

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. 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.

Method

We report a theoretical experiment targeted 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;
- ▶ $P_i = \frac{A_i}{T_i}$ as the fraction of the studied chemical species collected in the i -th sample;
- ▶ $f_i = \frac{I_i}{T_i}$ 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**. 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.

The dummy datasets

In the definition of a dummy dataset, some hypothesis are formulated on the following parameters, which are neither measured nor simulated:

- ▶ A_i = mass of the studied chemical species emitted by the plant and collected in the i -th sample;
- ▶ AC_i = mass of the studied chemical species emitted by the surrounding sources and collected in the i -th sample;
- ▶ $FAL_i = \frac{A_i}{T_i}$ fraction of the target chemical species in the aerosol emitted by the plant;
- ▶ $FAC_i = \frac{AC_i}{C_i}$ fraction of the target chemical species in the aerosol not emitted by the plant under study.

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.

- ▶ Sensitivity of the method to the number of samples collected;

- ▶ the relative quantity of the chemical species chosen as "stack tracer" and found in the environmental aerosol sampled, is one of the key factors;
- ▶ the impact of the smokestack is recognized

only if its emission is quite different from the background presence of the chemical species chosen as tracer.

Dataset #1: a realistic case

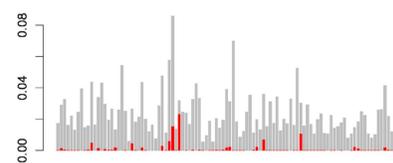


Figure 1: mass of the studied chemical species sampled; in grey the total amount, in red the part emitted by the plant

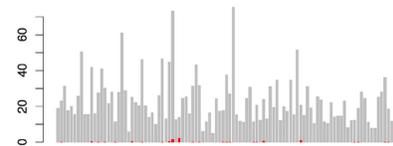


Figure 2: mass of aerosol sampled; in grey the total amount, in red the part emitted by the plant

This dataset 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 (Fig.3) is high**. By far higher than the correlation between A and I (Fig.4).

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 $\mu_C = 20$ and $\sigma_C = 0.5$;
- ▶ I is a random variable generated according to a log-normal distribution with parameters $\mu_I = 0.02$ and $\sigma_I = 1.8$;
- ▶ no correlation between I and C ;
- ▶ FAL normally distributed with mean 0.1% and standard deviation 0.01%;
- ▶ FAC normally distributed with mean 1% and standard deviation 0.1%.

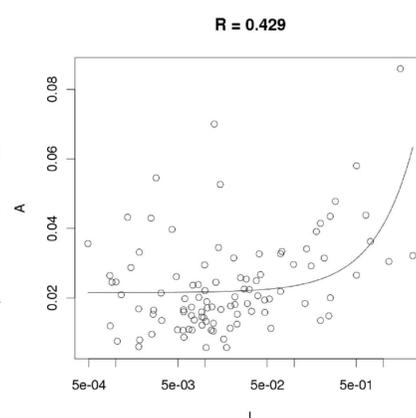


Figure 3: Correlation and linear fit between A and I ...

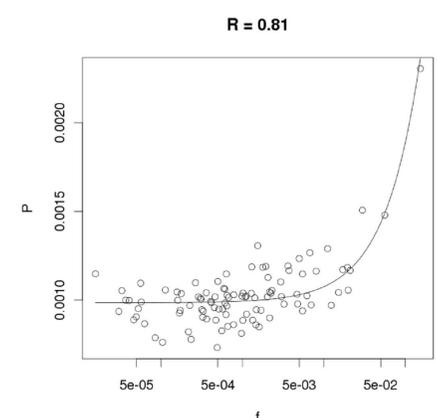


Figure 4: ...and between f and P

Datasets #2 and #3: sensitivity to background aerosol concentrations and to relative quantity of the chemical species

Starting from the first dataset, other datasets (#2) are built simply modifying μ_C and leaving fixed $\frac{\mu_C}{\mu_I} = 10$. As shows figure 5, the correlation between f and P doesn't change significantly (~ 0.8).

Again, starting from the first dataset, other datasets (#3) are built modifying $\frac{\mu_C}{\mu_I}$, leaving fixed μ_C , and with $n = 100000$. As shows figure 6, the correlation between f and P grows non-linearly with $\frac{\mu_C}{\mu_I}$. Values of $\frac{\mu_C}{\mu_I}$ in the range 5-10 lead to correlations 0.5-0.8.

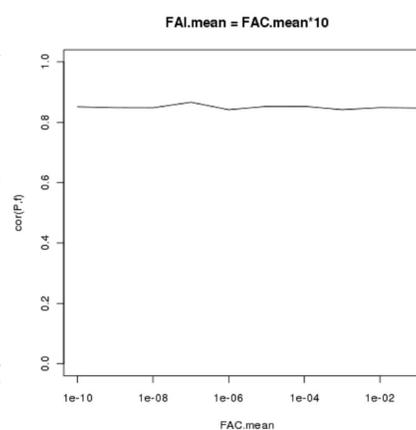


Figure 5: Datasets #2 evaluation

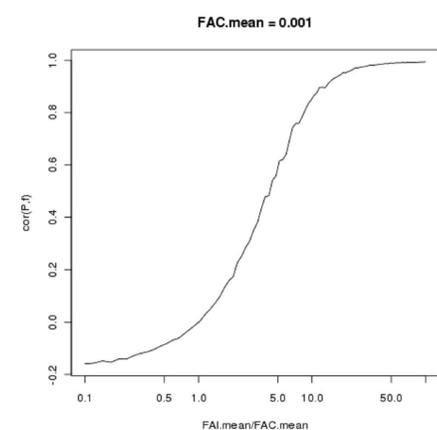


Figure 6: Datasets #3 evaluation

Datasets #4 and #5: sensitivity to the number of samples

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 $\frac{\mu_C}{\mu_I} \gtrsim 50$, if $n = 50$ (datasets #4, figure 7, lowest dashed line);
- ▶ with $\frac{\mu_C}{\mu_I} \gtrsim 100$, if $n = 20$ (datasets #5, figure 8, lowest dashed line).

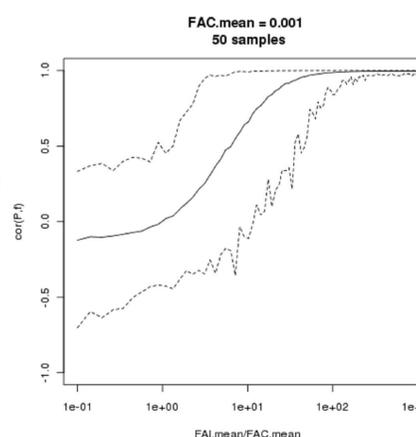


Figure 7: Datasets #4 evaluation

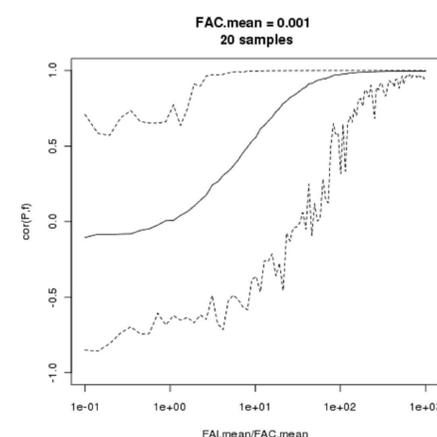


Figure 8: Datasets #5 evaluation