SPATIO-TEMPORAL PROBABILISTIC ENVIRONMENTAL MODELLING

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INTRODUCTION

Water/air/soil pollution, changes in structure and function of ecosystems, soils, hydrology,…, deforestation, global warming, and others are some of the main environmental problems that mankind is facing now. These processes can be modelled on different scales and with different complexity. Sometimes, generic/empirical approaches are used but unfortunately, these do not account for uncertainty, spatial and temporal variability. Environmental variables are considered as single, crisp values. But in reality, an environmental output can vary in time and space and is characterised by uncertainty and other forms of variability. Uncertainty represents ignorance or measurement error and can partly be reduced through further research. Uncertainty is usually represented by a confidence band or interval. Variability represents inherent heterogeneity or diversity, which is not reducible through further measurements. Typically, the two most important sources of variability for environmental variables are spatial and temporal variability. The contribution of spatial variability to the total environmental variability can be quite high. For example, atrazine concentrations in the Belgian surface water can vary over more than five orders of magnitude. The goal of this paper is to present a sequence of environmental modelling frameworks, where each time, a component of the variability is explicitly considered and refined. This work is partly based on existing work and partly on new developments. As an illustration, references to case studies of exposure modelling of individual chemicals were made.

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In a probabilistic analysis, the inherent spatial and temporal variability and the uncertainty of the environmental variable of interest is quantified and simulated by means of probability distributions (Verdonck et al., 2001) (see Figure 1 top). A very common sampling method for propagating variability or uncertainty through a mathematical model is Monte Carlo simulation. In a first order Monte Carlo, either variability or uncertainty can be propagated through a model. In most current assessments, variability and uncertainty are not treated separately although they are two different concepts as explained in the introduction. To deal with this issue, a second order (or 2-dimensional) Monte Carlo simulation is needed (Cullen and Frey, 1999). It simply consists in two Monte Carlo loops, one nested inside the other. The inner one deals with the variability of the input variables, while the outer one deals with uncertainty.

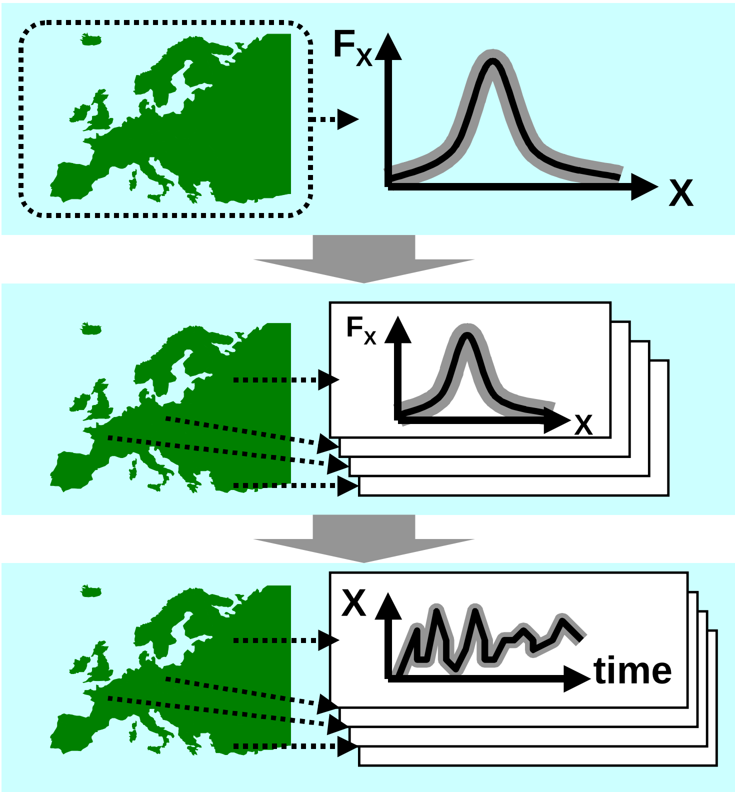

Figure 1: Sequence of environmental modelling frameworks, where each time, a component of the variability (spatial and temporal) of an environmental variable X is explicitly considered and refined (top: probabilistic, middle: geo-referenced, bottom: dynamic/temporal)

GEO-REFERENCED PROBABILISTIC ENVIRONMENTAL MODELLING

Incorporating spatial characteristics of the environmental variables (GIS: geographical information systems) in the models can further increase realism. By geo-referencing the environmental assessment, the spatial variability is explicitly accounted for and as a result the remaining overall variability of the results can be reduced (see Figure 1 middle). In such studies, a second order Monte Carlo analysis

would now only propagate uncertainty, temporal and other variability but not spatial variability as the Monte Carlo analysis is performed at each spatial unit.
Examples are given in Verdonck et al. (1999) and Matamoros et al. (2001) on exposure modelling of respectively point and non-point sources of individual chemicals. Both examples use mathematical models combined with GIS. Geo-referenced exposure modelling appears to be more accurate compared to the deterministic approach but have the disadvantage of having a higher need for data.

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The temporal variability in an environmental analysis can be amounted for means of a dynamic modelling approach. The resulting outputs of such models are timeseries (with uncertainty bands) instead of probability distributions (with uncertainty bands) at every spatial location (see Figure 1 bottom). In such studies, a second order Monte Carlo analysis would now only propagate uncertainty and other types of variability but not spatial or temporal variability as the Monte Carlo analysis is performed at each spatial unit and at each time step.
As an illustration, Deksissa and Vanrolleghem (2001) used a dynamic conceptual hydraulic models and first order kinetics in combination with a simple one-dimensional dynamic exposure model in three environmental compartments (air, water and benthic-sediment) to assess the short-term fate of a detergent chemical in the river environment. In this model, both flow and chemical emission vary in time only longitudinally along the river stretch (without uncertainty).
In Vandenberghe et al. (in press), optimal experimental design is applied on a dynamical river water quality model. By reducing the uncertainty on the input parameters of the model, smaller uncertainty bounds around the model results (time series of dissolved oxygen) are obtained.

CONCLUSIONS

Several tiers of environmental modelling techniques were presented. Probabilistic techniques account for the uncertainty and spatial and temporal variability. Georeferencing refines the spatial variability. Dynamic simulations refine the temporal variability. Unfortunately, availability of data is often the limiting factor to use these advanced approaches. However, they improve transparency, credibility, it focuses data collection, it avoids worst-case assumptions and thus, it may improve decision support.

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