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Quantifying Uncertainties in Spatially Distributed Hydrologic Models: Application to Flood Forecasting in New Zealand.

M. Clark (1), **R. Woods** (2), R. Ibbitt (2), J. Schmidt (2), and X. Zheng (2)
(1) University of Colorado, USA, (2) NIWA, New Zealand

Uncertainties in hydrologic predictions stem from uncertainties in model inputs, uncertainties in model parameters, and weaknesses in model structure. Model uncertainty has previously been quantified by using multiple models to produce multiple "equiprobable" simulations of streamflow. In this context different models are constructed by perturbing model parameters (e.g., saturated hydraulic conductivity), by changing the model components (e.g., methods to model infiltration of water into the soil), and by changing the model structure (e.g., methods for modeling sub-grid heterogeneity in soils/topography). Generation of multiple models is usually accomplished by randomising the parameters for a fixed model structure, although to be perfectly general both model components and whole model structures should be interchanged.

The use of brute force Monte Carlo (MC) methods to assess model uncertainty through parameter randomisation is flawed for three reasons: (1) it ignores interactions between the various sources of uncertainty; (2) it ignores the propagation of errors through the hydrologic model; and (3) there is no clear way to ensure that the differences among streamflow simulations from the selected models are a good proxy for model errors.

This presentation will summarize our recent efforts to quantify uncertainties in spatially distributed hydrologic models configured for basins in New Zealand. We will introduce new methods for quantifying errors in spatial estimates of precipitation, as well as methods for quantifying uncertainties in model parameters. For each model component we will describe how the typical challenges associated with parameter interactions, data errors, and incomplete process representations lead to the problems

of parameter identifiability, parameter uncertainty, and complete lack of realism of parameter values. We will then discuss how methods of error propagation, sequential calibration, state updating, and creative uses of new and existing data sources can improve not only model simulations but also the quantitative estimates of model uncertainty. Finally, we will discuss the applications of our methods, which include using the model error estimates for data assimilation and improving the representation of the total error (model +forecast) in operational flood forecasts.