Geostatistical assessment of long term human exposure to air pollution

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Objectives

To illustrate the efficiency of geostatistics in providing the basic figures to perform an Health Impact Assessment (HIA) of ambient air pollution.

Key points:

- HIA requires the accurate assessment of the population exposure to air pollutants.
- Case Study from UNECE-WHO Pan European Program for Transport, Health and Environment: “Transport-related health impacts and their costs and benefits with a particular focus on children”.
- Poor efficiency of linear estimation techniques (kriging/cokriging) to solve non linear problems and perform risk analysis

  ⇒ Stochastic simulations of PM10 that integrate:
  - correlation between PM10 and more densely acquired NO_2 data,
  - more recent PM10 data that supplemented the PM10 monitoring network.

- Population exposure to different levels of concentrations, once air concentration results are coupled with geo-data from the last national census (1999).

Contents

Introduction

Health Impact Assessment (HIA)

- Scientific approach that allows to forecast impact of air pollution on public health.
- Epidemiological studies investigate the relationship between
  - temporal variation of pollutant air concentrations (data from air monitoring network) and
  - health outcomes in the population (data from hospitals, other public health institutions, measured in representative sample of the population).

⇒ Exposure response function (ERF): estimate the number of cases (morbidity or mortality) for a given atmospheric concentration of a given air pollution indicator.

Specific HIA on transport-related air pollution

- Accurate assessment of the population exposure to chemical compounds that are indicators of transport-related pollution.
- Numerous epidemiological study results established ERF between PM10 (particulate matter with an aerodynamic diameter less than 10 micron) air concentration and increased frequency in many health outcomes.
- Preliminary step of this HIA: the assessment, with data from the French air monitoring network, of PM10 ambient air concentrations.

Introduction

Presentation of the approach:

- Data analysis and spatial modeling of average annual PM10 concentrations from existing measuring stations in France in year 2000 (interest is put on long-term exposure effects).

- Significant increase in the reliability of the results by taking into account:
  - the correlation between PM10 and more densely acquired NO2 data,
  - more recent PM10 data that supplement the PM10 monitoring network in otherwise entirely non sampled areas.

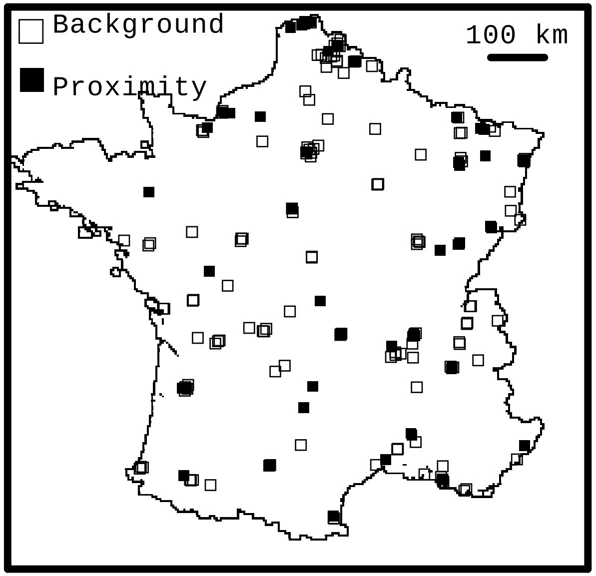
- Linear estimation techniques not adapted for non linear calculations and risk analysis $\Rightarrow$ conditional cosimulations of PM10 concentrations.

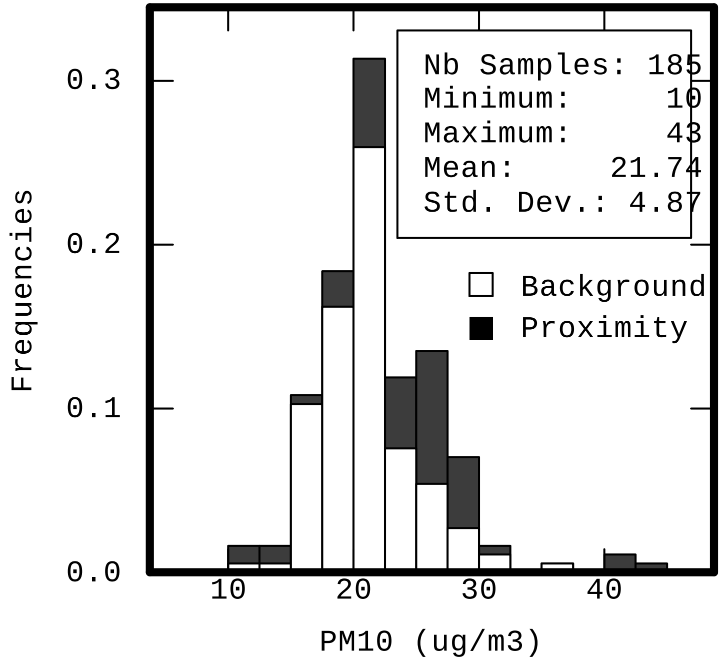
- Coupling air concentration results with geo-data from the last national census (1999), the population exposed to different levels of average annual concentrations is calculated.
- Statistical parameters from the resulting distributions are derived in the perspective of carrying out the HIA study on transport related air pollution.

- All geostatistical calculations performed using Isatis® software.

Spatial modeling

- Data analysis of average annual PM10 concentrations
  - 185 measured stations in year 2000 (54 proximity stations)

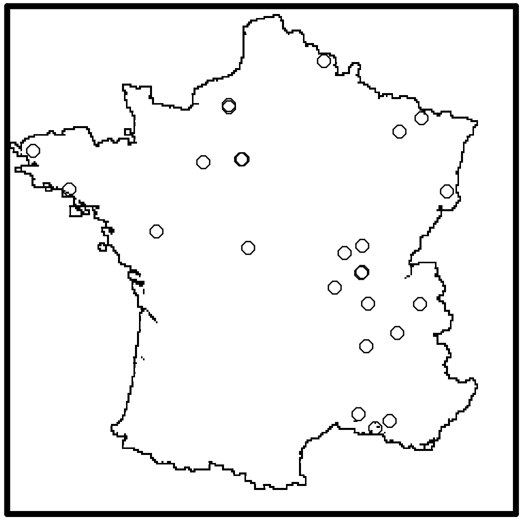


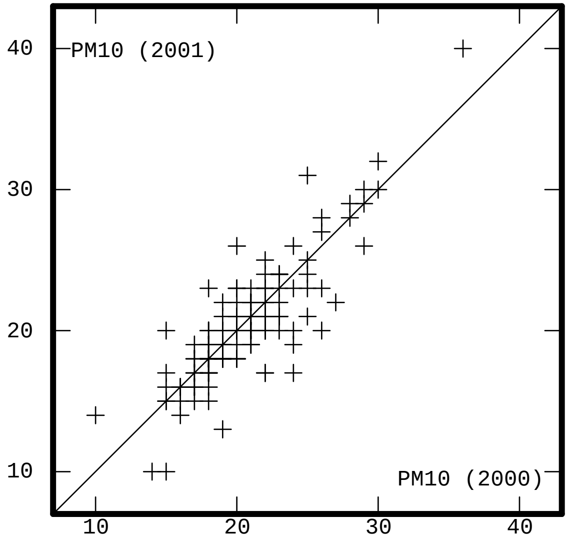


  - Proximity stations excluded from the analysis (lack of spatial representativity)

Spatial modeling

- Correlations:
  - PM10 measured in 2001:
    - 23 additional samples
    - Correlation coeff.: 0.84



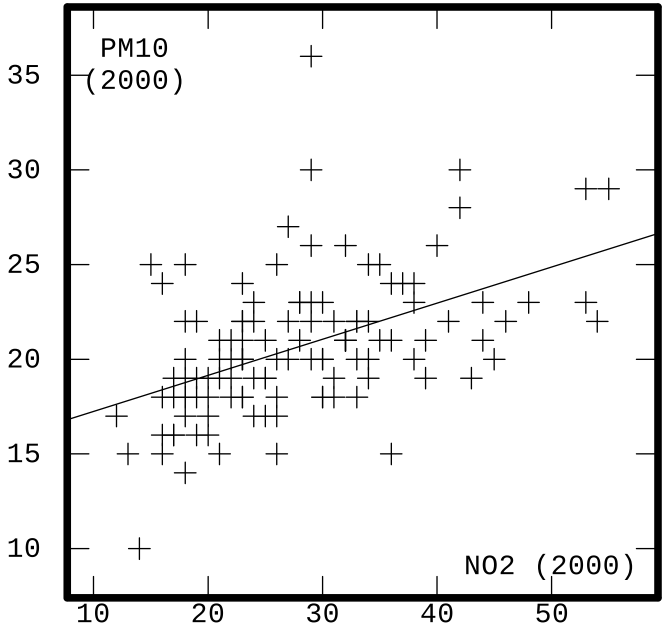


  - Possible models to integrate these additional data:
    - Standard cokriging between PM10 (2000) and PM10 (2001)
    - Kriging of PM10 (2000) completed by 2001 measures, the latter being penalized by a Variance of Measurement Error (equal to the variance of the residuals around linear regression)

Spatial modeling

Correlations:

- NO2 data:
  - Measured at 296 stations in 200(including 259 background stations
    (to be compared with PM10: 131)
  - Correlation coeff. with PM10: 0.49

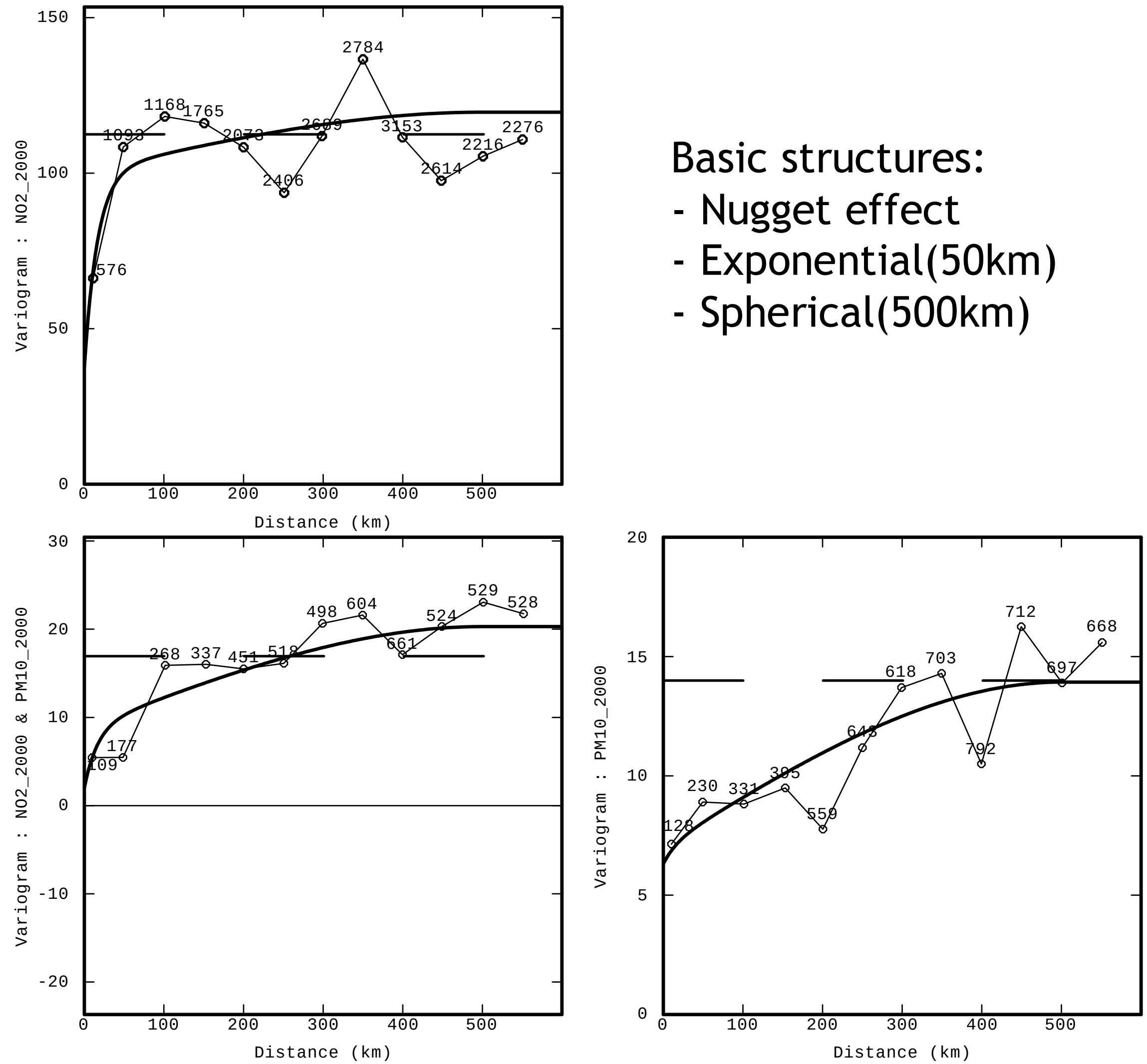


- Model: ordinary cokriging with PM10

Spatial modeling

- Variogram model

  (linear model of coregionalization)



Basic structures:
- Nugget effect
- Exponential(50km)
- Spherical(500km)

Spatial modeling

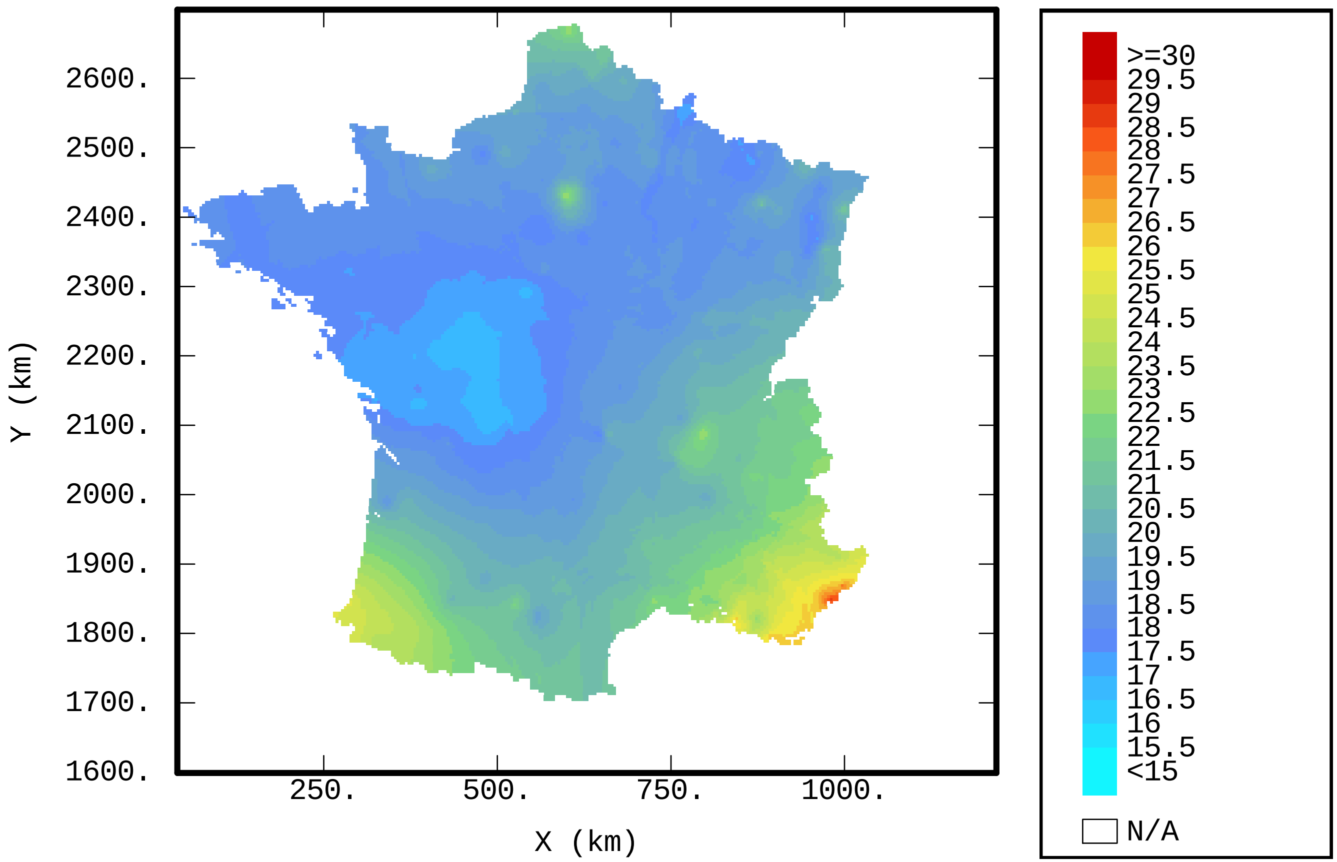
- Several models to estimate PM10 (2000):
  - Ord. kriging of PM10 (2000),
  - Ord. kriging of PM10 (2000 completed by 2001 with VME),
  - Ord. cokriging of PM10 (2000) and PM10 (2001),
  - Ord. cokriging of PM10 (2000 completed by 2001) and NO2 (2000).
- Validation:
  - Calculation of the Mean Quadratic Error (MQE) on five validation sets (22 to 30 datapoints per set):

	Validation set					
	1	2	3	4	5	Mean Rank
1/d2 PM10 2000	26,5	13,9	16,5	12,4	21,6	4,6
OK PM10 2000	**10,1**	7,4	15,4	**11,9**	6,8	2,8
OK PM10 2000 comp2001	11,8	**6,5**	12,2	14,9	4,2	2,8
OCK PM10 2000 / PM10 2001	**10,2**	6,8	12,4	13,4	6,4	3,0
OCK PM10 2000_comp / NO2 2000	10,5	6,7	**11,8**	12,2	**4,1**	1,8

(Ranked MQE, 1=best, 5=worst)
(Raw MQE)

Spatial modeling

- Resulting mapping of PM10 (2000)



Population exposure

- Poor efficiency of linear estimation techniques to solve non linear problems and perform risk analysis

  ⇒ **Stochastic simulations of PM10 using the model previously established.**

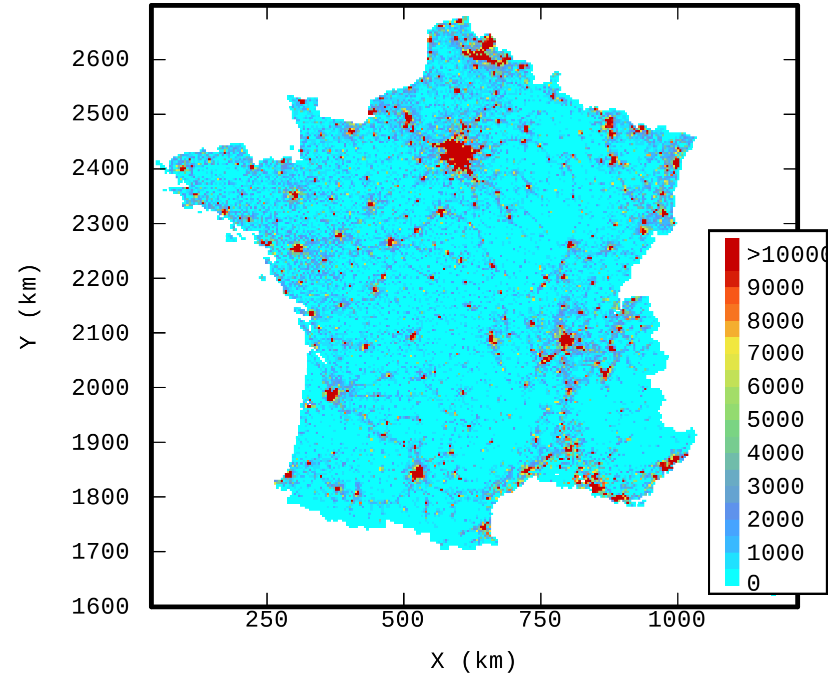
- Analysis of gaussian transforms (anamorphosis)
  - PM10 data have been transformed into gaussian data, and the anamorphosis function has been modeled (data clustering taken into account to avoid bias).
  - Though our interest is on PM10, NO2 has been transformed too:
    - correlation analysis and bivariable spatial structure between two gaussian transforms usually yields to better results and ensures the homogeneity of the process,
    - the Turning Bands co-simulation algorithm requires first the non conditional simulation of both variables, that should be gaussian.
  - Calculation and modeling of variograms of PM10 and NO2 gaussian transforms using the same basic structures as for the raw concentrations.

Population exposure

- Co-simulation of PM10 and NO2 concentrations
  - 200 conditional co-simulations have been performed using the Turning Bands technique, with 500 turning bands.
    - TB algorithm simplifies the 2D simulation in several 1D simulations along randomly generated lines, then reconstruct the 2D simulation by averaging the projected values from the 1D simulations (Matheron, 1973).
    - Number of turning bands: only parameter required to ensure the consistency of the resulting simulations (histogram and variogram reproduction).
    - Cosimulations obtained by simulating each basic structure, using the linear model of coregionalization decomposition.
  - Adequacy of this number of turning bands has been verified on a few simulations, in terms of histogram and variogram reproduction, before the back-transformation in raw scale.
  - Once simulations are obtained and validated, end of the geostatistical work…

Population exposure

- Population exposure:
  - Number of inhabitants known for each 4km x 4km grid cell (last national census of 1999).
  - For each PM10 simulation, computation of the population exposed to a given interval of pollution, for example: population exposed to PM10 concentrations between 5 and 10 μg/m³.



- Repeat for all simulations ⇒ distribution of the population exposed for example to an average annual PM10 concentration between 5 and 10 μg/m³.

- Characteristics about this statistical distribution derived for conducting the HIA:

	5-10 µg/m3	10-15 µg/m3	15-20 µg/m3	20-25 µg/m3	25-30 µg/m3	30-35 µg/m3	35-40 µg/m3
Mean	0,23	2,09	28,50	22,09	4,49	0,61	0,21
Std. Deviation	0,14	0,50	1,53	1,36	0,81	0,28	0,15
Quantile 2.5%	0,08	1,13	25,65	19,33	2,82	0,18	0,01
Quantile 97.5%	0,50	3,13	31,68	24,47	6,11	1,30	0,55

Conclusions (1/2)

- Efficiency of geostatistics to provide the basic figures of a specific HIA on air pollution, based on PM10:
  - The geostatistical framework offers the possibility to generate several realizations of the phenomenon of interest, here the annual PM10 concentrations.
  - Realizations obtained by means of conditional cosimulations between PM10 and NO_2 (Turning Bands algorithm)
  - Integration of complementary PM10 data from 2001 through a variance of measurement error approach.
  - Calculation of the population exposed to different levels of PM10 concentrations for each realization.
  - Statistical results are then used for carrying out the HIA.

Conclusions (2/2)

- ## Future work:
  - Part of the PM10 pollution specifically attributable to traffic.
  - Integration of auxiliary variables (like NO2, soil occupation, etc) does not replace information linked to the physico-chemical process of the pollution (obtained from detailed analysis of the emissions and transformation process, through a classical numerical simulation of transport).
  - The latter could be incorporated in the geostatistical method as an accurate cofactor (collocated cokriging, kriging with external drift).
  - Advantage of this model: integrate the actual data from the air monitoring network and the best knowledge on the pollution phenomenon.

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Just in case…

- Kriging with variance of measurement error (VME)
  - Numeric values with varying level of precision might be available for the variable of interest. For example, the data may come from several surveys: old ones and new ones, the latter being more accurate due to advances in measurement techniques.
  - In such cases error variances albeit different for each sub-population may be known. Certain data might be assumed to have an error variance of 0, whilst some indirect or old measures are uncertain with a known error variance.
  - Assumption: instead of the "true" concentration value z_i we only know z_i+e_i with e_i a random error satisfying the following conditions for each sampling point *i*: $E[e_i]=0$, $Cov[e_i, e_k]=0$ for k ? i, $Cov[z_i, e_i]=0$ and $Var[e_i]=V_i$.
  - Kriging with variance of measurement error (VME) integrates these error variances. From a kriging system point of view, the VME approach simply consists in adding the V_i values to the diagonal covariance terms.