Water-CO_2 Tradeoffs in Electricity Generation Planning

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In 2011, the state of Texas experienced the lowest annual rainfall on record[1], with similar droughts affecting East Africa, China, and Australia. Climate change is expected to further increase the likelihood and severity of future droughts[2]. Simultaneously, population and industrial growth increases demand for drought-stressed water resources[3] and energy, including electricity. In the U.S., nearly half of water withdrawals are for electricity generation[4], much of which currently comes from greenhouse gas emitting fossil fuel combustion. The result is a three-way tension among efforts to meet growing energy demands while reducing greenhouse gas emissions and water withdrawals, a critical issue within the so-called water-energy nexus. We focus on this interaction within the electric sector by using a generation expansion planning model to explore the tradeoffs. We show that 1) large reductions in CO_2 emissions would likely increase water withdrawals for electricity generation in the absence of limits on water usage and, 2) that simultaneous restriction of CO_2 emissions and water withdrawals requires a different generation technology mix and higher costs than one would plan to reduce either CO_2 or water alone.

Previous studies have focused on various aspects of the water-energy linkage, including aggregate views across sectors[5−6], energy use in the water sector[7], and impacts of regional variation in water shortages[8] on electricity generation. Studies on the electric sector have primarily focused on the engineering design of alternative water cooling technologies for generation, their reduction in water withdrawals and consumption, and their incremental costs[3,9−12]. For example, Stillwell and Webber[8] demonstrate the economic feasibility of alternative cooling technologies using a river basin water resources model for 39 generation facilities in Texas. They found that water diversions could be reduced by 247-703 million m^3 (33-93%).

The predominant uses of water in thermoelectric generation are process steam to drive turbines and cooling. Most existing facilities in the U.S. use open-loop or once-through cooling. In this system, freshwater is removed from a source such as a river, the water is used for cooling, and then most is returned to the source at a higher temperature. To minimize environmental impacts, the temperature of the returned water is regulated and must be within established limits. This highlights a key distinction in water use for electricity generation: water withdrawal, the gross amount removed from the water source, is typically much larger than water consumption, the net difference between withdrawn and returned water from the source. However, withdrawal creates competition for water resources not completely mitigated by the fact that most is eventually returned[5].

With growing concern over water resources, several alternative cooling technologies have been developed or proposed. The least expensive is closed-loop, in which water is kept within the facility and recycled. This usually requires cooling towers to sufficiently lower the water temperature before reuse, which imposes additional capital and operating costs to the facility. Periodic withdrawals of additional water are needed to replace water lost in the cooling process, but much less water is withdrawn than for open-loop cooling. Dry cooling, in which steam is cooled for reuse using air forced over heat exchangers, uses even less water but has higher capital and operating costs than closed-loop wet cooling. A third option of hybrid wet-dry cooling has been proposed that use a combination of cooling towers and air cooling, which would have the highest capital costs, but lower operating costs than dry cooling. The precise water requirements and costs for these cooling technologies vary with different generation technology types. The lower thermal efficiencies of nuclear and coal generation require more water for cooling than natural gas combined cycle units, while natural gas combustion turbines don't have a steam cycle and hence use effectively zero water.

Just as interactions between regional air quality and climate change have been explored under the concept of ancillary benefits, two related questions for the water-energy nexus are 1) whether restricting CO_2 emissions from electricity generation reduces water intakes, and 2) whether restricting water use for generation as well as CO_2 emissions requires a different technology mix in the electric sector than for emissions reductions alone? Addressing these questions requires a holistic assessment of a power system rather than focusing on one facility or river-basin and requires quantitative analysis to provide more rigorous insights into the relative tradeoffs. Here we present the results of a generation capacity planning model of the Electric Reliability Council of Texas (ERCOT), which manages the power grid for the majority of the state. ERCOT is a useful region for study because it is an isolated electricity grid, and because Texas has already faced repeated droughts that will likely continue and worsen over time. We use a standard generation capacity expansion model[13−15], which solves a mixed integer linear program (MILP) to find the least-cost power system to meet demand and other constraints (including CO_2 emissions and water withdrawals). Although Texas and many other regions have deregulated the market for generation, such models are useful for investigating the system-wide minimum cost mix of generation, which then provides guidance to regulators in designing incentives for future investments by private entities. In fact, it has been shown that an ideal market based on marginal prices and the centrally planned least-cost solutions are the same[16]. The full model, including model equations and data, is provided in the supplemental material (SM).

We solve our model of the ERCOT region for the future year of 2050, for a peak demand of 136 GW[17] (see SM). We assume no existing generation, since most existing units will likely retire by 2050. The set of generation technologies considered includes nuclear, supercritical pulverized coal (Coal), natural gas combined-cycle (NGCC), natural gas combustion turbine (NGCT), wind, photovoltaics (solar), and options for the coal and NGCC to have carbon capture and sequestration (CCS). Each of these technologies (excluding NGCT, wind, and solar PV) can have three different cooling types: wet (we assume closed-loop), hybrid, and dry. We focus on the comparison of three scenarios for carbon and water withdrawal limits: 1) no limits on either carbon emissions or water withdrawals; 2) a limit on carbon emissions that requires a 75% reduction below the no limit case; and 3) a 75% reduction in carbon emissions and a 50% reduction in water withdrawal relative to the no limit case. Alternative limits for carbon and/or water are explored in the SM, but the qualitative results do not change. As a baseline, we use generation cost and efficiency assumptions from the U.S. Energy Information Administration (EIA)[18], and water requirements and incremental costs of cooling from National Energy Technology Laboratory (NETL)[11,19]. Note that in this study, we only consider the supply-side alternatives to meet a given demand, although impacts could also be reduced by energy efficiency measures to lower demand. The costs of energy efficiency cannot easily be captured in our model, but we explore alternative demand levels in the SM.

We show the optimal generation mix for the three scenarios in Fig. 1. For this reference case, we assume baseline capital and operating costs for all generation technologies and median projected prices for 2050 for natural gas and coal of \$12.60 and \$3.50 per MMBTU respectively (see SM). In the absence of any limits on carbon emissions or water withdrawals, the cost minimizing mix consists of coal, natural gas combined cycle, and natural gas combustion turbine generation. To achieve a 75% reduction in CO_2 emissions, most of the coal capacity is replaced with nuclear capacity, with a small increase in natural gas combined cycle capacity. This is consistent with the findings of other studies of the effects of CO_2 caps on generation technology choice[20−22]. The water withdrawal under the CO_2 limit is 64% greater than that under the no limit case, due to the additional water withdrawals for nuclear generation. Limits on both carbon emissions and water withdrawals results in a very different mix. Nuclear generation capacity is reduced by 40% and requires hybrid cooling systems. Natural gas combined cycle capacity roughly doubles compared with the no limit scenario, and the majority of these units require dry cooling systems. Finally, roughly 8 GW of wind (5% of total capacity) is installed.

The results shown above depend critically on assumptions about the prices of fuels (natural gas and coal) and about the capital costs and efficiency of generation technologies. In order to draw robust qualitative insights about the relationship between CO_2 emission limits, water withdrawals, and generation mix, we perform a Monte Carlo simulation with 1000 scenarios using Latin Hypercube sampling[23]. The range of uncertainty in future prices is calibrated to EIA projections[24] and uncertainty in technology costs are based on a set of expert elicitations by Anadon et al.[25−27] (see SM for uncertainty methods and assumptions). In this way, we explore the effect of reducing CO_2 only, and of reducing CO_2 and water simultaneously, over a broad of possible futures.

The results of the Monte Carlo simulation are represented in Figs. 2 and 3 using box plots. The boundary of the box closest to zero indicates the 25th percentile, a line within the box marks the median, and the boundary of the box farthest from zero indicates the 75th percentile. Whiskers (error bars) above and below the box indicate the 90th and 10th percentiles, and the dots above and below the whiskers represent the 5th and 95th percentiles. These results demonstrate that the general trends from the baseline are robust across a wide range of scenarios. In the absence of CO_2 limits, emissions may be higher or lower than the reference case emissions of 537 Mt CO_2 (Fig. 2). The effect of a CO_2 emissions reduction without any limit on water withdrawals is to increase water withdrawals; the median of the distribution increases from below 400 billion gallons to above 600 billion gallons.

The shift in the probability distributions of carbon emissions and water withdrawals can be understood by examining the distributions of generation capacity for each technology (Fig. 3). Even under the broad range of uncertainty in future costs, wind generation is economic in fewer than 2% of the cases without any CO_2 limits, but this increases to 13% with only a CO_2 limit and to 85% of the cases with CO_2 and water limits. Solar generation (not shown in figure) is economic in only 0.1% for both scenarios without water limits; with limits on water withdrawals as well as on CO_2 this increases to 4%. Thus renewable sources constitute a larger contribution when the impacts of electricity on both carbon and water are considered.

In terms of thermal generation sources, the qualitative trend is the same across the broad range of cases as for the reference assumptions. In the absence of CO_2 limits, the relative shares of coal, nuclear, and natural gas vary widely depending on the relative costs and fuel prices. The effect of reducing CO_2 emissions for the majority of cases is to shift away from coal generation in favor of more reliance on nuclear generation and a slight increase in natural gas generation. Reducing CO_2 emissions and water withdrawals shifts even further from coal and also from nuclear in favor of natural gas generation, much of which uses hybrid or dry cooling systems to reduce the water withdrawals.

Finally, the impact on carbon capture technologies (CCS) depends on the specific fuel. Coal with CCS is economic as part of the mix for 10% of the cases with a CO_2 limit only, but restricting water reduces the likelihood that coal CCS will play a role to 0.2%. In contrast, natural gas combined cycle with CCS is part of the mix in 20% of the cases with a CO_2 limit only, but in nearly 40% of the cases when both CO_2 and water are constrained. The higher water requirements for coal-CCS systems and the cost of adding water reduction technologies to a coal unit with CCS makes this technology too costly across the broad sample of possible futures. Thus, the main contribution from carbon capture technologies may ultimately be for gas-fired generation, especially when multiple environmental factors are considered.

Additional analysis and insights are described in the SM, including results for other water and carbon limits, and several sensitivity analyses to natural gas prices, solar capital costs, coal-CCS costs, demand, and nuclear dry cooling availability. Overall, the key point of this analysis is that the resulting mix depends critically on the interactions of the generation technologies with each other, and that considering water limits along with CO_2 limits could dramatically change the configuration of the electric sector from what is typically predicted from energy-climate models that do not consider water.

A future where large reductions in greenhouse gases are desirable is also likely to be one in which water resources are even more constrained than they are today. Although the electricity sector is only one part of the energy-water nexus, it is a critical one. Assumptions about the future technology mix in a low-carbon world typically have not considered simultaneous water use reductions. However, this research shows that water restrictions can play a critical role in the optimal generation mix. Utilities planning future generation and policymakers considering future regulator designs or R&D investments should consider including water in their models to avoid biased results and incorrect inferences. The general policy implication is that cost-competitive low-carbon technologies tend to also be more water-intensive than today's power system. In contrast, many technologies that do not seem cost-effective as part of a low-carbon system, such as wind or solar, may be justified when considering the full set of environment challenges including water use. Finally, a water and carbon-constrained world will likely need cooling processes that use less water; reducing the current uncertainty in the cost and performance of hybrid or dry cooling through utility-scale demonstration projects would inform which mix of energy technologies will be more desirable. In particular, the feasibility of nuclear generation with partial or total air cooling needs to be better understood.

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Supplemental Material

Model Formulation

We use a standard static generation capacity expansion model, with simplified operations performing economic dispatch for an 8760 hour load duration curve. Below, we list the equations of the model and give the data assumptions in tables. The model is written in the GAMS programming language as a Mixed Integer Linear Programming (MILP) problem and solved using the commercial solver CPLEX 12.2. We use MILP to enforce that the number of generators of each type must be integer, where each generator technology type has a standard unit size. The model minimizes total system cost Z (A.1) subject to constraints(A.2)-(A.9) specified below.

$$\max_{n_g, e_{g,d}} Z = C^F_{OM} + C^V_{OM} + C^V_{FC} + C^F_I. \tag{A.1}$$

The control variables are the number of generation units n_g to build of each technology type g, and the energy generated $e_{g,d}$ by each unit of type g for demand time block d. The total cost is the sum of the fixed O&M costs C^F_{OM}, the variable O&M costs C^V_{OM}, the fuel costs C^V_{FC}, and the investment cost to build the capacity C^F_I. We constrain the total generation in each time block to be equal to the total demand for that block (i.e., no non-served energy),

$$\sum_g [e_{g,d}] = D_d \; \forall d. \tag{A.2}$$

Total emissions of CO_2 over the year must be below the cap E_{lim} if one is set,

$$\sum_d \sum_g [e_{g,d} * HR_g * E_g] \leq E_{lim}. \tag{A.3}$$

The total emissions are the sum over all demand blocks and all generation technologies of the product of the power output, the heat rate of the technology HR_g (the inverse of the efficiency), and the carbon content of the fuel E_g. Similarly, total water withdrawals must be below the cap W_{lim} if one is set,

$$\sum_d \sum_g [e_{g,d} * HR_g * W_g] \leq W_{lim}, \tag{A.4}$$

where W_g is the water withdrawal rate for technology t. The remaining constraints (A.5)-(A.9) define intermediate variables in terms of the underlying data.

The capacity in MW of each technology is equal to the number of installed units multiplied by the standard unit size,

$$CAP_g = n_g * SIZE_g. \tag{A.5}$$

Capital costs are defined as the installed capacity multiplied by the annualized cost of capital, using a capital recovery factor

$$C^F_I = \sum_g CAP_g * CRF. \tag{A.6}$$

Total fixed O&M costs are the sum over technology types of fixed O&M costs multiplied by the capacity of that technology.

$$C^F_{OM} = \sum_g [CAP_g * C^F_{OM,t}]. \tag{A.7}$$

Total variable O&M costs are the sum over all demand blocks and all technology types of the variable O&M costs.

$$C^V_{OM} = \sum_d \sum_g [e_{g,d} * C^V_{OM,t}]. \tag{A.8}$$

Finally, the capital recover factor CRF is defined in terms of the weighted average cost of capital ($WACC$) and the economic lifetime of the unit L.

$$CRF = \frac{WACC}{1 - \frac{1}{(1+WACC)^L}}. \tag{A.9}$$

We assume a weighted average cost of capital of 8%, and a 30yr lifetime for all generation technologies, except for wind with a 20 year life.

Of particular concern is the availability of a generation mix to meet demand with minimal loss of load. We require a "planning reserve," $a^{PlanReserve}$, of "firm" capacity to be built beyond that required by the peak demand:

$$\sum_g a_g^{firm} CAP_g \geq (1 + a^{PlanReserve}) \max_d (D_d). \tag{A.10}$$

The planning reserve accounts for both the peak period operating reserve requirements and uncertainty in load growth projections. Firm capacity relates to installed capacity based on the firm capacity ratio, a^{firm}, which captures the amount of generating capacity that can be counted on during peak periods. The standard approach for all technologies is to use the Effective Load Carrying Capacity (ELCC) that computes the equivalent (smaller) firm generation capacity that maintains the same probability of lost load. For thermal plants, this is well approximated as 100% minus the chance the unit is not available when dispatched, referred to as the Effective Forced Outage Rate (EFOR). For variable renewables (wind and solar) the ELCC depends on the penetration level considered, and is a complex function of the other generators on the system[A.1].

Reference Case Data and Assumptions

Key assumptions about generation costs, efficiency, standard unit size, and water withdrawal rates are given in Table A.1. Capital costs, fixed and variable operations and maintenance (O&M) costs, the heat rate are based on the Energy Information Administration (EIA)[17]. The heat rate is the inverse of the efficiency, in units of MMBTU / MWh, and is used to compute the fuel usage for a given amount of generation output. Capital costs are based on building two co-located units. The water withdrawal rates are taken from a report of the National Energy Technology Laboratory (NETL)[10]. The unit sizes are an assumption based on commonly observed generation unit sizes of each type, in order to simulate the building of discrete units and on EIA[17].

For planning reserve margin calculations, we use ERCOT's target of 13.75%[A.2]. Thermal unit firm capacity is computed as 100% minus EFOR. For combined cycle natural gas plants the EFOR is assumed to be offset by duct-firing capabilities that enable higher than rated output during peaking periods, resulting in a capacity credit of 1.0. In ERCOT there has been considerable debate about the ELCC for wind, with two recent reports finding values of 12.2% and 8.7%. We assume 10.5% ELCC for wind, which isthe average of these estimates[A.2,A.3]. The ELCC of solar is assumed to be 60%[A.4] (Table A.1).

Fuel-related assumptions are given in Table A.2. Fuel prices for coal and natural gas are based on median projections calibrated to future price scenarios by the EIA Annual Energy Outlook[A.5] (see next section for detailed projection methodology). The price for uranium-235 is based on a study by the Royal Academy of Engineering[A.6]. The carbon content of fuels is based on data from the EIA program on voluntary reporting of greenhouse gas emissions[A.7].

Table A.1: Generation Data Assumptions

Technology	Var. O&M [$ /MWh]	Fixed O&M [$/kW-yr]	Capital Cost [$/kW]	Heat Rate [MMBTU/MWh]	Plant Size [MW]	Water With. Rate [gal/MMBTU]	ELCC
Nuclear Wet	2	89	5335	10.4	1350	105.9	0.96
Nuclear Hybrid	2	89	5558	10.4	1350	60.5	0.96
Nuclear Dry	2	89	5808	10.4	1350	15.1	0.96
Coal Wet	4.25	30	2844	9	600	65.3	0.93
Coal Hybrid	4.25	30	2945	9	600	37.3	0.93
Coal Dry	4.25	30	3059	9	600	9.3	0.93
Coal CCS Wet	9	63	4579	11.88	600	92.4	0.93
Coal CCS Hybrid	9	63	4807	11.88	600	76.3	0.93
Coal CCS Dry	9	63	5063	11.88	600	60.1	0.93
Gas CCGT Wet	3	15	1003	6.93	400	37.2	1.0
Gas CCGT Hybrid	3	15	1093	6.93	400	19	1.0
Gas CCGT Dry	3	15	1211	6.93	400	0.9	1.0
Gas CCGT CCS Wet	6.5	30	2060	9.15	400	55.1	1.0
Gas CCGT CCS Hybrid	6.5	30	2206	9.15	400	47.9	1.0
Gas CCGT CCS Dry	6.5	30	2396	9.15	400	40	1.0
Gas CT	10	7	665	11.87	230	0	0.95
Wind	0	28	2438	1	50	0	0.105
Solar	0	17	4755	1	50	0	0.60

Table A.2: Fuel Cost and Carbon Content

Fuel	Price ($/MMBTU)	CO_2 (t/MMBTU)
Uranium-235	0.766	0
Coal	3.5	0.0965
Natural Gas	12.6	0.0531
Wind	0	0
Solar	0	0

The reference demand is based on 2009 ERCOT demand. We scale the 8760 hour demand data for ERCOT by a factor of 2.15 (Figure A.1), based on an extrapolation of the trends in the ERCOT demand forecast[17]. See below for alternative assumptions.

Monte Carlo Simulation Data and Methods

This section describes the data and assumptions for the Monte Carlo simulations. Uncertainty is modeled in future prices of coal and natural gas, in the capital costs of generation technologies, and in the incremental costs of carbon capture and dry and hybrid cooling technologies. Uncertainty in fuel prices is modeled using a random walk approach, and future generation cost uncertainties are taken from the results of expert elicitations.

Figures A.2 and A.3 show the historical prices of coal and natural gas in the U.S. from 1980 to 2011. A standard approach to modeling long-term commodity price uncertainty is as a random walk stochastic process with drift[A.8,A.9]. We adopt this approach here to model the uncertainty in future gas and coal prices. Specifically, prices are modeled as a Markov process that evolves as

$$ln(p_{t+1}) = ln(p_t) + \epsilon \qquad \epsilon \sim N(\mu, \sigma) \tag{A.11}$$

where μ is the long-run average trend and σ is the volatility. A typical application of this method would use historical price movements to estimate the mean trend and volatility parameters. However, because future structural changes in the industries may dominate past determinants of trend and volatility, rather than calibrate to historical prices, we calibrate our random walk parameters (the drift term μ and the volatility σ) such that the interquartile range (50% probability) matches the high and low scenarios of the EIA Annual Energy Outlook[A.5], and the median is close to the reference EIA scenario. This procedure leads to estimates for natural gas of $\mu = 0.03$ and $\sigma = 0.1$, and for coal $\mu = 0.01$ and $\sigma = 0.15$. The resulting projections are shown in Figs. A.2 and A.3.

For the uncertainty costs of generation technologies, we develop probability distributions based on the expert elicitations performed by Anadon et al[A.10−A.12]. These studies report the elicited quantiles for capital cost (and efficiency penalty for CCS) by individual expert. In their studies, 13 experts provide judgements about fossil technologies, 11 provide judgements about solar PV, and 25 experts provide judgements for next generation (GEN III) nuclear technologies. For the current analysis, the objective is to obtain plausible probability distributions that cover a broad range of possible futures. We therefore first combine the experts for each technology by weighting each expert equally. This is performed by simulating an off-line Monte Carlo simulation in which, for a given technology, each expert's individual distribution is sampled 1000 times, and the set of all samples across all experts are then used to estimate a single distribution that best fits the data. This single distribution is then sampled for the model simulations in the current study.

For wind generation, there are no published expert elicitations of uncertainty in future capital costs. Instead, we use a probability distribution calibrated to projections for on-shore wind capital costs from the Transparent Costs Database by Open Energy Information[A.13], a project sponsored in part by DOE/NREL.

In addition to capital costs for the base generation technology, we also model uncertainty in the costs of carbon capture and of the water reduction cooling systems (hybrid and dry cooling). Uncertainty in the capital costs for CCS applied to coal steam (supercritical) or natural gas combined cycle units are also taken from the studies by Anadon et al. We convert the uncertainty in costs to distributions of the incremental costs of adding CCS.

The uncertainty estimates for the incremental costs of hybrid and dry cooling are taken from a survey of the literature in Stillwell and Webber[A.14]. Based on the ranges given in this study, we assume that the uncertainty in these quantities are normally distributed around the reference assumptions with a standard deviation of 25%. We use the same distribution for the heatrate penalty of CCS. The distributions used are summarized in Table and box plots are shown in Figure A.4.

Table A.3: Fuel Cost and Carbon Content

Model Assumption	Distribution Type	Dist Param 1	Dist Param 2
Nuclear Capital Cost	Lognormal	1.0027	0.43153
Coal Capital Cost	Lognormal	0.99786	0.34551
NGCC Capital Cost	Lognormal	0.99748	0.49709
NGCT Capital Cost	Lognormal	0.99743	0.49693
Wind Capital Cost	Lognormal	0.99985	0.098555
Solar PV Capital Cost	Lognormal	1.0173	0.65486
CCS Capital Markup	Weibull	1.7592	1.1684
CCS Heatrate Markup	Normal	1.0	0.25
Hybrid Cooling Markup	Normal	1.0	0.25
Dry Cooling Markup	Normal	1.0	0.25

A final critical assumption in a Monte Carlo simulation is the correlation induced when sampling from the marginal distributions. We assume three sets of correlation in generating random sample sets of parameters. The first is the correlation between the capital costs of natural gas combined cycle and of natural gas combustion turbine (or open-cycle). Because combined cycle plants consist of turbines plus other components, we assume a correlation of 0.5. Second, we assume that the incremental capital costs for hybrid and dry cooling are highly correlated, with a value of 0.8. Finally, we assume that coal and natural gas prices by 2050 are weakly correlated (0.2).

We use Latin Hypercube Sampling[A.15] to draw 1000 samples for the parameters, and rerun the model for each sample and each emissions/water limit scenario.

Additional Results

In this section, we present additional results not shown in the main text. In addition to the scenarios described in the text (no limits, 75% reduction in CO_2, 75% reduction in CO_2 and 50% reduction in water), we explore a broader range of illustrative CO_2 and water limits using reference assumptions for costs and prices (i.e., deterministic). We solve the model for all combinations of limits on CO_2 (none; 25% reduction; 50% reduction; 75% reduction) with limits on water withdrawals (none; 25% reduction; 50% reduction). The general trends across the additional policy scenarios is the same as those in the main text. CO_2 limits alone lead to substitution of nuclear for coal generation (Fig. A.5). The effect of water limits alone is to alter the cooling technology on increasing amounts of the coal and gas generation. Limits on both CO_2 and water result in technology mixes that are different than either limit alone would induce. We also show the relative shares of energy produced (MWh) in Fig. A.6; the trends are the same, but the impact on actual production is larger for baseload technologies (e.g., coal and nuclear), and smaller for peak technologies (e.g., NGCT).

Sensitivity to Electricity Demand

An alternative strategy for reducing CO_2 emissions and water usage, as well as other environmental impacts, is to use less electricity. There is a significant literature on energy efficiency measures and technologies. Here, we take an agnostic view of how much of the growth in demand can be met through energy efficiency as opposed to increased generation. Demand is an exogenous assumption for the capacity expansion methodology employed here. We therefore perform sensitivity analysis by repeating the simulations for different levels of demand. For clarity of exposition, the sensitivity analysis is conducted for the deterministic case with reference cost and fuel price assumptions, as described in the main text.

We test two additional scenarios for electricity demand growth: a 20% reduction (peak load of 108 GW) and a 40% reduction (peak load of 82.6 GW) from the reference demand scenario (peak load of 137 GW). These levels are based roughly on the range of growth rates in electricity demand impacts of energy efficiency by EPRI, "EIA projects that peak demand in the United States will grow at an annual rate of 1.5% from 2008 through 2030. The combination of energy efficiency and demand response programs has the potential to realistically reduce this growth rate to 0.83% per year. Under an ideal set of conditions conducive to energy efficiency and demand response programs, this growth rate can be reduced to as low as 0.53% per year.[A.16]" Note that the 40% reduction case would mean very little growth by 2050 from 2009 demand in ERCOT (peak load of 63.5 GW). For each demand scenario, we repeat the three policy cases from the main text: no limits on CO_2 or water, a 75% reduction in CO_2, and a 75% reduction in CO_2 and 50% reduction in water withdrawals. We show the resulting technology mix in Fig. A.7. In the absence of CO_2 and water limits, the mix is essentially the same for the reference cost/price assumptions: coal baseload, natural gas combined cycle, and natural gas combustion turbines for peaking units. The absolute magnitudes of installed MW differ of course since the demands are different, but the relative shares are roughly constant. This is also the case for limits only on CO_2. The primary difference across the results for the CO_2 case are that because of the lower demand, the emissions limit is easier to achieve, and coal generation substitutes for nuclear generation. With less electricity production in total because of energy efficiency, the mix does not need to be as low in carbon intensity. This effect of allowing a higher carbon-intensive mix for lower demand scenarios also drives the differences across the CO_2 and water limit cases. The shares of nuclear and NGCT generation are roughly constant as demand varies. However, at lower demand the mix can be both more carbon-intensive and water-intensive. As a result, the large share of NGCC with dry cooling technology can be gradually substituted by coal, and by more water-intensive cooling applied to coal and gas generation.

Overall, the qualitative conclusions remain the same as in the main text. The effect of CO_2 limits alone mostly tends to increase the amount of water withdrawals for cooling. Imposing limits on both CO_2 and water results in a qualitatively different mix. The details of that mix will depend on the energy efficiency improvements that may be implemented in parallel. Energy efficiency is another useful strategy for reducing environmental impacts. The socially optimal mix of energy efficiency and alternative energy technologies is beyond the scope of this study. Nevertheless, whatever the level of electricity demand to met in the future, the proper mix of technologies will depend on the environmental impacts we consider and the regulatory structure that will guide individual investments.

Sensitivity to Natural Gas Prices

One of the most significant drivers of uncertainty in the generation mix under the various policy cases is the price of natural gas. We therefore augment the results of the Monte Carlo simulation with a sensitivity analysis varying only the price of natural gas, holding all other parameters at reference values. Based on the 95% probability range of projected natural gas price by 2050, we explore prices between $3 and $27 per MMBTU. In the absence of limits on water or carbon (Fig. A.8(a)), the least cost generation mix ranges from the typical coal / NGCC / NGCT mix to one that is only gas (NGCC/NGCT) when the price is $6 or less. With limits on carbon emissions only (Fig. A.8(b)), high gas prices lead to displacement of some coal generation by nuclear. As the price of gas decreases, more coal is displaced by natural gas generation. At very low gas prices, the mix is all natural gas, and includes some NGCC with carbon capture. Under limits on both carbon and water (Fig. A.8(c)), 20% of the capacity is provided by wind, regardless of the gas price. At low gas prices, the majority of the generation capacity is still natural gas-based, but includes some NGCC with carbon capture and some NGCC with dry cooling technology. At high gas prices, some of the gas generation is displaced by coal with dry cooling technology, nuclear, and solar generation.

Sensitivity to Solar Capital Costs

In the uncertainty analysis results presented in the main text, there were very few samples in which solar played a significant role in the generation mix. This is a result of the current estimated capital cost, which is quite high. Even with the uncertainty in this cost, solar is only cost-effective when natural gas prices are higher and alternative technologies (e.g., wind) are also higher cost. To complement these results, we present here a sensitivity analysis varying only the capital cost of solar, holding all other parameters at reference values. We compare the resulting technology mix under each policy scenario for capital costs at the original EIA estimated cost ($4755 / KW), and then at 60%, 50%, 40%, 30%, 20%, and 10% of this cost. In the absence of limits on water or carbon (Fig. A.9(a)), the least cost generation mix remains the typical coal / NGCC / NGCT mix unless the capital cost of solar falls to at least 30%, in which case, solar would be part of the mix even in the absence of carbon or water policy. Similarly, with limits on carbon emissions only (Fig. A.9(b)), costs must also fall to at least 30% of current estimates before solar would be part of the mix, displacing both nuclear and gas generation. Under limits on both carbon and water (Fig. A.9(c)), solar provides a larger share of capacity. Under this policy scenario, a reduction of at least 50% is required before solar is part of the generation mix.

Sensitivity to Costs of Coal with Carbon Capture

Another technology that is present in the mix in only relatively few samples is coal with CCS. As with solar, this is a result of the higher expected costs relative to nuclear generation, the most similar low-carbon baseload technology, and the fact that both the capital costs and the operating costs need to be lower than the expected values to compete. For CCS, the parasitic energy demand to power the carbon capture process reduces the effective efficiency of the unit, and is represented by a higher heatrate (lower efficiency) than coal without CCS. Coal-CCS will only contribute to the mix in samples for which nuclear capital costs are higher, the capital costs of coal-CCS are lower, the heatrate of coal-CCS is lower, and gas prices are relatively high.

As an illustration of typical solutions when these conditions are met, we show the capacity mix that results when both capital costs and heatrate of coal-CCS are 50% lower than the reference assumptions, and when the nuclear capital costs are 40%, 50%, and 60% higher than the reference assumption (Fig. A.10). All other parameters are held at reference values. As elsewhere, we focus on the three policy cases of no carbon or water limits, a 75% reduction in CO_2 emissions, and a 75% reduction in CO_2 and a 50% reduction in water withdrawals. We also show the results for a limit only on water withdrawals (50% reduction). The resulting mix for no limits and for water limits only are the same across the three levels of nuclear costs, so those are shown only once. The difference across the solutions occurs when CO_2 is limited, with or without concurrent water limits. With only CO_2 limits, coal-CCS substitutes for nuclear if nuclear costs are 50% higher or more than reference. For limits on CO_2 and water, coal-CCS only plays a role if nuclear capital costs are at least 60% higher than reference, and in this case wind also takes a significant share. If the capital costs and heatrate for coal are higher than these cases, then even higher costs for nuclear and higher natural gas prices are necessary for coal-CCS to be part of the least cost mix. In general, the qualitative results of the main analysis would be unchanged if CCS costs were dramatically lower, with the only change that coal-CCSS would take on the role of nuclear in the earlier results.

Sensitivity to Availability of Nuclear Plants with Hybrid or Dry Cooling

A critical assumption in the previous results is that hybrid cooling technology is available to be used for nuclear generation if it is required to meet the policy constraints and is part of the least-cost mix. Nuclear generation with dry cooling is also available in the model for selection, but within the range of uncertainty considered is never present in the generation mix because of its high costs.

Nuclear generation with hybrid or dry cooling is controversial because of potential safety concerns, and to date no facility has yet been licensed.

Because nuclear with hybrid cooling is part of the mix for policies that limit both CO_2 and water, we solve for those scenarios again without the possibility of nuclear with hybrid or dry cooling. The results in Figure A.11 compare the share of total capacity by technology under the subset of policy scenarios that place some limit on both carbon and water when these cooling options are not available to the capacity shares when they are (results with nuclear hybrid are the same as in Fig A.5). For smaller reductions of CO_2, the main impact of nuclear hybrid not being available is to instead use nuclear with closed-loop (wet) cooling combined with natural gas combined cycle using dry cooling. For larger CO_2 reductions (-75%), larger shares of renewables (wind and solar PV) are used when nuclear hybrid is not available.

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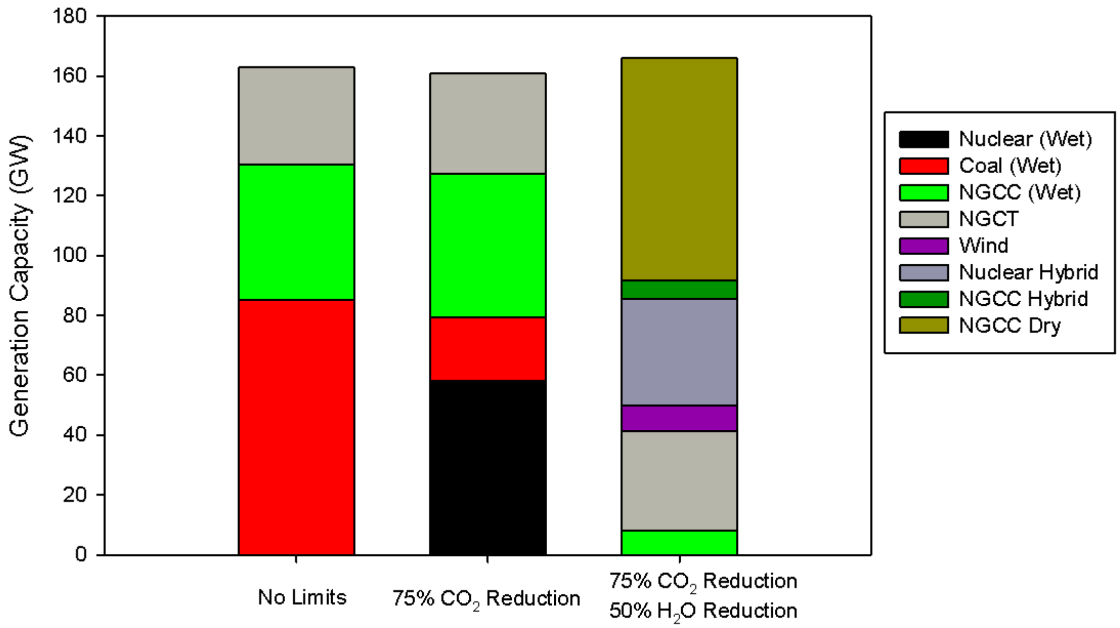

Figure 1: Generation capacity mix as a function of water and carbon limits for reference cost assumptions.

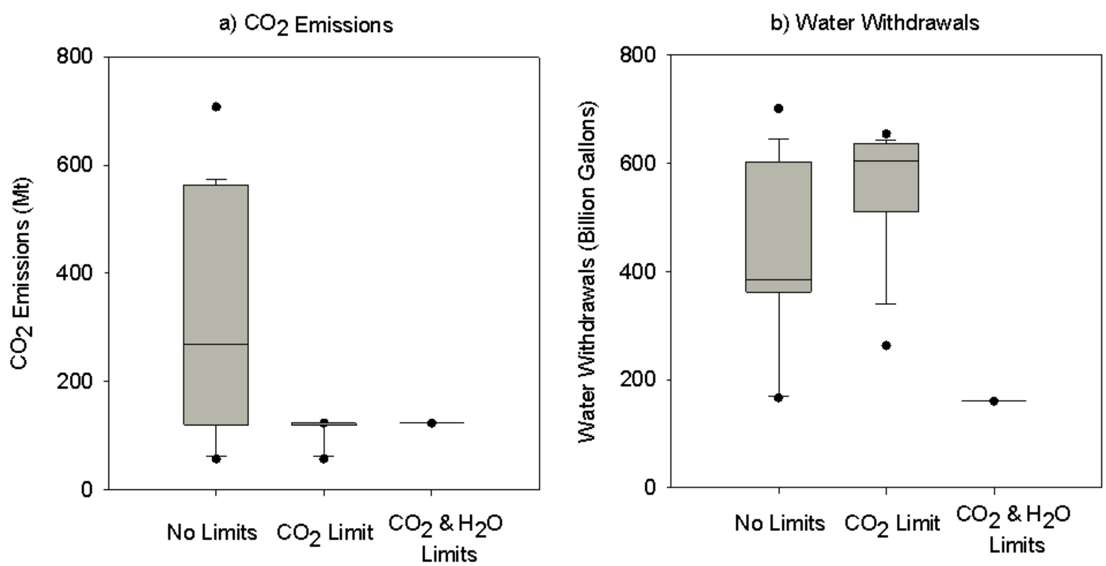

Figure 2: Uncertainty in the annual carbon dioxide emissions and water withdrawals as a function of water and carbon limits.

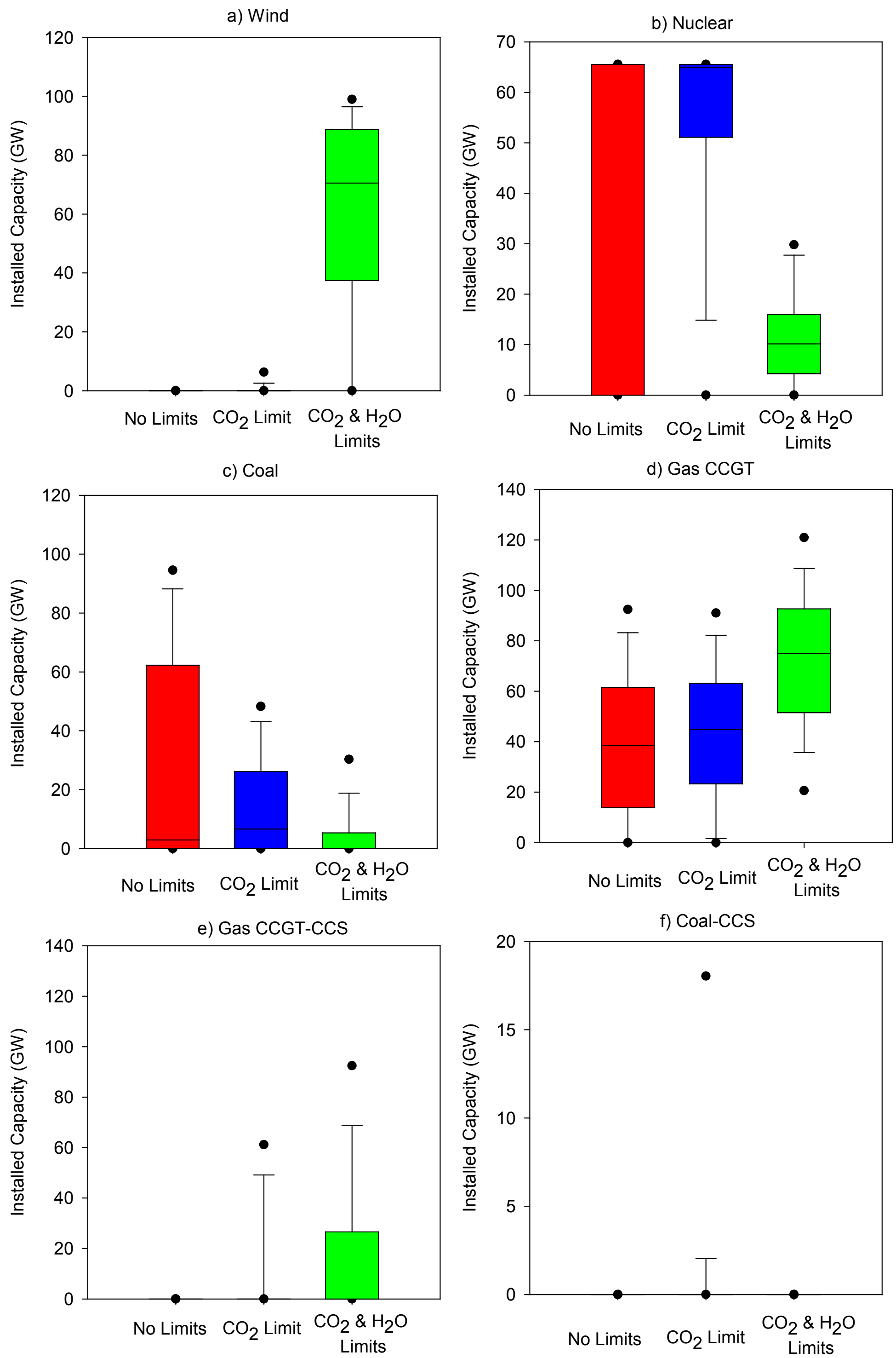

Figure 3: Uncertainty in the capacity mix of electricity generation as a function of water and carbon limits. Technologies with zero capacity built in more than 95% of samples are not shown.

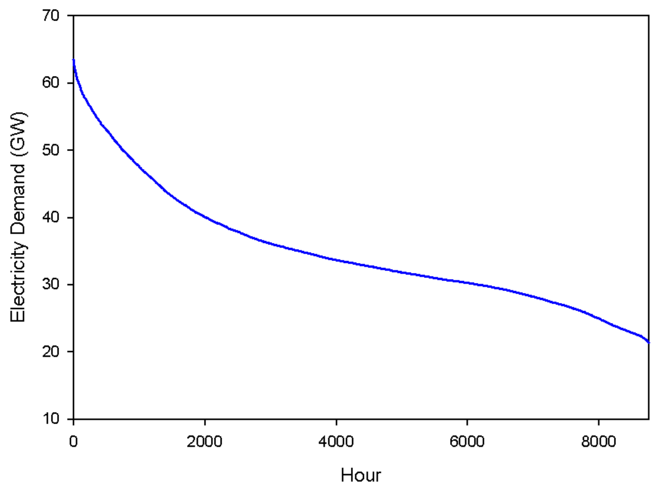

Figure A.1: Projected Load Duration Curve for ERCOT Demand in 2050.

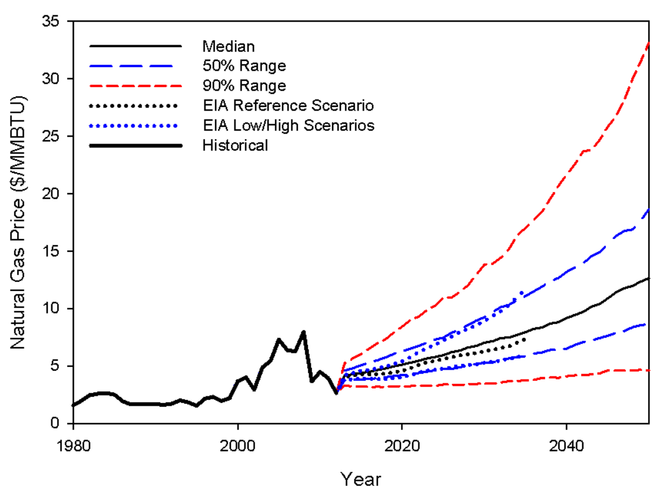

Figure A.2: Historical and Projected Natural Gas Prices.

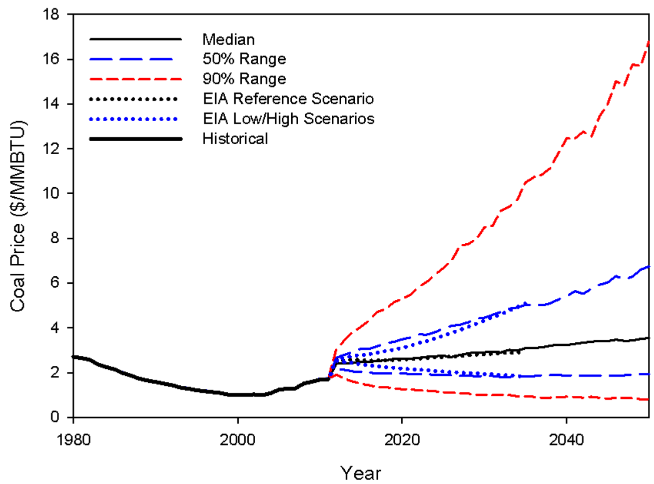

Figure A.3: Historical and Projected Coal Prices.

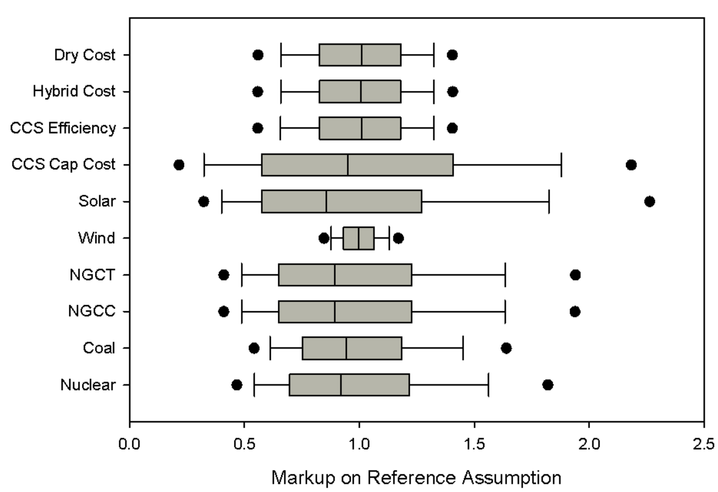

Figure A.4: Probability Distributions for Technology Cost and Performance Parameters (Relative to Reference Assumptions).

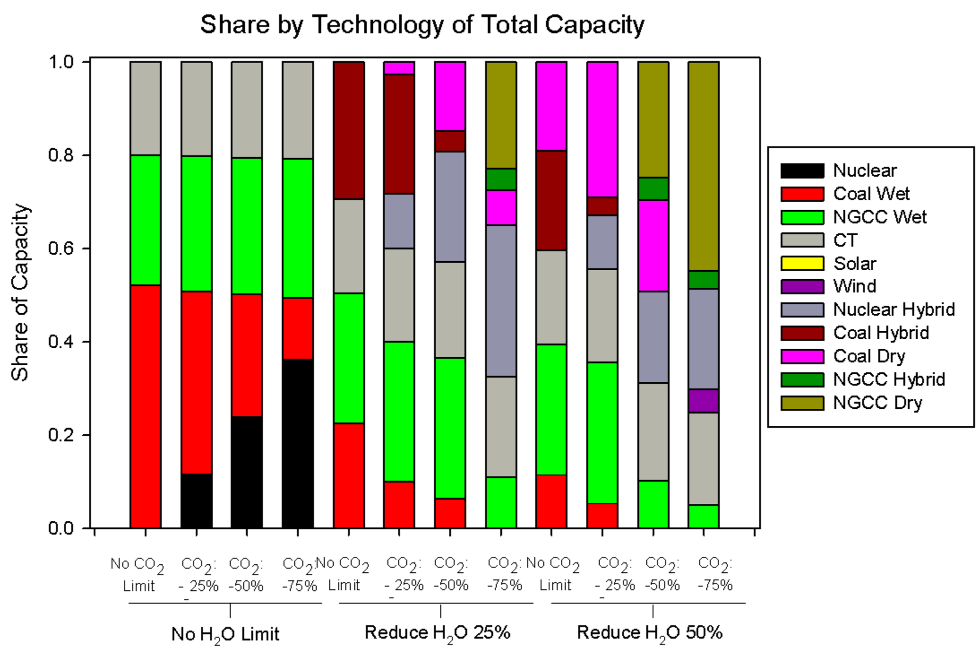

Figure A.5: Capacity mix as a function of water and carbon limits for reference cost assumptions.

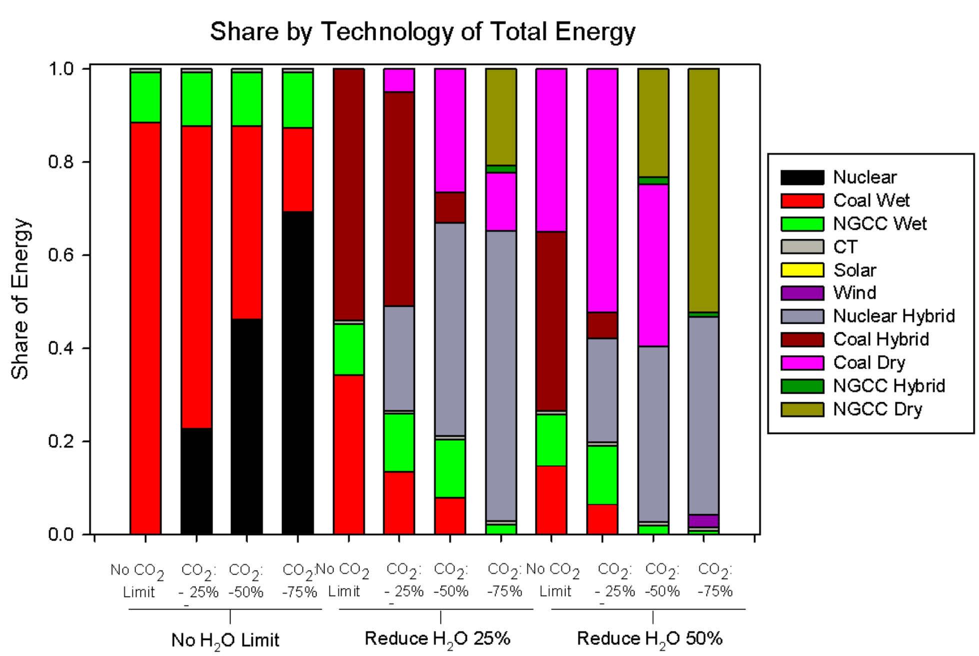

Figure A.6: Energy mix as a function of water and carbon limits for reference cost assumptions.

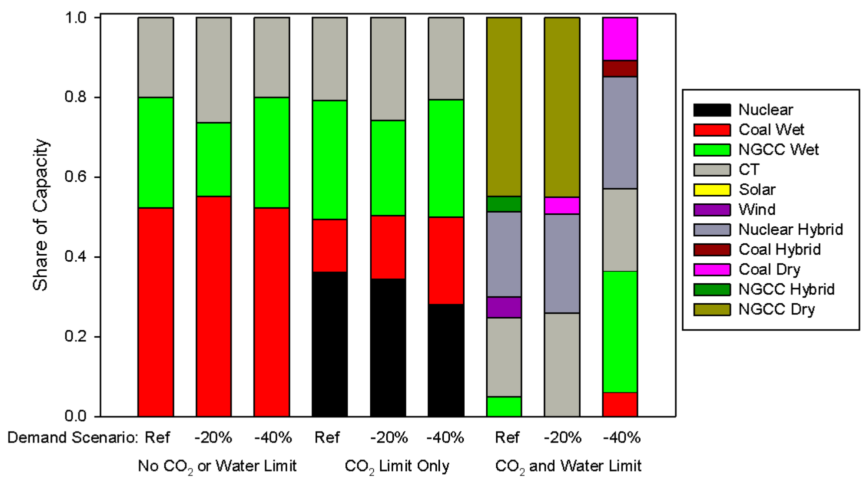

Figure A.7: Sensitivity of capacity mix to demand as a function of water and carbon limits.

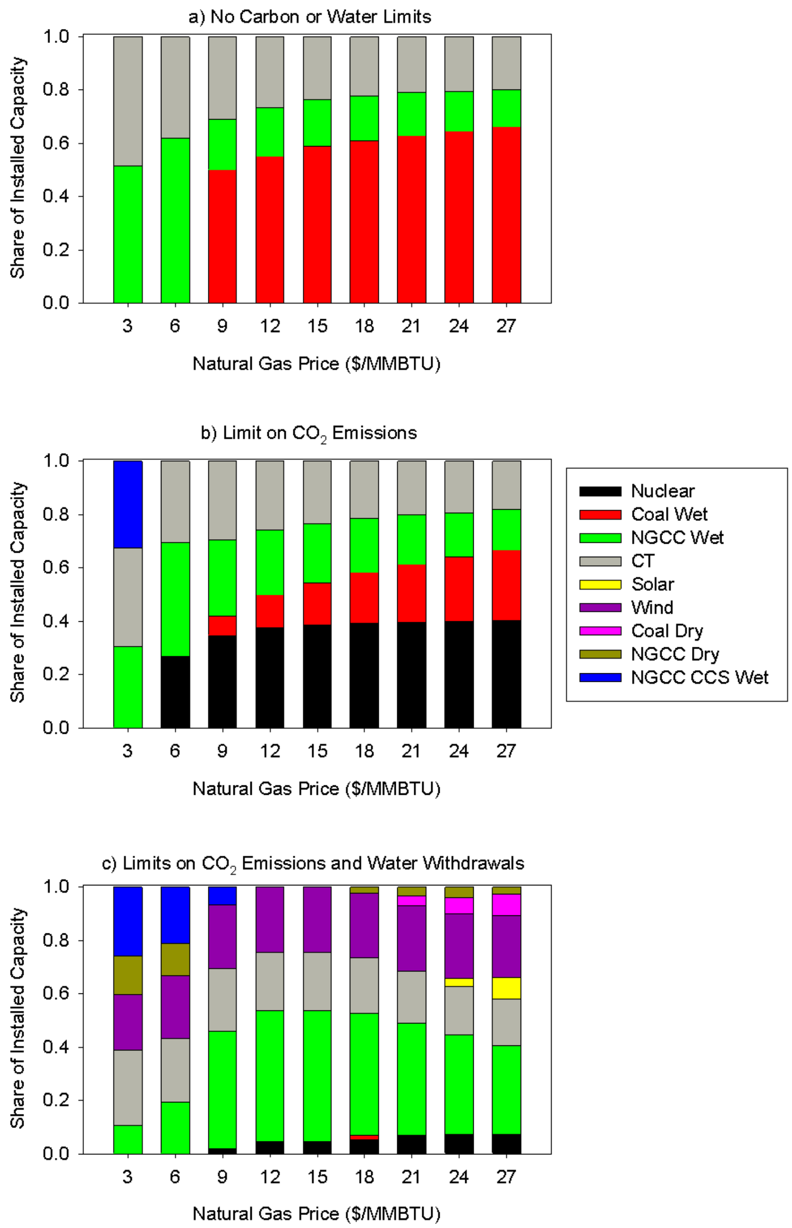

Figure A.8: Generation technology mix as a function of natural gas price.

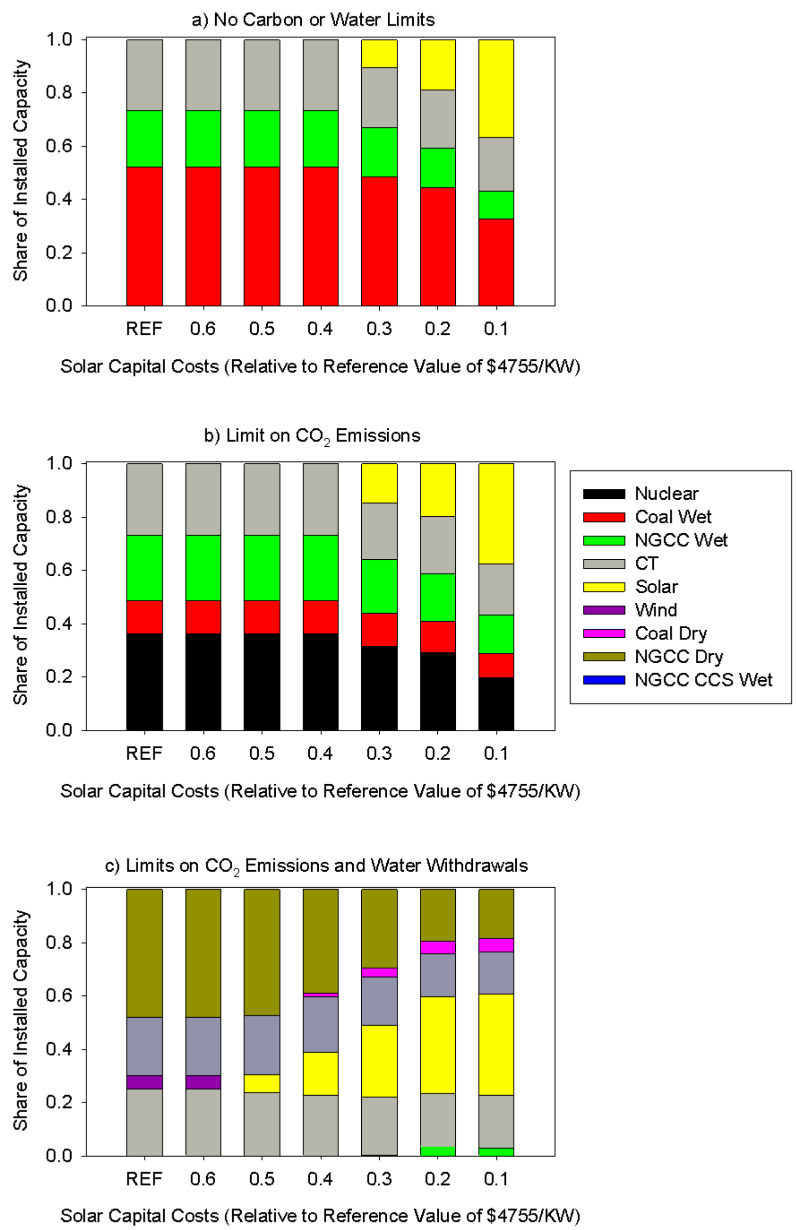

Figure A.9: Generation technology mix as a function of solar capital costs.

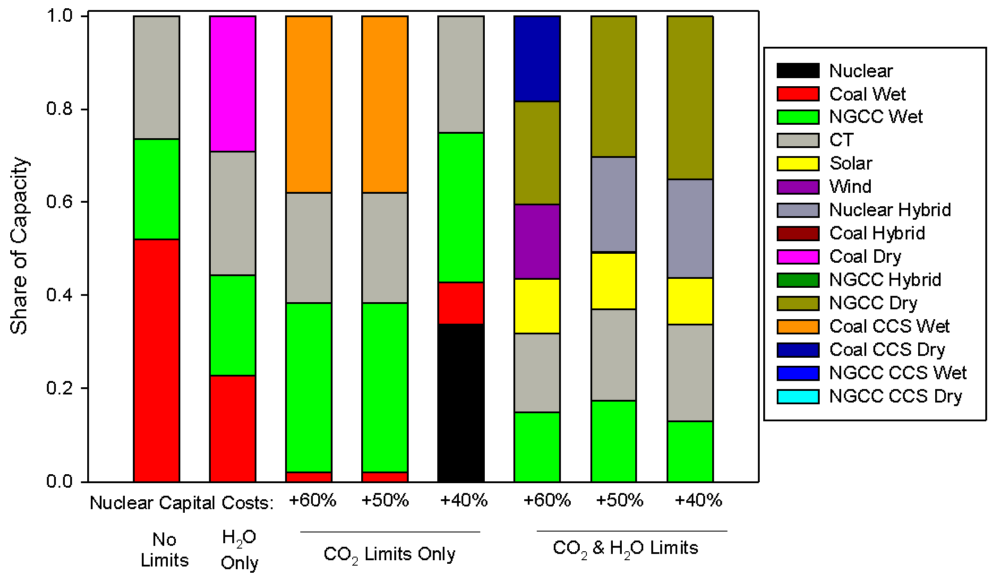

Figure A.10: Generation technology mix when CCS incremental capital and operating costs are reduced by 50%, as a function of policy limits and nuclear capital costs.

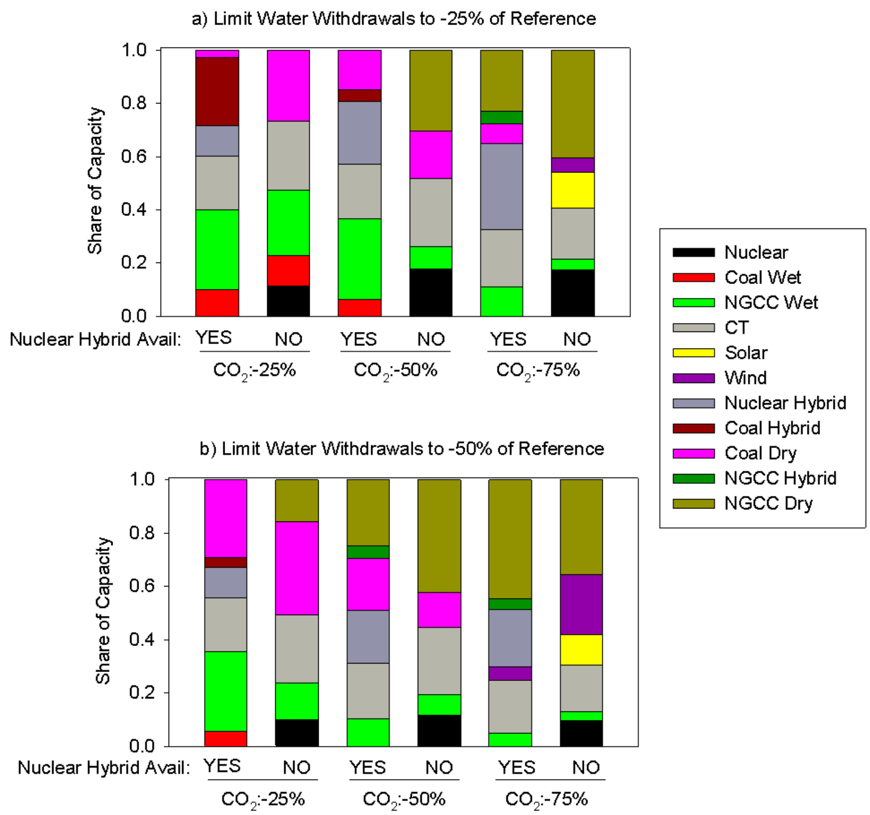

Figure A.11: Generation technology mix when nuclear technology is or is not available with hybrid cooling, as a function of CO_2 and water limits.