Journal of Renewable and Sustainable Energy
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PLEASE CITE THIS ARTICLE AS DOI: 10.1063/5.0081905

Accepted to J. Renew. Sustain. Energy 10.1063/5.0081905

Estimating the Economic Impacts of Improved Wind Speed Forecasts in the United States Electricity Sector

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22 November 2021

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Journal of Renewable and Sustainable Energy ACCEPTED MANUSCRIPT

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Abstract

Each year the U.S. government makes significant investments in improving weather forecast models. In this paper we use a multidisciplinary approach to examine how utilities can benefit from improved wind-speed forecasts to more efficiently use wind-generated electricity and subsequently increase economic activity. Specifically, we examine how improvements to the National Oceanic and Atmospheric Administration's (NOAA) High-Resolution Rapid Refresh model (HRRR) wind forecasts can provide 1) cost savings for utilities, and 2) increases in real household income. To do so we compare 12-hour-ahead wind forecasts with real-time observations for two HRRR model transitions (i.e., when one model is operational and the other is being tested). We compare estimates of actual and predicted wind power under the publicly available and developmental models, with reduced forecast errors allowing for better utility decision-making and lower production costs. We then translate potential cost savings into electricity price changes, which are entered as exogenous shocks to eight regional Computable General Equilibrium (CGE) models constructed for the U.S. Overall, we find that households would have seen a potential $60 million increase in real income for our sample (13 percent of all contiguous US land-based turbine capacity) had the updated HRRR models been in place during the two transition periods; applying our estimated savings for the sample of turbines to the entire array of turbines shows a potential real household income increase of approximately $384 million during these time frames.

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1. Introduction

Each year the U.S. government makes significant investments to improve the accuracy of weather forecast models. The National Oceanic and Atmospheric Administration (NOAA) is the lead institution in these endeavors. Although the primary purpose is to protect life and property, these models inform a large variety of economic decisions. In this paper we examine how electric utilities can benefit from improved wind-speed forecasts to more efficiently integrate wind-generated power into the electric grid and lower electricity prices, leading to increased economic activity.

In the U.S., wind power is an important, low-cost contributor to the electricity grid, and its share of total production is steadily increasing. However, because it is intermittent, wind power generation can be highly variable. Accordingly, an increased reliance on wind can make it more difficult for utilities to optimize their production decisions across their portfolio of sources (e.g., wind, gas and coal). Better wind-speed forecasts allow a cost-minimizing utility to optimize the mix of their own production sources, potentially reducing or eliminating the need to purchase electricity on the typically more expensive spot-market when own-supply falls short of demand. When these lower costs are passed onto users, the economy benefits.

We pursue this analysis in several steps. First, we document the increased savings afforded to utilities through improved wind forecasts. To do so, we compare potential wind power estimates under various versions of a prominent weather forecasting model developed and run operationally by NOAA. The High Rapid Resolution Refresh (HRRR) model provides hourly-updated weather forecasts for every 3km-by-3km grid in the contiguous US, up to at least 18 hours in advance (the most recent version of the HRRR provides a 48-hour forecast every 6 hours, with 18-hour forecasts provided for the other initialization times; for more detail see Dowell et al. (2021)). Here we evaluate forecast improvements by exploiting the fact that when NOAA introduces a new version of HRRR to operational status within the National Weather Service, it tests the model for approximately a year, while the previous variant continues to provide public forecasts.

Using geo-located data on every wind-turbine in the contiguous United States (CONUS)--including capacity--we match up the 12-hour-ahead wind forecasts from each version of the HRRR model with observed wind-speeds near the turbines to generate both predicted wind power output and estimates of actual wind power output. We are interested in the differences; i.e., when the predicted wind power over- and under-estimates the actual wind power. In the overestimation case, utilities will produce less electricity from the turbine than expected. When such “mistakes” are made, utilities must turn to the spot market, which can be expensive if the marginal generation source is fossil-fueled. In the underestimation case, utilities have committed to more expensive sources, and costs needlessly rise.

We then turn our attention to estimating how such cost savings can benefit electricity users. We introduce this linkage in a computable general equilibrium (CGE) model that estimates a variety of economic impacts (e.g., output, employment and wages) due to changing electricity

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prices in eight different Bureau of Economic Analysis (BEA) regions of the U.S. We find that the cost savings achieved through better wind forecasts can lead to slight declines in electricity production costs and prices that can lead to small, but important economic gains nationwide.

In the next section, we review the related literature, emphasizing: i) the impacts of increased wind penetration and improved wind forecasts on wholesale electricity prices, and ii) the approaches some others have used to simulate the economy-wide impacts of changing electricity prices. In section 3, we describe the basic economic problem. Specifically, utilities must commit in advance to providing electricity using the power sources amongst their portfolio that allows them to meet expected demand at the lowest cost possible, subject to the uncertainty inherent in wind and solar production. We also present the eight region CGE model used in our analysis. Electricity is a key sector in these models, and we describe how price changes can affect economic activity. In section 4, we describe a state-of-the art weather forecast model developed by NOAA and estimate the (potential) cost savings arising from improvements in wind speed forecast accuracy. Section 5 presents the cost savings and fall in retail electricity prices. In section 6, we describe how the simulations are set up and the results from a series of economic simulations where we reduce electricity prices—arising from cost savings owing to improved wind forecasts. Section 7 is our conclusion.

2. Literature review

We review papers that examine i) the effects of increased wind penetration on electricity wholesale prices and price volatility, and ii) the effects of improved wind-speed forecasts on reducing price volatility through improved predictability. Overall, these papers suggest improved wind forecasts can indeed lower electricity prices. Typically, these approaches are partial equilibrium, as they look at only the effects in the electricity market. General equilibrium models provide a broader approach, looking at how price changes in one sector reverberate through the overall economy. The second section describes several models used to examine the economic impacts of changing electricity prices. These models are kindred spirits to the one we use in our analysis but have not been used to evaluate improved wind-speed forecasts. Our paper's primary contribution is integrating the two topics that we review here.

2.1 Wind penetration, electricity prices and improved forecast accuracy

Several studies show an increase in the share of electricity produced from wind power can reduce electricity prices (e.g., De Miera et al. (2008), Quint and Dahlke (2019), Csereklyei et al. (2019)). Despite wind power's lower marginal cost, intermittency impedes its full adoption. One pecuniary effect is an increase in electricity price volatility, which can increase the financial burden on producers via increased risk management costs (Woo et al. (2011), Ketterer (2014)). Chao (2011) simulates various pricing strategies to help better deal with uncertainty due to intermittency.

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Three notable studies of German electricity markets relating forecast accuracy and pricing bear attention. Gürtler and Paulsen (2018) show that better renewable power forecasts reduce price volatility in both day-ahead and intraday markets, with forecasting errors in wind power inducing substantial changes in both market prices, which they quantified at 1-to-5 €/MWh per GWh forecasting error. Hagemann's (2015) study indicates that wind forecasting errors have larger impacts on intraday prices than power outages and solar forecasting errors, ranging from 2-to-3 €/MWh per GWh forecasting error. Kulakov and Ziel (2019) find wind forecasting errors increase both intraday prices and intraday price volatility in a non-linear manner. For Norway and Denmark, Karanfil and Li (2017) investigate causality between wind power forecast errors and the price difference between the day-ahead and intraday markets , documenting a negative causal relationship from wind forecast errors to intraday price, which differs from the day-ahead market price.

For the U.S., Martinez-Anido et al. (2016) use the Independent System Operator-New England (ISO-NE) production cost model to show that over-forecasting wind generation increases electricity prices while under-forecasts reduce them. Kiesel and Paraschiv (2017) estimate the impact of updated wind and photovoltaic (PV) forecasting from the most-current weather forecasts on the intraday spot price at the EPEX. In particular, the higher expected volume of wind and PV in the day-ahead market yields the higher demand quote, where electricity producers plan less traditional capacity. Intuitively, negative forecasting errors lead to increased intraday prices, while prices decrease in positive forecasting errors. See Swinand and O'Mahoney (2015) and Goodarzi et al. (2019) for more examples of reduced wind forecast errors leading to a more efficient use of wind.

2.2 Modeling the economic impacts of electricity price changes

Although CGE models are widely used for policy analysis, model specification and refinement are important themes in the academic literature. Early CGE models were often "top-down," meaning that economic sectors were often highly aggregated, with little attention paid to the unique aspects of any particular one, including the electricity sector. When applied to energy issues, the focus was often on the demand side, considering how various consumer groups (e.g., commercial, residential) would be affected by energy price increases. For example, Bergman (1988) examines the impact of a hypothetical 50 percent increase in electricity prices in Sweden, which is modeled such that output prices reflect, in part, the various input prices. Output price increases subsequently impact households both directly (through lower real income) and indirectly (through labor market impacts).

Within the "economics of climate change" literature, CGE models are widely used in renewable energy policy analysis, with the increased penetration of renewables being one of the more researched topics. For example, Bohringer and Loschel (2006) consider the economic and environmental effects of promoting renewable energy in the European Union. Dai et al. (2016) look at the viability of increased wind penetration by 2050 on a global scale, linking a CGE model with an onshore wind resource model to investigate the impacts of new investments through 96 unique scenarios. Cohen and Caron (2018) consider a similar question for the

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United States, estimating the welfare and distributional impacts of increased investment in wind power. CGE models are also widely used to estimate the impacts of carbon taxes. For example, Coxhead et al. (2013) examine such a policy in Vietnam via *ad valorem* tax changes on coal and refined fuels, while Jorgenson et al (2015) examine the impacts of a tax on emissions in the U.S. Additionally, CGE models can be used to examine (directly, at least) non-pecuniary policy changes, such as emissions trading (Elkins and Baker (2001)). Kat et al. (2018) construct a CGE model for Turkey to simulate the economic impacts of following the guidelines of the 2015 Paris Agreement. The transition away from fossil fuels and towards renewables causes a slight increase in electricity prices, resulting in a 0.8 – 1.0 percent fall in economic activity.

Some modeling efforts (e.g., "top-down/bottom-up" or hybrid models) dis-aggregate the electricity sector using technology-specific production functions to allow for important differences in alternative generation technologies (e.g., wind versus gas) (Wing (2006), Cai and Arora (2015)). By incorporating specific production technologies, producers can substitute among alternative sources to meet expected demand, based largely on relative changes in production costs (e.g., Bohringer and Loschel (2006)). In some cases, these changes are exogenous (such as imposing a carbon tax); in other cases, relative price changes are determined by changes in supply arising from increased subsidies or investment (e.g., Cohen and Caron (2018)). In a similar vein, Nong (2018) uses the GTAP-E-PowerS CGE to examine the impacts of a carbon tax in South Africa to help transition to renewable energy. They show that increasing electricity prices results in a small decline in economic activity.

3. The Decision-maker's Cost Minimization Problem

In order to meet the expected demand, utility operators need to schedule in advance the amount of power they can generate from various sources. In the short run, we assume that utilities follow "merit order"; that is, they choose amongst their portfolio of power generation options to minimize the marginal cost of producing any particular level of output. For example, if a utility has three power sources in its portfolio, it will compare the marginal costs across the three, producing as much as possible from its lowest cost source, then moving on to its next cheapest source, etc. Although some generation capacities are easily modeled due to certainties in production capacity and input availability (e.g., coal and natural gas), others are subject to greater uncertainty, due to stochastic fluctuations in input availability (e.g., wind and sunshine).

Recent research shows that, over the past several years, wind and solar power have relatively low marginal production costs compared to nuclear, natural gas, and coal (Lazard 2020). Because of this (and the fact that they have no emissions), renewable energy is a favored power source by utilities seeking to provide low-cost electricity. However, a greater uncertainty in predicted output--combined with the necessity to provide power when it is needed--means the utility manager faces a difficult problem in trading-off higher costs with more certain production.

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In Figure 1, we provide an overview of the general problem. We assume that utility managers use wind-speed forecasts to develop estimates of expected wind energy production. We refer to these energy forecasts as “commitment”: the amount of electricity the utility commits to producing from wind from its total generation portfolio. “Better” forecasts reduce error, thereby improving decision-making and reducing costs. Meanwhile, poor forecasts--especially when the wind doesn’t blow as hard as it is expected to--can be very costly to remedy, as power companies often need to turn to the spot-market when they cannot produce an adequate supply from their own portfolio. In our analysis, the HRRR model is the sole source of 12-hour-ahead wind forecasts, and actual wind-speeds are measured at Meteorological Aerodrome Reports (METAR) stations “near” the wind turbines.

Figure 1. The decision-maker’s problem

4. Assessing Wind Forecast Accuracy and Its Impact on Power Generation

NOAA’s HRRR model generates the hourly wind-speed forecast data we use in this paper. Since 2014, the HRRR model has served as one of the foundational components for local weather forecasts across the United States. HRRR forecasts are made at the 3km-by-3km scale over the contiguous United States. The model is initialized every hour, assimilating radar, radiosonde, METAR, aircraft, and other data, and produces hourly forecasts out to at least 15 hours for each initialization (later versions of the model produce longer forecasts (e.g., out to 36 hours) at regular intervals). For our analysis, we utilize 12-hour-ahead forecasts of wind-speeds for each hour of the day.

Between 2015 and 2018, NOAA created three new HRRR versions (i.e., HRRR1, HRRR2 and HRRR3) (Dowell et al. 2021). Each version is tested extensively against a wide range of observations before being released to the public (Turner et al (2020)). Testing includes simultaneously running the new and previous HRRR versions and recording both forecasts. For the primary differences between the versions of HRRR, see Table 2 in Turner et al. (2021).
To evaluate improvements on the wind power forecasts, we analyze the reported wind forecasts for the periods of overlap between HRRR versions. For example, there was approximately a 15-month testing overlap between HRRR1 and HRRR2 (June 2015 to August 2016). During this period, the operational forecasts reported to the general public were from HRRR1, but experimental HRRR2 forecasts, which were being generated as part of the testing/release process, were also stored on NOAA servers. Analogously, we examined the July 2017 to June 2018 for the overlap period between HRRR2 and HRRR3. The overlap periods present a convenient experiment for evaluating the potential economic impacts of improved wind forecasting. Unfortunately, forecast data was not available for every hour between 2015 and 2018. The servers running and storing the experimental HRRR model forecasts sometimes required maintenance; although forecasts were still made during maintenance periods, they were not stored. As a result, about 10 percent of the forecast data from the experimental HRRR versions for the overlap periods was lost.

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Observed wind-speed data for the concomitant time periods are collected from METAR stations. Thousands of METAR stations are spread across North America, recording hourly, providing single coordinate location observations of wind-speed, measured in meters per second. Thus, observed wind-speeds can be compared to the HRRR forecast wind-speeds based upon geographic location. These observations, and the HRRR-forecasted winds, were made at 10-m above the surface, and are used as a proxy for the wind speeds at turbine hub height (which is between 80 to 100 m) due to the paucity of publicly available observed wind speeds at those heights.

Wind turbine data are reported by the United States Geological Survey (USGS). This dataset provides geographic coordinates for all land-based and offshore turbines in the United States and their capacity. Because HRRR forecasts, METAR stations and USGS Wind Turbine data all have geographic markers, we can associate them with one another using geographic information system (GIS).

There are approximately 65,000 wind turbines in the Unites States, about 55,000 of which are land-based. However, because wind-speeds can vary greatly over relatively small geographic distances, we limit our set of turbines to those within a "reasonable distance" (i.e., 20km radius) from a METAR station, eliminating the remainder from our analysis.[1] A key assumption is that the reported wind-speeds are consistent for all wind turbines within the 20km zones surrounding a given METAR station. A limitation of this technique is that it restricts the number of METAR stations used in the analysis to 245 and the number of wind turbines to 8,435 (about 15.5 percent of the land-based US wind turbine count, or 13 percent of installed capacity). However, in order to include more turbines, we need to extend the radius. In such cases, METAR readings may not accurately reflect actual wind-speeds at the turbine.

Figures 2a and 2b portray the distribution of wind turbines across the United States, without and with the 20km buffer restriction, respectively. These images suggest that the distribution of wind turbines for the 20km buffer zone restriction is relatively consistent with that of all wind turbines. Overall, wind production is most prominent in the upper Midwest and south-central states (described more below).

Figure 2a. All land-based wind turbines, 2019
Figure 2b. Wind turbines within 20 km buffer

For our economic modeling (described in Section 6), we disaggregate the CONUS into eight economic regions (Figure 3), as defined by the Bureau of Economic Analysis. We chose BEA regions as they are commonly referenced economic units in the U.S., and allow for sub-national

[1] The HRRR's horizontal grid-spacing is 3 km, but its true resolution is about 6-to-8 times larger (i.e., 18-to-24 km) (Skamarock 2004). Thus, we chose 20 km as compromise between representing the HRRR's spatial resolution properly and being as close to the observation sites as possible.

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economic heterogeneity. We assign the wind turbines shown in Figure 2b and the relevant METAR stations to their host economic region.

Figure 3. The Eight Bureau of Economic Analysis Region

We provide select economic and wind generation statistics for each of the eight regions in Table I. In the first two data columns, we see that the employment and GDP total are largest in the Southeast and smallest in the Rocky Mountain region. According to U.S. Energy Information Administration (EIA), and consistent with Figure 2a, the Plains region led the nation in installed wind capacity, with 12,948 turbines capable of producing 22.6 GW. In contrast, only 499 wind turbines were located in the Southeast region.

Translating improved wind forecasts into better estimates of daily generation capacity

With the data described, our first objective is to determine if predicted electricity output forecasts improve as the HRRR model evolves. To do so, we compare predicted (expected) power under various wind forecasts (e.g., HRRR2 versus HRRR3) with estimates of actual (potential) output. Forecast accuracy improves as:

$$\text{Forecast error} = |\text{Actual Output} - \text{Predicted Output}| \rightarrow 0 \qquad (1)$$

Rather than measuring wind-speed forecasts error themselves, we consider the error in wind energy production forecasts, relying on a wind-speed-to-power conversion equation (Wilczak (2019)),

$$Power = \begin{cases} 0, & if\ 0 \leq S < 3\,, or\ S > 25 \\ 1, & if\ 16 < S \leq 25 \\ C_0 + C_1 S + C_2 S^2 + C_3 S^3 + C_4 S^4 + C_5 S^5 + C_6 S^6 + C_7 S^7, & if\ 3 \leq S \leq 16 \end{cases} \qquad (2)$$

where *power* is the normalized power values (or production as percentage of capacity) for different wind-speeds, S is the wind-speed in m/s (meters per second), and C_0 to C_7 are estimated coefficients (see Wilczak (2019) for specific coefficients).

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Table I. States, number of MSAs, total turbine capacity, and number of turbines within each BEA region (2018)

BEA Region	States	Regional employment (millions)	Regional GDP (trillions of $)	Total regional turbine capacity (kW)	Number of regional turbines	Turbine capacity within 20km buffer zone (kW) (% of total)	Number of turbines within 20km buffer zone (% of total)
New England	CT, ME, MA, NH, RI, VT	9.99	1.09	1,434,065	650	210,765 (14.7%)	123 (18.9%)
Mideast	DE, DC, MD, NJ, NY, PA	31.23	3.72	3,408,460	1,873	171,275 (5.0%)	79 (4.2%)
Great Lakes	IL, IN, MI, OH, WI	28.34	2.77	9,800,118	5,629	1,204,288 (12.3%)	709 (12.6%)
Plains	IA, KS, MN, MO, NE, ND, SD	14.07	1.29	22,555,838	12,948	2,533,352 (11.2%)	1,461 (11.3%)
Southeast	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV	49.29	4.35	922,880	499	83,280 (9.0%)	53 (10.6%)
Southwest	AZ, NM, OK, TX	24.88	2.45	32,786,460	17,789	3,755,350 (11.5%)	2,184 (12.3%)
Rocky Mountain	CO, ID, MT, UT, WY	8.05	0.72	6,699,610	4,229	700,370 (10.5%)	404 (9.6%
Far West	AK, CA, HI, NV, OR, WA	34.43	4.11	12,316,156	10,811	3,048,176 (24.7%)	3,422 (31.7%)
Totals		200.28	20.5	89,923,587	54,428	11,706,856 (13.0%)	8,435 (15.5%)

Sources: GDP and Employment figures are taken from the Bureau of Economic Analysis (2018). Wind turbine and capacity figures are collected from the US Energy Information Administration (EIA, 2018).

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Figure 4 shows the wind-speed-to-power conversion curve from equation (2). As an example, if a wind power utility owns 10 turbines, each with a capacity of 2 MW, a 10 m/s wind-speed for one hour means these turbines can generate 80 percent of their capacity, or 1.6 MWh. Note that there is no power generated when the wind-speed is less than 3 meters per second, as the wind is too slow to generate electricity. When the wind-speed is greater than 25 meters per second, a turbine is shut off so as to avoid damage. These two cases are eliminated from our analysis. Wind-speeds between 16 and 25 meters per second allow a turbine to produce at its full capacity. Note that we do not account for potential interactions among the turbines (e.g., the development of a wake that impacts the power derived from downstream turbines) in our analysis.

Figure 4. Normalized Power Curve for an average of several International Electrotechnical Commission (IEC) class 2 wind turbines

We consider two types of forecast errors. *Overprediction* errors are those where the 12-hour wind-speed forecasts are greater than the observed wind-speed. In such cases, the utility has overcommitted to wind power, meaning that it is unable to meet actual demand when the electricity is needed. Table II presents the forecast errors for the first overlap period. The most notable aspect of the HRRR1/HRRR2 transition is that the forecast error for HRRR2 has diminished substantially compared to using HRRR1. Excluding the Southeast which produces little wind energy, New England experienced a decline in the forecast error by a factor of eight. For the HRRR2/HRRR3 period, there are reductions in the forecast error for HRRR3 (Table II), but it is not as dramatic as the HRRR1/HRRR2 case.

An *underprediction* error arises when the forecasted output is less than actual (potential) output (i.e., the wind blows harder than predicted). In Table III we provide the estimated sum of the hourly forecast errors between HRRR1 and HRRR2 and HRRR2 and HRRR3 for each of the eight economic regions. The gains in accuracy are greater for HRRR2 compared to HRRR1 than for the HRRR2/HRRR3 case. However, the gains in the overprediction case far exceed the gains in the underprediction case.

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Table II. Overprediction (In thousands of MWh)

BEA Region	HRRR1 versus HRRR2					HRRR2 versus HRRR3				
	Electricity generation	HRRR2 Error	HRRR1 Error	% of forecasting error from HRRR2	% of forecasting error from HRRR1	Electricity generation (MWh)	HRRR3 Error (MWh)	HRRR2 Error (MWh)	% of forecasting error from HRRR3	% of forecasting error from HRRR2
New England	81.8	5.7	49.4	7%	60%	75.8	7.45	13.22	10%	18%
Mideast	95.5	3.5	14.5	4%	15%	90.1	7.09	186.56	8%	15%
Great Lakes	674.2	90.9	407.4	13%	60%	531.4	104.83	212.99	20%	35%
Plains	2,368.7	91.7	396.0	4%	17%	1,960.9	104.62	2.63	5%	11%
Southeast	14.6	2.3	26.9	16%	184%	12.3	1.23	326.65	10%	21%
Southwest	3,363.4	184.4	812.4	5%	24%	3,132.3	169.25	36.69	5%	10%
Rocky Mountain	664.5	26.6	155.9	4%	23%	621.3	15.63	325.63	3%	6%
Far West	3,450.8	123.6	623.1	4%	18%	2,751.9	172.90	13.22	3%	6%
Total	10,713.5	528.9	2,485.5			9,176.0	582.99	1,118.16		

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Table III. Underprediction (In thousands of MWh)

BEA Region	HRRR1 versus HRRR2					HRRR2 versus HRRR3				
	Electricity generation (MWh)	HRRR2 Error (MWh)	HRRR1 Error (MWh)	% of forecasting error from H2	% of forecasting error from H1	Electricity generation (MWh)	HRRR3 Error (MWh)	HRRR2 Error (MWh)	% of forecasting error from H3	% of forecasting error from H2
New England	81.8	18.4	27.2	22%	33%	75.8	18.9	25.3	25%	33%
Mideast	95.5	23.1	43.8	24%	46%	90.1	16.7	21.6	19%	24%
Great Lakes	674.2	73.6	149.3	11%	22%	531.4	60.4	82.4	11%	16%
Plains	2,368.7	400.4	794.2	17%	34%	1,960.9	281.7	396.5	14%	20%
Southeast	14.6	3.0	4.9	21%	34%	12.3	2.6	3.4	21%	28%
Southwest	3,363.4	617.3	1,166.8	18%	35%	3,132.3	463.7	646.1	15%	21%
Rocky Mountain	664.5	162.4	269.1	24%	41%	621.3	107.0	146.6	17%	24%
Far West	3,450.8	649.4	1,283.2	19%	37%	2,751.9	468.4	648.7	17%	24%
Total	10,713.5	1,947.6	3,738.5			9,176	1,419.4	1,970.6		

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Accepted to J. Renew. Sustain. Energy 10.1063/5.0081905

5. Converting wind forecast errors into electricity price changes

Previous research shows that increased wind penetration can lower electricity prices. In this section we describe how we convert reduced wind forecast errors into lower electricity prices, using a two-step procedure. In step one, we estimate the percentage reduction in total production costs that accrues due to improved wind forecasts. We begin step two by assuming that electricity sellers employ mark-up pricing (i.e., output prices are proportionately related to the marginal cost of production). We then simply apply the percentage cost reduction to the market price of electricity. Our assumption in step two is supported by general economic theory that says that prices should move with marginal costs, even in monopoly markets.

For the first step, we simply divide the potential cost savings under each HRRR model transition by the total costs of production during the overlap period. Total production costs for the time frames of interest are calculated by summing estimated monthly production costs for each region. These costs are based on i) monthly data from the U.S. Energy Information Administration (EIA), which provides total production, by source, for each state, and ii) national levelized (average) production costs for each source (Table I). Total production costs, by region, are the sum product of the two (Table IV). Note that we do not have the cost data for energy produced by petroleum, biomass and other sources. However, the production cost calculated involves more than 95 percent of the total energy production. Therefore, omitting the cost of the three sources should not affect our estimation critically.

Table IV. Total regional production costs during transition periods (in millions)

	Total Production Costs During Transition Period	
BEA Region	HRRR1 to HRRR2	HRRR2 to HRRR3
New England	9,560	7,825
Mideast	48,367	41,340
Great Lakes	65,967	54,999
Plains	35,507	28,452
Southeast	131,899	105,509
Southwest	63,609	48,275
Rocky Mountain	18,897	13,810
Far West	22,137	17,638
Total	395,943	317,848

5.1 Overprediction

As defined above, *overprediction* errors are those where the 12-hour-ahead wind-speed forecasts are greater than the observed wind-speed. In such cases, the utility has overcommitted to wind power, meaning that it is unable to meet actual demand from their own sources when the electricity is needed. To correct this deficiency, the utility must turn to the spot market to purchase the shortage. The per megawatt costs of such “mistakes” are the difference between the price a utility pays to purchase a megawatt from the spot market and the marginal cost of production for wind (assumed $2/MWh). For example, if the spot market

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price is \$30, then the cost of a one MWh overprediction forecast error is \$28. Equation (3) describes how we estimate potential cost savings in overprediction cases; the index *j* refers to the eight BEA regions.

$$\text{Potential cost savings (over)}_j = |(\textstyle\sum_j \text{HRRR2 error}_j - \sum_j \text{HRRR1 error}_j)|*(\text{spot price}_j - \$2.00) \quad (3)$$

Ideally, equation (3) would incorporate observed daily spot price data; in practice, however, such data is quite limited. Instead, equation (3) is populated by "adjusting" readily available EIA day-ahead (i.e., inter-day) prices for each regional wholesale hub: Mid–C, PJM West, SP15-1 (SP15-2), Palo Verde, Mass Hub, Indiana Hub, NP15, and ERCOT North (see Figure 5).

Figure 5. Locations of Wholesale Hubs

Regarding our adjustment, previous research shows that inter-day prices differ slightly from intraday prices, owing to the fact that day ahead predictions do not always meet real-time electricity demand. For example, Damien et al (2019) compare day ahead market prices with real-time prices in Texas (ERCOT) for the period 2011-2016, estimating daily forecast errors between 1.2 percent and 7.3 percent (these errors reflect risk premiums). In Table V we show the estimated average weighted daily spot prices for each region for the two model overlap periods. These are simply the average daily day-ahead prices for each hub, accounting for forecast errors. Lower bound estimates are the average day-ahead price times 101.2 percent, while upper bound estimates are the average day ahead price times 107.3 percent. In the interest of conservative estimation, we only use the lower-bound spot market price estimates for our analysis.

Table V. The estimated lower- and upper-bound spot market electricity prices

BEA Region	Electricity Hub	HRRR1 versus HRRR2		HRRR2 versus HRRR3	
		lower bound	upper bound	lower bound	upper bound
New England	Mass Hub	\$31.46	\$33.42	\$39.74	\$42.22
Mideast	PJM West	\$32.63	\$34.67	\$37.33	\$39.66
Great Lakes	Indiana Hub	\$29.09	\$30.91	\$36.33	\$38.60
Plains	Indiana Hub	\$29.09	\$30.91	\$36.33	\$38.60
Southeast[a]	PJM West, Indiana Hub	\$30.86	\$32.79	\$36.83	\$39.13
Southwest	ERCOT North, Palo Verde	\$24.88	\$26.43	\$29.54	\$31.39
Rocky Mountain[a]	Indiana Hub	\$29.09	\$30.91	\$36.33	\$38.60
Far West	Mid-C, NP-15, SP-15	\$27.86	\$29.59	\$38.57	\$40.97

a: These regions do not have an associated wholesale hub; we choose the nearest neighbor to approximate the local spot market price.

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In Table VI we provide our savings estimates (equation 3) for each region due to reduced overprediction forecast errors. Overall, had HRRR2 been in place rather than HRRR1, savings due to reduced overprediction errors would have totaled $49.9 million (0.012 percent) during the overlap period.

Table VI. Estimated Savings from More Accurate Wind Forecasting (overprediction) HRRR1 vs HRRR2 and HRRR2 vs HRRR3)

	HRRR1 vs HRRR2 (lower-bound)			HRRR2 vs HRRR3 (lower-bound)		
BEA Region	Savings (in dollars)	Savings as Share of Total Costs	Price Adjustment	Savings (in dollars)	Savings as Share of Total Costs	Price Adjustment
New England	1,286,175	0.0135%	0.999865	238,793	0.0031%	0.999969
Mideast	335,553	0.0007%	0.999993	216,598	0.0005%	0.999995
Great Lakes	8,574,747	0.0130%	0.999870	2,806,232	0.0051%	0.999949
Plains	8,245,311	0.0232%	0.999768	3,720,831	0.0131%	0.999869
Southeast	708,776	0.0005%	0.999995	48,976	0.00005%	0.9999995
Southwest	14,364,192	0.0226%	0.999774	4,335,420	0.0090%	0.999910
Rocky Mountain	3,502,230	0.0185%	0.999815	723,263	0.0052%	0.999948
Far West	12,913,449	0.0583%	0.999417	5,585,121	0.0317%	0.999683
Total	49,930,433	0.0126%		17,675,233	0.0056%	

In Table VI we also show our price adjustments. We begin by showing savings as a share of total costs for each model transition. This is determined by dividing the value of savings shown in the first and fourth data columns of Table VI by values of total energy production costs shown in Table IV. To translate these cost changes into price changes we assume that cost savings are fully passed on to consumers in the form of lower electricity prices. We believe this assumption is reasonable both in real-time pricing markets, and in pre-set rate markets where prices and production costs should be highly correlated in the long-run.

The price adjustment is calculated as 100 percent minus the percentage cost savings. Although these savings are small as a percentage, they are economically important in a $20 trillion economy. Had HRRR3 been in place rather than HRRR2, savings in the overprediction case would have totaled $17.67 million. Please note that the estimated savings in Table VI only represent 15.5 percent of U.S. land-based turbines (reasons for using a subset of turbines are mentioned in Section 4). Therefore, the real savings are greater than the numbers calculated and are discussed in the conclusion.

5.2 Underprediction

In this section, we focus on the cases when the wind blows more than expected but the utilities have already committed to producing electricity from costlier sources. Underprediction results in a financial penalty, as the utility could have used wind power instead of its next lowest cost option. These cost savings are calculated as:

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$$\text{Potential cost savings (under)}_j = (\Sigma_j \text{HRRR2 error}_j - \Sigma_j \text{HRRR1 error}_j)*(\$26.00) \quad (4)$$

with the multiple $26.00 representing the difference between the marginal cost of producing a MWh of electricity from combined cycle gas—the next cheapest option—and wind (per Lazard (2020)). We chose the cheapest non-renewable resource as the next choice for a utility because we lack information on the specific portfolios for each utility. In some cases, a utility may have scheduled a more expensive "next best" option (e.g., coal), as they may not have natural gas as part of its portfolio. As such, these potential cost savings estimates are likely conservative.

Table VII illustrates the cost savings from reduced underprediction due to accurate wind forecasting. Had HRRR2 been in place rather than HRRR1, utilities would have saved $46.6 million. Had HRRR3 been in place rather than HRRR2, savings would have totaled $14.3 million due to reduced overprediction errors in the overlap period. Again, the estimated savings only show the result of 15.5 percent of wind turbines in our study during the overlap period.

Table VII. Estimated Savings from More Accurate Wind Forecasting (Underprediction)

BEA Region	HRRR1 versus HRRR2			HRRR2 versus HRRR3		
	Savings (in dollars)	Savings as Share of Total Costs	Price Adjustment	Savings (in dollars)	Savings as Share of Total Costs	Price Adjustment
New England	$ 230,716	0.0024%	0.999999	$ 165,584	0.0021%	0.999979
Mideast	$ 537,645	0.0011%	0.999989	$ 127,649	0.0003%	0.999997
Great Lakes	$ 1,967,684	0.0030%	0.999970	$ 571,100	0.0010%	0.999990
Plains	$ 10,239,030	0.0288%	0.999712	$ 2,984,752	0.0105%	0.999895
Southeast	$ 49,690	0.00004%	0.9999996	$ 22,669	0.00002%	0.9999998
Southwest	$ 14,288,882	0.0225%	0.999775	$ 4,740,715	0.0098%	0.999902
Rocky Mountain	$ 2,775,561	0.0147%	0.999853	$ 1,029,317	0.0075%	0.999925
Far West	$ 16,479,790	0.0744%	0.999256	$ 4,688,553	0.0266%	0.999734
Total	$ 46,569,000	0.0118%		$ 14,330,338	0.0045%	

6. Eight Regional CGE Models

Computable general equilibrium (CGE) models can represent a national or regional economy, focusing on interactions among producers, households—who are both workers and consumers--and government. CGE models are founded in microeconomic theory and are used to describe how some economic change—either endogenous or exogenous—affects each set of economic actors. For example, a CGE model is useful to examine how electricity price increases affect residential customers, and subsequently businesses, when consumers have less spending power. Important economic indicators of interest include output (i.e., GDP), employment, real household income (i.e., income adjusted for price changes) and tax revenue. For a general review of CGE models, see Partridge and Rickman (2010); for a review of CGE models in energy economics, see Matsumoto and Fujimori, (2019); for model applications in climate change mitigation policies, see Babatunde, Begum and Said (2017).

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Accepted to J. Renew. Sustain. Energy 10.1063/5.0081905

In Cutler et al (2016) and Cutler, Shields and Davies (2018) we provide the particulars on the CGE model we use in our work, but we provide a brief overview here. The economics data collected is organized in a social accounting matrix (SAM) which describes the flow of economic activity between households, firms and the relevant government entity. For the commercial sectors, we use the two-digit North American Industry Classification System (NAICS) groups that consists of manufacturing, construction, retail, etc. The model consists of nine household groups, delineated by annual income. The lowest household group earns less than $10,000 annually and the highest group earns more than $150,000 annually.

The basic logic of the CGE model is that the commercial sectors employ workers, the workers bring the labor income to the households, and the households buy goods and services. The CGE model is calibrated when the model can exactly reproduce the data in the SAM and then simulations can be computed. The CGE model is identical for each BEA region but the SAMs organized for each region differ. We use the General Algebraic Modeling System (GAMS) proprietary software program to calibrate the model and run simulations. In the context of this paper, lower electricity prices due to the improved wind forecasts reduce the consumer price index for each household, resulting in an increase in real household income and thus an increase in household expenditures.

In the U.S., the number of utility-scale wind energy installations has significantly increased, but the development differs across the country, based on the regional characteristics (e.g., the quality on-shore wind power resources (Brown et al. (2012)). To allow for regional heterogeneity, we decompose the country along the lines of eight sub-national Bureau of Economic (BEA) regions (Figure 3) and construct individual CGE models for each. (In Table I we provide a summary of economic statistics important to our models.) The Southeast has the nation's largest share of total employment and real GDP levels, the Far West has the second largest, while the Rocky Mountain region has the smallest.

The model's consideration of electricity prices warrants particular attention, so we describe it here. On the production side, we assume profit maximizing firms operate in perfectly competitive output markets. Their constant returns to scale production technology employs a variety of inputs, including labor and capital, and intermediate inputs. The level of output and the relative input prices and their productivity affect the demand for each input. Electricity is one important input, and firms are sensitive to its price. Accordingly, lower electricity prices reduce the marginal cost of production, shifting a firm's (industry's) supply curve to the right. This increases firm output and lowers the market price of its good.

There are two important effects. First, output increases lead to additional labor demand, providing households with additional jobs and wage income. Second, the economy's price level (CPI) falls, with lower residential electricity prices leading to higher real household income. The effects on firms are reflected in the following equation:

$$V_I = V0_I \Pi_J (P_J TT_J\ (1 + \Sigma_{GS} TAUC_{GS,J}) / (P0_J (1 + \Sigma_{GS} TAUQ_{GS,J})^{DELTA_{J,I}} \qquad (5)$$

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Equation (5) describes the demand for intermediate inputs (V_I), where *I* is a matrix and it represents all commercial sectors (*J* is the transpose of *I*), and *GS* represents all government sectors. P_J is output prices. $TAUC_{GS,I}$ and $TAUQ_{GS,I}$ are sales and property tax rates, and DELTA reflects own and cross price elasticities and Π_J is the product operator. Any variable with a *0* at the end is a baseline value. For simulation purposes, the parameter TT_I is a vector of ones in the base data, and is changed to represent exogenous electricity price changes. When TT is lowered, V_I increases.

Price change effects on households are reflected in the following two equations:

$$CPI_H = \Sigma_I P_I\, TT_I(1 + \Sigma_{GS} TAUC_{GS,I})CH_{I,H} / \Sigma_I(P0_I(1 + \Sigma_{GS} TAUQ_{GS,I}))CH_{I,H} \tag{6}$$

$$CH_{I,H} = CH0_{I,H}((YD_H/YD0_H)/(CPI_H/CPI0_H))^{BETA_{I,H}}\, \Pi_J\, (P_J TT_J(1 + \Sigma_{GS} TAUC_{GS,J})/ (P0_J\,(1 + \Sigma_{GS} TAUQ_{GS,J}))^{LAMBDA_{J,I}} \tag{7}$$

In equation (6) we show the impacts of electricity changes on economy wide price levels (CPI_H). The index *H* represents households (distinguished by annual income), while $CH_{I,H}$ is household consumption across sectors and households. Here electricity price changes once again affect the economy price level through changes in *TT*.

In equation (7) we see changes in real household consumption. Here, *YD* is real disposable income. *Lambda* is a square matrix of own and cross price elasticities. Although output demand equations are not specified here, it is important to keep in mind that changes in (7) affect local producers. Here, lower electricity prices affect consumption both directly, through changes to TT, and indirectly, through changes in the CPI (per equation 6).

7. Select economic impacts of (potential) reductions in electricity prices facilitated by improved wind forecasts

7.1 Setting up the simulations

Previously, Kat, Paltsev and Yuan (2018) and Nong (2018) constructed detailed energy sectors to examine the change in energy prices as significant transitions occur out of fossil fuels and into renewables. Because our analysis emphasizes a much smaller adjustment in the use of wind, there is no need for detailed modeling of individual production technologies. Instead, we simply scale electricity prices. We do this by changing $TT_{ELECTRICITY}$ to less than unity, based on the estimated cost savings shown in Tables VII and VIII. For example, in New England for the transition from HRRR1 to HRRR2, TT is changed from 100 percent to 99.9976 percent. There is some nuance of note--$P_{ELECTRICITY}$ is an endogenous variable, but $TT_{ELECTRICITY}$ scales down the price paid by households and firms.

7.2 Simulation results

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In our CGE model, we can report impacts on regional GDP and employment, household consumption, real household income and a myriad of other variables. For this paper, we report the impacts on real household income for two reasons. First, improved wind forecast accuracy reduces electricity prices and the consumer price index (CPI) faced by households. A reduced CPI results in current levels of household income to be able to purchase more goods and services which reflects an increase in real household income. This channel is the primary factor in the CGE model reflecting lower electricity prices. Second, focusing on household income provides a specific metric describing changes in household welfare.

Also tied to increases in real household income is an increase in nominal household income which is the basis for changes in federal income tax revenue collected. This metric provides context of how investments in HRRR result in gains in federal government revenue.

In Table VIII we provide simulated impacts of the price reductions resulting from lower overprediction errors. For the HRRR1-to-HRRR2 case, the aggregate increase in real household income across the eight BEA regions is $17.15 million, with the Far West benefiting by the largest amount ($8.1 million). The gains from the HRRR2-to-HRRR3 case are smaller as the improvement in forecast accuracy is relatively smaller between HRRR2 and HRRR3 than between HRRR1 and HRRR2. A similar comparison is arrived at for federal income tax revenue. Here, had HRRR2 been in place rather than HRRR1, reduced overprediction errors would have increased total federal tax revenue by $1.57 million during the overlap period.

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Table VIII. Estimated Savings from More Accurate Wind Forecasting (Overprediction)

BEA region	HRRR1 versus HRRR2		HRRR2 versus HRRR3	
	Household Income (millions of $)	Federal Income Tax Revenue (millions of $)	Household Income (millions of $)	Federal Income Tax Revenue (millions of $)
New England	$1.91	$0.13	$0.11	$0.01
Mideast	0.10	0.01	0.15	0.01
Great Lakes	1.93	0.11	0.76	0.07
Plains	1.68	0.10	0.95	0.10
Southeast	0.14	0.00	0.01	0.00
Southwest	2.81	0.04	1.12	0.05
Rocky Mountain	0.48	0.14	0.18	0.01
Far West	8.10	0.39	4.38	0.44
Total	17.15	0.93	7.65	0.69

In Table IX we present the results for the underprediction cases. During the transition period from HRRR1-to-HRRR2 household income would have been $16.7 million higher had the newer model been in use, supporting an additional $740,000 in federal tax revenue. During the transition from HRRR2 to HRRR3, gains to household income due to reduced underprediction errors would have totaled $18.25 million, and supported $1.37 million in additional federal tax revenue. The savings reported here are very small relative to the overall size of the regional economies. Thus, the real household impacts are small, but the aggregate impacts are notable.

Note that the length of HRRR1-versus-HRRR2 period differs from the length of HRRR2-versus-HRRR3 period. Also, since the two overlap periods were not observed at the same time, the CGE results for those overlap periods cannot be compared directly.

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Table IX. Estimated Savings from More Accurate Wind Forecasting (Underprediction)

BEA Region	HRRR1 versus HRRR2		HRRR2 versus HRRR3	
	Household Income (millions of $)	Federal Income Tax Revenue (millions of $)	Household Income (millions of $)	Federal Income Tax Revenue (millions of $)
New England	0.37	0.02	0.25	0.02
Mideast	0.16	0.01	0.45	0.06
Great Lakes	0.44	0.03	0.52	0.05
Plains	2.09	0.12	3.09	0.35
Southeast	0.01	0.00	0.02	0.00
Southwest	2.80	0.04	5.18	0.15
Rocky Mountain	0.51	0.01	1.08	0.06
Far West	10.33	0.50	7.65	0.68
Total	16.70	0.74	18.25	1.37

Extrapolating the sample to the CONUS

It is important to point out that we only evaluate approximately 13 percent of the installed wind capacity in the U.S. (turbines located within 20km of METAR stations), and our reported cost savings are based on this sample. Recall from Table II, however, that there were approximately 54,000 land-based turbines in the CONUS during the test period, while our sample consists of approximately 8,400 turbines. This is a large sample of the population in a statistical sense. Thus, there is a desire to estimate the economic impact of the improved forecasts over the entire land-based turbine dataset.

Figures 2a and 2b show the population and sample of turbines across the country, respectively. Visual inspection suggests that the sample shown in Figure 2b appears to represent the entire population well, except for the Columbia Gorge along the Washington-Oregon border. There is often significant wind energy resource in complex terrain, such as the Columbian Gorge (e.g., Shaw et al. 2019), so underrepresenting these regions with our subsampling adds additional uncertainty when scaling the results from the subset of 13% of the turbines to all of them.

If we assume that the sample is representative of the population, we can estimate the overall economic impacts by scaling up our results. To do so, we use the ratio of turbine capacity within the 20km distance from the METAR stations to total regional turbine capacity (Table II) to calculate the relative size of the sample for each of the eight BEA regions. The ratios were as low as 4.2 percent for the Mideast and as high as 24.7 percent for the Far West.

To scale-up our results to the population of CONUS turbines we multiplied the inverse of these ratios by the values for real household income and federal income tax revenue from Tables 9 and 10 (over- and under-prediction) to estimate the potential gains from updates to the HRRR system for the entire country. For the HRRR1/HRRR2 overlap period, the potential gains to real

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household income are $208.1 million, while federal income tax revenue would have potentially increased by $10.3 million.

For the HRRR2/HRRR3 period, the use of HRRR3 benefits households for the over-and underprediction cases include a potential $26 million increase in real household income for the turbines in the sample. The scaling factor results in potential increases in real household income and federal income tax revenues of $176.7 and $13.5 million, respectively, over the 11-month time period when the two versions were run simultaneously.

8. Summary and conclusions

The forecasts from the HRRR--which is run operationally by the National Weather Service--provides foundational information used by the energy community in their day-ahead decision-making process. This study demonstrates how the continued development of the HRRR has a large economic impact for the energy community, and provides an important impetus to continue the development of storm-scale models like the HRRR for renewable energy applications. We forward a multidisciplinary approach to estimate the economic value of improved wind-speed forecasts on the integration of wind-generated power into the electric grid. First, we organize daily wind forecasts for overlapping periods from different versions of the HRRR weather prediction model system. We compare forecasts to actual wind-speeds recorded by METAR stations across the CONUS to calculate forecast errors. Actual and forecasted wind speeds are inserted into equations to reflect wind-generated electricity that utilities use to develop the cost minimizing optimal combination of all sources of electricity (fossil fuels, hydro, nuclear). Reductions in electricity prices are fed into eight BEA regional CGE models to estimate the economic impact of improved forecast accuracy.

Our results show investments in improved wind-speed forecasts provide valuable positive impacts on economic activity. When comparing the HRRR2 (test model) to HRRR1 (operational), the combined impact of the over-and underprediction cases results in an approximately $34 million potential increase in real household income. Given that we are only examining 13 percent of the turbines in the U.S., our estimates are likely biased downward. Our proposed scaling method indicates that the gains from HRRR2 and HRRR3 are close to $200 million.

The development of the HRRR system is also important in forecasting precipitation, temperature, and cloud cover. Hartman et al. (2021) estimates the savings in commuting time across the eight BEA regions with respect to improved HRRR precipitation forecasts and finds the economic savings is another $200 million. There are potentially other economic savings that can be accrued from the HRRR wind forecasts such as in the airline industry. Having improved wind forecasts permits the FAA to improve airline routes that minimize the impacts of headwinds in airline travel. Savings in travel time and fuel costs could be substantial. Another application is relying on improved precipitation forecasts that influences decisions on outdoor sporting events or family functions.

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Our research opens several avenues for future work. We are currently organizing data regarding changes in cloud cover forecast accuracy for the HRRR4 system in order to evaluate more efficient use of solar energy in producing electricity. Future HRRR development also seeks to better model wind ramps (i.e., the rapid change in the wind speed over a short time period (e.g., 1-2 hours)). Unanticipated wind ramps can result in significant over- or under-estimation of the wind resource. We have shown in this paper that these two scenarios both have negative economic impacts on the utility. Thus, the utility greatly desires weather forecasts that indicate that there will be a wind ramp in the day-ahead forecast so that it can plan for the event. The analysis in this paper did not directly address wind ramps; they were included with the rest of the base statistics performed. We are currently looking at the economic impacts of better forecasting wind ramp events, which will be the subject of a future paper.

More generally, there is a need for better understanding the impacts of increased wind and solar penetration on U.S. electricity markets, which will help validate our work. In this paper we examine a simple price change for electricity, driven by predicted savings in production costs. Although several papers have explored the effects of wind forecasts on electricity prices in Europe, this has not been done for the U.S., to the best of our knowledge. Future work should examine the extent to which the lessons learned in Europe apply to the U.S. One stumbling block is that it is difficult to obtain hourly price data for the assorted U.S. wholesale spot markets.

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Acknowledgments

We would like to thank Kevin Kelleher and Jenn Mahoney, the former and current Directors of the NOAA Global Systems Laboratory, for their encouragement and support of this work. This project was partially supported by the NOAA Atmospheric Science for Renewable Energy (ASRE) Program.

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Author Contributions

Author	Contribution
Cutler	All
Hill	Funding acquisition, conceptualization
Lu	Data curation, writing and editing
Jeon	Data curation, writing and editing
Hartman	Data curation, writing and editing
Hu	Data curation
Shields	All
Turner	Conceptualization, methodology, validation, investigation, writing and editing

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Figure 1. The decision-maker's problem

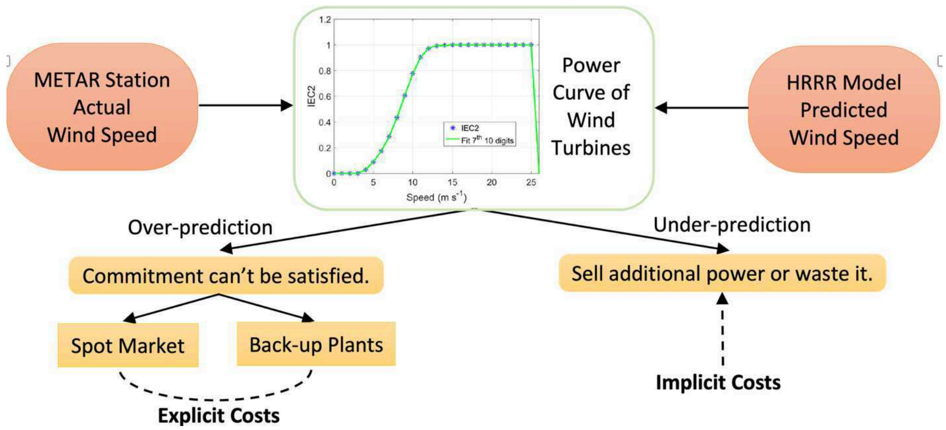

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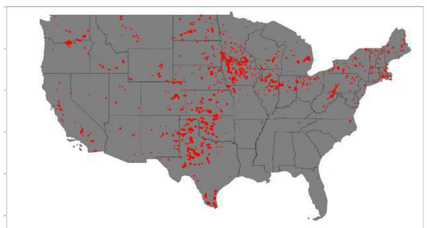
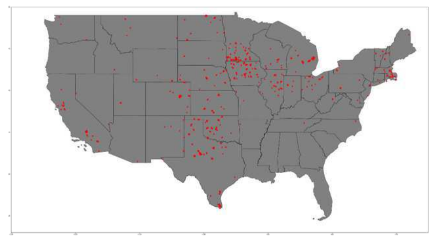
Figure 2a. All land-based wind turbines, 2019   Figure 2b. Wind turbines within 20 km buffer





Source: Image rendered in GIS using 2018 US Geological Survey wind turbine location, and capacity along with 2018 METAR station coordinates.

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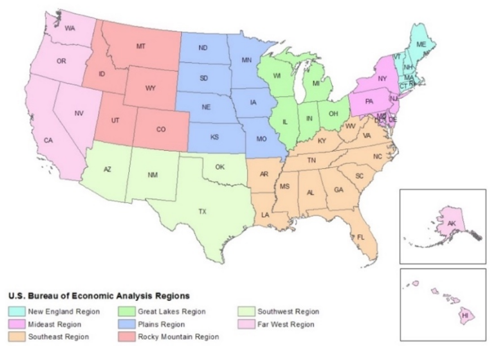
Figure 3: The Eight Bureau of Economic Analysis Region



Source: BEA.gov

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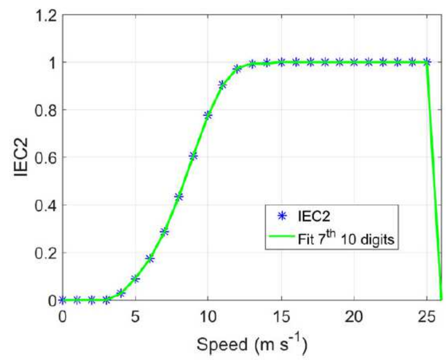
Figure 4. Normalized Power Curve for an average of several International Electrotechnical Commission (IEC) class 2 wind turbines.



Source: Wilczak (2019)

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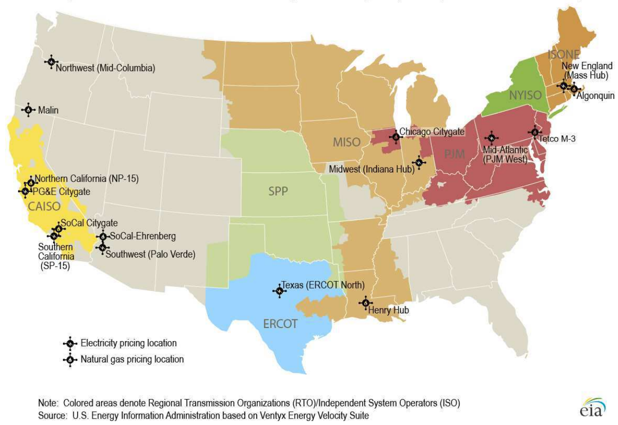
Figure 5. Locations of Wholesale Hubs

Selected price hub locations for wholesale electricity and natural gas reported by Intercontinental Exchange



Note: Colored areas denote Regional Transmission Organizations (RTO)/Independent System Operators (ISO)
Source: U.S. Energy Information Administration based on Ventyx Energy Velocity Suite