Investigating the Relationship Between Precipitation and Model Parameter Distribution During Calibration: Initial Results from 72 Canadian Basins

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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 initial results from an analysis of 72 Canadian reference hydrometric basins (RHBN) modelled using MAC-HBV calibrated using three different precipitation products.

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.

GEM-GEPS – The GEM-NWP model was used to generate a re-forecast experiment of the Global Ensemble Prediction System where a forecast was initialized every 7 days and aggregated for the first 9 days of the forecast. At the start of each 7 day forecast a member was chosen at random and precipitation and temperature extracted for the 9 day forecast.

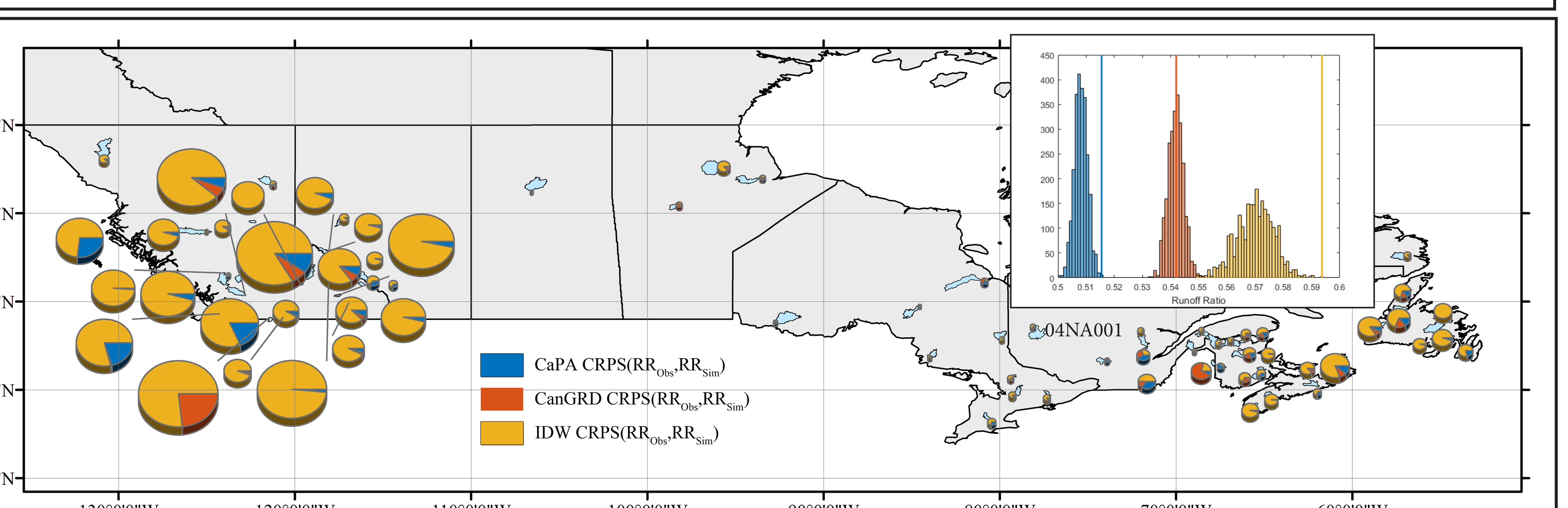


Figure 1: 72 RHBN watersheds with the CRPS of the runoff ratio (RR) of the respective precipitation and observed flows compared to MAC-HBV simulations. The size of the pie chart is proportional to the total CRPS for all three precipitation products. The inset shows a histogram of RR for each MAC-HBV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

Model & Methods

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[7] after which 2500 parameter sets were randomly chosen from the final distribution of 10000 parameters for each precipitation type.

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, except for GEM-GEPS forecasts. Since the GEM-GEPS forecasts were initialized once every 7 days the forecast skill of the model using GEM-GEPS was evaluated from 2003 (using 2002 as spin up) to June 2012. For each forecast the model was initialized with the respective precipitation products and associated parameter distributions. GEM-GEPS precipitation and temperature were then used for force MAC-HBV to produce a 9 day forecast.

CRPSS: The Continuous Ranked Probability Score integrates the difference between an ensemble simulation and the observation at a particular time. Its mean value can be normalized by a reference forecast, which is the 30 year daily streamflow climatology herein, to develop a skill score between -∞ and 1. A CRPSS of 0 has ensemble skill equal to climatology and 1 is a perfect simulation.

Results

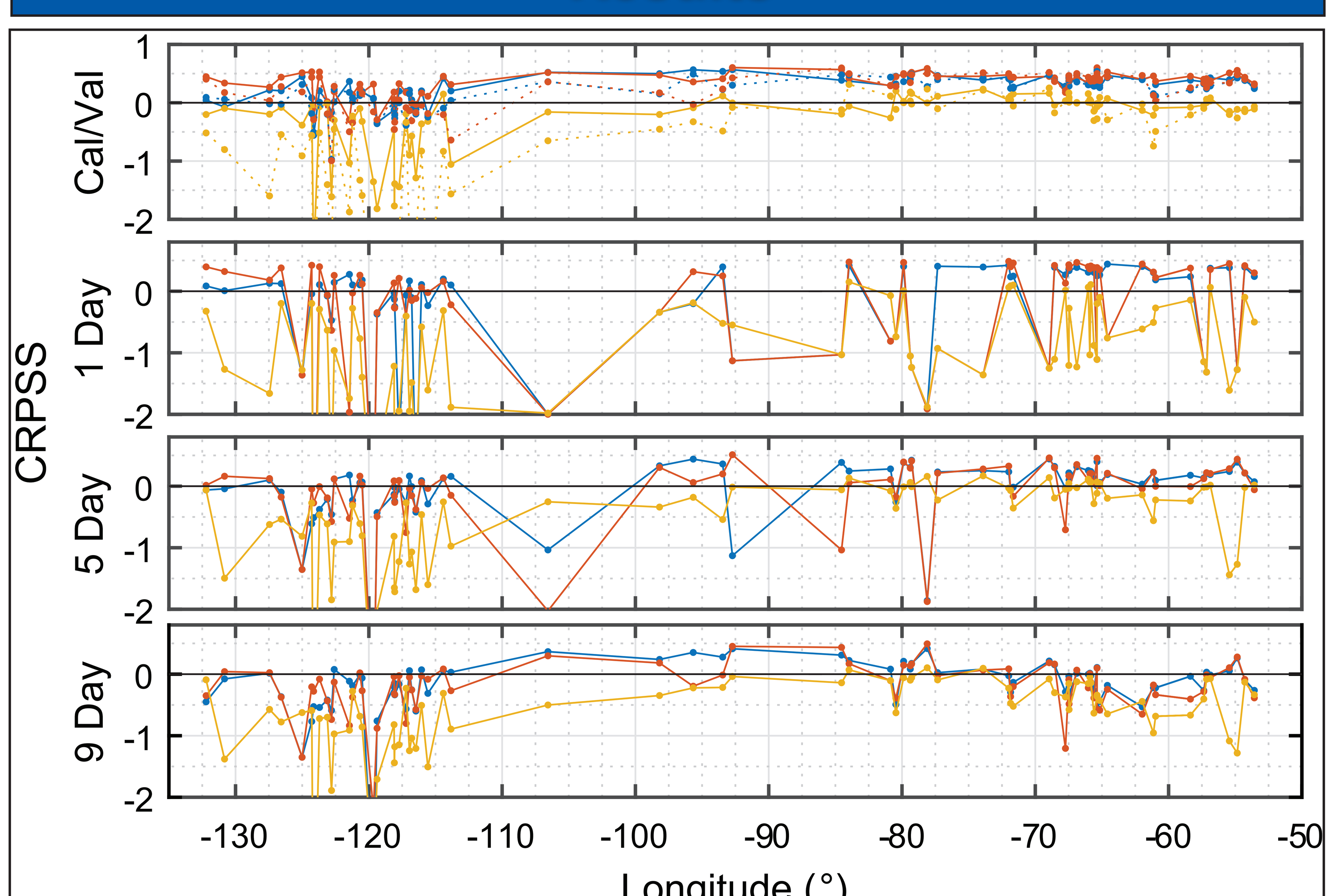
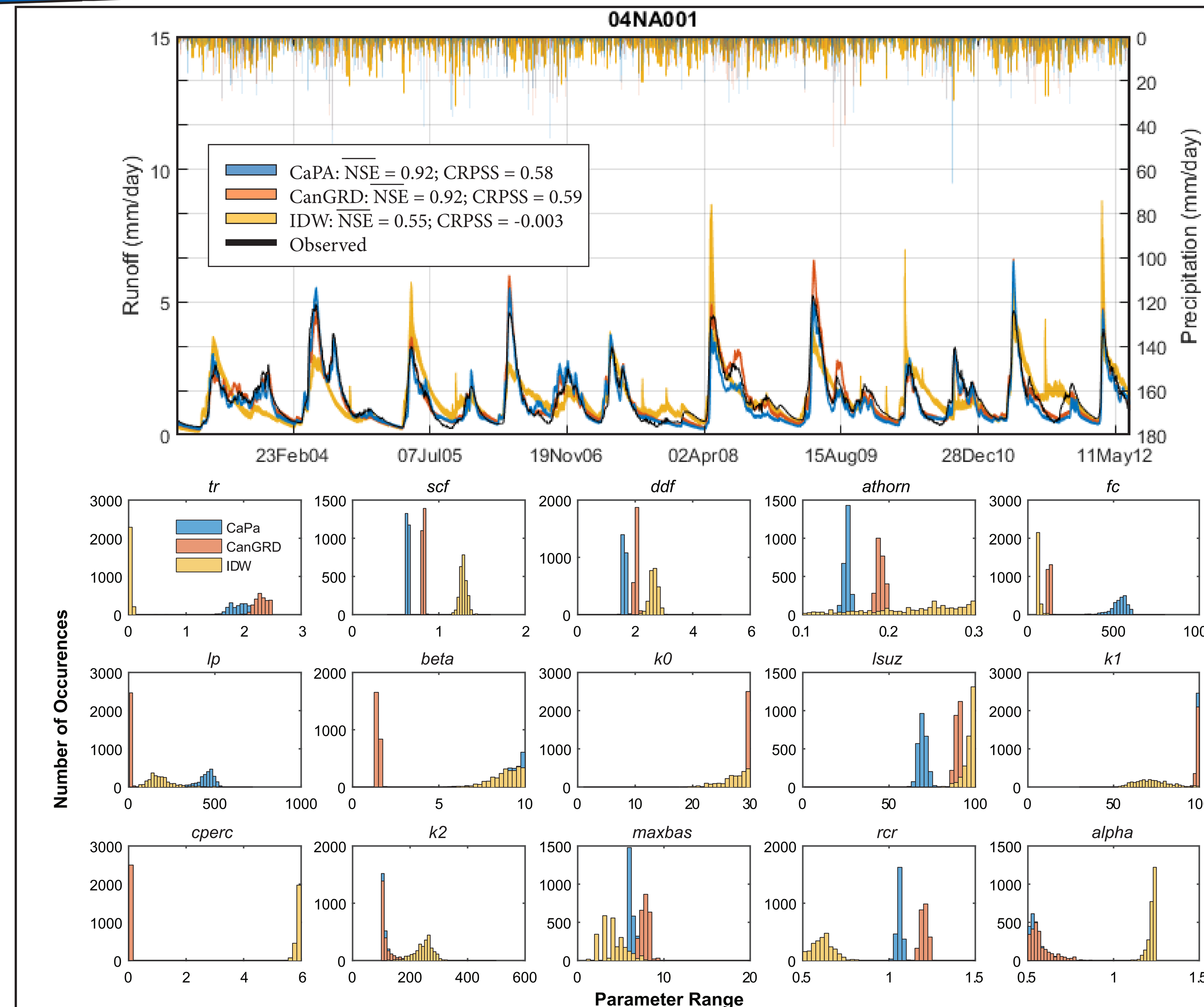


Figure 2: CRPSS of Cal(solid)/Val(dash) simulations (top) and 1, 5, and 9 day GEM-GEPS forecasts (solid) using parameters optimized with CaPA (blue), CanGRD (red) and IDW (gold). The horizontal black line represents the skill of a 30 year daily streamflow climatology.



tr: Rainfall threshold temperature
scf: Snow correction factor
ddf: Degree day factor
athorn: Modified Thornwaite coeff.
fc: Max soil moisture storage
lp: Soil moist. where AET=PET
beta: Contribution from precip to runoff
k0: Upper reservoir outflow parameter
lsuz: Upper reservoir storage threshold
k1: Upper reservoir outflow parameter
cperc: Percolation parameter
k2: Lower reservoir outflow parameter
maxbas: routing transform
rcr: Rainfall correction factor
alpha: Lower zone outflow parameter

Figure 3: Hydrograph for basin 04NA001 (Rivière Harricana) (top) of parameter ensemble simulated flows and their associated parameter distributions (bottom). The QR code and url links to a web map with all basin parameter distributions where marker colours refer to difference in CRPSS between CaPA and CanGRD (red < 0.01; 0.01 ≥ blue ≤0.05 ; green > 0.05).

http://arcg.is/1r0tgbf

Conclusions

- MAC-HBV calibrated with CanGRD outperforms CaPA in 53/72 basins, but produces lower quality forecasts in most basins using GEM-GEPS. This is possibly due to the shared model physics between GEM and CaPA.
- All models performed worse in western Canada, presumably due to the presence of the Rocky Mountains. This also influences the IDW preciptiation performance.
- Similar performance was achieved in many basins with both CaPA and CanGRD precipitation despite well defined differences in the parameter distrubtion and therefore model behaviour. Further work is required to define the impact of precipitation uncertainty on model equifinality.
- CaPA is generally wetter with more high precipitation events, resulting in model parameter distributions that favour quick basin responses.

References

1. Menne, M.J., I. Durre, R.S. Vose, B.E. Gleason, & T.G. Houston (2012) An overview of the Global Historical Climatology Network-Daily Database. *J. Atmos. Ocean Technol.* 29, 897-910.
2. Hutchinson, M.F., D.W. McKenney, K. Lawrence, J.H. Pedlar, R.F. Hopkinson, E. Milewska, & P. Papadopol (2009) Development and testing of Canada-Wide interpolated spatial modesl of daily minimum-maximum temperature and precipitation for 1961-2003. *Am. Met. Society (April)* 725-741.
3. Mahfouf, J.-F., B. Brasnett, & S. Gagnon (2007) A Canadian Precipitation Analysis (CaPA) project: Description and preliminary results. *Atmos. Ocean.* 45, 1-17.
4. Samuel, J., P. Coulibaly, & R.A. Metcalfe (2012) Identification of rainfall-runoff model for improved baseflow estimation in ungauged basins. *Hydrol. Process.* 26, 356-366.
5. Laloy, E. & J. Vrugt (2012) High-dimensional posterior exploration of hydrologic models using multiple-try DREAM(ZS) and high-performance computing. *Water Resour. Res.* 48, W01526
6. Thiemann, M., M. Trosset, H. Gupta, & S. Sorooshian (2001) Bayesian recursive parameter estimation for hydrologic models. *Water Resour. Res.* 37, 2521-2535.
7. Brooks, S.P., & R. Gelman (1998) General methods for monitoring convergence of iterative simulations. *J. Comput. Graph. Stat.* 7, 434-455.

Thanks to J. Vrugt for providing the DREAM Toolbox.