Statistical downscaling of WRF mesoscale simulations using an artificial neural network to forecast winds at local, unresolved scale

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I. Introduction

Motivation

Calculate the **atmospheric dispersion** of pollutants emitted in an industrial center (Cadarache), using daily forecasts made with the WRF model at a 3 km horizontal resolution.

Context

- **Complex topography** (situated in a small valley)
  → has effects on the low level transport
- High occurrence of clear skies
  → favors **stable conditions** that decreases vertical mixing
- The KASCADE experiment (Duine, 2015) highlights the importance of such conditions that generate a Cadarache down-valley wind (CDV)

At a 3 km resolution, these effects cannot be simulated, which may invalidate the prediction of atmospheric dispersion in low wind stable conditions.

Issue

How to predict low level winds forced by the small scale topography using mesoscale forecasts at a coarser resolution?

II. Methodology

WRF mesoscale (3km horizontal resolution) forecasts and local observations are available hourly on a 1 year period

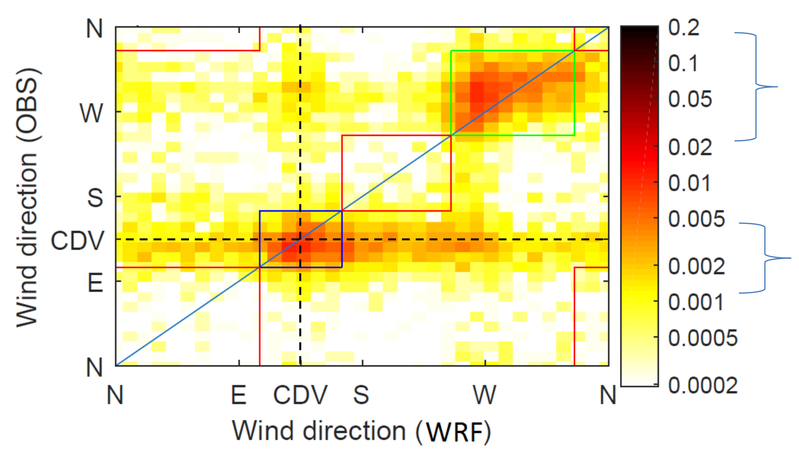

Fig 1: Comparison of the 2m wind observed and forecasted, represented by the probability density function in color, for the direction (a) and the speed (b). The colored frames refer to the wind sectors of figure 2.

Good prediction of N-W synoptically forced winds

Poor prediction of CDV because topographic effects are not accounted for

Only half of the WRF predictions matches the observations:
→ improvement required.

Use of an **Artificial Neural Network** (ANN) to generate a **statistical forecast** of the wind at 2m

The Artificial Neural Network

- is a statistical tool commonly used for atmospheric studies (Gardner and Dorling, 1998), only with observed data up to now
- is particularly suitable for non linear problems
- searches a relation between some input variables (**WRF variables**) and the **wind components observed at 2m**

The method is assessed by using the following indexes, in complement to usual statistical indexes:
- DACC (fraction of forecast that matches observations at +/-45°)
- PC (fraction of forecast directions that fall within the wind sectors as defined in figure 2)

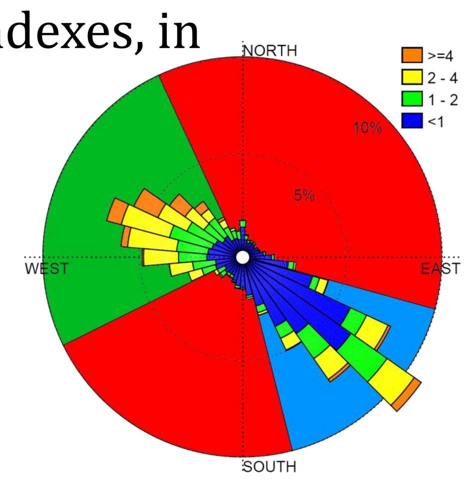

Fig 2: Wind rose for the observations at 2m and separation of the wind into three classes (blue for down-valley winds, green for up-valley and red for others).

Winds lower than 0.50 m/s are not considered for the calculation of performances because of the lack of precision on their direction.

III. Results

Several WRF variables (linked with the stability, the daily cycle, the synoptic forcing and the wind) are used as inputs to the ANN

→ The 4 most suitable variables are:
- the wind components at 10m u_{10} and v_{10}
- a difference of potential temperature $\Delta\theta_{(110m-2m)}$
- the wind speed at 110m U_{110}.

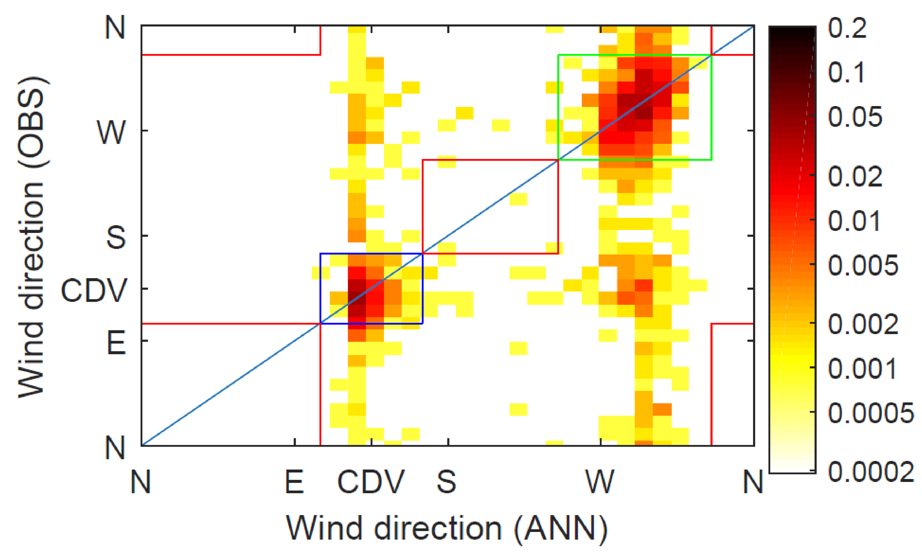

Fig 3: Same as Fig 1 for the comparison of the 2m wind observed and calculated by the ANN.

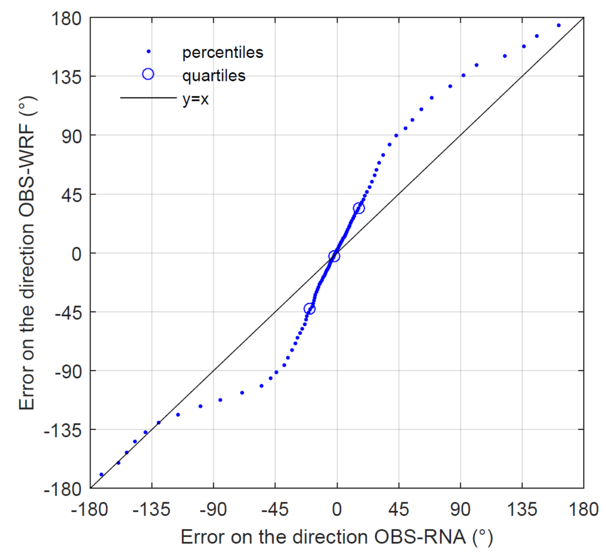

Fig 4: Q-Q plot of the error of forecasting on wind direction. X-axis for the error of WRF and Y-axis for the ANN error.

	DACC	PC	Ru	Rv	Rspeed	Bias	MAE
WRF	0.55	0.50	0.70	0.59	0.72	+1.79 m/s	2.00 m/s
ANN	0.75	0.73	0.80	0.71	0.74	-0.46 m/s	0.81 m/s

IV. Discussion

Relative role of each input variable
- u_{10} and v_{10} are fundamental for the calculation of outputs
- $\Delta\theta_{(110m-2m)}$ improves the calculation of down-valley thermal winds
- The role of U_{110} is not well defined

The performance is dependent on the speed, increasing with the wind speed

	ANN obs
DACC	0.86
PC	0.91
Ru	0.93
Rv	0.86
Rspeed	0.89
Bias	-0.17 m/s
MAE	0.50 m/s

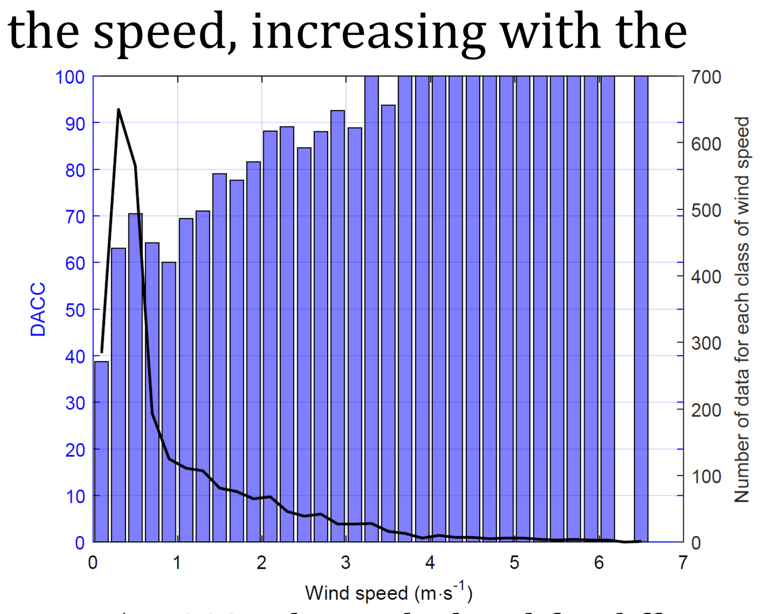

Fig 5: DACC values calculated for different wind speed classes (blue columns). Number of data in each class (black line).

Better predictions of the local valley wind are obtained when using the same input variables with their **observed** values, highlighting the effect of the quality of input variables on the performance of the ANN.

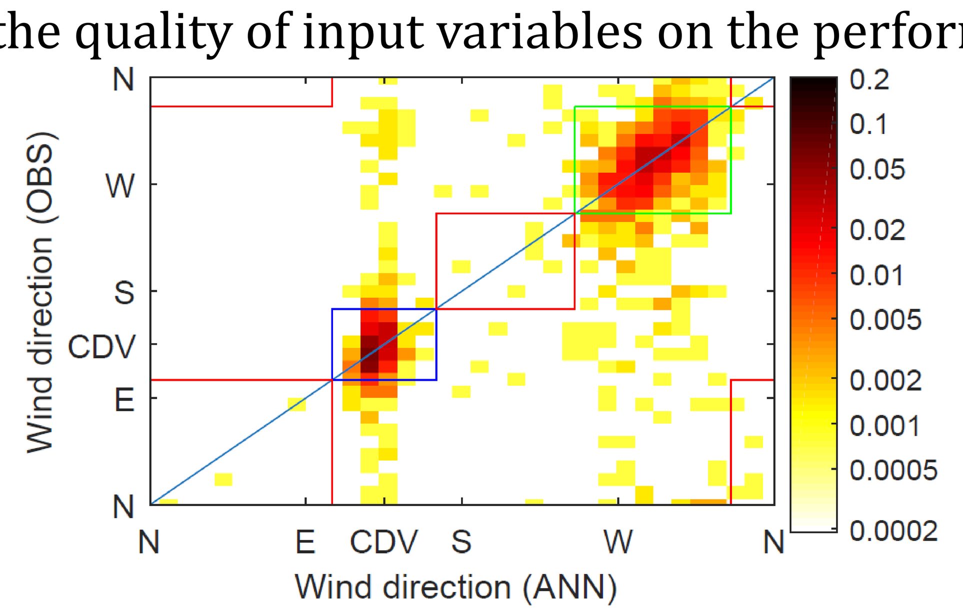

Fig 6: Same as Fig 1 for the comparison of the 2m wind observed and calculated by the ANN using observations as inputs.

V. Conclusion

- The statistical forecast of a valley wind based on using an ANN in conjunction with mesoscale simulations is successful
- The ANN performance remains dependent on the precision of the mesoscale simulations (for the input variables)
- In spite of the large size of the dataset, the ANN failed to reproduce wind directions falling in the red sector (figure 2)
- The ANN needs both wind and stability data to calculate the valley wind because they often have a thermal origin

Duine, G.-J. (2015). *Characterization of down-valley winds in stable stratification from KASCADE field campaign and WRF mesoscale simulations.* Theses, Université Toulouse III Paul Sabatier
Gardner, M. and Dorling, S. (1998). *Artificial neural networks (the multilayer perceptron)-a review of applications in the atmospheric sciences.* Atmospheric environment, 32(14) :2627-2636.