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Assessing Predictions of Australian Offshore Wind Energy Resources from Reanalysis Datasets

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Abstract: Offshore wind farms are a current area of interest in Australia due to their ability to support its transition to renewable energy. Climate reanalysis datasets that provide simulated wind speed data are frequently used to evaluate the potential of proposed offshore wind farm locations. However, there has been a lack of comparative studies of the accuracy of wind speed predictions from different reanalysis datasets for offshore wind farms in Australian waters. This paper assesses wind speed distribution accuracy and compares predictions of offshore wind turbine power output in Australia from three international reanalysis datasets: BARRA, ERA5, and MERRA-2. Pressure level data were used to determine wind speeds and capacity factors were calculated using a turbine bounding curve. Predictions across the datasets show consistent spatial and temporal variations in the predicted plant capacity factors, but the magnitudes differ substantially. Compared to weather station data, wind speed predictions from the BARRA dataset were found to be the most accurate, with a higher correlation and lower average error than ERA5 and MERRA-2. Significant variation was seen in predictions and there was a lack of similarity with weather station measurements, which highlights the need for additional site-based measurements.

Keywords: renewable resource estimation; energy transition; numerical analysis; offshore wind

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1. Introduction

Wind farms are currently the largest source of large-scale clean electricity generation in Australia—accounting for 35.9% of renewable energy generated in 2021 [1]. Although all Australian wind farms have been land-based to date, offshore wind farms present a key opportunity for further growth. Offshore wind farms could support Australia's transition to renewable energy due to their ability to generate electricity at times when power from solar and onshore wind farms is unavailable [2]. As Australia begins to develop offshore wind as part of its transition to 100% renewable electricity generation, new tools are needed to understand the spatial and temporal distribution of this new resource. Climate reanalysis datasets that provide simulated wind speed data are frequently used to assess and determine the potential of proposed offshore wind farm locations. However, the accuracy of these predictions is not well understood. This paper assesses the accuracy of wind speed distributions predicted by three climate reanalysis datasets, BARRA, ERA5, and MERRA-2, and compares their predictions of potential offshore wind turbine power.

1.1. Australian Offshore Wind Resources

The average wind speeds for offshore regions are higher and more consistent than wind speeds over land and, unlike solar power, wind farms are not restricted to operating only during daylight. Due to their location away from human and land-based animal populations, larger turbines can be used for offshore wind farms, and the impacts of noise and aesthetics are reduced [3]. Studies such as that by Jensen et al. [4], which considered the impact of wind farms on people living nearby, suggest that compared to those located onshore, offshore wind farms generally have fewer negative effects on people. Globally, the majority of offshore wind farms currently in operation are in Europe, where a large-scale commercial industry has been established, particularly in regions near the North Sea due to the high average wind speeds and proximity to population centres [3]. While all existing Australian wind farms are located on land [1], the data suggest that some offshore areas of Australia have average wind speeds comparable to those near the North Sea and thus are ideal regions for the development of offshore wind farms [2]. The potential for offshore wind in Australia has been recognised, and in August 2022, the federal government announced six zones thought to be suitable locations for offshore wind farms. These locations are indicated in Figure 1, with Perth and Bunbury being considered a single zone due to their proximity.

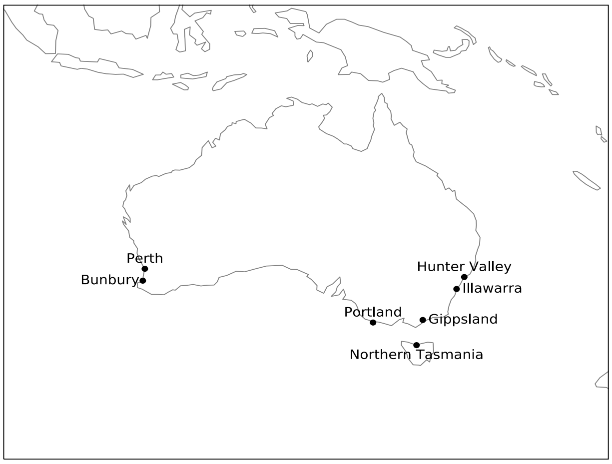

Figure 1. Locations identified as having potential for offshore wind energy generation [5].

Many factors must be taken into account when selecting these potential locations. As well as environmental and economic conditions, two of the most important considerations are the average wind speeds of the region and the proposed wind farm's potential to generate electricity [6,7]. Both of these measures rely on accurate, long-term, and site-specific wind data being available. Australia's offshore wind journey is beginning to progress beyond these initial site selections into planning and financial investment. The Australian Energy Market Operator (AEMO) has included four offshore wind zones, each with a nominal capacity of 10 GW, in its planning [8]. Based on this assumption that offshore wind will eventually be incorporated into the nationwide electricity generation approach, research has begun to consider the impact of this on the total and excess power generated, and the financial consequences on electricity prices for consumers [9]. The Victorian government has also recognised offshore wind farms as a key part of the state's transition to renewable energy, particularly due to the limited non-agricultural land available onshore in Victoria [10]. In March 2022, the Victoria government announced an Energy Innovation Fund with nearly $40 million allocated to support the development of three offshore wind farms, including the first proposed in Australia, the Star of the South [10]. This large financial investment and the planning performed by AEMO are primarily based on assumptions regarding the amount of energy that could be generated by offshore wind farms at particular locations. Again, this assumes there are accurate data to obtain these estimates.

Much of the current research in Australia is focused on how to choose the optimal location for an offshore wind farm. As illustrated by Golestani et al. [6], who propose a game-theory-based decision-making framework, selecting offshore wind farm locations is a complex process that requires the consideration of many factors. Some of these factors include average wind speeds, ocean depth, distance from shore, and electricity demand, as considered by Messali et al. [7] in their study, which was one of the first to attempt to identify offshore wind farm locations in Australia. While both of these studies make valuable contributions to the Australian-specific offshore wind farm literature, there are some limitations. While Golestani et al. [6] outline a high-level framework approach, a significant amount of data inputs will be required for it to be used by organisations in the future. Messali et al. [7] acknowledge in their paper that they lacked complete wind speed data. Their original assumptions have been overtaken by the rapid growth in technology and access to information over the last decade. However, both studies highlight the need for accurate and comprehensive wind speed data to allow good decisions to be made.

A more recent paper by Briggs and coworkers [2] builds upon the work of Messali et al. [7] in undertaking a comprehensive review of offshore wind opportunities in Australia. Briggs et al. [2] considered factors such as average wind conditions, technical capabilities of the local workforce, and ease of connecting to the electricity grid before ultimately recommending 12 potential sites that would be most suitable for the construction of offshore wind farms. As well as considering the average wind speeds, Briggs et al. [2] calculated the predicted capacity factor of offshore wind farms as part of their method. The capacity factor represents the ratio of energy actually generated compared to the maximum rated capacity of the turbines and is typically measured over the period of a year [11]. Wind turbines are unable to produce their rated capacities due to variation in wind speed with location, time of day, and year, as well as downtimes for maintenance or repair [11]. Capacity factors are, therefore, an extremely valuable measure to consider when selecting a wind farm location as they can provide an estimate of the average annual power production.

1.2. Climate Reanalysis Datasets

If a wind farm's ultimate position is known, capacity factors can be estimated from wind speed measurements taken at that location. However, in the early planning stages, a proxy must be used to select the approximate location for the wind farm. Climate reanalysis datasets are often used for this purpose, as they may include hourly estimates of local wind speeds dating back several years, if not decades. A thorough review of global and regional reanalysis datasets can be found in Gualtieri et al. [12]. Here, we consider three different reanalysis datasets that provide detailed information for the Australian region: ERA5, MERRA-2, and BARRA. The quality and similarity of these datasets are the focus of this study, and they will be described in more depth below.

To determine the capacity factors used in their analysis, Briggs et al. [2] used the ERA5 dataset. This dataset was produced by the European Centre for Medium-Range Weather Forecasts in conjunction with the Copernicus Climate Change Service and provides hourly estimates for atmospheric variables such as pressure, temperature, and wind across the globe [13]. ERA5 is a reanalysis—a dataset that combines historical observations and models to create a complete and cohesive set of values for essential climate variables [14]. ERA5 is based on data from 1979 to the present and provides information globally on a 30 km grid [13].

ERA5 is widely used in studies about offshore wind farms (e.g., [2]) and consequently, there is a growing field of research assessing the accuracy of its data for this application. Jiang et al. [15] compared ERA5 data for near-surface wind speeds to local meteorological observations over the South China Sea and Hainan Island. They found that although the overall trends in wind speed provided by ERA5 were consistent with what was observed, there were significant deviations in the predictions of their magnitude, with ERA5 tending to overestimate wind speeds [15]. Concerningly, for offshore wind farm applications, this discrepancy was greater over the sea and islands compared to the mainland [15]. A similar comparative study was performed in Europe by Molina et al. [16], who used wind observations from 245 weather stations throughout Europe to assess the accuracy of ERA5. Overall, ERA5 was well correlated with the local observations, even when considering hourly data, and ERA5 was able to provide a good representation of the monthly variability observed in wind speeds [16]. However, like [15], ERA5 tended to predict larger maximum wind speeds than what was observed [16].

The United States National Aeronautics and Space Administration has also developed a similar global reanalysis dataset called the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2). Like ERA5, MERRA-2 performs a reanalysis using data from 1980 to the present and provides values for a range of atmospheric variables [17]. However, the spatial resolution of MERRA-2 is slightly less well-resolved, with data available on a grid of approximately 50 km [17]. Research has also been undertaken to assess the accuracy of MERRA-2's wind predictions. Mamani et al. [18] compared MERRA-2 to local data and a numerical weather prediction model in Bolivia and found significant discrepancies, potentially due to the high altitudes of the locations considered. A study on Pakistan had similar findings and also raised the issue of a lack of regional data available to be used in the MERRA-2 reanalysis [19]. A broader investigation into MERRA-2's accuracy was carried out by Khatibi et al. [20], who considered a variety of locations all around the world, including in Switzerland, Australia (Brisbane), the USA, Chile, Germany, Iran, and offshore sites in Denmark and Japan. They compared the average wind speeds from MERRA-2 with data from Meteonorm, who collate information from weather stations globally, and found that overall the correlations were good [20]. Of particular interest to this research are the findings that Brisbane had the lowest correlation coefficient (0.81), while the correlations for the offshore sites were quite high, with 0.99 and 0.88 for Denmark and Japan, respectively [20]. This suggests that MERRA-2 could be useful for offshore wind farm investigation; however, the study was limited as it did not consider any temporal variations, instead only looking at the average wind speed. A study by Staffell et al. [21] compared MERRA-2 to local weather observations in Europe, with similar results to those obtained by [16] for ERA5. Staffell et al. [21] found that although MERRA-2 accounted well for temporal variations in wind speed, with data following an accurate trend for monthly and seasonal changes, the actual speeds estimated deviated from the observations, and the extent of these discrepancies varied with the geographic location. The study also demonstrates the significance of the variances of the resulting capacity factors calculated, with errors as extreme as a 30% underestimation of capacity factors in the Mediterranean and a 60% overestimation in the northwest of Europe [21]. However, and promisingly for this study's application, Staffell et al. [21] do note that MERRA-2's predictions for offshore wind speeds and capacity factors appear to be more accurate than those onshore.

As well as these studies designed to assess the accuracy of the ERA5 and MERRA-2 datasets, research has been conducted to directly compare the predictions made by ERA5 and MERRA-2. Plauson et al. [22] compared the capacity factors using the ERA5 and MERRA-2 wind speed data to actual capacity factors from wind farms in Germany, Denmark, France, Sweden, and the USA. Overall, ERA5 was found to be more accurate, with errors up to 20% lower than MERRA-2, as well as higher correlation coefficients and more similar distributions of hourly data [22]. The use of capacity factors rather than just average wind speeds makes this a particularly valuable finding for future research; however, it is limited to the specific locations studied and cannot necessarily be generalised globally. Gruber and coworkers [23] address this limitation to some extent in their comparative study by deliberately selecting countries that vary geographically and in climate. In this study, the wind speed data from ERA5 and MERRA-2 were used to simulate wind power generation, which was then compared to actual wind power outputs from the USA, Brazil, South Africa, and New Zealand. Like [23], found that ERA5 performed better overall. Although the only statistically significant finding was that ERA5 predictions had lower errors than MERRA-2 when compared to data from the USA and Brazil, ERA5 generally had lower errors and higher median correlation factors than MERRA-2 in most cases [23]. However, predictions made from the MERRA-2 data outperformed those from ERA5 in New Zealand [23]. It is also interesting to note that, in some instances, ERA5 underestimated wind power generation by up to 40% while MERRA-2 overestimated it by the same amount [23].

A critical review by Gualtier [12] summarised the findings from the studies described above, in addition to many others. The results from research that considered 322 locations globally were compiled, and it was found that predictions from ERA5 regarding wind speed and wind farm power generation were generally more accurate than those from MERRA-2 (the results were not restricted to ERA5 and MERRA-2 versions). However, ERA5 was the only dataset used for the estimation of offshore wind, and thus these findings are based primarily on onshore data. Furthermore, only one of the 322 locations considered was in Australia, and it was an inland, highly forested area in Central Victoria. The only other study found to consider Australia was Khatibi et al. [20], which looked at data from Brisbane, and as such, the findings discussed thus far may have limited applicability to Australia. Gualtier et al. [12] found that higher-resolution regional reanalyses typically outperformed the global datasets of ERA5 and MERRA-2. Although not considered in the critical review, there is a reanalysis dataset specific to Australia and the surrounding regions. The Bureau of Meteorology Atmospheric high-resolution Reanalysis for Australia (BARRA) provides atmospheric data for Australia, New Zealand, and South East Asia at a resolution of 12 km [24]. BARRA is based on data from 1990 to 2019, which is a smaller range than what ERA5 and MERRA-2 consider; however, it provides a significantly higher spatial resolution [13,17,24]. As part of its initial release, Su et al. [24] compared BARRA to MERRA-2 and ERA-Interim, which was the predecessor to ERA5. When evaluated against land observations for 10 m wind speed, BARRA had a lower error than ERA-Interim and MERRA-2; however, all three reanalyses tended to underestimate strong winds [24].

The objective of this paper is to compare the predictions of potential offshore wind resources in Australia from different reanalysis datasets. It builds on the work of Su et al. [24] to assess the accuracy of BARRA, ERA5, and MERRA-2 in Australia with a specific focus on offshore regions. Few previous studies have evaluated ERA5 and MERRA-2 predictions for offshore wind, and none were found to have considered Australia [12]. Hence, we also compare the predictions for offshore wind farm capacity factors across all three datasets.

2. Methodology

In this paper, we compare capacity factor estimates for offshore wind farms obtained using three climate reanalysis datasets: ERA5, MERRA-2, and BARRA. We also compare the wind speeds predicted by these datasets against BoM data at several key locations around Australia. Table 1 provides a summary of the attributes from each of the datasets that are considered in this analysis. Wind speed data are available for each pressure level as well as the stated altitudes. It should be noted that the pressure level information refers to the standard pressure levels that outputs and predictions are provided for and is typically less than the total number of levels used in the model. Although the ERA5 and MERRA-2 datasets are continuously being updated, only data for the ten year period from 2009–2018 will be considered in this paper to maintain consistency with the time period covered by the BARRA dataset so that fair comparisons can be made.

Table 1. Summary of relevant attributes of the three reanalysis datasets [13,17,24,25].

Dataset	Spatial Resolution	Pressure Levels	Pressure Level Range	Dates Available	Temporal Resolution
BARRA	12 km	37	0.1–1000 hPa	1990–2019 (Feb.)	Hourly
ERA5	30 km	37	1–1000 hPa	1979–present	Hourly
MERRA-2	50 km	42	0.1–1000 hPa	1980–present	3 h

Instantaneous, as opposed to time-averaged, data are generally preferred for this analysis. Lee et al. [26] found this ensemble data to be more accurate than means provided by reanalyses. However, hourly instantaneous data from the MERRA-2 dataset are only available at a single pressure level, not over multiple levels as required [27]. Thus, the 3-hourly instantaneous data were used instead for the MERRA-2 analysis.

As the BARRA dataset uses a horizontally staggered Arakawa-C grid to allow for finite differencing, the different sets of data in the model are staggered by half a grid [24,28]. It is, therefore, important for later calculations that the dataset be re-gridded so that the values are aligned. This was performed by linearly interpolating the wind speed values to their centre points, at which other data such as geopotential height are given. In addition, as the datasets all have different spatial resolutions, interpolation was required to create a consistent grid spacing so that they could easily be compared. The final grid adopted was based on that of the BARRA dataset.

The present research is primarily focused on offshore wind opportunities for Australia. As such, the region considered will be set to include longitudes from 100.035° E to 168.015° E and latitudes from 50.095° S to 0.045° S. This is smaller than the scope of the BARRA dataset but still contains a significant amount of the ocean surrounding Australia and includes its mainland-adjacent Exclusive Economic Zone.

The average hub height of an offshore wind turbine is 150 m, and thus the wind speed at this height was used to determine the most accurate representation of the capacity factors that could be expected [2]. As none of the datasets provides wind speed data at 150 m, interpolation using pressure level data is required. The average air pressure at 150 m is approximately 995 hPa, so the pressure levels used for interpolation were 1000 hPa, 975 hPa, and 950 hPa. All three datasets include average wind speed data at these standard pressure levels. The geopotential height corresponding to each pressure level was used to interpolate to 150 m, using a simple quadratic interpolation of the form $f(x) = ax^2 + bx + c$.

Capacity factors were calculated using an average wind turbine power curve derived from manufacturer turbine data and the Weibull wind speed distribution predicted by each dataset. A probability distribution was fit to the data, rather than calculating the capacity factors directly, to minimise the computational time required to obtain results for this very large dataset. This approach is widely used in the literature (e.g., [21,29]). The Weibull distribution is often used to describe wind speed variations using the following equations, where ν is the wind speed, k is the shape factor, and λ is the scale factor:

$$f(\nu) = \frac{k}{\lambda}\left(\frac{\nu}{\lambda}\right)^{k-1} \exp(-(\nu/\lambda)^k)\,. \tag{1}$$

The mean μ and standard deviation σ of the Weibull distribution are given by

$$\mu = \lambda\Gamma(1 + 1/k) \tag{2}$$

$$\sigma = \lambda\sqrt{\Gamma(1 + 2/k) - \Gamma^2(1 + 1/k)}\,. \tag{3}$$

These relationships were used to create a lookup table to describe how k scales with σ and μ. Based on the mean and standard deviation of the wind speed predictions and this lookup table, k was calculated and then used to determine λ. The Weibull distribution was fit using data from each dataset over the entire 10-year period (2009–2018) for each of the seven locations (Figure 1), giving a total of 920,832 data points for each location. The cumulative distribution function (CDF) for each location was calculated empirically by sorting the data. The results of this were then compared to the CDF from the Weibull distribution. A Kolmogorov–Smirnov test was performed to quantitatively assess the Weibull distribution fit and compare it to the alternative approach of using a Rayleigh distribution. The Rayleigh distribution is a special case of the Weibull distribution where the shape factor (k) is 2. Although the p-value was less than 0.05 in most cases, the average K-S statistic (D) was 0.0142 for the Weibull distribution compared to 0.0304 for the Rayleigh distribution. Therefore, the Weibull distribution was adopted for the distributions in this study.

The corresponding capacity factor for any given wind speed was then determined, as illustrated in Figure 2. For the non-rated region, where wind speeds are below the rated speed at which the turbine can produce its maximum rated power (P_r), a bounding curve ($\phi(v)$) was used to estimate the maximum potential power that could be generated. The mathematical representation of the non-rated region of the bounding curve was established by fitting a 6th-order polynomial, as described in [30], to data provided by the Open

Energy Platform [31] on manufacturer-specified wind turbine power curves. Refs. [29,30] demonstrate how the wind turbine bounding curve is derived in detail.

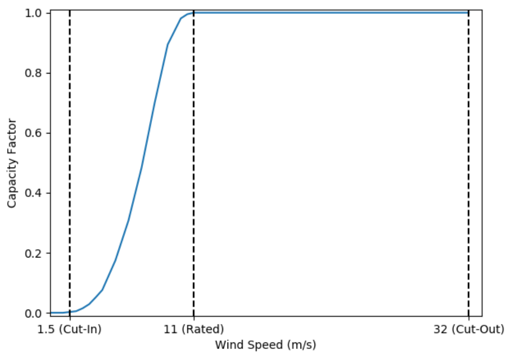

Figure 2. Wind turbine power curve used, with bounding curve calculated from all available turbine data provided by the Open Energy Platform [31].

The mean power output, and thus the capacity factor, was determined using the following equation.

$$P_{avg} = P_r \int_{v_c}^{v_r} \phi(v) f(v)\, dv + P_r \int_{v_r}^{v_f} f(v)\, dv \tag{4}$$

where v_c, v_r, and v_f, represent the cut-in, rated, and cut-out wind speeds, respectively.

Differences in capacity factors predicted by the BARRA, ERA5 and MERRA-2 datasets were then compared and evaluated for consistency. This was achieved through visual comparisons, such as plots of the percentage differences between each, as well as statistical methods to quantitatively describe the differences between the datasets. Pearson's linear correlation coefficient (r) was used as the measure of correlation to indicate the strength of the similarities in the predictions (as also carried out in [22–24]).

As a key benefit of offshore wind is its potential to generate electricity at times when less solar and onshore wind power are available, it was important to consider the temporal variation in the capacity factor predictions across the datasets. For this purpose, seven key locations were selected as the most relevant in accordance with the federal government's announcement of zones with potential for offshore wind energy (Figure 1). Although Perth/Bunbury were defined as a single zone, each location was considered separately to increase the sample size.

Temporal variations in the capacity factor were considered at each of these locations on an annual, monthly, and hourly basis. The gridded data were linearly interpolated to the specific coordinates. As the MERRA-2 dataset provides values every three hours, compared to hourly for BARRA and ERA5, interpolation was again required to directly compare the hourly variation in capacity factors. The timestamps of the data were also accounted for in this step to ensure consistency in the data being compared. Only the original (i.e., not temporally interpolated) data were used for the annual and monthly comparisons. This resulted in a sample size of 87,648 data points from the BARRA and ERA5 datasets and 10,956 from MERRA-2 for each location.

As there are currently no Australian offshore wind farms in operation to provide actual power outputs to compare the capacity factor predictions against, which was the approach taken in [22,23], the assessment of the accuracy of each of the datasets was based on the average wind speeds. Additionally, and again partly due to the lack of offshore wind farm infrastructure, there appear to be no publicly available sources of offshore wind speed data. The most advanced Australian offshore wind farm project, the Star of the South, is currently collecting wind LiDAR data in their region of interest near Gippsland; however, the study is limited to that specific location and has not been released to the public [32]. As a result, the wind speed values provided by BARRA, ERA5, and MERRA-2 were compared to averages obtained from the Bureau of Meteorology weather stations. Although these data are limited due to the varying elevations of the weather stations and the fact that they are mostly located onshore, it appears to be the most reliable source of comparative data currently available. Many previous studies (e.g., [16,21]) have used local weather observations to assess the accuracy of reanalysis datasets. To maintain consistency with the locations considered in the capacity factor comparisons and ensure relevance with the key areas identified as having offshore wind energy potential, the Bureau of Meteorology weather stations nearest to these offshore energy zones were selected. The description and location of each are outlined in Table 2. The Australian Bureau of Meteorology provides monthly averages for wind speeds at 9 am and 3 pm, as well as the monthly maximum gust for each of these locations [33]. Interpolation was used to obtain equivalent wind speed records for these locations from each dataset.

Table 2. Bureau of Meteorology weather station used for assessing wind speed predictions [33].

Offshore Wind Zone	Weather Station	Coordinates	Elevation	Dates
Bunbury	Bunbury	33.36° S, 115.64° E	5 m	2003–2022
Gippsland	East Sale	38.12° S, 147.13° E	5 m	1991–2017
Hunter Valley	Newcastle Nobbys Signal Station	32.92° S, 151.80° E	33 m	1991–2020
Illawarra	Bellambi AWS	34.37° S, 150.93° E	10 m	2003–2022
Northern Tasmania	Devonport Airport	41.17° S, 146.43° E	8 m	1996–2020
Perth	Perth Metro	31.92° S, 115.87° E	25 m	2003–2022
Portland	Cape Nelson Lighthouse	38.43° S, 141.54° E	45 m	2003–2022

3. Results and Discussion

This section discusses the similarities and differences in capacity factors obtained from each of the datasets, followed by an assessment of the accuracy of the wind speeds predicted by each in comparison to the Bureau of Meteorology weather station data.

3.1. Cross Dataset Comparison

The average capacity factor for the 10-year period from 2009 to 2018 over the entire spatial domain was calculated using the BARRA, ERA5, and MERRA-2 data. The results of this are illustrated in Figure 3. There is a good spatial consistency between the datasets, with the highest capacity factors occurring in the south near Antarctica and the lowest values in northern Western Australia/Northern Territory in every case. The regions of relatively high capacity factors near the southwest coast of Western Australia, northern Queensland, Victoria, and Tasmania also appear consistent. These visual results are supported by the statistical findings. As outlined in Table 3, the capacity factor predictions from the ERA5 and MERRA-2 datasets were the most closely correlated ($r = 0.977$). These datasets are more closely correlated with each other than either is to BARRA, with correlation coefficients of 0.811 and 0.779 between BARRA with ERA5 and MERRA-2, respectively. Nevertheless, these values are still indicative of a strong correlation between the capacity factor predictions from each dataset.

Although there is a good spatial similarity between the datasets, the magnitude of the capacity factor predictions made by each varies. Figure 4 illustrates the percentage difference in the average capacity factor predicted by each dataset over the 10-year period. In each case, the dataset listed first was taken as the basis of comparison. As indicated by Figure 4, the capacity factor predictions from ERA5 data were generally higher than those from both BARRA and MERRA-2. In addition, the predictions from the BARRA dataset were generally greater than those from MERRA-2. This was consistent across the entire spatial domain except for the region of northern Australia near Cape York. MERRA-2's tendency to produce smaller estimations is particularly pronounced along the Victorian and New South Wales coastline, as indicated by the darker green regions in Figure 4. The magnitude of these variances in the capacity factor predictions was quite large.

The average absolute difference in capacity factors was 0.128 and 0.111 between BARRA compared to MERRA-2 and ERA5, respectively (Table 3). Again, the greater similarity between the ERA5 and MERRA-2 datasets is evident, with these datasets having a smaller average absolute difference of 0.048. Considering the possible range for capacity factor values is between 0 and 1, these differences are substantial. Furthermore, the differences in the capacity factor predictions at some locations were even greater, with a maximum absolute difference in the capacity factors of 0.902 between the BARRA and MERRA-2 datasets.

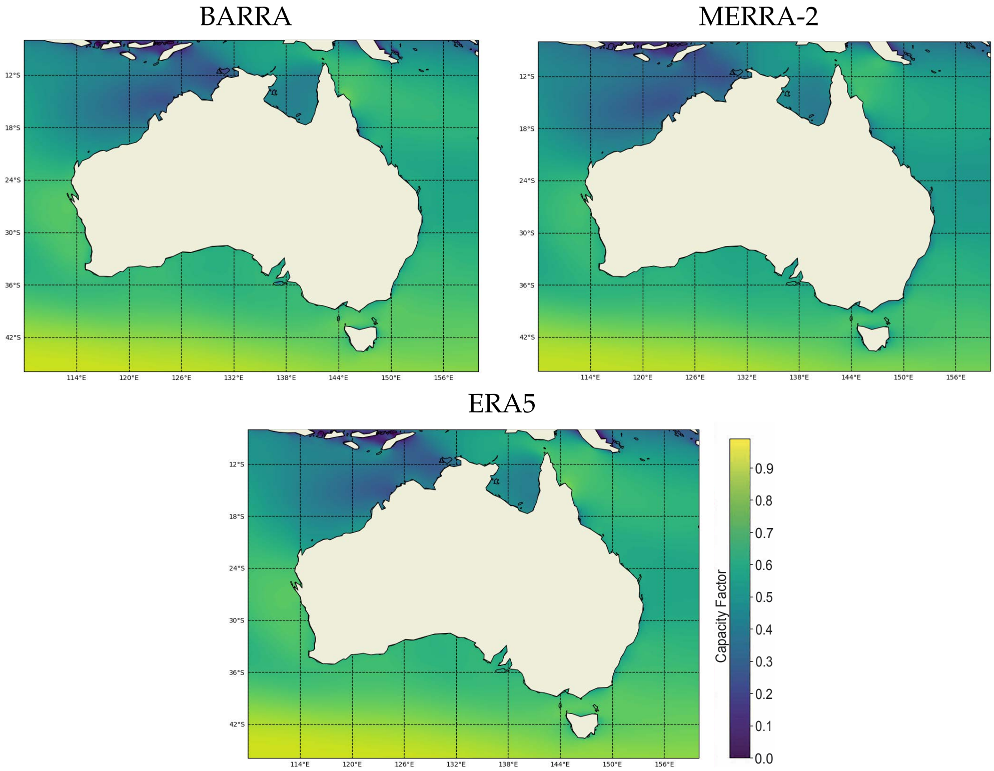

Figure 3. Maps of average capacity factors (2009–2018) predicted by each dataset.

Table 3. Variation in capacity factors predicted by each dataset

	BARRA and MERRA-2	**BARRA and ERA5**	**ERA5 and MERRA-2**
Correlation coefficient	0.779	0.811	0.977
Average absolute difference	0.128	0.111	0.048
Maximum absolute difference	0.902	0.792	0.886

3.2. Temporal Comparisons at Specific Locations

To further examine the spatial similarity between the datasets, the 10-year average capacity factor data were extracted for the seven key locations aligned with potential offshore energy zones. The average capacity factor at each of these locations was compared against the overall average capacity across the entire domain. As illustrated by Figure 5, there is promising consistency between the datasets. In each case, the capacity factor predicted for Bunbury, Gippsland, Northern Tasmania, Perth, and Portland was greater than the overall average. The capacity factors for the Hunter Valley and Illawarra were below the overall average; however, this average is likely skewed as it includes the region of very high capacity factors near Antarctica, and thus these locations may still have good offshore wind energy potential. On average, the capacity factor predicted by ERA5 for these locations was 18.2% higher than the overall average, which was a larger difference than for the BARRA (1.7%) and MERRA-2 (5.0%) datasets. This finding demonstrates the usefulness of these reanalysis datasets for determining locations with potential to conduct further, more detailed assessments, and it is affirming that the same finding could be drawn from any of the datasets.

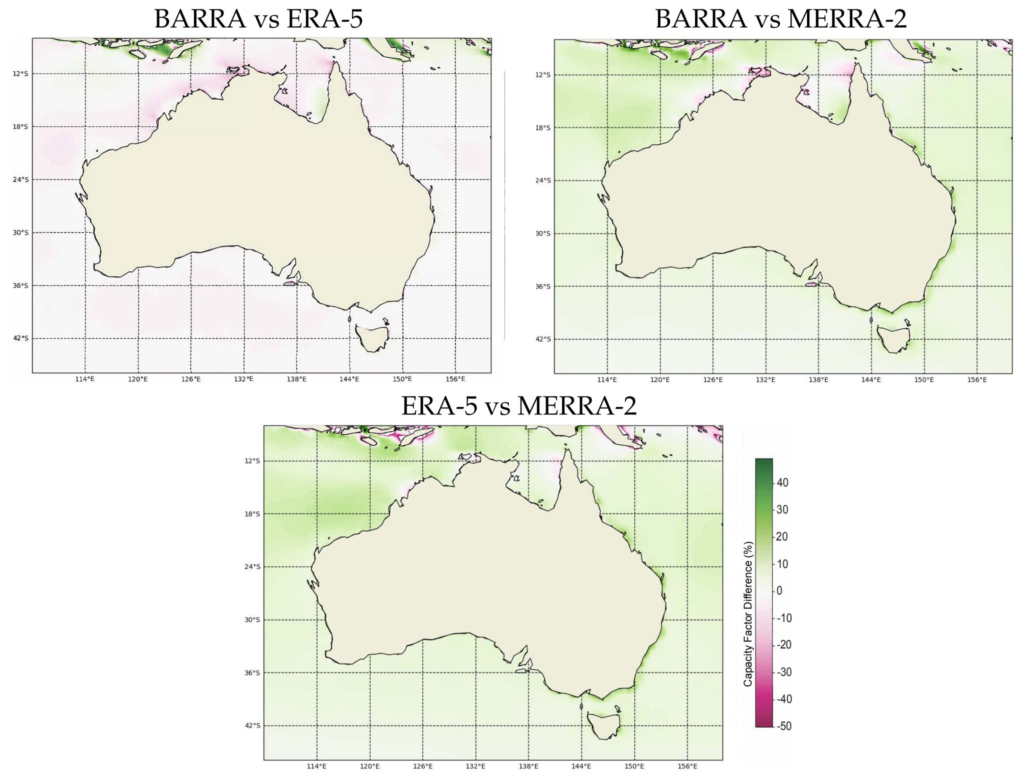

Figure 4. Percentage differences in average capacity factors (2009-2018) predicted by the datasets.

The temporal variation of the capacity factors at these locations was then considered. This is important when considering potential offshore wind farms as it is desirable to have the greatest capacity factors at times of the year or day when other renewable energy sources such as solar are less able to meet energy demands [2]. It was found that there is annual variation in the capacity factors at each location, and this is consistent across all datasets. As outlined in Table 4, the capacity factor predictions between the datasets were well correlated when considering these annual averages. Conversely to the findings across the entire spatial domain, ERA5 and MERRA-2 were the least closely correlated in this case ($r = 0.788$), followed by BARRA and MERRA-2 ($r = 0.799$), with BARRA and ERA5 being the most closely correlated ($r = 0.892$). The monthly variation was also considered, and the results for Gippsland and Perth are illustrated in Figure 6. As indicated in Figure 6, consistent temporal variation is evident in the predictions made with each dataset. The correlation coefficients (Table 4) are aligned with the observation, indicating a high degree of similarity in the capacity factor predictions across the datasets. The average correlation coefficients were 0.932 between BARRA and MERRA-2, 0.930 between BARRA and ERA5, and 0.960 between ERA5 and MERRA-2. The highest degree of correlation was at Perth, with an extremely high average correlation coefficient across each of the datasets of 0.990. As well as indicating the degree of similarity, the results plotted in Figure 6 offer an insight into the potential usefulness of each location as the site of an offshore wind farm. The capacity factor predicted by each dataset peaks in August for Gippsland, Portland, and Northern Tasmania. This is desirable as a key benefit of offshore wind farms is their ability to generate electricity at times when solar is less available. In contrast, the capacity factor is highest in January and December for Perth and Bunbury, which may have less practical benefit.

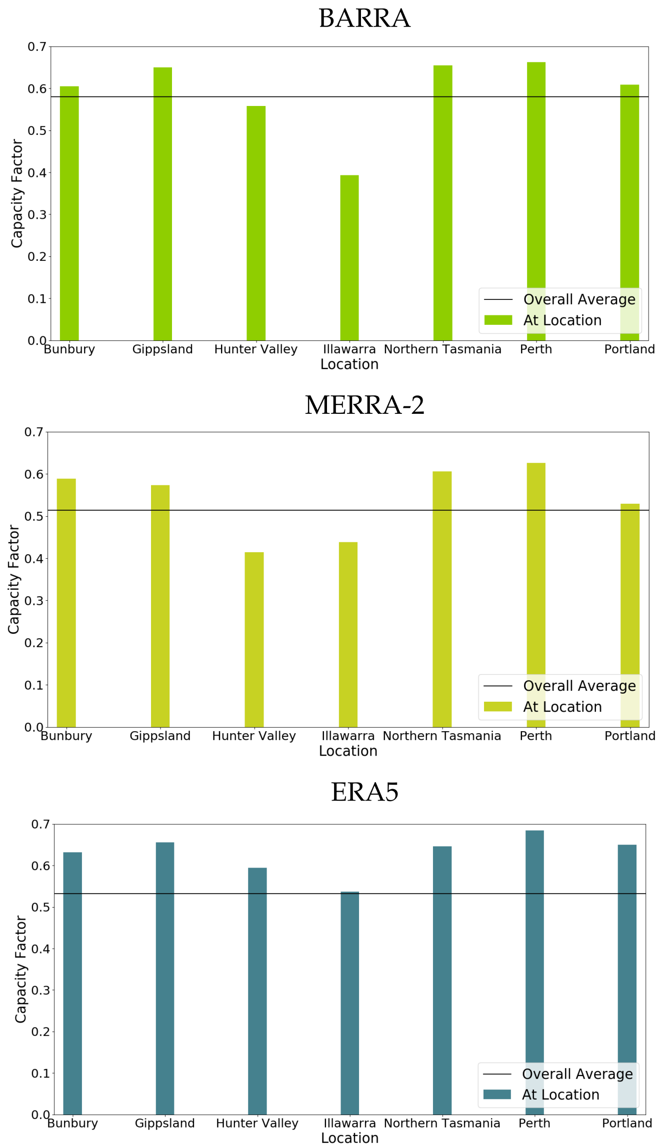

Figure 5. Average capacity factor (2009–2018) predicted using each dataset for key locations compared to whole-domain average

Like the annual and monthly findings, the datasets generally demonstrate the same temporal variation when considering hourly changes in the capacity factor. This can be seen in the plots in Figure 7, where the same general trend in the capacity factor across the time of day is evident across all datasets. However, the statistical correlation between the datasets is much lower. The strongest correlation is between ERA5 and MERRA-2 (0.692), and the correlation coefficient is even lower for BARRA and ERA5 (0.378) and BARRA and MERRA-2 (0.292). This may be due to the average hourly values used to determine these coefficients consisting of a greater number of data points compared to the annual and monthly comparisons. It should also be noted that the coarser-resolution MERRA-2 data were interpolated to calculate the correlations, which may limit their relevance. In addition, the largest mean differences between the datasets were primarily found when considering the hourly variation, as opposed to the annual and monthly variation. The greatest difference between the MERRA-2 predictions and both other datasets was for the Hunter Valley, with a difference of 25.18% and 29.08% when compared to BARRA and ERA5, respectively. There was an even greater difference (37.85%) between the BARRA and ERA5 predictions for Illawarra.

Figure 6. Comparison between monthly variation in average capacity factors predicted for Gippsland and Perth using each dataset.

The amount of variation with time of day differs between locations. As illustrated in Figure 7, there is relatively little fluctuation in the capacity factor at Gippsland. In contrast, there is a large amount of capacity factor variance at Perth, with the highest values occurring overnight. This again has implications for the potential of these locations to support useful offshore wind farms.

Although the average correlation between the datasets varied substantially between the yearly, monthly, and hourly comparisons, the average percentage error remained approximately the same. As outlined in Table 5, the average percentage difference between BARRA and MERRA-2 ranged from 6.78 to 7.82% across each temporal comparison. This was lower than the difference between BARRA and ERA5 (−9.46—8.13%) and ERA5 and MERRA-2 (14.44–14.70%).

The findings discussed thus far compare the offshore wind capacity factor predictions made using each dataset as there are currently no publicly available Australian offshore wind data to evaluate against. As such, it is difficult to make any comparisons between these results and previous findings in the literature. The differences in the capacity factors may be explained by the differences in the input data and climate models used for each dataset. In addition, the finer resolution of the BARRA dataset may have improved the quality of the interpolation for this dataset when extracting the capacity factors at specific locations. The differences found in the capacity factor predictions were large, with differences of up to 37.85% when considering hourly variation. These discrepancies may therefore have a significant impact on the results obtained in studies assessing the feasibility of potential offshore wind farm locations.

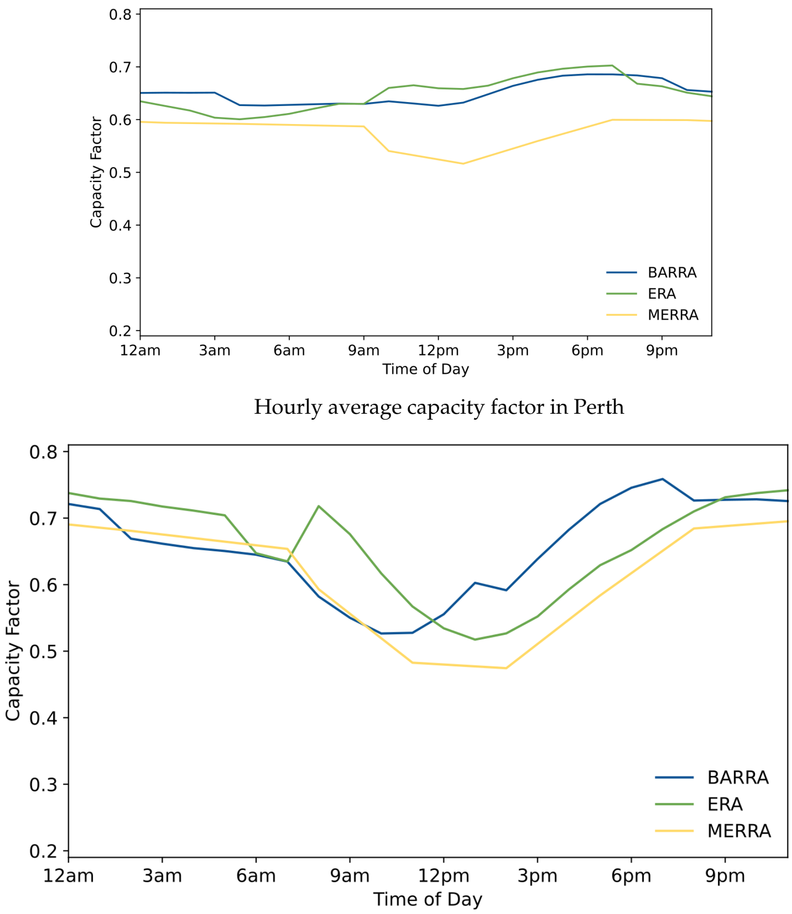

Figure 7. Comparison between hourly variation in average capacity factors predicted for Gippsland and Perth using each dataset.

Table 4. Average correlation coefficient between capacity factors predicted using each dataset at key locations.

	BARRA and MERRA-2	BARRA and ERA5	ERA5 and MERRA-2
Yearly	0.799	0.892	0.788
Monthly	0.932	0.930	0.960
Hourly	0.292	0.378	0.692

Table 5. Average percentage difference (%) between capacity factors predicted using each dataset at key locations.

	BARRA and MERRA-2	BARRA and ERA5	ERA5 and MERRA-2
Yearly	7.816	−8.131	14.436
Monthly	7.783	−8.235	14.506
Hourly	6.784	−9.456	14.704

3.3. Comparison with Measured Wind speed

To evaluate the wind speed predictions, the results were compared to the Bureau of Meteorology data at weather stations near the identified zones with offshore wind energy potential. It should be emphasised that these weather stations are all located onshore and thus the results presented in the following section may not represent the accuracy of each dataset for offshore applications. The weather stations are primarily at coastal locations and have varying terrains and elevations that have an influence on the wind conditions at each. In addition, the available Bureau of Meteorology data for 9 am and 3 pm average wind speeds were based on data collected between 1991 and 2010 [33]. However, as this range, and the range of the data extracted from the reanalyses (2009–2018) are both greater than 10 years, this is a sufficiently large sample of data across which to compare averages. Annual variations in wind speed at typically within 10% of the true long-term average [34]. The upper plots in Figure 8 show the average wind speed at 9 am by month for Gippsland and Pert, from the Bureau of Meteorology (BoM) data and as predicted using each of the reanalysis datasets. As illustrated in the figures, there is a significant degree of variation among the wind speeds from each source. In general, the average wind speeds from BARRA, ERA5, and MERRA-2 were greater than the measured BoM data. There appears to be a small amount of temporal (monthly) variation in the average wind speeds seen consistently across each data source. The predictions from BARRA had the lowest average percentage error (31.5%), followed by MERRA-2 (38.2%) and ERA5 (51.6%). However, there was a large range in the percentage errors across locations for each dataset, as illustrated in Figure 9. The greatest degree of error was in the wind speeds for Perth, with an average difference of over 100% for both MERRA-2 (113.7%) and ERA5 (109.1%), and a still-substantial error of 72.88% for BARRA. This difference is evident in Figure 8. There was also a relatively large range in the correlation with the BoM data, both across and within the datasets, as indicated in Figure 9.

In general, there was less deviation from the BoM data in the predicted 3 pm average wind speeds compared to the comparison for 9 am. The average wind speeds are higher than at 9 am, and there is greater consistency between the predictions made using each dataset and the measured data from BoM. This is supported by the statistical findings, with lower average percentage errors and high correlation coefficients at 3 pm compared to 9 am (Figure 9). In contrast to the findings for 9 am, the largest average error was for the BARRA predictions (25.8%), followed by MERRA-2 (25.4%), with the smallest average error found in the wind speeds predicted by ERA5 (17.0%). Another notable finding is the greater consistency within each dataset, i.e., across the different locations considered. This is particularly evident in the correlation coefficients for the BARRA data, as seen by the small range in the box plot (Figure 9).

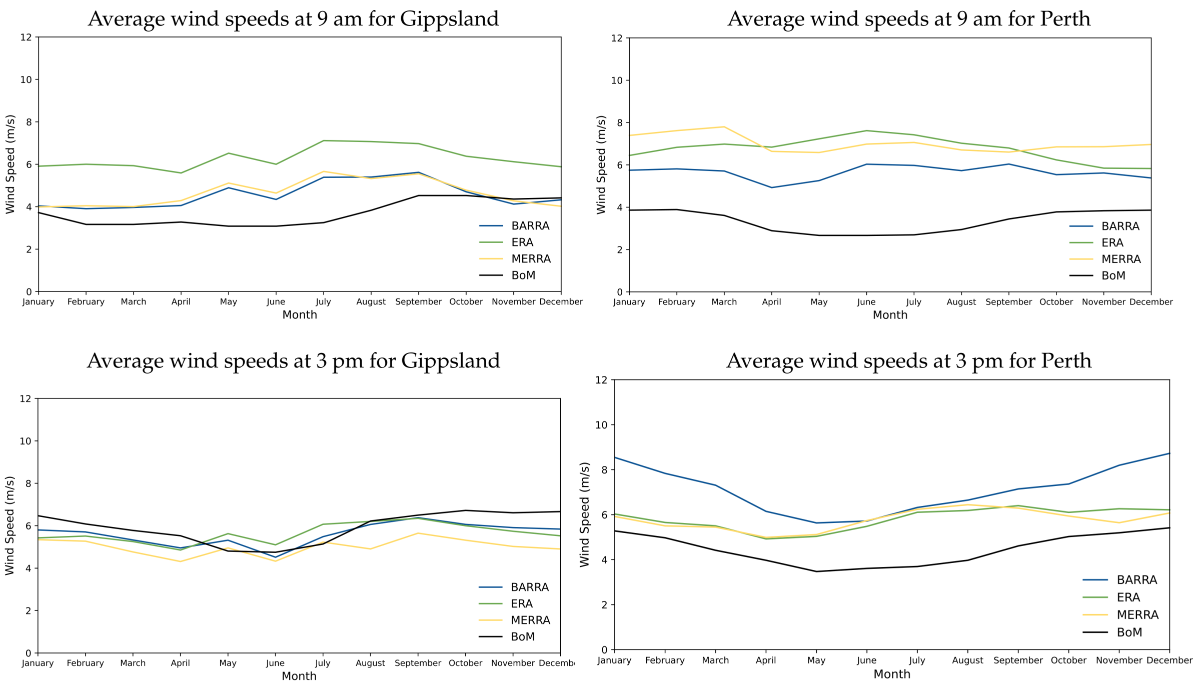

Figure 8. Predicted average wind speeds and BoM weather station data for Gippsland and Perth at 9 am and 3 pm.

The findings discussed thus far are summarised in Figure 10, which plots the magnitude and direction of error in the wind speed predicted by each dataset at both 9 am and 3 pm across all the locations compared to the measured data from BoM. This figure illustrates the observation that wind speeds are generally higher at 3 pm compared to 9 am. A clear trend in the error is also evident; the reanalyses tend to predict larger values than those measured by the BoM for low wind speeds (<4 m/s), and conversely, predict smaller values when the wind speeds are high (>7 m/s). The lowest errors appear to occur at moderate wind speeds. For some locations, namely Bunbury, Perth, Gippsland, and Portland, there is seasonal fluctuation in the error between the datasets and BoM. The greatest error occurs at these locations in June and July, which may be related to the highest wind speeds occurring in these months.

The maximum wind speeds were then compared. The time periods used to obtain the data presented below were more closely aligned, with the BoM data including recent observations for most locations. Figure 11 gives an indication of the gusts at each location. The maximum wind speeds were very high, particularly at the Hunter Valley, Illawarra, and Gippsland, where speeds of up to 40 m/s were measured. In general, the maximum gust wind speeds from the BoM were generally higher than those predicted using the reanalyses. It is to be expected that the BoM maximum is the single largest value measured across the time period, which may have only occurred briefly, while the maximums were obtained from the datasets by determining the largest data point for the given month. This finding is also consistent with the literature, with Su et al. [24] also finding a tendency across all three datasets to underestimate strong winds. As illustrated in Figure 9, all measures of statistical variation are much more consistent across the datasets than for the 9 am and 3 pm averages. This is particularly evident in the average percentage errors, with the BARRA, ERA5, and MERRA-2 datasets having errors of 33.6%, 31.5%, and 34.6%, respectively. The root mean square error (RMSE) is also considerably higher than in the other cases, likely due to the much greater magnitude of wind speeds being assessed.

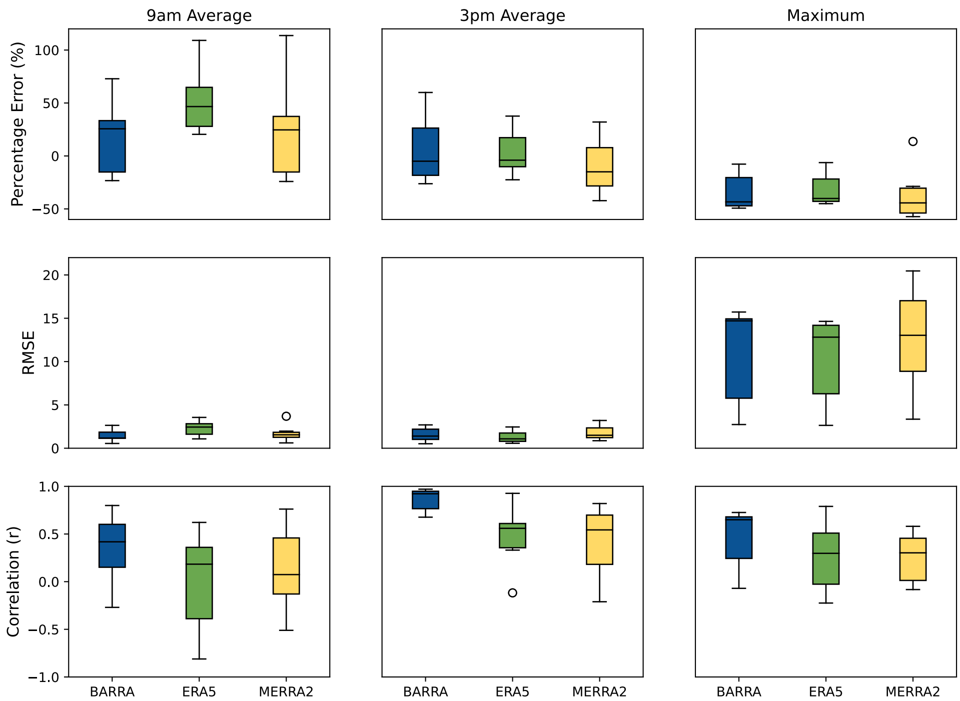

Figure 9. Summary of statistical variance from Bureau of Meteorology weather station data across all locations analysed.

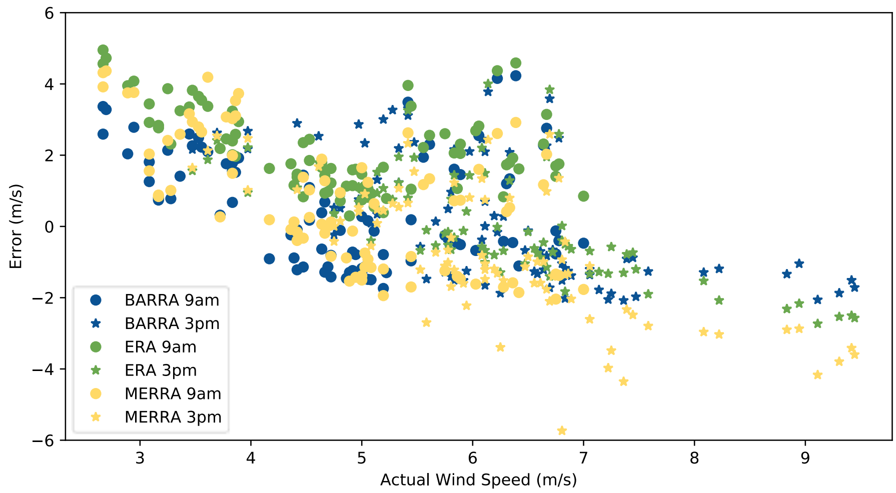

Figure 10. Error in 10 m wind speed predicted using each dataset against actual 10 m wind speed measured by Bureau of Meteorology weather stations.

The wind speeds predicted using the BARRA dataset were found to be the most accurate, with the highest average correlation coefficient (0.585) and lowest percentage error (30.2%). Su et al. [24] also found wind speed predictions from BARRA to have lower errors than ERA5 and MERRA-2. However, the ERA5 predictions had a slightly lower root mean square error (4.58) than BARRA (4.73). The wind speeds from ERA5 were more strongly correlated to the BoM data (r = 0.442) than those from MERRA-2 (r = 0.385), although the average percentage error was marginally lower for MERRA-2 (32.7% compared to 33.4%). These results are consistent with the findings from previous research (e.g., [12,22,23]). Although the magnitudes of the predicted wind speeds differ from the measured values, the plots shown in the earlier figures demonstrate similar temporal variations. This is congruent with the findings of Staffell et al. [21] and Molina et al. [16].

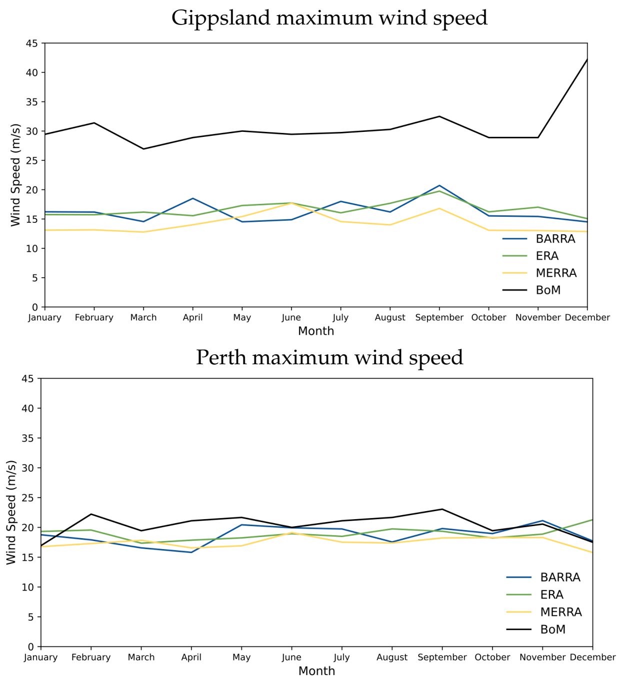

Figure 11. Comparison between predicted maximum wind speeds and BoM weather station gust data for Gippsland and Perth.

The differences in the inputs and models used in each of the datasets offer a potential explanation for the variances in predictions. Each of the reanalyses uses data from satellites, radiosondes, balloons, and buoys as inputs; however, neither ERA5 nor MERRA-2 incorporate any input from land-surface measurements [13,17]. In contrast, BARRA does use land-surface observations, including data from Bureau of Meteorology weather stations [24]. This offers a reasonable explanation as to why it is more closely correlated with the raw BoM data used in the assessment. There are also differences in the data assimilation scheme used in each dataset. Both BARRA and ERA5 use the more accurate four-dimensional variational data assimilation system (4D-Var), while MERRA-2 implements a three-dimensional approach (3D-Var). This may explain why the BARRA and ERA5 predictions generally tend to outperform those from MERRA-2. In addition, there are differences in the spatial resolution of each dataset. BARRA (12 km grid) has a significantly finer resolution than both ERA5 (30 km grid) and MERRA-2 (50 km grid), which may improve the accuracy of its predictions [13,17,24]. Although the results suggest that BARRA outperforms ERA5 and MERRA-2, and ERA5 appears to be better than MERRA-2, none of the datasets produced results in this study that were highly accurate. The average percentage error for all three datasets was approximately 30%. This is a key finding that demonstrates that the regional datasets may not necessarily provide precise data for specific locations.

Nevertheless, it should also be noted that these comparisons use data from weather stations in proximity to the coastline. Gualtieri et al. [12] found that reanalysis datasets generally perform worse at coastal locations. The poor performance at coastal regions was attributed to the topological and roughness transitions at these locations combined with complex microclimates. These local variations are not captured by the reanalysis datasets, which represent regional averages. Hence, while the datasets may be poor predictors for coastal weather station data, the accuracy of the datasets may be greater for more homogeneous offshore regions.

The impact of the variances in wind speed on the resultant capacity factors was also considered. The average of the monthly 9 am and 3 pm wind speed data was taken across all locations for each data source and scaled to the average offshore wind turbine hub height of 150 m. The corresponding capacity factors were then calculated in accordance with the method outlined earlier. The results are displayed in Figure 12. As illustrated, the average wind speeds from each reanalysis dataset appear visually similar to those determined from the BoM data, particularly at 3 pm. However, there is significant variation in the corresponding capacity factors, as seen in the right-hand column of Figure 12. This highlights the impact of seemingly small differences in wind speeds on the subsequent power that could be generated. It is also important to note that at 9 am, the predicted capacity factors from the BoM data are considerably lower than those from BARRA and MERRA-2, and up to four times lower than the predictions from ERA5.

The differences in inputs and models used in each reanalysis offer an explanation for the variations in the predictions. There are also elements of the method that introduce uncertainty to the results. A primary source of error is likely to be due to the interpolation required to perform the comparisons. The spatial resolution of each dataset is different, so data from MERRA-2 and ERA5 had to be interpolated to match the grid size of BARRA to compare the capacity factors across the entire domain. The values for each of the datasets were also interpolated to the specific locations and weather stations considered. This introduces a degree of uncertainty in the data used due to the wide grid spacing of the datasets. Interpolation was also required to determine the wind speeds at 150 m, using data from three pressure levels, as well as for the comparisons with the BoM data.

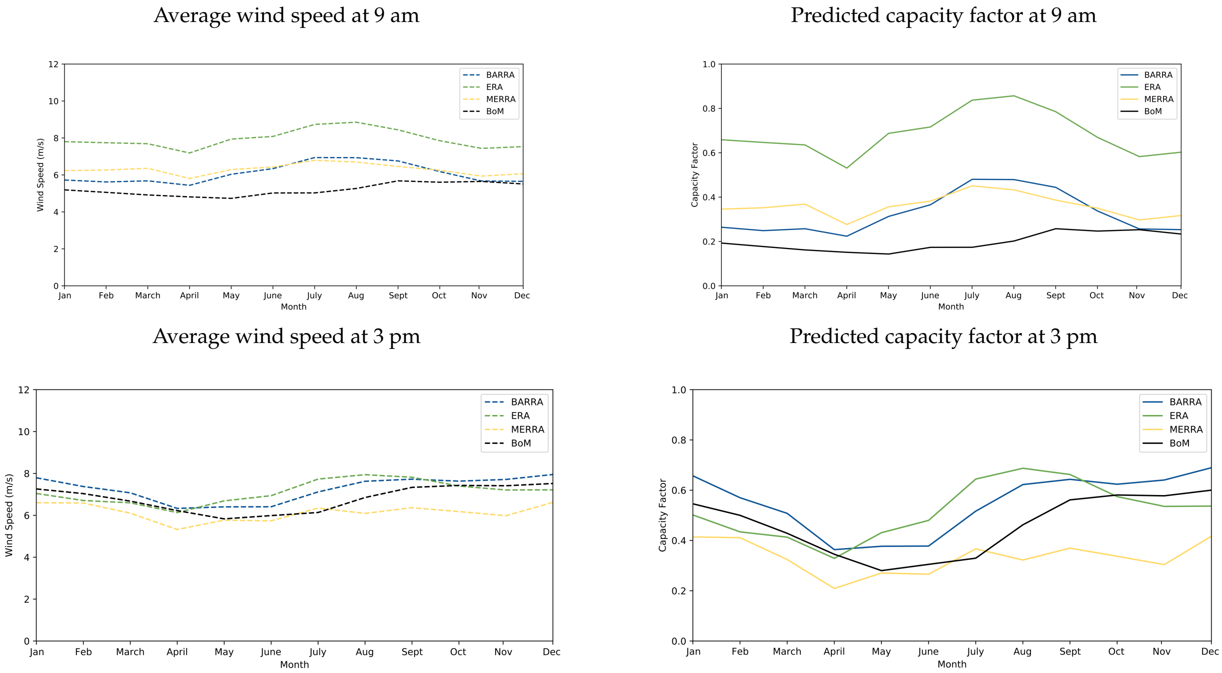

Figure 12. Comparison between average wind speed at 150 m across key locations and corresponding capacity factor predicted using each data source

Nevertheless, the discrepancies between the wind speed and capacity factor predictions from the individual datasets and the discrepancies with the station measurements point to the need for more publicly available direct wind speed measurements (e.g., from SODAR or LIDAR). The present situation would be improved with the introduction of standardized reporting for wind farms as part of the exploration and development phases—similar to the reporting standards and requirements in place for mineral resources projects (e.g., [35]). These industry data could be augmented with publicly funded (and publicly available) direct data collection efforts. As with other sectors, the development of such precompetitive datasets for wind energy would serve the interests of both the public and the industry by avoiding needless repetition and better illuminating the nature of the resource [36].

4. Conclusions

This paper considered the wind speed distribution accuracy and compared predictions of offshore wind turbine power output in Australia based on different wind data models. It was found that the capacity factor predictions across the datasets show consistent spatial and temporal features, but the magnitudes differ substantially. Across the entire domain over the 10-year period, the capacity factors were strongly correlated. The overall correlation coefficients were 0.779 between BARRA and MERRA-2, 0.811 for BARRA and ERA5, and 0.977 between ERA5 and MERRA-2. There was consistent spatial variation in the overall capacity factors across the datasets, and the results from all three confirmed key locations as having above-average offshore wind energy generation potential. However, the differences in magnitude of the capacity factors were large. The average difference in the overall capacity factor predicted using BARRA was 0.128 and 0.111 compared to MERRA-2 and ERA5, respectively. The smallest average difference was between ERA5 and MERRA-2 (0.048), consistent with these datasets being the most strongly correlated. When considering the temporal variation in the capacity factors at specific locations of interest, there was again good consistency across the datasets. This was particularly evident when considering monthly variations, with strong correlation coefficients found of 0.932 (BARRA and MERRA-2), 0.930 (BARRA and ERA5), and 0.960 (ERA5 and MERRA-2). Large differences were again found in the magnitudes of the capacity factors predicted at these locations, with differences of up to 37.85% between the datasets when considering hourly variation.

The results from all the datasets indicated that the same areas were comparatively better than other locations, which suggests that similar high-potential locations are likely to be identified regardless of the dataset used. However, the absolute results are likely to differ, with the magnitudes of the capacity factors at key locations predicted in this study varying by an average of 10% among datasets.

The paper also considered the accuracy of the offshore wind speed predictions made using each dataset. Due to a lack of offshore data available for comparison, coastal weather station data from the Bureau of Meteorology (BoM) at the relevant locations were used as a proxy. BARRA was found to be the most accurate, with the highest average correlation coefficient (0.585) and lowest percentage error (30.2%). This is likely due to its higher spatial resolution and use of land-based observations, including BoM data, as inputs. ERA5 was generally shown to outperform MERRA-2, with a lower root mean square error (4.58) and higher correlation coefficient (0.442). The greatest amount of error was in the 9 am wind speeds for Perth, with an average difference of over 100% for both MERRA-2 (113.7%) and ERA5 (109.1%), and a still-substantial error of 72.88% for BARRA. The largest errors were found to occur for actual wind speeds less than 4 m/s and greater than 7 m/s. Although the magnitudes differed substantially, temporal variation was shown to be consistent with the measured data. In general, the predictions from the datasets overestimated the mean wind speeds and underestimated the maximum gust speeds. It was also demonstrated that small differences in the wind speeds can have a large effect on the resultant capacity factor.

The wide variation seen in the predictions and the lack of similarity with the weather station data demonstrates that raw reanalysis data should only be used for preliminary modelling. This research serves as a reminder of the limitations of reanalysis datasets, as global-scale models cannot be expected to give a highly reliable representation of local conditions at a small scale. This study also highlights the need for more publicly available Australian offshore wind data to enable more accurate assessments of both datasets and potential site locations in the future. Finally, it should also be reiterated that the wind speed and potential capacity factor are only one aspect of evaluating the feasibility of an offshore wind farm and other factors such as the proximity to the electricity grid, environmental impact, and financial viability must also be considered.

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