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Constraining the Ensemble Kalman Filter for improved streamflow forecasting

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Data assimilation techniques such as the Kalman Filter and its variants are often applied to hydrological models with minimal state volume/capacity constraints. Flux constraints are rarely, if ever, applied. Consequently, model states can be adjusted beyond physically reasonable limits, compromising the integrity of model output. In this presentation, we investigate the effect of constraining the Ensemble Kalman Filter (EnKF) on forecast performance. An EnKF implementation with no constraints is compared to model output with no assimilation, followed by a 'typical' hydrological implementation (in which mass constraints are enforced to ensure non-negativity and capacity thresholds of model states are not exceeded), and then a more tightly constrained implementation where flux as well as mass constraints are imposed to limit the rate of water movement within a state. A three year period (2008-2010) with no significant data gaps and representative of the range of flows observed over the fuller 1976-2010 record was selected for analysis. Over this period, the standard implementation of the EnKF (no constraints) contained eight hydrological events where (multiple) physically inconsistent state adjustments were made. All were selected for analysis. Overall, neither the unconstrained nor the "typically" mass-constrained forecasts were significantly better than the non-filtered forecasts; in fact several were significantly degraded. Flux constraints (in conjunction with mass constraints) significantly improved the forecast performance of six events relative to all other implementations, while the remaining two events showed no significant difference in performance. We conclude that placing flux as well as mass constraints on the data assimilation framework encourages physically consistent state updating and results in more accurate and reliable forward predictions of streamflow for robust decision-making. We also experiment with the observation error, and find that this term can have a profound effect on filter performance. We note an interesting tension exists between specifying an error which reflects known uncertainties and errors in the measurement versus an error that allows "optimal" filter updating.