

Contents

1	Me	teorological Parameters	2
1.	1	Method	2
1.	2	Data Recovery	3
1.	3	Results	3
2	Me	teorological Dataset Development	5
2.	1	TAPM	5
2.	2	Calmet	5
Figu	res		
Figu	re 1	1: chi-squared outcomes	3
Figui	re 1	2: Mann-Whitney U-Test z-score outcomes	4
Figui	re 1	3: Box & Whisker Plot of Temperature (min, Q1, median, Q3, max)	4
Figui	re 2	2-1: Annual and Seasonal Windroses for Hybrid derived Site-representative 2021	Meteorology
(mod	delle	ed)	7
_		2-2: Time of Day Windroses for Hybrid derived Site-representative 2021 Meteorolog	
		2-3: Annual X-Y scatter plot diurnal temperatures for 2021 (modelled)	
		2-4: Average Monthly temperatures for 2021 (modelled)	
		2-5: Annual X-Y scatter plot diurnal mixing height for Locality (modelled)	
		2-6: Annual stability class frequency for Locality (modelled)	
Tabl	les		
Tabl	e 1-	-1: Method of Wind Speed versus Wind Direction	2
Tabl	e 1-	-2: Data Recovery Statistics	3
Tabl	e 1-	-3: chi-squared outcomes	3
Tabl	e 1-	-4: Temperature Observations within Degrees (°C) Bins	4
Tabl	e 2-	-1: Calmet Key Variables (Grid Configuration WGS-84 UTM Zone 50S)	5
Tabl	e 2-	-2: Stability Classes	6



1 Meteorological Parameters

- When undertaking dispersion modelling for odour, the wind vector (speed and direction) is critical in determining the magnitude of the odour impacts downwind of an odour emission source(s), where;
 - o This vector carries the largest weight in terms of a representative year for odour impacts.
- > Temperature is also important within odour dispersion modelling for understanding vertical mixing layers, and inversion layers within the domain assessed by the dispersion model; and
- Rainfall has importance empirically when observing odour impacts at ground level;
 - Relative humidity is also a useful parameter within the dispersion modelling assessment when considering the density of the air within the vertical mixing layers.

1.1 Method

Five (5) years of the latest annual meteorological (met) data is sourced from the nearest, or multiple, Bureau of Meteorology (BoM) Automatic Weather Station (AWS).

The data is arranged into annual observations and the primary *vector* of wind is sorted into 'bins' of wind speed and direction, for example:

Table 1-1: Method of Wind Speed versus Wind Direction

2018		CHECK #	8760			
$WD\!\downarrowWS\!\!\to\!$	0	2	4	6	>6	TOTAL
0	0	0	0	0	0	0
90	0	407	457	305	136	1305
180	0	822	1560	919	152	3453
270	0	278	848	1243	527	2896
360	0	124	273	222	487	1106
TOTAL	0	1631	3138	2689	1302	8760

The *chi-squared* test shows a statistical relationship between two categorical variables. The statistic is a single number that shows how much difference exists between observed counts and the counts expected if there were no relationship at all in the population.

- For determining the representative met year, each of the annual period five year counts, for grouped wind speed and direction, are compared to the averaged dataset of all five years of grouped wind speed and direction, where;
 - A low value for chi-square means there is a high correlation between two sets of data. In theory, if the observed and expected values were equal ("no difference") then chi-square would be zero an event that is unlikely to happen in real life.

The *Mann-Whitney U-Test* is another statistical way of determining differences between values. A null hypothesis is tested where there are no significant differences between two values. In this case, the hourly values within one year compared to the long-term average over five years.



 Mann-Whitney U-Test can be used to determine the representative year based on the scalar of temperature.

1.2 Data Recovery

The five (5) annual periods were sorted, and errors, blanks and nil values were removed, to include removing wind speed stalls and directions of '0'.

Once the erroneous data was removed the data recovery was found to be:

Table 1-2: Data Recovery Statistics

Year	Ambient Temp	Wind Direction	Wind Speed (m/s)
2018	99.85%	97.67%	97.15%
2019	97.51%	93.16%	92.71%
2020	97.97%	92.68%	92.27%
2021	96.62%	90.33%	89.87%
2022	98.53%	93.97%	93.50%

1.3 Results

Comparing the annual periods of 2018 – 2022 inclusive for the Mandurah BoM AWS and deriving the representative year based on the vector of wind, the representative year derived using the chi-squared relationship was 2020, **2021**, 2018, 2019 and 2022.

Table 1-3: chi-squared outcomes

Annual Period	chi-squared
2018	44.7
2019	71.0
2020	43.9
2021	47.0
2022	87.0

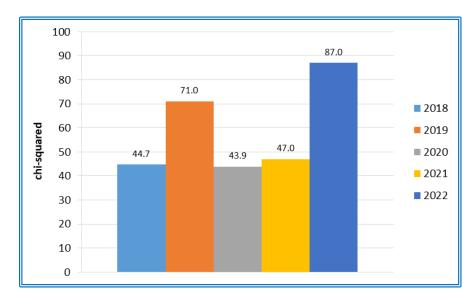


Figure 1-1: chi-squared outcomes



Comparing the annual periods of 2008 – 2022 inclusive for the Mandurah BoM AWS and deriving the representative year based on the scalar of Temperature, the representative year derived using the Mann-Whitney U-Test was **2021**, 2022, 2019, 2020 and 2018.

Table 1-4: Temperature Observations within Degrees (°C) Bins

	<u> </u>		3 ,						
°C 2018		2019	2020	2021	2022	5-Year			
0 - 5	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%			
5 - 10	2.41%	2.77%	1.71%	2.41%	2.32%	2.32%			
10 - 15	20.91%	21.49%	19.59%	21.67%	23.08%	21.35%			
15 - 20	43.05%	39.50%	41.45%	39.79%	38.45%	40.46%			
20 - 25	24.71%	24.70%	24.26%	22.66%	21.58%	23.59%			
25 - 30	7.28%	8.67%	9.98%	9.44%	10.66%	9.20%			
30 - 35	1.57%	2.65%	2.67%	3.47%	3.63%	2.79%			
>35	0.07%	0.21%	0.34%	0.56%	0.28%	0.29%			
TOTAL	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%			

0.3 0.2 0.1 0 = 2018 = 2019 = 2020 = 2021 = 2022 -0.3 -0.4 -0.5

Figure 1-2: Mann-Whitney U-Test z-score outcomes

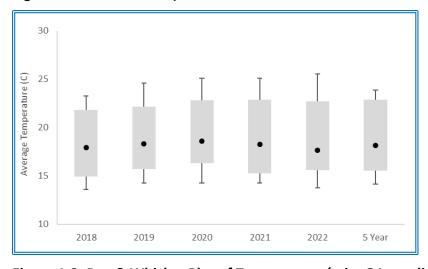


Figure 1-3: Box & Whisker Plot of Temperature (min, Q1, median, Q3, max)



2 Meteorological Dataset Development

2.1 TAPM

2.2 Calmet

The TAPM met data was used to initialise the diagnostic functions of the Calmet module to produce a full 3D meteorology site-representative dataset that was input into the Aermod Modelling Assessment.

Table 2-1 shows key variable fields selected when initialising the Calmet module.

Table 2-1: Calmet Key Variables (Grid Configuration WGS-84 UTM Zone 50S)

Table 2 1. Ca		ive, o	u: 1451	<u>'</u>	On a	0.	iiigai a		00 0 + 1	5 1 1 VI 2 C	110 303	<u> </u>		
100							NX Cells							
100							NY Cells							
0.20							Cell Size (km)							
379.740 6396.870							SW Corner (km)							
11						Vertical Layers								
ZFACE (m) 0 20			40	8	0 16	0	320	640	1000	1500	2000	2500	3000	
LAYER	1	2	3	4	1 5		6	7	8	9	10	11	-	
MID-PT (m)	10	30	60	0 120		0	480	820	1250	1750	2250	2750	-	
							Wind Field Settings							
Valu	ıe		Foun	ıd	Typical		Values							
TERR	AD		6		None	5	Terrain scale (km) for terrain effects							
IEXTRP			-4		4,-4		Similarity extrap. of wind (-4 ignore upper stn sfc)							
ICAL		0		0		Do Not extrapolate calm winds								
RMA	X1		3		None	9	MAX radius of influence over land in layer 1 (km)							
RMA	4		None	9	MAX radius of influence over land aloft (km)									
R1		4		None	2	Distance (km) where OBS wt = IGF wt in layer 1								
R2		5		None		Distance (km) where OBS wt = IGF wt aloft								
							Data Choices							
Valu	Foun	ıd	Туріс	al	Values									
NOOBS			1		0,1,2	2	0=w/Obs; 1=Partial Obs/No-Obs; 2=No-Obs				os mode			
ITPR	1		0,1,2	2	0=Obs.; 1=Obs.Sfc/Prog.Upr; 2=Prog. tempera				eratures					
ITWPI	1		0,1,2	2	0=Obs.; 1=Obs.T_Diff/Prog.Lapse; 2=Prog. Over				verwater T					

The characteristics of the Calmet hybrid dataset for wind direction versus wind speed are illustrated in Figures 2-1 and 2-2.



It can be seen from **Figure 2-1** that the characteristics of wind speed and direction (annual and seasonal) have been hybridised well using the Mandurah AWS data (refer main report). **Figure 2-2** shows the hourly met characteristics for the hybrid met dataset.

Other met trends, including stability class frequency, are illustrated in **Figures 2-3 to 2-6** to follow, with **Figure 2-6** showing that F Class Atmospheric Stability (very stable conditions) is prominent.

F Class Stability (very stable) is prominent during the hours of 5PM – 6AM inclusive i.e., during nighttime hours.

Stable and very stable atmospheric conditions typically dominant those nighttime meteorological characteristics within the locality.

Under stable conditions mechanical dispersion plays a larger role in dispersion and vertical mixing of emission plumes when there is complexity in the terrain and surface roughness. In low surface roughness terrain (as is the Facility's locality), the effects of mechanical turbulence are weakened, to include a decrease in vertical mixing, and ground level emission plumes tend to have larger impacts over longer downwind distances from the emission source.

Stability refers to the atmosphere's ability to resist or enhance vertical motion resulting in turbulence. Stability encompasses (among others) temperature changes with atmospheric height (lapse rate), wind speed and surface roughness. The six classes of stability are:

Table 2-2: Stability Classes

- A very unstable
- **B** unstable
- c slightly unstable
- D neutral
- **E** stable
- F very stable
- Unstable conditions enhance turbulence and subsequent dispersion;
- Neutral stability neither enhances nor reduces turbulence; and
- Stable conditions reduce turbulence and therefore dispersion is reduced.



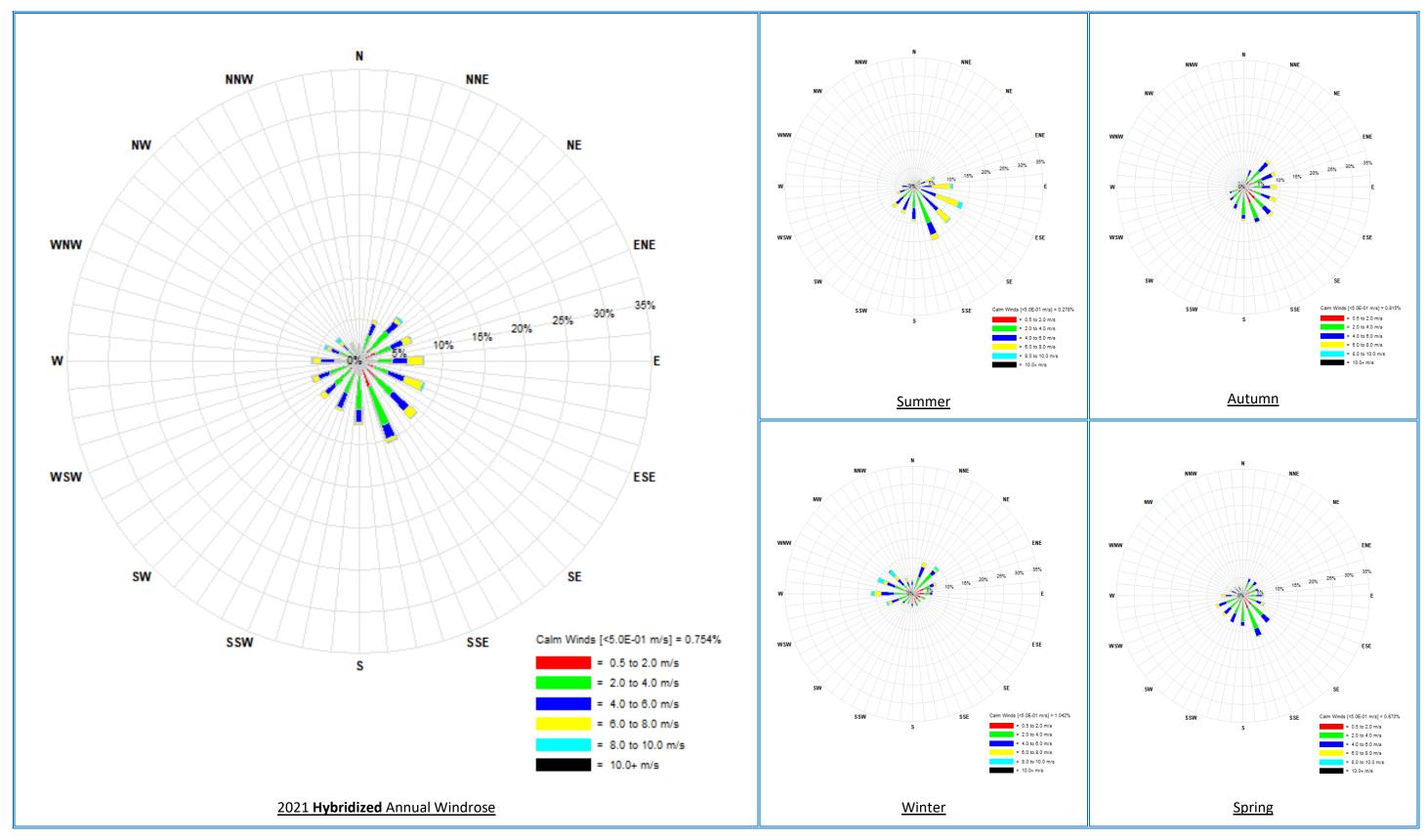


Figure 2-1: Annual and Seasonal Windroses for Hybrid derived Site-representative 2021 Meteorology (modelled)

Appendix A (Met Rep Year & Met)

P a g e | 7 5 November 2023



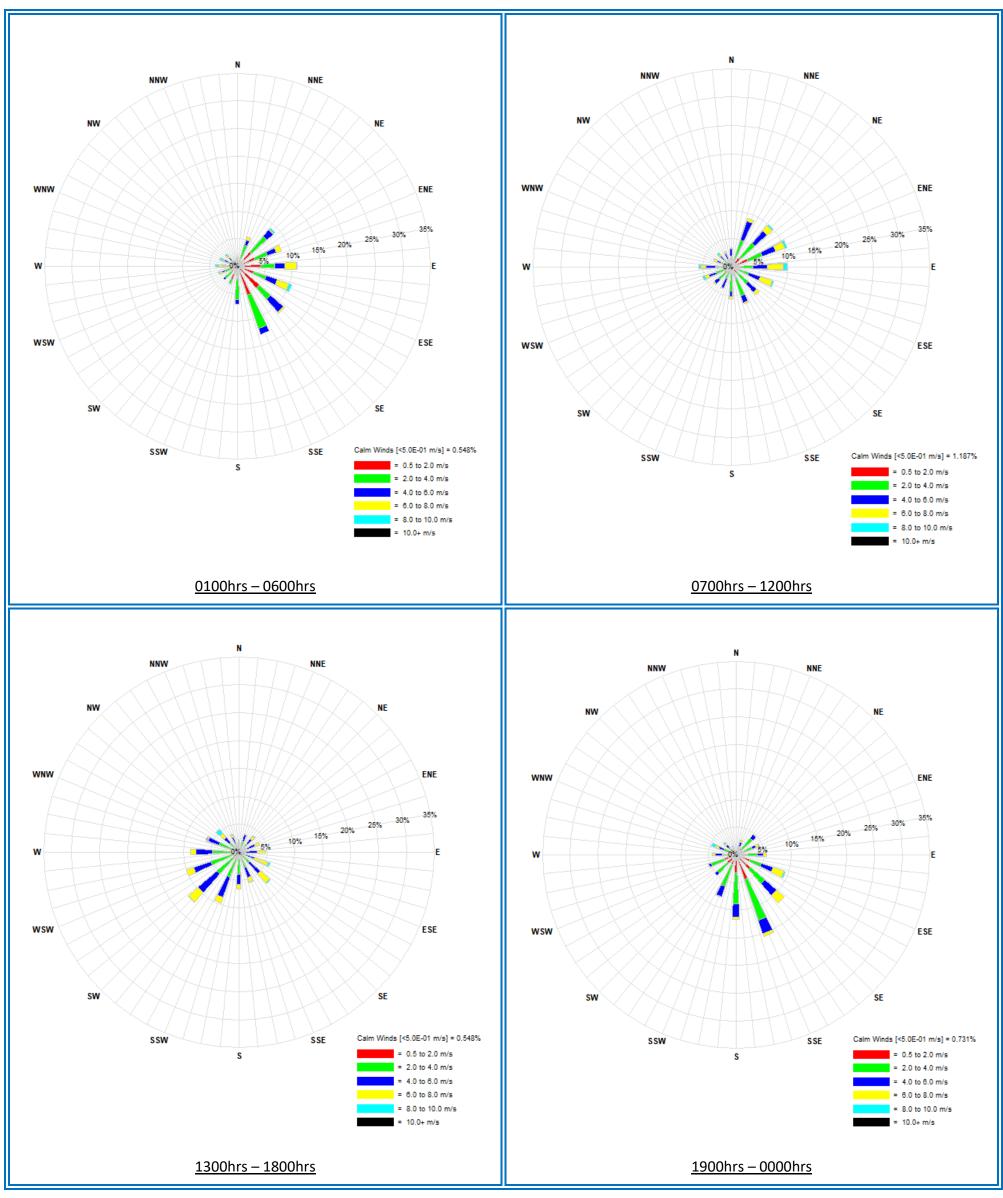


Figure 2-2: Time of Day Windroses for Hybrid derived Site-representative 2021 Meteorology (modelled)

Appendix A (Met Rep Year & Met)

P a g e | 8 5 November 2023



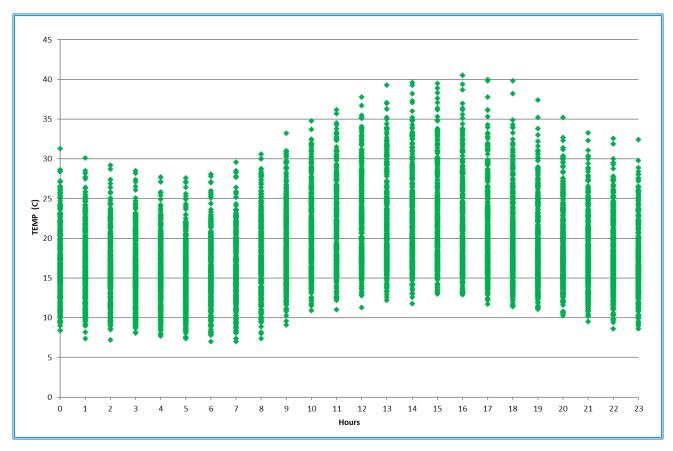


Figure 2-3: Annual X-Y scatter plot diurnal temperatures for 2021 (modelled)

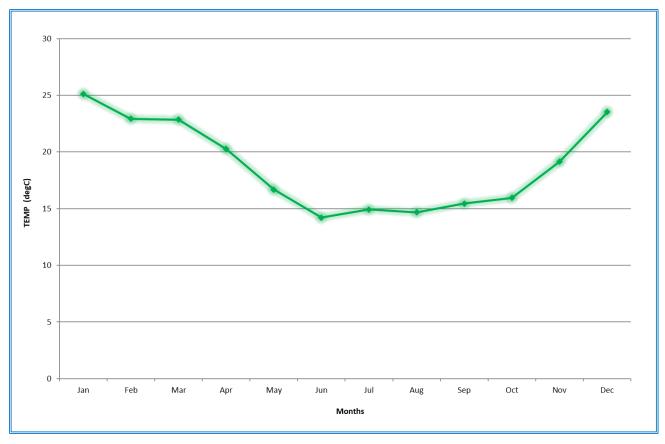


Figure 2-4: Average Monthly temperatures for 2021 (modelled)



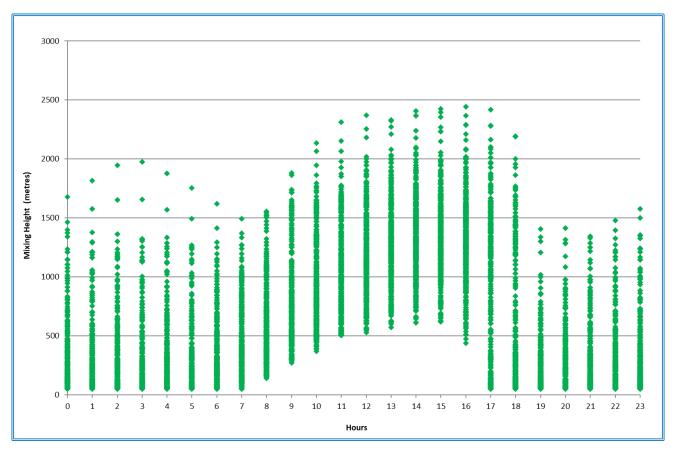


Figure 2-5: Annual X-Y scatter plot diurnal mixing height for Locality (modelled)

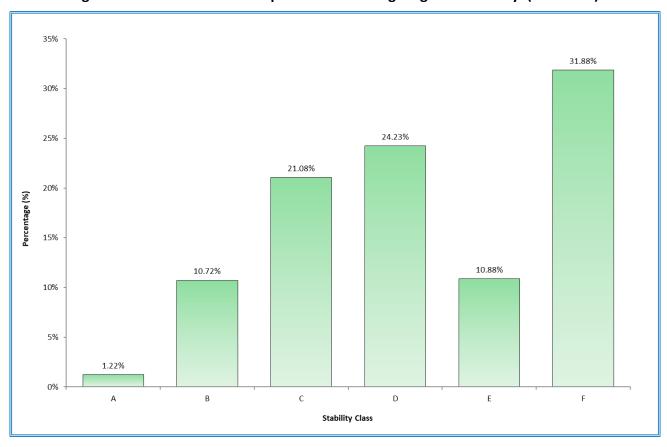


Figure 2-6: Annual stability class frequency for Locality (modelled)