

## 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

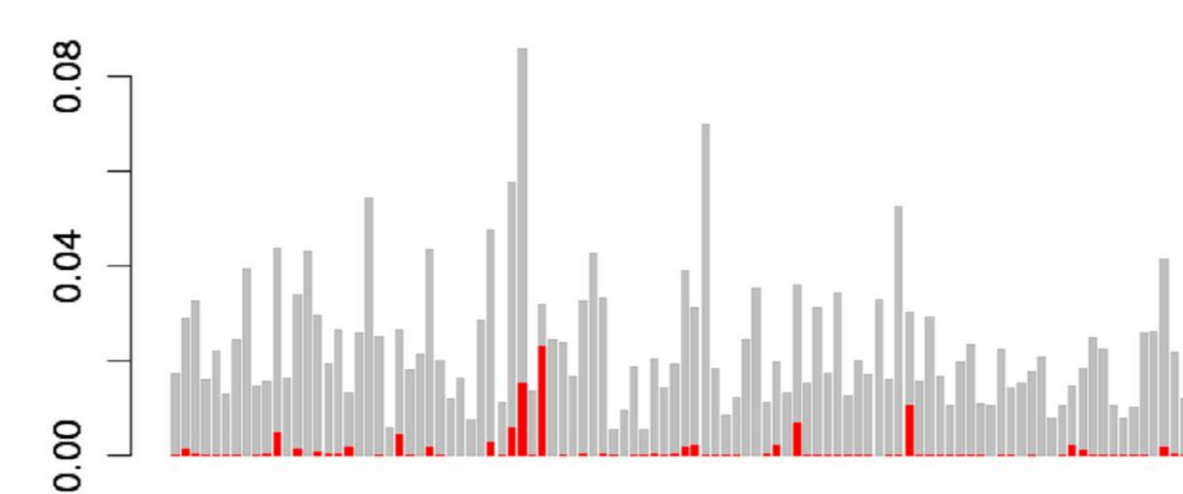


Figure 1: mass of the studied chemical species sampled; in grey the total amount, in red the part emitted by the plant

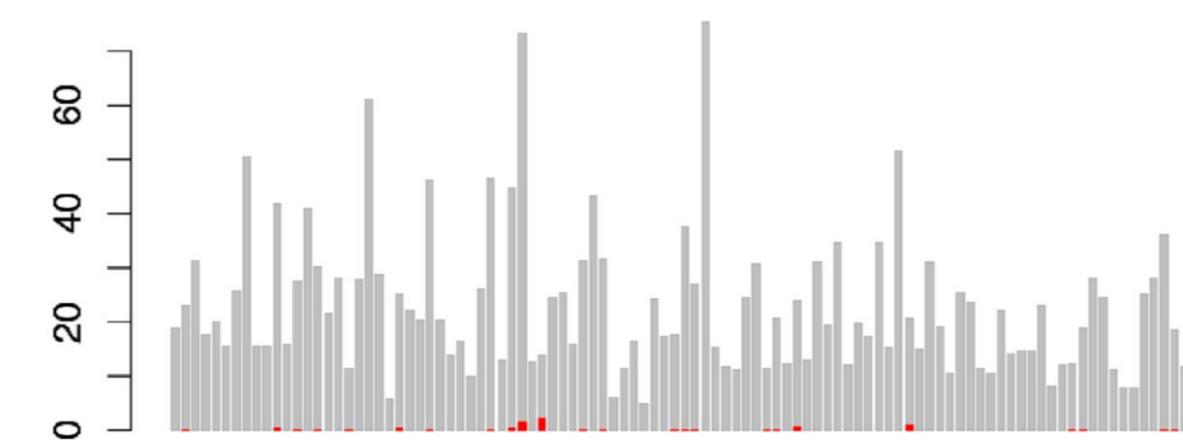


Figure 2: mass of aerosol sampled; in grey the total amount, in red the part emitted by the plant

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%.

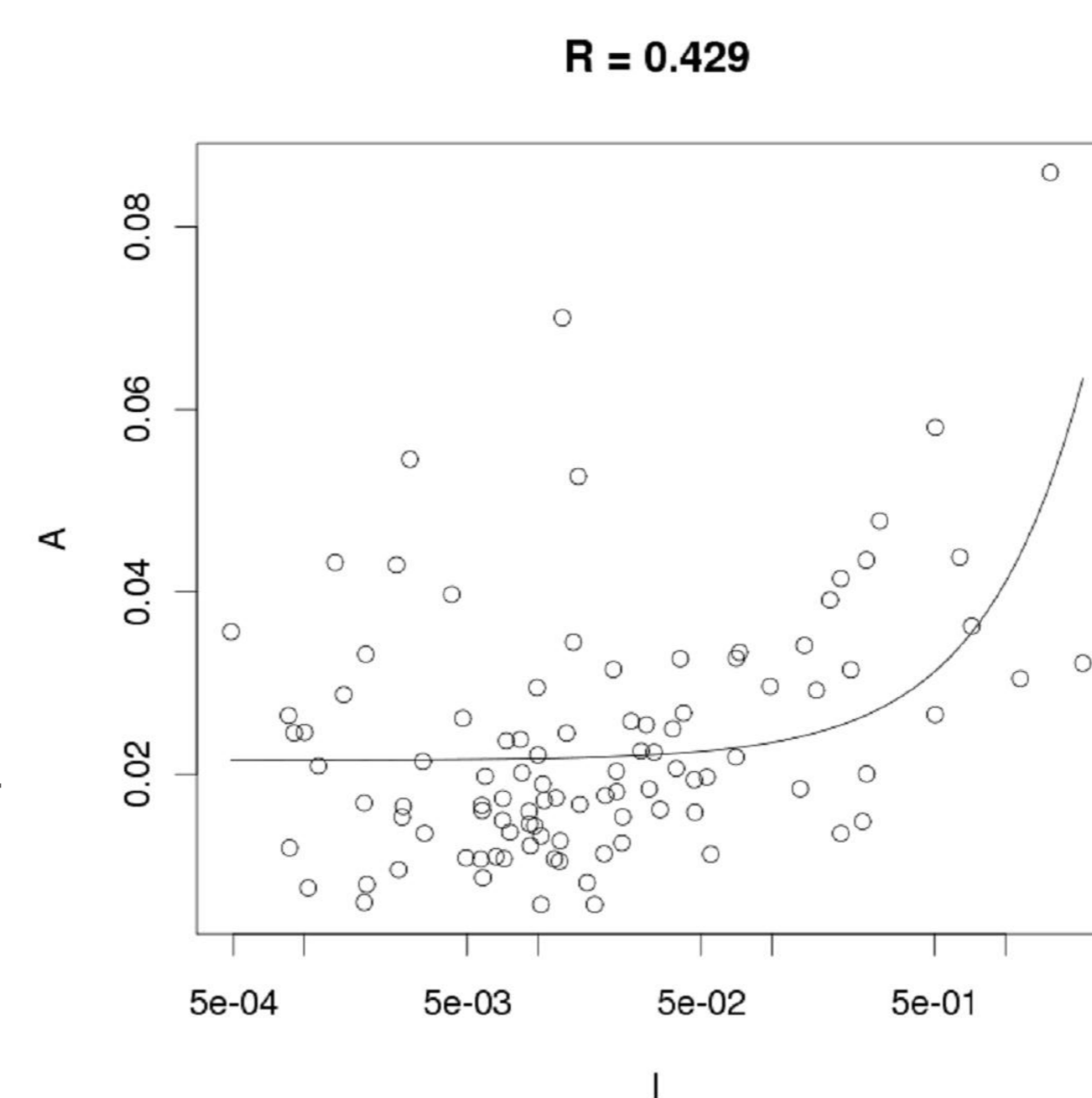


Figure 3: Correlation and linear fit between  $A$  and  $I$ ...

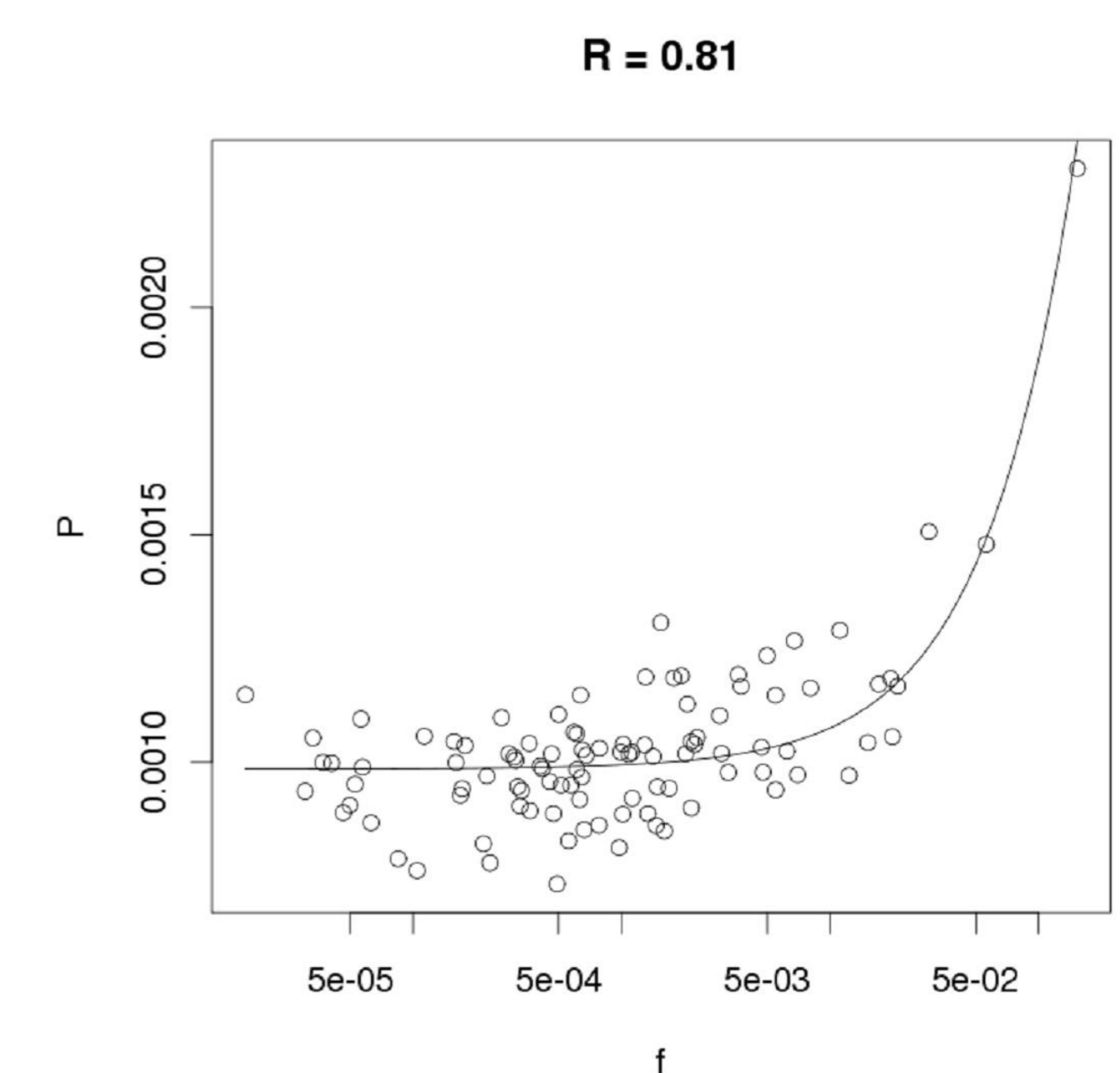


Figure 4: ...and between  $f$  and  $P$

## 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  $\mu_C$  and leaving fixed  $\frac{\mu_C}{\mu_I} = 10$ . As shows figure 5, the correlation between  $f$  and  $P$  doesn't change significantly ( $\sim 0.8$ ).

Again, starting from the first dataset, other datasets (#3) are built modifying  $\frac{\mu_C}{\mu_I}$ , leaving fixed  $\mu_C$ , 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.

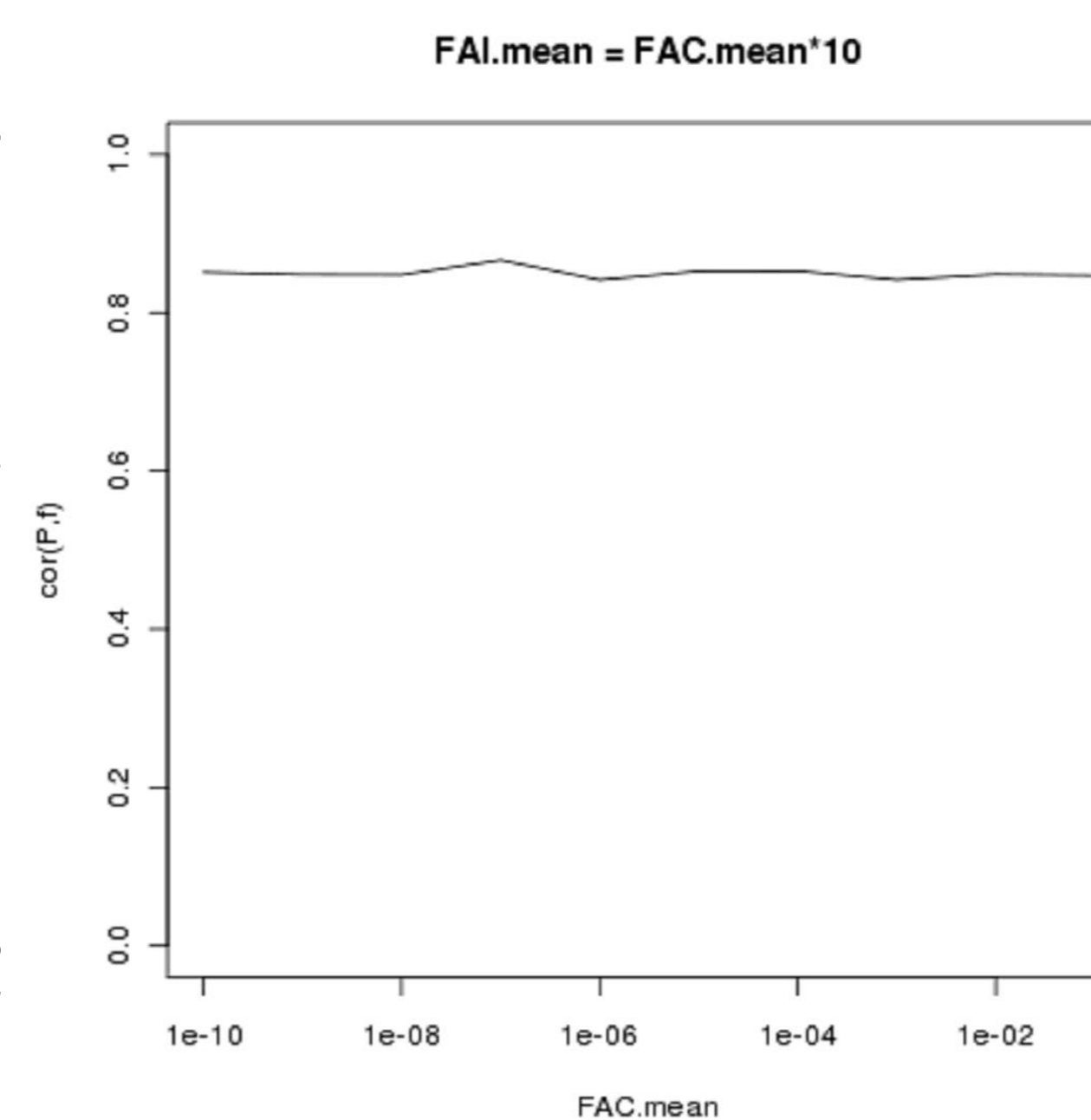


Figure 5: Datasets #2 evaluation

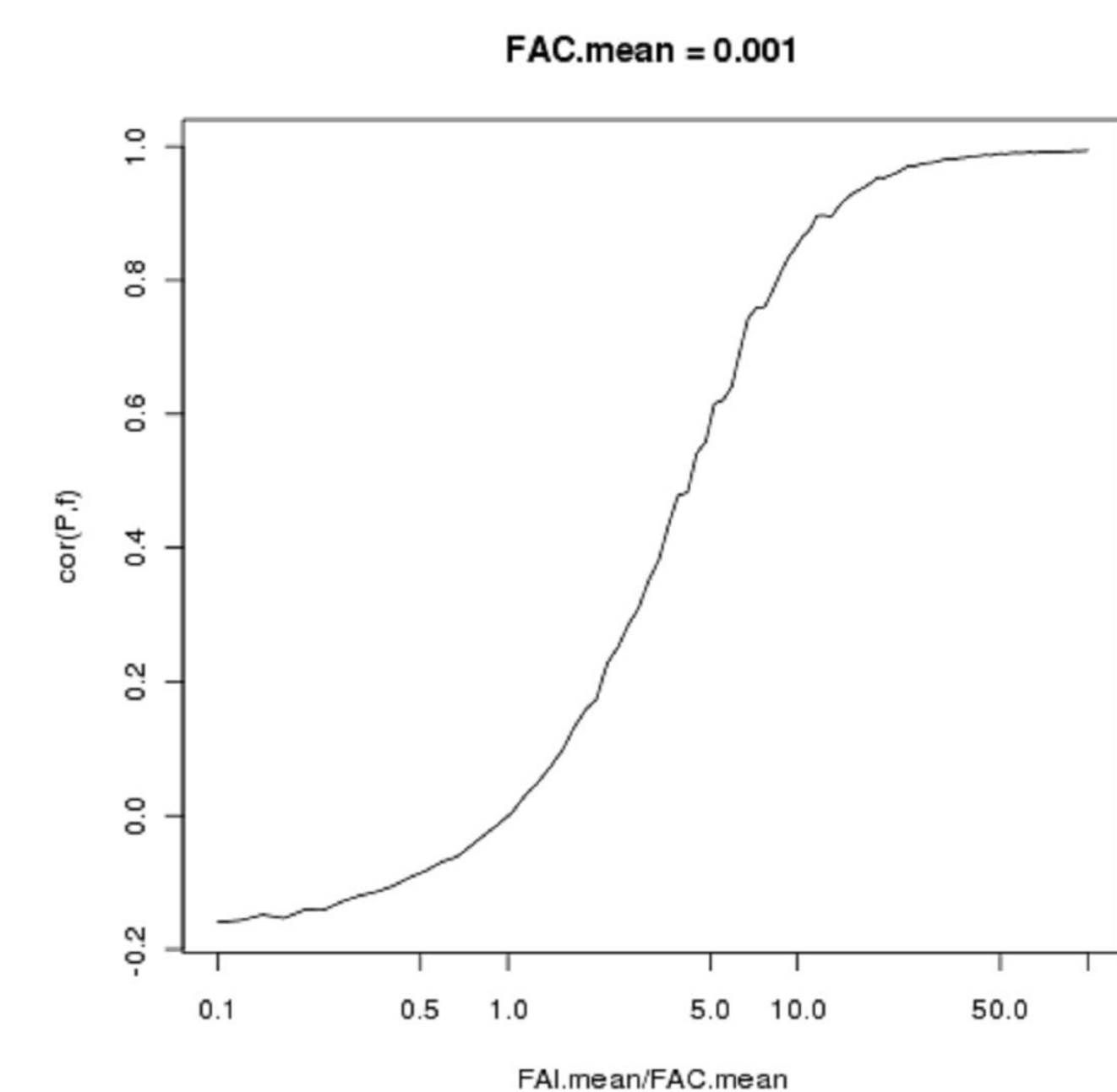


Figure 6: Datasets #3 evaluation

## 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).

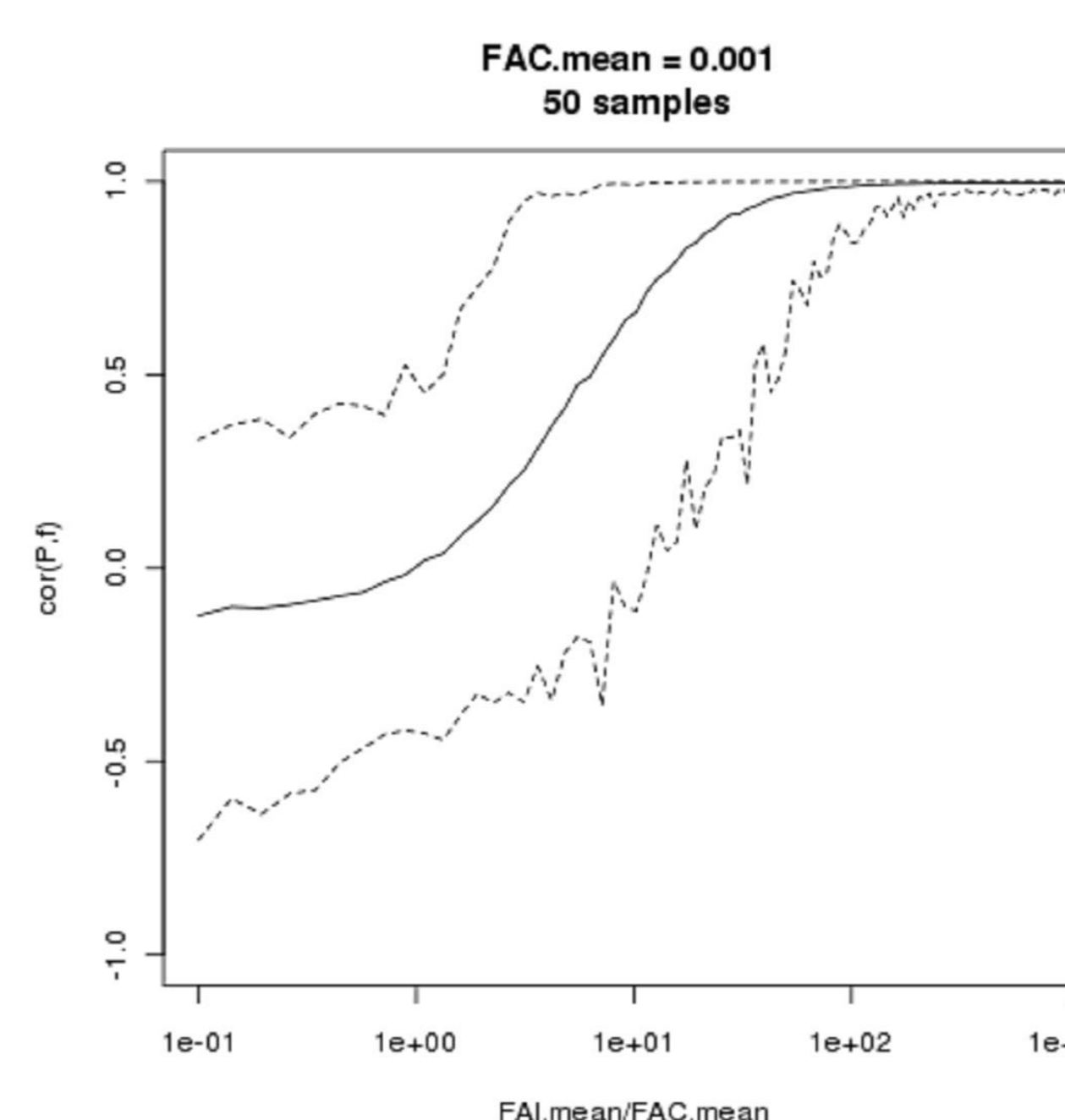


Figure 7: Datasets #4 evaluation

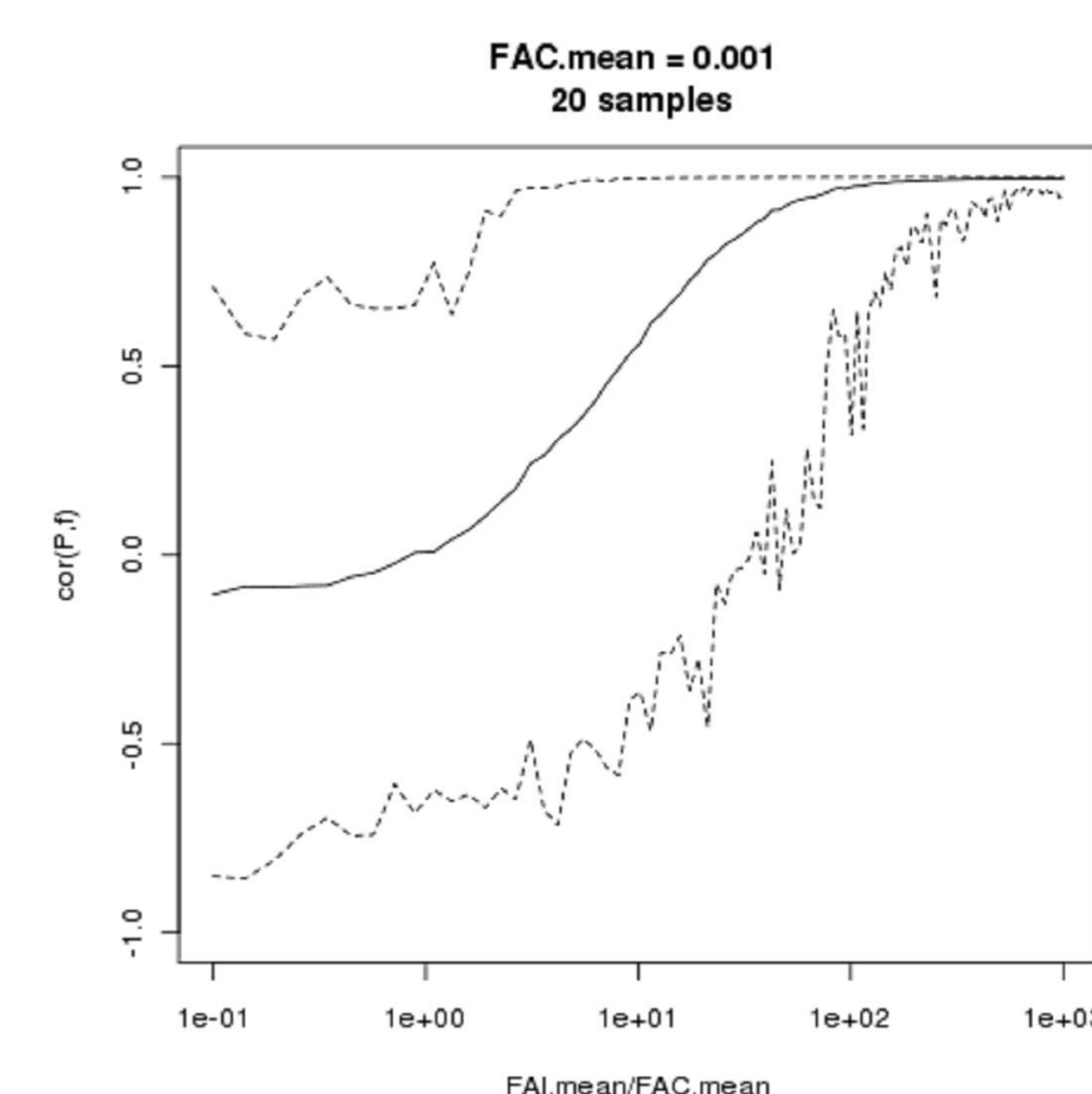


Figure 8: Datasets #5 evaluation