H14-272

A NEW PROPOSAL FOR DETECTING THE IMPACT OF A SMOKESTACK WITH THE HELP OF A DISPERSION MODEL

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Abstract: A method is described and discussed in order to take into account a dispersion model output in the interpretation of data collected in a monitoring campaign, which aims to evaluate the impact of a punctual emission source. The method is applied to some dummy datasets in order to evaluate its theoretical capability to recognize the impact of the target source.

Key words: *measure interpreting, monitoring.*

INTRODUCTION

The correct interpretation of a punctual emission impact over the air quality is a well known challenging task, especially if the background is not neglectable. In fact it is often found smokestacks as a part of a complex environmental texture with high concentration of the same pollutants emitted either from the stacks under study or other surrounding sources, etc. Most of the times a specific marker of the interesting plant is not known

We think that a non-stationary dispersion model can be helpful in this cases, providing information about the theoretical impacts over the monitoring sites, caused by the source on focus. This new proposal can be useful for interpreting the data of the air quality campaign measurements. In this paper a new proposal is described and discussed, with the aim to give a new tool to evaluate the responsibility of a single plant surrounded by other emission sources and heavy boundary conditions.

In this first study, this method has been applied to some dummy datasets in order to evaluate its theoretical capability to recognize the environmental impact of the source under investigation.

METHOD

The method is based on an indicator (called *f*), built in order to be useful for the interpretation of the data of a monitoring campaign dataset, with the aim to evaluate the impact of a punctual emission source on the air quality. In this paper we report a theoretical experiment target to assess the power of our method for this task. Data interpretation is carried out with an univariate approach: every single chemical species (or linear combination of relative concentration of different species) is considered separately. The aerosol has been treated as a passive species when simulated at the considered scale.

Given the *i*-th sample collected in the measuring campaign, these elements have been considered:

- I_i as the total mass of aerosol emitted by the plant and collected in the *i*-th sample;
- C_i as the total mass of aerosol not emitted by the plant under study and collected in the *i*-th sample;
- $T_i = I_i + C_i$ as the total mass of aerosol collected in the *i*-th sample;
- A_i as the mass of the studied chemical species collected in the *i*-th sample;
- $P_i = A_i / T_i$ as the fraction of the studied chemical species collected in the *i*-th sample;
- $f_i = I_i / T_i$ as the relative contribution of the plant to the aerosol collected in the *i*-th sample.

T_i and A_i can be obtained in a measuring campaign while the parameter I_i can be assessed with a dispersion model. Note that this method doesn't need the emission rate of the studied chemical species *A*, but only the bulk aerosol emission.

The method is based on the fact that if a good correlation is found between *f* and *P*, then it is possible to assert that the plant under study emits aerosol with a relative fraction of *A* higher than the relative fraction of *A* intaked in air by other sources of aerosol. Hereafter this statement is discussed: the method has been applied to some dummy datasets, and has been studied in such conditions that a good correlation between *f* and *P* can be found.

RESULTS

First, we introduce some new parameters, which are neither measured nor simulated:

- A_{Ii} = mass of the studied chemical species emitted by the plant and collected in the i-th sample;
- A_{Ci} = mass of the studied chemical species emitted by the surrounding sources and collected in the i-th sample;
- $F_{AIi} = A_{Ii} / I_i$ fraction of the target chemical species in the aerosol emitted by the plant;
- $F_{ACi} = A_{Ci} / C_i$ fraction of the target chemical species in the aerosol not emitted by the plant under study.

In the definition of a dummy dataset, some hypothesis are formulated on F_{AI} and F_{AC} .

The method is applied to the dummy dataset #1, built with the following characteristics:

- number of samples n =100;
- *C* is a random variable generated according to a log-normal distribution with parameters μ_C=20 and σ_C=0.5;
- *I* is a random variable generated according to a log-normal distribution with parameters μ_I=0.02 and σ_I=1.8;
- no correlation between *I* and *C*;
- F_{AI} normally distributed with mean 0.1% and standard deviation 0.01%;
- F_{AC} normally distributed with mean 1% and standard deviation 0.1%.

This dataset (Figure 1) should be considered as a realistic representation of a real case, with a plant which contributes to about 1/1000 of the background aerosol concentrations. As expected, the correlation between *f* and *P* (Figure 2, right panel) is high. By far higher than the correlation between *A* and *I* (Figure 2, left panel).

Starting from the first dataset, other datasets (#2) are built simply modifying μ_C and leaving fixed $\mu_C / \mu_I = 10$. As shows figure 3 (left panel), the correlation between *f* and *P* doesn't change significantly (about 0.8).

Again, starting from the first dataset, other datasets (#3) are built modifying μ_C / μ_I, leaving fixed μ_C, and with n = 100.000. As shows figure 3 (right panel), the correlation between *f* and *P* grows non-linearly with μ_C / μ_I . Values of μ_C / μ_I in the range 5-10 lead to correlations 0.5-0.8.

In the last two tests the sensitivity to the number of samples has been evaluated. Starting from datasets #3, the number of samples *n* is reduced to 50 (datasets #4) and to 20 (datasets #5), and for every combination of parameters, 1000 datasets are generated and evaluated, in order to get more robust results. In the worst case, correlations higher than 0.5 are reached:

- with $\mu_C / \mu_I > 50$ approximately, if n = 50 (datasets #4, figure 4, left panel, lowest dashed lines);
- with $\mu_C / \mu_I > 100$ approximately, if n = 20 (datasets #5, figure 4, right panel, lowest dashed lines).

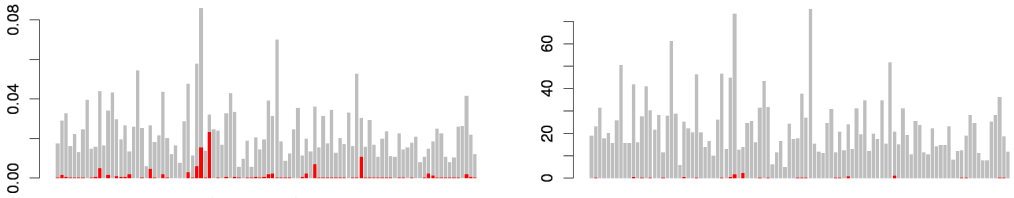

Figure 8. Dummy dataset #1. Left: mass of the studied chemical species sampled; in grey the total amount, in red the part emitted by the plant. Right: mass of aerosol sampled; in grey the total amount, in red the part emitted by the plant.

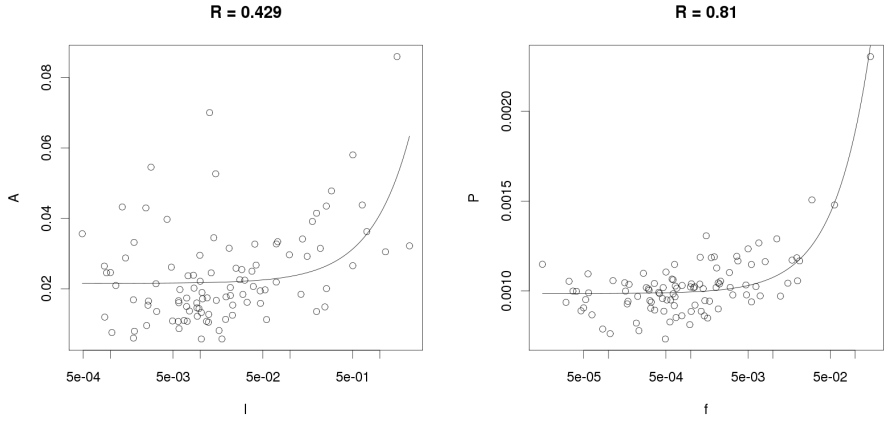

Figure 9. Dummy dataset #1. Correlation and linear fit between *A* and *I* (left), and between *f* and *P* (right).

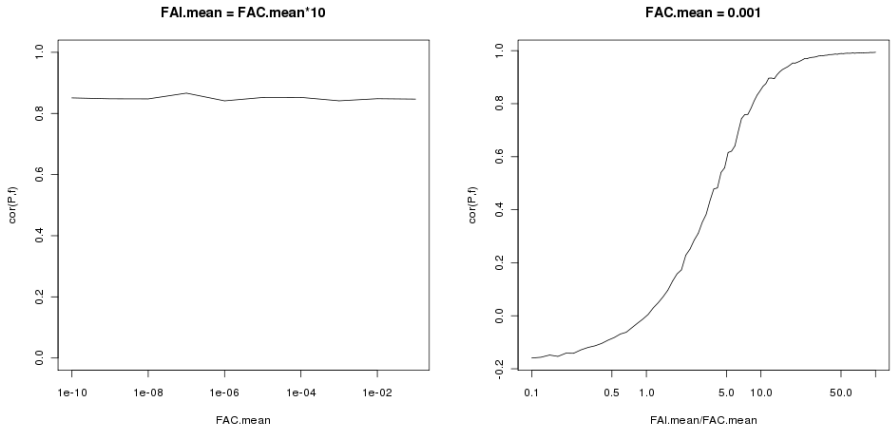

Figure 10. Evaluation of datasets #2 (left) and #3 (right).

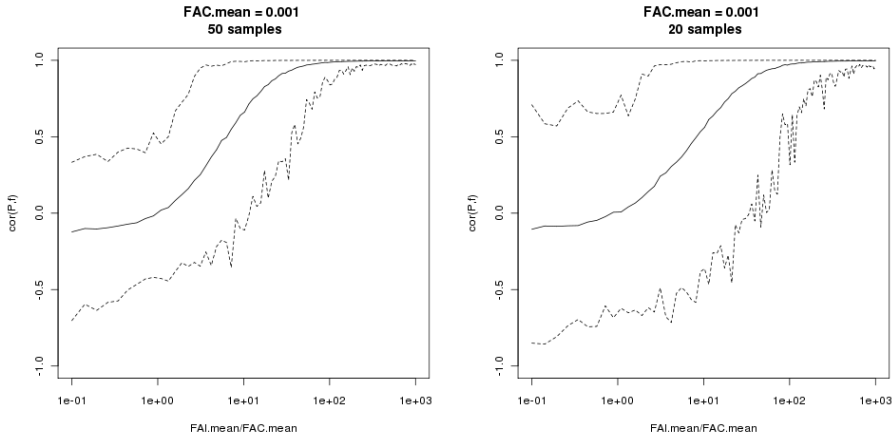

Figure 11. Evaluation of datasets #4 (left) and #5 (right).

CONCLUSIONS

A new proposal for detecting the impact of a single plant surrounded by other emission sources and heavy boundary conditions is described and discussed. The method is based either on a non-stationary dispersion model and on an air quality campaign carried out in the nearby of the stack under study.

In this first paper, this method has been applied to some dummy datasets in order to show how it is good for the impact evaluation of one specific source in a complex environmental situation. The method showed sensitivity to the number of samples collected. The relative quantity of the chemical species choosen as "stack tracer" and found in the environmental aerosol sampled, is one of the key factors. This theoretical exercise shows that the impact of the smokestack is recognized only if its emission is quite different from the background presence of the chemical species choosen as tracer.