

Spatial and temporal variation of offshore wind power and its value along the Central California Coast

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Abstract

The analysis of the spatiotemporal variability of wind power remains limited during the planning stage of an offshore wind farm. This study provides a framework to investigate how offshore wind power varies along the Central California Coast over diurnal and seasonal time scales, which is critical for reliability and functionality of the grid system. We find that offshore wind power in this region peaks during evening hours across all seasons and maximizes in spring and summer. The timing of peak offshore wind power production better aligns with that of peak demand across California than solar and land-based wind power production, highlighting its potential to fill the supply gap when demand is high and power production from other renewable energy sources is low. We further assess the value of offshore wind power using demand-based and wholesale market metrics. Both metrics indicate high potential value of offshore wind power over most areas in this region. Finally, we show that the estimate of power production is significantly biased when using mean wind speeds that do not account for temporal variability, leading to potentially inaccurate predictions about locations that are expected to produce the most power. These results reiterate the importance in considering spatiotemporal variability in wind power for accurately calculating the value of offshore wind development.

1. Introduction

Renewable energy production has accelerated in recent years, representing a substantial proportion of broader energy portfolios (Graabak and Korpås 2016). Offshore wind energy in particular has grown significantly because it offers several advantages over land-based winds and solar energy, including stronger and more consistent winds over the ocean, and less likely to impact other land-use activities (Sun *et al* 2012). To date, most wind farms are installed in relatively shallow waters (<50 m) using fixed foundations (Musial *et al* 2016). However, technology is rapidly advancing, and floating wind farms are being deployed worldwide in deeper waters (e.g., 120 m depth) farther from shore (Global Wind Energy Council GWEC 2017). In 2017, the first demonstration-scale floating offshore wind farm (Hywind) began operation off of the Scotland coast (Equinor 2018). Several other deep, offshore floating wind farms are under development or in the planning phase in other regions of the world (Global Wind Energy Council GWEC 2017), including in the United States off the California Coast (Bureau of Ocean Energy Management BOEM 2019).

To guide the evaluation and optimal planning of offshore wind energy, it is critical to consider both spatial and temporal variability in energy production across a range of scales (Lee *et al* 2018). Offshore winds, such as

along the California Coast, vary on interannual, seasonal (peaks in the spring), synoptic, and daily time scales (peaks in the early evening), in addition to being spatially variable (Walter *et al* 2018, Wang *et al* 2019). This spatiotemporal variability becomes critical in estimating power production since the power produced by a turbine depends on the cube of the wind speed, a nonlinear relationship that amplifies the effects of small changes in wind speed. Moreover, temporal variability of wind power impacts its value within electricity markets (Fripp and Wiser 2008). For example, the economic value of offshore wind production along the East Coast of the United States varies with time and space, driven by electricity pricing and production fluctuations (Mills *et al* 2018). The value of offshore wind to a broader energy portfolio (including both renewable and non-renewable sources) is driven by both the seasonal and daily variability in power production from wind and the other sources, as well as seasonal and daily variations in grid demand for power (Sinden 2007, Fripp and Wiser 2008, Wiser *et al* 2017). Alignment between production and demand over seasonal and daily time scales is thus critical for reliability and functionality of the grid system (Shaner *et al* 2018). However, these factors are not specifically considered by previous studies when assessing the value of power produced (e.g. Mills *et al* 2018 and references therein).

Despite its importance, areas for offshore wind commercial development are commonly identified based on annual wind speed, without considering temporal variability of the wind (Marine Scotland Science 2018). The approach of averaging higher-frequency temporal variability has the potential to lead to significantly biased power estimates (Karnauskas *et al* 2018). Considering the role of seasonal and daily variations in power production in the grid system, spatial patterns of offshore wind speed across seasonal and daily time scales are documented by Wang *et al* (2019); however, realistic power generation estimates are missing, making it difficult to assess their value. Previous studies that consider variations in offshore wind power generation either considered the spatial patterns of temporal variability on time scales longer than the diurnal cycle (e.g. Hong and Möller 2011, Dvorak *et al* 2012, He and Kammen 2014) or the daily and seasonal variability subjected to specific spatial points like buoy sites or spatial aggregation over a domain (e.g. Stoutenburg *et al* 2010, Musial *et al* 2016). As more offshore wind projects are proposed, a comprehensive analysis of offshore wind power patterns over spatial, diurnal, and seasonal scales is needed.

This study aims to assess the spatial and temporal patterns of potential offshore wind power production along the Central California Coast. This region is ideal for offshore wind development because wind speeds are generally strong (albeit highly variable), there are existing nearby connections on land to the state's electrical grid, much of the coast is outside of National Marine Sanctuaries where disturbance to the seabed is prohibited, and the region is between major population centers with high power demand in Northern and Southern California (see figure S1 is available online at stacks.iop.org/ERC/1/121001/mmedia for geographic information/details). Consequently, the Central Coast contains two of three sites proposed by the Bureau of Ocean Energy Management (BOEM), the agency that manages lease requests in US federal waters, for offshore wind development in California (Bureau of Ocean Energy Management BOEM 2019). Moreover, California has enacted laws mandating ambitious goals of providing 60% renewable energy by 2030 and 100% by 2045 (SB-100, California Renewables Portfolio Standard Program). These laws will require California to diversify its renewable energy portfolio, and offshore wind will likely be a part of this energy mix. A detailed study of the variability of offshore wind power will improve the accuracy of power estimates to inform decision makers and also provide a framework to assess power generation and its compatibility to meet grid demand with other energy resources in future projects.

This study shows how power production and its value varies seasonally and daily along the Central California Coast, and further highlights the added benefit of considering temporal variation in wind speeds by comparing power production estimates from hourly wind speed data with those calculated using annual mean wind speeds. We compare the diurnal and seasonal patterns of offshore wind power production to diurnal and seasonal patterns of power demand across the state of California, as well as to power production from other renewables such as solar and land-based wind. We use the relative alignment between the power production of the various renewables and demand to calculate a demand-based value. Finally, we consider daily and seasonal fluctuations in recent wholesale prices of power to generate an estimate of the wholesale dollar value of power produced. The framework by which we assess spatial and temporal patterns in offshore wind energy production and its value can be applied to other regions where offshore wind is being considered.

2. Data

WIND Toolkit is a simulated historic dataset for wind power application developed by the National Renewable Energy Laboratory (<https://www.nrel.gov/grid/wind-toolkit.html>). The model is based on a Weather Research Forecast regional model, details of which can be found in Draxl *et al* (2015a, 2015b). The model's spatial resolution is 2 km and its availability spans from 2007 to 2013. WIND Toolkit provides hourly winds from 10 m

to 160 m above sea level at approximately 20 m intervals, as well as other meteorological data (<https://github.com/NREL/hsds-examples>). WIND Toolkit's 10 m wind speed and direction data were validated against buoy measurements along the Central California Coast, and WIND Toolkit was determined to be the best dataset for offshore wind energy production estimates for the region (Wang *et al* 2019).

Given the lack of observational datasets at altitude with an appropriate spatiotemporal resolution to assess error metrics, we assume that model performance aloft (i.e., at hub height) is comparable to the model performance near ocean surface (see Wang *et al* 2019 for details on model validation). Because the WIND Toolkit does not provide hub-height air density, we used the North American Regional Reanalysis (NARR; <https://www.esrl.noaa.gov/psd>), which is available from the surface to top of the atmosphere over three decades and provides needed parameters for air density calculations, to help estimate hub-height air density (supplemental material).

For assessing electricity demand and power generation from other renewable sources, we obtained hourly-averaged historic data of power generation from every energy resource in California assessed by the California Independent System Operator (CAISO) (<http://www.aiso.com/market/Pages/ReportsBulletins/RenewablesReporting.aspx>) (supplemental material). We calculated hourly demand by summing all of the sources of power production.

CAISO data also allows us to assess patterns of energy production from other renewables, including land-based wind, which typically have hub heights between 80 m and 100 m high (WINDExchange 2019), and solar production. Here, solar production includes both photovoltaic (PV) and thermal generation; they are grouped together in the CAISO data even though PV solar provides the vast majority of solar energy production. We note that there is a positive trend of solar production since 2012 due to growing development of commercial and residential PV solar in California (figure S2). In comparison, development of land-based wind facilities has been relatively modest and no long-term trend is found for electricity demand in the state (figure S2). The pronounced trend in solar production leads to biases when considering seasonal variations. To reduce long-term trends and to focus on current renewable production and demand, we use only the most recent year of CAISO data, 2018.

3. Methods

3.1. Wind power production calculation

Although WIND Toolkit provides power estimates using a generic power curve with a rated power of 2.0 MW (e.g., King *et al* 2014), this particular power curve does not capture recent advancements in turbine technology for offshore wind (Musial *et al* 2016). For example, the proposed wind farms in California plan to use at least 10 MW turbines (Trident Winds 2016). Therefore, we estimated power using the power curve of the 10 MW turbine with the 125 m hub height from Musial *et al* (2016) (figure S3), which is the largest rated wind turbine in their study. The temporal and spatial patterns, as well as major conclusions, were similar using the 8 MW turbine (not shown).

We estimate wind speeds at the hub height of the 10 MW using a power law interpolation following Draxl *et al* (2015a). We calculated the power law exponent at each spatial point each hour using wind speeds at two adjacent altitudes (120 m and 140 m), and then obtained the hub-height wind speed with the calculated power law exponent and the 120 m wind speed. Considering temporal and spatial changes in the exponent yields more accurate wind speeds than using a constant exponent value (Holt and Wang 2012).

To incorporate air density variations, we estimated air density at hub height using the NARR data and then used hub-height air density with the interpolated wind speed at hub height and the turbine reference density to obtain an effective wind speed at hub height following International Electrotechnical Commission IEC (2005) (supplemental material). With the effective wind speed at hub height, we estimated power production using the 10 MW power curve.

3.2. Calculation of composite averages and demand-based relative value

To assess the daily and seasonal patterns of offshore wind, land-based wind, and solar power production, as well as power demand, we calculated composite averages of power ($power_{ij}$) for each respective source (offshore wind, onshore wind, and solar) and demand ($demand_{ij}$) over all hours (i) in a given month (j) (i.e., averages fixed to 24 h over each of the 12 months). For offshore wind, we calculated these composite averages at every spatial point (2 km resolution) in our study domain. For the land-based wind, solar, and grid demand, we calculated this for the single time-series aggregated across the state of California. Note that the CAISO data (2018) and the WIND Toolkit data (2007–2013) are available during different time periods, but we assume that the offshore wind field composite averages created using the seven years of available data are representative of typical offshore wind conditions and are less impacted by interannual variability.

We develop a demand-based measure of relative energy need, which quantifies the relative alignment of composite averages of production with those of demand, while still capturing seasonal and daily variability. This method does not consider absolute magnitudes of the various production sources and demand, but rather enables us to compare the temporal alignment between production and demand for different sources of production. This is particularly applicable in areas like the Central California Coast, where there is currently no offshore wind power production so the magnitude of production is unknown, and yet stakeholders need estimates of the value of offshore wind projects to evaluate their feasibility. To calculate the demand-based relative values, we first normalized composite averages of power (\overline{power}_{ij}) and demand (\overline{demand}_{ij}) by dividing each respective curve by the maximum over all months and hours of each respective curve, such that each respective curve varies between 0 and 1. Demand-based relative values at a given hour (i) and month (j) are then obtained by multiplying the respective normalized power by the normalized demand:

$$value_{ij} = \overline{power}_{ij} \times \overline{demand}_{ij}. \quad (1)$$

When a normalized production composite aligns with the normalized demand composite at a given time of the day and month, then the demand-based relative value is high, and vice-versa.

3.3. Calculation of wholesale value

To assess the monetary value of offshore wind power, we match wholesale energy prices with the average hourly offshore wind power production over the seven-year dataset at every spatial point. Wholesale prices are based on hourly day-ahead prices for the ZP 26 Central California hub in 2018 from CAISO. We rely on 2018 wholesale prices for the most recent complete year of price data available. Given the recent trend in solar power development in California, diurnal wholesale prices have changed considerably in recent years towards a pattern with a more pronounced trough in mid-day energy prices, which makes 2018 prices appropriate for measuring the current value of offshore wind energy.

4. Results

4.1. Spatiotemporal variations in offshore wind power production

Offshore wind production along the Central California Coast peaks during the evening hours across all seasons and shows seasonal maximums during the spring and summer (figure 1). This daily and seasonal variability is consistent with that of wind speeds at hub height (figure 1, figure S4). Spatial patterns show lower production close to the coastline where wind speeds are lower and higher production further from the coastline and in the region around Point Conception (cf Fewings *et al* 2016).

4.2. Impact of using mean wind speed on production estimates

We average hourly power production at each spatial point to examine spatial variation in mean power production (figure 2(a)); the magnitude of spatial variation at a given point in time is relatively modest compared to hourly or seasonal variation (figures 1 and 2(a)). Although mean power production provides a general picture of power potential, the conventional approach to identify areas with abundant wind resources is based on mean wind speed, not energy production. To illustrate the impact of using mean wind speed, instead of a time series of wind speed, for estimating power production, we compared the power production using annual mean wind speed with the mean power production estimated from hourly wind speed (cf figures 2(b) and (a)). We found the conventional approach to underestimate power production by over 1 MW near the shore (figure 2(c)), which is approximately 10% to 50% lower than the mean power production calculated from hourly wind speed (figure 2(d)). Further offshore, the conventional approach overestimates power production by as much as 0.5 MW (~30% higher than the mean power production calculated from hourly wind speed).

The bias from using mean wind speed is magnified when the power production using annual mean wind speed is compared to averaged power production estimated from hourly wind speed during different hours and seasons (figure S5). These results indicate that the mean wind speed is unable to characterize temporal variability of wind power production and can lead to both positive and negative biases in mean power estimates.

4.3. Temporal variation in electricity demand and production from renewable resources

To investigate the relationship between the temporal variability of offshore wind power, and other renewable sources, in relation to the temporal variability of demand, we displayed hourly composite averages in each month for electricity demand (black), production for statewide solar (red), statewide land-based wind (green), and offshore wind at the spatial point closest to the buoy site 46028 (blue) (figure 3). The specific point is chosen for demonstration due to its proximity to the area where industry is pursuing development. The daily and seasonal patterns of wind power generation at this point are consistent with those aggregated over the entire

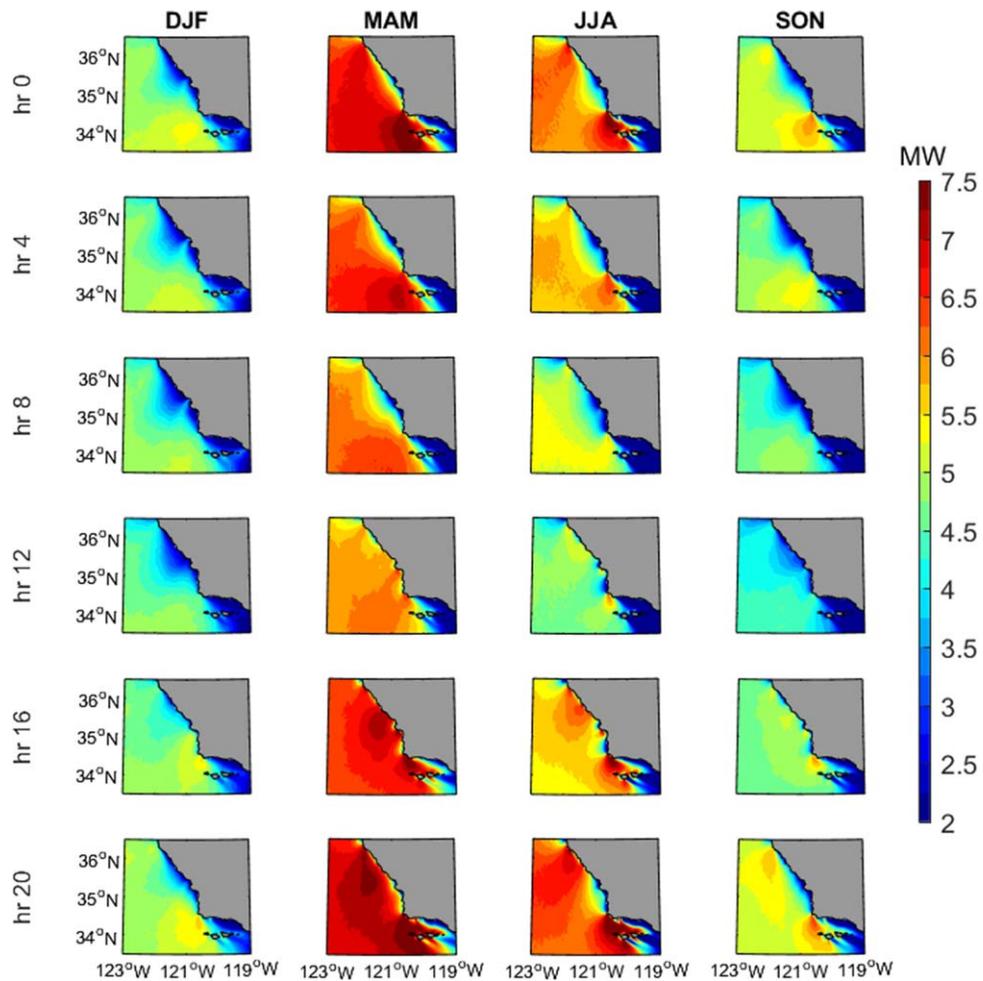


Figure 1. Averages of the hourly wind production based on the NREL's 10 MW wind turbine from WIND Toolkit over 2007–2013 at different hours and four seasons. Each column from the left to the right represents winter (December-January-February, DJF), spring (March-April-May, MAM), summer (June-July-August, JJA), and fall (September-October-November, SON). Each row from the top to the bottom represents 00 PST, 04 PST, 08 PST, 12 PST, 16 PST, and 20 PST.

study domain of interest (figure S6). Each respective quantity has unique diurnal cycles, which evolve throughout the year (figure 3). Overall, electricity demand is higher in the summer than the winter due to more air-conditioner use on high temperature days (California Energy Commission CEC 2017).

While there are two high demand periods during the day in winter months, one that is relatively lower at around 8:00 am and a second that is relatively higher at around 7:00 pm, there is one peak around 6:00 pm in summer months (figure 3). Like electricity demand, solar and land-based wind generation have their seasonal peak in the summer. For diurnal cycles, solar and land-based wind generation show opposite behaviors, particularly during non-winter months: solar peaks around noon, whereas land-based wind peaks around midnight. Although solar and land-based wind are important contributors to supply electricity at different times of the day, neither of them peak in generation at a time of day coincident with peaks in demand. Conversely, offshore wind power generation aligns well with daily peak demand (i.e., daily peak at 7–8:00 pm, depending on the month). Note that the timing of daily peak offshore wind generation coincides with the evening hours when net demand (demand minus wind and solar production) ramps up quickly (figure S7), highlighting the potential of offshore wind generation to accommodate high ramp rates and reduce solar curtailment.

4.4. Temporal variation in demand-based value of offshore wind production

The value of a power source depends not only on its production, but also by the relationship between power produced and electricity demand (Sinden 2007). To factor in temporal correspondence between power and demand, we calculate a demand-based relative value of energy at each hour in each month for each respective renewable energy source. This approach illustrates the relative value of power produced at various times during the day by giving more weight to power produced during high demand periods, and vice versa.

The demand-based relative value of each of the renewables considered showed a different daily and monthly pattern compared to its power production composite average (cf figures 3 and 4). For example, peak solar

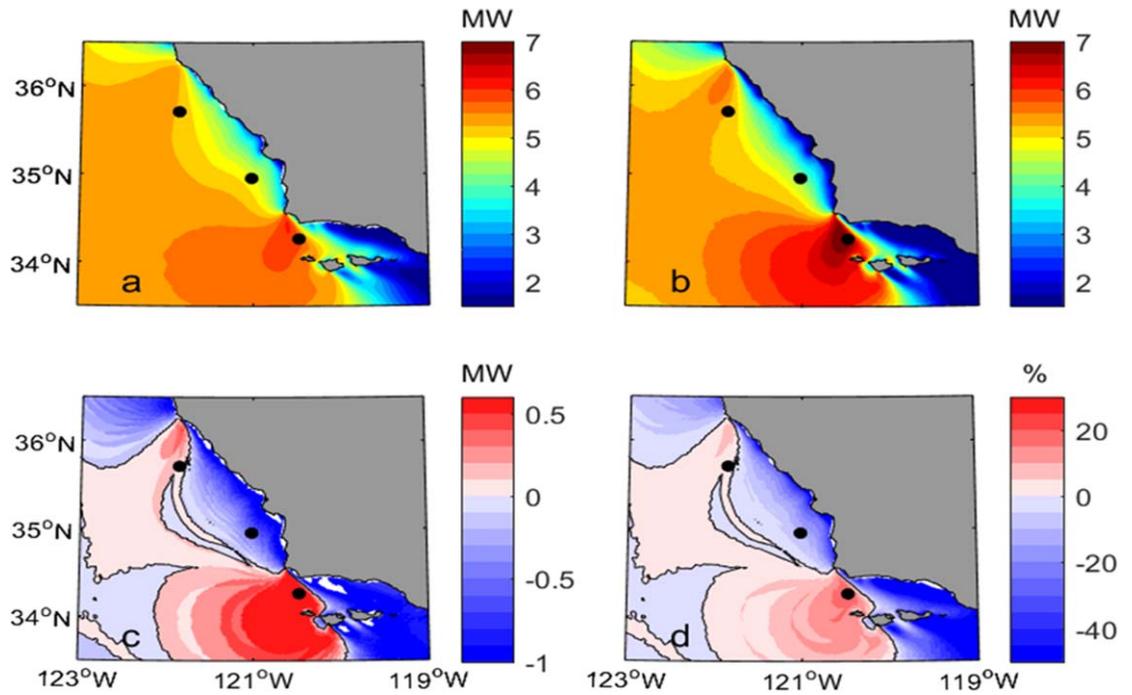


Figure 2. (a) Mean wind power production using hourly power production over the 2007–2013 period. (b) Wind power production calculated from mean wind speeds over the same period as (a). Both productions are based on the NREL’s 10-MW power curve. (c) The absolute difference between (b) and (a) $(b)-(a)$ in which 0 MW is marked by black contours. (d) The percent difference between (b) and (a) in relation to (a) $[(b)-(a)/a]$ in which 0% is marked by black contours. Local buoy sites are displayed by black circles in all plots.

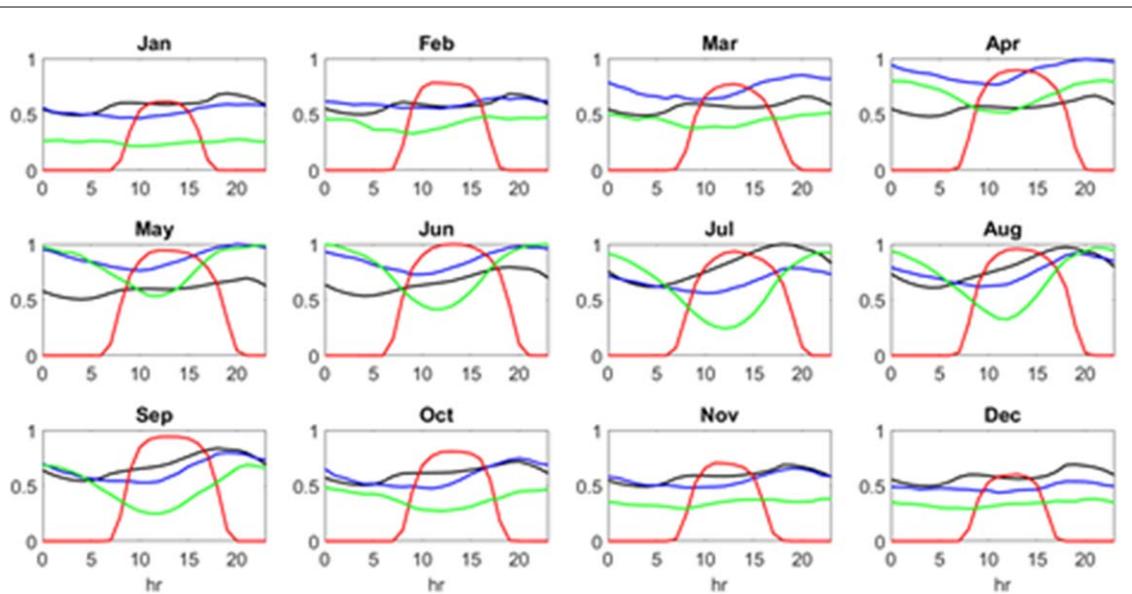


Figure 3. Daily composite averages of hourly California electricity demand (black), solar production (red), onshore wind production (green), and offshore wind production near 46028 (blue) in each month (see text for details). Composite averages are normalized by the maximum over all months and hours of each respective curve. Data from CAISO (<http://www.caiso.com/market/Pages/ReportsBulletins/RenewablesReporting.aspx>).

generation occurs in June at noon, whereas its peak demand-based value occurs in July/August at 4 pm. Land-based wind also shifts, from peak generation in June at midnight to peak value in August at 10 pm. Offshore wind also shifts, but mainly seasonally, from the spring to the summer. Of the three renewable energy sources considered, offshore wind demonstrates superior temporal alignment with demand and hence has the largest demand-based value.

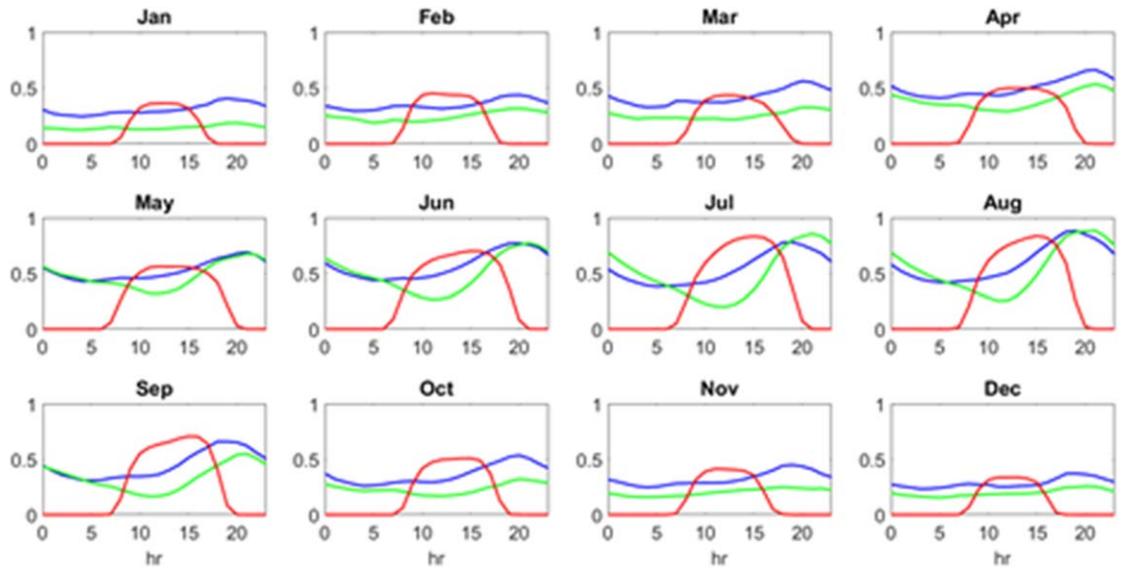


Figure 4. Hourly demand-based values (equation (1)) of solar production (red), onshore wind production (green), and offshore wind production near 46028 (blue) in each month.

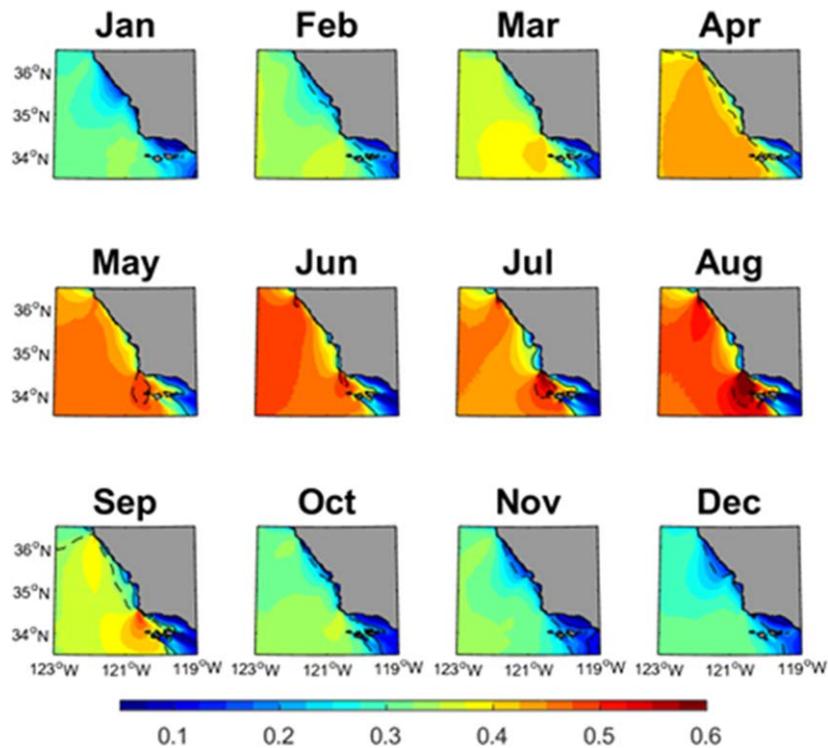
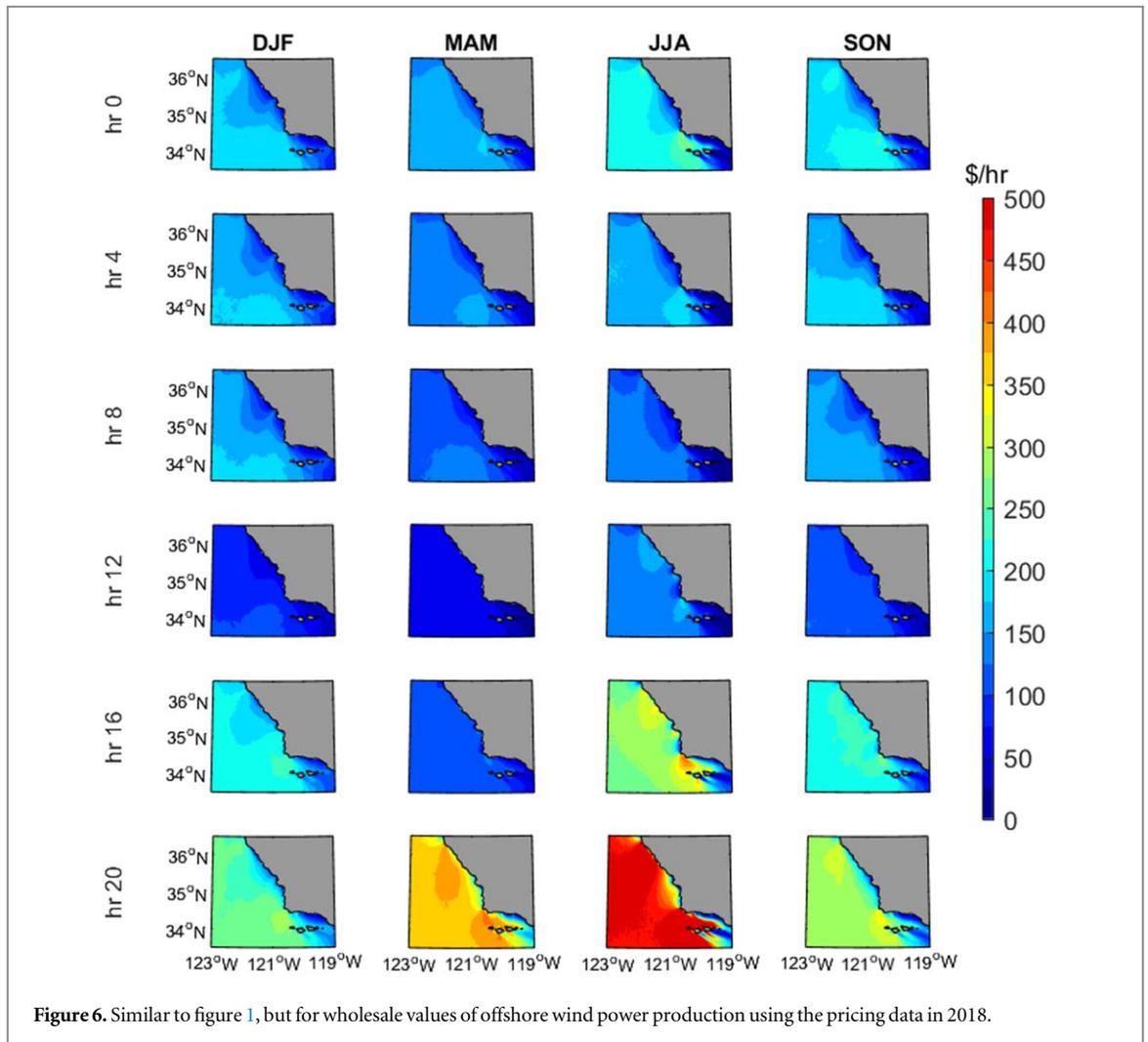


Figure 5. Monthly average demand-based values for offshore wind production shown in color (see text for details), for statewide solar production shown as solid contours and statewide land-based wind production shown as dashed contour (contours are typically very close to shore).

To further understand the seasonal variations in demand-based values and their spatial dependence, we calculate monthly average demand-based values by averaging composite-average hourly values over a given month for each renewable. This monthly average demand-based value also represents the proportion of full-capacity power production that is perfectly aligned with full constant demand in a given month. Figure 5 shows maps of monthly average demand-based values of offshore wind generation along with that of solar (solid line) and land-based wind (dashed line) generation. Although the value of offshore wind generation displays monthly and spatial variability, it is higher than that of solar and land-based wind throughout the year. In winter months, offshore wind is two to four times more valuable than solar and land-based wind generation over most areas.



Although solar and land-based wind have higher values in summer than winter, they are still smaller than offshore wind over most areas. In general, offshore wind power production along the Central California Coast is better suited to meet demand than existing major renewables.

4.5. Temporal variation in wholesale value of offshore wind production

We also assess the relationship between power production variability and local pricing variability, the latter of which is influenced by a number of factors such as demand variability, outages of electrical facilities, and fluctuation of other forms of power generation (Woo *et al* 2016 and references therein). Figure 6 shows the average of hourly wholesale value of offshore wind production at every spatial point over different hours and seasons. Due to strong variations in pricing, wholesale values of offshore wind show more extreme daily and seasonal changes than power production (cf figures 1 and 6). The wholesale value of power is close to zero on a typical spring noon driven by overgeneration from solar (e.g., Denholm *et al* 2015), whereas it peaks during evening hours when solar generation is low and demand is high. Note that the diurnal and seasonal patterns of the wholesale value change quantitatively, but not qualitatively, using other years (figure S8). This metric indicates the time-varying economic benefits of offshore wind that can inform stakeholders in offshore wind projects.

5. Discussion and conclusion

We calculate the diurnal and seasonal pattern of offshore wind power produced across the Central California Coast and the value of wind power based on future wind turbine specifications and current wholesale energy prices. Like wind speed, offshore wind power production increases during evening hours and is maximized in the spring and summer months. Power production is lower near the shore and higher further offshore.

We show that understanding the daily, seasonal, and spatial variations in offshore wind power can benefit planning and management of commercial development. We demonstrate that using annual mean wind speed for power production estimates leads to significant biases compared to using a time-varying wind speed for power production estimates. These biased wind resource assessments could mislead decision making in an offshore wind project and lead to suboptimal site choices. We also found the timing of daily peak offshore wind production across the Central California Coast to better align with daily peaks in State demand compared to statewide solar generation and land-based wind generation. This close temporal alignment between production of offshore wind and demand highlights the important role offshore wind power could play in filling the supply gap when other forms of renewable generation are low and demand is high.

To quantify the value of power generation, we developed useful metrics from two contexts—a demand-based value which measures power production variability in relation to demand variability, and a wholesale value which measures power variability in relation to local wholesale pricing variability. Both metrics contextualize the value of offshore wind energy along the Central California Coast as the State of California works towards meeting its renewable energy portfolio target.

Due to the availability of certain data in certain years (see Methods), we use composite averages to yield robust diurnal and seasonal patterns of power and demand (Fripp and Wiser 2008) and to further obtain that of demand-based relative values. Yet, in real life, power systems balance electricity generation and demand instantly; thus their simultaneous relationship at higher-frequency time scales (e.g. hour-to-hour variability) is important (e.g., Schill 2014, Brown *et al* 2018, Koivisto *et al* 2018) and should be considered in future work. Moreover, due to the lack of development of offshore renewable energy in California, the cost of offshore wind energy development remains largely uncertain. Hence, this study did not perform a full economic analysis since we have no information about the cost involved in offshore wind farm construction and operation, and policy incentives associated with siting locations, nor the losses caused by transmission and other reasons in our power estimation. Instead, we focused on the variability of offshore wind values in relation to the daily and seasonal variability of electricity demand and other primary renewable generation to highlight the revenue potential of offshore wind energy production at different time scales.

In summary, daily and seasonal variation in offshore wind power generation across space is of great importance and should be investigated in detail. While we focused on offshore wind power and its value along the Central California Coast in particular, this study also serves as a framework that is easily applicable to offshore wind development elsewhere. Our analysis of power production variability and metrics of values can be adopted separately and combined with other analyses.

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