Supplemental Comments on Model Uncertainty

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Background

The Eastern Snake Hydrologic Modeling Committee (ESHMC or "Committee") has been investigating the matter of uncertainty in the Eastern Snake Plain Aquifer Model (ESPAM or "Model"). This investigation stems from goals identified by the Committee in 2007, from findings made by Hearing Officer Schroeder in 2008, and from questions asked by IDWR Director Tuthill in 2009. Interim Director Spackman has more recently solicited input on the topic.

A previous White Paper on Model Uncertainty was assembled in 2009 from contributions by various Committee members and by IDWR staff. I provided two contributions to this earlier effort: "Comments on Model Uncertainty" dated January 2009, and "Comments on Trimline and Model Uncertainty" dated July 2009. At its December, 2011, meeting, the Committee agreed to update the 2009 White Paper.

The comments herein are my contribution to this update. I have tried to avoid repetition of my previous contributions, though some of this is inevitable.

Some Definitions and Distinctions

There is no universally applicable definition of uncertainty in the field of environmental modeling (of which groundwater modeling is a subset). Where modeling is used to support regulatory decision-making, uncertainty can be viewed as a property of the information upon which a decision is based or as a manifestation of the confidence that the decision-maker has in that information (Refsgaard, et. al., 2007). The present discussion of ESPAM uncertainty is focused on the former, though arguably the latter is the more important for policymaking.

Uncertainty can be classified as *reducible* or *irreducible* (Matott, et. al., 2009). Reducible uncertainty can, at least theoretically, be diminished by further efforts at data acquisition, refinement of model structure, more extensive calibration, etc. Irreducible uncertainty, such as that associated with prediction of future outcomes, cannot be so diminished because we simply cannot know the future state of all the factors and forces reflected in the model. The present discussion of ESPAM uncertainty focuses on the former, though the latter is inevitably present.

Uncertainty is often thought of in terms of *accuracy* and *precision*. Accuracy is the degree to which a measurement or model result reflects the "true" value or nature of the underlying parameter or process. In practice, many of the effects we seek to represent with ESPAM cannot be measured directly, so the model's ability to accurately simulate them is inherently uncertain.

Precision is the degree to which a procedure can repeatedly achieve the same result given the same inputs. Since the groundwater model is a deterministic model, it is, in this sense, perfectly precise. The term precision often is also used to describe the level of detail with which a model result can be expressed. Because the model code carries out computations to many decimal places, it is possible to display model results using far greater precision than is present in the underlying spatial and temporal data used as model input.

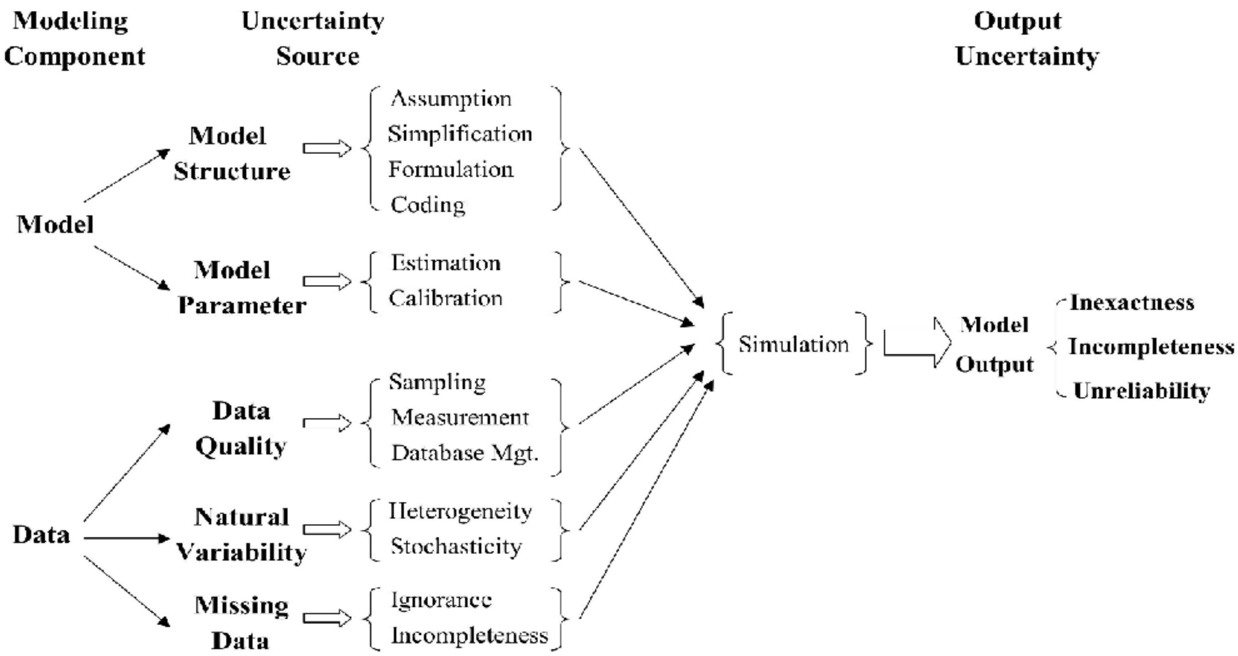
This data precision issue is related to the concept of *scale*. The model is populated with data that is collected and represented at various spatial and temporal scales, many of the different from the scales represented in the model. For example, precipitation is measured daily (or at even shorter durations) at a handful of specific locations, while modeling the aquifer requires estimates of monthly precipitation everywhere on the Plain. Aquifer transmissivity is assumed to be constant throughout a model cell, though fractures and interfaces may significantly affect individual water level observations and spring flows. The spatial and temporal resolution of input data and parameters must be considered in evaluating confidence in model results.

Sources of Model Uncertainty

As highlighted in my earlier submittals, model uncertainty arises from a number of sources. Most generally these can be lumped as pertaining to the model (structure and parameters) and to the data used in the model. The figure on the following page depicts where uncertainties arise and how they flow through to modeling results.

Uncertainty related to model structure (sometimes referred to as conceptual uncertainty) is seldom evaluated. It is costly and time-consuming to do so, and it is difficult to ascertain whether the set of plausible models has been fully explored (Refsgaard, et.al., 2007). In the vast majority of cases, this dimension of model uncertainty is ignored in favor of optimizing a chosen model structure (Neuman and Weirenga, 2003).

In the case of the ESPA, the chosen model structure is that of a single-layered, homogeneous, isotropic porous medium. While this may be adequate for regional-scale analyses, it does not represent the governing equations of fracture or conduit flow which may dominate site-specific phenomena, such as flows from particular spring outlets.



Source: Li and Wu, 2006.

Model parameterization is also a source of uncertainty. The model structure dictates the structure of the parameters, and initial parameter estimates are adjusted through a process of history-matching ("calibration") that tries to minimize the difference between model results and historical observations. Increased computing power has permitted the use of more parameters, which can often lead to better calibration (Hunt and Doherty, 2007). However, increased parameterization brings increased risk that the calibrated parameter set is non-unique (Doherty and Johnston, 2003), that is, that other combinations of parameters will result in similarly acceptable matches to historical observations.

That the risk of non-unique calibration solutions is endemic to modeling is well established (e.g., Konikow and Bredehoeft, 1992; Beven, 2006). Furthermore, if model structure is not a separate subject of uncertainty evaluation, the calibration process may conflate error in both model structure and parameterization in achieving an acceptable match (Beven, 2006). It is not sufficient that a model work well, it must "…work well for the right reasons" (Klemes, 1986).

The ESPAM can be considered moderately to highly parameterized. In addition to transmissivity and storativity terms, calibrated parameters include streambed and drain conductances, drain elevations, and a host of factors influencing the aquifer water budget. This has led to a relatively well-calibrated model. The use of multiple calibration targets has probably reduced, though it has not eliminated, the risk that parameter solutions are non-unique.

Uncertainty is also introduced via the data used in the model. Data quality issues can include sample bias and measurement error, error stemming from interpolation and extrapolation to derive intermediate or missing data points, and use of data collected at different spatial and temporal scales than that required by modeling (Li and Wu, 2006). While considerable care has been taken with data gathering for the ESPAM, many important input data sets reflect rough estimates rather than measurements (e.g., tributary underflows) and reflect extrapolation from coarse spatial and temporal scales to the relatively fine scale of the model (e.g., crop distribution data is collected only at a county level, yet the county average is assumed to be valid for every irrigated cell in the county).

Data uncertainty also stems from natural variability. This is related to the concepts of irreducible uncertainty and of scale discussed at the outset of these comments.

Overall model uncertainty is a function of all of these. Model uncertainty may be different for different scenarios depending, for example, on how well the model represents aquifer hydrogeology in different locations or how different the water budget terms (e.g., aquifer stresses) are between scenarios. It is also likely that uncertainty increases with the level of detail being sought. This stems in part from the issue of scale discussed previously, and suggests that less confidence be placed in more detailed predictions.

Evaluating Uncertainty

Because it arises from so many sources, rigorous exploration of uncertainty in groundwater modeling is extremely difficult. Even with a costly and time-consuming effort, only a portion of model uncertainty will be illuminated.

Approaches for comprehensive uncertainty evaluation have been proposed (e.g., Pappenberger and Beven, 2006; Refsgarrd, et. al., 2007). However, conventional practice usually adopts a much more limited scope (Neuman and Weirenga, 2003). Post-audits of model performance have been recommended (Anderson, 1992) as a means of assessing model validity, with mixed results (Konikow, 1986).

The uncertainty evaluation being carried out for the ESPAM is termed a "predictive uncertainty analysis." It focuses primarily on the degree to which relatively constrained changes in parameter values will alter key model predictions. Model and parameter structure are assumed fixed, as are many data inputs. This approach is valuable in illuminating those parameters for which further investigation could reduce the uncertainty of the chosen model (James, et. al., 2009), but does not address larger questions of model uncertainty described above.

More exhaustive evaluation approaches, such as Monte Carlo simulation, may shed greater light on the probability distributions of model errors. However, unless such approaches address all the dimensions of model uncertainty they too will be incomplete.

Conclusions

The Committee, IWRRI and IDWR have made significant effort to develop the ESPAM in a transparent and objective way. There have been many instances in which collaborative thought and deeper investigation have led to significant model improvements. However, the development process has been inevitably constrained by time and available resources. Even with such resources it is not likely to be possible to fully explore and quantify model uncertainty, and not possible to unambiguously derive policy from such a quantification. The use of the ESPAM in policymaking and administration will always require exercise of discretion and judgment by decision-makers.

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