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Evaluating the Financial Vulnerability of a Major Electric Utility in the Southeastern U.S. to Drought under Climate Change and an Evolving Generation Mix

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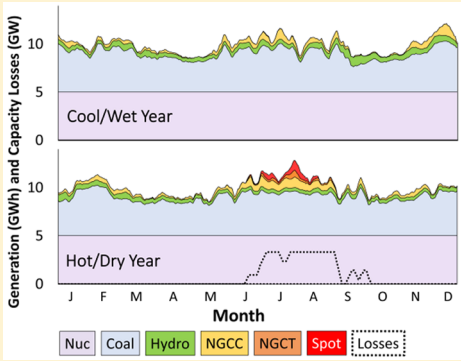
Supporting Information

ABSTRACT: There is increasing recognition of the vulnerability of electric power systems to drought and the potential for both climate change and a shifting generation mix to alter this vulnerability. Nonetheless, the considerable research in this area has not been synthesized to inform electric utilities with respect to a key factor that influences their decisions about critical infrastructure: financial risk for shareholders. This study addresses this gap in knowledge by developing a systems framework for assessing the financial exposure of utilities to drought, with further consideration of the effects of climate change and a shifting generation mix. We then apply this framework to a major utility in the Southeastern U.S. Results suggest that extreme drought could cause profit shortfalls of more than $100 million if water temperature regulations are strictly enforced. However, even losses of this magnitude would not significantly impact returns for shareholders. This may inadvertently reduce pressure internally at utilities to incorporate drought vulnerability into long-term strategic planning, potentially leaving utilities and their customers at greater risk in the future.



1. INTRODUCTION

The U.S. electric power industry is increasingly cognizant of its vulnerability to drought.[1−9] Drought impacts power systems in two main ways: (1) it reduces hydropower production via lower streamflow;[10,11] and (2) it disrupts operations at steam-based thermal power plants (nuclear, coal, and even natural gas) that require large quantities of cooling water. The latter primarily occurs when a combination of low streamflow and high air temperatures contribute to prohibitively high water temperatures in the cooling water source.[12,13] High enough water temperatures can exhaust the ability of a thermal power plant's cooling system to absorb waste heat without depleting available water resources or violating regulatory constraints on thermal effluent temperatures.[2,6,14]

A number of previous efforts have attempted to characterize the current threat that drought poses to hydropower and thermal generation in the U.S. and globally,[1,4−7,9,15] as well as the potential for climate change to exacerbate this exposure in the future.[14,16−21] Absent from these efforts, however, is the consideration of utilities' rapid shift away from coal fired power plants toward natural gas combined cycle plants and renewables—a change that could significantly reduce life-cycle water consumption[22−26] and power systems' vulnerability to drought.[7,18,19]

In a few cases, these previous studies have estimated increased market prices[2,6] and/or costs[3,4,20] associated with a loss in production from hydropower or thermal power plants. Nonetheless, the extent to which drought poses a financial risk for electric utilities—that is, the extent to which it threatens their ability to repay lenders and/or return profits to shareholders—remains largely unknown. In recent years, some utility shareholder groups, aware of the mounting evidence that drought poses operational risks for power systems, have pushed utilities to study this risk more closely.[27,28] However, to date, no analysis of utilities' financial vulnerability to drought has been made publicly available.

This paper addresses a key gap in knowledge by developing a systems framework for assessing the financial exposure of utilities to drought under climate change and a shifting generation mix. This framework is then applied to major utility in the Southeastern U.S.—Duke Energy Carolinas (DEC), a 19,467 MW system that serves the western half of North Carolina and a large part of South Carolina. The DEC system is increasingly confronting water scarcity as an operational

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concern.[12,29] This system also typifies the rapid shift in generation mix that is occurring at U.S. electric utilities in response to low natural gas prices, falling renewable energy costs, and new environmental regulations.[30,31] The results of this study provide important insights into whether shareholder groups could become increasingly important proponents of studying and investing in approaches to mitigate drought vulnerability at utilities.

2. MODELING

2.1. Systems Framework and Scenario Development.

A systems framework (Figure 1) is used to quantify drought-related financial risks for DEC shareholders. At the core of this framework are coupled interactions between: (1) climate, weather, and hydrology (i.e., air temperatures and streamflows), which drive the availability of water for hydropower production and cooling at thermal power plants, electricity demand, and solar power production; and (2) human engineered and financial systems related to the operation of electric power infrastructure.

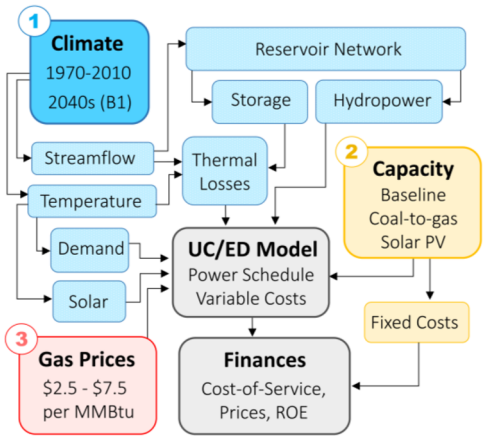

Figure 1. Modeling framework employed in this study. Twenty-four scenarios are tested, each one a unique combination of: (1) climate state; (2) capacity portfolio; and (3) natural gas price. For each climate state, 1000 years of synthetic streamflow and temperature data are created and translated to time series of electricity demand, solar power production, hydropower availability, and thermal capacity losses. These data are forced through the UC/ED model, alongside a specified capacity portfolio and a natural gas price. Simulation results are then converted to distributions of total costs (cost-of-service), retail prices, and shareholders' return-on-equity (ROE).

DEC system operations are simulated under 24 different scenarios, each a unique combination of: (1) climate state; (2) capacity portfolio (i.e., the mix of power plants employed); and (3) natural gas price.

Climate change is expected to reduce the availability of water for thermal power plant cooling and potentially hydropower production,[14,16,17,19] alter seasonal electricity demands,[32] reduce plant efficiency,[21] and increase other temperature related losses on the grid.[33] To assess whether these changes could impact drought-related financial risks for DEC shareholders, the system is modeled under two different climate states: (1) current (1970−2010); and (2) a 2040s B1 scenario. Although B1 is a somewhat "optimistic" future climate change state,[34] differences between this and more pessimistic future states (e.g., an A2 scenario) are projected to be quite small in the 2040s, with more pronounced differences manifesting by the year 2100.[17] The impacts of climate change are only investigated out to the 2040s to mirror the typical investment horizon for generation infrastructure (25−30 years). Each of these two modeled climate states is associated with different statistical distributions of daily air temperatures and daily streamflow, which serve as the principal drivers of modeled system dynamics. Streamflow controls hydropower availability; air temperatures determine electricity demand and influence solar power production, and both streamflow and air temperatures control cooling water temperatures, which trigger potential losses of useable capacity at thermal power plants.

To quantify drought-related financial impacts for DEC shareholders in a probabilistic or "risk-based" manner, system behavior is evaluated over a large sample of representative test years. Concurrent 1000 year records of daily air temperatures and streamflow are synthesized for each modeled climate state, effectively serving as Monte Carlo samples of annual weather/hydrological conditions. Synthetic records of daily air temperatures and streamflow are then converted to corresponding time series of cooling water-related capacity losses at thermal power plants, hydropower availability, electricity demand, and solar power production. These times series serve as the primary inputs to a "unit commitment/economic dispatch" (UC/ED) model, which schedules hourly generation at power plants in the DEC system to minimize the cost of meeting fluctuating electricity demand.

There is also interest in assessing how reliance on different combinations of power plant types affects the DEC system's vulnerability to drought, so several different capacity portfolios are explored (Table 1). First, a "Baseline" portfolio is tested; this portfolio, which is heavily reliant on river-based coal power plants with once-through cooling, is meant to mirror DEC's installed capacity in the year 2010. Next, a "Coal-to-Gas" (C2G) portfolio is modeled, which represents DEC's ongoing transition away from coal since 2010. In the C2G portfolio, all river-based coal plants are replaced with natural gas combined cycle (NGCC) plants with recirculating cooling, which are less

Table 1. Six Different Capacity Portfolios (Versions of the Physical DEC System) Explored in This Study[a]

capacity (MW)	baseline	coal-to-gas (C2G)	solar PV 1	solar PV 2	solar PV 3	solar PV 4
nuclear (reservoir)	5030	5030	5030	5030	5030	5030
hydro	1437	1437	1437	1437	1437	1437
coal (reservoir)	4156	4156	4156	4156	4156	4156
coal (river - OT)	2681	0	0	0	0	0
coal (river - CL)	1155	1155	1155	1155	1155	1155
NGCC (river - CL)	0	2681	2381	2081	1781	1481
NGCT	3573	3573	3573	3573	3573	3573
solar PV	0	0	1000	2000	3000	4000

[a]Capacity numbers listed here are for the 1970−2010 climate state; under a 2040s B1 climate state, an additional 500 MW of NGCC and NGCT are added to account for higher peak annual electricity demand. OT = once-through cooling system; CL = closed-loop cooling system. The estimated susceptibility of river-based OT and CL cooling systems to water temperature-related losses is detailed in Table S2 of the Supporting Information section.

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vulnerable to drought. Last, four different "Solar PV" portfolios are tested. The Solar PV portfolios are similar to the C2G portfolio in that all river-based coal plants are retired; but in this case, between 1 and 4 GW of utility-scale solar capacity is added to partially offset additions of NGCC capacity that replace retiring coal power plants. NGCC capacity is replaced at a ratio of 0.3 MW for every 1 MW of solar, based on conservative estimates of the capacity value of solar from previous studies.[32]

In addition to evaluating the behavior of the DEC system under different climate states and capacity portfolios, system operations are also simulated under three different natural gas prices: \$2.5/MMBtu, \$5/MMBtu, and \$7.5/MMBtu. Natural gas power plants frequently serve as marginal and "back-up" generators in power systems, making them the obvious choice to replace thermal capacity and hydropower generation that is lost to drought. This effectively ties the cost of drought to the price of natural gas.[11]

Each scenario (i.e., each combination of climate state, capacity portfolio, and natural gas price) is simulated in the UC/ED model using 1000-year synthetic time series of cooling water-related capacity losses at thermal power plants, hydropower availability, electricity demand, and solar power production. Outputs of these simulations are corresponding 1000-year distributions of system costs for each scenario, which are used to set retail electricity prices, calculate distributions of annual operating income (profits), and quantify the probability of DEC shareholders' experiencing negative financial outcomes related to drought.

In addition to the descriptions below, details of each component of the system framework depicted in Figure 1 can be found in the Supporting Information section.

2.2. Dynamic System Drivers. *Streamflows and Air Temperatures.* A suite of stochastic modeling approaches is used to create 1000-year synthetic records of daily streamflow and daily air temperatures for each climate state and then translate these into relevant inputs for the UC/ED model.

For the current (1970−2010) climate state, a 1000 year synthetic record of daily streamflow at multiple, spatially distributed sites throughout the DEC reservoir network is generated by resampling daily streamflow fractions from the period 1970−2010 and pairing these with total annual flows simulated by an autoregressive process.[35] The main advantages of this approach are an ability to replicate the statistical properties, temporal autocorrelation, and spatial cross-correlation of observed streamflow throughout DEC's reservoir network.

The newly created synthetic daily streamflow record is then used to condition a statistical resampling of historical daily air temperatures for the Charlotte metropolitan area (the primary demand center in the DEC system), as follows. For each one of the 1000 years of newly created synthetic streamflow, average summer (June to August) streamflow is recorded, and a group of "nearest neighbors" (most proximate values) is identified in the historical record (1970−2010). These nearest neighbors from the historical record are then ranked by absolute difference, weighted accordingly, and randomly sampled. Daily air temperatures for the historical year that is sampled are then extracted and paired with daily streamflow values from the specified year in the new synthetic record. This approach helps preserve observed negative correlations between summer streamflow and air temperatures on a seasonal basis (i.e., hot summers are more likely to also be dry summers).

Modeled impacts of climate change on streamflow are tied to the work of van Vliet et al.,[17] which projects a 0−25% reduction in the lower 10th percentile of streamflow for the Southeastern U.S under a 2040s B1 climate state. In this study, a 12.5% reduction in low flows is assumed, which is achieved by increasing the variance (but not the mean) of synthetic daily streamflow simulated for the current climate (1970−2010) state. This is in line with more detailed climate change assessments for the Southeastern U.S.,[36] which project limited impacts on mean annual streamflow but greater variability.

Increased air temperatures under a 2040s B1 climate state are simulated using downscaled, bias corrected constructed analogs projections of daily temperatures.[37] Temperature projections for nine different global climate models are averaged to find expected temperature increases in the 2040s by calendar day. Smoothed daily increases are then added to the synthetic temperature record generated for current climate conditions (1970−2010).

Hydropower Availability. The time series of daily hydropower availability are simulated using a model developed jointly by DEC and the states of North and South Carolina that represents the operations of the network of dams and reservoirs in the DEC system.[38] The model uses nodal water/mass balance equations and a wide range of operational constraints (e.g., environmental flow releases and target lake elevations, etc.) to make storage and release decisions at reservoirs, given inputs of daily streamflow and human (urban and industrial) water demands. Daily reservoir releases are converted to a daily record of available hydropower production, which is sent to the UC/ED model and scheduled on an hourly basis according to its cost minimization objective.

Electricity Demand. Synthetic records of air temperatures are used to simulate "peak" (maximum) hourly electricity demand on a daily basis using linear regression models calibrated for each day-of-the-week. All regression models have the following structure, which predicts peak demand using heating degree days (HDD) and cooling degree days (CDD) as independent variables and an autocorrelated white noise process (ε_t) to represent all nontemperature related meteorological forcings.

$$\text{Peak Demand}_d = C + \alpha \times \text{HDD}_d + \beta \times \text{CDD}_d + \varepsilon_d \tag{1}$$

$$\text{HDD}_d = \max(65 - T, 0) \tag{2}$$

$$CDD_d = \max(T - 65, 0) \tag{3}$$

where T = daily average temperature in °F, ε_d autocorrelated residuals, C = peak electricity demand on a day with a mean temperature of T = 65 °F, and α,β = fitted regression coefficients.

Fitted model parameters and model diagnostics for the peak electricity demand model are shown in Table S1 in the Supporting Information section. Based on projected temperature increases, eq 1 indicates that peak summer electricity demand in the DEC system will increase by approximately 1000 MW under a 2040s B1 climate state. As a result, for each scenario that simulates DEC operations under a 2040s B1 climate, a commensurate amount of capacity (a combination of baseload and peaking natural gas) is added to maintain the same system reserve margin.

After simulating peak hourly electricity demand for each day using eq 1, a time series of hourly demand is created by

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multiplying peak demand by unitless 24 h demand profiles for each calendar day of the year (eq 4). Hourly demand profiles for each calendar day are developed empirically using 11 years (2005−2015) of observed hourly electricity demand.

$$S_{h,d} = \frac{1}{11} \sum_{y=2005}^{2015} \frac{L_{h,d,y}}{L'_{d,y}} \tag{4}$$

where $S_{h,d}$ = 24 × 365 matrix of fractional hourly demand profiles for each calendar day, $L_{h,d,y}$ = the demand at hour h in calendar day d in year y, $L'_{d,y}$ = peak hourly demand in day d in year y, h = hour of the day ∈ {1...24}, d = calendar day ∈{1...365}, and y = year is ∈{2005...2015}.

Utility Scale Solar Production. The time series of hourly solar power production are simulated using the system advisory model (SAM) developed by the National Renewable Energy Laboratory.[39] First, hourly production is simulated over 21 years (1970−1990) using historical temperature and irradiance data from NREL's National Solar Radiation Data Base,[40] which include cloud effects. To build 1000 year synthetic records of solar power production, the simulated hourly solar power production over the period 1970−1990 is resampled based on the calendar day and synthetic air temperature (this preserves temperature effects on panel output). Hourly solar production is then scaled accordingly to model any desired installed capacity level.

Thermal Plant Capacity Losses. We represent the impacts of drought on thermal power plants in two respects: 1) complete shut-downs caused by water levels falling below cooling system intakes in reservoirs (which are exceedingly rare events); and 2) losses in useable capacity due to prohibitively high temperatures in cooling water bodies. For the latter, we rely on estimates from van Vliet et al.[17] of river-based thermal capacity losses due to cooling water temperatures under a current (1970−2010) and a 2040s B1 climate state. These estimates assume effluent temperature regulations are strictly enforced; as a result, they likely overestimate actual water temperature-related thermal capacity losses in the DEC system.[13,21,41] As part of a widely cited previous study, they represent a reasonable benchmark for understanding how losses on this scale could contribute to financial risk for utilities. However, from the perspective DEC shareholders, it should be understood that losses projected by van Vliet et al. represent not only drought risk, but also the risk that environmental regulations are enforced much more strictly than they are today.

Roughly 20% (3836 MW) of the thermal capacity in the DEC system is dependent on river water and thus assumed to be affected by water temperature issues (see Table 1). Each affected plant in the DEC system is classified by its existing cooling system, with once-through systems assumed to experience more frequent and severe losses than recirculating systems. Based on this characterization, plants are assigned a cumulative number of days over the entire 1000-year synthetic record in which cooling water issues cause capacity losses of 25%, 50% and 100%, respectively (see Table S2 in the Supporting Information section).

We then assign each day in the 1000 year simulation period a weight (eq 5) using a calibrated water temperature model for a river system with similar characteristics.[42]

$$W_i = \mu + \frac{\alpha - \mu}{1 + \exp[\gamma(\beta - T_i)]} + \frac{n}{Q_i} \tag{5}$$

where W_i = weight assigned to day i (estimated river temperature in °F), T_i = 10 day central moving average air temperature (°F), Q_i = 10 day central moving average streamflow (m^3s^{-1}), and μ, α, γ, β, and n = empirical parameters.

Capacity losses of 25%, 50%, and 100% for each affected plant in the DEC system are then distributed over the entire simulation period, with the highest daily weights being assigned the largest losses. Ultimately, this produces a daily time series of thermal capacity losses for the DEC system, with maximum losses occurring on days with the highest modeled water temperature and average annual losses over the entire 1000 year simulation period equivalent to those reported in van Vliet et al.[17]

2.3. Power System Operations. For each scenario (i.e., each unique combination of climate state, capacity portfolio, and natural gas price), the synthetic time series of hourly electricity demand, available hydropower generation, thermal capacity losses, and solar power production are passed to a "unit commitment/economic dispatch" (UC/ED) model, which simulates the operation of the DEC system. UC/ED models are a standard approach for scheduling generation throughout a network of power plants. They employ mixed integer optimization to minimize the cost of meeting hourly electricity demand, while obeying the specific operating constraints of each power plant in the system. UC/ED models have been used in the past to study power system impacts from a number of exogenous drivers, including increasing renewable energy penetration,[43] water scarcity,[11] and water use penalties.[8]

Operating characteristics for each power plant type in the DEC system are obtained from publicly available academic, industry, and government sources[31,44−47] and translated into discrete mathematical representations. The UC/ED model also includes a variable representing the "spot" electricity market (i.e., a very costly generator of last resort that DEC can access to help meet demand in extreme circumstances). The spot market variable is an import inclusion, as it prevents the DEC system from experiencing a "loss of load", or a shortage in generation that prevents it from meeting electricity demand.

Outputs from the UC/ED model are an hourly generation schedule for every power plant in the DEC system, as well as an annual time series of variable costs for the system.

2.4. Financial Analysis. An important consideration of this study that distinguishes it from previous efforts to quantify the impacts of droughts on power systems is detailed financial modeling.

For each scenario considered, DEC's annual "cost-of-service" is calculated for each year in the 1000 year synthetic record as the sum of: annualized capital costs for power plants (different across scenarios) and transmission and distribution infrastructure (static across scenarios); and variable costs (determined by the UC/ED model).

For each scenario, retail prices are then calculated ex post as the average annual $-per-MWh amount required to cover DEC's cost-of-service plus a 10% return-on-equity (ROE) based on the value of its depreciated physical assets (its "equity base") (eq 6). Note that DEC's equity base is a function of its underlying capacity portfolio, so this value varies somewhat by scenario.

$$\text{Price}_s = \frac{1}{1000} \sum_{y=1}^{1000} \frac{\text{CoS}_{s,y} + 10\% \times \text{Equity Base}_s}{\text{Demand}_{s,y}} \tag{6}$$

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where Price_s = retail price determined for scenario s, $\text{CoS}_{g,y}$ = total cost of service for scenario s in year y, Equity Base_s = Equity financed portion of all DEC capital assets in scenario s, and $\text{Demand}_{s,y}$ = annual electricity demand for scenario s in simulation year y.

After retail prices are determined, annual pretax operating income (profits) and shareholders' return-on-equity are calculated on an annual basis as follows:

$$\text{Operating Income}_{s,y} = \text{Demand}_{s,y} \times \text{Price}_s - \text{CoS}_{s,y} \quad (7)$$

$$\text{ROE}_{s,y} = \frac{\text{Operating Income}_{s,y}}{\text{Equity Base}_s} \quad (8)$$

where $\text{Operating Income}_{s,y}$ = profits under scenario s in simulation year y and $\text{ROE}_{s,y}$ = shareholders' return on equity (%) under scenario s in simulation year y.

Retail prices are set such that, in a year with average electricity demand, hydropower availability, and thermal capacity losses, DEC's operating income will be equal to 10% times its equity base. During drought years, DEC experiences higher than average variable costs, which increases the $\text{CoS}_{s,y}$ term in eq 7. As a result, the retail price (Price_s), which is set based on a 1000 year expectation, is too low, and operating income yields an ROE below 10%.

We quantify financial risk for DEC in terms of: (1) the worst single year operating income and ROE experienced by DEC; and (2) the conditional value-at-risk (CVaR), a commonly used metric that represents the average operating income experienced in the bottom fifth percentile of each 1000 year simulation.

3. RESULTS AND DISCUSSION

We are interested in tying financial risk for DEC shareholders to drought and evaluating the sensitivity of this risk to (1) climate state, (2) capacity portfolio, and (3) natural gas prices. This section proceeds accordingly, with an initial exploration of the impacts of these factors on the annual generation mix (i.e., the % of total electricity demand met by each plant type), followed by a discussion of their impacts on variable costs, cost-of-service, electricity prices, and financial risk for DEC shareholders.

Tables S3−S5 in the Supporting Information section detail the generation mixes for each scenario considered, organized by year type (i.e., hot/dry; cool/wet; other). Hot/dry years, which are associated with higher demand, decreased hydropower production, and more frequent thermal capacity losses, force the DEC system to rely more on natural gas combustion turbine (NGCT) plants and the spot market. These impacts also mirror the main effects of a 2040s B1 climate state on the generation mix for the DEC system.

Figure 2 compares daily operations in a cool/wet year (top panel) and hot/dry year (bottom panel) for the Coal-to-Gas (C2G) portfolio under a 1970−2010 climate state and a $5/MMBtu gas price. In the hot/dry year the DEC system experiences higher electricity demand and water temperature related thermal capacity losses (black dotted line) during summer months. This causes the DEC system to increase its reliance on natural gas combined cycle (NGCC) plants (yellow), NGCT plants (orange), and electricity from the spot market (red). Note that, although capacity losses are shown to overlay generation from nuclear power plants, modeled thermal capacity losses are actually affecting river-based coal and natural gas plants. Nuclear power plants in the DEC system are located on large reservoirs that are unaffected by water temperature issues.

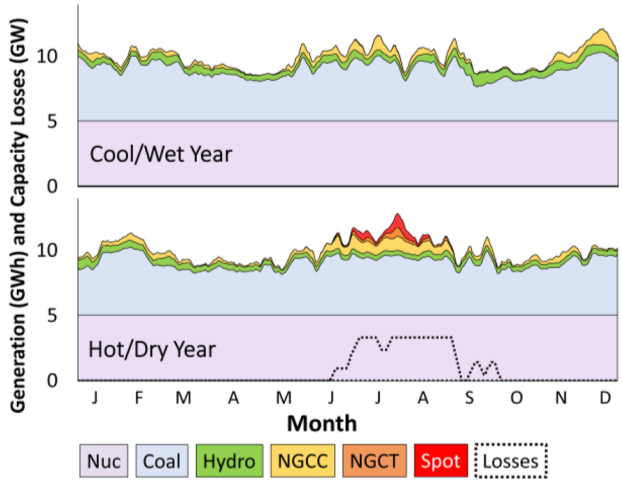

Figure 2. Hourly operations for the Coal-to-Gas (C2G) portfolio under a current (1970−2010) climate state and a $5/MMBtu gas price. Top panel: generation (colors) in an extremely cool/wet year. Bottom panel: generation (colors) and thermal capacity losses (black dotted line) in an extremely hot/dry. All data have been smoothed with a 7 day moving average filter. Note in the bottom panel that, although capacity losses overlay generation from nuclear power plants, modeled thermal capacity losses are actually affecting river-based coal and natural gas plants. Nuclear power plants in the DEC system are located on large reservoirs that are unaffected by water temperature issues.

By increasing DEC's reliance on more expensive generation sources, hot/dry years can significantly impact system-wide variable costs. Figure 3 (top panel) shows 1000 year distributions of variable costs for a selected group of scenarios. Distributions of variable costs are shown to be non-Gaussian with "fat tails" associated with infrequent, high cost hot/dry years. Figure 3 (top panel) also shows that the sensitivity of variable costs to drought differs by scenario. Take the following scenario: a C2G portfolio, 1970−2010 climate, and a $2.5/MMBtu natural gas price. For this scenario, the difference between mean variable costs and the 1000 year maximum (i.e., variable costs experienced during the most severe drought realized) is $170 million. But, under a different scenario: a C2G portfolio, 2040s B1 climate, and $7.5/MMBtu natural gas price, the most extreme drought realized increases variable costs to $430 million above their expected value, because thermal capacity losses are more frequent and severe, and replacing this lost capacity is more expensive due to a higher price of natural gas.

The fact that variable costs are more/less sensitive to drought in different scenarios presents trade-offs for the DEC system. For example, if natural gas prices are low ($2.5/MMBtu), the DEC system could somewhat reduce the potential for drought to cause spikes in variable costs by switching from the Baseline portfolio (which is more susceptible to high water temperatures) to the C2G portfolio. However, this benefit vanishes if gas prices increase. By replacing older coal plants with newer NGCC plants, DEC is essentially trading exposure to drought for exposure to high natural gas prices.

A related question of interest is whether replacing some new NGCC plants in the C2G scenario with solar capacity could help the DEC system reduce its exposure to drought while also

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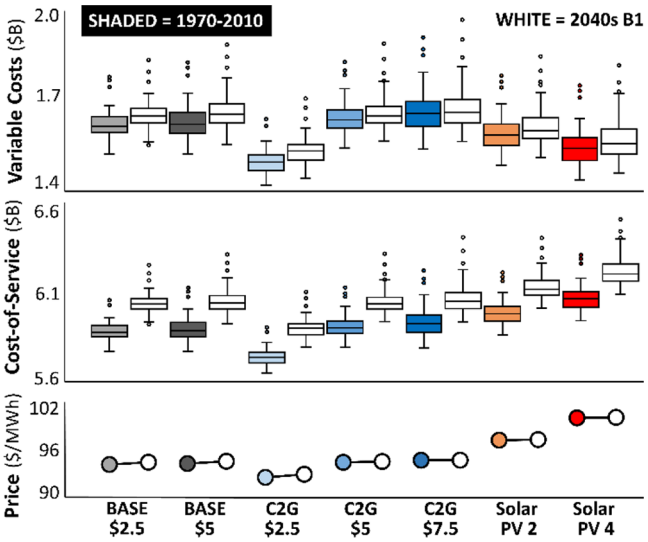

Figure 3. Distributions of annual variable costs (top panel), cost-of-service (middle panel), and retail electricity prices (bottom panel) for selected capacity portfolios ("Baseline" = BASE; "Coal-to-Gas" = C2G), climate states, and natural gas prices ($2.5–7.5/MMBtu). Distributions of variable costs and cost-of-service are shown to exhibit "fat tails" with outliers caused by drought years. Increases in cost-of-service associated with climate change are primarily driven by installed capacity additions necessary to account for higher peak summer demand. Solar PV scenarios are shown to decrease variable costs relative to C2G but increase cost-of-service and retail prices due to higher capital costs.

moderating increased sensitivity to gas prices. Figure 3 (top panel) shows the variable cost distribution for the C2G scenario at $5/MMBtu alongside those of two Solar PV portfolios (2 and 4 GW), which are also modeled using a gas price of $5/MMBtu. Adding solar shifts the mean of the variable cost distributions downward, but there are essentially no benefits in terms of reducing deviation above the mean. This is likely the case for two reasons. First, modeled thermal capacity losses are assumed to have a duration of 24 h (12 am to 12 am); this limits the value of solar as a "hedge" against drought to a few mid-day hours. Second, replacing NGCC plants with the solar can in some cases reduce the ability of the DEC system to respond to unexpected losses of other thermal capacity and forces it to make greater use of the costly spot market.

The middle panel of Figure 3 shows distributions of annual cost-of-service, which combines system variable costs alongside annualized capital costs. One noticeable difference here is the impact of the Solar PV scenarios. While adding solar decreases variable costs in the DEC system, it significantly increases the total cost-of-service due to comparatively high capital costs. The middle panel of Figure 3 also shows that, relative to a current (1970–2010) climate, a 2040s B1 climate state yields a slightly higher annual cost-of-service. This increase is driven primarily by the cost of new capacity needed to account for higher peak annual demand.

The bottom panel of Figure 3 shows retail prices for the same group of selected scenarios, which generally track average cost-of-service across each scenario. Note, however, that increases in cost-of-service associated with a 2040s B1 climate state have limited impacts on retail prices. This is due to corresponding increases in demand (the denominator of eq 6) in the 2040s B1 scenarios, which help keep $/MWh rates at roughly the same level.

Compared to the 1000 year distributions of variable costs and annual cost-of-service shown in Figure 3, corresponding distributions of operating income (profits) for each scenario are much more Gaussian. This is due to the fact that years with the highest costs (i.e., hot/dry years) are also associated with the highest electricity demand, which simultaneously increases revenues (see eq 7).

To assess drought-related financial risk for DEC shareholders, probability density functions of operating income are standardized across each scenario in terms of equivalent ROE (%) (see eq 8). The severity of a drought's impact on shareholders is then measured by comparing the actual percentage return experienced to the target of 10%. Figure 4

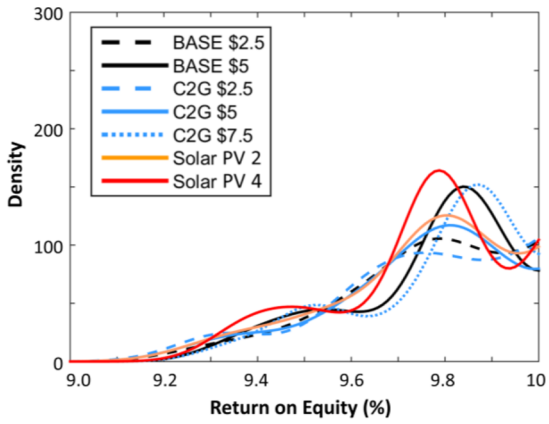

Figure 4. Lower tails of probability density functions of shareholders' return on equity (ROE) for selected scenarios. All data shown are for 1970–2010 climate state. Assuming a target return on equity of 10%, results show the maximum impacts of drought are a reduction to 8.9%. Risks to shareholders (pdfs of ROE) are mostly homogeneous across scenarios.

shows probability density functions of shareholders' ROE for a selected number of scenarios under a current (1970–2010) climate state. The means of these functions are all located at 10%, but only the portion of the distributions associated with financial shortfalls (i.e., ROE < 10%) are shown.

Table 2 shows additional financial results for each scenario considered, including: (1) annual operating income required to meet the 10% ROE target; (2) the 5% CVaR, listed in terms of operating income; and (3) the lowest, single-year operating income and corresponding ROE. Across all scenarios considered, results suggest that drought, in the most extreme circumstances, could cause a $ 170 million shortfall in operating income. Although this is a substantial amount of money, DEC's target operating income is on the order of $ 2 billion per year. Thus, results indicate that, at most, drought would cause ROE for shareholders to fall from 10% to 8.9%. These findings are largely consistent across scenarios.

Overall, this indicates that drought in the DEC system could send a weak financial signal to shareholders. A growing body of work from the research community suggests that drought, now and in the future, poses a serious physical risk for power systems. There is evidence that some shareholder groups, perhaps in response to this research, are becoming more active in pressing utilities to incorporate drought vulnerability in long-term planning. However, the findings of this study suggest that

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Table 2. Financial Risk Posed by Drought under 1970−2010 and 2040s B1 Climate States, Distinguished by Underlying Capacity Portfolio [Baseline, Coal-to-Gas (C2G), and Solar PV 1-4 GW] and Natural Gas Price ($2.5/MMBtu, $5/MMBtu, $7.5/MMBtu)

			baseline			coal-to-gas (C2G)		solar (GW)			
								1	2	3	4
	natural gas price ($/MMBtu)	2.5	5	7.5	2.5	5	7.5	5	5	5	5
1970−2010	mean cost-of-service ($B/y)	5.88	5.89	5.89	5.73	5.90	5.92	5.94	5.98	6.02	6.06
	retail price ($/MWh)	95.0	95.1	95.2	93.3	95.3	95.6	96.8	98.2	99.6	101.1
	operating income at 10% ROE ($B/y)	2.06	2.06	2.06	2.06	2.06	2.06	2.15	2.23	2.31	2.39
	5% CVaR: operating income ($B/y)	1.93	1.94	1.94	1.92	1.93	1.95	2.01	2.09	2.17	2.26
	lowest 1-year operating income ($B/y)	1.92	1.92	1.92	1.91	1.91	1.93	2.00	2.08	2.16	2.25
	lowest 1-year ROE (%)	9.05	9.10	9.10	8.95	9.00	9.15	9.05	9.10	9.15	9.20
2040s B1	mean cost-of-service ($B/y)	6.03	6.04	6.05	5.89	6.04	6.05	6.08	6.12	6.16	6.21
	retail price ($/MWh)	95.3	95.4	95.5	93.7	95.4	95.6	96.8	98.3	99.7	101.2
	operating income at 10% ROE ($B/y)	2.11	2.11	2.11	2.11	2.11	2.11	2.19	2.27	2.36	2.44
	5% CVaR: operating income ($B/y)	1.95	1.95	1.96	1.94	1.94	1.96	2.03	2.11	2.19	2.27
	lowest 1-year operating income ($B/y)	1.95	1.95	1.96	1.94	1.94	1.96	2.03	2.11	2.19	2.27
	lowest 1-year ROE (%)	8.95	9.00	9.05	8.95	8.90	9.00	9.00	9.00	9.05	9.10

drought poses quite modest long-term financial risks for DEC. Given the array of other existential challenges facing utilities today (e.g., carbon-related regulatory risk, eroding market share from distributed resources), shareholders at many utilities may justifiably not view drought as a concern. To be sure, many decision makers at utilities (and at public bodies charged with oversight of power systems) take the threat of drought seriously. It is possible, however, that a lack of pressure from shareholders could reduce internal pressure at utilities to study and manage drought as a contingency, ultimately leaving them and their customers more exposed in the future.

These results may be somewhat tied to our focus on a large "vertically integrated" utility in a regulated market. In the DEC system, the annual cost-of-service is dominated by fixed costs. Thus, even when drought causes variable costs to spike above their expected value by hundreds of millions of dollars, this increase remains a relatively small fraction of the annual cost-of-service to customers, which is typically around $ 6 billion. Another factor limiting the financial impacts of drought for the DEC system is the high correlation between variable costs and revenues, which are both closely linked to electricity demand.

There are other caveats to this work that deserve mention. First, the primary mechanism through which drought impacts thermal power plants are the cooling water related capacity losses reported by van Vliet et al.[17] These projected losses are based on an underlying assumption of a strictly enforced rule governing cooling water effluent temperatures. In practice, utilities are often able to acquire regulatory approval to temporarily breach upper temperature limits.[13] This suggests that drought related financial losses for the DEC system are in reality even lower than we report.

Nonetheless, other aspects of our approach may contribute to underestimated financial risks from drought. Although the DEC system is representative of power systems found across the U.S. in many ways, other systems may have a greater fraction of river-based power plants that are susceptible to cooling water issues. Other systems may also have financial structures (e.g., higher debt-to-equity ratios) or participate in riskier (i.e., more competitive) market environments that would make them more susceptible to financial impacts during drought.

We also deliberately isolate the financial risk posed by drought from risks in other areas, which may occur in tandem with (and have nonlinear impacts on) the cost of drought (e.g., unexpected increases in the price of natural gas).

Last, our use of the "spot market" as a power plant of last resort in the UC/ED model inherently assumes that hydropower and thermal generation lost to drought can always be replaced by a merchant generator or the wholesale market. This means DEC never experiences an actual loss of load (e.g., a blackout), which would add considerably to the cost of drought and broaden its economic impacts. A risk not captured in this study is an exceptional drought that simultaneously impacts the capabilities of all utilities and merchant power producers in the region. In reality, there may be a thin line between a drought that causes financial losses easily absorbed by a utility and a drought that causes systemic failures. Quantifying the probability of such events to cause critical grid failures would require significantly increasing in the scale and complexity of the modeling presented here, and it remains an outstanding challenge.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.6b05460.

Detailed information on the systems modeling framework employed (PDF)

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Environ. Sci. Technol. 2017, 51, 8815−8823

REFERENCES

(1) Elcock, D.; Kuiper, J. *Water vulnerabilities for existing coal-fired power plants*; DOE/NETL-2010/1429, August 2010.

(2) Boogert, A.; Dupont, D. The nature of supply side effects on electricity prices: The impact of water temperature. *Econ. Lett.* **2005**, *88* (1), 121−125.

(3) Gleick, P. *Impacts of california's ongoing drought: Hydroelectricity generation*; Pacific Institute, 2015.

(4) Harto, C.; Yan, Y.; Demissie, Y.; Elcock, D.; Tidwell, V.; Hallett, K.; Macknick, J.; Wigmosta, M.; Tesfa, T. *Analysis of drought impacts on electricity production in the western and Texas interconnections of the United States*; Argonne National Laboratory, 2011; ANL/EVS/R-11/14.

(5) Lund, J.; Palmer, R. Drought and power production. *J. Water Res. Plan. Mgt.* **1986**, *112* (4), 469−484.

(6) McDermott, G.; Nilsen, O. *Electricity prices, river temperatures and cooling water scarcity*; Institute for the Study of Labor (IZA) Discussion Paper Series, 2012; no. 6842.

(7) Scanlon, B.; Duncan, I.; Reedy, R. Drought and the water-energy nexus in texas. *Environ. Res. Lett.* **2013**, *8* (4), 045033.

(8) Sanders, K.; Blackhurst, M.; King, C.; Webber, M. The impact of water use fees on dispatching and water requirements for water-cooled power Plants in texas. *Environ. Sci. Technol.* **2014**, *48* (12), 7128−7134.

(9) Kimmell, T. *Impact of drought on U.S. steam electric power plant cooling water intakes and related water resource management issues*; U.S. Department of Energy, 2009; NETL-2009/1364.

(10) Foster, B.; Kern, J.; Characklis, G. Mitigating hydrologic financial risk in hydropower generation using index-based financial instruments. *Water Resources and Economics* **2015**, *10*, 45−67.

(11) Kern, J.; Characklis, G.; Foster, B. Natural gas price uncertainty and the cost effectiveness of hedging against low hydropower revenues caused by drought. *Water Resour. Res.* **2015**, *51* (4), 2412−2427.

(12) Beshears, E. Obstacle to more power: Hot water: River temperature so high that duke energy curtails work at 2 plants. *Charlotte Observer*. August 12, 2007.

(13) Madden, N.; Lewis, A.; Davis, M. Thermal effluent from the power sector: An analysis of once-through cooling system impacts on surface water temperature. *Environ. Res. Lett.* **2013**, *8*, 035006.

(14) Koch, H.; Vögele, S. Dynamic modelling of water demand, water availability and adaptation strategies for power plants to global change. *Ecol. Econom.* **2009**, *68*, 2031−2039.

(15) Stillwell, A.; Webber, M. Evaluation of power generation operations in response to changes in surface water reservoir storage. *Environ. Res. Lett.* **2013**, *8*, 025014.

(16) Forster, H.; Lilliestam, J. Modeling thermoelectric power generation in view of climate change. *Reg. Environ. Change.* **2011**, *4*, 327−338.

(17) van Vliet, M.; Yearsley, J.; Ludwig, F.; Vogele, S.; Lettenmaier, D.; Kabat, P. Vulnerability of US and european electricity supply to climate change. *Nat. Clim. Change* **2012**, *2*, 676−681.

(18) Miara, A.; Vorosmarty, C.; Stewart, R.; Wollheim, W.; Rosenzweig, B. Riverine ecosystem services and the thermoelectric sector: Strategic issues facing the northeastern united states. *Environ. Res. Lett.* **2013**, *8*, 025017.

(19) van Vliet, M.; Wiberg, D.; Leduc, S.; Riahi, K. Power-generation system vulnerability and adaptation to changes in climate and water resources. *Nat. Clim. Change* **2016**, *6*, 375−380.

(20) Strzepek, K.; Fant, C.; Gebretsadik, Y., et al. *Water body temperature model for assessing climate change impacts on thermal cooling*; MIT Joint Program on the Science and Policy of Global Change, 2015; report no. 280.

(21) Henry, C.; Pratson, L. Effects of environmental temperature change on the efficiency of coal- and natural gas-fired power Plants. *Environ. Sci. Technol.* **2016**, *50* (17), 9764−9772.

(22) Sanders, K. Critical review: Uncharted waters? the future of the electricity-water nexus. *Environ. Sci. Technol.* **2015**, *49* (1), 51−66.

(23) Macknick, J.; Newmark, R.; Heath, G.; Hallett, K. Operational water consumption and withdrawal factors for electricity generating technologies: A review of existing literature. *Environ. Res. Lett.* **2012**, *7*, 045802.

(24) Tidwell, V.; Malczynski, L.; Kobos, P.; Klise, G.; Shuster, E. Potential impacts of electric power Production utilizing natural gas, renewables and carbon capture and sequestration on U.S. freshwater resources. *Environ. Sci. Technol.* **2013**, *47* (15), 8940−8947.

(25) Grubert, E.; Beach, F.; Webber, M. Can switching fuels save water? A life cycle quantification of freshwater consumption for texas coal- and natural gas-fired electricity. *Environ. Res. Lett.* **2012**, *7*, 045801.

(26) Miara, A.; Tarr, C.; Spellman, R.; Vorosmarty, C.; Macknick, J. The power of efficiency: Optimizing environmental and social benefits through demand-side-management. *Energy* **2014**, *76*, 502−512.

(27) Murphy, S. Shareholders pressure utilities. *Motley Fool*, March 1, 2013. Available from: https://www.fool.com/investing/general/2013/03/01/shareholders-pressure-utilities.aspx.

(28) Bendersky, C. Electric utilities must reduce their climate risks. *Guardian*, April 16, 2013. Available from: https://www.theguardian.com/sustainable-business/blog/electric-utilities-must-reduce-climate-risks.

(29) Weiss, M. Drought could force nuclear plants to shut down. *Associated Press*, Jan 23, 2008. Available from: http://www.wral.com/news/state/story/2343605/.

(30) U.S. Energy Information Administration. Planned coal-fired power plant retirements continue to increase. http://www.eia.gov/todayinenergy/detail.cfm?id=15491. Updated 2014. Accessed July 7, 2014.

(31) Duke Energy Carolinas. *Integrated resource plan*, 2015.

(32) Sullivan, P.; Colman, J.; Kalendra, E. *Predicting the response of electricity load to climate change*, 2015; NREL/TP-6A20-64297.

(33) Jerez, S.; Tobin, I.; Vautard, R.; et al. The impact of climate change on photovoltaic power generation in europe. *Nat. Commun.* **2015**, *6*, 10014.

(34) International Energy Agency. *Energy and climate change: World energy outlook special briefing for COP21*, 2015.

(35) Nowak, K.; Prairie, J.; Rajagopalan, B.; Lall, U. A nonparametric stochastic approach for multisite disaggregation of annual to daily streamflow. *Water Resour. Res.* **2010**, *46*, W08529.

(36) Sun, G.; Caldwell, P. V.; McNulty, S. G.; Georgakakos, A.; Arumugam, S.; Cruise, J.; McNider, R.; Terando, A.; Conrads, P.; Feldt, J.; Misra, V.; Romolo, L.; Rasmussen, T.; Marion, D. *Impacts of climate change and variability on water resources in the southeast USA*, 2013; NCA Southeast Technical Report 204−234.

(37) U.S. Bureau of Reclamation. *Downscaled CMIP3 and CMIP5 climate and hydrology projections: Release of downscaled CMIP5 climate projections, comparison with preceding information, and summary of user needs*, 2013; U.S. Department of the Interior, Bureau of Reclamation, Technical Services Center, Denver, CO.

(38) Catawba-Wateree Water Management Group. *Catawba-Wateree River Basin Water Supply Master Plan*, 2014.

(39) Blair, N.; Dobos, A.; Freeman, J.; Neises, T.; Wagner, M.; Ferguson, T.; Gilman, P.; Janzou, S. *System advisor model, SAM 2014.1.14: General description*, 2014; NREL/TP-6A20-61019.

(40) National Renewable Energy Laboratory. *User's manual: National solar radiation data base*, 1992; Version 1.0.

(41) Henry, C.; Pratson, L. Response to comment on "Effects of environmental temperature change on the efficiency of coal- and natural gas-fired power plants. *Environ. Sci. Technol.* **2017**, *51* (9), 5345−5346.

(42) van Vliet, M.; Ludwig, F.; Zwolsman, J.; Weedon, G.; Kabat, P. Global river temperatures and sensitivity to atmospheric warming and changes in river flow. *Water Resour. Res.* **2011**, *47*, W02544.

(43) Kern, J.; Patino-Echeverri, D.; Characklis, G. The impacts of wind power integration on sub-daily variation in river flow downstream of hydroelectric dams. *Environ. Sci. Technol.* **2014**, *48* (16), 9844−9851.

(44) Wong, P.; Albrecht, P.; Allan, R.; Billington, R. The IEEE reliability test system-1996: A report prepared by the reliability test

DOI: 10.1021/acs.est.6b05460
Environ. Sci. Technol. 2017, 51, 8815−8823

system task force of the application of probability methods subcommittee. *IEEE T. Power Syst.* **1999**, *14* (3), 1010−1020.
(45) Fenton, F. Survey of cyclic load capabilities of fossil-steam generating units. *IEEE Trans. Power Appar. Syst.* **1982**, *6*, 1410−1419.
(46) U.S. Environmental Protection Agency. Emissions & generation resource integrated database (eGRID). http://www2.epa.gov/energy/egrid. Updated 2015. Accessed Nov 7, 2015.
(47) Tidball, R.; Bluestein, J.; Rodriguez, N.; Knoke, S. *Cost and performance assumptions for modeling electricity generation technologies*, 2010; NREL/SR-6A20-48595.

DOI: 10.1021/acs.est.6b05460
Environ. Sci. Technol. 2017, 51, 8815−8823