INVESTIGATION OF WIND REGIMES IN KUWAIT AND THE NORTHEASTERN U.S. COAST USING OBSERVATIONS AND SELF-ORGANIZING MAPS OF MODEL OUTPUT

A Dissertation in
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by

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ABSTRACT

Optimal wind energy utilization requires accurate wind forecasts, which in turn require an understanding of regional wind regimes. Armed with knowledge of when wind speeds will increase or decrease, electric grid operators can make more informed decisions on resource management. In this dissertation, an analysis of wind climatology is done for the Middle East with a focus on the Shagaya Renewable Energy Park in Kuwait. Wind observations from five wind turbines provide insight to how wind evolves at hub height throughout the day and throughout the year. A major feature was the identification of a regional weather pattern known as the summer shamal. The summer shamal is a quasi-permanent, strong, northwesterly wind, and it can increase Shagaya wind power production by 24%. On the diurnal scale, wind power tends to ramp up near sunset, and then ramp back down near sunrise. Additional analysis with data from meteorological towers and surface weather stations in the park determined that these wind power ramps are due to the formation of the nocturnal boundary layer and a low-level jet at sunset, followed by the deterioration of the nocturnal boundary layer due to convective turbulence at sunrise.

While observations at Shagaya provide a local depiction of wind, a deeper investigation into the wind regimes the Middle East experiences requires the Weather Research and Forecasting (WRF) model, which provides regional data to assess synoptic-scale wind patterns. To aid in the analysis of the WRF dataset, a machine learning method called self-organizing maps (SOMs) cluster the WRF wind data into a grid of six primary wind regimes. One of the wind regimes the SOMs identify is the summer shamal. Two wind regimes that also indicate increased wind speeds and thus increased wind power production at Shagaya include a deep daytime convective layer and a shallow, cold-season low over the Red Sea. The remaining three regimes
are of either divergent flow or a nocturnal low-level jet over northeastern Africa and all are associated with weaker wind speeds at Kuwait.

Applying SOMs to a different environment, another grid of SOMs is trained on hub-height wind data from the High-Resolution Rapid Refresh (HRRR) model with a focus on the northeastern U.S. coastal region. The main wind patterns SOMs identify are unidirectional flow, confluent/diffluent flow near the coast, and winds circulating around a pressure system. Several regimes SOMs identify are associated with wind speeds adequate for offshore wind power production. However, the remaining regimes typically represent either a low-/high-pressure system or a confluence/diffluence zone in the domain and are associated with weak wind speeds near the coast. Investigation of the probability of regimes persisting or transitioning over time indicates that all regimes can be associated with the progression of low- and high-pressure systems either within or outside the domain. Wind shear is another concern for wind farm operators, so SOMs trained on 10–80-m wind component differences allow investigation of regimes that cause higher wind shear. When warmer air advects over cooler waters in the North Atlantic, near-surface air stabilizes and decouples, leading to 10–80-m wind component differences of up to 5 m s$^{-1}$. HRRR captures the main features of hub-height wind speed that a buoy (E05) in the waters off of Long Island, New York, can observe. HRRR and E05 indicate a minimum in hub-height wind speed in the summer, as well as decreased wind speeds when a high-pressure regime is dominant. After autumn 2020, there can be a difference in monthly-averaged wind speed of $\geq 5$ m s$^{-1}$ between HRRR and E05 for some regimes.
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Chapter 1

Introduction

Wind is an abundant and ever-present energy resource, and the world is continually moving towards using more renewable energy resources like wind. Global renewable energy generation increased by 7% from 2019 to 2020, which led to renewable energy use increasing by 3% while demand for all other fuels decreased (IEA 2021). IEA (2021) also reports that the global share of electricity generation from renewable sources was 29% in 2020.

Although a vast majority of energy consumption in the Middle East comes from fossil fuels, the Middle East has been recently increasing their consumption of renewables (bp 2021). From 2019 to 2020, the Middle East increased their renewable energy consumption from 120 Petajoules to 170 Petajoules, or about 33 Terawatt-hours to 47 Terawatt-hours. Therefore, exploration in renewable energy resource availability also becomes increasingly important. The Shagaya Renewable Energy Park in Kuwait recently had performance evaluated for its solar (Al-Rasheedi et al. 2020) and wind farms (Al-Rasheedi et al. 2021; Al-Khayat et al. 2021), both of which provide increased energy production during the summer when energy demand is higher. The summer increase in wind speeds can be attributed to a regional wind pattern called a shamal, characterized by a quasi-permanent northerly to northwesterly wind with above-average wind speeds (Hubert et al. 1983; Yu et al. 2016). Wind patterns like the summer shamal that can increase wind energy production at Shagaya warrant a deeper exploration of wind in the Middle East region.

As the world’s secondary leader in wind energy capacity with 117.7 GW in 2020, the U.S. is committed to harnessing wind for electricity (IRENA 2021). In 2021, 20% of utility-scale electricity generation in the U.S. was from renewables (EIA 2022). There is potential for the U.S.
to harness even more wind power with wind over the Atlantic. The vast potential of ocean-based wind energy is not easily overstated; winds of the Middle Atlantic Bight can produce 330 GW of power (Kempton et al. 2007), while one-third of U.S. energy demand can be supplied by winds from the waters of the U.S. East Coast region (Dvorak et al. 2012a). However, as of 2020 there were only two operational offshore wind farms that had a combined potential generating capacity of 35 MW (Musial et al. 2021). With such a large investment in renewable energy and a large resource in wind, a thorough background in how variable renewable energy resources like wind can be impacted by weather becomes imperative.

One obstacle with observational data is the difficulty of obtaining a dense, spatially uniform array of observations. Numerical models can therefore supplement observations by providing fields of meteorological variables where observations are sparse. With the benefit of filling in gaps of data, however, comes the extra cost of analyzing what can be large datasets. Machine learning can reduce the extra cost by automatically clustering model output into primary groups or regimes. One such machine learning method is self-organizing maps (SOMs), which can reduce the dimensionality of a high-dimensional dataset by using competitive learning to cluster data based on topological features (Kohonen 1982; Kohonen 1990). Some of its numerous uses are for object and pattern recognition (Beard and Rattan 1989; Tanomaru and Inubushi 1995), image segmentation for medical applications (Li and Chi 2005; Chang and Teng 2007; Wehrens 2009; Kanimozhi and Bindu 2013), speech recognition (Kohonen and Somervuo 1997), and robot navigation (Ishii et al. 2004; Sharma et al. 2011; Zhu et al. 2017). SOMs have also been recently used across atmospheric science, primarily in recognizing patterns in meteorological variables (Liu and Weisberg 2011). Examples include sea level pressure (Hewitson and Crane 2002; Cassano et al. 2006), geopotential height (Michaelides et al. 2007), and precipitation (Cavazos 2000; Nishiyama et al. 2007; Pelletier et al. 2009).
Greater climatological 80-m wind speeds occur over the Great Plains, the Midwest, and the Northeastern U.S. compared to the rest of the country (Yu et al. 2015), and the coastal waters of the Northeast are also reported to have average 90-m wind speeds > 9.5 m s\(^{-1}\) (Musial and Ram 2010). Yu et al. (2015) also reported stronger winds in the winter and weaker winds in the summer for the continental U.S. If the findings of Yu et al. (2015) can be extended to the nearby waters of the Northeast, then it would suggest that the Northeast coast could not only be a great site for future offshore wind farms, but they could provide even more energy resource in the winter. The New York Bight jet investigated by Colle and Novak (2010) identified a nocturnal low-level jet near the coasts of New Jersey and Long Island, New York, suggesting that any wind farms operating in the region can expect occasional upward ramps of wind power in the evening. Wilczak et al. (2015) demonstrated that incorporating additional data assimilation and improving numerical model physics improved wind power forecasts, including wind power ramp events. These studies highlight a few cases when wind climatology can contribute to knowledge of regional wind resource and thus help wind farm planning.

More knowledge on wind near hub-height on different timescales can have several additional benefits for the wind energy industry. Sub-hourly wind forecasts are important for grid operators who utilize wind energy to ensure a non-fluctuating flow of electricity. Next-day wind forecasts allow the allocation of sufficient alternate resources like fossil fuels to supplement wind energy. Monthly or seasonal wind averages can allow wind farm managers to know when a better time is to perform maintenance like turbine repair or upgrades. Long-term wind resource estimation over a region of interest can indicate areas more beneficial to harvesting wind energy and thus better sites for planning and installing wind farms.

As indicated thus far, wind is a prevalent and therefore valuable resource for both Kuwait and the Northeastern U.S., but a deeper analysis of geographic and temporal patterns in wind is needed to i) provide forecasters a more extensive climatological background for each region, and
ii) inform electric grid operators in each region wind resource availability on a spectrum of scales. Wind climatology will be explored for Shagaya in Kuwait in Chapter 2, including how it affects wind power production. Then Chapter 3 will introduce wind regimes identified by SOMs trained on Weather Research and Forecasting (WRF) model hub-height wind speeds in the Middle East. Similarly, Chapter 4 will explore SOMs trained on High-Resolution Rapid Refresh (HRRR) model hub-height wind speeds in the Northeastern U.S. coastal region, investigate the probabilities of wind regime transitions over several days, and compare the SOMs with buoy observations.
Chapter 2

Climatology of Wind Variability for the Shagaya Region in Kuwait

This chapter has been extracted from Naegele et al. (2020).

Electrical system operators utilizing wind energy production need accurate wind power forecasts to prepare for changes in power production. To understand the forecast problem and sources of forecast uncertainty, a climatology of the region of interest is needed. For Shagaya Renewable Energy Park in Kuwait, seasonal and diurnal wind patterns and the atmospheric phenomena that cause them are identified using observations from meteorological towers, surface weather stations, and wind turbines. A setup conducive to shamals increases hub-height wind speed by up to 3 m s\(^{-1}\) from May to August and thereby increases power production of the Shagaya wind turbines by 24%, in a season with higher energy demand for cooling homes and businesses. Near sunset, wind speed ramps up and remains faster throughout the night due to the prevalent nocturnal low-level jet. Wind speed ramps back down after sunrise when the nocturnal boundary layer is eroded by convective turbulence, which leads to more short-term fluctuations in wind speed and wind power during the day. Given knowledge on these seasonal and diurnal cycles of short-term and long-term wind power variability, wind power has clear potential to meet a significant portion of Kuwait’s energy needs.

2.1 Introduction

Much of the world’s fleet of energy generation capacity is transitioning to renewables, with global renewable energy capacity doubling from 1.14 terawatts (TW) in 2009 to 2.35 TW in 2018 (IRENA 2019a). As of 2018, Kuwait has less than 1% (80 MW) of their total power
production coming from renewable energy, but by 2035 they plan for renewables to comprise 16% of total capacity (KISR 2019). To accomplish this, Kuwait plans to greatly increase both wind and solar installed capacity at the Shagaya Renewable Energy Park by 2027 from 70 MW to 5 GW in total (KISR 2019). To incorporate more wind energy in the Kuwait electrical grid in the coming years, the system operators must be able to plan for the variability of this generation resource resulting from local meteorological conditions. Understanding this wind variability on seasonal and diurnal scales could provide a clearer picture of how to most economically and efficiently integrate wind power at Shagaya.

Kuwait has a desert climate, so its seasonal and diurnal cycles of electricity demand are primarily influenced by summertime and daytime heating. It was determined by Wood and Alsayegh (2014) that during 2008 the summer load was double the base load. They also found that the load at local hour 20:00 is similar to peak load at local hour 15:00, which they attribute to inefficient air conditioning use and the thermal inertia of buildings. Therefore, there is a seasonal increase in power demand in Kuwait during the summer and a diurnal increase from mid-afternoon to early evening, due to increased air conditioning use.

Wind energy generation cycles must match those of energy demand to be an optimal resource. With plans to expand the Shagaya wind farm, understanding wind speed variability, and thus wind power variability, in Kuwait becomes important. Seasonally, Kuwait is typically hot, arid, and clear during the summer Tye et al. (2019) and experiences a strong, predominantly northwesterly wind lasting from May through August known as the summer shamal (Membrey 1983; Middleton 1984; Houssos et al. 2015; Yu et al. 2016). It is therefore during the summer that wind power production in Kuwait should be greater than average. On the diurnal time scale, low-level jets (LLJs) are known to increase near-surface wind speeds at night in many regions around the world (Blackadar 1957; Stull 1988). It was postulated by Blackadar (1957) that LLJs form due to the lack of surface heating at night, causing stabilization of the near-surface boundary layer
and consequent reduction in friction, leading to a wind maximum at the top of the stable boundary layer. The LLJ has been shown to increase wind power capacity factors to greater than 60% in the southern plains of the United States (Wilczak et al. 2015) and thus contributes significant supplemental wind power to the region at night, but there are limited studies as to how much LLJ’s can affect wind power in other regions of the world. By identifying LLJs throughout the world, Rife et al. (2010) determined that LLJ formation could be due to changes in horizontal baroclinicity from variations in topography and surface heating. Kuwait is located between the Zagros Mountains in Iran and the relatively flat central and eastern Arabian Peninsula, which could provide diurnal baroclinicity gradients and thus motivates investigation into the presence of a LLJ at Shagaya.

In addition to seasonal and diurnal variability, grid operators need to anticipate significant increases or decreases in wind power over shorter time intervals, which are commonly referred to as wind power ramps. Wind power ramps were identified during LLJ formation (Deppe et al. 2013; Yang et al. 2013; Vanderwende et al. 2015; Wilczak et al. 2015), as the jet would cause wind speeds to ramp up. Several studies have investigated how to best define these ramps, with different definitions used in each. Broadly, Bianco et al. (2016) defined a wind power ramp as a change in X% capacity in Y time, where X and Y can represent different magnitudes depending on the needs of the user. Studies generally define wind power ramps with changes of 10–50% capacity and durations of 30 minutes to 6 hours (Ela and Kemper 2009; Wilczak et al. 2015; Cui et al. 2017; Zhang et al. 2017). Additionally, Wan (2011) analyzed 1-hour and 10-minute power data to identify the start and end of wind power ramp events. The 10-minute power changes provide early indication of more significant hourly power changes, suggesting the value of simultaneously using multiple wind power ramp definitions. These papers use multiple definitions for wind power ramps based on the duration of interest and the total capacity of the wind turbines being used. Thus, this study will use a wind power ramp definition specific for the
Shagaya wind farm, ± 50% power capacity in one hour, which will be described further in Section 2.2 with analysis in Section 2.3.

This study will quantify the annual and diurnal patterns of wind power and wind speed in Shagaya, Kuwait and the underlying atmospheric phenomena so that grid operators can better understand expected seasonal and diurnal variability in wind power generation. The atmospheric data used from the Shagaya wind farm and a description on how wind power ramps and wind speed variability are defined in this paper are given in Section 2.2. The results of the seasonal and diurnal analysis of wind speed and wind power variability are described in Section 2.3. Concluding remarks and areas of future work are discussed in Section 2.4.

2.2 Data and Methods

Meteorological and wind power data were provided by the Kuwait Institute for Scientific Research (KISR) and their contractors. The data were recorded using multiple meteorological towers, surface weather stations, and measurements from wind turbine nacelles, the locations of which are provided in Figure 2.1. Basic information on the data is given in Table 2.1. Data were collected for five wind turbines (WTG) from 01 September 2017 to 31 August 2019. The 78-m Elecnor meteorological tower (ELE) had a data outage resulting from a major power supply failure from 06 April 2018 to 05 July 2018 and experienced complications with data collection in 2019. Thus, for this tower only data from 01 September 2017 to 31 August 2018 were used. Surface weather station (SWS) data from 01 September 2017 to 31 August 2018 were also used in conjunction with ELE data when calculating bulk Richardson number as outlined in Section 2.2.1. The 100-m KISR Shagaya meteorological tower (SHA) had data available from 01 September 2017 only until 26 June 2018. Models and accuracy for the sensors are given in the fifth and sixth rows of Table 2.1 where available.
Figure 2.1: (top) Map of Kuwait showing the outline of the Shagaya Renewable Energy Park; (bottom) map of sensor locations within the Shagaya plant. SWS locations are represented by yellow pins within the 10-MW photovoltaic solar plant (outlined in purple), meteorological tower locations are red pins, and wind turbine locations are turbine icons.
Table 2.1: Latitude, longitude, and elevation of the meteorological towers, weather stations, and wind turbines, as well as heights of the sensors, frequency of the data, sensor model, and sensor accuracy.

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<th>Wind turbines (WTG)</th>
</tr>
</thead>
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<td>29.21°N, 47.06°E</td>
<td>29.22°N, 47.04°E</td>
<td>SWS 2 – 29.2053°N, 47.0505°E</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>SWS 3 – 29.2052°N, 47.0545°E</td>
</tr>
<tr>
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<td></td>
<td></td>
<td>WTG 1 – 29.2279°N, 47.0563°E</td>
</tr>
<tr>
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<td></td>
<td></td>
<td>WTG 2 – 29.2272°N, 47.0531°E</td>
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<td>WTG 4 – 29.2257°N, 47.0465°E</td>
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<td>WTG 5 – 29.2249°N, 47.0432°E</td>
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<td>WTG 5 – 243</td>
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<td><strong>Observation heights (m) and variables measured</strong></td>
<td>2 – air temperature [°C], relative humidity [%], air pressure [hPa], wind speed [m s⁻¹], wind direction [°]</td>
<td>76 – air temperature [°C], relative humidity [%], air pressure [hPa], wind speed [m s⁻¹], wind direction [°]</td>
<td>3 – air temperature [°C], relative humidity [%], air pressure [hPa], wind speed [m s⁻¹], wind direction [°]</td>
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<td>4 – wind speed [m s⁻¹], wind direction [°]</td>
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<td></td>
<td></td>
<td>78 – power [% capacity], nacelle wind speed [m s⁻¹], nacelle air temperature [°C]</td>
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<td><strong>Frequency of data</strong></td>
<td>10-minute average (time-ending)</td>
<td>10-minute average (time-ending)</td>
<td>5-minute average (time-ending)</td>
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<td><strong>Sensor Model/Type</strong></td>
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<td>Temperature – Pt100 thermistor</td>
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<td>Relative humidity – NRG Systems RH5X/RH5XC</td>
<td>Relative humidity – capacitive polymer</td>
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<td>Air pressure – NRG Systems BP20</td>
<td>Wind speed – anemometer</td>
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<td>Anemometer – Ammonit Theis First Class Advanced S11100/S11100H</td>
<td>Wind direction – anemometer</td>
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<tr>
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<td>Wind vane – Ammonit Theis First Class POT</td>
<td>n/a</td>
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<td><strong>Accuracy (where known)</strong></td>
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<td>Temperature – offset = ±0.8°C (±1.4°F) maximum, linearity = ±0.33°C (±0.6°F) maximum, total error = ±1.1°C (±2°F) maximum</td>
<td>Temperature – ±0.1°C (±0.18°F) maximum, linearity = ±0.02°C (±0.04°F) maximum, total error = ±±0.08°C (±0.16°F) maximum</td>
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<td>Relative humidity - ±2% RH (k=2) from 10%-90% RH @ 25°C (77°F), ±3% RH (max) from 5%-10% RH and 90%-95% RH @ 25°C (77°F)</td>
<td>Anemometer (wind speed) – ±0.5% of measuring range (0-60 m s⁻¹)</td>
</tr>
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<td></td>
<td></td>
<td>Air pressure - ±1.5 kPa (± 0.443 in Hg) max uncorrected offset</td>
<td>Anemometer (wind direction) – ±2% of measuring range (0-360°)</td>
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<td>Anemometer – from 0.3-50 m/s, 1% of measured value or 0.2 m/s</td>
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<tr>
<td></td>
<td></td>
<td>Wind vane - ±1°</td>
<td></td>
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</tbody>
</table>
2.2.1 Bulk Richardson Number calculation

Bulk Richardson number ($Ri_B$), a dimensionless ratio of buoyancy-driven turbulence to shear-driven turbulence, was used to assess diurnal patterns in atmospheric stability (Stull 1988). It was calculated in 10-minute intervals during those periods when data were available for all three sources (i.e. ELE, SWS2, and SWS3). At each 10-minute interval and for each SWS variable, the two 5-minute averages from SWS2 and SWS3 were averaged. The Shagaya meteorological tower was not used in the $Ri_B$ calculation because that tower showed a bias in its temperature observations, but we used its wind speed and wind direction data to create the wind roses in Section 2.3.1 as it did not have a known bias in those variables.

Calculation of vertical difference in virtual potential temperature ($\Delta \theta_v$) for the $Ri_B$ equation required the calculation of saturation vapor pressure ($e_s$), which was found using a form of the Clausius-Clapeyron equation (Bohren and Albrecht 1998):

$$e_s \approx 6.11 \exp \left( \frac{L_v}{R_v} \left( \frac{1}{T_0} - \frac{1}{T} \right) \right),$$

where $L_v$ is the latent heat of vaporization ($2.5 \times 10^6 \, J \, kg^{-1}$), $R_v$ is the gas constant for water vapor ($461.0 \, J \, kg^{-1}K^{-1}$), $T_0$ is a reference temperature of 273.15 K, and $T$ represents either the 76-m ELE air temperature or mean 3-m air temperature between SWS2 and SWS3 in degrees Celsius, depending on the vertical level for which $e_s$ is being calculated. Vapor pressure ($e$) required $e_s$ and relative humidity ($RH$), $e = e_s \cdot (RH/100)$, with 3-m RH computed as an average between that of SWS2 and SWS3. Then $e$ and $e_s$ were combined to produce a mixing ratio ($r_v$) (NOAA 2018):

$$r_v = 621.97 \cdot \frac{e_s}{(p-e)_s},$$
where $P$ stands for air pressure (in Pa).

Because SWS2 and SWS3 do not have pressure observations, the hydrostatic approximation was used to estimate pressure at 3 m (in Pa) (Wallace and Hobbs 1977):

$$P_{3m} = P_{76m} \cdot e^{\left(\frac{g(76m-3m)}{R_d T}\right)}.$$  \hspace{1cm} (3)

where $g$ is acceleration due to gravity, $R_d$ is the gas constant for dry air, and $T$ is the mean temperature of the layer. Potential temperature (AMS 2012a) was calculated at 76 m, with a base pressure at $P_{3m}$:

$$\theta_{76m} = T_{76m} \left(\frac{P_{3m}}{P_{76m}}\right)^{\kappa}.$$  \hspace{1cm} (4)

where $\kappa$ is Poisson’s constant ($\kappa \approx 0.2854$). This was done so that $\theta_{3m} = T_{3m}$, and thus virtual potential temperature at 3 m, $\theta_{(v,3m)} = T_{(v,3m)} = T_{3m}(1 + 0.61r_{(v,3m)})$. Virtual potential temperature (AMS 2012b) at 76 m is

$$\theta_{(v,76m)} = \theta_{76m}(1 + 0.61r_{(v,76m)}).$$  \hspace{1cm} (5)

Bulk Richardson number ($Ri_B$) (Stull 1988) can now be represented as

$$Ri_B = \frac{\left(\frac{g}{g_d}\right)\Delta \theta \Delta z}{(\Delta u)^2 + (\Delta v)^2}.$$  \hspace{1cm} (6)
where \( \overline{\theta_v} \) represents the mean virtual potential temperature between 3 m and 76 m, \( \Delta \theta_v \) is the difference in virtual potential temperature, and \( \Delta u \) and \( \Delta v \) are differences in zonal and meridional wind components, respectively.

### 2.2.2 Wind power ramp calculation

The presence of a wind power ramp at a given 15-minute interval was determined if, at a given 15-minute interval, the difference of the average hub-height wind power of all turbines for i) the hour after the given 15-minute period and ii) the hour leading up to the given 15-minute period, equals or exceeds 50% of the power capacity. This definition was chosen to identify inter-hour atmospheric events that can cause major changes in wind power production. Thus,

\[
\text{wind power ramps} = \frac{100\%}{4 \cdot \text{Power}_{\max}} \left( \sum_{k=1}^{4} \text{Power}(t + k) - \sum_{-3}^{0} \text{Power}(t + k) \right), \tag{7}
\]

where \( \text{Power}(t + k) \) is 15-minute time-ending average power, with \( t \) representing the 15-minute interval ending at the current time. In Figure 2.2, \( t \) would be 01:45–02:00, and the wind power ramp would be categorized as a 02:00 ramp. This enabled production of figures with respect to hour of the day; if a ramp is centered on any 15-min period within a given hour, then that hour was flagged as having a ramp.

### 2.2.3 Wind speed variability calculation

Wind speed variability is defined to be present if the difference between turbine-average wind speed of the next 15-minute interval and that in the current 15-minute interval equals or exceeds 1 \( m \ s^{-1} \), represented as follows:
Figure 2.2: Pictorial representation of a wind power ramp for a 2-MW turbine as defined in this paper. In this example, the wind power ramp is defined as the difference between the 2–3 PM average wind power and the 1–2 PM average wind power, and is considered a 2 PM wind power ramp for the purposes of the heatmap in Figure 2.8.

\[
\Delta \text{ capacity factor} = \frac{|\text{2-3 PM hour-avg power} - \text{1-2 PM hour-avg power}|_{\text{max power}}} = \frac{1900\ kW}{2000\ kW} - \frac{900\ kW}{2000\ kW} = \frac{1000\ kW}{2000\ kW} * 100\% = +50\% \text{ in 1 hour}
\]

\[|\bar{v}_{t+1} - \bar{v}_t| \geq 1 \ m \ s^{-1}. \quad (8)\]

This threshold represents a wind speed difference that corresponds to an approximate wind power difference of 250 kW near the inflection point of the wind power curve to be described later in Figure 2.4 (7–8 m s\(^{-1}\)). It represents one-fourth of the wind power ramp threshold in one-fourth of the power ramp duration for this wind farm, and thus wind speed differences that are the result of shorter-lived atmospheric phenomena.
2.2.4 Percentage of time calculation

To quantify the diurnal cycle of wind ramps and wind speed variability, the count of events exceeding our thresholds was made for each hour of the day (00, 01, 02, ..., 23 UTC). The counts for each hour were normalized by the maximum counts possible for that hour, a quantity determined by data availability. Then the percentage of time, hereafter \( \% \text{time} \), that wind power ramps or wind speed variability occurred for that hour was calculated as follows:

\[
(\% \text{time})_{\text{hour}} = \frac{\text{count}_{\text{hour}} \times 100\%}{\text{highest possible count}_{\text{hour}}}. \tag{9}
\]

2.3 Results and Discussion

2.3.1 Seasonal climatology

The Kuwait wind resource is well matched to the seasonal energy demand cycle. Performance of a turbine or wind farm is quantified by the capacity factor, which is the power produced over a given time divided by the maximum possible power that could be produced in that time. The capacity factor measures not only the resource, but also the performance of a wind plant. From January to May of 2018 and 2019, the monthly average Shagaya capacity factor (Figure 2.3) was in the range of 33–44% until increasing abruptly above 58% from June to August, and then decreasing back to less than 43%. Figure 2.3 also indicates that the average Shagaya wind farm capacity factor from Sep 2017 to Aug 2019 was near 45%. Note that times when all turbines had missing data were excluded from any averaging. As a comparison, the average wind power capacity was approximately 42% (onshore) for Latin America in 2014.
Figure 2.3: Monthly-averaged wind power capacity factor for the entire wind farm from September 2017 through August 2019, with the average capacity factor for the entire year (black dotted). Please note that missing data was excluded from any averaging.

(IRENA 2016), 32% for Southeast Asia in 2016 (IRENA 2018), 35% for the United States in 2017 (Wiser and Bolinger 2018), 24% for Europe in 2018 (WindEurope 2019), and the global weighted average of 2018 onshore capacity factor was 34% (IRENA 2019b). Thus, Kuwait is an excellent wind resource, particularly during the summer when the capacity factor exceeds 50%.

The substantial increase in wind power production during the summer was caused by higher average wind speeds within the cubic portion of the turbines’ wind power curve. An example of the turbines’ power curve is shown in Figure 2.4, with the cubic portion of the power curve occurring for wind speeds between 3–12 \( m \, s^{-1} \). The average wind speed was 9.7 \( m \, s^{-1} \) for summer months and 7.0 \( m \, s^{-1} \) for non-summer months, which according to Figure 2.4 results in
Figure 2.4: Wind power conversion curve that estimates turbine-generated wind power from nacelle wind speed. Mean wind for summer months (June, July, and August) and non-summer months from September 2017 to August 2019 are in red-dashed and blue-dashed respectively.

Figure 2.5 shows a heatmap of hourly-average 78-m (hereafter, hub-height) turbine wind speeds with respect to month and hour (UTC). From June through August wind speeds were 2–3 $m\,s^{-1}$ faster compared to other calendar months. This strong increase in hub-height wind speed is likely due to the summer Middle Eastern shamal. It was found by (Yu et al. 2016) that during the summer a heat low over Iran and a high-pressure center over the eastern Mediterranean Sea create a strengthened pressure gradient, which causes faster-than-average shamal-like winds over the Kuwait region. Hub-height wind roses from SHA and ELE for June through August of 2018 indicate that winds in Kuwait were predominantly from the north to northwest, with wind speeds up to 15–18 $m\,s^{-1}$ (Figures 2.6a–b). During these three months, 75–85% of winds were from the north to northwest, which indicates the presence of
The summer shamal. The summer shamal was the driving force for capacity factors above 50% for June, July, and August as shown in Figure 2.3. Other times of the year, represented by Figures 2.6c–d, winds from the southeast quadrant were more prominent and had generally slower speeds of up to 9–12 m s\(^{-1}\). Northwest is still a dominant wind direction during this time of the year, albeit with smaller wind speeds than the summer months. This wind direction variability indicates that other synoptic processes besides the shamal are likely driving winds during the rest of the year.

---

**Figure 2.5**: Temporal heatmap of farm-averaged wind speed (m s\(^{-1}\)) for each month (rows) and hour of the day (columns; UTC). Please note that the date range is from 01 Sep 2017 to 31 Aug 2019.
Figure 2.6: Wind roses of hub-height wind speeds (m s\(^{-1}\)) for SHA and ELE during a–b) summer months and c–d) non-summer months. The radial coordinate is percent of data within the subset of months and filled contours are wind speed. Please note for a) that the SHA dataset ended 26 Jun 2018 and for b) ELE experienced a data outage for the entirety of June. Also note that the date range for ELE is from 01 Sep 2017 to 31 Aug 2018.

2.3.2 Diurnal climatology

The largest electric loads in Kuwait occur in the late afternoon to early evening due to air conditioning usage from peak daytime heat load (Wood and Alsayegh 2014). During this same
time frame, the solar zenith angle decreases sharply, so solar energy availability declines. Therefore, to meet the increase in energy demand via renewable energy during this time period, wind energy becomes more important.

Fortuitously, hub-height wind speed at Shagaya has a diurnal cycle that complements the cycles of consumers’ daily energy demand and solar energy availability. Wind speed increases around sunset (1330–1530 UTC), as indicated by the hour-average wind speeds in Figure 2.5, and remain higher throughout the night until sunrise (0130–0330 UTC) the next day. Concurrently, the wind tends to veer from northwesterly during the day to southeasterly at night (not shown) and then either back or veer to northwesterly again the next day. This strengthening and veering of the wind at night matches the pattern seen in nocturnal LLJs (Blackadar 1957; Stull 1988). This diagnosis can be supported by an analysis of the diurnal cycle of static stability in the near-surface boundary layer.

As noted by (Blackadar 1957) the LLJ results from stabilization of the lowest portion of the boundary layer and the resultant decrease in turbulent drag. This results in less vertical mixing of momentum, causing low-level wind speeds to be slower and more elevated winds to be faster than during the daytime. Near-surface boundary layer stability can be quantified from the Shagaya data using the bulk Richardson number \( R_i_B \) as defined in Eq. (6). \( R_i_B \) was computed using ELE and SWS data in Eq. (6) in 10-minute intervals between 01 Sep 2017 and 31 Aug 2018. Each 10-minute \( R_i_B \) was binned based on month and hour of the day (0000–2300 UTC), and then a median \( R_i_B \) was calculated for each bin (Figure 2.7). Median \( R_i_B \) was calculated due to the \( R_i_B \) distribution being skewed by instances of small wind shear, so that the mean yielded unrepresentatively large values.

After sunrise (0300–0600 UTC), the near-surface boundary layer destabilizes and \( R_i_B \) decreases, as does wind speed (cf. Figures 2.5 and 2.7; please note that May and June do not have \( R_i_B \) values in Figure 2.7 due to data collection issues with ELE during those months). Near sunset
Figure 2.7: As in Figure 2.5, but for bulk Richardson number. The median Richardson number was calculated for each month and hour to avoid times with large Richardson number due to small wind shear biasing the average. Please note that no values were calculated for May and June due to ELE missing data for the entirety of those months, which precludes calculation of that derived variable. Also note that the date range for Figure 2.7 is from 01 Sep 2017 to 31 Aug 2018 due to data collection issues for ELE in part of 2019.

(1300–1700 UTC), wind speed increases and $Ri_B$ increases from negative to positive as the near-surface boundary layer stabilizes. The nocturnal presence of increased wind speed and veering wind direction coincident with near-surface boundary layer stabilization is indicative of the formation of a LLJ as described in (Blackadar 1957). As shown in Figure 2.5, the LLJ increases average wind speed from $7.0 \ m \ s^{-1}$ at 1300 UTC to $8.1 \ m \ s^{-1}$ at 1700 UTC during non-summer months. The difference in wind speed happens to occur in the steep cubic portion of the turbines’ power curve, and thus, results in a large increase of wind power. Therefore, LLJ formation can increase hub-height wind speeds during the evening and provide an operationally significant increase in wind power at a time when homes are consuming more energy and solar energy is not available.
2.3.3 Wind power ramps and wind speed variability

Large wind power changes over several hours or less, otherwise known as wind power ramps, can be troublesome for grid operators to compensate for with appropriate operating reserves. With multiple definitions for what constitutes a wind power ramp, it is important to pick thresholds appropriate to a specific operator’s needs. As stated previously, wind power ramps are defined here as differences of at least 50% power capacity in 1 hour. This will provide insight to large atmospheric phenomena like stabilization of the near-surface boundary layer and LLJ formation. Variability in wind speed, defined here as 15-minute fluctuations in hub-height wind speed greater than or equal to $1 \text{ m s}^{-1}$ according to Eq. 8, can indicate convective turbulence resulting from destabilization.

Wind power ramp occurrence slightly peaks near sunrise, when vertical wind shear of the nocturnal LLJ is eroding, producing inter-hour variations of wind speed (Figure 2.8a). After sunrise in Kuwait (0300–0600 UTC), near-surface boundary layer destabilization enhances turbulent mixing, thus causing the average hub-height wind speed to decrease as noted in Section 3.2. This eddy transport of momentum results primarily in down ramps via transport upward across the vertical gradient below the LLJ, with the percentage of time ($\%time_{ramp}$) of down ramps peaking near 1.0% at 0400 UTC while up ramps were simultaneously near 0.25% according to Figure 2.8a.

At approximately 0500 UTC, bulk Richardson number transitions from positive to negative as daytime heating causes the near-surface boundary layer to destabilize up to hub height (Figure 2.9a). Convective thermals induce mixing that erodes the LLJ and thus decreases shear-driven turbulence induced by the LLJ, as indicated by the local minimum in standard deviation of wind speed among the turbines ($\sigma_{(v,farm)}$) and the $\%time$ of wind speed variability ($\%time_{var}$) near 0700 UTC in Figures 2.9b–c. As the day progresses, further daytime heating increases
Figure 2.8: a) Percent of collective time that up ramps (blue), down ramps (red), and total ramps (black) occur for each hour of the day. b) Temporal heatmap for collective time that a farm-averaged wind power ramp occurs for a given month and hour of the day. Please note that the date range is from 01 Sep 2017 to 31 Aug 2019.
convectively-driven turbulence until $\sigma_{(v,farm)}$ and $\%time_{var}$ peak near 0.24 m s$^{-1}$ and 14%, respectively. Later in the day, $\sigma_{(v,farm)}$ and $\%time_{var}$ decrease with decreasing daytime heating until about 1700 UTC, after which the return of the LLJ and its shear-driven turbulence keep $\sigma_{(v,farm)}$ between 0.17–0.20 m s$^{-1}$ and $\%time_{var}$ near 8–9%. This surface heating is usually greatest on afternoons during warmer months, and is thus when convective instability is strongest according to Figure 2.7. Therefore, $\%time_{var}$ peaks during the afternoon (0900–1400 UTC) from late spring to early autumn according to Figure 2.9d. The fraction of the day experiencing this increased wind speed variability and, thus, short-term power variability decreases to its lowest values during colder months as daytime heating decreases. A minimum in wind power ramps also occurs midday (Figure 2.8), suggesting that convective instability is producing primarily short-lived turbulent eddies.

After sunset, wind power ramps increase again because the onset of the LLJ increases vertical wind shear (Figure 2.8a). These are mostly up ramps as average hub-height wind speed increases at night (Figure 2.5). These ramps occur more often with $\%time_{ramp}$ 0.8–1.9%, and their occurrence extends well into the night, especially in springtime (Figure 2.8b). Short-term wind speed variability decreases into the night as upward heat flux becomes negative which terminates convective instability. In Figure 2.9d, the presence of wind speed variability decreases at a slower rate in spring and summer months. This could be due to the persistence of convective turbulence as supported by bulk Richardson numbers in Figure 2.7 being negative or positive but small ($-0.01 < Ri_B < 0.06$) for April and July during the evening hours, indicating that the mixing out of instability and the associated stabilization occur more slowly.

Overall, Figures 2.5 and 2.7–2.9 reflect the main stages of the near-surface boundary layer diurnal evolution and how they affect wind power in an average day. First, the nocturnal boundary layer stability and resultant LLJ cause increased hub-height winds and thus larger wind
Figure 2.9: a) Ri, b) standard deviation of hub-height wind speed of all turbines and turbine-averaged wind power, and c) temporal variability of turbine-averaged wind speed, averaged by hour of the day. d) Temporal heatmap for collective time that farm-averaged wind speed variability occurs for a given month and hour of the day. Please note that the date range is from 01 Sep 2017 to 31 Aug 2018 for Figure 2.9a and 01 Sep 2017 to 31 Aug 2019 for Figures 2.9b–d.
power production during the night. Morning destabilization then erodes the nocturnal LLJ, causing down ramps in wind power and turbulent variability to temporarily decrease. Subsequent solar heating results in convective turbulence, causing a decrease in the number of wind power ramps and an increase in short-term wind speed variability, peaking in the afternoon. The evening cessation of solar heating and consequent nocturnal LLJ formation cause wind power to ramp up and lead to larger-than-average wind power at night, completing the cycle. This diurnal pattern of wind power ramps is primarily due to the LLJ and makes Kuwait a relatively reliable wind resource.

### 2.4 Conclusions

Based on wind power and meteorological data from 01 Sep 2017 to 31 Aug 2019, the Shagaya wind power complements seasonal and diurnal demand cycles in Kuwait. Shamal-like winds cause a substantial increase in hub-height wind speed from June to August. This provides more wind energy to meet the increased demand from air conditioning in the summer. The formation of the nocturnal low-level jet causes hub-height wind speed to increase in the evening hours and at night, allowing wind power to complement the availability of solar power. Greater wind power production during Kuwait’s seasonal and diurnal peaks of demand highlights the benefit of integrating wind energy in Kuwait’s electrical grid.

In addition to knowing when wind energy complements demand, grid operators must compensate for short-term variations in wind power, so knowing when wind power ramps are more likely during the day and the year could be helpful. On the diurnal scale, erosion (formation) of the nocturnal LLJ can cause hour-average wind speed to ramp down (up) by 50% capacity after sunrise (sunset). After dawn, shear-driven turbulence results in both up ramps and
down ramps, with a slight majority of down ramps, as well as small-scale wind speed variability. Wind speed variability increases throughout the day until peaking at midday, and then decreases steadily into the evening. Wind power ramps, primarily up ramps, are most common in the evening during the spring, thus large hour-to-hour wind power variability is most frequent during these times as the LLJ forms. Convectively-induced turbulence during the day and during warmer months can cause 15-minute wind speed variability to peak during times of large upward surface heat fluxes, the mixing from which decreases the likelihood of wind power ramps. Understanding the increase in frequency of significant fluctuations in wind power production near sunrise and sunset could allow Kuwaiti grid operators at the National Control Center to better prepare for short-term wind power ramps and variability.

Kuwait’s energy grid operators will benefit from a better understanding of the magnitude and variability of wind power on seasonal and diurnal time scales. We have shown higher wind power production at night and during the summer, which supports the initiative of installing and integrating more wind power in Kuwait, including at Shagaya.

Future work will focus on how synoptic and mesoscale events, such as storms, dust storms, and fronts, affect hub-height wind speeds and thus wind power in Kuwait. Also, we plan to compare these observations to Weather Research and Forecasting (WRF) model simulations to investigate whether the WRF can capture seasonal and diurnal variability of hub-height wind speed and how well WRF can predict hub-height wind, as well as provide insight to potential areas of improvement in the model.
Chapter 3

Identifying Wind Regimes Near Kuwait Using Self-Organizing Maps

Optimization of wind energy integration requires knowledge of the relationship between weather patterns and the winds they cause. For a region with less-studied weather such as the Middle East, knowing its climatology becomes more vital. The Shagaya Renewable Energy Park in development in Kuwait experiences regional wind regimes that affect their wind power production. Through a collaboration with the Kuwait Institute for Scientific Research (KISR) and the National Center for Atmospheric Research (NCAR), output from the Weather Research and Forecasting (WRF) model allowed investigation into the weather regimes most likely to impact Shagaya. A machine-learning method known as self-organizing maps (SOMs) clustered the WRF output into six primary weather regimes experienced by the Middle East. Of these six regimes, three were conducive to wind speeds favorable to wind power production in Kuwait. One depicts a strong northwesterly wind called the summer shamal, the second is associated with a deep daytime boundary layer, and the third represents cold season northwesterlies from a shallow low-pressure system near the Red Sea. The remaining three SOMs represent regimes less favorable for wind power in the remainder of the year.

3.1 Introduction

A complete understanding of wind patterns is necessary for wind energy to be properly incorporated into the electrical grid. It can help with wind farm siting (Dvorak et al. 2012b, Wilczak et al. 2019), turbine positioning (Archer et al. 2013; Ghaisas and Archer 2016), or resource utilization (Kempton et al. 2010). Kuwaiti energy demand changes throughout the day
and the year. Alotaibi (2011) shows that monthly fuel consumption in Kuwait is positively correlated with monthly mean temperature, with the peak electrical load in July being two to three times greater than peak electrical load in February. During the day, the electric load in Kuwait changes by more than 8% of the total installed capacity on average (Wood and Alsayegh 2014). The wind itself can also be diurnally and seasonally variable in Kuwait, as explored in Chapter 2. Knowing when wind is more likely to fluctuate and by how much is necessary to meet the ever-changing energy demand in a region with a growing investment in renewable energy. It is therefore imperative that the primary wind regimes in the region of interest are studied to ensure the growth of the wind energy industry.

Kuwait plans to increase their solar and wind energy capacity from 70 MW to 4 GW at the Shagaya Renewable Energy Park (KISR 2019). However, wind climatology of the Middle East is not as extensively studied as some other regions of the world. Vojtesak (1992) did a climatological study of the Arabian Peninsula where several semipermanent climatic controls and weather patterns were described. One common regional weather pattern with a major impact on wind is the shamal (Perrone 1979; Hubert et al. 1983; Middleton 1986). “Shamal” derives from the Arabic word for “north,” and there are two varieties of shamal that occur in winter and summer. Both bring increased wind speeds to the Lower Mesopotamia region and Kuwait, although the summer shamal is characterized by semi-permanent stronger winds that last throughout the summer (Yu et al. 2016) while the winter shamal lasts for several days but occurs several times throughout the winter (Rao et al. 2001).

Identifying these synoptic patterns among years of data can be arduous and time-consuming, but the machine-learning method known as self-organizing maps (SOMs) can identify patterns in large datasets in relatively short periods of time. SOMs have already been used across atmospheric sciences and throughout the world, including the Madden–Julian Oscillation (Chattopadhyay et al. 2013), El Niño and La Niña (Li et al. 2015), Arctic atmospheric
circulation patterns (Skific et al. 2009), Antarctic surface wind patterns (Nigro and Cassano 2014), and New Zealand valley and ridgetop boundary layers (Katurji et al. 2015). For the Middle East region, SOMs have identified patterns in 500-hPa geopotential height (Cavazos 2000; Michaelides et al. 2007) and surface wind (Berkovic 2017). Naegele et al. (2020) and Al-Rasheedi et al. (2021) determined that the summer shamal produces a substantial increase in generated wind power for the Shagaya Park, indicating summer is a season of favorable wind energy production for Kuwait. However, further investigation is needed to study the geographical and seasonal characteristics of common wind patterns that are beneficial to wind energy in the region like the summer shamal, as well as common wind patterns less favorable for wind energy.

This paper will expand our understanding of Middle Eastern wind regimes by using SOMs to identify wind patterns in Kuwait near the hub height of wind turbines using the Weather Research and Forecasting (WRF) model. Identifying these wind patterns are particularly important to energy grid operators as mentioned above. A short summary of the WRF dataset and the SOM methodology is presented in Section 3.2. A discussion of the SOMs trained on WRF hub-height wind speed centered over Kuwait is in Section 3.3. Section 3.4 includes concluding remarks.

3.2 Data and Methods

3.2.1 WRF

While Shagaya has the benefit of having meteorological towers and surface weather stations at the park, SOMs require wind data that has higher spatial and temporal resolution than what these observational sites provide. Therefore, the Weather Research and Forecasting (WRF) model was chosen, which allows the use of custom variables that would not otherwise be
included in a reanalysis dataset. Through a collaboration between the Kuwait Institute for Scientific Research (KISR) and the National Center for Atmospheric Research (NCAR), output from the WRF model (Skamarock et al. 2021) version 4.2.2 was centered over the Middle East. The specific version of WRF used for this study includes specific customizations for solar energy forecasting and is hence designated WRF-Solar (Jiménez et al. 2016a–b; Haupt et al. 2018). It was designed to optimize irradiance prediction with improvements to aerosol-radiation feedback and cloud-radiation feedback, incorporation of cloud-aerosol interactions, and diagnosing of parameters relevant to solar industry. In addition to studies specifically focused on solar forecasting (Lee et al. 2017; Verbois et al. 2018; Kim et al. 2021; Juliano et al. 2022), WRF-Solar has also been used in wind energy studies (Mahoney et al. 2012; James et al. 2017; Siuta et al. 2017; Lee et al. 2018; Haupt et al. 2020; Tan et al. 2021), making it the ideal model choice for this study. Simulations using WRF-Solar have a 9-km outer grid domain centered on the Arabian Peninsula (Figure 3.1). WRF forecasts are initialized with Global Forecast System (GFS) initial and lateral boundary conditions daily at 0000 UTC from 01 September 2017 to 31 August 2019. Forecasts are output hourly for up to 48 hours, although only output from 24 to 48 hours ahead was used for this study to avoid spin-up issues in the first few hours of each simulation. Namelist options are provided in Table 3.1.

### 3.2.2 SOMs

SOMs are the tool used here to identify the main wind regimes, as SOMs are known for organizing high-dimensional datasets based on topological (mathematically distinct) features to reduce their dimensionality (Kohonen 1982). In order to reduce the computational cost of SOM training, the WRF output grid size was thinned by keeping every fifth grid point during training, and the easternmost grid points were omitted from the output. SOM training requires data to be 1-
Figure 3.1: The WRF domain used for this study, with the location of the Shagaya Renewable Energy Park indicated by the star near the center of the domain.

Table 3.1: Namelist options for WRFv4.2.2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Option</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time step</td>
<td>50 s</td>
</tr>
<tr>
<td>Grid points</td>
<td>401x301</td>
</tr>
<tr>
<td>Number of vertical levels</td>
<td>45</td>
</tr>
<tr>
<td>Top of model</td>
<td>50 hPa</td>
</tr>
<tr>
<td>Microphysics</td>
<td>Thompson (Thompson et al. 2008)</td>
</tr>
<tr>
<td>Longwave radiation</td>
<td>RRTMG (Iacono et al. 2008)</td>
</tr>
<tr>
<td>Shortwave radiation</td>
<td>RRTMG (Iacono et al. 2008)</td>
</tr>
<tr>
<td>Radiation time step</td>
<td>5 min</td>
</tr>
<tr>
<td>Surface layer</td>
<td>Revised MM5 Similarity scheme (Jiménez et al. 2012)</td>
</tr>
<tr>
<td>Land surface</td>
<td>Noah Land-Surface Model (Ek et al. 2003)</td>
</tr>
<tr>
<td>Boundary layer</td>
<td>MYNN 2.5-level TKE scheme (Nakanishi and Niino 2006)</td>
</tr>
<tr>
<td>Cumulus</td>
<td>Grell-Freitas ensemble scheme (Grell and Freitas 2014)</td>
</tr>
<tr>
<td>Aerosol input option for radiation</td>
<td>1</td>
</tr>
</tbody>
</table>
dimensional, so each WRF map is reshaped to be a vector of length 1200. Weight vectors of equal size are randomly initialized and assigned to each point in SOM map space, or SOM node. In order to cluster the dataset into its main features, the grid size for the nodes must be pre-defined with the number of nodes corresponding to the number of features sought in the dataset. Determining the ideal SOM dimensions usually requires experimentation for a given dataset, as will be briefly described below.

During training, SOM node weight vectors are iteratively altered to transform the data through competitive learning (Kohonen 1990). For each WRF hourly output time, the map node (or neuron) that most closely resembles the input is designated the best matching unit (BMU) and the output time is assigned to that BMU. In MATLAB, the function ‘selforgmap’ uses a distance function called the link distance, or the number of steps to get from one node to another, to determine the nodes within an iteratively smaller radius, or neighborhood. Within the neighborhood, weight vectors for each map node are adjusted incrementally closer to the input vector. The ‘selforgmap’ function also uses a neighborhood function called ‘hextop’ as the default neighborhood function and arranges the neurons in a hexagonal pattern. Through the described iterative training process, SOM nodes converge to resemble the most prominent topological features of the data with surrounding nodes representing similar features. Other methods like k-means cluster analysis do not utilize a neighborhood function and thus do not produce nodes with features similar to those of their respective neighboring nodes. For this case, each SOM node itself represents a map of wind speed with adjacent nodes having similar features, and together they form a grid of maps of dominant wind patterns in the Middle East.

In this study, a grid size of 3×2 is chosen, the reasons for which are twofold. First, the minimum number of regimes with distinct climatological timing is predicted to be four: summer shamil conditions and conditions during periods outside of summer months, for both daytime and nighttime hours. In addition to these four, two more are added, ideally to represent regimes of
timescales intermediate between annual and diurnal. Second, we also subjectively determine that SOMs of larger grid sizes have subsets of maps that are too similar to each other and thus add little additional value to the overall analysis.

For each output time, training on hub-height (defined here as 80-m) horizontal wind (U- and V-wind) components determines the best SOM node to represent that time. More specifically, the hourly 80-m horizontal wind components forecasted from 24 to 48 hours ahead serve as training variables for SOMs. After the SOM algorithm is complete, each node itself represents a two-dimensional map of wind components averaged grid point by grid point over time periods when the given node is the dominant node. The result in this study is therefore a 3×2 grid of maps, with each of the six maps representing a wind regime.

The seasonality of each SOM node is determined by counting the output times, or hours, that are clustered to each SOM node per month. For example, if the SOM algorithm determines that the dominant SOM node is node 1 for the entirety of January, then the seasonal pattern would simply be expressed as 31 days • 24 hours/day = 744 hours for node 1, the maximum number of hours for January, and 0 hours for nodes 2–6.

Because each output time has a dominant SOM node associated with it, they can be used to determine the relationship of these wind regimes to other WRF variables. For example, with the times associated with each SOM node, one can calculate the time-average wind speed at each WRF grid point for each SOM node. And with the same times, one can also determine the time-average of other model variables. Thus, geopotential height can be averaged over the same time periods that result from SOM training on hub-height winds, thus depicting the upper-level flow pattern associated with each wind regime. Thus, if a SOM node that represents a map of increased wind speeds is, for example, associated with a map of higher geopotential heights, then it can be inferred that the two patterns are correlated, and future forecasts of higher geopotential height could indicate increased wind speeds. The relationship between wind and other meteorological
variables motivates investigation of the weather patterns that cause the wind regimes identified by
SOMs and can indicate what model variables forecasters should be investigating for a given wind
regime.

3.2.3 Distributions of wind speed and wind power

At the WRF grid point with latitude and longitude coordinates closest to the coordinates
of Shagaya, U- and V-wind components are converted to wind speed for each output time. Then,
wind speeds for output times associated with each SOM node are used to iteratively assemble a
histogram for that node at the grid point closest to Shagaya. The difference in mean wind speed
occurs because during SOM training the input dataset is the concatenation of the U- and V-wind
component vectors, and thus the result after training is six 2-D arrays of node-average U-wind
and six 2-D arrays of node-average V-wind. The arrays are then converted to six 2-D arrays of
average wind vectors for each SOM node. As a result of Jensen’s inequality (Bessac et al. 2019,
McCandless and Haupt 2019), reversal of the order of the averaging and non-linear wind speed
calculation results in the wind speeds computed from the SOM nodes being less than the mean of
the wind speeds for the cases assigned to those nodes. The advantage of the SOM approach is that
it provides average wind vectors and thus can represent wind flow pattern. In contrast, the wind
speed histograms are better suited for computing wind power. The distributions have the
advantage of providing the average wind speed magnitude that hypothetical wind turbines would
experience at Shagaya in the WRF model, as the average is calculated after the conversion from
the U- and V-wind components to full magnitude.
3.2.4 Wind power density

Wind power density can help indicate wind resource in a particular area regardless of the wind turbine installed. In order to calculate wind power density, virtual temperature at hub height must first be determined:

\[ T_v = T(1 + 0.61q), \quad (1) \]

where \( T \) is the air temperature at hub height, in this case 80 m, and \( q \) is mixing ratio at hub height. Virtual temperature is then used to calculate air density \( \rho \) at hub height, given by the ideal gas law:

\[ \rho = \frac{P}{R_{dry} T_v}, \quad (2) \]

where \( P \) is air pressure at hub height and \( R_{dry} \) is the gas constant of dry air, 287 J kg\(^{-1}\) K\(^{-1}\).

Finally, wind power density can be defined as

\[ WPD = \frac{1}{2} \rho v^3, \quad (3) \]

where \( WPD \) is wind power density and \( v \) is wind speed at hub height.

3.3 Results and Discussion

The SOM of WRF 80-m hourly 24-h to 48-h forecasted horizontal wind components captures synoptic wind patterns on seasonal and diurnal time scales (Figure 3.2). The SOM is explained further using a histogram and a heatmap of output times represented by each SOM node and month (Figure 3.3), and a histogram similar to that from Figure 3.3 but with separate counts for daytime and nighttime data (Figure 3.4). The underlying meteorology is then determined using SOMs trained on 80-m wind but with node-averages of other meteorological variables plotted instead: 850-hPa geopotential height (Figure 3.5), 500-hPa geopotential height
Node 1 shows an axis of northwesterly winds with wind speeds up to 10 m s\(^{-1}\) through the Lower Mesopotamia region in Iraq to Kuwait and the northern Arabian Gulf (Figure 3.2). Node 1 is by far the most common node for the months of June, July, and August (Figure 3.3). For node 1, generally anti-cyclonic wind circulation and higher 850-hPa geopotential height over Egypt are observed (Figures 3.2 and 3.5), with lower heights near the Zagros Mountains in Iran. All these features reflect the geographic and temporal pattern characteristic of the summer shamal. The features outlined above align with findings from Naegele et al. (2020) and Al-Rasheedi et al. (2021). Thus, node 1 captures a regime of great importance for wind energy.

Node 2 shows strong westerly winds in western Saudi Arabia (Figure 3.2), primarily in the winter-to-spring timeframe (Figure 3.3). Figures 3.5–3.6 indicate that there is on average a vertically-stacked trough over Turkey. The relationship between the winds and geopotential heights of node 2 suggests a regime characterized by a deteriorated low-level low north of the domain and prevailing westerlies. Kuwait is within a region of calmer wind speeds, and thus the SOM-indicated node 2 not as likely to produce as much wind energy as node 1.

For node 3, stronger winds are primarily in regions of higher terrain such as the Zagros Mountains in Iran and the east and west coasts of the Red Sea, with southwesterly wind flow originating from the Africa (Figure 3.2). Node 3 occurs from autumn to spring (Figure 3.3) with a slight preference for daytime hours (Figure 3.4). Figures 3.8–3.9 indicate regions of locally greater PBL depth and frictional velocity (\(u^*\)) near the coast of the Red Sea. Due to the higher terrain in these regions, the land surface is heated more than the surrounding air, causing local regions of ascent and mixing, and thus regional flow toward these areas. In contrast, outside of these areas are more quiescent conditions; Kuwait experiences relatively calm conditions with wind speeds < 5 m s\(^{-1}\). The typical cut-in wind speed of a wind turbine is 3–4 m s\(^{-1}\), below which
Figure 3.2: SOMs trained on WRF 80-m horizontal wind components from 01 September 2017 to 31 August 2019. Filled contours represent 80-m wind speed while red arrowed lines indicate 80-m wind flow. Please note the first contour represents a range of 0–3 m s$^{-1}$, or wind speeds below the estimated cut-in wind speed of a typical wind turbine.
Figure 3.3: a) Number of forecast hours clustered to a particular SOM map node. b) As in a), but further clustered by month.
As in Figure 3.3a, but with nighttime data parsed from daytime data. Here, nighttime refers to output times between 1500 and 0300 UTC. Turbine blades cannot rotate to generate wind power (EERE 2022). Thus, node 3 suggests a regime that is not ideal for wind energy production at Shagaya.

Nodes 4 and 5 have similar seasonal timing and geopotential height patterns but different flow patterns. Node 4 has weaker winds along the western coast of the Arabian Gulf and stronger winds over northeastern Africa, while wind flow in node 5 has a stronger westerly component in the eastern half of the domain (Figure 3.2). However, both node 4 and node 5 are more common in the autumn and spring (Figure 3.3), and both have higher geopotential heights west of Egypt (Figures 3.5–3.6). Node 4 is also largely a nighttime regime whereas node 5 largely a daytime regime (Figure 3.4). Associated with the stronger nighttime winds over northeastern Africa in
**Figure 3.5:** 850-hPa geopotential height for SOMs trained on WRF 80-m horizontal wind components from 01 September 2017 to 31 August 2019. Please note that areas in pure white represent land surface area that is higher than the 850-hPa surface.

Node 4 are shallower PBL depths and less surface heat flux, whereas node 5 has the largest values of all nodes for both variables (Figures 3.7–3.8). Thus, node 4 represents a nocturnal low-level jet pattern over Africa while node 5 represents a daytime well-mixed and deep PBL. While node 4...
Figure 3.6: As in Figure 3.5, but for 500-hPa geopotential height.

suggests calm winds for Kuwait, node 5 indicates more favorable wind speeds of 5–7 m s$^{-1}$, and is thus better for wind energy at Shagaya.

Node 6 has a wind flow pattern that resembles a weak low-pressure system over the southern Red Sea (Figure 3.2). It primarily occurs from November 2017 to March 2018 and October 2018 to May 2019, suggesting that it is a cold-season wind regime. According to Figures
Figure 3.7: As in Figure 3.5, but for surface heat flux.

3.5–3.6, the relatively higher mean 500-hPa geopotential heights are associated with a region of slightly lower 850-hPa heights relative to the surroundings. Thus, the 500-hPa and 850-hPa geopotential heights suggest a shallow low that locally increases average wind speeds, especially in regions of higher terrain. These winds converge with northwesterlies of increased wind speeds in the lower Mesopotamia region and are likely the cause of calmer winds west of Kuwait.
Shagaya is on the edge of the axis of increased wind speeds near the Zagros Mountains, suggesting that node 6 is good for Kuwaiti wind energy production.

Further investigation of the impacts of these regimes on wind power for Shagaya requires distributions of wind speed for each SOM node at the grid point closest to the location of Shagaya, as detailed in Section 3.2.3. In the wind speed distribution for a given SOM node, wind
Figure 3.9: As in Figure 3.5, but for frictional velocity ($U^*$).

Speed at each output time is also converted to an estimated wind power. Shagaya is part of a pilot project that meets the IEC Class IIA and IIB requirements according to the IEC 61400–1 Edition 3 standard, so the turbine chosen for that site was the 2-MW Siemens-Gamesa G97. Therefore, estimates of wind power for each node at Shagaya are calculated using the estimated Gamesa G97 turbine power curve from Figure 2.4. This provides a WRF wind power distribution close to
Shagaya for each SOM node, which are provided in Figures 3.10–3.15. According to Figure 3.10, the shamal in node 1 causes WRF wind power (averaged across each 2-MW turbine) to be between 1900 kW and full capacity of 2000 kW per turbine roughly a third of the time. Node 1 also has an average approximate wind power of 1370 kW per turbine, closely resembling the approximate 1500 kW average per turbine converted from the observed summer mean wind speed in Figure 2.4. These results again exemplify the benefits of the summer shamal to wind power production at Shagaya. Node 2 has a similar distribution to node 1, with almost a quarter of its wind power being 1900–2000 kW per turbine and an average wind power near 1080 kW per turbine. The greater average wind speed in Figure 3.11a compared to the wind speed near Shagaya in Figure 3.2 suggests that at any given time, the wind vector in node 2 is likely to have a more northerly or southerly component, and upon averaging these signals are averaged out and thus the average wind speed near Shagaya in Figure 3.2 decreases. Figure 3.11 therefore indicates that node 2 is also beneficial to wind energy. Nodes 3–6 have slightly positively skewed power distributions, with the peaks of their distributions representing wind power of 0–100 kW per turbine (Figures 3.12–3.15). Nodes 3–6 also have an average wind power of 520–818 kW per turbine, a fraction of the average wind power from node 1. These nodes are thus more likely than nodes 1 or 2 to represent wind patterns too weak to turn the blades of the wind turbines at Shagaya.

If another turbine besides the Gamesa G97 is installed at Shagaya or anywhere in the Kuwait region, an analysis of wind power density (WPD) can provide a turbine-independent approach to determining which nodes are better for providing wind power. Figure 3.16 provides WPD at hub height averaged across each node, calculated using Eq. (3.3). Node 1 has the largest WPD near Shagaya, approximately 550 W m$^{-2}$, reinforcing the idea that node 1 is the most beneficial to Shagaya wind energy production. Additionally, WPD values are between 600–1000 W m$^{-2}$ immediately east and further north, in Lower Mesopotamia, indicating that any wind farms
Figure 3.10: a) Wind speed and b) wind power distributions for SOM node 1 for the WRF input grid point closest to Shagaya Park. Wind power was calculated using the turbine power curve in from Figure 2.4.
Figure 3.11: As in Figure 3.10, but for SOM node 2.
Figure 3.12: As in Figure 3.10, but for SOM node 3.
Figure 3.13: As in Figure 3.10, but for SOM node 4.
Figure 3.14: As in Figure 3.10, but for SOM node 5.
Figure 3.15: As in Figure 3.10, but for SOM node 6.
Figure 3.16: As in Figure 3.5, but for power density.

in southeastern Iraq and eastern Kuwait are more likely to benefit from the summer shamal in harvesting wind energy. Node 2 has WPD near 500–600 W m⁻² across much of southern Iraq, Kuwait, and northern Saudi Arabia, suggesting that the widespread westerlies of node 2 would provide adequate wind energy throughout the northern Arabian Peninsula for turbines at 80 m.
Nodes 3–6 have WPD between 180–310 W m\(^{-2}\) near Shagaya, which further indicates the decrease in wind power that these nodes can provide to Shagaya and most of the region.

In general, SOMs depict a climatological shift from stronger westerly to northwesterly flow at Shagaya in nodes 1 and 2, to weaker flow in nodes 3–6. There are also climatology shifts from a strong summer signal in node 1, to a late spring/early autumn signal in nodes 4 and 5, to a late autumn, winter, and early spring signal in nodes 2, 3, and 6. Near Shagaya, node 1 has an average wind speed of 9.9 m s\(^{-1}\) and an average wind power of 1370 kW per turbine, node 2 has an average of 8.6 m s\(^{-1}\) and an average wind power of 1080 kW per turbine, and nodes 3–6 have average wind speeds between 5.7–7.2 m s\(^{-1}\) and average wind power between 520–818 kW per turbine. Thus, node 1 represents the wind regime best suited for wind power production at the Shagaya wind farm in Kuwait, with the strongest winds in the most predictable time frame. The next best wind regime is node 2, followed by the remaining nodes.

### 3.4 Conclusions

When trained on WRF 80-m horizontal wind components from 1 September 2017 to 31 August 2019, SOMs reveal dominant wind regimes. Three out of the six mapped wind regimes suggest wind speeds at Shagaya, Kuwait, that are favorable for wind power production. Among these wind regimes is one that represents a well-known regional weather phenomenon known as the summer shamal, which was shown by Naegele et al. (2020) and Al-Rasheedi et al. (2021) to be significantly beneficial to wind power at the Shagaya Renewable Energy Park in Kuwait.

SOM analysis indicates that while summer is by far the most beneficial for wind energy in Kuwait, the deep daytime PBL of node 5 and the cold-season northwesterlies of node 6 can also lead to greater wind speeds in Kuwait during the rest of the year. Node 5 is associated with a deep daytime convective layer, while node 6 represents a shallow low-pressure system over the
Red Sea. Nodes 2 and 3 indicate that when there is divergent flow from Egypt or the Red Sea then it is more likely that Kuwait will experience calmer conditions. Node 4 suggests that a nocturnal LLJ over northeastern Africa is correlated with calm winds over Kuwait.

A deeper analysis involving distributions of node-averaged wind speeds at Shagaya revealed that the southwesterlies in node 3 have the weakest average wind speed and the westerlies in node 2 have the strongest average wind speed behind node 1. Thus, when SOMs are trained on wind components, they can provide average wind flow patterns. But to determine average wind speeds at Shagaya and thus the impact of each SOM node on wind energy at Shagaya, they need to be supplemented with distributions of the forecasted wind speed.

This type of analysis can assist in seasonal forecasting. For example, if long-term forecasts indicate a prevalence of a Rossby wave trough over eastern Europe in the winter, this suggests a wind regime resembling that of the westerlies in node 2. Therefore, Kuwait would expect a wintertime increase in wind power production. However, if the Rossby wave is expected to be located further to the west, as indicated in node 3, Kuwait is more likely to experience weaker southeasterlies and wintertime power production will be reduced. The described SOM analysis can also aid with planning future wind farm development. Evidence provided here suggests that wind turbines with a hub height of 80 m would produce substantial summertime wind power if installed in the Lower Mesopotamia, and turbines in the northern Arabian Peninsula would receive adequate wind power from westerlies from autumn to spring.

Additionally, those forecasting wind speeds at Shagaya Renewable Energy Park in Kuwait could use future model forecasts to determine the current wind regime and its likely impact on the wind resource in the near future. For example, if a model is forecasting a wind pattern the next day in June that resembles the wind regime in node 1, electric grid operators could then anticipate the forming of the summer shamal and thus prepare to utilize more wind energy not only the following day but until the end of summer. Similarly, if the model is
forecasting a strong nocturnal low-level jet over northeastern Africa like in node 4, then it is more likely that wind speeds in Kuwait will be weaker that night and wind energy will have to supplemented with additional resources.
Chapter 4

Analyzing Self-Organizing Maps of Modeled U.S. Coastal Wind Regimes with a Comparison to Observations

Wind offshore of the United States is a vast and plentiful resource. However, wind is also variable, which needs to be accounted for when offshore wind farms are planned, installed, and connected to the power grid. Therefore, increased knowledge of four general areas becomes vital: 1) common coastal wind patterns and their impact on wind energy availability, 2) how these patterns change over time, 3) how much wind shear a turbine can be expected to experience across its blades, and 4) how numerical forecast models compare to observations when predicting these wind characteristics. Wind data from the High-Resolution Rapid Refresh (HRRR) model is clustered using a machine learning method known as self-organizing maps (SOMs) to address areas 1–3). Regarding 4), modeled winds are compared to lidar observations from a buoy in the waters of New York and New Jersey for each regime identified by the SOMs.

4.1 Introduction

In the renewable energy industry, accurate forecasts of variable energy sources are vital to both facility siting and subsequent management of its day-to-day integration into the power grid. In the case of wind power, these tasks require determining the wind patterns that are prevalent, the most extreme, and are subject to the most variability, as well as accurately forecasting the weather that causes these wind patterns to occur.

The worldwide market of renewable energy is rapidly increasing, with global capacity increasing by more than double from 1.14 to 2.35 terawatts (TW) between 2009 and 2018.
In the U.S. alone, wind capacity increased by an estimated 14.8 gigawatts (GW) in 2020 (EIA 2021), bringing U.S. total wind capacity to approximately 118 GW (bp 2021). However, most U.S. wind power is land-based, despite NREL (2016) reporting that there is 2.06 TW of technical potential offshore wind resource capacity. The state of New York plans to develop 2.4 GW of offshore wind energy by 2030 (NYSERDA 2018). With an increasing investment in offshore wind energy, there is an increasing need for accurate assessment and forecasting of the wind resource.

In order to accommodate the rise in development of offshore wind energy, the offshore region of the eastern U.S. has been the focus of several studies on wind energy assessment. These studies show that the northeast U.S. region is a great source of ocean-based wind energy (Kempton et al. 2007; Dvorak et al. 2012a) with more energy than land-based wind resource (Garvine and Kempton 2008). Offshore wind energy has a seasonal peak in the winter, whereas summer is a seasonal minimum (Garvine and Kempton 2008; Woods et al. 2013). However, the New York Bight jet near the New Jersey coast peaks in the summer (Colle and Novak 2010), which could be a source of wind energy near that region in the summer. Low- and high-pressure systems can also produce uninterrupted wind power for extended periods of time, as indicated by Kempton et al. (2010) for a simulated transmission grid. Manwell et al. (2002) estimated a 5-month mean wind speed of 7.9 m s\(^{-1}\) near a wind turbine’s hub height at 60 m for a site in Nantucket Sound, near Massachusetts, which indicates significant wind speeds for this region. Since the findings of Manwell et al. (2002), average hub height for land-based turbines increased to near 90 m in 2020 (DOE 2021), and water-based turbines have similarly grown, allowing turbines to harness even greater wind speeds higher aloft.

Numerical model data can fill in gaps left by observational datasets, particularly in areas like coastal regions that have a paucity in observational datasets compared to the mainland. However, one drawback with using model data is that the abundance of it can make identification
of key features cumbersome. Machine learning automates and speeds up the process of feature identification, at times with little user input. An example is a method known as self-organizing maps (SOMs), a type of neural network introduced by Kohonen (1982) to cluster data based on topological features. SOMs have wide applications across atmospheric sciences, including identifying continental precipitation regions (Swenson and Grotjahn 2019), decadal climate variability (Gu and Gervais 2020), oceanic temperature (Liu et al. 2006; Wu et al. 2012), and model error (Kolczynski and Hacker 2014). This paper will branch out into using SOMs to identify coastal wind patterns at 80 meters above sea level, which is the HRRR model level closest to the average wind turbine’s hub height of 90 meters as noted above.

Errors in wind-related model variables like near-surface wind speed and surface-to-blade-tip wind shear need to be addressed to improve wind energy forecasts (Schreck et al. 2008). Errors in forecasted ocean-based wind speeds within the lowest 100 m can exceed 2–2.5 m s⁻¹, with 3-hour forecasts tending to underpredict wind speed and 12-hour forecasts overpredicting wind speed (Banta et al. 2018). Forecast errors can arise due to weather phenomena like the New York Bight jet (Colle et al. 2016), coastal wind speed gradients (Musial and Ram 2010), and extratropical and tropical cyclones. Banta et al. (2013) stress the need for using observations from instruments like lidars to verify numerical models, particularly in day-ahead wind forecasts.

This research is an effort to explore numerical simulations of ocean-based wind patterns and help bridge the gap between simulations and observations. Thus, this paper will cluster output from the High-Resolution Rapid Refresh (HRRR) model centered over the northeastern U.S. coast using SOMs and compare monthly averages of hub-height wind speed from each SOM node to buoy lidar observations. A brief summary of the datasets from the buoy and the HRRR, and an overview of the SOM methodology used, is given in Section 4.2. An analysis of the SOMs trained on HRRR hub-height wind speed and how they compare to buoy lidar observations is
provided in Section 4.3. Also included is an analysis of SOMs trained on lower-level wind shear. Concluding remarks are discussed in Section 4.4.

4.2 Data and Methods

A pair of buoys were deployed in the New York Bight as part of a plan by the New York State Energy Research and Development Authority (NYSERDA) to increase wind speed measurements in the northeastern U.S. coastal region (DNV 2022). These buoys are of the EOLOS FLS200 model, which measure wind using ZX Lidars 300M continuous wave lidar. These vertically pointing lidars measure wind from 20–200 m in 20-m intervals, which provides basic insight to low-level wind profiles affecting offshore wind turbines. The buoys are designated Hudson North (E05) and Hudson South (E06), and their locations are provided in Figure 4.1. Observations from E05 began on 12 August 2019 and on 04 September 2019 for E06, and for the purposes of this study the E05 dataset ends on 11 August 2021 and the E06 dataset ends on 04 September 2021 to provide two full years for E05. However, only E05 observations are compared to SOMs in Section 4.3.6, due to E06 experiencing several months with significant data outages as highlighted in Figure 4.4.

Understanding regional wind patterns requires more than a single lidar, so NOAA’s High-Resolution Rapid Refresh (HRRR) model is used to provide simulated wind data over the entire northeastern United States. The model version was HRRRv3 until 2 December 2020, when NOAA upgraded it to HRRRv4. California atmospheric river events are forecasted more accurately in HRRRv4 compared to HRRRv3 (English et al. 2021), but no known studies compare the two model versions regarding wind. HRRR has a 3-km horizontal grid spacing, and output is generated hourly. Of particular interest is wind, with the HRRR output including wind components (U- and V-wind speed) at 10 m and 80 m. To capture the predominant wind regimes
relevant to offshore wind turbines in the northeastern U.S. region, each SOM was trained on HRRR 80-m wind components in the region shown in Figure 4.2.

SOMs are a type of unsupervised artificial neural network, the purpose of which is to reduce the dimensionality of a dataset by clustering (Kohonen 1982). In this study, the size of a data vector is the product of the input array’s dimensions. To reduce computational cost of assimilating and training SOMs on the full HRRR domain every hour across two years of data, and to narrow focus to weather systems impacting the northeast coast, the grid was reduced to the size depicted in Figure 4.2, with a size of 180×106. For the SOMs to train on the input, each input map is vectorized into a 1-dimensional vector of length 19080. The SOM algorithm then randomly initializes weight vectors for each point in map space (node). These weight vectors will serve to update each node to resemble the data more closely, also stored as vectors of size 19080 elements. The SOM algorithm then determines the node closest to each input vector in Euclidean
space (best matching unit; BMU) and updates the weight vectors for nodes in the neighborhood surrounding the BMU by making them closer to the input vector. This process is known as a neighborhood function, and it allows the clusters to be similar to other neighboring clusters after mapping. SOMs have been shown to better explore the search space of data compared to another clustering method known as k-means (Bação et al. 2005). SOMs can even outperform k-means (Riveros et al. 2019). The similarity of neighboring SOM nodes is important for weather pattern identification, as the weather is constantly evolving and weather patterns form a continuum rather than discrete clusters. Other analysis methods such as empirical orthogonal functions (EOFs) have been introduced to meteorology (Lorenz 1956). EOFs generally determine mathematically independent, or orthogonal patterns in data, and are thus used for analyzing variability of an atmospheric field. While it has been argued that EOF patterns of atmospheric fields are not

Figure 4.2: Approximate subdomain of HRRR domain used for this study, given by the orange box. Locations of the buoys in Figure 4.1 are indicated by orange pins.
necessarily independent (Monahan et al. 2009), this study will benefit more from the continuum of wind regimes that SOMs can provide.

SOMs have been used in a variety of studies across atmospheric science in recent years, including the investigation of El Niño and La Niña (Li et al. 2015), sea surface temperature variability (Liu et al. 2006), precipitation (Swenson and Grotjahn 2019), and tornadic environments and climatology (Nowotarski and Jensen 2013; Anderson-Frey et al. 2017; Hua and Anderson-Frey 2022). SOMs have even been used to identify model error (Kolczynski and Hacker 2014). In work more closely related to the current study, SOMs have helped identify Antarctic wind patterns (Nigro and Cassano 2014). However, as of this writing, no studies to the author’s knowledge have investigated U.S. wind patterns using SOMs.

In this study, SOMs are clustering maps of HRRR 80-m three-hourly (3H) horizontal wind components (U and V) from 12 Aug 2019 to 11 Aug 2021 from approximately 37°–48°N and 62°–80°W in the northeastern U.S. region. The northeastern coastal U.S. was chosen to capture the synoptic scale of any coastal wind regimes affecting the two buoys. After training, each HRRR model output time is assigned a best matching SOM node, thus creating a SOM node climatology.

SOMs were created in MATLAB using the function ‘selforgmap’, with all parameters set to their default values except for the desired SOM grid size. Finding the optimal grid size must be done manually through trial and error. As in the cases of Nowotarski and Jensen (2013), Nigro and Cassano (2014), and Anderson-Frey et al. (2017), too few nodes produced nodes too similar to the mean of the dataset while too many nodes resulted in nodes that were too similar to each other. For this study, a 4×3 grid was chosen to capture the spectrum of common regional wind patterns the northeastern U.S. experiences. Furthermore, a 4×3 grid allows a smoother continuum of node-to-node transitions as wind patterns change over the course of several days compared to smaller grid sizes such as 3×2. Distinct patterns in the 4×3 grid are merged to be represented by
one node in the smaller grids. Larger grid sizes like $5 \times 4$ introduce more distinct patterns, but for a balance of information and succinctness, the $4 \times 3$ grid was the optimal grid size. More details on this will be provided in Section 4.3.3.

In meteorology, weather patterns change over time, and thus one would expect the best matching SOM node to change as the HRRR wind pattern evolves. Similar to the transition probabilities in Gu and Gervais (2020), probabilities of SOM node transitions over periods from several hours to 10 days were calculated to determine how long a regime represented by a particular node persisted, what nodes were the most likely to follow them, and if these SOM node transitions resembled real weather pattern transitions. The day-to-day node transitions can also indicate how long the region will remain in regimes more/less conducive to wind power production when starting in a given regime.

Because low-level wind shear can affect wind turbine performance, a second set of SOMs was trained on wind component differences between two levels relevant to wind turbines. HRRR 10-m wind components were used with the 80-m wind components to calculate low-level wind differences that would affect offshore wind turbines. Thus, wind shear is defined here as the difference between HRRR 10-m and 80-m horizontal wind components. The 10–80-m U-wind difference and the 10–80-m V-wind difference are thus the variables on which the SOM algorithm is trained. These vector wind shear-trained SOMs identify regimes of high wind shear that are more likely to cause stress on turbine blades.

While the comparison of point-based observations to gridded model data is difficult, a) only gridded data from the point closest to the E05 buoy is being used, and b) monthly averages of wind speed are being compared, which can smooth out any short-term differences. Please note, however, there is still representativeness error due to the spatially smoothed model data being compared to point-based observations. The SOM algorithm assigns each HRRR output time a best-matching SOM node, indicating which map in the SOM grid most closely resembles the
wind pattern at that time. Assigning a BMU to each output time allows computation of monthly averaged wind speed for each SOM node. Timestamps of when each SOM node is predominant also allow averaging of observed monthly wind speed for each SOM node.

4.3 Results

4.3.1 Observations

When lidar-observed wind speed data at each height is averaged per month as in Figure 4.3, distinct features emerge across both NYSERDA buoys. Average wind speed increases with height from around 8.0 m s\(^{-1}\) at 20 m to 10.3 m s\(^{-1}\) at 200 m for E05 and from 7.9 m s\(^{-1}\) at 20 m to 10.3 m s\(^{-1}\) at 200 m for E06. Average wind speed decreases during June–October for E05 and June–August for E06, when wind speeds are generally 3–4 m s\(^{-1}\) weaker at all observation heights compared to the remainder of the year. However, note that E06 had multi-month data outages when nearly 100% of the wind data was unrecorded from October–December 2020 and September–October 2021 while E05 appeared to be fully operational with no major wind data outages (Figure 4.4). Therefore, future references to observations will refer solely to E05.
Figure 4.3: Monthly means of lidar-observed wind speed with height at a) E05 and b) E06.
Figure 4.4: As in Figure 4.3, but depicting percentage of missing data.

4.3.2 HRRR 80-m wind SOMs

When SOMs are trained on 80-m U- and V-wind components, three primary types of wind flow patterns emerge: unidirectional wind, confluence/diffluence, and cyclonic/anticyclonic circulation (Figure 4.5). These general patterns emerged when using a 3×2, a 4×3, and a 5×4 grid. The optimal grid size was selected to be a 4×3 grid, as it resulted in a balance of providing new,
distinct wind patterns while producing concise, easy-to-understand plots. More details on the identified wind patterns follow, and a brief comparison of these patterns when using different SOM grid sizes will be provided in Section 4.3.3.

Falling under the first wind pattern category (unidirectional wind), nodes 4, 9, and 10 represent flow off the coast from the south-southeast, the northwest, and the west, respectively. The 80-m wind speeds near the buoys are strong for these nodes — near 8 m s\(^{-1}\) for node 4, near 10 m s\(^{-1}\) for node 9, and near 11 m s\(^{-1}\) for node 10, according to Figure 4.5. Figure 4.6 indicates that node 4 occurs mostly during summer and autumn months with a peak in June and nodes 9 and 10 mainly occur during winter and spring. Warm-season southerlies and cold-season northwesterlies near the northeast U.S. coast are observed climatologically, as indicated when IRI (2022) plot monthly wind climatology using the NCEP-NCAR Reanalysis dataset (Kalnay et al. 1996).

Figures 4.7–4.8 show SOMs trained on HRRR 80-m forecasted wind components, but instead of plotting 80-m wind they provide the corresponding average 500-hPa geopotential height and mean sea level pressure (MSLP). For node 4, there is on average a shortwave trough with lower heights and associated lower surface pressure to the northwest, indicating a low-pressure system somewhere near the Great Lakes region. The location of the mean low-pressure system therefore results in the south-southeasterly winds seen in Figure 4.5. Node 9 represents lower heights to the northeast in Figure 4.7 and an area of slightly lower pressure east of the domain. For node 10, Figures 4.7–4.8 indicate a deep trough with lower heights to the north and a low-pressure system northeast of the domain, with lower average pressure compared to node 4. Thus, the low-pressure system is either stronger or closer to the domain, causing the strong westerly winds in Figure 4.5. Because these nodes represent strong winds near the buoys, with
Figure 4.5: SOMs trained on HRRR 80-m horizontal wind components from 01 September 2019 to 31 August 2021. Filled contours represent 80-m wind speed while red arrowed lines indicate 80-m wind flow. Please note the first contour represents a range of 0–3 m s$^{-1}$, or wind speeds below the estimated cut-in wind speed of a wind turbine. NYSERDA buoy locations are marked by stars.

node 4 occurring primarily in summer and autumn and nodes 9–10 primarily occurring in winter and spring, nodes 4, 9, and 10 indicate that offshore wind energy is plentiful and could be associated with nearby low-pressure systems.
Nodes 2, 3, 5, 7, and 11 in Figure 4.5 show confluence or diffluence of flow from two different directions but flowing along the same axis that is parallel to the overall flow. All these nodes suggest an area of increased wind speeds near the coast, with nodes 2 and 3 having maxima near the buoys, nodes 5 and 7 having maxima further north near Maine, and node 11 having a maximum southeast of the buoys. Figure 4.7 indicates shallow ridges for nodes 2 and 3, and generally zonal isohypses for nodes 5, 7, and 11. Figure 4.8 shows little domain-wide pressure variation for nodes 2, 3, 5, and 11, while nodes 5 and 7 indicate weak lows northeast and north of the domain. The causes of these confluence/diffluence patterns were outside of the scope of this research, although it hypothesized that the wind flow and the weak low-pressure region in the
Figure 4.6 indicates that nodes 2 and 3 occur mostly in autumn, node 5 is more common from autumn to spring, and nodes 7 and 11 peak in summer. Since wind speeds are toward the middle of the upper portion of the domain of node 7 indicated a cold front (Lackmann 2011). Figure 4.7: 500-hPa geopotential height for each SOM node trained on 80-m wind components. NYSERDA buoy locations are marked by stars.
Figure 4.8: Mean sea-level pressure (MSLP) for each SOM node trained on 80-m wind components. NYSERDA buoy locations are marked by stars.

Spectrum near the buoys, nodes 2, 3, 5, 7, and 11 are likely conducive to adequate but slightly less offshore wind energy than nodes 4, 9, and 10.

Nodes 1, 6, 8, and 12 are associated with flow curving around a synoptic pressure system in or near the domain. As indicated by the wind flow with node 1 in Figure 4.5, Atlantic air
rotates counterclockwise and converges to a point east of the buoys, with wind speed generally decreasing as it does so. The wind pattern in node 1 suggests a low-pressure system several hundred kilometers east of New Jersey, which is supported by the relative minimum of MSLP in Figure 4.8. Node 1 has a more uniform seasonal distribution compared to most other nodes (Figure 4.6). Due to the low-pressure system that is depicted in Figure 4.8 representing the average of a number of such cyclones, the location of the cyclone is blurred and the intensity of the winds decreased from what would be observed in the day-to-day maps of these moving cyclones. Thus, while Figure 4.5 indicates a reduction in wind speeds near the center of rotation, including those at the buoys, this is not necessarily the case for individual time periods represented by node 1 and there is therefore greater uncertainty in how beneficial node 1 is for wind energy. Due to the transient nature of these cyclones wind power would vary significantly on timescales of a day or less.

Node 6 depicts weak winds diverging clockwise from a point over the waters of southern Maine, resembling a high-pressure system (Figure 4.5). Figures 4.7–4.8 also indicate the presence of a high-pressure system, with zonal isohypses and higher MSLP over the region of interest. Node 6 additionally is more common in the summer and autumn according to Figure 4.6, but is still a common occurrence in winter and spring. Thus, the regime of the weakest wind speeds, and thus the least offshore wind energy, in node 6 can occur year-round.

Node 8 represents southerly winds in the southern part of the domain in Figure 4.5, transitioning to southeasterly in the northern part of the domain and indicating the presence of a low-pressure system near southern Quebec that is depicted in Figure 4.8. Similarly, node 12 shows westerlies near the buoys transitioning to northerlies near Nova Scotia. Wind speeds are strong over much of the Atlantic region shown for both nodes, although average speeds in Figure 4.5 are around 12 m s⁻¹ near the buoys for node 12 while a strong gradient is present near the buoys for node 8. They are also the least common nodes, with shallow peaks in winter and spring
(Figure 4.6). However, with strong wind speeds near much of the shore, they are more regimes likely associated with increased offshore wind energy.

4.3.3 Determining SOM grid size

During SOM training, the number of nodes and the configuration of the grid in which they are arranged is not predetermined and must be provided by the user. A 4×3 grid was chosen for reasons already described in Section 4.2; however, a brief comparison with additional grid sizes was done to ensure the optimal grid size was chosen. When the SOM grid was in a 3×2 formation, distinct wind patterns were merged. For example, cross-referencing Figures 4.5–4.6 and 4.9–4.10, the circulating flow in node 4 of the 3×2 grid is a merge of the flow patterns from nodes 1, 3, 8, and 11 from the 4×3 grid. Node 3 in the 4×3 grid represents primarily weaker easterlies, a pattern that is not by itself represented by the 3×2 grid. When using a 5×4 grid, more distinct wind patterns are represented as depicted in Figures 4.11–4.12, but having 20 total nodes results in dense, less user-friendly figures, as well as an overabundance of SOM node transition figures, a type of plot that will be explored further in the following section. Therefore, the 4×3 grid was chosen as the best balance of depicting distinct wind regimes while also being concise.
Figure 4.9: As in Figure 4.5, but for a 3x2 grid of SOM nodes.
Figure 4.10: As in Figure 4.6, but for a 3×2 grid of SOM nodes.
Figure 4.11: As in Figure 4.5, but for a 5×4 grid of SOM nodes.
4.3.4 SOM node transitions

Knowing how wind patterns transition from one SOM node to another can give additional insight to the associated meteorology and make it possible to predict what wind pattern is likely to follow another one and when. These transitions are represented as probabilities over a range of lead times from 1 to 240 hours. As an example, Figure 4.13 depicts the probability of node 1 persisting after a given transition time. Gu and Gervais (2020) had a similar approach when they calculated SOM node transition probability tables for a given transition lead time, or lag, to predict sea surface temperature (SST). They used anomaly correlation coefficient to determine the quality of their predictions; however, this study uses traditional chi-squared and p-
values to determine whether this study can reject the null hypothesis that the transition probabilities depend solely on node occurrence climatology rather than also depending on the current node. Gu and Gervais (2020) then used the methodology of Gervais et al. (2020) to determine a mean SST pattern at a given lag by weighing each SOM node by its frequency of occurrence and taking the sum over all nodes. A similar methodology could be applied to this work to determine what a future wind pattern is likely to be given the current SOM node and the lag. However, the main purpose of these SOM transitions was to show the most common SOM node cycles and indicate their similarity to regional weather patterns. In general, a node persists for 12–24 hours before the probability of persistence is surpassed by that of a node transition.

Figure 4.13: Probability, in percentage, of SOM node 1 either remaining the dominant SOM node or transitioning to another SOM node after a given number of forecast hours.
After 48–72 hours, the probabilities of the initial node remaining or transitioning to any other node have converged to climatology.

Focusing on node 1 (cyclonic winds), Figure 4.13 indicates that after 24 hours there is an approximately equal chance of persistence, a node 1-2 transition, or a node 1-9 transition, with all other transitions being less likely. By 72 hours, the 1-2 and 1-9 transition probabilities decrease to <9%, 1-5, 1-6, and 1-7 transition probabilities increase to 10–15%, and the remaining transition probabilities are generally 5–10%. The evolution of transition probabilities means that the cyclonic winds represented by node 1 generally last for a day before there is an approximately equal likelihood that the wind pattern transitions into the moderate northerlies of node 2 or strong northwesterlies of node 9. Given the patterns in 500-hPa geopotential height and MSLP, these probabilities suggest that a node 1-2 transition represents the low-pressure system in node 1 progressing southeastward of the domain and shifting wind direction in the domain to northerly, while a node 1-9 transition depicts the low moving eastward and shifting winds to be from the northwest. After three days a transition from coastal cyclonic circulation to weak northwesterlies, a coastal anticyclonic circulation with weak winds, or moderate southwesterlies are the most likely.

When similar node transition matrices are created for all nodes and they are considered together, they reveal many different cycles of SOM nodes, the most significant of which are represented by the diagram in Figure 4.14. In order to create Figure 4.14, the average probability that the starting node will transition to another node is calculated for each starting node and transition time. Afterwards, the standard deviation is determined for the given starting node and transition time. The mean and standard deviation are then added to define the threshold for a transition probability to surpass to be considered significant. For example, the average probability of node 1 transitioning to any other node after a 24-hour transition period is 7.63% according to Figure 4.13, and the standard deviation is 5.31%. Therefore, the threshold to be surpassed in this
Figure 4.14: Diagram of SOM nodes from Figure 4.5, with green arrows depicting examples of major node transitions.

case is 12.94%, which nodes 2 and 9 meet. Hence the arrows leading from node 1 to node 2 and node 1 to node 9 in Figure 4.14. One cycle of node transitions in Figure 4.14 is a transition from node 7 to node 5, then node 5 to node 6, and node 6 to node 7. Cross-referencing Figures 4.8 and 4.14, the node 7-5-6-7 cycle can be interpreted as a low-pressure system north of the domain progressing eastward, causing winds to transition from southwesterly to northwesterly/westerly and weaken as a high-pressure system continues to weaken wind speeds for any offshore wind farms, and later a low-pressure system again settles into eastern Canada. Another cycle shown in Figure 4.14 is a 2-3-4-7-5-2 cycle, where a high-pressure regime is replaced with a low-pressure
system north of the domain that increases coastal wind speeds, and then moves east over the Atlantic as pressure increases again and winds weaken slightly. These node cycles and others depicted in Figure 4.14 resemble weather patterns typically observed in the region (Lackmann 2011), indicating the credibility of each node representing common regional weather patterns. Considering that node 6 represents the largest percentage of the HRRR dataset and it transitions to/from several other nodes in around 24 hours, wind farms near the east coast can experience frequent changes in wind power production, particularly in summer and autumn when node 6 is most common (Figure 4.6). Some node cycles like 7-5-6-7 include transitions from one regime conducive to greater wind speeds to another, and thus extend the time that offshore wind farms experience greater wind power production.

In order to reject the null hypothesis that the distribution of nodes following transition from a given node at a given time is indistinguishable from the climatological distribution of SOM node counts from Figure 4.6, chi-squared ($\chi^2$) values are provided for each node and each transition lead time (Figure 4.15). In this case, $\chi^2$ essentially serves as a measure of the difference between the forecast, or node transition histogram for a particular starting node and transition lead time, and the climatology. Greater $\chi^2$ indicates a greater difference between the forecast and climatology distributions than smaller $\chi^2$. Figure 4.15 depicts large $\chi^2$ for the first several transition lead times and quickly decreases after a lead time of one to two days. Thus, transition times of less than 24 hours result in SOM node transition probabilities that have the largest difference from climatology, with longer transition times leading to a SOM node transition probability distribution closer to climatology.

The $\chi^2$ values from Figure 4.15 can also be expressed in terms of p-values, which yields the odds of falsely rejecting the null hypothesis that knowing the starting node provides no predictive skill beyond that inherent in climatology. Smaller p-values are indicative of greater certainty in the existence of forecast skill. Here, p-values are defined as the complement of the
Figure 4.15: Chi-squared values for each initial SOM node from Figure 4.5 and a given node transition time period.

cumulative distribution function of $\chi^2$ assuming 5 degrees of freedom, where values closer to zero represent that forecast differing from climatology are more skillful. All p-values are $\leq 10^{-4}$ (not shown), indicating that there is skill in using the SOM node transition probabilities for any initial SOM node and transition time over climatology. However, the chi-squared values beyond 24 hours are likely not operationally significant, owing their statistical significance to their large sample size.
4.3.5 10–80-m wind component difference SOMs

When SOMs are trained on 10–80-m wind component differences (Figure 4.16), two corners of the grid represent lower-level environments of greater over-water wind differences whereas the other two corners and the middle of the grid indicate over-water environments with fewer 10–80-m wind differences. Nodes 5, 9, and 10 have regimes with some of the largest Atlantic wind component differences along the coasts of Maine and Nova Scotia, peaking near 5 m s\(^{-1}\) in node 5. Near the buoys, 10–80-m wind speed differences are around 3 m s\(^{-1}\). The area of greater wind differences lies primarily north of 42°N, and peaks in June but remains common throughout the summer and autumn (Figure 4.17). The greater differences are a result of warm air blowing over cooler waters north of the Gulf Stream causing lower-level stabilization and thus frictional decoupling. These wind differences occur over a layer that is likely thinner than the vertical extent of an offshore wind turbine’s blades, and thus introduces added stress to any wind turbines installed in the northeastern U.S. coastal region. Nodes 4 and 8 have similarly placed but smaller areas of greater 10–80-m wind differences several hundred kilometers from shore northeast of the buoys, and node 4 has a second maxima south of the buoys. It is also mostly a summer pattern and is thus likely resulting from the same physical process as nodes 5, 9, and 10. For the remaining nodes, the ocean-based wind component differences near the buoys are smaller (0–2 m s\(^{-1}\)), and they have different magnitudes of land-based wind component differences. According to Figure 4.18, nodes 7 and 10 are significantly more representative of daytime data while nodes 1, 11, and 12 are noticeably more representative of nighttime data, indicating a slight resemblance of diurnal wind shear regimes. Node 7 is most common in the summer to autumn (Figure 4.17), and depicts domain-wide calm winds in Figures 4.19–4.20, leading to the small differences in Figure 4.16. Node 10 represents primarily summertime, Atlantic southerlies to
Figure 4.16: As in Figure 4.5, but with SOMs trained on differences between wind components at the 10-m and 80-m levels. Filled contours represent wind shear magnitude and red arrowed lines indicate the wind shear vector.

southwesterlies up to 7 m s$^{-1}$ at 10 m and 8 m s$^{-1}$ at 80 m, with calmer winds over land at both levels (Figures 4.17, 4.19–4.20). Node 10 has moderate 10–80-m wind differences of up to 3.5 m s$^{-1}$ according to Figure 4.16, likely due to warm air advection increasing lower-level stability and frictional decoupling, but not to the extent of nodes 5 or 9 due to relatively warmer waters
Figure 4.17: As in Figure 4.6, but for SOMs trained on 10–80m wind component differences.

moderating the lower-level stability (Figures 4.21–4.22). Node 1 represents south-southeasterly flow occurring from autumn to winter, with up to 2.5 m s\(^{-1}\) of near-shore 10–80-m wind differences (Figure 4.16). Wind differences increase to over 5 m s\(^{-1}\) on land, due to small surface heat flux (Figure 4.22) that causes increased lower-level stability and frictional decoupling, leading to land-based 80-m winds to greatly surpass 10-m winds. Nodes 11 and 12 represent westerly and northwesterly winds advecting cold continental air over the warmer Atlantic (Figures 4.19–4.21), generally from autumn to spring (Figure 4.17). Cold air reduces any lower-level stability and frictional decoupling, keeps the air better mixed, and lowers 10–80-m wind differences over the Atlantic.
Figure 4.18: Number of forecast hours clustered to a particular SOM map node from the SOMs trained on 10–80m wind component differences, separated into nighttime and daytime.
Figure 4.19: As in Figure 4.16, but with 10-m wind plotted instead of the 10–80-m wind component differences. Filled contours represent 10-m wind speed and red arrowed lines indicate 10-m wind flow.
Figure 4.20: As in Figure 4.16, but with 80-m wind plotted instead of the 10–80-m wind component differences. Filled contours represent 80-m wind speed and red arrowed lines indicate 80-m wind flow.
Figure 4.21: As in Figure 4.16, but with 2-m potential temperature plotted instead of the 10–80-m wind component differences.
Figure 4.2: As in Figure 4.16, but with surface heat flux (SHTFL) plotted instead of the 10–80-m wind component differences.

4.3.6 80-m wind SOMs vs observations

When the monthly-averaged wind speed for each SOM node is compared to lidar observations, several features in the observations are captured by HRRR. Most noteworthy is the minimum in wind speeds during July, August, and September seen in both HRRR (Figure 4.23)
Figure 4.23: Average HRRR 80-m wind speed for each month and SOM node for the grid point closest to the latitude and longitude of E05. Note that NaNs occur because no output times were represented by those month-node combinations.

and E05 (Figure 4.24). A decrease in summer wind speed was also reflected at all heights observed by both E05 and E06, as indicated in Figure 4.3. Therefore, HRRR can capture the summer decrease seasonal pattern and SOMs can show that while the summer decrease occurs for every node except for node 6 in the first year for E05, and nodes 5 and 6 for HRRR in both years. Node 5 is the node representing primarily non-summer northwesterlies and calmer wind speeds near the buoys, and node 6 is the node with a high-pressure system and thus calm winds at the buoys on average. Nodes 5 and 6 are thus have weaker monthly mean wind speeds throughout the year.

A total of 58 month-node combinations in HRRR and 49 in observations experience average wind speeds ≥ 12 m s$^{-1}$, the approximate rated wind speed for the power curve in Figure 2.4. Nodes 8 (strong southerly to southeasterly winds) and 12 (strong westerly to northerly winds) are the nodes with the most month-node mean wind speeds ≥ 12 m s$^{-1}$, mostly representing months between October and April. Of particular note is a mean wind speed for node 8 of 16.2 m
Figure 4.24: As in Figure 4.23, but for E05 80-m wind speed.

s\(^{-1}\) in observations and 16.6 m s\(^{-1}\) in HRRR for November 2019 (Figures 4.23–4.24), indicating that any wind turbines near E05 experiencing southerly winds during the month of November are likely to be at maximum capacity. Nodes 5 (calmer northwesterlies) and 6 (high-pressure system) have no HRRR month-node average wind speeds ≥ 12 m s\(^{-1}\) and one when using observations, further showing that nodes 5 and 6 are the regimes least conducive to wind power production.

Even with large average 80-m wind speeds for some nodes in a given month, differences between these averages for E05 and HRRR are generally ≤ 3 m s\(^{-1}\) up to autumn 2020, when HRRR slightly underforecasts 80-m wind speed (Figure 4.25). After autumn 2020, differences between node-month averages increase and HRRR begins to overforecast for all nodes except nodes 5 and 6, to which HRRR begins severely underforecasting. Thus, Figure 4.25 suggests that the benefit of nodes 1–4 and 7–12 to wind energy production are overestimated by HRRRv4. Similarly, while nodes 5 and 6 have some of the weakest monthly wind speeds, their estimated wind energy production is greater than forecasted by HRRRv4. Node 1 in March 2021, node 3 in May 2021, and node 11 in March 2021 had the largest average wind speed differences, which
Figure 4.25: Differences in wind speed between Figure 4.23 and Figure 4.24. Positive values (blue shading) indicate HRRR has a greater wind speed, while negative values (red shading) indicate E05 has a greater wind speed.

were ≥ 13 m s\(^{-1}\) when comparing model and observations. In all three cases it was the result of HRRR overpredicting the average wind speed, with mean wind speeds of 19.1, 15.2, and 18.4 m s\(^{-1}\) while the average wind speeds observed at E05 for the same timestamps were only 5.3, 2.2, and 4.8 m s\(^{-1}\). However, the large differences are at least partially due to the averages being calculated for 6–8 output times, which introduces greater dependence on the precise timing of the HRRR forecasting the increased wind speeds. Also, the change in model performance after autumn 2020 could potentially be an indirect effect of HRRR upgrading from HRRRv3 to HRRRv4 on 2 December 2020. If the HRRR version is in fact the cause, post-processing techniques like bias correction could be a way to determine node-month averages closer to observations. However, as Turner et al. (2022) note, the biyearly updates to HRRR make the multiyear datasets needed to determine bias corrections not possible, so another solution would need to be derived to improve future wind energy forecasting for the northeastern U.S. coastal region.
4.4 Conclusions

In this study, lidar observations and HRRR model output were analyzed to identify wind regimes in the Northeastern U.S. coastal region. A brief analysis of the lidar observations indicated a few main features, including average wind speeds with height in the lowest 200 m and how monthly averages decrease in the summer. For more thorough analysis, the model output was clustered using SOMs. SOMs identified three general types of wind patterns, which included uniform flow, confluent/diffluent flow, and flow associated with nearby cyclonic/anticyclonic circulation systems.

Some nodes indicate the presence of low-pressure systems that cause stronger wind speeds that are either summer-to-autumn south-southeasterlies or winter-to-spring northwesterlies and westerlies. The nodes depicting confluent/diffluent flow have slightly smaller wind speeds near the buoys and can occur all year. The remaining nodes depict circulating wind flow within the domain that further exemplifies the influence of pressure systems on the primary wind regimes in the coastal region of the U.S. Of these remaining nodes, one represents a high-pressure system with weak wind speeds throughout the region and a strong presence year-round albeit more common in summer than in autumn. Another node indicates a coastal low-pressure system that can occur year-round and on average brings weaker winds to the buoy locations. The final two nodes indicate a low-pressure system further north from the buoys with flow curving from southerly to southeasterly or from westerly to southerly, and bringing increased wind speeds to most of the coastal region, including near the buoys. It can therefore be suggested that unidirectional wind and a low-pressure system north of the buoys are wind regimes sufficient for offshore wind energy while coastal confluence/diffluence zones and near-coast pressure systems are more likely to cause less offshore wind energy.
Probability of SOM node transition after a given time indicates how long until a node is more likely to transition than persist, and what node is the most likely to follow. The node transitions identified further allow verification that the wind regimes identified in each node evolve according to known meteorological weather patterns. A common node transition like that from strong south-southeasterlies in node 4 to strong south-southwesterlies in node 7 indicates that on average a low-pressure system north of the domain progresses eastward and the winds circulating around the low shift wind direction while a similar wind speed near the buoys would continue to provide sufficient offshore wind energy. There is also a significant probability of transitioning to a low, a high, or a confluence/diffluence zone within the domain that decreases average Atlantic wind speeds. 

Wind shear can greatly affect wind turbine performance, so a separate set of SOMs were trained on the differences between the HRRR 10–80-m wind components. Two opposite corners of the grid that contained five nodes represented regimes of higher Atlantic wind shear which were caused by warm air advection over cooler northern waters that then caused the atmospheric surface layer to stabilize and decouple. 

Overall, HRRR monthly-averaged wind speed for each SOM node in the original set of SOMs compared generally well to observations. HRRR depicted a summertime decrease in wind speed, and virtually all nodes had greater monthly-averaged wind speeds that were reflected in the observations. Differences between HRRR and observations were less than 3 m s\(^{-1}\) until autumn 2020 when several nodes had monthly averages \(\geq 12\) m s\(^{-1}\). Differences increased after autumn 2020, up to ±13 m s\(^{-1}\). 

This work demonstrates the ability of SOMs to cluster model wind data into primary wind regimes for the Northeast U.S. coastal region. Transitions between nodes reflect the evolution of observed weather systems. The general agreement between the HRRR-based SOMs and lidar-based observations indicates that HRRR 3-hourly forecasts are representative enough of
real ocean-based wind speeds to motivate further study of U.S. coastal wind regimes and development of offshore wind farms.
Chapter 5

Conclusions

This work investigated wind regimes for two locations that would be beneficial for wind energy production. The first location was the Shagaya Renewable Energy Park in Kuwait, and it experiences wind variability on seasonal and diurnal scales. The prominent seasonal wind regime is the summer shamal which can increase monthly-averaged wind speeds by 3 m s$^{-1}$ in June, July, and August. The nocturnal low-level jet also increases wind speeds by 1 m s$^{-1}$ between sunset and sunrise. Both peaks in wind speeds occur during periods of increased power consumption in Kuwait and emphasize the need for harnessing more wind energy to meet the increased electricity demand. Furthermore, Chapter 2 indicates that increased background knowledge on regional wind regimes can provide additional insight to when and how Kuwait can meet their electricity needs.

SOMs allowed further investigation of synoptic wind regimes in the Middle East that can affect wind power in Kuwait. Out of six SOM nodes, one node represents the summer shamal, with a geographic wind pattern that resembles results noted in Yu et al. (2016) and causes average hub-height wind speeds to reach 10 m s$^{-1}$. Two other nodes represent a deep, daytime convective boundary layer for most of the Middle East and a shallow low-pressure system over the Red Sea with northwesterlies in the Lower Mesopotamia region, both of which also lead to wind speeds in Kuwait to be beneficial for wind power production. The remaining three nodes suggest that diverging winds over the Red Sea or a nocturnal low-level jet over northeastern Africa leads to calmer winds in Kuwait.

SOMs identified wind flow patterns in the northeastern U.S. coastal region that had unidirectional flow, confluent/diffluent flow near the coast, or flow circulating around a pressure
system in or near the domain. Greater wind speeds are associated with wind flow and MSLP patterns indicating a low-pressure system north or east of the domain. A low- or high-pressure system within the domain leads to decreased ocean-based wind speeds on average. SOM node transition probabilities indicate that most nodes have the greatest chance of persisting for 24 hours, after which another node will have an equal or greater chance of becoming the dominant node. The most common transitions create cycles of node transitions, which are consistent with real weather patterns like the eastward progression of a low-pressure system north of the domain or the replacement of a high with a low. While the most common node replacement cycles include a high-pressure system and its associated lower wind speeds, some cycles can prolong greater Atlantic wind speeds for several days. When HRRR monthly-averaged hub-height wind speed for each SOM node was compared to lidar-observed hub-height wind speed, HRRR was shown to capture the decrease in average wind speed for summer months. Time periods best represented by the high-pressure system node also had decreased wind speeds in both HRRR and the observations.

Wind shear can affect wind turbine performance and is thus another variable worth exploring for the northeastern U.S. coastal region. A separate set of U.S.-based SOMs trained on HRRR 10–80-m wind component differences had nodes that represented higher wind shear in the North Atlantic. They were due to warm air advection over colder waters that caused lower-level stability, frictional decoupling, and thus greater wind shear. When considered with the LLJ formation investigated at Shagaya, these two cases exemplify how two different regions with contrasting environments can both have wind turbines experience wind shear from different causes.

Both Kuwait and the northeastern U.S. coastal region experience wind regimes that are beneficial to wind farms, motivating further development in both regions. However, optimal wind
power forecasting in both regions requires knowledge of how to recognize these wind regimes and how long they will likely persist, including what regimes are most likely to follow.

5.1 Synthesis

This research shows how SOMs can be utilized as a tool for deeper analysis of weather patterns for any region. Here, two regions of contrasting climatology were studied: the arid desert of the Middle East, and the northeastern Atlantic coast of the United States. In both regions, SOMs revealed the geographic and climatological structure of wind patterns near the height that a wind turbine’s blades typically rotate. From the provided analysis, potential effects on wind power production for each region can be determined.

SOMs from both regions indicate wind patterns more conducive to generating wind energy. Knowledge of the average geographic structure and scale of these wind patterns, timing, and duration is what grid operators in both regions need to efficiently utilize wind energy. The work described earlier has shown that both regions are favorable for wind energy development. Also shown is the utility of SOMs in narrowing down a large, 3-D dataset of wind data in any given region into a 2-D array of maps of several key wind regimes.

SOMs focused on the Middle East identify that the summer is the best time of year for wind power production. Wind speeds in Kuwait increase in the summer due to a quasi-permanent setup of a low-pressure system to the east over Iran and a high-pressure system in the west near the Mediterranean Sea, causing winds to funnel through the lower elevations of Lower Mesopotamia. The calmest wind speeds in Kuwait occur from autumn to spring when weak southerlies form along the Zagros Mountain range. In the opposite case, SOMs focused on the northeastern U.S. coast indicate stronger winds from autumn to spring and weaker monthly-averaged winds in the summer. The wind regime that represents the weakest winds for the coastal
region includes a high-pressure system, while regimes with stronger wind speeds are associated with low-pressure systems north of the domain. Nodes would transition to each other in cycles reminiscent of observable weather patterns like low-pressure systems moving offshore and winds weakening as a high-pressure system builds into the region.

SOMs have proven to be a guide to additional insight into the climatology of any region that has or could have wind turbines installed and incorporated in their power grids. SOMs can also provide a synopsis of the main weather patterns a region is most likely to experience and when they are most likely to occur, which can aid researchers and forecasters in anything from next-day forecasting to seasonal forecasting.
Bibliography


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Awards

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  - *Tenth Biennial NOAA EPP/MSI Education and Science Forum*
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