Space-Time Urban Air Pollution Forecasts

A. Russo (1), A. Soares (2), R.M. Trigo (1)

(1) University of Lisbon, CGUL, IDL, Lisbon, Portugal; (2) Technical University of Lisbon, IST, CERENA, Lisbon, Portugal

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1. Motivation

The established **association between poor air quality** (AQ) and human **health** constitutes an immediate concern for many health experts, responsible entities and common citizens [1,2]. The development of tools that are able to identify and predict harmful air pollution (AP) episodes is vital.

The procedure presented here will allow to **forecast AP episodes**. Afterwards, it will be possible to **provide AQ alerts**, allowing a sustainable management of environmental risks for the public health.

2. Background

AP may be considered a **space-time process**. However, the simultaneous integration of time and space is not an easy task to perform, due to the existence of different uncertainties levels and data characteristics [3].

Spatial-temporal (**ST**) geostatistical models allow the **characterization of uncertainty**, supplying equiprobable images that reproduce patterns of spatial continuity quantified by the observations available. ST and neural network (**NN**) models are able to **identify complex non-linear relations** between inputs and outputs [4,5], incorporating the complex combination of factors that play a significant role in an AQ system (e.g. meteorology, physical obstacles and interaction between pollutants) [3,6,7]. However, physics and chemical behavior of AP aren't unique problems regarding AQ modeling.

Shortcomings of the standard methods:

(1) Only present a **singular solution**, not allowing the characterization of uncertainty [6,7];

(2) Present **coarse resolutions**, which can affect model predictions by introducing artificial dilution [8];

(3) Require a **large amount of accurate input data**, which are difficult to collect and control;

(4) Include **rough parameterizations** that do not describe the processes and interactions that control the transport and behavior of pollutants in the atmosphere [9].

3. Objective

To produce an AQ model which allows forecasting PM10 episodes based on the combined use of neural network (NN) models and stochastic simulations (SS).

4. AQ Forecasts

NN

PREDICTORS

The **best predictors** (*Daily, hourly and maximum PM10 concentrations from the previous day; previous day NO2 and CO concentrations; wind direction, humidity, maximum temperature and boundary layer height*) where **chosen independently** for each monitoring station through a backward stepwise regression (**BSR**). The application of the BSR has reduced the complexity by retaining substantially less variables.

FORECASTS

After the pre-processing of the data, **NN models** were applied to **produce short-term PM10 forecasts**. Validation results showed that, for an independent sample, a high correlation (>80%) between the predicted and observed values is reached. NN time-series forecasts act as a local conditioner to a fine grid SS model.

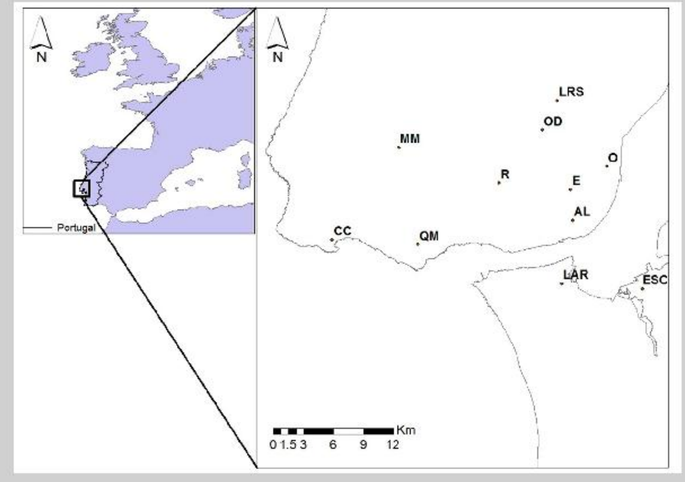

Figure 1 – Case study area. Location of the monitoring stations where PM10 was measured

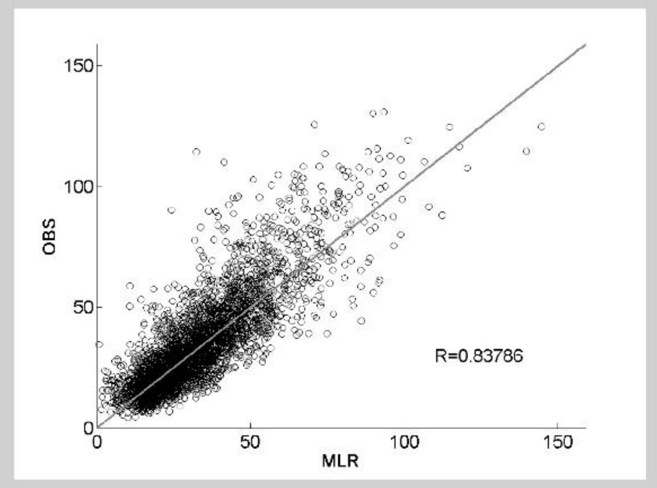

Figure 2 – Validation results for the 11 monitoring stations

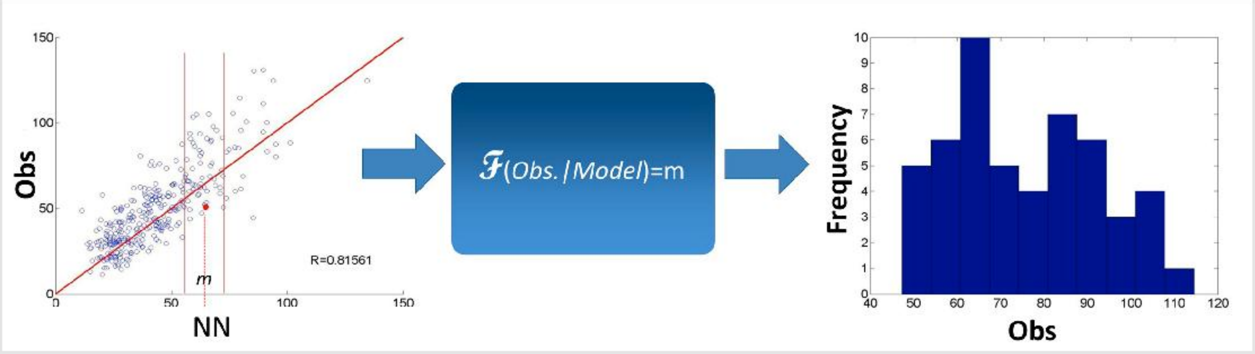

Figure 3 – Local bivariate distributions (LBD) between predicted and observed values . LBD estimated based on independent historical data that was not used on the construction of the NN model for each monitoring station

SS

After PM10 NN forecasts have been completed for each monitoring station, **local conditional distributions of observed PM10 vs. NN forecasts** (Figure 3) are used to perform the spatial simulations for the entire area, and consequently **evaluate the spatial uncertainty** of NN results (Figure 4). Spatial simulation is performed through direct sequential simulations (**DSS**) **with local distributions** [7,10].

Based on this approach one succeed to produce ***spatial-temporal PM10 forecasts***, accounting for temporal and spatial uncertainties (NN's efficiency at each local monitoring station is incorporated through LBD and also spatial uncertainty revealed by the spatial variograms).

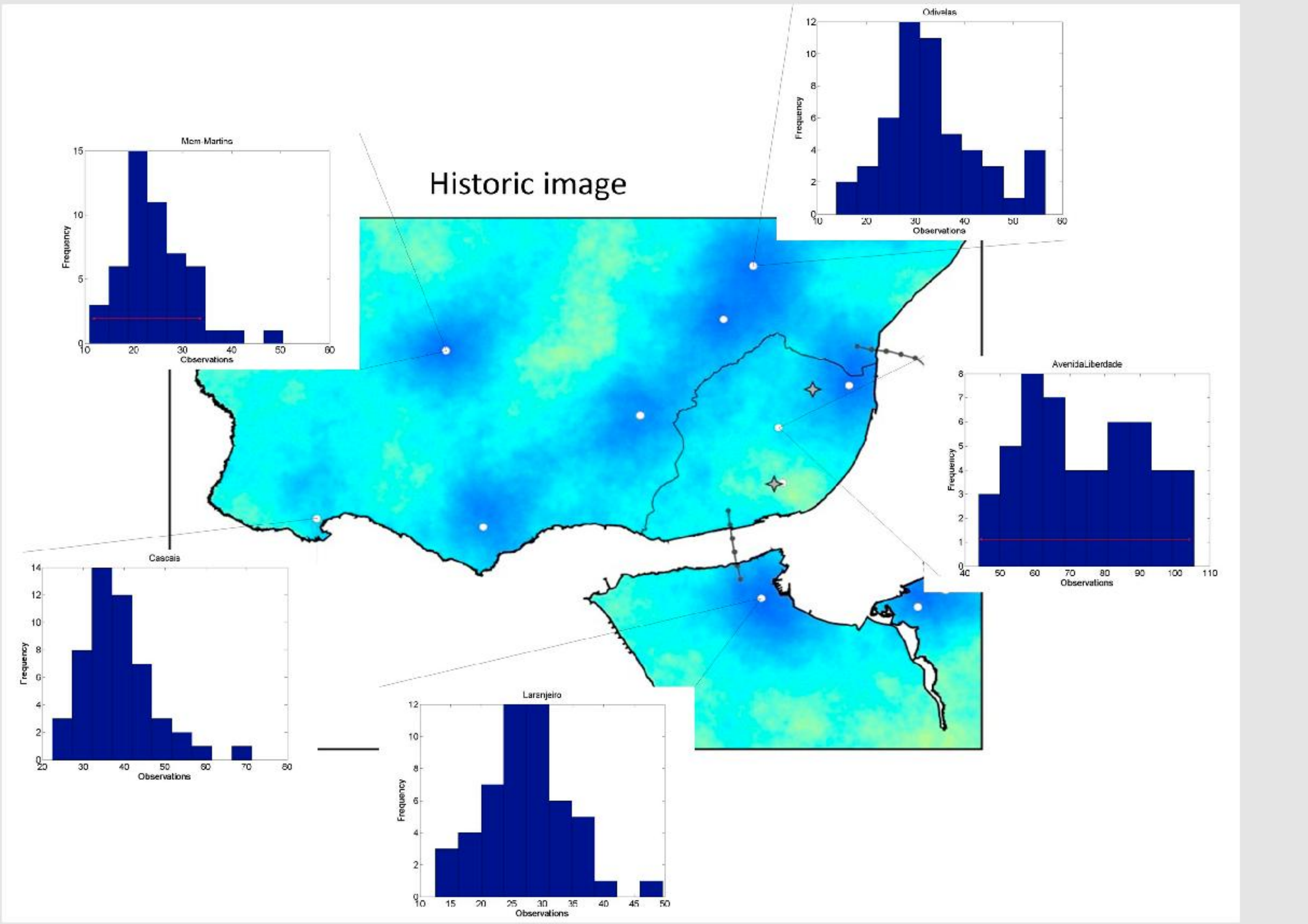

Figure 4 – Estimation of conditional distribution functions for each monitoring station. NN's efficiency is reflected on each histogram.

5. Results

DSS with local distributions (**DSS-NN**) was applied for each day through the DSS algorithm [7]. 50 **equiprobable images** were generated with a spacing of **100x100 meters**, using as trend an image the observed average of the previous day. Later, the 50 images were reduced to an **average image** (Figure 5). These models integrate simultaneously space and time, producing **daily forecasts**. Based on the produced maps, the identification of AP episodes can be done and AP alerts can be issued.

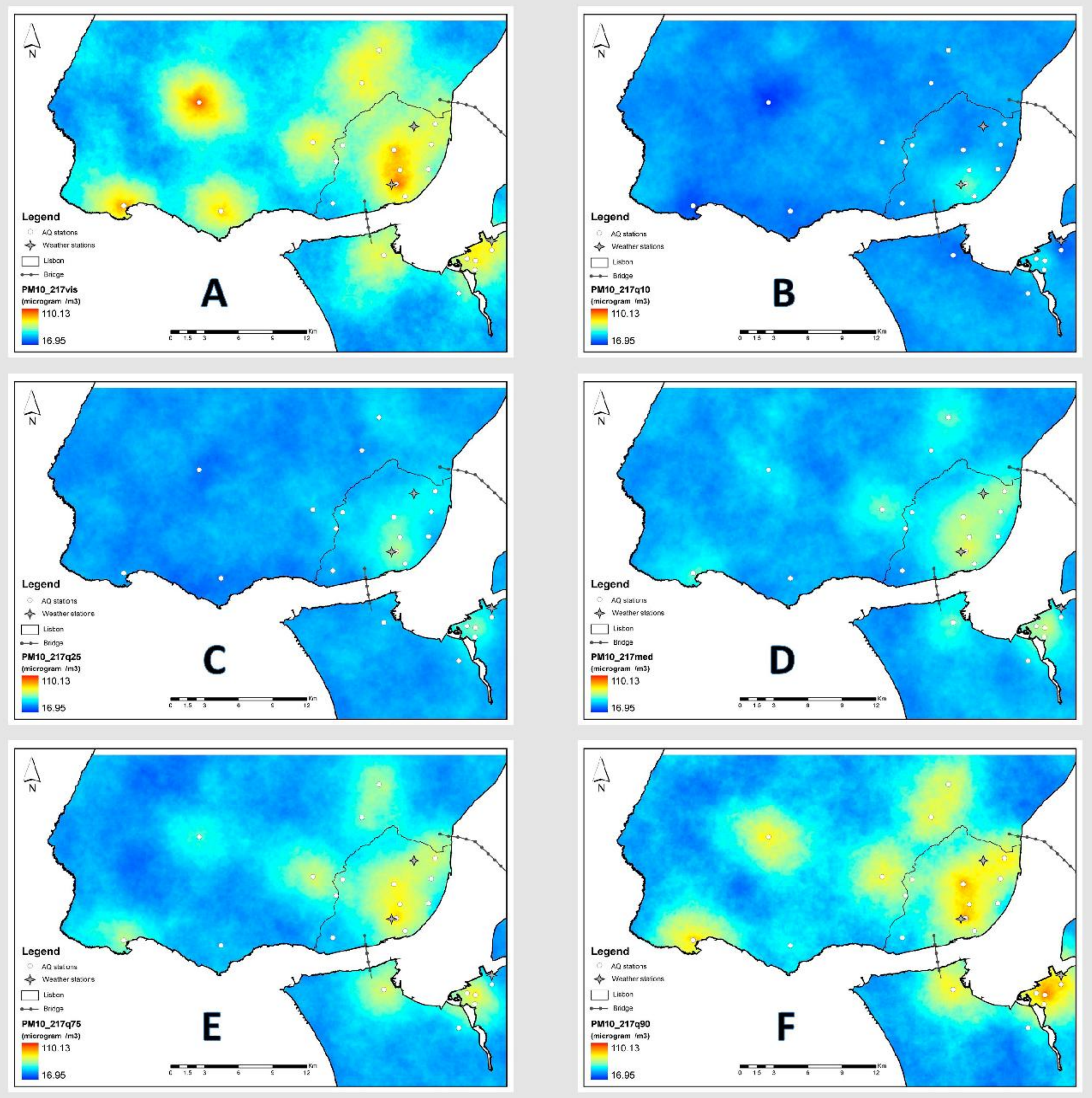

Figure 5: Results for PM10 (7/8/2006): (A) Observed (B) DSS-NN for 10th percentile (C) DSS-NN for 25th percentile (D) DSS-NN for the average (E) DSS-NN for 75th percentile (F) DSS-NN for 90th percentile

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