# Daily and seasonal variability of offshore wind power on the Central California Coast and statewide demand

Senior Project

By

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April 22, 2019

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# 1 Introduction

In September of 2018, California approved the 100 Percent Clean Energy Act of 2018 (Senate Bill 100), which strengthened and accelerated its existing renewable energy portfolio benchmark. Specifically, the legislation states utilities in California produce 60 percent of their energy via renewable sources by the end of 2030 and commits to 100 percent by the end of 2045 (Hernandez et al., 2018). Current renewable energy sources in the California include solar, land-based wind, geothermal, and hydroelectric (CAISO, 2019). Another type of renewable energy source that has been increasingly implemented in Europe and Asia is offshore wind (Wang et al., 2019). Offshore wind power shows the greatest potential for future growth and is advantageous over other renewables, such as onshore wind, due to its consistency and power production potential (Sun et al., 2012). Furthermore, offshore wind power production tends to peak in similar hours of the day as demand (Carvalho et al., 2018). Renewable energy sources that match peak demand will decrease the usage of peaking power plants adding to its economic benefits.

Currently, the Central California Coast contains two call areas proposed by the Bureau of Ocean Energy Management (BOEM) for future offshore wind development. There is existing electrical infrastructure to connect offshore turbines into the state grid from locations in Morro Bay, Diablo Canyon, and Vandenberg Air Force Base. In these areas, wind speeds are moderately strong, but they are also variable on both seasonal and diurnal time scales. Figure 1 depicts geographical information of the Central California Coast study domain (Wang et al., 2019).

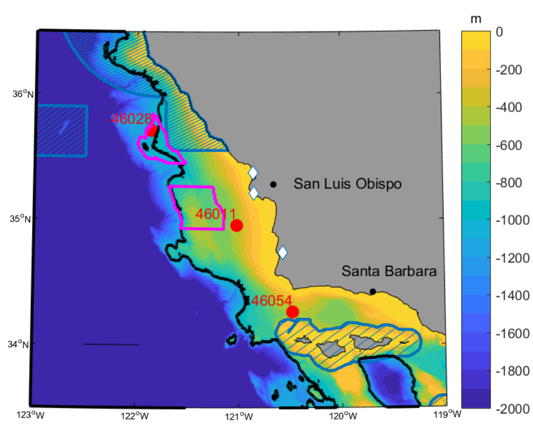


Figure 1: Central California Coast offshore wind spatial domain. Areas boxed by a magenta line are BOEM call areas, dashed blue lines are national marine sanctuaries, red dots indicate local buoys, and white diamonds show local grid connections. The colors shown highlight the bathymetry, and the solid black line denotes the 1000 m isobath.

This study aims at developing an understanding of the variability of offshore wind production off of the Central Coast using a variety of statistical methods and determining how production correlates with current energy demand patterns across California.

## 2 Data and Methods

### 2.1 California Demand Data

In this study we analyzed California's energy demand recorded by the California Independent System Operator (CAISO) (http://www.caiso.com/market/Pages/ReportsBulletins/Renewables Reporting.aspx). To generate hourly averaged total demand, we summed all of the hourly energy production sources together for the total time period spanning from January 1, 2011 to January 1, 2018. To analyze the seasonal-hourly variability of California's energy demand we determined the statistical average and standard deviation for each month and hour in the seven-year dataset.

To assess seasonal and daily variability in peak energy demand, we ranked the CAISO demand data into the top 5%, 10%, and 15% of hourly demand throughout the seven-year dataset. Following this, the month and hour of peak demand in each of the stated percentiles above were identified.

### 2.2 Wind Model Dataset

To analyze the variability of offshore wind production, we utilized the National Renewable Energy Laboratory's (NREL) Wind Integration National (WIND) Toolkit. NREL's WIND Toolkit contains offshore wind velocity fields. The model's horizontal spatial resolution is 2 km and its data range from 2007 until 2013 in hourly intervals. WIND Toolkit outputs velocity at 10 m and from 40 m to 160 m in 20 m intervals (Draxl et al., 2015). This dataset was previously validated for surface winds relative to in-situ buoy measurements (Wang et al., 2019), and here we assume that the model also performs well at altitude (e.g., hub height) where no in-situ measurements are available for comparison.

Using the velocity output from the WIND Toolkit, we estimated the power production using a standard power curve for a 10 MW turbine, which generates no power when wind speed is below its cut-in speed, increases power production proportional to the wind speed cubed until reaching its rated output, and stops power generation when wind speed exceeds its cut-out speed (Musial et. al 2016). The choice of a 10 MW wind turbine is reasonable given current offshore wind energy proposals in California are calling for at least 10 MW turbines (Trident Winds, Alla Weinstein - Personal Communication).

To analyze the variability of offshore power production we first looked at the seven year month-hour composite average (e.g., average power calculated using all data over all years from a particular hour during each respective month, cf. Wang et al., 2019) and standard deviation of 10 MW power production first at a single location. This sample location is near buoy 46028, which is a buoy the WIND Toolkit was validated against, and is within a proposed call area for an offshore wind farm in California (Figure 1). We also analyzed month-hour composite histograms of power distribution. Similar calculations were performed over the Central California study domain. Furthermore, we produced seasonal-hourly maps of the standard deviation and coefficient of variation to compare different seasons of the year. We also included month-hour maps of distribution when power generation was zero and when power generation was at the full rated power (i.e., 10 MW).

# 3 Results and Discussion

## 3.1 California Energy Demand

The month of and time of day (hour) of the peak energy demand from the top percentiles (5, 10, and 15) are shown in Figure 2.

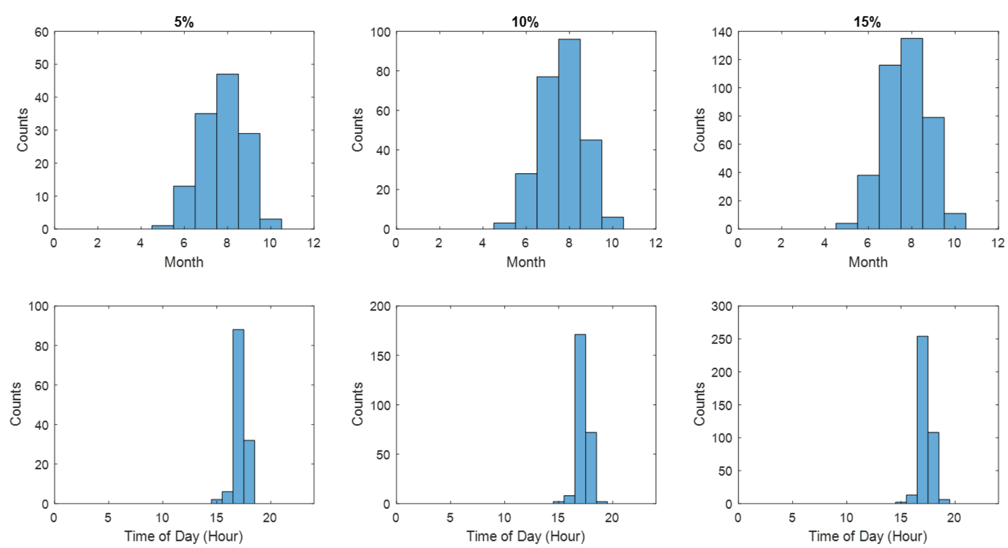


Figure 2: Top percentile energy demand statistics across California. The rows are separated into the month of the year (top) and the local time of day (bottom) when peak demand occurs. The columns are separated into the top 5, 10, and 15 percentiles.

Peak energy demand occurs during the summer, most often in the month of August. Furthermore, peak energy demand happens in the evening hours of the day, most often at 5:00 PM local time. Renewable energy sources that best correlate with energy demand are going to provide the largest value since current energy storage methods and peaking power plants are inefficient and expensive.

To characterize the mean pattern and variability of Californias energy demand, we investigated the composite average and standard deviation ($\sigma$) (Figure 3). These statistics provide insight about peak load values and how much peak load varies in a given time of the day and month of the year.

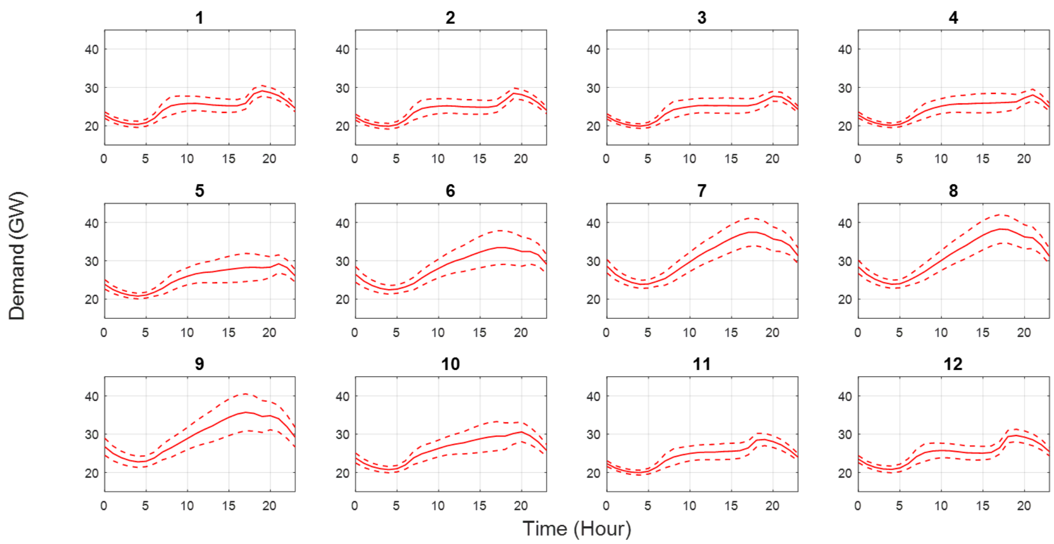


Figure 3: Energy demand month-hour average distribution across California. Solid red lines are the hourly average and dashed red lines denote one standard deviation away from the mean in a given month. Months are labeled with their respective number (i.e. January is 1, February is 2, etc.).

In any given month, energy demand is largest during the evening hours (∼15:00 to 20:00) and smallest during the middle of the night (∼00:00 to 05:00). The largest average demands occur in the summer months (see also Figure 2). Furthermore, using the standard deviation, the largest variability in energy demand occurs when it peaks in the summer months and during the evening hours. To address these periods of variable demand, renewable energy production will need to remain as consistent as possible to reduce uncertainty in power supply and demand across the state.

## 3.2 Central California Offshore Wind Production

Understanding the variability of power production of offshore wind power along the Central Coast allows us to determine its compatibility with energy demand. Figure 4 shows the standard deviation and composite average from offshore wind power production near the proposed call area along the Central Coast (i.e. near buoy 46028).

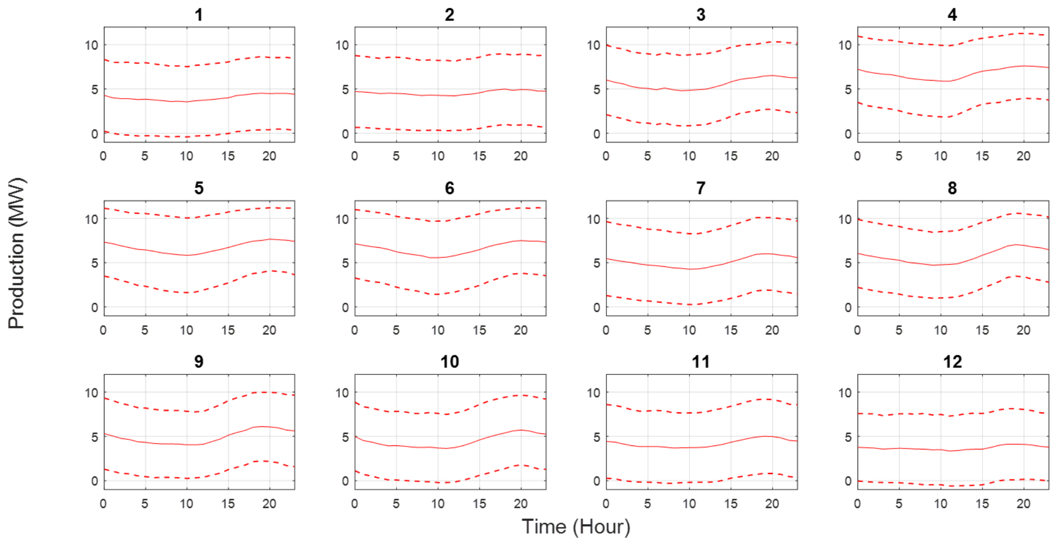


Figure 4: Same as Figure 3 except offshore wind power production near buoy 46028.

Average offshore wind power production tends to be largest in the spring and summer months with daily peaks in the evening, the latter of which coincides with the demand data. However, the variability of power production is large at this location. In most cases, the standard deviation is the same order as the average value and stays relatively consistent regardless of the time of day. Therefore, using the standard deviation and the average alone are not sufficient to fully describe the distribution offshore wind energy production.

To further investigate the large variability in offshore wind energy production, histograms of power production across each month and hour of the day are shown in Figure 5.

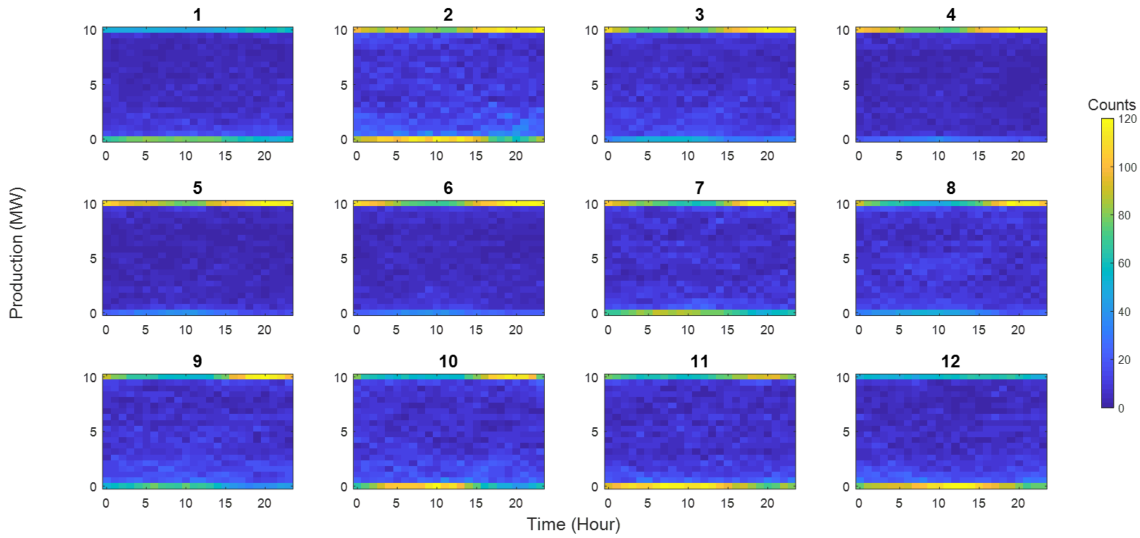


Figure 5: Histograms of offshore wind power production over the seven year period near buoy 46028. The colors denote the number of data points that fall into the particular power bin in the respective month and hour of day. Same data used as in Figure 3 but displaying the data as composite distributions over the seven year period near buoy 46028. Months are labeled with their respective number (i.e. January is 1, February is 2, etc.).

The distributions highlight wind production is generating power most often at either 0 MW or 10 MW of power, due to the cut-in and cut-out speed, respectively, of a specific turbine. This bimodal distribution explains the large standard deviation seen in Figure 4, as well as the similar standard deviation observed across all months.

We extended our analysis to every spatial point on the Central Coast study domain to highlight spatial variability. Seasonal-hour composite averages of power production are shown in Figure 6.

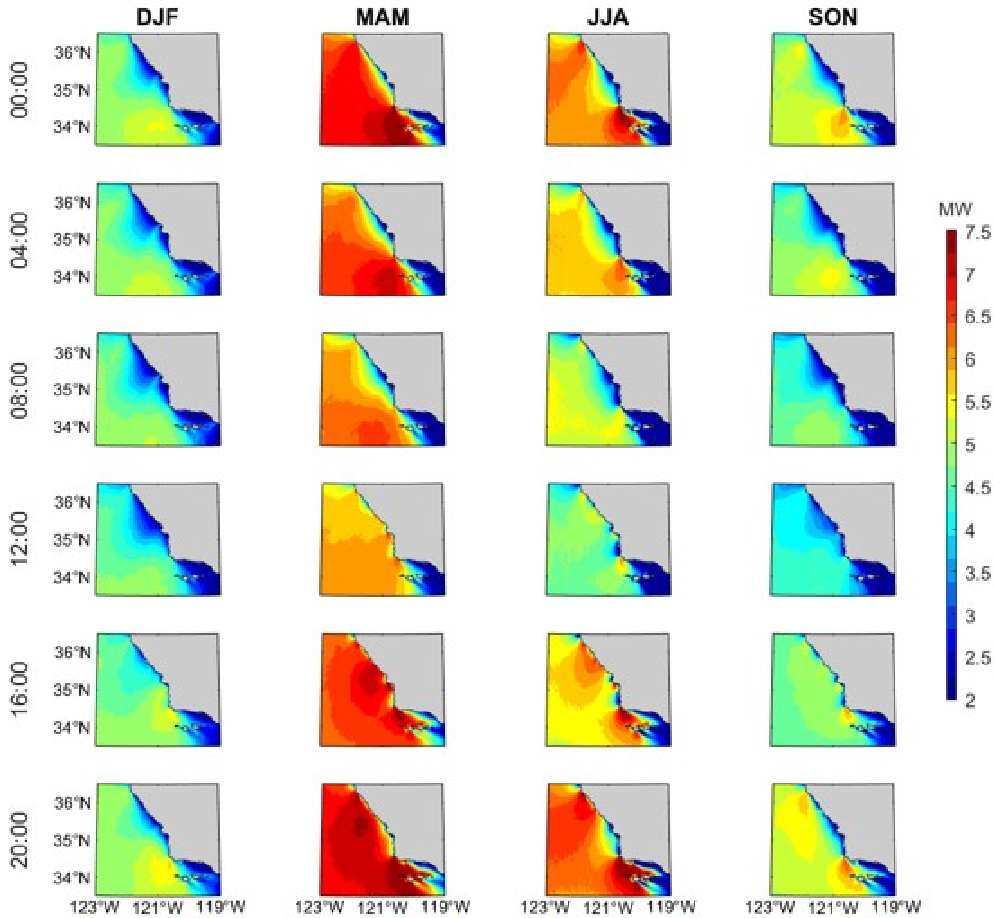


Figure 6: Offshore wind production composite averages from 2007-2013. Each row is an hour of the day starting at local midnight increasing in four hour intervals. Each column is a season where DJF (December, January, February) is winter, MAM (March, April, May) is spring, JJA (June, July August) is summer, and SON (September, October, November) is autumn.

The largest composite averages of wind power production occur during the spring and summer, with the winter and autumn being smaller. Power production peaks in the late afternoon and evening which nicely lines up with power demand across the state of California. However, peak power production of offshore wind energy occurs in the spring time which does not align with Californias peak energy demand in the summer.

Maps of standard deviation, which highlight wind variability, are shown in Figure 7.

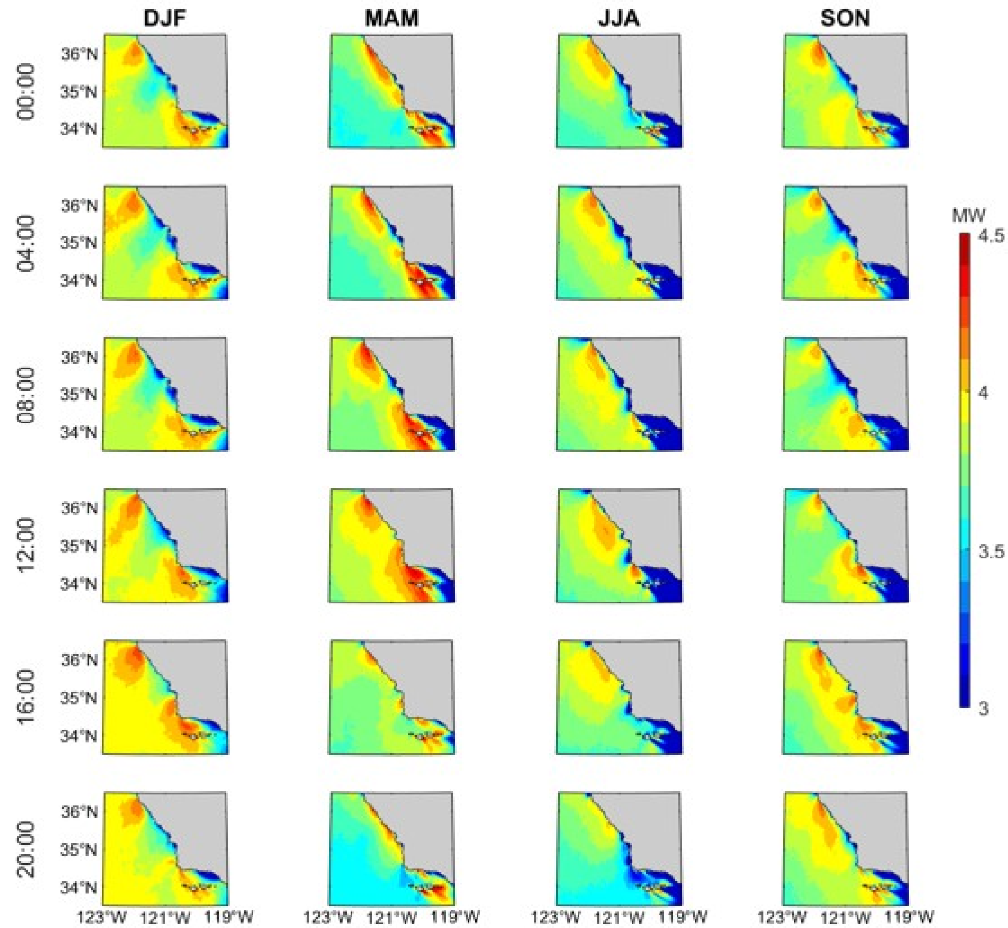


Figure 7: Same as Figure 6, but with the standard deviation of offshore wind power production.

These maps demonstrate offshore wind energy is highly variable in all areas across the Central Coast, particularly closer to shore. The largest deviations from the mean occur in the winter months, and closer to the shore in the spring. However, in the late afternoon and early evening of spring and summer months, variability tends to be smaller compared to other times of the day across other seasons. These periods of low variability in the spring and summer evening production also correspond to peaks in demand.

Although the standard deviation provides information about how variable wind power production during a particular hour and season, the coefficient of variation ($\mu$) quantifies the variability (i.e., standard deviation) relative to the mean value (cf., Lee et al., 2018). Spatial distributions of the coefficient of variation are shown in Figure 8.

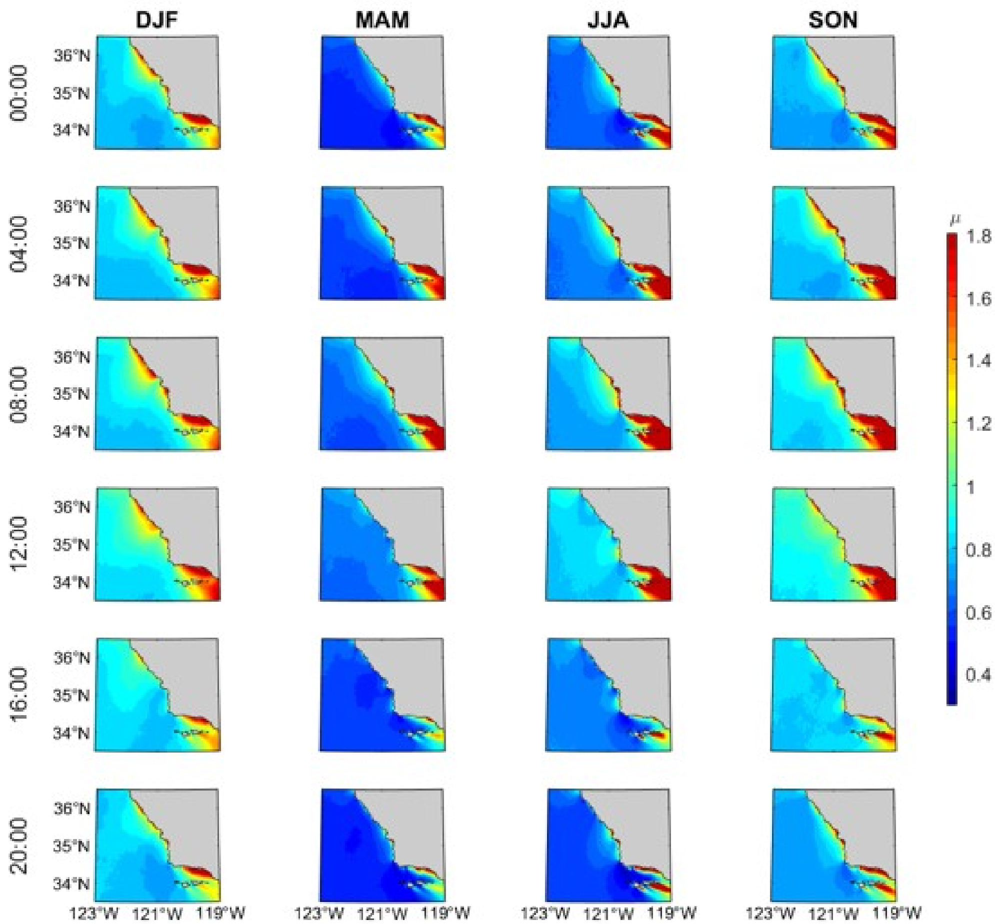


Figure 8: Same as Figure 6, but with the coefficient of variation of offshore wind production.

For offshore wind production, a smaller coefficient of variation is ideal since this corresponds to periods where variability is small relative to the mean (i.e., more consistent power production). Lower values for the coefficient of variation occur in the spring and summer, and generally north of Point Conception.

To further investigate the variability, the percent of the time offshore wind energy is producing power at its maximum capacity (10 MW) and minimum capacity (0 MW) is shown in Figure 9 and Figure 10 respectively.

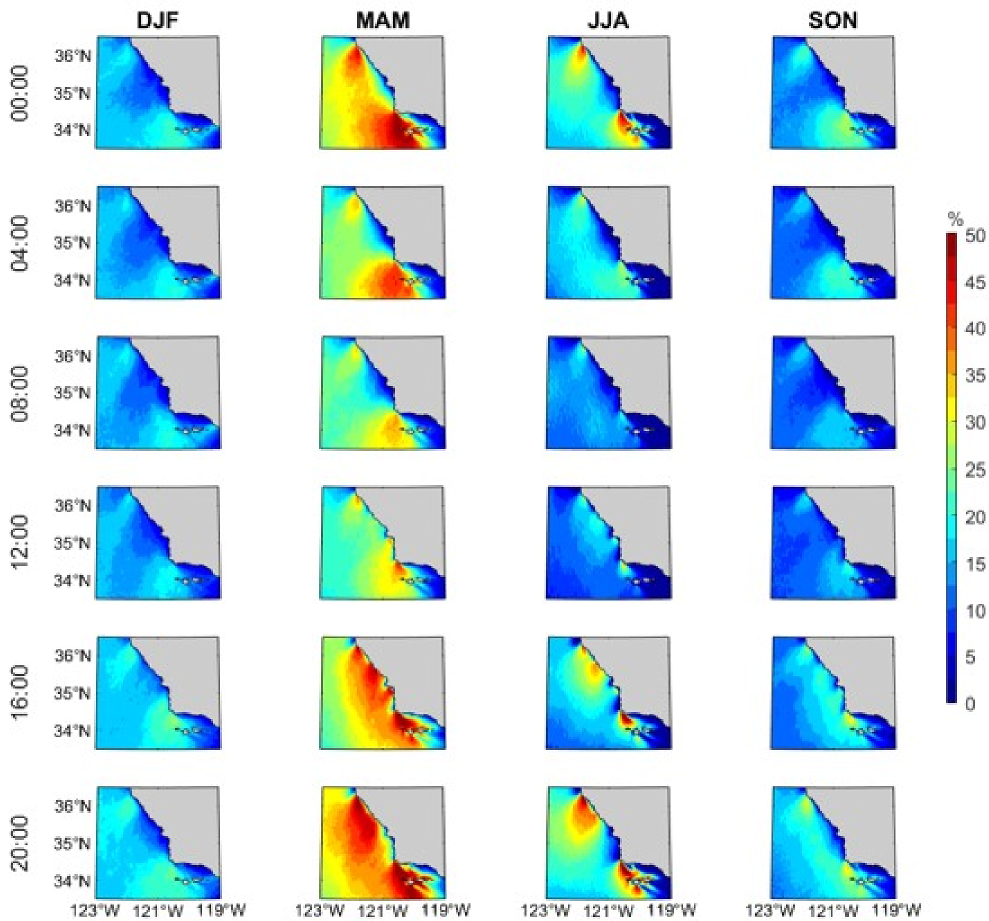


Figure 9: Same as Figure 5 except it shows the percent of time turbines produce 100% of their 10 MW capacity over the seven year period.

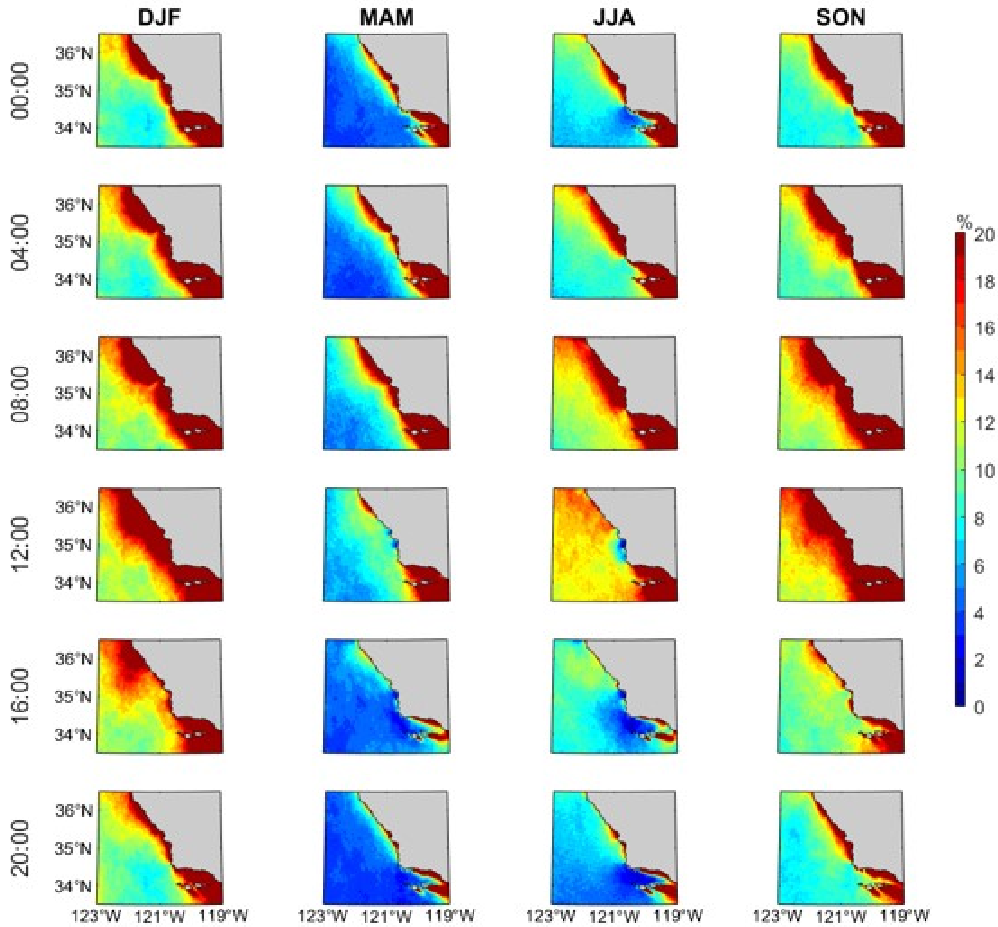


Figure 10: Same as Figure 5 except it shows the percent of time no power is produced over the seven year period.

Peak power production (i.e., 10 MW) occurs the greatest percentage of the time (∼50%) in the spring, particularly during the late afternoon and evening hours. The spring months also have the smallest percentage of the time at zero power (less than 10%). In contrast, during the autumn and winter months, there is a small percentage of the time (∼10-20%) the plants are operating at full capacity and a relatively large percentage of the time (∼20% near the coastline) turbines are operating at zero capacity. During the summer, wind farms operate at full capacity during the evenings (∼25+%). However, over the summer daytime turbines operate at peak capacity only about 10-15% of the time. Furthermore, a large percentage of the time (∼10+%) in the summer plants are operating at zero capacity, especially near the proposed wind farm locations. These results indicate the significance that offshore wind energy alone may struggle to coincide with peak energy demand in the summer months.

## 4 Discussion and Conclusion

We have highlighted the seasonal and daily variation of wind power production off of the Central Coast of California in relation to California's energy demand. Seasonally, offshore wind turbines produce their peak average production in the spring and summer months, particularly during the evening hours. Interestingly, offshore wind power production largely follows a bimodal distribution throughout the day, either producing zero power or full capacity (10 MW), which leads to large temporal standard deviations. This suggests the average value may not be an appropriate metric when considering the ability of offshore power production to meet grid demand. Grid energy demand peaks in the summer months in the evening hours, and its demand throughout the day is larger on average compared to other months of the year. However, zero production rates decrease in the evening hours of the summer at the location of the call areas. This indicates offshore wind energy ramps up its power production in the evenings complimenting peak energy demand, thereby providing a significant advantage over other renewable energy sources such as solar that ramp-down during peak demand times (e.g., solar peaks midday and decreases into the evenings, whereas demand and offshore wind decrease midday and increase into the evening). These findings suggest renewable energy portfolios will need to be diverse and consider temporal (both seasonal and diurnal) variability when assessed against demand data.

Future work should pursue a variety of other statistics due to the bimodal distribution of power production. Other studies suggest evaluating the robust coefficient of variation, skewness, and kurtosis, provide a better approach to evaluate the bimodal distribution of wind power production (Lee et al., 2018). For now, our statistical analysis of both California energy demand and offshore wind power production provides the foundation to further develop analysis of the Central Coast and offshore wind projects.

## 5 Acknowledgements

I want to thank Dr. Yi Hui Wang for her contributions towards this project. She collaborated with me consistently and provided valuable insight about how to manage and perform statistical analysis. Furthermore, she laid the groundwork for the project by providing both wind power production data and California energy demand data used to evaluate wind power potential. Additionally, I want to thank Dr. Ryan Walter for his guidance and mentorship. His advice led to discussions on data analysis which created fresh perspectives about statistics and data visualization. Skills and techniques I acquired throughout the project, from both Dr. Wang and Dr. Walter, will help guide my future research in graduate school.

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