

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
 - \Rightarrow Stochastic simulations of PM10 that integrate:
 - correlation between PM10 and more densely acquired NO₂ 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).



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Introduction

Spatial Modeling

Population exposure



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).

 \Rightarrow **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.

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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.

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• 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)

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• Correlations:

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

Spatial Modeling



- 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)

Population exposure



• Correlations:

- NO2 data:
 - Measured at 296 stations in 2 including 259 background stations (to be compared with PM10: 131)
 - Correlation coeff. with PM10: 0.49



- Model: ordinary cokriging with PM10

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• Variogram model

(linear model of coregionalization)

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• 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:

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- 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, ð	13, 9	16, 5	12, 3	21,6	4,6
	OK PM10 2000	10,1	7, 3	15, 3	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, 3	13, 4	6, 3	3,0
	OCK PM10 2000_comp / NO2 2000	10, 5	6, Z	11, 8	12,2	4,1	1,8
	(Ranked M(QEv, 14QEs)t, 5=worst)						
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• Resulting mapping of PM10 (2000)



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

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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...

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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 \Rightarrow distribution of the population exposed for example to an average annual PM10 concentration between 5 and 10 μ g/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

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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.
- Acknowledgments: my co-authors, and the financial support of the French agency ADEME (Agence de l'Environnement et de la Maîtrise de l'Energie) through contracts nº 03 62 C0023 and nº 03 62 C0053.

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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.

