EXPLORING ERROR TYPES AND PERFORMANCE OF AN AIR QUALITY MODEL THROUGH CLUSTERING ANALYSIS

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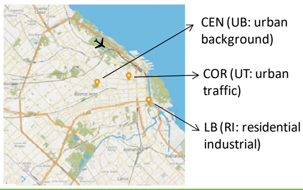
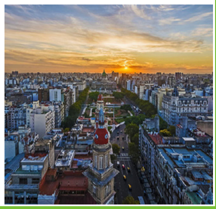
MOTIVATION & OBJECTIVES

Performance evaluation is a key aspect in the development of air quality models. When only a few air quality (AQ) monitoring sites are available, a comprehensive analysis of long-term series may help to better understand model behaviour under different conditions. In a previous work [1], the urban scale atmospheric dispersion model DAUMOD-GRS showed an overall good performance to estimate nitrogen dioxide (NO_2) concentrations using four years of observations from the three AQ monitoring sites of the city of Buenos Aires.

Here, we present a simple approach based on clustering analysis to further explore model results using these long-term series. The objective is to assess whether different model performance levels are associated with specific input data conditions. The method is also used to analyse the impact of a previously proposed model change.

AQ monitoring sites in Buenos Aires city





METHODOLOGY

➢ The DAUMOD-GRS model [2] is applied over the Metropolitan Area of Buenos Aires (3830 km^2) considering:

- Four years (2009-2012) of surface hourly meteorological data from the domestic airport (✈)
- Emissions of nitrogen oxides and volatile organic compounds from the high resolution (1km x 1km) emissions inventory developed by [3].
- Clean air concentration values as regional background levels.

➢ NO_2 hourly concentrations measured at the three AQ monitoring stations: CEN, COR and LB.

➢ At each site, three model performance metrics [4] [fractional bias (FB), normalised mean square error (NMSE) and correlation coefficient (R)] are computed daily:

$$FB = (\overline{C_o} - \overline{C_m})/0.5(\overline{C_o} + \overline{C_m})$$

$$NMSE = \overline{(C_o - C_m)^2}/\overline{C_o}\,\overline{C_m}$$

$$R = \overline{(C_o - \overline{C_o})(C_m - \overline{C_m})}/\sigma_{C_m}\sigma_{C_o}$$

➢ A k-means algorithm [5] is applied to classify days based on their FB, NMSE and R values. The silhouette criterion [6] is used to determine a suitable number of clusters.

➢ Clusters are ordered from "best" to "worst" model performing days, considering increasing values of the sum:

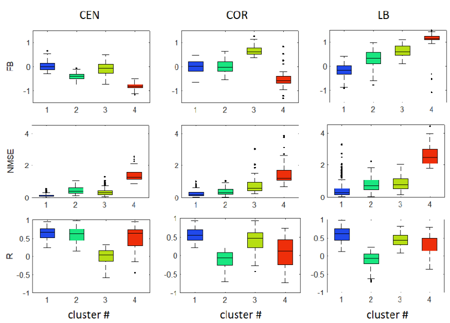
$$S_j = \overline{|FB|} + \overline{NMSE} + (1 - \overline{|R|})$$

where the over bar indicates the average over all members of cluster j.

➢ Once days are classified, the daily mean values of model input variables [wind speed (WS), wind direction (WD), air temperature (T), sky cover (SC), solar radiation (TSR), PGT atmospheric stability class (KST)] are statistically compared applying a Kruskal-Wallis test.

RESULTS

Box plots of three metrics (FB, NMSE, R) by cluster at each AQ monitoring site.

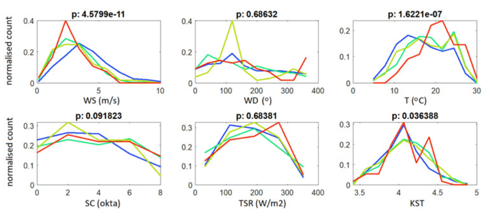


Distribution of days by cluster and site.

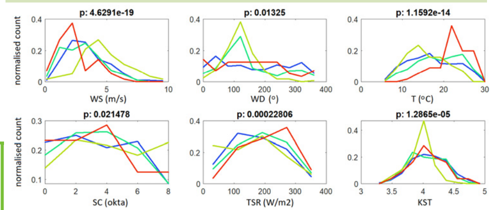
Site	Cluster number				Total days
	1	2	3	4	
CEN	325	231	177	55	788
COR	340	255	115	56	766
LB	364	213	265	80	922

Distributions of daily mean meteorological by cluster, at each AQ site. The largest statistical difference between the cluster distributions is indicated with the p-value.

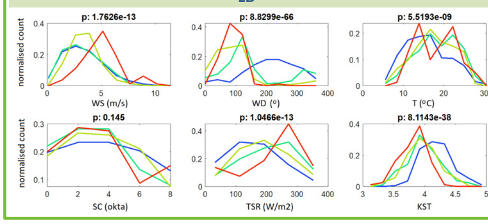
CEN



COR

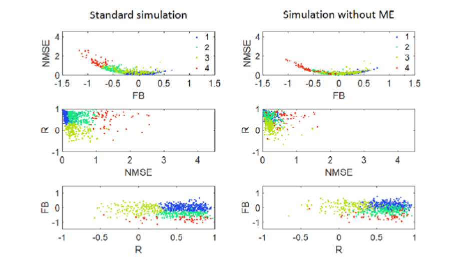


LB

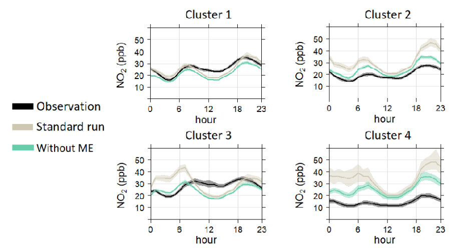


Impact of removing the "memory effect" (ME) at CEN

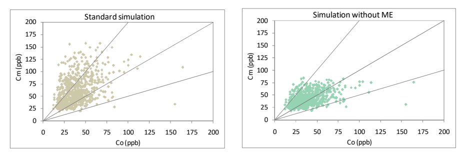
Distributions of cluster members (days) over different metric planes.



Cluster-averaged diurnal profiles of observed and modelled NO_2 concentrations.



Scatter plots of modelled (Cm) and observed (Co) daily maximum NO_2 concentrations.



CONCLUSIONS

- Four clusters are found to better describe model performance differences at the three sites.
- At the UB site, the largest statistical differences between "best" and "worst" performing days are found between the distributions of WS and T daily mean values.
- At the RI site, clusters show clear significant differences in most meteorological variables and suggest a potential role from the emissions coming from the power plants that are located on the coast.
- When removing the ME from the model its performance improves, with the largest impact on the nocturnal and daily peak NO_2 concentration values.
- Overall, a better understanding of the DAUMOD-GRS model performance and how it changes with different conditions is obtained.

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