Adjusting the complexity level of groundwater models

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Key words: groundwater modeling, complexity level, optimization

Introduction

Numerical models are now commonly used to optimize pumping strategies of well fields, define legal frameworks of water resources development, or investigating the resilience of groundwater resources to global change. In these applications, models are of interest for their predictive potential to address current environmental challenges such as: What is the best pumping strategy to reduce water contamination and pumping costs? How much will river baseflow be affected by a changing environment?

Model analysis methods aims at quantifying the uncertainty on model predictions and defining optimal strategies to reach an acceptable level of uncertainty. One of the reasons that leads to disregard this essential step is the computational burden associated with complex models [1]. A single model run may take several hours up to several days to be completed, even on currently available computational resources. In addition, large scale, physically-based models are highly parameterized so that dozens up to hundreds of thousand model runs are necessary to complete model analysis. Though critical, model analysis is often neglected for operational studies, which makes models poorly relevant [2]. To which extent should we sacrifice physical accuracy for a model to become robust and practical?

The trade-off between model complexity and practicality

The physics behind multiphase flow and transport of heat or dissolved species in heterogeneous geological medium is of an appalling complexity. This complexity is emphasized when accounting for the interactions between surface and subsurface processes. It is well known that no model will be able to account for each of these processes and interactions. Models are necessarily a simplified description of the reality. The choice of the complexity level is intrinsic to any modeling studies.

With the advent of massive computational capabilities and cloud computing, the temptation to push the cursor to more complexity arises. The debate regarding complexity evolves, but remains: though colossal, computational resources are finite and should be employed smartly. A discussion should be raised from the premises and along the course of model development so as to identify the processes that may, or may not, be explicitly simulated by the model. Excessive simplicity leads to inaccurate model, but irrelevant complexity increases the computational burden and impedes the use of advanced model analysis or optimization methods. In many circumstances, model complexity makes the model analysis impractical and the benefits of modeling becomes questionable.

Guidelines for adjusting the complexity cursor

Several studies advocated for the reduction of the number of model parameters so as to tend to a well-posed inverse problem and facilitate the convergence of parameter estimation algorithms [3]. Others argue that ill-posed problems may by addressed with various forms of regularization [4]. It seems hardly defensible to adjust
the level of complexity to the available data. Parsimonious models with well-constrained parameters are welcome but should not be obtained by means of “naïve” simplicity [5].

In numerous cases, simplifying hypothesis may dramatically reduce the computational burden without degrading the accuracy of model predictions. Groundwater recharge may be simulated with a conceptual model rather than with variably-saturated flow. The reduction of model dimensionality may dramatically reduce the computational burden and solutions exist to consider 3D flow within 2D models [6], particularly at the stream-aquifer interface [7]. It may also be advantageous to consider transient behaviors as a succession of steady states [8].

Rather than considering the model as faithful description of a complex reality, prediction-based model development aims at focusing on the complexity that actually matters for the model outputs of interest [9]. In some contexts, the actual output of interest may not be obtained with practical models. An alternative is to find other variables that may be considered as indicators or proxies for the variable of initial interest. An example is the use of mixing ratios instead of contaminant concentrations [10].

These efforts may yet remain insufficient when complex processes are of critical importance for the forecast of interest. This should not be a reason to circumvent parameter estimation and disregard uncertainty analysis. When complexity cannot be avoided, surrogate models may be employed [11] [12] and the use frugal analysis method should be considered [13].

The approach will be illustrated with practical case-studies: a well-field model vulnerable to a contaminated stream and a regional-scale groundwater model. These examples will highlight the benefits of choosing the relevant level of model complexity.

References