Geophysical Research Abstracts
Vol. 14, EGU2012-10597, 2012
EGU General Assembly 2012

An OSSE Approach to Evaluating the Utility of Data Assimilation

G. Nearing and H. Gupta
United States (grey@email.arizona.edu)

We demonstrate a novel, quantitative observing system simulation experiment (OSSE; Arnold and Dey, 1986) approach to evaluating the utility and assumptions of data assimilation. The approach employs an information-theoretic metric to quantify uncertainty reduction due to exact probabilistic data assimilation under ideal conditions (all assumptions valid) given a stochastic emulator of a physics simulation model and a particular uncertainty scenario; that is, we provide a theoretical upper bound on the utility of data assimilation without presupposing any particular assimilation algorithm. This improves standard OSSE approaches by providing an objective and quantitative partitioning of effects on assimilation results due to observation uncertainty and assimilation algorithm assumptions. The approach also provides a performance baseline and a framework for comparing algorithms and assumptions.

Assuming a discrete-time deterministic hidden Markov simulator with states (X), outputs (Y), and structure (M), typical data assimilation approaches seek to improve estimates of X under uncertainty in M (and possibly some system inputs, which we shall ignore without loss of generality) given observations of output (Z) (Liu and Gupta, 2007). The conditional entropy of simulator state is expressed as H(X|R) where R is the collection of emulator state vectors lagged by one time step, and after probabilistic data assimilation, the conditional entropy of the simulator state will be H(X|Z,R). The expected decrease in entropy from a perfect filter is the difference α = H(X|R) - H(X|Z,R). It is not necessary to perform data assimilation to compute α. This metric provides an upper limit on the expected reduction in uncertainty resulting from the application of any type of probabilistic data assimilation and thus represents a benchmark against which algorithms and assumptions can be tested. The key benefit of this metric is that it can be used to delineate inefficiencies in algorithms from inefficiencies due to epistemic modeling uncertainty.

This OSSE approach is demonstrated using a Lorenz attractor with uncertainty in M: parameters and perturbations to the state-transition equations, and is used to compare four types of assimilation algorithms: parameter estimation, the ensemble Kalman filter, a Bayesian particle resampling filter, and a variational smoother. Results show that (i) the utilities of assimilation algorithms are highly dependent on the particular uncertainty scenario, and (ii) it is common, although not universal, for no assimilation strategy to reach the theoretical potential under a given uncertainty scenario. This method thus provides a way for choosing a problem-specific data assimilation approach.

Arnold, C.P., & Dey, C.H. (1986). Observing-systems simulation experiments - past, present, and future. Bulletin of the American Meteorological Society, 67.

Liu, Y.Q., & Gupta, H.V. (2007). Uncertainty in hydrologic modeling: Toward an integrated data assimilation framework. Water Resources Research, 43.