## **LETTER • OPEN ACCESS**

# Effects on power system operations of potential changes in wind and solar generation potential under climate change

To cite this article: Michael T Craig et al 2019 Environ. Res. Lett. **14** 034014

View the [article online](https://doi.org/10.1088/1748-9326/aaf93b) for updates and enhancements.

## **Environmental Research Letters**

## LETTER

OPEN ACCESS

CrossMark

RECEIVED 5 September 2018

REVISED 12 December 2018

ACCEPTED FOR PUBLICATION 14 December 2018

PUBLISHED 15 March 2019

Original content from this work may be used under the terms of the [Creative](http://creativecommons.org/licenses/by/3.0) [Commons Attribution 3.0](http://creativecommons.org/licenses/by/3.0) [licence.](http://creativecommons.org/licenses/by/3.0)

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.



Effects on power system operations of potential changes in wind and solar generation potential under climate change

Michael T Craig **.** Ignacio Losada Carreño, Michael Rossol, Bri-Mathias Hodge and Carlo Brancucci<sup>®</sup> National Renewable Energy Laboratory, 15013 Denver West Parkway, Golden, CO 80401, United States of America E-mail: [carlo.brancucci@nrel.gov](mailto:carlo.brancucci@nrel.gov)

Keywords: climate change, power system operations, wind power, solar power Supplementary material for this article is available [online](https://doi.org/10.1088/1748-9326/aaf93b)

## Abstract

Climate change will likely impact wind and solar resources. As power systems increasingly shift towards wind and solar power, these resource changes will increasingly impact power system operations.We assess how power system operations will be affected by climate change impacts on wind and solar resources by generating wind and solar generation profiles for a reference period and five climate change projections.We then run a unit commitment and economic dispatch model to dispatch a highrenewable generator fleet with these profiles. For climate change projections, we use 2041–2050 output from five global climate models (GCMs) for Representative Concentration Pathway 8.5 for Texas, our study system. All five GCMs indicate increased wind generation potential by 1%–4% under climate change in Texas, while three and two GCMs indicate increased and decreased solar generation potential, respectively, by up to 1%. Uneven generation potential changes across time result in greater changes in dispatched generation byfuel type. Notably, nuclear generation decreases across GCMs by up to 7%, largely in low-demand (winter) months when nuclear plants, which have a high minimum stable load, must reduce their generation to avoid overgeneration. Increased wind and/or solar generation result in reduced system CO<sub>2</sub> emissions and electricity production costs across four of the five GCMs by 8–16 million tons and \$216–516 million, or by 2% and 1%, respectively. Future research should assess the atmospheric and climate dynamics that underlie such changes in power system operations.

## 1. Introduction

Over the coming decades, climate change will likely harm natural and anthropogenic systems and individuals (Fri et al [2010](#page-10-0)). As part of a broad effort to mitigate climate change, many international, national and state governmental bodies have promoted zerocarbon electricity generation technologies, particularly wind and solar (Meckling et al [2017](#page-11-0)). Consequently, over the past decade installed wind and solar capacity has grown rapidly, reaching in [2017a](#page-11-0) combined capacity of 130 GW in the United States (US Energy Information Administration [2017b](#page-11-0)) and 915 GW globally (BP [2018](#page-10-0)). Installed capacity growth has reduced wind and solar costs, so that they are often cost-competitive with other generation technologies in the US (Barbose et al [2017](#page-10-0), Lazard [2017](#page-11-0), Wiser et al [2017](#page-11-0)), enabling continued growth.

© 2019 The Author(s). Published by IOP Publishing Ltd

Despite wind and solar growth and other climate change mitigation efforts, annual average temperatures over the contiguous US have increased 1.8 °F since 1901 (US Global Change Research Program [2017](#page-11-0)). Furthermore, emission reduction pledges recently submitted at the 2015 Conference of Parties in Paris would slow, but not stop, future temperature increases (Fawcett et al [2015](#page-10-0), Rogelj et al [2016](#page-11-0)). Temperature increases and other impacts of climate change will have demand- and supply-side effects on the electric power system (Schaeffer et al [2012,](#page-11-0) Chandramowli and Felder [2014](#page-10-0), Bonjean Stanton et al [2016,](#page-10-0) Craig et al [2018a](#page-10-0)) including on wind and solar resources and generation (Pryor et al. [2012](#page-11-0), Wild et al [2015](#page-11-0), Haupt et al [2016](#page-11-0), Karnauskas et al [2018](#page-11-0), Carreño et al [2018](#page-10-0)). As wind and solar capacities continue to increase across the United States, climate change impacts on wind and solar generation will increasingly affect power system operations.

In general, studies forecast wind resources will decrease on average across the United States but increase in some regions by 2050 across potential climate futures. Karnauskas et al ([2018](#page-11-0)) find ten global climate models (GCMs) agree that wind power will decrease in the central United States by 8%–10% but increase in the east central United States under Representative Concentration Pathways (RCPs) 4.5–8.5 (Stocker et al [2013](#page-11-0)) by 2050. Alternatively, Pryor et al ([2012](#page-11-0)) find agreement among more than ten pairs of GCMs and regional climate models(RCMs) that mean annual wind speeds will increase in North Texas and Kansas, but decrease in the west, northwest, central east and northeast United States by 2041–2062 under RCP 8.5. Similarly, Johnson and Erhardt ([2016](#page-11-0)) find consensus among 4 GCM-RCM pairs that wind energy densities will increase in the north Texas region and decrease in the northeast and northwest by 2038–2070 under RCP 8.5. Crucially, Haupt et al ([2016](#page-11-0)) illustrate that wind speed changes under climate change will significantly vary across seasons and regions by 2040–2069. For instance, in the morning hours in Texas they find wind speeds will increase by up to 10% in the summer and fall but decrease by up to 6% in the winter and spring.

Less consensus exists among studies on future solar resources than wind resources, but studies generally indicate solar resources will decline in California and increase across the southeast United States. Across the 39 GCMs included in the Coupled Model Intercomparison Project Phase 5 (CMIP5), Wild et al ([2015](#page-11-0)) only find consensus in solar photovoltaic (PV) generation increasing (by up to 3%) in the southeast and decreasing (by up to 3%) in California and the northwest by 2049 under RCP 8.5. Across the same GCMs, Wild et al ([2017](#page-11-0)) only find statistically significant changes in median concentrating solar power (CSP) generation in the southeast, which they forecast will increase by up to 11% by 2049 under RCP 8.5. Similarly, using two GCMs Crook et al ([2011](#page-10-0)) forecast solar PV and CSP generation will increase in the southeast and decrease elsewhere by 2080 under RCP 6.0. As with wind speeds, though, how climate change affects solar resources by 2040–2069 will vary seasonally and spatially (Haupt  $et al 2016$  $et al 2016$ ).

Notably, while the above and related studies quantify wind and solar resources under climate change, they do not link changes in those resources to planning or operational impacts on the electric power system. Due to the interconnected nature of the power system, changes in wind and solar resources would affect other aspects of the power system. For instance, reduced wind and solar generation would need to be compensated for by increasing generation or decreasing demand. Increased generation may come from fossilfired resources, increasing carbon dioxide  $(CO<sub>2</sub>)$ emissions and making decarbonization targets more difficult to achieve. Alternatively, reduced wind and solar resources in high-renewable systems may endanger security of supply, e.g. by reducing generation coincident with peak demand.

Here, we build on prior work by capturing power system operational impacts of climate change effects on wind and solar resources. Specifically, for a reference period and five climate change projections assuming a high-renewable generator fleet, we generate hourly wind and solar generation profiles, then dispatch the fleet using a unit commitment and economic dispatch (UCED) model. By comparing system operations under the reference period and climate change projections, we quantify how climate change impacts on wind and solar electricity generation affect power system operations in terms of generation mix, wind and solar curtailment, system production costs and CO<sub>2</sub> emissions.

## 2. Methods

Due to its strong wind and solar resources (US National Renewable Energy Laboratory [2016](#page-11-0)), limited interconnections with neighboring systems (Electric Reliability Council of Texas [2017](#page-10-0)), and forecasted effects of climate change on wind and solar resources (Pryor et al [2012,](#page-11-0) Haupt et al [2016](#page-11-0), Johnson and Erhardt [2016](#page-11-0)), we use the Electric Reliability Council of Texas (ERCOT) power system as our study system. Throughout this paper, we present costs in 2017 USD using the Producer Price Index for electric utilities (Federal Reserve Bank of St. Louis [2017](#page-10-0)).

## 2.1. Calculating wind and solar generation under reference and climate change conditions

To obtain high-resolution wind and solar electricity generation profiles, we first obtain hourly air temperature and pressure; wind speed and direction; and global horizontal irradiance, direct normal irradiance (DNI) and direct horizontal irradiance (DHI) for Texas in  $4 \times 4$  km grid cells using the Weather Research and Forecasting (WRF) model version 3.8 (Skamarock et al [2008](#page-11-0)). The WRF grid is centered at 31.00°N and 100.00°W and consists of 340 points in the latitude direction and 340 points in the longitude direction, so that WRF's domain covers Texas. To better forecast solar electricity generation, we configure WRF to use the rapid transfer radiative model (RRTM) for longwave radiation and direct aerosol effects to an optical depth of 550 nm from WRF-Solar (Jimenez et al [2016](#page-11-0)).

To model reference and climate change conditions, we use different sets of boundary conditions that force WRF every 6 h (figure [1](#page-3-0)). To model reference conditions, we set boundary conditions with the North American Regional Reanalysis (NARR) data set for 1995–2005 (Mesinger et al [2006](#page-11-0)). To model climate change conditions, we modify NARR data on a cellby-cell basis with average monthly changes in sea surface temperature and atmospheric moisture and



<span id="page-3-0"></span>

temperature under climate change for 2040–2050 and RCP 8.5. We then use this modified NARR data to set boundary conditions (for more details and validation of this approach, see Carreño et al ([2018](#page-10-0))). To understand the robustness of our results across GCMs, we calculate the average monthly changes under RCP 8.5 using five GCMs (ACCESS, CCSM4, GFDL, IPSL and MPI) dynamically downscaled with the regional climate model system version 4 (RegCM4). Downscaling RegCM4 yields weather variables at 6 hour resolution, so we further downscale output from RegCM4 using WRF to generate weather variables at hourly resolution and at a higher spatial resolution. By doing so, we better capture spatial and temporal variability in climate change impacts on wind and solar generation and align the temporal resolution of weather variables with the resolution of our power system operational model (section 2.2). We select the five GCMs included in our analysis to represent the range of annual mean precipitation projections in Texas across 11 GCMs dynamically downscaled with RegCM4 (Ashfaq et al [2016](#page-10-0)). Overall, we generate 11 years of hourly time series of atmospheric and irradiance variables for each  $4 \times 4$  km grid cell in a reference period (1995–2005) and five climate change projections(2040–2050).

For each grid cell in the reference period and each climate change projection, we input hourly DNI, DHI, air temperature and surface wind speed into the System Advisor Model (SAM) (US National Renewable Energy Laboratory [2017](#page-11-0)) to calculate hourly solar generation potential assuming fixed tilt panels, and we input hourly wind speed and direction, and atmospheric pressure and temperature (all at 100 m hub height) into SAM to calculate hourly wind generation potential assuming IEC-2 composite turbines with 100 m hub heights. For further details on calculating wind and solar generation, see Carreño et al ([2018](#page-10-0)).

To maintain synchronicity between wind and solar generation and electricity demand, we use hourly demand from ERCOT for the reference period years, i.e. 1995–2005 (Electric Reliability Council of Texas [2018](#page-10-0)). No demand data is available for 1995 or 2001, so we exclude those years from our analysis in the reference period and the corresponding years (2040 and 2046) in the climate change projections. Consequently, our reference period spans 1996–2005 excluding 2001 and our climate change projections span 2041–2050 excluding 2046. Directly utilizing 1996–2005 demand, which has annual peaks ranging from 48 GW in 1996 to 60 GW in 2005, in conjunction with our 2017 generator fleet, which has a total capacity of 86 GW, would result in significant over-capacity. To avoid this issue, while preserving the hourly demand profile each year, we multiply hourly demand in each year by the ratio of total demand in 2017 to total demand in each year. These ratios range from 1.2–1.5 across years (supplemental information (SI) section SI.1, available online at [stacks.iop.org](http://stacks.iop.org/ERL/14/034014/mmedia)/ERL/ 14/034014/[mmedia](http://stacks.iop.org/ERL/14/034014/mmedia)). To isolate the operational effects of climate change impact on wind and solar generation, we use the same demand profiles for the reference period and climate change projections. In so doing, though, we miss how inter-annual climatic variability affects demand, deferring to future research the interaction of climate change impacts on wind and solar generation and demand.

## 2.2. UCED model

To capture the operational impact of shifting wind and solar resources under climate change, we use a UCED model (Morales-españa et al [2013](#page-11-0), Craig et al [2018b](#page-10-0)). The UCED model optimizes electricity generation and reserve provision to minimize variable electricity generation costs, regulation reserve provision costs, and start-up costs subject to system-wide reserve requirements, electricity demand and generator-level unit commitment constraints (SI.2). To account for inter-day generator operations, the UCED model runs hourly for a 24 hour optimization window plus a 24 hour look-ahead period. The solution of the 24 hour optimization window determines the initial conditions for the following UCED run. We build the UCED model in the General Algebraic Modeling System Version 25.0.1 (GAMS Development Corporation [2013](#page-10-0)) and solve it using CPLEX Version 12 (IBM [2014](#page-11-0)).

To estimate electricity generation costs, we use linear piecewise approximations of heat rate curves for thermal generators with sufficient data and constant heat rates for all other generators (section [2.3](#page-4-0)). Given current standard operations, we only permit coal steam, natural gas steam and natural gas combined cycle (NGCC) generators to provide reserves (Craig

<span id="page-4-0"></span>

Table 1. Reserve types, response timeframes and hourly requirements in the UCED model. SR and WR indicate reserve requirement components based on wind and solar generation, respectively, while r and f index regulation and flexibility reserve components.



#### Table 2. Capacity by plant type in generator fleet.



et al [2018b](#page-10-0)). While other technologies that will likely be deployed at large-scale by midcentury could provide these reserves, e.g. grid-scale batteries, we defer an analysis including those technologies to future research. To co-optimize energy and reserves, we set regulation provision costs to \$10, \$6 and \$4 ( $\mathfrak{s}_{2017}$ ) per megawatt-hour (MWh) for coal, NGCC and natural gas steam units, respectively. These costs capture variable operation and maintenance (VOM) and heat rate degradation costs incurred while providing reserves (Craig et al [2018b](#page-10-0)).

Since ERCOT has limited interconnections (1.2 GW relative to 70 GW of peak load in 2017) with neighboring systems (Electric Reliability Council of Texas [2017](#page-10-0)), the UCED model ignores power flows with neighboring systems. In addition, given recent transmission expansion to better integrate renewables (Electric Reliability Council of Texas [2015](#page-10-0)) and uncertain transmission constraints by 2041–2050 (the timeframe of our climate change projections), we assume no transmission constraints exist, but test the sensitivity of our results to pipeflow transmission constraints between five zones of 7 GW (SI.1).

The UCED model considers wind and solar generators as dispatchable resources constrained by hourly capacity factors that vary across the reference period and climate change projections (section 2.3). To ensure system reliability against variable wind and solar generation and unexpected generator and transmission outages, as well as to approximate current reserve classes in ERCOT (Electric Reliability Council of Texas [2013](#page-10-0)), the UCED model includes three reserve classes: regulation, flexibility and contingency reserves (table 1) (SI.1). To capture greater reserve requirements at high wind and solar penetrations modeled here, the three reserve classes vary with load and wind and solar generation (Craig et al [2018b](#page-10-0), Lew et al [2013](#page-11-0)). All reserve classes procure positive or up reserves, i.e. spare capacity for increased generation, given the challenge of inadequate spare capacity during periods of over-forecasted renewable generation.

#### 2.3. Generator fleet

Given the rapid pace of wind capacity additions and thermal plant retirements in ERCOT, we base our generator fleet on an up-to-date generator fleet using ERCOT's Capacity, Demand, and Reserves (CDR) December 2017 report (Electric Reliability Council of Texas [2017](#page-10-0)) (table 2). The CDR report provides each generator's name, county, fuel type, and capacity. Since hydropower accounts for less than 1% of the fleet capacity, we subtract the estimated hourly generation by hydropower units from demand, then remove them from our fleet (SI.1). We augment the CDR generator fleet with carbon dioxide  $(CO<sub>2</sub>)$  emission rates by fuel type (US Energy Information Administration [2017a](#page-11-0)); unit commitment parameters by plant and fuel type and capacity (Craig et al [2018b](#page-10-0)); VOM costs by fuel type (Craig et al [2018b](#page-10-0)); and latitudes and longitudes (US Environmental Protection Agency [2017](#page-11-0)) (SI.1). Based on 2017 data for Texas, we set coal, natural gas and nuclear fuel costs equal to \$2.21, \$3.26 and \$0.65 per MMBtu ( $\hat{s}_{2017}$ ) (US Energy Information Administration [2018](#page-11-0)), but test the sensitivity of our results to higher natural gas prices of \$6 per MMBtu  $(\$_{2017})$ .

We also augment the CDR fleet with constant and linear piecewise heat rate curves from the National Electric Energy Data System (US Environmental Protection Agency [2015](#page-11-0)) and continuous emission monitoring systems (US Environmental Protection Agency [2018](#page-11-0)) data, respectively. To approximate linear piecewise heat rate curves, we use an iterative algorithm that yields a convex curve with up to three bands (Magnani and Boyd [2009](#page-11-0)) (SI.1). Due to data availability and quality issues, we can only estimate linear piecewise heat rate curves for 114 (out of 271) generators. For the remaining 157 generators, we use constant heat rates.

Since we conduct our analysis for 2041–2050 climate change conditions and given recent continued growth in Texas renewable penetrations, we add 15 GW wind and 30.5 GW solar to the CDR fleet (which originally contained 20 GW wind and 1 GW solar) to

<span id="page-5-0"></span>Table 3. Total change in wind and solar generation potential summed over all 9 years from the reference period to each climate change projection. Reference wind and solar generation potential summed over all 9 years equal 1047 and 443 TWh, respectively. Red italics values indicate decreased generation potential.

|           | Total Change in Generation Potential from Reference<br>Period to Climate Change Projection (TWh) |       |      |      |     |
|-----------|--|-------|------|------|-----|
| Fuel Type | <b>ACCESS</b>  | CCSM4 | GFDL | IPSL | MPI |
| Wind      | 36   | 30    | 8    | 20   | 31  |
| Solar     | 13   | 11    |      | $-3$ |     |

construct a high-renewable fleet with roughly 25% wind and 15% solar penetration by energy. We use greater wind than solar capacity to reflect results of studies on cost-optimal high-renewable generation fleets (Hand et al [2012](#page-11-0), Craig et al [2018b](#page-10-0)). Given that adding renewables increases system reserve and flexibility requirements, we do not remove generators from the CDR fleet. We set locations for added wind and solar generators using output from the Regional Energy Deployment System (Eurek et al [2016](#page-10-0)) for a wind and solar penetration scenario similar to that assumed in this paper(for a map of added wind and solar plants, see SI.1). For each wind and solar generator, we use the hourly generation profile for the nearest WRF grid cell. To isolate the operational effects of climate change impact on wind and solar generation, we use the same generator fleet (summarized in table [2](#page-4-0)) in the reference period and each climate change projection.

## 3. Results

To understand how climate change impacts on wind and solar resources may affect power system operations, we first summarize aggregate changes in wind and solar generation potential from the reference period to climate change projections for our generator fleet. Using our UCED model, we then present how those generation potential changes translate to changes in dispatching and system production costs and  $CO<sub>2</sub>$  emissions from the reference period to climate change projections.

## 3.1. Changes in maximum potential wind and solar generation

We quantify changes in total wind and solar generation potential, which ignores curtailment during dispatching, under climate change by subtracting total wind and solar generation potential (as output by SAM) in the reference period from total wind and solar generation potential (as output by SAM) in each climate change projection. Aggregating across wind generators, all five GCMs agree that climate change will increase total wind generation potential (table 3). Across 802 wind farms with a combined capacity of 35



GW, total wind generation potential increases by 8–36 TWh across GCMs, or by 1%–4% of total reference generation potential. Aggregating across solar generators, GCMs differ as to whether total solar generation potential will increase or decrease under climate change (table 3). Across 239 solar PV farms with a combined capacity of 31.5 GW, three GCMs yield an increase of 2–13 TWh, or up to 1% of the reference generation potential, whereas the other two yield a decrease of 1–3 TWh, or of less than 1%.

To better understand temporal patterns in wind and solar generation potential changes under climate change, we quantify monthly generation potential changes from the reference period in each climate change projection (figure [2](#page-6-0)). Four or more GCMs indicate wind generation potential increases in all months except in winter (November, January and February) and mid-summer (July). No months exhibit decreased wind generation potential across most GCMs. With respect to solar generation potential, four or more GCMs indicate increased generation potential in spring (April to June) and fall (September and October), whereas all GCMs indicate decreased generation potential in winter (January and December). These trends largely hold across years for each GCM as well, so that no single year drives total monthly changes in wind or solar generation potential (SI.3).

Changes in wind and solar generation potential under climate change also exhibit consistent patterns by hour of day across GCM (figure [3](#page-6-0)). In four of the five GCMs, wind generation increases in all hours of the day, and all GCMs indicate wind generation increases more at night than during the day. Conversely, in all GCMs, solar generation tends to increase in the morning, then that increase tails off throughout the day. In three GCMs, solar generation decreases throughout the afternoon, whereas in the other two decreases only occur in the late afternoon to early evening.

## 3.2. Changes in dispatched generation by fuel type and wind and solar curtailments

Changes in wind and solar generation potential under climate change presented in the prior section might translate to changes in dispatched wind and solar generation, which in turn might affect generation by other fuel types, the focus of this section. In the reference period, total dispatched generation equals 3196 TWh and is 8% coal, 38% gas, 11% nuclear, 31% wind and 13% solar. From the reference period to four or more climate change projections, wind generation increases (by up to 3%), while coal, gas and nuclear generation decrease (by up to 5%, 1% and 7%, respectively) (figure [4](#page-6-0)). Dispatched solar generation increases (by up to 2%) in two GCMs, decreases (by up to 1%) in two GCMs and changes negligibly in one GCM (figure [4](#page-6-0)). The



<span id="page-6-0"></span>







relative differences between GCMs of changes in potential and dispatched wind generation are similar, e.g. GFDL has the least increase across GCMs of increased potential and dispatched wind generation (table [3](#page-5-0) and figure 4). The same is true for solar generation, except in the case of GFDL, which is



<span id="page-7-0"></span>

Figure 5. Total change across the 9 year period in monthly generation by fuel type from the reference period to each climate change projection.



discussed below. The maximum hourly penetration of dispatched wind, solar and wind plus solar generation equal 85%, 78%–79% and 85%, respectively, across GCMs.

In response to wind and solar generation changes under climate change, nuclear generation decreases more than other fuel types. On a monthly basis (figure 5), nuclear generation declines from October to May (months with lower demand) but not from June to September (months with higher demand) (SI.4), despite comparable increases in wind and/or solar generation in both sets of months. Consequently, increased wind and/or solar generation under climate change only reduce nuclear generation during periods of low demand, when ramping and minimum stable load constraints on nuclear generators, which are tighter than other generators (SI.1), may force it to turn off.

GFDL is unique among GCMs with respect to changes in generation by fuel type in several ways. First, under GFDL total solar generation potential increases but dispatched generation decreases (table [3](#page-5-0) and figure [4](#page-6-0)). In most months, changes in solar potential and dispatched generation are similar under the GFDL projection, but in winter months (November to February) curtailment increases (figure 6) despite decreasing generation potential on an aggregate basis (figure [2](#page-6-0)), reducing dispatched generation (SI.4). GFDL also differs from other GCMs in that coal- and gas-fired generation increase to replace decreased solar and nuclear generation, the latter of which still decreases due to increased wind generation in lowdemand months.

Increased wind generation potential leads to increased curtailed wind energy in all GCMs (by 0.6–7.3 TWh) (figure 6) (SI.5), which translates to





Table 4. Change in total system production costs and CO<sub>2</sub> emissions over the 9 year period from the reference period to each climate change projection. Total reference costs and emissions equal \$46 000 million and 826 million tons, respectively. Red italics indicate decreased costs or emissions.



slight changes in wind curtailment as a percentage of generation potential across GCMs (−0.1 to 0.5 percentage points relative to average curtailment in the reference period of 6.6%). Similarly, increased and decreased solar generation potential leads to increased and decreased curtailed solar energy, respectively (by  $-0.8$  to [6](#page-7-0).0 TWh) (figure 6) (SI.5), which translates to slight changes in solar curtailment as a percentage of generation potential across GCMs (−0.2 to 1.3 percentage points relative to average curtailment in the reference period of 9.5%). Across months, increases in wind and solar curtailment are least in highdemand months, i.e. summer, and greatest in lowdemand months, i.e. winter.

#### 3.3. Changes in system emissions and costs

Dispatching changes under climate change cause system production cost and  $CO<sub>2</sub>$  emission changes, which we quantify by subtracting total system production costs and  $CO<sub>2</sub>$  emissions in the reference period from total system production costs and  $CO<sub>2</sub>$ emissions in each climate change projection (table 4). Total system  $CO<sub>2</sub>$  emissions decrease in four of the five GCMs by 8–17 million tons (1%–2%) and increase in one GCM (GFDL) by 27 million tons (3%). These emission changes parallel changes in generation by fuel type, as  $CO<sub>2</sub>$ -emitting coal- and gas-fired generation decreases in all GCMs except GFDL. This is particularly evident with monthly emission changes, as coal-fired generation increases most in November to February in GFDL, in which  $CO<sub>2</sub>$  emissions also increase the most (figure 7). Notably, declining nuclear generation is more than offset by increasing wind and/or solar generation, so that  $CO<sub>2</sub>$  emissions decrease even with large nuclear generation reductions. On a monthly basis, system emissions decrease across four or more GCMs for six months (figure 7), mostly in the summer when wind and solar generation increase (figure [5](#page-7-0)) with little increased curtailment (figure [6](#page-7-0)).

Paralleling changes in system emissions, total system production costs totaled across all 9 years decline in four out of the five GCMs by \$200–500 million (up to 1%) and increase in one GCM (GFDL) by \$1 200 million (2%) (table 4). Increased coal and gas generation in GFDL combined with no net change in wind and solar generation and reduced nuclear generation increase system production costs, whereas in other GCMs system production costs decrease due to increased wind and solar generation. Monthly trends in system cost changes (figure [8](#page-9-0)) parallel those of system emission changes (figure 7). Furthermore, monthly trends in changes in system costs and emissions largely hold across the years for each GCM, so that monthly increases or decreases in total monthly costs or emissions are reflected in increases or decreases in monthly costs or emissions in most years(SI.6).



<span id="page-9-0"></span>

## 3.4. Sensitivity to high natural gas prices and zonal transmission constraints

Increasing natural gas prices from \$3.3 to \$6 per MMBtu, which reduces gas-fired generation in the reference period by 40%, has little impact on our results. At higher natural gas prices, changes in wind and solar generation under climate change reduce system costs and  $CO<sub>2</sub>$  emissions in four of the five climate change projections by up to 1% and 2%, respectively, comparable to our above results. These reductions are driven by changes in generation by fuel type that are similar to our above results. Specifically, coal- and gas-fired generation decrease in four and three climate change projections by up to 5% and 2%, respectively, while nuclear-fired generation decreases in all five climate change projections by up to 7%.

Assuming interzonal transmission constraints instead of no transmission constraints (SI.1) also has little impact on our results. With interzonal transmission constraints, changes in wind and solar generation yield similar changes in generation by fuel type, as in figure [5.](#page-7-0) Consequently, as in our main analysis, system production costs decrease in four of the five GCMs by up to 1% and decrease in one GCM by 2%. Similarly, system  $CO<sub>2</sub>$  emissions decrease by up to 2% in four of the five GCMs and increase by 3% in one GCM.

## 4. Discussion

To understand how changes in wind and solar generation under climate change might affect power system operations, we compare dispatching of a highrenewable generator fleet with hourly wind and solar generation profiles from a reference period and five climate change projections. Across climate change projections, total wind generation potential of our generator fleet increases from the reference period, but solar generation potential increases in some climate change projections and decreases in others. Using a UCED model, we find these changes in generation potential largely translate to similar changes in dispatched wind and solar generation. However, because changes in generation potential differ temporally, dispatched generation of other fuel types differs more drastically between the reference period and climate change projections. In particular, nuclear generation decreases across climate change projections by up to 7%, or by more than changes in wind and solar generation potential, because of its relative inflexibility and increased wind and solar generation during low-demand periods. Thus, capturing variability across time in changes in wind and solar generation potential under climate change is crucial to fully understanding how those changes might impact power system operations.

To assess the robustness of our results to climate change projections, we quantify the operational impact of wind and solar generation changes using output from five GCMs. Relative to the reference period, we find changes in wind and solar generation will reduce total system production costs and  $CO<sub>2</sub>$  emissions by up to 1% and 2%, respectively, in four of the five GCMs. These results suggest that in Texas, our study system, climate change will make meeting decarbonization targets through wind and solar deployment slightly easier. However, wind and solar resources and generation potential might decrease in other parts of the United States (Pryor et al [2012](#page-11-0), Johnson and Erhardt [2016,](#page-11-0) Karnauskas et al [2018](#page-11-0)), where the opposite could occur. Our results also indicate climate change will have a modest impact on power system operations over long time periods, e.g. on an annual basis. Consequently, technological changes in the power sector not captured in this study, e.g. increasing penetration of grid-scale batteries, could



<span id="page-10-0"></span>have a larger effect on operations than climate change. Future work should study this potential interaction.

One limitation of our analysis is that it only spans 9 years and includes five GCMs. While we select these five GCMs to represent the range of climate change projections of eleven GCMs, a larger ensemble would provide more confidence that our results reflect a consistent response to climate change rather than a GCMspecific response. In addition, including more years, e.g. 30, would better capture long-term climate variability. Both changes would allow for more robust conclusions, and merit future research. Climate modeling improvements, e.g. development of higher-resolution GCMs, might yield different climate change projections, which future research should capture.

This research can be expanded in several other ways. First, while we focus on climate change impact on wind and solar generation potential, climate change might also impact other power system components, most notably electricity demand. Future research should explore how including a broader suite of component-level climate change impacts might alter power system operations. Second, shifting wind and solar generation potential under climate change might also affect power system planning, e.g. by changing the capacity value of wind and solar. Third, our analysis focuses on fleet-wide wind and solar generation changes, but larger changes could occur at individual wind and solar farms under climate change. These changes could have significant implications for the financial viability and optimal placement of individual wind and solar farms. Finally, we view this research as a starting point for a broader future research agenda aimed at better understanding how climate change affects weather dynamics and how altered weather dynamics in turn affect power system operations. Items in this future agenda include exploring the physical weather processes that underlie future changes in wind and solar resources, and drilling down on power system operational responses at finer temporal and spatial scales. Such research would yield more confidence in power system operational changes similar to those documented here and also inform the generalizability of the results to other regions that exhibit similar weather patterns.

## Acknowledgments

Thanks to Wesley Cole and Jonathan Ho for future generator fleet data. This work was authored by the National Renewable Energy Laboratory (NREL), operated by Alliance for Sustainable Energy, LLC, for the US Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. This work was supported by the Laboratory Directed Research and Development (LDRD) Program at NREL. The views expressed in the article do not necessarily represent the views of the DOE or the US Government. The US Government retains and the publisher, by accepting the article for publication, acknowledges that the US Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for US Government purposes.

## ORCID iDs

Michael T Crai[g](https://orcid.org/0000-0002-3031-5041)  $\bullet$  [https:](https://orcid.org/0000-0002-3031-5041)//orcid.org/[0000-0002-](https://orcid.org/0000-0002-3031-5041) [3031-5041](https://orcid.org/0000-0002-3031-5041) Carlo Brancucci <sup>th</sup> [https:](https://orcid.org/0000-0002-3605-6730)//orcid.org/[0000-0002-](https://orcid.org/0000-0002-3605-6730) [3605-6730](https://orcid.org/0000-0002-3605-6730)

### References

- Ashfaq M, Rastogi D, Mei R, Kao S, Gangrade S, Naz B S and Touma D 2016 High-resolution ensemble projections of near-term regional climate over the continental United States J. Geophys. Res. Atmos. 121 [9943](https://doi.org/10.1002/2016JD025285)–63
- Barbose G, Darghouth N, Millstein D, LaCommare K, Disanti N and Widiss R 2017 Tracking the Sun 10 1–50
- Bonjean Stanton M C, Dessai S and Paavola J 2016 A systematic review of the impacts of climate variability and change on electricity systems in Europe Energy 109 [1148](https://doi.org/10.1016/j.energy.2016.05.015)–59 BP 2018 BP Statistical Review of World Energy: Renewable energy
- Carreño I L, Craig M T, Rossol M, Ashfaq M, Batibeniz F, Haupt S E, Ammann C, Draxl C, Hodge B-M and Brancucci C 2018 Potential impacts of climate change on wind and solar electricity generation in Texas Renew. Energy submitted
- Chandramowli S N and Felder F A 2014 Impact of climate change on electricity systems and markets—a review of models and forecasts Sustain. Energy Technol. Assessments 5 [62](https://doi.org/10.1016/j.seta.2013.11.003)–74
- Craig M T, Cohen S, Macknick J, Draxl C, Guerra O J, Sengupta M, Haupt S E, Hodge B-M and Brancucci C 2018a A review of the potential impacts of climate change on bulk power system planning and operations in the United States Renew. Sustain. Energy Rev. 98 [255](https://doi.org/10.1016/j.rser.2018.09.022)–67
- Craig M T, Jaramillo P and Hodge B-M 2018b Carbon dioxide emissions effects of grid-scale electricity storage in a decarbonizing power system Environ. Res. Lett. [2](https://doi.org/10.1088/1748-9326/aa9a78) 1[–](https://doi.org/10.1088/1748-9326/aa9a78)[11](https://doi.org/10.1088/1748-9326/aa9a78)
- Crook J A, Jones L A, Forster P M and Crook R 2011 Climate change impacts on future photovoltaic and concentrated solar power energy output Energy Environ. Sci. 4 [3101](https://doi.org/10.1039/C1EE01495A)
- Electric Reliability Council of Texas 2013 Future Ancillary Services in ERCOT
- Electric Reliability Council of Texas 2018 Hourly load data archives ERCOT.com
- Electric Reliability Council of Texas 2015 Report on existing and potential electric system constraints and needs 1–42 Online: (http://ercot.com/content/news/[presentations](http://ercot.com/content/news/presentations/2016/2015ERCOTConstraintsAndNeedsReport.pdf)/2016/ [2015ERCOTConstraintsAndNeedsReport.pdf](http://ercot.com/content/news/presentations/2016/2015ERCOTConstraintsAndNeedsReport.pdf))
- Electric Reliability Council of Texas 2017 Report on the capacity, demand and reserves (CDR) in the ERCOT region, 2018–2027 Online: (http://[ercot.com](http://ercot.com/content/wcm/lists/143977/CapacityDemandandReserveReport-Dec2017.xlsx)/content/wcm/lists/143977/ [CapacityDemandandReserveReport-Dec2017.xlsx](http://ercot.com/content/wcm/lists/143977/CapacityDemandandReserveReport-Dec2017.xlsx))
- Eurek Ket al 2016 Regional energy deployment system (ReEDS): Model documentation Version 2016 National Renewable Energy Laboratory
- Fawcett A A et al 2015 Can Paris pledges avert severe climate change? Science 350 [1168](https://doi.org/10.1126/science.aad5761)–9
- Federal Reserve Bank of St. Louis 2017 Producer Price Index by industry: Electric power generation: Utilities FRED Econ. Data Online:(https://[fred.stlouisfed.org](https://fred.stlouisfed.org/series/PCU2211102211104)/series/ [PCU2211102211104](https://fred.stlouisfed.org/series/PCU2211102211104))
- Fri R W et al 2010 Limiting the Magnitude of Future Climate Change GAMS Development Corporation 2013 The GAMS Development Corporation Website Online: (http://[gams.com](http://gams.com/)/)



- <span id="page-11-0"></span>Hand M M, Baldwin S, Demeo E, Reilly J, Mai T, Arent D, Porro G, Meshek M and Sandor D 2012 Renewable Electricity Futures Study (http://nrel.gov/analysis/[re\\_futures](http://nrel.gov/analysis/re_futures/)/)
- Haupt S E, Copeland J, Cheng W Y Y, Zhang Y, Ammann C and Sullivan P 2016 A method to assess the wind and solar resource and to quantify interannual variability over the United States under current and projected future climate J. Appl. Meteorol. Climatol. 55 [345](https://doi.org/10.1175/JAMC-D-15-0011.1)–63
- IBM 2014 IBM ILOG CPLEX Optimization Studio: CPLEX User's Manual. Version 12 Release 6.
- Jimenez P A, Hacker J P, Dudhia J, Haupt S E, Ruiz-Arias J A, Gueymard C A, Thompson G, Eidhammer T and Deng A 2016 WRF-SOLAR: description and clear-sky assessment of an augmented NWP model for solar power prediction Bull. Am. Meteorol. Soc. 97 [1249](https://doi.org/10.1175/BAMS-D-14-00279.1)–64
- Johnson D L and Erhardt R J 2016 Projected impacts of climate change on wind energy density in the United States Renew. Energy [85](https://doi.org/10.1016/j.renene.2015.06.005) 66–73
- Karnauskas K B, Lundquist J K and Zhang L 2018 Southward shift of the global wind energy resource under high carbon dioxide emissions Nat. Geosci. [11](https://doi.org/10.1038/s41561-017-0029-9) 38–43
- Lazard 2017 Lazard's Levelized Cost of Energy Analysis Version 11.0 Lew D, Brinkman G, Ibanez E, Florita A, Heaney M, Hodge B, Hummon M and King J 2013 The Western Wind and Solar Integration Study Phase 2 Natl. Renew. Energy Lab
- Magnani A and Boyd S P 2009 Convex piecewise-linear fitting Optim. Eng. [10](https://doi.org/10.1007/s11081-008-9045-3) 1–17
- Meckling J, Sterner T and Wagner G 2017 Policy sequencing toward decarbonization Nat. Energy 2 [918](https://doi.org/10.1038/s41560-018-0089-0)–22
- Mesinger F et al 2006 North American Regional Reanalysis Bull. Am. Meteorol. Soc. 87 [343](https://doi.org/10.1175/BAMS-87-3-343)–60
- Morales-españa G, Member S, Latorre J M and Ramos A 2013 Tight and compact MILP formulation of start-up and shut-down ramping in unit commitment IEEE Trans. Power Syst. [28](https://doi.org/10.1109/TPWRS.2012.2222938) [1288](https://doi.org/10.1109/TPWRS.2012.2222938)–96
- Pryor S C, Barthelmie R J and Schoof J T 2012 Past and future wind climates over the contiguous USA based on the North American Regional Climate Change Assessment program model suite J. Geophys. Res. Atmos. [117](https://doi.org/10.1029/2012JD017449) 1–17
- Rogelj J, Elzen M D, Höhne N, Fransen T, Fekete H, Winkler H, Schaeffer R, Sha F, Riahi K and Meinshausen M 2016 Paris agreement climate proposals need a boost to keep warming well below 2 °C Nature [534](https://doi.org/10.1038/nature18307) 631–9
- Schaeffer R, Szklo A S, Pereira de Lucena A F, Moreira Cesar Borba B S, Pupo Nogueira L P, Fleming F P,

Troccoli A, Harrison M and Boulahya M S 2012 Energy sector vulnerability to climate change: a review Energy [38](https://doi.org/10.1016/j.energy.2011.11.056) 1–12

- Skamarock W C, Klemp J B, Dudhi J, Gill D O, Barker D M, Duda M G, Huang X-Y, Wang W and Powers J G 2008 A description of the advanced research WRF version 3 NCAR Tech. Note 113 1–113
- Stocker T F, Dahe Q and Plattner G-K 2013 Technical summary Intergov. Panel Clim. Chang. Phys. Sci. Basis
- US Energy Information Administration 2017a How much carbon dioxide is produced when different fuels are burned? EIA.Gov
- US Energy Information Administration 2018 table 3: Energy Prices by Sector and Source (Reference Case, East South Central Region) Annu. Energy Outlook 2018 Online: (https://[eia.gov](https://eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2018®ion=16&cases=ref2018&start=2016&end=2050&f=A&linechart=ref2018-d121317a.33-AEO2018.16&map=ref2018-d121317a.43-AEO2018.16&sourcekey=0)/ [outlooks](https://eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2018®ion=16&cases=ref2018&start=2016&end=2050&f=A&linechart=ref2018-d121317a.33-AEO2018.16&map=ref2018-d121317a.43-AEO2018.16&sourcekey=0)/aeo/data/browser/#/?id=3- [AEO2018&region](https://eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2018®ion=16&cases=ref2018&start=2016&end=2050&f=A&linechart=ref2018-d121317a.33-AEO2018.16&map=ref2018-d121317a.43-AEO2018.16&sourcekey=0)=1–6&cases=ref2018&start=2016&en nd=2050&f=A&linechart=[ref2018-d121317a.3](https://eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2018®ion=16&cases=ref2018&start=2016&end=2050&f=A&linechart=ref2018-d121317a.33-AEO2018.16&map=ref2018-d121317a.43-AEO2018.16&sourcekey=0)–3-
	- [AEO2018.1](https://eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2018®ion=16&cases=ref2018&start=2016&end=2050&f=A&linechart=ref2018-d121317a.33-AEO2018.16&map=ref2018-d121317a.43-AEO2018.16&sourcekey=0)–6&map=[ref2018-d121317a.4](https://eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2018®ion=16&cases=ref2018&start=2016&end=2050&f=A&linechart=ref2018-d121317a.33-AEO2018.16&map=ref2018-d121317a.43-AEO2018.16&sourcekey=0)–3-AEO2018. [1](https://eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2018®ion=16&cases=ref2018&start=2016&end=2050&f=A&linechart=ref2018-d121317a.33-AEO2018.16&map=ref2018-d121317a.43-AEO2018.16&sourcekey=0)–[6&sourcekey](https://eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2018®ion=16&cases=ref2018&start=2016&end=2050&f=A&linechart=ref2018-d121317a.33-AEO2018.16&map=ref2018-d121317a.43-AEO2018.16&sourcekey=0)=0)
- US Energy Information Administration 2017b table 6.2B Electr. Power Mon. Online: (https://eia.gov/[electricity](https://eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_6_02_b)/monthly/ [epm\\_table\\_grapher.php?t](https://eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_6_02_b)=epmt\_6\_02\_b)
- US Environmental Protection Agency 2018 Continuous Emission Monitoring Systems epa.gov
- US Environmental Protection Agency 2017 Emissions & Generation Resource Integrated Database (eGRID) Online:([https:](https://epa.gov/energy/emissions-generation-resource-integrated-database-egrid)//epa. gov/energy/[emissions-generation-resource-integrated](https://epa.gov/energy/emissions-generation-resource-integrated-database-egrid)[database-egrid](https://epa.gov/energy/emissions-generation-resource-integrated-database-egrid))
- US Environmental Protection Agency 2015 National Electric Energy Data System (Version 5.15) Online: (http://[epa.gov](http://epa.gov/airmarkets/power-sector-modeling-platform-v515)/ airmarkets/[power-sector-modeling-platform-v515](http://epa.gov/airmarkets/power-sector-modeling-platform-v515))
- US Global Change Research Program 2017 Fourth National Climate Assessment
- US National Renewable Energy Laboratory 2016 Renewable resource data center NREL.gov Online: (http://[www.nrel.](http://www.nrel.gov/rredc/) gov/[rredc](http://www.nrel.gov/rredc/)/)
- US National Renewable Energy Laboratory 2017 System Advisor Model SAM.NREL.gov Online: (https://[sam.nrel.gov](https://sam.nrel.gov/)/)
- Wild M, Folini D and Henschel F 2017 Impact of climate change on future concentrated solar power(CSP) production AIP Conf. Proc.(https://doi.org/10.1063/[1.4975562](https://doi.org/10.1063/1.4975562))
- Wild M, Folini D, Henschel F, Fischer N and Müller B 2015 Projections of long-term changes in solar radiation based on CMIP5 climate models and their influence on energy yields of photovoltaic systems Sol. Energy [116](https://doi.org/10.1016/j.solener.2015.03.039) 12–24
- Wiser R et al 2017 2016 Wind Technologies Market Report