



A novel data-driven approach to model error estimation in Data Assimilation

Sahani Pathiraja (1), Hamid Moradkhani (2), Lucy Marshall (1), and Ashish Sharma (1)

(1) School of Civil and Environmental Engineering, University of New South Wales, Sydney, Australia (s.pathiraja@unsw.edu.au), (2) Department of Civil and Environmental Engineering, Portland State University, Oregon, United States

Error characterisation is a fundamental component of Data Assimilation (DA) studies. Effectively describing model error statistics has been a challenging area, with many traditional methods requiring some level of subjectivity (for instance in defining the error covariance structure). Recent advances have focused on removing the need for tuning of error parameters, although there are still some outstanding issues. Many methods focus only on the first and second moments, and rely on assuming multivariate Gaussian statistics. We propose a non-parametric, data-driven framework to estimate the full distributional form of model error, ie. the transition density $p(x_t|x_{t-1})$. All sources of uncertainty associated with the model simulations are considered, without needing to assign error characteristics/devise stochastic perturbations for individual components of model uncertainty (eg. input, parameter and structural). A training period is used to derive the error distribution of observed variables, conditioned on (potentially hidden) states. Errors in hidden states are estimated from the conditional distribution of observed variables using non-linear optimization. The framework is discussed in detail, and an application to a hydrologic case study with hidden states for one-day ahead streamflow prediction is presented. Results demonstrate improved predictions and more realistic uncertainty bounds compared to a standard tuning approach.