# Metrics for Environmental Simulation in Decision Support

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Our understanding of hydraulic processes allows us to develop complex numerical models that purport to simulate the details of water and solute movement in natural systems. We presume to know the partial differential equations that govern these processes. But do these equations apply at the scale at which environmental management must take place? Conversely, while we can measure the properties of the surface/subsurface at the small scale at which these equations apply, can we upscale these properties to the management scale?

While management of our environment will continue to rely on our awkward attempts to simulate natural processes, it should not rest on an assumption that we simulate these processes correctly. Rather, simulation should be viewed as one component of a more complex numerical enterprise. The premise of this enterprise must be that predictions of the future behaviour of managed natural systems (especially subsurface systems) are uncertain. Management therefore involves risks. However it may be possible to reduce the uncertainties of decision-critical predictions through assimilation of expert knowledge as it pertains to a particular site, and of historical measurements of system states and fluxes that have been made at that site. Model-based processing of all of this information may therefore reduce the risks associated with environmental management. Achievement of this outcome constitutes a return on the investments made in acquiring this information.

For numerical simulation to serve the decision-making process most effectively, its deployment must reflect its role in that process. This role is to provide receptacles for information that can reduce the uncertainties of decision-critical model predictions. In playing this role, it must be used in partnership with equally sophisticated numerical software that facilitates passage of information to the receptacles that it provides, and that can quantify the post-assimilation uncertainties of its predictions. Furthermore, design and deployment of numerical models must be tailored for use with this kind of software, at the same time as it must acknowledge the fact that a simulator must be run hundreds, maybe thousands, of times under the control of this software. This requires that a numerical simulator be numerically stable, and that its run times be reasonably short. Unfortunately, these requirements may hamper its ability to apply differential equations at the scale to which these equations apply. Errors incurred through loss of this ability may contribute to the uncertainties of some of its predictions. However these errors may be small compared to the reductions in predictive uncertainty that may be accrued through use of an appropriately-designed, fast running and numerically stable approximate simulator in conjunction with partnered data assimilation and uncertainty quantification software.
It is apparent that modelling for decision-support requires compromises. It also requires a mindset that understands the necessity for these compromises, and that can assess the costs and benefits of these compromises. More than this, it requires the development of a modelling culture that is united by common metrics for decision-support modelling against which the costs and benefits of different approaches can be assessed. While faithfulness to the differential equations that purportedly describe a natural system may be desirable and useful in some circumstances, this cannot be the metric which defines this new culture. It can only be the premise that the uncertainties of decision-critical model predictions be quantified, and that, through assimilation of pertinent data, these uncertainties be reduced to levels that allow stakeholders to know the risks associated with a particular choice of management action.

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