Journal of Business Administration Online

ARKANSAS TECH UNIVERSITY College of Business HTTPS://JBAO.ATU.EDU

Fall 2023, Vol. 17 No. 2

Uncoupling Electricity Generating Organizations from Climate Change: A Policy Perspective

Christopher A. Craig, Murray State University

Siyao Ma, University of Arkansas

Song Feng, University of Arkansas

Brittany Wood, Murray State University

Abstract

In response to climate change, a primary objective of electric energy policy is the transition to renewable electricity generation. Electricity generation and climate change represent a coupled human-natural system when fuel sources for generation are nonrenewable (e.g., coal). What remains unstudied in the United States is which states have nonrenewable electricity generation not coupled with climate. Further, while the management discipline has investigated the electric power industry within a context of climate change, to the best of our knowledge the inquiries have not integrated climate science. To address the two knowledge gaps, this study investigates state-level: (1) changes to climate (1981-2020) and (2) climate and nonrenewable electricity generation interrelations (2001-2020). Climate and climate change are operationalized as cooling and heating degree days, or the number of degrees above/below a temperature threshold. Results indicate (1) all states observed a warming climate, and (2) climate improved retrospective forecasts for 36 of the 48 United States. The latter finding indicates that nonrenewable generation was coupled with climate for 75% of the observations. Since law makers and regulators provide oversight for the electric power industry, domestic and international policy implications are discussed.

Introduction

Climate change is a salient, discipline-spanning phenomenon that impacts economies and ecosystems (e.g., IPCC 2021). One industry that creates barriers to climate change response is the electric power industry. The contributions of electricity generating organizations to climate change (e.g., Fia & Omorim, 2022; Heede, 2014; Reidmiller et al., 2018) as well as attempts to maintain business-as-usual (e.g., Delmas et al., 2016; Supran & Oreskes, 2021) are well-established. In response, state and federal policies in the United States are facilitating transitions toward renewable electricity generation (e.g., National Conference of State Legislatures [NCSL] 2023; Newell et al., 2019). The electric power industry has received considerable attention by the management discipline, including within a climate change context (e.g., Delmas et al., 2016; Dutt &

Joseph, 2019; Dutt & Mitchell, 2020; Holburn & Zelner, 2012; Kim & Youm, 2017). What remains understudied by the discipline, however, is the application of climate science to investigations of the electric power industry.

To address this knowledge gap, the study presents the case of the United States electric power industry to explore the interconnections between nonrenewable electricity generation and climate. Electricity generation is among the largest contributor to global carbon emissions, the primary driver of anthropogenic climate change (Heede, 2014; IPCC, 2021). With temperatures warming as a process of climate change (e.g., IPCC, 2021), our study provides a fertile case to study the complex interrelations between climate and the electric power industry's continued reliance on fossil fuels.

Climate change is operationalized using the cooling degree days (CDD) and heating degree days (HDD) (1981-2020). Degree days are the number of degrees above or below a baseline temperature, typically 65º Fahrenheit (º F) in the United States (NOAA, 2022). Degree days are more reliable than temperature alone for modeling energy (Mourshed, 2012). The study dependent variable is monthly state-level nonrenewable generation (2001-2020). The operationalization allows us to investigate state-level (1) changes to climate over the span of four decades and (2) interrelations that CDD/HDD have with nonrenewable electricity generation using retrospective forecasting.

Looking forward, the study overviews select literature related to (1) weather, climate, and climate change and (2) electricity generation and climate change. Next are (1) materials and methods, (2) results and analysis, and (3) discussion and conclusion sections.

Weather, Climate, and Climate Change

Weather, climate, and climate change are interrelated but not synonymous. For example, today's temperature is a measure of weather whereas the multiple decades average of temperature is a measure of climate. Climate change refers to the departure from long-term weather averages (i.e., climate) over the span of decades. Long-term warming has been observed in the United States and throughout the world (e.g., IPCC, 20021; NOAA, 2021; Reidmiller et al., 2018) and without intervention is projected to continue through 2080-2099 in the United States (Petri & Caldeira, 2015).

Warming temperatures are exposing vulnerabilities of the electric power industry to a changing climate (Golub et al., 2022). The climate measures most closely related to warming and electricity generation are CDD and HDD. Degree days "are more reliable indicators than temperature alone when considering electricity" (Craig & Feng, 2016, p. 603). For this reason, financial markets created CDD and HDD options that electricity generating organizations can purchase to hedge against the financial risks of a warming climate (CME Group, 2016). CDD and HDD are calculated using daily temperature, where degrees above a 65ºF baseline are counted (EPA, 2021). The 65ºF baseline is the cutoff used by the National Weather Service in the United States (NOAA, 2022). For instance, a 100ºF day is equivalent to 35 CDD. CDD and HDD are calculated for the contiguous United States to (1) establish long-term change from 1981 to 2020 and (2) match with monthly state-level electricity generation data. CDD and HDD are preferable to average temperature when the resolution of data is monthly (e.g., electricity generation) because the counts above the threshold better capture within month variability than average temperature.

To observe interrelations between climate, climate change, and organizational metrics for the electric power industry (i.e., non-renewable electricity generation) requires the application of climate science. Management scholars have demonstrated an interest in these interrelations, though to the best of our knowledge, have not integrated climate science into the explorations (e.g., Delmas et al., 2016; Weinhofer & Hoffman, 2008). For example, Delmas et al. (2016) analyzed contributions of “dirty” firms (e.g., those in the electric power industry) to regulatory lobbying efforts. Weinhofer and Hoffman (2008) considered CO2 emissions for electricity producers, though did so through the lens of strategy adaptation, not climate and emissions interrelations. We address this research gap as the first known study within a managerial context to apply climate science to the investigation of the electric power industry. Encouragingly, there have been a few studies in management journals that utilized climate science to study the alpine ski industry (Tashman & Rivera, 2016; Rivera & Clement, 2019), so there is precedent for our study’s operationalization.

Electricity Generation and Climate change

Globally, energy generation remains the largest contributor to carbon dioxide (CO2) emissions ahead of transportation (Richie et al., 2020). Consequently, warming temperatures from climate change contributes to increased demand for electricity generation, especially in summer (e.g., air conditioning) (Mideksa & Kallbekken, 2010; Lundgren-Kownacki et al., 2018). Organizations that generate electricity are coupled with the natural environment, contributing to climate change (e.g., CO2 emissions) while being influenced by the effects of climate change (e.g., Chen &Chen, 2017; Liu et al., 2007; McFarland et al., 2015). For example, an increase in temperature requires additional electricity generation, and when this generation is from fossil fuel sources (e.g., coal, natural gas, other nonrenewable gases, petroleum), more GHG is omitted into the atmosphere contributing to climate change.

The historical interrelations between nonrenewable electricity generation and climate change are representative of a coupled human-natural system with feedback loops between the two (Lui et al., 2007). The goal of renewable energy policy and targets is to uncouple the feedback loops where organizational processes (e.g., electricity generation) no longer negatively contribute to climate change (e.g., Jiang et al., 2023). Since climate influences electricity generation, and is changing as a process of climate change, electricity generation investigations (past, present, and future) should include observed historical, forecasted (future short-term), and projected (future long-term) conditions. The study begins this inquiry by retrospectively investigating (1) changes to CDD and HDD over four decades and (2) the influence of CDD and HDD on GHG emitting nonrenewable electricity generation.

> *Research Question 1: What state-level changes to CDD and HDD are observed (1981-2020)?*
>
> *Research Question 2: Where do CDD and HDD improve retrospective nonrenewable generation forecasts (2001-2020)?*

Materials and Methods

Electric Generating Organizations

Our sample consists of electric utilities (n=2,938) and independent generators (n=unknown) that generate and distribute electricity (EIA, 2019b). There are three types of electric utility organizations: publicly owned utilities (POU; 67%), cooperative utilities (non-profit; 28%), and investor owned utilities (IOU; 6%) (EIA, 2019b). Comparatively, IOUs serve over 70% of United States consumers. Independent electricity generators are legal entities that own/operate electricity generation facilities for public use that are not themselves utilities (EIA, 2021a). Independent generators provide electricity to utilities for distribution and also electricity to large commercial/industrial consumers.

Data

There are two sources of data used for the analysis: climate and electricity generation. First, the study operationalized climate using cooling CDD and HDD. To calculate degree days we obtained daily maximum temperature at approximately the four-kilometer grid cell resolution for the contiguous United States from 1981 to 2020 (Di Luzio et al., 2008). Consistent with NOAA's (2022) operationalization of CDD and HDD the daily maximum and minimum temperature were arithmetically averaged to get daily values where degrees above and below 65ºF were counted, respectively. The grid-level CDD and HDD data were then aggregated to state-level means based on coordinates using "map2SpatialPolygons" function in "maptools" package and "SpatialPoints" function in "sp" package in R. Data from 1981 to 2020 were used to establish climate change, and data from 2001 to 2020 was used to match with state-level electricity generation to conduct retrospective forecasting.

Second, state-level monthly electricity generation data were obtained from EIA (2021b) from 2001 to 2020. Generation data for electric power generators and distributors (i.e., utilities and independent electric generators) were then aggregated for all nonrenewable fuel sources (i.e.,, coal, natural gas, other nonrenewable gas, petroleum). Units for generation are megawatt hours (MWH), or 1,000 kilowatt hours.

Statistical Analysis

To test Research Question 1, graphs were produced comparing the most recent 10-years of climate data to the first 10-years of climate data of the analyzed period. This is a commonly used method to detect climate change over the span of decades (e.g., IPCC, 2021).

To test Research Question 2, Autoregressive Integration Moving Average (ARIMA) models were utilized. ARIMA is a retrospective forecasting method that explores past states of a time series on current and future states allowing for the inclusion of factors external to the time series (Craig & Feng, 2016). Our two focal external factors are CDD and HDD, measures of climate. To capture the meteorological seasonality inherent to electricity generation the study used seasonal ARIMA (i.e., SARIMA) (Tripathi et al., 2008). For climate-related phenomenon where seasonality is inherent (e.g., energy supply and demand) SARIMA models produce more accurate predictions (Kaur & Ahuja, 2019; Kuru & Calis, 2019; Tadesse & Dinka, 2017) and have proven useful to assess electricity markets (e.g., Rostamnia & Rashid, 2019). The SARIMA retrospective method allows us to examine the relative improvement of forecast accuracy with the inclusion of CDD and HDD compared to forecasts based on historical generation data alone. Implicitly captured within historical electricity generation are influencing factors such as consumption, other economic factors (e.g., population, income), transmission, and plant efficiency.

The “lmtest,” and “forecast” packages in R were used for model selection criteria and model statistics, applying the Akaike Information Criterion (AIC) to minimize overfit and underfit models. Three SARIMA models were computed for each state sorted by nonrenewable and renewable generation types that included: (1) the univariate retrospective electricity generation data, (2) CDD as the exogenous factor, and (3) HDD as the exogenous factor. For each model 19 years of data (January 2001-December 2019) were used as training datasets to build the model, and then used the model to predict electricity generation in the last one year (January 2020-December 2020). Finally, the model prediction values were compared with the actual observation during the last one year to test the model accuracy. Performance of the SARIMA models was assessed using the Root Mean Square Error (RMSE). RMSE is an absolute measure of fit, meaning the RMSE values in Table 1 actual MWH (reported in the ,000s; see Table 1). The absolute values allow us to determine percentage improvement/decline of models without and with weather (i.e., CDD and HDD). States where improvement occurred indicate that nonrenewable electricity generation and climate (i.e., the consequence of climate change) remain coupled.

SARIMA models consist of four terms: (1) automatic regression (AR), (2) integration (I), (3) moving average (MA), and (4) seasonal (S). The AR terms aims to model the current observation against previous observations; the MA terms aims to model the current observation against previous process errors; the I term aims to stabilize un-stational series; and the S term indicates previous seasons are taken into account. The SARIMA model notation is (p,d,q)(P,D,Q)[s] where (p) is the non-seasonal linear AR, (d) is the non-seasonal difference, (q) is the non-seasonal MA, (P) is the seasonal linear AR, (D) is the seasonal difference, (Q) is the seasonal MA, and (s) is the length of seasonality. The d and D parameters are greater than 0 when the series is not stationary.

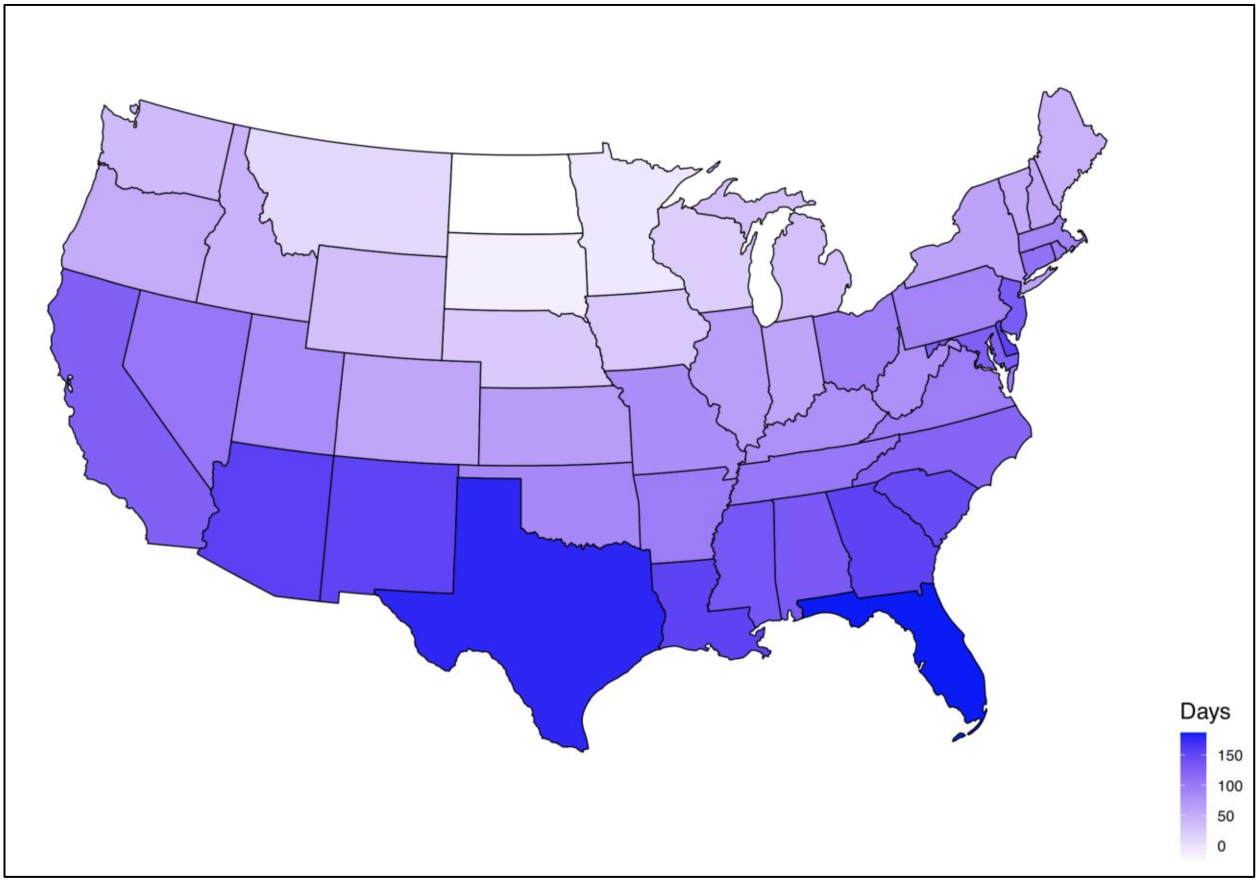
For example, the notation for the nonrenewable generation SARIMA model in Kentucky with CDD as the exogenous factor is (1,0,1)(0,1,1)[12] (see Table 1). This is interpreted as (p) one AR lag (e.g., July’s generation is related to June’s generation), (d) zero differencing for the stationary time series (e.g., 19 years of training data are stable), (q) one MA lag (e.g., July’s forecast error is related to June’s forecast error), (P) zero lags to the stationary time series (e.g., July 2020 nonrenewable generation is not related to July generation in previous years), (D) one seasonal difference is needed to stabilize the time series, (Q) one MA lag (e.g., July 2020 forecast error is related to July 2019 forecast error), and (s) there are 12 intervals for the monthly data.

Results and Analysis

Research Question 1

A map was produced to demonstrate changes to CDD and HDD from 1981 to 2020 for state-level climate. As visualized in Figures 1 and 2, changes were calculated by comparing the most historic running 10-years of observations (i.e., 1981-1990) to the most recent 10-years of observations (i.e., 2011-2020). These results are consistent with the trends in CDD and HDD projected by Petri and Caldeira (2015) through the end of the century. There were observed changes for each state, with the smallest changes for both CDD and HDD in North Dakota. The most intense changes for CDD were in the lower-latitude states.

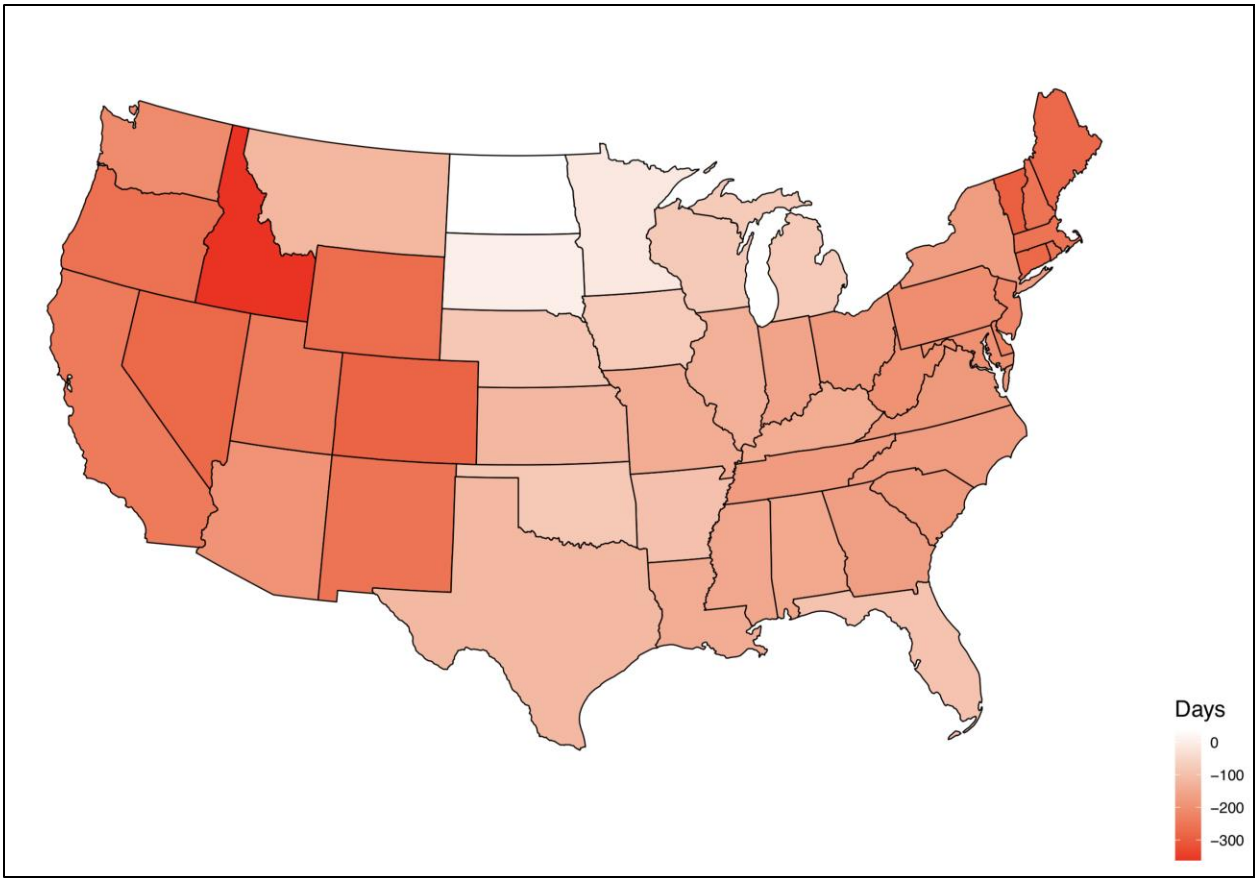
Figure 1. Change in Cooling Degree Days (CDDs) (2011-2020 minus 1981-1990)



Research Question 2

Results from SARIMA models reveal that for nonrenewable generation, CDD and HDD improve forecast accuracy for the majority of states (Table 1). That is, most (75%) states remain coupled (i.e., interrelated) to climate. The RMSE decreased when adding the exogenous CDD and HDD for most states, an indication of the direct effect of climate on MWH generation from nonrenewable sources. For models with CDD, there was an improvement in explanations of MWH for 28 states, no change for two states, and a decline for 18 states. For models with HDD, there was an improvement in explanations of MWH for 23 states, no change for 11 states, and a decline for 14 states. The two states where CDD had the greatest effect on MWH forecasts are Alabama (424,000 MWH, 29% model improvement) and Kentucky (396,000 MWH, 39% model improvement); the two states where HDD had the greatest effect are Texas (329,000 MWH, 15% model improvement) and Kentucky (256,000 MWH, 25% model improvement). Across the contiguous United States, CDD contributed to 2.5 million MWHs generated and HDD 687,000 in 2020 alone.

Figure 2. Change in Heating Degree Days (HDDs) (2011-2020 minus 1981-1990)



Total, 36 of the 48 states (75%) remained coupled to CDD and/or HDD. Eight of the 12 states (67%) that observed uncoupling had mandatory Renewable Portfolio Standards in place (see Table 2) (NCLS, 2023). These states (1) demonstrate that mandatory commitments to renewables can negate relationships shared between weather and nonrenewable generation, and (2) offer exemplary examples of mandatory renewable policy that has been successful. For the remaining states, results should be interpreted with caution. First, AR, KS, and WY all export substantial amounts of electricity to other states (EIA, 2023a). Second, KS is the third largest wind producer in the United States (EIA, 2023b). Comparatively, AR and WY only produce around 8% of electricity from renewables (EIA, 2023c, d). Large infrastructure investments are linked to decoupling the relationship with climate change (e.g., Gates, 2021), a possible explanation for uncoupling in KS. And third, LA is one of the most consumptive states in the United States due to energy-intensive industries (e.g., chemical, petroleum) (EIA, 2023e), industries that are not inherently exposed to climate.

Table 1. SARIMA Models for Nonrenewable Generation, CDD, and HDD from 2001 to 2020.

State Abb.	*SARIMA non-renewable*	*SARIMA w/ CDD*	*SARIMA w/ HDD*	*RMSE non-renewable*	*RMSE w/ CDD*	*%Δ MWH*	*# Δ MWH*	*RMSE w/ HDD*	*%Δ MWH*	*# Δ MHW*
AL	(0,0,3)(0,1,1)[12]	(5,1,1)(1,0,0)[12]	(0,0,3)(0,1,1)[12]	1474	1050	29%	424	1474	0%	0
AZ	(1,0,1)(0,1,1)[12]	(2,0,1)(1,1,2)[12]	(1,0,1)(0,1,1)[12]	482	527	-9%	-44	482	0%	0
AR	(1,0,0)(0,1,1)[12]	(2,1,3)(1,0,0)[12]	(1,0,0)(0,1,1)[12]	1038	1104	-6%	-66	1059	-2%	-22
CA	(1,0,2)(1,1,1)[12]	(4,0,2)(1,1,2)[12]	(1,0,2)(1,1,1)[12]	715	713	0%	2	715	0%	0
CO	(1,0,2)(2,1,2)[12]	(2,0,2)(1,1,1)[12]	(1,0,2)(0,1,1)[12]	493	515	-4%	-21	492	0%	1
CT	(3,0,0)(1,1,1)[12]	(1,1,1)(0,0,2)[12]	(1,1,1)(2,0,0)[12]	238	108	54%	129	154	35%	84
DE	(1,0,0)(2,0,0)[12]	(1,0,0)(1,0,0)[12]	(1,0,0)(2,0,0)[12]	138	104	25%	34	136	1%	2
FL	(1,0,0)(2,1,0)[12]	(1,1,1)(2,0,0)[12]	(1,0,0)(2,1,0)[12]	815	530	35%	285	859	-5%	-44
GA	(2,0,2)(0,1,1)[12]	(2,1,4)(1,0,0)[12]	(2,0,1)(2,1,1)[12]	1330	1101	17%	229	1336	0%	-5
ID	(1,0,0)(1,1,1)[12]	(2,0,0)(1,1,1)[12]	(2,0,0)(1,1,1)[12]	61	60	2%	1	59	4%	2
IL	(1,1,1)(1,1,0)[12]	(0,1,2)(1,1,0)[12]	(1,1,1)(1,1,0)[12]	1304	1051	19%	253	1195	8%	109
IN	(0,0,3)(0,1,1)[12]	(2,0,2)(0,1,1)[12]	(0,0,1)(0,1,1)[12]	1105	936	15%	169	1104	0%	1
IA	(1,0,2)(0,1,1)[12]	(4,1,0)(1,0,0)[12]	(1,0,2)(0,1,1)[12]	715	530	26%	184	684	4%	31
KS	(2,1,2)(0,1,1)[12]	(2,1,2)(2,0,0)[12]	(2,1,1)(0,1,1)[12]	198	203	-3%	-5	207	-5%	-9
KY	(0,0,3)(0,1,1)[12]	(2,1,1)(0,1,1)[12]	(1,0,1)(0,1,1)[12]	1023	626	39%	396	767	25%	256
LA	(1,0,1)(2,1,1)[12]	(5,1,0)(2,0,0)[12]	(1,0,2)(2,1,1)[12]	590	626	-6%	-36	602	-2%	-12
ME	(2,1,1)(2,0,0)[12]	(1,1,2)(1,0,0)[12]	(2,1,1)(2,0,0)[12]	68	40	42%	28	70	-3%	-2
MD	(5,1,0)(2,0,0)[12]	(2,1,2)(2,0,0)[12]	(5,1,1)(2,0,0)[12]	336	346	-3%	-10	380	-13%	-44
MA	(1,1,1)(2,1,2)[12]	(1,1,1)(2,0,0)[12]	(1,1,1)(2,0,0)[12]	302	319	-6%	-17	322	-7%	-20
MI	(0,0,3)(0,1,1)[12]	(1,1,2)(0,0,2)[12]	(0,0,3)(0,1,1)[12]	1212	1222	-1%	-10	1212	0%	0
MN	(1,0,1)(1,1,0)[12]	(3,0,1)(0,1,1)[12]	(3,0,1)(0,1,1)[12]	594	559	6%	35	579	3%	16
MS	(1,0,0)(1,1,1)[12]	(1,1,1)(2,0,0)[12]	(1,0,2)(1,1,1)[12]	331	418	-26%	-87	262	21%	70
MO	(2,1,2)(1,1,2)[12]	(2,1,3)(1,1,2)[12]	(2,1,2)(1,1,2)[12]	603	584	3%	20	631	-5%	-27
MT	(0,0,3)(0,1,1)[12]	(0,0,3)(0,1,1)[12]	(0,0,3)(0,1,1)[12]	511	510	0%	0	511	0%	0
NE	(2,0,2)(0,1,1)[12]	(2,0,2)(0,1,2)[12]	(1,0,3)(1,1,2)[12]	283	287	-2%	-4	239	16%	44

NV	(2,0,0)(2,1,2)[12]	(2,0,0)(2,1,2)[12]	(2,0,0)(2,1,2)[12]	195	193	1%	2	191	2%	4
NH	(1,1,1)(0,0,2)[12]	(0,1,5)(0,0,1)[12]	(1,1,1)(0,0,2)[12]	103	97	6%	6	109	-6%	-6
NJ	(2,0,0)(1,1,2)[12]	(1,1,2)(0,0,1)[12]	(2,0,0)(1,1,2)[12]	1031	969	6%	61	1024	1%	6
NM	(1,0,2)(2,1,1)[12]	(1,1,1)(0,0,2)[12]	(2,1,1)(2,0,0)[12]	318	326	-3%	-8	347	-9%	-29
NY	(0,0,4)(1,1,2)[12]	(2,1,2)(0,0,2)[12]	(3,0,0)(1,1,1)[12]	549	500	9%	49	621	-13%	-73
NC	(2,0,0)(1,1,2)[12]	(1,0,0)(1,0,0)[12]	(1,0,0)(2,1,2)[12]	1173	1127	4%	46	1122	4%	51
ND	(1,0,0)(0,1,1)[12]	(1,0,0)(0,1,1)[12]	(1,0,0)(0,1,1)[12]	146	147	-1%	-1	141	3%	4
OH	(1,0,1)(0,1,1)[12]	(2,0,1)(0,1,2)[12]	(2,0,2)(0,1,2)[12]	794	816	-3%	-22	775	2%	19
OK	(1,1,1)(0,1,1)[12]	(1,1,1)(2,0,0)[12]	(1,1,1)(0,1,1)[12]	420	477	-13%	-56	400	5%	20
OR	(1,0,1)(0,1,1)[12]	(1,0,1)(0,1,1)[12]	(3,0,2)(0,1,1)[12]	258	260	-1%	-2	271	-5%	-13
PA	(3,0,0)(2,1,0)[12]	(2,0,0)(1,1,0)[12]	(2,0,0)(0,1,1)[12]	1358	1159	15%	198	1538	-13%	-180
RI	(2,0,2)(0,1,1)[12]	(1,1,1)(0,0,2)[12]	(1,1,1)(1,0,0)[12]	128	109	15%	19	117	8%	11
SC	(3,0,0)(0,1,1)[12]	(4,1,1)(0,0,1)[12]	(0,0,3)(0,1,1)[12]	332	251	24%	81	276	17%	56
SD	(1,1,3)(0,0,2)[12]	(0,1,2)(0,0,2)[12]	(0,1,3)(0,0,2)[12]	88	86	2%	2	88	0%	0
TN	(1,1,1)(1,0,0)[12]	(0,1,3)(1,0,0)[12]	(1,1,1)(1,0,0)[12]	802	584	27%	218	773	4%	29
TX	(1,0,0)(1,1,1)[12]	(3,0,0)(0,1,1)[12]	(1,0,0)(0,1,1)[12]	2262	2218	2%	44	1933	15%	329
UT	(2,0,3)(0,1,2)[12]	(2,0,3)(0,1,2)[12]	(2,0,3)(0,1,2)[12]	325	323	1%	2	324	0%	1
VT	(3,1,1)(1,0,1)[12]	(4,1,0)(2,0,0)[12]	(3,1,1)(2,0,0)[12]	0	0	40%	0	0	1%	0
VA	(1,1,2)(0,1,1)[12]	(1,1,1)(1,1,2)[12]	(0,1,2)(0,1,1)[12]	579	641	-11%	-63	568	2%	11
WA	(1,0,2)(0,1,1)[12]	(1,0,2)(0,1,1)[12]	(1,0,2)(0,1,1)[12]	418	414	1%	4	429	-3%	-11
WV	(1,0,0)(2,1,0)[12]	(1,1,2)(2,0,0)[12]	(2,0,2)(1,1,0)[12]	731	717	2%	13	705	4%	26
WY	(2,0,2)(2,1,2)[12]	(1,0,0)(1,1,2)[12]	(1,0,1)(1,1,2)[12]	448	465	-4%	-17	447	0%	1

**REMSE reported in MWH; MWH reported in ,000s.*

ŧSee https://www.faa.gov/air_traffic/publications/atpubs/cnt_html/appendix_a.html for two-letter state abbreviations

Table 2. Uncoupled states

State	Renewable Energy Standard or Target	2017 Primary Affiliations	Designation
AZ	Renewable Portfolio Standard	48%D, 52%R	Competitive
AR	No standards or targets	36%D, 45%R	Lean R
CA	Renewable Portfolio Standard	51%D, 30%R	Solid D
CO	Renewable Portfolio Standard	46%D, 37%R	Lean D
KS	Renewable Energy Goal (expired)	34%D, 48%R	Solid R
LA	No standards or targets	40%D, 43%R	Competitive
MD	Renewable Portfolio Standard	56%D, 28%R	Solid D
MA	Renewable Portfolio Standard	57%D, 26%R	Solid D
MI	Renewable Portfolio Standard	45%D, 38%R	Lean D
NM	Renewable Portfolio Standard	48%D, 34%R	Solid D
OR	Renewable Portfolio Standard	49%D, 34%R	Solid D
WY	No standards or targets	27%D, 56%R	Solid R

**2017 affiliations and designations from Gallup (2017) survey; D=Democrat/Lean Democrat; R=Republican/Lead Republican*

Discussion

The widespread attention climate change has received across disciplines is indicative of the need for organizations—irrespective industry—to decouple contributions of organizational systems (e.g., CO2 emissions) from future climate change. This is particularly true for the electric power industry in the United States, an industry long-known to inequivalently emit CO2 into the atmosphere contributing to climate change (e.g., Heede, 2014; Reidmiller et al., 2018). In fact, "decarbonizing the electric sector is one of the most cost-effective ways to reduce emissions and can help decarbonize other sectors with increased electrification" (Sattler et al., 2022, p. 1). Despite the attention management scholars have given to the electric power industry (e.g., Delmas et al., 2016; Dutt & Mitchell, 2020), we are not aware of prior investigations of the industry inclusive climate science. This study explicitly addresses this research gap.

Results from our retrospective analysis demonstrate changes to climate (i.e., CDD and HDD) in each state when comparing the study's most historical 10-years (1981-1990) to its most modern 10-years (2011-2020; see Figure 1). On the aggregate, results indicate climate, are still coupled with nonrenewable electricity generation throughout much of the United States (75% of states). Furthermore, the two characteristics for uncoupled states were (1) mandatory Renewable Portfolio Standards and (2) extensive clean energy infrastructure already in place (e.g., 45% of KS production comes from wind) (EIA, 2023b; NCLS, 2023). With federal policy objectives to transition to renewable infrastructure in the United States (The Executive Office of the White House, 2021), the results are of immediate interest to regulators, policy makers, and leaders in the electric power industry. Since the electric power industry on the aggregate has oversight from law makers and regulators (EPA, 2010), managerial implications for our findings are primarily policy-based. Below, implications as well as limitations and future research sections are provided.

Policy Implications

First, state- and federal-level regulators and policy makers should consider making renewable energy targets mandatory. This is because mandatory renewable energy targets have proven to be more effective than voluntary targets (Delmas & Montes-Sancho, 2011). For instance, the Executive Office of the White House (2021) issued a press release outlining efforts to reduce emissions in 2030 by 50-52% compared to 2005 levels. Despite the non-binding national target, electricity generation regulation primarily occurs at the state-level, overseen by public utility commissions comprised of governor appointed or elected commissioners (EPA, 2010). Currently, discrepancies in state-level renewable energy targets vary, with 24 of the contiguous states having mandatory renewable targets while the other half of the 48 states either have no or voluntary targets NCSL (2023). Meeting the binding, mandatory emissions targets outlined in the Paris Agreement (United Nations [UN], 2015) will likely require mandating renewable infrastructure, whether that be at the federal- and/or state-level. For example, the United States (like many other signatory countries) is presently not making sufficient progress towards emissions reductions to meet obligations of the Paris Agreement (Perdana & Tyeres, 2020).

A second policy implication is related to the scale of infrastructure. For renewable infrastructure to adequately combat climate change it needs to be deployed at a scale great enough where generation does not continue to contribute to climate change (Gates, 2021; Reidmiller et al., 2018). This is because states that respond to warming temperatures with nonrenewable electricity generation also contribute to a warming climate (EPA, 2018). The finding that KS—a state the generates almost half of its electricity from wind—is uncoupled to nonrenewable generation supports this assertion. Looking forward, regulators, policy makers, and the electric power industry alike will need to maintain a dual focus on how to transition to renewable fuel sources while also producing supply to respond to a changing climate. The manner (e.g., mandatory, voluntary), and speed, at which targets are adopted and enacted will be critical to uncoupling nonrenewable generation from climate change (Delmas & Montes-Sancho, 2011; Garcia-Gusano & Iribarren, 2018; Gates, 2021).

A third implication is related is building policy support among state- and local-level policy makers. For instance, Craig and Allen (2014) conducted a state-level survey finding Democrats were more supportive of renewable subsidies and adaptation of renewable infrastructure by utilities than other party affiliations. When comparing party affiliations for uncoupled states (Table 2), other than Arizona (competitive), each state with Renewable Portfolio Standards were majority Democrat. Also, attorney generals from states reliant on fossil fuels filed a lawsuit against renewable regulatory actions by the federal government (Craig, 2018). Comparably, local policy actors who perceive fossil fuels as important to local economies are less likely to support renewable regulations (Mayer, 2019). To enact large-scale policy will require more wide-spread support across the political spectrum in the United States than presently observed. Economics losses—real or perceived—are known to counter renewable energy support (e.g., Craig & Allen, 2014; Stokes & Warshaw, 2017). For unsupportive parties, messages that highlight renewable policy counters economic threats (if true and accurate) are favorable (e.g., Craig & Allen, 2014). Also, Stokes and Warshaw (2017) found that messages highlighting pollution benefits were linked to Republican support of renewable policy.

For an international audience, the case of the electric power industry in the United States should serve as a cautionary tale. Currently, state-level renewable electricity policy is splintered in the United States where some states have aggressive renewable targets, while other states (1) lack targets and/or (2) actively oppose federal renewable policies (Craig, 2018; DSIRE, 2022). Signatory countries to the binding Paris Agreement (UN, 2015) should strive to enact mandatory, federal-level policies to promote the consistent adoption and enactment of renewable policies nationally (e.g., Delmas and Montes-Sancho, 2011). As our results indicate, a related concern for international audiences is the scale at which renewable infrastructure is deployed. For countries with states required to annually balance budgets like the United States (NCSL, 1999), it may be necessary to enact federal economic policies such as tax credits and subsidies to support large-scale investment (Newell et al., 2019).

Limitations and Future Research

While this study is novel, it is not without limitations. First, monthly generation data was only available from 2001 to 2020 (EIA, 2021b) limiting our ability to demonstrate the effects of climate change on electricity generation. However, using historical CDD and HDD (i.e., 1981 to 1990) compared to the most recent 10-year period (i.e., 2011-2020), climate change was empirically observed. Also, state-level GDP data was only available annually, requiring the data to be converted to monthly to run the analysis. Future research should utilize higher-resolution data and longer timespans to study weather/climate, income, and generation relationships. For example, Takakura et al. (2019) introduced a method to reconstruct site-specific hour temperatures at six locations in Japan which has the potential to match with site-specific observations at generation facilities (if access to high-resolution is made available).

Second, only state-level data was available from 2001 to 2020 (EIA 2021b). Despite initially calculating CDD and HDD (i.e., our focal climate resources) daily using high resolution grid cells, data had to be aggregated to monthly and averaged by state to match with monthly electricity generation data. Future researchers should seek to (1) more closely align geographic locations with climate resource occurrence and (2) match performance data at those locations with high resolution climate resource data. It would also be helpful for future researchers to expand the number of locations beyond the 48 states captured in this study.

Lastly, there are some dynamics in addition to climate and income that the state-level datasets do not capture. For instance, some states export generation (e.g., Arkansas) and others import generation (e.g., Connecticut). However, most exports go to neighboring states that also experience similar climate changes (Karl & Koss, 1984, Feng & Hu, 2004). Regardless, states are the regulatorily units responsible for crafting and enacting renewable energy policy, meaning the state-level implications remain meaningful. Future researchers should strive to more closely match generation with location of consumption to better understand the coupled dynamics in the electrical power industry. A related challenge is that the EIA (2021b) only provides national consumption data—not state-level—at the monthly temporal resolution. This is a minor issue, however, considering that generation and consumption are very highly correlated (Craig &Feng, 2017). Other economic data (e.g., population change, GDP) would also be useful to include in future studies, though in the United States this data is not available at a high enough resolution to match with our monthly climate and generation data.

Conclusion

A salient goal of renewable energy policy is to uncouple non-renewable electricity generation from climate change. For instance, non-renewable electricity generation contributes CO2 to the atmosphere where the observable effects are warming temperatures. When the electric power industry responds to warming temperatures (e.g., increasing CDD, decreasing HDD) with non-renewable generation, the systems remains coupled. As evidenced from by our analysis, we observed that the majority of states' non-renewable generation (75%) remains coupled to climate. For the states that are uncoupled, two best practices include (1) mandatory state-level renewable policies and (2) large-scale development of renewable generation infrastructure. State-level policies and electricity generation objectives differ widely in the United States, suggesting federal intervention may be necessary. Based on state-level best practices, two such interventions include: (1) adopt consistent national renewable electricity generation policies and (2) make capital available to states to develop large-scale renewable electricity infrastructure projects.

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