IMPROVING OPERATIONAL WIND FORECASTS IN A SMALL UNRESOLVED VALLEY USING ARTIFICIAL NEURAL NETWORK

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INTRODUCTION

- Societal relevance
  - health issues

What influences WRF and ANN forecast quality?

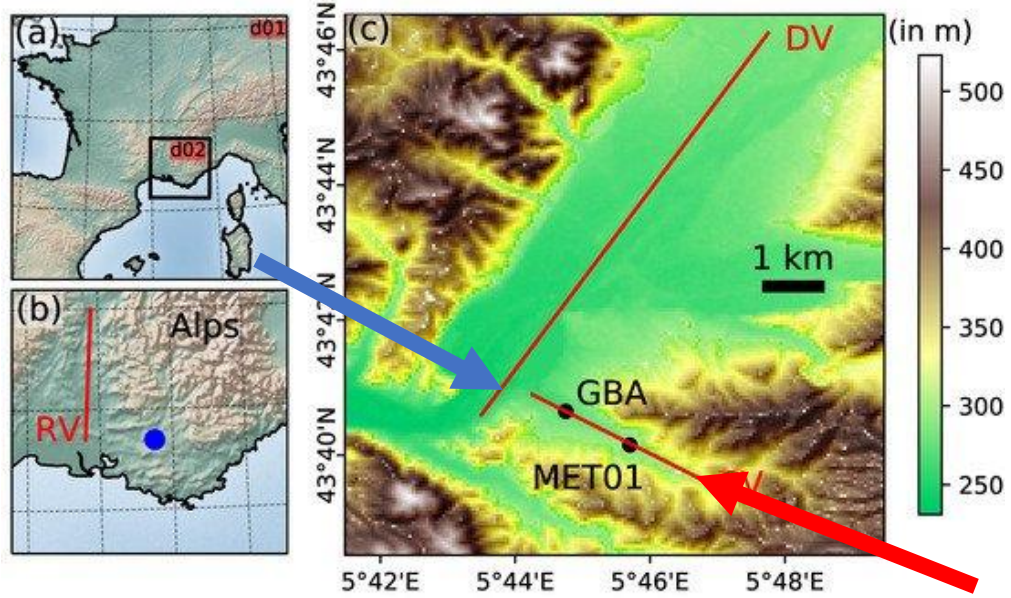
a) Climatological factors
   1. Diurnal variation
   2. Bad WRF forecasts
   3. Atmospheric stability

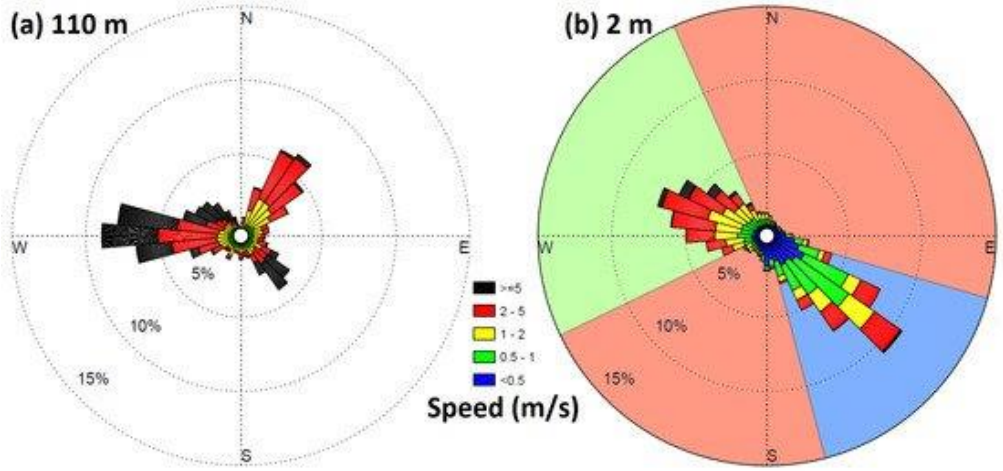
b) Numerical factors
   1. WRF forecast lead time
   2. Domain grid spacing



Image: ITER organisation

CADARACHE VALLEY AND WIND REGIMES



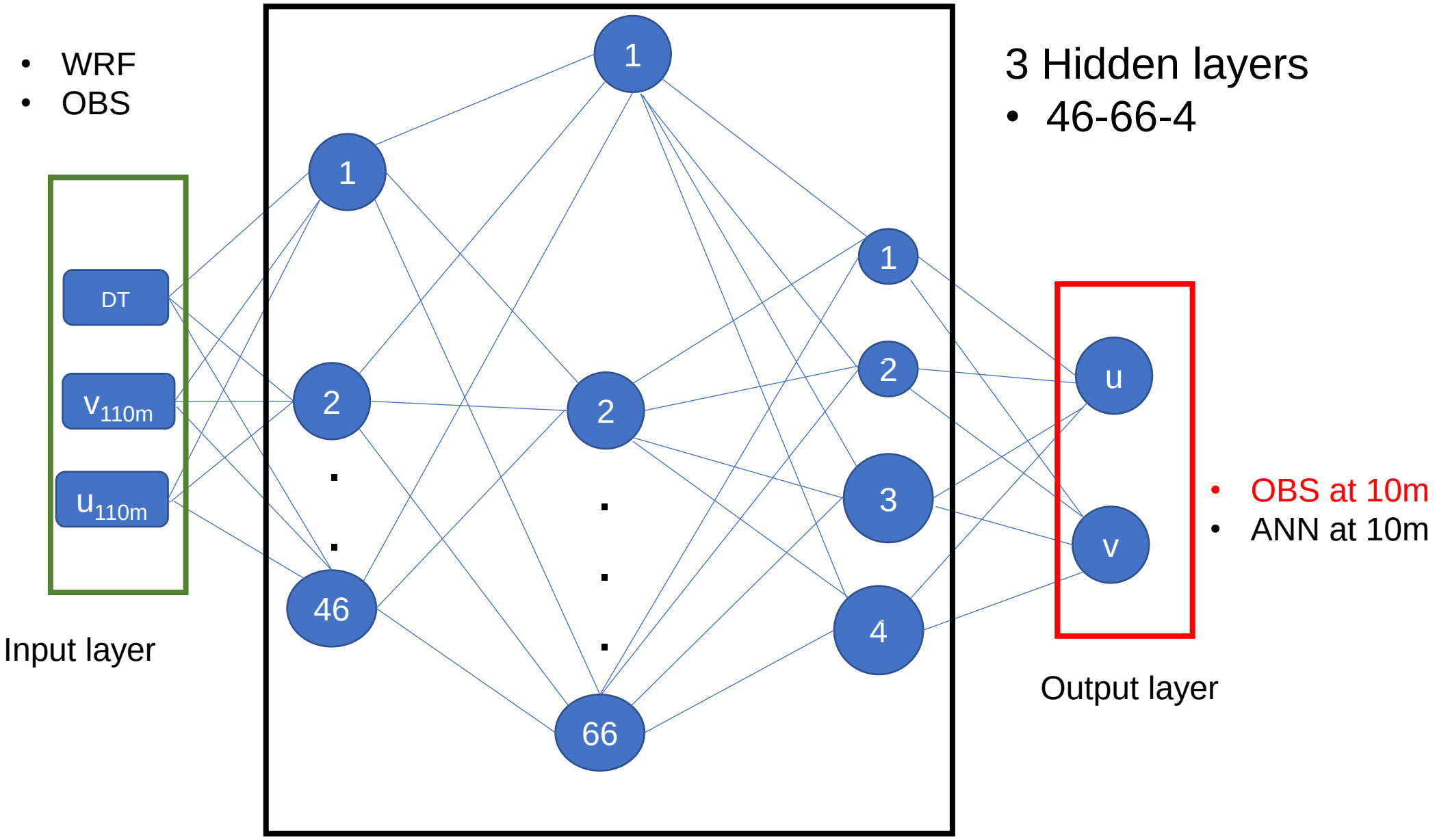


Source: Dupuy et al, 2021

- SITE DESCRIPTION
  - Depth : 100m
  - Width : 1-2km
  - Length: ~ 6km
  - Mean slope: 1.2°
  - Two observation sites within at 110m and 10m
    - ~ approx. 1km apart
- WIND REGIMES
  - Day time
    - North-westerly wind
    - Up-valley (CUV)
  - Night time
    - South-easterly wind (SE)
    - Down-valley (CDV)
    - Usually characterised by stable conditions

METHODS: ARTIFICIAL NEURAL NETWORK STRUCTURE (ANN)

- WRF
- OBS



Input layer

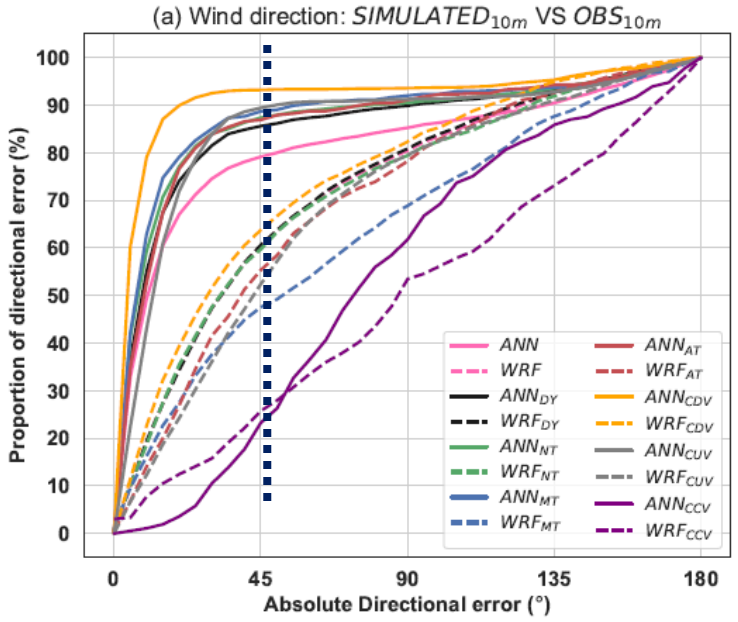
3 Hidden layers

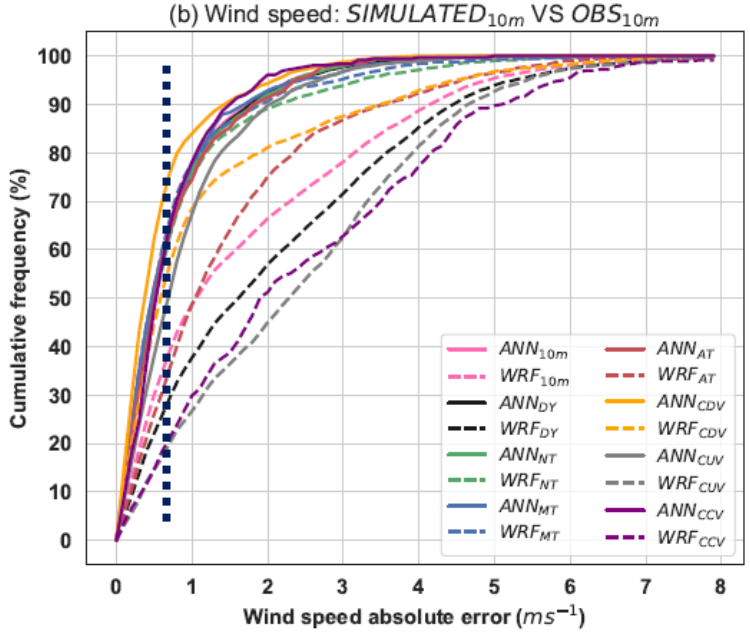
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Output layer

- OBS at 10m
- ANN at 10m

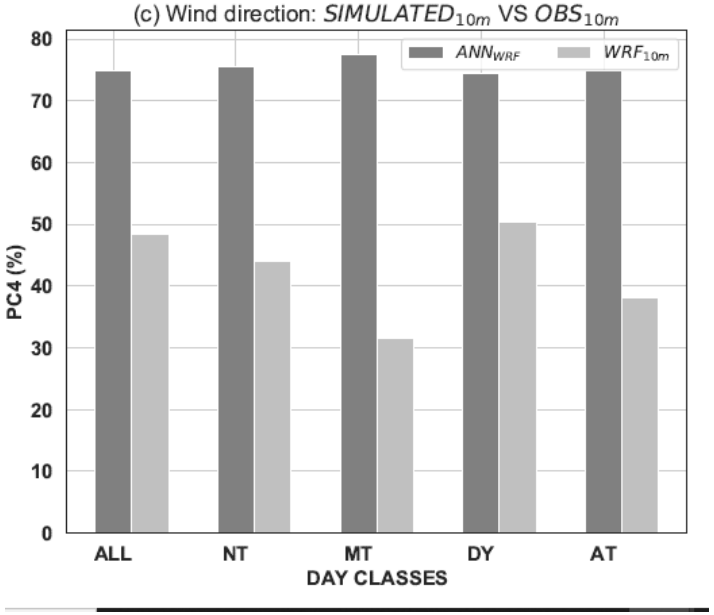
RESULTS: DIURNAL VARIATION



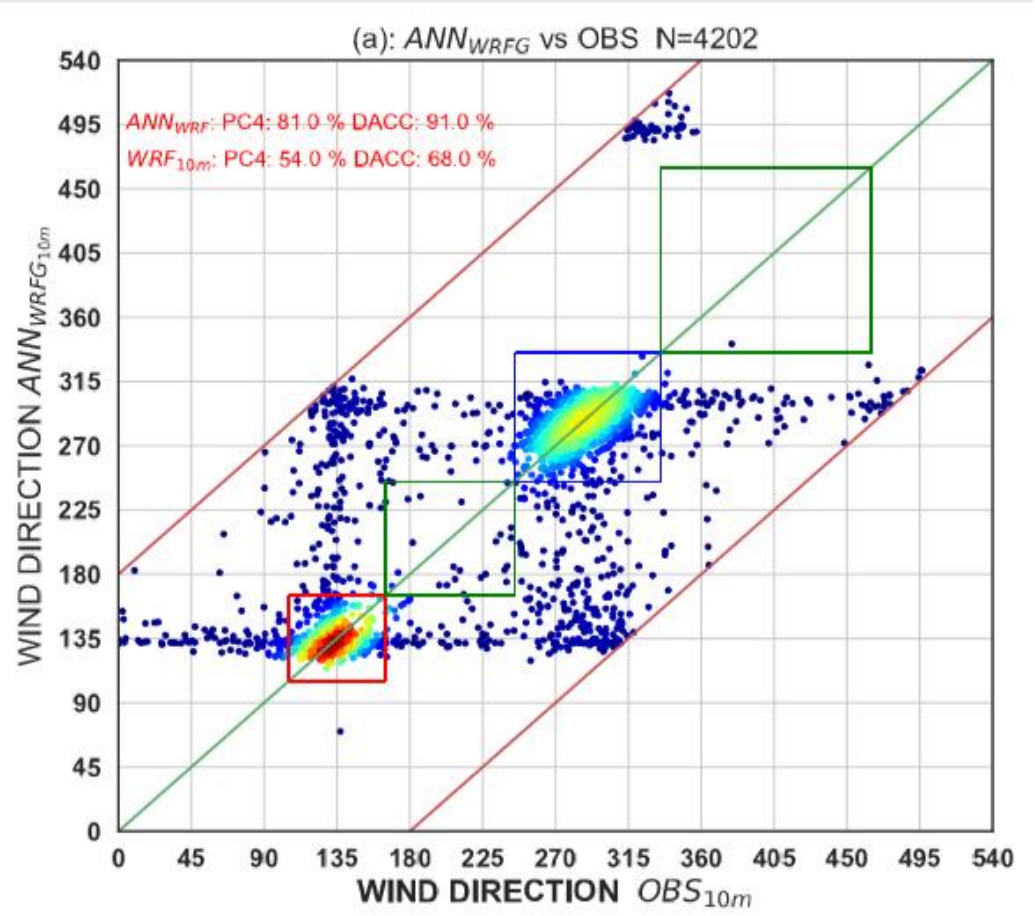


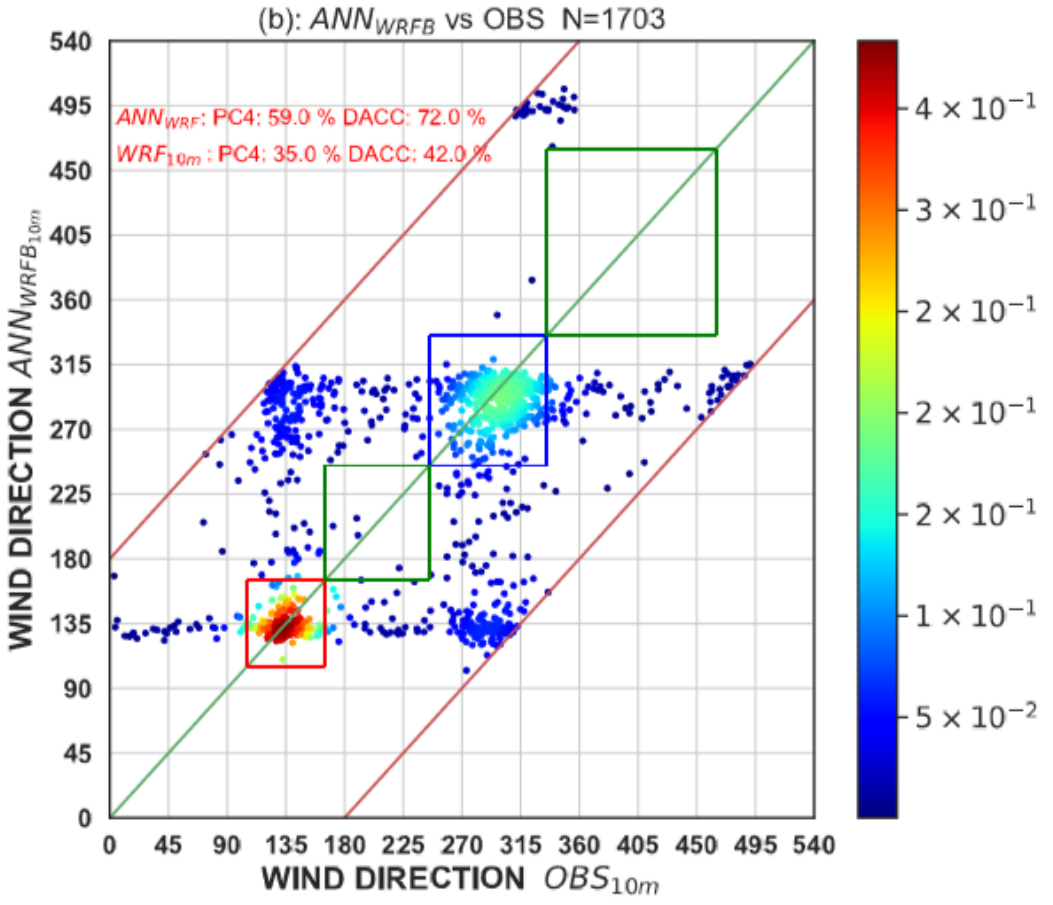
- Equal performance during all phases of boundary layer growth
- Role of CCV
  - Low winds-poor performance
- Wind speed
  - Overestimation by WRF
    - DY
    - AT

		Wind forecast success at MET01 10 m station [%]							
		Phase of the day				Wind direction class			**Overall**
Indicator type	Case	DY	NT	MT	AT	CDV	CUV	CCV	
$DACC_{45}$	WRF20	61	60	48	55	64	52	26	**60**
	$ANN_{WRF19}(2020)$	86	87	89	87	93	89	24	**79**
SP_{08}	WRF20	33	68	72	40	61	23	24	**43**
	$ANN_{WRF19}(2020)$	68	70	68	68	80	57	70	**70**



EFFECT OF BAD WRF FORECAST

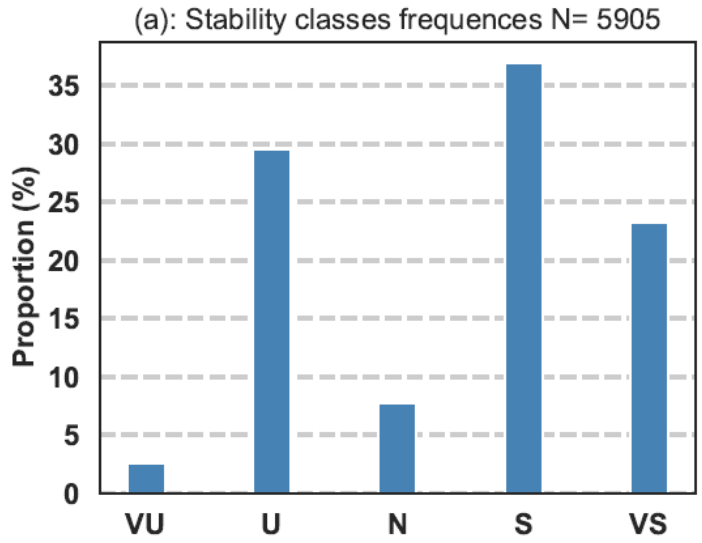


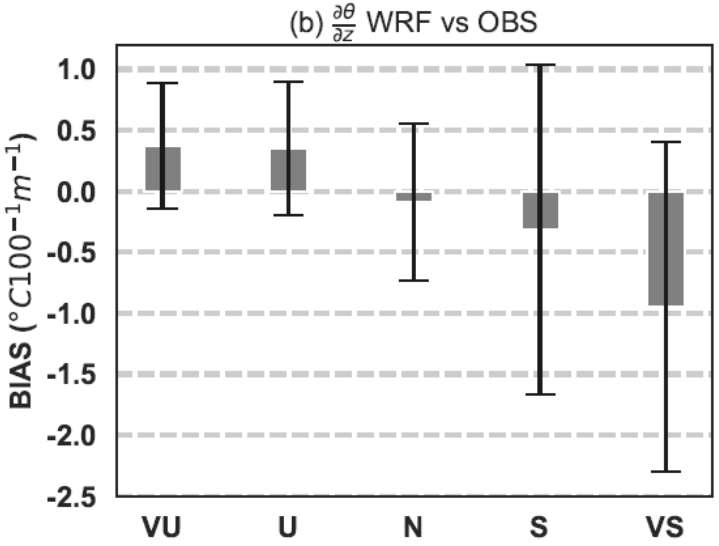


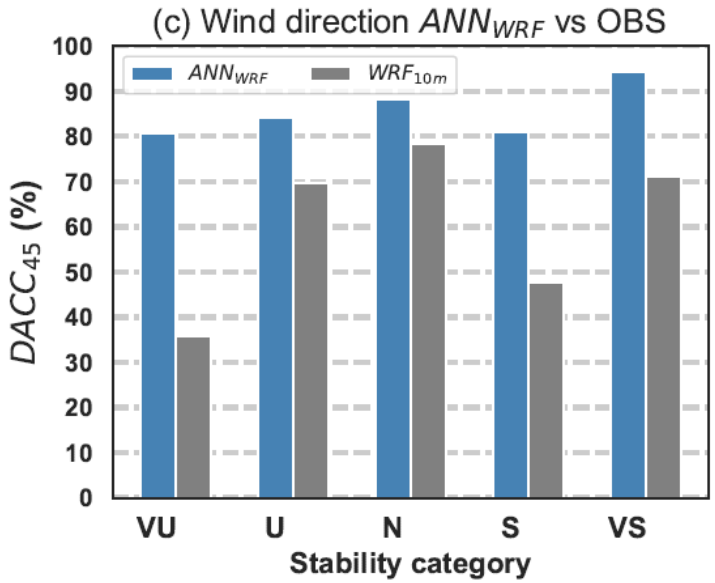
- Good WRF forecasts
  - DACC 23 ↑
  - PC4 27 ↑

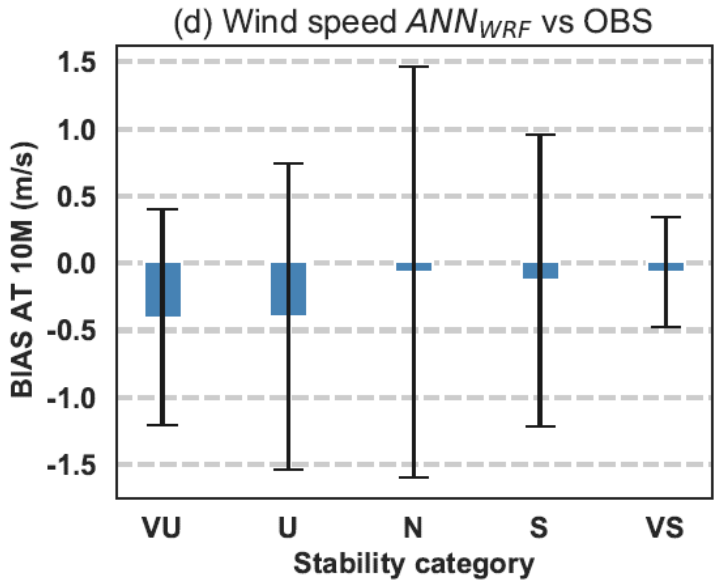
- Bad WRF forecasts
  - DACC 30 ↑
  - PC4 24 ↑

DOES BOUNDARY LAYER STABILITY AFFECT ANN?









- Higher proportion of stable (S) and unstable conditions (U)
- WRF Temperature gradient
  - Strongly underestimated VS conditions
  - Overestimate U and VU conditions
  - Performed better in N conditions
- Wind prediction
  - WRF
    - Better in neutral (N) conditions
    - Poor DACC in VU and S conditions
  - ANN
    - Improved DACC in all classes
      - Highest in VS due to decoupling

EFFECT OF LEAD TIME AND GRID SPACING

	Case name	Year	Domain resolution	Forecast lead time [h]	Directional indicators [%]			Wind Speed indicators		
					$DACC_{45}$	PC2	PC4	Pearson correlation	Bias $[m\,s^{-1}]$	MAE $[m\,s^{-1}]$
	$WRF19_{110m}$	2019	3 km	[24,47]	72	-	-	0.75	0.93	1.96
	$WRF19_{10m}$	2019	3 km	[24,47]	56	72	47	0.76	1.78	1.94
1	**ANN_{WRF19}**	**2019**	**3 km**	**[24,47]**	**79 [78,80]**	**84 [82,85]**	**70 [69,71]**	**0.79 [0.78,0.81]**	**-0.32 [-0.36,-0.28]**	**0.74 [0.72,0.77]**
	(Dupuy et al. 2021)	2015-2016	3 km	[24,47]	68 [66,70]	76 [75,78]	Excluded	0.78 [0.76,0.80]	-0.34 [-0.37,-0.31]	0.62 [0.60,0.65]
2	ANN_{WRF19}**-0.5**	2019	3 km	[24,47]	85 [84,87]	89 [88,90]	78 [77,79]	0.79 [0.78,0.81]	-0.25 [-0.30,-0.20]	0.76 [0.73,0.78]
3	$ANN_{WRF19}(2020)$	**2020**	3 km	[24,47]	79 [78,80]	85 [84,86]	68 [67,69]	0.75 [0.73,0.77]	-0.30 [-0.34,-0.26]	0.72 [0.70,0.74]
4	$ANN_{WRF19}([12,35])$	2020	3 km	**[12,35]**	80 [79,81]	84 [83,85]	68 [67,69]	0.74 [0.72,0.76]	-0.20 [-0.25,-0.16]	0.70 [0.67,0.72]
5	ANN_{WRF19}(1 km)	2020	**1 km**	[24,47]	79 [78,80]	84 [83,85]	68 [67,70]	0.76 [0.74,0.78]	-0.30 [-0.34,-0.26]	0.70 [0.60,0.73]

CONCLUSIONS

- **What influences WRF and ANN forecast quality?**
  - WRF
    - Better $DACC_{45}$ during neutral (N) conditions
    - Poor $DACC_{45}$ during very unstable (VU) and stable (S) conditions
    - Poor performance during transitions
  - ANN
    - Bad WRF forecasts
      - ANN improved $DACC_{45}$ by over 30 %
    - Insignificant influence of both transition and stability classes
    - Low wind substantially affect ANN performance

References

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