Equifinality and Disaggregating Sources of Error in Uncertainty Estimation: an Extended GLUE methodology

Keith Beven, Jim Freer and friends
Lancaster University, Lancaster, LA1 4YQ, UK

A Brief Summary of The Equifinality Thesis

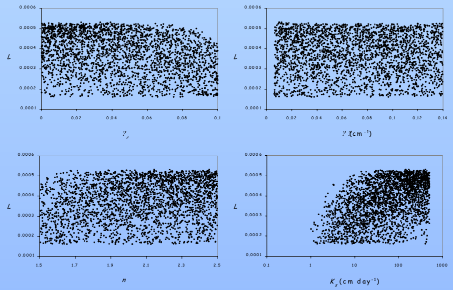
•The aim of science as a single true description of reality is difficult to achieve in applications to places that are all **unique** and where (nonlinear) predictions are subject to input errors, evaluation errors, and model structural errors

•There may instead be many descriptions that are compatible with current understanding and available observations

•The concept of the single description may remain a philosophical axiom or theoretical aim but is impossible to achieve in practice

•So we must accept that there may be many feasible descriptions, or a concept of **equifinality**, as the basis for a new approach

Equifinality as an Empirical Result



Fitting van Genuchten parameters in modelling recharge
after Binley and Beven, Groundwater, 2003

Generalised Likelihood Uncertainty Estimation (GLUE)

•Take a (large) random sample of models (structures and parameter sets)

•Evaluate performance using one or more measures

•Reject those that do not provide acceptable performance

•Retain remaining *behavioural* models in prediction

•Weight predictions according to performance to form CDF of predicted variables

Note 1: it is the parameter <u>set</u> in combination with the given input and boundary condition data that gives a behavioural model - complex parameter interactions may mean that marginal distributions and global covariances have little relevance

Note 2: implicit treatment of complex errors in likelihood weighting of simulations (effectively assuming that prediction errors for any behavioural model in prediction will be “similar” to conditioning periods)

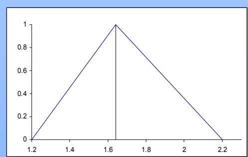
Note 3: prediction limits are conditional on choices

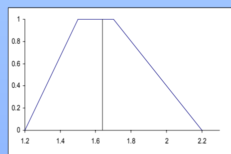
Note 4: depends on having sufficient sample to find upper limit of performance

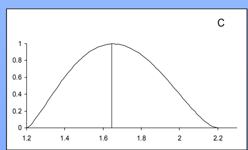
An Extended GLUE methodology

- Should not use input and observation data as if it were error free
- Available variables <u>may not be those required by the model</u> because of scale or incommensurability effects (even if they have the same *name*)
- Should therefore try to evaluate “effective observational error” or “acceptable observation error” <u>independently of the model runs</u> (though may not be independent of the model *implementation* e.g. grid scale, type of boundary condition etc.)
- Insist on a model providing predictions within range of error in evaluation variables
- Models providing predictions outside range are rejected as non-behavioural
- Correlation in error handled implicitly in this way
- Success may depend on allowing realisations of error in input and boundary condition data
- But retains the possibility that all models may be rejected

Bounded measures for representing acceptable Effective Observational Errors







A. Triangular, with peak at recorded value

B. Trapezoidal, allowing for some true measurement error

C. Beta function

Predictive distribution over all behavioural models: information in quantile deviations