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Uncertainty evaluation in air quality planning decisions: a case study for Northern Italy

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ABSTRACT

In recent years, evaluating the robustness of environmental models results has become essential in order to effectively support decision makers to define suitable emission control strategies. This evaluation is performed in literature through uncertainty and sensitivity analyses. Therefore, the application of such methodologies to air quality Integrated Assessment Models (IAMs) is extremely challenging. In fact, in this case uncertainty and sensitivity analyses should be assessed not only for each single component of the system, but also for the overall IAM. In the paper, an attempt is made to extend and systematize the information available on uncertainty/sensitivity analysis, at first considering environmental models in general, and then focusing on air quality IAMs. The study aims to offer a tentative framework addressed to modelers and decision makers in the implementation of IAM and evaluation of its results. The framework has been tested on Lombardy region (Northern Italy). The results show how the uncertainty on Drivers of emissions propagates on the whole modelling chain characterizing an integrated assessment study.

1. Introduction

In recent years, environmental models are becoming more and more important as intermediary between policy and science, supporting decision makers in management and planning/strategic choices. These applications are very challenging for the complexity of the involved phenomena and (perhaps, mainly) for the socio-economic impacts of the policy decisions. So, as models are becoming more and more important in the policy arena, the complexity of the relationship between their output and the consequent decisions together with the limited evaluation of their robustness can cause a lack of confidence, and a possible growing mistrust on the capability of systems to support important strategic choices.

A rigorous robustness analysis approach may be the answer to overcome this problem. The US Environmental Protection Agency indeed recommends that both model developers and users perform such an analysis to help determining when a model can be used to take reliable decisions (EPA, 2009). Similarly, in Europe, the FAIRMODE (Forum for Air Quality Modelling) initiative is dealing with guidelines on "fitness for purpose" to assess if an air quality model reaches the minimum level of quality to be used in the science-to-policy interface (Thunis et al., 2015).

In the case of Integrated Assessment Models (IAMs), the analysis becomes even more complex, since it does not consider a single model, but a set of interlinked specific models. It means that the robustness analysis should assess the uncertainty and sensitivity not only for each single component of the system, but also for the system in its entirety (Amann et al., 2011).

To be more specific, let us consider the case of Integrated Assessment Modelling (IAM) in the air quality field. In this context, the analyst should answer questions such as:

- Does the preferable decision change, if it is assessed that the results of the model of the (physical, economic, social) system are inaccurate?

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- How much risk affects the implementation of a certain decision, given that there is no certainty about the model result?

The results of an air quality IAM may be inaccurate for a number of different reasons that are common to any modelling exercise, going from the too simplistic formulation to the impossibility of measuring the necessary inputs. In addition, uncertainty might derive from various sources that are peculiar to this context. The space of feasible actions (options/alternatives/decisions) is normally very limited and, more precisely, the granularity of the decision is much coarser than the granularity of the model results (e.g. the concentration at many receptors can be computed at many different times, but then we can just decide to stop or not the traffic in the entire centre of a city).

This implies that all the information derived from the integrated models of the (physical/environmental, economic, social) system(s) needs to be "squeezed" into very few and simply countable variables (e.g. the yearly number of exceedances of a given concentration threshold somewhere in the domain) thus strongly filtering out much of the temporal and spatial variations.

The models are used in this perspective to compute values that are different, by definition, from those experienced in the past. Thus, there is no way to test if they will closely represent the possible outcomes of our decision or not. This is also true for the other boundary conditions which are supposed to represent future (new) scenarios, consequent to other decisions or to other uncertain factors (e.g. climate change). This is particularly important when (practically always) the domain in which decisions are implemented (often defined by some administrative boundary) differs from the physical domain and thus the outcomes of the decisions of one administrative entity will (possibly, strongly) depend on the decision of others.

In this paper, the authors aim to extend and systematize the information available on uncertainty analysis/sensitivity analysis (UA/SA), at first considering environmental models in general, and then focusing on air quality IAM. The study is one of the first to focus on the overall IAM and not only on a single component and would offer a tentative framework for both modelers and decision makers in the implementation of IAM and evaluation of its results and weakness. The paper is organized in two parts, the first related to the framework and the second concerning the application of the defined framework to a case study, showing how the uncertainty on Drivers of emissions propagates along the whole modelling chain that characterizes an integrated assessment study.

2. Uncertainty & sensitivity analysis framework

Uncertainty and sensitivity analysis are key issues in the definition and evaluation of IAMs. The main goal of uncertainty analysis is to quantitatively assess the impact of the input (measured, estimated or assumed) uncertainties on the computed output results. It is worth to note that in the literature, the term "uncertainty" has been mostly associated with the process of model validation, as suggested by the current EU legislative framework.

Sensitivity analysis is, on the other hand, defined as the study of how model output variation can be apportioned, qualitatively or quantitatively, to different sources.

The two approaches have to be used together and integrated, usually starting by the uncertainty analysis.

One of the most important issues to be addressed at the beginning of both the analyses is the definition of what can be considered as input. In this context, each factor that may lead to a variation in the in the model output is considered an input. Consequently, not only the traditional "model input" i.e. the physical causes determining the output, but also the model parameterizations and the numerical algorithms may be characterized as input.

In the next sections a review of the main techniques, both analytical and numerical, that can be used to perform uncertainty and sensitivity analysis will be briefly presented and the application impact of these analysis will be investigated in the IAM framework introduced in (Guariso et al., this issue).

2.1. Analytical methods

When dealing with linear or relatively "simple" nonlinear systems, analytical methods for statistical error propagation can be used for uncertainty analysis. Variance propagation is the analytical approach most frequently used for simple equations (Martz and Waller, 1982; Morgan and Henrion, 1990).

As for the sensitivity analysis, the partial derivative study (Vlachokostas et al., 2009) is the only analytical technique used. Indeed, the derivative $\partial Y/\partial U_i$ of an output Y versus an input U_i can be thought as a mathematical definition of the sensitivity of Y versus U_i. Unfortunately, often the analytical computation of the partial derivatives may be very difficult due to the complexity of the involved relationships (e.g. constraints, strong nonlinearity).

2.2. Numerical methods

To overcome problems related to analytical methods, a series of numerical methods has been presented in literature.

In general, all the procedures develop the following steps:

- definition of the bound/probability distribution of each source of uncertainty taken into account;
- definition of the output variable to be analysed;
- Design of Experiments (DoEs), closely related to the selected method, with the purpose of propagating the source uncertainty through the model;
- computation of the model output for the scenarios defined in (3);
- computation of the uncertainty/sensitivity measures of interest.

According to literature, the most commonly techniques used for uncertainty analysis are:

- Monte Carlo simulation (Rubinstein, 1981), where a relatively large set of sampling values from the input space are used to drive the model (or a statistically simplified version of the model) and the variance of the results is estimated (Downing et al., 1985). The sampling is usually performed using either the Simple Random Sampling or the Latin Hypercube Sampling (Morgan and Henrion, 1990).
- Differential uncertainty analysis (Cacuci, 1981 Worley, 1987), in which the numerical value of the partial derivatives of the model response with respect to the input are used to estimate uncertainty.
- First-order analysis using Taylor series expansions (Scavia et al., 1981), or polynomial chaos expansions (Cheng and Sandu, 2009) where a numerical approximation of the analytical variance propagation equation is computed.

A large number of approaches exist in the literature to perform a sensitivity analysis (Saltelli et al., 2000).

In general, the numerical sensitivity methods can be grouped in four different families:

- Numerical implementation of partial derivative methods. Various software implementations of models include routines for the efficient computation of system derivatives (Rabitz, 1989; Turanyi, 1990; Varma et al., 1999; Saltelli et al., 2000). This

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