COMPARATIVE STUDY OF WRF AND TAPM METEOROLOGICAL MODELS IN SOUTHEAST AND NORTHWEST QUEENSLAND

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Abstract

The Weather Research and Forecasting (WRF) model has been used to generate numerical weather predictions at locations in Southeast and Northwest Queensland, Australia. The model's predictions were then evaluated against observational data from various surface weather stations operated by the Bureau of Meteorology and the Department of Environment, Science and Innovation, with performance assessed using statistical methods. Additionally, the model's predictions were compared to those of TAPM, one of the most widely used prognostic models in Australia, to compare the performance of the two models.

WRF demonstrated a higher index of agreement between its predictions and observations, particularly for wind speed, wind components (u and v), and temperature. TAPM predictions presented a lower agreement with observations, and performance varied depending on the geographical location.

Given its superior performance compared to TAPM, WRF is the preferred choice for generating prognostic datasets for air dispersion modelling in Queensland, provided that higher accuracy is required for the project goals and justifies the computational investment.

Keywords: WRF, TAPM, modelling, meteorology.

1. Introduction

Meteorological modelling is a critical first step in air dispersion modelling, as it forms the basis for predicting pollutant dispersion. The accuracy and representativeness of the prognostic meteorological data used are therefore crucial for a reliable assessment.

In Australia, the Air Pollution Model (TAPM) developed by CSIRO is one of the most commonly used models for generating prognostic datasets for modelling. TAPM v4, its latest version, is widely accepted by regulatory bodies as a suitable source of prognostic data for air quality assessments and has demonstrated adequate performance for this purpose (Hurley, Edwards & Ji 2009). However, CSIRO will not provide any further updates to the model and potentially could stop providing the latest meteorological input data for running the model. This lack of future development and potentially limited access to meteorological data could lead to TAPM eventually becoming obsolete for air quality assessments.

An alternative to TAPM is the Weather Research and Forecasting Model (WRF), developed by the US National Centre for Atmospheric Research (NCAR) in partnership with the National Oceanic and Atmospheric Administration (NOAA) (Skamarock et al. 2021). The WRF model is a mesoscale numerical weather prediction system well-suited for air quality modelling applications. It can produce simulations based on actual atmospheric conditions, i.e. from observations and analysis or idealised conditions. It is a mature and sophisticated model at the cost of being computationally intensive. While a TAPM run can be completed on a standard modelling machine (e.g., 8 to 16 core processors such as Intel i7 or higher) for a 1-year period and several nested domains in less than 12 hours, achieving the same outcome with WRF typically requires access to High-Performance Computing (HPC) systems, making it more complex to be adopted in day-to-day air quality modelling applications.

Unlike TAPM, WRF offers a wider range of user-selectable physics options, including microphysics, planetary boundary layer (PBL) schemes, and cumulus parameterisations. However, this flexibility comes with the added complexity of selecting the most suitable combination for a specific application and region. Studies in Southeast Queensland (Evans, Ekstrom & Luhar 2012) have shown the performance of WRF can be sensitive to these physics choices.

Another relevant aspect of WRF is the availability of multiple datasets with various spatial and temporal resolutions to be used as inputs in the run. Studies to determine the sensitivity of the WRF model to six different input datasets have already been conducted for the Southeast Queensland region by Putland, Ward & Rollings (2021).

To evaluate the performance of the WRF model, this study was conducted by comparing its predictions with surface meteorological observations of key parameters such as wind speed and direction and temperature from multiple stations located in Northwest and Southeast Queensland over a period of 1 year. A comparative analysis with TAPM is also included in the analysis.

2. Methodology

2.1. Meteorological Inputs

Meteorological inputs for WRF were obtained from the NCAR Research Data Archive. The GFS-FNL (0.25 degree) dataset has been selected based on results from the sensitivity analysis conducted by Putland, Ward & Rollings (2021). The study suggests that higher spatial resolution datasets appear to provide more accurate predictions in terms of wind speed and direction. It is also noted that the ERA5 dataset with similar resolution performed almost as well as the GFS-FNL (0.25 degree).

It is important to note that most WRF physics options do not predict sea-surface temperature (SST) during the simulation. Instead, they rely on an initial SST value from the input data. This approach is sufficient for shorter simulations. However, for simulations exceeding 5 days, the "sst-update" option is available to incorporate time-varying SST data (UCAR 2024a). Since this study focuses on long term comparisons and the GFS-FNL dataset presents low temporal resolution, time-varying SST values obtained from the ERA5 Reanalysis (6-hourly) dataset were included in the model runs.

2.2. Modelling Domains

To compare the performance of WRF against TAPM in diverse topographical conditions, modelling domains were established in both Northwest and Southeast Queensland (Figure 1 and Figure 2). Due to the sparser distribution of surface weather stations in the Northwest region, three modelling domains were implemented to capture data from Cloncurry Airport, Georgetown Airport, and Normanton Airport, all stations managed by the Bureau of Meteorology (BoM). The Southeast Queensland domain is centred over Brisbane.

In configuring the WRF nested domains, a best practice is to follow a 3:1 or 5:1 nesting ratio (UCAR 2024b). Ideally, this recommendation would also apply to the ratio between the input data resolution and the parent domain. However, considering the relatively coarse resolution of the input data (~28 km), achieving a desired inner domain resolution of 1 km using this approach would require at least three nested domains. This would significantly increase the computational times of the simulations. Since this study also aims to assess the viability of running the model on a standard workstation, only two nested domains were implemented. The chosen grid resolutions were 3 km for the parent domain and 1 km for the inner domain. All domains utilised a grid size of 100x100.

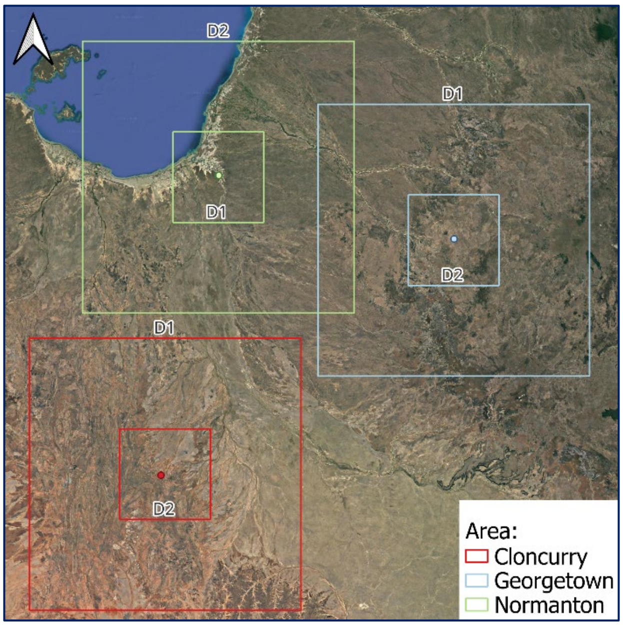

Figure 1. Modelled WRF domains (Northwest Queensland).

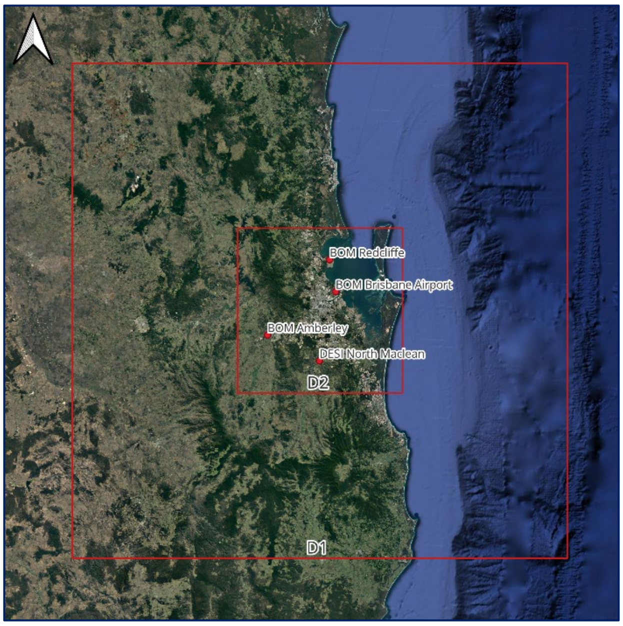

Figure 2. Modelled WRF domains (Southeast Queensland).

2.3. WRF Model Settings

Four 1-month model runs were conducted for each domain (Cloncurry, Normanton, Georgetown and

SEQ) as a compromise between run times and seasonal variations. The months of January, April, July and October were selected. Model years varied based on TAPM runs already generated for the study areas and are presented in Table 1. WRF model version 4.5.2 has been used in this study.

Table 1. Modelled years

Domain	Year
Cloncurry	2017
Georgetown	2021
Normanton	2021
SEQ	2020

The mandatory static geographical data required for the geogrid preprocessor was sourced from the UCAR website. The default options for topography height (using the GMTED2010 30-second global topographic dataset) and land use (using MODIS30 with 21 categories) were selected.

Table 2 presents the settings selected for all the modelling runs. FDDA nudging has not been implemented due to the high resolution of the domains. All physics options were selected based on study undertaken by Evans, Ekstrom & Luhar (2012) and consistent with those used by Putland, Ward & Rollings (2021).

Table 2. WRF setup

Parameter	Value/Setting
interval_seconds	21,600
history_interval (min)	60
time_step (sec)	15
feedback	0
Microphysics	WSM 5
Cumulus Parametrization	BMJ
Planetary Boundary Layer	MYJ
Longwave Radiation	RRTM
Shortwave Radiation	Dudhia
Surface Layer	ETA Similarity
Land Surface	Noah LSM

2.4. TAPM Model Settings

In this study, TAPM v4 was configured with 30 vertical grid levels and four nested domains, with a grid size of 40x40 points and grid spacings of 30, 10, 3, and 1 kilometres, respectively.

2.5. Evaluation Methods

Model predictions for wind speed, u and v components of wind and 2-m temperature were assessed through two evaluation metrics, the Root Mean Square Error (RMSE) and Index of Agreement (IOA). The RMSE provides information on the average magnitude of the errors in the model's predictions. It quantifies how much the model's values deviate from the observed values, on average. The IOA, on the other hand, focuses on the degree of agreement between the model's predictions and the observed data. It indicates how well the model captures the variance and pattern of the observed data, considering both overestimation and underestimation.

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{N}} \quad (1)$$

$$IOA = 1 - \frac{\sum_{i=1}^{N}|y_i - \hat{y}_i|}{\sum_{i=1}^{N}[\hat{y}_i - \bar{y}] + |y_i - \bar{y}|} \quad (2)$$

Where:

y_i: Observed value

$\hat{y}_i$: Predicted value

$\bar{y}$: Average of observations

N: Number of observations

All WRF and TAPM results were compared to surface meteorological data obtained from three BoM stations in the Northwest regions and four stations in the Southeast region (three BoM and one Department of Environment and Innovation (DESI) station).

3. Results

The RMSE and IOA are presented in Table 3 for each parameter, model, location, and modelled period. Lower RMSE values indicate better model performance, signifying a smaller average difference between predicted and observed values. Conversely, IOA values closer to 1 reflect a stronger agreement between the model's predictions and the actual observations. IOAs greater than 0.5 are considered a good agreement based on a review of multiple model evaluation studies undertaken by Hurley (2000). The highlighted values indicate the better-performing model.

The combined wind roses for each modelling scenario are presented in the Appendix.

Table 3. Model evaluation metrics

Wind Speed	January				April				July				October			
	RMSE		IOA		RMSE		IOA		RMSE		IOA		RMSE		IOA	
Location	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM
Cloncurry	1.82	1.87	0.65	0.64	1.09	2.11	0.85	0.64	1.22	1.57	0.82	0.69	1.84	2.35	0.73	0.59
Georgetown	1.45	1.59	0.68	0.54	1.38	1.51	0.78	0.73	1.37	1.59	0.64	0.53	1.60	1.54	0.56	0.51
Normanton	1.48	2.26	0.82	0.41	1.10	1.40	0.80	0.73	1.05	2.08	0.91	0.68	1.22	2.37	0.86	0.55
Amberley	1.37	2.28	0.89	0.64	1.52	1.82	0.77	0.58	1.68	1.58	0.82	0.75	1.57	2.60	0.86	0.48
Bris Airport	1.66	2.15	0.78	0.66	1.26	1.69	0.78	0.59	1.52	1.61	0.77	0.72	1.64	2.21	0.82	0.62
North Maclean	2.36	1.23	0.64	0.77	2.06	1.09	0.42	0.59	2.18	1.12	0.62	0.78	2.44	1.12	0.62	0.75
Redcliffe	2.68	3.89	0.71	0.53	1.87	2.80	0.72	0.51	1.51	1.83	0.76	0.62	2.33	3.46	0.73	0.54
U Component	January				April				July				October			
	RMSE		IOA		RMSE		IOA		RMSE		IOA		RMSE		IOA	
Location	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM
Cloncurry	1.94	2.18	0.79	0.72	1.30	1.89	0.90	0.75	1.72	1.63	0.81	0.74	2.26	2.09	0.76	0.68
Georgetown	1.84	1.94	0.72	0.60	1.66	1.88	0.84	0.77	1.62	2.10	0.84	0.71	1.99	2.09	0.80	0.75
Normanton	2.00	2.02	0.76	0.57	1.41	1.65	0.89	0.75	1.15	1.38	0.90	0.75	1.59	2.45	0.89	0.62
Amberley	1.89	2.39	0.84	0.63	1.72	1.91	0.87	0.72	1.69	1.78	0.89	0.83	2.02	4.39	0.87	0.43
Brisb Airport	1.54	1.59	0.80	0.70	1.61	1.95	0.87	0.75	1.95	2.58	0.87	0.77	1.58	1.95	0.87	0.72
North Maclean	2.03	1.30	0.72	0.73	2.38	1.65	0.56	0.58	1.85	1.56	0.75	0.74	1.97	1.47	0.81	0.75
Redcliffe	1.95	2.41	0.79	0.61	1.96	2.40	0.86	0.67	2.17	2.44	0.82	0.75	1.92	2.67	0.86	0.61
V Component	January				April				July				October			
	RMSE		IOA		RMSE		IOA		RMSE		IOA		RMSE		IOA	
Location	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM
Cloncurry	1.67	2.24	0.77	0.66	1.26	1.67	0.92	0.86	1.48	1.60	0.89	0.85	2.48	2.65	0.87	0.81
Georgetown	1.82	1.60	0.58	0.48	1.34	1.38	0.71	0.63	1.21	1.41	0.82	0.78	1.99	1.94	0.74	0.60
Normanton	2.10	2.68	0.82	0.44	1.62	1.81	0.87	0.78	1.35	2.26	0.96	0.84	1.93	2.66	0.88	0.72
Amberley	1.50	1.46	0.85	0.79	1.81	1.62	0.73	0.66	1.94	1.63	0.76	0.72	1.88	2.31	0.77	0.34
Bris Airport	1.77	2.30	0.91	0.83	1.64	1.92	0.90	0.83	1.51	1.67	0.85	0.81	1.82	2.32	0.92	0.84
North Maclean	2.33	1.51	0.62	0.73	2.19	1.79	0.36	0.36	2.07	1.21	0.57	0.73	2.38	1.32	0.52	0.69
Redcliffe	2.74	3.60	0.87	0.72	2.22	2.73	0.86	0.73	2.05	2.41	0.81	0.68	2.48	3.16	0.89	0.77
Temperature	January				April				July				October			
	RMSE		IOA		RMSE		IOA		RMSE		IOA		RMSE		IOA	
Location	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM	WRF	TAPM
Cloncurry	2.16	2.42	0.91	0.89	1.78	2.40	0.97	0.95	1.97	2.02	0.96	0.96	2.01	2.47	0.95	0.93
Georgetown	1.69	2.28	0.94	0.90	1.63	2.23	0.96	0.92	2.23	2.50	0.96	0.94	2.73	3.01	0.93	0.91
Normanton	1.81	2.26	0.92	0.88	2.21	1.93	0.93	0.94	2.00	1.83	0.96	0.96	1.87	2.48	0.95	0.91
Amberley	1.60	2.22	0.96	0.89	2.05	3.43	0.96	0.82	2.61	3.47	0.93	0.84	1.92	2.95	0.96	0.89
Bris Airport	1.08	1.31	0.92	0.92	2.14	2.28	0.87	0.80	2.28	2.40	0.88	0.84	2.24	2.06	0.91	0.78
North Maclean	1.66	1.68	0.95	0.91	1.64	2.86	0.97	0.85	1.82	2.85	0.96	0.88	1.59	2.40	0.97	0.87
Redcliffe	1.30	1.33	0.88	0.86	1.75	2.12	0.89	0.78	1.88	2.17	0.90	0.84	1.27	1.83	0.92	0.81

4. Discussion

With a few exceptions, WRF generally outperformed TAPM in the Northwest region for most parameters and periods analysed. WRF exhibited lower RMSE and higher IOA values, indicating a closer match between its predicted values and the observed data and a stronger ability to capture the variations and patterns in the data compared to TAPM. However, WRF's RMSE for Georgetown in October was slightly higher than TAPM's.

Both models struggled with calm wind condition, leading to a better agreement for the u and v wind components than wind speed. Despite this, most IOA values fell between 0.64 and 0.91, suggesting a moderate to good level of agreement between predictions and observations. Exceptions include the October run in Georgetown for wind speed and the January v-component simulation at Georgetown (IOA below 0.7). Nevertheless WRF performed better than TAPM in these situations.

The trend continued in Southeast Queensland, with WRF significantly outperforming TAPM at all BoM stations but not at the DESI station (North Maclean). For stations like Amberley, Brisbane Airport, and Redcliffe, WRF achieved good agreement (IOA ranging from 0.71 to 0.89 for wind speed and 0.73 to 0.92 for u and v components).

Both models underperformed at North Maclean during the April run. However, TAPM showed moderate agreement with observations for other periods at this location. As depicted in Figure A6 (Appendix), WRF appears to overestimate wind speeds at North Maclean, and compared with observations shifts easterly winds towards the northeast and westerly winds towards the southwest. Further investigation is required to ascertain whether the poorer performance at this location is attributable to data quality issues or the representativeness of the North Maclean observations. This could include running the models for different years to assess consistency.

In terms of temperature, WRF performed significantly better than TAPM in both regions with IOA above 0.88 for all locations and periods.

Overall, the prognostic datasets effectively represent the wind patterns and temperature of the selected areas, proving suitable for air dispersion modelling. The WRF model, in particular, appears to offer a more representative dataset than TAPM.

An interesting finding is that running WRF with only two nested domains produced a good-quality prognostic dataset suitable for air dispersion modelling. This suggests the possibility of achieving accurate results without the increased computational cost and longer run times associated with using additional nested domains. However, further investigation is warranted to determine the impact of additional nested domains on the model output quality. While a single domain might be sufficient for some applications, including more nested domains could potentially improve the model's ability to capture fine-scale features or complex terrain variations. This is less important if the output data is processed through a meteorological preprocessor such as Calmet that is capable of adjusting the data to better fit the local terrain and land use.

In summary, WRF consistently outperformed TAPM in predicting wind speed, wind direction, and temperature. For wind speed and wind direction, WRF presented a lower RMSE in 76% of tests and a higher IOA in 88% of the tests compared to TAPM. For temperature, WRF outperformed TAPM in 93% of the tests for RMSE and 86% for IOA.

5. Conclusions

A comparative study has been conducted to assess the performance of the WRF and TAPM prognostic models in the Northwest and Southeast regions of Queensland, Australia. A group of three surface weather stations in the Northwest and four in the Southeast have been used to compare their predictions and calculate two evaluation metrics, the RMSE and the IOA.

Overall, WRF presented a better agreement with the surface observations in both regions for parameters such as wind speed, u and v components of wind and temperature.

Further research topics include:

- Additional studies to determine the reason behind the poorer performance at the North Maclean station location.
- Additional parameters relevant to air dispersion modelling such as rainfall, relative humidity and mixing heights.
- Sensitivity analysis of adding additional nesting domains.

References

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Appendix – Combined data wind roses

This Appendix presents the combined data (January, April, July and October) wind roses for all the studied locations.

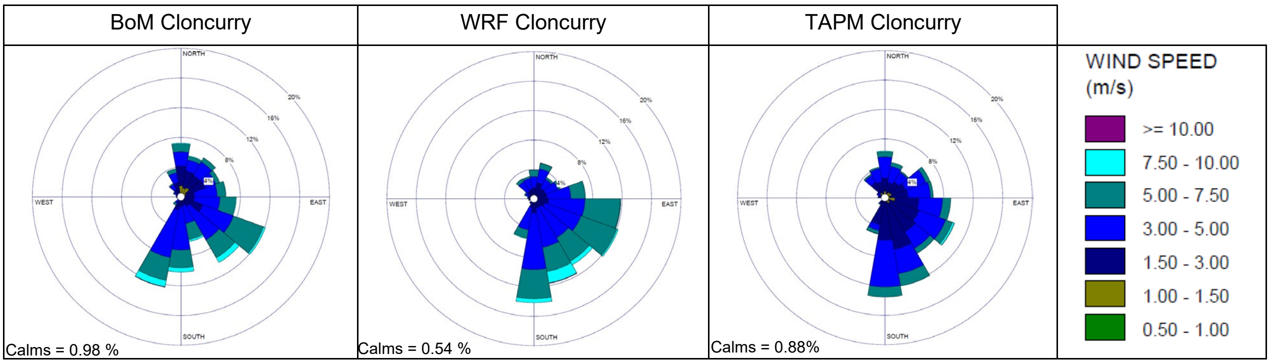

Figure A1. Wind roses for Cloncurry (combined January, April, July and October data).

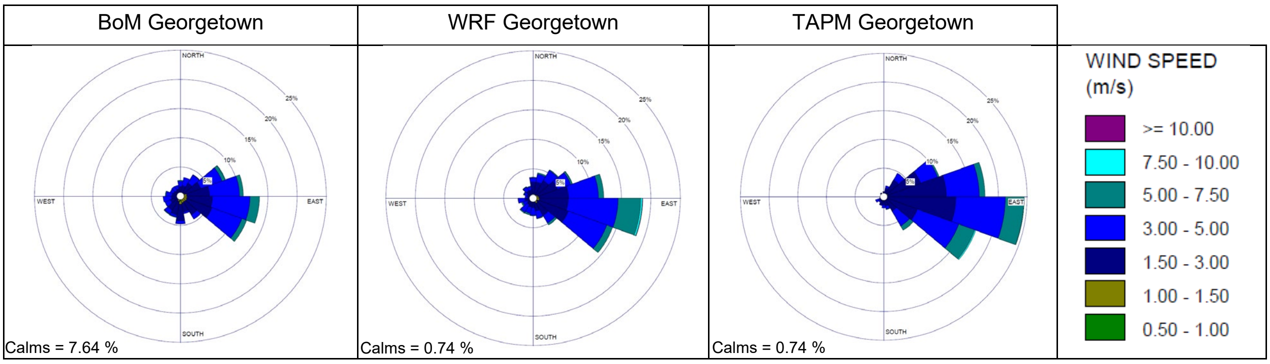

Figure A2. Wind roses for Georgetown (combined January, April, July and October data).

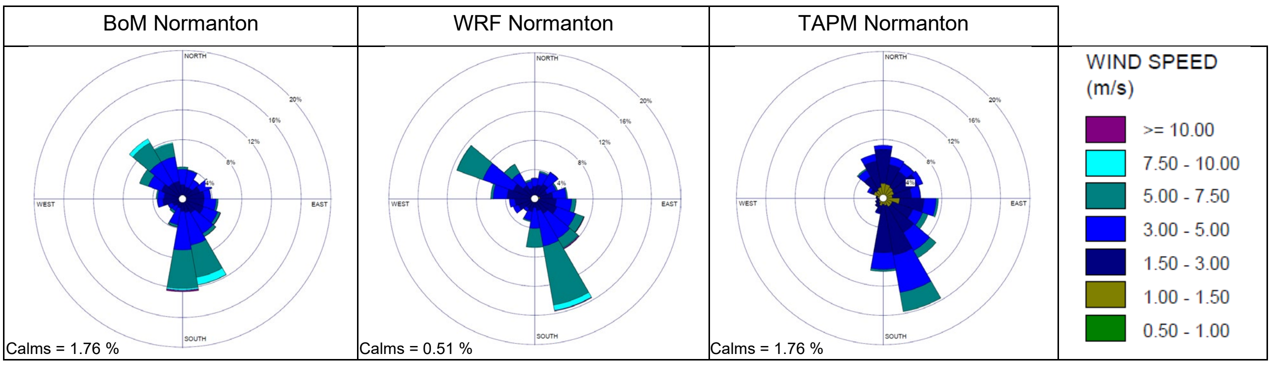

Figure A3. Wind roses for Normanton (combined January, April, July and October data).

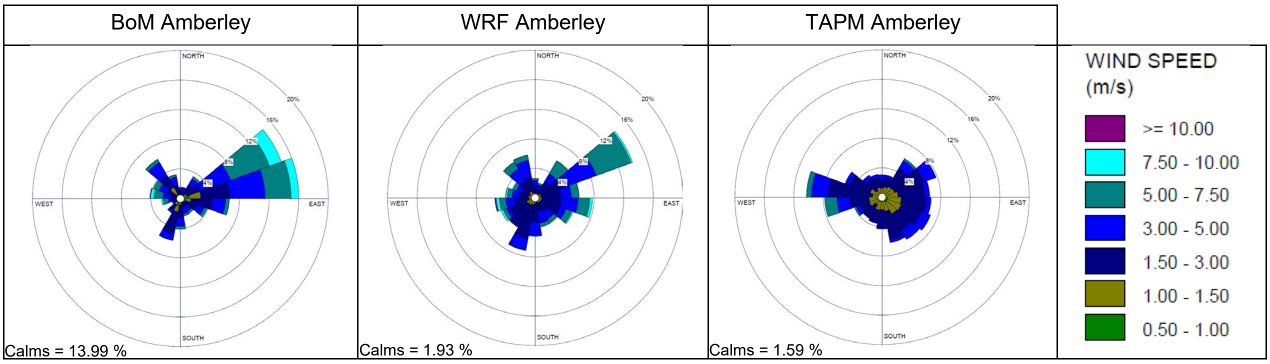

Figure A4. Wind roses for Amberley (combined January, April, July and October data).

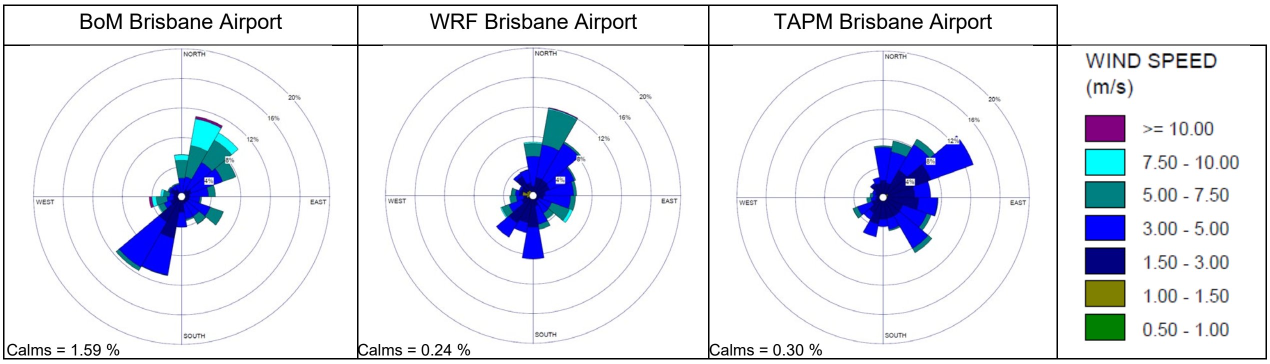

Figure A5. Wind roses for Brisbane Airport (combined January, April, July and October data).

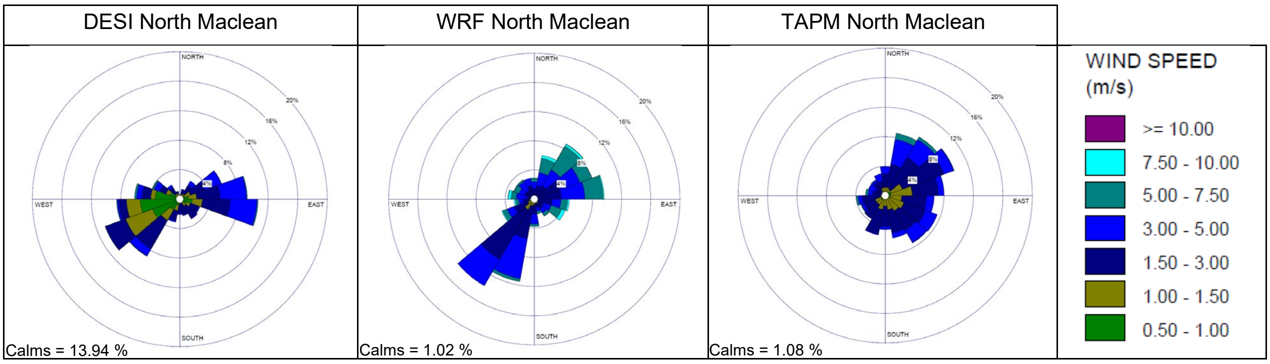

Figure A6. Wind roses for North Maclean (combined January, April, July and October data).

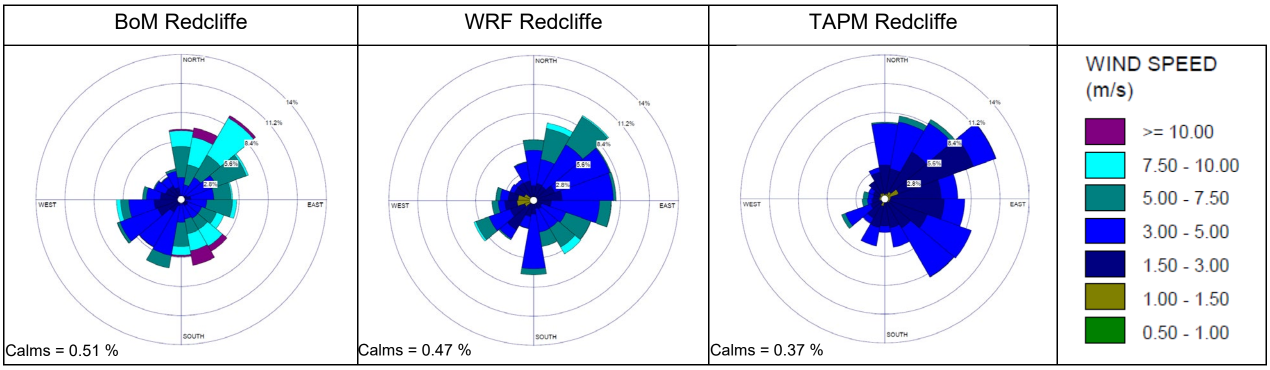

Figure A7. Wind roses for Redcliffe (combined January, April, July and October data).