Interdependance of Hydrological Model Parameters and Precipitation

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Introduction

Model calibration is a critical step in the development of any hydrological forecasting system. Model parameters are tuned to minimize some cost function that defines the fit between the model and the set of observations given a set of model inputs and boundary conditions. In traditional model calibration approaches the uncertainty in the model inputs and streamflow observations are not considered and the resulting model parameters should be considered as being conditioned to these particular sets of forcing variables. In a forecast, the model is often forced with output from a numerical weather prediction (NWP) model which may have different characteristics than the forcing data used to calibrate the model. This study presents results from an uncertainty and sensitivity analysis on 72 Canadian reference hydrometric basins (RHBN) using Mac-HBV.

Study Area & Data

Streamflow: Fig. 1 shows 72 RHBN watersheds that were unregulated with > 30 years of data and drainage areas between 100 km^2 and 5000 km^2.

IDW – Daily precipitation from the Global Historical Climatology Network[1] was interpolated to the centre of each watershed using Inverse Distance Weighting from the nearest 30 stations.

CanGRD – The Canadian Gridded Daily precipitation was produced using the ANUSPLIN method[2]. Daily precipitation and temperature were aggregated using Voronoi weighting from a resolution of 8 km. Temperature used for force MAC-HBV during cal/val was also from CanGRD.

CaPA – The Canadian Precipitation Analysis is produced by the Meteorological Service of Canada[3]. An optimal interpolation filter assimilates precipitation observations into the 6h NWP forecast at a resolution of 10 km every 6 hours. The 6 hr CaPA products were temporally and spatially aggregated using Voronoi weighting for each basin. The data were available continuously from 2002 to 30 June 2012.

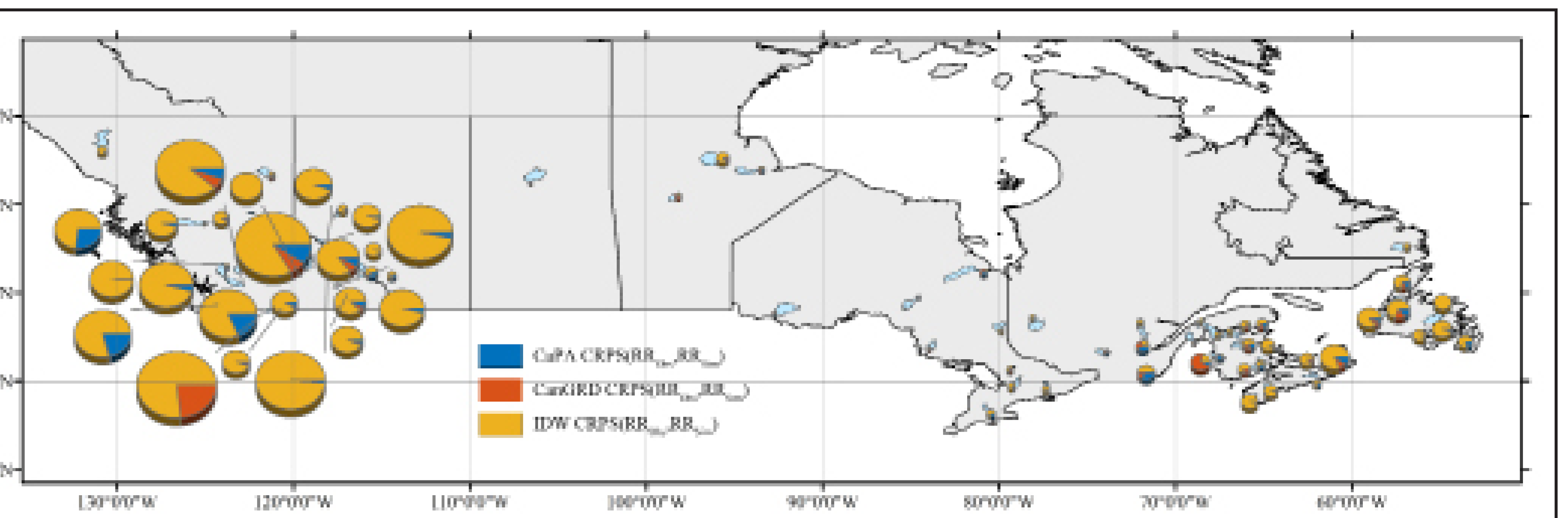


Figure 1: 72 RHBN watersheds with the CRPS of the runoff ratio (RR) of the respective precipitation and observed flows compared to MAC-HBV simulations. The size of the pie chart is proportional to the total CRPS for all three precipitation products. The inset shows a histogram of RR for each MAC-HBV parameter ensemble and the observed streamflow with the respective precipitation (solid line) at 04NA001.

Model

MAC-HBV: MAC-HBV is a non-linear variant of HBV[4].

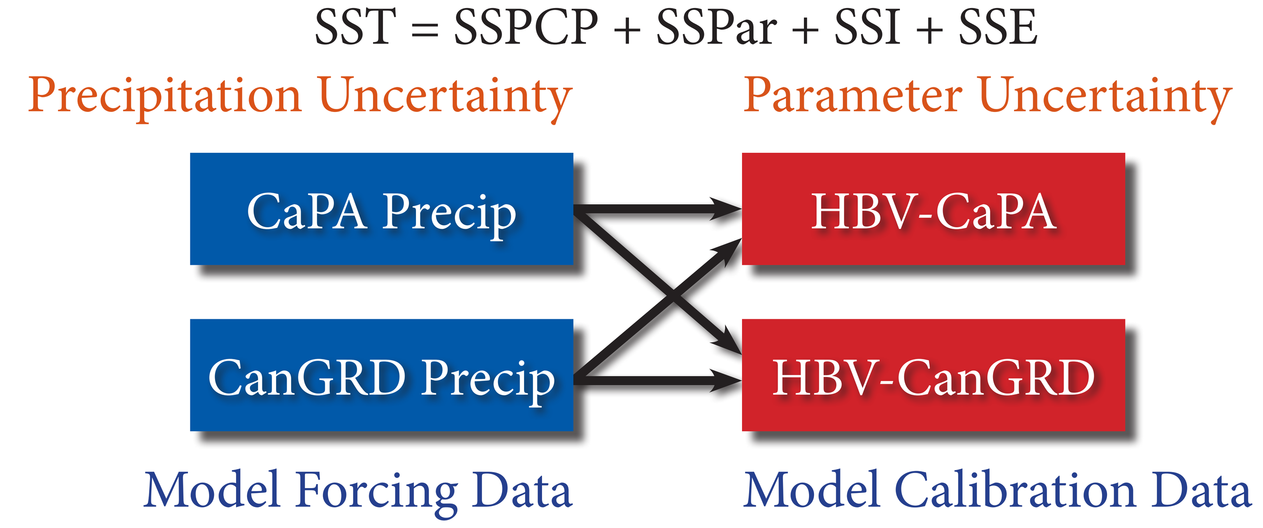
MT-DREAM$_{ZS}$: The Multi-Try DiffeRential Evolution Adaptive Metropolis with external archive (Z) and Snooker updating[5] is a Bayesian MCMC sampler used to calibrate MAC-HBV for each basin and precipitation type. The likelihood function of [6] was used and convergence confirmed after which 2500 parameter sets were randomly chosen from the second half of the converged chaing.

Model Setup: MAC-HBV was calibrated for the period 2002-2008 with 2002 dropped as spin-up. The model validation period was 1 Jan 2009-30 June 2012 due to the availability of CaPA. The model was re-calibrated with the respective precipitation data sets.

ANOVA Uncertainty Analysis

ANOVA was used to determine the relative contribution to total model uncertainty from precipitation forcing of either CaPA or CanGRD (SSPCP), the model parameters that resulted from calibrating the model using either forcing set (SSPar), the interactions between SSPCP and SSPar (SSI) as well as random model errors (SSE) where the total error is given by:

$$SST = SSPCP + SSPar + SSI + SSE$$



Low flows -> parameter uncertainty

High flows -> precipitation & parameter uncertainty

NSE -> interaction uncertainty

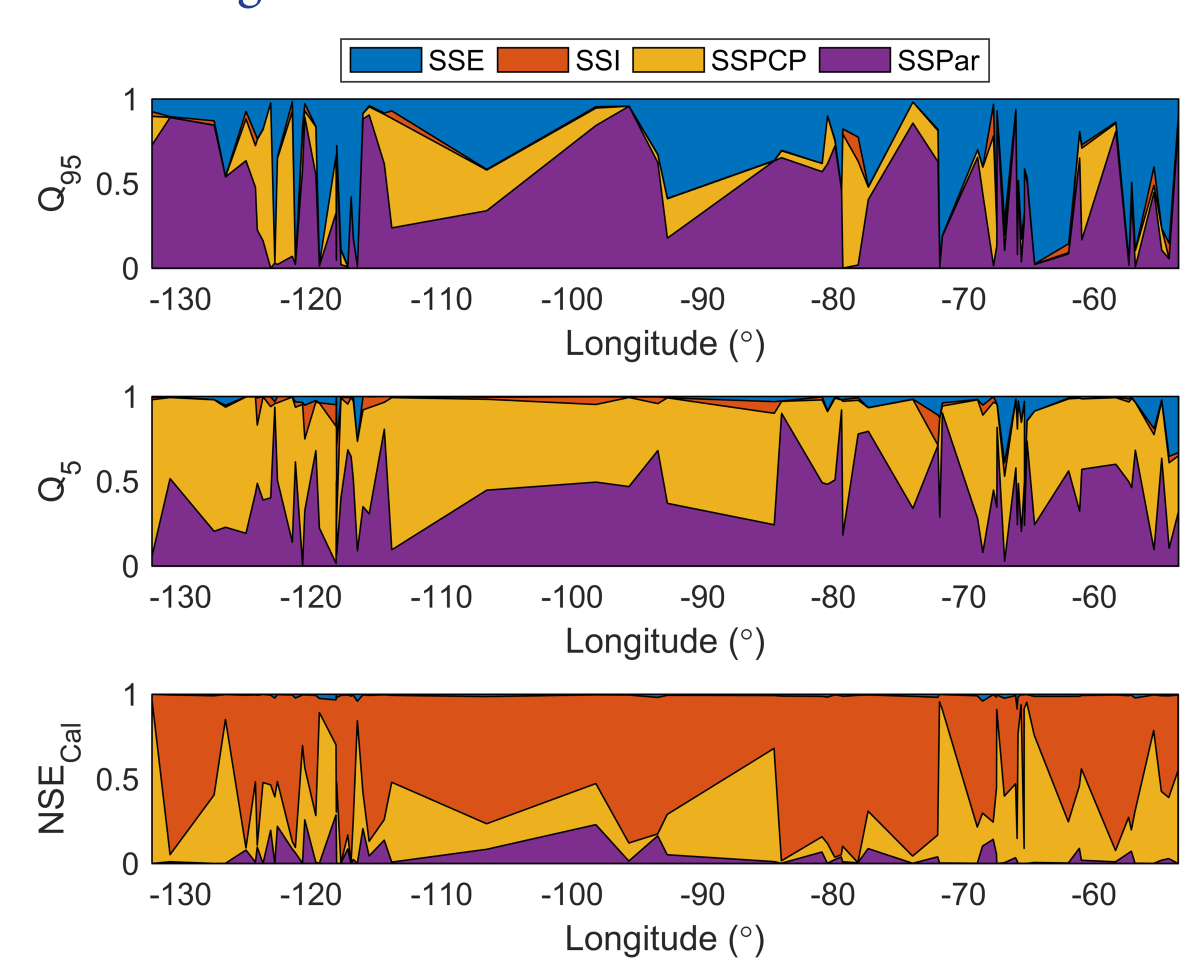
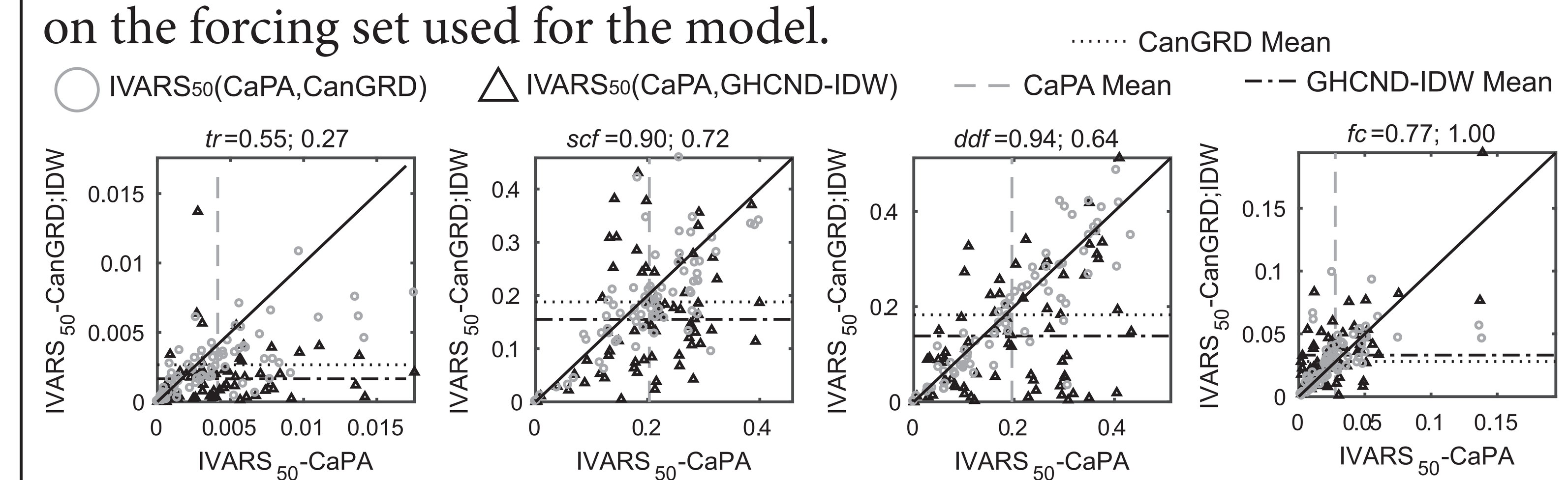


Figure 2: Relative source of total uncertainty (SST) for the 72 RHBN Basins.

Results show that parameters and their interaction with precipitation are a significant source of overall uncertainty which is generally equal to or greater than precipitation uncertainty.

VARS Sensitivity Analysis

The variogram of the response surface (VARS)[7] can be integrated across the maximum variogram sample range (50%) to give a global indication of model sensitivity (IVARS$_{50}$). A sensitivity analysis was conducted for each basin using each of the three precipitation products. The scatter plot in Fig. 3 shows a comparison of parameter sensitivity when either CaPA or CanGRD/GHCND-IDW were used to force the model. If precipitation products were not a contributing factor all points, representing an individual basin, would fall on the 1:1 line and have a high correlation. The results show that most parameters have a slope less than 1, meaning the model forced with CaPA is more sensitive and a correlation between 0.7 and 0.9 for R(CaPA,CanGRD) and lower when GHCND-IDW is used. This demonstrates that model parameter sensitivity, and therefore represented processes, was dependent on the forcing set used for the model.



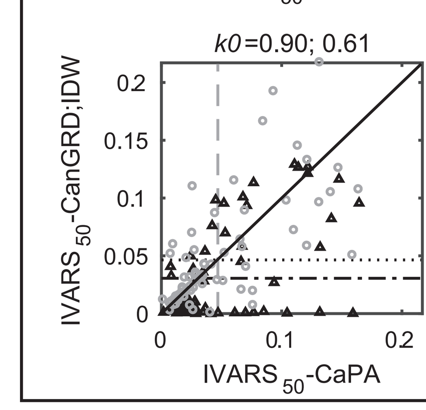


Figure 3: Sensitivity of select MAC-HBV parameters with each of the model forcing data sets. A slope greater or less than 1 indicates systematic dependence of parameter sensitivity to forcing data and the spread of the point cloud indicates the consistency of the relationships.

Conclusions

- Model response, sensitivity and uncertainty for the same time period varies notably based on the precipitation input used.
- Parameters were clearly found to compensate for the individual characteristics of the precipitation product used during model calibration.
- The interaction between model parameters and precipitation results in unique behavioural models that were not readily verified with external data.
- The experimental setup explicitly avoids non-stationarity as a reason for parameter uncertainty.
- The conceptual boundaries of a model should extend to include the characteristics of the precipitation used during calibration as this conditions model parameters.
- Model calibration should explicitly account for precipitation induced parameters uncertainty for extrapolation and forecasting applications.

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