Pathways to national-scale adoption of enhanced geothermal power through experience-driven cost reductions

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Abstract

Enhanced geothermal systems (EGS) are one of a small number of emerging energy technologies with the potential to deliver firm carbon-free electricity at large scale but are often excluded from macro-scale decarbonization studies due to uncertainties regarding their cost and resource potential. Here we combine empirically-grounded near-term EGS cost estimates with an experience curves framework, by which costs fall as a function of cumulative deployment, to model EGS deployment pathways and impacts on the United States electricity sector from the present through 2050. We find that by initially exploiting limited high-quality geothermal resources in the Western US, EGS could achieve early commercialization and experience-based cost reductions that enable it to supply up to a fifth of total US electricity generation by 2050 and substantially reduce the cost of decarbonization nationwide. Higher-than-expected initial EGS costs could inhibit early growth and constrain the technology's long-run potential, though supportive policies counteract these effects.

1 Introduction

There is broad consensus in the macro-energy systems literature that low-cost wind and solar power, in combination with various forms of energy storage and demand flexibility, can play a central role in the decarbonization of the electricity sector[1–3]. Nevertheless, studies have also shown that the cost of *complete* decarbonization is highly sensitive to the cost and availability of 'clean firm' resources - those that can be relied on to deliver carbon-free generation regardless of weather conditions[4–6]. Incorporation of even relatively expensive clean firm resources can lower the total cost of a zero-carbon electricity system by reducing the need to overbuild variable renewable energy (VRE) and storage resources to meet demand during extended periods of low VRE output[4].

Enhanced geothermal systems (EGS), which employ advanced drilling and reservoir engineering techniques to enable geothermal power generation in areas that lack natural hydrothermal features, are one emerging energy technology with the potential to fill this clean firm role. With ongoing commercial-scale demonstration programs and an estimated global resource base of hundreds of terawatts[7–9], EGS is one of only a handful of technologies that could plausibly deliver new clean firm generation on the scale and timeline necessary to contribute meaningfully toward mid-century decarbonization goals[10]. Other potential candidates include nuclear fission and fossil technologies utilizing carbon capture and sequestration (CCS), both of which have relatively high technology readiness levels and terawatt-scale resource potentials[11,12]. Conventional geothermal power (also referred to as hydrothermal) is a proven clean firm generation technology, but faces extreme resource limitations due to its reliance on rare geologic features. For example, while the United States has already developed the majority of its available high-temperature hydrothermal resources, these resources exist exclusively in the western half of the country and currently account for only 0.4% of national electricity generation[13]. Biomass combustion and reservoir hydropower are also mature clean firm technologies, but sustainability concerns and resource limitations, including a lack of undeveloped hydropower potential in many regions of the world and strong demand for biomass in other economic sectors, mean these technologies will not likely be able to meet the full clean firm power needs of future electricity systems in most geographies[14–16]. Nuclear fusion and space-based solar power are both potential sources of nearly unlimited clean firm power, but both require major technological breakthroughs and have yet to be demonstrated at any scale. Finally, while long-duration energy storage (LDES) resources with very low energy capacity costs (e.g., geologic storage of electrolysis-derived hydrogen or emerging low-cost battery chemistries) can provide sustained generation during VRE droughts, results from the literature suggest that storage and input energy constraints prevent them from acting as 1:1 substitutes for firm resources[5,17]. We therefore consider LDES to be a separate resource class in this paper.

Despite its status as one the few potential near-term scalable options in the critical clean firm technology category, EGS has only rarely been included in macro-scale energy systems decarbonization studies to date (see e.g., its omission in Larson et al.[1], Williams et al.[2], and Denholm et al.[3]). In many cases EGS has been excluded due to data limitations, as comprehensive temperature-at-depth datasets are unavailable for most regions outside of the contiguous United States. Even where such data is available, the lack of adequate real-world EGS cost and performance data has in the past forced modelers to make highly speculative assumptions. Past studies that include EGS in the pool of available resources have thus focused on scenarios where it is either an undemonstrated technology with prohibitive costs[3,18,19], or a fully-commercialized one available to be deployed at multi-gigawatt scale and at low cost[18–21].

In the present work we address these gaps in the literature by utilizing newly-available data from recent EGS demonstration projects to develop an empirically-grounded near-term cost and performance baseline for the technology. We use these baseline assumptions to develop high-resolution supply curves for EGS in the contiguous United States, and incorporate these supply curves into an electricity system capacity expansion model simulating the evolution of the US electricity sector from the present day through 2050 across multiple sequential planning periods. For EGS and other emerging clean firm technologies, the model incorporates endogenous experience curves - by which technology costs decline with increasing deployment as a result of learning-by-doing - and deployment rate limits that constrain the pace of growth in annual capacity additions. Thus, future scale-up and cost reductions for these nascent technologies are dependent on their ability to achieve initial commercial uptake.

We find that despite prohibitively high near-term EGS costs in most regions of the contiguous US, sufficient high-quality geothermal resources likely exist in the western half of the country to enable commercially-competitive deployment under baseline cost assumptions in the early 2030s. This early deployment can in turn drive cost reductions via learning-by-doing that enable economic exploitation of lower-quality and deeper resources, leading to hundreds of gigawatts of EGS deployment nationally by 2050 across a wide range of technology cost and policy scenarios. Long-run EGS deployment in these scenarios is geographically widespread, with more capacity installed in the eastern US than in the west in many cases despite a significantly lower quality geothermal resource base. While higher-than-anticipated EGS costs could delay or prevent early commercialization and constrain long-run deployment potential to regions with the highest quality resources, targeted near-term policies can counteract these effects. These results suggest that EGS could play a far larger role in decarbonization of the US electricity sector than has been previously assumed, and that policies promoting early deployment of EGS and other clean firm technologies could be of critical importance to the success of long-run decarbonization efforts.

2 Results

2.1 Near-Term Cost Estimates for Enhanced Geothermal Systems

Results from recent public and private MW-scale EGS demonstration projects in the United States have helped to reduce uncertainties in key cost and performance metrics for the technology, including the cost of drilling in hard high-temperature basement formations, fracture hydraulic conductivity in engineered EGS reservoirs, uniformity of flow across wellbore production zones, and hydromechanical behavior of reservoirs under flexible operating conditions[7,8,22]. Here we incorporate data reported from these projects into an EGS cost model developed in prior work[21], such that assigned values for these wellfield cost and performance parameters are representative of the current state of the art. We model a near-term commercial reservoir design consisting of five parallel wells with 2.29 km (7500 ft) lateral sections spaced at $\sim$0.24 km (800 ft) intervals horizontally (see Figure S1). We assume this reservoir configuration is achievable after development of approximately 500 MW of demonstration-stage EGS projects, a figure based on currently contracted capacity[23,24]. We use this model to estimate near-term (circa 2030) commercial EGS project capital and operating costs as a function of reservoir temperature, depth and surface ambient air temperature for over 80,000 candidate project areas (CPAs) across the continental US, incorporating both deep temperature-at-depth data sourced from Blackwell et al.[25] and calculated temperature-at-depth values for 'near-field' regions immediately surrounding large hydrothermal reservoirs. Cost modeling and resource base assumptions are discussed in greater detail in the Methods section and the Supplementary Information. Due to temperature limitations for existing drilling and stimulation equipment, we consider only resources with reservoir temperatures $\leq 250°$C to be developable initially.

Results of this calculation are shown in Figure 1 in the form of near-term EGS supply curves for the three major synchronized electrical interconnections serving the continental US, for resources with temperatures in the 150-250°C range (a similar plot including resource with temperatures up to 350°C is shown in Figure S2). The figure shows unsubsidized project CAPEX (in 2021 USD) and approximate real levelized cost of electricity (LCOE) as functions of developable EGS potential in each region for both baseline cost assumptions and low/high cost cases that modify all wellfield costs by -33%/+50% to reflect remaining uncertainty. Surface plant costs remain unchanged across these cases, reflecting lower uncertainty.

Total capital costs for the first 100 GW of supply are substantially lower in the Western Interconnection than in the other grid regions, due in part to the availability of near-field resources proximate to identified hydrothermal reservoirs. Baseline EGS costs start at just under $5000/kW at the best near-field sites in the Western US and increase rapidly thereafter as these limited resources are used up. Baseline LCOE for near-field EGS resources (~$55-80/MWh) is competitive with recent power purchase agreement prices for conventional hydrothermal power[26,27]. Initial baseline costs for deep EGS resources outside of near-field regions are generally greater than $8000/kW in the Western Interconnection, and greater than $10,000/kW in the Texas and Eastern Interconnections, with LCOE values much higher than current wholesale electricity prices even in the low cost case[28]. Wellfield costs account for the large majority of total CAPEX for all but the highest-quality resources (Figure S3).

High-quality geothermal resources that enable low-cost EGS are not evenly spread across the large grid regions shown in Figure 1. As illustrated in Figures S4-S9, near-field resources are concentrated near nine large hydrothermal sites in the Western US, with the vast majority surrounding the Geysers and Salton Sea hydrothermal areas in California. While deep EGS resources are more evenly distributed across the Western US in the Blackwell et al.[25] dataset, high-quality deep resources elsewhere are concentrated in the Gulf Coast and Appalachian regions.

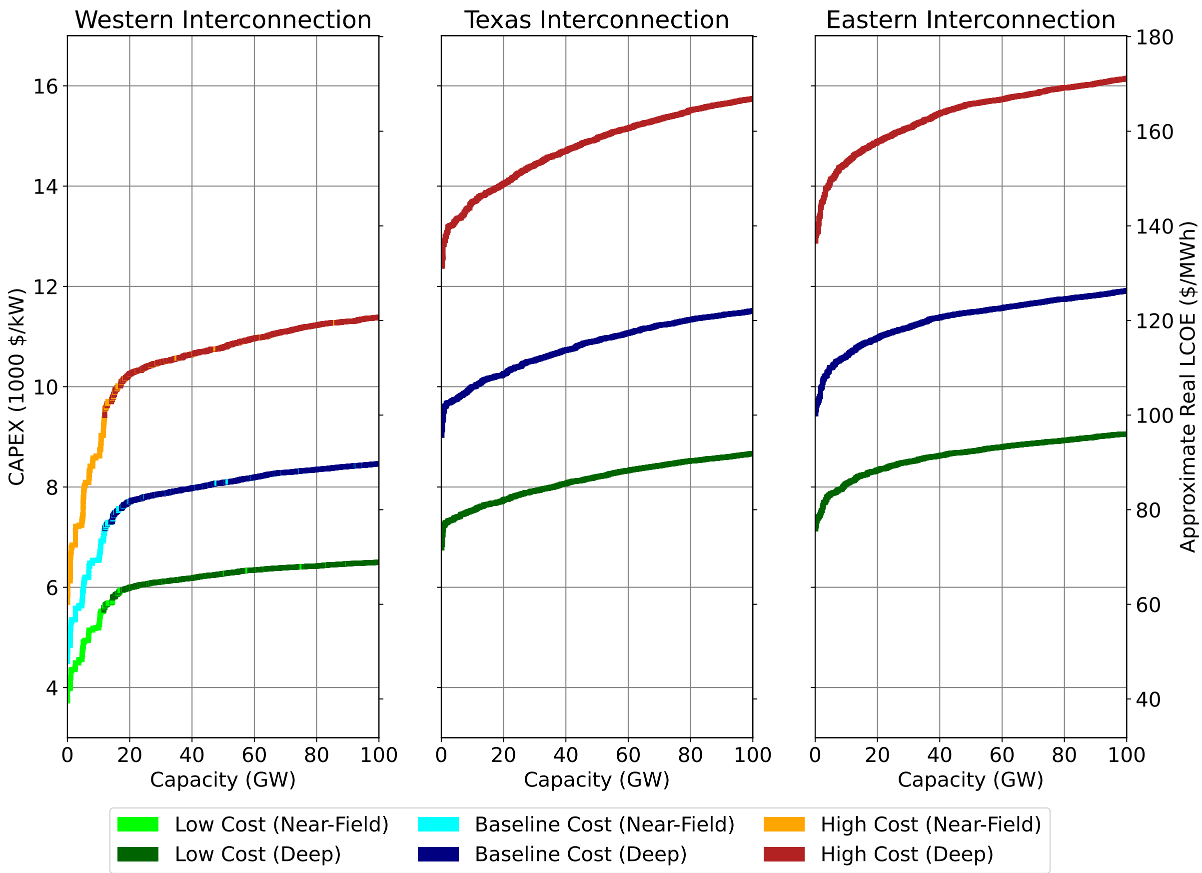

Figure 1: Near-term (circa 2030) unsubsidized EGS CAPEX (total capital expenditure per unit of installed AC electric generating capacity) and approximate real (inflation-adjusted) LCOE as functions of total developable capacity for the three synchronous grids serving the contiguous US, for resources with reservoir temperatures in the 150-250°C range, under three different well-field cost scenarios. Contributions from both near-field and deep resources are shown. Scaling of LCOE with CAPEX is approximate due to variations in ratios of surface to subsurface capital and operating costs. Monetary values here and elsewhere in this paper are given in 2021 USD.

2.2 Experience Curve Analysis of Long-Run EGS Potential

We use multi-stage electricity system capacity expansion modeling with an endogenous representation of learning-driven cost reductions for EGS and other emerging clean firm technologies - nuclear small modular reactors (SMRs) and Allam cycle oxycombustion natural gas plants with 100% CCS* - to assess potential deployment pathways from 2030 through 2050 within a 15-zone model of the contiguous US electricity system (Figure S10). The analysis assumes that costs for these technologies follow a single-factor experience curve given by Wright's Law, such that costs fall by a fixed percentage (the learning rate) for every doubling of total installed capacity from some starting point[29–32].

For nuclear SMRs and Allam cycle gas plants we adopt learning rates of 5% and assumed starting capacities of 500 MW in 2030, based on estimates from the existing literature and announced demonstration projects respectively[31–35]. For EGS we consider learning for wellfields and surface binary-cycle power plants separately, and adopt a 15% baseline learning rate for wellfields and a 10% baseline learning rate for surface facilities. Due to a lack of existing literature estimates or sufficient empirical data with which to calculate EGS learning rates, we use a combination of qualitative assessment following a framework proposed by Malhotra and Schmidt[32] and a review of empirical learning rate observations for analogous technologies - most notably unconventional oil and gas development[36] - to inform these baseline assumptions. We assume that 500 MW-electric of EGS wellfield capacity has been installed by 2030 under demonstration programs and pilot commercial developments[23,24], and that this capacity represents the starting point for wellfield learning. We use the global installed capacity of $\sim$4 GW of binary-cycle power plants as the starting point for surface plant learning[37]. On top of learning-driven cost reductions, we also assume that costs for all emerging technologies fall by 0.5% per year due to ongoing R&D, in line with the convention used in the US National Renewable Energy Laboratory's Annual Technology Baseline[38]. A more complete discussion of experience curve assumptions for emerging technologies is available in the Methods.

We consider only EGS resources up to 250°C to be developable initially due to off-the-shelf equipment temperature limitations, and we assume that higher-temperature resources up to a maximum limit of 350°C are unlocked gradually as a result of successful development in these lower-temperature environments. We also impose a 50% limit on the annual rate of growth in new capacity additions for EGS and competing clean firm technologies in order to reflect limits on the rate at which the necessary supply chains and workforces for these technologies can be expanded. We further assume as a baseline that EGS plants are able to operate flexibly, as described in Ricks et al.[39] and Ricks et al.[21], using results from recent field tests to constrain flexible performance. The approach used to model these capabilities is discussed in greater detail in the Methods section and the Supplementary Information.

Figure 2 illustrates modeled nationwide deployment pathways for EGS under low, baseline, and high initial wellfield cost assumptions under two policy scenarios: 'current policy' and 'net-zero policy,' where the latter imposes a nationwide requirement for 80% carbon-free electricity in 2035 and ratchets up to a net-zero economy by 2050, with either a requirement for zero electricity sector emissions by that date or a \$300/tCO_2 carbon price for any residual emissions (illustrative of the potential cost of offsetting carbon removals or societal willingess-to-pay for further mitigation). Results for installed EGS capacity indicate robust growth in the 2030s at low and baseline costs in all policy scenarios, with deployments being limited by build rate constraints in early periods. This early growth drives reductions in EGS costs, primarily in the less-mature wellfield, enabling additional deployments that reduce costs further in turn. Total installed EGS

*In general we refer to Allam cycle plants as 'carbon-free' in this paper due to a lack of direct emissions. Policies or classifications that categorize technologies based on lifecycle emissions (e.g. technology-neutral clean energy tax credits modeled here) may not recognize this technology as carbon-free due to upstream methane leakage.

capacity in 2050 exceeds 250 GW in all of these scenarios, and reaches more than 850 GW in the low EGS cost, zero-emissions policy scenario. Such extensive deployment is enabled by substantial learning-driven cost reductions, with surface power plant costs reduced by roughly 50% compared to the baseline and wellfield costs reduced by 75% or more by the beginning of the final period. Long-term deployment outcomes for the low and baseline cost cases are fairly similar, likely because the absolute difference in EGS cost between these two cases becomes relatively smaller after substantial learning has occurred.

In the high EGS cost case (where the lowest cost near-field resources cost $\geq$\$6,000/kW), deployment is more sluggish, and the technology fails to achieve large-scale commercial uptake in the early 2030s. This lack of initial deployments in turn causes costs to remain high, making EGS a less competitive option even as the value of clean firm power increases in the later stages of decarbonization. In the current policy scenario, commercial liftoff begins in the late 2030s, leading to only 45 GW of EGS deployed nationwide by 2050. Greater deployment occurs in the net-zero policy scenarios, particularly when there is a requirement for zero electricity sector emissions, but still lags behind the deployment levels observed in the lower-cost cases.

The lower panes of Figure 2 show how deployment of EGS affects wholesale electricity prices in these scenarios. Under current policy, prices fall continuously through 2050 even without EGS deployment, but are reduced further by the availability of EGS at low or baseline costs. As shown in Figure S11, EGS deployment also leads to 6-64% lower electricity sector emissions in these scenarios. Under a net-zero policy requirement, consumer electricity prices rise by 29-85% in the final stage of decarbonization when EGS is unavailable, reaching \$85/MWh in the zero-emissions case. Deployment of EGS reduces wholesale electricity costs by 22-55% (\$13-47/MWh) across the three cost cases. In particular, the availability of EGS substantially reduces the cost premium associated with achieving a zero-emissions electricity sector.

Current US federal supports for clean electricity – primarily the technology-neutral carbon-free electricity investment tax credit (ITC) – are critical to the successful scale-up of EGS technology. In Figure S12 we show outcomes under an alternate policy scenario where these tax credits are rolled back. In this scenario only low-cost EGS experiences substantial long-run deployment.

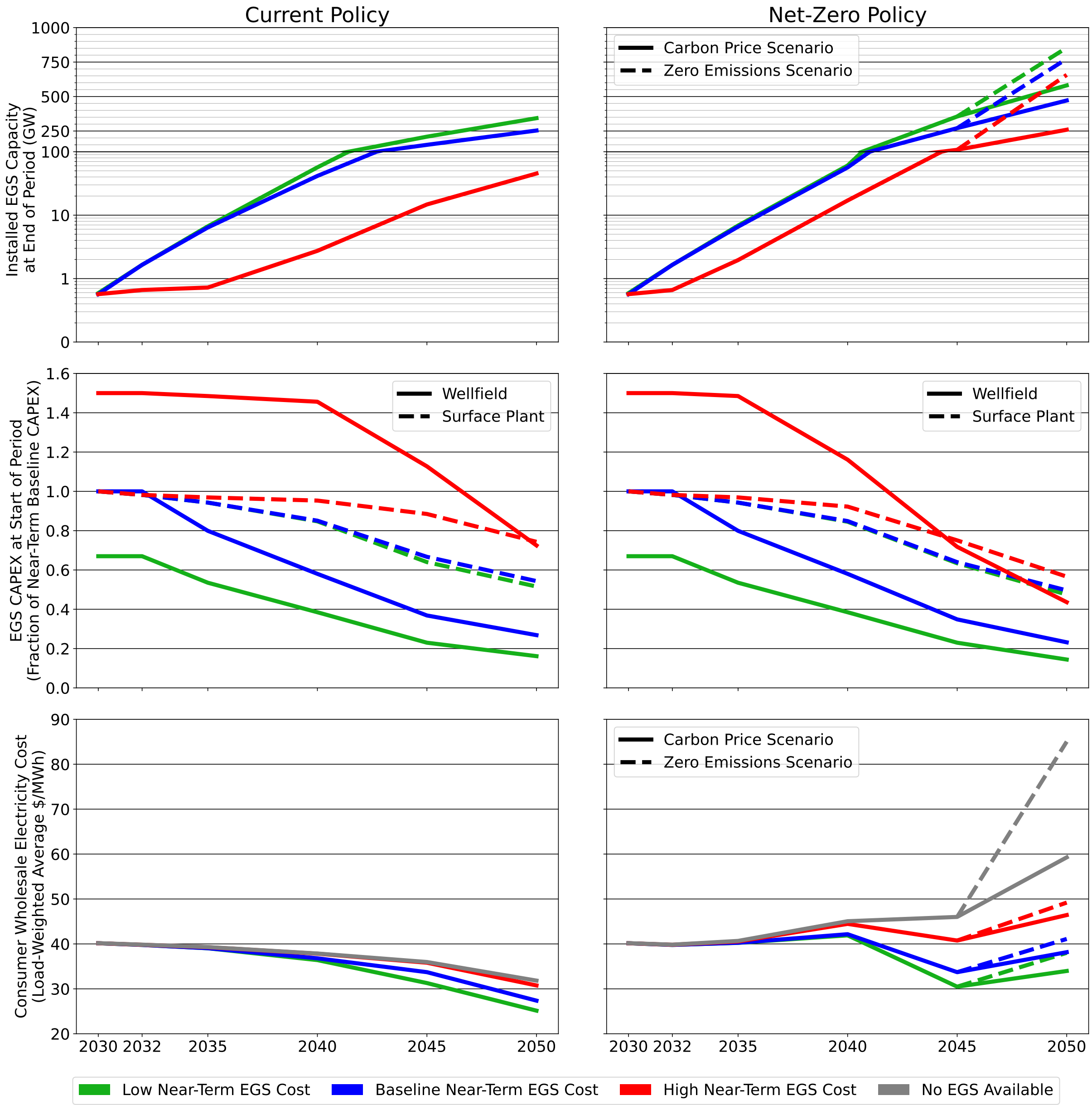

Figure 2: Trajectories of enhanced geothermal systems deployment, capital costs, and consumer electricity costs. Results are presented for current policy and net-zero policy scenarios and for three different EGS cost cases. Capacities are plotted on a logarithmic scale for values below 100 GW and a linear scale thereafter. Consumer electricity costs are calculated as the consumption-weighted average cost of wholesale power generation, including energy costs, capacity costs, and policy costs reflected in model shadow prices. Inflation Reduction Act subsidies that reduce final consumer costs remain in effect in all periods in the current policy scenario and phase out after the statutory emissions threshold ($< 25\%$ of 2022 emissions) is achieved in 2045 in the net-zero policy scenario.

2.3 The Role of EGS in the Energy System

Figures 3 and 4 illustrate the modeled evolution of the US electricity sector capacity and energy mixes over the 2030-2050 period under both current and net-zero policies, for scenarios with and without EGS available. In all scenarios, wind and solar power account for the vast majority of both installed capacity and generation. Under current policies and without EGS available (Figures 3 and 4, panel (a)), the system trends toward use of unabated natural gas as the primary firm complement to wind and solar. Under current policy, clean firm alternatives are unable to compete with unabated gas power and achieve initial commercial liftoff in the absence of a national decarbonization mandate (assuming initial unsubsidized CAPEX of $9,459/kW for nuclear SMRs and $2,777/kW for Allam cycle gas plants). Even under a net-zero policy, non-EGS clean firm resources see no uptake until the latest stages of decarbonization due to their high initial costs. Due to lack of early deployment, costs remain high and build rate constraints limit the scale-up of these resources through 2050, forcing reliance on remaining unabated gas (in the scenario with a carbon price) or extensive buildout of VREs, batteries, and hydrogen LDES (in the zero-emission scenario) to meet system reliability needs.

Despite higher *average* initial costs than competing clean firm technologies in all regions of the country (Figure S13), the existence of limited high-quality near-field geothermal resources in the Western US enables economic deployment of EGS in earlier modeled periods in scenarios where it is available at baseline costs (Figures 3 and 4, panel (b)). As discussed above, these early deployments lead to sufficient learning-driven cost reductions and supply chain scale-up to enable substantial EGS deployment by 2050. When deployed at scale, EGS acts as a clean firm complement to wind and solar power, substantially reducing the need to retain gas-fired capacity or overbuild VREs and storage (Figures 3 and 4, panel (c)). In net-zero policy scenarios EGS meets nearly all of the country's clean firm power needs and supplies up to a fifth of total generation in 2050. As discussed in Ricks et al.[21], flexible operation of wellfields allows EGS plants to ramp down during periods of abundant VRE generation and shift output to periods of VRE drought, thereby supporting system reliability while maximizing utilization of both the subsurface heat resource and low-cost wind and solar power. Figure S14 shows that EGS surface plants are optimally oversized by 25% or more relative to the capacity at which the wellfield can deliver sustainable baseload power, enabling temporarily increased output during periods when the system's capacity needs are greatest and the value of electricity is highest. In the zero-emissions policy case EGS peak generating capacity is nearly double its baseload generating capacity, suggesting that it is able to serve as a low-utilization peaking resource in the absence of cost-effective zero-emissions alternatives.

Although geothermal resources in the Western US are much higher quality than those elsewhere in the country, we find that optimal long-run EGS deployment is not necessarily constrained to this region. Figure 5 shows optimal regional capacity mixes in 2050 across three selected scenarios with very low (a), moderately high (b), and very high (c) EGS deployment, and illustrates that while deployment of high-cost EGS is concentrated in regions with the highest resource quality, installations are much more evenly distributed when EGS has lower costs or greater system value due to policy. Notably, more EGS capacity is deployed in the Eastern Interconnection than in the Western Interconnection in both of the scenarios shown in panels (b) and (c) of Figure 5, with capacity in the east reaching more than double the capacity deployed in western states in (c). This outcome is primarily attributable to much greater total electricity demand in the Eastern Interconnection, and EGS makes up a relatively smaller share of total installed capacity in this region than it does in the west due to higher costs. In all cases, EGS deployment is lowest in regions with the highest-quality wind power resources.

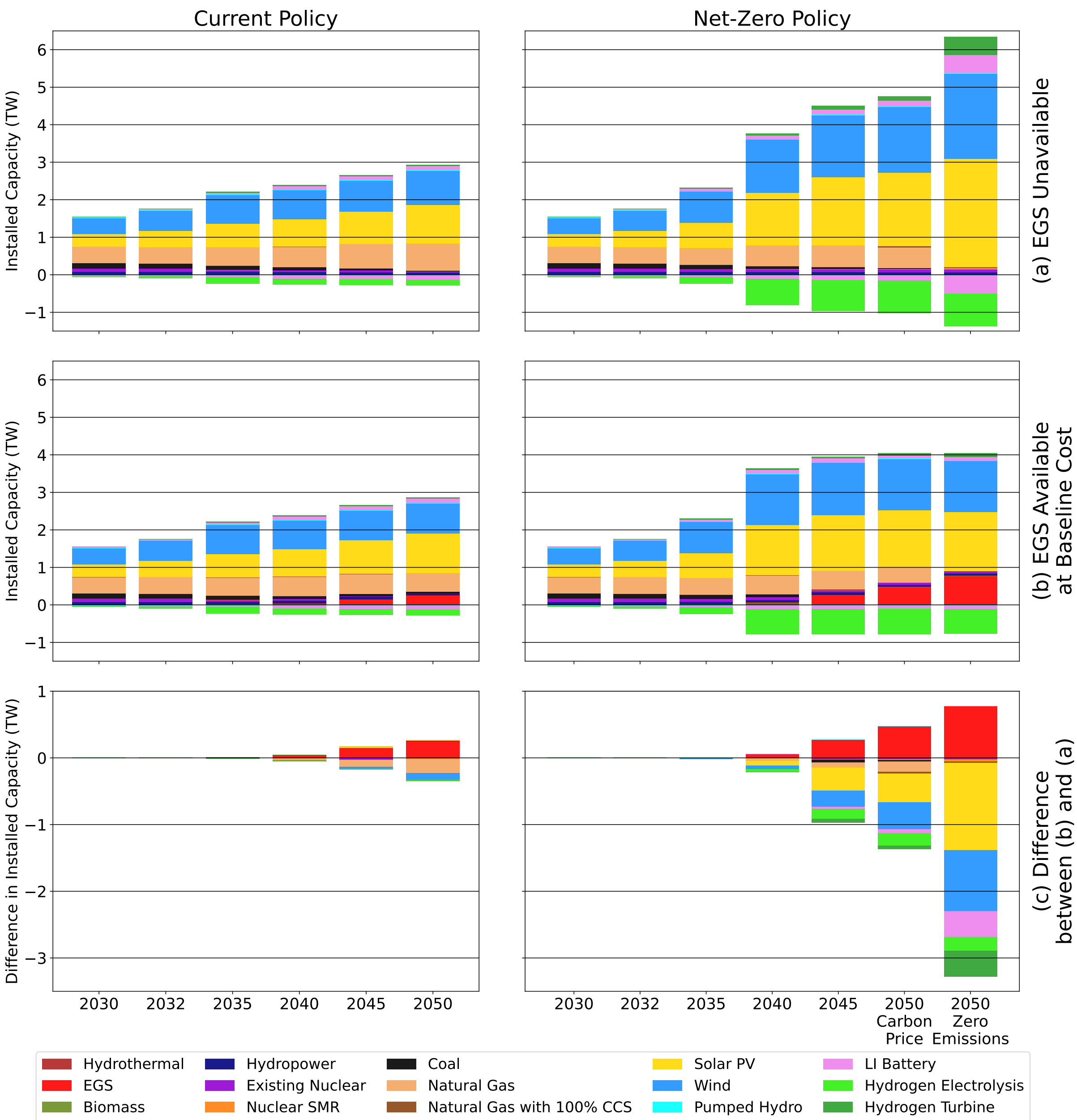

Figure 3: Total installed AC generating and storage power capacity by planning period and technology, for current policy and net-zero policy scenarios in cases without EGS available (a), and with EGS available at baseline costs (b). Panel (c) shows differences in capacity deployment between the cases shown in panels (b) and (a). Two alternate 2050 mixes are shown for the net-zero policy scenario: one with a $300/t$CO_2$ price on residual emissions and one with a zero-emissions requirement. The ‘Wind’ technology category includes both onshore and offshore wind resources, and ‘Hydropower’ includes both reservoir and run-of-river resources.

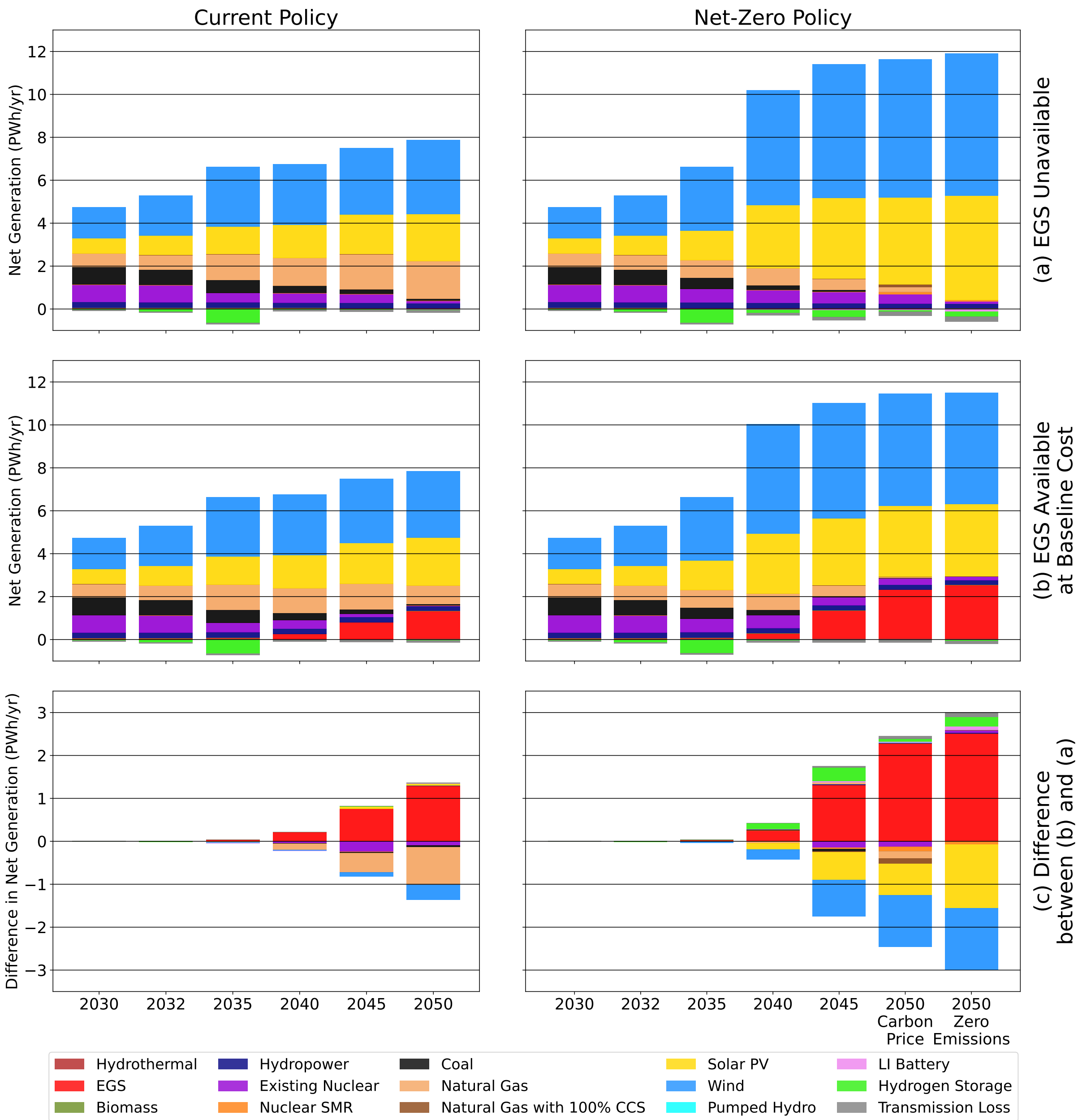

Figure 4: Same as Figure 3, showing net electricity generation by planning period and technology. Net power consumption by the hydrogen storage technology does not include power used to produce hydrogen that serves exogenous hydrogen demand in non-electricity applications.

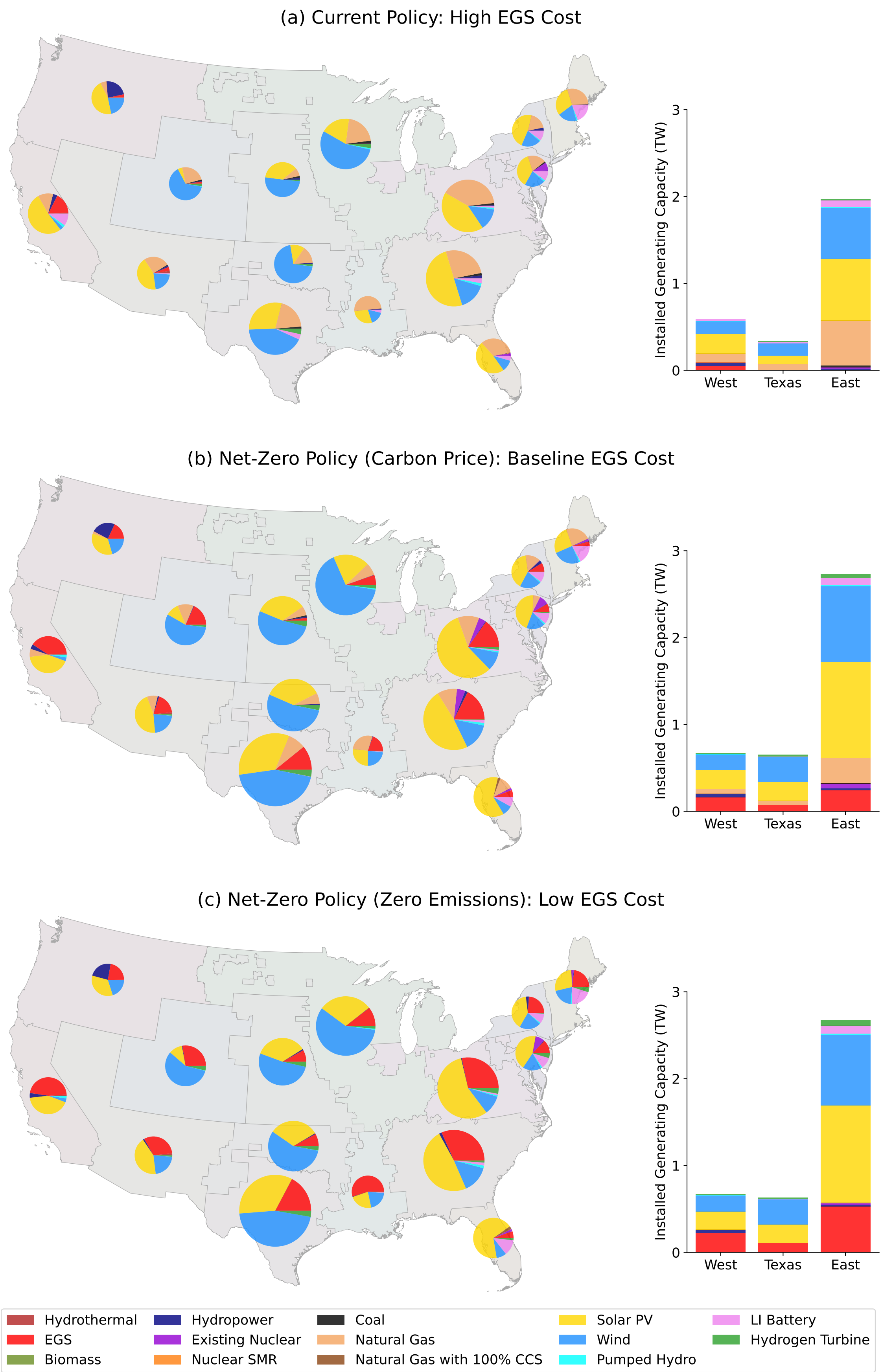

Figure 5: Generating capacity mixes by model zone and synchronous interconnection in 2050 for three selected scenarios. Pie chart area is directly proportional to total installed generating capacity in the zone.

2.4 Sensitivity of Outcomes

The results presented in previous sections are sensitive to uncertainties in policy conditions, costs for non-EGS energy technologies, as well as assumptions regarding EGS learning rates, performance, and resource availability. As noted above and illustrated in Figure 2, high upfront costs can delay commercial liftoff of EGS and limit the technology's long-run deployment. Policy solutions specifically designed to address the challenge of early deployments for EGS and other clean firm technologies can improve long-run outcomes. While EGS sees only limited long-run deployment under high cost assumptions and current policies (Figure 6, panel (a)), long-run deployment of EGS triples under policies that either amend the existing clean electricity ITC to provide an addition 10% capital subsidy for clean firm power[†], mandate 4.5 GW of deployment for all clean firm resources by 2035, or create technology-agnostic demand for '24/7 carbon-free electricity' equivalent to a small percentage of total electricity demand in all hours and grid regions[40] (Figure 6, panels (b), (c), and (d), respectively). These policies all help high-cost EGS achieve earlier initial deployment than it otherwise would, leading to greater compounding of learning effects and moderately reducing long-run consumer electricity prices (Figures S16 and S17). The effects of supportive near-term policies are less apparent for EGS in the baseline- and low-cost cases where early deployment is already rate-limited, suggesting that the value of these policies lies in ensuring achievement of commercial liftoff even under pessimistic initial cost assumptions. While supportive policies do help drive early deployment other clean firm technologies in addition to EGS, we do not observe substantial changes in the long-run penetration of these technologies in any scenario. We discuss this phenomenon in greater detail in the Discussion.

[†]We assume that Allam cycle gas plants do not qualify for the Section 48E ITC due to upstream methane emissions, and instead add 10% to the Section 45Q CCS tax credit in this case to reflect similar support to EGS and nuclear SMRs. See also a case where these respective adders are increased to 20%, shown in Figure S15.

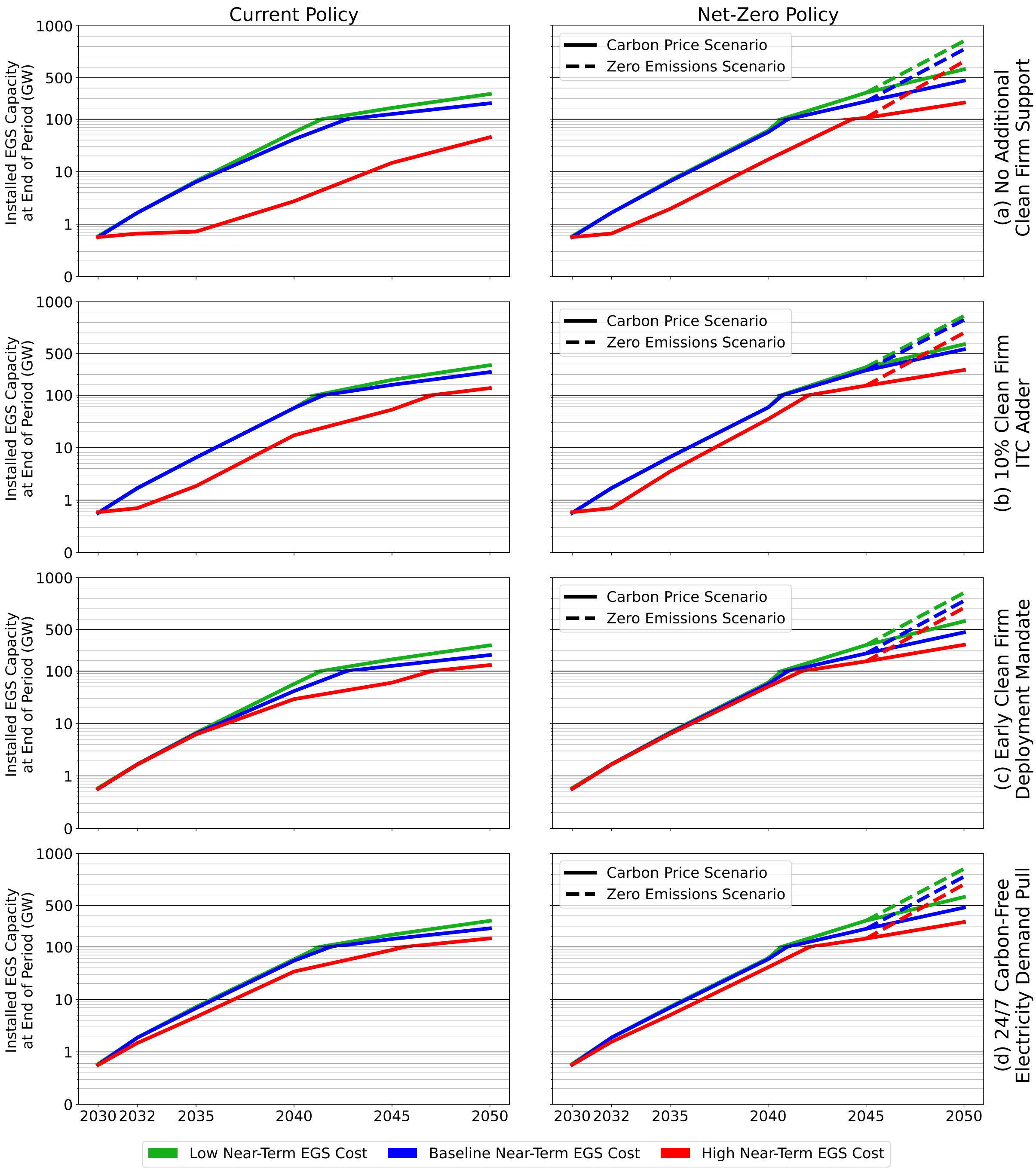

Figure 6: Trajectories of EGS deployments under current policy and net-zero policy scenarios, for cases with and without additional policy support for EGS and other emerging technologies. Capacities are plotted on a logarithmic scale for values below 100 GW and a linear scale thereafter.

As shown in Figure 7, panel (a), EGS deployment pathways are relatively insensitive to variations in the cost of VREs, batteries, and long-duration hydrogen energy storage. Cost ranges for these technologies are discussed in Supplementary Information section 2.5. Variations in the price of natural gas do lead to notable changes in long-run EGS deployment in the current policy scenario: low gas prices ($\sim$ 20% lower on average than the default assumption – see Figure S28) reduce installed EGS capacity in 2050 by more than 50%, though EGS still reaches $\sim$100 GW by 2050 in this scenario, roughly comparable in scale to current US nuclear fission fleet. In a net-zero policy scenario, EGS deployment is initially sluggish with low gas prices, but regains pace with the baseline scenario as the financial penalty for CO_2 emissions from gas dominates the base fuel price in later years. Notably, we find no change in EGS deployment in a scenario with a 33% reduction in the fixed costs of nuclear SMR (to $6,243/kW initial CAPEX) and Allam cycle gas (to $1,833/kW initial CAPEX). While Allam cycle gas does achieve some initial deployment at this cost, lower learning rates and the eventual expiration of federal subsidies for carbon sequestration lead to EGS dominating the clean firm niche beyond the early 2030s.

We observe much greater variability in EGS deployment pathways resulting from changes in EGS-specific assumptions. Figure 7, panel (b) illustrates the high sensitivity of deployment outcomes to the assumed learning rate for EGS, a metric that cannot be empirically derived at this early stage in the technology's development and which is thus subject to significant uncertainty. If we optimistically assume that EGS learning rates are double the baseline values used in this paper (rising from 15% for wellfields and 10% for surface facilities to 30% and 20%, respectively), final EGS deployment more than doubles in the current policy scenario and rises substantially in the net-zero scenarios as well, though it does not exceed 1 TW. While one of the only literature estimates for the learning rate of conventional hydrothermal power does suggest a value of 30%[31] (see our discussion of literature relevant to EGS learning estimates in the Methods), we consider such a high learning rate to be unrealistic for both hydrothermal power and EGS because it suggests levels of modularity and standardization similar to those of solar power or lithium-ion batteries[32] and implies a reduction in EGS wellfield costs of almost 95% after 100 GW of deployment. While we are able to project plausible advancements in EGS reservoir design that could enable long-run wellfield cost reductions on par with those we observe in baseline learning scenarios (see the Discussion and Figure 9), we do not see a plausible pathway to a cost reduction as large as 95% without one or more technology breakthroughs or step changes in drilling or hydraulic fracturing costs. On the other hand, we find that learning rates lower than our baseline values could constrain (but not on their own eliminate) the role of EGS in future grids. Cutting assumed EGS learning rates to 1/2 or 1/4 of their baseline values (reflecting a more pessimistic assessment of the technology's amenability to learning-by-doing) leads to a slower acceleration of deployments after 2035 and noticeably lower installed capacities in 2050 due to higher costs, with 2050 capacities falling by more than 2/3 in the 1/4 learning case. If we assume that EGS benefits from no experience-driven cost reductions at all, perhaps based on the judgment that all major pathways for EGS wellfield cost reduction have already been fully exploited in the unconventional oil and gas industry, final deployment falls marginally from the 1/4 learning case, though it still reaches over 500 GW in a zero-emissions policy scenario. These results suggest that learning rate assumptions represent a major source of uncertainty in the assessment of long-run EGS deployment potential, though a negligible learning potential would not on its own preclude EGS from playing a role in a net-zero carbon energy system.

Outcomes are also sensitive to variations in EGS performance and resource base assumptions. For example, forcing EGS plants to operate at a constant flow rate rather than flexibly leads to very similar long-run outcomes to the 1/2 learning rate case, though with a more delayed scaleup. In this case the loss of value from flexibility both constrains the role of EGS in VRE-dominated 2050 grids and inhibits early deployment, limiting learning opportunities. As shown in Figures S4-S9, a large share of the most cost-effective EGS resources outside of near-field

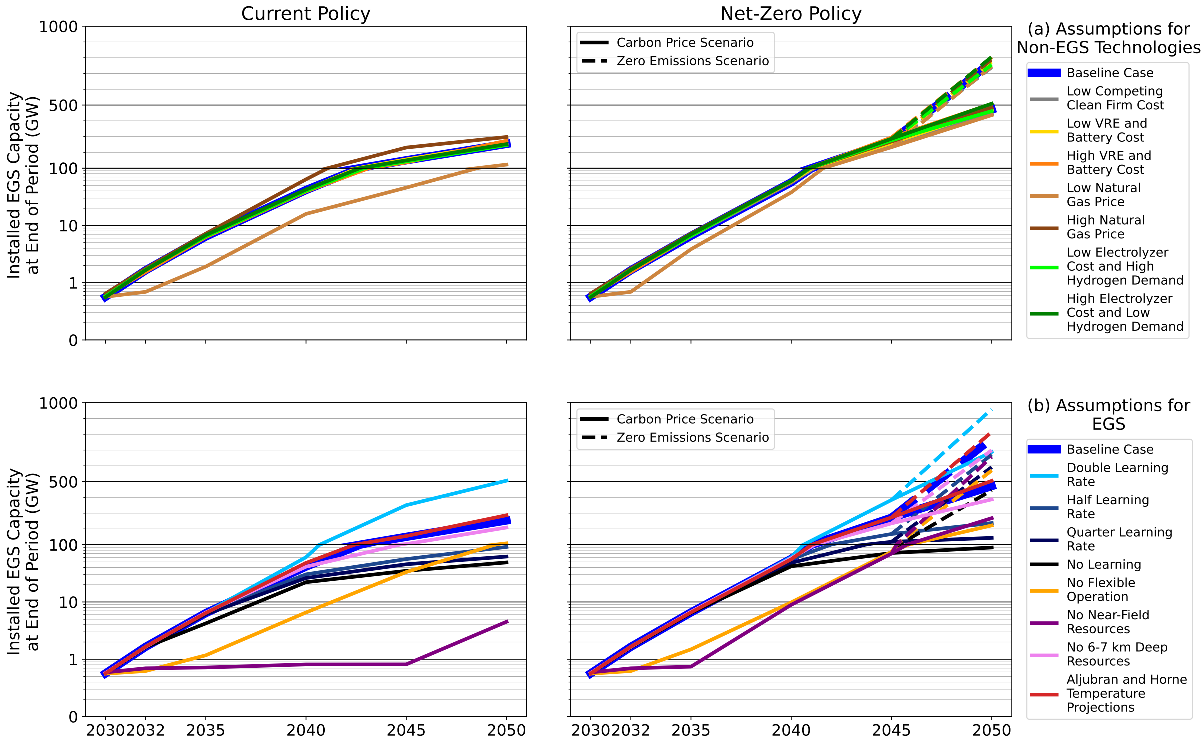

Figure 7: Trajectories of EGS deployments at baseline costs under current policy and net-zero policy scenarios, for (a) cases varying the costs of competing energy technologies and (b) cases varying learning rate, performance, and resource base assumptions for EGS. Capacities are plotted on a logarithmic scale for values below 100 GW and a linear scale thereafter.

areas are located at the greatest modeled depths, in the 6-7 km range. We find that removing these deepest resources from the available pool (reflecting potential challenges with ultra-deep drilling) does not affect early EGS deployments but moderately reduces long-run potential. Removal of near-field resources from the available pool is much more consequential, constraining EGS deployment to nearly nothing in the current policy scenario and substantially limiting it in net-zero policy scenarios. This result reflects the critical importance of the near-field resource base as a pathway to early EGS deployments and catalyst for learning-based cost reductions.

Figure 7 also shows a case where temperature-at-depth data for deep EGS resources from Blackwell et al.[25] are replaced with similar data from a recent study by Aljubran and Horne[41]. As illustrated in Figures S18-S22, the Aljubran and Horne[41] dataset predicts much greater subsurface temperatures (and therefore lower EGS costs) across most of the contiguous US, though it lacks certain hot spots in the eastern half of the country that are present in the Blackwell et al.[25] dataset. Despite these differences in predicted temperature, national EGS deployment trajectories are nearly identical between the two datasets.

Although the above result suggests that long-run EGS deployment is insensitive to variations in the deep geothermal resource base, temperature-at-depth uncertainties may still create considerable practical barriers that could constrain EGS deployment if left unaddressed. One important challenge is optimal project siting, which can vary substantially with different temperature-at-depth predictions even as optimal aggregate EGS deployment remains similar. This phenomenon is illustrated in Figure 8, which shows a comparison of optimal EGS deployment locations over time for cases using the Blackwell et al.[25] and Aljubran and Horne[41] temperature-at-depth maps in the net-zero, carbon price policy scenario, downscaled to the level of individual EGS CPAs. While early deployments are concentrated at near-field sites in both cases, there is little geographic overlap in the deep EGS deployments that account for the bulk

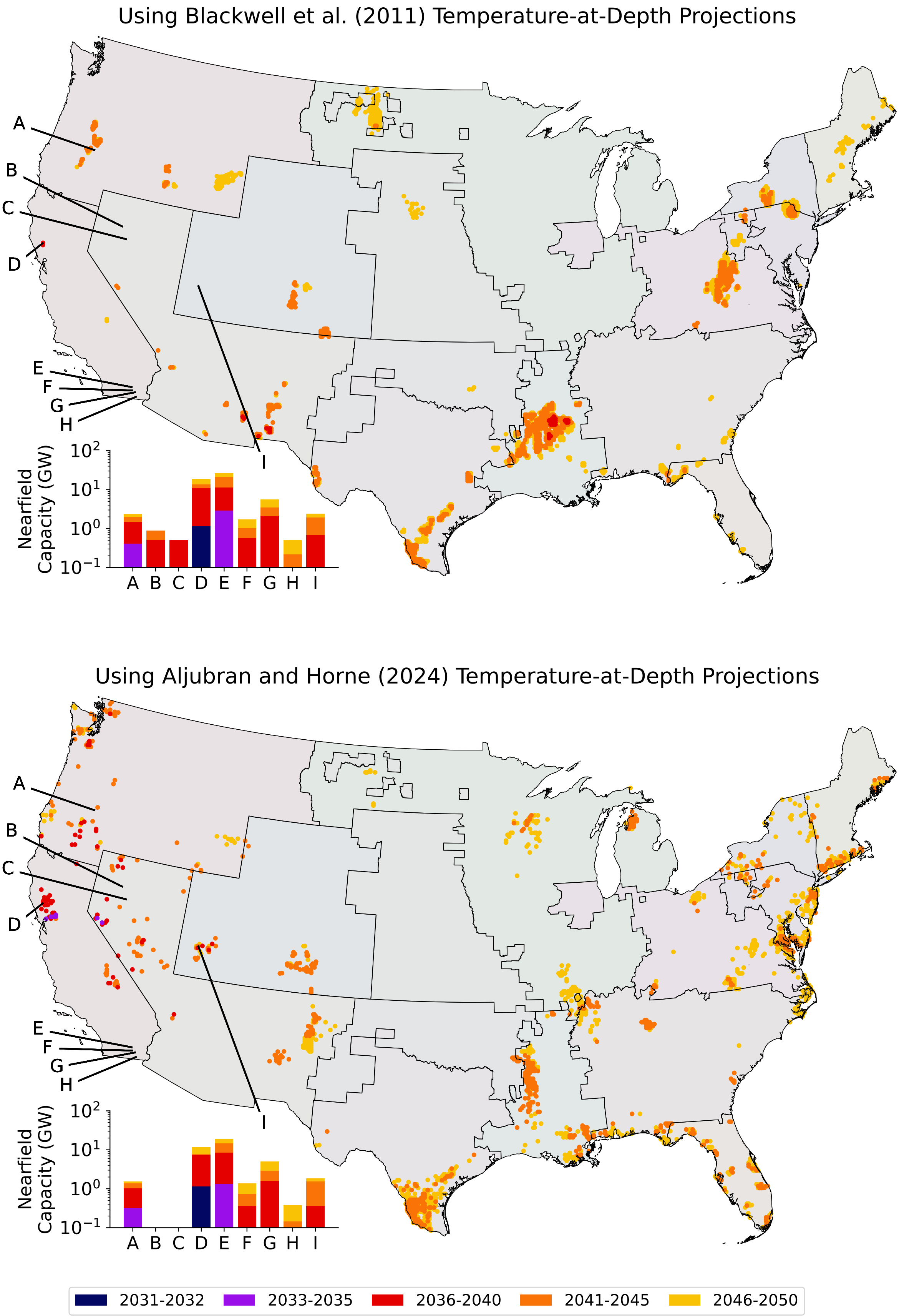

Figure 8: Downscaled optimal EGS deployments by location and planning period using different deep temperature-at-depth datasets, assuming baseline EGS costs and a net-zero policy with a \$300/tCO_2 carbon price for residual emissions. Colors indicate the first year EGS is deployed at a given CPA, and individual CPAs may host multiple surface EGS facilities with reservoirs at different depths. Letters indicate near-field sites, with capacity deployments by site and planning period shown in the lower left of each panel.

of capacity installed in later planning stages. Exploration efforts that minimize deep resource uncertainty and identify promising basins for large-scale development will therefore be critical to realizing the long-run potential of EGS on a national scale.

3 Discussion

The analysis presented here identifies a much broader potential role for EGS in the long-run decarbonization of the US electricity sector than similar prior studies, which see wide-scale EGS deployment restricted to high-potential regions even under low cost assumptions[18–20,27]. This difference in observed outcomes is largely explained by the present study's handling of learning-driven cost reductions for EGS and other emerging clean firm technologies: whereas prior analyses have assumed that these technologies are available at exogenously-fixed costs and unlimited scale, we endogenously model the dependence of costs and build rate limits on their deployment history. This direct consideration of experience curve effects benefits EGS in comparison to its clean firm competitors due to its higher assumed learning rate and the heterogeneity of the US geothermal resource base, which creates earlier opportunities for economic EGS deployment at near-field sites with much lower effective levelized costs than the national average. Even when EGS learning rate assumptions are lowered to be in line with or below assumed values for nuclear SMRs and Allam cycle gas plants (Figure 7), these early deployments spur a virtuous cycle of growth and further cost reductions that eventually allows the technology to achieve lower costs and greater deployment than its competitors even in regions where EGS is initially more expensive. These results highlight the nonlinear dynamics of technological competition in an experience curves framework, where technologies that achieve earlier deployment can come to dominate a market over the long run as learning and growth compound[42].

The learning-driven EGS cost reductions necessary to achieve our modeled results are substantial, with wellfield costs eventually falling by nearly 80% compared to their assumed near-term values in some cases (see Figure 2). While experience curves are a well-studied phenomenon and similarly drastic reductions in cost have been observed for other energy technologies[43], including unconventional oil and gas production that serves as a close technological analogue to EGS[36], the plausibility of our findings still depends on the existence of material pathways by which EGS wellfield costs could fall to such a degree. Drilling and stimulation account for the bulk of wellfield costs, but are relatively mature following their development and use in oil and gas extraction and may not see substantial additional learning-driven unit cost reductions when applied toward EGS. On the other hand, the present cost of drilling in the novel hard, deep, and hot basement environments seen in EGS development remains notably higher than the cost of equivalent drilling in the shallower sedimentary formations where oil and gas extraction typically occurs, suggesting that there is ample room for further innovation and drilling cost reductions in the EGS context[27]. More importantly, as shown in Figure 9, incremental advances in reservoir design that increase the achievable *flow rate* per well or reduce the effective cost of achieving the same flow rate - larger arrays of well laterals, longer lateral lengths, greater lateral spacing, and open-hole completion of production laterals - have the potential to reduce wellfield per-kW CAPEX by two thirds or more without any changes in the unit costs of drilling and stimulation. This hypothetical design-driven cost reduction pathway mirrors trends observed in the unconventional oil and gas industry, where the effective drilling and completion cost for a well with a given set of parameters did not change substantially during the first decade of the US shale revolution even as overall production costs fell enormously[36,44]. Just as changes in well design philosophy - e.g. an effective quadrupling of average lateral length between 2006 and 2022[44,45] - were the primary driver behind improvements in unconventional oil and gas economics, we expect that advancements in reservoir design will account for the large majority of future reductions in per-kW EGS wellfield costs. In combination with more marginal reductions in the cost of drilling in novel environments, these observations suggest a plausible pathway to the long-run wellfield cost reductions illustrated in Figure 2.

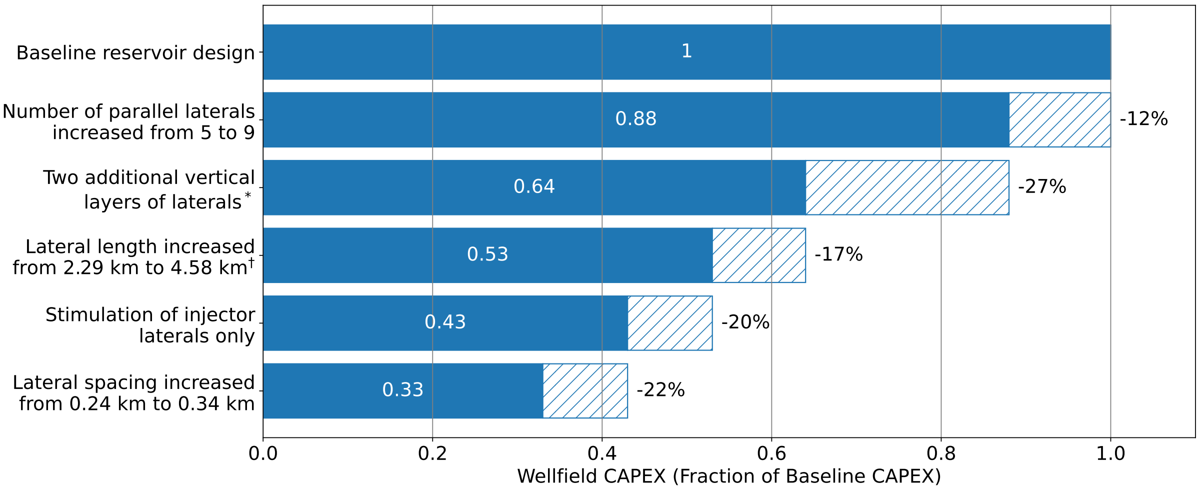

Figure 9: Impact of changes in reservoir design on EGS wellfield per-kW cost. Costs for different reservoir designs are calculated using the same EGS cost model used to create the baseline supply curves used in this work, and presented reductions are equal to the average values observed for representative EGS resources with temperatures of 175-300°C and depths of 2.5-6.5 km. Listed design changes are retained moving down the chart. For iterations marked with * and †, average well costs are increased by 10% and 20% from the baseline, respectively, to account for greater diameters needed to handle higher flow rates while minimizing parasitic pumping losses.

The EGS surface plant cost reductions implied by our results are smaller than those for wellfields due to the relatively greater maturity of binary-cycle power plant technology (~4 GW of global installed capacity today). While binary-cycle projects today are bespoke, with typical capacities less than 25 MW and systems custom-built for specific resource temperatures and chemistries, EGS could enable much greater design standardization due to more direct control over reservoir properties and larger project sizes. Akar et al.[46] find that the cost of binary-cycle turbines can be reduced by 80% or more through mass standardized manufacturing, suggesting that the overall surface plant cost reductions illustrated in Figure 2 are a plausible result of multi-GW scale binary-cycle deployment in an EGS context.

While the more optimistic long-term outcomes presented here are therefore plausible, they are by no means guaranteed. EGS costs that start at or above the upper end of the range modeled in this paper, low learning rates, low natural gas prices, a lack of supportive policies, or some combination of these unfavorable conditions could all constrain EGS to regional, niche, or irrelevant status. Empirical evidence from the first tranche of large-scale EGS demonstration projects will be needed to more accurately constrain cost and learning rate uncertainties, which we find to have the largest potential impacts on long-run deployment (see Figures 2 and 7).

If near-term EGS costs do fall within the range depicted in Figure 1 and learning-driven cost reductions at the scale described above can be achieved, our analysis suggests that EGS grow to could become a key third source of clean generation in a decarbonized US electricity system alongside wind and solar power. As demonstrated in prior work, EGS can provide both clean firm generation and long-duration energy storage via flexible operation[21,39]. As such, widespread availability of the technology could substantially reduce the cost of delivering round-the-clock carbon-free electricity on a nationwide basis. Although there is not yet sufficient temperature-at-depth data to accurately assess EGS potential in most regions of the world, our US-specific results suggest that EGS could become a major contributor to electricity decarbonization across a wide range of geographies if the technology can be successfully demonstrated at large scale and its costs can be brought down via learning-by-doing. Efforts to promote early EGS developments in high-potential regions and spur learning-driven cost reductions could thus have a facilitating impact on long-term decarbonization that far exceeds the direct impacts of the projects themselves.

4 Methods

4.1 Resource availability

4.1.1 Lead Contact

Further information and requests for resources and materials should be directed to and will be fulfilled by the lead contact Jesse D. Jenkins (jdj2@princeton.edu).

4.1.2 Materials availability

This study did not generate new unique materials.

4.1.3 Data and code availability

Original data for this paper, as well as the code used for simulation and analyses, are archived at a public repository[47].

4.2 EGS Cost and Performance Assumptions

In this work we update the EGS costing model described in Ricks et al.[21] to directly incorporate cost and performance data from recent EGS demonstration projects. We utilize data published by private developer Fervo Energy for projects in Nevada and Utah, and by the US Department of Energy's FORGE project in Utah. Both sets of projects report significantly improved drilling performance compared to assumptions made in prior studies of EGS, attributable to both learning-by-doing and use of polycrystalline diamond drill bits better suited to drilling in hard formations[18,22,27]. We use reported drilling costs of \$4.8 million (in 2024 USD) for deviated wells with 2.5 km vertical depth, 1.5 km lateral sections, and 22.2 cm (8.75 inch) production casing outer diameter reported by El-Sadi et al.[22] to recalibrate baseline drilling cost curves developed for the US Department of Energy's *GeoVision* report[18]. This recalibration results in a roughly 30% reduction in real drilling costs compared to the *GeoVision* assumptions, attributable to both the improvements in hard rock drilling performance discussed above and reductions in the overall drilling producer price index compared to the values used by *GeoVision*[48]. For wells stimulated via hydraulic fracturing, we adopt a stimulation cost of \$1522 per lateral meter from a recent report by the US Energy Information Administration on upstream oil and gas costs[44].

We use reported stimulation and reservoir performance data from a recent 3.5 MW EGS pilot project in Nevada to inform performance and design assumptions for a near-term commercial-scale reservoir design[7]. This project involved a single well pair drilled to a total vertical depth of $\sim$2.5 km, with $\sim$1 km lateral sections deviated at 90 degrees from the vertical and spaced approximately 0.11 km (365 ft) apart. Both wells were cased and stimulated in multiple stages, creating an artificial fracture network with fracture half-lengths of 0.24 km (800 ft) and half-heights of 0.12 km (400 ft) as measured via low-frequency acoustic sensing. An initial 37-day circulation test at this site achieved a peak production flow rate of 65 l/s and a sustained rate of roughly 40 l/s, and pressure differentials across the stimulated reservoir indicated an effective fracture conductivity of 1.2×10^{-13} m^3 averaged over an assumed 75 discreet fractures. At the Utah FORGE site, which uses a very similar doublet reservoir design, a recent 9-hour circulation test demonstrated production flow rates up to 22 l/s - though the use of fewer stimulated stages and different stimulation techniques in each stage (to assess their relative effectiveness) makes this project less representative of a commercial design[8].

Given the demonstrated performance metrics from these and other projects, we assume that standardized reservoirs with the following design parameters can be consistently engineered following 500 MW of further EGS demonstration development:

- Lateral lengths of 2.29 km, more than double the demonstrated length reported in Norbeck and Latimer[7] but less than half the maximum lateral length in unconventional oil and gas operations today[45];
- Five lateral wells placed in series, with wells 1, 3, and 5 acting as producers and wells 2 and 4 as injectors, to maximize utilization of the stimulated area in comparison to a single well pair;
- Lateral spacing of 0.24 km horizontally, equal to the fracture half-length reported in Norbeck and Latimer[7];
- Stimulation of both injector and producer laterals;
- Effective fracture conductivity of 1.2×10^{-13} m^3, as reported in Norbeck and Latimer[7], for an assumed 150 discreet fractures over the stimulated lateral length; and
- A target steady-state flow rate of 123 l/s per injection well, designed to maintain the reservoir thermal decline at 35°C over 30 years, as discussed below.

A schematic of this assumed near-term commercial reservoir design is shown in Figure S1. Baseline drilling cost curves for wells with 2.29 km lateral lengths are shown in Figure S23. Beyond the initial reservoir design itself, we assume a standard reservoir water loss rate equivalent to 7.5% of injected fluid. This assumption is based on average water losses of 10-20% reported by Norbeck and Latimer[7] after a 37-day circulation test, and the observation by Brown et al.[49] that water losses at the Fenton Hill EGS test project in 1989 fell substantially over the course of extended operation. We assume a cost for makeup water of $275/Ml based on default cost assumptions in Mines[50], though this cost may vary by location. Additional cost and performance assumptions are discussed in Supplementary Information section 2.1, and the cost model is available as a Python script ('EGS_Costs.py') online at Ricks and Jenkins[47]. As a point of reference, our baseline cost model predicts a near-term CAPEX of $4,886/kW for an EGS plant exploiting a 250°C resource at a depth of 3.5 km, compared with projected average values of $4,513 and $6,889 during the 2031-2032 period for identical resources under 'Advanced' and 'Moderate' cost cases from the latest (2024) edition of the National Renewable Energy Laboratory's Annual Technology Baseline (NREL ATB)[51].

We note that while the assumptions described above are intended to represent a plausible evolution of EGS reservoir design over the course of a large-scale demonstration program and are grounded in performance metrics that have been demonstrated as of the time of writing, there are large remaining uncertainties that could lead to a wide range of near-term cost outcomes. Substantially worse thermal performance than anticipated could reduce effective reservoir lifetime and require makeup drilling, increasing costs, while advancements in drilling and reservoir engineering could proceed more slowly or quickly than anticipated. To assess the impact of these uncertainties, we include scenarios where all subsurface costs are alternatively increased by 50% or reduced by 33%. We do not vary initial surface plant costs from the baseline, as binary-cycle power plants are a relatively more established technology and initial cost estimates are more reliably established[50].

4.3 EGS Supply Curves

We use the EGS cost model discussed above in combination with temperature-at-depth and ambient air temperature datasets (which affect thermodynamic performance of air-cooled binary cycle plants[52]) to create EGS supply curves and capacity factor time series for the contiguous US. For 'deep' EGS resources in the 3-7 km depth range and outside of known hydrothermal systems, we use temperature-at-depth maps from Blackwell et al.[25] to assess EGS cost and capacity across over 80,000 individual surface candidate project areas (CPAs) at 9 km^2 resolution. In sensitivity cases where we use deep temperature-at-depth maps recently published by Aljubran and Horne[41], we match this data to the closest CPAs in the Blackwell et al.[25] dataset. In all cases we exclude CPAs featuring significant land access barriers following Young et al.[53], and furthermore remove CPAs immediately adjacent to large known hydrothermal reservoirs. For 'near-field' resources in areas close to these large hydrothermal systems, we calculate temperature-at-depth values for depths from 2-7 km based on extrapolation of trends from a detailed study of near-field resources at the Roosevelt Hot Springs geothermal area[54,55]. For all near-field and deep CPAs we source hourly surface ambient air temperature data for the 2012 weather year from NASA's MERRA-2 dataset[56], matching each EGS CPA to the closest MERRA-2 grid point. Hourly ambient air temperature is used to calculate hourly EGS capacity factor time series under the assumption that surface plants are air-cooled binary-cycle, and annual average air temperature is used as the surface plant's design point in the EGS cost model. Using this ambient temperature input alongside resource depth and temperature, the cost model calculates both EGS wellfield cost and developable capacity and surface plant cost for each CPA. In total we find 90 GW of developable near-field EGS capacity associated with known hydrothermal sites at depths of 2-7 km and resource temperatures of 150-350°C in the contiguous US, 8619 GW of developable deep EGS at depths of 3-7 km using the Blackwell et al.[25] dataset, and 18233 GW of developable deep EGS using the Aljubran and Horne[41] dataset.

We calculate grid interconnection costs for all CPAs using a transmission routing algorithm described in Patankar et al.[57] (see Figure S24). Combination of these interconnection costs with the site-specific costs calculated via the EGS costing model leads to the supply curves shown in Figure 1 and Figures S2-S9 and S18-S22. See Supplementary Information section 2.2 for more detailed discussion of the procedure used to build EGS supply curves in this work.

4.4 Electricity System Capacity Expansion

We simulate the evolution of the electricity sector in the contiguous US from the present day through 2050 using a modified version of the v0.3 release of the open-source GenX electricity system capacity expansion model[58], which optimizes technology investment and operational decisions to minimize electricity system costs in a given future planning year subject to detailed physical, operational, and policy constraints[59]. This methodology captures the declining marginal value of energy resources with increasing penetration and identifies least-cost equilibrium system configurations that replicate outcomes under both well functioning competitive electricity markets and central planning. It is therefore well suited to capturing the conditions under which particular energy technologies can be expected to achieve commercial uptake. The full mathematical formulation for the base GenX model is available at `https://genxproject.github.io/GenX.jl/stable/`.

For this study we modify the public release of GenX in several ways. First, we incorporate the flexible EGS optimization module presented in Ricks et al. [39] and Ricks et al. [21] that allows for detailed optimization of EGS plant component sizing and flexible wellfield operations (including in-reservoir energy storage) while accurately capturing key hydromechanical behavior in the reservoir. The implementation of this module in the present work is discussed in greater detail in Supplementary Information section 2.3. Second, we introduce a modified handling of electrolytic hydrogen production that directly incorporates firm exogenous clean hydrogen demand from outside the power sector (e.g., industry, transportation, fuel production) and optimizes deployment and operations of electrolyzers to meet this demand, in addition to allowing for deployment of coupled geologic hydrogen storage and hydrogen combustion turbines for electricity generation. This formulation allows for implementation of hourly matching requirements for clean electricity used in hydrogen production, which are also employed in the ”24/7 Carbon-Free Electricity Demand Pull” sensitivity case discussed in Section 2.4. The mathematical formulation of these new constraints is presented in Supplementary Information section 2.4. Finally, we modify GenX inputs to run the model at 2-hourly time resolution, modeling 4380 individual timesteps in each planning year. This choice was made to maintain computational feasibility given the large geographic scope of the study and the heavy computational burden associated with the flexible EGS optimization model. Preliminary testing indicated that this simplification leads to an error of less than 2% in both optimal system costs and optimal installed EGS capacity. The full source code for the modified version of GenX used in this work is available at Ricks and Jenkins [47].

We employ GenX in a zonal configuration that simulates and optimizes expansion of transmission pathways between 15 large regions of the US grid, which are implicitly assumed to be internally well-connected. The 15-zone model topology is illustrated in Figure S10, and represents the western interconnection as four zones, the Texas interconnection as a single zone, and the eastern interconnection as ten zones, with the goal of minimizing intra-zonal transmission constraints. We model the evolution of the electricity sector over six planning periods: 2025-2030, 2031-2032, 2033-2035, 2036-2040, 2041-2045, and 2046-2050. The 2031-2035 period is split into two planning periods to both capture changes in policy in 2032 (expiration of certain credits established by the Inflation Reduction Act) and capture early learning curve dynamics for emerging technologies with greater granularity (see below). For each period, we compile demand, technology cost, weather, and policy input data for GenX using the PowerGenome tool[60], a process that is discussed further in Supplementary Information section 2.5. Unlike previous studies using GenX, we include exogenous demand for electrolysis-derived hydrogen in each model zone in addition to electricity demand, with hydrogen demand values adopted from Jenkins et al. [61]. In all periods, new deployment of onshore and offshore wind power, solar photovoltaic power, lithium ion batteries, combined cycle gas power plants, and open-cycle gas combustion turbines is permitted. Deployment of emerging clean firm technologies and hydrogen electrolysis with geologic storage is permitted subject to build rate constraints, as discussed below.

Each modeled period is a myopic optimization, such that the model identifies a least-cost system for the period's target year without any foresight into the needs of the system in future periods. In addition to minimizing computational burden, the choice of a myopic approach reflects the assumption that near-term planners and investors do not have accurate foresight into electricity demand, technology costs, and other factors years or decades into the future. Emerging technologies are therefore not deployed on the basis of expected future learning-based cost reductions if the initial projects are not economically viable. We run planning periods in sequential order, and existing resource inputs for each period are updated based on capacity deployed and retired in previous periods. The multi-period optimization is run within a wrapper script, published online at Ricks and Jenkins[47], that runs individual GenX instances for each period and updates inputs between periods.

4.5 Cost and Learning Assumptions for Emerging Technologies

It is a widely recognized phenomenon that emerging technologies typically follow 'experience curves', (also known as 'learning curves') with costs falling as a function of increasing deployment[30–32]. Although this observation implies a bidirectional relationship between technology cost and deployment, the vast majority of energy systems modeling studies treat all technology costs as exogenous assumptions. This approach is most appropriate when technologies are well-established or globalized, such that changes in deployment within the modeled region are unlikely to affect costs to a large degree. While this assumption may hold for technologies like wind, solar, and natural gas power, it is much less appropriate for emerging technologies that have yet to achieve commercialization at any significant scale. We therefore model learning endogenously in this work for three emerging technologies: EGS, nuclear small modular reactors (SMRs), and Allam cycle oxycombustion gas plants. For EGS we model learning for wellfields and surface plants separately due to different driving factors and technological maturities. While hydrogen electrolysis is also modeled and is significantly less mature than wind, solar, battery, and gas resources, we represent its costs in the model exogenously due to the existence of strong policy support and multi-GW planned electrolyzer production capacity in both the US and abroad[62].

We assume that nuclear SMRs, Allam cycle gas plants, and EGS first become available for commercial deployment in the 2031-2032 planning period after an exogenously fixed 500 MW of in-model deployment in the 2025-2030 planning period representing an initial demonstration program and/or loss-leading commercial deployments. While these 2030 commercialization date and 500 MW starting capacity projections are necessarily approximate, they are generally in line with the capacity and timeline of announced initial projects in each technology category[23,24,33–35]. We note that there are multiple similarly-sized nuclear SMR demonstrations underway in North America utilizing different reactor technologies, and that our study implicitly assumes that learning is not shared between these technologies and that one of them becomes dominant. For EGS binary-cycle surface power plants, we establish a conservative starting capacity by adding the 500 MW of EGS demonstration capacity to the approximately 4 GW[37] of current global installed capacity of binary-cycle systems in all applications.

From the 2031-2032 planning stage onward, we assume that the fixed costs of each technology (both CAPEX and fixed O&M) in planning period p are determined via the following equation:

$$C_p = C_1 \cdot (Y_{p-1}/Y_1)^{log_2(1-b)} \cdot r_p \tag{1}$$

where C_p is the fixed cost of the technology used as an input for the optimization in period p, C_1 is the initial fixed cost of the technology after approximately 500 MW of demonstration deployment, Y_{p-1} is the cumulative capacity of the technology deployed through the planning period prior to period p, Y_1 is the installed capacity of the technology upon initial commercialization (in this case 500 MW), and b is the learning rate - the fraction by which the technology's costs fall after each doubling of total installed capacity[29,31]. As it has been shown that learning rates are relatively consistent over the long term[63], we assume that b for each technology is fixed for the entire modeled period. We also include a multiplier r_p representing small incremental reductions in cost of 0.5% per year due to ongoing research and development, in line with the minimum annual cost reduction applied to all technologies in the NREL ATB in the absence of technological learning[38]. Input fixed costs for each technology are therefore 9.6% lower in 2050 than in 2030 if no commercial deployment occurs. The experience curve calculation described here implicitly assumes

Technology	Nuclear SMR	Allam cycle gas
CAPEX ($/kW)	9459	2777
Fixed O&M ($/kW-yr)	119	74
Variable O&M ($/MWh)	3	3.25
Heat Rate (MMBTU/MWh)	10.45	7.07

Table 1: Initial national average cost and performance assumptions for non-EGS clean firm technologies.

that all learning for these technologies is localized in the US. Simultaneous development in other geographies in combination with robust knowledge transfer could potentially lead to more rapid learning than assumed here.

Initial costs C_1 for all emerging technologies are intended to represent 'second-of-a-kind' commercial deployments where the technology has been successfully de-risked via at least one large demonstration project but does not have a mature supply chain and has not yet benefited from significant learning-by-doing. For nuclear SMRs we adopt initial costs from the 2023 edition of the NREL ATB[38], using the 'Conservative' cost case and 'Market Factors' financial case to represent the cost of a technology in the early stages of deployment. For Allam cycle gas plants we adopt CAPEX, fixed O&M cost, variable O&M cost, and heat rate values from White and Weiland[64]. We increase the CAPEX and fixed O&M values reported in White and Weiland[64] by 20% to account for the nascency of the technology, as their analysis assumed fully scaled-up supply chains. We additionally use PowerGenome to calculate CO_2 pipeline and injection facility fixed and variable costs for Allam cycle plants in each GenX model zone. Due to the unavailability of suitable injection basins, Allam cycle plants are not deployable in the ISNE, NY, and PJME model zones. Average initial cost and performance parameters (not including regional cost multipliers or CO_2 disposal costs) are shown in Table S1. For EGS plants we use site-specific costs calculated using the procedures described above. This means that while technological learning for EGS reduces the cost of developing a specific resource by a predictable amount, declining resource quality as the most suitable sites are used up could lead the marginal cost of EGS in the model to decline more slowly or not at all, as has been observed in fossil fuel extraction historically[63]. We adopt cost of capital figures for each emerging technology from the NREL ATB, implicitly assuming that each is sufficiently demonstrated to access financing at typical rates.

Given the inherent lack of empirical data on learning rates for nascent technologies, we use a combination of prior literature estimates, comparison to technological analogues, and a qualitative framework developed by Malhotra and Schmidt[32] to inform learning rate assumptions for nuclear SMRs, Allam cycle gas plants, and EGS. For nuclear SMRs and Allam cycle gas plants we follow the Malhotra and Schmidt[32] classification of these resources as 'Type 3' technologies with relatively high complexity but some potential for standardization, and therefore assign them both a default 5% learning rate. Learning rates for these technologies have also been directly estimated in past studies (e.g. those referenced in Rubin et al.[31]), and we find that our 5% baseline rate is in good agreement with the values reported in these studies. As these nuclear SMRs and Allam cycle plants do not see initial deployment at baseline costs in our central cases, we do not explore the potential impact of more rapid learning in this work.

For EGS, we note a lack of existing literature estimating learning rates. While the latest version of the NREL ATB adopts an 18% learning rate in its near-term EGS cost projections[51], this value is based on EGS learning rate assumptions from Latimer and Meier[65], which are in turn based on a general survey of energy technology learning rates rather than a specific analysis of EGS. In this paper we therefore use a combination of comparison to close technological analogues and qualitative assessment to inform learning rate assumptions for both wellfields and binary-cycle surface plants. We model learning for these two major cost components separately due to their different characteristics and current maturities. For both wellfields and surface facilities, we first consider the suitability of conventional hydrothermal power as a technological analogue. Literature learning rate estimates for hydrothermal power are sparse, with empirically-derived values of 30% being reported by both Nagy et al.[66] and Rubin et al.[31] based on the same underlying data from Schilling and Esmundo[67] providing levelized cost estimates for geothermal power in the US between 1980 and 2005. However, this data covers a relatively small amount of total geothermal deployment and is based on cost estimates only rather than reported project costs, as the variance in resource quality at real projects makes differences in baseline costs difficult to extract. We consider the 30% learning rate for hydrothermal power suggested by this data be unrealistically high from a qualitative standpoint, as it implies an amenability to learning-by-doing only typically seen in much more modular and standardized technologies like solar power or lithium-ion batteries[32]. Using their qualitative framework, Malhotra and Schmidt[32] instead classify conventional hydrothermal power as a 'Type 3' technology with an implied learning rate of around 5%, as all aspects of hydrothermal wellfield development and power plant design must be customized to the unique conditions of a given hydrothermal reservoir. The small sizes of hydrothermal projects (averaging 26 MW for projects deployed in the US from 2016 through 2019[68]) and unique thermal and chemical properties of each reservoir both help to prevent efficient transfer of drilling and reservoir management knowledge from project to project[27]. In addition, because conventional geothermal surface power plants must be designed with respect to the specific temperature and chemistry of the geofluid, the small sizes of conventional geothermal projects prevent any form of mass-standardized manufacturing that could substantially reduce the costs of turbines and other components[46].

By contrast, without its reliance on naturally-occurring hydrothermal reservoirs, EGS offers a potential pathway to much greater standardization of reservoir and surface power plant designs. We consider EGS to be, in technology and amenability to learning, much more analogous to unconventional oil and gas development than to conventional hydrothermal power. Rather than identifying and exploiting relatively small, unique natural reservoirs, EGS development involves the creation of standardized artificial reservoirs (e.g. the one illustrated in Figure S1) with a basic set of tools almost identical to those used in shale oil and gas field development. While the goals of EGS reservoir engineering (creation of high-transmissivity, uniform flow pathways to connect injection and production wells and enable efficient heat sweep in hard, hot basement formations) are distinct from those of unconventional oil and gas development (efficient extraction of hydrocarbons from lower-temperature shale formations), both technologies utilize horizontal drilling and multi-stage hydraulic fracturing to create artificial reservoirs that can be replicated across an entire geologic formation, and should therefore benefit from similar well-to-well and field-to-field learning mechanisms. Based on these similarities, we adopt unconventional oil and gas extraction as the closest existing technological analogue to EGS wellfield development. The only literature assessment of learning rates for this technology comes from Fukui et al.[36], who find a 13% learning rate for shale gas development in the US based on wellhead gas prices, though this assessment does not take into account degrading resource quality or other non-learning factors that could affect price. From a qualitative perspective, we consider EGS wellfields to be a 'Type 2' technology following the Malhotra and Schmidt[32] framework due to their small unit sizes (individual wells) and the potential for mass standardization similar to what is observed in unconventional oil and gas basins today, where nearly identical well designs are deployed repeatedly across large relatively homogeneous geologic formations[69]. We therefore assign a 15% default learning rate representative of the mid-range for this technology type in Malhotra and Schmidt[32], and slightly higher than the 13% reported in Fukui et al.[36], which did not incorporate the counteractive effects of declining resource quality. We note that this value is slightly more conservative the assumed learning rate for EGS as a whole from the NREL ATB[51]. We also note that the classification of EGS wellfields as 'Type 2' in the Malhotra and Schmidt[32] framework implies similar learning characteristics to onshore wind power, the most well-studied technology in this category. We therefore briefly compare the high-level learning-relevant characteristics of these two technologies to assess the reasonableness of our EGS classification. Both standardization and modularity have been referenced repeatedly as important drivers of learning[31,32,70], and we find that EGS wellfields and onshore wind turbines are similar in both of these areas. Both technologies employ relatively standardized platforms (basic reservoir designs and turbine configurations) that must be optimized with respect to geologic or weather conditions on a regional basis (that is, many projects can still make use of effectively identical designs)[71]. Onshore wind turbines and EGS wellfields also have similar unit sizes, with the capacities of individual onshore wind turbines today (up to 5 MW[71]) being similar to the capacities of individual geothermal wells in our baseline reservoir design (2-7 MWe per well for resource temperatures ranging from 150-300 C). These similarities lead us to conclude that the classification of EGS wellfield learning potential as similar to that of onshore wind power is not unreasonable.

For EGS surface plants we note that while binary-cycle power plant technology has been applied at GW scale in hydrothermal contexts, lack of standardization due to small project sizes and variable reservoir conditions has drastically limited any opportunities for learning-based cost reductions. Akar et al.[46] note that standard practice at present is to design geothermal turbines and other power plant equipment with respect to the specific conditions (e.g. temperature and chemistry) of a geothermal reservoir. Because conventional geothermal developments are often small[68] and exploit unique natural systems, power plant equipment is typically manufactured on an one-off basis. Akar et al.[46] find that the cost of binary-cycle turbine systems could be reduced substantially through mass standardized manufacturing, implying significant learning potential if these systems are deployed in a standardized EGS context where large formations with similar temperatures and chemistries can be developed in blocks of hundreds of megawatts or more. We therefore consider binary-cycle surface plants to also be a 'Type 2' technology in the Malhotra and Schmidt[32] framework when deployed for EGS, but assign them a lower learning rate than wellfields - 10% - in recognition of their greater complexity and larger unit sizes.

To reflect logistical limitations on supply chain and workforce scale-up, we also adopt constraints that limit the change in annual deployment rates for the three emerging technologies modeled in this work (EGS, nuclear SMRs, and Allam cycle), as well as for less-mature hydrogen electrolyzers. Based on observed early growth rates for other energy technologies[72–74], we adopt a limit of 50% year-over-year growth in the annual rate of capacity additions for each of these technologies. We assume that deployment rate growth within each modeled planning period follows this same exponential trajectory, such that total capacity additions in the last year of a five-year planning period are assumed to be equal to 38% of total additions over the entire period. For example, the maximum growth rate in a subsequent five-year period is equal to $\sim$7.6 times the realized growth rate in a prior five-year period. We assume starting capacities of 500 MW for each emerging technology in 2030 and capacity additions in that year of 200 MW/yr. For hydrogen electrolyzers we assume a maximum capacity in 2030 of 20 GW with capacity additions of 8 GW/yr that year.

For EGS resources we also assume that initial commercial development in the 2031-2032 planning period cannot occur in formations with temperatures greater than 250°C due to a lack of off-the-shelf commercial directional drilling and stimulation equipment rated for these temperatures. This initial maximum temperature threshold is roughly 25°C higher than the reservoir temperatures encountered at the Utah FORGE EGS demonstration project, which recently undertook a successful stimulation program[8]. In subsequent periods, we assume that hotter resources become available in 25°C temperature bands if at least 50 MW of development occurred in the immediately previous band in a prior period. Resources up to 350°C are therefore developable in the 2046-2050 planning period if commercial deployment begins in the 2031-2032 period and continuously targets the highest-temperature resources available.

4.6 Limitations and Opportunities

We note several limitations of the present work. First, while we use data from EGS field demonstrations to constrain uncertainties in several key wellfield cost and performance parameters in this work, there are important remaining uncertainties that could affect the near-term EGS cost baseline presented here. Long-term reservoir thermal decline rates cannot be reliably determined through short-term circulation tests, and rates that are more rapid than those simulated here could reduce the effective lifetime of EGS wellfields or require lower flow rates to compensate. Long-term subsurface water loss trends are also the subject of uncertainty, and will require years of operational data to fully characterize. Substantial water losses could both incur large additional costs for makeup water and raise sustainability concerns in drought-prone regions, though the ability of EGS plants to utilize non-potable water may alleviate these concerns somewhat[18]. These and other EGS performance metrics are also likely to vary based on geologic conditions (e.g. lithology and state of stress), though the magnitude of this variance is currently unknown. In general, data from additional commercial-scale EGS demonstration projects beyond the ones cited here will be necessary to more tightly bound the values and variance of key reservoir performance parameters across a variety of geologic conditions.

Second, our analysis assumes that EGS developers have sufficient knowledge of subsurface conditions to site projects optimally and exploit the highest-quality geothermal resources available. In reality there is significant disagreement between existing temperature-at-depth datasets even in regions where such projections are available, and direct exploration will likely be required to sufficiently characterize the actual geothermal resources of any given area. We also assume uniform geologic conditions and seismic risk profiles in building supply curves due to a lack of sufficiently granular data in either category, though in reality these will have nonuniform impacts on the relative viability of EGS development across various geographies.

Third, we impose a maximum temperature limit of 350°C on developable EGS resources in this work due to uncertainties in the viability of hydraulic stimulation in ductile crustal environments above this temperature and the in-applicability of the reservoir simulations used here to supercritical reservoir conditions (374°C and above)[75]. If supercritical geothermal resources can be successfully developed, this could be a pathway to substantially lower EGS costs than those considered in this work in regions where such resources are accessible[76].

Finally, while the capacity expansion modeling approach used here evaluates only the economics of technologies in a cost-optimal evolution of the electricity sector, there are other non-modeled objectives and phenomena that could affect the deployment of EGS or its competitors to varying degrees. Non-cost considerations such as land or material requirements, water consumption, climate impacts, real or perceived project risks (including exploration risk and seismic risk) that affect financing and public acceptance, air quality impacts, and employment can and do impact private investment and centralized resource planning decisions in the electricity sector. Given the sensitivity of long-run outcomes to early-stage deployments in a model considering experience curves, decisions by various actors to preferentially support particular technologies in their early stages of development could lead to substantially different long-term outcomes from those that would be observed in a cost-minimizing model. Additionally, value streams from outside the electricity sector could affect technology deployment trajectories in ways not modeled here. Heating demand could be particularly relevant to the long-run economics of EGS, which can generate many times more low-to-medium grade heat than electricity from the same wellfield due to the fairly low thermal-electric efficiency of binary-cycle surface power plants. The potential impact of widespread EGS adoption for direct heating applications on both heat decarbonization and EGS learning trajectories should be a subject of future research.

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Contributions

W.R. and J.D.J. conceptualized the study. W.R. and J.D.J. developed the experimental design. W.R. developed the models and inputs used. W.R. performed the formal analysis, visualization and investigation, and produced the figures. W.R. drafted the manuscript. J.D.J. advised on the analysis and reviewed and revised the manuscript.

Declaration of Interests

J.D.J. and W.R. are recipients of research funding from Fervo Energy, a developer of enhanced geothermal energy systems. W.R. has performed consulting work for Isometric, a carbon removal standard and registry, The Climate Group, a climate and energy nonprofit, and Rhodium Group, an independent provider of climate and energy research. J.D.J. is part owner of DeSolve, LLC, which provides techno-economic analysis and decision support for clean energy technology ventures and investors. A list of clients can be found at https://www.linkedin.com/in/jessedjenkins. He serves on the advisory boards of Eavor Technologies Inc., a closed-loop geothermal technology company, Rondo Energy, a provider of high-temperature thermal energy storage and industrial decarbonization solutions, and Dig Energy, a developer of low-cost drilling solutions for ground-source heat pumps and has an equity interest in each company. He also serves as a technical advisor to MUUS Climate Partners and Energy Impact Partners, both investors in early-stage climate technology companies.

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