International Environmental Modelling and Software Society (iEMSs)
2010 International Congress on Environmental Modelling and Software
Modelling for Environment's Sake, Fifth Biennial Meeting, Ottawa, Canada
David A. Swayne, Wanhong Yang, A. A. Voinov, A. Rizzoli, T. Filatova (Eds.)
http://www.iemss.org/iemss2010/index.php?n=Main.Proceedings

Complexity Reduction in Environmental Models Using Cascading Simulation Framework

Marina G. Erechtchoukova[1] **and Peter A. Khaiter**[1]

[1]*York University, Toronto, Canada (marina/pkhaiter@yorku.ca)*

Environmental decision making requires data about current status of the environment and possible environmental states after anthropogenic impact. Environmental models are aimed to produce the results which complement observations on environmental indicators when the latter cannot be obtained directly, e.g. missing observations or predictions. One of the approaches to environmental modeling rests on process-based models. Environmental indicators relevant to an investigated case study are selected and their spatial and/or temporal dynamics is imitated by describing natural processes affecting the indicators based on mathematical formulae. The set of indicators determines the number of model state variables and processes which must be taken into account. The processes which significantly contribute to indicators' variability are included into a model using balance equations. It may call for additional processes to be added to the model and each process to be described by a particular mathematical term. Alternatively, several natural processes can be described by one aggregated term.

It might seem that the more processes are taken into account and included into the model, the better simulation results describe the reality, i.e. the more precise the model is. At the same time, an increasing level of details leads to a more complex model. Usually, additional processes increase the number of model state variables and parameters which both traditionally characterize model complexity. The role of complex models has received due attention in modern literature (e.g., Scheffer & Beets, 1994; Reichert & Omlin, 1997; Van Ness & Scheffer, 2005). While benefits and disadvantages of complex and simple models are elaborated, the verge between these two groups is not delineated.

Model complexity is considered based on an intuitive definition which attributes it to a large number of state variables, natural processes affecting these variables and, hence, a huge number of model parameters to be identified. With this respect, the concept of model complexity requires a formal definition, and the index of complexity, perhaps, deserves further elaboration.

An attempt to formalize the concept of model complexity was made by Snowling & Kramer (2001) where the complexity index was introduced. The index was aimed to reflect the model structure and the level of details in the description of processes included into the model and was evaluated based on the Peterson matrix. The index counts the number of parameters and number of arithmetic operations for each term of the model and for the entire model. The index can be used to compare models with different mathematical expressions. Unfortunately, the complexity index does not reflect the type of mathematical terms used in the model, since both linear and non-linear terms can be described by the same score, whereas non-linear models should be considered as more complex than linear ones.

When an environmental model is built based on mass-balance differential equations, the same natural processes can be described by either linear or non-linear terms. For such models, non-linearity introduces additional stationary points of equilibrium which change the stability portrait of the model solutions affecting and their dynamic behavior. That is why, a simple replacement of non-linear terms for certain processes by their linear approximation can be done for applications in which simulations actually interpolate values of state variables. However, such substitution may not be valid for long term predictions where complex interactions of processes create notable effects on investigated state variables. Likewise, reactions of an investigated system to various perturbations cannot be fully described by only linear approximation of a model when interactions are imitated by non-linear terms.

In the latter case, the reduction of model complexity can be done by employing a well-known cascading simulation framework (e.g. Ambrose et al., 1993). A model with a large number of state variables can be split into blocks. Each block contains processes significantly affecting a part of model state variables. Blocks can be formed according to the nature of the processes involved.

The approach to the building a model with reduced complexity will be considered in the paper. The model constructed based on a cascading simulation framework consists of a few blocks. Each block supplies values of its state variables as parameters for upper level blocks. In many cases, models contain a large number of state variables describing environmental indicators. All these variables are necessary for simulation, but only a few of them correspond to indicators interesting or important for a problem at hand, e.g., they are used to predict events, to compare their values with existing objectives or standards or to compute specific indicators. Other state variables play a secondary role. The interesting variables can identify the top block of the model producing results required for decision making process. The sensitivity analysis of the top block helps to distinguish between factors significantly affecting the block's state variables and those, whose effect can be described by aggregated values. For important factors, another block supplying input data for the top block should be constructed and analyzed. The analysis will indicate whether another block is required or not. The equations in each block can be non-linear. Since each block contains sufficiently lesser number of state variables and actually global analysis is replaced by its local versions, the proposed scheme significantly reduces computational cost. Application of the framework will be illustrated by a case study on water quality simulation.

REFERENCES

Ambrose, R.B., T.A. Wool, J.L. Martin, 1993. The Water Quality Analysis Simulation Program, WASP5. Part A: Model documentation. USEPA ERL, Athens, GA 30613.

Reichert, P., and M. Omlin, 1997. On the usefulness of overparameterized ecological models. Ecological Modelling, 95: 289-299.

Scheffer, M. and J. Beets, 1994. Ecological models and pitfalls of causality. Hydrobiologia, 275/276: 115-124.

Snowling, S.D. and J.R. Kramer, 2001. Evaluating modeling uncertainty for model selection. Ecological Modelling, 138: 17-30.

Van Ness, E.H. and M. Scheffer, 2005. A strategy to improve the contribution of complex simulation models to ecological theory. Ecological Modelling, 185: 153-164.