

Mesoscale model parameterisation of fog in arid environments

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PREFACE

This thesis is submitted in article format as the majority of the chapters have been published in international journals. The student was the main author on all the articles and performed the majority of the research and writing. The following published articles are presented as chapters in this thesis.

The following chapters were published in international journals. The copyright in each journal allows for this work to be included in a thesis.

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Chapter 3: Weston, M.J., Temimi, M., 2020. Application of a night time fog detection method using SEVIRI over an arid environment. Remote Sens. 12. <https://doi.org/10.3390/rs12142281>

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Chapter 4: Weston, M., Chaouch, N., Valappil, V., Temimi, M., Ek, M., Zheng, W., 2018. Assessment of the Sensitivity to the Thermal Roughness Length in Noah and Noah-MP Land Surface Model Using WRF in an Arid Region. Pure Appl. Geophys. <https://doi.org/10.1007/s00024-018-1901-2>

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Chapter 5: Weston, M., Temimi, M., Morais, R., Reddy, N., Francis, D., Piketh, S., 2021. A rule-based method for diagnosing radiation fog in an arid region from NWP forecasts. J. Hydrol. 597, 126189. <https://doi.org/10.1016/j.jhydrol.2021.126189>

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ABSTRACT

Key terms: WRF, fog, arid, forecast

Fog is a natural hazard as it causes visibility to drop below 1 km due to condensation processes in the atmosphere. Yet, fog is not a standard output from numerical weather prediction models which are used for operational weather forecasts. Instead, proxy indicators are calculated in the model post processing to indicate if fog is forecast. There are traditionally three approaches to achieve this, the first is to use the liquid water content at the lowest model level, the second is to define visibility based on model output variables and the third is to use a multi rule based approach, also based on model variables. All of these approaches are affected by model bias and model parameterisation which will ultimately affect the forecast skill. While these methods have been reported on in the literature for localities in non-arid regions there has been little application to fog in arid environments. In this thesis we aim to explore and optimise these methods for forecasting fog in arid environments using the Weather Research and Forecasting (WRF) numerical weather prediction (NWP) model.

The main study site was Abu Dhabi International Airport in the United Arab Emirates (UAE). The first fog climatology for the region is presented in Chapter 2 based on Meteorological Aerodrome Reports (METAR) and radiosonde data, an important long term data set. In addition, the first spatial dynamics of fog is presented in Chapter 3 utilising the Spinning Enhanced Visible and InfraRed Imager (SEVIRI) on board the Meteosat satellite. An important result from the fog climatology analysis helped guide the methodology in Chapter 5, “A rule-based method for diagnosing radiation fog in an arid region from NWP forecasts”. This was related to the surface inversion depth, which was deeper on fog mornings. A rule was applied to the model where inversion depth needed to be greater than 250 m to diagnose fog. This ruled helped separate fog days from non-fog days in the model simulations and improved the fog forecast. The satellite data was used extensively for a qualitative assessment of the modelled fog patch.

Model physics is introduced in Chapter 4, more specifically, the land surface model in WRF. A nocturnal cold bias in the model simulations was identified at the Abu Dhabi study site. This resulted in overactive saturation and therefore false alarms in the forecast. To address this cold bias, the model code was adapted to indirectly adjust the thermal roughness length per land cover type. For the arid desert this meant a decrease in the roughness length of heat, Z_{0t} , which will decrease the coefficient of heat exchange, C_H , and therefore increase of land surface temperature and by association increase the 2m air temperature. The thermal roughness length was adjusted through the Zilitinkevich parameter (C_{zil}), an input variable in the model. The default value for all

land cover types is 0.1, but we found that a value of 0.5 for desert improved the mean gross error in late afternoon/early evening temperature up to 1.48 °C. This chapter showed that the bias could be solved in part through adjusting the Czil parameter.

The main focus of Chapter 5 was to implement a multi rule based method to diagnose fog from the model. The methodology made use of readily available meteorological parameters to define the rules so that the method is transferable to other sites. The final model performance compared favourably to studies in wetter regions. A main finding in this chapter, and as already mentioned, was the implementation of the inversion depth as a rule, which had not been applied previously. The inclusion of this rule outperformed the Modified Richardson index (MRI), another parameter that represents vertical stability in the atmosphere. Furthermore, the multi-rule method also outperformed liquid water content from the model. A qualitative assessment on the spatial distribution of fog patches was conducted by comparing the model with satellite RGB images. The results showed realism in the model fog patch as it managed to represent the extent and boundaries of observed fog events. This suggests that the geophysical parameters from the observations at a single point used to define the rules were applicable over a larger area. Overall this method exceeded expectations.

In Chapter 6 the focus moved towards cloud microphysics as NWU was involved in a field campaign in Namibia where these measurements were taken. This allowed for the implementation of an aerosol aware microphysics scheme in the model, which represents the process of cloud droplet activation, and subsequently using liquid water content to define fog. The major finding from this chapter is that the model underestimates droplet activation during a fog event. The model code was modified to increase the droplet activation in the lowest model levels. This resulted in improved simulation of droplet number concentration and droplet size distribution.

In summary, both the rule based method and the aerosol aware microphysics require that modelled state parameters are performing adequately. To some extent, the rule based method is more lenient in this regard as it implements threshold values. However, the microphysics approach demonstrates a great deal of potential and improvements in performance were achieved rapidly, through a few model scenarios and with far less analysis of observed data. Furthermore, the code is primed to ingest custom spatial data in terms of initial CCN concentrations or even coupled online CCN. Based on the results presented in this thesis, the rule based method is currently a more robust method to diagnose next day fog in the model.

TABLE OF CONTENTS

PREFACE	I
ABSTRACT	III
CHAPTER 1 INTRODUCTION.....	1
1.1 Literature Study	1
1.1.1 Approaches to diagnosing fog	1
1.1.2 Parameterisation of the land surface model in WRF	3
1.1.3 Rule based method	3
1.1.4 A simplified visibility equation	5
1.1.5 Cloud condensation nuclei (CCN) modification in microphysics	5
1.2 Problem Statement.....	6
1.3 Gaps in literature and recent studies.....	6
1.4 Research Aim and Objectives	7
1.5 Methods.....	8
1.5.1 Study areas	9
1.5.1.1 Abu Dhabi, United Arab Emirates	9
1.5.1.2 Henties Bay, Namibia	9
1.5.2 Data.....	10
1.5.2.1 UAE Observations	10
1.5.2.2 Namibia Observations	10
1.6 References	10
CHAPTER 2 A FOG CLIMATOLOGY AT ABU DHABI INTERNATIONAL AIRPORT... 	15

2.1	Introduction	15
2.2	Method.....	20
2.2.1	METAR Data	20
2.2.2	Vertical temperature profiles	21
2.3	Results and Discussion	22
2.3.1	METAR data coverage	22
2.3.2	Meteorological Climatology.....	23
2.3.3	Fog climatology	24
2.3.4	Importance of land–sea breeze	32
2.3.5	Vertical temperature profile.....	36
2.4	Conclusions.....	37
2.5	References	38
CHAPTER 3 APPLICATION OF A NIGHTTIME FOG DETECTION METHOD USING SEVIRI OVER AN ARID ENVIRONMENT.....		43
3.1	Introduction	43
3.2	Materials and Methods.....	45
3.2.1	Study Area.....	45
3.2.2	Datasets	46
3.2.2.1	SEVIRI Data	46
3.2.2.2	METAR Data	47
3.2.2.3	ERA5 Data	47
3.2.3	Fog/Low Clouds Detection.....	47

3.2.4	Low Cloud Detection.....	49
3.2.5	Verification.....	50
3.3	Results and Discussion	51
3.3.1	Histograms	51
3.3.2	Monthly Threshold Maps: ems(3.9).....	54
3.3.3	Assessment Over Two Fog Seasons.....	56
3.3.4	Analysis of Fog Frequency	57
3.4	Discussion	61
3.5	Conclusions.....	61
3.6	References	63
CHAPTER 4 ASSESSMENT OF THE SENSITIVITY TO THE THERMAL ROUGHNESS LENGTH IN NOAH AND NOAH-MP LAND SURFACE MODEL USING WRF IN AN ARID REGION		65
4.1	Introduction	66
4.2	Study area	68
4.3	Methodology	69
4.3.1	WRF model	69
4.3.2	Noah land surface model description	71
4.3.3	WRF Configuration	73
4.3.4	Model Verification	75
4.4	Results and discussion.....	75
4.5	Conclusions.....	90
4.6	References	91

CHAPTER 5 A RULE-BASED METHOD FOR DIAGNOSING RADIATION FOG IN AN ARID REGION FROM NWP FORECASTS	95
5.1 Introduction	96
5.2 Methodology	99
5.2.1 Study Area.....	99
5.2.2 Study Period.....	100
5.2.3 Data Sets.....	100
5.2.3.1 METAR data.....	100
5.2.3.2 Radiosonde	101
5.2.3.3 SEVIRI	101
5.2.4 Defining Rules	102
5.2.5 WRF model	103
5.2.6 Model verification.....	105
5.2.6.1 Meteorological variables	105
5.2.6.2 Fog verification	105
5.3 Rule-based Method.....	106
5.3.1 Summary of rules	106
5.3.2 Dew point depression and wind speed	107
5.3.3 Atmospheric Stability	109
5.3.4 Relative Humidity and Visibility	110
5.4 Model verification	112
5.4.1 WRF Meteorological verification	112
5.4.2 WRF fog verification	113

5.4.3	Spatial comparison with satellite	118
5.5	Summary	122
5.6	References	123
 CHAPTER 6 SENSITIVITY ANALYSIS OF AN AEROSOL AWARE MICROPHYSICS SCHEME IN WRF DURING CASE STUDIES OF FOG IN NAMIBIA		129
6.1	Introduction	130
6.2	Methodology	132
6.2.1	Study area	132
6.2.2	Observations	132
6.2.2.1	Henties Bay Meteorology.....	132
6.2.2.2	SEVIRI	133
6.2.3	Model Configuration.....	133
6.2.3.1	Fog microphysics.....	134
6.2.3.2	Configuration of the aerosol aware sensitivity study	135
6.3	Results and Discussion	137
6.3.1	Case Study Description	137
6.3.2	WRF	140
6.3.2.1	Met verification/Vertical profile comparisons	140
6.3.2.2	Spatial distributions of CCN and Cloud droplet concentration	144
6.3.2.3	WRF vs FM100.....	151
6.3.2.4	WRF vertical evolution.....	157
6.4	Conclusions.....	158

6.5	References	159
CHAPTER 7	CONCLUSION	163
7.1	Summary and Conclusion.....	163
7.1.1	Objective 1	163
7.1.2	Objective 2	164
7.1.3	Objective 3	165
7.1.4	Objective 4	165
7.1.5	Closing remarks and future work	166
	BIBLIOGRAPHY	169
7.2	Bibliography.....	169

LIST OF TABLES

Table 2-1:	METAR codes used to define fog.....	20
Table 2-2:	Description of report codes	23
Table 2-3:	Monthly percentiles of fog duration in hours.	32
Table 3-1:	Contingency table.	51
Table 3-2:	Dec 2016–Mar 2018.....	59
Table 4-1:	WRF configuration for control and experiment	71
Table 4-2:	Czil values applied to each LULC.....	74
Table 5-1:	METAR codes used to define fog.....	101
Table 5-2:	Contingency table of modelled forecast (WRF) vs. observations (METAR).....	105
Table 5-3:	Summary of rules and related thresholds for diagnosing fog from the model.	107
Table 5-4:	Sensitivity test results of visibility equation. m = slope; c = y- intercept.	112
Table 5-5:	Statistical scores from bias, mean gross error and RMSE for modelled Tdep, wind speed and relative humidity at AUH. Tdep (RH) is verified for the daily minimum (maximum). Thus, n is sample size in either days (Tdep/RH) or hours (wind speed).	113
Table 5-6:	Contingency table results of the multi rule-based method applied to observations.....	114
Table 5-7:	Contingency table results of the multi rule-based method applied to WRF.....	116
Table 6-1:	WRF model scenarios.....	137

LIST OF FIGURES

Figure 2-1:	a.) Abu Dhabi (triangle) is located in the United Arab Emirates (UAE) on the Arabian Peninsula. b.) AUH is located on the mainland.....	19
Figure 2-2:	Conceptual diagram of fog formation process in the UAE. Black dot is Abu Dhabi International Airport. Block arrows indicate the wind direction. The color gradient indicates the relative difference in temperature of the land surface to the gulf surface.	19
Figure 2-3:	a.) Data coverage in hours from 1983-2018 including the type of report (view with Table 2-2). The grey horizontal line represents 8760 hours in a non-leap year. FM-12 does not contain any information on METAR codes and can mostly be ignored. b.) Percentage breakdown of fog codes reported (view with Table 2-1) at Abu Dhabi International Airport.	22
Figure 2-4:	Seasonal cycle of monthly mean meteorological variables for a.) temperature (dashed lines are daily maximum and minimum), b.) water vapour mixing ratio and c.) wind speed at AUH for the time period January 2000 to April 2018.	24
Figure 2-5:	a.) Fog days per year from 1983-2018 at Abu Dhabi International Airport and b.) histogram of fog days per year (years 80% data coverage or higher). Solid and dotted lines in b.) are the mean and standard deviation respectively.....	25
Figure 2-6:	Boxplot of fog days per month from 1983-2018 at Abu Dhabi International Airport. Circles represent outliers which are greater than quartile 3+(1.5*inter quartile range). Dark horizontal lines are medians. Lower whisker is quartile 1-(1.5*inter quartile range). Quartile 1 is the bottom of box. Quartile 3 is the top of box.	27
Figure 2-7:	Diurnal frequency of fog per month from 1983-2018 at Abu Dhabi International Airport. Black dotted line indicates time of sunrise and sunset.	30

Figure 2-8:	Fog duration in hours per month from 1983-2018 at Abu Dhabi International Airport. Count refers to the number of events observed. ...	31
Figure 2-9:	Diurnal wind roses for (a-d) September to March (fog months), 1983-2018 at Abu Dhabi International Airport. a.) and b.) show the persistent sea breeze from 12-20 LT. c.) and d.) Show the shift to the weaker land breeze from 03 to 08 LT. (e-h) is the same as (a-d) but for April to August.....	33
Figure 2-10:	a.) Dew point depression rose for all months, 1983-2018, 00-23 LT at Abu Dhabi International Airport. b.) and c.) are the same as a.) but from 00 – 06 LT during non-fog conditions (b) and fog conditions (c).	34
Figure 2-11:	a.) Histogram of wind speed from 19h00 to 11h00 LT for fog and non-fog hours at AUH. The grey colour indicates overlap between the distributions. b.) Scatter plot of wind speed and temperature depression (Tdep) from 19h00 to 11h00 LT with linear relationship for both fog and no fog days. Colour represents the number of hours in that part of the scatter plot. Windrose for same hours as a.) for c.) no fog and d.) fog hours.....	35
Figure 2-12:	a.) Box plot of inversion depth for clear and fog days at 00 UTC/04 LT. Data is from October to March, 2000-2016. b.) Box plot of lapse rate for clear and fog days.....	36
Figure 3-1:	(a) The United Arab Emirates (UAE) is located on the Arabian Peninsula. (b) Terrain (meters above sea level) and location of meteorological aerodrome report (METAR) stations used for verification.....	46
Figure 3-2:	Schematic indicating how the threshold value was selected based on the histogram of pseudo-emissivity at each pixel.	49
Figure 3-3:	Overview of the Spinning-Enhanced Visible and Infrared Imager (SEVIRI) fog detection methodology. Gray boxes represent data layers and white boxes represent data processing. The numbers on the arrows represent the path on the first and second iteration, respectively. This method was applied per pixel and over a one-month period for each month in the study period.	50

Figure 3-4:	a) Example of calculated optimal threshold at Abu Dhabi (OMAA) for January 2018. Here the optimal threshold is 0.80 (POD=1, FAR=0.2). b) The calculated threshold was 0.82.	52
Figure 3-5:	Histogram of $\text{ems}(3.9)$ at a) Abu Dhabi (OMAA) b) Dubai (OMDB), c) Al Ain (OMAL) and d) Al Maktoum (OMDW). Monthly threshold values are indicated by closed circles on the pseudo emissivity plots. Placement on the y-axis is arbitrary for these dots in order to avoid concealment from overlap.	53
Figure 3-6:	Spatial distribution of monthly threshold value of $\text{ems}(3.9)$ from (a–d) December 2016 to March 2017 and (e–j) October 2017 to March 2018.	55
Figure 3-7:	a) Example of $\text{ems}(3.9)$ -low cloud fog classification in comparison with b) the EUMETSAT night microphysical product (EUMETSAT, 2009) for 2018-01-15 0300 local time.	56
Figure 3-8:	Fog frequency in days for $\text{ems}(3.9)$ -low cloud over the 10 month period. Verification sites are indicated by red circles.	59
Figure 3-9:	Hourly fog frequency from 20:00 h to 06:00 h local time.	60
Figure 4-1:	WRF model domains D01 (12 km) and D02 (4 km) with the USGS land cover. White is open water. The three airports used for verification are 1. Abu Dhabi, 2. Dubai and 3. Al Ain.	69
Figure 4-2:	The problem. Average temperature at 2 m at Abu Dhabi airport for winter 2016/2017 (2016-10-18 to 2017-02-27). WRF shows a warm bias in the morning after sunrise and a cold bias in later afternoon/early evening. Time is in UTC. Site is UTC+4.	76
Figure 4-3:	Temperature mean gross error with bias as the sign for Noah with Czil values of 0.1 (blue line) and 0.5 (black line). a.) is the 24 hour forecast and b.) is the 48 hour forecacst respectively. This is the mean gross error for all case studies at Abu Dhabi Airport. Time is in UTC. Site is UTC+4.	77

Figure 4-4:	Air temperature at 2 m for three WRF configurations, Noah0.1, Noahmp0.1 and NoahmpCzil at Abu Dhabi Airport. Improvements in cold bias are achieved by changing the Czil, and not by changing the LSM. Time is in UTC. Site is UTC+4.	78
Figure 4-5:	Difference in maximum land surface temperature for Noahmp (with variable Czil) runs with different vertical levels. This is for case study 2016-01-19. The extra vertical level closer to the ground decreases the land surface temperature and dampens the daily maximum air temperature at 2 m. Time is in UTC. Site is UTC+4.....	79
Figure 4-6:	Temperature mean gross error (with bias as the sign) for Noah0.1 (blue line) and NoahmpCzil (black line) at a.) Abu Dhabi 24 hour forecast and b.) 48 hour forecast, c.) Dubai 24 hour forecast and d.) 48 hour forecast, and e.) Al Ain 24 hour forecast and f.) 48 hour forecast. Time is in UTC. Site is UTC+4.....	80
Figure 4-7:	Mean diurnal temperature for all case studies at a.) Abu Dhabi, b.) Dubai and c.) Al Ain. The black line represents the end of the 24 hour forecast and start of the 48 hour forecast. Time is in UTC. Site is UTC+4.	82
Figure 4-8:	Mean diurnal relative humidity for all case studies at a.) Abu Dhabi, b.) Dubai and c.) Al Ain. The black line represents the end of the 24 hour forecast and start of the 48 hour forecast. Time is in UTC. Site is UTC+4.	84
Figure 4-9:	Mean diurnal sensible heat flux for all case studies at a.) Abu Dhabi, b.) Dubai and c.) Al Ain. The black line represents the end of the 24 hour forecast and start of the 48 hour forecast. Time is in UTC. Site is UTC+4.	86
Figure 4-10:	Mean diurnal land surface temperature for all case studies at a.) Abu Dhabi, b.) Dubai and c.) Al Ain. The black line represents the end of the 24 hour forecast and start of the 48 hour forecast. Time is in UTC. Site is UTC+4.	87
Figure 4-11:	Meteorological parameters for case study 2016-02-20 for a.) Temperature, b.) Wind direction, c.) Water vapour mixing ratio and d.) Relative humidity at Abu Dhabi Airport. Sea breeze duration increases	

	when the air temperature over land is improved. Time is in UTC. Site is UTC+4.	89
Figure 5-1:	Map of the United Arab Emirates (UAE) on the Arabian Peninsula. Abu Dhabi's International Airport (black triangle) is situated on the coast line. Black box represents 4 km WRF domain. The map represents the 12 km WRF domain.	100
Figure 5-2:	(a) Orography (m) and (b) soil texture in the WRF's 4 km grid over the UAE. Points on the map represent the study site (Abu Dhabi) in relation to other airports in the region.	104
Figure 5-3:	a.) Histogram of METAR Tdep under fog and non-fog conditions and b.) histogram of METAR wind speed under fog and non-fog conditions. Vertical black lines represent the threshold used in Rule #1.....	108
Figure 5-4:	Density scatter plot of Tdep and wind speed during fog conditions at AUH. Black dashed boxes indicate the three categories in the sliding rule (Rule #2).	109
Figure 5-5:	Sounding and METAR data used to calculate the MRi as given by Equation (10). The black line represents MRi of 0.04. Green dots represent observed fog events that have observed MRi of 0.001 to 0.037, while red dots are observed fog events that have an observed MRi ≥ 0.04	110
Figure 5-6:	METAR relative humidity and visibility for October to March, 2000 to 2016. Blue (red) dots indicate fog (non-fog) cases. Thick solid horizontal line is 1 km visibility. Black line is the optimal equation. Dashed line is the POD=1 equation. Grey lines are the remaining equations from Table 5-4.	112
Figure 5-7:	Time series of observed (blue bars) and forecast (red bars) fog days for the study period. For clarity, the red bars have half the height of the blue bars.....	117
Figure 5-8:	Summary of the results of rule-based studies. The bubble size is indicative of the forecast hour when fog occurred, whereas the bubble labels refer to the study. The red bubble indicates an ideal forecast	

	score (size is irrelevant). This study (W20) is in orange. Z10=Zhou and Du (2010), B12=Bartok <i>et al.</i> (2012), M14=Menut <i>et al.</i> (2014), R-C16=Román-Cascón <i>et al.</i> (2016), W20=this study.....	118
Figure 5-9:	(a) SEVIRI 2017-01-04 at 0100 UTC, and (b) WRF fog mask (grey corresponds to no fog, while black indicates to the presence of fog). (c-d) As (a-b) but on 2016-12-30 at 23 UTC. (e-f) As (a-b) but on 2016-12-27 at 2100 UTC.....	120
Figure 5-10:	As Figure 5-9 but on (a-b) 2018-03-16 at 0200 UTC. (c-d) 2017-12-25 at 0000 UTC. Grey in WRF mask corresponds to no fog, while black indicates to the presence of fog.....	121
Figure 6-1:	a.) WRF model domains and b.) insert showing the Henties Bay (star) and inland site (circle).	134
Figure 6-2:	CCN activation look up table. Activation sensitivity to a.) CCN b.) updraft, c.) radius, d.) temperature and e.) kappa. For each plot, the remaining four variables are kept constant as follows: CCN=316 cc, updraft=0.316 ms ⁻¹ , radius=0.04 µm, temperature=2813.15 K and kappa=0.4.	136
Figure 6-3:	Meteorology variables and visibility from the transmissometer shows the two fog events. Vertical black dashed (solid) lines indicate fog start (end) times. Times are in UTC (Site is UTC+2).	138
Figure 6-4:	SEVIRI images of night microphysical RGB product and day visible channels for the fog event on 2017-09-09. Site is UTC+2.	139
Figure 6-5:	SEVIRI images of night microphysical RGB product and day visible channels for the fog event on 2017-09-10. Site is UTC+2.	140
Figure 6-6:	Timeseries of model and observed meteorological variables at Henties Bay for a.) temperature, b.) wind speed, c.) water vapour mixing ratio, d.) wind direction and e.) relative humidity. Times are in UTC (Site is UTC+2).	142

Figure 6-7:	Radiosonde profiles of a.) temperature and b.) relative humidity from Jakkalsputz on 2017-09-09. The Sonde was launched at 07:50 UTC and the model is from 08 UTC. Site is UTC+2.....	143
Figure 6-8:	Radiosonde profiles of a.) temperature and b.) relative humidity from Jakkalsputz on 2017-09-10. The Sonde was launched at 09:10 UTC and the model is from 09 UTC.	144
Figure 6-9:	Initial and mean CCN concentration for scenarios a and b.) CCN_300, c and d.) CCN_300_landsea and e and f.) CCN_C10. Note different scale on c. Black dot is Henties Bay.	146
Figure 6-10:	Evolution of CCN concentration for the event on 2017-09-10 for scenario CCN_300. Black dot is Henties Bay. Time is in UTC (site is UTC+2).	147
Figure 6-11:	Cloud droplet onset for the event on 2017-09-10 for scenario CCN_300. Black dot is Henties Bay. Time is in UTC (site is UTC+2).....	148
Figure 6-12:	Cloud droplet during maximum extent and highest concentration for the event on 2017-09-10 for scenario CCN_300. Maximum extent was at a.) 04 UTC and maximum concentration at Henties Bay was at d.) 07 UTC. Black dot is Henties Bay.....	148
Figure 6-13:	Evolution of CCN concentration for the event on 2017-09-10 for scenario CCN_C10. Black dot is Henties Bay.	149
Figure 6-14:	Cloud droplet onset for the event on 2017-09-10 for scenario CCN_C10. Black dot is Henties Bay.....	150
Figure 6-15:	Cloud droplet during maximum extent and highest concentration for the event on 2017-09-10 for scenario CCN_C10. Maximum extent was at a.) 04 UTC and maximum concentration at Henties Bay was at d.) 07 UTC. Black dot is Henties Bay.....	150
Figure 6-16:	Observed and modelled a.) Nt, b.) LWC and c.) MVD at Henties Bay. Model is hourly and black dots are 1 minute observations. d.) Modelled concentrations of water friendly aerosols. Black dashed horizontal lines indicate the observed range of mean CCN reported by Formenti et al 2019. e.) Modelled updraft speed in lowest model level with solid black	

	line at minimum updraft in microphysics scheme. Vertical dashed black line is fog start (Vis < 1km). Vertical solid black is fog end time. Time is in UTC (site is UTC+2).	152
Figure 6-17:	Size distribution for the two case studies when visibility was 1 km or less. Solid lines are the observed distributions. Dashed lines are the equivalent theoretical gamma distribution applied to the observed data. Time is in UTC (site is UTC+2).....	154
Figure 6-18:	Observed and modelled size distribution for a.) case 1 and b.) case 2. Black solid lines are the observed distributions. Black dashed lines are the equivalent theoretical gamma distribution applied to the observed data. Other dashed lines are model distributions. Vertical solid lines represent the MVD.	155
Figure 6-19:	Observed and modelled size distribution for a.) case 1 and b.) case 2. Black solid lines are the observed distributions. Black dashed lines are the equivalent theoretical gamma distribution applied to the observed data. Other dashed lines are model distributions. Vertical solid lines represent the MVD. Time is in UTC (site is UTC+2).	156
Figure 6-20:	Observed and modelled size distribution for a.) case 1 and b.) case 2. Black solid lines are the observed distributions. Black dashed lines are the equivalent theoretical gamma distribution applied to the observed data. Other dashed lines are model distributions. Vertical solid lines represent the MVD. Time is in UTC (site is UTC+2).	157
Figure 6-21:	Profiles of LWC over time at Henties Bay for a.) CCN_300, b.) CCN_300_landsea and c.) CCN_C10. Time is in UTC (site is UTC+2).	158

CHAPTER 1 INTRODUCTION

1.1 Literature Study

Fog is an atmospheric phenomenon that occurs near the earth's surface when a moist air mass reaches dew point temperature which promotes the condensation of water vapour to liquid. These water droplets cause a decrease in visibility where fog is defined by a visibility of less than 1 km (World Meteorological Organization, 2008b). Fog has an adverse effect on road and aviation transport networks as the low visibility increases the risk of collisions as well as hindering ground operations. Forecasting of fog acts as an early warning system for the public and aviation operators. A forecast with a long lead time can mitigate against the negative impacts of fog as end users can plan around the conditions.

Numerical weather prediction (NWP) models are a tool for forecasting the weather. They can provide predictions of about 6 hours to 7 days in advance as they are based on the physical processes working in the atmosphere (Bauer et al., 2015). The NWP model forms part of a forecasting system, which can also include current observations, forecaster experience, model output statistics or ensemble modelling. The aim of the project was to create a spatial distribution of fog normally presented as a binary mask of 0 (no fog) and 1 (fog), hereafter referred to as a fog field, from a forecast using the Weather Research and Forecast model and assess it for next day fog forecast.

Operational forecasts centres currently issue regional simulations between 2 to 9 km resolution, with European Centre for Medium Range Forecasts (ECMWF) Integrated Forecast System (IFS), National Ocean Atmosphere Administration (NOAA) High-Resolution Rapid Refresh (HRRR) and UK Met Office forecasts at 9 km, 3 km and 2 km respectively (Benjamin et al., 2016; ECMWF, 2021; UK Met Office, 2019). The ability of these resolutions to capture fog depends on the fog characteristic and patch size within the area of interest. Typically, 9 km will be too coarse as fog can vary in density within this distance, but 2 to 3 km can be suitable. Results in this thesis will use simulations of 3 to 4 km resolution, as it is suitable to capture the fog patches observed in the study areas.

1.1.1 Approaches to diagnosing fog

Historically, fog is difficult to diagnose from mesoscale model variables (Bergot et al., 2015; Bergot et al., 2007; Yang et al., 2010). One option for defining fog in the model is to use the cloud water mixing ratio, sometimes referred to as liquid water content (LWC), in the lowest model level. If positive or in excess of a given threshold, fog is deemed to be present at the

site. A variant of this method is to integrate the cloud water mixing ratio over a set of model levels instead of just taking the value at the lowest level, an approach followed e.g. by Yang et al. (2010). However, mesoscale models are often too coarse in resolution to solve this condensation process explicitly or display deficiencies in the physical parameterization at these scales (e.g. (Bergot et al., 2017)). Furthermore, the challenge to separate fog ($\text{vis} < 1 \text{ km}$) from mist ($1 \text{ km} < \text{vis} < 5 \text{ km}$) and haze still remains.

The final desired model diagnostic of a fog forecast is visibility. Many visibility equations have been published based on observations using LWC as the main dependent variable, with variations that include water vapour mixing ratio, wind speed or relative humidity (RH) (Bang et al., 2008; Clark et al., 2008; Gultepe & Milbrandt, 2007; Gultepe et al., 2006; Smirnova et al., 2000; Stoelinga et al., 1999). A visibility forecast provides actionable information to end users. The physics of visibility is based on Mie theory and the associated extinction efficiency related to particle size. However, in situ information on particle size is scarce, and has been shown to vary from case to case at a single location (e.g. (Zhang et al., 2014)). The main drawback of this approach is, again, the dependence on model performance in simulating LWC, droplet number and droplet size distribution, which is calculated within the microphysics scheme. This has led to the development of visibility equations based on relative humidity in place of droplet information (e.g. (Bang et al., 2008; Bieringer et al., 2006; Smirnova et al., 2000)).

Alternatively, a multi-variable rule-based method can be used, where model variables within a certain range, or below a predefined threshold, indicate fog conditions, as was first proposed by Croft et al. (1997). This approach has been shown to improve forecast skill compared to LWC methods (Zhou & Du, 2010).

An ongoing discussion in the literature on how best to parameterise NWP models for fog forecasting is guided by these methods described above. Some argue that optimising the microphysics scheme provides the best performance (Bott, 1991; Boutle et al., 2018), while others argue that the choice of a planetary boundary layer scheme provides more sensitivity (Juliano et al., 2019). In general, the model first needs to simulate the meteorological parameters associated with moisture and temperature adequately before customising microphysical schemes. In this thesis, I approach the problem from both directions. I address a bias in simulated temperature through parameterising the land surface scheme within the NWP model. I investigate a rule based method based on an analysis of long term

observations. Finally, an aerosol aware microphysics parameterisation is presented. These approaches are discussed in more detail in the following sections.

1.1.2 Parameterisation of the land surface model in WRF

Atmospheric models are known to underestimate land surface temperature and, by association, 2 m air temperature over dry arid regions during the day due to the treatment of the thermal roughness length also known as roughness length of heat (Chen et al., 1997; Zheng et al., 2012). The thermal roughness length can be controlled by the Zilitinkevich parameter, known as Czil, which is a tuneable parameter within the models (Chen et al., 1997; Chen & Zhang, 2009; Zilitinkevich, 1995). The Czil parameter that has an effect on the thermal roughness length, Z_{0t} as follows:

$$\frac{Z_{0m}}{Z_{0t}} = \exp(k \text{ Czil } \sqrt{Re^*})$$

Where Z_{0m} = momentum roughness length, $k = 0.4$ (von Karman constant), Re^* = Reynolds number.

Z_{0t} controls how quickly heat is lost from the surface layer to the atmosphere. In short, an increase in Czil will decrease the roughness length of heat, Z_{0t} , which will increase the 2m air temperature (Niu et al., 2011). Czil is currently a constant value within the WRF modelling system. However, modifications can be made to assign a Czil value per land cover type in the Noah-MP, a land surface model available in WRF. This will then reduce the cold bias in the forecast and consequently provide a more realistic relative humidity, which is a key parameter for diagnosing fog.

1.1.3 Rule based method

Historically, fog is difficult to diagnose from mesoscale model variables. One option for defining fog in the model is to use the cloud mixing ratio, sometimes referred to as liquid water content (LWC), in the lowest model level. However, mesoscale models are often too coarse in resolution to solve this condensation process explicitly. Model resolution is considered coarse when the feature of interest and its related atmospheric processes, in this case fog, is smaller than the model resolution. Furthermore, the challenge to separate fog from mist and haze still remains. Another option is to define visibility directly from model variables. Many visibility equations have been published based on observations using LWC as the main dependent variable with variations that include water vapour mixing ratio, wind speed or relative humidity

(Bang et al., 2008; Clark et al., 2008; Gultepe & Milbrandt, 2007; Gultepe et al., 2006; Smirnova et al., 2000; Stoelinga et al., 1999). The main drawback of this approach is, again, the dependence on model performance in representing LWC, droplet number and droplet size distribution. Alternatively, a multi variable rule based method can be used, where model variables within a certain range, or below a threshold, indicate fog conditions, as was first proposed by Croft et al. (1997). This approach has been shown to improve forecast skill compared to LWC methods (Zhou & Du, 2010). Zhou and Du (2010) defined a set of variables to represent fog conditions for the different types of fog described by Tardif and Rasmussen (2007). Either of the following conditions needed to be met; $LWC \geq 0.015 \text{ g kg}^{-1}$ or cloud top $\leq 400\text{m}$ and cloud base $\leq 50 \text{ m}$ or 10 m wind speed $\leq 2 \text{ m s}^{-1}$ and $2 \text{ m RH} \geq 90 \%$. These three categories allowed for types of fog like advection, stratus lowering or ground fog. The hit rate, or probability of detection (POD), using these criteria ranged from 0.1 to 0.6 which was overall higher than using $LWC > 0$ criteria for fog. The false alarm ratio ranged from about 0.4 to 0.65 for these criteria, which was about the same as the $LWC > 0$ method. Baker et al. (2002) used a different set of criteria to diagnose radiation fog which accounted for vertical mixing of moisture and atmospheric stability. Firstly, like Zhou and Du's third condition, they assume that the surface relative humidity is high and that wind speed is low. In addition, they define two new parameters, the cross over temperature, which is the 2 m dew point temperature during the warmest hours of the day, and a modified Richardson index, which indicates vertical stability due to temperature and wind speed. Although the model performance is not reported, the modified Richardson parameter will be discussed in the methodology section, as it proves useful for radiation fog cases. Payra and Mohan (2014) used surface relative humidity and wind speed ($< 2.8 \text{ ms}^{-1}$) to define fog over Northern India and report high POD results, in excess of 0.9 (theoretical maximum of 1). However they do not report the false alarm ratio which is assumed to be high as well. Menut et al. (2014) added a new rule to diagnose fog, which is the rate of cooling in the hours preceding radiation fog events in Paris. Their main aim was to model pre-fog conditions and they found that the rate of change of 2 m temperature should be $\leq -0.5 \text{ }^{\circ}\text{C}$ over a 3 hour period. In addition, and due to the availability of measurements at their sites of interest over the month of November 2011, they include that the net infrared flux should be $< -10 \text{ Wm}^{-2}$, which means that surface cooling should be occurring. They also included that $\text{RH } 2 \text{ m} > 90 \%$ and 10 m wind speed $< 3 \text{ ms}^{-1}$. Their best model POD (FAR) were 0.58 (0.37) to 0.74 (0.37) and is the best performance so far for a multi rule based approach. Interestingly, they also applied these thresholds to the observed data at their site and reported a POD (FAR) of 0.87 (0.39). In other words, if the model simulated the observations exactly, this is the theoretical best performance that can be

achieved with these criteria and thresholds. C. Román-Cascón et al. (2016) later applied the same criteria to two sites in Europe, one in the Netherlands and one in Spain. When using the same threshold values, their model forecast POD (FAR) were 0.33 (0.12) and 0.33 (0.16) for Netherlands and Spain respectively, which is a poor forecast performance. However, when applied to the observed data, a 6-year climatology at their sites of interest, the POD (FAR) were 0.86 (0.21) and 0.64 (0.14) for Netherlands and Spain respectively, which is very good. Due to the bad model performance, they decided to adjust the threshold values based on observations at their site, and later improved the model POD (FAR) to 0.73 (0.34) and 0.47 (0.31) for Netherlands and Spain respectively. The observed POD (FAR) also improved. While criteria variables remained the same in this instance, the optimum threshold can change from site to site and can only be determined if site specific observations are available.

1.1.4 A simplified visibility equation

Visibility equations have been developed but generally depend on an exponential extinction factor based on droplet size (Clark et al., 2008, Gultepe and Milbrandt, 2007, Stoelinga et al., 1999, Bang et al., 2009, Smirnova et al., 2000, Gultepe et al., 2006). While this is physically correct, it is inaccurate to apply these formula to model output as the error range on LWC is high. Furthermore, LWC are not readily available in observations for verification of the model. While existing equations are derived from field campaigns and empirical data, the field campaigns are often in very different environments to arid, warm fog regions. Hence, in the thesis it is proposed using simplified equation for visibility of fog events. The advantage of this approach is that the equation is only valid for a segment of the extinction curve equations. Thus, instead of attempting a one-size-fits-all method, an equation can be created based on readily available measurements, allowing for a dynamic methodology for defining visibility.

1.1.5 Cloud condensation nuclei (CCN) modification in microphysics

Droplet number concentration and size distribution effect the intensity and duration of fog events (Bergot & Lestringant, 2019; Boutle et al., 2018; Poku et al., 2019). Droplet size also effects the dissipation time, as the curvature effect of the droplet controls the evaporation rate and conversion to smaller droplet sizes (Steeneveld et al., 2014). These processes are controlled by the microphysics scheme in the WRF model and, more specifically, can be parameterised in the Thompson aerosol aware scheme (Thompson & Eidhammer, 2014). This scheme is a bulk, double-moment microphysics scheme. In a bulk scheme the size distribution of the particles is estimated and normally assigned an exponential or gamma distribution. This is a computationally efficient way to deal with different size particles and their related settling,

evaporation or growth rate. A more accurate method is a bin microphysics scheme, which calculates the droplet number concentration for each diameter bin size, allowing for more explicit calculation of sedimentation, evaporation and growth. This is computationally expensive and generally only applied in idealised simulations and not operational cases. In single moment schemes, only the droplet mass mixing ratio is calculated (e.g. (Thompson et al., 2004)), while mass mixing ratio and number concentration per hydrometeor is calculated in a double moment scheme (e.g. (Thompson & Eidhammer, 2014)). Thus, a double moment scheme imitates a bin scheme, allowing for realistic representation of droplet processes and is computationally economical (Iguel et al., 2015).

Aerosol aware schemes are a relatively new development in the mesoscale models (Thompson & Eidhammer, 2014; Wilkinson et al., 2013). This allows the user to customise the CCN activation based on observations in the region of interest. In this chapter, we parameterise this relationship between CCN and droplet activation based on the observations of CCN and fog microphysics during the Aerosol, Radiation and Clouds in Southern Africa (AEROCLO-SA) field campaign in Namibia (Formenti et al., 2019). Activation in the Thompson aerosol aware microphysics scheme is based on the parcel method and is designed with cloud formation, and not specifically fog formation, in mind. Fog is known to differ from clouds, mainly due to the proximity to the ground and an associated increase in CCN load compared to clouds higher up in the atmosphere (e.g. (Mazoyer et al., 2019)). For this reason, changes to the scheme are applied only near the surface where possible. The aim of the chapter is to simulate a realistic balance between CCN and activated cloud droplets for a fog case study.

1.2 Problem Statement

Fog is not a standard output from NWP models and therefore needs to be calculated as a diagnostic variable (Zhou & Du, 2010). There are traditionally three approaches to achieve this, the first is to use the LWC at the lowest model level, the second is to define visibility based on model output variables and the third is to use a multi rule based approach, also based on model variables. All of these approaches are affected by model bias and model parameterisation which will ultimately affect the forecast skill.

1.3 Gaps in literature and recent studies

Fog occurs in arid environments around the world, including Chile, Mexico, Namibia, Northern India, Western Australia and the Arabian Peninsula (Klemm et al., 2012). While these methods have been reported on in the literature for fog events at various localities in non-arid regions

(Gultepe & Milbrandt, 2007; Menut et al., 2014; C. Román-Cascón et al., 2016; Steeneveld & de Bode, 2018; Steeneveld et al., 2014; Tardif & Rasmussen, 2007; Zhou & Du, 2010; Zhou et al., 2012), there has been little application to fog in arid environments. Although fog forecasting in arid environments has been reported on (Bartok et al., 2012; Chaouch et al., 2016; Payra & Mohan, 2014) and some effort has been made to improve model bias over arid regions (Zheng et al., 2017), these studies have not focussed on improving the diagnosis of fog from the NWP models. As such, the application of these methods to fog in arid regions remains largely unexplored and warrants further investigation.

1.4 Research Aim and Objectives

The overall aim of this research is to improve next day fog forecast in the Weather Research and Forecasting (WRF) model over arid environments through model parameterisation and post processing. Fog formation is complex and is dependent on the atmospheric thermodynamic (radiation, turbulence and mixing) and surface conditions (albedo, soil characteristics, roughness length, moisture content). As such, the following research objectives and sub-objectives have been formulated to achieve this aim:

Objective 1 – describe the observed fog dynamics and mechanisms over the United Arab Emirates, an arid region by:

- a) using a long term dataset to develop a fog climatology.
- b) Employ remote sensing methods to investigate the spatial patterns of fog.

This objective is addressed in Chapters 2 and 3. While this work is specific to the United Arab Emirates, the methodology can be applied in other arid regions. Furthermore, the results from this process inform the methodology in objective 3, which can also be applied to other arid regions.

Objective 2 – evaluate the land surface model and its coupling with the atmosphere by assessing whether 2 meter air temperature forecast can be improved by adjusting the thermal roughness length through the Czil parameter. This is predicated on the finding of a cold bias in the night time 2 meter air temperature over sites in central USA and the United Arab Emirates. This objective focuses on parameterising the land surface model, but verifying the results against atmospheric measurements of 2 m air temperature. The study region for this objective is the United Arab Emirates, but the methodology is applicable to any arid region. This objective is addressed in Chapter 4.

Objective 3 – assess whether multiple criteria can be used to diagnose fog from the model by:

- c) considering multiple aspects of fog formation, including radiative cooling, atmospheric stability and moisture transport.
- d) Identifying the criteria which perform best.

The study region for this objective is the United Arab Emirates, but the methodology is applicable to any arid region. This objective is addressed in Chapter 5.

Objective 4 – investigate whether an aerosol aware microphysics scheme can forecast fog in the WRF model. Microphysics schemes represent the complex processes of cloud droplet nuclei activation, growth, evaporation and deposition. This objective will be achieved by:

- a) parameterising an aerosol aware microphysics scheme based on observation of fog microphysics
- b) assessing if the parameterisation improves the fog forecast and characteristics.

The study region for this objective is Namibia, but the methodology is applicable to any arid region. This objective is addressed in Chapter 6.

1.5 Methods

Two arid regions were selected as study sites in this thesis namely the United Arab Emirates and Namibia. Firstly, fog is characterised at each site using available in situ and satellite data. NWP model simulations are then conducted using the WRF Model (Skamarock et al., 2008a) which is assessed against the observations. WRF has many physics configuration options contributed by the community as it is designed in a modular way. This is an advantage as it allows for highly customisable simulations as the user can choose a configuration that performs well for their region or feature of interest (in this case fog). However, choosing the setup can be time consuming and is a combination of literature review and running many sensitivity tests. An overview of the study sites and available data is given below and further details on model configuration are provided in the relevant chapters.

1.5.1 Study areas

1.5.1.1 Abu Dhabi, United Arab Emirates

The United Arab Emirates (UAE) is an arid country located on the northeastern edge of the Arabian Peninsula with a mean annual rainfall of about 78 mm (Ouarda & Charron, 2014; Wehbe et al., 2017; Wehbe et al., 2018). It covers an area of 83,600 km², which is mostly sparse to bare vegetation, and the main soil type is sand and loamy sand. It relies heavily on groundwater and desalination as sources of fresh water and treated sewage effluent for irrigation (Aldababseh et al., 2018). Despite being an arid region, the mean water vapour mixing ratio can reach 11 (18) g/kg in winter (summer), and the region experiences frequent fog in winter, which can extend over most of the country (Aldababseh & Temimi, 2017; Bartok et al., 2012; De Villiers & Van Heerden, 2007; Weston, Temimi, Burger, et al., 2021). The study site of interest in the UAE is Abu Dhabi International Airport which is located on the mainland about 4 km from the nearest sea canal and at an elevation of 27 m above sea level.

1.5.1.2 Henties Bay, Namibia

The Central Namib is a coastal desert on the West Coast of Namibia. It lies between the Atlantic Ocean to the West and the escarpment over 1000 m in elevation to the east. The annual rainfall is highest at the escarpment (100 mm) and decreases towards the coast (< 50 mm) (Lancaster et al., 1984; Spirig et al., 2019). The land cover type undergoes a stark transition at the ephemeral Kuseib River with the rocky Gravel Plains to the north and large sand dunes to the south. Surface air flow along the coast is dominated by an onshore wind, predominantly from the south-west (Lindesay & Tyson, 1990). This flow can be amplified by the synoptic scale circulation of the South Atlantic High pressure system. However the onshore flow does not penetrate far inland where the surface air flow is controlled by the mountain-plain wind. The easterly wind is much drier and limits moisture transport inland. As a result, fog forms in a narrow band along the coastline. The area is interesting for studying fog formation as it represents a pristine environment. The study site of interest in Namibia is Henties Bay (-22.09495 °S, 14.2591 °E) which was the ground based supersite during the AEROCLO-SA field campaign which took place from 23 August to 12 September 2017. The site was at the University of Namibia campus which is situated on the coast line (elevation 20 m.a.s.l) and at the mouth of the non-perennial Omaruru River. The overall aim of AEROCLO-SA was to improve the understanding of the role of aerosols on the regional climate of the southeast Atlantic Ocean. This was achieved through airborne platforms, ground based stations, satellite data and coupled atmospheric chemistry models.

1.5.2 Data

1.5.2.1 UAE Observations

The Abu Dhabi International Airport (AUH) has over 30 years of aviation routine weather reports (METARS). These reports include information on the weather type (e.g. rain, fog, dust, clear) and visibility and are often the only long term record of low visibility events. In addition, there is over 20 years of radiosonde data available at the site, which is important in characterising the stable atmosphere conditions during fog events and how they differ to non-fog days. These data sets are used extensively in the chapters specific to the UAE. METAR data is also available from three international airports that are in relative close proximity to Abu Dhabi International Airport. These are Dubai International (about 110 km northeast of AUH), Al Maktoum (70 km northeast) and Al Ain (100 km inland, east-south-east of AUH).

Satellite data is available from the Spinning-Enhanced Visible and Infrared Imager (SEVIRI) instrument on board Meteosat-10, which is part of the Meteosat Second Generation (MSG), situated over 9.5°. This geostationary satellite provides data every 15 minutes at about 3km resolution. Nighttime fog products and day time visible products are used extensively in the relevant chapters.

1.5.2.2 Namibia Observations

Microphysical measurements of fog were undertaken Henties Bay using the Fog-Monitor 100 (FM100). This is the main reason for selecting this site as these measurements include liquid water content, droplet number concentration, mean volumetric diameter and droplet size distribution. In addition, surface meteorological variables, including visibility, are available along with radiosonde that were launched during the campaign. A full description of the measurements is available in Formenti et al. (2019).

Satellite data is available from the Spinning-Enhanced Visible and Infrared Imager (SEVIRI) instrument on board Meteosat-11 situated over 0°. This geostationary satellite provides data every 15 minutes at about 3km resolution. Nighttime fog products and day time visible products are used extensively in the relevant chapter.

1.6 References

Aldababseh, A., & Temimi, M. (2017). Analysis of the long-term variability of poor visibility events in the UAE and the link with climate dynamics. *Atmosphere*, 8(12), 18--20. <https://doi.org/10.3390/atmos8120242>

- Aldababseh, A., Temimi, M., Maghelal, P., Branch, O., & Wulfmeyer, V. (2018). Multi-criteria evaluation of irrigated agriculture suitability to achieve food security in an arid environment. *Sustainability (Switzerland)*, 10(3). <https://doi.org/10.3390/su10030803>
- Baker, R., Cramer, J., & Peters, J. (2002). Radiation Fog: UPS Airlines Conceptual Models And Forecast Methods. *10th Conference on Aviation, Range, and Aerospace Meteorology*, 116(3), 505--524. http://ams.confex.com/ams/13ac10av/techprogram/paper/_39165.htm \% 5Cn<http://ams.confex.com/ams/13ac10av/10ARAM/abstracts/39165.htm>
- Bang, C.-h., Lee, J.-w., & Hong, S.-y. (2009). Predictability Experiments of Fog and Visibility in Local Airports over Korea using the WRF Model. *Journal of Korean Society for Atmospheric Environment*, 24(2008), 92--101.
- Bartok, J., Bott, A., & Gera, M. (2012). Fog Prediction for Road Traffic Safety in a Coastal Desert Region: Improvement of Nowcasting Skills by the Machine-Learning Approach. *Boundary-Layer Meteorology*, 157(3), 501--516. <https://doi.org/10.1007/s10546-015-0069-x>
- Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. *Nature*, 525(7567), 47-55. <https://doi.org/10.1038/nature14956>
- Bergot, T., Escobar, J., & Masson, V. (2015). Effect of small-scale surface heterogeneities and buildings on radiation fog: Large-eddy simulation study at paris-charles de gaulle airport. *Quarterly Journal of the Royal Meteorological Society*, 141(686), 285--298. <https://doi.org/10.1002/qj.2358>
- Bergot, T., Lac, C., Burnet, F., Martinet, P., Bouteloup, Y., & Bouysse, F. (2017). Towards a three-dimensional prediction of fog on airports with the M'et'e o-France operational forecast model AROME. *WMO Aeronautical Meteorology Scientific Conference*.
- Bergot, T., & Lestringant, R. (2019). On the predictability of radiation fog formation in a mesoscale model: A case study in heterogeneous terrain. *Atmosphere*, 10(4), 1--19. <https://doi.org/10.3390/atmos10040165>
- Bergot, T., Terradellas, E., Cuxart, J., Mira, A., Leichti, O., Mueller, M., & Nielsen, N. W. (2007). Intercomparison of single-column numerical models for the prediction of radiation fog. *Journal of Applied Meteorology and Climatology*, 46(4), 504--521. <https://doi.org/10.1175/JAM2475.1>
- Bieringer, P. E., Donovan, M., Robasky, F., Clark, D. A., & Hurst, J. (2006). A characterization of NWP ceiling and visibility forecasts for the terminal airspace.
- Bott, A. (1991). On the influence of the physico-chemical properties of aerosols on the life cycle of radiation fogs. *Boundary-Layer Meteorology*, 56(1), 1--31. <https://doi.org/10.1007/BF00119960>
- Boutle, I., Price, J., Kudzotsa, I., Kokkola, H., & Romakkaniemi, S. (2018). Aerosol-fog interaction and the transition to well-mixed radiation fog. *Atmospheric Chemistry and Physics*, 18(11), 7827--7840. <https://doi.org/10.5194/acp-18-7827-2018>
- Chaouch, N., Temimi, M., Weston, M., & Ghedira, H. (2016). Sensitivity of the meteorological model WRF-ARW to planetary boundary layer schemes during fog conditions in a coastal arid region. *Atmospheric Research*, 187, 106--127. <https://doi.org/10.1016/j.atmosres.2016.12.009>
- Chen, F., Janjić, Z., & Mitchell, K. (1997). Impact of Atmospheric Surface-layer Parameterizations in the new Land-surface Scheme of the NCEP Mesoscale Eta Model. *Boundary-Layer Meteorology*, 85, 391-421.
- Chen, F., & Zhang, Y. (2009). On the coupling strength between the land surface and the atmosphere: From viewpoint of surface exchange coefficients. *Geophysical Research Letters*, vol.36, issue 10.
- Clark, P. A., Harcourt, S. A., Macpherson, B., Mathison, C. T., Cusack, S., & Naylor, M. (2008). Prediction of visibility and aerosol within the operational Met office unified model.I: Model formulation and variational assimilation. *Quarterly Journal of the Royal Meteorological Society*, 134(636), 1801--1816. <https://doi.org/10.1002/qj.318>

- Croft, P. J., Pfost, R. L., Medlin, J. M., & Johnson, G. A. (1997). Fog Forecasting for the Southern Region: A Conceptual Model Approach. *Weather and Forecasting*, 12(3), 545--556. [https://doi.org/10.1175/1520-0434\(1997\)012<0545:FFFTSR>2.0.CO;2](https://doi.org/10.1175/1520-0434(1997)012<0545:FFFTSR>2.0.CO;2)
- De Villiers, M. P., & Van Heerden, J. (2007). Fog at Abu Dhabi international airport. *Weather*, 62, 209-214.
- Formenti, P., D'Anna, B., Flamant, C., Mallet, M., Piketh, S. J., Schepanski, K., Waquet, F., Auriol, F., Brogniez, G., Burnet, F., Chaboureaud, J. P., & Chauvign. (2019). The aerosols, radiation and clouds in southern Africa field campaign in Namibia overview, illustrative observations, and way forward. *Bulletin of the American Meteorological Society*, 100(7), 1277--1298. <https://doi.org/10.1175/BAMS-D-17-0278.1>
- Gultepe, I., & Milbrandt, J. A. (2007). Microphysical observations and mesoscale model simulation of warm fog case during FRAM project. *Pure and Applied Geophysics*, 164(6-7), 1161--1178. <https://doi.org/10.1007/s00024-007-0212-9>
- Gultepe, I., Mller, M. D., & Boybeyi, Z. (2006). A new visibility parameterization for warm-fog applications in numerical weather prediction models. *Journal of Applied Meteorology and Climatology*, 45(11), 1469--1480. <https://doi.org/10.1175/JAM2423.1>
- Gultepe, I., Müller, M. D., & Boybeyi, Z. (2006). A new visibility parameterization for warm-fog applications in numerical weather prediction models. *Journal of Applied Meteorology and Climatology*, 45, 1469-1480. <https://doi.org/10.1175/JAM2423.1>
- Igel, A. L., Igel, M. R., & van den Heever, S. C. (2015). Make it a double? Sobering results from simulations using single-moment microphysics schemes. *Journal of the Atmospheric Sciences*, 72(2), 910--925. <https://doi.org/10.1175/JAS-D-14-0107.1>
- Juliano, T. W., Coggon, M. M., Thompson, G., Rahn, D. A., Seinfeld, J. H., Sorooshian, A., & Lebo, Z. J. (2019). Marine boundary layer clouds associated with coastally trapped disturbances: Observations and model simulations. *Journal of the Atmospheric Sciences*, 76(9), 2963--2993. <https://doi.org/10.1175/JAS-D-18-0317.1>
- Klemm, O., Schemenauer, R. S., Lummerich, A., Cereceda, P., Marzol, V., & Corell, D. a. (2012). Fog as a fresh-water resource: Overview and perspectives. *Ambio*, 41(3), 221-234. <https://doi.org/10.1007/s13280-012-0247-8>
- Lancaster, J., Lancaster, N., & Seely, M. K. (1984). Climate of the central Namib Desert. *Madoqua*, 1984(1), 5--61. https://doi.org/10.10520/AJA10115498_484
- Lindesay, J. A., & Tyson, P. D. (1990). Climate and Near-surface Airflow Over the Central Namib. (7), 27--37.
- Mazoyer, M., Burnet, F., Denjean, C., Roberts, G. C., Haeffelin, M., Dupont, J. C., & Elias, T. (2019). Experimental study of the aerosol impact on fog microphysics. *Atmospheric Chemistry and Physics*, 19(7), 4323--4344. <https://doi.org/10.5194/acp-19-4323-2019>
- Menut, L., Mailler, S., Dupont, J. C., Haeffelin, M., & Elias, T. (2014). Predictability of the Meteorological Conditions Favourable to Radiative Fog Formation During the 2011 ParisFog Campaign. *Boundary-Layer Meteorology*, 150(2), 277-297. <https://doi.org/10.1007/s10546-013-9875-1>
- Niu, G. Y., Yang, Z. L., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., Kumar, A., Manning, K., Niyogi, D., Rosero, E., Tewari, M., & Xia, Y. (2011). The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. *Journal of Geophysical Research Atmospheres*, 116(12), 1-19.
- Ouarda, T. B. M. J., & Charron, C. a. (2014). Evolution of the rainfall regime in the united arab emirates. *Journal of Hydrology*, 514, 258--270. <https://doi.org/10.1016/j.jhydrol.2014.04.032>
- Payra, S., & Mohan, M. (2014). Multirule based diagnostic approach for the fog predictions using WRF modelling tool. *Advances in Meteorology*, 2014. <https://doi.org/10.1155/2014/456065>

- Poku, C., Ross, A. N., Blyth, A. M., Hill, A. A., & Price, J. D. (2019). How important are aerosol–fog interactions for the successful modelling of nocturnal radiation fog? *Weather*, 74(7), 237–243. <https://doi.org/10.1002/wea.3503>
- Román-Cascón, C., Steeneveld, G. J., Yagüe, C., Sastre, M., Arrillaga, J. A., & Maqueda, G. (2016). Forecasting radiation fog at climatologically contrasting sites: evaluation of statistical methods and WRF. *Quarterly Journal of the Royal Meteorological Society*, 142(695), 1048–1063. <https://doi.org/10.1002/qj.2708>
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., Huang, X.-Y., Wang, W., & Powers, J. G. (2008). *A Description of the Advanced Research WRF Version 3*.
- Smirnova, T. G., Benjamin, S. G., & Brown, J. M. (2000). Case study verification of RUCS/MAPS fog and visibility forecasts. 9th Conf. on Aviation, Range, and Aerospace Meteorology (AMS),
- Spirig, R., Vogt, R., Larsen, J. A., Feigenwinter, C., Wicki, A., Franceschi, J., Parlow, E., Adler, B., Kalthoff, N., Cermak, J., Andersen, H., Fuchs, J., Bott, A., Hacker, M., Wagner, N., Maggs-Killing, G., Wassenaar, T., & Seely, M. (2019). Probing the fog life cycles in the Namib desert. *Bulletin of the American Meteorological Society*, 100(12), 2491–2507. <https://doi.org/10.1175/BAMS-D-18-0142.1>
- Steeneveld, G. J., & de Bode, M. (2018). Unravelling the relative roles of physical processes in modelling the life cycle of a warm radiation fog. *Quarterly Journal of the Royal Meteorological Society*, 144(714), 1539–1554. <https://doi.org/10.1002/qj.3300>
- Steeneveld, G. J., Ronda, R. J., & Holtslag, A. A. M. (2014). The Challenge of Forecasting the Onset and Development of Radiation Fog Using Mesoscale Atmospheric Models. *Boundary-Layer Meteorology*, 154(2), 265–289. <https://doi.org/10.1007/s10546-014-9973-8>
- Stoelinga, M. T., Warner, T. T., Stoelinga, M. T., & Warner, T. T. (1999). Nonhydrostatic, Mesobeta-Scale Model Simulations of Cloud Ceiling and Visibility for an East Coast Winter Precipitation Event. *Journal of Applied Meteorology*, 38(4), 385–404. [https://doi.org/10.1175/1520-0450\(1999\)038<0385:NMSMSO>2.0.CO;2](https://doi.org/10.1175/1520-0450(1999)038<0385:NMSMSO>2.0.CO;2)
- Tardif, R., & Rasmussen, R. M. (2007). Event-based climatology and typology of fog in the New York City region. *Journal of Applied Meteorology and Climatology*, 46(8), 1141–1168. <https://doi.org/10.1175/JAM2516.1>
- Thompson, G., Rasmussen, R. M., & Manning, K. (2004). Explicit Forecasts of Winter Precipitation Using an Improved Bulk Microphysics Scheme . Part I : Description and Sensitivity Analysis. *Monthly Weather Review*, 132, 519–542.
- Thompson, G., & Eidhammer, T. (2014). A Study of Aerosol Impacts on Clouds and Precipitation Development in a Large Winter Cyclone. *Journal of the Atmospheric Sciences*, 71(10), 3636–3658. <https://doi.org/10.1175/JAS-D-13-0305.1>
- Wehbe, Y., Ghebreyesus, D., Temimi, M., & Milewski, A. a. (2017). Assessment of the consistency among global precipitation products over the United Arab Emirates. *Journal of Hydrology: Regional Studies*, 12(May), 122–135. <https://doi.org/10.1016/j.ejrh.2017.05.002>
- Wehbe, Y., Temimi, M., Ghebreyesus, D. T., Milewski, A., Norouzi, H., & Ibrahim, E. (2018). Consistency of precipitation products over the Arabian Peninsula and interactions with soil moisture and water storage. *Hydrological Sciences Journal*, 63(3), 408–425. <https://doi.org/10.1080/02626667.2018.1431647>
- Weston, M., Temimi, M., Burger, R., & Piketh, S. (2021). A Fog Climatology at Abu Dhabi International Airport. *Journal of Applied Meteorology and Climatology*(Early online release). <https://doi.org/10.1175/JAMC-D-20-0168.1>
- Wilkinson, J. M., Porson, A. N. F., Bornemann, F. J., Weeks, M., Field, P. R., & Lock, A. P. (2013). Improved microphysical parametrization of drizzle and fog for operational forecasting using the Met Office Unified Model. *Quarterly Journal of the Royal Meteorological Society*, 139(671), 488–500. <https://doi.org/10.1002/qj.1975>

- World Meteorological Organization. (2008). Aerodrome reports and forecasts: a users' handbook to the codes.
- Yang, D., Ritchie, H., Desjardins, S., Pearson, G., MacAfee, A., & Gultepe, I. (2010). High-Resolution GEM-LAM Application in Marine Fog Prediction: Evaluation and Diagnosis. *Weather and Forecasting*, 25(2), 727--748. <https://doi.org/10.1175/2009WAF2222337.1>
- Zhang, J., Xue, H., Deng, Z., Ma, N., Zhao, C., & Zhang, Q. (2014). A comparison of the parameterization schemes of fog visibility using the in-situ measurements in the North China Plain. *Atmospheric Environment*, 92, 44--50. <https://doi.org/10.1016/j.atmosenv.2014.03.068>
- Zheng, W., Ek, M., Mitchell, K., Wei, H., Meng, J., Zheng, W., Ek, M., Mitchell, K., Wei, H., & Meng, J. (2017). Improving the Stable Surface Layer in the NCEP Global Forecast System. *Monthly Weather Review*, 145(10), 3969--3987. <https://doi.org/10.1175/MWR-D-16-0438.1>
- Zheng, W., Wei, H., Wang, Z., Zeng, X., Meng, J., Ek, M., Mitchell, K., & Derber, J. (2012). *Journal of Geophysical Research: Atmospheres*, Vol.117, D6.
- Zhou, B., & Du, J. (2010). Fog Prediction from a Multimodel Mesoscale Ensemble Prediction System. *Weather and Forecasting*, 25, 303--322. <https://doi.org/10.1175/2009WAF2222289.1>
- Zhou, B., Du, J., Gultepe, I., & Dimego, G. (2012). Forecast of low visibility and fog from NCEP: Current status and efforts. *Pure and Applied Geophysics*, 169(5-6), 895--909. <https://doi.org/10.1007/s00024-011-0327-x>
- Zilitinkevich, S. S. (1995). *Air Pollution III—Volume I. Air Pollution Theory and Simulation: pollution dispersion aspects of coherent structure of convective flows* (Vol. 6). Computational Mechanics Publ.

CHAPTER 2 A FOG CLIMATOLOGY AT ABU DHABI INTERNATIONAL AIRPORT

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ABSTRACT: Fog has a significant effect on aviation and road transport networks around the world. The International Airport in Abu Dhabi, United Arab Emirates, experiences dense fog during winter months that affect operations at the airport. We describe the fog climatology at the airport using 36 years of aviation routine weather reports (METAR), an important long-term data source, and report on the number of fog days per year, the seasonal cycle, the diurnal cycle, and the duration of fog events. Fog days per year vary from 8 to 51, with a mean of ~23.91 days (standard deviation of 9.83). Events are most frequent from September until March, with December and January being the most active months. November, unexpectedly, has a low number of fog days, which appears to be due to a decrease in aerosol loading in the atmosphere. The most fog days experienced in one month is 13 (March 2004). Fog occurs any time from 1900 to 1100 local time, and the frequency increases as night progresses, peaking around sunrise. Fog events most frequently last 1 h or less. Events of 9 h or more were recorded in January and December, with the longest event lasting 16 h. Events are strongly dependent on the land–sea breeze and seldom form when the wind is blowing from the Arabian Gulf. The thickness of the nocturnal inversion layer increases up to about 500 m AGL on fog days as compared with 273 m AGL on clear-sky days. This study is the first to use the 36-yr dataset to characterize fog climatology at Abu Dhabi Airport.

Keywords: Atmosphere; Asia; Fog; Climate classification/regimes; Soundings; Seasonal cycle

2.1 Introduction

Fog is when horizontal visibility drops below 1 km as a result of condensation in the atmosphere and has a significant effect on aviation and road transport networks (World Meteorological Organization, 2008b). Fog has an impact on airports across the world. Average fog days per year have been reported for airports in Lisbon, Portugal (28); Canberra, Australia

(46); New Delhi, India (48); and Cape Town, South Africa (50) (Fabbian, 2007; Ghude et al., 2017; Teixeira & Miranda, 2001; van Schalkwyk & Dyson, 2013). Often, the only record of these events is through data from the airports in the form of aviation routine weather reports (METARS) or meteorological stations. This is also the case for the Abu Dhabi International Airport (AUH) in the United Arab Emirates (UAE). Dense fog during winter months affects operations at the airport, often resulting in airport closure (De Villiers & Van Heerden, 2007). AUH is a growing international hub with year-on-year increases in passenger traffic and flight numbers between 2013 and 2016 (Abu Dhabi Airports, 2017). Because the airport expects to increase the passenger numbers by 10 % a year until 2025 (Abu Dhabi Airports, 2019), planning for fog events becomes more important as their economic impact increases. In 2016, the airport reported annual passenger traffic of 24.4 million and total flights of 172 069, almost all of which was international traffic and connecting flights (Abu Dhabi Airports, 2017). Of the international airports in the UAE older than 10 years, AUH experiences the highest number of hours (88) per year during which visibility drops below 1 km as a result of wet conditions (Aldababseh & Temimi, 2017). Dubai International Airport (DXB, 110 km northeast of AUH) experiences almost half that number at 43 h per year. It is worth noting the DXB is an urban airport in the heart of the city of Dubai, whereas AUH is suburban, built outside the island of Abu Dhabi.

Fog is not uncommon in arid regions and has been found to occur along the west coasts of South America and southern Africa, parts of Mexico, Morocco and the Iberian Peninsula, Croatia, the Arabian Peninsula, northern India, Nepal, and Australia (Cereceda & Schemenauer, 1991; del Río et al., 2018; Ghude et al., 2017; Klemm et al., 2012; Martorell & Ezcurra, 2002; Olivier, 1995; Pithani et al., 2019; Seely & Henschel, 1998). There are five main types of fog: precipitation, radiation, advection, cloud-base lowering, and morning evaporation fog (Tardif & Rasmussen, 2007). The delineation of these classes can be divided into two main factors: the source of the moisture and the mechanism for cooling the air to dew point temperature. Cloud interception with land is sometimes referred to as high fog (Seely & Henschel, 1998), and Gultepe et al. (2007) include advection–radiation as a fog type. Advection–radiation fog refers to coastal areas where moisture is first advected over the land and then cools. In strict terms, this is different from radiation fog for which the source of moisture would be from the land itself. Fog can occur in arid regions that are in proximity to water bodies, and such fog is usually classified as radiation, advection, or advection–radiation fog.

Two previous studies (Aldababseh & Temimi, 2017; De Villiers & Van Heerden, 2007) investigated fog climatology at Abu Dhabi Airport and led to contradictory findings, most likely because of a difference in methods. For example, de Villiers and Van Heerden (2007) report 17 fog days in October 1991, whereas Aldababseh and Temimi (2017) reports a total of 20 fog hours in the entire year of 1991. The probability that 17 of 20 h of fog occurred in one month alone is low, and these results are inconsistent. The objective of this study is to provide an updated climatology that is based on 36 years of data, including a characterization of diurnal and seasonal fog events at AUH. The climatology is extended to include the vertical atmospheric thermodynamic profiles, which were touched on in previous studies (De Villiers & Van Heerden, 2007). This research will provide a definitive climatology of fog at AUH and serves as a consistent reference for future research on fog in the region. An understanding of the fog phenology and dynamics at this site can improve numerical weather prediction model outputs and associated forecast.

Abu Dhabi is a coastal city located in the UAE, which is an arid region located on the north eastern edge of the Arabian Peninsula (Figure 2-1). AUH is located on the mainland about 4 km from the nearest sea canal and at an elevation of 27m above sea level. It has a mean annual rainfall of about 78 mm (Ouarda & Charron, 2014), and the dominant land-cover type is bare or sparsely vegetated desert. The Gulf is a warm and shallow water body and is located to the north of the UAE. The shallow waters, which are around 20m deep along the UAE coast and less than 100m at the deepest point (Al Azhar et al., 2016), are heated by the sun and are guarded from cold ocean upwelling. Subsequently, the water is warm, with an average water temperature of 20 °C in winter and 33 °C in summer along the coast (Elhakeem et al., 2015; Sheppard et al., 2010). As a result, there is a high evaporation rate and supply of moisture in the low levels of the atmosphere, which aids fog formation in the winter months.

The synoptic circulation is dominated by the descending limb of the Hadley cell. The semipermanent high pressure system will limit vertical mixing in the atmosphere and is associated with clear skies and light to variable winds. A persistent inversion layer is present between 3800 and 5000m above ground level (Reid, Piketh, et al., 2008). These stable conditions allow the formation of a temperature gradient between the land and sea and promote the formation of thermally driven winds like the land–sea breeze (Eager et al., 2008). The land–sea breeze is an important dynamic in fog formation as explained in the next section. It occurs over 70% of the time over the UAE during winter months (Eager et al., 2008).

Radiation fog, or in a more strict sense advection–radiation fog, is the dominant fog type in Abu Dhabi (De Villiers & Van Heerden, 2007; Gultepe et al., 2007) and the process of fog formation in the UAE has been well documented (Bartok et al., 2012; De Villiers & Van Heerden, 2007). In summary, fog formation requires a land–sea-breeze circulation, calm conditions, and a nocturnal surface inversion layer. These conditions fall under the radiation fog classification described by Tardif and Rasmussen (2007). During the day, the sea breeze transports moisture from over the gulf toward the land (Figure 2-2) and can extend up to 130 km inland based on in situ observations (Eager et al., 2008). However, fog has been observed up to 200 km inland from Abu Dhabi from satellite data indicating that the sea breeze can extend further inland (Temimi et al., 2020). This results in high water vapour mixing ratios near the surface. At night, the air over the desert cools quickly as a result of radiative cooling, and this change in the thermodynamic gradient causes the sea breeze to weaken while the wind veers toward a land breeze (Bartok et al., 2012; De Villiers & Van Heerden, 2007; Weston et al., 2018). This weakening of the sea breeze is crucial because it reduces the effect of warm nocturnal maritime temperatures and promotes surface radiative cooling over the desert further. This cooling results in the formation of a surface inversion layer that traps the moisture near the surface, maintaining the high mixing ratio (Chaouch et al., 2016; Temimi et al., 2020). Eventually, as the radiative cooling intensifies and expands vertically through the night, dewpoint temperature is reached and fog may be formed. The overlying anticyclonic circulation leads to calm and stable atmospheric conditions that restrict vertical and horizontal mixing that promotes the processes just described.

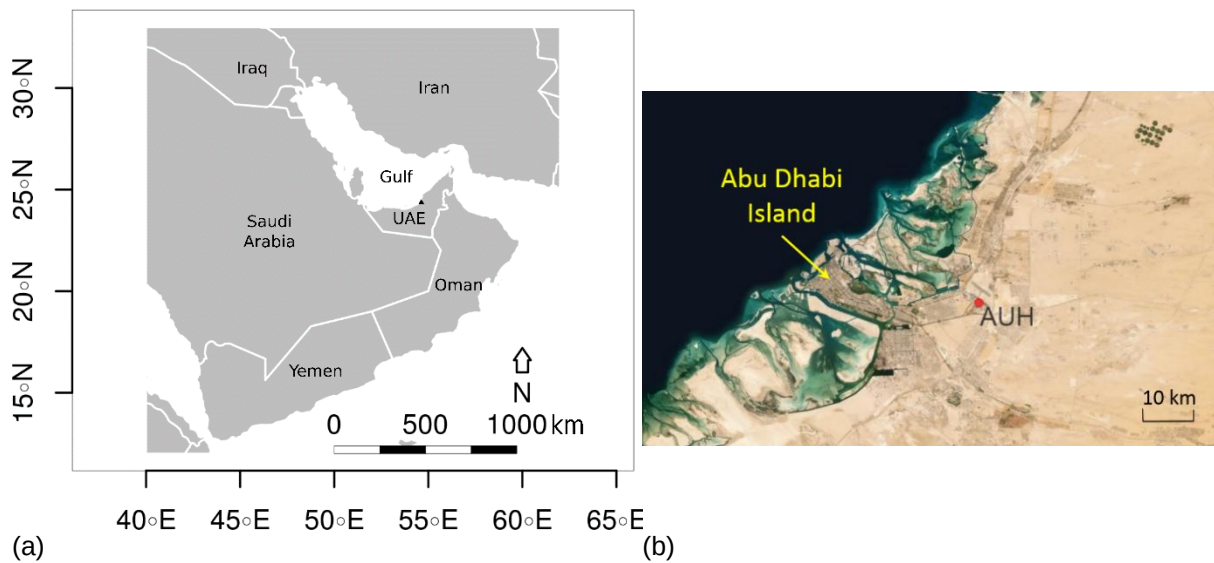


Figure 2-1: a.) Abu Dhabi (triangle) is located in the United Arab Emirates (UAE) on the Arabian Peninsula. b.) AUH is located on the mainland.

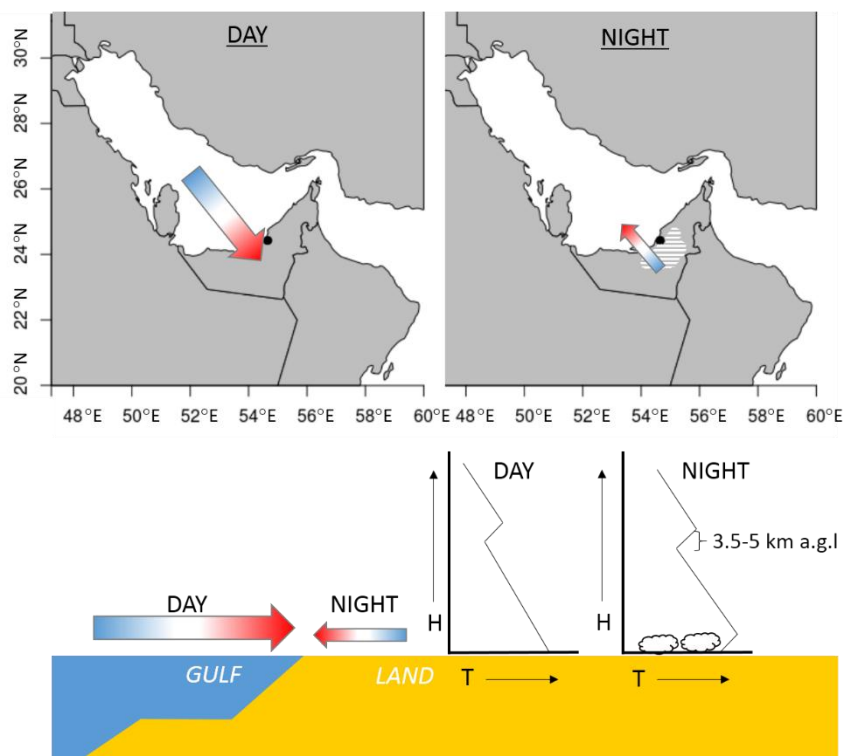


Figure 2-2: Conceptual diagram of fog formation process in the UAE. Black dot is Abu Dhabi International Airport. Block arrows indicate the wind direction. The color gradient indicates the relative difference in temperature of the land surface to the gulf surface.

2.2 Method

2.2.1 METAR Data

For this analysis we used 36 years of meteorological aerodrome reports from 1983 until the end of 2018 at AUH. Data were downloaded from NOAA National Climatic Data Center (NCDC) database in the integrated surface data (ISD) format (NCEI, 2001). Hourly and special reports (subhourly) were used to identify fog events based on the weather description codes defined in Table 2-1 (NOAA & USAAF, 2018). The fog patch weather code (BCFG) often corresponds to visibility conditions that are above 1 km but below 2 km and therefore means that fog is, in strict terms, not present at the station. However, it is included in the analysis because it means that fog is nearby and thus is still valid in terms of a fog climatology. All records related to an outlook for the next few hours were scrubbed because these refer to a forecast and not an observation. These were indicated in the data with the code BECMG or TEMPO (NOAA & USAAF, 2018). Data were consolidated to an hourly resolution, meaning that a regular report and a special report were only counted once when reported in the same hour. Similarly, duplicate time stamps from multiple report codes, if any, were consolidated to a single time stamp. The following statistics were calculated: fog days per year, fog days per month, fog frequency per hour of day (diurnal cycle), and fog event duration in hours for each month.

Table 2-1: METAR codes used to define fog

METAR Code	Description
FG	Fog
GNDFG	Ground fog
FZFG	Freezing fog
45FG	Fog: No sky visible
44FG	Partial Fog
42FG	Fog: Sky visible
VCFG	Fog in Vicinity
BCFG	Fog patch

Because the fog is mostly nocturnal, we define fog days as the period from sunset until midday the following day. If a fog event occurs in this time it is recorded as a fog day. If multiple events occur, interspersed by nonfog conditions, it is only recorded as one fog day.

Fog duration is calculated as the number of consecutive recorded time stamps, minus 1. For example, a 1-h fog event is deemed to occur if fog is reported in two consecutive time stamps, that is, the first time stamp is considered as the start time and the second time stamp is considered as the end time, and the difference is 1 h. If fog is recorded in a single time stamp, the event is considered to last less than 1 h.

In addition, records of dewpoint temperature depression (Tdep) and associated wind direction were analyzed in this study along with the reported fog events.

The METAR data are already quality controlled, and minimal data cleaning was applied. However, two data points were removed from the record because they were considered to be erroneous. These were 1100 UTC 21 October 1991 and 1100 UTC 13 April 2017, where fog was reported. Upon inspection of the time series for these days it showed these two data points as rapid and unrealistic changes in conditions. Further inspection suggested that these data points had the incorrect time stamp, and they were removed from the dataset.

A subset of METAR data was downloaded from the University of Wyoming website (Oolman, 2019). These data provide atmospheric pressure that is mostly set to a missing value in the NCDC dataset. Atmospheric pressure is required for the calculation of the water vapor mixing ratio. This subset, from January 2000 to April 2018, is used to plot the seasonal cycle of temperature, water vapour mixing ratio, and wind speed.

2.2.2 Vertical temperature profiles

Radiosonde data were used to analyze vertical profiles of temperature during fog and clear-sky days at AUH. Seventeen years of data from 2000 to 2016 were obtained from the University of Wyoming website (Oolman, 2019). The 0000 UTC sounding was analyzed because it corresponds to 0400 local time (LT), which is when fog usually occurs (De Villiers & Van Heerden, 2007). Profiles for fog conditions were identified by matching the date of fog days from the NCDC METAR data described above. Clear-sky conditions were defined as days that lacked cloud cover codes in the METAR (defined as OVC = overcast or 8/8, BKN = broken or 7/8, SCT = scattered or 4/8, and FEW = few or 2/8) and lacked the fog code. October–March were considered for this analysis.

2.3 Results and Discussion

2.3.1 METAR data coverage

Data coverage is more than 80% for all years except 1983 and 1986 (66% and 76%, respectively) (Figure 2-3a). The report type is mostly METAR (FM-15) followed by Synoptic merged with METAR (SY-MT) (Table 2-2). From 2013 onward there was systematic change in reporting where Synoptic (FM-12) replaced Synoptic merged with METAR (SY-MT). This resulted in duplicate time stamps between FM-15 and FM-12. However, the FM-12 reports do not include the METAR codes for fog (or other weather types) and can mostly be ignored as all codes are reported in the METAR (FM-15) data. The fog codes reported is fog (FG at 50%), fog patches (BCFG at 37%), fog in the vicinity (VCFG at 12%), and other at 1% (Figure 2-3b).

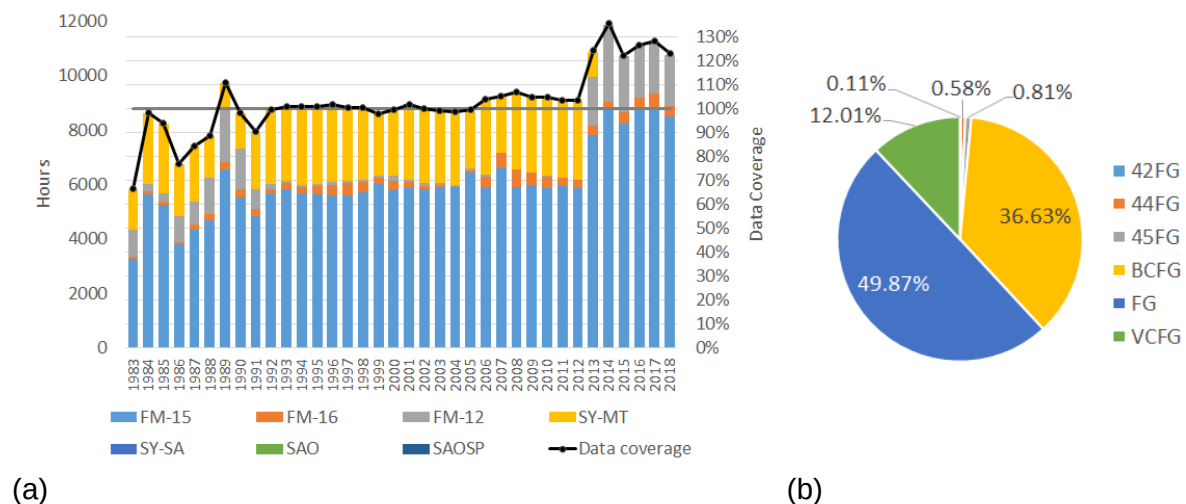


Figure 2-3: a.) Data coverage in hours from 1983-2018 including the type of report (view with Table 2-2). The grey horizontal line represents 8760 hours in a non-leap year. FM-12 does not contain any information on METAR codes and can mostly be ignored. b.) Percentage breakdown of fog codes reported (view with Table 2-1) at Abu Dhabi International Airport.

Table 2-2: Description of report codes

Report Code	Report Description
FM-15	METAR
FM-16	Special
FM-12	Synoptic Station
SY-MT	Synoptic and METAR merged report
SY-SA	Synoptic and airways merged report
SAO	Airways report
SAOSP	Airways special report

2.3.2 Meteorological Climatology

The mean summer temperatures are around 35 °C, and winter temperatures are below 25 °C (Figure 2-4). The range between the mean minimum and maximum varies from 10 to 15 °C through the year. Mean water vapor mixing ratio is highest in summer months, reaching about 0.018 kg kg⁻¹, and drops to about 0.009 kg kg⁻¹ in January. The high summer values are due to the warm water temperatures in the gulf and associated high evaporation rates. The monthly wind speed is above 4 ms⁻¹ from February to August, and the lowest wind speeds are from October to December below 3.5 ms⁻¹. These seasonal cycles will inform the fog climatology and will be discussed in more detail in due course.

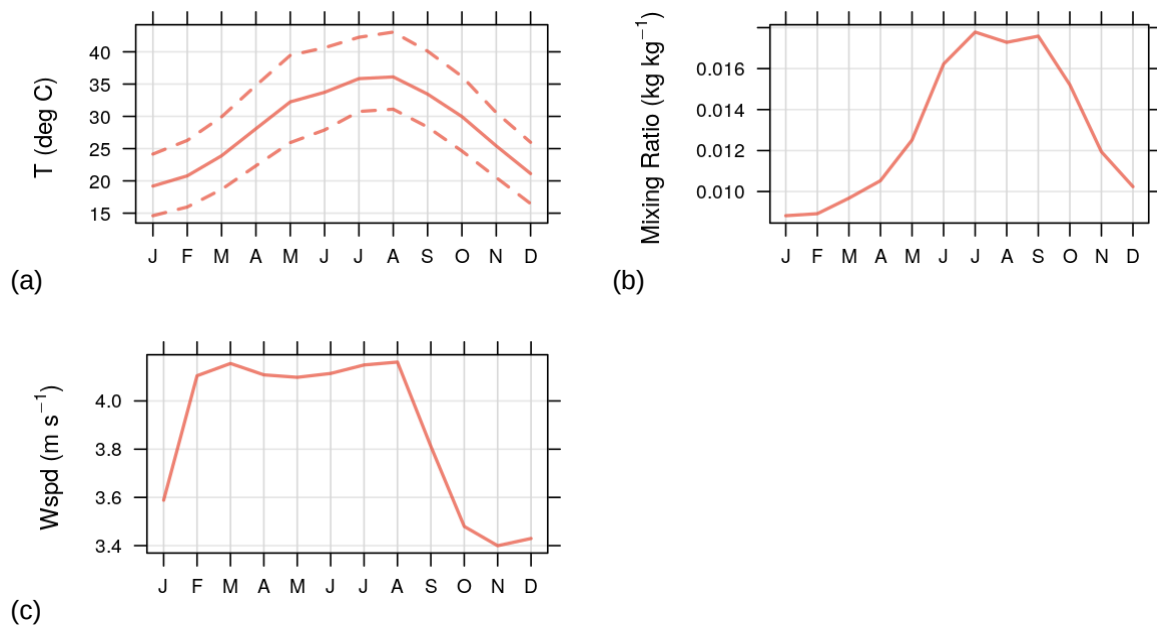


Figure 2-4: Seasonal cycle of monthly mean meteorological variables for a.) temperature (dashed lines are daily maximum and minimum), b.) water vapour mixing ratio and c.) wind speed at AUH for the time period January 2000 to April 2018.

2.3.3 Fog climatology

Days of fog per year, where a year is defined from January to December, were calculated for years that have 80% data coverage or higher (i.e., 1983 and 1986 were excluded). Days of fog per year ranged from 8 to 51 in 1990/92 and 2001, respectively (Figure 2-5a). The average number of fog days per year is 23.91 (standard deviation of 9.83) (Figure 2-5b). The highest frequency years that fell outside the standard deviation were 2001 (51), 2000 (45), 2004 (37), and 2017 (35).

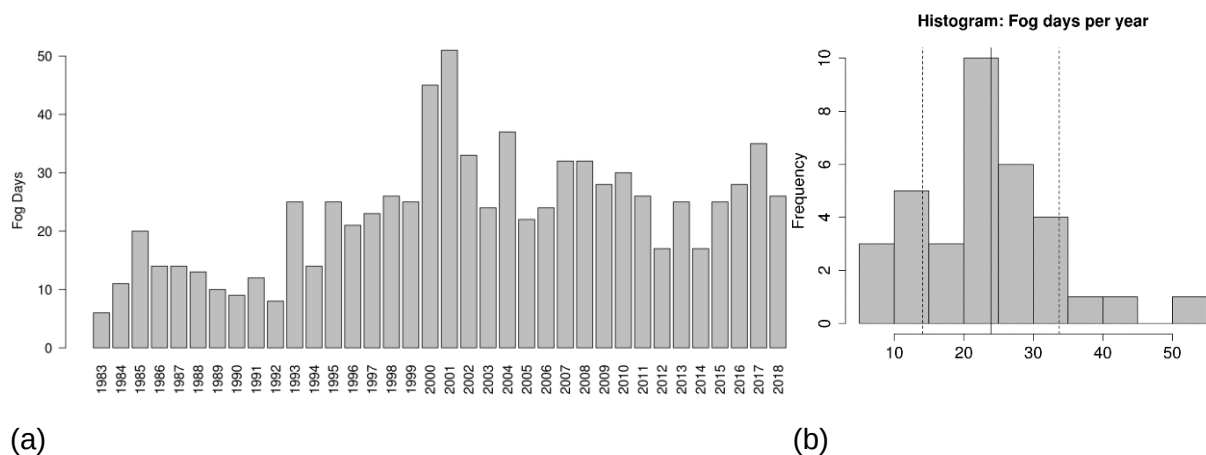


Figure 2-5: a.) Fog days per year from 1983-2018 at Abu Dhabi International Airport and b.) histogram of fog days per year (years 80% data coverage or higher). Solid and dotted lines in b.) are the mean and standard deviation respectively.

As indicated in section 1, AUH reports more fog days than other airports in the UAE (Aldababseh & Temimi, 2017). A spatial analysis of fog frequency over the UAE using satellite data was presented by Weston and Temimi (2020). The findings suggest that fog frequency increases with distance inland from the coast with a peak frequency at about 50 km inland followed by a gradual decrease. Fog in the UAE can form inland first, before extending to the coast. These patterns are in contrast to other coastal desert areas that experience fog.

In the central Namib, the highest frequency of fog days occurs along the coast, with the average fog days per year ranging from 65 to 120 (Lancaster et al., 1984; Olivier, 1995; Seely & Henschel, 1998; Spirig et al., 2019). Fog in the central Namib results from a stratiform cloud that intersects with the ground and is defined as advective or high fog (Andersen et al., 2020; Andersen et al., 2019). The number of fog days per year decreases with distance from the coast to around 40 at 40 km inland (Olivier, 1995; Spirig et al., 2019). Fog in the Atacama Desert is similar to the central Namib in that it is associated with the low stratus deck from the Pacific Ocean (del Río et al., 2018; Lehnert et al., 2018). The number of fog days per year along the coast is estimated at 38 and decreases inland until an elevation of about 900 m.a.s.l, where orographic fog is frequent. In Saudi Arabia, the mountains along the Red Sea coast experience fog when clouds form on the mountain slopes. During one season, 38 fog days were reported (Gandhidasan & Abualhamayel, 2012). In contrast to these sites that

experience a type of advective/intersecting or lowering stratiform cloud type of fog, AUH experiences fewer fog days per year.

A trend analysis of fog events at Abu Dhabi has been presented in the literature and showed a single changepoint at the year 1999 (Aldababseh & Temimi, 2017). This changepoint was shown to be related to El Niño–Southern Oscillation (ENSO) where fog days per year were less frequent prior to 1999. A similar study on rainfall days was presented by Ouarda et al. (2014) and showed the same changepoint at the year 1999, where rain day frequency was higher prior to 1999. They also associated the rainfall pattern to ENSO, where the period prior to 1999 was a warm phase and post 1999 was a cold phase. Yousef et al. (2019) presented total cloud cover trends over the Arabian Peninsula and also identified 1998 as a changepoint in cloud cover where total cloud cover was higher pre-1999 and lower post-1999. The lower number of fog days associated with the higher number of rain/total cloud cover days is reasonable. Rain days is associated with unstable atmosphere and the cloud cover inhibits the radiative cooling required for fog formation. It is worth noting that climatological trends in surface wind speed at Abu Dhabi showed a different changepoint around the year 2005, where wind speeds prior to 2005 were lower (Naizghi & Ouarda, 2017). This changepoint could not be linked to a single climate index.

The trend analysis and changepoint from Aldababseh and Temimi (2017) was used to split the dataset from Figure 2-5a into two periods. This results in two datasets of 16 years from 1983 to 1998 and 20 years from 1999 to 2018. Fog days per year pre-1999 range from 8 to 26 with a mean of 16.5 (standard deviation 6.5), and post-1999 they range from 17 to 51 with a mean of 29 (standard deviation 8.4). The peak fog years of 2000 and 2001 occurred when ENSO was shifting from warm phase to cold phase.

There are some inconsistencies with the previously reported climatology by de Villiers and Van Heerden (2007), which we assume are due to differences in the methods. However, we highlight a few of these here. For example, they report the highest number of fog days of 56 in the year 2000. However, we find only 45 fog days for the year 2000 and the highest number of fog days of 51 in 2001 (Figure 2-5a). Similarly, the lowest number previously reported is 23 days in 1992, whereas we find 8 days for the same year. Given that we have complete data coverage for these years (1992, 2000, and 2001), we must assume that two different sources of data were used in each study or different definitions of fog were used. We suspect the former is the case, because they report receiving data directly from the airport, which may have information from multiple visibility instruments associated with the instrument landing

system. Our minimum and maximum fog days are also less than those previously reported, which supports the idea that more sensors were used previously, thus providing more fog observations. However, these differences should not affect the seasonal and diurnal trends reported here.

The seasonal cycle shows that the fog is most active from September through to March (Figure 2-6). The most fog days observed in a month is 13 in March 2004 and between 10 and 12 days from October to December. Oddly, fewer fog days are observed in November, whereas October and December both have more occurrences. If not for the outlier year of 11 days in November 2007, it is identical to May. Fog is observed on at least one day for each month of the year.

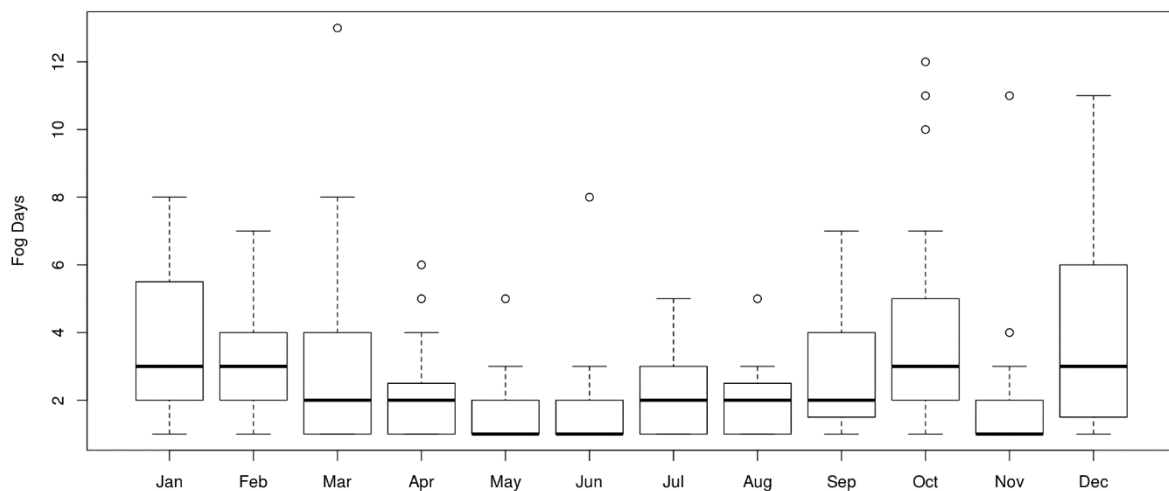


Figure 2-6: Boxplot of fog days per month from 1983-2018 at Abu Dhabi International Airport. Circles represent outliers which are greater than quartile 3+(1.5*inter quartile range). Dark horizontal lines are medians. Lower whisker is quartile 1-(1.5*inter quartile range). Quartile 1 is the bottom of box. Quartile 3 is the top of box.

The month of November can be considered as an outlier in the seasonal cycle of fog days. In terms of visibility, November is the clearest month with the fewest occurrences of low visibility events (Aldababseh & Temimi, 2017). The meteorological variables in November are not necessarily different from those in December. The land–sea breeze is still prevalent (Eager et al., 2008), and the mixing ratio is higher than December (Figure 2-4). However, the mean wind speed is lower than in December (Figure 2-4) (Naizghi & Ouarda, 2017). Fog formation is dependent on droplet microphysics, aerosol chemistry, radiation, turbulence and mixing, and

surface conditions (Gultepe et al., 2007; Haeffelin et al., 2013). Potentially, the decrease in November could be due to a decrease in aerosols. Filioglou et al. (2020) conducted 1 year of ground-based aerosol and CCN measurements in the UAE and report that boundary layer aerosol optical depth (AOD) is lowest in November. The mechanism for the low AOD is not yet clear but could be related to the lower mean wind speeds, which may constrain suspension and transport of aerosols over AUH. As regional transport of aerosols contributes to the aerosol loading over the UAE (Reid, Reid, et al., 2008), it could be that a change in wind speeds outside of the UAE during November is responsible for the decrease in aerosol loading. Further investigation should focus on the conditions between November and December to detail this mechanism, which is outside the scope of this study.

Previously, the autumn months of September and October were highlighted as the most active fog months (De Villiers & Van Heerden, 2007). However, our analysis shows that December and January are equally, if not more, active months for fog formation in terms of fog days (Figure 2-6). This is similar to previous reports of low visibility events (i.e., fog and dust) (Aldababseh & Temimi, 2017).

The diurnal cycle of fog events shows that fog occurs most frequently around sunrise (early morning). Fog occurs anywhere from 1900 to 1100 LT. Typically, fog starts to form at around midnight steadily increasing to sunrise. This indicates that radiative cooling and associated calm winds are required throughout the night in order to reach dewpoint temperature in the morning hours. After the sun has risen, the fog dissipates rapidly because of the thermal heating of the fog and the surface (Figure 2-7). There is a slight seasonal shift in the time of maximum fog events. Between September and March (autumn and winter) the highest number of events occur between 0600 and 0700 LT. From April to August the fog occurs earlier in response to an earlier sunrise in spring and summer. In December, fog can start in the evening as early as 2000 LT, and in other winter months it can start as early as 2100 LT.

Fog events are more common during the winter months because of longer nights and therefore enough time to reach the dewpoint via radiative cooling. This radiative cooling leads to the formation of a surface inversion layer, which traps the moisture advected during the day near the surface (Chaouch et al., 2016; De Villiers & Van Heerden, 2007; Temimi et al., 2020). The moisture and longer nights together lead to the formation of fog, usually when the lowest temperatures are reached in the early morning.

Fog events most frequently last 1 h or less throughout the year (Figure 2-8 and Table 2-3). The longest event on record of 16 h was recorded on 22–23 December 2017 (Figure 2-8).

This event started soon after sunset at 1900 LT and persisted until just 1100 LT the following day. This onset time is only reported in December and is not frequent. Events of 9 h or more have been observed from November to March; however, the frequency of these events is low. January and December have 90th percentiles of about 9 h, meaning that these events are most likely to occur in these months. In other words, fog events last longer during January and December, the month of maximum radiative cooling over the region.

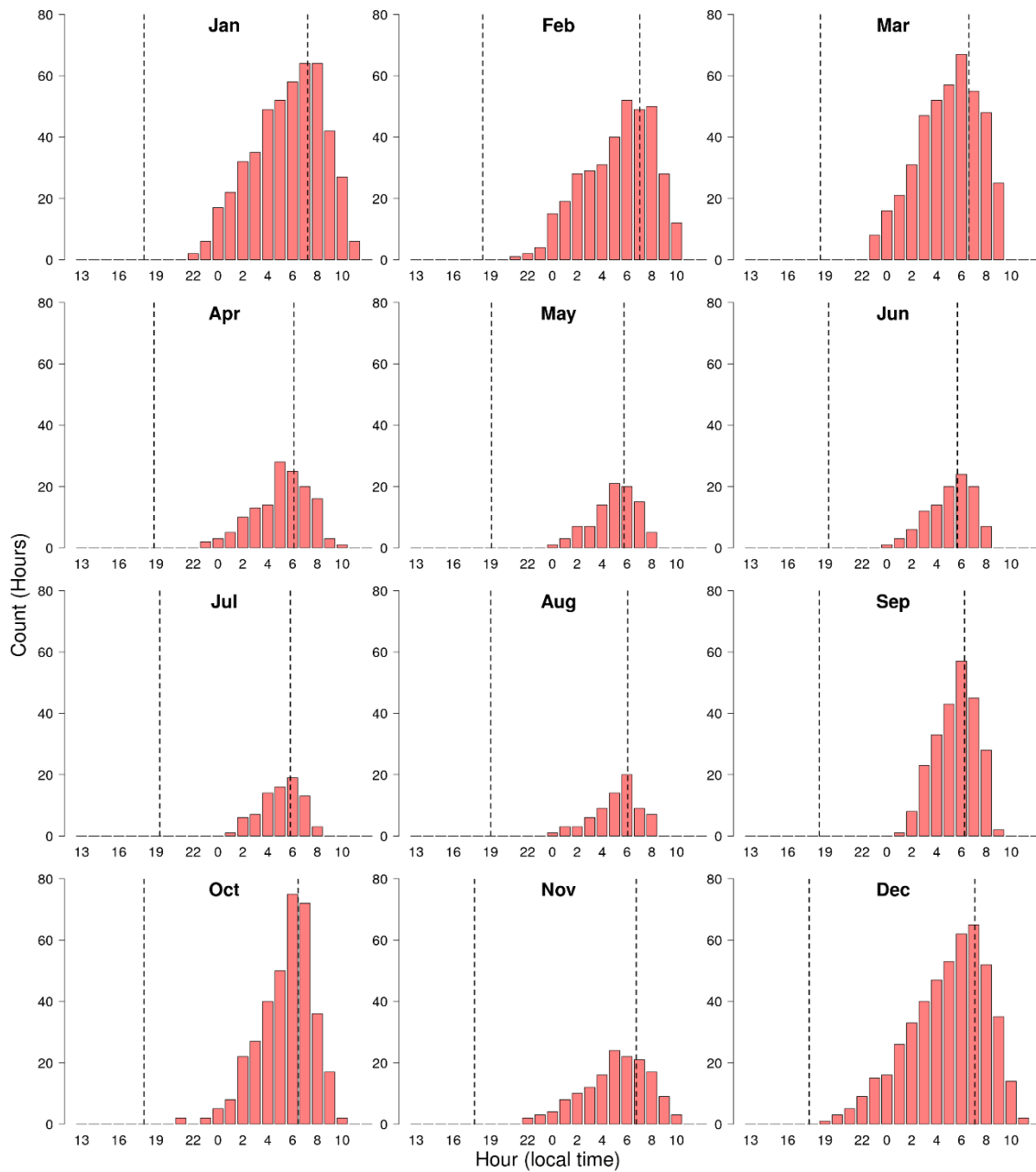


Figure 2-7: Diurnal frequency of fog per month from 1983-2018 at Abu Dhabi International Airport. Black dotted line indicates time of sunrise and sunset.

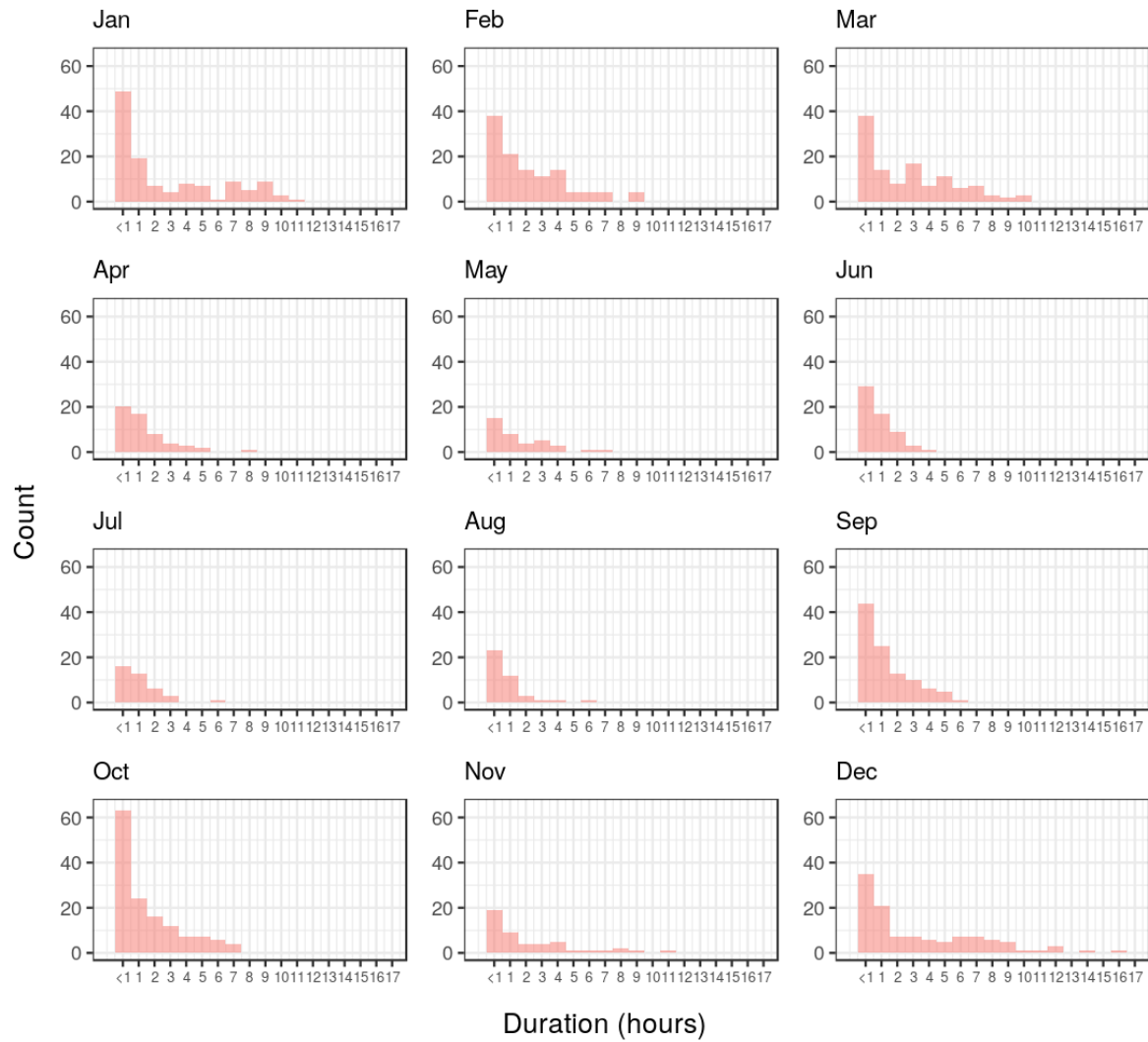


Figure 2-8: Fog duration in hours per month from 1983-2018 at Abu Dhabi International Airport. Count refers to the number of events observed.

Table 2-3: Monthly percentiles of fog duration in hours.

Month	30%	50%	75%	90%	95%	99%	100%
Jan	< 1	1	5	8.9	9	10	11
Feb	< 1	1	4	5.7	7	9	9
Mar	< 1	2	5	7	8	10	10
Apr	< 1	1	2	3.6	4.3	6.38	8
May	< 1	1	3	4	4.4	6.64	7
Jun	< 1	1	1	2	3	3.42	4
Jul	< 1	1	1.5	2.2	3	4.86	6
Aug	< 1	0.5	1	2	3	5.2	6
Sep	< 1	1	2	4	4.85	5	6
Oct	< 1	1	3	5	6	7	7
Nov	< 1	1	3.25	6.3	8	10.06	11
Dec	< 1	2	6	8.8	10.4	13.76	16

2.3.4 Importance of land–sea breeze

Here, we demonstrate why the shift to a land breeze is important for fog formation by presenting the wind direction at the time of highest fog frequency from 0000 to 0600 LT for the years 1983–2018. The formation of the land breeze has been described fully in section 1. The dominant wind pattern at Abu Dhabi is a land-sea-breeze circulation (Eager et al., 2008). The sea breeze occurs during the day from about midday onward (Figure 2-9a,b,e,f). This weakens during the night and the wind veers to a land breeze that is much weaker (Figure 2-9c,d,g,h). This pattern is sometimes overridden by passing synoptic circulations that may produce a dominant wind direction for days at a time (e.g., northwesterlies and shamal winds can persist for 4–5 days in winter; (Vinod Kumar et al., 2014)). During the day, moisture is transported over the desert by the sea breeze followed by cooler air associated with the light land breeze. This shift is important, as winds from the southeast bring cooler nighttime air from the desert.

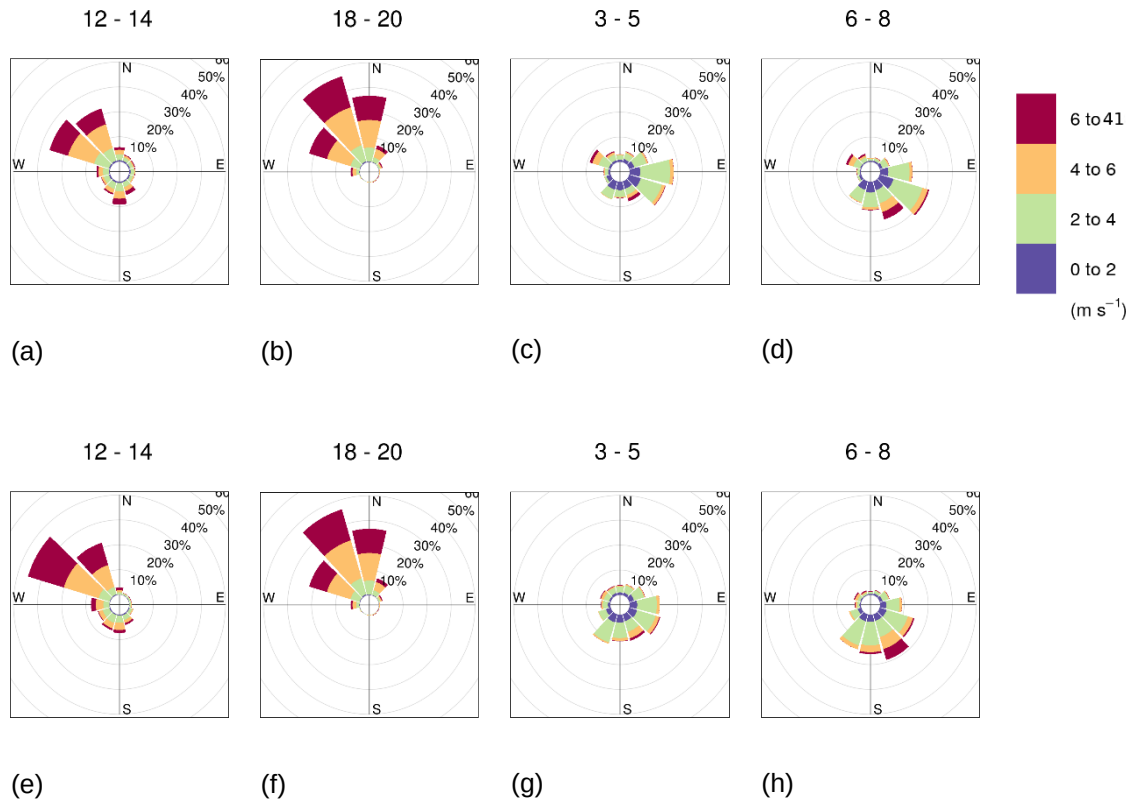


Figure 2-9: Diurnal wind roses for (a-d) September to March (fog months), 1983-2018 at Abu Dhabi International Airport. a.) and b.) show the persistent sea breeze from 12-20 LT. c.) and d.) Show the shift to the weaker land breeze from 03 to 08 LT. (e-h) is the same as (a-d) but for April to August.

The result of this circulation is that the dewpoint depression drops when the regime shifts to the land breeze (Figure 2-10a). On fog days, the wind direction is seldom from the northwest at the time of fog; rather, it is most frequently from the landward side (Figure 2-10c). This analysis of the wind direction during fog conditions confirms that fog seldom forms in the presence of northwesterly to northeasterly winds and that typically a shift in wind direction is required (Weston et al., 2018).

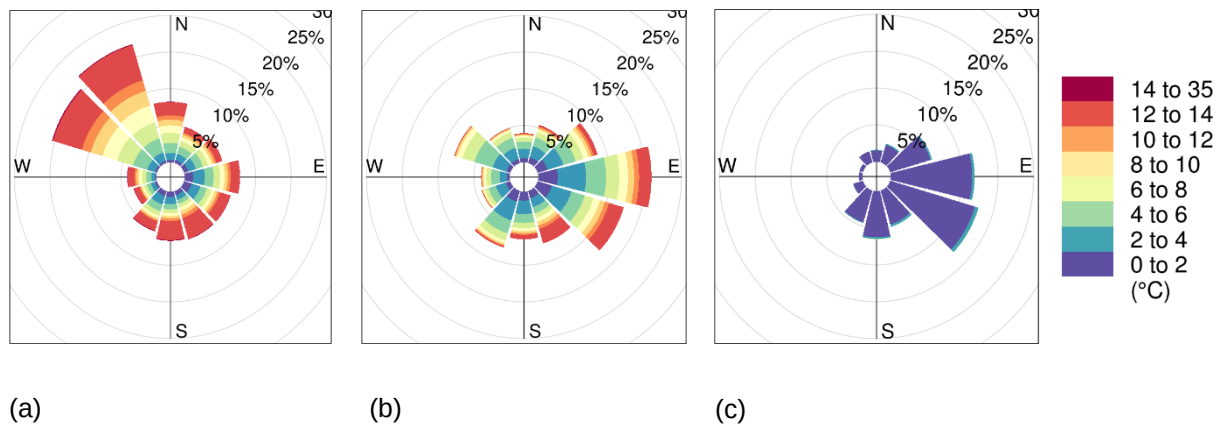


Figure 2-10: a.) Dew point depression rose for all months, 1983-2018, 00-23 LT at Abu Dhabi International Airport. b.) and c.) are the same as a.) but from 00 – 06 LT during non-fog conditions (b) and fog conditions (c).

Low wind speed is crucial for radiation fog to form. De Villiers and Van Heerden (2007) state that low wind speed of $1.5\text{--}3\text{ ms}^{-1}$ is observed during fog onset in Abu Dhabi. Radiation fog forms under calm wind conditions that promote radiative cooling and the formation on the surface inversion layer (Tardif & Rasmussen, 2007). An analysis of the METAR wind speed during fog hours (1900–1100 LT) shows that wind speed is below 5 ms^{-1} and most frequently below 3 ms^{-1} (Figure 2-11a). Furthermore, there is a positive relationship between the wind speed and the Tdep, where lower Tdep values are observed at lower wind speeds (Figure 2-11b). Because there is a large overlap of calm conditions between fog and nonfog days, this suggests that the low wind speed in combination with the land breeze is important in reaching dewpoint temperature. This further highlights that it is a combination of these factors that must occur to promote fog formation.

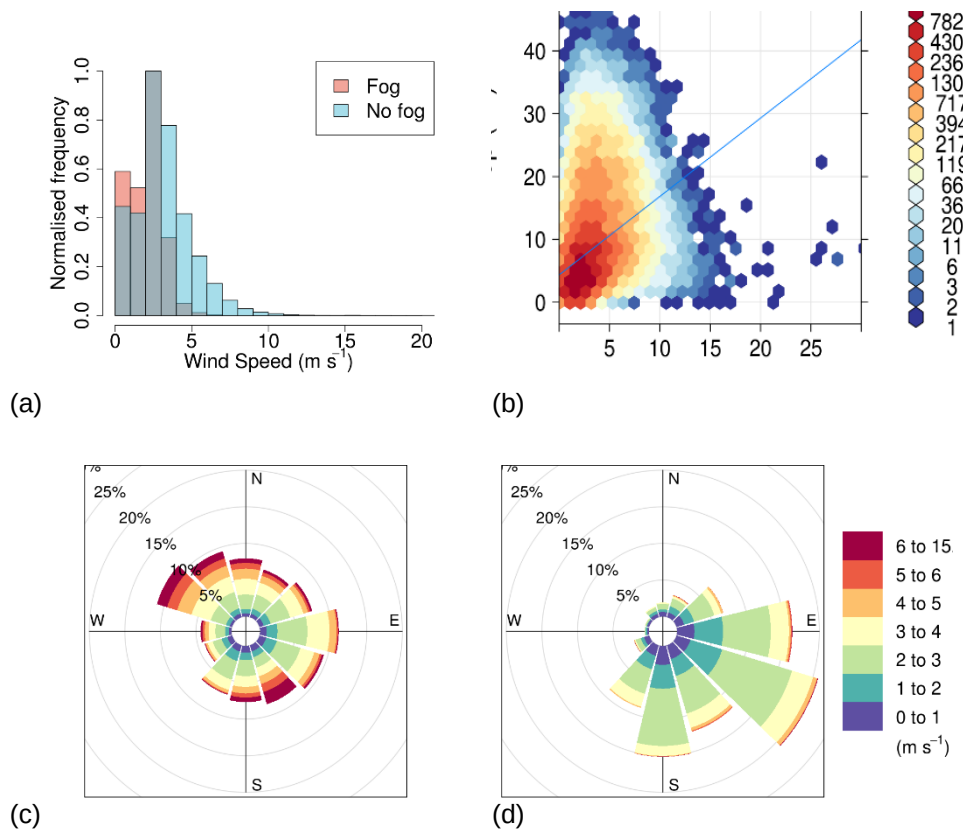


Figure 2-11: a.) Histogram of wind speed from 19h00 to 11h00 LT for fog and non-fog hours at AUH. The grey colour indicates overlap between the distributions. b.) Scatter plot of wind speed and temperature depression (Tdep) from 19h00 to 11h00 LT with linear relationship for both fog and no fog days. Colour represents the number of hours in that part of the scatter plot. Windrose for same hours as a.) for c.) no fog and d.) fog hours.

Calm wind conditions have been observed at various sites where radiation fog occurs (Haeffelin et al., 2013; Steeneveld & de Bode, 2018; Steeneveld et al., 2014; Sterk et al., 2015; Terpstra, 1999). The threshold wind speed that defines calm conditions differs per site where reported thresholds include 3.5 ms⁻¹ (Haeffelin et al., 2013), 2.8 ms⁻¹ (Payra & Mohan, 2014), 2.5 ms⁻¹ (C. Román-Cascón et al., 2016; Tardif & Rasmussen, 2007) and 2 ms⁻¹ (Terpstra, 1999). Some authors report that some wind is needed to allow for turbulent mixing of moisture below the surface inversion layer and that very calm conditions could inhibit fog formation. For example, Payra and Mohan (2014) report that wind speed should be 1.4 ms⁻¹, Terpstra (1999) report that speeds should be 1 ms⁻¹, and Haeffelin et al. (2013) report that speeds should be

0.5 ms⁻¹. In modeling studies, wind speed is often one of several parameters used to define radiation fog conditions (Menut et al., 2014; Payra & Mohan, 2014; C. Román-Cascón et al., 2016; Steeneveld et al., 2008; Zhou & Du, 2010).

2.3.5 Vertical temperature profile

In this section we compare radiosonde data of surface inversion layer depth and lapse rate of fog and clear-sky days at the airport. The boxplot of surface inversion depth at 0000 UTC (i.e., 0400 LT) for “fog” and “clear sky” days is shown in Figure 2-12. The depth represents the distance from the surface to the top of the inversion layer. Surface inversions were present on 97.8% (92 of the 94) of fog-day profiles and 56.9% (1659 of 2914) of clear-sky days. On fog days, the depth of the inversion layer increases up to about 500m above ground level (AGL), as compared with clearsky conditions where it extends to about 273m (AGL). The depth of the inversion is indicative of the strength of the radiative cooling. A t test between the two datasets returned t and p values of 24.0576 and 0.000 180 2, respectively. This confirms that the inversion is deeper during fog conditions. The frequency of surface inversions on fog days suggests that this is a requirement for fog formation with a few exceptions. The surface inversion traps the moisture near ground level, enhancing the water vapor mixing ratio. While the presence of the nocturnal inversion layer during fog conditions has been reported for isolated cases studies (Chaouch et al., 2016; Temimi et al., 2020), these results show the persistence of this phenomenon. Thus, we conclude that an inversion with a vertical extent of 300–500m AGL is required for fog formation at and around the airport.

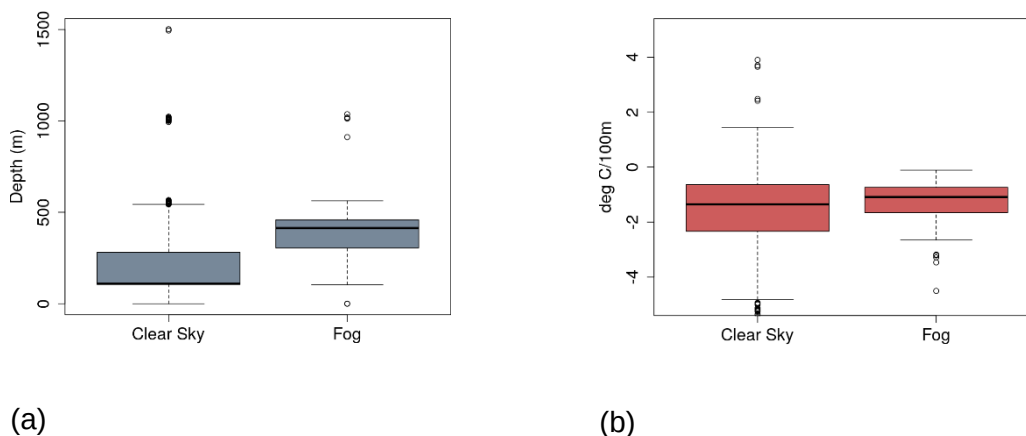


Figure 2-12: a.) Box plot of inversion depth for clear and fog days at 00 UTC/04 LT. Data is from October to March, 2000-2016. b.) Box plot of lapse rate for clear and fog days.

An interesting feature that is reported in the literature is the cooling of the air above an established fog layer (Gultepe et al., 2007; Nakanishi, 2000; Carlos Román-Cascón et al., 2016; Steeneveld & de Bode, 2018). This is due to the fog top acting as the land surface from which radiation is lost, resulting in a radiative cooling cascading from the fog top. In addition, several cases report that turbulent mixing within an established fog layer can reduce the temperature inversion strength to the point of an isotherm from surface to fog top (Haeffelin et al., 2013; Nakanishi, 2000; Price, 2011). This feature has yet to be observed on a consistent basis at Abu Dhabi. Temimi et al. (2020) report a case study period of six nights from 5 to 12 February 2018 at Abu Dhabi using a microwave radiometer to measure temperature profiles every 5 min. Surface inversions were present on all six nights, but fog only occurred on four nights. Surface cooling was not observed at the top of the fog layer and isotherm conditions were only reached once out of the four events. It could be that over the desert the inversion strength is stronger than at other radiation fog sites in Europe or Asia where the isotherm is observed, and that more time is needed to mix the fog layer in Abu Dhabi. This feature will be investigated further in the future as a longer record of fog events captured with the microwave radiometer is made available.

2.4 Conclusions

We presented a comprehensive fog climatology analysis based on 36 years of observations at Abu Dhabi International Airport based on METAR data. This data source is important in understanding the fog climatology in the region, where observations of low visibility events are limited. On average, the airport experiences 23.91 fog days per year (standard deviation of 9.83). As the airport expects to increase the passenger numbers by 10% a year until 2025 (Abu Dhabi Airports, 2019), planning for fog events becomes more important as their economic impact increases. These implications can be extended to ground transit. Heavy vehicle traffic (i.e., cargo) is prohibited under fog conditions, which results in delays of ground operations like construction. Previously, the autumn months of September and October were highlighted as the most active fog months. However, our analysis shows that December and January are equally, if not more, active months for fog formation in terms of fog days. This is similar to previous reports of low visibility events (i.e., fog and dust) by Aldababseh and Temimi (2017) who used the same dataset (METAR) as this study but did not report on fog days or duration specifically. November is an outlier in the seasonal cycle with fewer fog days than October and December. This appears to be due to a decrease in aerosol loading in November. The diurnal cycle shows that fog occurs anywhere from 1900 to 1100 local time, and the frequency increases as night progresses, peaking around sunrise. As such, fog events are

shown here to last more than 9 h during January and December when nights are longer. Still, a fog duration of 1 h or less is most frequent through the year. Last, a climatology of the temperature vertical profile was presented and showed that the depth of the nocturnal inversion layer is deeper during fog days than clear-sky days. This updated climatology serves as a consistent reference for future studies and will hopefully inform future analyses and direction in developing research frameworks.

Data availability statement: METAR data are available online from the NCDC (<ftp.ncdc.noaa.gov/pub/data/noaa/>). Radiosonde data are available from the University of Wyoming (<http://weather.uwyo.edu/>).

2.5 References

- Abu Dhabi Airports. (2017). *Annual Report 2016*. <http://www.adac.ae/english/media-centre/annual-reports>
- Abu Dhabi Airports. (2019). *Abu Dhabi Airport*. Retrieved 2 March 2020 from <https://www.abudhabiairport.ae/en/about/overview>
- Al Azhar, M., Temimi, M., Zhao, J., & Ghedira, H. (2016). Modeling of circulation in the Arabian Gulf and the Sea of Oman: Skill assessment and seasonal thermohaline structure. *Journal of Geophysical Research: Oceans*, 121(3), 1700-1720. <https://doi.org/10.1002/2015JC011038>
- Aldababseh, A., & Temimi, M. (2017). Analysis of the long-term variability of poor visibility events in the UAE and the link with climate dynamics. *Atmosphere*, 8, 18-20. <https://doi.org/10.3390/atmos8120242>
- Andersen, H., Cermak, J., Fuchs, J., Knippertz, P., Gaetani, M., Quinting, J., Sippel, S., & Vogt, R. (2020). Synoptic-scale controls of fog and low-cloud variability in the Namib Desert. *Atmospheric Chemistry and Physics*, 20(6), 3415-3438. <https://doi.org/10.5194/acp-20-3415-2020>
- Andersen, H., Cermak, J., Solodovnik, I., Lelli, L., & Vogt, R. (2019). Spatiotemporal dynamics of fog and low clouds in the Namib unveiled with ground- and space-based observations. *Atmospheric Chemistry and Physics*, 19(7), 4383-4392. <https://doi.org/10.5194/acp-19-4383-2019>
- Bartok, J., Bott, A., & Gera, M. (2012). Fog Prediction for Road Traffic Safety in a Coastal Desert Region: Improvement of Nowcasting Skills by the Machine-Learning Approach. *Boundary-Layer Meteorology*, 157, 501-516. <https://doi.org/10.1007/s10546-015-0069-x>
- Cereceda, P., & Schemenauer, R. S. (1991). The occurrence of fog in Chile. *Journal of Applied Meteorology*, 30(8), 1097-1105. [https://doi.org/10.1175/1520-0450\(1991\)030<1097:TOOFIC>2.0.CO;2](https://doi.org/10.1175/1520-0450(1991)030<1097:TOOFIC>2.0.CO;2)
- Chaouch, N., Temimi, M., Weston, M., & Ghedira, H. (2016). Sensitivity of the meteorological model WRF-ARW to planetary boundary layer schemes during fog conditions in a coastal arid region. *Atmospheric Research*, 187, 106-127. <https://doi.org/10.1016/j.atmosres.2016.12.009>
- De Villiers, M. P., & Van Heerden, J. (2007). Fog at Abu Dhabi international airport. *Weather*, 62, 209-214.
- del Río, C., Rivera, D., Siegmund, A., Wolf, N., Cereceda, P., Larraín, H., Lobos, F., Garcia, J.-L., Osses, P., Zanetta, N., & Lambert, F. (2018). ENSO Influence on Coastal Fog-

- Water Yield in the Atacama Desert, Chile. *Aerosol and Air Quality Research*, 18(1), 127-144. <https://doi.org/10.4209/aaqr.2017.01.0022>
- Eager, R. E., Raman, S., Wootten, A., Westphal, D. L., Reid, J. S., & Mandoos, A. A. (2008). A climatological study of the sea and land breezes in the Arabian Gulf region. *Journal of Geophysical Research Atmospheres*, 113(15), 1-12. <https://doi.org/10.1029/2007JD009710>
- Elhakeem, A., Elshorbagy, W., & Bleninger, T. (2015). Long-term hydrodynamic modeling of the Arabian Gulf. *Marine Pollution Bulletin*, 94(1-2), 19-36. <https://doi.org/10.1016/j.marpolbul.2015.03.020>
- Fabbian, D. a. (2007). Application of artificial neural network forecasts to predict fog at Canberra International Airport. *Weather and Forecasting*, 22(2), 372-381. <https://doi.org/10.1175/WAF980.1>
- Filioglou, M., Giannakaki, E., Backman, J., Kesti, J., Hirsikko, A., Engelmann, R., Connor, E. O., Leskinen, J. T. T., Shang, X., Korhonen, H., Lihavainen, H., Oapos, Connor, E., Leskinen, J. T. T., Shang, X., Korhonen, H., Lihavainen, H., Romakkaniemi, S., & Komppula, M. (2020). Optical and geometrical aerosol particle properties over the United Arab Emirates. *Atmospheric Chemistry and Physics Discussions*(March), 1-26. <https://doi.org/10.5194/acp-2020-133>
- Gandhidasan, P., & Abualhamayel, H. I. (2012). Exploring fog water harvesting potential and quality in the Asir region, Kingdom of Saudi Arabia. *Pure and Applied Geophysics*, 169(5-6), 1019-1036. <https://doi.org/10.1007/s00024-011-0341-z>
- Ghude, S. D., Bhat, G. S., Prabhakaran, T., Jenamani, R. K., Chate, D. M., Safai, P. D., Karipot, A. K., Konwar, M., Pithani, P., Sinha, V., Rao, P. S. P., Dixit, S. A., Tiwari, S., Todekar, K., Varpe, S., Srivastava, A. K., Bisht, D. S., Murugavel, P., Ali, K., Mina, U., & Dharua, M. a. (2017). Winter fog experiment over the Indo-Gangetic plains of India. *Current Science*, 112(4), 767-784. <https://doi.org/10.18520/cs/v112/i04/767-784>
- Gultepe, I., Tardif, R., Michaelides, S. C., Cermak, J., Bott, A., Bendix, J., Mller, M. D., Pagowski, M., Hansen, B., Ellrod, G., Jacobs, W., Toth, G., & Cober, S. G. (2007). Fog Research: A Review of Past Achievements and Future Perspectives. *Pure Appl. Geophys.*, 164, 1121-1159. <https://doi.org/10.1007/s00024-007-0211-x>
- Haefelin, M., Dupont, J. C., Boyouk, N., Baumgardner, D., Gomes, L., Roberts, G., & Elias, T. (2013). A Comparative Study of Radiation Fog and Quasi-Fog Formation Processes During the ParisFog Field Experiment 2007. *Pure and Applied Geophysics*, 170(12), 2283-2303. <https://doi.org/10.1007/s00024-013-0672-z>
- Klemm, O., Schemenauer, R. S., Lummerich, A., Cereceda, P., Marzol, V., & Corell, D. a. (2012). Fog as a fresh-water resource: Overview and perspectives. *Ambio*, 41(3), 221-234. <https://doi.org/10.1007/s13280-012-0247-8>
- Lancaster, J., N., L., & Seely, M. K. (1984). Climate of the central Namib Desert. *Madoqua*, 1984(1), 5-61. https://doi.org/10.10520/AJA10115498_484
- Lehnert, L. W., Thies, B., Trachte, K., Achilles, S., Osses, P., Baumann, K., Schmidt, J., Samolov, E., Jung, P., Leinweber, P., Karsten, U., Bdel, B., & Bendix, J. (2018). A case study on fog/low stratus occurrence at las lomas, atacama desert (Chile) as a water source for biological soil crusts. *Aerosol and Air Quality Research*, 18(1), 254-269. <https://doi.org/10.4209/aaqr.2017.01.0021>
- Martorell, C., & Ezcurra, E. (2002). Rosette scrub occurrence and fog availability in arid mountains of Mexico. *Journal of Vegetation Science*, 13(5), 651-662. <https://doi.org/10.1111/j.1654-1103.2002.tb02093.x>
- Menut, L., Mailler, S., Dupont, J. C., Haefelin, M., & Elias, T. (2014). Predictability of the Meteorological Conditions Favourable to Radiative Fog Formation During the 2011 ParisFog Campaign. *Boundary-Layer Meteorology*, 150(2), 277-297. <https://doi.org/10.1007/s10546-013-9875-1>

- Naizghi, M. S., & Ouarda, T. B. M. J. (2017). Teleconnections and analysis of long-term wind speed variability in the UAE. *International Journal of Climatology*, 37(1), 230-248. <https://doi.org/10.1002/joc.4700>
- Nakanishi, M. (2000). Large-eddy simulation of radiation fog. *Boundary-Layer Meteorology*, 94(3), 461-493. <https://doi.org/10.1023/A:1002490423389>
- NCEI, N. (2001). *Integrated Global Surface Hourly Dataset* ftp.ncdc.noaa.gov/pub/data/noaa/
- NOAA, & USAAF. (2018). *Federal Climate Complex Data Documentation for Integrated Surface Data (ISD)*.
- Olivier, J. (1995). Spatial distribution of fog in the Namib. *Journal of Arid Environments*, 29(2), 129-138. [https://doi.org/https://doi.org/10.1016/S0140-1963\(05\)80084-9](https://doi.org/https://doi.org/10.1016/S0140-1963(05)80084-9)
- Oolman, L. (2019). *Wyoming Weather Web*. Retrieved July 2019 from <http://weather.uwyo.edu>
- Ouarda, T. B. M. J., Charron, C., Niranjan Kumar, K., Marpu, P. R., Ghedira, H., Molini, A., & Khayal, I. (2014). Evolution of the rainfall regime in the united arab emirates. *Journal of Hydrology*, 514, 258-270. <https://doi.org/10.1016/j.jhydrol.2014.04.032>
- Payra, S., & Mohan, M. (2014). Multirule based diagnostic approach for the fog predictions using WRF modelling tool. *Advances in Meteorology*, 2014. <https://doi.org/10.1155/2014/456065>
- Pithani, P., Ghude, S. D., Chennu, V. N., Kulkarni, R. G., Steeneveld, G. J., Sharma, A., Prabhakaran, T., Chate, D. M., Gultepe, I., Jenamani, R. K., & Madhavan, R. (2019). WRF Model Prediction of a Dense Fog Event Occurred During the Winter Fog Experiment (WIFEX). *Pure and Applied Geophysics*, 176(4), 1827-1846. <https://doi.org/10.1007/s00024-018-2053-0>
- Price, J. (2011). Radiation Fog. Part I: Observations of Stability and Drop Size Distributions. *Boundary-Layer Meteorology*, 139(2), 167--191. <https://doi.org/10.1007/s10546-010-9580-2>
- Reid, J. S., Piketh, S. J., Walker, A. L., Burger, R. P., Ross, K. E., Westphal, D. L., Brientjes, R. T., Holben, B. N., Hsu, C., Jensen, T. L., Kahn, R. A., Kuciauskas, A. P., Mandoos, A. A., Mangoosh, A. A., Miller, S. D., Porter, J. N., Reid, E. A., & Tsay, S. C. (2008). An overview of UAE2 flight operations: Observations of summertime atmospheric thermodynamic and aerosol profiles of the southern Arabian Gulf. *Journal of Geophysical Research Atmospheres*, 113(14), 1-14. <https://doi.org/10.1029/2007JD009435>
- Reid, J. S., Reid, E. A., Walker, A., Piketh, S., Cliff, S., Mandoos, A. A., Tsay, S. C., & Eck, T. F. (2008). Dynamics of southwest Asian dust particle size characteristics with implications for global dust research. *Journal of Geophysical Research Atmospheres*, 113(14), 1-14. <https://doi.org/10.1029/2007JD009752>
- Román-Cascón, C., Steeneveld, G. J., Yagüe, C., Sastre, M., Arrillaga, J. A., & Maqueda, G. (2016). Forecasting radiation fog at climatologically contrasting sites: evaluation of statistical methods and WRF. *Quarterly Journal of the Royal Meteorological Society*, 142(695), 1048-1063. <https://doi.org/10.1002/qj.2708>
- Román-Cascón, C., Yagüe, C., Steeneveld, G.-J., Sastre, M., Arrillaga, J. A., & Maqueda, G. (2016). Estimating fog-top height through near-surface micrometeorological measurements. *Atmospheric Research*, 170, 76-86. <https://doi.org/10.1016/j.atmosres.2015.11.016>
- Seely, M., & Henschel, J. R. (1998). The climatology of Namib fog. 19-24.
- Sheppard, C., Al-Husiani, M., Al-Jamali, F., Al-Yamani, F., Baldwin, R., Bishop, J., Benzoni, F., Dutrieux, E., Dulvy, N. K., Durvasula, S. R. V., Jones, D. A., Loughland, R., Medio, D., Nithyanandan, M., Pilling, G. M., Polikarpov, I., Price, A. R. G., Purkis, S., Riegl, B., Saburova, M., Namin, K. S., Taylor, O., Wilson, S., & Zainal, K. (2010). The Gulf: A young sea in decline. *Marine Pollution Bulletin*, 60(1), 13-38. <https://doi.org/10.1016/j.marpolbul.2009.10.017>

- Spirig, R., Vogt, R., Larsen, J. A., Feigenwinter, C., Wicki, A., Franceschi, J., Parlow, E., Adler, B., Kalthoff, N., Cermak, J., Andersen, H., Fuchs, J., Bott, A., Hacker, M., Wagner, N., Maggs-Killing, G., Wassenaar, T., & Seely, M. (2019). Probing the fog life cycles in the Namib desert. *Bulletin of the American Meteorological Society*, 100(12), 2491-2507. <https://doi.org/10.1175/BAMS-D-18-0142.1>
- Steeneveld, G. J., & de Bode, M. (2018). Unravelling the relative roles of physical processes in modelling the life cycle of a warm radiation fog. *Quarterly Journal of the Royal Meteorological Society*, 144(714), 1539-1554. <https://doi.org/10.1002/qj.3300>
- Steeneveld, G. J., Hartogensis, O. K., Moene, a. F., Baltink, H. K., & Holtslag, a. a. M. (2008). WRF Visitors Program Report Evaluation of WRF model improvements with novel boundary - layer observations - Focus on diurnal cycle and stable boundary layer. *WRF Visitors Program Report*, 1-17.
- Steeneveld, G. J., Ronda, R. J., & Holtslag, A. A. M. (2014). The Challenge of Forecasting the Onset and Development of Radiation Fog Using Mesoscale Atmospheric Models. *Boundary-Layer Meteorology*, 154(2), 265-289. <https://doi.org/10.1007/s10546-014-9973-8>
- Sterk, H. A. M., Steeneveld, G. J., Vihma, T., Anderson, P. S., Bosveld, F. C., & Holtslag, A. A. M. (2015). Clear-sky stable boundary layers with low winds over snow-covered surfaces. Part 1: WRF model evaluation. *Quarterly Journal of the Royal Meteorological Society*, 141(691), 2165-2184. <https://doi.org/10.1002/qj.2513>
- Tardif, R., & Rasmussen, R. M. (2007). Event-based climatology and typology of fog in the New York City region. *Journal of Applied Meteorology and Climatology*, 46(8), 1141-1168. <https://doi.org/10.1175/JAM2516.1>
- Teixeira, J., & Miranda, P. M. A. (2001). Fog prediction at Lisbon airport using a one-dimensional boundary layer model. *Meteorological Applications*, 8(4), 497-505. <https://doi.org/10.1017/S135048270100411X>
- Temimi, M., Fonseca, R. M., Nelli, N. R., Valappil, V. K., Weston, M. J., Thota, M. S., Wehbe, Y., & Yousef, L. (2020). On the analysis of ground-based microwave radiometer data during fog conditions. *Atmospheric Research*, 231, 104652. <https://doi.org/10.1016/j.atmosres.2019.104652>
- Terpstra, J. (1999). *De invloed van de grondwaterstand, wind, temperatuur en dauwpunt op de vorming van stralingsmist: een kwantitatieve benadering*.
- van Schalkwyk, L., & Dyson, L. L. (2013). Climatological characteristics of fog at cape town international airport. *Weather and Forecasting*, 28(3), 631-646. <https://doi.org/10.1175/WAF-D-12-00028.1>
- Vinod Kumar, K., Seemanth, M., Vethamony, P., & Aboobacker, V. M. (2014). On the spatial structure and time evolution of shamal winds over the Arabian Sea - a case study through numerical modelling. *International Journal of Climatology*, 34(6), 2122-2128. <https://doi.org/10.1002/joc.3819>
- Weston, M., Chaouch, N., Valappil, V., Temimi, M., Ek, M., & Zheng, W. (2018). Assessment of the Sensitivity to the Thermal Roughness Length in Noah and Noah-MP Land Surface Model Using WRF in an Arid Region. *Pure and Applied Geophysics*. <https://doi.org/10.1007/s00024-018-1901-2>
- Weston, M. J., & Temimi, M. (2020). Application of a night time fog detection method using SEVIRI over an arid environment. *Remote Sensing*, 12(14). <https://doi.org/10.3390/rs12142281>
- World Meteorological Organization. (2008). Aerodrome reports and forecasts: a users' handbook to the codes.
- Yousef, L. A., Temimi, M., & Wehbe, Y. a. (2019). Total cloud cover climatology over the United Arab Emirates. *Atmospheric Science Letters*, 20(2), 1-10. <https://doi.org/10.1002/asl.883>

Zhou, B., & Du, J. (2010). Fog Prediction from a Multimodel Mesoscale Ensemble Prediction System. *Weather and Forecasting*, 25, 303-322.
<https://doi.org/10.1175/2009WAF2222289.1>

CHAPTER 3 APPLICATION OF A NIGHTTIME FOG DETECTION METHOD USING SEVIRI OVER AN ARID ENVIRONMENT

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Abstract: Fog degrades horizontal visibility causing significant adverse impacts on transport systems. The detection of fog from satellite data remains challenging especially in the presence of higher clouds, dust, mist, or unknown underlying soil conditions. Observations from Meteosat second generation Spinning-Enhanced Visible and Infrared Imager (MSG SEVIRI) over the United Arab Emirates (UAE), an arid area on the Arabian Peninsula, from 2016 to 2018 (two fog seasons) are used in this study. We implement an adaptive threshold-based technique using pseudo emissivity values to detect nocturnal fog from SEVIRI. The method allows the threshold to vary spatially and temporally. Low clouds are detected with the analysis of the vertical temperature gradient. Fog classification was verified against four stations in the UAE, namely Abu Dhabi, Dubai, Al Ain, and Al Maktoum, where visibility and meteorological observations are available. The probability of detection (POD) (false alarm ratio (FAR)) was 0.81 (0.40), 0.83 (0.50), 0.83 (0.33), and 0.77 (0.44) at Abu Dhabi, Dubai, Al Ain, and Al Maktoum, respectively. In addition, the spatial frequency of fog is presented, which provides new insights into the fog dynamics in the region.

Keywords: fog; SEVIRI; desert; pseudo-emissivity; brightness temperature difference

3.1 Introduction

The detection of fog and low cloud (FLC) from satellite data remains challenging despite advances in methodologies and technology. However, satellite products remain beneficial and informative in areas where there is a low density of observations, which is often the case in desert areas (Gultepe et al., 2019). Satellite-based approaches of fog detection make use of channel brightness temperature difference. In the case of dense ground observation networks, fog detection could rely on surface observations. A combination of satellite- and ground-based

observation is also possible to enhance fog detection and tracking. In such contexts, ground observations could be invaluable in the case of obstruction by higher clouds (Yousef et al., 2019) or in the presence of mist or haze, which could lead to false alarms in the satellite products.

The most widely satellite-based approach implemented to detect FLC is the brightness temperature difference method (BTD). This method was first implemented on polar orbiting satellites (Eyre et al., 1984; Turner et al., 1986), but has since been adapted to geostationary instruments including the Spinning-Enhanced Visible and Infrared Imager (SEVIRI) on board Meteosat (Cermak & Bendix, 2007, 2008; Nilo et al., 2018). In brief, the brightness temperature difference between the 10.8 and 3.9 μm channels is calculated based on the theory that fog droplets produce a lower emissivity at 3.9 than 10.8 μm (Cermak & Bendix, 2007, 2008; Nilo et al., 2018). As described by Cermak and Bendix (2008), a threshold value can be identified from the BTD distribution, which distinguishes clear sky from FLC as they are located on different parts of the distribution. This threshold is then applied to the BTD producing a FLC mask image. Two limitations of this method are that it is only effective at nighttime and that fog cannot be distinguished from low cloud.

The problem at daytime is that the reflectance of sunlight from clouds overrides the brightness temperature signal in the infrared channels. Twilight hours can also be challenging as sunlight can reflect off the top of the atmosphere. To overcome this, some studies define separate algorithms for night and day (e.g. (Cermak & Bendix, 2007, 2008)) or develop new methods for daytime detection (e.g. (Andersen & Cermak, 2018; Cermak, 2012; Egli et al., 2018; Nilo et al., 2018)).

One option to distinguish fog from low cloud is to use real time observations or forecasts of land surface temperature (LST) and to compare it to satellite surface brightness temperature usually at 10.8 μm that could be considered as a proxy for LST (Calvert & Pavolonis, 2010). The assumption is that observations at the 10.8 channel represent cloud top temperature. In the absence of low cloud or fog, observations at the 10.8 channel should be close to the LST. Hence, a significant difference between simulated LST and cloud top temperature should eliminate low cloud from the classification. If these differ beyond a threshold value it is then assumed that FLC is low cloud and not fog.

An alternative methodology to BTM was proposed which makes use of the same channel information, but calculates a pseudo-emissivity for channel 3.9 μm ($\text{ems}(3.9)$) (Calvert & Pavolonis, 2010; Pavolonis & Heidinger, 2005). The pseudo emissivity method has been shown to return higher skill scores than the BTM method (Calvert & Pavolonis, 2010) on the GOES-R Advanced Baseline Imager (ABI). In this approach, the blackbody radiance at 3.9 μm is calculated using the brightness temperature from the 10.8 μm channel. This is then used, along with the radiance at 3.9 μm , to calculate the pseudo-emissivity. Like the BTM, the theory behind this method is that small cloud droplets in fog have a smaller emissivity at 3.9 than 10.8 μm . The approach in calculating the threshold $\text{ems}(3.9)$ is similar to BTM. A frequency distribution of $\text{ems}(3.9)$ is calculated where the peak frequency represents clear sky and fog conditions occur to the left of the peak (Cermak & Bendix, 2008). The threshold is a point that divides these parts of the distribution. This method has the same limitations as the BTM method: it is effective at night and it requires the removal of low cloud from the classification.

This study is a continuation of the above-mentioned effort to detect fog using satellite observations. This study introduces an adaptive threshold-based method that accounts for the temporal and spatial variability of fog conditions and their spectral signatures (Cermak & Bendix, 2007, 2008). We test the pseudo-emissivity method for nighttime fog detection over a desert area in the UAE and expand it to SEVIRI observations after being tested on Geostationary Operational Environmental Satellite-R Series Advanced Baseline Imager (GOES-R ABI) data. Eventually, the developed fog detection approach leads to a better understanding of fog dynamics and climatology across the UAE.

3.2 Materials and Methods

3.2.1 Study Area

The United Arab Emirates (UAE) is an arid country located on the northeastern edge of the Arabian Peninsula (Figure 3-1). It has sparse to bare vegetation and the main soil type is sand and loamy sand. It has a mean annual rainfall of about 78 mm (Ouarda & Charron, 2014), and the dominant land cover type is bare or sparsely vegetated desert. The UAE experiences radiation fog, most frequently in winter months (De Villiers & Van Heerden, 2007; Thota et al., 2020). Low visibility events are more often associated with humid atmospheric conditions than with dry and dusty conditions (Aldababseh & Temimi, 2017; Karagulian et al., 2019). The Persian Gulf is a warm and shallow water body and is located to the north of the UAE which is a source of water vapor in the atmosphere (Elhakeem et al., 2015; Sheppard et al., 2010). Fog formation requires that moisture be advected over the land from the Gulf during the day

(Bartok et al., 2012; Weston et al., 2018). During the night, the land cools down quickly due to the high albedo of the desert and radiative cooling (Bartok et al., 2012). Fog forms mostly at night with peak fog occurring around sunrise (De Villiers & Van Heerden, 2007). Fog quickly dissipates after sunrise, although thick fog can persist until 10:00 h local time. Fog is often associated with a strong surface inversion layer (Chaouch et al., 2016; Temimi et al., 2020). Fog occurs most frequently over the land with a clear boundary at the coastline. The air over the Gulf is warmer at night and dew point temperature is seldom reached. Although marine fog does occur, it is less frequent than fog over the land.

3.2.2 Datasets

3.2.2.1 SEVIRI Data

SEVIRI data from Meteosat-10 situated over 9.5 °E was utilized for this study. The period of investigation covered two fog seasons namely December 2016 to March 2017 and October 2017 to March 2018. Channel data from channel 4 (IR 3.9 μm) and 9 (IR 10.8 μm) were used in the fog detection algorithm (Calvert & Pavolonis, 2010; Pavolonis & Heidinger, 2005). The scene was subset to the region of interest and the resolution is around 3 km. Although SEVIRI data are available every 15 minutes, only hourly data (top of the hour) were used in the verification process, as they are coincident with meteorological aerodrome report (METAR) observations. The final fog mask field was further clipped to the borders of the UAE.

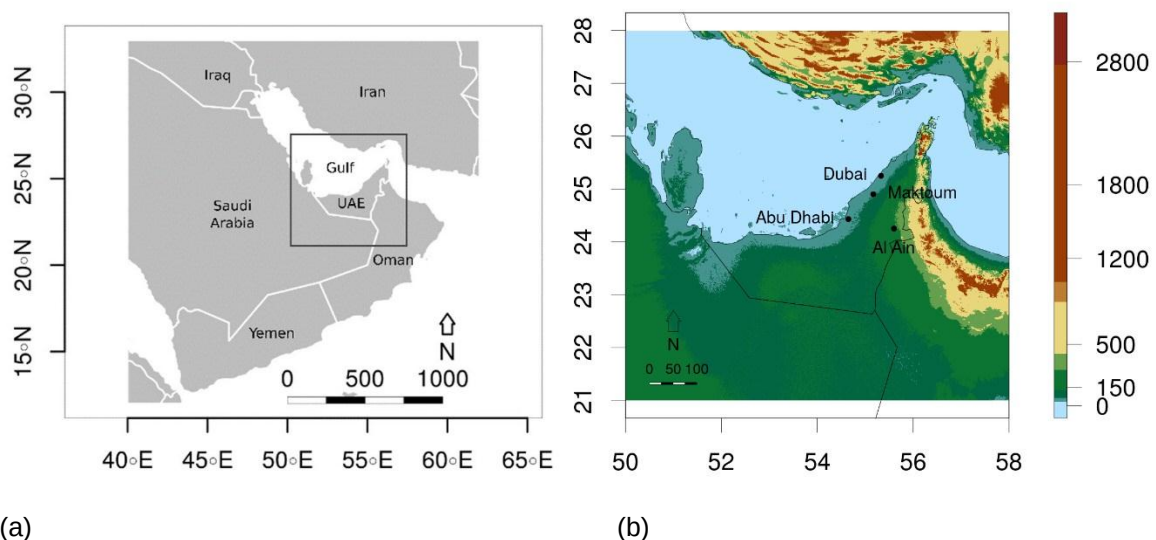


Figure 3-1: (a) The United Arab Emirates (UAE) is located on the Arabian Peninsula. (b) Terrain (meters above sea level) and location of

meteorological aerodrome report (METAR) stations used for verification.

3.2.2.2 METAR Data

Meteorological aerodrome reports (METAR) were downloaded from NOAA National Climatic Data Center (NCDC) database in the integrated surface data (ISD) format. Data from four stations were used for verification, namely Abu Dhabi (OMAA, 54.65E, 24.43N), Dubai (OMDB, 55.33E, 25.25N) Al Ain (OMAL, 55.60E, 24.25N), and Al Maktoum (OMDW, 55.17E, 24.90N). These four stations have the highest frequency of fog events in the UAE (Aldababseh & Temimi, 2017). Hourly and special reports (sub hourly) were used to identify fog events based on the weather description codes that indicate fog and where visibility was below 1000 m.

3.2.2.3 ERA5 Data

Land surface temperature from ERA5 data was used in the process of low cloud removal. ERA5 is a global atmospheric reanalysis product which is available from 1979 until the present (Copernicus Climate Change Service (C3S), 2017; Hersbach et al., 2019). Data is available hourly and at a resolution of 30 km. The data is the result of an ensemble of models, combined with observations. The land surface temperature field was downloaded from the Copernicus Climate Data Store for the months of interest (Copernicus Climate Change Service (C3S), 2017).

3.2.3 Fog/Low Clouds Detection

We test a threshold-based method for detecting fog/low cloud from SEVIRI data. The method uses pseudo-emissivity (ems(3.9)), as described by Calvert and Pavolonis (2010) (Calvert & Pavolonis, 2010; Pavolonis & Heidinger, 2005), to detect fog and low cloud. It uses adaptive threshold values that are determined on a pixel basis and vary monthly. The threshold was determined dynamically by modifying the method described by Cermak and Bendix (2008). In this method, the frequency distribution of pseudo-emissivity is calculated on a pixel basis. A threshold value along the distribution indicates a change in frequency, which represents a change in sky conditions. The assumption is that this threshold separates clear sky from fog cases. The threshold based method in Cermak and Bendix (2008) was applied to the entire scene without accounting for potential spatial and temporal variabilities of the determined

thresholds. In the present study, the threshold-based method is applied on a pixel basis while accounting for the monthly variability.

Our hypothesis is that the distribution should change in space, and thus a single threshold value across space will result in biases. A histogram of $ems(3.9)$ was calculated per month for each pixel using a bin size of 0.032 and ranging from 0.4 to 1.072.

Pseudo-emissivity was calculated using equation (1) (Calvert & Pavolonis, 2010).

$$ems(3.9) = \frac{R_{Obs}(3.9)}{B(3.9, BT(10.8))}, \quad (1)$$

where R_{Obs} is the radiance at $3.9\mu m$ observed in the satellite data, BT is the brightness temperature at $10.8\mu m$, and B is the Planck function defined in equation (2) (Cao, 2013).

$$B(v, t) = \frac{C_1 v^3}{e^{C_2/v} - 1}, \quad (2)$$

where $B(v, t)$ is the blackbody radiance ($mW/m^2 \cdot sr \cdot cm^{-1}$), $C_1 = 1.19104 \times 10^{-5} (mW/m^2 \cdot sr \cdot cm^{-4})$, $C_2 = 1.43877 \times 10 (K \cdot cm)$, v = wavenumber (cm^{-1}), λ = wavelength (μm), and t = blackbody temperature (K).

Nighttime hours from 20:00 to 06:00 h local time were included in the sample size. The threshold value was determined from the first two values after the maximum count in the histogram, depending on which had the largest decrease in counts compared to the adjacent bin. In other words, if;

$(count(indexmax) - (count(indexmax - 1))) > (count(indexmax - 1) - count(indexmax - 2));$

then

$ems[index(countmax)-1]$ (line 1 in Figure 3-2), ;

else

$ems[index(countmax) - 2]$ (line 2 in Figure 3-2).

A further condition was activated if $ems[index(count_{max}) - 2]$ was selected, where half the bin size, 0.016 was added to the pseudo-emissivity value. A schematic of this approach is presented in Figure 3-2. This approach is dynamic and returns varying threshold spatially, which should result in increased verification scores.

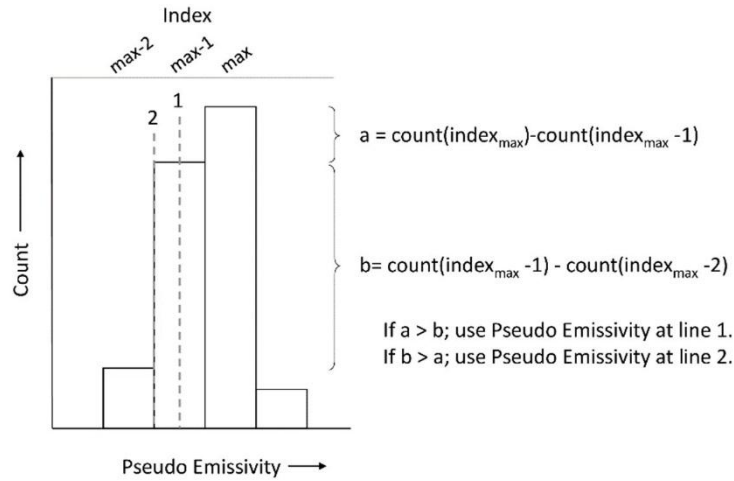


Figure 3-2: Schematic indicating how the threshold value was selected based on the histogram of pseudo-emissivity at each pixel.

The determination of the threshold described above is conducted by running an optimization process on the satellite data over the selected test sites. In this process, a range of threshold values for our verification sites is applied to obtain the first guess of the thresholds that should provide the best POD and FAR (described in section 3.2.5) when compared to observed fog cases. Furthermore, the sensitivity of the obtained thresholds to the bin size was accounted for. Calvert and Pavlonis (2010) proposed a bin size of 0.02. In this study, we found that the larger bin size of 0.032 along with the method for finding the threshold performed best for our region.

3.2.4 Low Cloud Detection

In the final analysis, fog and low cloud were distinguished from each other using a temperature difference method. This method makes use of an observed or proxy surface temperature value and the brightness temperature of the 10.8 channel. Similar approaches have been described by Ellrod (2002) and Calvert and Pavlonis (2010). The theory here is that the window channel (10.8) is an approximation of land surface temperature for non-cloudy scenes, and cloud top temperature for cloudy scenes. When scenes are cloud free the temperature should be close to each other and when scenes contain cloud they should be further apart. ERA5 data was used in place of land surface temperature (LST) observations and 10.8 μm as the satellite brightness temperature (BT). Low cloud was defined when $\text{BT}(10.8) - \text{ERA5}(\text{LST}) < -4 \text{ K}$. The threshold values were compared to fog cases and found to be suitable for our region. This threshold should be region-specific. An overview of the methodology is provided in Figure 3-3.

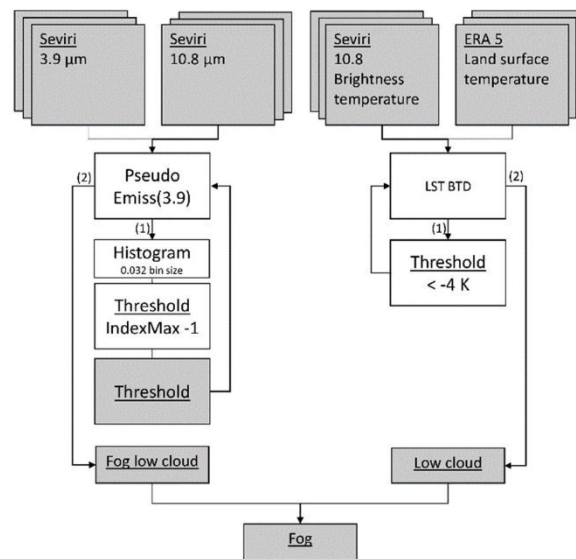


Figure 3-3: Overview of the Spinning-Enhanced Visible and Infrared Imager (SEVIRI) fog detection methodology. Gray boxes represent data layers and white boxes represent data processing. The numbers on the arrows represent the path on the first and second iteration, respectively. This method was applied per pixel and over a one-month period for each month in the study period.

3.2.5 Verification

An assessment period of ten months, from December 2016 to March 2017 and October 2017 to March 2018, was used to determine the thresholds using a combination of collocated satellite and METAR records. This period is representative of two fog seasons. The satellite product was assessed over a 6-hour window from 00:00 to 06:00 h local time over the 10 month period. A hit is recorded when fog occurs in the METAR in any of the six hours and in the airport pixel from SEVIRI for any of the six hours (Table 3-1). This window was chosen as it was the period that fog was most active and it avoided sunlight hour events (solar zenith angle was greater than 90 at all verification points). Hourly matches were avoided as there was frequent contamination from higher thin cloud which affected the overall statistics. The aim was to assess daily fog frequency and not to assess hourly performance.

Table 3-1: Contingency table.

	METAR fog yes	METAR fog no
SEVIRI fog yes	Hits	False Alarms
SEVIRI fog no	Misses	Correct Negative

The probability of detection (POD), which is sometimes called hit rate, was calculated as follows:

$$POD = \frac{Total\ hits}{Total\ hits + total\ misses}, \quad (3)$$

where 1 is a perfect score. A score of 0.8 can be interpreted as 8 out of 10 observations are correctly identified. The false alarm ratio was calculated as follows:

$$FAR = \frac{Total\ false\ alarms}{Total\ hits + total\ false\ alarms}, \quad (4)$$

where 0 is a perfect score as it would indicate no false alarms and the theoretical maximum is 1 (all events were false alarms). A score of 0.4 can be interpreted as 4 out of 10 identified events were false alarms.

3.3 Results and Discussion

3.3.1 Histograms

A comparison between the optimal threshold and the calculated threshold at Abu Dhabi for January 2018 is shown in Figure 3-4. The optimal threshold was calculated as 0.80 (POD=1, FAR=0.2), while the calculated threshold was 0.82 (POD=1, FAR=0.33). Other months and sites (not shown) provided similar results. The similarity between the optimal and calculated thresholds demonstrate that the method used to determine the threshold value is suitable.

Initially our threshold value was $index_{max}-1$. After the optimization, the thresholds were revised to allow lower values in some cases, which led to the inclusion of $index_{max}-2$ (i.e. line 1 and 2 in Figure 3-2).

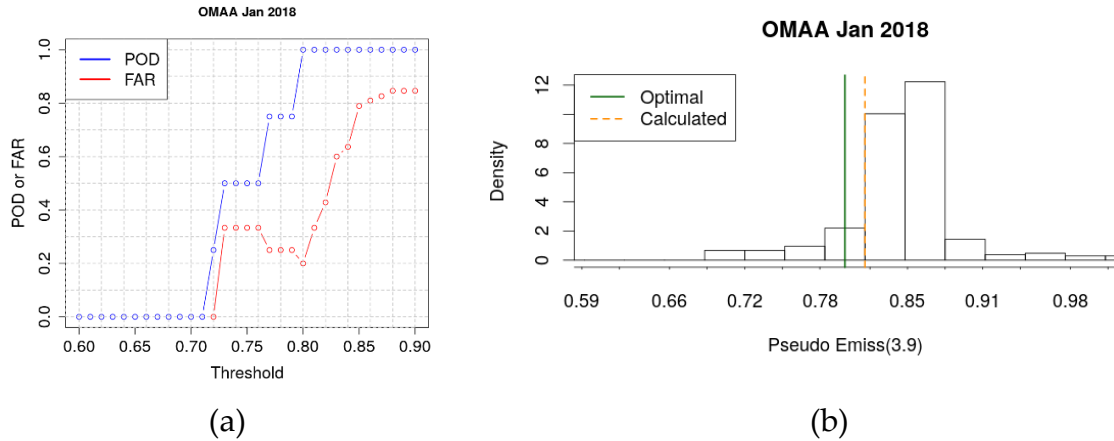


Figure 3-4: a) Example of calculated optimal threshold at Abu Dhabi (OMAA) for January 2018. Here the optimal threshold is 0.80 (POD=1, FAR=0.2). b) The calculated threshold was 0.82.

The $\text{ems}(3.9)$ histogram shows a large spread in threshold values, which is due to the monthly variability of the calculated $\text{ems}(3.9)$ values (Figure 3-5). Calvert and Pavolonis (2010) found the optimal threshold to be 0.7. However, our results range from 0.78 to 0.85.

The threshold used by Calvert and Pavolonis (2010) is intended for the ABI instrument on GOES-R. This instrument has a narrower bandwidth for the 3.9 μm channel of 0.2 μm compared to the SEVIRI instrument which has a bandwidth of 0.88 μm for the 3.9 μm channel (Dammann et al., 2005). SEVIRI also has a broader bandwidth for the 10.8 μm channel. This will result in different pseudo-emissivity values and alone may be the reason for the difference in threshold values.

However, three additional possibilities for this discrepancy are proposed. The first is that we use a dynamic threshold, both spatially and temporally. Our thresholds vary between sites and across the desert, which may suggest that a static threshold value may not be appropriate for the study case.

The second is a simple trade off. If we went with a more conservative threshold of 0.7, we would miss some events and decrease the POD score. In our approach we have tried to capture all possible events that were not affected by cloud cover. As such, the determined thresholds are more inclusive and may produce more false alarms. However, the third reason is that the study region is mostly homogenous in comparison to the study area in Calvert and Pavolonis (2010).

The study region in this paper is homogenous in many ways; the land cover is mostly desert, the terrain where fog forms is mostly flat/not complex, and the cloud phase is mostly warm and occurs in one season-winter. In comparison to Calvert and Pavolonis (2010), study sites cover much more diverse characteristics over a larger area. As such our thresholds may be optimal for our region. Cermak (2012) reported similarly in their study, that thresholds determined for Namibia may not be transferable to other regions. However, here we would like to highlight that our method in determining the threshold value is adaptive and has the potential to be transferred to other regions.

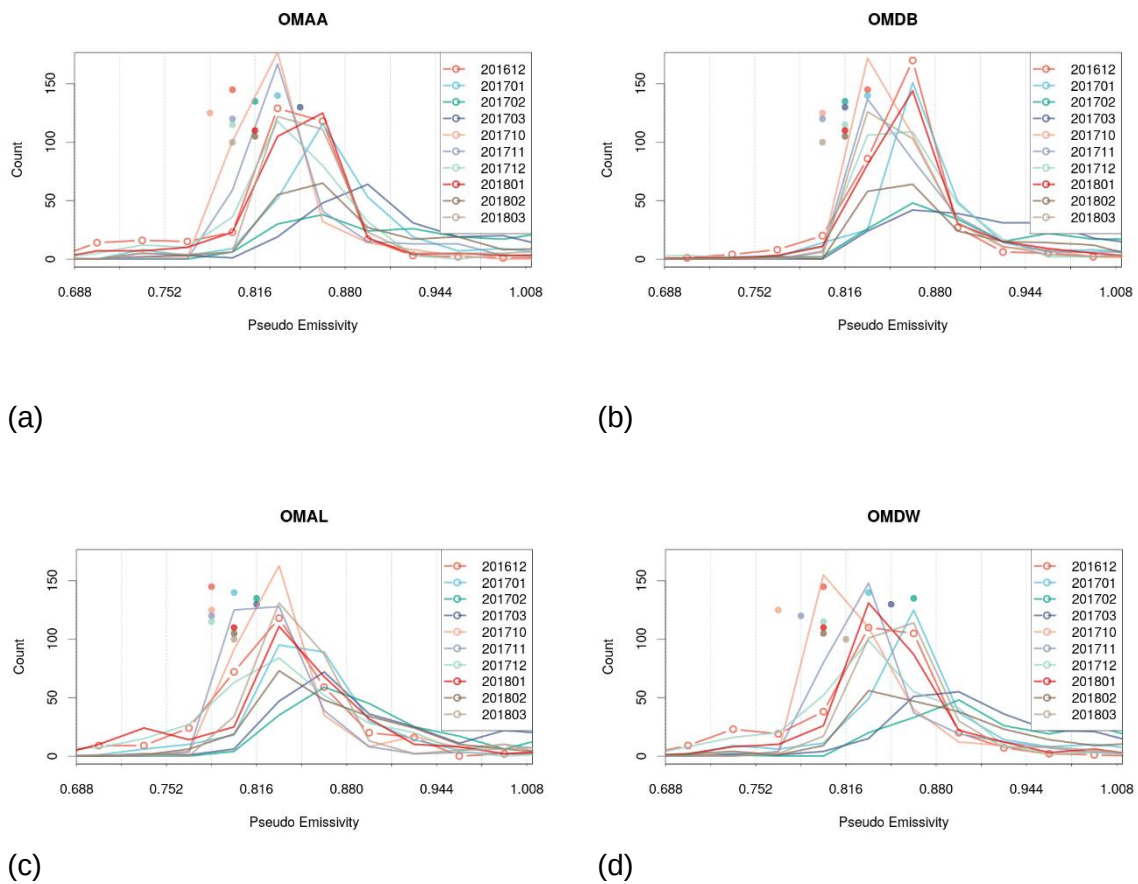


Figure 3-5: Histogram of $\text{ems}(3.9)$ at a) Abu Dhabi (OMAA) b) Dubai (OMDB), c) Al Ain (OMAL) and d) Al Maktoum (OMDW). Monthly threshold values are indicated by closed circles on the pseudo emissivity plots. Placement on the y-axis is arbitrary for these dots in order to avoid concealment from overlap.

3.3.2 Monthly Threshold Maps: ems(3.9)

Monthly threshold maps produce similar spatial patterns of threshold values, with higher thresholds along the coast and lower thresholds further south at the start of the Empty Quarter (area of Saudi Arabia directly South of the UAE) (Figure 3-6). This suggests that the method accounts for the underlying spatial variation of emissivity from the desert (Hulley et al., 2015), and that a spatially dynamic threshold is required for fog detection. The method shows gradual changes in spatial distribution from month to month, supporting that monthly threshold values should be used when identifying fog and low cloud. The ems(3.9) threshold shows a smooth transition from one threshold to the next along a gradient (i.e., there is no obvious inter pixel noise). This could be due to the choice of bin size in the histogram and the optimization approaches mentioned in the methodology section.

An example of the ems(3.9)-low cloud classification is shown in Figure 3-7 for an event at 03:00 h local time on 15 January 2018. This case is compared to the false color composite of the night microphysical product from EUMETSAT (EUMETSAT, 2009). In this product, red is the difference between 12.0 and 10.8 μm channels (linear stretch -4 to 2 K), green is the difference between 10.8 and 3.9 μm channels (linear stretch 0 to 10 K) and blue is the 10.8 μm channel (linear stretch 243 to 293 K). This event is interesting as the fog patch extends across the threshold gradient from north to south, and yet is captured by the classification. This is true for many more cases (see Figures S1–S6 in the supplementary material) which corroborate that the reliability of the threshold value method is correct and should not create any spatial bias in determining fog frequency.

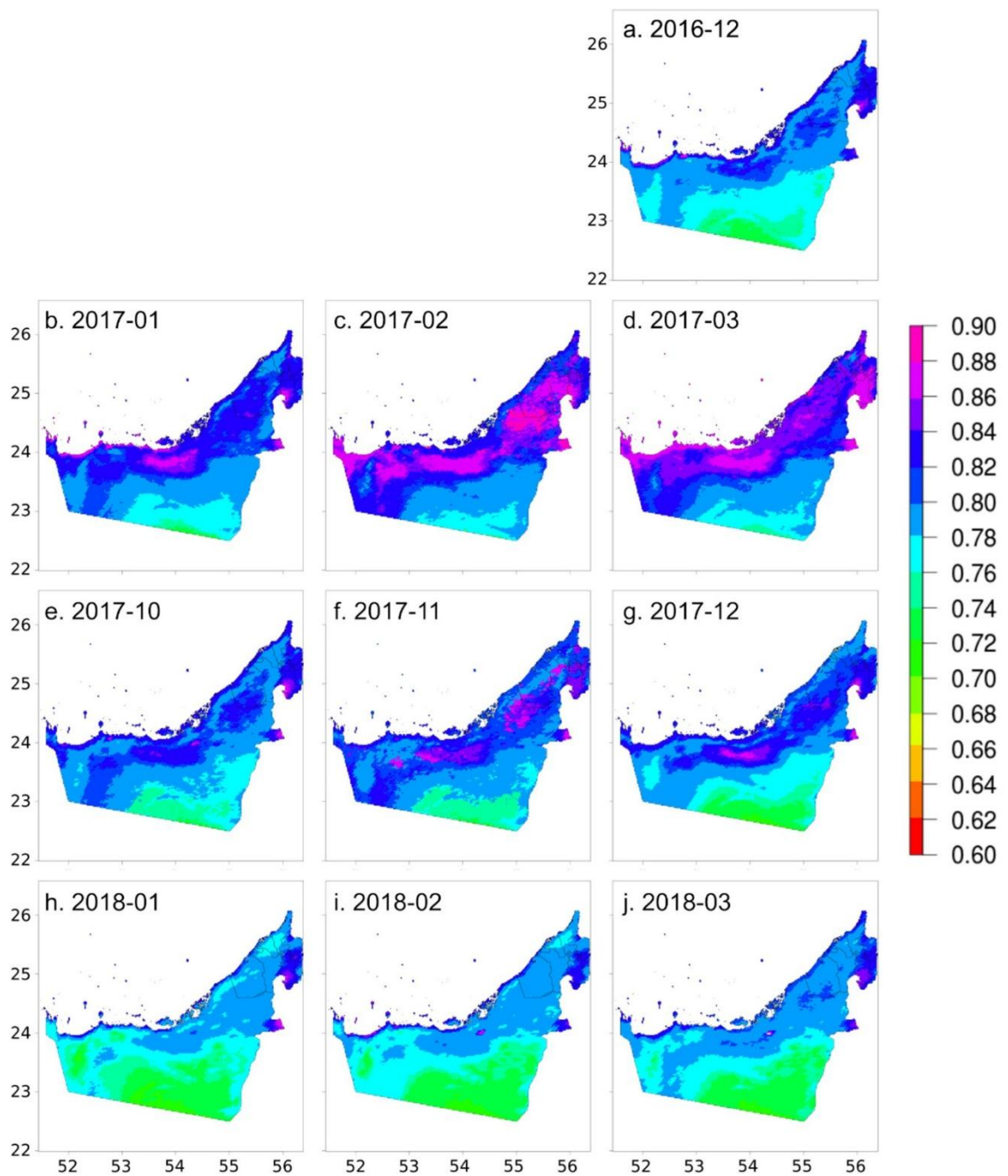


Figure 3-6: Spatial distribution of monthly threshold value of $ems(3.9)$ from (a–d) December 2016 to March 2017 and (e–j) October 2017 to March 2018.

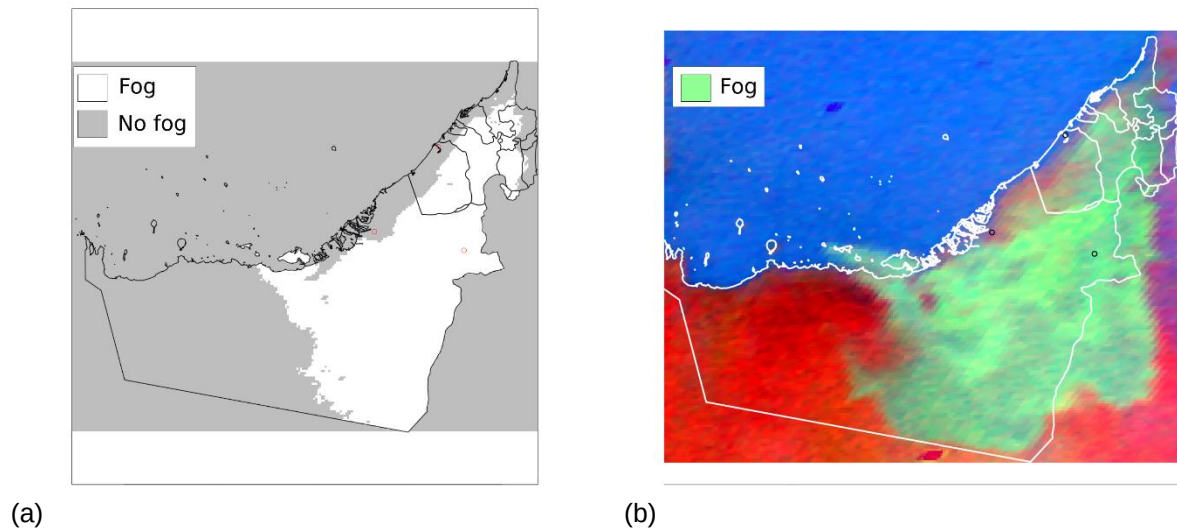


Figure 3-7: a) Example of ems(3.9)-low cloud fog classification in comparison with b) the EUMETSAT night microphysical product (EUMETSAT, 2009) for 2018-01-15 0300 local time.

3.3.3 Assessment Over Two Fog Seasons

Here, we present the statistical verification of the ems(3.9) method over two fog seasons where 32 fog days were observed at Abu Dhabi, 12 at Dubai, 24 at Al Ain, and 30 at Al Maktoum. The first season is December 2016 to March 2017 and the second is October 2017 to March 2018, comprising 303 days in total.

The POD (FAR) was 0.81 (0.40), 0.83 (0.50), 0.83 (0.33), and 0.77 (0.44) at Abu Dhabi, Dubai, Al Ain, and Al Maktoum, respectively (Table 3-2). In all cases the total false alarms exceeded the total missed events, which means there is a positive bias in the fog classification. These biases were 34%, 66%, 25%, and 36% for Abu Dhabi, Dubai, Al Ain, and Al Maktoum, respectively. Of the six missed events at Abu Dhabi, three were affected by overhead cloud, two were events that occurred at 06:00 h local time (detection has a negative bias at 06:00 h), and one was due to the thick fog being thrown out as low cloud. Of the 10 missed events at Dubai, at least two were actual fog events (2016-12-27 and 2017-12-25), but surprisingly the visibility reported in the METAR was greater than 1 km. An inspection of the hourly fog masks revealed that many of the false alarms occurred when Dubai airport was on the edge of the fog event. The detection in these cases was larger than the actual event, which may be due to haze and mist at the edge of the fog being included in the classification. Thus, we suspect that the classification is including haze and mist in some cases. Similar cases of fog edge

were identified for false alarms at Al Ain, although the performance at Al Ain was the best of the verification sites.

We acknowledge that further analysis, such as edge detection, can be applied to filter the false alarms and, therefore, improve the statistics which could be addressed in a future work. Other studies of nighttime fog detection have achieved lower FAR values after applying additional filters following the initial fog detection process (Andersen & Cermak, 2018; Calvert & Pavolonis, 2010; Cermak & Bendix, 2007; Ellrod, 2002). Over Europe, Cermak and Bendix (2007) achieved POD (FAR) of 0.47 (0.17) using the BTM method on Meteosat SEVIRI. The low POD (below 0.5) is assigned to uncertainty in the observations by the authors. However, an important aspect in their study is that they account for the broader bandwidth of the 3.9 μ m channel in SEVIRI which overlaps with CO₂ absorption. This is possibly more important for scenes over Europe which have a lower viewing angle, but we note that we have not applied any such correction for our scene, which covers a much smaller area (i.e. CO₂ absorption is more consistent across the scene). Application of the BTM method over desert regions and using GOES-R ABI produced POD (FAR) of 0.73 (0.14) (Ellrod, 2002). Calvert and Pavolonis (2010) applied the pseudo-emissivity method over the eastern United States (i.e., not desert) and reported POD (FAR) of 0.70 (0.15). The results from the last two studies suggest that the narrower bands on the GOES-R may allow for more distinct clustering of the histogram. Andersen and Cermak (2018) applied a diurnal algorithm using SEVIRI over the Namib Desert and achieved POD (FAR) of 0.94 (0.12). In this case fog and low stratus were included in the verification, as that region experiences a high percentage of both cloud conditions. We have not included low cloud in our verification as the focus was on fog events mostly which were verified using METAR surface visibility observations. These comparisons confirm that the proposed methodology, despite its simplicity, produce a POD that is in the order of those obtained previous studies and serve as a good basis for further processing to reduce the FAR.

3.3.4 Analysis of Fog Frequency

The highest fog frequency of 80 days occurs inland and parallel to the coast, before decreasing to 25 days further inland (Figure 3-8). This is due to the fog dynamics in the region, which requires moisture transport from the gulf during the day and radiative cooling over the desert at night. The strip of land along the coast does not cool down as quickly as the inland desert as it is moderated by the maritime air. Thus, although it may have higher moisture content, dew point temperature is not reached as often. The area of highest fog activity is where both criteria are met: moisture is available and the air cools to dew point temperature.

While further inland, fog is limited by moisture content. An interesting result is the area east of Dubai, where a small fog patch is often observed in the hourly maps that is disconnected from larger fog patches. This area is a strip of narrow land between the coast and the Hajar Mountains and most likely has slightly different dynamics in fog formation than the larger, inland fog patch.

The spatial distribution of fog days indicates that our verification sites occur outside the area of maximum fog activity. This supports the earlier statement that the stations are often at the edge of fog patches. The maximum value reported is 80 days of fog out of a maximum of 303 days in the sample. This may be an overestimate of 25% to 35 %, in line with the Abu Dhabi and Al Ain results presented in Table 3-2. However, this should not affect the spatial distribution, which would remain similar even if the magnitude was adjusted (i.e. scaled down). Upon inspection of hourly fog masks, we found the classification to be in line with the distributions seen here. To our knowledge, this is the first time the spatial distribution of fog over the UAE has been presented and verified.

Information on fog, the timing of fog formation, and its distribution throughout the UAE could be inferred from Figure 3-9. Two areas are visible as hot spots for fog formation, which are clearly demonstrated in the 21:00 h (local time) panel in Figure 3-9. The first area is situated between the three verification stations of Abu Dhabi, Dubai, and Al Ain (over the Sweihan desert) and the other is South West of Abu Dhabi. These areas remain visible up until hour 02:00 h when they merge. Thus, fog onset is much earlier in these hotspot areas.

The hourly maps do reveal a diurnal cycle that is in line with previously published results from the METAR observations (De Villiers & Van Heerden, 2007). Fog frequency increases as night progresses, highlighting the dependence on radiative cooling for fog formation. This is consistent with the obtained results especially those related to the spatial pattern of fog frequency, which may suggest that the proposed algorithm for determining the threshold does not require additional adjustment to account for diurnal variability, which seems to be correctly captured in Figure 3-9. Fog is shown to peak at 05:00 h local time and then decrease at 06:00 h. This is not in line with METAR observations which show that fog frequency is highest at 06:00 h and 07:00 h (De Villiers & Van Heerden, 2007). Thus, we should expect 06:00 h to be higher, however, analysis revealed a systematic bias at 06:00 h. Although we included 06:00 h in the sample as the solar zenith angle was greater than 90 (below the horizon), it is possible that there is some reflection at the top of the atmosphere, which increase the $\text{ems}(3.9)$ value to increase above the threshold value. This is only expected to occur in October and March.

Table 3-2: Dec 2016–Mar 2018.

	OMAA	OMDB	OMAL	OMDW
Statistic	ems(3.9) - Low cloud	ems(3.9) - Low cloud	ems(3.9) - Low cloud	ems(3.9) - Low cloud
Total Hits	26	10	20	23
Total Miss	6	2	4	7
Total False Alarms	17	10	10	18
POD	0.81	0.83	0.83	0.77
FAR	0.40	0.50	0.33	0.44
Bias score	1.34	1.66	1.25	1.36

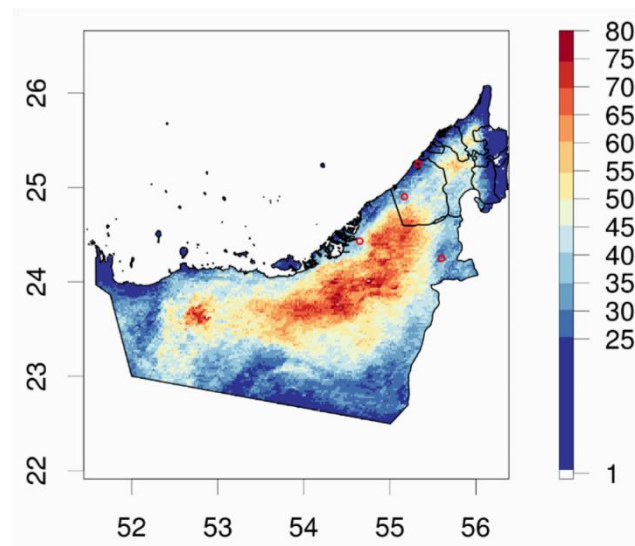


Figure 3-8: Fog frequency in days for ems(3.9)-low cloud over the 10 month period. Verification sites are indicated by red circles.

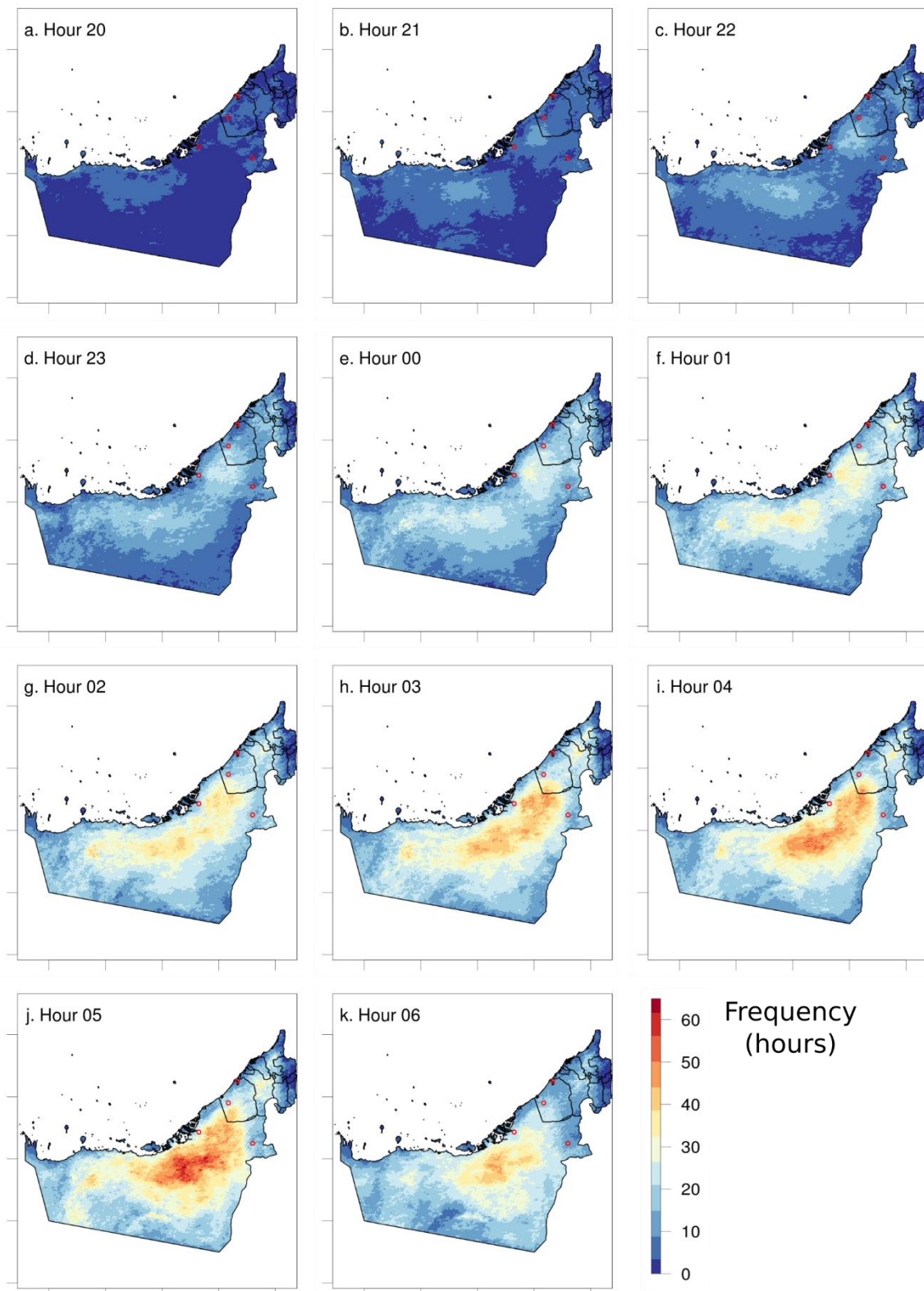


Figure 3-9: Hourly fog frequency from 20:00 h to 06:00 h local time.

3.4 Discussion

The following limitations have been identified in this study and are recommended for further refinement in future studies. The negative bias at 06:00 h can most likely be corrected for by removing the reflected component of the radiance in the satellite observations. This should be useful as 06:00 h is still a nighttime hour and it will improve the verification and the diurnal cycle maps.

The method for removing low cloud could be improved upon. While it appears to work for our case, we identified potential issues, most notably that there is a diurnal cycle of the difference between BT(10.8) and LST(ERA5). This makes sense for cloud cases, where there is a lag between surface cooling and upper air cooling. As such, the constant threshold of -4 K used in this study may need to be adjusted diurnally. In some cases, low cloud was classified when no cloud was present. This can be for various reasons, like upper air dust or thin cloud (Weston et al., 2020), or a bias in the ERA5 data. However, these cases did not coincide with fog detection, and did not degrade the performance of the fog classification.

Haze and mist were often included in the classification, either in the hours preceding fog onset or at the edge of fog patches. These could potentially be reduced through a layer thickness approach similar to Cermak (2012), where they calculate cloud top height to determine cloud thickness. The assumption here is that haze and mist may return lower cloud top heights than fully developed fog, but this remains to be tested.

3.5 Conclusions

In this paper we present the assessment of the pseudo-emissivity method for nighttime fog detection using the SEVIRI instrument from Meteosat-10. The method is similar to the one proposed for the GOES-R ABI which is largely untested with SEVIRI data. In addition, we implement an adaptive threshold method that allows the threshold to vary spatially and temporally. The spatial variation reduces the number of false alarms in the fog classification. The study area was the United Arab Emirates (UAE), a desert region on the Arabian Peninsula that experiences extensive fog during the winter months. The method verified well, with POD (FAR) ranging from 0.77 to 0.83 (0.33 to 0.5). We present the fog frequency for 10 months when fog is present over the UAE. This is the first time the spatial distribution of fog has been presented seamlessly across the UAE using satellite data. Previous studies relying on scarce station data did not capture the full spatial pattern of fog formation in the country and its dynamics. The fog classification had a positive bias, ranging from 25 % to 66 %, mostly due

to the inclusion of haze and mist in the classification. The hourly frequency is presented and is in line with in situ measurements, indicating peak fog frequency at 05:00 h local time. The results confirm that the pseudo-emissivity method is a reliable separator for fog detection in the UAE using SEVIRI data.

Supplementary Materials: The following are available online at www.mdpi.com/2072-4292/12/14/2281/s1, Figure S1. Examples of hits at Abu Dhabi at 2016-12-07 0200 (a–d) and Al Ain at (c,d). Times in UTC. Figure S2. Example of cloud affected fog days. The cloud in the RGB has a $\text{ems}(3.9)$ above the threshold value and is not captured in the fog mask. Times in UTC. Figure S3. Example of miss at Al Ain. Although this was a miss at one location, the patch was still well represented and will, correctly, form part of the fog frequency map. Times in UTC. Figure S4. Example of false alarms at Dubai (a,b) and Abu Dhabi (c,d). Although images a-b are false alarms in the METAR, a fog patch is visible in the RGB adjacent to the airport. The patch is well represented and considered correct in terms of the fog frequency. The image c,d has no fog in the RGB and is a total false alarm. Times in UTC. Figure S5. Example of a false classification outside of airports. Although no fog was classified at any of the airports, there is a general over estimate of fog in this scene in the interior. This may contribute to an overestimation of fog frequency. Times in UTC. Figure S6. Examples of underestimation of fog at 06:00 h local time (UTC+4). This is most likely due to reflection at the top of the atmosphere just before sunrise. Times in UTC.

3.6 References

- Aldababseh, A., & Temimi, M. (2017). Analysis of the long-term variability of poor visibility events in the UAE and the link with climate dynamics. *Atmosphere*, 8(12), 18--20. doi:10.3390/atmos8120242
- Andersen, H., & Cermak, J. (2018). First fully diurnal fog and low cloud satellite detection reveals life cycle in the Namib. *Atmospheric Measurement Techniques*, 11(10), 5461-5470. doi:10.5194/amt-11-5461-2018
- Bartok, J., et al. (2012). Fog Prediction for Road Traffic Safety in a Coastal Desert Region: Improvement of Nowcasting Skills by the Machine-Learning Approach. *Boundary-Layer Meteorology*, 157(3), 501--516. doi:10.1007/s10546-015-0069-x
- Calvert, C., & Pavolonis, M. (2010). *GOES-R Advanced Baseline Imager (ABI) Algorithm Theoretical Basis Document for Low Cloud and Fog*. Retrieved from
- Cao, C. a. S., Xi. (2013). Planck Function. NOAA NESDIS. Retrieved from <https://ncc.nesdis.noaa.gov/data/planck.html>
- Cermak, J. (2012). Low clouds and fog along the South-Western African coast - Satellite-based retrieval and spatial patterns. *Atmospheric Research*, 116, 15--21. doi:10.1016/j.atmosres.2011.02.012
- Cermak, J., & Bendix, J. (2007). Dynamical nighttime fog/low stratus detection based on Meteosat SEVIRI data: A feasibility study. *Pure and Applied Geophysics*, 164(6-7), 1179--1192. doi:10.1007/s00024-007-0213-8
- Cermak, J., & Bendix, J. (2008). A novel approach to fog/low stratus detection using Meteosat 8 data. *Atmospheric Research*, 87(3-4), 279--292. doi:10.1016/j.atmosres.2007.11.009
- Chaouch, N., et al. (2016). Sensitivity of the meteorological model WRF-ARW to planetary boundary layer schemes during fog conditions in a coastal arid region. *Atmospheric Research*, 187, 106--127. doi:10.1016/j.atmosres.2016.12.009
- Copernicus Climate Change Service (C3S). (2017). ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate.
- Dammann, K., et al. (2005). MSG level 1.5 image data format description. EUMETSAT, Darmstadt, Technical Report EUM/MSG/ICD/105 Issue, 3.
- De Villiers, M. a. V. H., J. (2007). Fog at Abu Dhabi international airport. *Weather*, 62(8), 209--214.
- Egli, S., et al. (2018). A hybrid approach for fog retrieval based on a combination of satellite and ground truth data. *Remote Sensing*, 10(4). doi:10.3390/rs10040628
- Elhakeem, A., et al. (2015). Long-term hydrodynamic modeling of the Arabian Gulf. *Marine Pollution Bulletin*, 94(1-2), 19--36. doi:10.1016/j.marpolbul.2015.03.020
- Ellrod, G. P. G. P. (2002). Estimation of low cloud base heights at night from satellite infrared and surface temperature data. *National Weather Digest*, 26(1,2), 39--44.
- EUMETSAT. (2009). *Best practices for RGB compositing of multi-spectral imagery*. Retrieved from http://oiswww.eumetsat.int/~idders/html/doc/best_practices.pdf
- Eyre, J. R., et al. (1984). Detection of fog at night using Advanced Very High Resolution Radiometer (AVHRR) imagery. *Meteorological Magazine*, 113, 266-271.
- Gultepe, I., et al. (2019). A Review of High Impact Weather for Aviation Meteorology (Vol. 176, pp. 1869--1921).
- Hersbach, H., et al. (2019). Global reanalysis: goodbye ERA-Interim, hello ERA5. *ECMWF Newsletter*(159), 17--24. doi:10.21957/vf291hehd7
- Hulley, G. C., et al. (2015). The ASTER Global Emissivity Dataset (ASTER GED): Mapping Earth's emissivity at 100 meter spatial scale. *Geophysical Research Letters*, 42(19), 7966--7976. doi:10.1002/2015GL065564

- Karagulian, F., *et al.* (2019). Analysis of a severe dust storm and its impact on air quality conditions using WRF-Chem modeling , satellite imagery , and ground observations. *Air Quality, Atmosphere & Health*, 1--18. doi:10.1007/s11869-019-00674-z
- Nilo, S. T., *et al.* (2018). Fog detection based on Meteosat Second Generation-Spinning enhanced visible and infrared imager high resolution visible channel. *Remote Sensing*, 10(4), 1--20. doi:10.3390/rs10040541
- Ouarda, T. B. M. J., & Charron, C. a. (2014). Evolution of the rainfall regime in the united arab emirates. *Journal of Hydrology*, 514, 258--270. doi:10.1016/j.jhydrol.2014.04.032
- Pavolonis, M. J., & Heidinger, A. K. (2005). Advancements in identifying cirrus and multilayered cloud systems from operational satellite imagers at night. *Applications with Weather Satellites II*, 5658, 225. doi:10.1117/12.577640
- Sheppard, C., *et al.* (2010). The Gulf: A young sea in decline. *Marine Pollution Bulletin*, 60(1), 13--38. doi:10.1016/j.marpolbul.2009.10.017
- Temimi, M., *et al.* (2020). On the analysis of ground-based microwave radiometer data during fog conditions. *Atmospheric Research*, 231(August 2019), 104652. doi:10.1016/j.atmosres.2019.104652
- Thota, M. S., *et al.* (2020). On the investigation of the typology of fog events in an arid environment and the link with climate patterns. *Monthly Weather Review*. doi:10.1175/mwr-d-20-0073.1
- Turner, J., *et al.* (1986). A case-study of the detection of fog at night using channels 3 and 4 on the Advanced Very High-Resolution Radiometer (AVHRR). *Meteorological Magazine*, 115(1370), 285--290.
- Weston, M., *et al.* (2018). Assessment of the Sensitivity to the Thermal Roughness Length in Noah and Noah-MP Land Surface Model Using WRF in an Arid Region. *Pure and Applied Geophysics*. doi:10.1007/s00024-018-1901-2
- Weston, M. J., *et al.* (2020). On the Analysis of the Low-Level Double Temperature Inversion Over the United Arab Emirates : A Case Study During April 2019. *Ieee Geoscience and Remote Sensing Letters*. doi:10.1109/LGRS.2020.2972597
- Yousef, L. A., *et al.* (2019). Total cloud cover climatology over the United Arab Emirates. *Atmospheric Science Letters*, 20(2), 1--10. doi:10.1002/asl.883

CHAPTER 4 ASSESSMENT OF THE SENSITIVITY TO THE THERMAL ROUGHNESS LENGTH IN NOAH AND NOAH-MP LAND SURFACE MODEL USING WRF IN AN ARID REGION

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Abstract: Atmospheric models are known to underestimate land surface temperature and, by association, 2 m air temperature over dry arid regions during the day due to the treatment of the thermal roughness length also known as roughness length of heat. The thermal roughness length can be controlled by the Zilitinkevich parameter, known as Czil, which is a tuneable parameter within the models.

Three different scenarios with the WRF model are run to test the impact of the Czil parameter on the simulations using two land surface models: the Noah and Noah-MP models. In this study a modified version of the Noah-MP model is tested, in which the Czil parameter, and therefore the thermal roughness length varies depending on the land cover and vegetation height.

The model domain is over the United Arab Emirates (UAE) where the major land cover type is desert. Simulations of 8 case studies between January-March 2016 were verified. The following configurations are tested: the Noah model with Czil=0.1, Noah model with Czil=0.5 and the Noah-MP model with Czil=0.5 over desert. Results of 2 m air temperature are verified against three stations in the UAE. Mean gross error of the diurnal 2 m temperature was reduced by up to 1.48 °C and 1.54 °C in the 24 hour and 48 hour forecasts, respectively. This reduced the cold bias in the model. This improvement in air temperature showed to improve the diurnal cycle of relative humidity at the three monitoring stations as well as the duration of the sea-breeze in some cases.

Keywords: Czil, roughness length, arid, 2 m temperature, WRF, Noah-MP.

4.1 Introduction

Land surface processes play an important role in both regional and mesoscale atmospheric models and climate models as they control the heat, momentum and water exchanges between the surface and the atmosphere (Pitman, 2003). An accurate land surface model that simulates the initial and the progress of the ground state is necessary to properly simulate the diurnal and vertical structure of the planetary boundary layer (PBL). Modeling the interaction between the surface and the atmosphere is critical to reproduce the physical processes between the PBL and the surface-land to simulate the turbulent heat and water exchanges. Several physical representations of land-atmosphere interactions at the surface with different degrees of complexity in terms of number of parameters, number of soil layers and, vegetation characteristics, have been proposed in the literature. Different performances among the schemes in portioning the water and energy fluxes depending on the time, spatial scales and applications were found for both and, coupled with atmospheric models runs (Liang et al., 1998; Pitman et al., 1999; Timbal & Henderson-Sellers, 1998; Wood et al., 1998a, 1998b). Wood et al. (1998a) compared sixteen land surface models and showed the importance of the calibration of the models for the prediction of the energy and water fluxes. In addition, different models showed different sensitivity to the same parameter depending on the model structure and locations (Bastidas et al., 2006). Depending on the application, there are trade-offs between models complexity and performances (Bastidas et al., 2006; Hogue et al., 2006).

For regional weather forecasting, the Weather Research and Forecasting (WRF) model with the Advanced Research WRF (ARW) core (Huang et al., 2008; Skamarock et al., 2008a; Wang et al., 2009) is widely used for both research and operational applications. It offers a wide range of physical parameterizations representing the interaction between the atmosphere, the soil and, the surface. The WRF mode makes use of a coupled land surface model for lower boundary simulation of the heat and moisture fluxes conditions.

The Noah Land Surface Model (LSM) is widely coupled with general circulation models and mesoscale atmospheric models because of its relative simplicity for real time global and regional weather and hydrology applications (Chen & Dudhia, 2001; Ek et al., 2003; Tewari et al., 2004). The Noah Land Surface Model (LSM) has been implemented in the National Centers for Environment Prediction (NCEP) operational Eta Model for global and regional forecasts (Ek et al., 2003). It has also been coupled with the Penn State-NCAR fifth generation Mesoscale Model (Chen & Dudhia, 2001). Finally, the Noah Land Surface Model is being used

for both research and operational purposes. An updated version of this model, namely Noah-MP, which includes multi parameterization options has also been implemented in different mesoscale atmospheric models (Niu et al., 2011).

For arid and semi-arid regions, the surface soil heat flux and, the turbulent sensible heat fluxes, dominate the surface energy budget because of the lack of precipitation. The thermal and aerodynamic roughness lengths constitute the main parameters for the bulk transfer equations to calculate the turbulent fluxes in the LSMs (Chen et al., 2011; Chen et al., 2010; Zheng et al., 2012). Wei et al. (2013) tested the Noah LSM and found a large bias of the latent heat, total runoff and land surface temperature during the warm, spring and summer, seasons over vegetated areas. Zheng et al. (2012) reported that the Global Forecast System (GFS) model underestimates land surface skin temperatures during daytime over arid regions of the United States when the surface roughness for heat was considered equal to the momentum surface length. The decrease of the thermal surface roughness through the use of vegetation dependent formulation for the calculation of the momentum and thermal roughness lengths reduces the daytime cold bias over arid and semiarid regions during warm season. Chen et al. (2010) tested different thermal roughness length formulations with Noah LSM model and found an underestimation of the land surface temperature and overestimation of the sensible heat flux. Similar results were also found by other works (Hogue et al., 2005; LeMone et al., 2008). Better performance is obtained when thermal roughness parameter values higher than the default are considered (LeMone et al., 2008). Chen and Zhang (2009) showed the importance of considering variable roughness length for heat and moisture depending on the land cover and vegetation height to better simulate the surface exchange coefficient. Improved results were also obtained when the diurnal variation of the thermal roughness length is considered (Chen et al., 2011; Chen et al., 2010; Yang et al., 2008).

This paper aims to study the sensitivity of WRF to land surface models, namely Noah and Noah-MP, for the simulation of meteorological parameters in the United Arab Emirates (UAE). For this purpose, a sensitivity analysis of WRF model to the thermal roughness parameter, and therefore to the surface exchange coefficient for heat, was conducted for eight events with fog conditions recorded at Abu Dhabi Airport and at other locations in the UAE. Fog is one of the most hazardous weather conditions that affects road and air transportation in the UAE. Fog forms as a results of the strong temperature inversion overnight and the large difference between inland and the sea temperatures, especially during winter (De Villiers & Van Heerden, 2007). In the region, limited works addressed this particular issue. Chaouch et al. (2016) compared different PBL schemes in WRF with different lead times under fog

conditions in the UAE. Bartokova et al. (2015) used the combination of WRF and a decision tree-based model for fog nowcasting in Dubai. Ajjaji et al. (2008) compared different PBL, radiation, and microphysics schemes during fog conditions in the UAE. This study builds upon previous investigations and places a particular interest on the effect of the land surface model scheme in WRF simulating different thermodynamic variables during fog and no-fog conditions. The model is verified using in situ observations of air temperature, relative humidity and wind speed at three airports in the UAE: Abu Dhabi, Dubai and Al Ain.

4.2 Study area

The United Arab Emirates (UAE) is located in the north-eastern side of the Arabian Peninsula (Figure 4-1). It is surrounded by the Arabian Gulf from the north and the west, by the Gulf of Oman from the east, and by Saudi Arabia from the south and west. The UAE is an arid region with an average annual precipitation of around 100 mm (Harris et al., 2014). The eastern and northern part of the UAE usually record the highest precipitation amount because of the presence of the Al Hajar Mountains in the east, which foster local convective processes and rainfall in the summer season. Vegetation is mostly present in the eastern region due to the summer rainfall and available ground water. Desert dominates the rest of the country except around the Country's large cities.

Fog events are usually reported in the region especially during fall and winter seasons. They usually lead to a significant degradation in visibility below 100 m. This has an adverse impact on all transportation systems and air traffic (Bartok et al., 2012). Most fog events are observed during the night and they are characterized by calm wind and humidity that can reach 80%. The fog formation in the region is mainly due to the combination of the advection of warm and moist air from the sea with the radiation cooling during the night (De Villiers & Van Heerden, 2007). The sea and land breezes in the area prompt the formation of fog. Two types of sea breeze can occur in the region. The first is the bay breeze, which is due to the temperature gradient between the coastline and the gulf, this fosters the condensation and fog formation inland during the night. The second is the ocean breeze which is controlled by the large scale processes (Abbs & Physick, 1992). During the day, the water vapour from the Gulf and the ocean is transported and then trapped inland during the night because of the low wind speed.

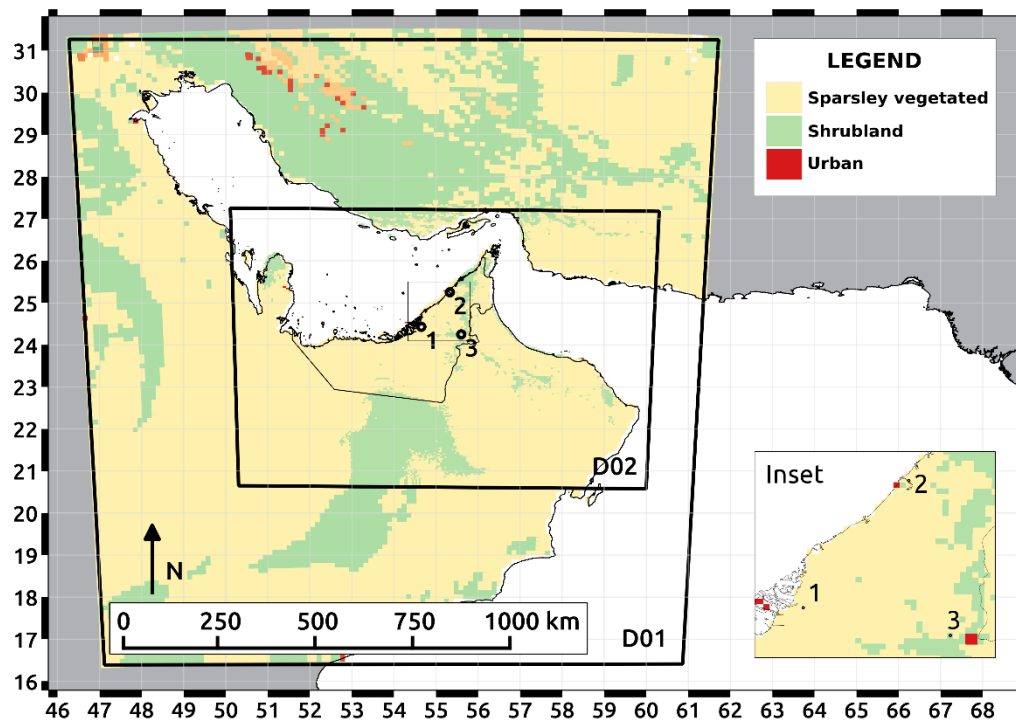


Figure 4-1: WRF model domains D01 (12 km) and D02 (4 km) with the USGS land cover. White is open water. The three airports used for verification are 1. Abu Dhabi, 2. Dubai and 3. Al Ain.

4.3 Methodology

We run the WRF model with two main configurations for 8 case studies between January-March 2016. The configurations, described in detail below, test the effect of the Zilitinkevich parameter (Czil) in two land-surface models in WRF, namely Noah and Noah-MP. The model results are verified for 2 m air temperature at three sites in the United Arab Emirates.

4.3.1 WRF model

The Advanced Research WRF (WRF-ARW) mesoscale model V3.7.1 developed by the National Center for Atmospheric Research with one way nesting has been used. The WRF model is a compressible and non-hydrostatic atmospheric model that uses terrain-following hydrostatic pressure vertical coordinate. Two domains, with 12 km and 4 km horizontal spatial resolutions, were considered for the parent and nested domains, respectively. The parent domain extended over the Arabian Peninsula, parts of the Arabian Gulf and the Sea of Oman (latitude: 16.3 °N-31.5 °N, longitude: 47 °E-61 °E). On the other hand, the nested domain

covered the UAE Region (Figure 4-1). The nest domain for the Noah-MP runs was slightly larger (extended east of the UAE) than the nest domain for Noah runs to reduce numerical instability in the model over the Hajar mountains which occurred during testing when increasing the vertical resolution in the model. This change was not expected to alter the dynamics in the region of interest where the model was verified. The meteorological data from the National Center for Environmental Prediction (NCEP-GFS) at 0.5° spatial resolution and at 06 UTC initialization time were used for the initial and lateral boundary conditions in the parent domain.

Table 4-1 summarizes all the parameterization schemes that were used in the simulations. The default USGS landuse land cover data set were used. For all simulations, the WRF Single-Moment 3-class (WSM3) scheme was used to represent the grid-scale water vapour, cloud and precipitation processes (Hong et al., 2004). The sub-grid scale clouds were represented with the Kain-Fritsch scheme in the 12 km domain but was deactivated in the 4 km domain (Kain, 2004b; Kain & Fritsch, 1990). The atmospheric heating was calculated using the Rapid Radiative Transfer Model (RRTM) longwave radiation (Eli J Mlawer et al., 1997) and RRTMG shortwave radiation (Iacono et al., 2008) schemes. The exchanges of mass, energy and moisture between land and atmosphere was determined using the Quasi-Normal Scale Elimination (QNSE) scheme (Sukoriansky et al., 2005). The model variables like potential temperature, latent heat fluxes, sensible heat fluxes, three dimensional wind, pressure and water vapour at the surface and at different pressure levels was written at hourly intervals. The land cover was basically composed of four classes, namely water, urban and built-up land, shrubland, and barren or sparsely vegetated (Figure 4-1).

Eight case studies, January 19th and 22nd, February 15th, 16th, 18th, 19th and 20th and March 10th, 2016 were considered for this work. The above dates, except the 19th of January, corresponded to recorded fog events at Abu Dhabi Airport. For Dubai and Al Ain, these dates correspond to both fog conditions and no fog conditions. Fog corresponded to conditions when visibility falls below 1000 m according to the METAR data collected from the Global Surface Observation Network (<http://weather.uwyo.edu/surface/meteorogram/>). For each case study, Noah and Noah MP land surface models using 45 and 46 pressure levels with 50 hPa top pressure value were tested. For the 46 pressure level run, a new sigma level at 0.996 was added near the surface.

Table 4-1: WRF configuration for control and experiment

WRF parameters		Noah0.1 (control)	NoahmpCzil (Experiment)
Data		NCEP GFS 0.5°	
Initial time		06 UTC	
Domain size	12 km	125 x 140	125 x 140
	4 km	187 x 184	253 x 184
Time interval		6 h	
Model time step		60 s	
PBL/Surface layer		QNSE/QNSE	
Microphysics		WSM3	
Cumulus		Kain-Fritsch (new Eta)	
LWR		RRTM	
SWR		RRTMG	
LSM		Noah	Noah-MP
Surface layer drag coefficient			Original Noah
Czil		0.1 constant for all LULC	0.5 for desert (see Table 4-2)
LULC		USGS	
Vertical levels (lowest 3 and 4 sigma levels)		45 (1, 0.993, 0.983)	46 (1, 0.996, 0.993, 0.983)

4.3.2 Noah land surface model description

Land surface models (LSM) provide the lower boundary conditions to the atmosphere via heat and moisture fluxes. These fluxes are derived through simulated interactions of the land surface model with the radiation scheme, surface layer scheme, microphysics, and convective schemes (Skamarock et al., 2008a). Two Noah land surface model versions namely the Unified Noah (Noah) (Chen & Dudhia, 2001) and the Noah multiparameterization (Noah-MP) (Niu et al., 2011) land surface model are available in the WRF model. The Noah model is a simple scheme that represents the soil temperature and moisture in four layers up to 1 m below the surface. It calculates the surface energy fluxes over a combined surface layer of both vegetation and soil (Chen & Dudhia, 2001). The Noah-MP scheme is an updated version of the Noah with multiparameterization options of a number of processes. Updates present in Noah-MP that are relevant to this study are the inclusion of a vegetation canopy, which requires vegetation height, and bare ground fraction to calculate the fluxes to the atmosphere.

In atmospheric modelling, air temperature at 2 meters above ground level is derived from land surface temperature, heat flux and the coefficient of heat exchange as follows (Niu et al., 2011):

$$T2 = LST - \frac{HFX}{RHO * CP * C_H} \quad (5)$$

Where T2 is air temperature at 2 m above the ground (K), LST land surface temperature (K), HFX is net upward heat flux at the surface (Wm⁻²), RHO is air density (kg m⁻³), CP is heat capacity of dry air (Jkg⁻¹K⁻¹) and C_H is the exchange coefficient for heat at 2 m above ground (ms⁻¹). RHO and CP are two constants. Changes to the land surface temperature, heat flux or the coefficient of heat exchange alter the air temperature at 2 m above the ground.

The Zilitinkevich coefficient parameter (Czil) in the WRF model effects land surface temperature and the coefficient of heat exchange. Therefore, the Czil plays a role in diagnosing 2 m air temperature (Zilitinkevich, 1995). Czil is a tunable parameter that effects the aerodynamic resistance of the surface layer (Mitchell et al., 2005). It controls the relationship between Z_{om}/Z_{ot} and the roughness Reynolds number (Re*) (Chen et al., 1997). In other words, it links the type of air flow, whether laminar or turbulent, to the roughness length of heat. As it will be described below, the effect of increasing Czil results into a decrease in the roughness length of heat, Z_{ot}, which will decrease the coefficient of heat exchange, C_H, and therefore, in an increase of land surface temperature. This is achieved by controlling the ratio of the roughness length of heat with the roughness length of momentum according to (Eq. (6)) (Chen et al., 1997; Zilitinkevich, 1995):

$$\frac{Z_{om}}{Z_{ot}} = \exp(k \text{ Czil } \sqrt{Re^*}) \quad (6)$$

Where Z_{om} is momentum roughness length, Z_{ot} is thermal roughness length, k is the von Karman constant of 0.4, Czil is the Czil parameter and Re* is the Reynolds number. The Reynolds number is dependent on frictional velocity. Thus, when Czil is set to a constant, as it is currently in WRF, the ratio of Z_{ot} to Z_{om} varies with frictional velocity (Eq. (7)).

$$Re^* = \frac{u_0^* Z_{om}}{v} \quad (7)$$

Where u₀^{*} is the frictional velocity and v is kinematic viscosity (~1.5×10⁻⁵). The effect of increasing Czil results into a decrease in the heat roughness length, Z_{ot}, which will decrease

the coefficient of heat exchange, C_H according to (Eq. (8)) (Chen et al., 1997; Niu et al., 2011). C_H is calculated as:

$$C_H = k^2 / \left[\ln \left(\frac{z}{z_{0m}} \right) - \Psi_m \left(\frac{z}{L} \right) + \Psi_m \left(\frac{z_{0m}}{L} \right) \right] \left[\ln \left(\frac{z}{z_{0t}} \right) - \Psi_h \left(\frac{z}{L} \right) + \Psi_h \left(\frac{z_{0t}}{L} \right) \right] \quad (8)$$

Where k is the Von Karman constant, z is the reference height, L is the Monin-Obukhov length, and Ψ is a stability correction function.

The value for C_{zil} has evolved over time. Before the introduction of C_{zil} , assumptions were made on the relationship between Z_{0m} and Z_{0t} . As outlined by (Chen et al., 1997), early efforts assumed $Z_{0m}=Z_{0t}$. However this created problems when using land surface temperature to solve the Monin-Obukhov similarity theory, as the boundary conditions were incorrect. To overcome this issue, Z_{0t} was decreased so that $Z_{0m}/Z_{0t}=10$ (Braud et al., 1993). However, this was a fixed value and was not applicable for all land cover types. Zilitinkevich (1995) then proposed the tunable value of 0.1, which effectively allowed the ratio of Z_{0m}/Z_{0t} to vary with frictional velocity. Chen et al. (1997) verified this value of 0.1 by comparing modelled and measured values of C_H , and found it to be the most favourable value for most land cover types. Other values of 0.01 and 1 were also tested but did not perform as well. The deficiency of this approach ($C_{zil}=0.1$) is that land surface temperature can be overestimated during the daytime and underestimated at night time. Lastly Chen and Zhang (2009) proposed that C_{zil} varies with vegetation height as follows:

$$C_{zil} = 10^{(-kh)} \quad (9)$$

Where k is the Von Karman constant of 0.4 and h is the vegetation height. We use this approach for our vegetated land classes.

4.3.3 WRF Configuration

For both WRF domains, different simulations were conducted with both versions of Noah LSM model using different heat roughness parameter values and pressure levels. Three different scenarios were tested.

Scenario 1: the control run uses the Unified Noah LSM with 45 pressure level and C_{zil} equals to 0.1 (default in WRF V3.7), referred to hereafter as Noah0.1.

Scenario 2: A constant C_{zil} equals to 0.5 with the Unified Noah LSM version and referred to hereafter as Noah0.5 was tested.

Scenario 3: a variable Czil in Noah-MP LSM depending on the vegetation height as proposed by Chen and Zhang (2009) according to Eq. (9) was tested and referred to NoahmpCzil.

For the study domain, the vegetation height formula is only relevant for shrubland and sparsely vegetated areas which are dominant in arid and semi-arid environments. For the sparsely vegetated areas (i.e. desert), a value of 0.5 is applied after a process of trial and error (Table 4-2). A different set of runs using Czil value of 0.8 as suggested by (Zheng et al., 2012) for desert were tested but showed an excess increase of the air temperature at 2 m during daytime. For urban and water areas, the default value of 0.1 is applied, as in the default configuration of WRF (Table 4-2). Moreover, under this scenario simulations were conducted with 46 pressure levels unlike the first two scenarios where 45 pressure levels were used. The extra vertical level near the surface affects the local closure of flux calculations and should therefore affect the calculation of air temperature.

Table 4-2: Czil values applied to each LULC.

Land use/land cover	Czil
Open Water	0.1
Barren or Sparsely Vegetated (desert)	0.5
Shrubland	0.36
Urban	0.1

The Noah-MP LSM code was modified and adapted in WRF to read the land cover specific Czil values (Table 4-2) from a lookup table (MPTABLE) when calculating the surface layer drag. This approach is novel in the context of arid regions as the option of using a dynamic Czil value that varies with vegetation height (Eq. (9)) is active in WRF version 3.7.1 only for few PBL schemes such as, the YSU and MYNN PBL and surface layer option of MYNN and MM5 Monin-Obukhov schemes. In this work, we used QNSE PBL scheme and QNSE surface layer option which was found to outperform the other schemes in the simulation of the air temperature, humidity and wind speed during fog events (Chaouch et al., 2016). Hence, the new combination QNSE PBL scheme with a variable Czil value in the Noah-MP was tested in this study.

4.3.4 Model Verification

Three airport stations, Abu Dhabi Airport (24.43°N, 54.65°E), Dubai airport (25.25°N, 55.33°E) and Al Ain airport (24.25°N, 55.60°E) are used for the validation (Figure 4-1). Both Abu Dhabi and Dubai airports are characterized as barren and sparsely vegetation. Both these airports are coastal airports. On the other hand, Al Ain airport is an inland airport located in shrubland vegetation class. The nearest model grid point to the airport site was extracted for verification.

Model results were presented in UTC time and divided into two forecast periods namely, the first 24 hour valid forecast and the 48 hour forecast. The mean gross error and bias in 2 m air temperature and relative humidity were calculated for each case study and averaged per hour for each forecast. For the first 24 hours forecast, the comparison between the simulated and the observation data were done for the last 18 hours from 12 UTC to 06 UTC of the following day of each case study. The first 6 hours were excluded and considered as model spin up time. The 48 hour forecast evaluation considered the second 24 hours from 07 UTC of day two to 06 UTC of day 3 of each case study. An improvement in model performance should show a decrease in the mean gross error. Each model scenario was verified against in situ observations data at the three sites.

4.4 Results and discussion

The analysis of the mean values of simulated air temperature using the control run configuration (Noah with Czil equal to 0.1 and 45 pressure levels, Noah0.1) presented a warm bias just after the sunrise and early morning when compared with in situ observations data taken between October 18th 2016 and February 27th, 2017, at Abu Dhabi Airport (Figure 4-2). The simulated diurnal air temperature also showed an early heating during the morning and a quick cooling during the afternoon and early evening. The resulting daytime cold bias is consistent with all the simulations using the Unified Noah LSM version with the control run conditions. The same behaviour was also reported by Zheng et al. (2012) using the GFS model and default Noah LSM for the simulated land surface skin temperatures during daytime over arid regions of the United States. They showed that this behaviour is mostly due to the surface turbulent heat transfer simulation within Noah LSM which is controlled mainly by the roughness length for heat, and thus, by the Czil value (Eqs. 2-5). The comparison between the WRF simulated air temperatures using the Noah LSM with Czil of 0.1 (Noah0.1, control run) and using Czil of 0.5 (Noah0.5) showed a similar trend and almost no improvement in simulating the air temperature (Figure 4-3). The improvement in mean gross error was less than 1 °C when changing Czil from 0.1 to 0.5 using Noah LSM. In WRF V.3.7.1, the Czil

parameter is no longer active in the Noah LSM and is instead used within the surface layer schemes. This explains in part the small difference obtained in the simulated 2 m temperature when changing the Czil parameter (Figure 4-3), as it has no direct effect on land surface temperature.

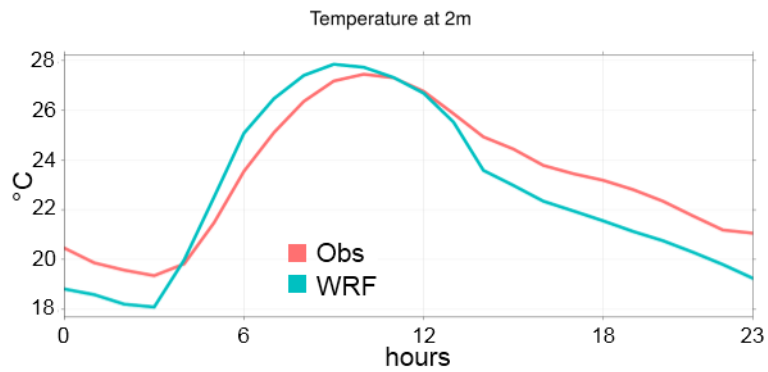
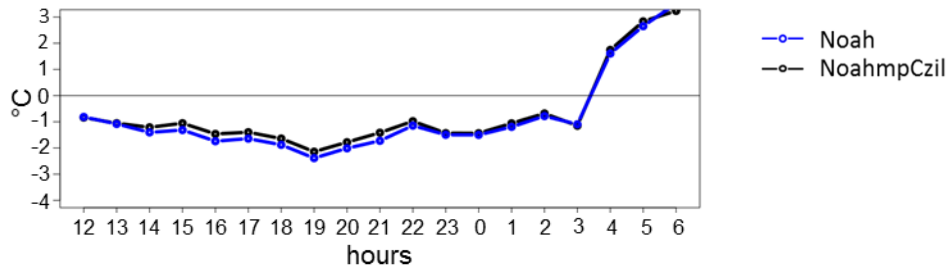


Figure 4-2: The problem. Average temperature at 2 m at Abu Dhabi airport for winter 2016/2017 (2016-10-18 to 2017-02-27). WRF shows a warm bias in the morning after sunrise and a cold bias in later afternoon/early evening. Time is in UTC. Site is UTC+4.

a.)



b.)

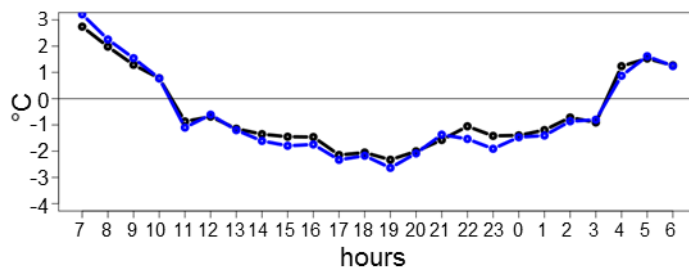


Figure 4-3: Temperature mean gross error with bias as the sign for Noah with Czil values of 0.1 (blue line) and 0.5 (black line). a.) is the 24 hour forecast and b.) is the 48 hour forecast respectively. This is the mean gross error for all case studies at Abu Dhabi Airport. Time is in UTC. Site is UTC+4.

The diurnal variability of the simulated air temperature using Noah0.1, Noahmp0.1 (Noah-MP with constant Czil of 0.1) and NoahmpCzil for the case study of February 19th, 2016 showed an improvement of the simulation of the air temperature when Czil value is changed to 0.5 for the desert area and using Noah-MP (Figure 4-4). Minor difference between Noah0.1 and Noahmp0.1 simulated air temperature are observed. Using a constant Czil value of 0.1 for the whole domain, presented the same simulated diurnal air temperature trend (i.e. cold bias in later afternoon/evening) with both versions of Noah LSM. The effect of increasing Czil to 0.5 is a decrease in the thermal roughness length, Z_{0t} , which will decrease the coefficient of heat exchange, C_H , which will increase the land surface temperature. Even though the value of 0.1 of Czil was previously obtained by the comparison of modelled and measured values of C_H for most land cover types (Chen et al., 1997).

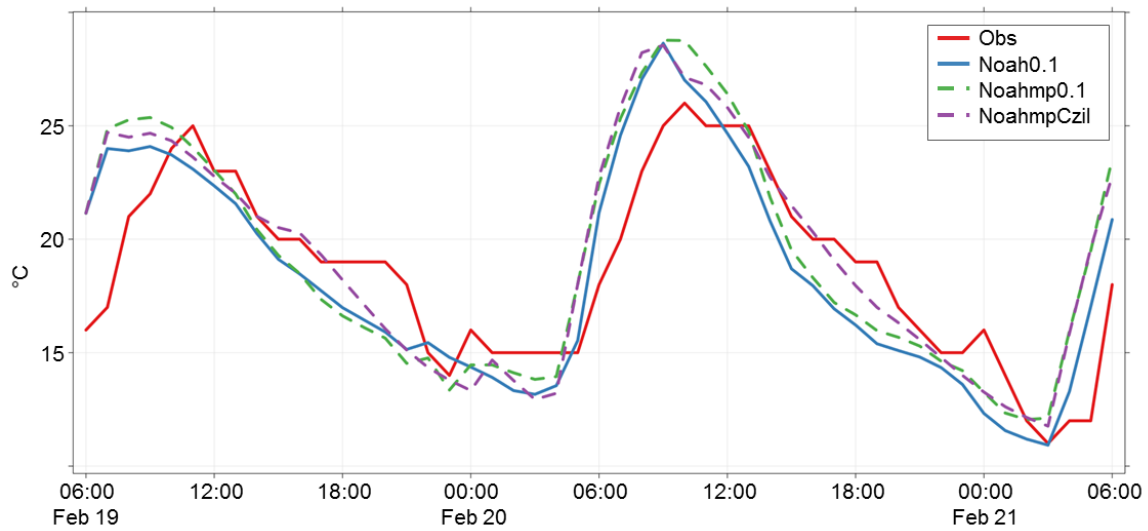


Figure 4-4: Air temperature at 2 m for three WRF configurations, Noah0.1, Noahmp0.1 and NoahmpCzil at Abu Dhabi Airport. Improvements in cold bias are achieved by changing the Czil, and not by changing the LSM. Time is in UTC. Site is UTC+4.

Results in this study showed the importance of increasing the Czil value to improve the forecasts and decrease the cold bias during daytime within WRF. Similarly, Zheng et al. (2012) adjusted the Czil value to 0.8 in the GFS model to correct for the model bias in land surface temperature for arid region in the US. LeMone et al. (2008) found a better simulation of the latent and sensible heat fluxes and land surface temperature when a value of Czil of 0.5 is considered especially in the Great Plains in the Oklahoma Panhandle during summer time.

The addition of the extra vertical level near the surface helped to dampen the effect of increasing the daily maximum temperature (Figure 4-5). The example of the case study of February 19th, 2016 using both Noah-MP configurations, one with 46 vertical levels where the extra level is closer to the ground and the second with 45 vertical levels as the control run showed lower maximum LST of 1.2 - 1.5 Kelvin using 46 pressure levels (Figure 4-5). Using equation (5), this leads to a lower air temperature at 2 m above ground. Chen et al. (1997) noted also that the increase in Czil value induced an increase in the maximum LST and therefore increase of the daily maximum temperature (Eq. (5)). The extra vertical level near the surface affects the local closure of flux calculations, causing the fluxes to increase and the LST to decrease, and consequently, a decrease in the daily maximum temperature.

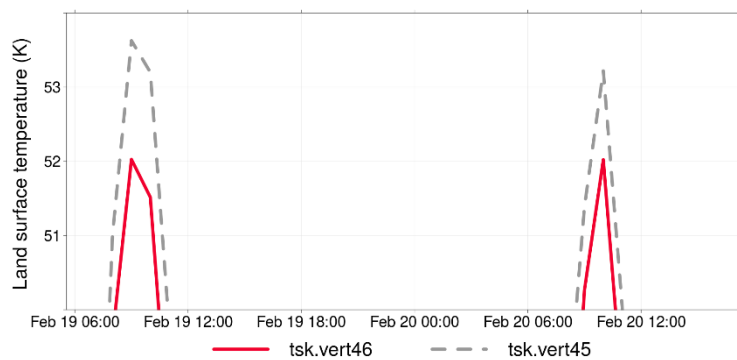


Figure 4-5: Difference in maximum land surface temperature for Noahmp (with variable Czil) runs with different vertical levels. This is for case study 2016-01-19. The extra vertical level closer to the ground decreases the land surface temperature and dampens the daily maximum air temperature at 2 m. Time is in UTC. Site is UTC+4.

The comparison between Noah0.1 (control run) and the NoahmpCzil in simulating the 2 m air temperature showed better results when a variable Czil value is assigned. For Noah0.1, the mean gross error reached 2 °C for the control run during the late afternoon to evening at Abu Dhabi and Dubai airports for both forecast (Figure 4-6). For NoahmpCzil at Abu Dhabi airport, mean gross error was decreased down to 1.48 °C for the first 24 hour forecast and up to 1.54 °C for the 48 hour forecast (Figure 4-6a and b). However, after sunrise, NoahmpCzil heats up faster than Noah0.1 and reaches higher maximum air temperature values. The same behavior was also noted and described by Chen and Zhang (2009). This causes an increase in the mean gross error of up to 1.43 and 1.56 °C in the 24 hours and 48 hours forecast, respectively. At Dubai airport, the mean gross error improved by up to 0.94 and 1.4 °C for the 24 and 48 hour forecasts (Figure 4-6c and d) respectively. On the other hand, for Al Ain airport, the mean gross error improvements reached up to 0.61 and 0.49 °C for the 24 and 48 hours forecast (Figure 4-6e and f), respectively.

The largest improvement in air temperature was achieved between 5 pm to 1 am local time at Abu Dhabi (Figure 4-6a). The same performance of both model configurations was observed just before sunrise (at 2 am UTC) for the first 24 hours forecast. For the 48 hours forecast, NoahmpCzil extends the improvement to 6 am local time of the second day, generating a more reliable forecast. This is also true for the Dubai forecast. For both forecast, NoahmpCzil slightly improves the minimum temperature forecast during the night. The improvement in mean gross error starts later in the day than Abu Dhabi, from 8 pm local time instead of 5 pm. The gains

at Al Ain are minor which can be due first to the fact that the cold bias at Al Ain was not as large as it is in the other land use land cover type. Secondly, the Czil value of 0.36 is more conservative than 0.5. In addition, the inland dynamics are much different than the two coastal sites.

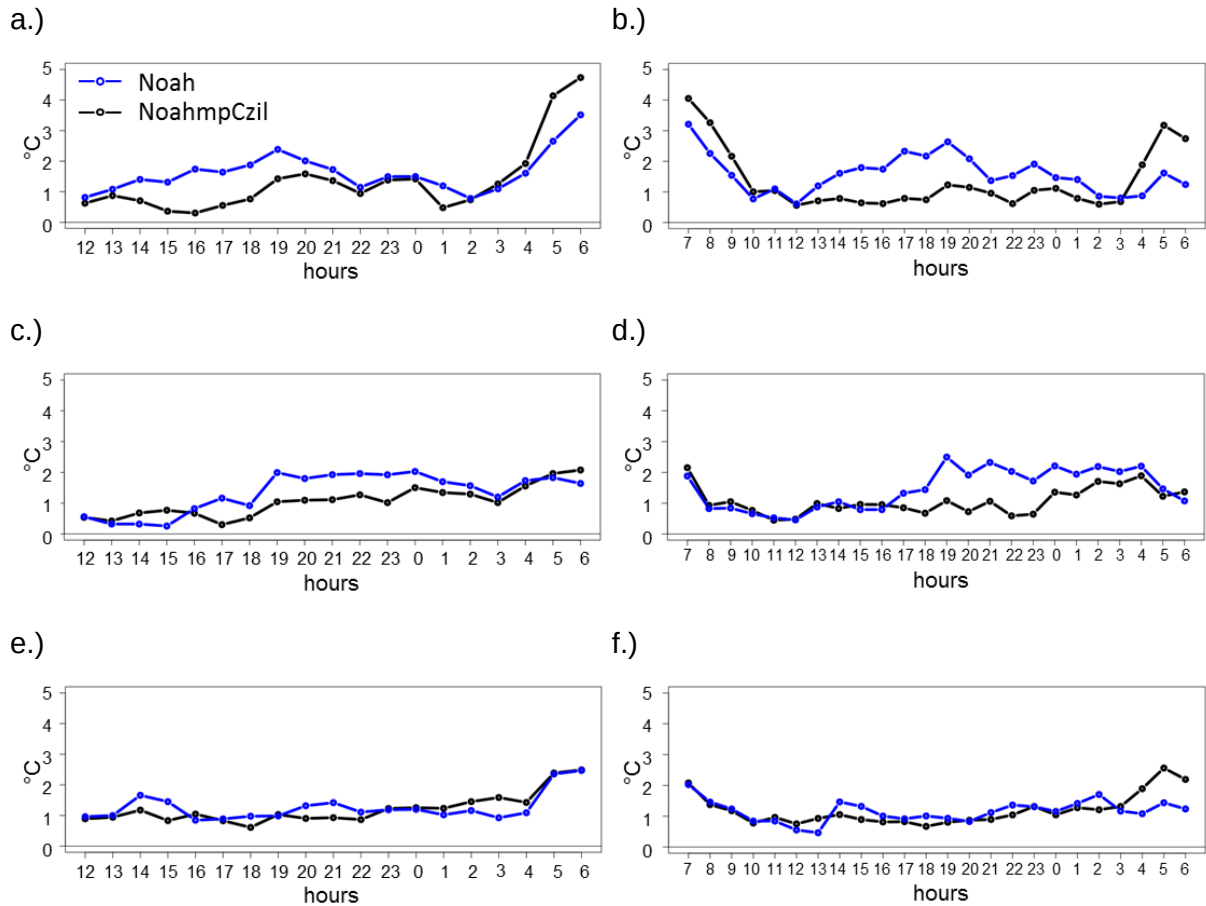
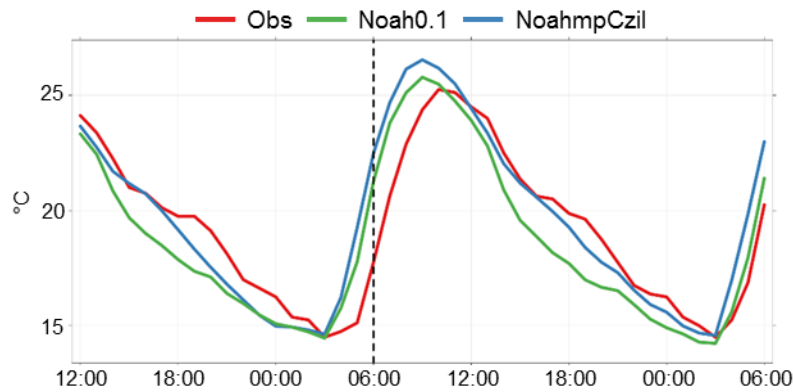


Figure 4-6: Temperature mean gross error (with bias as the sign) for Noah0.1 (blue line) and NoahmpCzil (black line) at a.) Abu Dhabi 24 hour forecast and b.) 48 hour forecast, c.) Dubai 24 hour forecast and d.) 48 hour forecast, and e.) Al Ain 24 hour forecast and f.) 48 hour forecast. Time is in UTC. Site is UTC+4.

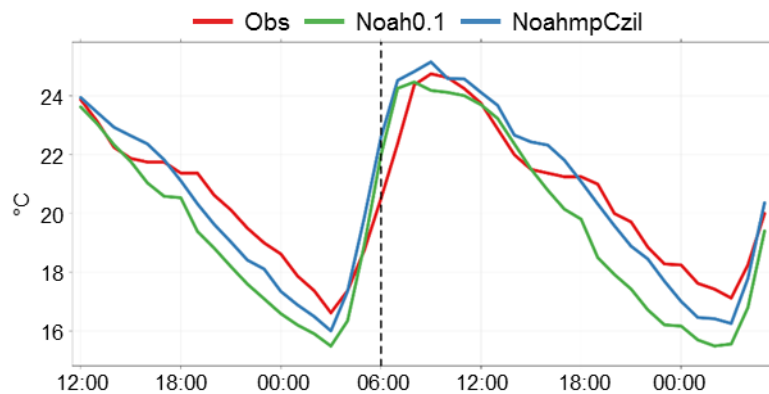
The mean diurnal air temperature results for all cases and for both forecast at the three sites are presented in Figure 4-7. These results show that NoahmpCzil makes an improvement in the cold bias that occurs in the late afternoon to the evening at Abu Dhabi and Dubai airports. However, it does not make any improvement to the early heating observed just after sunrise, which suggests that the early heating is caused by different physical mechanism in the model.

At this point, it is worth noting that Abu Dhabi observations heat up after Dubai, and this may be due to the fog bank over Abu Dhabi. In addition, the model heating rate is faster than the observations at the three sites. This may be due to aerosols that are not adequately accounted for in the radiation scheme in the model. Thus, the real benefit of the NoahmpCzil is the decrease in the cold bias occurring just after the daily maximum temperature.

a.)



b.)



c.)

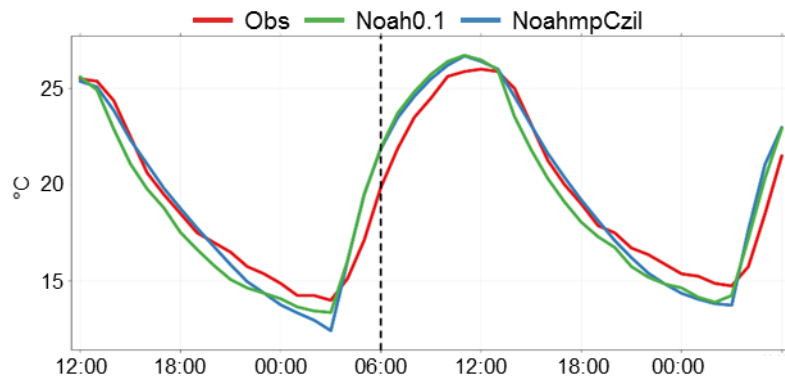
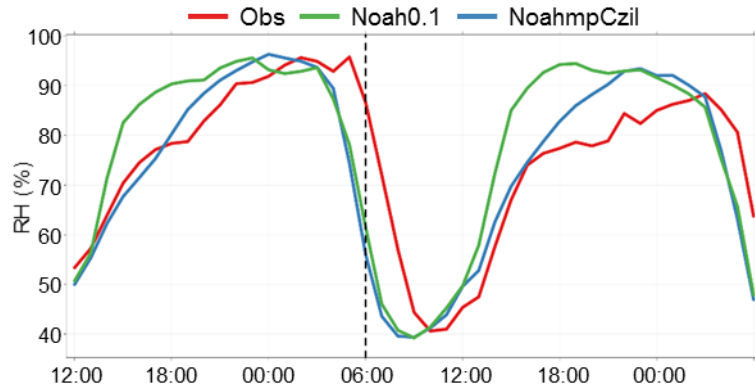


Figure 4-7: Mean diurnal temperature for all case studies at a.) Abu Dhabi, b.) Dubai and c.) Al Ain. The black line represents the end of the 24 hour forecast and start of the 48 hour forecast. Time is in UTC. Site is UTC+4.

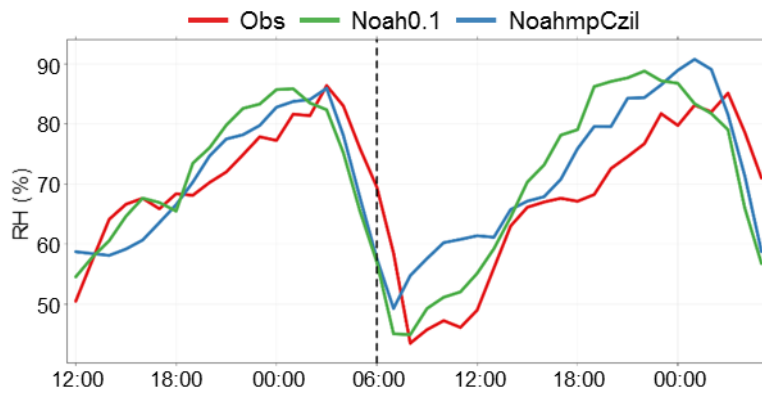
The analysis of the mean diurnal forecast of the relative humidity at 2 m above the ground also showed an improvement using the NoahmpCzil configuration. The control run with Noah0.1 causes relative humidity to increase too early in the evening when compared to the

observations (Figure 4-8). This is due to the cold bias in the model as the relative humidity is a diagnostic variable that is calculated from the temperature and water vapour mixing ratio. The NoahmpCzil runs improve the timing of the peak of the relative humidity that occurs later due to the improvement in temperature. The mean gross error of the simulated maximum relative humidity is less than 5 % for the 24 hours forecast, while the 48 hours forecast overestimates relative humidity by over 5 % using the NoahmpCzil configuration. This is partially due to the remaining cold bias in the NoahmpCzil 48 hours forecast (although decreased), and also to the excess in water vapour simulation (not shown). The excess water vapour is linked to different model parameterisations that falls outside the scope of the Czil tests.

a.)



b.)



c.)

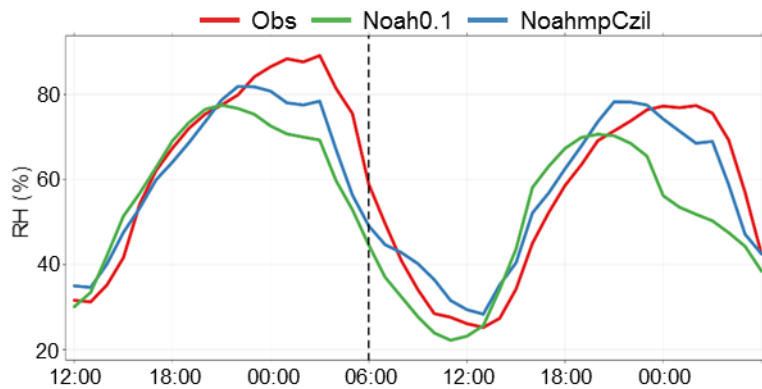
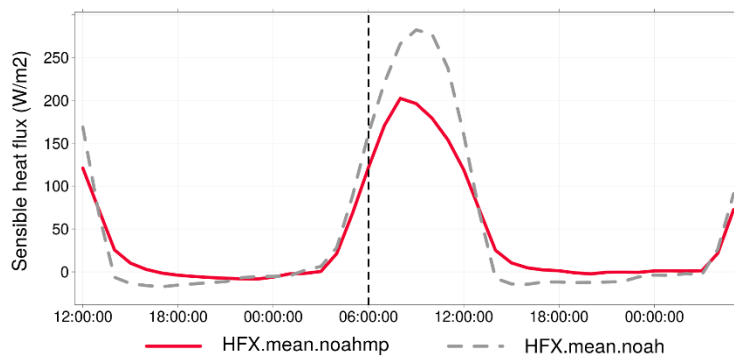


Figure 4-8: Mean diurnal relative humidity for all case studies at a.) Abu Dhabi, b.) Dubai and c.) Al Ain. The black line represents the end of the 24 hour forecast and start of the 48 hour forecast. Time is in UTC. Site is UTC+4.

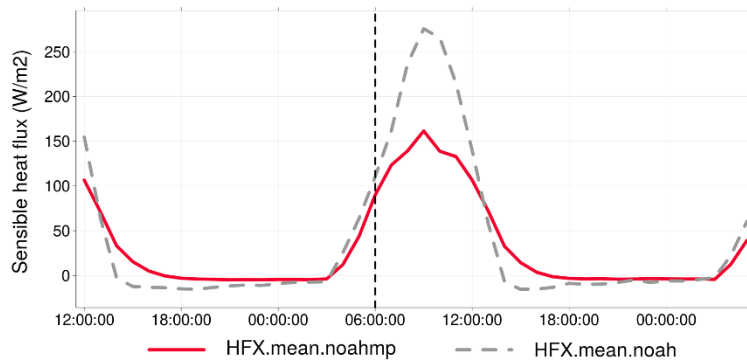
The comparison of the sensible heat flux and land surface temperature between model simulations (due to lack of observations) showed an excess of the surface heat flux between the land and the atmosphere using the Noah0.1 configuration. As expected, by increasing Czil

value, a decrease of the mean sensible heat flux by 75 - 100 Wm^{-2} at Abu Dhabi and Dubai, and about 120 Wm^{-2} in Al Ain are achieved (Figure 4-9). This increased the peak LST by about 15 K at Abu Dhabi and Dubai and by 13 K at Al Ain (Figure 4-10). As per the equation (5), this increase in LST and decrease in the surface turbulent exchange coefficient resulted in the decreased bias in the 2 m temperature simulation.

a.)



b.)



c.)

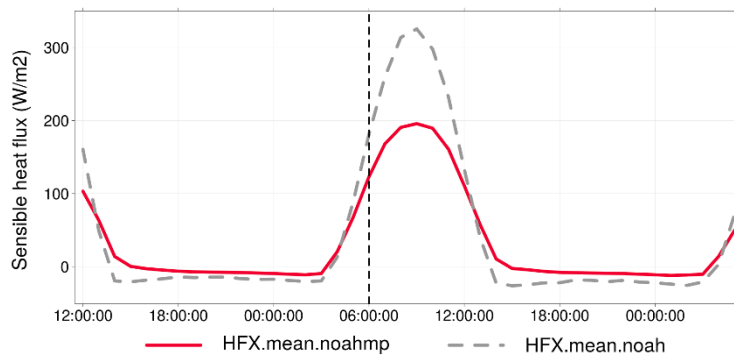
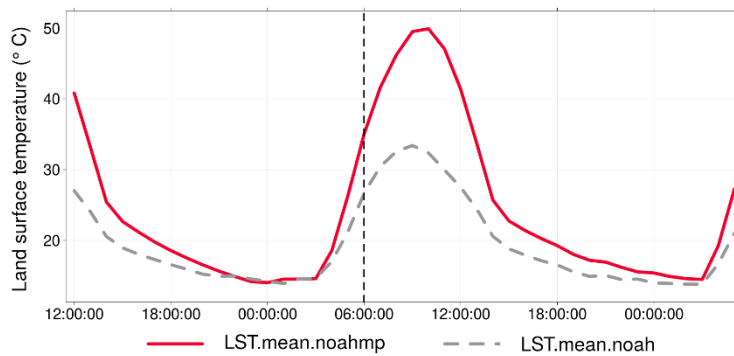
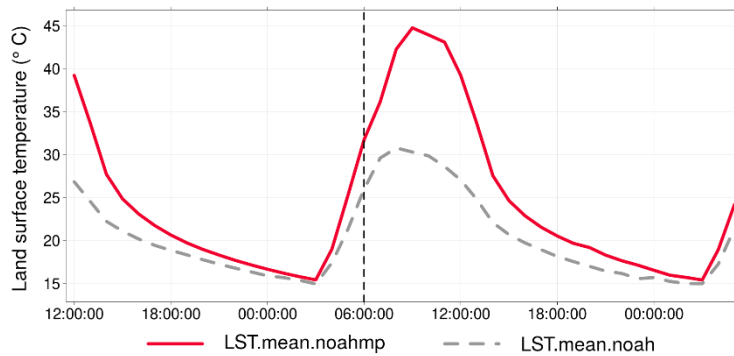


Figure 4-9: Mean diurnal sensible heat flux for all case studies at a.) Abu Dhabi, b.) Dubai and c.) Al Ain. The black line represents the end of the 24 hour forecast and start of the 48 hour forecast. Time is in UTC. Site is UTC+4.

a.)



b.)



c.)

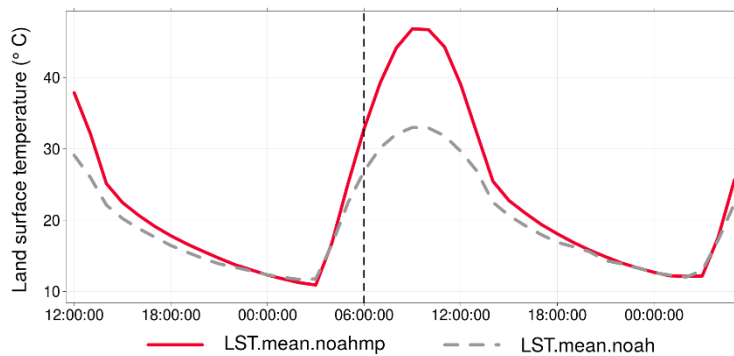


Figure 4-10: Mean diurnal land surface temperature for all case studies at a.) Abu Dhabi, b.) Dubai and c.) Al Ain. The black line represents the end of the 24 hour forecast and start of the 48 hour forecast. Time is in UTC. Site is UTC+4.

In addition, the increase of the Czil value resulted in an improvement in the diurnal wind pattern by increasing the duration of the sea breeze (wind direction higher than 300 degrees) (Figure

4-11). The sea breeze is driven by the temperature gradient between the air over the land and the adjacent Gulf waters. The sea breeze blows when the air over the land is warmer. During nighttime, the wind shifts to a land breeze when the land cools down. In the control simulations, the land cools down too quickly, which appears to result in an early shift of the sea breeze (Figure 4-11b). With the NoahmpCzil configuration, the land remains warmer for longer resulting in longer duration of the sea breeze. While the land temperature only represents half the problem in this situation (where sea surface temperature is the other half), our model simulations form part of the solution. The duration of the sea breeze in the model is important for the determination of the amount of moisture that is transported inland during the day. Typically, for observed fog events, moisture is transported inland during the day as the sea breeze blows. This loads the lower atmosphere with moisture, which is transported back towards the coast at night when the land breeze blows. As the air cools over the desert faster than most land cover types, dew point is reached quickly and fog forms. However, for the case study of February 20th for example, a lag effect between sea breeze and water vapour content at around 22:00 UTC in the 48 hour forecast is observed (Figure 4-11b and c). When the sea breeze duration is too short, there is an underestimation in vapour mixing ratio at around 22:00 UTC. When the duration is increased, an increase of the vapour content is also observed at night.

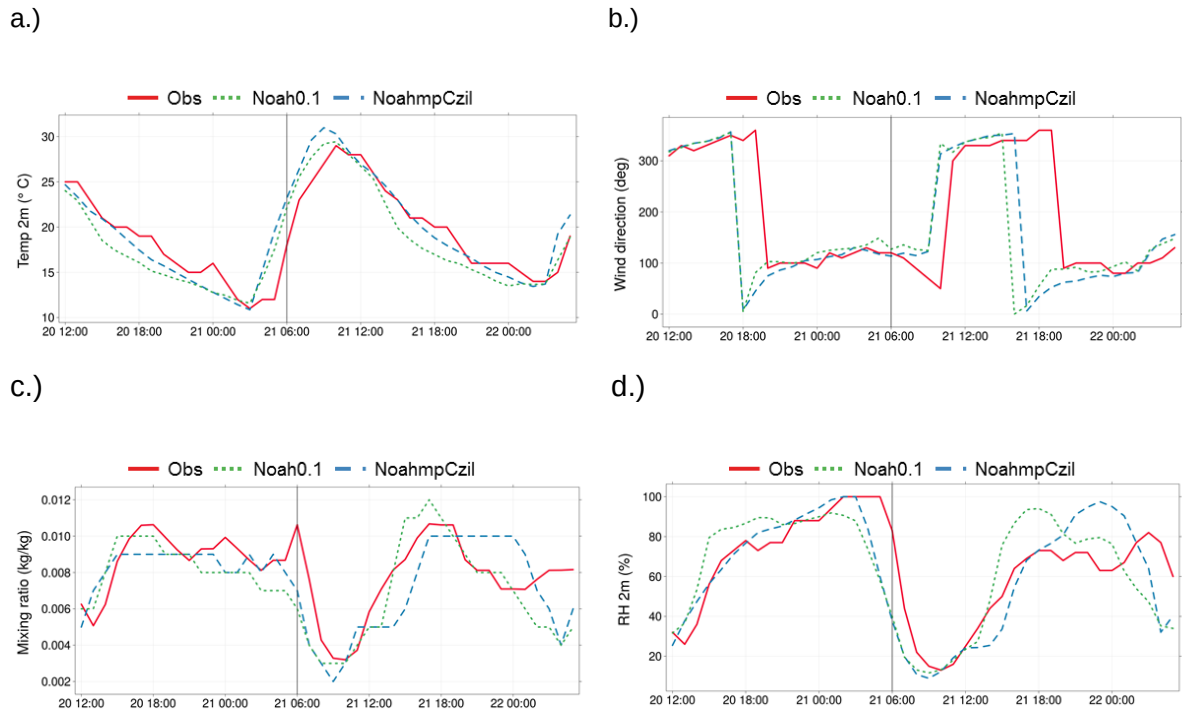


Figure 4-11: Meteorological parameters for case study 2016-02-20 for a.) Temperature, b.) Wind direction, c.) Water vapour mixing ratio and d.) Relative humidity at Abu Dhabi Airport. Sea breeze duration increases when the air temperature over land is improved. Time is in UTC. Site is UTC+4.

The decrease of the cold bias in the late afternoon and the evening resulted in an improvement in simulating the relative humidity and therefore, potentially an improvement in the visibility forecast. Visibility is often estimated from relative humidity or a proxy parameter like temperature depression or cloud liquid water content (Bang et al., 2008; Gultepe et al., 2007). Visibility has been shown to be dependent on liquid water content (LWC) and droplet number concentration (Nd) (Gultepe et al., 2006; Gultepe et al., 2009). An accurate prediction of these meteorological variables that are associated with fog is then crucial and are strongly dependent on the moisture saturation in the model, which is represented by relative humidity. Accurate simulation of these variables is especially complicated for fog forecasting, as fog occurs close to ground level. This is the interface of four parameterization schemes in the model, namely the radiation, land surface model, atmospheric surface layer and planetary boundary layer. The complex interactions between these schemes and their numerous variables determines whether fog forms in the model. The intensity of the fog formation is then further parameterised based on modelled LWC or Nd. With the control runs, the relative

humidity is too high in the early evening which may result in visibility forecasts that are too low for the same period. These high values of the relative humidity and low values of the temperature may result in erroneously low visibility estimates from the model. Thus, the improvement in the timing of the daily maximum relative humidity with the new NoahmpCzil configuration should reduce this error and obtain better visibility estimates.

Finally, the adaptive increase in the Czil value according to land cover and land use conditions improved the WRF cold bias during late afternoon and the evening. However, there was no improvement in the early increase of the simulated air temperature and early decrease of the relative humidity with the NoahmpCzil runs. Future work will address the analysis of the diurnal variability of land surface emissivity and its impact on heat exchange. Previous studies showed that desert surface emissivity have an impact of GFS simulations (Yan & Weng, 2011) and showed a significant difference between day and night time surface emissivity estimates (Norouzi et al., 2015). An analysis of the impact of soil moisture on land surface emissivity should be carefully addressed. Reliable estimates of soil moisture in desert are available from several satellite missions (Fares et al., 2013) and could be used to study the impact on the performance of WRF.

4.5 Conclusions

This study focuses on the evaluation of the Noah land surface model within WRF V3.7.1 in the UAE to predict different meteorological variables. Eight dates characterized mostly by fog conditions are simulated to assess the performance of both the default Noah LSM and the Noah-MP with variable thermal roughness length in predicting the air temperature and the relative humidity at 2 m at Abu Dhabi, Dubai and Al Ain airports.

The findings were as follows:

The modified Noah-MP LSM improved the diurnal temperature profile by decreasing the cold bias. Cold bias is an issue over arid regions and needs to be improved upon in the WRF model. The application of Czil per land cover type, in combination with the Noah-MP land surface model in WRF, has decreased the mean gross error in 2 m air temperature by up to 1.54 °C. This reduces the cold bias observed in the control run. The improvement is achieved after the daily maximum temperature in the afternoon and early evening for both forecast horizons. The configuration does not solve the rapid heating after sunrise, which suggests that this artefact is controlled by another physical processes in the model.

The modified Noah-MP LSM improved the 2 m relative humidity forecast. The improvement in 2 m temperature mentioned above resulted in better performance in predicting the relative humidity at 2 m above the ground.

In some cases, the correction to the air temperature above the land resulted in improving the duration of the sea breeze in the model. This is expected as the sea breeze is controlled by the temperature differential of air over the gulf and land.

The following limitations to this work are acknowledged. The sample size of fog cases is small and limited to a single season. Physical conditions may change from season to season and the model performance may vary as a result. Furthermore, the number of stations used for verification is few and the study would benefit from additional stations over a variety of locations in the desert. However, these results, which represent eight case studies from winter to spring, are encouraging and promote further testing of this configuration over a longer period to determine its validity and application across seasons.

4.6 References

- Abbs, D. J., & Physick, W. (1992). Sea-breeze observations and modelling: a review. *Australian Meteorological Magazine*, 41, 7-19.
- Ajjaji, R., Al-katheri, A. A., & Khaled, A. L. (2008). Evaluation of United Arab Emirates WRF two-way nested model on a set of thick coastal fog situations. *United Nations Development Programme, Air Force and Air Defense Meteorological Department*
- Bang, C.-H., Lee, J.-W., & Hong, S.-Y. (2008). Predictability experiments of fog and visibility in local airports over Korea using the WRF model. *Journal of Korean Society for Atmospheric Environment*, 24(E2), 92-101.
- Bartok, J., Bott, A., & Gera, M. (2012). Fog Prediction for Road Traffic Safety in a Coastal Desert Region: Improvement of Nowcasting Skills by the Machine-Learning Approach. *Boundary-Layer Meteorology*, 157(3), 501-516. <https://doi.org/10.1007/s10546-015-0069-x>
- Bartoková, I., Bott, A., Bartok, J., & Gera, M. (2015). Fog Prediction for Road Traffic Safety in a Coastal Desert Region: Improvement of Nowcasting Skills by the Machine-Learning Approach. *Boundary-Layer Meteorology*, 157(3), 501-516.
- Bastidas, L. A., Hogue, T. S., Sorooshian, S., Gupta, H. V., & Shuttleworth, W. J. (2006). Parameter sensitivity analysis for different complexity land surface models using multicriteria methods. *Journal of Geophysical Research: Atmospheres*, 111(D20).
- Braud, I., Noilhan, J., Bessemoulin, P., Mascart, P., Haverkamp, R., & Vauclin, M. (1993). Bare-ground surface heat and water exchanges under dry conditions: Observations and parameterization. *Boundary-Layer Meteorology*, 66(1), 173-200.
- Chaouch, N., Temimi, M., Weston, M., & Ghedira, H. (2017). Sensitivity of the meteorological model WRF-ARW to planetary boundary layer schemes during fog conditions in a coastal arid region. *Atmospheric Research*, 187, 106-127.
- Chen, F., & Dudhia, J. (2001). Coupling an Advanced Land Surface Hydrology Model with the Penn State NCAR MM5 Modeling System. Part I: Model Implementation and Sensitivity. *Monthly Weather Review*, 129(4), 569-585.

- Chen, F., Janjić, Z., & Mitchell, K. (1997). Impact of Atmospheric Surface-layer Parameterizations in the new Land-surface Scheme of the NCEP Mesoscale Eta Model. *Boundary-Layer Meteorology*, 85, 391-421.
- Chen, F., & Zhang, Y. (2009). On the coupling strength between the land surface and the atmosphere: From viewpoint of surface exchange coefficients. *Geophysical Research Letters*, vol.36, issue 10.
- Chen, Y., Yang, K., He, J., Qin, J., Shi, J., Du, J., & He, Q. (2011). Improving land surface temperature modeling for dry land of China. *Journal of Geophysical Research: Atmospheres*, 116(D20).
- Chen, Y., Yang, K., Zhou, D., Qin, J., & Guo, X. (2010). Improving the Noah land surface model in arid regions with an appropriate parameterization of the thermal roughness length. *Journal of Hydrometeorology*, 11(4), 995-1006.
- De Villiers, M. P., & Van Heerden, J. (2007). Fog at Abu Dhabi international airport. *Weather*, 62(8), 209-214.
- Ek, M. B., Mitchell, K. E., Lin, Y., Rogers, E., Grunmann, P., Koren, V., Gayno, G., & Tarpley, J. D. (2003). Implementation of Noah land surface model advances in the National Centers for Environmental Prediction operational mesoscale Eta model. *Journal of Geophysical Research: Atmospheres*, 108(D22).
- Fares, A., Temimi, M., Morgan, K., & Kelleners, T. J. (2013). In-Situ and Remote Soil Moisture Sensing Technologies for Vadose Zone Hydrology. *Vadose Zone Journal*, 12(2), vzj2013.2003.0058. <https://doi.org/10.2136/vzj2013.03.0058>
- Gultepe, I., Müller, M. D., & Boybeyi, Z. (2006). A New Visibility Parameterization for Warm-Fog Applications in Numerical Weather Prediction Models. *Journal of Applied Meteorology and Climatology*, 45(11), 1469-1480. <https://doi.org/10.1175/jam2423.1>
- Gultepe, I., Pearson, G., Milbrandt, J. A., Hansen, B., Platnick, S., Taylor, P., Gordon, M., Oakley, J. P., & Cober, S. G. (2009). The Fog Remote Sensing and Modeling Field Project. *Bulletin of the American Meteorological Society*, 90(3), 341-360. <https://doi.org/10.1175/2008bams2354.1>
- Gultepe, I., Tardif, R., Michaelides, S. C., Cermak, J., Bott, A., Bendix, J., Müller, M. D., Pagowski, M., Hansen, B., Ellrod, G., Jacobs, W., Toth, G., & Cober, S. G. (2007). Fog Research: A Review of Past Achievements and Future Perspectives. *Pure and Applied Geophysics*, 164(6), 1121-1159. <https://doi.org/10.1007/s00024-007-0211-x>
- Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology*, 34(3), 623-642. <https://doi.org/10.1002/joc.3711>
- Hogue, T. S., Bastidas, L., Gupta, H., Sorooshian, S., Mitchell, K., & Emmerich, W. (2005). Evaluation and transferability of the Noah land surface model in semiarid environments. *Journal of Hydrometeorology*, 6(1), 68-84.
- Hogue, T. S., Bastidas, L. A., Gupta, H. V., & Sorooshian, S. (2006). Evaluating model performance and parameter behavior for varying levels of land surface model complexity. *Water resources research*, 42(8).
- Hong, S.-Y., Dudhia, J., & Chen, S.-H. (2004). A Revised Approach to Ice Microphysical Processes for the Bulk Parameterization of Clouds and Precipitation. *Monthly Weather Review*, Vol. 132, issue 1, 103-120.
- Huang, X., Wang, W., & Powers, J. (2008). A description of the advanced research WRF version 3. *NCAR technical note, NCAR, Boulder* Speer M, Wiles P, Pepler A (2009)
- Iacono, M. J., Delamere, J. S., Mlawer, E. J., Shephard, M. W., Clough, S. A., & Collins, W. D. (2008). Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *J. Geophys. Res.*, 113.
- Kain, J. S. (2004). The Kain-Fritsch convective parameterization: an update. *Journal of Applied Meteorology*, 43(1), 170-181.

- Kain, J. S., & Fritsch, J. M. (1990). A one-dimensional entraining/detraining plume model and its application in convective parameterization. *Journal of the Atmospheric Sciences*, 47(23), 2784-2802.
- LeMone, M. A., Tewari, M., Chen, F., Alfieri, J. G., & Niyogi, D. (2008). Evaluation of the Noah land surface model using data from a fair-weather IHOP_2002 day with heterogeneous surface fluxes. *Monthly Weather Review*, 136(12), 4915-4941.
- Liang, X., Wood, E. F., Lettenmaier, D. P., Lohmann, D., Boone, A., Chang, S., Chen, F., Dai, Y., Desborough, C., & Dickinson, R. E. (1998). The Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) phase 2 (c) Red-Arkansas River basin experiment:: 2. Spatial and temporal analysis of energy fluxes. *Global and Planetary Change*, 19(1), 137-159.
- Mitchell, K., Ek, M., Wong, V., Lohmann, D., Koren, V., Schaake, J., Duan, Q., Gayno, G., Moore, B., Grunmann, P., Tarpley, D., Ramsay, B., Chen, F., Kim, J., Pan, H.-I., Lin, Y., Marshall, C., Mahrt, L., Meyers, T., & Ruscher, P. (2005). *Noah Land Surface Model (LSM) User's Guide* (NCAR Research Application Laboratory (RAL), Issue.
- Mlawer, E. J., Taubman, S. J., Brown, P. D., Iacono, M. J., & Clough, S. A. (1997). Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. *Journal of Geophysical Research: Atmospheres*, 102(D14), 16663-16682.
- Niu, G. Y., Yang, Z. L., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., Kumar, A., Manning, K., Niyogi, D., Rosero, E., Tewari, M., & Xia, Y. (2011). The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. *Journal of Geophysical Research Atmospheres*, 116(12), 1-19.
- Norouzi, H., Temimi, M., Prigent, C., Turk, J., Khanbilvardi, R., Tian, Y., Furuzawa, F. A., & Masunaga, H. (2015). Assessment of the consistency among global microwave land surface emissivity products. *Atmos. Meas. Tech.*, 8(3), 1197-1205. <https://doi.org/10.5194/amt-8-1197-2015>
- Pitman, A. J. (2003). The evolution of, and revolution in, land surface schemes designed for climate models. *International Journal of Climatology*, 23(5), 479-510.
- Pitman, A. J., Henderson-Sellers, A., Desborough, C. E., Yang, Z.-L., Abramopoulos, F., Boone, A., Dickinson, R. E., Gedney, N., Koster, R., & Kowalczyk, E. (1999). Key results and implications from phase 1 (c) of the project for intercomparison of land-surface parametrization schemes. *Climate Dynamics*, 15(9), 673-684.
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., Huang, X.-Y., Wang, W., & Powers, J. G. (2008). *A Description of the Advanced Research WRF Version 3*.
- Sukoriansky, S., Galperin, B., & Perov, V. (2005). Application of a New Spectral Theory of Stably Stratified Turbulence to the Atmospheric Boundary Layer over Sea Ice. *Boundary-Layer Meteorology*, Vol.117, issue 2, 231-257.
- Tewari, M., Chen, F., Wang, W., Dudhia, J., LeMone, M. A., Mitchell, K., Ek, M., Gayno, G., Wegiel, J., & Cuenca, R. H. (2004). Implementation and verification of the unified NOAH land surface model in the WRF model. 20th conference on weather analysis and forecasting/16th conference on numerical weather prediction,
- Timbal, B., & Henderson-Sellers, A. (1998). Intercomparisons of land-surface parameterizations coupled to a limited area forecast model. *Global and Planetary Change*, 19(1), 247-260.
- Wang, W., Bruyère, C., Duda, M., Dudhia, J., Gill, D., Lin, H. C., Michalakes, J., Rizvi, S., & Zhang, X. (2009). *Advanced Research WRF (ARW) Version 3 Modeling Users Guide, Mesoscale & Microscale Meteorology Division* (National Center for Atmospheric Research (NCAR), USA. http://www.mmm.ucar.edu.ar/wrf/users/docs/arw_v3.pdf, Issue.

- Wei, H., Xia, Y., Mitchell, K. E., & Ek, M. B. (2013). Improvement of the Noah land surface model for warm season processes: Evaluation of water and energy flux simulation. *Hydrological Processes*, 27(2), 297-303.
- Wood, E. F., Lettenmaier, D. P., Liang, X., Lohmann, D., Boone, A., Chang, S., Chen, F., Dai, Y., Dickinson, R. E., & Duan, Q. (1998a). The Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) Phase 2 (c) Redâ€“Arkansas River basin experiment:: 1. Experiment description and summary intercomparisons. *Global and Planetary Change*, 19(1), 115-135.
- Wood, E. F., Lettenmaier, D. P., Liang, X., Lohmann, D., Boone, A., Chang, S., Chen, F., Dai, Y., Dickinson, R. E., & Duan, Q. (1998b). The Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) Phase 2 (c) Redâ€“Arkansas River basin experiment:: 1. Experiment description and summary intercomparisons. *Global and Planetary Change*, 19(1), 115-135.
- Yan, B., & Weng, F. (2011). Effects of Microwave Desert Surface Emissivity on AMSU-A Data Assimilation. *IEEE Transactions on Geoscience and Remote Sensing*, 49(4), 1263-1276. <https://doi.org/10.1109/TGRS.2010.2091508>
- Yang, K., Koike, T., Ishikawa, H., Kim, J., Li, X., Liu, H., Liu, S., Ma, Y., & Wang, J. (2008). Turbulent flux transfer over bare-soil surfaces: characteristics and parameterization. *Journal of Applied Meteorology and Climatology*, 47(1), 276-290.
- Zheng, W., Wei, H., Wang, Z., Zeng, X., Meng, J., Ek, M., Mitchell, K., & Derber, J. (2012). *Journal of Geophysical Research: Atmospheres*, Vol.117, D6.
- Zilitinkevich, S. S. (1995). *Air Pollution III—Volume I. Air Pollution Theory and Simulation: pollution dispersion aspects of coherent structure of convective flows* (Vol. 6). Computational Mechanics Publ.

CHAPTER 5 A RULE-BASED METHOD FOR DIAGNOSING RADIATION FOG IN AN ARID REGION FROM NWP FORECASTS

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Abstract: A reliable fog forecast can assist in water resource management and mitigate against hazardous effects on transport networks. However, diagnosing fog from numerical weather prediction models remains a challenge and various methods have been developed to achieve this. One approach is to use a multi rule-based method, where threshold values of multiple variables are employed to define fog conditions in the forecast. Such a method is presented here for next day forecasts of radiation fog at Abu Dhabi in the United Arab Emirates. The study period covered 10 winter months (303 days), comprising 35 fog days at Abu Dhabi, over two seasons. The first season is from December 2016 to March 2017 and the second season is October 2017 to March 2018. Variables tested include the dew point depression, wind speed, modified Richardson index, inversion depth, relative humidity and liquid water content. Of these, the best performing rule included relative humidity ($\geq 94\%$), wind speed ($\leq 3 \text{ ms}^{-1}$) and inversion depth ($> 250 \text{ m}$) with a probability of detection (POD) (false alarm ratio (FAR)) of 0.62 (0.37). The worst performing rule was liquid water content with a POD (FAR) of 0.37 (0.31). Model performance was more sensitive to inversion depth than wind speed, and rules that included inversion depth performed better than rules that included the modified Richardson number. A qualitative spatial analysis showed that rules produced realistic fog patches when compared to satellite images. This suggests that the geophysical parameters chosen to define rules are well suited for defining fog as long as the model bias is sufficiently small to fall within the threshold values. This method worked well for the study region and did not demonstrate any seasonal bias.

Keywords: radiation fog, operational forecast, rule-based method, LWC, visibility, Tdep, WRF, arid region.

5.1 Introduction

A reliable fog forecast can assist in water resource management and mitigate against hazardous effects on transport networks (De Villiers & Van Heerden, 2007; Gultepe et al., 2009; Gultepe et al., 2007; Stolaki et al., 2009; Westcott & Kristovich, 2009). However, diagnosing fog from numerical weather prediction models remains a challenge (Bergot et al., 2015; Bergot et al., 2007; Yang et al., 2010) and various methods have been developed to achieve this. One approach is to use a multi rule-based method, where threshold values of multiple variables are employed to define fog conditions in the forecast (e.g. (Zhou & Du, 2010)). Such a method is presented here for next day forecasts of radiation fog at Abu Dhabi in the United Arab Emirates.

Fog is defined as conditions where visibility is less than 1000 m due to the presence of water droplets (World Meteorological Organization, 2008a). It is the most extreme condition of low visibility from condensation followed by mist ($1 \text{ km} < \text{vis} < 5 \text{ km}$), and haze ($\text{vis} < 5 \text{ km}$). Haze is due to high water vapour mixing ratio but relative humidity is below 90 %. Historically, fog is difficult to diagnose from mesoscale model variables (Bergot et al., 2015; Bergot et al., 2007; Yang et al., 2010). One option for defining fog in the model is to use the cloud water mixing ratio, sometimes referred to as liquid water content (LWC), in the lowest model level. If positive or in excess of a given threshold, fog is deemed to be present at the site. A variant of this method is to integrate the cloud water mixing ratio over a set of model levels instead of just taking the value at the lowest level, an approach followed e.g. by Yang et al. (2010). However, mesoscale models are often too coarse in resolution to solve this condensation process explicitly or display deficiencies in the physical parameterization at these scales (e.g. (Bergot et al., 2017)). Furthermore, the challenge to separate fog from mist and haze still remains.

The final desired model diagnostic of a fog forecast is visibility. Many visibility equations have been published based on observations using LWC as the main dependent variable, with variations that include water vapour mixing ratio, wind speed or relative humidity (RH) (Bang et al., 2008; Clark et al., 2008; Gultepe & Milbrandt, 2007; Gultepe et al., 2006; Smirnova et al., 2000; Stoelinga et al., 1999). A visibility forecast provides actionable information to end users. The physics of visibility is based on Mie theory and the associated extinction efficiency related to particle size. However, in situ information on particle size is scarce, and has been

shown to vary from case to case at a single location (e.g. (Zhang et al., 2014)). The main drawback of this approach is, again, the dependence on model performance of LWC, droplet number and droplet size distribution. This has led to the development of visibility equations based on relative humidity in place of droplet information (e.g. (Bang et al., 2008; Bieringer et al., 2006; Smirnova et al., 2000)).

Alternatively, a multi-variable rule-based method can be used, where model variables within a certain range, or below a predefined threshold, indicate fog conditions, as was first proposed by Croft et al. (1997). This approach has been shown to improve forecast skill compared to LWC methods (Zhou & Du, 2010). Zhou and Du (2010) defined a set of variables to represent fog conditions for the different types of fog described by Tardif and Rasmussen (2007). For fog to be present, either of the following conditions need to be met: (i) $LWC \geq 0.015 \text{ g kg}^{-1}$, or (ii) cloud top $\leq 400\text{m}$ and cloud base $\leq 50 \text{ m}$, or (iii) $10 \text{ m wind speed} \leq 2 \text{ m s}^{-1}$ and $2 \text{ m RH} \geq 90\%$. These three categories accounted for types of fog like advection, stratus lowering or ground fog. The hit rate, or probability of detection (POD), the fraction of the fog events that are successfully predicted by the model (optimal score of 1), using these criteria ranged from 0.1 to 0.6, which was overall higher than using a $LWC > 0$ criteria for fog. The false alarm ratio, the fraction of the model forecasts that turned out not to be correct (optimal score of 0), ranged from about 0.4 to 0.65 for these criteria, which was about the same as the $LWC > 0$ method. Baker et al. (2002) used a different set of criteria to diagnose radiation fog, which accounted for vertical mixing of moisture and atmospheric stability. Firstly, like Zhou and Du's third condition, they assume that the surface relative humidity is above 95 % and that wind speed is calm and below 3 ms^{-1} . In addition, they define two new parameters, the cross over temperature, which is the 2 m dew point temperature during the warmest hours of the day, and a modified Richardson index, which indicates vertical stability due to temperature and wind speed. The thresholds proposed for these two new parameters are $T_{\text{crossover}} - 1.66 \text{ }^{\circ}\text{C}$ and 0.04, respectively. Although they do not report on model performance, we will discuss more on the use of the modified Richardson parameter in the methodology section, as it proves useful for radiation fog cases. Payra and Mohan (2014) used (i) near-surface relative humidity gradient ($RH_{2\text{-meters}} - RH_{\text{surface}} < -4.5\%$), (ii) 10-meter wind speed ($1.4\text{-}2.8 \text{ ms}^{-1}$), (iii) near-surface temperature gradient ($T_{\text{surface}} - T_{2\text{-meters}} > 0 \text{ }^{\circ}\text{C}$), and (iv) dew point depression less than $8 \text{ }^{\circ}\text{C}$ criteria to define fog over Northern India, and reported high POD results, in excess of 90%. However they do not state the false alarm ratio, which we assume to be high as well. Menut et al. (2014) added a new rule to diagnose fog, which is the rate of cooling in the hours preceding radiation fog events in Paris. Their main aim was to model pre-fog conditions, and they found that the cooling rate of 2 m temperature should be $> 0.5 \text{ }^{\circ}\text{C}$ over a 3 hour period.

In addition, and due to the availability of measurements at their sites of interest, they required the net infrared flux to be $< -10 \text{ Wm}^{-2}$, which means that surface cooling should be occurring, the RH 2 m $> 90 \%$, and 10 m wind speed $< 3 \text{ ms}^{-1}$. Their best model POD (FAR) scores were 0.58 (0.37) to 0.74 (0.37), which corresponds to the best performance so far for a multi rule-based approach. Interestingly, they also applied these thresholds to the observed data at their site and reported a POD (FAR) of 0.87 (0.39). In other words, if the model simulated the observations exactly, this is the theoretical best performance that can be achieved with the employed criteria and thresholds. C. Román-Cascón et al. (2016) later applied the same criteria to two sites in Europe, one in the Netherlands and one in Spain. When using the same threshold values, their model forecast POD (FAR) scores were 0.20 (0.10) and 0.34 (0.17) for the Netherlands and Spain, respectively, which is a rather poor forecast performance. However, when applied to the observed data, the POD (FAR) scores were 0.86 (0.21) and 0.64 (0.14), respectively, which is a very good result. Due to the poor model performance, they adjusted the threshold values based on observations collected at the sites, and later improved the model POD (FAR) scores to 0.86 (0.37) and 0.59 (0.35) for Netherlands and Spain respectively. The observed POD (FAR) scores also improved to 82.1 (30.6) and 73.9 (22.3), respectively. While criteria variables remained the same in this instance, the optimum threshold can change from site to site, which can only be determined if site specific observations are available.

In this paper, a rule-based application of diagnosing fog from an operational version of the Weather Research and Forecasting (WRF) model is presented. The rules are based on commonly available variables from automatic weather stations and soundings so that the method is transferable to other locations with similar measurements. The performance of the next day's forecast is assessed against station data from Abu Dhabi's International Airport and the results are discussed with reference to previous studies that are summarized above. Finally, a qualitative spatial comparison of the model fog mask and the satellite RGB image is presented. The work is structured as follows. In section 2, a description of the observational datasets, the rule-based method, and the setup of the WRF model is presented. In section 3, the thresholds employed for each criterion are determined. In Section 4 the performance of the WRF model is evaluated. A summary of the main findings is given in section 5.

5.2 Methodology

5.2.1 Study Area

The United Arab Emirates (UAE) is an arid country located on the northeastern edge of the Arabian Peninsula (Figure 5-1) with a mean spatial annual rainfall of about 78 mm/year (Ouarda & Charron, 2014; Wehbe et al., 2017; Wehbe et al., 2018). It covers an area of 83,600 km², which is mostly sparse to bare vegetation, and the main soil type is sand and loamy sand. It relies heavily on groundwater and desalination as sources of fresh water and treated sewage effluent for irrigation (Aldababseh et al., 2018). Despite being an arid region, the mean water vapour mixing ratio can reach 11 (18) g/kg in winter (summer), and the region experiences frequent fog in winter, which can extend over most of the country (Aldababseh & Temimi, 2017; Bartok et al., 2012; De Villiers & Van Heerden, 2007; Weston, Temimi, Burger, et al., 2021).

Abu Dhabi's International Airport experiences radiation fog (De Villiers & Van Heerden, 2007) between 8 and 51 days per year (Weston, Temimi, Burger, et al., 2021). The sea-breeze transports moisture from the Arabian Gulf to the interior, and can penetrate 130 km inland (Eager et al., 2008), while fog can extend up to about 200 km inland at the Southern border with Saudi Arabia (e.g. Weston and Temimi (2020)). Fog in the UAE forms under calm conditions on winter nights. The clear night sky, combined with the high albedo desert surface, means that the air temperature drops quickly at night. This leads to the formation of nocturnal inversion layers, which trap advected moisture near the surface (eg. (Temimi et al., 2020)). Moisture is transported in during the day with the sea breeze. At night, the return land breeze is weaker and often calm. Fog is most frequent at the coldest time of the night just before sunrise and dissipates shortly after sunrise (De Villiers & Van Heerden, 2007; Weston, Temimi, Burger, et al., 2021).

The Emirates have an expanding agricultural sector and have utilized groundwater, waste water and desalinated water (Aldababseh et al., 2018). Fog harvesting sites in neighboring Saudi Arabia captured between 2,500 and 3,200 liters of water in less than three months during the fog season (Gandhidasan & Abualhamayel, 2012). However, fog harvesting has yet to be considered as a source of fresh water to supplement agricultural irrigation in the UAE.

The study site is Abu Dhabi's International Airport (AUH), which is located on the mainland coast line in Abu Dhabi City. The airport is at the edge of the city and is mostly surrounded by

bare ground rather than urban area. The airport has Meteorological Aerodrome Reports (METAR) hourly observations that include standard atmospheric state measurements along with visibility and weather codes.

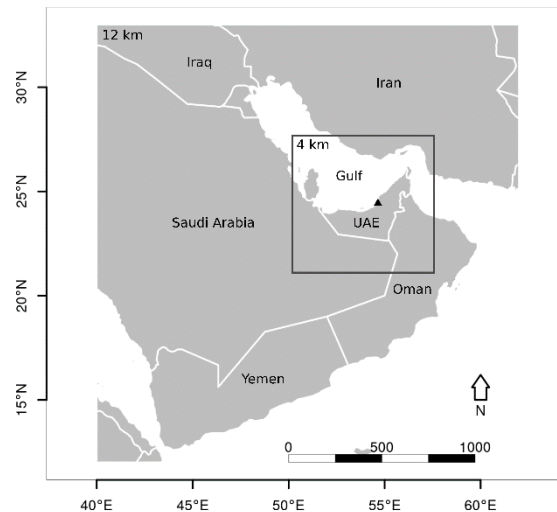


Figure 5-1: Map of the United Arab Emirates (UAE) on the Arabian Peninsula. Abu Dhabi's International Airport (black triangle) is situated on the coast line. Black box represents 4 km WRF domain. The map represents the 12 km WRF domain.

5.2.2 Study Period

The study period covered 10 winter months (303 days) over two seasons. The first season is from December 2016 to March 2017 and the second season is October 2017 to March 2018. During this period, 35 fog days were recorded at AUH.

5.2.3 Data Sets

5.2.3.1 METAR data

METAR observations from AUH were used to identify fog conditions and for model verification. Data was downloaded from the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC) database (NCEI, 2001). These reports include visibility measurements and a weather code indicating the presence of fog (Table 2-1:). Fog was defined as conditions where visibility was less than or equal to 1,000 m and one of the fog codes were present. Both parameters are required to define fog as low visibility can also occur

due to dust events or rainfall events. Relative humidity cannot be used to define fog events as it is high during rainfall events.

Table 5-1: METAR codes used to define fog

METAR Code	Description
FG	Fog
GNDFG	Ground fog
FZFG	Freezing fog
45FG	Fog: No sky visible
44FG	Partial Fog
42FG	Fog: Sky visible
VCFG	Fog in Vicinity
BCFG	Fog patch

5.2.3.2 Radiosonde

Radiosonde data was used to characterize vertical profiles of temperature during fog and clear sky conditions. This was conducted to see if there is a difference in surface layer inversion characteristics under fog conditions that may be helpful in defining fog rules. Furthermore, the vertical temperature profiles forms part of the modified Richardson index (described in section 3.3) which is a parameter used to define some rules. Seventeen years of data from 2000 to 2017 were obtained from the University of Wyoming's website (Oolman, 2019). The 00 UTC sounding was analysed as it corresponds to 04h00 local standard time (LST), roughly when fog forms at the site (e.g. Chaouch et al., 2017; Weston et al., 2018). Profiles for fog conditions were identified by matching the date of fog days from the METAR data described above. Clear sky conditions were defined as days that lacked cloud cover codes in the METAR (defined as OVC=overcast or 8/8, BKN=broken or 7/8, SCT=scattered or 4/8 and FEW= few or 2/8) and lacked the fog code.

5.2.3.3 SEVIRI

The fog product (night microphysical) from the Spinning Enhanced Visible and Infrared Imager (SEVIRI) instrument on board Meteosat-10 (situated over 9.5 °E) was utilized for this study (Schmetz et al., 2002). The resolution is about 4 km and images are available every 15 minutes. In this fog product, the red channel is the difference between 12.0 and 10.8 μm

channels (linear stretch -4 to 2 K), the green channel is the difference between 10.8 and 3.9 μm channels (linear stretch 0 to 10 K) and the blue channel is the 10.8 μm channel (linear stretch 243 to 293 K). This is used for a qualitative assessment of the spatial extent of the model-predicted fog extent.

5.2.4 Defining Rules

In the rule-based approach, threshold values are defined for selected variables, namely, the 2-meter dew point depression, 10-meter horizontal wind speed, atmospheric stability, and visibility. A combination of these thresholds defines a rule.

In order to determine suitable threshold values at the site, the METAR data was analyzed for fog and non-fog conditions. The METAR data was analyzed for the years 2000-2016 and for the months of October to March (excluding December 2016, which is included in the model results). These months are when fog activity is highest and the sample period excludes the modelling period. Frequency distributions of surface variables, dew point depression and wind speed, are calculated and act as a guide for selecting a suitable threshold. The results of this analysis are presented in Section 3.

Radiation fog occurs under stable conditions. To represent the vertical stratification of the atmosphere, Baker *et al.* (2002) introduced a Modified Richardson Index (MRi), which accounts for the vertical temperature gradient and wind shear, and is defined as

$$MRi = \frac{T_b - T_{sfc}}{(u \times 1.943)^2}, \quad (10)$$

where T_b = boundary layer temperature ($^{\circ}\text{C}$), where boundary layer is at either 900 hPa or P_{sfc} -35 hPa pressure level), T_{sfc} = surface temperature ($^{\circ}\text{C}$), and u = surface wind speed (in ms^{-1}). Values of MRi above 0.04 are considered stable, 0.025-0.04 are indicative of marginally stable conditions, and < 0.025 corresponds to a mixed layer. The MRi was calculated at AUH using a combination of the METAR and radiosonde data. The suitability of the 0.04 value was assessed for fog cases at the AUH site. The results of the analysis are presented in Section 3. Radiosonde data was analyzed from January 2000 to March 2017.

A linear relationship between relative humidity and visibility was defined from the METAR observations. Visibility (in kilometers) was calculated using a linear equation where relative humidity is the independent variable (Eq. (11)). Visibility was assumed to be 0 m when relative humidity was 100 %.

$$Vis = m \cdot RH + c, (\text{when } RH > 85 \%) \quad (11)$$

Where m is the slope and c is the y-intercept. A visibility equation normally includes an exponential function over a large range in visibility (0 – 10 km) (Bang et al., 2008; Clark et al., 2008; Gultepe et al., 2006; Smirnova et al., 2000; Smith et al., 2002; Stoelinga et al., 1999). However, fog cases occur on a short segment of the exponential curve and near the y-limit (i.e. low visibility), which can be treated as a linear segment. A sensitivity analysis was conducted on the observed RH data by perturbing m and c and assessed against observed fog events. A contingency table was constructed for a time window of 00 to 12 local time. If fog was reported in this window and the visibility was ≤ 1000 m, it is considered a hit. The probability of detection (POD) and false alarm ratio (FAR) were calculated from the contingency table. The equation with the best score was applied to model output as the visibility rule for defining fog.

It is assumed that rules are relevant over land only as they are based on observations reported at a land based station. Marine fog is not considered at any level in the design or evaluation of the rules.

5.2.5 WRF model

A two-nest configuration of 12 and 4 km (Figure 5-1) with one-way feedback is run with WRF v4.1.2 (Skamarock et al., 2019). Only results from the 4 km domain are analyzed and presented in this paper. Simulations are initialized at 06 UTC with the 0.25 degree GFS (version 14, (NCEP, 2015)) and run for 48 hours. The first 30 hours from the forecast are selected for verification, excluding the first 6 hours which allow for model spin up (Chaouch et al., 2016; Weston et al., 2018). Land cover classes are taken from the United States Geological Survey (USGS) global database (Loveland et al., 2000; Sertel et al., 2010). Model physics parameterization included the rapid radiative transfer model for general circulation model applications (RRTMG) for short wave radiation and RRTM for longwave radiation (Iacono et al., 2008; Eli J. Mlawer et al., 1997). The Quasi-Normal Scale Elimination (QNSE) planetary boundary layer (PBL) scheme is implemented with its associated surface layer physics scheme (Sukoriansky et al., 2005). Chaouch et al., (2016) tested seven PBL parameterization schemes for five fog events in AUH, and found that the QNSE scheme gave the best results for fog events in the region, capturing the vertical temperature and moisture profiles at Abu Dhabi. The regular Thompson cloud microphysics scheme is employed (Thompson et al., 2008), following the results of (Fonseca et al., 2020; Schwitalla et al., 2020). The unified Noah land surface model is implemented for land surface physics. The Kain-

Fritsch cumulus scheme (Kain, 2004b) is active in the 12 km grid but is not employed in the 4 km domain. There were 45 vertical levels with the lowest four levels at about 26, 85, 160 and 250 m above ground level.

A night time cold bias in the WRF model has previously been reported for this region (Weston et al., 2018). Fonseca et al. (2019) have shown that modifications to the soil properties in arid areas can counter act this bias. For instance, a decrease in soil porosity reduces the air spaces between soil particles and effectively increases the thermal inertia of the surface. The net effect is a decrease in the daytime maximum and an increase in the night time minimum temperatures. The default soil texture in WRF is from the State Soil Geographic (STATSGO)/Food and Agriculture Organization (FAO) soil database (Dy & Fung, 2016; Sanchez et al., 2009). According to this dataset, the soil texture in the UAE is mostly sand, loamy sand and sandy loam, with some sections of clay near the coast. However, the results of an extensive local survey of soil texture reported most soil types as sand (EAD, 2009). Accordingly, “clay”, “sandy loam” and “loamy sand” soil types within the UAE were converted to “sand” in the nested WRF domain (Figure 5-2). “Loam” was left as is. Furthermore, the soil porosity was decreased by 10 percent over “sand” and by 30 percent over “loam”.

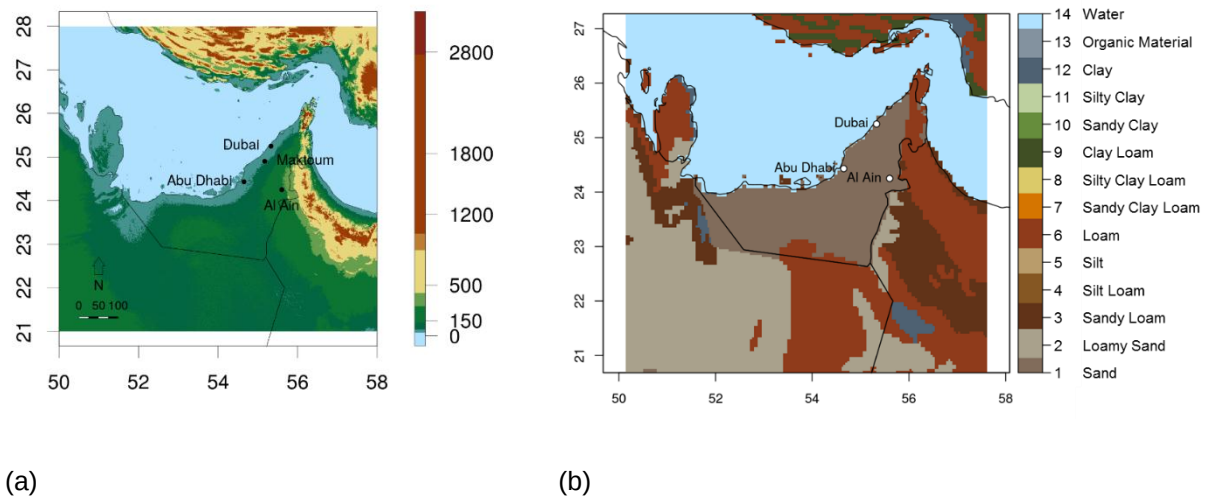


Figure 5-2: (a) Orography (m) and (b) soil texture in the WRF's 4 km grid over the UAE. Points on the map represent the study site (Abu Dhabi) in relation to other airports in the region.

5.2.6 Model verification

5.2.6.1 Meteorological variables

The model meteorological variables of temperature depression (Tdep), RH, wind speed, dry bulb temperature (T) and dew point temperature (Td) are verified against the METAR observations and the bias, mean gross error (MGE) and root mean square error (RMSE) was calculated. For Tdep (RH), the daily minimum (maximum) value was verified. For wind speed, hourly values from the morning window of 00h00 to 08h00 local time was verified.

5.2.6.2 Fog verification

The aim of the verification conducted in this study is to assess the model's performance in providing an accurate forecast for the following day. The model predictions from the closest grid point to the Abu Dhabi's International Airport are considered. This means that 24 hours from 16h00 to 10h00 next day LST (12h00 to 06h00 UTC) are considered as a valid forecast. An 8-hour window from 00h00 to 08h00 LST is subset from the valid forecast to evaluate whether fog was present in the METAR and was predicted by the model. This corresponds to forecast hours 15 to 23. From these results, the scores in the contingency table are computed, from which the probability of detection (POD) and false alarm ratio (FAR) are calculated.

Table 5-2: Contingency table of modelled forecast (WRF) vs. observations (METAR).

	METAR fog yes	METAR fog no
WRF fog yes	Hits	False Alarms
WRF fog no	Misses	Correct Negative

The probability of detection (POD), which is sometimes called hit rate, is calculated as follows:

$$POD = \frac{Total\ hits}{Total\ hits + total\ misses}, \quad (12)$$

where 1 is the perfect score. A score of 0.8 can be interpreted as 8 out of 10 observations are correctly predicted. The false alarm ratio is calculated using the equation below:

$$FAR = \frac{Total\ false\ alarms}{Total\ hits + total\ false\ alarms}, \quad (13)$$

The optimal score for the FAR is 0, as it would indicate no false alarms, and the theoretical maximum is 1 (all events are false alarms). A score of 0.4 can be interpreted as 4 out of 10 predicted events were not observed.

As a way of summarizing the results, the Euclidian distance to a perfect score is calculated as follows:

$$Euclidian\ distance = \sqrt{(1 - POD)^2 + (0 - FAR)^2}, \quad (14)$$

This is useful for evaluating cases that have different POD and FAR scores, as the case with the shortest distance to a perfect score constitutes a better result.

5.3 Rule-based Method

5.3.1 Summary of rules

A summary of the rules is presented here as a reference (Table 5-3). The rationale for these rules are discussed in this section.

Table 5-3: Summary of rules and related thresholds for diagnosing fog from the model.

Rule No.	Rule	Tdep (°C)	Wind Speed (m/s)	MRi	z_inv (m)	Vis (km) (RH ≥ 94)	LWC (g/kg)
1	Static	≤ 2	≤ 2.8				
2	Sliding	≤ 2/1/0	≤ 2/3/3.5				
3	Static + MRi 0.04	≤ 2	≤ 2.8	> 0.04			
4	Sliding + MRi 0.04	≤ 2/1/0	≤ 2/3/3.5	> 0.04			
5	Static + MRi 0.001	≤ 2	≤ 2.8	> 0.001			
6	Sliding + MRi 0.001	≤ 2/1/0	≤ 2/3/3.5	> 0.001			
7	Static + z_inv250m	≤ 2	≤ 2.8		> 250		
8	Sliding + z_inv250m	≤ 2/1/0	≤ 2/3/3.5		> 250		
9	Vis					Vis ≤ 1	
10	Vis + z_inv150m				> 150	Vis ≤ 1	
11	Vis + z_inv250m				> 250	Vis ≤ 1	
12	Vis + ws3		≤ 3			Vis ≤ 1	
13	Vis + z_inv250m + ws3		≤ 3		> 250	Vis ≤ 1	
14	Vis + MRi 0.001			> 0.001		Vis ≤ 1	
15	Vis + MRi 0.04			> 0.04		Vis ≤ 1	
16	RH 94 + z_inv + ws3		≤ 3		> 250	RH ≥ 94	
17	LWC						LWC > 0

5.3.2 Dew point depression and wind speed

Dew point depression (Tdep) and wind speed rules normally occur together for radiation fog. Dew point depression, the difference between the air temperature and the dew point temperature, is indicative of how close to saturation the air is with respect to water vapour. Dew point depression and relative humidity represent the same process in the atmosphere

(i.e. saturation), and can be used interchangeably to define fog conditions. A range in relative humidity from 90-100 % corresponds to a Tdep of 2-0 °C. Some published rule-based methods use relative humidity, such as (Menut et al., 2014; Zhou & Du, 2010; Zhou et al., 2012), while others use dewpoint depression (Payra & Mohan, 2014). Radiation fog requires calm conditions (Tardif & Rasmussen, 2007), and proposed thresholds of wind speed (ws) range from 1-3 ms⁻¹ (Menut et al., 2014; Payra & Mohan, 2014; Zhou & Du, 2010; Zhou et al., 2012).

An analysis of the METAR data showed that the 100th percentile for Tdep under fog conditions was 2 °C (Figure 5-3a). This was used as the Tdep threshold in defining the first rule. Similarly, the 90th percentile for wind speed was 3.1 ms⁻¹. An initial threshold of 2.8 ms⁻¹ was tested (as per Payra and Mohan (2014)) before increasing to 3 ms⁻¹. These thresholds are used in the static threshold rules. It is evident from Figure 5-3, that there is an overlap between fog and non-fog conditions, in particular for the wind speed. This is a limitation of the rule-based method, as non-fog conditions will always be captured in the threshold sample and therefore limit the verification scores even if the model produced a perfect forecast.

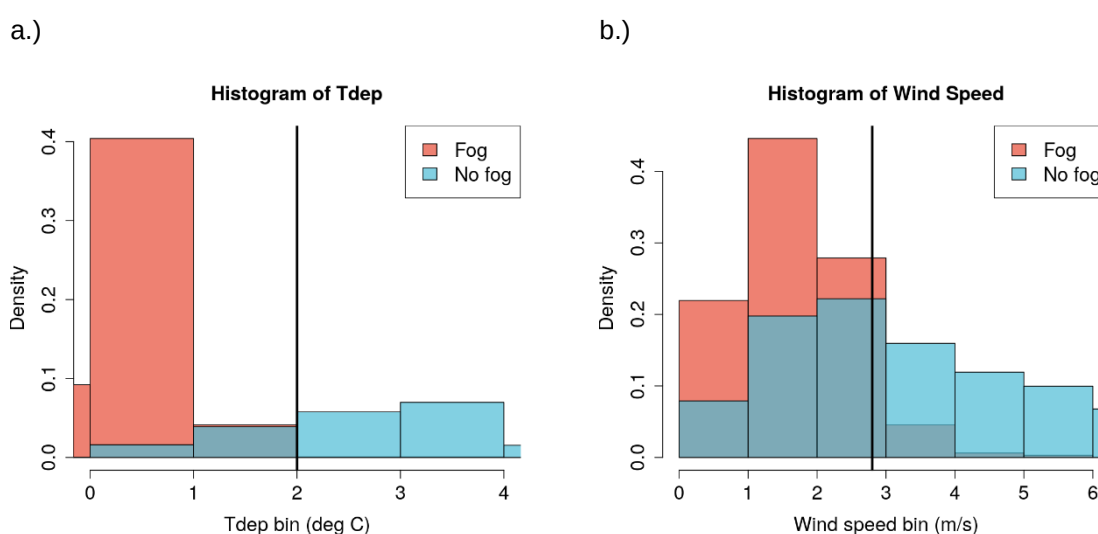


Figure 5-3: a.) Histogram of METAR Tdep under fog and non-fog conditions and b.) histogram of METAR wind speed under fog and non-fog conditions. Vertical black lines represent the threshold used in Rule #1.

A sliding rule was proposed as an alternative to the static thresholds where the thresholds change according to a category. As Tdep is decreased, the density of data points at higher

wind speeds increased during fog events (Figure 5-4). Three categories were defined with the following ranges for Tdep (wind speed); 0-2°C (0-2 ms⁻¹), 0-1°C (0-3 ms⁻¹), 0°C (3.5 ms⁻¹). If any of the three conditions occur it is assumed there is fog in the model.

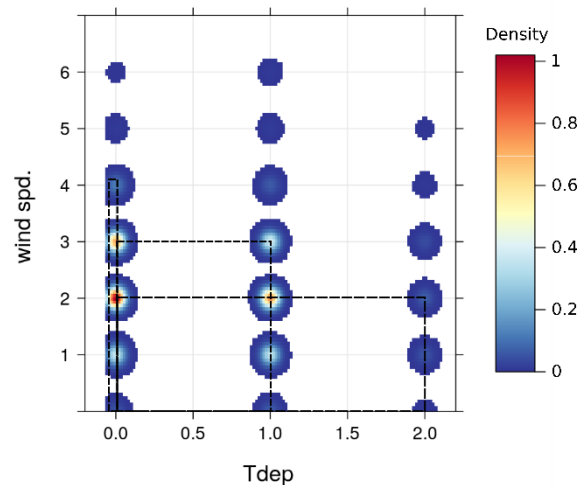


Figure 5-4: Density scatter plot of Tdep and wind speed during fog conditions at AUH. Black dashed boxes indicate the three categories in the sliding rule (Rule #2).

5.3.3 Atmospheric Stability

The radiosonde data was analysed to check for the suitability of using a MRi threshold of 0.04, highlighted with a black line in Figure 5-5. The red dots represent fog cases that are captured by the threshold of 0.04. The green dots, on the other hand, indicate fog events that have a MRi between 0.001 and 0.037. From this analysis we conclude that the 0.04 threshold could be too restrictive for diagnosing fog at this site. Thus, an extra threshold of 0.001 was tested as an additional rule.

A MRi greater than zero means that a temperature inversion is present, and the wind speed becomes less important. An argument can be made that if a temperature inversion is present and is sufficiently established there is no need to include the wind speed and associated wind shear, as the atmosphere is already stable. Furthermore, wind speed is already accounted for independently in the static rules and is not required as part of the stability rule. This led to adding an additional parameter to classify atmospheric stability, which is the depth of the nocturnal surface inversion layer (z_inv). This excludes wind speed or the inversion strength, and simply makes use of the depth of the inversion layer. Weston et al. (2021) reported that surface inversions are deeper during fog events than during clear sky conditions at Abu Dhabi

airport. One reason that may explain the deeper inversion layer during fog conditions is turbulence which promotes mixing below the top of the inversion. A few authors have indicated that some amount of turbulence is required for fog to form (e.g. (Gultepe et al., 2007; Haeffelin et al., 2013)) while too much turbulence will inhibit or dissipate fog (e.g Zhou and Ferrier, 2008). In some cases, a minimum wind speed and associated turbulence was identified in order for fog to form. Payra and Mohan (2014) report that wind speed should be $> 1.4 \text{ ms}^{-1}$, Terpstra (1999) report $> 1 \text{ ms}^{-1}$ and Haefflin et al (2013) report $> 0.5 \text{ ms}^{-1}$. Zhou and Ferrier (2008) show that turbulence has a positive correlation with the depth of saturated air near the surface. Furthermore, they indicate that fog is inhibited when the saturated air depth is shallow (less than 100 m). We have not included a rule that represents the depth of saturated air, as this would require us to use the liquid water content in the model. However, accounting for the depth of moisture near the surface may be considered in future studies. We run a sensitivity test using threshold values of 150 m and 250 m above ground level for the depth of the inversion layer, referred to as z_{inv} in the results section.

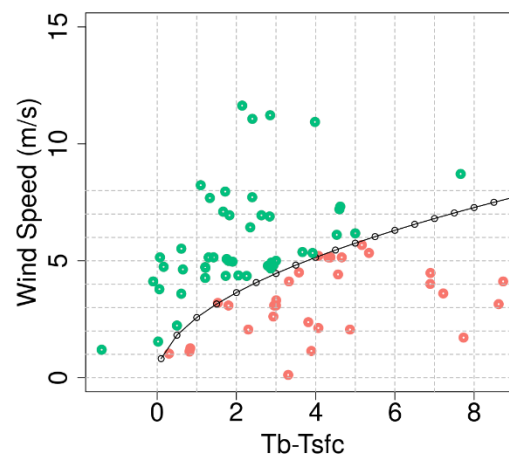


Figure 5-5: Sounding and METAR data used to calculate the MRI as given by Equation (10). The black line represents MRI of 0.04. Green dots represent observed fog events that have observed MRI of 0.001 to 0.037, while red dots are observed fog events that have an observed MRI ≥ 0.04 .

5.3.4 Relative Humidity and Visibility

Results of the METAR analysis at AUH show the challenge of fitting a line to the data, as the range in visibility is large at similar relative humidity (Figure 5-6). This may be in part due to a lack of precision in the METAR data. The relative humidity is derived from the dry bulb and

dew point temperatures, where the dew point temperature does not contain decimal places in METAR observations. The discontinuity of relative humidity in Figure 5-6 is attributed to this loss of precision in dew point temperature. This adds an additional challenge in fitting a curve to this data set. Nevertheless, the application of a linear relationship in the low visibility range of this data set proved to be helpful.

The results of the sensitivity analysis for a range of values of m and c are presented in Table 5-4. The best scores for POD (FAR) of 0.85 (0.33) were achieved with $m=-0.166$ and $c=16.66$. If the FAR was 0.5 or higher it means that half the forecasts are false alarms, and hence the method is not suitable to be employed. The results of this analysis indicate the best possible score that the model can achieve if using the visibility rule.

The straight line is effectively the same as using a static threshold for humidity of 94 %. This converts to a Tdep of about 1.4°C, which was not possible to test in the observed data due to the referred lack of precision. The range of visibility at similar relative humidity indicates that there are other driving forces to the fog formation. Clark et al. (2008) included the aerosol number in conjunction with relative humidity when defining visibility, as aerosol loading affects fog formation. Aerosol information is not available at this site, however other measurements in the country indicate that surface condensation nuclei loading is high throughout winter and that the fine aerosols are hygroscopic (Filioglou et al., 2020; Hamdan et al., 2018; Kaku et al., 2016).

This equation was applied to the model forecast and is referred to as the Vis rule although it is representing a static threshold of 94 % (1.4°C) for RH (Tdep).

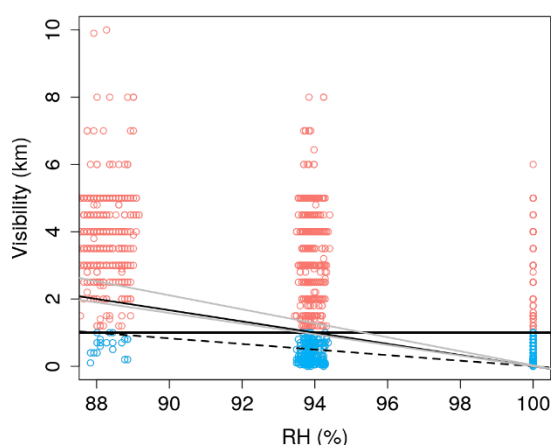


Figure 5-6: METAR relative humidity and visibility for October to March, 2000 to 2016. Blue (red) dots indicate fog (non-fog) cases. Thick solid horizontal line is 1 km visibility. Black line is the optimal equation. Dashed line is the POD=1 equation. Grey lines are the remaining equations from Table 5-4.

Table 5-4: Sensitivity test results of visibility equation. m = slope; c = y-intercept.

m	c	Hit	Miss	False	POD	FAR
-0.208	20.83	192	59	40	0.76	0.17
-0.166	16.66	213	38	106	0.85	0.33
-0.158	15.83	241	10	313	0.96	0.56
-0.083	8.3	251	0	671	1	0.72

5.4 Model verification

5.4.1 WRF Meteorological verification

The statistical verification of the daily minimum (maximum) of Tdep (RH) is presented in Table 5-5 along with the hourly verification of wind speed. Over all the mornings the Tdep is shown to have a cold (negative) bias with a mean gross error (MGE) of 1.7 °C. On fog mornings only, the Tdep has a warm (positive) bias with a MGE of 1.13 °C. Similarly, RH has an overall positive bias with MGE of 7.82 % but a negative bias on fog mornings with MGE of 5.29 %. The Td MGE (positive bias) on all days and non-fog days is larger than the T MGE. This is in agreement with the RH MGE (and bias) on these same days, and can be the reason for the

negative Tdep MGE. On fog days, the T MGE (positive bias) is larger than the Td MGE, which may result in a larger Tdep than observed and the reported positive bias. Wind speed has an overall positive bias and MGE of 1.23 ms^{-1} and fog mornings the bias is positive with a MGE of 0.90 ms^{-1} .

Table 5-5: Statistical scores from bias, mean gross error and RMSE for modelled Tdep, wind speed and relative humidity at AUH. Tdep (RH) is verified for the daily minimum (maximum). Thus, n is sample size in either days (Tdep/RH) or hours (wind speed).

Rule	n	Bias	Mean gross error	RMSE
Tdep (°C): All	293	-0.02	1.7	2.57
Tdep (°C): No fog	258	-0.16	1.78	2.67
Tdep (°C): Fog	35	1.02	1.13	1.68
Wind speed (ms^{-1}): All	2637	0.76	1.23	1.66
Wind speed (ms^{-1}): No fog	2472	0.79	1.25	1.69
Wind speed (ms^{-1}): Fog	165	0.31	0.90	1.18
RH (%): All	293	1.28	7.82	11.01
RH (%): No fog	258	1.97	8.16	11.30
RH (%): Fog	35	-3.87	5.29	8.57
T (°C): All	293	0.52	1.47	1.87
T (°C): No fog	258	0.34	1.42	1.83
T (°C): fog	35	1.81	1.84	2.15
Td (°C): All	293	0.55	1.71	2.41
Td (°C): No fog	258	0.52	1.73	2.45
Td (°C): fog	35	0.78	1.50	1.78

5.4.2 WRF fog verification

The rules in Table 5-3 were applied to the observed data and the results are reported in Table 5-6. The rationale of applying the rules to the observations is to indicate the best case scenario for the model if it performed perfectly for all the parameters. In general, rules containing the Vis (RH) threshold (rules 9 through 14) outperformed the static and sliding combinations (1 through 8), with rules 12 (Vis +ws3) and 9 (Vis) performing the best, with a POD (FAR) of 0.89

(0.24/0.28 respectively). Rules 10, 11 and 13 (Vis + z_250m, Vis + z_150m and Vis + z_250m +ws3) performed equally with POD (FAR) of 0.69 (0.14). In general, rules that include MRI $\geq$ 0.001 (i.e. an inversion is present) outperformed MRI $\geq$ 0.04 rules (e.g. 5 vs 3 and 15 vs 14). If the presence of an inversion is extrapolated to include the depth of the inversion, the FAR is further decreased (e.g rule 5 vs 7 and 14 vs 11).

Table 5-6: Contingency table results of the multi rule-based method applied to observations.

Rule No.	Rule	Hit	Miss	FALSE	POD	FAR	Euclidian Distance
1	Static	35	0	63	1.00	0.64	0.6429
2	Sliding	35	0	48	1.00	0.58	0.5783
3	Static + MRI 0.04	15	20	9	0.43	0.38	0.6835
4	Sliding + MRI 0.04	15	20	9	0.43	0.38	0.6835
5	Static + MRI 0.001	30	5	40	0.86	0.57	0.5890
6	Sliding + MRI 0.001	30	5	32	0.86	0.52	0.5355
7	Static + z_inv250m	25	9	15	0.74	0.38	0.4590
8	Sliding + z_inv250m	25	9	14	0.74	0.36	0.4460
9	Vis	31	4	12	0.89	0.28	0.3016
10	Vis + z_inv150m	24	11	4	0.69	0.14	0.3452
11	Vis + z_inv250m	24	11	4	0.69	0.14	0.3452
12	Vis + ws3	31	4	10	0.89	0.24	0.2694
13	Vis + z_inv250m + ws3	24	11	4	0.69	0.14	0.3452
14	Vis + MRI 0.001	26	9	7	0.74	0.21	0.3333
15	Vis + MRI 0.04	11	24	2	0.31	0.15	0.7028

The static and sliding rules provide the highest POD (0.8 and 0.71, respectively) and a good starting point in terms of FAR (0.58 and 0.54) (Table 5-7). Further changes are needed to achieve a FAR below 0.5, which is accomplished in some cases through the introduction of the atmospheric stability parameter. The addition of the MRI 0.04 criterion, rules #3-4, reduces the FAR to below 0.5 for both the static and sliding rules, while using 0.001 as a threshold for the MRI, rules #5-6, maintains a FAR above 0.5. This suggests that MRI 0.001 is too lenient. The sliding rule with MRI 0.04, rule #4, is eliminated due to a low POD score, which suggests that this combination is too restrictive. The addition of the z_inv 250 m condition, rules #7-8, achieves similar results to the static + MRI 0.004 rule, rule #3, but returns a lower distance score. Thus, the MRI rule is not required at this site. This pattern is reiterated when discussing

the visibility rule below. The general conclusion from these comparisons is that the static rule outperforms the sliding rule, and that the inversion depth can be used in place of the MRI for atmospheric stability.

The visibility rule is essentially a more restrictive version of the static rule, where relative humidity needs to be greater than or equal to 94 %, which equates to a Tdep threshold of about 1.4 °C. It is found that the visibility rule combined with a higher wind speed threshold of 3 ms⁻¹ performed better than the previous threshold of 2.8 ms⁻¹ (better FAR and distance, not shown). However, when the visibility rule is combined with the inversion depth (z_inv 250 m), rule #13, it outperforms the visibility + ws3 rule (#12) based on lower distance. This indicates that the stable atmosphere parameter holds more weight than the wind speed in diagnosing fog from the model. A sensitivity test to compare an inversion depth of 150 m and 250 m was conducted and showed that the 250 m threshold performed better (e.g. rules #10 and 11). All these parameters were combined and the final rule with the best performance was Rule #13 (visibility + z_inv250 m + ws3). This met the criteria with a POD (FAR) of 0.62 (0.37), and the lowest Euclidian distance of 0.5304. Rule #13 compared well to the observed POD (FAR) of 0.69 (0.14) (Table 5-6), and is most likely limited by the performance of RH during fog days. For example, rule #9 (Vis) only achieved a POD of 0.68 in the model, compared to 0.89 in the observed data. Future improvements in the model parameterisation schemes may further improve the prediction of RH, and hence the performance of this rule. As already discussed, the visibility rule is the same as using a static threshold of 94 % for relative humidity. Rule #16 confirmed this and showed the same results as rule #13. The use of liquid water content as a rule (#17) performed the worst with POD (FAR) of 0.37 (0.31). In this case, the rule-based method outperforms the use of LWC to diagnose fog in the model.

Table 5-7: Contingency table results of the multi rule-based method applied to WRF.

Rule No.	Rule	Hit	Miss	False	POD	FAR	POD - FAR	Euclidian distance
1	Static	28	7	40	0.8	0.58	0.22	0.6135
2	Sliding	25	10	30	0.71	0.54	0.17	0.6129
3	Static + MRi 0.04	22	13	20	0.63	0.48	0.15	0.6039
4	Sliding + MRi 0.04	19	16	11	0.54	0.37	0.18	0.5860
5	Static + MRi 0.001	27	8	35	0.77	0.56	0.21	0.6054
6	Sliding + MRi 0.001	24	11	26	0.68	0.52	0.16	0.6106
7	Static + z_inv250m	24	11	24	0.68	0.5	0.18	0.5936
8	Sliding + z_inv250m	21	14	17	0.6	0.44	0.16	0.5946
9	Vis	24	11	26	0.68	0.52	0.16	0.6106
10	Vis + z_inv150m	23	12	21	0.65	0.47	0.18	0.5860
11	Vis + z_inv250m	22	13	15	0.62	0.4	0.22	0.5517
12	Vis + ws3	24	11	23	0.68	0.49	0.19	0.5852
13	Vis + z_inv250m + ws3	22	13	13	0.62	0.37	0.25	0.5304
14	Vis + MRi 0.001	23	12	23	0.66	0.5	0.16	0.6063
15	Vis + MRi 0.04	19	16	10	0.54	0.34	0.2	0.5720
16	RH 94 + z_inv + ws3	22	13	13	0.62	0.37	0.25	0.5304
17	LWC	13	22	6	0.37	0.31	0.06	0.7021

A comparison of the observed fog days with the fog days from the model obtained with rule #13 indicates that the rule is applicable throughout the verification period (Figure 5-7). It generates hits in early season (October), mid-season (December and January) and at the end of the season (March). Notable performance is that February and November 2017 did not have any observed events and the model did not generate any false alarms in these months. In contrast, February 2018 had four fog days and the model did not capture any of these. Upon inspection it was noted that the model Tdep was larger than observations during February 2018 and no fog events were captured by the rule (Figure 5-7). The reason for this bias is not clear yet but may be due to some larger scale variability that is not captured in the simulations.

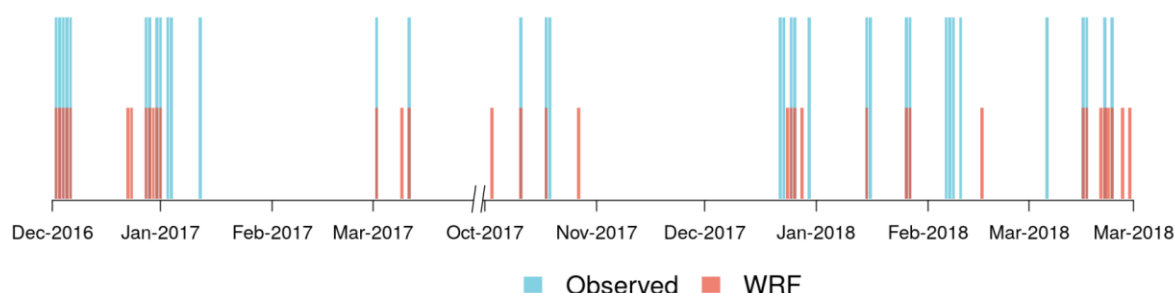


Figure 5-7: Time series of observed (blue bars) and forecast (red bars) fog days for the study period. For clarity, the red bars have half the height of the blue bars.

The results of previous rule-based studies discussed in the Introduction are summarized in Figure 5-8 along with this study. While the methodologies vary widely between these studies (e.g. model resolution, number of stations for verification, etc.), it does provide context on the model performance. The comparison shows that the results from this study are in the favorable range where POD is greater than 0.6 and FAR is below 0.5. Furthermore, the comparison indicates that simulations with longer lead times to the fog events return better scores. In the case of the UAE, the longer lead time makes sense as the fog formation depends on the advection of moisture during the day preceding the night time fog event. In addition the cooling cycle of the land is included in the forecast which should capture the fog events in the forecast. A fog forecast study from the UAE by Bartok et al. (2012) is included. In their study, fog was diagnosed using visibility from the PAFOG model and not a rule based method. It is interesting to note the high FAR from Bartok et al. (2012). While their study makes use of visibility, which is assumed to be derived from the cloud microphysics, it seems that their model system is overactive in the fog forecast. As pointed out earlier, for fog and non-fog conditions, Tdep and wind speed ranges overlap in the UAE, which also results in an overactive forecast. This was constrained through the addition of stricter thresholds and the inclusion of the inversion depth parameter. Thus, the rule-based method is shown to be useful in situations where fog forecasts are overactive.

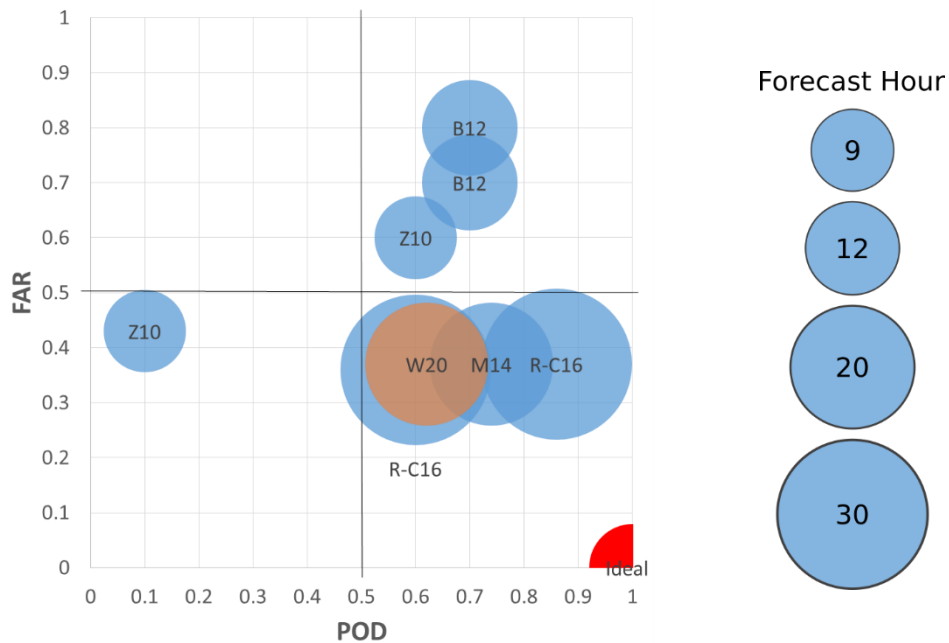


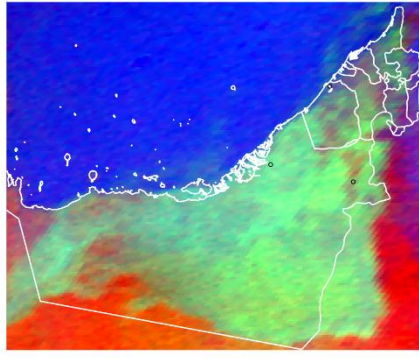
Figure 5-8: Summary of the results of rule-based studies. The bubble size is indicative of the forecast hour when fog occurred, whereas the bubble labels refer to the study. The red bubble indicates an ideal forecast score (size is irrelevant). This study (W20) is in orange. Z10=Zhou and Du (2010), B12=Bartok *et al.* (2012), M14=Menut *et al.* (2014), R-C16=Román-Cascón *et al.* (2016), W20=this study.

An important consideration regarding forecast assessment is its final application. For example, in terms of road safety, does a false alarm or a missed event hold more weight? If missed events are less desirable, then less restrictive rules can be implemented at the cost of increasing the false alarms. This will require more input from the forecaster with regards to decision making. It would require an analysis of the economic impact of the forecast through a cost-loss analysis (e.g. (Zhou *et al.*, 2012)). Such an analysis is beyond the scope of this study.

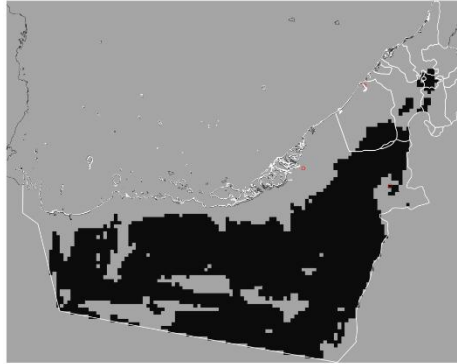
5.4.3 Spatial comparison with satellite

In this section, the Rule #13 is applied to all data points in the model domain to create a fog mask. A qualitative comparison is then made to the Meteosat 10 SEVIRI false colour composite fog product. An extensive fog patch occurred on 2017-01-04, which extended from the coast to about 200 km inland at the Southern border with Saudi Arabia (Figure 5-9a). The fog occurs over land and does not extend over the Gulf waters where the air temperature is warmer. This was a missed event in the model which, although it does not capture the fog at

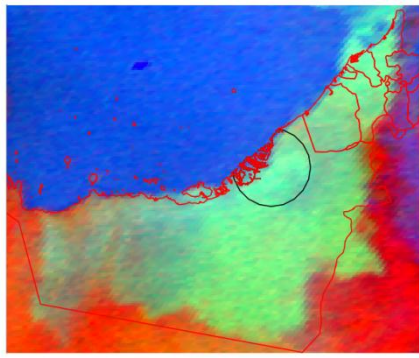
Abu Dhabi, it does capture the inland fog. This suggests that although the rule is based on observations at Abu Dhabi, it can be applied to the wider model domain. A similar event was observed on 2016-12-30 (Figure 5-9c) and was recorded as a hit in the forecast. In this case the model fog patch was along the coast and did not capture the inland fog (Figure 5-9d). Not all fog events extend inland as is the case on 2016-12-27 (Figure 5-9e-f) which occurs along the coast. Here the model captures the fog mask quite well. From the examples presented here it seems that the model captures the inland fog more often than not and that the geophysical parameters in Rule #13 are representing the physical process of fog formation (Figure 5-9 and Figure 5-10).



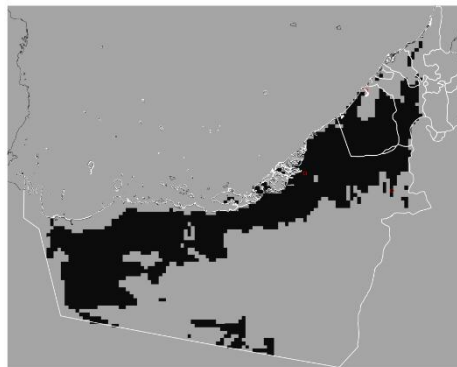
(a) 2017-01-04 0100



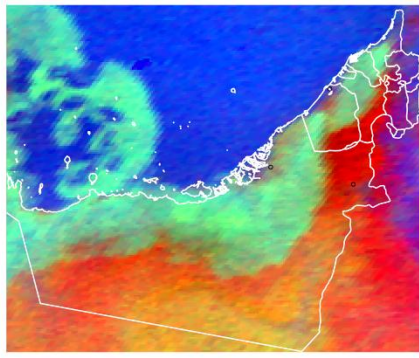
(b) 2017-01-04 0100



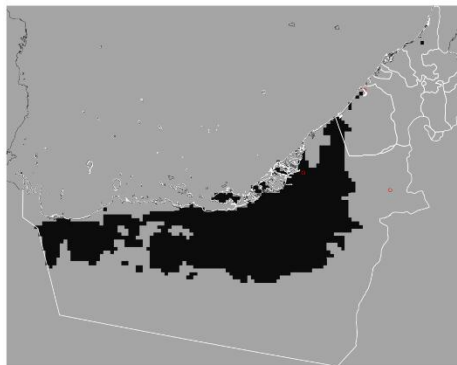
(c) 2016-12-30 2300



(d) 2016-12-30 2300



(e) 2016-12-27 2100



(f) 2016-12-27 2100

Figure 5-9: (a) SEVIRI 2017-01-04 at 0100 UTC, and (b) WRF fog mask (grey corresponds to no fog, while black indicates to the presence of fog). (c-d) As (a-b) but on 2016-12-30 at 23 UTC. (e-f) As (a-b) but on 2016-12-27 at 2100 UTC.

It often occurs that the fog patch does not extend continuously from West to East across the UAE, but rather features separate elements concentrated in specific regions (Figure 5-10). The reason for these patches could be related to the location of onshore flow or more precisely

the inhibition of onshore flow. For example, Steinhoff *et al*, (2018) demonstrated that the position of a surface low pressure over the Gulf can inhibit moisture transport over the eastern half of the UAE while promoting it over the western half. This blocking mechanism mostly occurs in summer but similar blocking mechanisms are most likely present in winter months. Similar circulation has been reported for summer (June/July) and up to October (Reid, Piketh, et al., 2008; Schwitalla et al., 2020). For our cases, there is a clear boundary in the satellite RGB between fog and no fog that is representative of a change in physical conditions (e.g. moisture or temperature). As the model is based on geophysical parameters, it appears to capture this boundary in the forecast fog patch for some cases. This suggests that there is a realism in the model simulations of these events. The conclusion from this qualitative analysis is that the multi rule-based method can produce realistic fog patches provided the model bias is within the threshold values.

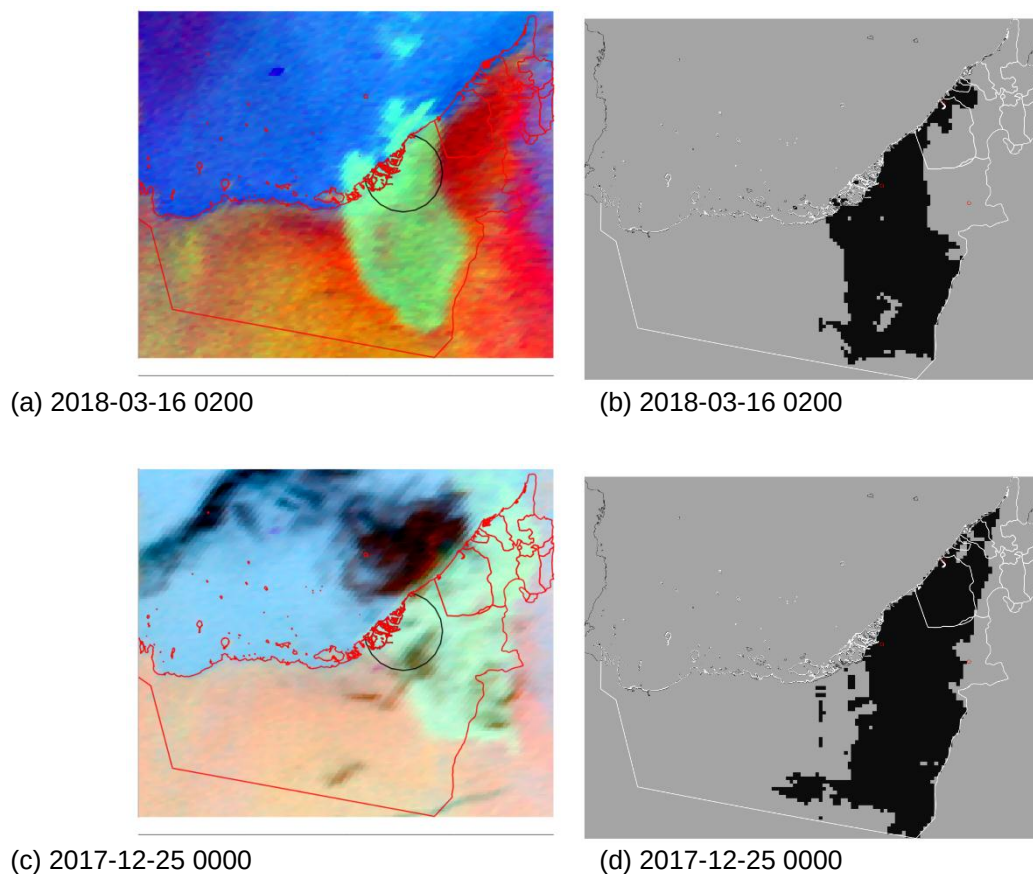


Figure 5-10: As Figure 5-9 but on (a-b) 2018-03-16 at 0200 UTC. (c-d) 2017-12-25 at 0000 UTC. Grey in WRF mask corresponds to no fog, while black indicates to the presence of fog.

5.5 Summary

Diagnosing fog from numerical weather prediction models is a challenge. Some approaches rely on liquid water content or diagnosing visibility as a model output. Another option is to use a multi rule-based approach where several criteria must be met in order to diagnose fog. In this paper we test a range of multi rule-based methods for forecasting next day fog at Abu Dhabi International Airport in the United Arab Emirates. The study period covered 10 winter months (303 days) over two seasons. The first season is from December 2016 to March 2017 and the second season is October 2017 to March 2018.

A range of rules were tested and evaluated against METAR observations at Abu Dhabi International airport. A combination of the following variables were used to define a rule: dew point depression, relative humidity, wind speed, modified Richardson index, depth of inversion layer and liquid water content.

The worst performing rule was rule #17, where liquid water content was greater than 0 g/kg. This produced a POD (FAR) of 0.37 (0.31). The best performing rule was rule #13/16, where relative humidity $\geq 94\%$, wind speed $\leq 3 \text{ ms}^{-1}$, and the depth of the inversion layer $> 250 \text{ m}$, are required for fog to be present at the site. The rule show no seasonal bias and achieved a POD (FAR) score of 0.62 (0.37) for forecasting fog on the following day. This is a good result in comparison to other rule-based studies with similar forecast lead times of about 14 hours. The depth of the inversion layer added value in defining fog conditions for this site. Inversion depth performed better in combination with relative humidity than with a wind speed or MRI condition. An inherent limitation of the rule-based method is that fog and non-fog conditions can exhibit similar geophysical conditions. As a result, the FAR was never lower than 0.3 in the model performance.

Fog formation occurred at around forecast hour 20 for these simulations. A comparison with other studies showed similar forecast hours were required (20 to 30) for forecasts with POD > 0.7 . This makes sense for radiation fog events that require the cooling cycle to be captured in the simulation for an accurate forecast.

Rule #13 was extended to the model domain and the fog mask was compared qualitatively against SEVIRI RGB fog products. This showed that the rule did well in capturing most of the observed fog patches, with the exception of February 2018. Furthermore, the modelled and observed fog patches exhibit clearly defined borders, suggesting that the geophysical

parameters used to diagnose fog are also simulated well in the model. This indicates that there is a realism in the model simulations of fog events.

The multi rule-based method is useful in this case for diagnosing fog and performed better than using liquid water content alone. If model performance of selected geophysical parameters (e.g. Tdep) are further improved through model parameterisation, this method will be even more robust. Thus, further improvement of the model meteorological variables will be useful in this case. Lastly, it is acknowledged that the number of cases available for model verification can be improved by running simulations over a longer period. This would allow for inter season variation of fog in the sample size and further test the veracity of this method.

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5.6 References

- Aldababseh, A., & Temimi, M. (2017). Analysis of the long-term variability of poor visibility events in the UAE and the link with climate dynamics. *Atmosphere*, 8(12), 18--20. <https://doi.org/10.3390/atmos8120242>
- Aldababseh, A., Temimi, M., Maghelal, P., Branch, O., & Wulfmeyer, V. (2018). Multi-criteria evaluation of irrigated agriculture suitability to achieve food security in an arid environment. *Sustainability (Switzerland)*, 10(3). <https://doi.org/10.3390/su10030803>
- Baker, R., Cramer, J., & Peters, J. (2002). Radiation Fog: UPS Airlines Conceptual Models And Forecast Methods. *10th Conference on Aviation, Range, and Aerospace Meteorology*, 116(3), 505--524. http://ams.confex.com/ams/13ac10av/techprogram/paper/_39165.htm \% 5Cn<http://ams.confex.com/ams/13ac10av/10ARAM/abstracts/39165.htm>
- Bang, C.-h., Lee, J.-w., & Hong, S.-y. (2009). Predictability Experiments of Fog and Visibility in Local Airports over Korea using the WRF Model. *Journal of Korean Society for Atmospheric Environment*, 24(2008), 92--101.
- Bartok, J., Bott, A., & Gera, M. (2012). Fog Prediction for Road Traffic Safety in a Coastal Desert Region: Improvement of Nowcasting Skills by the Machine-Learning Approach. *Boundary-Layer Meteorology*, 157(3), 501--516. <https://doi.org/10.1007/s10546-015-0069-x>
- Bergot, T., Escobar, J., & Masson, V. (2015). Effect of small-scale surface heterogeneities and buildings on radiation fog: Large-eddy simulation study at paris-charles de gaulle airport. *Quarterly Journal of the Royal Meteorological Society*, 141(686), 285--298. <https://doi.org/10.1002/qj.2358>

- Bergot, T., Lac, C., Burnet, F., Martinet, P., Bouteloup, Y., & Bouyssel, F. (2017). Towards a three-dimensional prediction of fog on airports with the M'et'e o-France operational forecast model AROME. *WMO Aeronautical Meteorology Scientific Conference*.
- Bergot, T., Terradellas, E., Cuxart, J., Mira, A., Leichti, O., Mueller, M., & Nielsen, N. W. (2007). Intercomparison of single-column numerical models for the prediction of radiation fog. *Journal of Applied Meteorology and Climatology*, 46(4), 504--521. <https://doi.org/10.1175/JAM2475.1>
- Bieringer, P. E., Donovan, M., Robasky, F., Clark, D. A., & Hurst, J. (2006). A characterization of NWP ceiling and visibility forecasts for the terminal airspace.
- Chaouch, N., Temimi, M., Weston, M., & Ghedira, H. (2016). Sensitivity of the meteorological model WRF-ARW to planetary boundary layer schemes during fog conditions in a coastal arid region. *Atmospheric Research*, 187, 106--127. <https://doi.org/10.1016/j.atmosres.2016.12.009>
- Clark, P. A., Harcourt, S. A., Macpherson, B., Mathison, C. T., Cusack, S., & Naylor, M. (2008). Prediction of visibility and aerosol within the operational Met office unified model.I: Model formulation and variational assimilation. *Quarterly Journal of the Royal Meteorological Society*, 134(636), 1801--1816. <https://doi.org/10.1002/qj.318>
- Croft, P. J., Pfost, R. L., Medlin, J. M., & Johnson, G. A. (1997). Fog Forecasting for the Southern Region: A Conceptual Model Approach. *Weather and Forecasting*, 12(3), 545--556. [https://doi.org/10.1175/1520-0434\(1997\)012<0545:FFFTSR>2.0.CO;2](https://doi.org/10.1175/1520-0434(1997)012<0545:FFFTSR>2.0.CO;2)
- De Villiers, M. P., & Van Heerden, J. (2007). Fog at Abu Dhabi international airport. *Weather*, 62, 209-214.
- Dy, C. Y., & Fung, J. C. H. (2016). Updated global soil map for the Weather Research and Forecasting model and soil moisture initialization for the Noah land surface model. *Journal of Geophysical Research*, 121(15), 8777--8800. <https://doi.org/10.1002/2015JD024558>
- Eager, R. E., Raman, S., Wootten, A., Westphal, D. L., Reid, J. S., & Mandoos, A. A. (2008). A climatological study of the sea and land breezes in the Arabian Gulf region. *Journal of Geophysical Research Atmospheres*, 113(15), 1--12. <https://doi.org/10.1029/2007JD009710>
- Environment Agency Abu Dhabi. (2009). *Soil Survey of Abu Dhabi Emirate*. <https://www.biosaline.org/projects/soil-survey-emirate-abu-dhabi>
- Filioglou, M., Giannakaki, E., Backman, J., Kesti, J., Hirsikko, A., Engelmann, R., Connor, E. O., Leskinen, J. T. T., Shang, X., Korhonen, H., Lihavainen, H., Oapos, Connor, E., Leskinen, J. T. T., Shang, X., Korhonen, H., Lihavainen, H., Romakkaniemi, S., & Komppula, M. (2020). Optical and geometrical aerosol particle properties over the United Arab Emirates. *Atmospheric Chemistry and Physics Discussions*(March), 1--26. <https://doi.org/10.5194/acp-2020-133>
- Fonseca, R., Temimi, M., Thota, M. S., Nelli, N. R., Weston, M. J., Suzuki, K., Uchida, J., Kumar, K. N., Branch, O., & Wehbe, Y. a. (2020). On the Analysis of the Performance of WRF and NICAM in a Hyperarid Environment. *Weather and Forecasting*, 35(3), 891-919. <https://doi.org/10.1175/waf-d-19-0210.1>

- Fonseca, R., Zorzano-Mier, M. P., Azua-Bustos, A., Gonzalez-Silva, C., & Martn-Torres, J. (2019). A surface temperature and moisture intercomparison study of the Weather Research and Forecasting model, in-situ measurements and satellite observations over the Atacama Desert. *Quarterly Journal of the Royal Meteorological Society*(November 2018), 2202--2220. <https://doi.org/10.1002/qj.3553>
- Gandhidasan, P., & Abualhamayel, H. I. (2012). Exploring fog water harvesting potential and quality in the Asir region, Kingdom of Saudi Arabia. *Pure and Applied Geophysics*, 169(5-6), 1019--1036. <https://doi.org/10.1007/s00024-011-0341-z>
- Gultepe, I., & Milbrandt, J. A. (2007). Microphysical observations and mesoscale model simulation of warm fog case during FRAM project. *Pure and Applied Geophysics*, 164(6-7), 1161--1178. <https://doi.org/10.1007/s00024-007-0212-9>
- Gultepe, I., Müller, M. D., & Boybeyi, Z. (2006). A new visibility parameterization for warm-fog applications in numerical weather prediction models. *Journal of Applied Meteorology and Climatology*, 45, 1469-1480. <https://doi.org/10.1175/JAM2423.1>
- Gultepe, I., Pearson, G., Milbrandt, J. A., Hansen, B., Platnick, S., Taylor, P., Gordon, M., Oakley, J. P., & Cober, S. G. (2009). The fog remote sensing and modeling field project. *Bulletin of the American Meteorological Society*, 90(3), 341--359. <https://doi.org/10.1175/2008BAMS2354.1>
- Gultepe, I., Tardif, R., Michaelides, S. C., Cermak, J., Bott, A., Bendix, J., Mller, M. D., Pagowski, M., Hansen, B., Ellrod, G., Jacobs, W., Toth, G., & Cober, S. G. (2007). Fog Research: A Review of Past Achievements and Future Perspectives. *Pure Appl. Geophys.*, 164, 1121--1159. <https://doi.org/10.1007/s00024-007-0211-x>
- Haefelin, M., Dupont, J. C., Boyouk, N., Baumgardner, D., Gomes, L., Roberts, G., & Elias, T. (2013). A Comparative Study of Radiation Fog and Quasi-Fog Formation Processes During the ParisFog Field Experiment 2007. *Pure and Applied Geophysics*, 170(12), 2283--2303. <https://doi.org/10.1007/s00024-013-0672-z>
- Hamdan, N. M., Alawadhi, H., Jisrawi, N., & Shameer, M. (2018). Characterization of fine particulate matter in Sharjah, United Arab Emirates using complementary experimental techniques. *Sustainability (Switzerland)*, 10(4). <https://doi.org/10.3390/su10041088>
- Iacono, M. J., Delamere, J. S., Mlawer, E. J., Shephard, M. W., Clough, S. A., & Collins, W. D. (2008). Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *J. Geophys. Res.*, 113. <https://doi.org/10.1029/2008JD009944>
- Kain, J. S. (2004). The Kain-Fritsch convective parameterization: an update. *Journal of Applied Meteorology*, 43(1), 170--181.
- Kaku, K. C., Reid, J. S., Reid, E. A., Ross-Langerman, K., Piketh, S., & Cliff, S. a. (2016). Investigation of the relative fine and coarse mode aerosol loadings and properties in the Southern Arabian Gulf region. *Atmospheric Research*, 169, 171--182. <https://doi.org/10.1016/j.atmosres.2015.09.029>
- Loveland, T. R., Reed, B. C., Ohlen, D. O., Brown, J. F., Zhu, Z., Yang, L., & Merchant, J. W. (2000). Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing*, 21(6-7), 1303--1330. <https://doi.org/10.1080/014311600210191>

- Menut, L., Mailler, S., Dupont, J. C., Haeffelin, M., & Elias, T. (2014). Predictability of the Meteorological Conditions Favourable to Radiative Fog Formation During the 2011 ParisFog Campaign. *Boundary-Layer Meteorology*, 150(2), 277--297. <https://doi.org/10.1007/s10546-013-9875-1>
- Mlawer, E. J., Taubman, S. J., Brown, P. D., Iacono, M. J., & Clough, S. A. (1997). Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. *Journal of Geophysical Research: Atmospheres* (1984–2012), 102(D14), 16663--16682.
- NCEI, N. (2001). *Integrated Global Surface Hourly Dataset* <ftp.ncdc.noaa.gov/pub/data/noaa/>
- NCEP. (2015). *NCEP GFS 0.25 Degree Global Forecast Grids Historical Archive*. <https://doi.org/10.5065/D65D8PWK>
- Oolman, L. (2019). *Wyoming Weather Web*. Retrieved July 2019 from <http://weather.uwyo.edu>
- Ouarda, T. B. M. J., & Charron, C. a. (2014). Evolution of the rainfall regime in the united arab emirates. *Journal of Hydrology*, 514, 258--270. <https://doi.org/10.1016/j.jhydrol.2014.04.032>
- Payra, S., & Mohan, M. (2014). Multirule based diagnostic approach for the fog predictions using WRF modelling tool. *Advances in Meteorology*, 2014. <https://doi.org/10.1155/2014/456065>
- Reid, J. S., Piketh, S. J., Walker, A. L., Burger, R. P., Ross, K. E., Westphal, D. L., Brientjes, R. T., Holben, B. N., Hsu, C., Jensen, T. L., Kahn, R. A., Kuciauskas, A. P., Mandoos, A. A., Mangoosh, A. A., Miller, S. D., Porter, J. N., Reid, E. A., & Tsay, S. C. (2008). An overview of UAE2 flight operations: Observations of summertime atmospheric thermodynamic and aerosol profiles of the southern Arabian Gulf. *Journal of Geophysical Research Atmospheres*, 113(14), 1--14. <https://doi.org/10.1029/2007JD009435>
- Román-Cascón, C., Steeneveld, G. J., Yagüe, C., Sastre, M., Arrillaga, J. A., & Maqueda, G. (2016). Forecasting radiation fog at climatologically contrasting sites: Evaluation of statistical methods and WRF. *Quarterly Journal of the Royal Meteorological Society*, 142, 1048-1063. <https://doi.org/10.1002/qj.2708>
- Sanchez, P. A., Ahamed, S., & Carr. (2009). Digital soil map of the world. *Science*, 325(5941), 680--681. <https://doi.org/10.1126/science.1175084>
- Schmetz, J., Pili, P., Tjemkes, S., Just, D., Kerkmann, J., Rota, S., & Ratier, A. (2002). An introduction to Meteosat Second Generation (MSG). *Bulletin of the American Meteorological Society*, 83(7), 977--992. [https://doi.org/10.1175/1520-0477\(2002\)083<0977:AITMSG>2.3.CO;2](https://doi.org/10.1175/1520-0477(2002)083<0977:AITMSG>2.3.CO;2)
- Schwitalla, T., Branch, O., & Wulfmeyer, V. (2020). Sensitivity study of the planetary boundary layer and microphysical schemes to the initialization of convection over the Arabian Peninsula. *Quarterly Journal of the Royal Meteorological Society*, 146(727), 846--869. <https://doi.org/10.1002/qj.3711>
- Sertel, E., Robock, A., & Ormeci, C. (2010). Impacts of land cover data quality on regional climate simulations. *International Journal of Climatology*, 30(13), 1942--1953. <https://doi.org/10.1002/joc.2036>

- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Zhiquan, L., Berner, J., Wang, W., Powers, J. G., Duda, M. G., Barker, D. M., & Huang, X.-Y. (2019). A Description of the Advanced Research WRF Model Version 4. *NCAR Technical Note NCAR/TN-475+STR*, 145. <https://doi.org/10.5065/1dfh-6p97>
- Smirnova, T. G., Benjamin, S. G., & Brown, J. M. (2000). Case study verification of RUCS/MAPS fog and visibility forecasts. 9th Conf. on Aviation, Range, and Aerospace Meteorology (AMS),
- Smith, T. L., Benjamin, S. G., & Brown, J. M. (2002). Visibility forecasts from the RUC20. 10th Conf. on Aviation, Range, and Aerospace Meteorology, Portland.
- Steinhoff, D. F., Bruintjes, R., Hackera, J., Keller, T., Williams, C., & Jensen, T. a. (2018). Influences of the monsoon trough and Arabian heat low on summer rainfall over the United Arab Emirates. *Monthly Weather Review*, 146(5), 1383--1403. <https://doi.org/10.1175/MWR-D-17-0296.1>
- Stoelinga, M. T., Warner, T. T., Stoelinga, M. T., & Warner, T. T. (1999). Nonhydrostatic, Mesobeta-Scale Model Simulations of Cloud Ceiling and Visibility for an East Coast Winter Precipitation Event. *Journal of Applied Meteorology*, 38(4), 385--404. [https://doi.org/10.1175/1520-0450\(1999\)038<0385:NMSMSO>2.0.CO;2](https://doi.org/10.1175/1520-0450(1999)038<0385:NMSMSO>2.0.CO;2)
- Stolaki, S. N., Kazadzis, S. A., Foris, D. V., & Karacostas, T. S. (2009). Fog characteristics at the airport of Thessaloniki, Greece. *Natural Hazards and Earth System Science*, 9(5), 1541--1549. <https://doi.org/10.5194/nhess-9-1541-2009>
- Sukoriansky, S., Galperin, B., & Perov, V. (2005). Application of a new spectral theory of stably stratified turbulence to the atmospheric boundary layer over sea ice. *Boundary-Layer Meteorology*, 117(2), 231--257. <https://doi.org/10.1007/s10546-004-6848-4>
- Tardif, R., & Rasmussen, R. M. (2007). Event-based climatology and typology of fog in the New York City region. *Journal of Applied Meteorology and Climatology*, 46(8), 1141--1168. <https://doi.org/10.1175/JAM2516.1>
- Temimi, M., Fonseca, R. M., Nelli, N. R., Valappil, V. K., Weston, M. J., Thota, M. S., Wehbe, Y., & Yousef, L. (2020). On the analysis of ground-based microwave radiometer data during fog conditions. *Atmospheric Research*, 231(August 2019), 104652. <https://doi.org/10.1016/j.atmosres.2019.104652>
- Terpstra, J. (1999). *De invloed van de grondwaterstand, wind, temperatuur en dauwpunt op de vorming van stralingsmist: een kwantitatieve benadering*.
- Thompson, G., Field, P. R., Rasmussen, R. M., & Hall, W. D. (2008). Explicit Forecasts of Winter Precipitation Using an Improved Bulk Microphysics Scheme. Part II: Description and Sensitivity Analysis. *Monthly Weather Review*, 132(2), 519--542. [https://doi.org/10.1175/1520-0493\(2004\)132<0519:EFOWPU>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<0519:EFOWPU>2.0.CO;2)
- Wehbe, Y., Ghebreyesus, D., Temimi, M., & Milewski, A. a. (2017). Assessment of the consistency among global precipitation products over the United Arab Emirates. *Journal of Hydrology: Regional Studies*, 12(May), 122--135. <https://doi.org/10.1016/j.ejrh.2017.05.002>
- Wehbe, Y., Temimi, M., Ghebreyesus, D. T., Milewski, A., Norouzi, H., & Ibrahim, E. (2018). Consistency of precipitation products over the Arabian Peninsula and interactions with

- soil moisture and water storage. *Hydrological Sciences Journal*, 63(3), 408--425. <https://doi.org/10.1080/02626667.2018.1431647>
- Westcott, N. E., & Kristovich, D. A. R. (2009). A climatology and case study of continental cold season dense fog associated with low clouds. *Journal of Applied Meteorology and Climatology*, 48(11), 2201--2214. <https://doi.org/10.1175/2009JAMC1999.1>
- Weston, M., Chaouch, N., Valappil, V., Temimi, M., Ek, M., & Zheng, W. (2018). Assessment of the Sensitivity to the Thermal Roughness Length in Noah and Noah-MP Land Surface Model Using WRF in an Arid Region. *Pure and Applied Geophysics*. <https://doi.org/10.1007/s00024-018-1901-2>
- Weston, M., Temimi, M., Burger, R., & Piketh, S. (2021). A Fog Climatology at Abu Dhabi International Airport. *Journal of Applied Meteorology and Climatology*(Early online release). <https://doi.org/10.1175/JAMC-D-20-0168.1>
- Weston, M. J., & Temimi, M. (2020). Application of a nighttime fog detection method using SEVIRI over an arid environment. *Remote Sensing*, 12(14). <https://doi.org/10.3390/rs12142281>
- World Meteorological Organization. (2008). Aerodrome reports and forecasts : a users' handbook to the codes., 81.
- Yang, D., Ritchie, H., Desjardins, S., Pearson, G., MacAfee, A., & Gultepe, I. (2010). High-Resolution GEM-LAM Application in Marine Fog Prediction: Evaluation and Diagnosis. *Weather and Forecasting*, 25(2), 727--748. <https://doi.org/10.1175/2009WAF2222337.1>
- Zhang, J., Xue, H., Deng, Z., Ma, N., Zhao, C., & Zhang, Q. (2014). A comparison of the parameterization schemes of fog visibility using the in-situ measurements in the North China Plain. *Atmospheric Environment*, 92, 44--50. <https://doi.org/10.1016/j.atmosenv.2014.03.068>
- Zhou, B., & Du, J. (2010). Fog Prediction from a Multimodel Mesoscale Ensemble Prediction System. *Weather and Forecasting*, 25, 303--322. <https://doi.org/10.1175/2009WAF2222289.1>
- Zhou, B., Du, J., Gultepe, I., & Dimego, G. (2012). Forecast of low visibility and fog from NCEP: Current status and efforts. *Pure and Applied Geophysics*, 169(5-6), 895--909. <https://doi.org/10.1007/s00024-011-0327-x>
- Zhou, B., & Ferrier, B. S. (2008). Asymptotic analysis of equilibrium in radiation fog. *Journal of Applied Meteorology and Climatology*, 47(6), 1704--1722. <https://doi.org/10.1175/2007JAMC1685.1>

CHAPTER 6 SENSITIVITY ANALYSIS OF AN AEROSOL AWARE MICROPHYSICS SCHEME IN WRF DURING CASE STUDIES OF FOG IN NAMIBIA

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Abstract: Microphysical measurements of fog were undertaken during the AEROCLO-SA field campaign at Henties Bay on the west coast of Namibia during September 2017. A fog monitor 100 (FM100) provided cloud droplet size distribution, number concentration, liquid water content and mean volumetric diameter. These measurements are used to evaluate and parameterise WRF model simulations which employed the Thompson aerosol aware microphysics scheme. A sensitivity analysis was conducted through variations to the initial CCN concentration, CCN radius and the minimum updraft speed, important factors that influence droplet activation in the microphysics scheme of the model. The first model scenario made use of the default settings with a constant initial CCN concentration of 300 cc and underestimated the cloud droplet number concentration while the LWC was in good agreement with the observations. This resulted in droplet size being larger than the observations. Another scenario used modelled data as CCN initial conditions which were an order of magnitude higher than other scenarios. However, these provided the most realistic values of Nt, LWC, MVD and droplet size distribution. From this it was concluded that CCN activation is too low in the simulations, around 10 %, while the observed appears to be higher, between 30-60 %. To achieve this level of activation in the model, the minimum updraft speed for CCN activation was increased from 0.01 to 0.1 ms⁻¹. This scenario provided Nt, LWC, MVD and droplet size distribution in the range of the observations with the added benefit of a realistic initial CCN concentration.

Keywords: fog; Namibia; WRF; microphysics; aerosol aware.

6.1 Introduction

The Central Namib Desert is situated along a narrow coastal area about 100 km wide on the Namibian Coast. It is adjacent to the cold Benguela current in the South Atlantic Ocean and subsequently experiences fog when the moist air from above the ocean is advected over the desert surface. As a vital source of fresh water in this arid ecosystem, fog has been a topic of study for decades (Cermak, 2012; Lancaster et al., 1984; Olivier, 1995; Seely & Henschel, 1998; Seely & Hamilton, 1976), and has recently motivated long-term distributed observations (the FogNet network) as well as intensive dedicated field campaigns (Spirig et al., 2019) that have shed new light on the spatial and temporal characteristics and dynamics of fog in the region. Fog occurs predominantly at night and early morning hours and is most frequent at coastal sites, reaching about 120 days a year and decreasing to 40 (5) fog days at sites 40 (100) km inland (Andersen & Cermak, 2018; Cermak, 2012; Olivier, 1995; Spirig et al., 2019). Fog is most frequent in winter (May - August) at coastal sites and in summer (Sep - Dec) at inland sites (Andersen et al., 2019; Lancaster et al., 1984; Nagel, 1962; Olivier, 1995; Spirig et al., 2019). The fog is predominantly advective and high fog (Andersen et al., 2020; Andersen et al., 2019) where high fog is when low stratus cloud intersects with the land. This is possible in the central Namib as the elevation gradually increases from the coast to 1000 m.a.s.l at the escarpment. In summer months the stratus layer occurs at around 500 m.a.s.l (Andersen et al., 2019) and allows the fog to penetrate further inland. In winter, the stratus layer is lower, which limits fog to the coastal area.

Fog formation and lifetime is dependent on the atmospheric thermodynamic (radiation, turbulence and mixing) and surface conditions (albedo, soil characteristics, roughness length, moisture content). Henceforth, the simulation of fog first requires that atmospheric variables related to temperature and moisture are simulated adequately by models, which implies representing the coupling of land-atmosphere interactions and good parameterisation schemes of the planetary boundary layer (PBL) (Bergot & Lestringant, 2019; Boutle et al., 2018; Juliano et al., 2019; Maronga & Bosveld, 2017; Steeneveld & de Bode, 2018).

Additionally, forecasts of fog required improved parameterisation of its microphysical properties (e.g. (Bott, 1991; Gultepe & Milbrandt, 2007; Tardif, 2007)). Several studies have demonstrated the importance of the cloud condensation nuclei (CCN) and cloud droplet relationship in simulating the fog life cycle (e.g. (Boutle et al., 2018; Maalick et al., 2016; Stolaki et al., 2015)). The formation of fog depends on the capabilities of the pre-existing aerosols to

act as CCN thereby providing a substrate for water vapour to condense and grow to form a fog droplet. The properties of the CCN aerosols play a role in shaping the microphysics of the fog droplets (Gultepe & Milbrandt, 2007; Haeffelin et al., 2013). The size distribution of the droplets has an important effect on the radiation balance (Boutle et al., 2018; Egli et al., 2015; Mazoyer et al., 2019; Poku et al., 2019). Mazoyer et al (2019) showed a widening of the droplet size distribution towards the fog top as droplets grew by collision and coalescence. Egli et al (2015) showed that LWC varies through the fog layer, usually with a maximum near the centre of the fog layer. In this case, the increase in LWC was due to an increase in number concentration and not the conversion of small droplets to larger droplets. These complex microphysical processes within the fog layer are increasingly being introduced into model simulations.

Aerosol-aware microphysics schemes, with the main function of representing grid scale clouds in a simulation (Thompson & Eidhammer, 2014; Wilkinson et al., 2013), are now being used to represent fog in the lowest model level and are showing encouraging results. Boulte et al (2018) and Poku et al (2019) demonstrated improved fog simulations of cloud droplet number and sedimentation based on model sensitivity to CCN concentrations in an aerosol aware scheme. Mazoyer et al (2019) demonstrated that improved supersaturation and activation of CCN improved forecast results of droplet concentration. As these schemes advance, more detailed information on CCN size distribution, chemistry and activation can be provided as input to models. For example, the complexity of droplet activation as described by Kohler theory has been parameterised and implemented by way of a lookup table of CCN activation in some models (see (Ghan et al., 2011; Saleeby & Cotton, 2004).

In this paper we present an assessment of the capabilities of the Weather Research and Forecasting (WRF) model to predict two fog events observed in September 2017 along the coast of Namibia. WRF has been used to simulate fog previously using rule based methods (C. Román-Cascón et al., 2016; Weston, Temimi, Morais, et al., 2021), however, we will focus on the aerosol aware microphysics scheme capabilities in the model. The area is interesting for studying fog formation as it represents a pristine environment. Previous research has shown that the influence of anthropogenic activities is minor (Formenti et al., 2019; Klopper et al., 2020).

Fog is diagnosed from the model using the LWC from an aerosol aware microphysics parameterisation scheme. This work takes advantage of the measurements of surface level fog microphysics that were performed at a ground-based site on the coast of Namibia as part

of the Aerosol, Radiation and Clouds in Southern Africa (AEROCLO-sA) campaign (Formenti et al., 2019).

The work is structured as follows. In section 2 a description of the study sites, data sets and model configuration is presented. Section 3 includes the model results and discussion. A summary of the main findings is given Section 4.

6.2 Methodology

6.2.1 Study area

The Central Namib is a coastal desert on the Coast of Namibia. It lies between the Atlantic Ocean to the West and the escarpment of over 1000 m in elevation to the east. The mean annual rainfall is highest at the escarpment (100 mm) and decreases towards the coast (< 50 mm) (Lancaster et al., 1984; Spirig et al., 2019). The land cover type undergoes a stark transition at the ephemeral Kuiseb River with the rocky Gravel Plains to the north and large sand dunes to the south. Surface air flow along the coast is dominated by an onshore wind, predominantly from the south-west (Lindesay & Tyson, 1990). This flow can be amplified by the synoptic scale circulation of the South Atlantic High pressure system. However the onshore flow does not penetrate far inland where the surface air flow is controlled by the mountain-plain wind. The easterly wind is much drier and limits moisture transport inland. As a result, fog forms in a narrow band along the coastline.

6.2.2 Observations

6.2.2.1 Henties Bay Meteorology

The AEROCLO-sA ground-based field campaign was conducted from 23 August to 12 September 2017 at the University of Namibia Campus in Henties Bay (-22.09495 °S, 14.2591 °E; (Formenti et al., 2019)). The campus is located on the coast line (elevation 20 m.a.s.l) and at the mouth of the non-perennial Omaruru River.

Measurements pertinent to this study include the meteorological measurements of temperature (2 m), relative humidity (2 m), wind speed (10 m), wind direction (10 m) from a Cimel Electronique Compact Weather Station (Formenti, 2020b). Meteorological data was supplemented with atmospheric pressure from the control WRF model simulation described later on. This allowed further variables to be derived like water vapour mixing ratio and air density. Visibility measurements were available from a transmissometer. Cloud droplet

measurements were conducted with a Fog Monitor 100 (FM100). This provides droplet number concentration, size distribution and liquid water content for particle sizes with optical equivalent diameter of 1 to 50 μm . Radiosonde measured atmospheric profiles of pressure, temperature, relative humidity, wind speed and wind direction (Formenti, 2020a).

6.2.2.2 SEVIRI

The spatial evolution of the cloud and fog is presented using the Spinning-Enhanced Visible and Infrared Imager (SEVIRI) from Meteosat Second Generation (MSG) (Schmetz et al., 2002). Night time scenes are false color composite images using the night microphysical product from EUMETSAT (EUMETSAT, 2009). In this product, red is the difference between 12.0 and 10.8 μm channels (linear stretch -4 to 2 K), green is the difference between 10.8 and 3.9 μm channels (linear stretch 0 to 10 K) and blue is the 10.8 μm channel (linear stretch 243 to 293 K). Day time scenes are an RGB of the visible channels (R:VIS 06, G: VIS 0.8, B: IR 1.6).

6.2.3 Model Configuration

The Weather Research and Forecast model (WRF v3.9.1, Skamarock et al, 2008) was used to forecast next day fog. The model domains comprised 3 domains with horizontal grid resolutions of 27-9-3 km and was run with one-way nesting (Figure 6-1). Although the parent domain is of similar resolution to the forcing data (mentioned later), this domain configuration follows the guidelines of nest ratio of 3:1 in WRF. Thus, the ratio is maintained with limited risk of the parent domain resolution being similar to the forcing data. Domain 1 was sufficiently large to allow the movement of low pressure cells in the easterlies and westerlies to pass through and provide boundary conditions to the nested domains. Domain 2 extended 4266 km from east to west and 2296 km from north to south. Domain 3 extended 1386 km from east to west and 720 km north to south. A total of 50 vertical levels were used with extra vertical levels added near the surface to allow for 11 model levels below 500 meters above ground level (m.a.g.l). The mean height of the lowest 5 levels is 34, 71, 109, 146 and 184 m above ground level. This is in line with the vertical profiles reported in the literature which show that the moisture is trapped below 500 m (e.g. (Andersen et al., 2019; Formenti et al., 2019; Spirig et al., 2019)). The model was initialised at 06 UTC (08h00 local) with Global Forecast System (GFS v14) data at 0.25 degree resolution and updated every 6 hours (NCEP, 2015).

The surface skin temperature over the ocean was allowed to follow a diurnal cycle in WRF using the method described by Zeng and Beljaars (2005). In the absence of this method, the

surface skin temperature over the ocean would remain constant before updating every 6 hours based on the sea surface temperature from the GFS, which is suboptimal. The Noah land surface model was used with land cover classes from the United States Geological Survey (USGS) (Loveland et al., 2000; Sertel et al., 2010). The default soil texture in WRF is from the State Soil Geographic (STATSGO)/Food and Agriculture Organization (FAO) soil database (Dy & Fung, 2016; Sanchez et al., 2009).

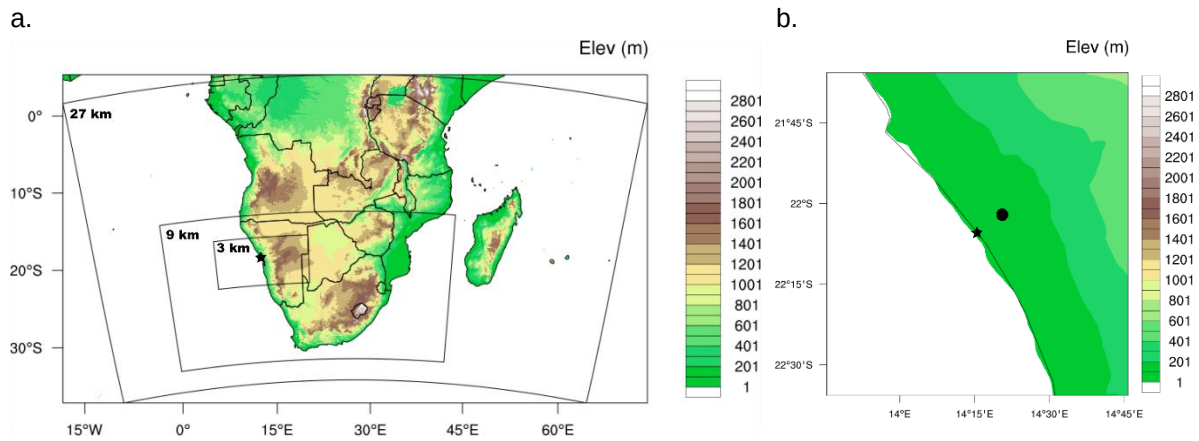


Figure 6-1: a.) WRF model domains and b.) insert showing the Henties Bay (star) and inland site (circle).

Shortwave and longwave radiation was controlled by the rapid radiative transfer model for general circulation model applications (RRTMG, (Iacono et al., 2008)). The revised MM5 scheme was used for the surface layer and the Mellor-Yamada Nakanishi and Niino Level 2.5 (MYNN2.5) scheme for the PBL physics parameterisation (Nakanishi & Niino, 2006). The Kain-Fritsch Cumulus physics was activated in domain 1 but deactivated in domain 2 and 3 (Kain, 2004a; Skamarock et al., 2008a). This allows for sub-grid scale precipitation in the coarse resolution parent domain allowing for realistic water balance when applying the one-way nesting.

6.2.3.1 Fog microphysics

The grid-scale cloud microphysics bulk scheme by Thompson and Eidhammer (2014) assumes a gamma distribution of cloud droplet size distribution $N(D)$ (m^{-3}) for particles diameters D comprised between 1 to 100 μm as:

$$N(D) = \frac{N_t}{\Gamma(\mu + 1)} \lambda^{\mu+1} D^\mu e^{-\lambda D} \quad (15)$$

where N_t is the total cloud droplet number concentration (m^{-3}), the unit for D is meter (m), Γ is the gamma function, μ is the shape parameter and λ is the slope. It is a double moment scheme, meaning that cloud droplet mass and number concentration (N_t) is calculated from the size distribution. The shape and slope parameters can be derived from N_t and liquid water content (LWC) as follows:

$$\mu = \min\left(\frac{1000}{N_t} + 2, 15\right) \quad (16)$$

Where N_t is in cubic centimetre (cc).

$$\lambda = \left[\frac{\pi}{6} \rho_w \frac{\Gamma(4 + \mu)}{\Gamma(1 + \mu)} \left(\frac{N_t}{LWC} \right) \right]^{\frac{1}{3}} \quad (17)$$

Where $\rho_w = 1000 \text{ kg m}^{-3}$ is water density and LWC is in kg cm^{-3} .

The median volume diameter (MVD) is calculated as:

$$MVD = \frac{3.672 + \mu}{\lambda} \quad (18)$$

Fog was defined where liquid water content was greater than 0 g kg^{-1} in the lowest model level. This is a reasonable assumption for simulations with a suitably high resolution (i.e. observed fog feature is larger than model grid cell) and a sophisticated microphysics scheme (Zhou et al., 2012).

6.2.3.2 Configuration of the aerosol aware sensitivity study

The Thompson aerosol aware microphysics scheme (hereafter T14) was activated in all three domains to represent grid scale cloud microphysics (Thompson & Eidhammer, 2014). The scheme is novel as it accounts for the initial number concentration, mean radius and hygroscopicity (κ) of CCN, CCN activation to cloud droplets (and other hydrometeor), and can limit the maximum number of cloud droplets. Although the default settings for these variables are based on observations and literature, users can fine tune the values based on their study area. Furthermore, the option exists to replace these constants with user generated 3-dimensional data fields of CCN as input. An example is provided with the model based on a 7-year climatology of aerosols produced by the NASA GEOS-4 model (Colarco et al., 2010). CCN activation is based on parcel method simulations by Eidhammer et al (2009). These simulations were used to create a look up table (available within WRF) that vary the CCN activation in response to number concentration, updraft speed, ambient temperature, CCN

mean radius diameter and kappa (hygroscopicity) values (Figure 6-2). It is important to keep in mind that CCN activation in the scheme assigns a minimum updraft speed of 1 cm s^{-1} when air is saturated. This allows for droplet activation under saturated conditions via the look up table even when the simulated updraft is negative. An additional novelty of this scheme is that it allows feedback of CCN and cloud droplets to the radiation schemes in shortwave and longwave, which was activated in the model simulations.

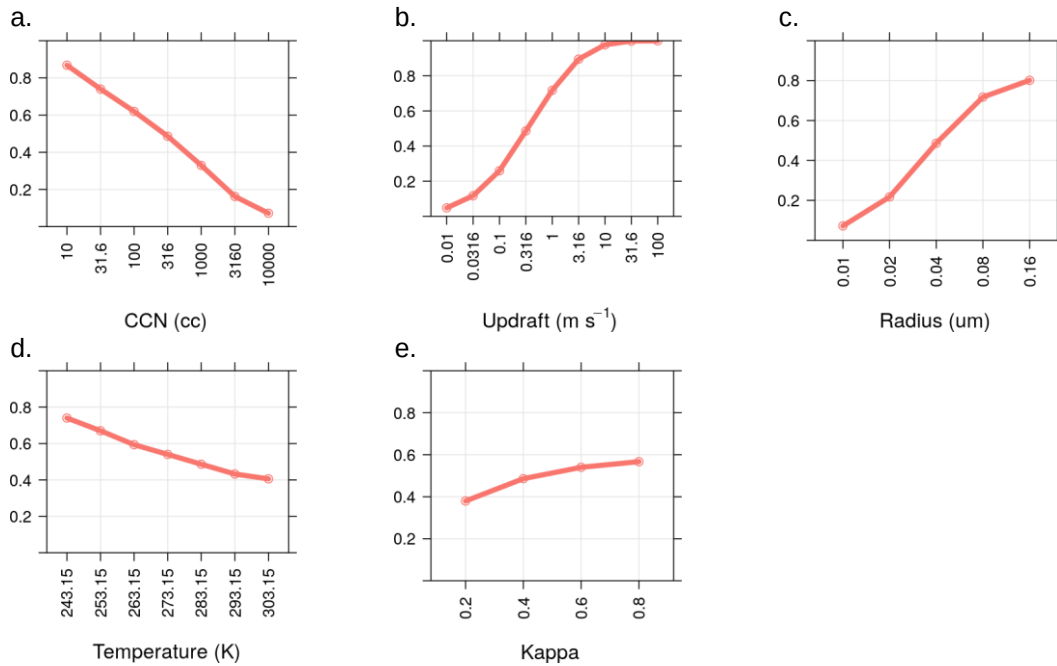


Figure 6-2: CCN activation look up table. Activation sensitivity to a.) CCN b.) updraft, c.) radius, d.) temperature and e.) kappa. For each plot, the remaining four variables are kept constant as follows: CCN=316 cc, updraft= 0.316 ms^{-1} , radius= $0.04 \mu\text{m}$, temperature=2813.15 K and kappa=0.4.

Model scenarios were based on configuration of the microphysics, where the default CCN radius is $0.04 \mu\text{m}$ and the kappa is 0.4 (Table 6-1). Scenario 1 used the default initial CCN value of 300 cc which is applied above both land and ocean (hereafter CCN_300). Thompson and Eidhammer (2014) proposed different initial CCN concentration for land (300 cc) and ocean (100 cc) which is currently not an available option in the model. However, we edited the code to implement this proposal for scenario 2 (hereafter CCN_300_landsea). Scenario 3 is the default model setting using the 3-D climatology CCN modified from Colarco et al. (2010) (hereafter CCN_C10). Simulations were run from 7 to 10 September 2017 to coincide with the best data from the FM100 instrument. Recall, simulations are initialised at 06 UTC and were

run for 48 hours. The first 6 hours are discarded as model spin up (i.e. day 0 06 – 11 UTC). The next 24 hours in the model are used to assess the next day fog (i.e. day 0 12 to day 1 11 UTC).

A sensitivity to CCN activation was carried out through permutations to the CCN and minimum updraft speed. This included an increased initial CCN to 500 cc (hereafter CCN_500), a smaller CCN mean radius of 0.02 (CCN_300_r0.02) and having a minimum updraft speed of 0.1 m s^{-1} (CCN_300_w0.1). For the last scenario, the minimum updraft speed was only assigned in the three lowest vertical levels in the model, and should not cause erroneous cloud at higher model levels.

Comparative statistics of model and observed cloud droplet count, LWC and MVD are presented in the results section. The model grid point that is closest to the site location is extracted for comparison with the observations. A second model grid point, hereafter referred to as “inland”, is extracted about 13 km inland when travelling perpendicularly to the coast to demonstrate the dynamics and gradients in the model (Figure 6-1b).

Table 6-1: WRF model scenarios

	Scenario	CCN	Kappa	Radius	Updraft
1	CCN_300	300	0.4	0.04	0.01
2	CCN_300_landsea	300/100	0.4	0.04	0.01
3	CCN_C10	Colarco 2010	0.4	0.04	0.01
4	CCN_500	500	0.4	0.04	0.01
5	CCN_300_r0.02	300	0.4	0.02	0.01
6	CCN_300_w0.1	300	0.4	0.04	0.1

6.3 Results and Discussion

6.3.1 Case Study Description

Two fog events were observed on consecutive days on 9 and 10 September 2017 (hereafter Case 1 and Case 2, respectively) during the AEROCLO-sA campaign at Henties Bay (Figure 6-3). Visibility dropped below 1 km from about 03 to 07 UTC during Case 1. The wind direction was predominantly north-westerly and shifting to north-easterly during these days, which is in contrast to the dominant wind direction of south-westerly during the full campaign dates. Wind speed was 2 ms^{-1} or less during the events. Water vapour mixing ratio ranged between 8 and 10 g kg^{-1} during the fog events, but was more than 10 g kg^{-1} during the day. The observed relative humidity remained over 90 % throughout the case study period. A temperature

inversion with a strength of about 10 °C was present on both mornings below 1000 m.a.s.l. Satellite images for case 1 indicate an isolated cloud over the study site from 00 UTC and by 03 UTC the patch is elongated along the coast line (Figure 6-4). No cloud is present over the ocean and this fog patch is not associated with a stratus deck. For Case 2, visibility dropped below 1 km from 04 to 07 UTC. Satellite images indicate that cloud was present over the site from 16 UTC the day before and was associated with stratus over the ocean (Figure 6-5). This cloud gradually advected over the land and by 21 UTC the visibility had decreased to 2 km. By 03 UTC, just before fog onset, the stratus deck had increased extent over the ocean. After sunrise, the cloud over the land dissipated while the cloud over the ocean remained through the day and into the following night.

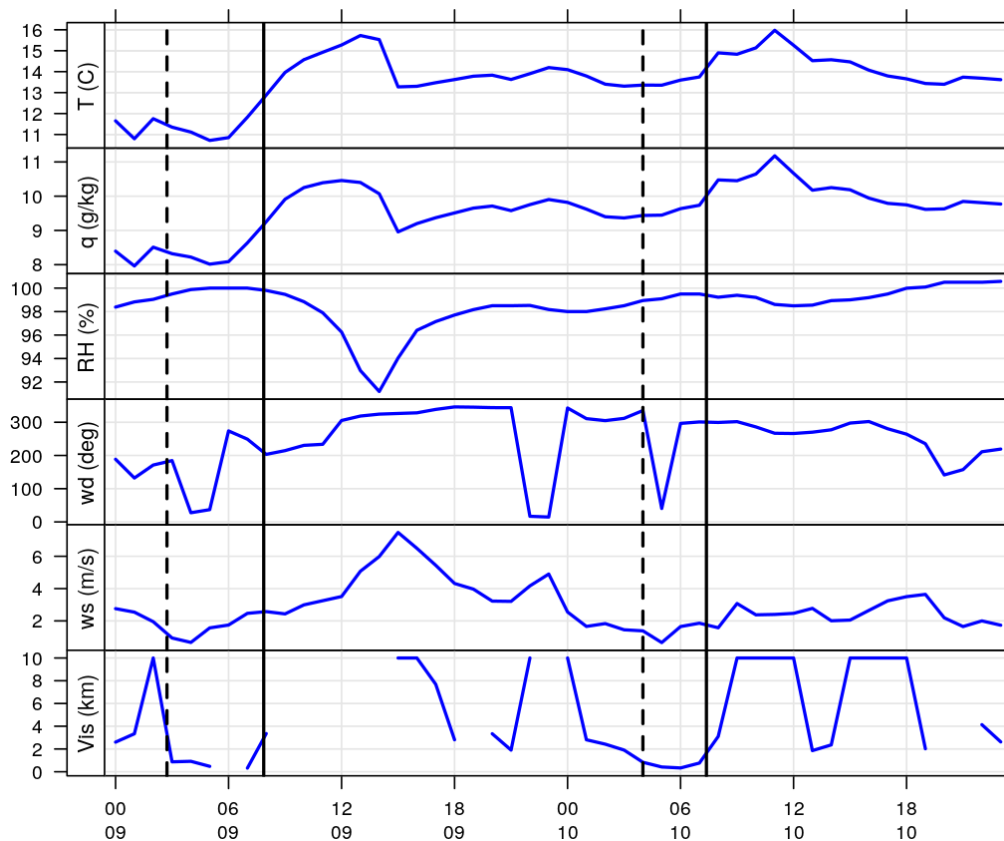


Figure 6-3: Meteorology variables and visibility from the transmissometer shows the two fog events. Vertical black dashed (solid) lines indicate fog start (end) times. Times are in UTC (Site is UTC+2).

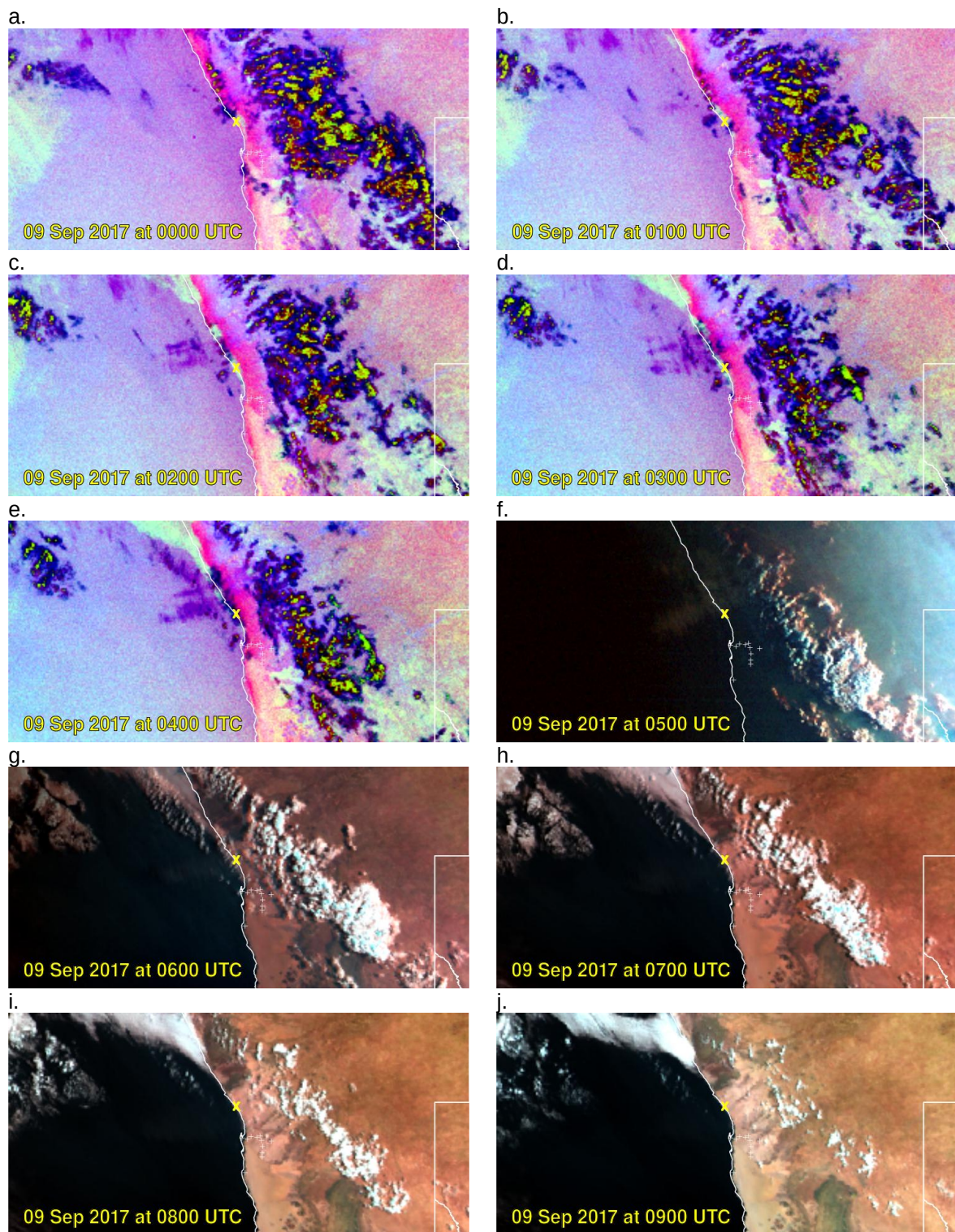


Figure 6-4: SEVIRI images of night microphysical RGB product and day visible channels for the fog event on 2017-09-09. Site is UTC+2.

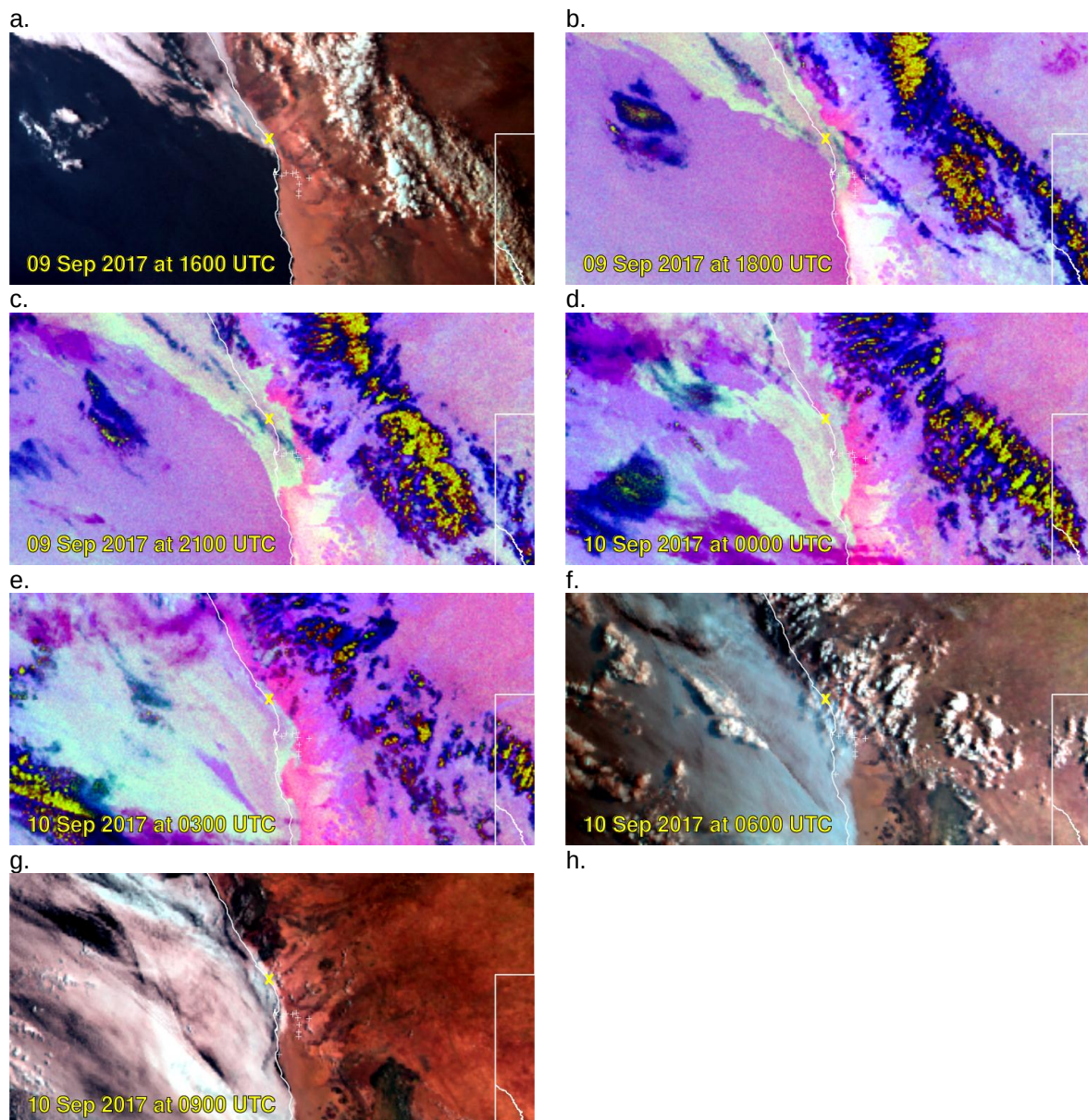


Figure 6-5: SEVIRI images of night microphysical RGB product and day visible channels for the fog event on 2017-09-10. Site is UTC+2.

6.3.2 WRF

6.3.2.1 Met verification/Vertical profile comparisons

The observed temperature range at the study site is narrow reaching up to 5 °C which is a clear indication of the maritime influence on modulating temperature (Figure 6-6a). The modelled diurnal temperature range is larger and more representative of a terrestrial site, with the maximum temperature being 4 to 5 °C warmer and the minimum between 1 to 5 °C colder

than the observed. The combination of model horizontal resolution and physics may be limited to resolve the exact location of the land-sea interface occurring at the site, which is within 200 m of the beach. Consequently, the cold bias may trigger early saturation, which is true in this case as evident in the relative humidity time series in Figure 6-6e. The water vapour mixing ratio is underestimated by 2 to 4 g kg⁻¹ during night time but this is not dry enough to prevent saturation. Simulated wind speed is within 1 ms⁻¹ for most of the simulation and more importantly during the observed fog periods (Figure 6-6b). However the maximum bias is 2 ms⁻¹ (negative) during the night of 8 September and the model underestimated the daytime wind speed on 9 September by approximately 2 ms⁻¹. The observed wind direction shifts from south-westerly on 8 September to northerly during the case studies. The simulation captures this progression, although the model shifts back to southerly during the day of 9 September (coinciding with the underestimated maximum wind speed) before veering back to northerly. The northerly wind direction plays an important role in CCN transport during the simulations as will be discussed in due course.

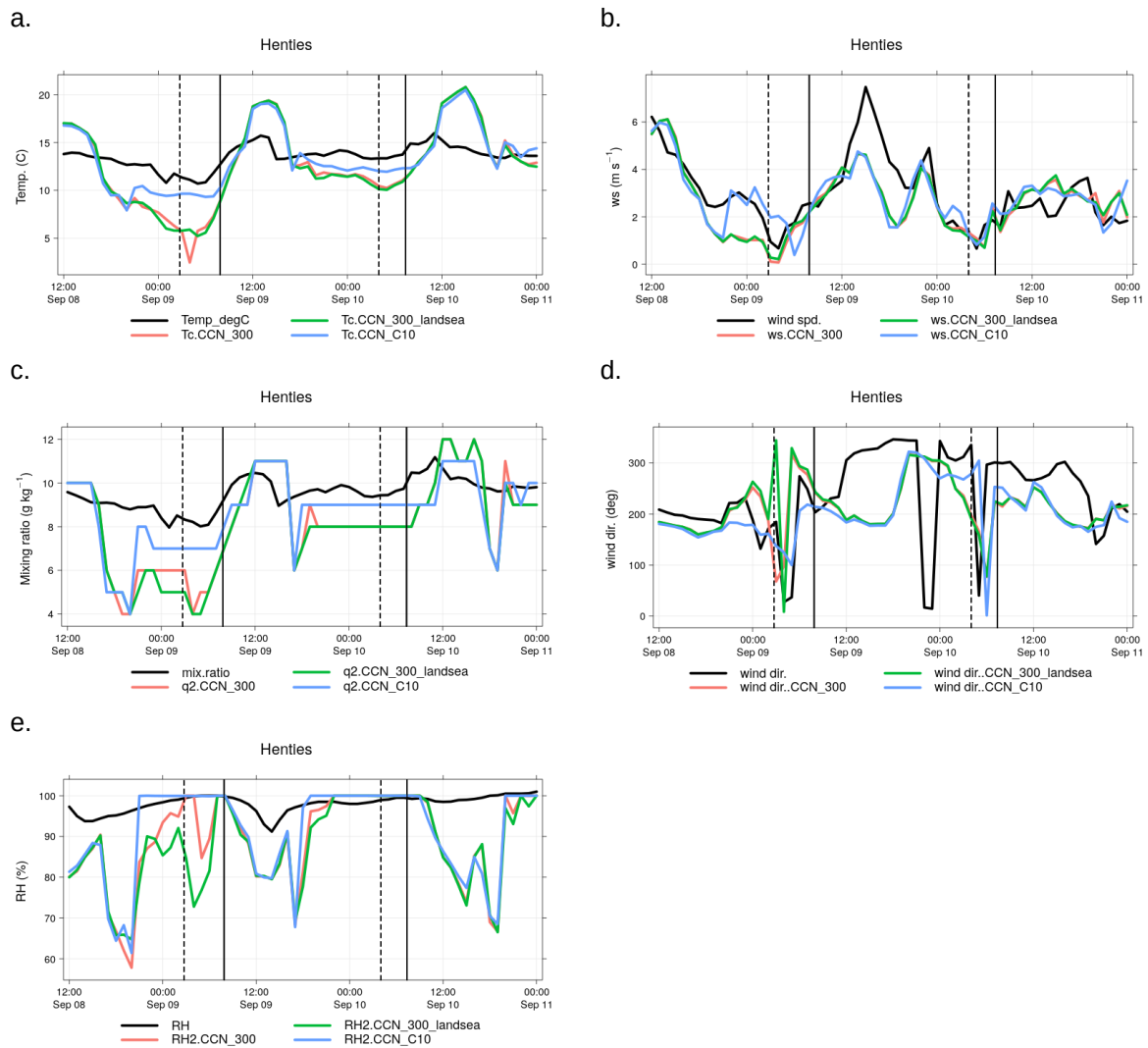


Figure 6-6: Timeseries of model and observed meteorological variables at Henties Bay for a.) temperature, b.) wind speed, c.) water vapour mixing ratio, d.) wind direction and e.) relative humidity. Times are in UTC (Site is UTC+2).

The modelled profiles of temperature and relative humidity displayed the low level inversion and moisture as seen in the observed profiles. For case 1, the model captured the near surface temperature inversion at about the same height (base of inversion is at ~250 m) and strength (~10 °C) as the observed inversion (Figure 6-7). Subsequently, the moisture and associated relative humidity was over 80 % near the surface and decreased rapidly from the base of the inversion to 10 % at around 600 m. It is worth noting that the observed relative humidity at the surface was below 100 % and peaked near 100 % at about 250 m, while the model was at 100 % at the corresponding heights. For case 2, the base of the observed temperature inversion was higher at about 800 m and coincided with the peak relative humidity of 100 % (Figure 6-8). The model inversion height was also higher than case 1 model results but was

still below 500 m. The reason for the higher inversion level during case 2 is not clear. This could be attributed to the difference in timing of the sonde (1 hour later), or that the fog event is optically thick and has a major effect on the radiation (as in Price (2011) and Boutle et al., (2018)). Nevertheless, the model is capturing a low level surface inversion trapping the moisture below this inversion, as in the observations.

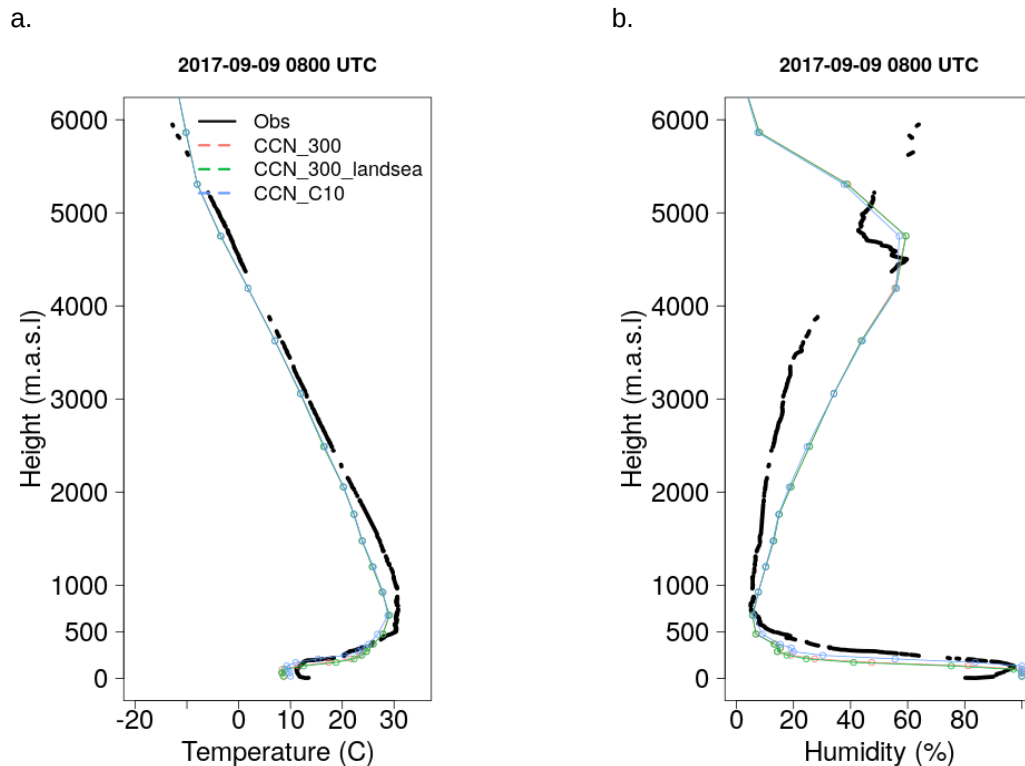


Figure 6-7: Radiosonde profiles of a.) temperature and b.) relative humidity from Jakkalsputz on 2017-09-09. The Sonde was launched at 07:50 UTC and the model is from 08 UTC. Site is UTC+2.

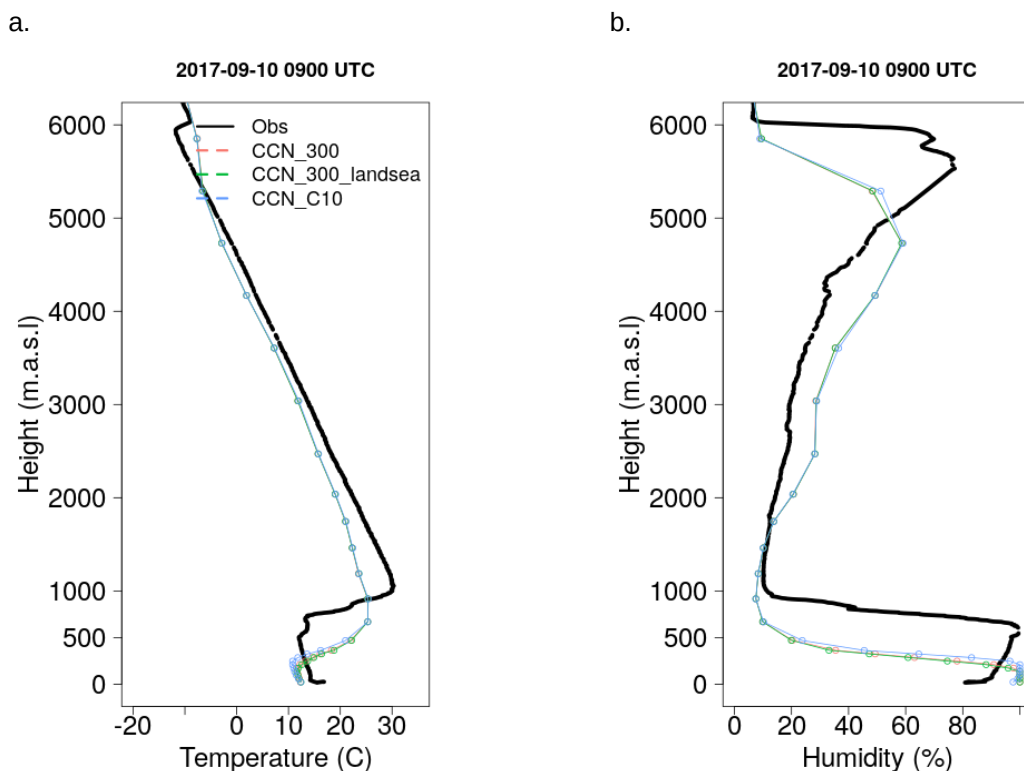


Figure 6-8: Radiosonde profiles of a.) temperature and b.) relative humidity from Jakkalsputz on 2017-09-10. The Sonde was launched at 09:10 UTC and the model is from 09 UTC.

6.3.2.2 Spatial distributions of CCN and Cloud droplet concentration

The initial CCN concentration for CCN_300 is similar over land and ocean (Figure 6-9a). However, over time the concentration over the ocean is relatively higher than over the land, as is evident in the mean concentration in Figure 6-9b. This is counter intuitive as observed CCN concentrations are typically lower over ocean than land (Seinfeld & Pandis, 2016). The relative decrease in concentration over the land is most likely due to the treatment of the vertical distribution of CCN in the scheme, which is terrain height dependent (as described in the physics release notes on the WRF users website (WRF Users Page, 2020)). In summary, the scheme assigns highest CCN concentration near the surface and follows an exponential decrease through the boundary layer to a minimum limit which is then assigned to the lower free troposphere. The depth of the boundary layer is made to vary for different terrain heights, ranging to about 1000 m at sea-level to less than 100 m where terrain is greater than 2500 m. The thinner boundary layer at increased terrain height would have a steeper drop off in CCN concentration with height and subsequent dilution during day time mixing. Furthermore, the

boundary conditions for scenario CCN_300 had relatively lower concentrations of CCN. This explains the lower CCN concentrations over the southern part of the ocean in the domain as clean air was advected from the boundary conditions.

The initial CCN concentration for scenario CCN_300_landsea shows a clear contrast, with lower concentration over the ocean than the land (Figure 6-9c). The lower concentration over the ocean counteracts the accumulation of CCN over time, as seen in CCN_300, resulting in a more balanced mean CCN concentration between land and ocean (Figure 6-9d). Scenario CCN_C10 has an order of magnitude higher concentrations of CCN (Figure 6-9e and f) and does exhibit higher concentrations over land than the ocean. This contrast is maintained throughout the simulation as the terrain dependent vertical profile described earlier is not applied to these CCN. Furthermore, as the CCN are a subset of a larger dataset, the boundary conditions include similarly higher concentrations of CCN and clean air is not advected into the domain.

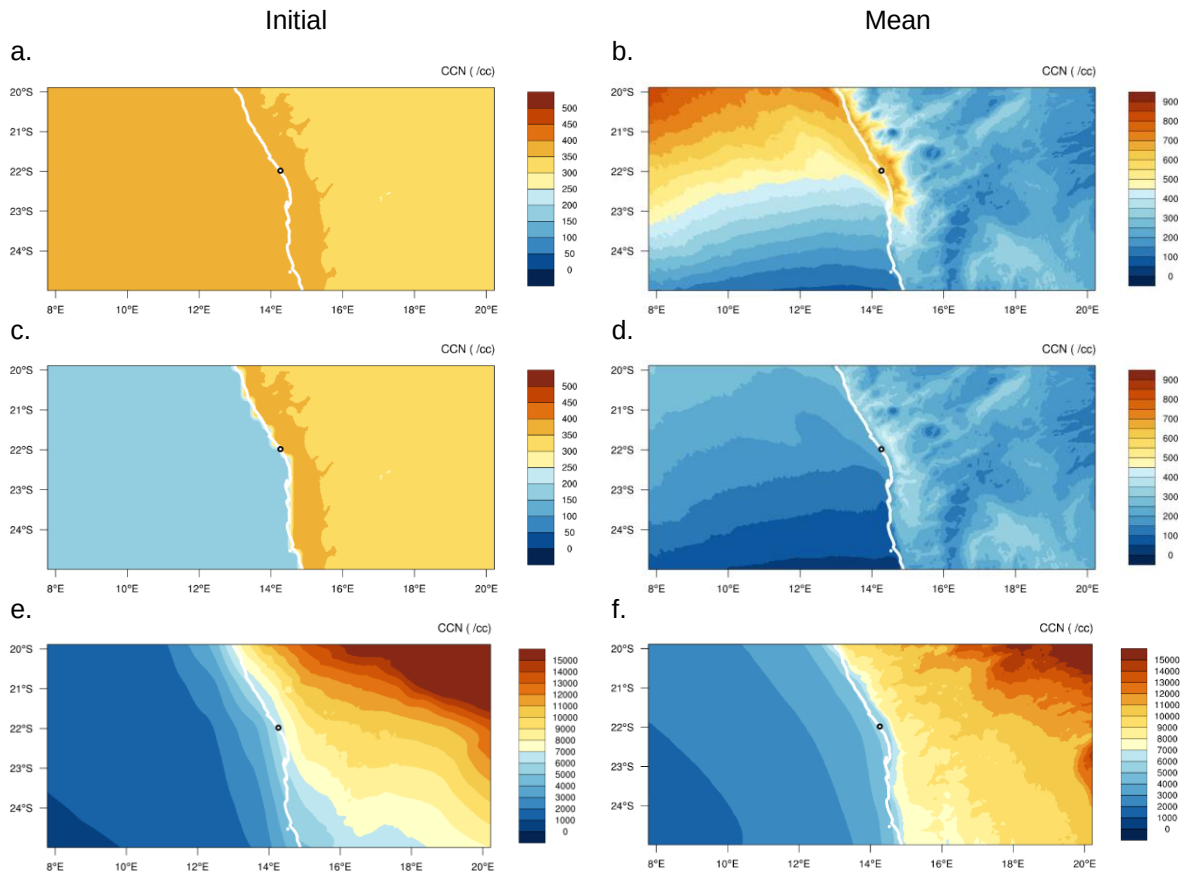


Figure 6-9: Initial and mean CCN concentration for scenarios a and b.) CCN_300, c and d.) CCN_300_landsea and e and f.) CCN_C10. Note different scale on c. Black dot is Henties Bay.

The evolution of CCN concentration for CCN_300 during case 2 is shown in Figure 6-10. It clearly shows that by 12 UTC (forecast hour 7) the concentration over the ocean is higher (500-600 cc) than over the land in the lowest model level. The clean air from the boundary conditions is evident in the south, and continues to propagate through the domain throughout the forecast. Ahead of this advection, concentration increases as CCN are transported from the south and accumulate. An onshore flow of CCN onto the low lying Namib Desert is also evident. At Henties Bay, the wind direction is south westerly (200 °) from 12 to 18 UTC and veers to north-westerly (300 °) from about 19 UTC to 06UTC. This north-westerly flow allows for the low level transport of the accumulated CCN back along the coastline.

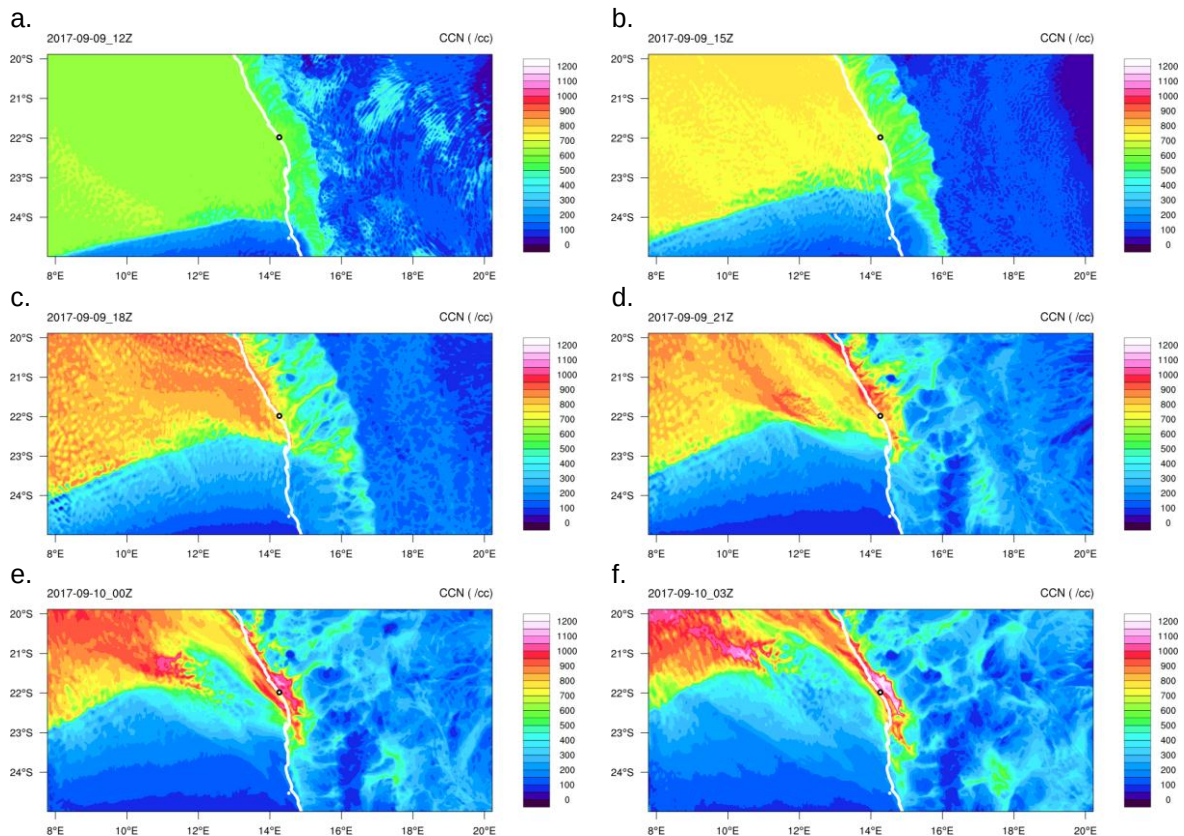


Figure 6-10: Evolution of CCN concentration for the event on 2017-09-10 for scenario CCN_300. Black dot is Henties Bay. Time is in UTC (site is UTC+2).

The fog onset, represented by cloud droplet concentration, is shown in Figure 6-11, where droplet concentration reached up to 50 cc. Over land, fog starts to form along the coast first and then extends further inland, signifying that the simulated fog is advection fog and not radiation fog. Radiation fog would be expected to form inland first or simultaneously with coastal fog as the radiative cooling should be stronger inland (e.g. (Weston & Temimi, 2020)). The fog reached maximum inland extent at 04 UTC (Figure 6-12a) before dissipating inland by 07 UTC (Figure 6-12d). Cloud droplets are present over the ocean from 21 to 07 UTC. The spatial distribution of CCN and cloud droplet concentration for CCN_300_landsea were similar to CCN_300 although the concentrations were generally lower.

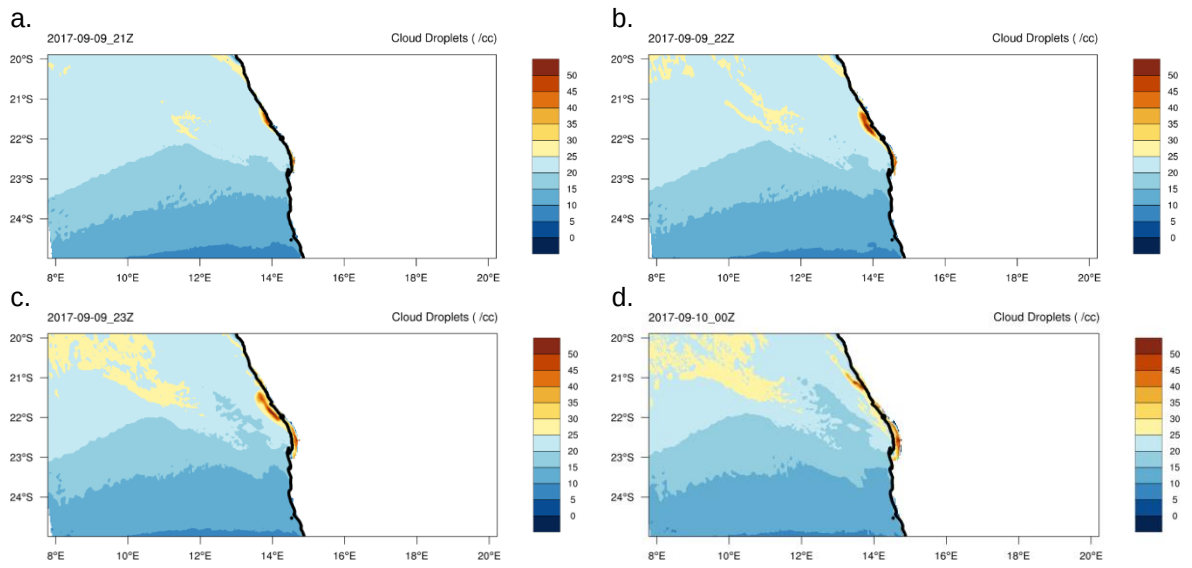


Figure 6-11: Cloud droplet onset for the event on 2017-09-10 for scenario CCN_300. Black dot is Henties Bay. Time is in UTC (site is UTC+2).

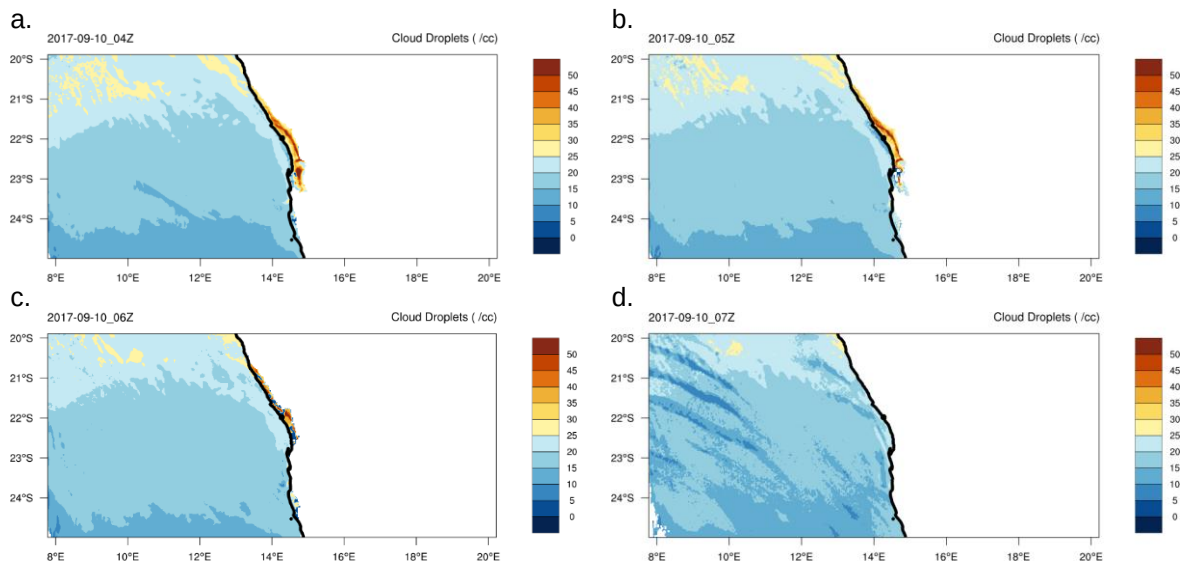


Figure 6-12: Cloud droplet during maximum extent and highest concentration for the event on 2017-09-10 for scenario CCN_300. Maximum extent was at a.) 04 UTC and maximum concentration at Henties Bay was at d.) 07 UTC. Black dot is Henties Bay.

The evolution of CCN concentration for CCN_C10 during case 2 is shown in Figure 6-13. What is notable is the lack of clean air advection from the boundary conditions, the relative contrast in concentration between land and ocean is maintained throughout and there is generally less

variation over time compared to CCN_300. However, the onshore flow and mixing of marine CCN in the Namib Desert is still evident, meaning that the study site is influenced by the marine CCN during these simulations.

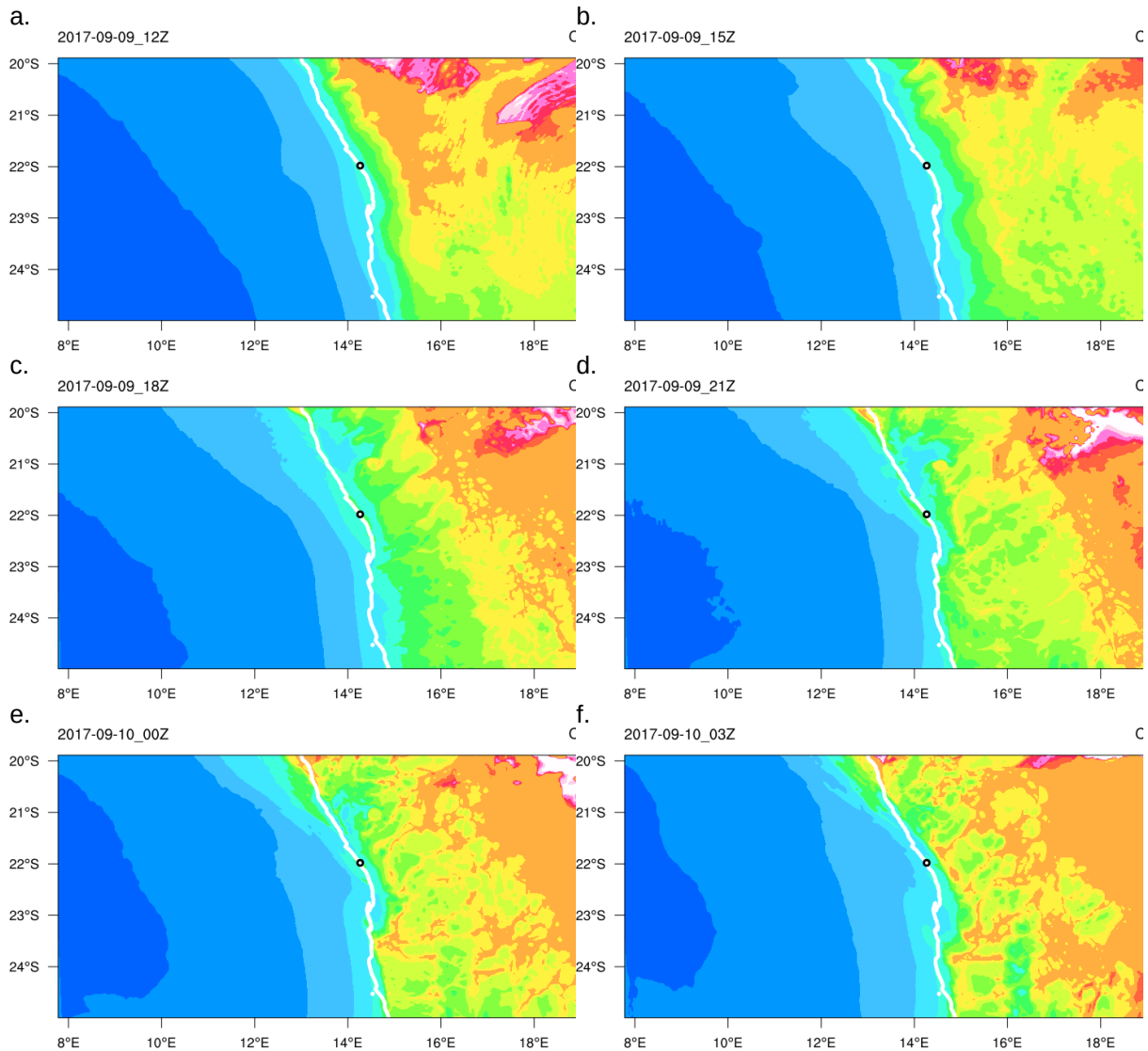


Figure 6-13: Evolution of CCN concentration for the event on 2017-09-10 for scenario CCN_C10. Black dot is Henties Bay.

Fog onset over the land is similar to CCN_300, as this is controlled by the ambient conditions. However, cloud droplet concentration is 2 to 3 times higher in general compared to CCN_300, reaching up to 150 cc (Figure 6-14). Even though the percentage of droplet activation decreases as CCN concentration increases (Figure 6-2a), the initial CCN is significantly high enough to activate more cloud droplets than CCN_300. As in CCN_300, cloud droplets are

present over the ocean from 21 to 07 UTC. The maximum fog extent over the land (Figure 6-15) is a good match to the satellite data (Figure 6-5).

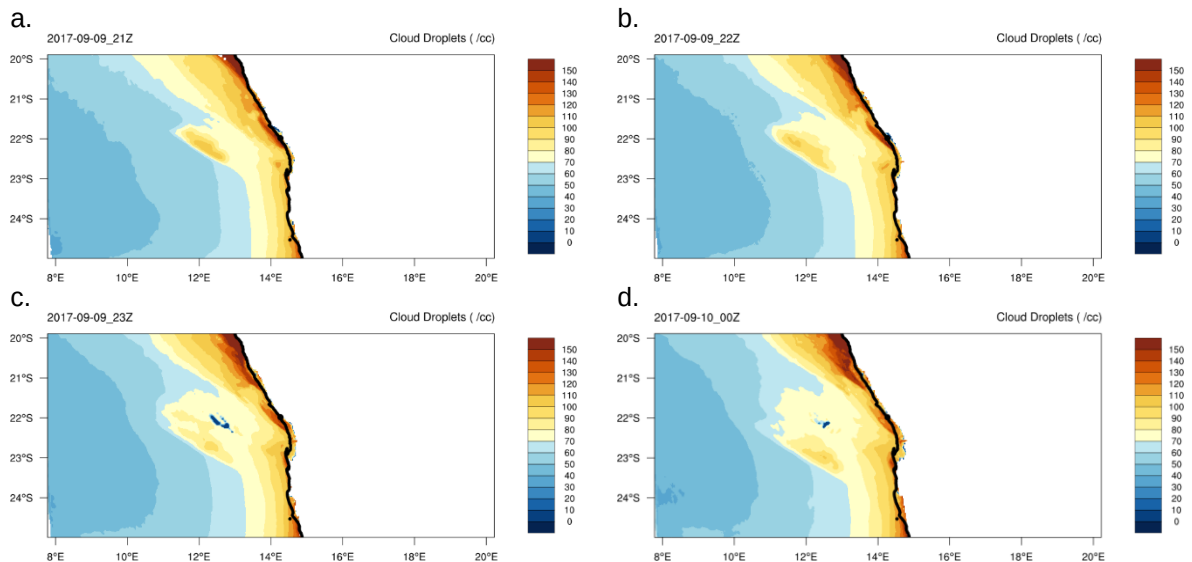


Figure 6-14: Cloud droplet onset for the event on 2017-09-10 for scenario CCN_C10. Black dot is Henties Bay.

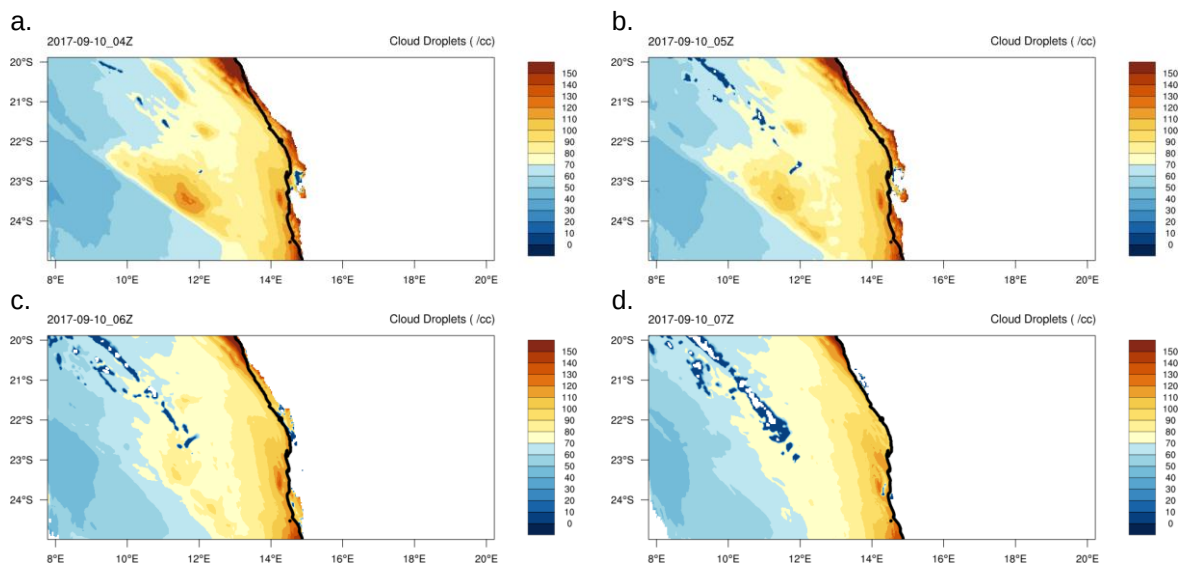


Figure 6-15: Cloud droplet during maximum extent and highest concentration for the event on 2017-09-10 for scenario CCN_C10. Maximum extent was at a.) 04 UTC and maximum concentration at Henties Bay was at d.) 07 UTC. Black dot is Henties Bay.

In general, the first three scenarios did well in capturing the fog extent over the land. They show the cloud forming at the coast first before moving inland, suggesting that the dynamics of the formation are captured in the model. Over the ocean cloud droplet activation is overactive, as a cloud deck is present from 21 UTC (Figure 6-11 and Figure 6-14a). At night, the air over the ocean is saturated (not shown) which we assume is from either a cold bias or positive bias in water vapour mixing ratio. Saturation is the first condition that must be met for droplet activation and it is assumed this is causing a persistent cloud deck over the ocean. The cloud deck was also present in case 1 simulations, while the satellite shows no cloud is present over the ocean. It has been demonstrated that in all scenarios there is a contrast between the land and ocean in terms of CCN and cloud droplet concentrations. Additionally, the semi-permanent cloud deck in the simulations impinges onto the adjacent land, mainly due to the onshore flow. Similar patterns of excess frequency of cloud cover (by 30 to 50 %) over the ocean were reported for a regional climate model simulation over Namibia (Haensler et al., 2011). They demonstrate the same high contrast between ocean and land and highlight that the study sites at the coast fall within a land-sea transition zone in the model. This suggests that there is a deficiency in the model physics over water and requires further investigation, however, this is outside the scope of this study. The study site is located at the interface between these two contrasting conditions and falls within the impingement zone of the simulations. This must be kept in consideration when comparing the model microphysics to the observations from the site, which will be discussed in the following section.

6.3.2.3 WRF vs FM100

The observed microphysics during case 1 showed cloud droplet number concentrations of up to 150 cc, maximum LWC around 0.25 g m^{-3} and MVD up to $27 \text{ }\mu\text{m}$ (Figure 6-16a-c). Case 2 demonstrated a higher mean number concentration, LWC peaked at 0.3 g m^{-3} and MVD was lower up to $21 \text{ }\mu\text{m}$.

Model cloud droplet number concentration during case 1 was below 25 cc for CCN₃₀₀, approximately six times less than the observations. However, the LWC was comparable to the observations at about 0.2 g m^{-3} . This means that the LWC is distributed among fewer droplets than the observations and that the size distribution will shift towards larger droplet diameters, which is evident in the MVD around $30 \text{ }\mu\text{m}$. The model exhibited higher number concentrations during case 2 which appears to be associated with higher CCN concentrations (Figure 6-16d). This in turn results in marginally increased LWC and an associated decrease in the MVD. As expected, CCN_{300_landsea} was similar to CCN₃₀₀ but with lower cloud droplet

concentrations due to lower CCN concentrations. The CCN concentrations were within the observed mean CCN concentration, which could be a good starting point for sensitivity tests on percentage droplet activation for the future.

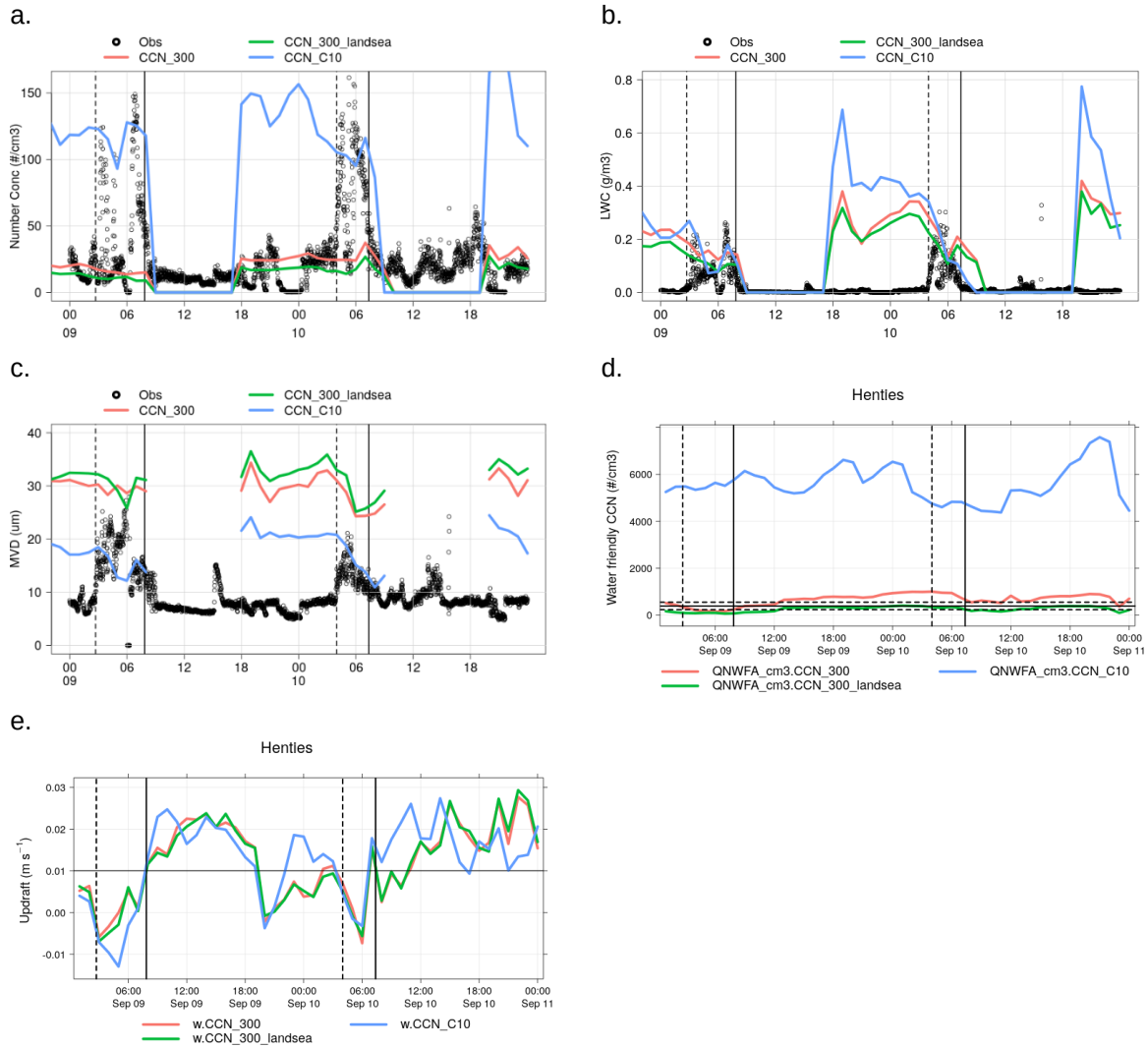


Figure 6-16: Observed and modelled a.) Nt, b.) LWC and c.) MVD at Henties Bay. Model is hourly and black dots are 1 minute observations. d.) Modelled concentrations of water friendly aerosols. Black dashed horizontal lines indicate the observed range of mean CCN reported by Formenti et al 2019. e.) Modelled updraft speed in lowest model level with solid black line at minimum updraft in microphysics scheme. Vertical dashed black line is fog start (Vis < 1km). Vertical solid black is fog end time. Time is in UTC (site is UTC+2).

The scenario CCN_C10 has around 10 times higher initial concentrations of CCN and throughout the simulation. This resulted in cloud droplet concentrations around 125 cc during case 1 and case 2, which was comparable with the observations. Case 2 was marginally lower than case 1 in this simulation as the CCN were lower. The maximum LWC during case 1 was about the same as the observed at 0.25 g m^{-3} and just over 0.3 g m^{-3} during case 2. As the cloud droplet number concentration and LWC are comparable to the observations, the MVD was much closer with a maximum around $20 \mu\text{m}$ for both cases. This scenario demonstrated the best performance in terms of cloud microphysics at the site, which is interesting as the initial CCN values appear to be largely overestimated. The reported mean of CCN at the site ranged from 230-550 cc (Formenti et al., 2019), while the modelled CCN was above 4000 cc throughout the simulation. This suggests that the percentage of CCN activated at the site should be roughly between 30 to 60 %, while the modelled activation is much lower, at around 10 %. To understand this further, we need to discuss CCN activation in the model scenarios.

CCN activation is most sensitive to CCN concentration and then updraft speed. For each scenario, the CCN concentration is always present and does not vary greatly. Keep in mind that the mean radius and kappa values are constant throughout. The updraft speed during both cases was negative, meaning that the minimum updraft of 1 cm s^{-1} is applied. If we consider case 2, we can see that the saturation is met at 18 UTC and droplets are formed, prior to the fog event (Figure 6-16a). From this point, droplets persist or are activated whenever saturation is met until the case 2 event. The potential drawback of using updraft velocity to define drop activation for fog formation has been discussed previously (Boutle et al., 2018; Poku et al., 2019). The argument is that fog often forms under stable conditions when no updraft is present and that activation is instead due to cooling of the air. In addition, the threshold updraft speed is often higher than the 0.01 ms^{-1} used in the T14 scheme, which effectively results in a higher super saturation and excess droplet activation than would be expected for a fog event. Reported activation fractions of CCN in fog are around 20 % but reach up to 40 % (Mazoyer et al., 2019). To some extent, the implementation of a relatively low updraft speed in the look up table mitigates against excess droplets forming in the T14 scheme. Activation at speeds less than 0.03 ms^{-1} are around 10 % or less. Thompson and Eidhammer (2014) acknowledge the use of updraft speed as a potential limitation in the scheme in terms of fog formation. Their proposed work around is to include cooling tendency as proxy for updraft speed and then assigning a speed that will activate the appropriate number of droplets. However, this may come with a new set of problems in terms of early activation but remains to be seen. In our case, the percent on CCN activated of 10 % or less appears to be too low and needs to be increased.

The observed size distribution needs to be transformed to a gamma distribution in order to compare it to the model. This is possible as the only inputs to the shape and slope parameters are the number concentration and LWC (Eq. 2 and 3). The mean number concentration and LWC for each case was used and the transformation of the observed (Obs_raw) and gamma distribution (Obs_gamma) can be seen in Figure 6-17. While the observations show signs of a trimodal distribution with peaks around 7, 16 and 30 μm , the gamma distribution has one peak at around 11 μm . The three modes in the observed distribution could be representative of the various CCN populations where larger salt particles with higher kappa values could represent the largest mode while the smaller sulphates represent the smaller modes. Droplet growth by collision and coalescence can be another explanation for the larger droplets and spectrum widening in a maturing cloud (e.g. (Egli et al., 2015; Mazoyer et al., 2019)). From the model scenarios, CNN_C10 demonstrates the best match with the observations (Figure 6-18), with the best performance in case 2. For the scenarios where initial CCN is constant, the distribution shifts to larger droplet sizes.

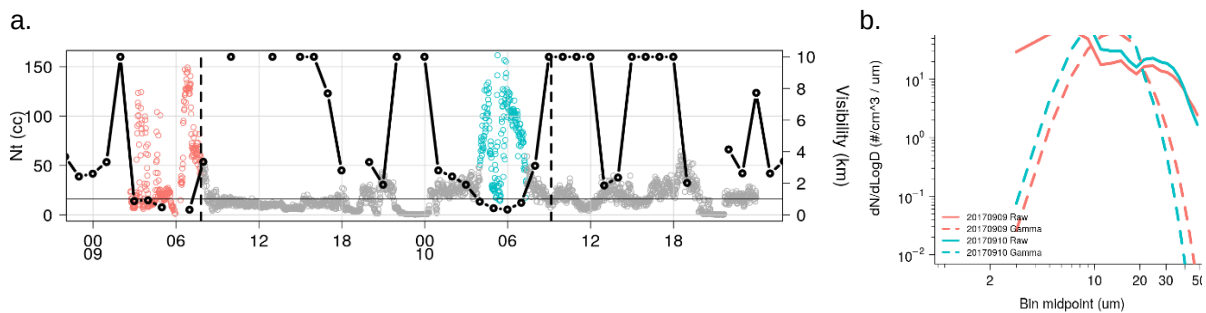


Figure 6-17: Size distribution for the two case studies when visibility was 1 km or less. Solid lines are the observed distributions. Dashed lines are the equivalent theoretical gamma distribution applied to the observed data. Time is in UTC (site is UTC+2).

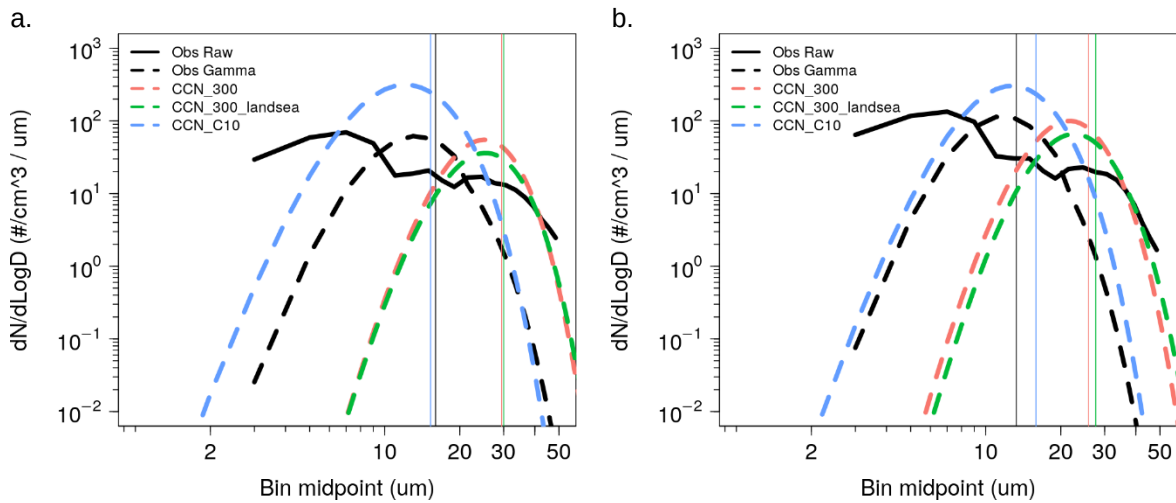


Figure 6-18: Observed and modelled size distribution for a.) case 1 and b.) case 2. Black solid lines are the observed distributions. Black dashed lines are the equivalent theoretical gamma distribution applied to the observed data. Other dashed lines are model distributions. Vertical solid lines represent the MVD.

The results of the sensitivity analysis are discussed below. The influence of number concentration on LWC and MVD is further highlighted by CNN_500 scenario. For all times, this scenario has higher cloud droplet concentrations than CCN_300 (Figure 6-19a). This results in overall higher LWC and lower MVD (Figure 6-19b and c). The inverse is shown with scenario CNN_300_r0.02. In this scenario the radius of the CCN was halved, which results in a lower number of activated droplets according to Kohler theory (Figure 6-2b). Similar sensitivity analyses have been reported by Poku et al. (2019) and Stolaki et al. (2015). The most interesting results come from scenario CCN_300_w0.1, which demonstrated the closest match to the observed number concentration, LWC and MVD. The logic behind this scenario was to increase the number of activated droplets by increasing the minimum updraft speed from 0.01 m s^{-1} to 0.1 m s^{-1} , which should allow around 30 % activation. Here we have a scenario where both the CCN and cloud droplet number are in line with the observations. This follows on from the discussion of using temperature tendency as a proxy for updraft speed, showing that it could work if the nucleation percentage is known, and an appropriate updraft speed assigned.

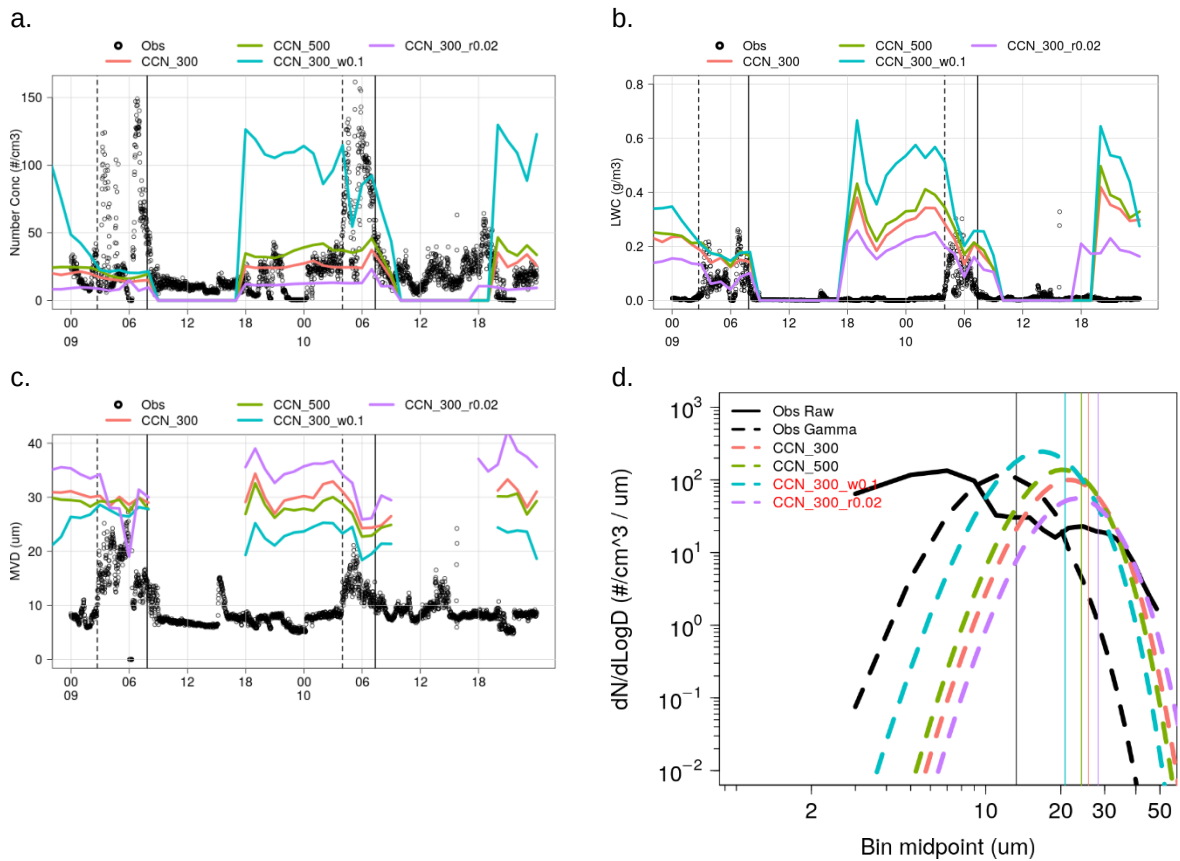


Figure 6-19: Observed and modelled size distribution for a.) case 1 and b.) case 2. Black solid lines are the observed distributions. Black dashed lines are the equivalent theoretical gamma distribution applied to the observed data. Other dashed lines are model distributions. Vertical solid lines represent the MVD. Time is in UTC (site is UTC+2).

As has been discussed, cloud droplets occur every night over the ocean in the simulations and this cloud deck impinges on the land adjacent to the coastline. To avoid this marine/coastal influence, a second point was extracted from the model about 13 km inland from the study site (labelled “Inland” in Figure 6-20). At this point it is clear that saturation and droplet onset is about 6 hours later than the coastal study site (Figure 6-20a). The number concentrations are similar between the coastal and inland site, while the LWC is lower than the coastal site. This means that the MVD is also lower and the DSD shifts to the left, resulting in a closer match the observed DSD (Figure 6-20). Scenario CCN_300_w0.1 is the best match to the observations in terms of number concentration, LWC, MVD and DSD.

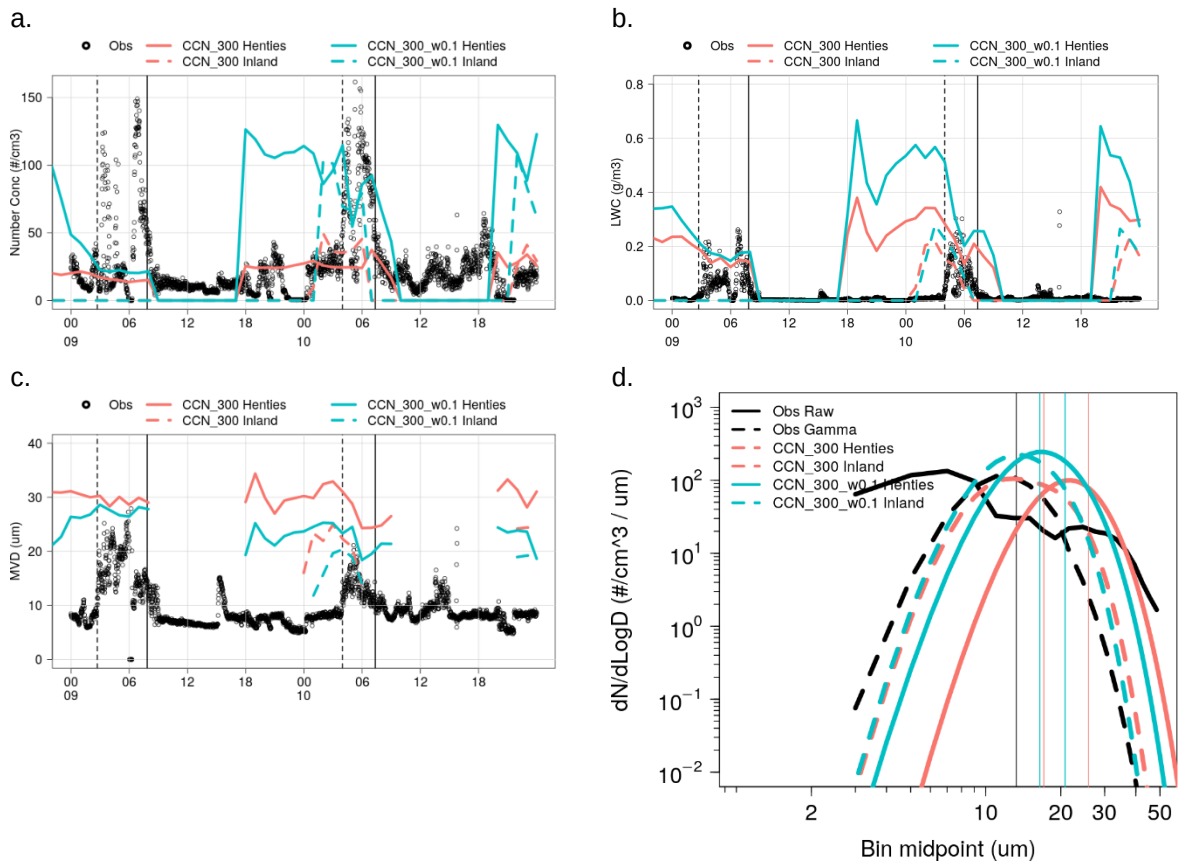


Figure 6-20: Observed and modelled size distribution for a.) case 1 and b.) case 2. Black solid lines are the observed distributions. Black dashed lines are the equivalent theoretical gamma distribution applied to the observed data. Other dashed lines are model distributions. Vertical solid lines represent the MVD. Time is in UTC (site is UTC+2).

6.3.2.4 WRF vertical evolution

In this section we present the fog top height and the vertical evolution of the fog over time (Figure 6-21). It was established previously that the fog onset in the model was associated with advection of marine fog. At the time of fog onset, LWC is only present in the lowest model level and incrementally extends to the layers above. Therefore, the model is not exhibiting any cloud base lowering. Cloud base lowering was deduced to have occurred during case 2, where cloud was observed over the site (Figure 6-5) hours before visibility decreased to less than 1 km. Fog top was higher for case 2 than case 1. Fog top was about 100 m for case 1 and 220 m for case 2 for the CNN_300 and CNN_300_landsea scenarios, while CNN_C10 showed fog tops at 220 m and 300 m respectively. Spirig et al. (2019) reported fog top at about 350 m.a.g.l at the Gobabeb site, which is about 56 km inland at an elevation of 406 m. Understandably,

the model fog top is lower than this based on the inversion level presented earlier. However, these results demonstrate the benefit of increasing the model vertical resolution near the ground, as it resolves the fog top height.

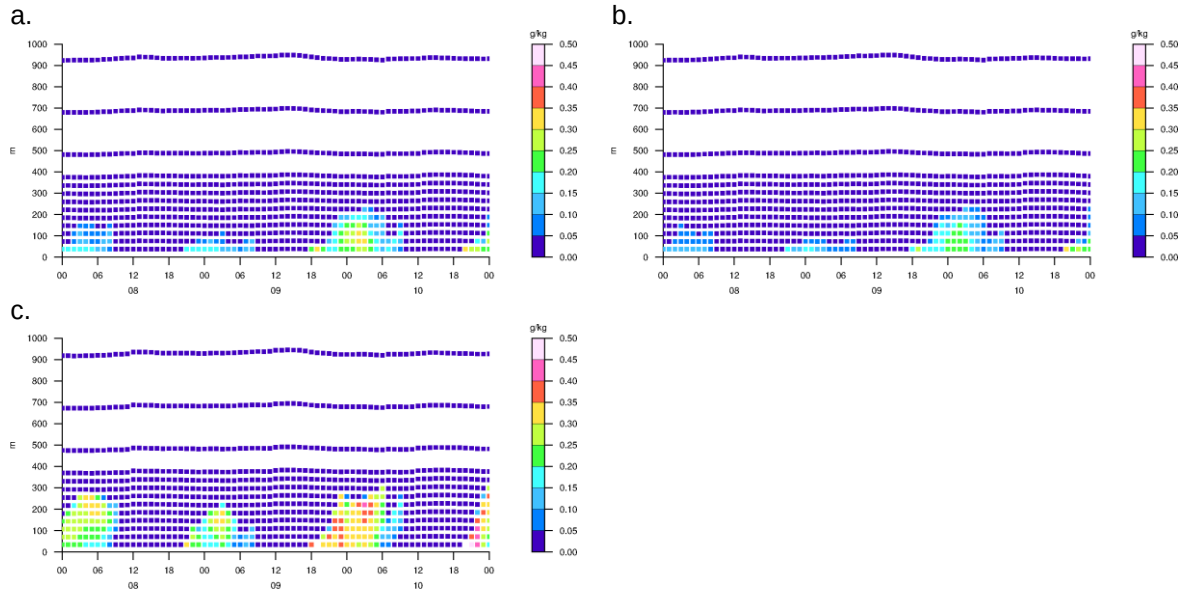


Figure 6-21: Profiles of LWC over time at Henties Bay for a.) CCN_300, b.) CCN_300_landsea and c.) CCN_C10. Time is in UTC (site is UTC+2).

6.4 Conclusions

This study compared WRF model simulations using the Thompson aerosol aware microphysics scheme to observations for two fog cases that occurred during the AEROCLOSA field campaign at Henties Bay, Namibia. A sensitivity analysis was conducted through variations to the initial CCN concentration, CCN radius and the minimum updraft speed, important factors that influence droplet activation in the microphysics scheme of the model. The first model scenario with initial CCN concentration of 300 cc (CCN_300) underestimated the cloud droplet number concentration while the LWC was in good agreement with the observations. This resulted in droplet size being larger than the observations. Another scenario used modelled data as CCN initial conditions (CCN_C10) which were an order of magnitude higher than other scenarios. However, these provided the most realistic values of Nt, LWC, MVD and droplet size distribution. From this it was concluded that CCN activation is too low in the simulations, around 10 %, while the observed appears to be higher, between 30-60 %. To achieve this level of activation in the model, the minimum updraft speed for CCN activation was increased from 0.01 to 0.1 ms^{-1} for the scenario CCN_300_w0.1. This scenario

provided Nt, LWC, MVD and droplet size distribution in the range of the observations with the added benefit of a realistic initial CCN concentration.

Further improvements in the timing of the simulated fog were realised by selecting a model grid point that was about 13 km inland from the site. This was conducted after it was realised that there was a persistent marine cloud cover that impinged on the coastline during the simulation. The persistent cloud cover appears to be related to a cold bias in the model which allows for saturation to occur, however, addressing this issue was beyond the scope of this study.

6.5 References

- Andersen, H., & Cermak, J. (2018). First fully diurnal fog and low cloud satellite detection reveals life cycle in the Namib. *Atmospheric Measurement Techniques*, 11(10), 5461–5470. <https://doi.org/10.5194/amt-11-5461-2018>
- Andersen, H., Cermak, J., Fuchs, J., Knippertz, P., Gaetani, M., Quinting, J., Sippel, S., & Vogt, R. (2020). Synoptic-scale controls of fog and low-cloud variability in the Namib Desert. *Atmospheric Chemistry and Physics*, 20(6), 3415–3438. <https://doi.org/10.5194/acp-20-3415-2020>
- Andersen, H., Cermak, J., Solodovnik, I., Lelli, L., & Vogt, R. (2019). Spatiotemporal dynamics of fog and low clouds in the Namib unveiled with ground- and space-based observations. *Atmospheric Chemistry and Physics*, 19(7), 4383–4392. <https://doi.org/10.5194/acp-19-4383-2019>
- Bergot, T., & Lestringant, R. (2019). On the predictability of radiation fog formation in a mesoscale model: A case study in heterogeneous terrain. *Atmosphere*, 10(4), 1–19. <https://doi.org/10.3390/atmos10040165>
- Bott, A. (1991). On the influence of the physico-chemical properties of aerosols on the life cycle of radiation fogs. *Boundary-Layer Meteorology*, 56(1), 1–31. <https://doi.org/10.1007/BF00119960>
- Boutle, I., Price, J., Kudzotsa, I., Kokkola, H., & Romakkaniemi, S. (2018). Aerosol-fog interaction and the transition to well-mixed radiation fog. *Atmospheric Chemistry and Physics*, 18(11), 7827–7840. <https://doi.org/10.5194/acp-18-7827-2018>
- Cermak, J. (2012). Low clouds and fog along the South-Western African coast - Satellite-based retrieval and spatial patterns. *Atmospheric Research*, 116, 15–21. <https://doi.org/10.1016/j.atmosres.2011.02.012>
- Colarco, P., da Silva, A., Chin, M., & Diehl, T. (2010). Online simulations of global aerosol distributions in the NASA GEOS-4 model and comparisons to satellite and ground-based aerosol optical depth. *Journal of Geophysical Research*, 115(D14). <https://doi.org/10.1029/2009jd012820>
- Dy, C. Y., & Fung, J. C. H. (2016). Updated global soil map for the Weather Research and Forecasting model and soil moisture initialization for the Noah land surface model. *Journal of Geophysical Research*, 121(15), 8777–8800. <https://doi.org/10.1002/2015JD024558>
- Egli, S., Maier, F., Bendix, J., & Thies, B. (2015). Vertical distribution of microphysical properties in radiation fogs - A case study. *Atmospheric Research*, 151, 130–145. <https://doi.org/10.1016/j.atmosres.2014.05.027>
- Eidhammer, T., Demott, P. J., & Kreidenweis, S. M. (2009). A comparison of heterogeneous ice nucleation parameterizations using a parcel model framework. *Journal of*

- Geophysical Research Atmospheres*, 114(6), 1--19.
<https://doi.org/10.1029/2008JD011095>
- EUMETSAT. (2009). *Best practices for RGB compositing of multi-spectral imagery*.
http://oiswww.eumetsat.int/~idders/html/doc/best_practices.pdf
- Formenti, P. (2020a). *AEROCLO-sA PEGASUS Radiosonde*.
<https://doi.org/10.6096/AEROCLO.1806>
- Formenti, P. (2020b). *AEROCLO-sA PEGASUS Surface Meteorology*.
<https://doi.org/10.6096/AEROCLO.1808>
- Formenti, P., D'Anna, B., Flamant, C., Mallet, M., Piketh, S. J., Schepanski, K., Waquet, F., Auriol, F., Brogniez, G., Burnet, F., Chaboureaud, J. P., & Chauvign. (2019). The aerosols, radiation and clouds in southern Africa field campaign in Namibia overview, illustrative observations, and way forward. *Bulletin of the American Meteorological Society*, 100(7), 1277--1298. <https://doi.org/10.1175/BAMS-D-17-0278.1>
- Ghan, S. J., Abdul-Razzak, H., Nenes, A., Ming, Y., Liu, X., Ovchinnikov, M., Shipway, B., Meskhidze, N., Xu, J., & Shi, X. (2011). Droplet nucleation: Physically-based parameterizations and comparative evaluation. *Journal of Advances in Modeling Earth Systems*, 3(4), 1--34. <https://doi.org/10.1029/2011ms000074>
- Gultepe, I., Tardif, R., Michaelides, S. C., Cermak, J., Bott, A., Bendix, J., Mller, M. D., Pagowski, M., Hansen, B., Ellrod, G., Jacobs, W., Toth, G., & Cober, S. G. (2007). Fog Research: A Review of Past Achievements and Future Perspectives. *Pure Appl. Geophys.*, 164, 1121--1159. <https://doi.org/10.1007/s00024-007-0211-x>
- Haefelin, M., Dupont, J. C., Boyouk, N., Baumgardner, D., Gomes, L., Roberts, G., & Elias, T. (2013). A Comparative Study of Radiation Fog and Quasi-Fog Formation Processes During the ParisFog Field Experiment 2007. *Pure and Applied Geophysics*, 170(12), 2283--2303. <https://doi.org/10.1007/s00024-013-0672-z>
- Haensler, A., Cermak, J., Hagemann, S., & Jacob, D. (2011). Will the southern african west coast fog be affected by future climate change?: Results of an initial fog projection using a regional climate model. *Erdkunde*, 65(3), 261--275. <https://doi.org/10.3112/erdkunde.2011.03.04>
- Iacono, M. J., Delamere, J. S., Mlawer, E. J., Shephard, M. W., Clough, S. A., & Collins, W. D. (2008). Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *J. Geophys. Res.*, 113. <https://doi.org/10.1029/2008JD009944>
- Juliano, T. W., Coggon, M. M., Thompson, G., Rahn, D. A., Seinfeld, J. H., Sorooshian, A., & Lebo, Z. J. (2019). Marine boundary layer clouds associated with coastally trapped disturbances: Observations and model simulations. *Journal of the Atmospheric Sciences*, 76(9), 2963--2993. <https://doi.org/10.1175/JAS-D-18-0317.1>
- Kain, J. S. (2004). The Kain-Fritsch convective parameterization: an update. *Journal of Applied Meteorology*, 43(1), 170--181.
- Klopper, D., Formenti, P., Namwoonde, A., Cazaunau, M., Chevaillier, S., Feron, A., Gaimoz, C., Hease, P., Lahmidi, F., Mirande-Bret, C., Triquet, S., Zeng, Z., & Piketh, S. (2020). Chemical composition and source apportionment of atmospheric aerosols on the Namibian coast. *Atmospheric Chemistry and Physics*(May), 1--43. <https://doi.org/10.5194/acp-2020-388>
- Lancaster, J., Lancaster, N., & Seely, M. K. (1984). Climate of the central Namib Desert. *Madoqua*, 1984(1), 5--61. https://doi.org/10.10520/AJA10115498_484
- Lindesay, J. A., & Tyson, P. D. (1990). Climate and Near-surface Airflow Over the Central Namib. (7), 27--37.
- Loveland, T. R., Reed, B. C., Ohlen, D. O., Brown, J. F., Zhu, Z., Yang, L., & Merchant, J. W. (2000). Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing*, 21(6-7), 1303--1330. <https://doi.org/10.1080/014311600210191>

- Maalick, Z., Khn, T., Korhonen, H., Kokkola, H., Laaksonen, A., & Romakkaniemi, S. (2016). Effect of aerosol concentration and absorbing aerosol on the radiation fog life cycle. *Atmospheric Environment*, 133, 26--33. <https://doi.org/10.1016/j.atmosenv.2016.03.018>
- Maronga, B., & Bosveld, F. C. (2017). Key parameters for the life cycle of nocturnal radiation fog: a comprehensive large-eddy simulation study. *Quarterly Journal of the Royal Meteorological Society*, 143(707), 2463--2480. <https://doi.org/10.1002/qj.3100>
- Mazoyer, M., Burnet, F., Denjean, C., Roberts, G. C., Haeffelin, M., Dupont, J. C., & Elias, T. (2019). Experimental study of the aerosol impact on fog microphysics. *Atmospheric Chemistry and Physics*, 19(7), 4323--4344. <https://doi.org/10.5194/acp-19-4323-2019>
- Nagel, J. (1962). Fog precipitation measurements on Africa's southwest coast. *Notos*, 11, 51-60.
- Nakanishi, M., & Niino, H. (2006). An improved Mellor-Yamada Level-3 model: Its numerical stability and application to a regional prediction of advection fog. *Boundary-Layer Meteorology*, 119(2), 397--407. <https://doi.org/10.1007/s10546-005-9030-8>
- NCEP. (2015). *NCEP GFS 0.25 Degree Global Forecast Grids Historical Archive* Version 14). <https://doi.org/10.5065/D65D8PWK>
- Olivier, J. (1995). Spatial distribution of fog in the Namib. *Journal of Arid Environments*, 29(2), 129--138. [https://doi.org/https://doi.org/10.1016/S0140-1963\(05\)80084-9](https://doi.org/https://doi.org/10.1016/S0140-1963(05)80084-9)
- Poku, C., Ross, A. N., Blyth, A. M., Hill, A. A., & Price, J. D. (2019). How important are aerosol-fog interactions for the successful modelling of nocturnal radiation fog? *Weather*, 74(7), 237--243. <https://doi.org/10.1002/wea.3503>
- Price, J. (2011). Radiation Fog. Part I: Observations of Stability and Drop Size Distributions. *Boundary-Layer Meteorology*, 139(2), 167--191. <https://doi.org/10.1007/s10546-010-9580-2>
- Román-Cascón, C., Steeneveld, G. J., Yagüe, C., Sastre, M., Arrillaga, J. A., & Maqueda, G. (2016). Forecasting radiation fog at climatologically contrasting sites: evaluation of statistical methods and WRF. *Quarterly Journal of the Royal Meteorological Society*, 142(695), 1048-1063. <https://doi.org/10.1002/qj.2708>
- Saleeby, S. M., & Cotton, W. R. (2004). A large-droplet mode and prognostic number concentration of cloud droplets in the Colorado State University Regional Atmospheric Modeling System (RAMS). Part I: Module descriptions and supercell test simulations. *Journal of Applied Meteorology*, 43(1), 182--195. [https://doi.org/10.1175/1520-0450\(2004\)043<0182:ALMAPN>2.0.CO;2](https://doi.org/10.1175/1520-0450(2004)043<0182:ALMAPN>2.0.CO;2)
- Sanchez, P. A., Ahamed, S., & Carr. (2009). Digital soil map of the world. *Science*, 325(5941), 680--681. <https://doi.org/10.1126/science.1175084>
- Schmetz, J., Pili, P., Tjemkes, S., Just, D., Kerkmann, J., Rota, S., & Ratier, A. (2002). An introduction to Meteosat Second Generation (MSG). *Bulletin of the American Meteorological Society*, 83(7), 977--992. [https://doi.org/10.1175/1520-0477\(2002\)083<0977:AITMSG>2.3.CO;2](https://doi.org/10.1175/1520-0477(2002)083<0977:AITMSG>2.3.CO;2)
- Seely, M., & Henschel, J. R. (1998). The climatology of Namib fog. 19--24.
- Seely, M. K., & Hamilton, W. J. (1976). Fog catchment sand trenches constructed by tenebrionid beetles, *Lepidochora*, from the Namib Desert. *Science*, 193(4252), 484--486. <https://doi.org/10.1126/science.193.4252.484>
- Seinfeld, J. H., & Pandis, S. N. (2016). *Atmospheric chemistry and physics: from air pollution to climate change*. John Wiley & Sons.
- Sertel, E., Robock, A., & Ormeci, C. (2010). Impacts of land cover data quality on regional climate simulations. *International Journal of Climatology*, 30(13), 1942--1953. <https://doi.org/10.1002/joc.2036>
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., Huang, X.-Y., Wang, W., & Powers, J. G. (2008). *A Description of the Advanced Research WRF Version 3*.
- Spirig, R., Vogt, R., Larsen, J. A., Feigenwinter, C., Wicki, A., Franceschi, J., Parlow, E., Adler, B., Kalthoff, N., Cermak, J., Andersen, H., Fuchs, J., Bott, A., Hacker, M., Wagner, N.,

- Maggs-Killing, G., Wassenaar, T., & Seely, M. (2019). Probing the fog life cycles in the Namib desert. *Bulletin of the American Meteorological Society*, 100(12), 2491--2507. <https://doi.org/10.1175/BAMS-D-18-0142.1>
- Statista. (2020). *Namibia: Population density from 2008 to 2018* Retrieved 17 November from <https://www.statista.com/statistics/971467/population-density-in-namibia/>
- Steenefeld, G. J., & de Bode, M. (2018). Unravelling the relative roles of physical processes in modelling the life cycle of a warm radiation fog. *Quarterly Journal of the Royal Meteorological Society*, 144(714), 1539--1554. <https://doi.org/10.1002/qj.3300>
- Stolaki, S., Haeffelin, M., Lac, C., Dupont, J. C., Elias, T., & Masson, V. (2015). Influence of aerosols on the life cycle of a radiation fog event. A numerical and observational study. *Atmospheric Research*, 151, 146--161. <https://doi.org/10.1016/j.atmosres.2014.04.013>
- Tardif, R. (2007). The impact of vertical resolution in the explicit numerical forecasting of radiation fog: A case study. *Pure and Applied Geophysics*, 164(6-7), 1221--1240. <https://doi.org/10.1007/s00024-007-0216-5>
- Thompson, G., & Eidhammer, T. (2014). A Study of Aerosol Impacts on Clouds and Precipitation Development in a Large Winter Cyclone. *Journal of the Atmospheric Sciences*, 71(10), 3636--3658. <https://doi.org/10.1175/JAS-D-13-0305.1>
- Weston, M., Temimi, M., Morais, R., Reddy, N., Francis, D., & Piketh, S. (2021). A rule-based method for diagnosing radiation fog in an arid region from NWP forecasts. *Journal of Hydrology*, 597, 126189. <https://doi.org/10.1016/j.jhydrol.2021.126189>
- Weston, M. J., & Temimi, M. (2020). Application of a night time fog detection method using SEVIRI over an arid environment. *Remote Sensing*, 12(14). <https://doi.org/10.3390/rs12142281>
- Wilkinson, J. M., Porson, A. N. F., Bornemann, F. J., Weeks, M., Field, P. R., & Lock, A. P. (2013). Improved microphysical parametrization of drizzle and fog for operational forecasting using the Met Office Unified Model. *Quarterly Journal of the Royal Meteorological Society*, 139(671), 488--500. <https://doi.org/10.1002/qj.1975>
- WRF Users Page. (2020). *Notes for running WRF with the Aerosol-aware Thompson Scheme (mp_physics = 28)*. Retrieved 2020-08-26 from https://www2.mmm.ucar.edu/wrf/users/physics/mp28_updated.html
- Zeng, X., & Beljaars, A. (2005). A prognostic scheme of sea surface skin temperature for modeling and data assimilation. *Geophysical Research Letters*, 32(14), 1--4. <https://doi.org/10.1029/2005GL023030>
- Zhou, B., Du, J., Gultepe, I., & Dimego, G. (2012). Forecast of low visibility and fog from NCEP: Current status and efforts. *Pure and Applied Geophysics*, 169(5-6), 895--909. <https://doi.org/10.1007/s00024-011-0327-x>

CHAPTER 7 CONCLUSION

7.1 Summary and Conclusion

Methods to diagnose fog in arid regions from mesoscale model variables have been presented in this thesis. The general approach was to i) characterise fog through available observations, ii) assess and address model bias in simulating state parameters important to fog and iii) apply and assess different methods for diagnosing fog.

7.1.1 Objective 1

Objective 1 was to characterise the observed fog over the UAE and was addressed in chapters 2 and 3. The results from this objective guided the model set up, model parameterisation and interpretation of model results. From these analyses it was decided to initialise the model at 06 UTC (10 LT) and to run simulations between October and March. Furthermore, fog dynamics were shown to have strong links to the land-sea breeze and inversion depth, which later aided the model parameterisation and interpretation. A summary of each chapter linked to this objective is given below.

The main study site was Abu Dhabi International Airport in the United Arab Emirates. The first fog climatology for this site, and the UAE, was presented in Chapter 2 based on METAR and radiosonde data. There were many interesting findings from this chapter. For example, while most fog events last 1 hour or less, events can last more than 9 hours in January and December. While fog is mainly a winter phenomenon with October, December and January being more active months, November was notably not as active for fog events. While a hypothesis was proposed for this based on observations from the literature, for example a decrease in aerosol loading, this pattern requires further investigation. In general, this chapter provided context for the following chapters and was included extensively in the introduction of each. However, an important result from this chapter helped guide the methodology in Chapter 5, “A rule-based method for diagnosing radiation fog in an arid region from NWP forecasts”. This was related to the surface inversion depth, which was deeper on fog mornings. A rule was applied to the model where inversion depth needed to be $> 250\text{m}$ to diagnose fog. This ruled helped separate fog days from non-fog days in the model simulations and improved the fog forecast. While this phenomenon is reported elsewhere, mainly cold climates in Europe, it does require further investigation for the study site and can be addressed in future studies.

In Chapter 3, satellite data was used to provide the first spatial dynamics of fog in the UAE over two seasons. It highlighted the need for a spatially varying threshold of brightness temperature or, in this case, pseudo emissivity to detect nocturnal fog. This chapter complements the results in Chapter 2 as it provides information on fog formation inland. At this stage fog in the UAE has been characterised as radiation fog and is dependent on the land-sea breeze circulation. The main finding was that fog often forms inland first before spreading towards the coast or further inland. This means that the number of fog days, and length of events is expected to be higher about 30 km inland than what was reported at the coastal site of Abu Dhabi. In addition, fog was found to occur up to 200 km inland, indicating that the sea-breeze can penetrate further than previously reported. This investigation into the spatial pattern of fog from satellite informed the model evaluation in Chapter 5.

7.1.2 Objective 2

Model physics is introduced in Chapter 4, more specifically, the land surface model in WRF. A nocturnal cold bias in the model simulations was identified at the Abu Dhabi study site. This resulted in overactive saturation represented by either relative humidity or temperature depression. This had implications for the multi-rule based approach, where one of these variables is utilised in defining a rule, and it would create a false alarm in the model. To address this cold bias, the model code was adapted to indirectly adjust the thermal roughness length per land cover type. For the arid desert this meant a decrease in the roughness length of heat, Z_{0t} , which will decrease the coefficient of heat exchange, C_H , and therefore increase of land surface temperature and by association increase the 2m air temperature. The thermal roughness length was adjusted through the Zilitinkevich parameter (Czil), an input variable in the model. The default value for all land cover types is 0.1, but my co-authors and I found that a value of 0.5 for desert improved the mean gross error in late afternoon/early evening temperature up to 1.48 °C. To better understand the cold bias in the model would require a suite of in situ measurements including radiation parameters. While the thermal roughness length is unlikely to be the sole source of the model bias, this chapter showed that the bias could be solved in part through adjusting the Czil parameter. The following limitations to this work are acknowledged. The sample size of fog cases is small and limited to a single season. Physical conditions may change from season to season and the model performance may vary as a result. Furthermore, the number of stations used for verification is few and the study would benefit from additional stations over a variety of locations in the desert.

7.1.3 Objective 3

The main focus of Chapter 5 was to implement a multi rule based method to diagnose fog from the model. The method is presented here for next day forecasts of radiation fog at Abu Dhabi in the United Arab Emirates. The study period covered 10 winter months (303 days), comprising 35 fog days at Abu Dhabi, over two seasons. The first season is from December 2016 to March 2017 and the second season is October 2017 to March 2018. There were many concepts in this chapter as it relied heavily on observations to try distinguish fog and non-fog conditions before any modelling was conducted. In addition, the cold bias was addressed from a different angle, this time by altering the soil characteristics, more specifically the soil porosity and texture, instead of the thermal roughness length presented in Chapter 4. One objective from this chapter was to use readily available meteorological parameters to define the rules so that the method is transferable to other sites. Previous studies may have relied on less common measurements related to cloud microphysics or radiation to define rules which were not necessarily helpful or applicable at the Abu Dhabi site. However, the final model performance compared favourably to other studies. In addressing sub objective 3a, the combination of rules that performed best were: relative humidity $\geq 94\%$, wind speed $\leq 3\text{ ms}^{-1}$, and the depth of the inversion layer $> 250\text{ m}$. A main finding in this chapter that addressed sub objective 3b, was the implementation of the inversion depth as a rule, which had not been applied previously. The inclusion of this rule outperformed the Modified Richardson index (MRI), another parameter that represents vertical stability in the atmosphere. Furthermore, the multi-rule method also outperformed LWC from the model, but this will be discussed in more detail in the Chapter 6 summary. The biggest limitation with this method is evident in the observed data when trying to differentiate fog and non-fog conditions, as there is a large overlap between these two datasets. A qualitative assessment on the spatial distribution of fog patches was conducted by comparing the model with satellite RGB images. The results showed realism in the model fog patch as it managed to represent the extent and boundaries of observed fog events. This suggests that the geophysical parameters from the observations at a single point used to define the rules were applicable over a larger area. Overall this method exceeded expectations.

7.1.4 Objective 4

In Chapter 6 the focus moved towards cloud microphysics as NWU was involved in a field campaign in Namibia where these measurements were taken. This allowed for the implementation of an aerosol aware microphysics scheme in the model, which represents the

process of cloud droplet activation, and subsequently using LWC to define fog. The observations are used to firstly assess the model performance based on default settings and then modify the parameterisation appropriately. The major finding from this chapter is that the model underestimates droplet activation during a fog event. In addressing sub objective 4a, the model code was modified to increase the droplet activation in the lowest model levels. This resulted in improved simulation of droplet number concentration and droplet size distribution, thus addressing sub objective 4b. A major limitation in the model simulations was the existence of a persistent cloud deck over the ocean which impinged on the land immediately adjacent to the ocean. The reason for this artefact is mostly likely due to a cold bias in the model. However, a full investigation into this was beyond the scope of the study and will have to be solved in the future.

7.1.5 Closing remarks and future work

In the previous section the results from each chapter were outlined. In this section I highlight some links between the chapters and propose considerations for future research. In Chapter 6 my co-authors and I depend on LWC to define fog while in Chapter 5 we state that it is not a good parameter to diagnose fog. This apparent contradiction occurs as two different microphysics schemes were implemented in each study. The benefit of trialling an aerosol aware scheme in the UAE was limited at the time, mainly due to the lack of microphysical measurements of fog. However, this is planned for the future and the work over Namibia will heavily inform the modelling methodology.

Some of the insights gained in Namibia shed light on the challenges in Abu Dhabi. For example, the proximity of the study site at Henties Bay to the coast highlighted the maritime influence on modulating temperature, which is not as prominent in the model. Up to now, this has not been considered as a cause of cold bias at the Abu Dhabi site, which is about 12 km from the nearest water way. Thus, there may be some artefact in the model when simulating the land-marine interface that can be investigated. This was a useful connection to make between the two study sites.

Overall, both the rule based method and the aerosol aware microphysics require that modelled state parameters are performing adequately. To some extent, the rule based method is more lenient in this regard as the threshold values cover a range of conditions. However, the microphysics approach demonstrates a great deal of potential. Improvements in performance were achieved rapidly, through a few model scenarios and with far less analysis of observed data. Furthermore, the code is primed to ingest custom spatial data in terms of initial CCN

concentrations or even coupled online CCN. However, based on the results presented in this thesis, the rule based method is currently a more robust method to diagnose next day fog in the model.

The following is possible future work based on the studies in the UAE. Investigate why the inversion depth is deeper on fog days. Is it an artefact of radiative cooling or a feedback from cloud droplets on the radiation? Long term measurements from the microwave radiometer which are currently underway can provide insight to these dynamics. From a modelling perspective, the aerosol aware scheme can be applied and verified in the UAE, which is possible now that a fog monitor has been deployed in the region since the writing of this thesis.

In Namibia, there is a persistent cloud deck over the ocean in the model simulations. This requires some investigation and model simulations over a longer period. Most likely, this will require an investigation into the radiation balance over the ocean, which could utilise satellite or reanalysis products to understand model bias.

It is acknowledged that in the larger context of global forecasts that new tools are advancing rapidly, namely machine learning (ML) and high resolution global forecasts, which may surpass regional models in performance. With regards to machine learning, some reviewers have gone on to say that it may replace NWP entirely if certain breakthroughs are achieved (Schultz et al., 2021). However, in its current form, ML has only been assessed for specific variables and usually at single locations (e.g. (Bartoková et al., 2015; Colabone et al., 2015)), while a full weather forecast requires multiple variables across a large spatial extent (Schultz et al., 2021). An additional concern of ML is that it does not recognise physical constraints, yet, these deficiencies are actively being addressed by through tweaks of ML methods to earth science (Kashinath et al., 2021). In addition, recent advances include the first ML dataset for benchmarking weather forecasts of 3 to 5 days (Rasp et al., 2020), thereby extending the validity of the ML forecasts. Thus, ML is expected to form part of a forecast system to a greater or lesser extent in the future.

In order to solve cumulus convection explicitly, regional and global forecasts are simulated at increasing high resolution. Current operational forecasts are still > 1 km resolution, with European Centre for Medium Range Forecasts (ECMWF) Integrated Forecast System (IFS), National Ocean Atmosphere Administration (NOAA) High-Resolution Rapid Refresh (HRRR) and UK Met Office forecasts at 9 km, 3 km and 2 km respectively (Benjamin et al., 2016; ECMWF, 2021; UK Met Office, 2019). However, offline global simulations have been conducted at 1 km resolution and 137 vertical levels (Wedi et al., 2020) and the climate change

community is advocating for similar resolutions for their longer simulations (Palmer & Stevens, 2019). When realised, these resolutions will solve non-cumulus clouds too and will be able to resolve fog formation. However, limited area regional models will still play a role in these global forecast systems, as they can be run more rapidly and allow for faster testing of physics schemes for specific atmospheric phenomenon, allowing for optimisation of physics suites on the global models.

In closing, the overall research aim on model parameterisation was met as well as the associated objectives on the fog climatology and spatial distribution which guided and informed the modelling process. Model cold bias was addressed using a physics based approach in the land surface model. Inversion depth was identified as a parameter to improve the rule based method performance. Droplet activation was increased to provide convergent cloud microphysics results. It is hoped that these results have highlighted some of the challenges of simulating fog, proposed ways to overcome the challenges and ultimately contribute to improved fog forecasts in arid regions.

BIBLIOGRAPHY

7.2 Bibliography

- Abbs, D. J., & Physick, W. (1992). Sea-breeze observations and modelling: a review. *Australian Meteorological Magazine*, 41, 7-19.
- Abu Dhabi Airports. (2017). *Annual Report 2016*. <http://www.adac.ae/english/media-centre/annual-reports>
- Abu Dhabi Airports. (2019). *Abu Dhabi Airport*. Retrieved 2 March 2020 from <https://www.abudhabiairport.ae/en/about/overview>
- Ajjaji, R., Al-katheri, A. A., & Khaled, A. L. (2008). Evaluation of United Arab Emirates WRF two-way nested model on a set of thick coastal fog situations. *United Nations Development Programme, Air Force and Air Defense Meteorological Department*.
- Al Azhar, M., Temimi, M., Zhao, J., & Ghedira, H. (2016). Modeling of circulation in the Arabian Gulf and the Sea of Oman: Skill assessment and seasonal thermohaline structure. *Journal of Geophysical Research: Oceans*, 121(3), 1700-1720. <https://doi.org/10.1002/2015JC011038>
- Aldababseh, A., & Temimi, M. (2017). Analysis of the long-term variability of poor visibility events in the UAE and the link with climate dynamics. *Atmosphere*, 8(12), 18-20. <https://doi.org/10.3390/atmos8120242>
- Aldababseh, A., Temimi, M., Maghelal, P., Branch, O., & Wulfmeyer, V. (2018). Multi-criteria evaluation of irrigated agriculture suitability to achieve food security in an arid environment. *Sustainability (Switzerland)*, 10(3). <https://doi.org/10.3390/su10030803>
- Andersen, H., & Cermak, J. (2018). First fully diurnal fog and low cloud satellite detection reveals life cycle in the Namib. *Atmospheric Measurement Techniques*, 11(10), 5461-5470. <https://doi.org/10.5194/amt-11-5461-2018>
- Andersen, H., Cermak, J., Fuchs, J., Knippertz, P., Gaetani, M., Quinting, J., Sippel, S., & Vogt, R. (2020). Synoptic-scale controls of fog and low-cloud variability in the Namib Desert. *Atmospheric Chemistry and Physics*, 20(6), 3415-3438. <https://doi.org/10.5194/acp-20-3415-2020>
- Andersen, H., Cermak, J., Solodovnik, I., Lelli, L., & Vogt, R. (2019). Spatiotemporal dynamics of fog and low clouds in the Namib unveiled with ground- And space-based observations. *Atmospheric Chemistry and Physics*, 19(7), 4383-4392. <https://doi.org/10.5194/acp-19-4383-2019>
- Baker, R., Cramer, J., & Peters, J. (2002). Radiation Fog: UPS Airlines Conceptual Models And Forecast Methods. *10th Conference on Aviation, Range, and Aerospace Meteorology*, 116(3), 505--524. http://ams.confex.com/ams/13ac10av/techprogram/paper_39165.htm _ 39165.htm \%
- Bang, C.-H., Lee, J.-W., & Hong, S.-Y. (2008). Predictability experiments of fog and visibility in local airports over Korea using the WRF model. *Journal of Korean Society for Atmospheric Environment*, 24(E2), 92-101.
- Bartok, J., Bott, A., & Gera, M. (2012). Fog Prediction for Road Traffic Safety in a Coastal Desert Region: Improvement of Nowcasting Skills by the Machine-Learning Approach. *Boundary-Layer Meteorology*, 157(3), 501--516. <https://doi.org/10.1007/s10546-015-0069-x>
- Bartoková, I., Bott, A., Bartok, J., & Gera, M. (2015). Fog Prediction for Road Traffic Safety in a Coastal Desert Region: Improvement of Nowcasting Skills by the Machine-Learning Approach. *Boundary-Layer Meteorology*, 157(3), 501-516.

- Bastidas, L. A., Hogue, T. S., Sorooshian, S., Gupta, H. V., & Shuttleworth, W. J. (2006). Parameter sensitivity analysis for different complexity land surface models using multicriteria methods. *Journal of Geophysical Research: Atmospheres*, 111(D20).
- Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. *Nature*, 525(7567), 47-55. <https://doi.org/10.1038/nature14956>
- Benjamin, S. G., Weygandt, S. S., Brown, J. M., Hu, M., Alexander, C. R., Smirnova, T. G., Olson, J. B., James, E. P., Dowell, D. C., Grell, G. A., Lin, H., Peckham, S. E., Smith, T. L., Moninger, W. R., Kenyon, J. S., & Manikin, G. S. (2016). A North American hourly assimilation and model forecast cycle: The rapid refresh. *Monthly Weather Review*, 144(4), 1669--1694. <https://doi.org/10.1175/MWR-D-15-0242.1>
- Bergot, T., Escobar, J., & Masson, V. (2015). Effect of small-scale surface heterogeneities and buildings on radiation fog: Large-eddy simulation study at paris-charles de gaulle airport. *Quarterly Journal of the Royal Meteorological Society*, 141(686), 285--298. <https://doi.org/10.1002/qj.2358>
- Bergot, T., Lac, C., Burnet, F., Martinet, P., Bouteloup, Y., & Bouyssel, F. (2017). Towards a three-dimensional prediction of fog on airports with the M'et'eo-France operational forecast model AROME. *WMO Aeronautical Meteorology Scientific Conference*.
- Bergot, T., & Lestringant, R. (2019). On the predictability of radiation fog formation in a mesoscale model: A case study in heterogeneous terrain. *Atmosphere*, 10(4), 1--19. <https://doi.org/10.3390/atmos10040165>
- Bergot, T., Terradellas, E., Cuxart, J., Mira, A., Leichti, O., Mueller, M., & Nielsen, N. W. (2007). Intercomparison of single-column numerical models for the prediction of radiation fog. *Journal of Applied Meteorology and Climatology*, 46(4), 504--521. <https://doi.org/10.1175/JAM2475.1>
- Bieringer, P. E., Donovan, M., Robasky, F., Clark, D. A., & Hurst, J. (2006). A characterization of NWP ceiling and visibility forecasts for the terminal airspace.
- Bott, A. (1991). On the influence of the physico-chemical properties of aerosols on the life cycle of radiation fogs. *Boundary-Layer Meteorology*, 56(1), 1--31. <https://doi.org/10.1007/BF00119960>
- Boutle, I., Price, J., Kudzotsa, I., Kokkola, H., & Romakkaniemi, S. (2018). Aerosol-fog interaction and the transition to well-mixed radiation fog. *Atmospheric Chemistry and Physics*, 18(11), 7827--7840. <https://doi.org/10.5194/acp-18-7827-2018>
- Braud, I., Noilhan, J., Bessemoulin, P., Mascart, P., Haverkamp, R., & Vauclin, M. (1993). Bare-ground surface heat and water exchanges under dry conditions: Observations and parameterization. *Boundary-Layer Meteorology*, 66(1), 173-200.
- Calvert, C., & Pavolonis, M. (2010). *GOES-R Advanced Baseline Imager (ABI) Algorithm Theoretical Basis Document for Low Cloud and Fog* (Algorithm Theoretical Basis Document Issue).
- Cao, C. a. S., Xi. (2013). *Planck Function*. Retrieved 26 September from <https://ncc.nesdis.noaa.gov/data/planck.html>
- Cereceda, P., & Schemenauer, R. S. (1991). The occurrence of fog in Chile. *Journal of Applied Meteorology*, 30(8), 1097-1105. [https://doi.org/10.1175/1520-0450\(1991\)030<1097:TOOFIC>2.0.CO;2](https://doi.org/10.1175/1520-0450(1991)030<1097:TOOFIC>2.0.CO;2)
- Cermak, J. (2012). Low clouds and fog along the South-Western African coast - Satellite-based retrieval and spatial patterns. *Atmospheric Research*, 116, 15--21. <https://doi.org/10.1016/j.atmosres.2011.02.012>
- Cermak, J., & Bendix, J. (2007). Dynamical nighttime fog/low stratus detection based on Meteosat SEVIRI data: A feasibility study. *Pure and Applied Geophysics*, 164(6-7), 1179--1192. <https://doi.org/10.1007/s00024-007-0213-8>
- Cermak, J., & Bendix, J. (2008). A novel approach to fog/low stratus detection using Meteosat 8 data. *Atmospheric Research*, 87(3-4), 279--292. <https://doi.org/10.1016/j.atmosres.2007.11.009>

- Chaouch, N., Temimi, M., Weston, M., & Ghedira, H. (2016). Sensitivity of the meteorological model WRF-ARW to planetary boundary layer schemes during fog conditions in a coastal arid region. *Atmospheric Research*, 187, 106-127. <https://doi.org/10.1016/j.atmosres.2016.12.009>
- Chen, F., & Dudhia, J. (2001). Coupling an Advanced Land Surface Hydrology Model with the Penn State NCAR MM5 Modeling System. Part I: Model Implementation and Sensitivity. *Monthly Weather Review*, 129(4), 569-585.
- Chen, F., Janjić, Z., & Mitchell, K. (1997). Impact of Atmospheric Surface-layer Parameterizations in the new Land-surface Scheme of the NCEP Mesoscale Eta Model. *Boundary-Layer Meteorology*, 85, 391-421.
- Chen, F., & Zhang, Y. (2009). On the coupling strength between the land surface and the atmosphere: From viewpoint of surface exchange coefficients. *Geophysical Research Letters*, vol.36, issue 10.
- Chen, Y., Yang, K., He, J., Qin, J., Shi, J., Du, J., & He, Q. (2011). Improving land surface temperature modeling for dry land of China. *Journal of Geophysical Research: Atmospheres*, 116(D20).
- Chen, Y., Yang, K., Zhou, D., Qin, J., & Guo, X. (2010). Improving the Noah land surface model in arid regions with an appropriate parameterization of the thermal roughness length. *Journal of Hydrometeorology*, 11(4), 995-1006.
- Clark, P. A., Harcourt, S. A., Macpherson, B., Mathison, C. T., Cusack, S., & Naylor, M. (2008). Prediction of visibility and aerosol within the operational Met office unified model.I: Model formulation and variational assimilation. *Quarterly Journal of the Royal Meteorological Society*, 134(636), 1801--1816. <https://doi.org/10.1002/qj.318>
- Colabone, R. D. O., Ferrari, A. L., Vecchia, F. A. d. S., & Tech, A. R. B. (2015). Application of artificial neural networks for fog forecast. *Journal of Aerospace Technology and Management*, 7(2), 240-246. <https://doi.org/10.5028/jatm.v7i2.446>
- Colarco, P., da Silva, A., Chin, M., & Diehl, T. (2010). Online simulations of global aerosol distributions in the NASA GEOS-4 model and comparisons to satellite and ground-based aerosol optical depth. *Journal of Geophysical Research*, 115(D14). <https://doi.org/10.1029/2009jd012820>
- Copernicus Climate Change Service (C3S). (2017). *ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate*
- Croft, P. J., Pfof, R. L., Medlin, J. M., & Johnson, G. A. (1997). Fog Forecasting for the Southern Region: A Conceptual Model Approach. *Weather and Forecasting*, 12(3), 545--556. [https://doi.org/10.1175/1520-0434\(1997\)012<0545:FFFTSR>2.0.CO;2](https://doi.org/10.1175/1520-0434(1997)012<0545:FFFTSR>2.0.CO;2)
- Dammann, K., Mueller, J., Hanson, C., Gartner, V., Flewin, J., & Williams, M. (2005). MSG level 1.5 image data format description. *EUMETSAT, Darmstadt, Technical Report EUM/MSG/ICD/105 Issue, 3*.
- De Villiers, M. P., & Van Heerden, J. (2007). Fog at Abu Dhabi international airport. *Weather*, 62, 209-214.
- del Río, C., Rivera, D., Siegmund, A., Wolf, N., Cereceda, P., Larraín, H., Lobos, F., Garcia, J.-L., Osses, P., Zanetta, N., & Lambert, F. (2018). ENSO Influence on Coastal Fog-Water Yield in the Atacama Desert, Chile. *Aerosol and Air Quality Research*, 18(1), 127-144. <https://doi.org/10.4209/aagr.2017.01.0022>
- Dy, C. Y., & Fung, J. C. H. (2016). Updated global soil map for the Weather Research and Forecasting model and soil moisture initialization for the Noah land surface model. *Journal of Geophysical Research*, 121(15), 8777--8800. <https://doi.org/10.1002/2015JD024558>
- Eager, R. E., Raman, S., Wootten, A., Westphal, D. L., Reid, J. S., & Mandoos, A. A. (2008). A climatological study of the sea and land breezes in the Arabian Gulf region. *Journal of Geophysical Research Atmospheres*, 113(15), 1-12. <https://doi.org/10.1029/2007JD009710>
- ECMWF. (2021). About our forecasts | ECMWF. In.

- Egli, S., Maier, F., Bendix, J., & Thies, B. (2015). Vertical distribution of microphysical properties in radiation fogs - A case study. *Atmospheric Research*, 151, 130--145. <https://doi.org/10.1016/j.atmosres.2014.05.027>
- Egli, S., Thies, B., & Bendix, J. (2018). A hybrid approach for fog retrieval based on a combination of satellite and ground truth data. *Remote Sensing*, 10(4). <https://doi.org/10.3390/rs10040628>
- Eidhammer, T., Demott, P. J., & Kreidenweis, S. M. (2009). A comparison of heterogeneous ice nucleation parameterizations using a parcel model framework. *Journal of Geophysical Research: Atmospheres*, 114(6), 1--19. <https://doi.org/10.1029/2008JD011095>
- Ek, M. B., Mitchell, K. E., Lin, Y., Rogers, E., Grunmann, P., Koren, V., Gayno, G., & Tarpley, J. D. (2003). Implementation of Noah land surface model advances in the National Centers for Environmental Prediction operational mesoscale Eta model. *Journal of Geophysical Research: Atmospheres*, 108(D22).
- Elhakeem, A., Elshorbagy, W., & Bleninger, T. (2015). Long-term hydrodynamic modeling of the Arabian Gulf. *Marine Pollution Bulletin*, 94(1-2), 19--36. <https://doi.org/10.1016/j.marpolbul.2015.03.020>
- Ellrod, G. P. G. P. (2002). Estimation of low cloud base heights at night from satellite infrared and surface temperature data. *National Weather Digest*, 26(1,2), 39--44. <http://nwas.org/digest/papers/2002/Vol26No12/Pg39-Ellrod.pdf>
- Environment Agency Abu Dhabi. (2009). *Soil Survey of Abu Dhabi Emirate*. <https://www.biosaline.org/projects/soil-survey-emirate-abu-dhabi>
- EUMETSAT. (2009). *Best practices for RGB compositing of multi-spectral imagery*. http://oiswww.eumetsat.int/~ids/html/doc/best_practices.pdf
- Eyre, J. R., Brownscombe, J. L., & Allam, R. J. (1984). Detection of fog at night using Advanced Very High Resolution Radiometer (AVHRR) imagery. *Meteorological Magazine*, 113, 266-271. <https://www.semanticscholar.org/paper/Detection-of-fog-at-night-using-Advanced-Very-High-Eyre-Brownscombe/243beb6f5c629a270bb292e99b66b42e87dd9335>
- Fabbian, D. a. (2007). Application of artificial neural network forecasts to predict fog at Canberra International Airport. *Weather and Forecasting*, 22(2), 372-381. <https://doi.org/10.1175/WAF980.1>
- Fares, A., Temimi, M., Morgan, K., & Kelleners, T. J. (2013). In-Situ and Remote Soil Moisture Sensing Technologies for Vadose Zone Hydrology. *Vadose Zone Journal*, 12(2), vzj2013.2003.0058. <https://doi.org/10.2136/vzj2013.03.0058>
- Filioglou, M., Giannakaki, E., Backman, J., Kesti, J., Hirsikko, A., Engelmann, R., Connor, E. O., Leskinen, J. T. T., Shang, X., Korhonen, H., Lihavainen, H., Oapos, Connor, E., Leskinen, J. T. T., Shang, X., Korhonen, H., Lihavainen, H., Romakkaniemi, S., & Komppula, M. (2020). Optical and geometrical aerosol particle properties over the United Arab Emirates. *Atmospheric Chemistry and Physics Discussions*(March), 1-26. <https://doi.org/10.5194/acp-2020-133>
- Fonseca, R., Temimi, M., Thota, M. S., Nelli, N. R., Weston, M. J., Suzuki, K., Uchida, J., Kumar, K. N., Branch, O., & Wehbe, Y. a. (2020). On the Analysis of the Performance of WRF and NICAM in a Hyperarid Environment. *Weather and Forecasting*, 35(3), 891-919. <https://doi.org/10.1175/waf-d-19-0210.1>
- Fonseca, R., Zorzano-Mier, M. P., Azua-Bustos, A., Gonzalez-Silva, C., & Martn-Torres, J. (2019). A surface temperature and moisture intercomparison study of the Weather Research and Forecasting model, in-situ measurements and satellite observations over the Atacama Desert. *Quarterly Journal of the Royal Meteorological Society*(November 2018), 2202--2220. <https://doi.org/10.1002/qj.3553>
- Formenti, P. (2020a). AEROCLO-sA PEGASUS Radiosonde. <https://doi.org/10.6096/AEROCLO.1806>

- Formenti, P. (2020b). AEROCLO-sA PEGASUS Surface Meteorology. <https://doi.org/10.6096/AEROCLO.1808>
- Formenti, P., D'Anna, B., Flamant, C., Mallet, M., Piketh, S. J., Schepanski, K., Waquet, F., Auriol, F., Brogniez, G., Burnet, F., Chaboureaud, J. P., & Chauvign. (2019). The aerosols, radiation and clouds in southern Africa field campaign in Namibia overview, illustrative observations, and way forward. *Bulletin of the American Meteorological Society*, 100(7), 1277--1298. <https://doi.org/10.1175/BAMS-D-17-0278.1>
- Gandhidasan, P., & Abualhamayel, H. I. (2012). Exploring fog water harvesting potential and quality in the Asir region, Kingdom of Saudi Arabia. *Pure and Applied Geophysics*, 169(5-6), 1019-1036. <https://doi.org/10.1007/s00024-011-0341-z>
- Ghan, S. J., Abdul-Razzak, H., Nenes, A., Ming, Y., Liu, X., Ovchinnikov, M., Shipway, B., Meskhidze, N., Xu, J., & Shi, X. (2011). Droplet nucleation: Physically-based parameterizations and comparative evaluation. *Journal of Advances in Modeling Earth Systems*, 3(4), 1--34. <https://doi.org/10.1029/2011ms000074>
- Ghude, S. D., Bhat, G. S., Prabhakaran, T., Jenamani, R. K., Chate, D. M., Safai, P. D., Karipot, A. K., Konwar, M., Pithani, P., Sinha, V., Rao, P. S. P., Dixit, S. A., Tiwari, S., Todekar, K., Varpe, S., Srivastava, A. K., Bisht, D. S., Murugavel, P., Ali, K., Mina, U., & Dharua, M. a. (2017). Winter fog experiment over the Indo-Gangetic plains of India. *Current Science*, 112(4), 767-784. <https://doi.org/10.18520/cs/v112/i04/767-784>
- Gultepe, I., & Milbrandt, J. A. (2007). Microphysical observations and mesoscale model simulation of warm fog case during FRAM project. *Pure and Applied Geophysics*, 164(6-7), 1161--1178. <https://doi.org/10.1007/s00024-007-0212-9>
- Gultepe, I., Müller, M. D., & Boybeyi, Z. (2006). A new visibility parameterization for warm-fog applications in numerical weather prediction models. *Journal of Applied Meteorology and Climatology*, 45, 1469-1480. <https://doi.org/10.1175/JAM2423.1>
- Gultepe, I., Pearson, G., Milbrandt, J. A., Hansen, B., Platnick, S., Taylor, P., Gordon, M., Oakley, J. P., & Cober, S. G. (2009). The Fog Remote Sensing and Modeling Field Project. *Bulletin of the American Meteorological Society*, 90(3), 341-360. <https://doi.org/10.1175/2008bams2354.1>
- Gultepe, I., Sharman, R., Williams, P. D., Zhou, B., Ellrod, G., Minnis, P., Trier, S., Griffin, S., Yum, S. S., Gharabaghi, B., Feltz, W., Temimi, M., Pu, Z., Storer, L. N., Kneringer, P., Weston, M. J., ya Chuang, H., Thobois, L., Dimri, A. P., Dietz, S. J., Frana, G. B., Almeida, M. V., & Neto, F. L. A. (2019). A Review of High Impact Weather for Aviation Meteorology. In (Vol. 176, pp. 1869--1921).
- Gultepe, I., Tardif, R., Michaelides, S. C., Cermak, J., Bott, A., Bendix, J., Mller, M. D., Pagowski, M., Hansen, B., Ellrod, G., Jacobs, W., Toth, G., & Cober, S. G. (2007). Fog Research: A Review of Past Achievements and Future Perspectives. *Pure Appl. Geophys.*, 164, 1121--1159. <https://doi.org/10.1007/s00024-007-0211-x>
- Haeffelin, M., Dupont, J. C., Boyouk, N., Baumgardner, D., Gomes, L., Roberts, G., & Elias, T. (2013). A Comparative Study of Radiation Fog and Quasi-Fog Formation Processes During the ParisFog Field Experiment 2007. *Pure and Applied Geophysics*, 170(12), 2283--2303. <https://doi.org/10.1007/s00024-013-0672-z>
- Haensler, A., Cermak, J., Hagemann, S., & Jacob, D. (2011). Will the southern african west coast fog be affected by future climate change?: Results of an initial fog projection using a regional climate model. *Erdkunde*, 65(3), 261--275. <https://doi.org/10.3112/erdkunde.2011.03.04>
- Hamdan, N. M., Alawadhi, H., Jisrawi, N., & Shameer, M. (2018). Characterization of fine particulate matter in Sharjah, United Arab Emirates using complementary experimental techniques. *Sustainability (Switzerland)*, 10(4). <https://doi.org/10.3390/su10041088>
- Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology*, 34(3), 623--642. <https://doi.org/10.1002/joc.3711>

- Hersbach, H., Bell, B., Berrisford, P., Hornyi, A., Sabater, J. M., Nicolas, J., Radu, R., Schepers, D., Simmons, A., Soci, C., & Dee, D. (2019). Global reanalysis: goodbye ERA-Interim, hello ERA5. *ECMWF Newsletter*(159), 17--24. <https://doi.org/10.21957/vf291hehd7>
- Hogue, T. S., Bastidas, L., Gupta, H., Sorooshian, S., Mitchell, K., & Emmerich, W. (2005). Evaluation and transferability of the Noah land surface model in semiarid environments. *Journal of Hydrometeorology*, 6(1), 68-84.
- Hogue, T. S., Bastidas, L. A., Gupta, H. V., & Sorooshian, S. (2006). Evaluating model performance and parameter behavior for varying levels of land surface model complexity. *Water resources research*, 42(8).
- Hong, S.-Y., Dudhia, J., & Chen, S.-H. (2004). A Revised Approach to Ice Microphysical Processes for the Bulk Parameterization of Clouds and Precipitation. *Monthly Weather Review*, Vol. 132, issue 1, 103-120.
- Huang, X., Wang, W., & Powers, J. (2008). A description of the advanced research WRF version 3. *NCAR technical note*, NCAR, Boulder Speer M, Wiles P, Pepler A (2009).
- Hulley, G. C., Hook, S. J., Abbott, E., Malakar, N., Islam, T., & Abrams, M. (2015). The ASTER Global Emissivity Dataset (ASTER GED): Mapping Earth's emissivity at 100 meter spatial scale. *Geophysical Research Letters*, 42(19), 7966--7976. <https://doi.org/10.1002/2015GL065564>
- Iacono, M. J., Delamere, J. S., Mlawer, E. J., Shephard, M. W., Clough, S. A., & Collins, W. D. (2008). Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *J. Geophys. Res*, 113.
- Igel, A. L., Igel, M. R., & van den Heever, S. C. (2015). Make it a double? Sobering results from simulations using single-moment microphysics schemes. *Journal of the Atmospheric Sciences*, 72(2), 910--925. <https://doi.org/10.1175/JAS-D-14-0107.1>
- Juliano, T. W., Coggon, M. M., Thompson, G., Rahn, D. A., Seinfeld, J. H., Sorooshian, A., & Lebo, Z. J. (2019). Marine boundary layer clouds associated with coastally trapped disturbances: Observations and model simulations. *Journal of the Atmospheric Sciences*, 76(9), 2963--2993. <https://doi.org/10.1175/JAS-D-18-0317.1>
- Kain, J. S. (2004a). The Kain-Fritsch convective parameterization: an update. *Journal of Applied Meteorology*, 43(1), 170--181.
- Kain, J. S. (2004b). The Kain-Fritsch Convective Parameterization: An Update. *Journal of Applied Meteorology*, 43(1), 170-181. [https://doi.org/10.1175/1520-0450\(2004\)043<0170:tkcpau>2.0.co;2](https://doi.org/10.1175/1520-0450(2004)043<0170:tkcpau>2.0.co;2)
- Kain, J. S., & Fritsch, J. M. (1990). A one-dimensional entraining/detraining plume model and its application in convective parameterization. *Journal of the Atmospheric Sciences*, 47(23), 2784-2802.
- Kaku, K. C., Reid, J. S., Reid, E. A., Ross-Langerman, K., Piketh, S., & Cliff, S. a. (2016). Investigation of the relative fine and coarse mode aerosol loadings and properties in the Southern Arabian Gulf region. *Atmospheric Research*, 169, 171--182. <https://doi.org/10.1016/j.atmosres.2015.09.029>
- Karagulian, F., Temimi, M., Ghebreyesus, D., Weston, M., Kondapalli, N. K., Valappil, V. K., Aldababesh, A., Lyapustin, A., Chaouch, N., & Hammadi, F. A. a. (2019). Analysis of a severe dust storm and its impact on air quality conditions using WRF-Chem modeling , satellite imagery , and ground observations. *Air Quality, Atmosphere l& Health*, 1--18. <https://doi.org/10.1007/s11869-019-00674-z>
- Kashinath, K., Mustafa, M., Albert, A., Wu, J. L., Jiang, C., Esmaeilzadeh, S., Azizzadenesheli, K., Wang, R., Chattopadhyay, A., Singh, A., Manepalli, A., Chirila, D., Yu, R., Walters, R., White, B., Xiao, H., Tchelepi, H. A., Marcus, P., Anandkumar, A., Hassanzadeh, P., & Prabhat. (2021). Physics-informed machine learning: Case studies for weather and climate modelling. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 379(2194). <https://doi.org/10.1098/rsta.2020.0093>

- Klemm, O., Schemenauer, R. S., Lummerich, A., Cereceda, P., Marzol, V., & Corell, D. a. (2012). Fog as a fresh-water resource: Overview and perspectives. *Ambio*, 41(3), 221-234. <https://doi.org/10.1007/s13280-012-0247-8>
- Klopper, D., Formenti, P., Namwoonde, A., Cazaunau, M., Chevaillier, S., Feron, A., Gaimoz, C., Hease, P., Lahmidi, F., Mirande-Bret, C., Triquet, S., Zeng, Z., & Piketh, S. (2020). Chemical composition and source apportionment of atmospheric aerosols on the Namibian coast. *Atmospheric Chemistry and Physics*(May), 1--43. <https://doi.org/10.5194/acp-2020-388>
- Lancaster, J., Lancaster, N., & Seely, M. K. (1984). Climate of the central Namib Desert. *Madoqua*, 1984(1), 5--61. https://doi.org/10.10520/AJA10115498_484
- Lehnert, L. W., Thies, B., Trachte, K., Achilles, S., Osses, P., Baumann, K., Schmidt, J., Samolov, E., Jung, P., Leinweber, P., Karsten, U., Bdel, B., & Bendix, J. (2018). A case study on fog/low stratus occurrence at las lomas, atacama desert (Chile) as a water source for biological soil crusts. *Aerosol and Air Quality Research*, 18(1), 254-269. <https://doi.org/10.4209/aagr.2017.01.0021>
- LeMone, M. A., Tewari, M., Chen, F., Alfieri, J. G., & Niyogi, D. (2008). Evaluation of the Noah land surface model using data from a fair-weather IHOP_2002 day with heterogeneous surface fluxes. *Monthly Weather Review*, 136(12), 4915-4941.
- Liang, X., Wood, E. F., Lettenmaier, D. P., Lohmann, D., Boone, A., Chang, S., Chen, F., Dai, Y., Desborough, C., & Dickinson, R. E. (1998). The Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) phase 2 (c) Red-Arkansas River basin experiment:: 2. Spatial and temporal analysis of energy fluxes. *Global and Planetary Change*, 19(1), 137-159.
- Lindesay, J. A., & Tyson, P. D. (1990). Climate and Near-surface Airflow Over the Central Namib. (7), 27--37.
- Loveland, T. R., Reed, B. C., Ohlen, D. O., Brown, J. F., Zhu, Z., Yang, L., & Merchant, J. W. (2000). Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing*, 21(6-7), 1303--1330. <https://doi.org/10.1080/014311600210191>
- Maalick, Z., Khn, T., Korhonen, H., Kokkola, H., Laaksonen, A., & Romakkaniemi, S. (2016). Effect of aerosol concentration and absorbing aerosol on the radiation fog life cycle. *Atmospheric Environment*, 133, 26--33. <https://doi.org/10.1016/j.atmosenv.2016.03.018>
- Maronga, B., & Bosveld, F. C. (2017). Key parameters for the life cycle of nocturnal radiation fog: a comprehensive large-eddy simulation study. *Quarterly Journal of the Royal Meteorological Society*, 143(707), 2463--2480. <https://doi.org/10.1002/qj.3100>
- Martorell, C., & Ezcurra, E. (2002). Rosette scrub occurrence and fog availability in arid mountains of Mexico. *Journal of Vegetation Science*, 13(5), 651-662. <https://doi.org/10.1111/j.1654-1103.2002.tb02093.x>
- Mazoyer, M., Burnet, F., Denjean, C., Roberts, G. C., Haeffelin, M., Dupont, J. C., & Elias, T. (2019). Experimental study of the aerosol impact on fog microphysics. *Atmospheric Chemistry and Physics*, 19(7), 4323--4344. <https://doi.org/10.5194/acp-19-4323-2019>
- Menut, L., Mailler, S., Dupont, J. C., Haeffelin, M., & Elias, T. (2014). Predictability of the Meteorological Conditions Favourable to Radiative Fog Formation During the 2011 ParisFog Campaign. *Boundary-Layer Meteorology*, 150(2), 277-297. <https://doi.org/10.1007/s10546-013-9875-1>
- Mitchell, K., Ek, M., Wong, V., Lohmann, D., Koren, V., Schaake, J., Duan, Q., Gayno, G., Moore, B., Grunmann, P., Tarpley, D., Ramsay, B., Chen, F., Kim, J., Pan, H.-I., Lin, Y., Marshall, C., Mahrt, L., Meyers, T., & Ruscher, P. (2005). *Noah Land Surface Model (LSM) User's Guide* (NCAR Research Application Laboratory (RAL), Issue.
- Mlawer, E. J., Taubman, S. J., Brown, P. D., Iacono, M. J., & Clough, S. A. (1997). Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for

- the longwave. *Journal of Geophysical Research: Atmospheres*, 102(D14), 16663-16682.
- Mlawer, E. J., Taubman, S. J., Brown, P. D., Iacono, M. J., & Clough, S. A. (1997). Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. *Journal of Geophysical Research: Atmospheres* (1984–2012), 102(D14), 16663--16682.
- Nagel, J. (1962). Fog precipitation measurements on Africa's southwest coast. *Notos*, 11, 51-60.
- Naizghi, M. S., & Ouarda, T. B. M. J. (2017). Teleconnections and analysis of long-term wind speed variability in the UAE. *International Journal of Climatology*, 37(1), 230-248. <https://doi.org/10.1002/joc.4700>
- Nakanishi, M. (2000). Large-eddy simulation of radiation fog. *Boundary-Layer Meteorology*, 94(3), 461-493. <https://doi.org/10.1023/A:1002490423389>
- Nakanishi, M., & Niino, H. (2006). An improved Mellor-Yamada Level-3 model: Its numerical stability and application to a regional prediction of advection fog. *Boundary-Layer Meteorology*, 119(2), 397--407. <https://doi.org/10.1007/s10546-005-9030-8>
- NCEI, N. (2001). *Integrated Global Surface Hourly Dataset* ftp.ncdc.noaa.gov/pub/data/noaa/
- NCEP. (2015). *NCEP GFS 0.25 Degree Global Forecast Grids Historical Archive*. <https://doi.org/10.5065/D65D8PWK>
- Nilo, S. T., Romano, F., Cermak, J., Cimini, D., Ricciardelli, E., & Cersosimo, A. a. (2018). Fog detection based on Meteosat Second Generation-Spinning enhanced visible and infrared imager high resolution visible channel. *Remote Sensing*, 10(4), 1--20. <https://doi.org/10.3390/rs10040541>
- Niu, G. Y., Yang, Z. L., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., Kumar, A., Manning, K., Niyogi, D., Rosero, E., Tewari, M., & Xia, Y. (2011). The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. *Journal of Geophysical Research Atmospheres*, 116(12), 1-19.
- NOAA, & USAAF. (2018). *Federal Climate Complex Data Documentation for Integrated Surface Data (ISD)*.
- Norouzi, H., Temimi, M., Prigent, C., Turk, J., Khanbilvardi, R., Tian, Y., Furuzawa, F. A., & Masunaga, H. (2015). Assessment of the consistency among global microwave land surface emissivity products. *Atmos. Meas. Tech.*, 8(3), 1197-1205. <https://doi.org/10.5194/amt-8-1197-2015>
- Olivier, J. (1995). Spatial distribution of fog in the Namib. *Journal of Arid Environments*, 29(2), 129-138. [https://doi.org/https://doi.org/10.1016/S0140-1963\(05\)80084-9](https://doi.org/https://doi.org/10.1016/S0140-1963(05)80084-9)
- Oolman, L. (2019). *Wyoming Weather Web*. Retrieved July 2019 from <http://weather.uwyo.edu>
- Ouarda, T. B. M. J., & Charron, C. a. (2014). Evolution of the rainfall regime in the united arab emirates. *Journal of Hydrology*, 514, 258--270. <https://doi.org/10.1016/j.jhydrol.2014.04.032>
- Palmer, T., & Stevens, B. (2019). The scientific challenge of understanding and estimating climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 116(49), 34390--34395. <https://doi.org/10.1073/pnas.1906691116>
- Pavolonis, M. J., & Heidinger, A. K. (2005). Advancements in identifying cirrus and multilayered cloud systems from operational satellite imagers at night. *Applications with Weather Satellites II*, 5658, 225. <https://doi.org/10.1117/12.577640>
- Payra, S., & Mohan, M. (2014). Multirule based diagnostic approach for the fog predictions using WRF modelling tool. *Advances in Meteorology*, 2014. <https://doi.org/10.1155/2014/456065>
- Pithani, P., Ghude, S. D., Chennu, V. N., Kulkarni, R. G., Steeneveld, G. J., Sharma, A., Prabhakaran, T., Chate, D. M., Gultepe, I., Jenamani, R. K., & Madhavan, R. (2019). WRF Model Prediction of a Dense Fog Event Occurred During the Winter Fog

- Experiment (WIFEX). *Pure and Applied Geophysics*, 176(4), 1827-1846. <https://doi.org/10.1007/s00024-018-2053-0>
- Pitman, A. J. (2003). The evolution of, and revolution in, land surface schemes designed for climate models. *International Journal of Climatology*, 23(5), 479-510.
- Pitman, A. J., Henderson-Sellers, A., Desborough, C. E., Yang, Z.-L., Abramopoulos, F., Boone, A., Dickinson, R. E., Gedney, N., Koster, R., & Kowalczyk, E. (1999). Key results and implications from phase 1 (c) of the project for intercomparison of land-surface parametrization schemes. *Climate Dynamics*, 15(9), 673-684.
- Poku, C., Ross, A. N., Blyth, A. M., Hill, A. A., & Price, J. D. (2019). How important are aerosol–fog interactions for the successful modelling of nocturnal radiation fog? *Weather*, 74(7), 237–243. <https://doi.org/10.1002/wea.3503>
- Price, J. (2011). Radiation Fog. Part I: Observations of Stability and Drop Size Distributions. *Boundary-Layer Meteorology*, 139(2), 167–191. <https://doi.org/10.1007/s10546-010-9580-2>
- Rasp, S., Dueben, P. D., Scher, S., Weyn, J. A., Mouatadid, S., & Thuerey, N. (2020). WeatherBench: A Benchmark Data Set for Data-Driven Weather Forecasting. *Journal of Advances in Modeling Earth Systems*, 12(11). <https://doi.org/10.1029/2020MS002203>
- Reid, J. S., Piketh, S. J., Walker, A. L., Burger, R. P., Ross, K. E., Westphal, D. L., Brientjes, R. T., Holben, B. N., Hsu, C., Jensen, T. L., Kahn, R. A., Kuciauskas, A. P., Mandoos, A. A., Mangoosh, A. A., Miller, S. D., Porter, J. N., Reid, E. A., & Tsay, S. C. (2008). An overview of UAE2 flight operations: Observations of summertime atmospheric thermodynamic and aerosol profiles of the southern Arabian Gulf. *Journal of Geophysical Research Atmospheres*, 113(14), 1-14. <https://doi.org/10.1029/2007JD009435>
- Reid, J. S., Reid, E. A., Walker, A., Piketh, S., Cliff, S., Mandoos, A. A., Tsay, S. C., & Eck, T. F. (2008). Dynamics of southwest Asian dust particle size characteristics with implications for global dust research. *Journal of Geophysical Research Atmospheres*, 113(14), 1-14. <https://doi.org/10.1029/2007JD009752>
- Román-Cascón, C., Steeneveld, G. J., Yagüe, C., Sastre, M., Arrillaga, J. A., & Maqueda, G. (2016). Forecasting radiation fog at climatologically contrasting sites: evaluation of statistical methods and WRF. *Quarterly Journal of the Royal Meteorological Society*, 142(695), 1048-1063. <https://doi.org/10.1002/qj.2708>
- Román-Cascón, C., Yagüe, C., Steeneveld, G.-J., Sastre, M., Arrillaga, J. A., & Maqueda, G. (2016). Estimating fog-top height through near-surface micrometeorological measurements. *Atmospheric Research*, 170, 76-86. <https://doi.org/10.1016/j.atmosres.2015.11.016>
- Saleeby, S. M., & Cotton, W. R. (2004). A large-droplet mode and prognostic number concentration of cloud droplets in the Colorado State University Regional Atmospheric Modeling System (RAMS). Part I: Module descriptions and supercell test simulations. *Journal of Applied Meteorology*, 43(1), 182--195. [https://doi.org/10.1175/1520-0450\(2004\)043<0182:ALMAPN>2.0.CO;2](https://doi.org/10.1175/1520-0450(2004)043<0182:ALMAPN>2.0.CO;2)
- Sanchez, P. A., Ahamed, S., & Carr. (2009). Digital soil map of the world. *Science*, 325(5941), 680--681. <https://doi.org/10.1126/science.1175084>
- Schmetz, J., Pili, P., Tjemkes, S., Just, D., Kerkmann, J., Rota, S., & Ratier, A. (2002). An introduction to Meteosat Second Generation (MSG). *Bulletin of the American Meteorological Society*, 83(7), 977--992. [https://doi.org/10.1175/1520-0477\(2002\)083<0977:AITMSG>2.3.CO;2](https://doi.org/10.1175/1520-0477(2002)083<0977:AITMSG>2.3.CO;2)
- Schultz, M. G., Betancourt, C., Gong, B., Kleinert, F., Langguth, M., Leufen, L. H., Mozaffari, A., & Stadler, S. (2021). Can deep learning beat numerical weather prediction? *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 379(2194). <https://doi.org/10.1098/rsta.2020.0097>

- Schwitalla, T., Branch, O., & Wulfmeyer, V. (2020). Sensitivity study of the planetary boundary layer and microphysical schemes to the initialization of convection over the Arabian Peninsula. *Quarterly Journal of the Royal Meteorological Society*, 146(727), 846--869. <https://doi.org/10.1002/qj.3711>
- Seely, M., & Henschel, J. R. (1998). The climatology of Namib fog. 19-24.
- Seely, M. K., & Hamilton, W. J. (1976). Fog catchment sand trenches constructed by tenebrionid beetles, *Lepidochora*, from the Namib Desert. *Science*, 193(4252), 484--486. <https://doi.org/10.1126/science.193.4252.484>
- Seinfeld, J. H., & Pandis, S. N. (2016). *Atmospheric chemistry and physics: from air pollution to climate change*. John Wiley & Sons.
- Sertel, E., Robock, A., & Ormeci, C. (2010). Impacts of land cover data quality on regional climate simulations. *International Journal of Climatology*, 30(13), 1942--1953. <https://doi.org/10.1002/joc.2036>
- Sheppard, C., Al-Husiani, M., Al-Jamali, F., Al-Yamani, F., Baldwin, R., Bishop, J., Benzoni, F., Dutrieux, E., Dulvy, N. K., Durvasula, S. R. V., Jones, D. A., Loughland, R., Medio, D., Nithyanandan, M., Pilling, G. M., Polikarpov, I., Price, A. R. G., Purkis, S., Riegl, B., Saburova, M., Namin, K. S., Taylor, O., Wilson, S., & Zainal, K. (2010). The Gulf: A young sea in decline. *Marine Pollution Bulletin*, 60(1), 13--38. <https://doi.org/10.1016/j.marpolbul.2009.10.017>
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., Huang, X.-Y., Wang, W., & Powers, J. G. (2008a). *A Description of the Advanced Research WRF Version 3*.
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., Huang, X.-Y., Wang, W., & Powers, J. G. (2008b). *A Description of the Advanced Research WRF Version 3*.
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Zhiquan, L., Berner, J., Wang, W., Powers, J. G., Duda, M. G., Barker, D. M., & Huang, X.-Y. (2019). A Description of the Advanced Research WRF Model Version 4. *NCAR Technical Note NCAR/TN-475+STR*, 145. <https://doi.org/10.5065/1dfh-6p97>
- Smirnova, T. G., Benjamin, S. G., & Brown, J. M. (2000). Case study verification of RUCS/MAPS fog and visibility forecasts. 9th Conf. on Aviation, Range, and Aerospace Meteorology (AMS),
- Smith, T. L., Benjamin, S. G., & Brown, J. M. (2002). Visibility forecasts from the RUC20. 10th Conf. on Aviation, Range, and Aerospace Meteorology, Portland.
- Spirig, R., Vogt, R., Larsen, J. A., Feigenwinter, C., Wicki, A., Franceschi, J., Parlow, E., Adler, B., Kalthoff, N., Cermak, J., Andersen, H., Fuchs, J., Bott, A., Hacker, M., Wagner, N., Maggs-Killing, G., Wassenaar, T., & Seely, M. (2019). Probing the fog life cycles in the Namib desert. *Bulletin of the American Meteorological Society*, 100(12), 2491--2507. <https://doi.org/10.1175/BAMS-D-18-0142.1>
- Steenneveld, G. J., & de Bode, M. (2018). Unravelling the relative roles of physical processes in modelling the life cycle of a warm radiation fog. *Quarterly Journal of the Royal Meteorological Society*, 144(714), 1539-1554. <https://doi.org/10.1002/qj.3300>
- Steenneveld, G. J., Hartogensis, O. K., Moene, a. F., Baltink, H. K., & Holtslag, a. a. M. (2008). WRF Visitors Program Report Evaluation of WRF model improvements with novel boundary - layer observations - Focus on diurnal cycle and stable boundary layer. *WRF Visitors Program Report*, 1-17.
- Steenneveld, G. J., Ronda, R. J., & Holtslag, A. A. M. (2014). The Challenge of Forecasting the Onset and Development of Radiation Fog Using Mesoscale Atmospheric Models. *Boundary-Layer Meteorology*, 154(2), 265-289. <https://doi.org/10.1007/s10546-014-9973-8>
- Steinhoff, D. F., Brientjes, R., Hackera, J., Keller, T., Williams, C., & Jensen, T. a. (2018). Influences of the monsoon trough and Arabian heat low on summer rainfall over the

- United Arab Emirates. *Monthly Weather Review*, 146(5), 1383--1403. <https://doi.org/10.1175/MWR-D-17-0296.1>
- Sterk, H. A. M., Steeneveld, G. J., Vihma, T., Anderson, P. S., Bosveld, F. C., & Holtslag, A. A. M. (2015). Clear-sky stable boundary layers with low winds over snow-covered surfaces. Part 1: WRF model evaluation. *Quarterly Journal of the Royal Meteorological Society*, 141(691), 2165-2184. <https://doi.org/10.1002/qj.2513>
- Stoelinga, M. T., Warner, T. T., Stoelinga, M. T., & Warner, T. T. (1999). Nonhydrostatic, Mesobeta-Scale Model Simulations of Cloud Ceiling and Visibility for an East Coast Winter Precipitation Event. *Journal of Applied Meteorology*, 38(4), 385--404. [https://doi.org/10.1175/1520-0450\(1999\)038<0385:NMSMSO>2.0.CO;2](https://doi.org/10.1175/1520-0450(1999)038<0385:NMSMSO>2.0.CO;2)
- Stolaki, S., Haeffelin, M., Lac, C., Dupont, J. C., Elias, T., & Masson, V. (2015). Influence of aerosols on the life cycle of a radiation fog event. A numerical and observational study. *Atmospheric Research*, 151, 146--161. <https://doi.org/10.1016/j.atmosres.2014.04.013>
- Stolaki, S. N., Kazadzis, S. A., Foris, D. V., & Karacostas, T. S. (2009). Fog characteristics at the airport of Thessaloniki, Greece. *Natural Hazards and Earth System Science*, 9(5), 1541--1549. <https://doi.org/10.5194/nhess-9-1541-2009>
- Sukoriansky, S., Galperin, B., & Perov, V. (2005). Application of a New Spectral Theory of Stably Stratified Turbulence to the Atmospheric Boundary Layer over Sea Ice. *Boundary-Layer Meteorology*, Vol.117, issue 2, 231-257.
- Tardif, R. (2007). The impact of vertical resolution in the explicit numerical forecasting of radiation fog: A case study. *Pure and Applied Geophysics*, 164(6-7), 1221--1240. <https://doi.org/10.1007/s00024-007-0216-5>
- Tardif, R., & Rasmussen, R. M. (2007). Event-based climatology and typology of fog in the New York City region. *Journal of Applied Meteorology and Climatology*, 46(8), 1141-1168. <https://doi.org/10.1175/JAM2516.1>
- Teixeira, J., & Miranda, P. M. A. (2001). Fog prediction at Lisbon airport using a one-dimensional boundary layer model. *Meteorological Applications*, 8(4), 497-505. <https://doi.org/10.1017/S135048270100411X>
- Temimi, M., Fonseca, R. M., Nelli, N. R., Valappil, V. K., Weston, M. J., Thota, M. S., Wehbe, Y., & Yousef, L. (2020). On the analysis of ground-based microwave radiometer data during fog conditions. *Atmospheric Research*, 231, 104652. <https://doi.org/10.1016/j.atmosres.2019.104652>
- Terpstra, J. (1999). *De invloed van de grondwaterstand, wind, temperatuur en dauwpunt op de vorming van stralingsmist: een kwantitatieve benadering*.
- Tewari, M., Chen, F., Wang, W., Dudhia, J., LeMone, M. A., Mitchell, K., Ek, M., Gayno, G., Wegiel, J., & Cuenca, R. H. (2004). Implementation and verification of the unified NOAA land surface model in the WRF model. 20th conference on weather analysis and forecasting/16th conference on numerical weather prediction,
- Thompson, G., & Eidhammer, T. (2014). A Study of Aerosol Impacts on Clouds and Precipitation Development in a Large Winter Cyclone. *Journal of the Atmospheric Sciences*, 71(10), 3636--3658. <https://doi.org/10.1175/JAS-D-13-0305.1>
- Thompson, G., Field, P. R., Rasmussen, R. M., & Hall, W. D. (2008). Explicit Forecasts of Winter Precipitation Using an Improved Bulk Microphysics Scheme. Part II: Description and Sensitivity Analysis. *Monthly Weather Review*, 132(2), 519--542. [https://doi.org/10.1175/1520-0493\(2004\)132<0519:EFOWPU>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<0519:EFOWPU>2.0.CO;2)
- Thompson, G., Rasmussen, R. M., & Manning, K. (2004). Explicit Forecasts of Winter Precipitation Using an Improved Bulk Microphysics Scheme . Part I : Description and Sensitivity Analysis. *Monthly Weather Review*, 132, 519--542.
- Thota, M. S., Temimi, M., Ajayamohan, R. S., N, N. R., Fonseca, R., Weston, M., & Valappil, V. (2020). On the investigation of the typology of fog events in an arid environment and the link with climate patterns. *Monthly Weather Review*. <https://doi.org/10.1175/mwr-d-20-0073.1>

- Timbal, B., & Henderson-Sellers, A. (1998). Intercomparisons of land-surface parameterizations coupled to a limited area forecast model. *Global and Planetary Change*, 19(1), 247-260.
- Turner, J., Allam, R. J., & Maine, D. R. (1986). A case-study of the detection of fog at night using channels 3 and 4 on the Advanced Very High-Resolution Radiometer (AVHRR). *Meteorological Magazine*, 115(1370), 285--290.
- UK Met Office. (2019). UK Atmospheric Hi-Res Model. https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/data/ukv_model_data_sheet_2019.pdf
- van Schalkwyk, L., & Dyson, L. L. (2013). Climatological characteristics of fog at cape town international airport. *Weather and Forecasting*, 28(3), 631-646. <https://doi.org/10.1175/WAF-D-12-00028.1>
- Vinod Kumar, K., Seemanth, M., Vethamony, P., & Aboobacker, V. M. (2014). On the spatial structure and time evolution of shamal winds over the Arabian Sea - a case study through numerical modelling. *International Journal of Climatology*, 34(6), 2122-2128. <https://doi.org/10.1002/joc.3819>
- Wang, W., Bruyère, C., Duda, M., Dudhia, J., Gill, D., Lin, H. C., Michalakes, J., Rizvi, S., & Zhang, X. (2009). *Advanced Research WRF (ARW) Version 3 Modeling Users Guide, Mesoscale & Microscale Meteorology Division* (National Center for Atmospheric Research (NCAR), USA. http://www.mmm.ucar.edu/arw/users/docs/arw_v3.pdf, Issue.
- Wedi, N. P., Polichtchouk, I., Dueben, P., Anantharaj, V. G., Bauer, P., Boussetta, S., Browne, P., Deconinck, W., Gaudin, W., Hadade, I., Hatfield, S., Iffrig, O., Lopez, P., Maciel, P., Mueller, A., Saarinen, S., Sandu, I., Quintino, T., & Vitart, F. (2020). A Baseline for Global Weather and Climate Simulations at 1 km Resolution. *Journal of Advances in Modeling Earth Systems*, 12(11), 1--17. <https://doi.org/10.1029/2020MS002192>
- Wehbe, Y., Ghebreyesus, D., Temimi, M., & Milewski, A. a. (2017). Assessment of the consistency among global precipitation products over the United Arab Emirates. *Journal of Hydrology: Regional Studies*, 12(May), 122--135. <https://doi.org/10.1016/j.ejrh.2017.05.002>
- Wehbe, Y., Temimi, M., Ghebreyesus, D. T., Milewski, A., Norouzi, H., & Ibrahim, E. (2018). Consistency of precipitation products over the Arabian Peninsula and interactions with soil moisture and water storage. *Hydrological Sciences Journal*, 63(3), 408--425. <https://doi.org/10.1080/02626667.2018.1431647>
- Wei, H., Xia, Y., Mitchell, K. E., & Ek, M. B. (2013). Improvement of the Noah land surface model for warm season processes: Evaluation of water and energy flux simulation. *Hydrological Processes*, 27(2), 297-303.
- Westcott, N. E., & Kristovich, D. A. R. (2009). A climatology and case study of continental cold season dense fog associated with low clouds. *Journal of Applied Meteorology and Climatology*, 48(11), 2201--2214. <https://doi.org/10.1175/2009JAMC1999.1>
- Weston, M., Chaouch, N., Valappil, V., Temimi, M., Ek, M., & Zheng, W. (2018). Assessment of the Sensitivity to the Thermal Roughness Length in Noah and Noah-MP Land Surface Model Using WRF in an Arid Region. *Pure and Applied Geophysics*. <https://doi.org/10.1007/s00024-018-1901-2>
- Weston, M., Temimi, M., Burger, R., & Piketh, S. (2021). A Fog Climatology at Abu Dhabi International Airport. *Journal of Applied Meteorology and Climatology*(Early online release). <https://doi.org/10.1175/JAMC-D-20-0168.1>
- Weston, M., Temimi, M., Morais, R., Reddy, N., Francis, D., & Piketh, S. (2021). A rule-based method for diagnosing radiation fog in an arid region from NWP forecasts. *Journal of Hydrology*, 597, 126189. <https://doi.org/10.1016/j.jhydrol.2021.126189>
- Weston, M. J., & Temimi, M. (2020). Application of a night time fog detection method using SEVIRI over an arid environment. *Remote Sensing*, 12(14). <https://doi.org/10.3390/rs12142281>

- Weston, M. J., Temimi, M., Nelli, N. R., & Fonseca, R. M. (2020). On the Analysis of the Low-Level Double Temperature Inversion Over the United Arab Emirates : A Case Study During April 2019. *Ieee Geoscience and Remote Sensing Letters*. <https://doi.org/10.1109/LGRS.2020.2972597>
- Wilkinson, J. M., Porson, A. N. F., Bornemann, F. J., Weeks, M., Field, P. R., & Lock, A. P. (2013). Improved microphysical parametrization of drizzle and fog for operational forecasting using the Met Office Unified Model. *Quarterly Journal of the Royal Meteorological Society*, 139(671), 488--500. <https://doi.org/10.1002/qj.1975>
- Wood, E. F., Lettenmaier, D. P., Liang, X., Lohmann, D., Boone, A., Chang, S., Chen, F., Dai, Y., Dickinson, R. E., & Duan, Q. (1998a). The Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) Phase 2 (c) RedâArkansas River basin experiment:: 1. Experiment description and summary intercomparisons. *Global and Planetary Change*, 19(1), 115-135.
- Wood, E. F., Lettenmaier, D. P., Liang, X., Lohmann, D., Boone, A., Chang, S., Chen, F., Dai, Y., Dickinson, R. E., & Duan, Q. (1998b). The Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) Phase 2 (c) RedâArkansas River basin experiment:: 1. Experiment description and summary intercomparisons. *Global and Planetary Change*, 19(1), 115-135.
- World Meteorological Organization. (2008a). Aerodrome reports and forecasts : a users' handbook to the codes., 81.
- World Meteorological Organization. (2008b). Aerodrome reports and forecasts: a users' handbook to the codes.
- WRF Users Page. (2020). *Notes for running WRF with the Aerosol-aware Thompson Scheme (mp_physics = 28)*. Retrieved 2020-08-26 from https://www2.mmm.ucar.edu/wrf/users/physics/mp28_updated.html
- Yan, B., & Weng, F. (2011). Effects of Microwave Desert Surface Emissivity on AMSU-A Data Assimilation. *IEEE Transactions on Geoscience and Remote Sensing*, 49(4), 1263-1276. <https://doi.org/10.1109/TGRS.2010.2091508>
- Yang, D., Ritchie, H., Desjardins, S., Pearson, G., MacAfee, A., & Gultepe, I. (2010). High-Resolution GEM-LAM Application in Marine Fog Prediction: Evaluation and Diagnosis. *Weather and Forecasting*, 25(2), 727--748. <https://doi.org/10.1175/2009WAF2222337.1>
- Yang, K., Koike, T., Ishikawa, H., Kim, J., Li, X., Liu, H., Liu, S., Ma, Y., & Wang, J. (2008). Turbulent flux transfer over bare-soil surfaces: characteristics and parameterization. *Journal of Applied Meteorology and Climatology*, 47(1), 276-290.
- Yousef, L. A., Temimi, M., & Wehbe, Y. a. (2019). Total cloud cover climatology over the United Arab Emirates. *Atmospheric Science Letters*, 20(2), 1--10. <https://doi.org/10.1002/asl.883>
- Zeng, X., & Beljaars, A. (2005). A prognostic scheme of sea surface skin temperature for modeling and data assimilation. *Geophysical Research Letters*, 32(14), 1--4. <https://doi.org/10.1029/2005GL023030>
- Zhang, J., Xue, H., Deng, Z., Ma, N., Zhao, C., & Zhang, Q. (2014). A comparison of the parameterization schemes of fog visibility using the in-situ measurements in the North China Plain. *Atmospheric Environment*, 92, 44--50. <https://doi.org/10.1016/j.atmosenv.2014.03.068>
- Zheng, W., Ek, M., Mitchell, K., Wei, H., Meng, J., Zheng, W., Ek, M., Mitchell, K., Wei, H., & Meng, J. (2017). Improving the Stable Surface Layer in the NCEP Global Forecast System. *Monthly Weather Review*, 145(10), 3969--3987. <https://doi.org/10.1175/MWR-D-16-0438.1>
- Zheng, W., Wei, H., Wang, Z., Zeng, X., Meng, J., Ek, M., Mitchell, K., & Derber, J. (2012). *Journal of Geophysical Research: Atmospheres*, Vol.117, D6.

- Zhou, B., & Du, J. (2010). Fog Prediction from a Multimodel Mesoscale Ensemble Prediction System. *Weather and Forecasting*, 25, 303--322.
<https://doi.org/10.1175/2009WAF2222289.1>
- Zhou, B., Du, J., Gultepe, I., & Dimego, G. (2012). Forecast of low visibility and fog from NCEP: Current status and efforts. *Pure and Applied Geophysics*, 169(5-6), 895--909.
<https://doi.org/10.1007/s00024-011-0327-x>
- Zhou, B., & Ferrier, B. S. (2008). Asymptotic analysis of equilibrium in radiation fog. *Journal of Applied Meteorology and Climatology*, 47(6), 1704--1722.
<https://doi.org/10.1175/2007JAMC1685.1>
- Zilitinkevich, S. S. (1995). *Air Pollution III—Volume I. Air Pollution Theory and Simulation: pollution dispersion aspects of coherent structure of convective flows* (Vol. 6). Computational Mechanics Publ.