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Compound hydrometeorological extremes across multiple timescales drive volatility in California electricity market prices and emissions

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HIGHLIGHTS

- Hydrometeorological variables drive prices and emissions on California's grid.
- Time scale controls which combination of variables exert the greatest influence.
- Market prices appear most sensitive to periods of extreme abundance (over supply)
- Historical data severely underrepresents the occurrence of these low price events.

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ABSTRACT

Hydrometeorological conditions influence the operations of bulk electric power systems and wholesale markets for electricity. Streamflow is the "fuel" for hydropower generation, wind speeds and solar irradiance dictate the availability of wind and solar power production, and air temperatures strongly affect heating and cooling demands. Despite growing concern about the vulnerability of power systems to hydrometeorological uncertainty, including "compound" extremes (multiple extremes occurring simultaneously), quantifying baseline probabilistic risks remains difficult even without factoring in climate change. Here, we use newly developed power system simulation software to show how uncertainties in spatially and temporally correlated hydrometeorological processes affect market prices and greenhouse gas emissions in California's wholesale electricity market. Results highlight the need for large synthetic datasets to access rare, yet plausible system states that have not occurred in the recent historical record. We find that time scale strongly controls which combinations of hydrometeorological variables cause extreme outcomes. Although scarcity caused by low streamflows and high air temperatures has long been considered a primary concern in Western power markets, market prices are more profoundly impacted by weather and streamflow conditions that lead to an overabundance of energy on the grid.

1. Introduction

Variability in hydrometeorological processes is known to affect electricity supply and demand [1], with corresponding impacts on emissions of greenhouse gases and other air pollutants, system cost [2] and reliability [3–7], and market prices [8–10]. However, historical observations of weather and streamflow capture a limited number of extreme events, necessitating the use of large stochastic simulations to assess risk. Stochastic simulations can enable higher fidelity characterization of the possible combinations of extreme hydrometeorological states, including rare yet plausible events outside recorded observations. However, care must be taken to reconstruct spatial and temporal statistical dependencies among multiple hydrometeorological variables and across scales. Risk characterization must also consider the interconnected topologies of bulk electric power systems, which give system operators some ability to manage spatially explicit hydrometeorological stress [11]. For example, an area experiencing high temperatures (electricity demand) and simultaneous scarcity in wind and water (electricity supply) may be able to cost-effectively transfer electricity from a distant system that is not experiencing

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extreme conditions [11].

Previous efforts to quantify the impacts of hydrometeorological extremes on large, interconnected power systems have not fully captured the joint uncertainties that occur in spatially distributed weather and streamflow processes [12–14,3,5], nor have they adequately explored the role of timescale in controlling which phenomena drive extreme outcomes on the grid. In this study, we simultaneously assess the role of stationary uncertainties in weather and streamflow on electricity market dynamics for a large, interconnected power system. Going beyond the historical record, we characterize risks from compound extreme events on multiple time scales, ranging from interannual to hourly. We assess system performance in terms of two key metrics: wholesale electricity prices and plant level greenhouse gas emissions (we do not account for upstream emissions from construction or the fuel cycle). Wholesale prices and emissions are of critical importance to the power sector, directly informing construction/decommission of power plants, investment in transmission infrastructure, and bidding strategies for market participants. Both also represent dynamic measures of system performance that aggregate information about generation resource availability (supply) and load (demand). Extreme high or low values may indicate periods of stress, when system operators struggle to achieve a balance between supply and demand. For example, very high prices indicate scarcity (e.g., periods of high demand and low availability of hydropower and variable renewable energy, when system operators are forced to use more expensive, fossil-fuel based thermoelectric power plants). Extremely low prices indicate "over-supply" (periods when production from hydropower, wind and solar and certain "must-run" resources (e.g. nuclear) is so great that these technologies satisfy or exceed demand).

We focus our analysis on the U.S. West Coast power system, and specifically the California Independent System Operator (CAISO). CAISO oversees one of the largest grids in the world (through which 80% of California's electricity flows) as well as a wholesale electricity market from which retail utilities in the state buy electricity to serve their roughly 30 million customers [15]. California's power grid is vulnerable to an array of hydrometeorological extremes. In an average year, 15% of California's electricity demand is met by hydropower produced within the state(California Energy [16]. Significant amounts of hydropower are also imported from the Pacific Northwest (primarily from dams in the Columbia River Basin) and Southwest (primarily from the Hoover Dam on the Colorado River), making California particularly exposed to periodic (though rare) West Coast-wide drought [17]. There is also increasing evidence that climate change is increasing the likelihood that precipitation deficits in California are associated with elevated temperatures (including heat waves [18,19]). This combination occurred recently during the state's historic 2012–2016 drought [18,20], leading to consecutive years of high electricity demand for cooling and low hydropower availability.

However, scarcity on the California grid is not the only potential outcome from compound hydrometeorological extremes. California is increasingly reliant on wind power (in-state generation has more than doubled since 2009) and solar power (more than quadrupled since 2009 [16]), both of which exhibit fluctuations due to variable meteorological conditions and climate modes [21]. As its dependence on variable renewable energy grows, California is experiencing more frequent periods of oversupply during which the available supply of renewable and must-run generation eclipses the grid's demand for electricity. A notable example occurred in early 2017, when California experienced an extreme wet period initiated by several atmospheric rivers, leading to high streamflow, an abundance of hydropower and, in combination with wind and solar, frequent negative prices and renewable energy curtailment throughout February and March [22].

Recent studies have explored the impacts of drought on hydropower availability and power sector emissions in California [23–25]; the role of hydrometeorological conditions in driving electricity demand in the state [26]; and the effects of uncertainty in variable renewable energy [27,28] production on outcomes in the CAISO market. However, no study has been able to fully characterize electricity price and emissions outcomes probabilistically under hydrometeorological uncertainty.

We employ a new open source simulation framework designed specifically to evaluate performance of the CAISO system under uncertainties in multiple spatially and temporally correlated hydrometeorological processes. The core of the model is a stochastic "engine" that generates synthetic daily records of temperatures, wind speeds, solar irradiance and unregulated streamflow at more than 100 monitoring stations distributed throughout the West Coast. The statistical properties (moments, cross correlations, spatial and temporal structure) of the synthetic hydrometeorological data mirror those of the historical record, and the large number of synthetic records (i.e., capable of observing hundreds or thousands of replicate worlds) allows for a better characterization of plausible compound extreme events. We then use the augmented synthetic records of hydrometeorological variables to simulate hourly electricity demand, wind power production, solar power production and hydropower availability. These synthetic power system inputs drive a multi-zone unit commitment and economic dispatch model that simulates the hourly operation of the West Coast power system (Fig. 1), including the CAISO market, outputting corresponding hourly time series of power plant CO_2 emissions and market prices for electricity. We quantify risks associated with compound hydrometeorological extremes by simulating system behavior over 1000 synthetic years, which previous results [29] suggest is a sufficient simulation length to capture uncertainty in the multivariate state space and produce higher fidelity estimates of plausible compound extreme events relative to the historical record. For comparison, we also simulated the model using historical hydrometeorological data from the years 2000–2017.

2. Methods

In this study we make use of the California and West Coast Power System (CAPOW) model, an open source simulation framework for evaluating risks from correlated hydrometeorological processes in bulk power systems and wholesale electricity markets. The modeling framework is Python-based and all code and data are freely available via online public repositories. CAPOW accurately reproduces historical price dynamics in CAISO, while also offering unique capabilities for stochastic simulation that are well suited to the challenge of isolating the role of hydrometeorological uncertainty (including compound extreme events) on electricity market outcomes. The following sections provide details about the two core components of the model: a simulation model for relevant electric power system infrastructure, and a stochastic "engine" that generates synthetic records of hydrometeorological variables. Full mathematical descriptions of the CAPOW model's core components, as well as extensive validation, can be found in a separate paper by the authors [29].

2.1. Power systems model

The model's geographical scope covers nearly the entirety of the U.S. West Coast bulk electric power system (Fig. 1), including most of the states of Washington, Oregon and California and the operations of two wholesale electricity markets, the Mid-Columbia (Mid-C) market in the Pacific Northwest and the California Independent System Operator (CAISO) in California. The modeled system topology is comprised of five major zones (one in the Pacific Northwest, and four in California), which are linked via aggregated high voltage transmission pathways. Interregional connectivity is also captured between California and the Southwest (power flows between these two regions are modeled statistically). Each zone is associated with a portfolio of generating resources and a separate time series of electricity demand. We simulate power system operations using a multi-zone unit commitment and economic dispatch (UC/ED) model formulated as a mixed integer linear

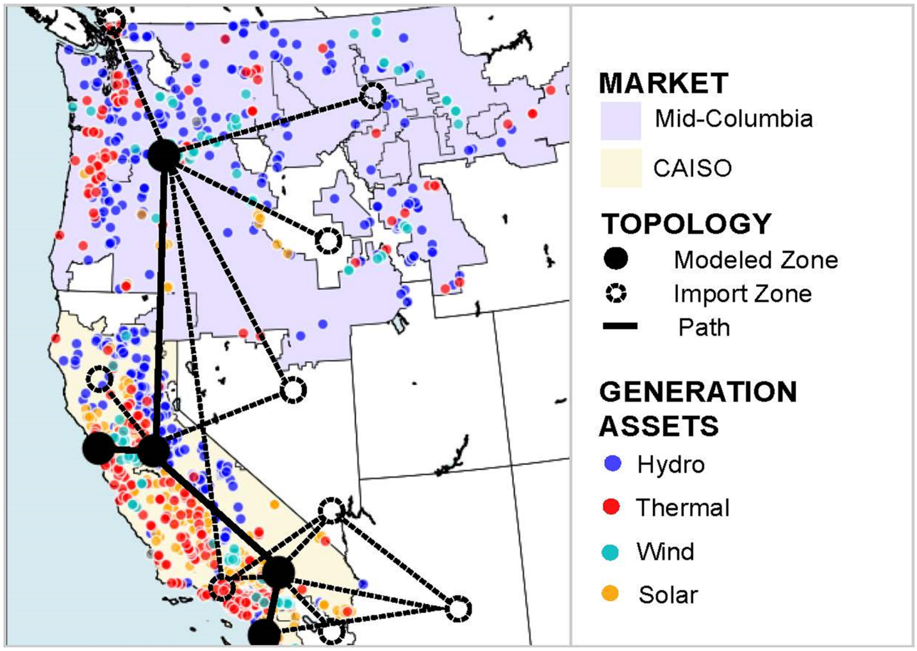

Fig. 1. Topology of the power system model used and map of existing generators.

program. The model's objective function is to minimize the cost of meeting demand for electricity and operating reserves in the two major markets represented, and its solution is constrained by limits on individual generators, the capacity of transmission pathways linking zones, and others.

The primary inputs to the model are time series of hourly electricity demand, available wind and solar power production in each zone, and available hydropower production on a daily basis, which the optimization program dispatches according to its least cost objectives. Measured outputs are hourly zonal electricity prices ($/MWh) and cumulative system wide emissions of CO_2. In a given hour, we estimate the market price of electricity for each zone as the shadow price of an energy balance constraint. In reality, locational marginal prices in California vary on a nodal basis, with the overall ('hub') price calculated as a weighted average of all the nodes. In order to estimate the overall CAISO price from our 4 modeled zonal prices, we apply a regression trained on historical (2012–2016) zonal price data. In this study, we assume 2016 grid resources, including thermal generators, hydroelectric dams, installed wind/solar power capacity, and high voltage transmission pathways. Power plant emissions (tracked in terms of CO_2 equivalents) are calculated on the individual generator level using the simulated generation amount (MWh) and an emission coefficient for each plant (kg/MWh) developed from the U.S. EPA eGrid [30] database.

2.2. Stochastic engine

The use of historical hydrometeorological observations to evaluate critical infrastructure performance has a long history of misrepresenting risks from extreme events [31–33]. This practice is particularly problematic when considering risks associated with compound events. Very long simulations may be needed to adequately explore complex joint uncertainties that exist across variables, time and space, and produce rare combinations of system states that are especially hazardous [34,31]. Thus, in this study we rely on an expanded (1000-year) synthetic dataset of relevant hydrometeorological variables and power system inputs, which is created as follows.

First, historical records of daily average temperature and wind speed data at 17 major airports (Fig. 2b, c, f, g) across the U.S. West Coast are gathered from the NOAA Global Historical Climatological Network [35]. Temperature data cover the period of 1970–2017, whereas wind data only cover 1998–2017. Missing wind data (1970–1998) at each site are filled by bootstrapping historical data, conditioned on minimizing the RMSE between daily temperatures. Concurrent records of global horizontal irradiance are taken from six sites (Fig. 2d, h) in the National Renewable Energy Laboratory's National Solar Radiation Database (NSRDB) [36]. Observed daily streamflow for 108 sites (Fig. 2a, e) throughout the Pacific Northwest and California are taken for 1954–2008 from the BPA Modified Streamflow database ([37]) and the California Data Exchange Center (CDEC) [38].

Synthetic hydrometeorological data is created in a manner that maintains the statistical moments for each individual process, as well as spatiotemporal and cross correlations among variables on multiple time scales (annual, seasonal, daily, hourly). Using the hourly historical data for temperatures and wind speeds described above, we generate an average 365-day profile for each observation site. Similarly, historical irradiance data is used to create a profile of average 'clear sky' conditions. The period 1998–2017 is selected to ensure contemporaneous records across variables. Then residuals of the temperature and wind profiles are generated by subtracting the average profile from observed data. A similar operation is done for irradiance data to calculate "losses" in irradiance from cloud coverage. All of the residuals are transformed to approximate Gaussian distributions, and then the transformed residuals are used to parameterize a vector autoregressive (VAR) model to capture both autocorrelation and covariance across variables. The error terms in the VAR model are generated from a multivariate Gaussian distribution whose covariance matrix is calculated from the historical residual dataset. The number of lags is determined using the Akaike Information Criteria (AIC). Synthetic residuals for temperatures, wind speeds and irradiance are then "unwhitened", back-transformed and added to the average profiles to simulate daily temperature, wind speed and irradiance values.

Creating synthetic streamflow records is a two-step process. First, Gaussian Copulas are used to capture observed statistical dependences among total annual streamflow at each gauge site, and between total annual streamflow and average air temperatures. To do this, a longer observed temperature record (1953–2008) at seven meteorological stations is transformed into heating and cooling degree days (HDDs and CDDs, respectively), which are measures of deviation from 18.33

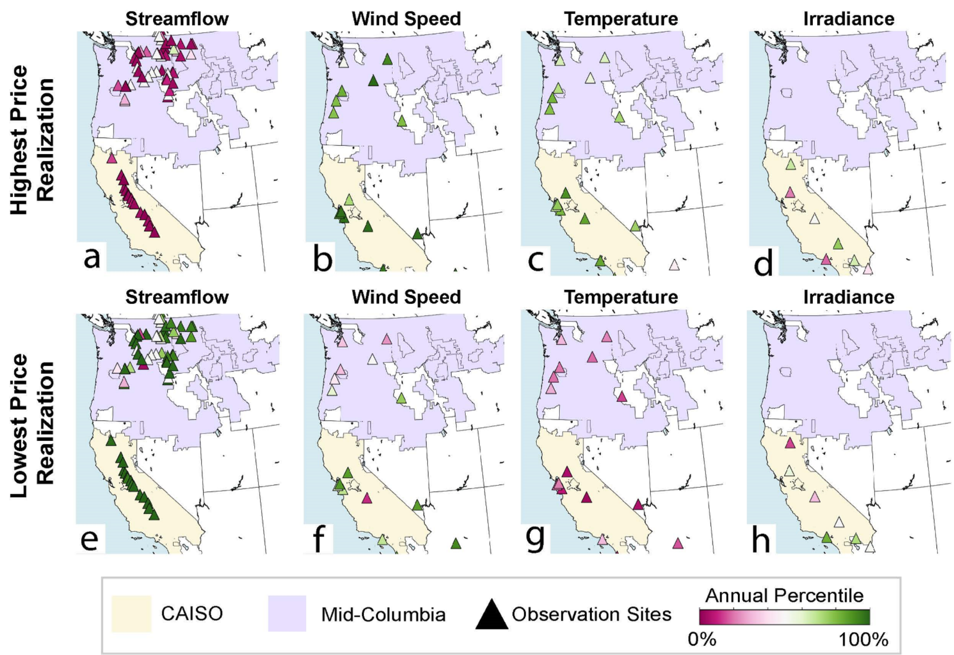

Fig. 2. Hydrometeorological observations for the highest price (panels a–d) and lowest price (panels e–h) realizations years in our 1000 synthetic simulation runs.

degrees Celsius. Then total annual HDDs and CDDs are calculated by summing the daily HDDs and CDDs for each year, providing a coarse measure of each historical year's "hotness" and "coolness". Historical annual HDDs, CDDs and total annual streamflow for all sites are then transformed into quantile space by calculating empirical cumulative probability distribution of each variable:

$$P = \mathrm{P}(Q \geq q) \tag{1}$$

where

Q = variable of interest (total annual streamflow, annual HDDs, annual CDDs)

The empirical distribution is transformed again into a uniform distribution between -1 and 1 to ensure a zero-mean coherent dataset:

$$Y = 2(P - 0.5) \tag{2}$$

Random samples are then drawn from a multivariate Gaussian distribution with mean 0 and covariance matrix $\boldsymbol{C}$ calculated across all sites and values of HDDs, CDDs and annual streamflow. The sampled data is then transformed back by reversing Eqs. (1) and (2).

The next step is to disaggregate total annual flows down to a daily time step. The synthetic samples of HDDs, CDDs and annual streamflow produced using the Gaussian Copula approach are matched with daily temperatures generated using the VAR model described above. For each year of synthetic data desired, a single year of HDDs and CDDs generated using the VAR model is selected via mean squared error. The corresponding daily temperatures are then compared alongside the historical record to find the year with the most similar spring and summer temperatures. Daily flow fractions for this historical year are then multiplied by total annual flows simulated via Gaussian Copula to produce a synthetic record of streamflow at each gauge site. This approach ensures that synthetic streamflow capture observed correlations across sites, as well as relationships with temperatures, on multiple time scales.

After synthetic records of hydrometeorological variables (temperatures, wind speeds, solar irradiance and streamflow) are created, these time series are translated into corresponding records of power system inputs. Using multi-variate regression models fitted to historical data, we use synthetic hydrometeorological data to create daily records of zonal electricity demand (via temperatures and wind speeds); wind power generation (via wind speeds); and solar power production (via irradiance), with regression residuals then represented using VAR processes. Hourly values are resampled from historical datasets maintained by Bonneville Power Administration and CAISO.

Daily values of available hydropower production are created by passing synthetic streamflow records through mass-balance hydrologic models of dams in the Columbia River basin and major storage reservoirs in in California, as well as through a machine learning representation of high altitude hydropower production in California; a small amount of remaining hydropower capacity is also represented via scaled model outputs. Daily hydropower availability is then dispatched optimally on an hourly basis by the UC/ED model. Detailed descriptions of all models used to translate raw hydrometeorological variables into power system inputs can be found in Su et al [29].

Synthetic records of zonal electricity demand, hydropower availability, and variable renewable energy production are then pushed through the UC/ED model, resulting in 1000-year empirical distributions of prices and emissions. In order to isolate the role of hydrometeorological uncertainty and compound extremes on system outcomes, we fix the price of natural gas at \$4.5/MMBtu. Thus, when we refer in this paper to prices in specific historical years (e.g. 2011), this should be interpreted as prices calculated by the model using observed 2011 hydrometeorological data, assuming a natural gas price of \$4.5/MMBtu.

2.3. Limitations

There are some limitations in this work that should be noted. The model employs a relatively coarse (zonal) resolution. This limitation is due mostly to a lack of detailed demand and transmission data in the system of interest. As a result, we do not capture impacts from local transmission congestion. At the same time, we also note that detailed representation of transmission systems may dramatically scale model computational requirements, making the probabilistic analysis performed here much more difficult.

3. Results and discussion

3.1. The most extreme simulations

We have structured the discussion of our results by time scale,

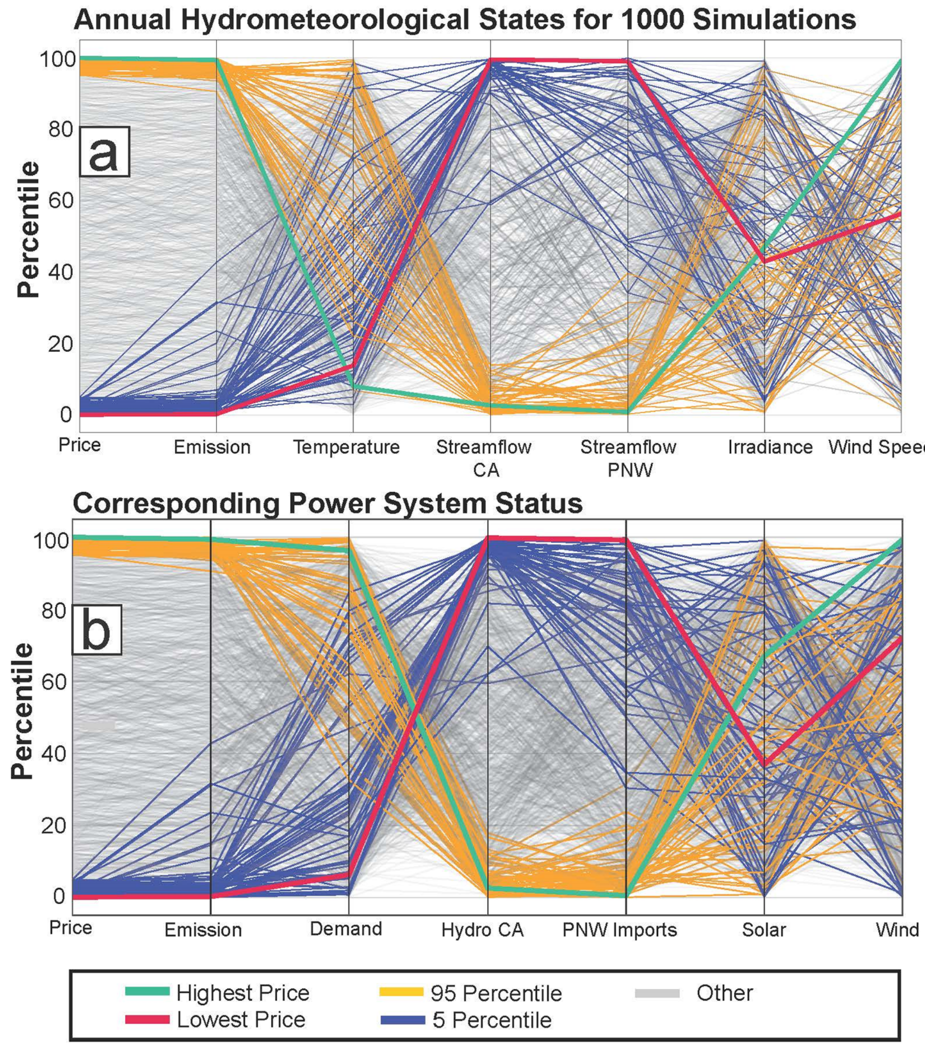

Fig. 3. Parallel coordinate plots of hydrometeorological state variables (panel a) and power system state variables (panel b) for all 1000 simulation realizations. The highest, lowest, 5th and 95th percentile price years are highlighted in color.

beginning with annual and then proceeding to seasonal, daily and hourly. On an annual time scale, we find that simultaneous extremes in temperatures and streamflow occurring across the entire West Coast cause the largest swings in market prices and CO_2 emissions (Fig. 2).

The year with the highest average price ($48/MWh) out of the 1000 synthetic realizations is an extremely “hot and dry” year (Fig. 2a–d). High air temperatures increase demand for electricity in California, while low streamflow across the West Coast decreases the availability of hydropower in California and the availability of hydropower imports from the Pacific Northwest (PNW). The lowest price year ($36/MWh) is on average extremely “cool and wet” (Fig. 2e–h). These conditions correspond to low electricity demand, plentiful hydropower in California, and abundant hydropower imports from the Pacific Northwest.

3.2. Extremes on an annual scale

Fig. 3 shows the direct relationship between hydrometeorological state variables (panel a), corresponding power system state variables (panel b), and performance metrics (prices and emissions) for all 1000 one-year realizations. Hydrometeorological variables shown are average values across all monitoring stations. For example, the temperature values shown represent averages across the 17 NOAA GHCN stations (Table S1). Average streamflow values are calculated across all the California streamflow sites (Table S4). PNW streamflow is represented using simulated flows at The Dalles (Dalles ARF), near the mouth of the Columbia River. Irradiance data are the average across the seven NREL NSRDB sites shown in Table S2. Wind speed data are calculated as the average across the 17 GHCN stations in Table S1. This figure confirms, once again, that West Coast-wide hot and dry conditions contribute to high prices and high emissions in the system, while cool and wet conditions drive low prices and emissions. Fig. 3b largely mirrors Fig. 3a – affirmation that power system state variables respond directly to hydrometeorological conditions during extreme price and emission years on both the high and low end.

The green lines in Fig. 3 track performance metrics (prices, emissions) and state variables for the same highest-price year depicted in Fig. 2a–d. This connection between “hot and dry” years and high average prices is largely consistent among years with prices at or above the 95th percentile (gold lines in Fig. 3). The red lines in panel Fig. 3 tracks performance metrics (prices, emissions) and state variables for the same lowest-price year depicted in Fig. 2e–h. The connection between “cool and wet” conditions and low prices is largely consistent among years that experience prices at or below the 5th percentile (blue lines in Fig. 3).

The 3D scatter plot in the lower diagonal of Fig. 4 shows how CAISO prices respond to different combinations of in-state hydropower production, PNW imports, and electricity demand over the 1000-year synthetic dataset. Note that the min and max price years (the same ones shown in Figs. 2 and 3) correspond to simultaneous extremes in these three state variables.

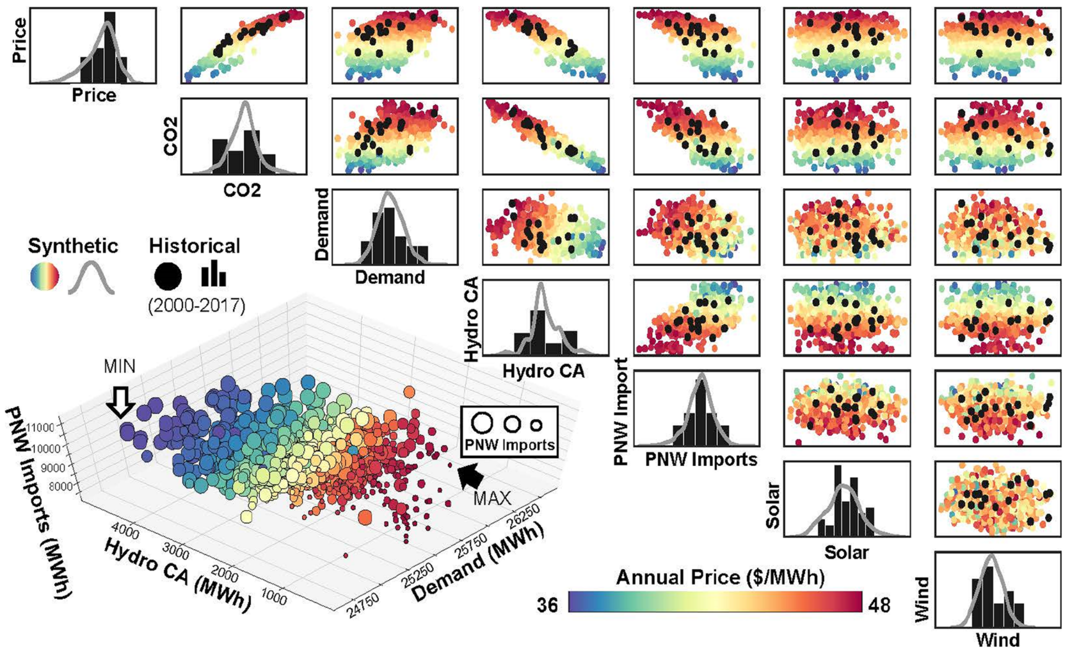

Fig. 4. Above diagonal: pair plots among the two performance metrics (market prices and CO_2 emissions) and five system state variables. Annual values from the stochastic simulation (colored dots) are plotted alongside annual values using historical hydrometeorology (black dots). Diagonal: distributions of power system state variables and performance metrics produced using historical (black) and synthetic (gray) hydrometeorological data. Below diagonal: 3D scatter plot for demand, California hydropower and PNW imports on an annual basis. Size of the dots correlate to the value of PNW imports. The diagonal plots are the distribution for each variable using either historical or synthetic datasets. Bottom half, color coded correlation for all variables.

The pair plots in the upper right show that our use of synthetic hydrometeorological data captures historical correlations among key state variables and performance metrics on an annual basis. The pair plots also highlight the importance of utilizing an expanded synthetic dataset to capture plausible compound extreme events that are not well represented within the limited length of the available historical record. In each plot along the diagonal, the stochastic results capture a wider range of decision relevant outcomes than what is produced by the historical data.

In particular, we find that using historical hydrometeorological data alone yields a systematic bias that underrepresents years in which the CAISO market may experience very low prices caused by "oversupply" (i.e., periods when available hydropower, variable renewable energy and must run resources exceed demand). The lowest-price year from the historical dataset is 2011— a wet year with relatively cool temperatures and an average price of $41.28/MWh. That price is equivalent to the 10th percentile of the 1000-year synthetic dataset, meaning there are many plausible combinations of hydrometeorological variables that force both prices (and emissions) considerably lower than 2011 (Table 1). In contrast, recent historical hydrometeorological data provide a better approximation of extreme scarcity on the California grid, thanks in part to the state having experienced a historic drought during 2012–2016 (an event with an estimated return period of between 1-in-500 and 1-in-1200 years) [39,40].

Hydrometeorological variables significantly impact GHG emissions in the system. The synthetic results suggest that there could be a 2× difference in GHG emissions from the best year (about 20 million tons in CO_2 equivalents) to the worst year (over 45 million tons). Our results also closely match historical observations. Using 2016 hydrometeorology, our modeling indicates that CAISO-wide emissions would be about 34 million tons of CO_2 equivalents, whereas emissions of 38 million tons were reported by CAISO for that year, assuming an 84%/16% split in in-state/out-of-state generation [41]. Note that our results only reflect emissions produced during active generation. We do not consider emissions from plant starts, which may partially explain the discrepancy between our results and historical observations.

We also find positive correlations between hydropower availability in California and PNW imports (which consist mostly of hydropower) (upper diagonal of Fig. 4), confirming a finding from previous studies [42,43] that these two regions, whose electricity systems are interdependent, are more likely to experience dry or wet hydrologic conditions simultaneously. Additionally, in California, dry conditions (low hydropower availability) and hot conditions (high electricity demand) are more likely to occur simultaneously. Thus, for the CAISO system, covariance among a few key hydrometeorological state variables and across space acts as a risk multiplier.

Throughout our remaining discussion of sub-annual time scales, we focus on our evaluation of the CAISO system's performance in terms of wholesale prices and not CO_2 emissions. There are two reasons for not considering CO_2 emissions: (1) prices and emissions show a very strong positive correlation (see Fig. 4), so high/low prices can be viewed as an indicator of high/low emissions; and (2) sub-annual dynamics in

Table 1
Comparison of annual power system performance metrics and state variables among the highest and lowest price years from the 1000-year synthetic dataset and historical dataset (1970–2017).

Simulation	Price	Emissions	Demand	Hydro CA	PNW Imports	Solar	Wind
Synthetic (MAX)	99.999%	99.40%	96.30%	2.60%	0.40%	67.10%	99.30%
Synthetic (MIN)	0.001%	0.20%	6.30%	99.80%	99.20%	37.10%	71.90%
Historical (2015)	98.34%	98.26%	92.19%	2.74%	16.45%	38.12%	26.33%
Historical (2011)	10.30%	9.30%	32.56%	89.04%	83.47%	75.83%	24.09%

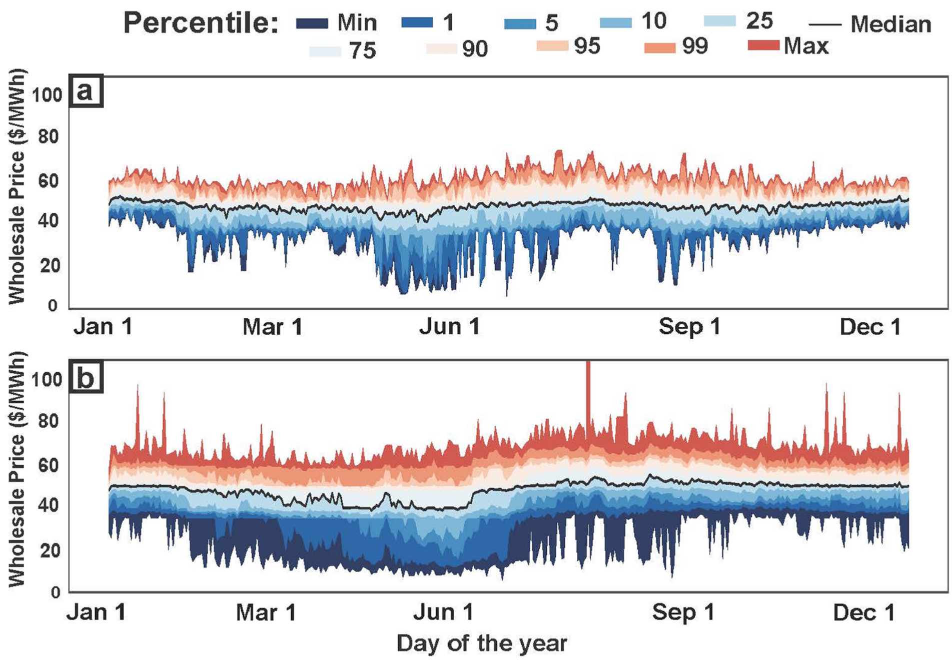

Fig. 5. (a) Distributions of daily wholesale prices in CAISO produced using historical hydrometeorological inputs. (b) Distributions of daily wholesale prices in CAISO produced synthetic inputs.

emissions are likely to pose smaller consequences for grid participants relative to volatility in market prices.

3.3. Extremes on a daily scale

Moving from annual to seasonal, daily and hourly time scales, we find important nuances in how different combinations of hydrometeorological states affect system performance. The distribution of daily electricity prices produced using historical (1970–2017) hydrometeorological data (Fig. 5a) shows low prices (as low as $5/MWh) are more likely to occur during the spring snowmelt (May-June), when hydropower produced in California and PNW imports are more abundant. High prices (as high as $68/MWh) are most likely to occur in late summer, when peak snowmelt (hydropower production) has subsided and temperatures (electricity demand) remain very high.

Prices produced using historical data alone (Fig. 5a) are a strongly biased underrepresentation of the higher order statistical moments for pricing in CAISO, especially at extreme outer quantiles. Although there is general agreement in terms of mean, seasonality, correlation among state variables, etc., the system's internal variability as captured in the 1000-year synthetic dataset yields a much wider range of extremes in market prices (empirical "min/max" values) (Fig. 5b). Underlying these wider extremes are rare but plausible combinations of hydrometeorological conditions that, while reflective of stationary uncertainty (i.e., no climate change), collectively fall outside the recent historical record.

Delta moment-independent sensitivity analysis [44,45] highlights the dominant factors that influence daily prices (Fig. 6). We find that the first order sensitivity of daily prices to uncertainty in power system state variables (especially electricity demand and West Coast-wide hydropower availability) peaks during spring. This is a notable result, and one that contributes insights beyond previous studies, which have focused mostly on the potential for supply shortfalls to occur in late summer [46,47] (typically a hot, dry period). While we also find greater potential for scarcity (and higher prices) during late summer, our results strongly suggest that hydrometeorological uncertainty is a more important driver of *market price volatility* during periods of relative abundance (spring).

There are two root causes for this phenomenon. First,

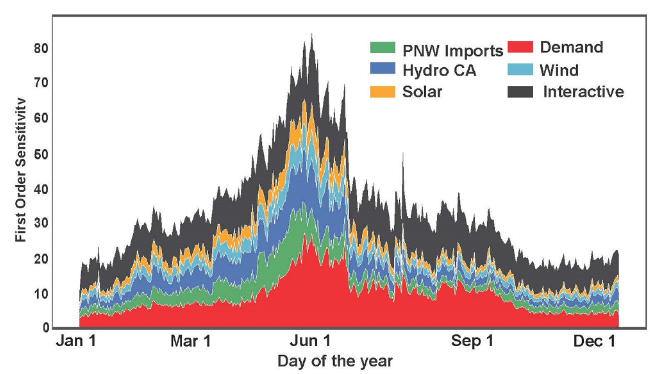

Fig. 6. First order sensitivity for power system state variables. (d) Power system state variables for yearly price extremes.

hydrometeorological uncertainty is greater during spring months (e.g., timing and amount of snowmelt in California and the Pacific Northwest). Second, it is a product of electricity markets' clearing mechanism and the evolving structure of power system supply curves, the bottom of which are increasingly made up of $0/MWh marginal cost wind and solar. During extremely wet years with low spring demand (mild temperatures), hydropower and variable renewables can combine to displace higher marginal cost, fossil-fuel power plants from the market. This causes daily prices to fall sharply.

3.4. Factors contributing to extreme outcomes across time scales

We also find that time scale is important for understanding how compound hydrometeorological extremes lead to price extremes (Fig. 7). The violin plots across different time scales (annual/daily/hourly) capture extremely high/low prices (defined here as 95th/5th percentile at an annual time step; 99th/1st percentile at daily/hourly time steps) as well as density maps for the five different power system state variables. The progression from annual (Fig. 7a) to daily (Fig. 7b) and then hourly time steps (Fig. 7c) reveals changes in how each state variable maps to extreme prices. At the annual scale (Fig. 7a), extreme high prices are driven by low hydropower availability across the West

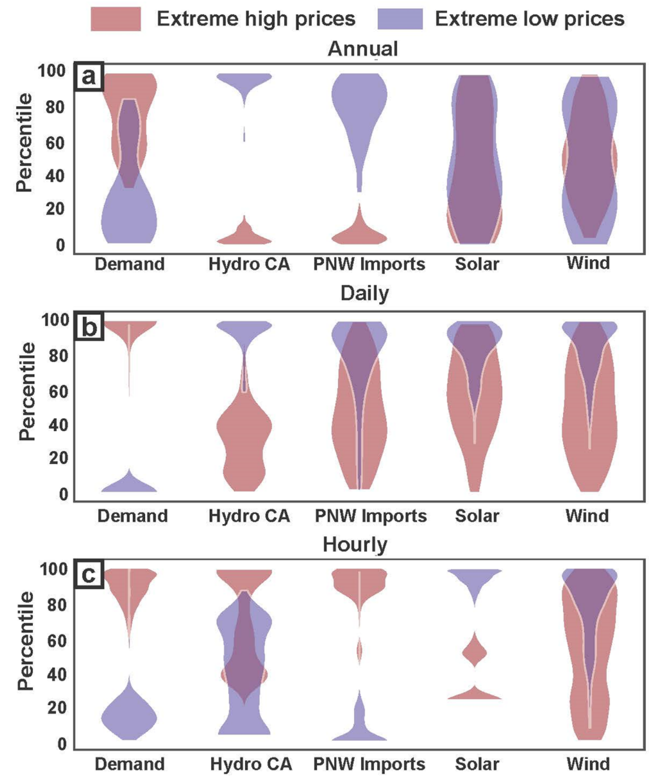

Fig. 7. (a) Power system state variables for yearly price extremes. (b) Power system state variables for daily price extremes. (c) Power system state variables for hourly price extremes.

Coast and high electricity demand; low price years experience the opposite. Transitioning to the daily time scale (Fig. 7b), very high demand days (e.g., heat waves in late summer) and very low demand days (e.g., 20 degreesC in May) are the most consistent predictors of price extremes. Very low daily prices also consistently map to very high values of California hydropower and PNW imports (often occurring during spring snowmelt), and the availability of wind and solar. Hourly extremes paint a somewhat different picture (Fig. 7c). In particular, a significant number of high price hours coincide with very high California hydropower production and hydropower imports from the PNW. This apparent flip in the response of price to hydropower production results from much of the West Coast's hydropower capacity operating strategically as "peaking" resources. Operators deliberately schedule inexpensive (but finite) hydropower generation to align with hours of high prices in order to maximize its value.

Generation mix dynamics at finer (daily and hourly) resolutions provide a more detailed mapping for how system operations and market prices are influenced by electricity demand and dynamic resource availability (Fig. 8). Note that "imports" shown in Fig. 8 are not limited to those from the PNW; they also include some generation imported from the Southwest. The generation mixes for the two synthetic years with the lowest (Fig. 8a) and highest (Fig. 8b) average wholesale price (also discussed in Figs. 2 and 3) show substantial differences. Periods of high demand and low hydropower availability (e.g., August in Fig. 8b) increase the need for generation from fossil fuel power plants (mostly natural gas); as this happens, the market price (system "shadow cost") increases. Periods of low demand and plentiful hydropower and variable renewable energy (e.g., beginning of June in Fig. 8a) have the opposite effect, with prices falling to $5/MWh when there is a glut of low marginal cost hydropower and renewable energy.

Overall one of the most pronounced differences in the monthly generation mix between the highest and lowest price synthetic years relates to the amount of hydropower and fossil fuel generation used. In the highest price year (Fig. 8b), the CAISO market meets 42.4% of its electricity demand using fossil fuel-based power plants, 7% from in-state hydropower and 21.5% is imported. In the lowest price year (Fig. 8a), CAISO only uses fossil fuel-based generation to meet 20% of its electricity demand, 24% comes from in-state hydropower and 26.2% from imports (including a greater amount of imported hydropower from the Pacific Northwest).

Zooming-in to two critical weeks of the highest and lowest price years, we distinguish how changes in the generation mix control acute price conditions on an hourly basis. In a particularly low-price two weeks during the spring of the lowest-price synthetic year (Fig. 8c), depressed electricity demand (driven by mild temperatures) coincides with high streamflow (an abundance of hydropower), must run generation, and variable renewable energy. Some fossil-fuel generation remains online, primarily to provide operational reserves, but most is forced out of the market. As a result, the price of electricity frequently falls to $5/MWh, especially during hours when solar irradiance is highest (the "belly" of California's "duck curve" [27].

Also note that despite lower wholesale prices on average, hourly and daily price patterns during the two-week period in the lowest-price year (Fig. 8c) are significantly more volatile than those in a dry, hot period in late summer in the highest-price year (Fig. 8d). Natural gas power plants must be turned on and ramped up quickly in the early evening as solar power production declines. In the course of a few hours, prices can jump from near $0/MWh to close to $50/MWh.

3.5. Results implications

Quantifying the uncertainties as well as defining the distribution of the possible outcomes can be used in many more ways. To facilitate better renewable development and helping to transition to a greener grid, both average and variance of energy prices are valuable information to help making investment decisions. For example, decision to build new wind farm may be contingent on the annual average prices as well as year to year variations. The decision to build an utility scale battery would require understanding of hourly prices distribution to optimize the physical specification of the battery.

Hydrometeorological uncertainties drive electricity market outcomes in complex ways that can significantly impact power system participants. On an annual level, our results suggest that California utilities may have experienced close to the worst-case drought scenario during 2012–2016. However, recent historical data is likely a poor representation of low price years caused by mild temperatures and high streamflow. Low market prices, while attractive to retail distribution companies, impact the financial viability of many projects (including renewable energy). Our results should aid system participants in accounting for such weather based price risk, which is important in developing operational, risk management, and long-term infrastructure strategies.

4. Conclusion

There is growing awareness of the economic and environmental hazards that hydrometeorological uncertainty, including compound extreme events, pose for grid operators and electricity market participants. However, previous efforts to characterize these risks probabilistically have fallen short in their consideration of interconnected system topologies and joint uncertainties across correlated variables. For the first time, we isolate the impacts of multiple hydrometeorological drivers on California's major wholesale electricity market and investigate how compound extremes translate to instances of extreme prices and CO_2 emissions on the grid. In the course of doing so, we also show that assessing risks associated with compound hydrometeorological events necessitates the use of larger synthetic

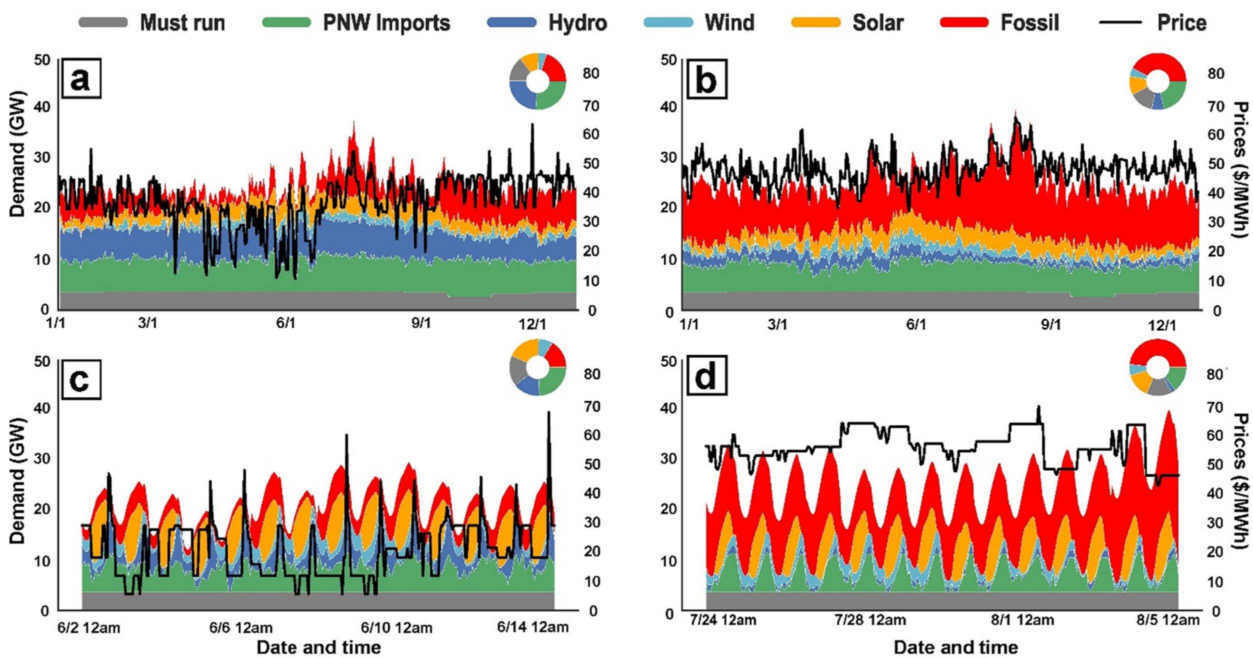

Fig. 8. (a) Daily generation mix for the synthetic year with the lowest average price; (b) Daily generation mix for the year with the highest average price; Electricity demand in each day/hour is equal to the (stacked) sum total of all active generation resources. The pie plots in the top right corner of each panel signify the average generation mix used during the period. (c) Hourly generation mix for a two week period selected from lowest price year; (d) Hourly generation mix for a two week period selected from highest price year. On both a daily and hourly level, low demand and high hydropower drive prices down; high demand and low hydropower lead to high prices. Renewable generation exerts more control on prices (particularly low prices) on an hourly scale.

datasets to access rare, yet plausible system states that have not occurred in the historical record. We find that time scale strongly effects which combinations of hydrometeorological variables cause extreme prices and emissions. At an annual time scale, simultaneous "hot and dry" or "wet and cool" conditions occurring across the West Coast result in the highest and lowest price/emissions outcomes, respectively. At a daily time scale, we find that very high demand (typically caused by heat waves) drives high price events, while extreme low daily prices are associated with a combinations of low demand (mild temperatures), high hydropower availability, and abundant wind and solar power production. Our modeling confirms a finding in previous studies that West Cost power systems experience the highest prices and greatest threats to reliability during combined hot and dry periods in late summer. However, we find that the market's response to compound hydrometeorological extremes (in terms of altered prices) is most pronounced during spring snowmelt, when demand is typically low (temperatures are mild) and there is often an overabundance of power, especially from hydroelectric dams, available on the grid.

It is important to note that the role that different hydrometeorological variables play in power system dynamics today is likely to change in the future as more variable renewable energy is added into the grid. An outstanding challenge remains understanding how future grid configurations, likely comprised of much larger shares of renewable energy, will be vulnerable to compound hydrometeorological extremes. In addition, future work should incorporate growing risks to power systems from discrete extreme events such as coastal and inland flooding and wildfire.

CRediT authorship contribution statement

Yufei Su: Software, Methodology, Conceptualization, Formal analysis, Visualization, Writing - original draft. **Jordan D. Kern:** Software, Conceptualization, Writing - original draft. **Patrick M. Reed:** Supervision, Writing - original draft. **Gregory W. Characklis:** Supervision, Writing - original draft.

Data availability

The data that were used in this analysis are available at the GitHub repository: https://github.com/romulus97/CAPOW_PY36.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

Y.S. and J.D.K. prepared the computer models. Y.S. conducted the simulation and performed the data analysis. J.D.K, P.M.R. and G.W.C supervised the project. All authors wrote the manuscript.

Code availability

The CAPOW model is available at: https://github.com/romulus97/CAPOW_PY36.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2020.115541.

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