 67% reduction by 2030 compared to 2020. While most near-cost-optimal net-zero pathways align with the least-cost deterministic pathway, leading to the elimination of coal in the electric sector by 2040, some pathways extend coal phase-out until 2050. This extension can be attributed, in part, to the availability of the IRA tax credits that enable continued electric sector coal use when combined with carbon capture and sequestration (CCS) technologies. As observed in the least-cost current-policy pathway, the IRA succeeds in reducing coal use while the tax credits are active. Still, there is a rebound to nearly pre-existing levels of coal use once these credits expire (typically by 2033 for most provisions).

Figure 1c shows that the distribution of natural gas use exhibits significant variation across the near cost-optimal pathways, with consumption in 2050 ranging from less than 3 EJ to 21 EJ, the latter being comparable to 2020 levels. This diversity in natural gas use is primarily driven by the industrial sector, which encompasses various applications, including direct air capture (DAC), hydrogen production through steam methane reforming (with and without CCS), and industrial manufacturing and non-manufacturing demands. In the least-cost current-policy pathway, industrial natural gas consumption increases steadily through 2050, surpassing the levels seen in any of the net-zero pathways. The range of industrial natural gas used in the near cost-optimal net-zero pathways often exceeds the results in the current-policy case until the last decade of the study period (i.e., 2040–2050). While natural gas use in the current-policy pathway may be comparable in magnitude to the decarbonization pathways, the drivers of such consumption differ. A substantial portion of natural gas is allocated to DAC or hydrogen production in the decarbonization pathways. For instance, the least-cost net-zero pathway uses about 8 EJ of natural gas for DAC in 2050, accounting for almost half of total natural gas use. In the current-policy pathway, these technologies are not widely adopted, and natural gas is primarily used for process heat or conventional boilers in the industrial sector. Within the electric sector, natural gas use undergoes a rapid reduction, declining from approximately 9 EJ in 2020 to less than 2.5 EJ by 2030 in over half of the near cost-optimal pathways. By mid-century, natural gas use in the electricity sector approaches zero in all modeled net-zero pathways. In the commercial sector, natural gas use remains relatively constant until 2035 across the pathways, after which it will decrease to approximately one-tenth of the current commercial natural gas use by 2050 (0.1–0.5 EJ, Interquartile Range, IQR). By contrast, the transition from natural gas in the residential sector is slower, with levels remaining relatively constant until 2040 before declining to a median of 0.3 EJ (0–0.9 EJ, IQR). Overall, reductions in natural gas use across all decarbonization pathways are a consequence of the increased electrification of end-use technologies in all sectors. However, despite substantial reductions, all decarbonization pathways retain some level of natural gas use. Compared to coal and petroleum, natural gas is a lower-carbon alternative, particularly for challenging-to-decarbonize processes in the industrial sector. It is important to acknowledge that factors not considered in Temoa, such as labor impacts and energy security perceptions, will likely influence natural gas use during a low-carbon transition.

Primary energy use from petroleum products, shown in Fig. 1e, consistently declines from 31 EJ in 2020 to 3.6 EJ (3.1–4.1, IQR) in 2050 across the decarbonization pathways. The transportation sector exhibits a steady decrease within a relatively narrow range of outcomes. By 2050, all pathways use more than 1.5 EJ of petroleum for transportation but less than 4.8 EJ, with the deterministic least-cost net-zero pathway falling on the higher end of this range. By contrast, petroleum use in the transportation sector will reach 10 EJ by 2050 in the least-cost current policy pathway (i.e., without a net-zero constraint). The adoption of electric vehicles (EVs), synthetic liquids, and hydrogen (discussed below) drives the reduction in petroleum use in the net-zero pathways. In the absence of additional decarbonization policies, substantial petroleum use will continue through 2050.

Net-zero pathways exhibit increased end-use electrification

Figure 2a illustrates that total electricity consumption within the near cost-optimal pathways consistently increases, reaching a median total use of 9400 terawatt-hours, TWh (9200–9500 TWh, IQR) by 2050. This growth is a three-fold increase in electricity use compared to current levels. While the range of total electricity consumption varies, all decarbonization pathways necessitate substantial and rapid investments in clean electric generation capacity to fulfill the needs of end-use sectors. Supplementary Fig. 12 disaggregates the electricity consumption by sector. Electricity demand in the least-cost net-zero pathway reaches 9200 TWh in 2050, placing it at the lower end of the distribution of all the near cost-optimal pathways. Although some pathways exhibit lower electricity consumption than the least-cost option, most pathways lean toward higher relative electricity use by 2050. By contrast, the least-cost current-policy pathway remains similar to net-zero trajectories until 2035 but diverges from the net-zero pathways after that year. Most provisions of the IRA expire by 2033. Without additional policy interventions after the IRA expires, electricity consumption would experience only modest increases to meet population and economic growth.

Figure 2b–f offer insights into the evolving generation sources within the power sector, and Supplementary Fig. 10 shows the capacities. Fig. 2b shows that even the most conservative decarbonization pathways require a ten-fold increase in solar generation by 2050, compared to current levels. This level of solar, totaling 3700 TWh (3600–4100 TWh, IQR), nearly matches the total power system generation from all sources in 2020. This trend highlights the magnitude of transformation required for deep decarbonization and emphasizes the pivotal role of solar power in a decarbonized power system. Across the modeled pathways, the greatest relative increase in solar generation occurs between 2025 and 2030, with a three-fold increase spurred by the federal Production and Investment Tax Credits (PTC and ITC) available through the IRA. Figure 2c shows that generation from wind also experiences substantial growth, reaching a median of 6700 TWh (6100–7400 TWh, IQR) in the net-zero pathways. Most of the wind generation and capacity comes from onshore resources, with a smaller contribution from offshore resources that produce a median 100 TWh (80–110 TWh, IQR) by 2050. Much like solar, the PTC and ITC incentives drive a two-fold or more increase in wind generation between 2025 and 2030. The rapid expansion of wind and solar power highlights the need for substantial and sustained investments in integrating these variable resources to achieve net-zero CO_2 emissions effectively. The growth of wind and solar in the net-zero pathways is complemented by the expansion of battery storage, with installed battery capacity projected to reach 380 gigawatts, GW (370–400 GW, IQR) by 2050, compared to less than 1 GW in 2020 (Fig. 2f). Further, Supplementary Fig. 11 shows that 94% of power generation in the median pathway comes from renewables by 2050 (93–95%, IQR), consistent with previous research[43]. Furthermore, variable renewable sources constitute an increasing share of all renewable generation, reaching 96% by 2050.

Notably, no new nuclear infrastructure is brought online across the decarbonization pathways. However, existing nuclear capacity remains available across all the near cost-optimal decarbonization pathways, contributing between 210 and 2000 TWh of generation and providing approximately 100 GW of capacity in 2050 (Fig. 2d and Supplementary Fig. 10). By contrast, most existing nuclear infrastructure retires by 2035 in the least-cost current policy pathway. This pattern suggests that while nuclear generation is an important component of a net-zero power sector capable of providing firm power, its continued use without an emissions constraint is not economical after the expiration of the IRA tax credits[46]. When considering both renewable energy and nuclear power, the median contribution to power generation is 98.1% (97.9–98.5%, IQR) by 2050, underscoring the importance of a low-carbon power system (Supplementary Fig. 11).

Figure 2e shows that electricity generation from natural gas decreases from present levels (~1300 TWh) to nearly zero for most near cost-optimal decarbonization pathways by 2050. This decrease is not strictly monotonic, as a temporary increase in natural gas electricity generation occurs between 2030 and 2035 when federal IRA tax credits expire. The rebound in natural gas consumption for power

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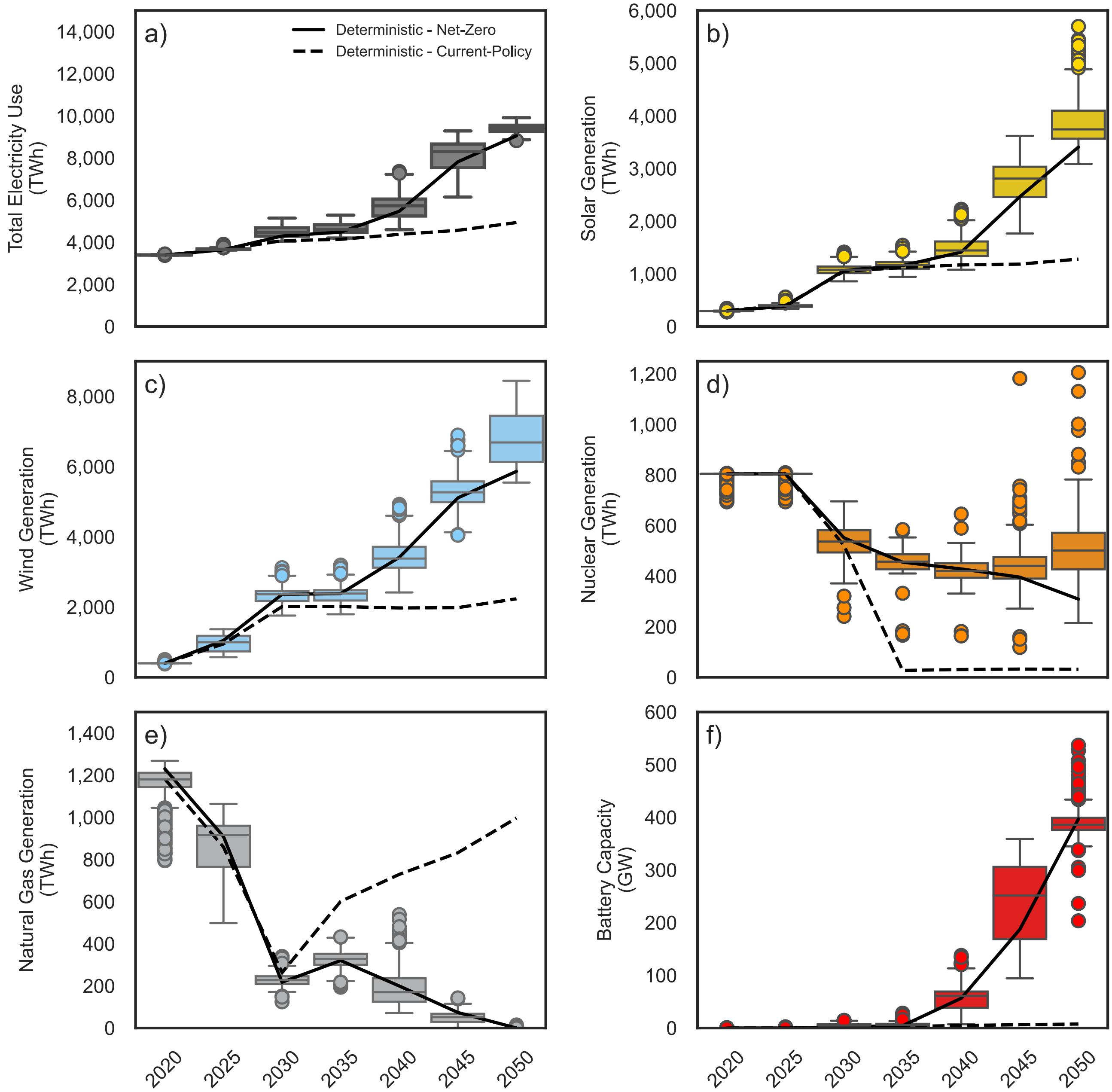

Fig. 2 | Power sector characteristics in near cost-optimal net-zero CO_2 pathways. Near cost-optimal pathways in the power sector where box plots show (**a**) total electricity use across the entire energy system, (**b**) electricity generation from solar, (**c**) electricity generation from wind, (**d**) electricity generation from nuclear and (**e**) electricity generation from natural gas all in terawatt-hours (TWh). **f** shows the battery capacity in gigawatts (GW) deployed in the near cost-optimal decarbonization pathways. The solid lines show the deterministic least-cost net-zero pathway, while the dashed lines depict the least-cost current-policy. Box plots indicate median (middle line), 25th, 75th percentile (box) and 1.5 times the inter-quartile range from the first and third quartiles (whiskers) as well as outliers (single points). Source data are provided as a Source Data file.

generation is most prominent in the least-cost current-policy scenario, exceeding 1000 TWh in 2050. Consequently, additional policy measures beyond the IRA will be essential to fully decarbonize the power sector.

Substantial investments in electricity transmission capacity will be necessary to support the high levels of electrification in the net-zero pathways. Based on the regional representation of the U.S. energy system in Temoa (Supplementary Fig. 1), the results suggest the need for 47 GW (46–49 GW, IQR) of new inter-regional transmission lines between California and the Southwest by 2050. Substantial transmission expansion also occurs between the Central and North-Central regions, totaling 50 GW (45–57 GW, IQR), with the highest pathway reaching 106 GW. Other pathways also indicate the need for transmission expansion in various regions, such as between California and the Northwest and between the Southwest and the Northwest. New transmission into and out of the Northeast, Mid-Atlantic, Southeast, and Texas is comparatively small. The consistent deployment of this transmission capacity in the near cost-optimal pathways highlights the benefits derived from inter-regional electricity transfer in these regions.

Hydrogen consistently meets hard-to-decarbonize demands

Hydrogen has the potential to play an important role in decarbonization efforts, particularly in the industrial and transportation sectors[47,48]. Consistent with other studies that identify hydrogen as a key component of a net-zero future, Fig. 3a shows a median

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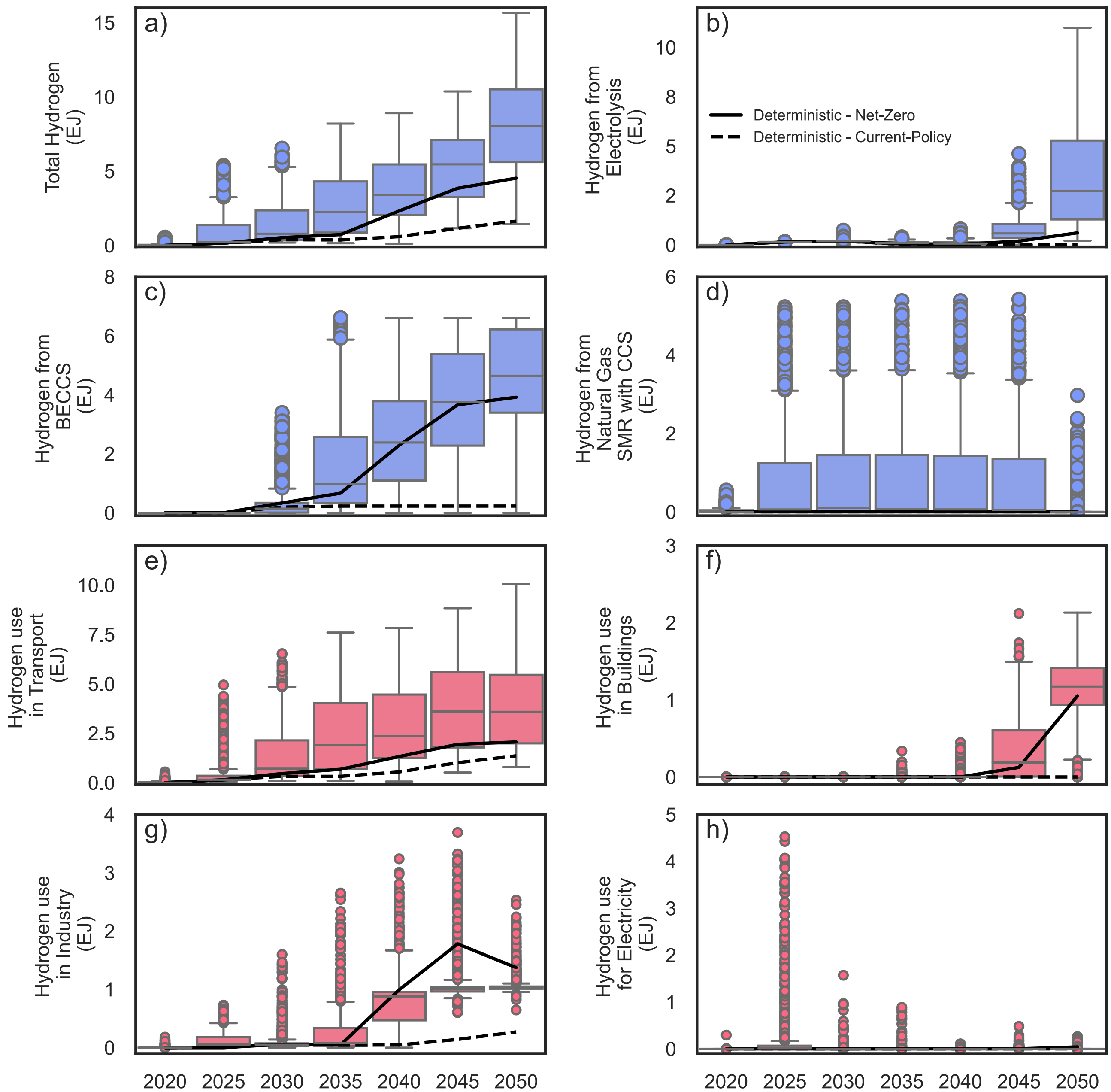

Fig. 3 | Hydrogen production and consumption in near-cost optimal net-zero CO_2 pathways. The box plots in panels (**a**–**d**) show hydrogen production from 1100 near cost-optimal net-zero pathways: (**a**) total hydrogen production, **b** hydrogen from electrolysis, **c** hydrogen from bioenergy with carbon capture and storage (BECCS), and (**d**) hydrogen from natural gas steam methane reforming with carbon capture and storage (SMR with CCS), all in exajoules (EJ). The box plots in panels (**e**–**h**) show where hydrogen is used across the energy system in the near cost-optimal net-zero pathways: (**e**) transportation, (**f**) buildings, (**g**) industrial, and (**h**) electric sectors. The solid lines show the deterministic least-cost net-zero pathways, while the dashed lines in each panel represent the deterministic current-policy pathways. Box plots indicate median (middle line), 25th, 75th percentile (box) and 1.5 times the inter-quartile range from the first and third quartiles (whiskers) as well as outliers (single points). Source data are provided as a Source Data file.

production of 8.0 EJ (5.6–10.5 EJ, IQR) by 2050[43]. While the least-cost net-zero pathway shows 3.5 EJ of hydrogen production in 2050, this value is at the lower end of a broad distribution of hydrogen production across the near cost-optimal net-zero pathways.

Figure 3b–d show that the primary mechanisms for hydrogen production up until 2040 are from natural gas steam-methane reforming and bioenergy with carbon capture and storage (BECCS). In 4% of the near cost-optimal pathways, steam methane reforming with CCS produces at least 1 EJ of hydrogen, reaching up to 3 EJ in pathways with the highest hydrogen production via this method. In 2045 and 2050, electrolysis emerges as a cost-competitive alternative, supplanting hydrogen production from natural gas steam-methane reforming. The IRA tax credit, Internal Revenue Code section 45 V, incentivizes green hydrogen production with a subsidy of up to \$3/kg of H_2. In the database used for this analysis, both electrolysis from new renewables and BECCS qualify for the full credit, while steam methane reforming with CCS qualifies for a \$1/kg of H_2 credit. These incentives result in an increase in total hydrogen production from 2030 onwards. While hydrogen proves to be an attractive energy carrier, the chosen pathway to production is sensitive to emissions and cost assumptions. For example, a sensitivity test on the exogenous fuel prices indicates that high fuel prices would result in considerably more hydrogen production via steam methane reforming in the early years of the modeling horizon (Supplementary Note 3). The carbon dioxide removal benefits from BECCS also prove to be an attractive way to take advantage of the federal tax credits and meet CO_2 constraints in the model.

Figure 3e–h illustrate that hydrogen is primarily used in the transportation sector, followed by industrial applications. In the transportation sector, 1.5 EJ (1.2–1.7 EJ, IQR) of hydrogen are used in 2050 for fueling fuel-cell vehicles, particularly heavy-duty vehicles. Additionally, 2.1 EJ (0.4–4.0 EJ, IQR) of hydrogen is used for synthetic fuel synthesis, serving several transportation demands. In the industrial sector, the primary role of hydrogen is to replace conventional boilers and meet the demand for process heat. Hydrogen use for industrial processes converges around 1.0 EJ in 2050 across all net-zero pathways. Hydrogen is used for synthetic natural gas production for heating in the residential and commercial sectors only in the final decade, with a median 2050 hydrogen use of 1.2 EJ (0.9–1.4 EJ, IQR). While hydrogen is a viable option for electricity generation in combined cycle power plants, it was seldom chosen in the near cost-optimal net-zero pathways. However, in a subset of these pathways, substantial amounts of hydrogen are used for electricity generation in 2025. The presence of two tax incentives in the IRA, one for hydrogen production and the other for clean electricity generation facilitates this choice. As the IRA provisions expire, the use of hydrogen-enabled power plants diminishes in future time periods, but the capacity remains to meet power sector reserve margins.

CO_2 removal and management span a range of deployment

As detailed above, all of the net-zero CO_2 emissions scenarios retain some fossil fuel use across in 2050. The resulting residual CO_2 emissions are primarily from hard-to-decarbonize sectors like aviation or high-temperature processes in the manufacturing sector. Given these residual emissions, carbon management, and particularly carbon dioxide removal (CDR), is likely to play a pivotal role in enabling net-zero futures. Figure 4 shows the carbon management technologies represented in the net-zero pathways, including bioenergy with carbon capture and storage (BECCS), coal and natural gas electricity generation with carbon capture and storage (CCS), and direct air capture (DAC). The near cost-optimal pathways exhibit a wide range of potential deployment levels for these technologies, with some pathways more heavily reliant on carbon mitigation options.

Figure 4a shows that most near cost-optimal pathways have a notable reliance on BECCS. BECCS can be an attractive tool in decarbonization efforts, as it couples the production of energy carriers (electricity or hydrogen) that can then meet service demands across the energy system with carbon dioxide removal. While the contribution to electricity generation from BECCS remains minimal in the near cost-optimal pathways, many pathways incorporate hydrogen production (discussed above). Coal power with CCS and natural gas steam methane reforming with CCS are not deployed in the least-cost current-policy or the least-cost net-zero pathways. By contrast, Figs. 4b, c depict that these technologies are extensively deployed in a small subset of near-cost-optimal net-zero pathways. Overall, total CCS, calculated as the sum of BECCS, coal CCS, and natural gas CCS, amounts to 690 Million tons of CO_2/year (Mt CO_2/yr) (250–1030 Mt CO_2/yr, IQR) in 2050 in these pathways (Fig. 4d).

Figure 4e shows that the median DAC deployment in 2030 (when the technology first becomes available in the model) is 0.45 gigatons of CO_2/year (Gt CO_2/yr) (0.10–1.18 Gt CO_2/yr, IQR). Currently, DAC is a nascent technology and has not been deployed on a large scale. However, the IRA tax credit (Internal Revenue Code section 45Q) can incentivize the adoption of DAC. Even in the least-cost current-policy scenario (i.e., without a net-zero requirement), DAC is employed to take advantage of the available tax credits. Consequently, the model builds and uses DAC capacity while these tax credits remain in effect until 2033. The tax credits catalyze capital investments, and the infrastructure continues to be used beyond the expiration of the credits. In 2050, DAC use is expanded in the net-zero pathways to compensate for residual CO_2 emissions from hard to decarbonize processes[49], reaching 1.22 Gt CO_2/yr (0.97–1.50 Gt CO_2 /yr, IQR). This wide range of outcomes suggests that DAC deployment is sensitive to cost shifts and incentives, at times serving as a backstop in achieving net-zero targets in response to changes in the rest of the energy system.

Figure 4f displays the range of total geologic sequestration, spanning 0.77 to 1.86 Gt CO_2/yr in 2050, with a median result of 1.70 Gt CO_2/yr. The least-cost net-zero pathway prioritizes the extensive sequestration of CO_2 rather than using it for synthetic fuel production[50]. However, near cost-optimal pathways indicate that net-zero futures are possible with lower levels of geologic sequestration of CO_2.

Near cost-optimal pathways may differ greatly from cost-optimal

To understand the characteristics of near cost-optimal decarbonization pathways in more detail, we used clustering approaches to identify "illustrative" pathways that represent groups of decarbonization pathways. These illustrative pathways offer insights into key differences between the least-cost solution and solutions obtained with a 1% slack on the total system cost. As described in Supplementary Method 2, the pathways are identified using k-means clustering on the near cost-optimal decarbonization pathways. Figure 5 shows results for six illustrative pathways that differ in the deployment of hydrogen, DAC, and energy system-wide electricity use. These groups were chosen as they represent important levers in decarbonization efforts[51–53].

Figure 5a presents carbon dioxide emissions for the chosen illustrative pathways. While the timing and magnitude of mitigation measures vary across the selected pathways, there are some observable common trends. The CO_2 constraints in this study apply a linear reduction to net-zero emissions by 2050. However, these limits are not binding in 2030 due to the decarbonization impacts of the IRA. Further, the power sector is generally the first to decarbonize, consistent with other studies[53]. The pathways representing low hydrogen and high electricity (Low H_2 and High Elec in Fig. 5) deploy coal power but mitigate these emissions with CCS. There are also commonalities in the primary energy consumption of illustrative pathways shown in Fig. 5b. Increased deployments of solar, wind, and biomass accompanied by reduced or eliminated coal and petroleum use are ubiquitous. All cases greatly reduce or eliminate power sector, transportation, and building emissions but must contend with residual CO_2 emissions from hard-to-decarbonize industrial processes and upstream fuel emissions.

Carbon management is required in all illustrative pathways, but there is heterogeneity in the technologies chosen for this purpose. For example, the low hydrogen and high electricity pathways rely on carbon management from several technologies. In contrast, other pathways, such as the ones representing high hydrogen or DAC use, rely heavily on one carbon management option. The carbon removal in the high DAC case allows for higher emissions across the energy sector, resulting in higher petroleum consumption and lower biomass use compared to the low DAC pathway. More carbon management is required in the low electricity pathway, with increased DAC use driving higher natural gas consumption compared to the high electricity pathway. Hydrogen can play an important role as a low-carbon energy carrier. Its absence in the low hydrogen pathway results in higher transportation and industrial emissions. The pathway with high hydrogen use shows increased biomass consumption compared to the low hydrogen case, indicative of the hydrogen production process via BECCS.

Tradeoffs and synergies in decarbonization technologies

Different energy sources and end-use technologies tend to be used more frequently alongside or in the absence of other options. Figure 6

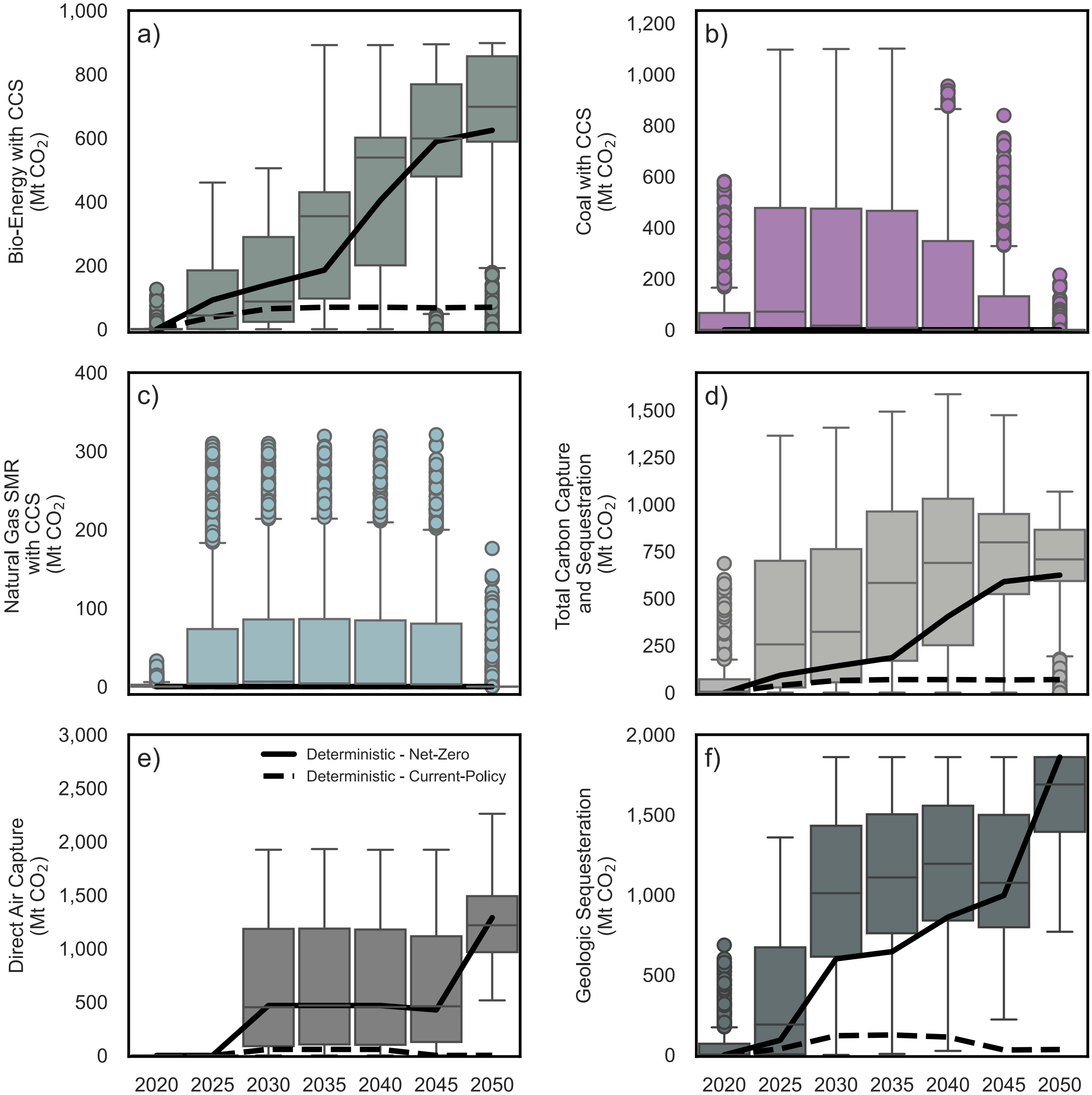

Fig. 4 | Carbon management technologies in near cost-optimal net-zero CO_2 pathways. The box plots show the deployment of (**a**) bio-energy with carbon capture and storage (BECCS), **b** carbon capture and storage from coal plants (Coal with CCS), **c** carbon capture and storage from natural gas steam methane reforming (natural gas SMR with CCS), **d** total carbon capture and storage (CCS) as the sum of BECCS, coal CCS, and natural gas CCS, **e** direct air capture, and (**f**) total geologic sequestration in million tons of CO_2/year (Mt CO_2/year) across 1100 near cost-optimal pathways to achieve net-zero CO_2 by 2050. The solid lines show the deterministic least-cost net-zero pathways, while the dashed lines in each panel represent the deterministic current-policy pathways. Box plots indicate median (middle line), 25th, 75th percentile (box) and 1.5 times the inter-quartile range from the first and third quartiles (whiskers) as well as outliers (single points). Source data are provided as a Source Data file.

explores the relationships between select technology deployments across the near cost-optimal decarbonization pathways in 2050, showing correlations among energy sources and carriers (Fig. 6a), among end-use technologies (Fig. 6b), and between these two groups (Fig. 6c). A positive correlation indicates that the technologies are more often deployed together, while a negative correlation suggests potential competition between technologies. The results only show the strength of the correlation. Two technologies may have a positive correlation even if both have low deployment levels or overall use is decreasing.

In Fig. 6a, solar generation, wind generation, and battery capacity demonstrate a notable positive correlation. This association stems from the critical role batteries play in ensuring reliability as the adoption of variable renewable energy sources like solar and wind increases. Hydrogen is produced extensively via electrolysis in the near cost-optimal net-zero pathways in 2050. This pattern drives the positive correlations between hydrogen production with wind generation, solar generation, and battery capacity, as additional renewable generation provides a carbon-free energy source for hydrogen electrolyzers. In relation to fossil fuels, increased hydrogen use leads to

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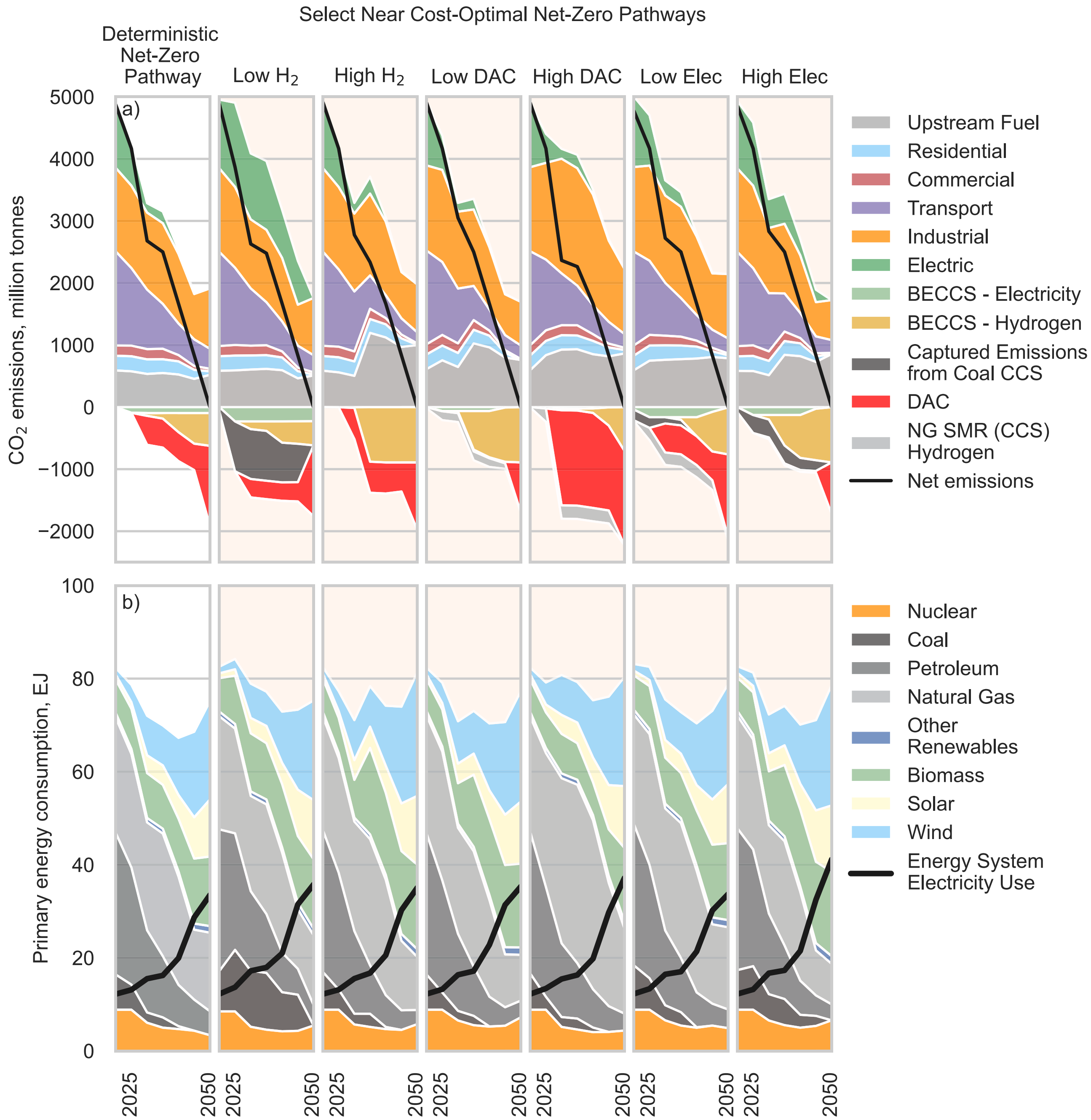

Fig. 5 | Illustrative near cost-optimal net-zero CO_2 pathways. a CO_2 emissions in million tons, and (**b**) primary energy consumption from 2020 to 2050 in exajoules (EJ) for the deterministic net-zero and illustrative near cost-optimal pathways with low/high hydrogen production (Low/High H_2), low/high direct air capture use (Low/High DAC), and low/high overall electricity use (Low/High Elec). BECCS–Electricity refers to bioenergy with carbon capture and storage to produce electricity. BECCS–Hydrogen refers to bioenergy with carbon capture and storage to produce hydrogen. NG SMR (CCS) refers to natural gas steam methane reforming with carbon capture and sequestration. Source data are provided as a Source Data file.

reduced coal consumption but has a less dramatic impact on natural gas consumption (Supplementary Note 4). While hydrogen commonly replaces natural gas in the industrial sector, this negative relationship is dampened due to pathways in which hydrogen is produced via steam methane reforming. Further, Fig. 6a shows that hydrogen is most negatively correlated with petroleum due to fuel switching in the transportation sector, particularly for heavy-duty vehicles. Additionally, biomass exhibits a positive correlation with hydrogen, given the prevalence of BECCS for hydrogen production. The positive correlation between biomass and synthetic liquids arises from the link between hydrogen and synthetic liquids (the latter uses the former for synthesis via the Fischer-Tropsch process). High synthetic fuel use narrows the range of outcomes in the power sector, most notably eliminating coal CCS plants (Supplementary Note 4).

When considering end-use technologies, EVs compete with hydrogen and internal combustion vehicles to meet transportation demand (Fig. 6b). Competition also exists between heat pumps and natural gas heaters in the buildings sector, as well as electric and hydrogen boilers in the industrial sector. Scenarios with more internal combustion engine (ICE) vehicle use are positively correlated with more natural gas heating of buildings. The persistence of these technologies is accompanied by increased DAC use, allowing net-zero emissions targets to be met. In pathways with more deployment of EVs or heat pumps, less DAC use is required. Moreover, electric industrial

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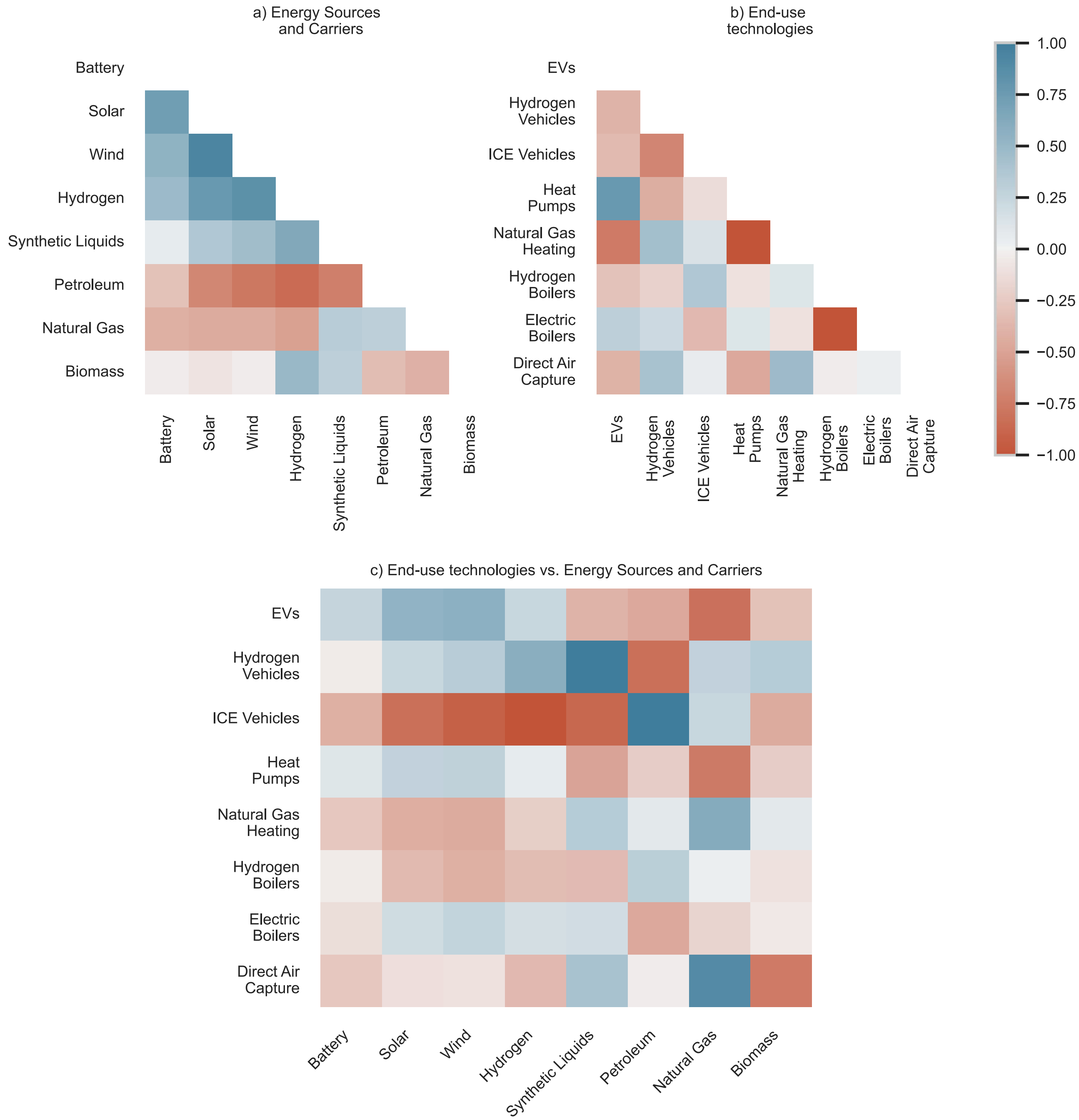

Fig. 6 | Correlations across key energy carriers and technologies across near cost-optimal net-zero CO_2 pathways. A correlation plot showing a subset of key (**a**) energy sources and carriers, (**b**) end-use technologies along with DAC, and (**c**) end-use technologies versus energy sources and carriers across the 1100 near cost-optimal pathways in 2050. Blue represents positive correlations; red represents negative correlations. Battery–battery capacity, Solar–solar generation, Wind–wind generation, Hydrogen–total hydrogen use, Synthetic Liquids–production via the Fischer-Tropsch process, Petroleum–primary energy petroleum use, Natural gas–primary energy natural gas use, Biomass–primary energy biomass use, EVs–electric vehicle use, H_2 vehicles–hydrogen used in transportation, ICE vehicles–internal combustion vehicle use, Heat pumps–heat pump use across the residential and commercial sectors, Natural gas heating–natural gas-based heating use in the residential and commercial sectors, Hydrogen boilers– hydrogen boiler use in the industrial sector, Electric boilers–electric boiler use in the industrial sector, DAC–direct air capture deployment. Source data are provided as a Source Data file.

boilers and heat pumps exhibit a positive correlation with EVs, indicating a trend where the electrification of various end-uses is interconnected. This counters the notion of exclusion or competition among different electrification methods for end-uses.

Figure 6c illustrates the correlation between end-use technologies and energy sources/carriers. Within the transportation sector, EV adoption shows a clear connection to increased renewable electricity generation, displaying positive correlations with wind and solar energy sources. Conversely, EV adoption exhibits negative relationships with petroleum, synthetic fuels, natural gas, and biomass utilization. The integration of hydrogen vehicles also contributes to increased demand for renewable electricity and synthetic liquids but tends to reduce petroleum use. There is a weak reliance on natural gas in net-zero pathways where more ICE vehicles persist. A weak negative correlation also exists between hydrogen and DAC, shaped by two competing patterns. When low- or zero-carbon hydrogen is introduced as an alternative energy carrier, there is a reduced dependency on DAC. However, when hydrogen facilitates the production of synthetic liquid fuels, DAC becomes necessary to capture resulting CO_2 emissions. Figure 6c also shows competition between biomass and DAC, which Supplementary Note 4 shows is driven by BECCS.

Discussion

Deterministic energy system optimization modeling can identify least-cost decarbonization pathways, but input assumptions, model representation, and scenario selection constrain insights. Parametric uncertainty methods quantify the impact of uncertain parameters on model outputs. However, diverse near cost-optimal solutions from an ESOM can provide additional insights that cannot be obtained from deterministic modeling alone. Applying MGA to energy systems models provides distinct and diverse alternative pathways that can be missed by parametric assessment methods. In this study, we applied MGA to assess decarbonization pathways for the U.S. energy system, considering path dependencies from early decision-making and the interactions between different sectors of the energy system. Our analysis reveals distinct categories of decarbonization options: those with consistent adoption across pathways, those experiencing universal decline or elimination, technologies with broad outcome distributions, and options highly adopted in only a few pathways. This categorization enhances our understanding of technology dynamics and decarbonization trends.

In the near cost-optimal decarbonization pathways examined in this paper, there is a notable trend toward widespread adoption of specific technologies such as solar and wind power, grid-connected energy storage, and electrification across various sectors, including industry, transportation, residential, and commercial sectors. These options are consistently chosen for achieving net-zero CO_2 outcomes. Our pathways also consistently show that eliminating coal power without CCS and substantial reductions in petroleum use are required for near cost-optimal decarbonization. Initiating planning now for a just and orderly transition away from these industries, considering the needs of affected communities, is imperative[54].

A broad range of outcomes is possible for emerging energy technologies that could enable decarbonization, such as hydrogen, DAC, CCS, and synthetic fuels. Currently, these options are either minimally deployed or not commercially available. In the near cost-optimal decarbonization pathways explored in this work, their deployment varies from trivial to pivotal, posing challenges for long-term planning. To enable their scaled deployment by mid-century, continued research and development, supportive policies, and early deployment requirements are needed. Widespread deployment of carbon management technologies must overcome many challenges, including biomass resource availability, CO_2 storage costs, and the development of supporting infrastructure such as CO_2 pipelines[55]. Furthermore, the availability of these novel technologies will have substantial implications for natural gas consumption in a decarbonized energy system. Natural gas consumption could remain near current levels in pathways where carbon management technologies are widely deployed. By contrast, pathways in which carbon management technologies are more restricted, natural gas consumption is nearly zero by 2050. The chosen pathway has significant implications for gas system infrastructure, including pipeline utilization, maintenance, and potential expansion or decommissioning. Planning must consider these factors to ensure a successful transition towards decarbonization.

The results indicate several technologies that exhibit a pattern of limited adoption across most decarbonization pathways but experience significant deployment in a small number of pathways. These technologies include new coal with CCS, natural gas SMR with CCS, and synthetic fuels. These technologies serve as potential insurance policies, ensuring that decarbonization goals can still be achieved in scenarios where renewable energy technologies face deployment challenges or substantial cost increases. However, the construction of such facilities requires substantial investment and commitment due to their size and complexity. Therefore, careful consideration is necessary when pursuing these options, weighing their potential benefits as fallback solutions against the overall decarbonization objectives.

The optimization framework used in this paper can help identify the solution space for energy system decarbonization. This solution space contains a diverse array of technically plausible energy pathways. However, technical plausibility is not the same as feasibility. The feasibility of the pathways in the solution space depends on attributes not well-represented in a least-cost optimization framework[56]. For example, consumer behavior and preferences could limit the transition to electric vehicles.[44]. In high-penetration renewable systems, tackling the rate of infrastructure buildout, such as the land requirements for wind and solar farms, can be challenging[57]. Furthermore, all the decarbonization pathways in the solution space would require large investments in supporting infrastructure like hydrogen and CO_2 pipelines, new transmission lines, and EV charging infrastructure. While the modeling to generate alternatives framework used in this paper can provide valuable insights into the decarbonization solution space, additional analytical tools will be required to identify feasible decarbonization options. Such feasibility analysis should consider material and natural resources constraints, labor implications, supply chain vulnerabilities, climate resilience, environmental justice, waste generation, and energy equity. Additionally, the range of plausible solutions and feasible space is likely to differ for different regions based on local resource availability, behavioral preferences, existing infrastructure and policy environments, among other factors.

Current and future U.S. policy will significantly shape the energy transition towards a net-zero CO_2 system. The debate over the optimal policy mechanisms to achieve this transition has been ongoing for decades. Existing policies have made progress towards decarbonization. However, our results suggest that reaching net-zero GHG emissions in the U.S. energy sector will require additional policy interventions after 2033, when key provisions of the IRA expire. Our results also highlight a large and diverse solution space for energy system decarbonization, in which technology deployment levels can vary widely. The results also indicate that deploying some technologies would lock in the need for synergistic technologies and push out the deployment of others. For example, expanding infrastructure for synthetic liquid fuels would, to a certain extent, reduce the need for EVs but would require DAC. Similarly, deploying EVs would likely be coupled with electrifying other end-uses in buildings and industry. While it is likely prudent to avoid locking out specific technologies, decisions made over the next decade will narrow the solution space and technology sets available to reach net-zero by 2050. Decision makers should thus be aware of potential path dependencies to avoid unintended consequences or unexpected outcomes as the United States moves toward a sustainable and decarbonized energy system.

Methods

Tools for energy model optimization and analysis (Temoa)

We use the Tools for Energy Model Optimization and Analysis (Temoa), an open-source technology-rich energy systems model. Temoa is structured as a linear problem that can generate the least-cost pathway for energy system development over a user-specified time horizon, subject to system- and user-defined constraints. Temoa represents the energy system as a network of interconnected technologies and commodities. This allows for technology-rich representations of the major sectors of the energy system, which are interlinked through a network. For example, there is competition for energy carriers such as electricity to meet different energy service demands across and within the different sectors. Supplementary Method 1 details the objective function, which calculates the present

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Table 1 | Summary of database assumptions to represent the U.S. energy system

Category	Description
Fuel Supply	Fossil fuel prices are specified exogenously from projections in the 2022 Energy Information Administration (EIA) Annual Energy Outlook's Reference Oil Price case for Net-Zero runs No-Policy runs[45]. A supply curve constructed from the 2016 Billion-Ton Report[61] reflects biomass costs and supply. There are no constraints placed on the availability of other fuels.
Electric	Costs and performance characteristics for new electric generators from the "Moderate-Market" scenario of the Annual Technology Baseline 2021[62].
Transportation	The transportation sector is divided into four modes: road, rail, air, and water. The demands, efficiencies, and costs for these modes are drawn from sources including the U.S. Environmental Protection Agency's (EPA) nine-region market allocation (MARKAL) database[59], Net-Zero America study[11], and the National Renewable Energy Laboratory's (NREL) Electrification Futures Study (EFS)[63].
Commercial	The service demands in the commercial sector are adopted from NREL EFS[63]. The techno-economic parameters of the end-use technology are from the EIA[64]. Existing capacity of technologies are from the EPA's MARKAL database[58,59].
Residential	The service demands in the residential sector are from NREL EFS[63]. The techno-economic parameters of the end-use technology are from the EIA[64]. Existing capacity of technologies are from the EPA MARKAL database[58,59].
Industrial	End-use demands in the industrial sector are aggregated based on the North American Industry Classification System. Demands are derived from the Manufacturing Energy Consumption Survey[65]. A set of common industrial processes represents the energy consumption in the manufacturing sector to account for the heterogeneity across the industrial sector. These industrial processes include 1) process heating, 2) conventional boiler use, 3) combined heat and power or co-generation systems, 4) machine drives, 5) facility heating ventilation and air conditioning systems, 6) process cooling and refrigeration and 7) a catch-all 'other' energy use category.
Hydrogen	Cost and efficiency assumptions from the International Energy Agency Future of Hydrogen Report[47].
Regions	The United States is divided into nine regions, as shown in Supplementary Fig. 1.
CCS	Bio-Energy Carbon Capture and Sequestration data are drawn from averages of Integrated Assessment Models[66]. Powerplant Carbon Capture and Sequestration data comes from PowerGenome[46].
Fischer-Tropsch Fuels	The capability of synthesizing Fischer-Tropsch fuels using H_2 and CO_2 is included in the model based on published techno-economic parameters[67].
Direct Air Capture	Capital and operating costs are from the literature[68]. The transport of CO_2 to sequestration sites is modeled using a cost curve, which has eight steps[11].
Renewable Resources and Transmission Build Out	Renewables data are compiled using PowerGenome[46], an open-source tool that allows users to create input datasets for power system capacity expansion models. Annual hourly variable renewables capacity factor data for a representative year (2012) are used to develop representative intra-annual time slices. Historical capacity factors of existing capacity are obtained from EIA, while data for potential new generators are obtained from datasets developed by Vibrant Clean Energy.
Inflation Reduction Act (IRA) Provisions	The database incorporates the IRA provisions, including the investment and production tax credits for renewable electricity generators, carbon capture, and use/sequestration, the production tax credit for existing nuclear capacity, the clean hydrogen production tax credit, and tax credits for passenger and commercial vehicles (Detailed in Supplementary Method 4 and Supplemental Table 1-4).
Discount Rate	Social discount rate is 5%. Technology-specific discount rates are from PowerGenome.

value of the cost of energy supply, considering financed capital costs, fixed costs, and variable costs. A demand constraint drives the model and ensures supply is met in every time interval. In Temoa, electricity demand is determined endogenously based on the requirements of the rest of the energy system, for which service demands are specified exogenously. A commodity balance constraint ensures that intermediate system commodity demands are met. A capacity constraint ensures that the capacity of a given process within the model is sufficient to support its activity. Installed capacities, associated activities, fuel shares, supply, and end-use technologies are all decision variables optimized in Temoa. Technology choice is based on several techno-economic criteria and endogenized within the model. The operational characteristics, costs, and lifetimes all influence which technologies are chosen. The model has perfect foresight across the time horizon, enabling decision-making with the knowledge of future developments like carbon emission targets or changes in fuel price. The optimization of technology choice in end-use technologies is one of the key features of Temoa, similar to the MARKAL TIMES model[58,59]. Finally, several physical and operational constraints like ramping considerations, energy storage charging and discharging rates, and reserve margin requirements are imposed on the linear problem. Supplementary Method 1 contains a description of the major constraints in the model while the complete algebraic formulation of Temoa is presented elsewhere[41]. The model source code[42], and datasets[60] are available on GitHub, with a commitment to full transparency to allow for easy replication of our analyses.

In the version of Temoa used in this work, the model balances energy commodity flows across a set of ordered time slices, which can represent different combinations of seasons and times of day to represent seasonal and diurnal variations in energy supply and demand. While it would be preferable to model the variation in electricity supply and demand for all 8760 h of the year, doing so would impose heavy computational constraints in running the model and would not allow us to deploy the MGA approach. Here, we use highly aggregated (12) time slices to allow for the additional computational burden imposed. Supplementary Note 1 discusses using this temporal resolution instead of representative days.

Input database description

For this analysis, we use a nine-region database of the U.S. energy system developed as part of the Open Energy Outlook Initiative[60]. Table 1 summarizes the information included in this database with more detail in Supplementary Method 3. Supplementary Method 4 also describes the IRA provisions included in this analysis. Supplementary Note 3 contains an assessment of parametric uncertainty on key uncertain input parameters of the database.

Details on MGA Formulation

Supplementary Fig. 1 shows a flow diagram laying out the main inputs detailed above, and the major outputs analyzed in this work. A deterministic least-cost solution is first obtained by minimizing the total system cost subject to physical, operation, and network constraints as described above and Supplementary Method 1. The net-zero scenario has an additional emissions constraint driving CO_2 to zero by 2050. Exogenously specified end-use demands drive the model which makes technology investment decisions such that the result is the lowest present value of the total system cost. In the case of MGA, the structure of the deterministic optimization problem changes by altering the model's original objective function and introducing a new constraint. This constraint allows the model to exceed the original objective function value (i.e., minimized total system cost) by a user-specified threshold or slack. The addition of this slack allows for exploring near-optimal solutions in the decision space by accepting a small increase in the total system cost relative to the optimal solution. Additionally, the objective function in MGA runs is reformulated to emphasize a search direction. In this work, the objective function minimizes the sum of weighted activity (or flow) of technologies across the time horizon in the model, i.e. each technology is represented by a cumulative activity across the model time horizon. The technology representation in the current work is diverse and all technologies are chosen agnostically to be a part of the objective function to influence the search direction. Weights were sampled from a uniform distribution [−1, 1], assigned independently for each activity, which allows for the development of larger solution diversity with fewer MGA runs. The activity variables are chosen instead of their capacity counterparts as they directly represent each technology's contribution towards meeting end-use demands. This formulation artificially incentivizes/de-incentivizes the activity of technologies based on the sign and magnitude of the coefficient. For example, larger weights put the associated decision variable at a relative disadvantage, allowing other technologies to enter the solution[30]. This process is repeated 1100 times, with each iteration including an updated set of objective function coefficients from the uniform distribution. Supplementary Note 2 contains justification for the chosen number of MGA iterations. In this way, MGA can explore the decision space to find alternative solutions that are very different in decision space but have a total cost close to the original solution and are bound by the user-specified slack value. Equation (1) summarized the MGA formulation.

$$\begin{aligned} &\text{Min} \sum_i w_i x_i \\ &\text{s.t. } f(x) \le f(x^*) \times (1+\delta) \end{aligned} \tag{1}$$

Where $w_i \in unif(-1,1), x_i$ represents the decision variables in the model, $f(x)$ is the new total system cost, $f(x^*)$ is the total system cost resulting from the least-cost optimization and δ is the percent additional slack on the total system cost (1% in our case). While deviations of a larger magnitude have been observed in the electric sector (average of 5%)[27], we chose 1% because our slack is applied broadly over the entire U.S. energy system and not just the electric sector, and we wish to explore pathways that are near cost-optimal that are not necessarily informed by historical deviations.

Data availability

Source data are provided with this paper.

Code availability

The code used to perform the modeling to generate alternative runs is available. (https://doi.org/10.5281/zenodo.13300106).

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Author contributions

A.S. wrote the initial draft, carried out the model runs, and performed the data analysis. A.V. provided technical support, aided in data analysis and provided edits and reviews for the draft. K.J. reviewed the final draft and contributed to the visualization of model results. C.W. provided technical support and reviewed the final draft. H.E. built the initial framework for the model runs. A.R.Q reviewed the draft and helped shape the final manuscript. J.X.J and P.J. conceptualized the project, acquired funding, and edited and reviewed the final manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Aditya Sinha.

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