Geophysical Research Abstracts
Vol. 21, EGU2019-19095, 2019
EGU General Assembly 2019

Using calibration period ensembles of climate and flow data to optimize the characterization of hydrologic model prediction uncertainty

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Current modelling practice to account for calibration period climate uncertainty or flow measurement uncertainty relies upon relatively simple stochastic measurement error models that are often calibrated in conjunction with hydrologic model parameters. Continued advances in uncertainty-based model calibration to account for data uncertainty, either through formal Bayesian inference, Approximate Bayesian Computation (ABC), or informal approaches like the limits of acceptability approach in GLUE, require that such calibration approaches can be applied using more complex stochastic measurement error models that are developed independent of hydrologic model application. Two such recent examples are 1) the Newman et al. (2015) gridded ensemble historical precipitation and temperature data set for the continental United States and parts of Canada and the 2) the hydraulics-based Bayesian rating curve uncertainty estimation method (BaRatin) (Le Coz et al., 2014). In the first case, Newman et al. (2015) produce ensembles of historical climate ready for direct use in hydrologic modelling. In the second case, the BaRatin software enables modellers or gauge station technicians to ultimately produce hydraulically informed, ensemble-based uncertainty bounds on the measured streamflow hydrograph. We demonstrate for the first time using the ensembles from these products in model calibration. To do so we developed a new, efficient non-Bayesian calibration framework designed to efficiently characterize model prediction uncertainty due to model parameters, calibration period climate data uncertainty and calibration period measured streamflow uncertainty. A key aspect to the framework is that the model calibration is focused on optimizing the characterization of model prediction bounds (e.g., spread and reliability) rather than only residual-based error metrics like Nash Sutcliffe or hydrologic signatures. For climate forcing uncertainty, our framework treats the ensemble climate members as a prior and calibration yields a filtered or posterior climate ensemble. For streamflow measurement uncertainty, we consider the streamflow ensemble as irreducible aleatory uncertainty and hence do not attempt to derive a new posterior distribution of streamflow measurement errors.

Experiments are conducted across 20 Quebec, Canada watersheds using the GR4J model for demonstration. Validation period results show calibration period climate uncertainty is critical to account for even when a validation period climate ensemble is available to instead consider only validation period climate uncertainty. Model parameters are dependent on the climate ensemble member utilized to derive the model parameters. Model prediction bounds considering calibration period climate data uncertainty are only very slightly improved when BaRatin derived streamflow measurement errors are utilized but importantly, they do not degrade. Results motivate future research to investigate the use state-of-the-art ensemble-based data uncertainty characterization tools like the Newman et al (2015) dataset and BaRatin (Le Coz et al., 2014) for streamflow uncertainty within an ABC or formal Bayesian inference approach to calibrate hydrologic models.

References

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