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Hydrology and Earth System Sciences Discussions

Interactive comment on "A trading-space-for-time approach to probabilistic continuous streamflow predictions in a changing climate" *by* R. Singh et al.

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Comment1. Page 6392, eq. (1): I am a bit confused by the formulation of the Bayes theorem. That's probably just because I am not used to see it written like that. The common formula is p(theta|data) = L(data|theta)*p0(theta) / (...), which expresses the gain of knowledge on parameters range (theta) after evidence has been observed (data). Now, S* is the signature predicted by the regional regression, i.e., the observed regional data. Is this the only information used in this paper to evaluate the posterior distribution of model parameters? In ungauged situations, that's the only data one has.

What about the gauged streams? In general, one would also use streamflow data to calibrate the model. Are the calibration-streamflow-data represented somehow in Eq. (1)?

Response1: Yes, in this particular study the only information used to constrain the response is the signature predicted from regional regression. The calibration-streamflow-data are not represented in Eq.(1). However, it is of course possible to use observed values of signatures, with assumptions about the measurement errors, in the same manner as described in Eq. (1). The recent paper by Wagener and Montanari (2011 in WRR) discusses the broader application of signatures in a Bayesian framework. While we limit the use to regional information on signatures in this paper, it does provide a generally applicable framework for both gauged and ungauged watersheds.

Comment2. Page 6394, lines 21-23: Maybe a brief comment would be useful here about the assumption of changes in the mean and not in the standard deviation (variability) of precipitation and temperature. If extremes were of interest (e.g., changes in floods), then changes in variability of the inputs would probably play a major role.

Response2: This is a good comment, which clarifies the applicability of our results in this particular study. The assumption of changes in mean and not in standard deviation will be included in the data section.

Comment3. Page 6397, lines 11-13: "Figure 3 shows that...". Just a suggestion: it is not very clear from Fig. 3 that C is closer than H to the observed points... Maybe another scatterplot would be useful here, "observed changes in streamflow" vs. "predicted changes in streamflow".

Response3: The observed variability in historical climate gave us only 20 points across 5 watersheds to compare Type C and Type H predictions. We feel that visual evaluation of the results (example in Figure 1) is not very effective. However, when the distances of the predictions based on Type C and Type H constraints, are calculated (see results in lines 13-18 on Page 6397), Type C predictions did show improvement over Type H predictions when the climate deviated significantly from historical periods.

Comment4. Page 6399, lines 18-29: is there any interpretation of why the uncertainty in predicted streamflow varies in the way showed in Fig. 4? Looking at the type C predictions, is there any reason why in wet catchments the uncertainty is more sensitive to changes in temperature than to changes in precipitation, while the opposite holds for dry catchments?

Response4: This is a good point for discussion. In general (and in our dataset) wet catchments are likely to be energy limited (PE/P<1) and dry catchments are likely to be moisture limited (PE/P>1). Therefore it is likely that changes to the limiting variable in these catchments will have a larger impact on the simulation than if the non-limiting variable is changed.

Comment5. Page 6399, lines 28-29: "The uncertainty is lowest in the dry catchments". This is a bit counterintuitive if one looks at Fig. 3, where greater prediction intervals are obtained for the drier catchments.

Response5: We agree that the way in which this issue appears is a bit misleading, it does, however, make sense nonetheless. There are two interacting issues at hand here. First, whether a watershed has been in a historically dry or wet climate. And second, whether the watershed's future climate is drier or wetter! If we look at Manuscript Figure 4, we find that for historically drier watersheds, higher uncertainty is observed if precipitation increases, which is the same result as shown in manuscript Figure 3. The decrease in uncertainty as seen for drier watersheds in Manuscript Figure 4 occurs only when precipitation decreases. All cases in which precipitation decreased from the historical or base period do show a decrease in uncertainty in Manuscript Figure 3 as well. Unfortunately, for the historically dry watersheds (Meramec and Yampa), we do not have validation points for the case of decreasing precipitation.

The statement made in the main text can therefore be improved as follows [Page 6399, lines 28-29]:

"Across both Type H and Type C predictions, uncertainty is lowest for the driest catchments if precipitation decreases and highest in the driest catchments if precipitation increases."

Comment6. Page 6400, line 10: I would not discuss floods here because the graph relates to monthly values.

Response6: The discussion on floods will be removed.

Comment7. Page 6404, line 8: the fact that "uniform random sampling" of parameters was used is mentioned here for the first time. It would be better to discuss it before, e.g., in the method section.

Response7: The use of uniform random sampling will be mentioned in the methods section.

Comment8. Page 6404, Conclusions section: In the sensitivity analysis, the changes in the inputs are assumed certain and the output changes are derived with uncertainty related to model parameters. Changes in the inputs, precipitation and temperature, are also uncertain. Would it be possible, through the procedure discussed in this paper, to propagate uncertainties in the inputs to the output? One comment on this issue could be proper in the conclusion section.

Response8: Yes, the next stage of our research will integrate input uncertainty in our framework. We presented some initial results on how to assess uncertainty in the downscaling of climate change scenarios in a companion paper by Ning et al. (in press). Ning et al. present a first test of a statistical downscaling strategy that quantifies the uncertainty in the mapping between GCM output and local precipitation time series. We will use this strategy to derive ensemble estimates of inputs (precipitation and temperature) to drive the hydrological model in a future study. We will add a statement about this work to the conclusions section.

Comment9. Fig 5a: the y-axis label should be "log(Predicted...)", isn't it?

Response9: Yes, it will be corrected.

References: Ningh, L., M. Mann, R. Crane, and T. Wagener (2011), Probabilistic Projections of Climate Change for the Mid-Atlantic Region of the United States - Validation of Precipitation Downscaling During the Historical Era, Journal of Climate, in press, doi: 10.1175/2011JCLI4091.1

Wagener, T. and A. Montanari (2011), Convergence of approaches toward reducing uncertainty in predictions in ungauged basins, Water Resour. Res., 47, W06301, doi:10.1029/2010WR009469.

Captions: Figure 1. Alternative representation of the results shown in Figure 3 in the current manuscript. Qv is the mean annual flow in the validation period and Qb is the mean annual flow in the base period. We feel that quantifying the performance differences is more effective than visualizing them in this manner.

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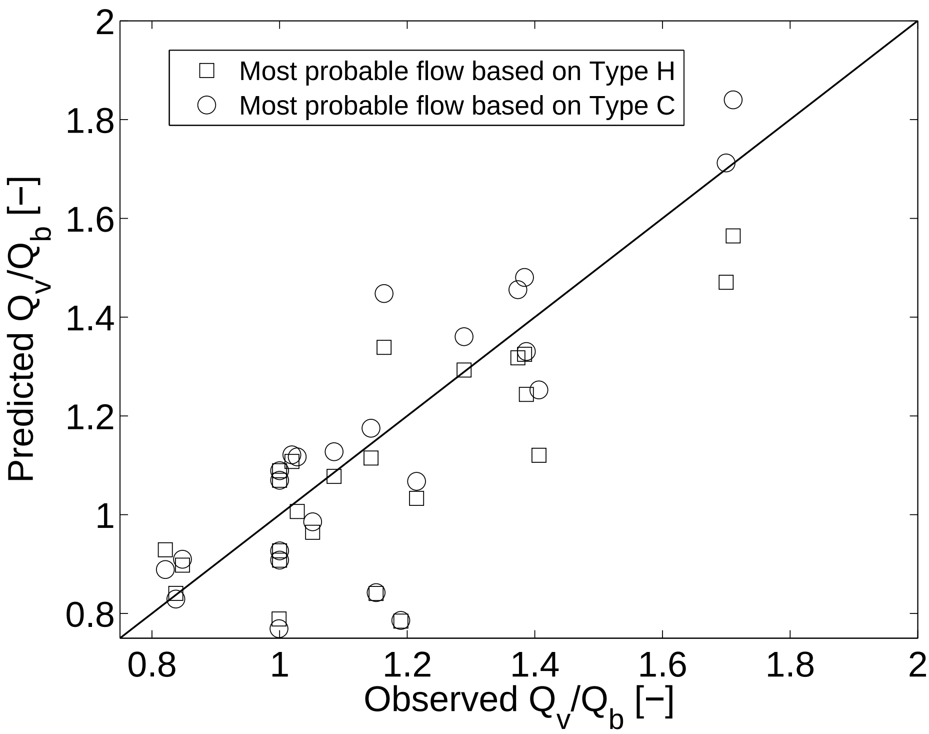

Fig. 1. Alternative representation of the results shown in Figure 3 in the current manuscript. Qv is the mean annual flow in the validation period and Qb is the mean annual flow in the base period.