Relative effects of statistical preprocessing and postprocessing on a regional hydrological ensemble prediction system

Sanjib Sharma, Ridwan Siddique, Seann Reed, Peter Ahnert, Pablo Mendoza, Alfonso Mejia

Response to the reviewers' comments

We are thankful to the Editor, Dr. Shraddhanand Shukla, and the reviewers for their thorough review of manuscript hess-2017-514. We have considered each comment and suggestion made by the reviewers when revising our manuscript. Below we provide a point-by-point response to each of the comments. The reviewers' comments are shown in blue font and our response follows immediately after that.

RESPONSE TO EDITOR'S COMMENTS

Comment from the editor: 1) Please do not exclude the summary/general statements (the first paragraph) made by the reviewers from your response. Please submit a revised version of your response that includes summary statements made by each of the reviewers.

Response to the editor: We have now added the summary statement made by each reviewer in the "Response to Reviewer" section.

Comment from the editor: 2) Reviewer #2, Comment #4: I do not think that dropping climate variability from this statement is fair. My suggestion would be to say something to the affect that both climate variability and climate change contribute to increased exposure increased exposure from expanding urbanization, and sea level rise are increasing.

Response to the editor: As suggested, we have now modified the sentence in P1 L30 to read as follows: "Both climate variability and climate change, increased exposure from expanding urbanization, and sea level rise are increasing the frequency of damaging flood events and making their prediction more challenging across the globe."

Comment from the editor: 3) Reviewer #2, Comment #10: Please specify here which comment of the reviewer #1 is similar to this comment, which you have already responded.

Response to the editor: We now indicate that our response to Reviewer #2 Comment #10 is similar to our response to Reviewer #1 Comment #3.

Comment from the editor: 4) Reviewer #2, Comment #11: It is not clear to me how the revised sentence add any clarity. My guess is that the reviewer would like you to be more specific about the metric score use for making this statement and perhaps also mention if the reliability improves for certain category of events.

Response to the editor: We used the reliability diagram to quantify the reliability of the forecasts. The reliability diagram shows the full joint distribution of forecasts and observations to reveal the reliability of the probability forecasts. Response to Comment #11 from Reviewer #2 now reads as follows: "We also computed reliability diagrams, as determined by Sharma et al. (2017), for the two postprocessors (plots not shown) and found that QR displays better reliability than ARX(1,1) across lead times, basins, and seasons." This information is incorporated in P11 L3-5 of the revised manuscript.

Comment from the editor: 5) Reviewer #3, Comment #1: Please provide a reference or example for your statement "since this is a temporal resolution commonly used in operational forecasting in the U.S."

Response to the editor: As suggested, a link to the website from Advanced Hydrologic Prediction Center is added. Response to Comment #1 from Reviewer #3 now reads as: "We also note that we use 6-hourly accumulations since this is the resolution of the GEFSRv2 data after day 4 and since this is a temporal resolution often used in operational forecasting in the U.S (http://water.weather.gov/ahps2/hydrograph.php?wfo=bgm&gage=cinn6)." This information is incorporated in P7 L3-6 of the revised manuscript.

Comment from the editor: 6) Reviewer #3, Comment #4: I am not satisfied with this response, my guess would be that the reviewer may not be either. Why highlight the difference in the model structure if it has no bearing on your results? Also there are of course other previous studies that have used distributed models.
Response to the editor: We understand the point of the reviewer and value the comment. However, we did conduct a very exhaustive literature review. We found that most, if not all, studies that use GEFS data as forcing are with lumped or semi-distributed models. The few studies that use a distributed model tend to use ECMWF forcing, not GEFS. Even though we do not emphasize the effect of model structure in the manuscript, the use of a distributed model affects quite a bit the way the forcing is used for both the streamflow simulations and forecasts. Hence, we still think that it is worth mentioning that this is point of distinction with previous studies.

Comment from the editor: 7) Reviewer #3, Comment #8: Please make sure to provide more details regarding the forcing. For example please briefly mention the method, sources of observations (e.g. station or satellite or both?), which other studies have used the data before and how it was validated.
Response to the editor: The information requested by the editor is already included in the original manuscript. The text in the original manuscript reads: "Both the MPEs and gridded near-surface air temperature data at 4 x 4 km2 resolution were provided by the NOAA's Middle Atlantic River Forecast Center (MARFC) (Siddique and Mejia 2017). Similar to the NCEP stage-IV 5 dataset(Moore et al., 2015; Prat and Nelson, 2015), the MARFC's MPEs represent a continuous time series of hourly, gridded precipitation observations at 4 x 4 km^2 cells, which are produced by combining multiple radar estimates and rain gauge measurements. The gridded near-surface air temperature data at 4 x 4 km2 resolution were developed by combining multiple temperature observation networks as described by Siddique and Mejia (2017)." This information can be found in P4 L8-13 of the revised manuscript.

RESPONSE TO REVIEWER #1

Comment from Reviewer #1: This manuscript studies the relative roles of statistical preprocessing of meteorological inputs in a hydrological forecast system and statistical postprocessing of the resulting flow forecasts for four basins in the US middle Atlantic region. The paper is well written, the structure is good, and the conclusions are interesting and relevant. The methodology is sound with two exceptions detailed below. These are major in the sense that they are scientifically problematic and may have an impact on the conclusions, but they can probably be addressed quite easily.
Response to reviewer #1: We thank the reviewer for reviewing the manuscript. We have now addressed the reviewer's concern as detailed in the next comments.

Comment from Reviewer #1: 1) p6, l4: pi_i is only a probability when y_i=0, otherwise a likelihood.
Response to reviewer #1: We agree with the reviewer and have accordingly changed the text in the revised manuscript to read as follows: "For this, the predicted probability or likelihood π_i of the ith observed outcome is determined as..." The suggested change can be found in P6 L12 of the revised manuscript.

Comment from Reviewer #1: 2) P7, l15: 'smallest mean CRPS is selected': I don't fully understand how this works. Apparently c_{i+1} changes over time, so what exactly is minimized here? The CRPS over some training data with a rolling training window? Please add some more explanation.
Response to reviewer #1: The postprocessor is implemented following a leave-one-out approach, which consists of using 7 years for training (i.e., to estimate c_{i+1}) and the 2 remaining years for verification purposes. This is done separately at each lead time until the entire 9 years have been verified independently from the training period. Thus, we determine a different value of c_{i+1} for each 7-year training period and lead time.

To select the value of c_{i+1} for each 7-year training period and lead time, we first generate ten equally spaced values of c_{i+1}. For each value of c_{i+1}, the ARX(1,1) model is trained and used to generate ensemble streamflow forecasts, which are in turn used to compute the mean continuous ranked probability score (CRPS) for the 7-year training period under consideration. Thus, the mean CRPS is computed for each value of c_{i+1}, and the value of c_{i+1} that produces the smallest mean CRPS is then selected for use in the 2-year verification period under consideration. This is repeated until all the years (2004-2012) have been postprocessed and verified independently of the training period. To address the reviewer's comment, we have now incorporated this explanation in P7 L24-28 of the revised manuscript.

Comment from Reviewer #1: 3) p8, l15-16: '... is focused on flood events ... by choosing flow amounts greater than ...': This kind of subsetting is very problematic and can lead to false conclusions about the relative predictive performance of different methods, see Lerch et al. (2017). Bellier et al (2017) give a discussion of pitfalls of sample stratification and make suggestions how one can stratify samples in a way that avoids these pitfalls.

Response to reviewer #1: We are thankful to the reviewer for this constructive comment. We have read the suggested papers and decided to use the entire flow values, as opposed to using a sample stratification approach, when computing the different verification metrics, with the exception of the Brier skill score. Accordingly, we revised Figures 3-7 in the new version of the manuscript. The revised figures are qualitatively similar to the previous ones. However, the revised figures are more consistent in showing the scenario involving both preprocessing and postprocessing, S6, as having better performance than the other scenarios. In addition, there are now clear differences between the warm and cool season, where the warm season shows the different scenarios, particularly S4-S6, as being more similar to each other, while the cool season results remained similar to the ones in the original manuscript. We have now modified the original manuscript in several locations to reflect the differences associated with the revised figures.

Comment from Reviewer #1: 4) Section 4.4.1: I'm not sure if this part of the analysis makes sense. In addition to the stratification issue (which demonstrably entails a bias), it is also known that the ensemble mean does not necessarily yield the best/appropriate point forecast when a relative error statistic is considered (see Gneiting 2011). I suggest either considering the mean error (over the entire verification data), or omitting this subsection entirely and maybe replace it by a subsection that studies reliability of threshold exceedance.

Response to reviewer #1: We again thank the reviewer for this constructive comment. As suggested by the reviewer, we have now removed the relative mean error statistic and this sub-section from the revised manuscript.

Comment from Reviewer #1: 5) P6, l31: hourly

Response to reviewer #1: Thanks for catching this. The typo has been corrected in the revised manuscript (see P7 L3).

Comment from Reviewer #1: 6) P7, eq (7): xi_{I+1} -> xi_{i+1}

Response to reviewer #1: Thanks for catching this. We incorporated this modification in P7 Eq. (7) of the revised manuscript.

Comment from Reviewer #1: 7) P9, l15: It sounds weird to say that one basin outperforms the other, please reformulate

Response to reviewer #1: We have now revised the text following the reviewer's suggestion. The revised sentence reads as follows (P9 L23-24): "Further, the performance of the calibrated simulation runs is similar across the four selected basins, although the largest size basin, WVYN6, shows slightly higher performance with Rm, NSE, and PB values of 0.85, 0.82, and -3%, respectively."

Comment from Reviewer #1: 8) p10, l24: Replace 'While' by 'The gains ..., on the other hand,'

Response to reviewer #1: Following the reviewer's suggestion, we incorporated this modification in P10 L36 of the revised manuscript.

RESPONSE TO REVIEWER #2

Comment from Reviewer #2: This review is for manuscript HESS-2017-514: Relative effects of statistical preprocessing and postprocessing on a regional hydrological ensemble prediction system, authored by Sanjib Sharma, Ridwan Siddique, Seann Reed, Peter Ahnert, Pablo Mendoza, and Alfonso Mejia. The manuscript is easy to follow. It presents some interesting results. In this work, a spatially distributed hydrological model is included in the study. Two postprocessors: an autoregressive model with a single exogenous variable and quantile regression, are comparatively evaluated. Below are my general and specific comments.
Response to reviewer #2: Thanks for reviewing the manuscript.

Comment from Reviewer #2: 1) I was intrigued by reading the statement "postprocessing alone performs similar, in terms of the relative mean error, skill, and reliability, to the more involved scenario that includes both preprocessing and postprocessing" in the Abstract (page 1, lines 24-25). This is one of the major conclusions of the work. However, further reading reveals that the results do not fully support this conclusive statement, for the following reasons:
i) Figures 5 and 6 show appreciable performance gains of S6 over S5 for 5 cases out of 8. One can see that S6 outperforms S5 in terms of forecast lead times by 12 hours to 3 days.
ii) The closeness of the results for the other cases (i.e., (e) and (f)) between S5 and S6 can be explained by the closeness of the raw GEFS and preprocessed GEFS precipitation, as shown in Figure 3.
iii) The verification appears to be only conducted for large observed events without considering large forecast events, which can generate false-alarms. In short, I find this conclusion is inaccurate and can be misleading.
Response to reviewer #2: We agree with the reviewer. We have now modified the revised manuscript to indicate that the scenario involving both preprocessing and postprocessing, S6, consistently outperforms the other scenarios. However, we also indicate that in some cases the differences between S5 (only postprocessing) and S6 are not as significant. We believe, as the reviewer suggested, that this statement and conclusion is more consistent with the overall results that are presented in the manuscript.

In regards to the reviewer's point iii), we have now revised Figures 3-7 in the new version of the manuscript by computing all the verification metrics over the entire verification period (please also see our response to reviewer # 1 comment #3 regarding this issue). The revised figures show more clearly that S6 is consistently better than the other scenarios. Qualitatively, the revised and original figures are overall similar. But some difference do emerge, as indicated in our response to reviewer 1, particularly between the warm and cool season. We have now revised the manuscript to note and discuss these differences.

Comment from Reviewer #2: 2) How are the GEFS precipitation and temperature downscaled to force the HR-RDHM? A description should be provided.
Response to reviewer #2: As suggested by the reviewer, we added the following text in the revised manuscript (P4 L25): "The GEFSRv2 data are bilinearly interpolated onto the 4 x 4 km^2 grid cell resolution of the HL-RDHM model."

Comment from Reviewer #2: 3) Page 1, Line 12: Do you mean "Is comprised of "by "is comprised by"?
Response to reviewer #2: This modification was incorporated into the revised manuscript (see P1 L12).

Comment from Reviewer #2: 4) Page 1, Line 28: In "The intersection of climate variability and change, increased exposure from expanding urbanization, and sea level rise are increasing", what do you mean by "The intersection of climate variability and change"?
Response to reviewer #2: We meant by this statement that climate variability and climate change, which act together, alongside expanding urbanization and sea level rise are making flood prediction more challenging. We now revised the manuscript (see P1 L30) to say "Both climate variability and climate change" as we think this makes the sentence clearer and easier to read.

Comment from Reviewer #2: 5) Page 2, Line 6: In "for research purposes, meet specific regional needs, and/or real-time forecasting applications", do you mean "to meet . . ."?
Response to reviewer #2: In P2 L9 of the revised manuscript, the suggested change was incorporated.

Comment from Reviewer #2: 6) Page 3, line 21: Shouldn't it be U.S. Middle Atlantic region?
Response to reviewer #2: We incorporated this modification into the revised manuscript (P3 L25).

Comment from Reviewer #2: 7) Page 5, line 16: "Also, HCLR has been shown to outperform other widely used preprocessors (Yang et al., 2017)". Should be more specific here since the paper only compares the HCLR and BMA.
Response to reviewer #2: Following the reviewer's comment, we made our statement more specific; it now reads as follows (P5 L25): "Also, HCLR has been shown to outperform other widely used preprocessors, such as Bayesian Model Averaging".

Comment from Reviewer #2: 8) Page 6, line 31: "6-houlry" is a typo.
Response to reviewer #2: Thanks for catching this. We incorporated this modification into the revised manuscript (P7 L3).

Comment from Reviewer #2: 9) Page 7, line 23: "QR has similar skill performance in streamflow and normal space". This sentence is not clear to me. Do you mean that QR has similar skill performance in the streamflow space as well as normal space?
Response to reviewer #2: We rephrased this sentence to incorporate the reviewer's comment. The revised sentence reads as follows (P8 L1-2): "QR is applied here in streamflow space, since it has been shown that, in hydrological forecasting applications, QR has similar skill performance in streamflow space as well as normal space (López et al., 2014)."

Comment from Reviewer #2: 10) Page 8, line 15: How many events result from this threshold? Is the sampled climatological probability distribution derived from the observed data? If so, will your conclusions still hold if events corresponding to forecasts with large magnitudes and high probabilities also included in the verification?
Response to reviewer #2: The reviewer makes a good point. We have now modified the manuscript by computing the metrics (Figs. 3-7) over the entire verification period. Overall, our conclusions did not change based on the revised figures. As noted before, we do see now some seasonal differences (mainly, the performance of scenarios S4-S6 is more similar to each other in the warm season than it was before in the original manuscript) and the ability of S6 to outperform the other scenarios is more clear now. Below we show in italic our complete answer to comment # 3 from Reviewer #1 which we think applies here as well.

We have decided to use the entire flow values, as opposed to using a sample stratification approach, when computing the different verification metrics, with the exception of the Brier skill score. Accordingly, we revised Figures 3-7 in the new version of the manuscript. The revised figures are qualitatively similar to the previous ones. However, the revised figures are more consistent in showing the scenario involving both preprocessing and postprocessing (scenario 6) as having better performance than the other scenarios. In addition, there are now clear differences between the warm and cool season, where the warm season shows the different scenarios, particularly S4-S6, as being more similar to each other, while the cool season results remained similar to the ones in the original manuscript. We have now modified the original manuscript in several locations to reflect the differences associated with the revised figures.

Comment from Reviewer #2: 11) Page 10, line 33: "QR displays better reliability than ARX (1,1) across lead times, basins, and seasons". By what measure(s)?

Response to reviewer #2: This sentence was slightly modified in the revised manuscript to add clarity and address the reviewer's comment. The new sentence reads (P11 L3-5): "We also computed reliability diagrams, as determined by Sharma et al. (2017), for the two postprocessors (plots not shown) and found that QR displays better reliability than ARX(1,1) across lead times, basins, and seasons." The figures are not shown simply to keep the length of the manuscript and number of figures manageable.

Comment from Reviewer #2: 12) Page 11, line 36: "reinforcing the fact that preprocessing may have little effect on the flood forecasts". See the General Comments.
Response to reviewer #2: Following the reviewer's comment, we removed the sentence from the revised manuscript.

RESPONSE TO REVIEWER #3

Comment from Reviewer #3: The manuscript describes a comparative analysis of pre and post processing approaches and their contributions to flood forecasting performance in the Middle Atlantic Region. The analysis starts by evaluating the hydrology model performance. Then authors evaluate one pre processor and confirm that it improves the skill of raw precipitation forecasts. Next they evaluate two post processors and select the most performing one. Finally, authors evaluate multiple cases: raw, with or without pre and post processors. The analysis focuses on two periods for the evaluations, and 4 basins of different sizes. Authors conclude that post processing for flood forecasting is necessary and provides the largest skill increase. Pre – processing appears unnecessary.
The paper is very well written and organized. The approach, application and conclusion are of interest to the HESS community which has published extensively on ensemble flow forecasting. I have some moderate and minor comments below that would need to be addressed.
Response to reviewer #3: We are thankful to the reviewer for taking the time to review our manuscript.

Comment from Reviewer #3: 1) the pre-processor is evaluated for 6 hourly 95th percentile events but is not evaluated for aggregated period events, which ultimately drive to floods. There is therefore a disconnection between the "value" of the post processor when evaluated independently, and the "value" of the pre – processor when verifying floods. The pre-processor has not been evaluated for the same "events".
Response to reviewer #3: The reviewer makes a good point. As we indicated before in our response to reviewer #1 and #2, we now use in the revised manuscript all the verification values when computing the verification metrics in Figures 3-7, i.e., we do not use any threshold or stratified sample. This means that all the preprocessed precipitation values and all the postprocessed flow values are used to compute the verification metrics.

We also note that we use 6-hourly accumulations since this is the resolution of the GEFSRv2 data after day 4 and since this is a temporal resolution often used in operational forecasting in the U.S. (http://water.weather.gov/ahps2/hydrograph.php?wfo=bgm&gage=cinn6). In Fig. 3, we want simply to illustrate the performance of S1 and S2 relative to each other, for this purpose using 6-hourly accumulations seems reasonable (i.e., the relative comparison between S1 and S2 is similar for 6-hourly or daily accumulations). Further, we use the 6-hourly precipitation accumulations to force the hydrological model and generate 6-hourly flows. Since the observed flow data are mean daily, we compute the mean daily flow forecast from the 6-hourly flows. The postprocessor is applied to the mean daily values since this is the resolution of the observations. But there is no mismatch between precipitation and flood events. This information was incorporated in P7 L3-6 of the revised manuscript.

Comment from Reviewer #3: 2) The conclusion that post processing only is needed to improve the skill of flow forecast seems to be based on statistics only and therefore you might get the right answer for the wrong reasons. The post processor maybe have the largest "value" but it does not mean that pre-processing steps should be skipped. I strongly recommend the authors to modify the conclusion to reflect that nuance.

Response to reviewer #3: We agree with the reviewer. As suggested by the reviewer's comment, we have now modified the conclusion to read as follows (P13 L28-31): "The scenario involving both preprocessing and postprocessing consistently outperforms the other scenarios. In some cases, however, the differences between the scenario involving preprocessing and postprocessing, and the scenario with postprocessing alone, are not as significant, suggesting for those cases that postprocessing alone can be effective in removing systematic biases."

Comment from Reviewer #3: 3) Literature review and contribution of the paper and conclusion: A HEPEX blog by Boucher A. M. (2015) provides a summary of the contribution of previous papers. She refers to the papers also mentioned below. i) The literature and the insight provided by this experiment should be put in perspective with what has been done and found by others before.
Response to reviewer #3: Thanks for pointing us to this blog. We were indeed aware of the blog by Boucher A. M. (2015) (https://hepex.irstea.fr/pre-post-processing-or-both/), which summarizes different papers (e.g., Kang et al. (2010), Zalachori et al. (2012), Verkade et al. (2013), and Roulin and Vannitsem (2015)) related to preprocessing and postprocessing in streamflow forecasting. In fact, we have already discussed these paper/studies and their major findings in the original manuscript. Furthermore, our research questions and experimental set-up for the manuscript were designed in part to address concerns raised in the blog.

ii) The fact that spatially disaggregated modeling is used might not be enough because there is no insight related to that modeling structure to the results. I would suggest framing the contribution differently.
Response to reviewer #3: We agree with the reviewer. It is not our intention to frame the contribution in terms of going from lumped to distributed hydrological modeling. However, we do note in the original manuscript that this is one aspect of the present study that differs from previous one. It was indeed surprising to us that most previous pre/postprocessing studies that use GEFS forcing have been done with lumped or semi-distributed models. Beyond the issue of model structure indicated by the reviewer, we think it is useful to mention this aspect of the study because the use of the forcing for simulating and forecasting streamflow is different than with a lumped model, and the application of the preprocessor is also different.

Comment from Reviewer #3: 4) Study domain – this corresponds to the Susquehanna Basin – why use MAR instead of the Susquehanna River Basin?
Response to reviewer #3: We agree with the reviewer and have now incorporated this modification into the revised manuscript (see P3 L25-37).

Comment from Reviewer #3: 5) Warm and cold seasons: can you describe the type of events expected in both seasons?
Response to reviewer #3: To address the reviewer's comment, we added the following information to the revised manuscript (P3 L28-32): "The climate in the upper MAR, where the NBSR basin is located, can be classified as warm, humid summers and snowy, cold winters with frozen precipitation (Polsky et al, 2000). During the cool season, a positive North Atlantic Oscillation phase generally results in increased precipitation amounts and occurrence of heavy snow (Durkee et al., 2007). Thus, flooding in the cool season is dominated by heavy precipitation events accompanied by snowmelt runoff. In the summer season, convective thunderstorms with increased intensity may lead to greater variability in streamflow."

Comment from Reviewer #3: 6) PG 6 L31: change to "hourly"
Response to reviewer #3: Thanks for catching this. We incorporated this modification into the revised manuscript (P7 L3).

Comment from Reviewer #3: 7) PG9 L4: add "observed" to "gridded precipitation"
Response to reviewer #3: We incorporated this modification in P9 L13 of the revised manuscript.

Comment from Reviewer #3: 8) PG9 L4: please specify the source of the gridded observed precipitation
Response to reviewer #3: The information requested by the reviewer is already included in the original manuscript. The text in the revised manuscript can be found in P4 L8-9 and reads as follows: "Both the MPEs and gridded near-surface air temperature data at 4 x 4 km^2 resolution were provided by the NOAA's Middle Atlantic River Forecast Center (MARFC) (Siddique and Mejia 2017)."

Comment from Reviewer #3: 9) PG9 L24: confusing; you mean "high precipitation events defined as 6-hourly accumulated precipitation events with a .95 non exceedance probability"? Also – see comment for the need to evaluate aggregated events
Response to reviewer #3: We have now modified the original manuscript to reflect the fact that we no longer use the 0.95 threshold but instead use all the verification data. We believe this change made the sentence more clear.

Comment from Reviewer #3: 10) PG10 – Line 35: how do you specify flood events? Are those also 6 hourly discharge event with a .95th non exceedance probability? Please clarify
Response to reviewer #3: We believe that our previous answer to the reviewer helps to address this question as well.

Comment from Reviewer #3: 11) Basins are not independent, could you add one comment how this might affect the results? In the result section at PG11 L34 it looks like you could see consistent results. It did not seem to be the case on the previous section.
Response to reviewer #3: We believe the results will be similar if we had selected basins that are geographically close to each other and of similar size to the ones we selected. In fact, we initially selected nested sub-basins in order to investigate the forecast performance with respect to basin size or, in other words, the scaling of verification metrics with basin size. However, we found that, although there is some tendency for the larger basins to show better forecast skill than the small ones, the scaling is rather mild and not consistent. The scaling tends to show significant variability so that it is not necessarily evident for the conditions considered (e.g., lead times and seasons). This information is now mentioned in the revised manuscript to read as follows (P11 L16-18): "Although there is some tendency for the large basins to show better forecast skill than the small ones, the scaling (i.e., the dependence of skill on the basin size) is rather mild and not consistent across the four basins.

List of major changes made in the manuscript (hess-2017-514)

The major changes that were incorporated into the revised manuscript are as follows:

- We now use the entire flow values, as opposed to using a sample stratification approach, when computing the different verification metrics, with the exception of the Brier skill score. Accordingly, we revised Figures 3-7 in the revised manuscript.
- We made changes throughout the result section of the manuscript to reflect the results shown in the revised Figures 3-7. The main difference in the revised figures with respect to the original ones is that seasonal differences become more obvious between the warm and cool season verification results. In addition, the verification results for the difference scenarios are more clear now than before.
- We removed from the manuscript the relative mean error statistic and the corresponding subsection since this was suggested by one of the reviewers.
- The conclusions of the paper were adjusted to reflect the result changes associated with using the entire flow values for the verification analysis.

Relative effects of statistical preprocessing and postprocessing on a regional hydrological ensemble prediction system

Sanjib Sharma[1], Ridwan Siddique[2], Seann Reed[3], Peter Ahnert[3], Pablo Mendoza[4], Alfonso Mejia[1]

[1]Department of Civil and Environmental Engineering, The Pennsylvania State University, University Park, PA, USA
[2]Northeast Climate Science Center, University of Massachusetts, Amherst, MA, USA
[3]National Weather Service, Middle Atlantic River Forecast Center, State College, PA, USA
[4]Advanced Mining Technology Center (AMTC), Universidad de Chile, Santiago, Chile

Correspondence to: Alfonso Mejia (amejia@engr.psu.edu)

Abstract. The relative roles of statistical weather preprocessing and streamflow postprocessing in hydrological ensemble forecasting at short- to medium-range forecast lead times (day 1-7) are investigated. For this purpose, a regional hydrologic ensemble prediction system (RHEPS) is developed and implemented. The RHEPS is comprised of~~by~~ the following components: i) hydrometeorological observations (multisensor precipitation estimates, gridded surface temperature, and gauged streamflow); ii) weather ensemble forecasts (precipitation and near-surface temperature) from the National Centers for Environmental Prediction 11-member Global Ensemble Forecast System Reforecast version 2 (GEFSRv2); iii) NOAA's Hydrology Laboratory-Research Distributed Hydrologic Model (HL-RDHM); iv) heteroscedastic censored logistic regression (HCLR) as the statistical preprocessor; v) two statistical postprocessors, an autoregressive model with a single exogenous variable (ARX(1,1)) and quantile regression (QR); and vi) a comprehensive verification strategy. To implement the RHEPS, 1 to 7 days weather forecasts from the GEFSRv2 are used to force HL-RDHM and generate raw ensemble streamflow forecasts. Forecasting experiments are conducted in four nested basins in the U.S. M~~m~~iddle Atlantic region, ranging in size from 381 to 12,362 km^2.

Results show that the HCLR preprocessed ensemble precipitation forecasts have greater skill than the raw forecasts. These improvements are more noticeable in the warm season at the longer lead times (>3 days). Both postprocessors, ARX(1,1) and QR, show gains in skill relative to the raw ensemble ~~flood~~ streamflow forecasts, particularly in the cool season, but QR outperforms ARX(1,1). The scenarios that implement p~~P~~reprocessing ~~alone~~ and postprocessing separately tend to perform similarly, although the postprocessing alone scenario is often more effective~~has little effect on improving the skill and reliability of the ensemble flood streamflow forecasts~~. The scenario involving both preprocessing and postprocessing consistently outperforms the other scenarios. In some cases, however, the differences between this scenario and the scenario with postprocessing alone are not as significant. We conclude that implementing both preprocessing and postprocessing ensures the most skill improvements, but postprocessing alone can often be a competitive alternative.~~Indeed, postprocessing alone performs similar, in terms of the relative mean error, skill, and reliability, to the more involved scenario that includes both preprocessing and postprocessing. We conclude that statistical preprocessing may not always be a necessary component of the ensemble flood forecasting chain. Indeed, the scenario including both preprocessing and postprocessing tends to slightly outperform, in terms of the skill and reliability, to the scenario including only postprocessing, but the differences among these scenarios are not as significant. We conclude that statistical postprocessing should be prioritized over preprocessing in the reprocessing may not always be a necessary component of the ensemble flood streamflow forecasting chain.~~

1 Introduction

Both ~~the~~ climate variability and climate change~~Changing cThe intersection of climate variability and change~~, increased exposure from expanding urbanization, and sea level rise are increasing the frequency of damaging flood events and making their prediction more challenging across the globe (Dankers et al., 2014; Wheater and Gober, 2015; Ward et al., 2015). Accordingly, current research and operational efforts in hydrological forecasting are seeking to develop and implement enhanced forecasting systems, with the goals of improving the skill and reliability of short- to medium-range ~~flood~~ streamflow forecasts (0-14 days), and providing more effective early warning services (Pagano et al., 2014; Thiemig et al., 2015; Emerton et al., 2016; Siddique and Mejia, 2017). Ensemble-based forecasting systems have become the preferred paradigm, showing substantial improvements over single-valued deterministic ones (Schaake et al., 2007; Cloke and Pappenberger, 2009; Demirel et al., 2013; Fan et al., 2014; Demargne et al., 2014; Schwanenberg et al., 2015; Siddique and Mejia, 2017). Ensemble ~~flood~~ streamflow forecasts can be generated in a number of ways, being the most common approach the use of meteorological forecast ensembles to force a hydrological model (Cloke and Pappenberger, 2009; Thiemig et al., 2015). Such meteorological forecasts can be generated by multiple alterations of a numerical weather prediction model, including perturbed initial conditions and/or multiple model physics and parameterizations.

A number of ensemble prediction systems (EPSs) are being used to generate ~~flood~~ streamflow forecasts. In the United States (U.S.), the NOAA's National Weather Service River Forecast Centers are implementing and using the Hydrological Ensemble Forecast Service to incorporate meteorological ensembles into their flood forecasting operations (Demargne et al., 2014; Brown et al., 2014). Likewise, the European Flood Awareness System from the European Commission (Alfieri et al., 2014) and the Flood Forecasting and Warming Service from the Australia Bureau of Meteorology (Pagano et al., 2016) have adopted the ensemble paradigm. Furthermore, different regional EPSs have been designed and implemented for research purposes, to meet specific regional needs, and/or for real-time forecasting applications. Two examples, among several others (Zappa et al., 2008; Zappa et al., 2011; Hopson and Webster, 2010; Demuth and Rademacher, 2016; Addor et al., 2011; Golding et al., 2016; Bennett et al., 2014; Schellekens et al., 2011), are the Stevens Institute of Technology's Stevens Flood Advisory System for short-range flood forecasting (Saleh et al., 2016), and the National Center for Atmospheric Research (NCAR)'s System for Hydromet Analysis, Research, and Prediction for medium-range streamflow forecasting (NCAR, 2017). Further efforts are underway to operationalize global ensemble flood forecasting and early warning systems, e.g., through the Global Flood Awareness System (Alfieri et al., 2013; Emerton et al., 2016).

EPSs are comprised by several system components. In this study, the Regional Hydrological Ensemble Prediction System (RHEPS) is used (Siddique and Mejia, 2017). The RHEPS is an ensemble-based research forecasting system, aimed primarily at bridging the gap between hydrological forecasting research and operations by creating an adaptable and modular forecast emulator. The goal with the RHEPS is to facilitate the integration and rigorous verification of new system components, enhanced physical parameterizations, and novel assimilation strategies. For this study, the RHEPS is comprised by the following system components: i) precipitation and near surface temperature ensemble forecasts from the National Centers for Environmental Prediction 11-member Global Ensemble Forecast System Reforecast version 2 (GEFSRv2), ii) NOAA's Hydrology Laboratory-Research Distributed Hydrologic Model (HL-RDHM) (Reed et al., 2004; Smith et al., 2012a; Smith et al., 2012b), iii) statistical weather preprocessor (hereafter referred to as preprocessing), iv) statistical streamflow postprocessor (hereafter referred to as postprocessing), v) hydrometeorological observations, and vi) verification strategy. Recently, Siddique and Mejia (2017) employed the RHEPS to produce and verify ensemble streamflow forecasts over some of the major river basins in the U.S. M~~m~~iddle Atlantic region. Here, the RHEPS is specifically implemented to investigate the relative roles played by preprocessing and postprocessing in enhancing the quality of ensemble streamflow~~flood~~ forecasts.

The goal with statistical processing is to use statistical tools to quantify the uncertainty of and remove systematic biases in the weather and streamflow forecasts in order to improve the skill and reliability of forecasts. In weather and hydrological forecasting, a number of studies have demonstrated the benefits of separately implementing preprocessing (Sloughter et al., 2007; Verkade et al., 2013; Messner et al., 2014a; Yang et al., 2017) and postprocessing (Shi et al., 2008; Brown and Seo, 2010; Madadgar et al., 2014; Ye et al., 2014; Wang et al., 2016; Siddique and Mejia, 2017). However, only a very limited number of studies have investigated the combined ability of preprocessing and postprocessing to improve the overall quality of ensemble streamflow forecasts (Kang et al., 2010; Zalachori et al., 2012; Roulin and Vannitsem, 2015; Abaza et al., 2017). At first glance, in the context of medium-range streamflow forecasting, preprocessing seems necessary and beneficial since meteorological forcing are often biased and their uncertainty more dominant than the hydrological one (Cloke and Pappenberger, 2009; Bennett et al., 2014; Siddique and Mejia, 2017). In addition, some streamflow postprocessors assume unbiased forcing (Zhao et al., 2011) and hydrological models can be sensitive to forcing biases (Renard et al., 2010).

The few studies that have analyzed the joint effects of preprocessing and postprocessing on short- to medium-range streamflow forecasts have mostly relied on weather ensembles from the European Centre for Medium-range Weather Forecasts (ECMWF) (Zalachori et al., 2012; Roulin and Vannitsem, 2015; Benninga et al., 2016). Kang et al. (2010) used different forcing but focused on monthly, as opposed to daily, streamflow. The conclusions from these studies have been mixed (Benninga et al., 2016). Some have found statistical processing to be useful (Yuan and Wood, 2012), particularly postprocessing, while others have found that it contributes little to forecast quality. Overall, studies indicate that the relative effects of preprocessing and postprocessing depend strongly on the forecasting system (e.g., forcing, hydrological model, statistical processing technique, etc.), and conditions (e.g., lead time, study area, season, etc.), underscoring the research need to rigorously verify and benchmark new forecasting systems that incorporate statistical processing.

The main objective of this study is to verify and assess the ability of preprocessing and postprocessing to improve ensemble streamflow~~flood~~ forecasts from the RHEPS. This study differs from previous ones in several important respects. The assessment of statistical processing is done using a spatially distributed hydrological model whereas previous studies have tended to emphasize spatially lumped models. Much of the previous studies have used ECMWF forecasts, here we rely on GEFSRv2 precipitation and temperature outputs. Also, we test and implement a preprocessor, namely heteroscedastic censored logistic regression (HCLR), which has not been used before in streamflow forecasting. We also consider a relatively wider range of ~~nested,~~ basin sizes and longer study period than in previous studies. In particular, this paper addresses the following questions:

- What are the separate and joint contributions of preprocessing and postprocessing over the raw RHEPS outputs?
- What forecast conditions (e.g., lead time, season, flow~~flood~~ threshold, and basin size) benefit potential increases in skill?
- How much skill improvement can be expected from statistical processing under different uncertainty scenarios (i.e., when skill is measured relative to observed or simulated flow conditions)?

The remainder of the paper is organized as follows. Section 2 presents the study area. Section 3 describes the different components of the RHEPS. The main results and their implications are examined in section 4. Lastly, section 5 summarizes key findings.

2 Study area

The North Branch Susquehanna River (NBSR) basin in the U.S. M~~m~~iddle Atlantic region (MAR) is selected as the study area (Fig. 1), with an overall drainage area of 12,362 km^2. The NBSR ~~Susquehanna River~~ basin~~is region~~ is selected as flooding is an important regional concern. This region~~e MAR~~ has a relatively high level of urbanization and high frequency of extreme weather events, making it particularly vulnerable to damaging flood events (Gitro et al., 2014; MARFC, 2017). The climate in the upper ~~Mid-Atlantic Region~~ MAR, where the NBSR basin is located, -can be classified as warm, humid summers and snowy, cold winters with frozen precipitation (Polsky et al, 2000). During the cool season, a positive North Atlantic Oscillation phase generally results in increased precipitation amounts and occurrence of heavy snow (Durkee et al., 2007). Thus, flooding in the cool season is dominated by heavy precipitation events accompanied by snowmelt runoff. ~~While i~~In the summer season, convective thunderstorms with increased intensity may lead to greater variability in streamflow. In the NBSR ~~North Branch Susquehanna River~~ basin, we select four different U.S. Geological Survey (USGS) daily gauge stations, representing a system of nested subbasins, ~~are selected~~ as the forecast locations (Fig. 1). The selected locations are the Ostellic River at Cincinnatus (USGS gauge 01510000), Chenango River at Chenango Forks (USGS gauge 01512500), Susquehanna River at Conklin (USGS gauge 01503000), and Susquehanna River at Waverly (USGS gauge 01515000) (Fig. 1). The drainage area of the selected basins ranges from 381 to 12,362 km^2. Table 1 outlines some key characteristics of the study basins.

[Insert Figure 1 here]

[Insert Table 1 here]

3 Approach

In this section, we describe the different components of the RHEPS, including the hydrometeorological observations, weather forecasts, preprocessor, postprocessors, hydrological model, and the forecasting experiments and verification strategy.

3.1 Hydrometeorological observations

Three main observation datasets are used: multisensor precipitation estimates (MPEs), gridded near-surface air temperature, and daily streamflow. MPEs and gridded near-surface air temperature are used to run the hydrological model in simulation mode for parameter calibration purposes and to initialize the RHEPS. Both the MPEs and gridded near-surface air temperature data at 4 x 4 km^2 resolution were provided by the NOAA's Middle Atlantic River Forecast Center (MARFC) (Siddique and Mejia 2017). Similar to the NCEP stage-IV dataset (Moore et al., 2015; Prat and Nelson, 2015), the MARFC's MPEs represent a continuous time series of hourly, gridded precipitation observations at 4 x 4 km^2 cells, which are produced by combining multiple radar estimates and rain gauge measurements. The gridded near-surface air temperature data at 4 x 4 km^2 resolution were developed by the MARFC by combining multiple temperature observation networks as described by Siddique and Mejia (2017). Daily streamflow observations for the selected basins were obtained from the USGS. The streamflow observations are used to verify the simulated flows, and the raw and postprocessed ensemble streamflow forecasts.

3.2 Meteorological forecasts

GEFSRv2 data are used for the ensemble precipitation and near-surface air temperature forecasts. The GEFSRv2 uses the same atmospheric model and initial conditions as the version 9.0.1 of the Global Ensemble Forecast System and runs at T254L42 (~0.50^o Gaussian grid spacing or ~55 km) and T190L42 (~0.67^o Gaussian grid spacing or ~73 km) resolutions for the first and second 8 days, respectively (Hamill et al., 2013). The reforecasts are initiated once daily at 00 Coordinated Universal Time. Each forecast cycle consists of 3 hourly accumulations for day 1 to day 3 and 6 hourly accumulations for day 4 to day 16. In this study, we use 9 years of GEFSRv2 data, from 2004 to 2012, and forecast lead times from 1 to 7 days. The period 2004 to 2012 is selected to take advantage of data that were previously available to us (i.e., GEFSRv2 and MPEs for the MAR) from a recent verification study (Siddique et al., 2015). Forecast lead times of up to 7 days are chosen since we previously found that the GEFSRv2 skill is low after 7 days (Siddique et al., 2015; Sharma et al., 2017). The GEFSRv2 data are bilinearly interpolated onto the 4 x 4 km^2 grid cell resolution of the HL-RDHM model.

3.3 Distributed hydrological model

NOAA’s HL-RDHM is used as the spatially distributed hydrological model (Koren et al., 2004). Within HL-RDHM, the Sacramento Soil Moisture Accounting model with Heat Transfer (SAC-HT) is used to represent hillslope runoff generation, and the SNOW-17 module is used to represent snow accumulation and melting.

HL-RDHM is a spatially distributed conceptual model, where the basin system is divided into regularly spaced, square grid cells to account for spatial heterogeneity. Each grid cell acts as a hillslope capable of generating surface, interflow and groundwater runoff that discharges directly into the streams. The cells are connected to each other through the stream network system. Further, the SNOW-17 module allows each cell to accumulate snow and generate hillslope snow melt based on the near-surface air temperature. The hillslope runoff, generated at each grid cell by SAC-HT and SNOW-17, is routed to the stream network using a nonlinear kinematic wave algorithm (Koren et al., 2004; Smith et al., 2012a). Likewise, flows in the stream network are routed downstream using a nonlinear kinematic wave algorithm that accounts for parameterized stream cross-section shapes (Koren et al., 2004; Smith et al., 2012a). In this study, we run HL-RDHM using a 2-km horizontal resolution. Further information about the HL-RDHM can be found elsewhere (Koren et al., 2004; Reed et al., 2007; Smith et al., 2012a; Fares et al., 2014; Rafieeinasab et al., 2015; Thorstensen et al., 2016; Siddique and Mejia 2017).

To calibrate HL-RHDM, we first run the model using a-priori parameter estimates previously derived from available datasets (Koren et al., 2000; Reed et al., 2004; Anderson et al., 2006). We then select 10 out of the 17 SAC-HT parameters for calibration based upon prior experience and preliminary sensitivity tests. During the calibration process, each a-priori parameter field is multiplied by a factor. Therefore, we calibrate these factors instead of the parameter values at all grid cells, assuming that the a-priori parameter distribution is true (e.g., Mendoza et al., 2012).The multiplying factors are adjusted manually first; once the manual changes do not yield noticeable improvements in model performance, the factors are tuned-up using stepwise line search (SLS; Kuzmin et al., 2008; Kuzmin, 2009). This method is readily available within HL-RDHM, and has been shown to provide reliable parameter estimates (Kuzmin et al., 2008; Kuzmin, 2009). With SLS, the following objective function is optimized:

$$OF = \sqrt{\sum_{i=1}^{m}[q_i - s_i(\Omega)]^2}\,, \qquad (1)$$

where $q_i$and s_i denote the daily observed and simulated flows at time i, respectively; Ω is the parameter vector being estimated; and m is the total number of days used for calibration. Three years (2003-2005) of streamflow data are used to calibrate the HL-RDHM for the selected basins. The first year (year 2003) is used to warm-up HL-RDHM. To assess the model performance during calibration, we use the percent bias (PB), modified correlation coefficient (R_m), and Nash-Sutcliffe efficiency (NSE) (see appendix for details). Note that these metrics are used during the manual phase of the calibration process, and to assess the final results from the implementation of the SLS. However, the actual implementation of the SLS is based on the objective function in Eq. (1).

3.4 Statistical weather preprocessor

Heteroscedastic censored logistic regression (HCLR) (Messner et al., 2014a; Yang et al., 2017) is implemented to preprocess the ensemble precipitation forecasts from the GEFSRv2. HCLR is selected since it offers the advantage, over other regression-based preprocessors (Wilks, 2009), of obtaining the full, continuous predictive probability density function (pdf) of precipitation forecasts (Messner et al., 2014b). Also, HCLR has been shown to outperform other widely used preprocessors, such as Bayesian Model Averaging (Yang et al., 2017). In principle, HCLR fits the conditional logistic probability distribution function to the transformed (here the square root) ensemble mean and bias corrected precipitation ensembles. Note that we tried different transformations (square root, cube root, and fourth root), and found a similar performance between the square and cube root, both outperforming the fourth root. In addition, HCLR uses the ensemble spread as a predictor, which allows the use of uncertainty information contained in the ensembles.

The development of the HCLR follows the logistic regression model initially proposed by Hamill et al. (2004) as well as the extended version of that model proposed by Wilks (2009). The extended logistic regression of Wilks (2009) is used to model the probability of binary responses such that

$$P(y \leq z|x) = \Lambda[\omega(z) - \delta(x)], \tag{2}$$

where $\Lambda(.)$ denotes the cumulative distribution function of the standard logistic distribution, y is the transformed precipitation, z is a specified threshold, x is a predictor variable that depends on the forecast members, $\delta(x)$ is a linear function of the predictor variable x , and the transformation $\omega(.)$ is a monotone nondecreasing function. Messner et al. (2014a) proposed the heteroscedastic extended logistic regression (HELR) preprocessor with an additional predictor variable φ to control the dispersion of the logistic predictive distribution,

$$P(y \leq z|x) = \Lambda\left\{\frac{\omega(z)-\delta(x)}{exp[\eta(\varphi)]}\right\}, \tag{3}$$

where $\eta(.)$ is a linear function of φ. The functions $\delta(.)$and $\eta(.)$ are defined as:

$$\delta(x) = a_0 + a_1 x, \text{ and} \tag{4}$$

$$\eta(\varphi) = b_0 + b_1 \varphi, \tag{5}$$

where a_0, a_1, b_0, and b_1 are parameters that need to be estimated; $x = \frac{1}{K}\sum_{k=1}^{K} f_k^{\frac{1}{2}}$, i.e., the predictor variable x is the mean of the transformed, via the square root, ensemble forecasts f; K is the total number of ensemble members; and φ is the standard deviation of the square root transformed, precipitation ensemble forecasts.

Maximum likelihood estimation with the log-likelihood function is used to estimate the parameters associated with Eq. (3) (Messner et al., 2014a; Messner et al., 2014b). ~~For this, the predicted probability π_i of the i^{th} observed outcome is determined.~~ One variation of the HELR preprocessor that can easily accommodate nonnegative variables, such as precipitation amounts, is HCLR. For this, the predicted probability or likelihood π_i of the i^{th} observed outcome is determined as~~., where π_i is defined as~~ (Messner et al., 2014b):

$$\pi_i = \begin{cases} \Lambda\left[\frac{\omega(0)-\delta(x)}{exp[\eta(\varphi)]}\right] & y_i = 0 \\ \lambda\left[\frac{\omega(y_i)-\delta(x)}{exp[\eta(\varphi)]}\right] & y_i > 0, \end{cases} \tag{6}$$

where $\lambda[.]$ denotes the likelihood function of the standard logistic function. As indicated by Eq. (6), HCLR fits a logistic error distribution with point mass at zero to the transformed predictand.

HCLR is applied here to each GEFSRv2 grid cell within the selected basins. At each cell, HCLR is implemented for the period 2004-2012 using a leave-one-out approach. For this, we select 7 years for training and the two remaining years for verification purposes. This is repeated until all the 9 years have been preprocessed and verified independently of the training period. This is done so that no training data is discarded and the entire 9-year period of analysis can be used to generate the precipitation forecasts. HCLR is employed for 6-hourly precipitation accumulations for lead times from 6 to 168 hours. To train the preprocessor, we use a stationary training period, as opposed to a moving window, for each season and year to be forecasted, comprised by the seasonal data from all the 7 training years. Thus, to forecast a given season and specific lead time, we use ~6930 forecasts (i.e., 11 members x 90 days per season x 7 years). We previously tested using a moving window training approach and found that the results were similar to the stationary window one (Yang et al., 2017). To make the implementation of HCLR as straightforward as possible, the stationary window is used here. Finally, the Schaake Shuffle method as applied by Clark et al. (2004) is implemented to maintain the observed space-time variability in the preprocessed GEFSRv2 precipitation forecasts. At each individual forecast time, the Schaake Shuffle is applied to produce a spatial and temporal rank structure for the ensemble precipitation values that is consistent with the ranks of the observations.

3.5 Statistical streamflow postprocessors

To statistically postprocess the flow forecasts generated by the RHEPS, two different approaches are tested, namely a first-order autoregressive model with a single exogenous variable, ARX(1,1), and quantile regression (QR). We select the ARX(1,1) postprocessor since it has been suggested and implemented for operational applications in the U.S. (Regonda et al., 2013). QR is chosen because it is of similar complexity as the ARX(1,1) postprocessor but for some forecasting conditions it has been shown to outperform it (Mendoza et al., 2016). Furthermore, the ARX (1,1) and QR postprocessors have not been compared against each other for the forecasting conditions specified by the RHEPS. The postprocessors are implemented for the years 2004-2012, using the same leave-one-out approach used for the preprocessor. ~~The postprocessors are applied at each individual lead time from day 1 to 7.~~ For this, the 6-hourly precipitation accumulations are used to force the HL-RDHM and generate 6-hourly flows. Note that we use 6-hourly accumulations since this is the resolution of the GEFSRv2 data after day 4 and ~~since~~ this is a temporal resolution often ~~commonly~~ used in operational forecasting in the U.S. Since the observed flow data are mean daily, we compute the mean daily flow forecast from the 6-hourly flows. The postprocessor is then applied to the mean daily values from day 1 to 7.~~For this, the 6-houlry streamflow forecasts from HL-RDHM are averaged over 24 hours to get the streamflow forecast for a particular day.~~

3.5.1 First-order autoregressive model with a single exogenous variable

To implement the ARX(1,1) postprocessor, the observation and forecast data are first transformed into standard normal deviates using the normal quantile transformation (NQT) (Krzysztofowicz, 1997; Bogner et al., 2012). The transformed observations and forecasts are then used as predictors in the ARX(1,1) model (Siddique and Mejia, 2017). Specifically, for each forecast lead time, the ARX (1,1) postprocessor is formulated as follows:

$$q_{i+1}^{T} = (1 - c_{i+1})q_{i}^{T} + c_{i+1}f_{i+1}^{T} + \xi_{i\cancel{1}+1}, \tag{7}$$

where q_{i}^{T} and q_{i+1}^{T} are the NQT transformed observed flows at time steps *i* and *i*+1, respectively; *c* is the regression coefficient; f_{i+1}^{T} is the NQT transformed forecast flow at time step *i*+1; and ξ is the residual error term. In Eq. (7), assuming that there is significant correlation between ξ_{i+1} and q_{i}^{T}, ξ_{i+1} can be calculated as:

$$\xi_{i+1} = \frac{\sigma_{\xi_{i+1}}}{\sigma_{\xi_{i}}}\rho(\xi_{i+1}, \xi_{i})\xi_{i} + \vartheta_{i+1}, \tag{8}$$

where σ_{ξ_i} and $\sigma_{\xi_{i+1}}$ are the standard deviation of ξ_i and ξ_{i+1}, respectively; $\rho(\xi_{i+1}, \xi_i)$ is the serial correlation between ξ_{i+1} and ξ_i; and ϑ_{i+1} is a random Gaussian error generated from $\mathrm{N}\left(0, \sigma_{\vartheta_{i+1}}^2\right)$. To estimate $\mathrm{N}\left(0, \sigma_{\vartheta_{i+1}}^2\right)$, the following equation is used:

$$\sigma_{\vartheta_{i+1}}^{2} = [1 - \rho^{2}(\xi_{i+1}, \xi_{i})]\sigma_{\xi_{i+1}}^{2}. \tag{9}$$

To implement Eq. (7), ten equally spaced values of c_{i+1} are selected from 0.1 to 0.9. For each value of c_{i+1}, $\sigma_{\vartheta_{i+1}}^2$ is determined from Eq. (9), using the training data to determine the other variables in Eq. (9). Then, ϑ_{i+1} is generated from $\mathrm{N}\left(0, \sigma_{\vartheta_{i+1}}^2\right)$ and ξ_{i+1} is calculated from Eq. (8). The result from Eq. (8) is used with Eq. (7) to generate a trace of q_{i+1}^{T} which is transformed back to real space using the inverse NQT. These steps are repeated to generate multiple traces for each value of c_{i+1}. For each value of c_{i+1}, the ARX(1,1) model is trained and used to generate ensemble streamflow forecasts, which are in turn used to compute the mean continuous ranked probability score (CRPS) for the 7-year training period under consideration. Thus, the mean CRPS is computed for each value of c_{i+1}, and the value of c_{i+1} that produces the smallest mean CRPS is then selected for use in the 2-year verification period under consideration. This is repeated until all the years (2004-2012) have been postprocessed and verified independently of the training period. ~~Lastly, the value of c_{i+1} that produces the ensemble forecast with the smallest mean continuous ranked probability skill (CRPS) is selected.~~ The ARX (1,1) postprocessor is applied at each individual lead time. For lead times beyond the initial one (day 1), one day-ahead predictions are used as the observed streamflow. For the cases where q_{i+1}^{T} falls beyond the historical maxima, extrapolation is used by modeling the upper tail of the forecast distribution as hyperbolic (Journel and Huijbregts, 1978).

3.5.2 Quantile regression

Quantile regression (QR; Koenker and Bassett Jr, 1978; Koenker, 2005) is employed to determine the error distribution, conditional on the ensemble mean, resulting from the difference between observations and forecasts (Dogulu et al., 2015; López et al., 2014; Weerts et al., 2011; Mendoza et al., 2016). QR is applied here in streamflow space, since it has been shown that, in hydrological forecasting applications, QR has similar skill performance in streamflow space as well as~~and~~ normal space (López et al., 2014). Another advantage of QR is that it does not make any prior assumptions regarding the shape of the distribution. Further, since QR results in conditional quantiles rather than conditional means, QR is less sensitive to the tail behavior of the streamflow dataset, and consequently, less sensitive to outliers. Note that although QR is here implemented separately for each lead time, the mathematical notation does not reflect this for simplicity.

The QR model is given by

$$\varepsilon'_\tau = d_\tau + e_\tau \bar{f}, \tag{10}$$

where ε'_τ is the error estimate at quantile interval τ; $\bar{f}$ is the ensemble mean; and d_τ and e_τ are the linear regression coefficients at τ. The coefficients are determined by minimizing the sum of the residuals based on the training data as follows:

$$\min \sum_{i=1}^{N} w_\tau\left[\varepsilon_{\tau,i} - \varepsilon'_\tau\left(i, \bar{f_i}\right)\right], \tag{11}$$

$\varepsilon_{\tau,i}$ and $\bar{f_i}$ are the i^{th} paired samples from a total of N samples; $\varepsilon_{\tau,i}$ is computed as the observed flow minus the forecasted one, $q_\tau - f_\tau$; and w_τ is the weighting function for the τ^{th} quantile defined as:

$$w_\tau(\zeta_i) = \begin{cases} (\tau-1)\zeta_i & if\ \zeta_i \leq 0 \\ \tau\zeta_i & if\ \ \zeta_i > 0. \end{cases} \tag{12}$$

ζ_i is the residual term defined as the difference between $\varepsilon_{\tau,i}$ and $\varepsilon'_\tau\left(i, \bar{f_i}\right)$ for the quantile τ. The minimization in Eq. (11) is solved using linear programming (Koenker, 2005).

Lastly, to obtain the calibrated forecast, f_τ, the following equation is used:

$$f_\tau = \bar{f} + \varepsilon'_\tau. \tag{13}$$

In Eq. (13), the estimated error quantiles and the ensemble mean are added to form a calibrated discrete quantile relationship for a particular forecast lead time and thus generate an ensemble streamflow forecast.

3.6. Forecast experiments and verification

The verification analysis is carried out using the Ensemble Verification System (Brown et al., 2010). For the verification, the following metrics are considered: ~~relative mean error (RME),~~ Brier skill score (BSS), mean continuous ranked probability skill score (CRPSS), and the decomposed components of the CRPS (Hersbach, 2000), i.e., the CRPS reliability ($CRPS_{rel}$) and CRPS potential ($CRPS_{pot}$). The definition of each of these metrics is provided in the appendix. Additional details about the verification metrics can be found elsewhere (Wilks, 2011; Jolliffe and Stephenson, 2012). Confidence intervals for the verification metrics are determined using the stationary block bootstrap technique (Politis and Romano, 1994), as done by Siddique et al. (2015). ~~The verification is focused on flood events by choosing flow amounts greater than that implied by a non-exceedance probability, in the sampled climatological probability distribution, of ~0.95. Thus, hereafter the term floods is used instead of streamflow to denote the forecasts generated by HL-RDHM.~~ All the forecast verifications are done for lead times from 1 to 7 days.

To verify the forecasts for the period 2004-2012, six different forecasting scenarios are considered (Table 2). The first (S1) and second (S2) scenario~~s~~ verify the raw and preprocessed ensemble precipitation forecasts, respectively. Scenarios 3 (S3), 4 (S4) and 5 (S5) verify the raw, preprocessed, and postprocessed ensemble ~~flood~~ streamflow forecasts, respectively. The last scenario, S6, verifies the combined preprocessed and postprocessed ensemble ~~flood~~ streamflow forecasts. In S1 and S2, the raw and preprocessed ensemble precipitation forecasts are verified against the MPEs. For the verification of S1 and S2, each grid cell is treated as a separate verification unit. Thus, for a particular basin, the average performance is obtained by averaging the verification results from different verification units. The ~~S~~streamflow forecast scenarios, S3-S6, are verified against mean daily streamflow observations from the USGS. The quality of the ~~flood~~streamflow forecasts is evaluated conditionally upon forecast lead time, season (cool and warm), and flow threshold.

[Insert Table 2 here]

4 Results and discussion

This section is divided into four subsections. The first subsection demonstrates the performance of the spatially distributed model, HL-RDHM. The second subsection describes the performance of the raw and preprocessed GEFSRv2 ensemble precipitation forecasts (forecasting scenarios S1 and S2). In the third subsection, the two statistical postprocessing techniques are compared. Lastly, the verification of different ensemble ~~flood~~ streamflow forecasting scenarios is shown in the fourth subsection (forecasting scenarios S3-S6).

4.1 Performance of the distributed hydrological model

To assess the performance of HL-RDHM, the model is used to generate streamflow simulations which are verified against daily observed flows, covering the entire period of analysis (years 2004-2012). Note that the simulated flows are obtained by forcing HL-RDHM with gridded observed precipitation and near surface temperature data~~observations~~. The verification is done for the four basin outlets shown in Fig. 1. To perform the verification and assess the quality of the streamflow simulations, the following statistical measures of performance are employed: modified correlation coefficient, R_m; Nash-Sutcliffe efficiency, NSE; and percent bias, PB. The mathematical definition of these metrics is provided in the appendix. The verification is done for both uncalibrated and calibrated simulation runs for the entire period of analysis. The main results from the verification of the streamflow simulations are summarized in Fig. 2.

[Insert Figure 2 here]

The performance of the calibrated simulation runs is satisfactory, with R_m values ranging from ~0.75 to 0.85 (Fig. 2a). Likewise, the NSE, which is sensitive to both the correlation and bias, ranges from ~0.69 to 0.82 for the calibrated runs (Fig. 2b), while the PB ranges from ~5 to -11% (Fig. 2c). Relative to the uncalibrated runs, the R_m, NSE, and PB values improve by ~18, 29, and 47%, respectively. Further, the performance of the calibrated simulation runs is similar across the four selected basins, although the largest size basin, WVYN6 (Fig. 2), shows ~~seems to~~ slightly higher performance~~outperform~~ ~~the other basins~~ with R_m, NSE, and PB values of 0.85, 0.82, and -3% (Fig. 2), respectively. The lowest performance is seen in CNON6 with R_m, NSE, and PB values of 0.75, 0.7, and -11% (Fig. 2), respectively. Nonetheless, the performance metrics for both the uncalibrated and calibrated simulation runs do not deviate widely from each other in the selected basins, with perhaps the only exception being PB (Fig. 2c).

4.2 Verification of the raw and preprocessed ensemble precipitation forecasts

To examine the skill of both the raw and preprocessed GEFSRv2 ensemble precipitation forecasts, we plot in Fig. 3 the CRPSS (relative to sampled climatology) as a function of the forecast lead time (day 1 to 7) and season for the selected basins. Two seasons are considered: cool (October-March) and warm (April-September). Note that a CRPSS value of zero means no skill (i.e., same skill as the reference system) and a value of one indicates maximum skill. The CRPSS is computed using 6 hourly precipitation accumulations.~~, and high precipitation events. High precipitation events are here defined by an amount greater than that implied by a non-exceedance probability, in the sampled climatological probability distribution, of ~0.95.~~

[Insert Figure 3 here]

The skill of both the raw and preprocessed ensemble precipitation forecasts tends to decline with increasing forecast lead time (Fig. 3). In the warm season (Figs. 3a-d), the CRPSS values vary overall, across all the basins, in the range from ~0.17~~2~~ to 0.5~~4~~ and from ~~~-~~0.0~~2~~ to 0.4~~3~~ for the preprocessed and raw forecasts, respectively; while in the cool season (Figs. 3e-h) the CRPSS values vary overall in the range from ~0.2~~51~~ to 0.6 and from ~0.1 to 0.6~~5~~ for the preprocessed and raw forecasts, respectively. The skill of the preprocessed ensemble precipitation forecasts tends to be greater than the raw ones across basins, seasons, and forecast lead times. Comparing the raw and preprocessed forecasts against each other, the relative skill gains from preprocessing are somewhat more apparent in the medium-range lead times (>3 days) and warm season. That is, the differences in skill seem not as significant in the short-range lead times (≤3 days). This seems particularly the case in the cool season where the confidence intervals for the raw and preprocessed forecasts tend to overlap (Figs. 3e-h).

Indeed, seasonal skill variations are noticeable in all the basins. Even though the relative gain in skill from preprocessing is slightly greater in the warm season, the overall skill of both the raw and preprocessed forecasts is better in the cool season than the warm one. This may be due, among other potential factors, to the greater uncertainty associated with modeling convective precipitation, which is more prevalent in the warm season, by the NWP model used to generate the GEFSRv2 outputs (Hamill et al., 2013; Baxter et al., 2014). Nonetheless, the warm season preprocessed forecasts show gains in skill across all the lead times and basins. For a particular season, the forecast ensembles across the different basins tend to display similar performance; i.e. the analysis does not reflect skill sensitivity to the basin size as in other studies (Siddique et al., 2015; Sharma et al., 2017). This is expected here since the verification is performed for each GEFSRv2 grid cell, rather than verifying the average for the entire basin. That is, the results in Fig. 3 are for the average skill performance obtained from verifying each individual grid cell within the selected basins.

Based on the results presented in Fig. 3, we may expect some skill contribution to the ~~flood~~ streamflow ensembles from forcing the HL-RDHM with the preprocessed precipitation, as opposed to using the raw forecast forcing. ~~Although the contribution may not be as large, since the differences between the preprocessed and raw precipitation forecasts are only mild.~~ It may also be expected that the contributions are greater for the medium-range lead times and warm season. This will be examined in subsection 4.4, prior to that we compare next the two postprocessors, namely ARX(1,1) and QR.

4.3 Selection of the ~~flood~~ streamflow postprocessor

The ability of the ARX(1,1) and QR postprocessors to improve ensemble streamflow~~flood~~ forecasts is investigated here. The postprocessors are applied to the raw streamflow ~~flood~~ ensembles at each forecast lead time from day 1 to 7. To examine the skill of the postprocessed ~~flood~~ streamflow forecasts, Fig. 4 displays the CRPSS (relative to the raw ensemble ~~flood~~ streamflow forecasts) versus the forecast lead time for all the selected basins, for both warm ~~cool~~ (Figs. 4a-d) and cool~~warm~~ (Figs. 4e-h) seasons. In the cool season (Figs. 4e-h), ~~T~~the ~~overall~~ tendency is for both postprocessing techniques to demonstrate improved forecast skill across all the ~~all the~~ basins~~, seasons,~~ and ~~most of the~~ lead times. The skill can improve as much as 40% at the later lead times (Fig. 4f). The skill improvements, however, from the ARX(1,1) postprocessor are not as consistent for the warm season (Figs. 4a-d), displaying negative skill values for some of the lead times in all the basins. The latter underscores an inability of the ARX(1,1) postprocessor to enhance the raw streamflow ensembles for the warm season. ~~The skill can improve as much as 40% at the later lead times (Fig. 4fb).~~ In some cases (Figs. 4b and 4e-f), ~~The general trend in Fig. 4 is for~~ the skill of the postprocessors shows an increasing trend with ~~to increase with increasing~~ the lead time. ~~Note that t~~This is the case since the skill is here measured relative to the raw streamflow~~flood~~ forecasts, which is done to better isolate the effect of the postprocessors on the ~~flood~~ streamflow forecasts. ~~This means that the postprocessors are more able to improve the medium-range (>3 days) forecasts than the short-range (≤3 days) ones.~~

[Insert Figure 4 here]

The gains in skill from QR vary from ~0~~5~~% (Fig. 4b~~a~~ at the day 1 lead time) to ~40% (Fig. 4f~~b~~ ~~at~~at the ~~the day 5 lead time~~ lead times > 4 days) depending upon the season and lead time. ~~While t~~The gains from ARX(1,1), on the other hand, vary from ~0~~4~~% (Fig. 4g~~be~~ at the day 1 lead time) to a much lower level of ~28~~52~~% (Fig. 4f~~e~~ at the day 4 lead time ~~of 4 days~~ ~~the day 2 lead time~~) during the cool season, while there are little to no gains in the warm season. In the cool season (Figs. 4e-h)~~most most cases~~, both postprocessors exhibit somewhat similar performance at different lead times ~~at the initial lead times (days 1-2)~~, with the exception of Fig. 4h ~~skills varying from nearly 0.1 (e.g., Figs. 4a and 4ce) at lead time of day 1 to 0.34 (Fig. 4df at the day 2 lead time) at lead time of day 7~~, but in the warm season QR tends to consistently perform better than ARX(1,1). The ~~However,~~ ~~At the later lead times~~ overall trend in Fig. 4 is for ~~shows that,(4-7 days),~~ QR to ~~tends~~ mostly~~to~~ o~~slightly o~~utperform ARX(1,1), with the difference in performance being as high as 30% (Fig. 4d at the day 7 lead time). This is noticeable across all the ~~basins~~ basins, except WVYN6 in Fig. 4h, most of the lead times and for both ~~and for both~~ seasons~~, with an exception at the WVYN6 during cool season~~. ~~The skill improvement of QR over ARX(1,1) is significant at later lead times (> day 3), as indicated by the fact that the confidence intervals for the curves representing the postprocessors in Fig. 4 often do not overlap.~~ ~~There are also seasonal differences in the performance of the postprocessors. In particular, the gains in skill from ARX(1,1) in the warm season can be quite low (Figs. 4a and 4d~~~~e~~~~).~~

As discussed and demonstrated in Fig. 4, QR performs better than ARX(1,1). We also computed reliability diagrams, as determined by Sharma et al., (2017), for the two postprocessors~~Indeed,~~ (plots not shown) and found that ~~we also found (plots not shown) that~~ QR tends to display~~s~~ better reliability than ARX(1,1) across lead times, basins, and seasons. Therefore, we select QR as the statistical ~~flood~~ streamflow postprocessor to examine the interplay between preprocessing and postprocessing in the RHEPS.

4.4 Verification of the ensemble ~~flood~~ streamflow forecasts for different statistical processing scenarios

In this subsection, we examine the effects of different statistical processing scenarios on the ensemble streamflow~~flood~~ forecasts from the RHEPS. ~~Recall that, to consider flood events, the verification is done for flow events with an amount greater than that implied by a non-exceedance probability, in the sampled climatological probability distribution, of ~0.95.~~ The forecasting scenarios considered here are S3-S6 (Table ~~1~~2 defines the scenarios). To facilitate presenting the verification results, this subsection is divided into the following three~~four~~ parts: ~~relative mean error,~~ CRPSS, CRPS decomposition, and BSS.

~~4.4.1 Relative mean error~~

~~To examine the bias associated with the mean ensemble flood forecasts under scenarios S3-S6, we plot the RME versus the forecast lead time for all the basins (Fig. 5), and the warm (Fig. 5a-d) and cool seasons (Fig. 5e-h). Results in Fig. 5 show that, under all the considered scenarios, the mean ensemble flood forecasts exhibit underforecasting bias across basins, lead times, and seasons. The underforecasting bias increases with the lead time, and decreases somewhat with the increase in basin size. For example, the bias for the largest basin, WVYN6, is -0.1 at the day 1 lead time and scenario S3 (Fig. 5d), while for the same lead time and scenario the bias is -0.35 for the smallest basin (Fig. 5a). In essence, the GEFSRv2-based flood ensembles exhibit a conditional bias that is consistent with the conditional bias (i.e., to significantly underforecast large events) for the GEFSRv2 precipitation ensembles (Siddique et al., 2015; Sharma et al., 2017).~~

~~[Insert Figure 5 here]~~

~~The two most striking features of Fig. 5 are: i) the significant difference in performance between the pair S3-S4 and S5-S6 and, in contrast, ii) the similarity in performance between S5 and S6. The former confirms that statistical processing, in particular postprocessing, has a significant effect on the flood ensembles. Recall that to generate the ensemble flood forecasts S5 only employs postprocessing, while S6 considers both preprocessing and postprocessing (Table 1). Yet, the RME across basins, lead times, and seasons for both S5 and S6 are quite similar, with differences tending to be not as significant. The similarity between S5 and S6 indicates that in this case preprocessing has a mild effect on the flood forecasts.~~

~~As a corollary to the latter comment, it can be argued that by only postprocessing the raw flood ensembles most of the benefits from statistical processing can be realized. This seems also supported by the results for S3 and S4 (Fig. 5). The differences between the RME of the flood forecasts generated by forcing the HL-RDHM with raw, S3, versus preprocessed precipitation ensembles, S4, are only significant at lead times greater than 4 days. In addition, the differences are not as large, with the largest one being ~-0.18 at the day 5 lead time in CNON6 (Fig. 5b). This is not entirely surprising as we previously saw (Fig. 3) that differences between the raw and preprocessed precipitation ensembles are only significant at the later lead times where the skill of the forecast is, in any case, already somewhat low. In terms of the seasonal analysis, both S5 and S6 tend to be less biased in the cool season than in the warm one, particularly at the short-range lead times (<3 days). This can be seen by comparing Fig. 4c against Fig. 4g at the day 1 lead time. The role played by preprocessing and postprocessing in ensemble flood forecasting is further evaluated next in terms of the forecast skill.~~

4.4.1~~2~~ CRPSS

The skill of the ensemble ~~flood~~ streamflow forecasts for S3-S6 is assessed using the CRPSS relative to the sampled climatology (Fig. 5~~6~~). The CRPSS in Fig. 5 is shown as a function of the forecast lead time for all the basins, and the warm (Fig. 5a-d) and cool (Fig. 5e-h) seasons~~Fig. 6 shows that, across lead times, basin sizes, and seasons, the results for the CRPPS are qualitatively similar to those for the RME (Fig. 5)~~. ~~That is, t~~The most salient feature of Fig. 5~~6~~ is that the performance of the ~~flood~~streamflow forecasts tends for the most part to progressively improve from S3 to S6. This means that the forecast skill tends to improve across lead times, basin sizes and seasons as additional statistical processing steps are included in the RHEPS' forecasting chain. Although there is some tendency for the large~~r~~ basins to show better forecast skill than the small ones, the scaling (i.e., the dependence of skill on the basin size) ~~scaling~~ is rather mild and not consistent across the four basins. ~~The scaling tends to show significant variability so that it is not necessarily evident for the conditions considered (e.g., lead times and seasons).~~

In Fig. 5, ~~T~~the skill first increases from the raw scenario (i.e., S3 where no statistical processing is done) to the scenario where only preprocessing is performed, S4. ~~However, t~~The gain in skill between S3 and S4 is generally small at the short lead times (< 3 days) but increases for the later lead times; this is somewhat more evident for the cool season than the warm one.~~, particularly at the short lead times, reinforcing the fact that preprocessing~~ alone ~~may have little effect on the~~ streamflow ~~flood forecasts~~. This skill trend between S3 and S4 is not entirely surprising as we previously saw (Fig. 3) that differences between the raw and preprocessed precipitation ensembles are more~~only~~ significant at the later lead times~~ where the skill of the forecast is, in any case, already somewhat low~~. The skill in Fig. 5 ~~then~~ then shows further improvements for ~~a more significant improvement for~~ both S5 and S6, relative to S4. ~~As was the case with the RME~~ Although S6 ~~Even though S6~~ tends to outperform both S4 and S5~~ in most of the lead times~~ in Fig. 5, the differences in skill among these three scenarios ~~between S5 and S6~~ are not as significant, their confidence intervals tend to overlap in most cases, with the exception of Fig. 5f where S4 underperforms relative to both S5 and S6. Fig. 5 shows that S6 is the preferred scenario in that it tends to more consistently improve the ensemble streamflow forecasts across basins, lead times and seasons than the other scenarios. It also shows that postprocessing alone, S5, may be slightly more effective than preprocessing alone, S4, in correcting the streamflow forecast biases. .~~, suggesting that postprocessing alone (i.e., without preprocessing) may be sufficient to remove systematic biases in the flood forecasts.~~

[Insert Figure ~~6~~5 here]

There are also seasonal differences in the forecast skill among the scenarios. The skill of the streamflow forecasts tends to be slightly greater in the warm season (Figs. 5a-d) than in the cool one (Figs. 5e-h) across all the basins and lead times. In the warm season (Figs. 5a-d), all the scenarios tend to show similar skill, except CNON6 (Fig. 5b), with S5 and S6 only slightly outperforming S3 and S4. In the cool season (Figs. 5e-h), with the exception of CNON6 (Fig. 5f), the performance is similar among the scenarios for the short lead times but S3 tends to consistently underperform for the later lead times relative to S4-S6. There is also a skill reversal between the seasons when comparing the ensemble precipitation (Fig. 3) and streamflow (Fig. 5) forecasts. That is, the skill tends to be higher in the cool season than the warm one in Fig. 3, but this trend reverses in Fig. 5. The reason for this reversal is that in the cool season hydrological conditions are strongly influenced by snow dynamics, which can be challenging to represent with HL-RDHM, particularly when specific snow information or data are not available. In any case, this could be a valuable area for future research since it appears here to have a significant influence on the skill of the ensemble streamflow forecasts.

The underperformance of S4 in the CNON6 basin (Fig. 5f), relative to the other scenarios, is in part due to the unusually low skill of the raw ensemble streamflow forecasts of S3, so that even after preprocessing the skill improvement attained with S4 is not comparable to that associated with S5 and S6. This is also the case for CNON6 in the warm season (Fig. 5b). However, in addition, during the cool season it is likely that streamflows in CNON6 are affected by a reservoir just upstream from the main outlet of CNON6. The reservoir is operated for flood control purposes. The reservoir affects during the cool season low flows by maintaining them somewhat higher than in natural conditions. Since we do not account for reservoir operations in our hydrological modeling, it is likely that part of the benefits of postprocessing are in this case to correct for this modeling bias. In fact, this is also reflected in the ~~The two most striking features of Fig. 5 are: i) the significant difference in performance between the pair S3-S4 and S5-S6 and, in contrast, ii) the similarity in performance between S5 and S6. The former confirms that statistical processing, in particular postprocessing, has a significant effect on the streamflow ensembles. Recall that to generate the ensemble streamflow~~

~~forecasts S5 only employs postprocessing, while S6 considers both preprocessing and postprocessing (Table 1). Yet, the CRPSS across basins, lead times, and seasons for both S5 and S6 are quite similar, with differences tending to be not as significant. The similarity between S5 and S6 indicates that in this case preprocessing has a mild effect on the streamflow forecasts.~~

~~Further, comparing the ensemble streamflow forecasts of S5 and S6 against each other, it appears that the general tendency is for the both scenarios to perform similarly. The S6, however, tends to show slight skill gain over S5 across all the basins and lead times, particularly in the cool season. While in the warm season, most part of the forecasting scenarios from S4 to S6 behave similarly with respect to each other. Indeed, S6 exhibit marginal skill gain at initial lead times (< day 3), but the skill performance becomes similar among S4 to S6 at later lead times, with an exception for CINN6 (Fig. 5a). In the case of CINN6 (Fig. 5a), S5 and S6 exhibit skill gain over S4 after lead times of 3 days.~~

~~In terms of the warm and cool seasons seasonal analysis, at the initial forecast lead times (≤ 2 days), the skill of the flood streamflow forecasts tends to be slightly greater in the cool warm season (Figs. 56ae-dh) than in the coolwarm one (Figs. 56ea-hd) across all the basins and lead times., with the exception of CNON6. The CNON6 exhibit lowest skill during both warm (Fig. 5b) and cool (Fig. 5f) seasons. This may be partly, among other potential factors, because of the effect of the Whitney Point reservoir that is located just upstream of the main outlet of the CNON6. The reservoir is mainly operated for flood control, thus modify the streamflow forecast at the basin outlet. As was the case in the~~ calibration results (e.g., in Fig. 2c), where the performance of ~~during the cool season~~ CNON6 is somewhat lower than in the other basins.~~has a lower performance prior to postprocessing (S3 or S4 in Fig. 56f) than the other basins.~~ Interestingly, after postprocessing (S5 in Fig. 5~~6~~f), the skill of CNON6 is as good as that of CINN6, even though at the day 1 lead time the skill for S3 is ~0.1~~3~~ for CNON6 (Fig. 5~~6~~f) and ~0.4~~5~~ for CINN6 (Fig. 5~~6~~e). Hence, the postprocessor seems capable to compensate some for the lesser performance of CNON6 in~~during~~ both calibration or after preprocessing in the cool season.

4.4.2~~3~~ CRPS decomposition

Fig. 6~~7~~ displays different components of the mean CRPS against lead times of 1, 3, and 7 days for all the basins according to both the warm (Figs. 6~~7~~a-d) and cool (Figs. 6~~7~~e-h) seasons. The components presented here are reliability (CRPS$_{rel}$) and potential CRPS (CRPS$_{pot}$) (Hersbach, 2000). CRPS$_{rel}$ measures the average reliability of the ensemble forecasts across all the possible events, i.e., it examines whether the fraction of observations that fall below the *j*-th of *n* ranked ensemble members is equal to *j*/*n* on average. CRPS$_{pot}$ represents the lowest possible CRPS that could be obtained if the forecasts were made perfectly reliable (i.e., CRPS$_{rel}$=0). Note that the CRPS, CRPS$_{rel}$, and CRPS$_{pot}$ are all negatively oriented, with perfect score of zero. Overall, as was the case with the ~~RME (Fig. 5) and~~ CRPSS (Fig. 5~~6~~), the CRPS decomposition reveals that forecast~~s~~ reliability tends mostly to progressively improve ~~increases~~ from S3 to S6.

[Insert Figure ~~7~~6 here]

Interestingly, improvements in forecast quality for S5 and S6, relative to the raw streamflow~~flood~~ forecasts of S3, are mainly due to reductions in CRPS$_{rel}$ (i.e., by making the forecasts more reliable), whereas for S4 better forecast quality is achieved~~, in part,~~ by reductions in both CRPS$_{rel}$ and CRPS$_{pot}$. CRPS$_{pot}$ appears to play a bigger role in S4 than in the other scenarios, since in many cases in Fig. 6 the CRPS$_{pot}$ value for S4 is the lowest among all the scenarios. ~~The latter is seen across all the basins, lead times, and seasons.~~ The explanation for this lies in the implementation of the HCLR preprocessor, which uses the ensemble spread as a predictor of the dispersion of the predictive pdf and the CRPS$_{pot}$ is sensitive to the spread (Messner et al., 2014a). ~~This indicates that The , CRPS decomposition demonstrates that the ensemble streamflow forecasts for S5 and S6 are more reliable than for S3 and S4. Although the It also shows that the forecasts from S5 and S6 exhibit similar reliability3 have lower CRPS$_{pot}$. However, ,~~

~~the ensemble streamflow forecasts including preprocessing and postprocessing, S5 and S6, ultimately result in lower CRPS. This indicates that, the forecasts for S5 and S6 are more reliable than for S3 and S4.The latter is seen across all the basins, lead times, and seasons.~~ In terms of the warm and cool seasons, ~~although ensemble streamflow forecasts from S5 and S6 exhibit similar reliability,~~ the warm season tends to show a slightly lower CRPS than the cool one for all the scenarios. There are other, more nuanced differences between the two seasons. For example, S5 is more reliable than S4 in several cases in Fig. 6, such as for the day 1 lead time in the cool season. The CRPS decomposition demonstrates that the ensemble streamflow forecasts for S5 and S6 tend to be more reliable than for S3 and S4. It also shows that the forecasts from S5 and S6 tend to exhibit comparable reliability. However, the ensemble streamflow forecasts generated using both preprocessing and postprocessing, S6, ultimately result in lower CRPS than the other scenarios. The latter is seen across all the basins, lead times, and seasons, except in one case (Fig. 6d at the day 7 lead time).

4.4.~~4~~3 BSS

In our final verification comparison, the BSS of the ensemble ~~flood~~ streamflow forecasts for S5 (Figs. 7~~8~~a-d) and S6 (Figs. 7~~8~~e-h) are plotted against the non-exceedance probability associated with different ~~flood~~ streamflow thresholds ranging from 0.95 to 0.99. The BSS is computed for all the basins, warm season, and lead times of 1, 3 and 7 days. In addition, the BSS is computed relative to both observed (solid lines in Fig. 7~~8~~) and simulated (dashed lines in Fig. 7~~8~~) flow~~ed~~s. When the BSS is computed relative to observed ~~floods~~ flows, it considers the effect on forecast skill of both meteorological and hydrological uncertainties. While the BSS relative to simulated ~~floods~~ flows is mainly affected by meteorological uncertainties. The difference between the two, i.e., the BSS relative to observed flows~~ods~~ minus the BSS relative to simulated ones, provides an estimate of the effect of hydrological uncertainties on the skill of the ~~flood~~ streamflow forecasts. Similar to the CRPSS, the BSS value of zero means no skill (i.e., same skill as the reference system) and a value of one indicates perfect skill.

[Insert Figure ~~8~~7 here]

In general, the skill of ~~flood~~ streamflow forecasts tends to decrease with lead time across the flow thresholds and basins. In contrast to the ~~As was the case with the~~ CRPSS (Fig. 5~~6~~) where S6 tends for the majority of cases to slightly outperform S5, the BSS values for the different flow thresholds appear similar for S5 (Figs. 7~~8~~a-d) and S6 (Figs. 7~~8~~e-h). The only exception is CKLN6 (Figs. 7~~8~~c and 7~~8~~g) where~~, at the higher flood flow thresholds,~~ S6 has better skill than S5 at the day 1 and 3 lead times, particularly at the highest flow thresholds considered. With respect to the basin size, the skill tends to improve some from the small to the large basin. For instance, for non-exceedance probabilities of 0.95 and 0.99 at the day 1 lead time, the BSS values for the smallest basin (Fig. 7~~8~~a), measured relative to the observed flows, are ~0.49 and 0.35, respectively. For the same conditions, both values increase to ~0.65 for the largest basin (Fig. 7~~8~~d).

~~Indeed, t~~The most notable feature in Fig. 7~~8~~ is that the effect of hydrological uncertainties on forecast skill is evident at the day 1 lead time, while meteorological uncertainties clearly dominate at the day 7 lead time. With respect to the latter, notice that the solid and dashed green lines for the day 7 lead time tend to be very close to each other in Fig. 7~~8~~, indicating that hydrological uncertainties are relatively small compared to meteorological ones. Hydrological uncertainties are largest at the day 1 lead time, particularly for the small basins (Figs. 7~~8~~a-b and 7~~8~~e-f). For example, for a non-exceedance probability of 0.95 and at a day 1 lead time (Fig. 7~~8~~b), the BSS value relative to the simulated and observed flows~~oods~~ are ~0.79 and 0.38, respectively, suggesting a reduction of ~50% skill due to hydrological uncertainties.

5 Summary and conclusion

In this study, we used the RHEPS to investigate the effect of statistical processing on short- to medium-range ensemble streamflow ~~flood~~ forecasts. First, we assessed the raw precipitation forecasts from the GEFSRv2 (S1), and compared them with the preprocessed precipitation ensembles (S2). Then, streamflow~~flood~~ ensembles were generated with the RHEPS for four different forecasting scenarios involving no statistical processing (S3), preprocessing alone (S4), postprocessing alone (S5), and both preprocessing and postprocessing (S6). The verification of ensemble precipitation and streamflow~~flood~~ forecasts was done for the years 2004-2012, using four nested, gauge locations in the ~~basins~~NBSR basin of ~~in~~ the U.S. MAR. We found that ~~– for the models, datasets, and study domain used here – the skill gains from joint preprocessing and postprocessing are similar to those from postprocessing alone.~~ the scenario involving both preprocessing and postprocessing consistently outperforms the other scenarios. In some cases, however, the differences between the scenario involving preprocessing and postprocessing, and the scenario with postprocessing alone~~,~~ are not as significant, suggesting for those cases (e.g., warm season) that postprocessing alone can be effective in removing systematic biases. Other specific findings are as follows:

- The HCLR preprocessed ensemble precipitation forecasts show improved skill relative to the raw forecasts. The improvements are more noticeable in the warm season at the longer lead times (>3 days).
- Both postprocessors, ARX(1,1) and QR, show gains in skill relative to the raw ensemble ~~flood~~ streamflow forecasts in the cool season. In contrast, in the warm season, ARX(1,1) shows little or no gains in skill. Overall, for the majority of cases analyzed, ~~For the medium-range lead times (>3 days) Across most of the lead times,~~ the gains with QR ~~, however,~~ tend to be greater than with ARX(1,1), specially ~~particularly~~ during the warm season.
- ~~By comparing different statistical processing scenarios for the ensemble flood streamflow forecasts, it was found that the scenario with preprocessing alone has little effect on improving the skill and reliability of the streamflowflood forecasts in contrast with the postprocessing alone scenario.~~
- In terms of the forecast skill (i.e., CRPSS), in the warm season ~~T~~the scenarios including only preprocessing and only postprocessing have a comparable performance to the ~~s similar, in terms of the relative mean error, CRPSS, and reliability, to the~~ more complex scenario consisting of both preprocessing and postprocessing ~~in the warm season~~. ~~It~~While in the cool season, the scenario involving both preprocessing and postprocessing consistently outperforms the other scenarios but the differences may not be ~~are not~~ as significant. ~~thus seems for our conditions, using GEFSRv2 forecasts, that preprocessing may be unnecessar~~
- The skill of the postprocessing alone scenario and the scenario that combines preprocessing and postprocessing was further assessed using the Brier skill score for different ~~flood~~ streamflow thresholds and the warm season. This assessment suggests that for high flow thresholds the similarities in skill between ~~further confirmed that~~ both scenarios, S5 and S6, ~~have similar skill and performance behavior~~ become greater.
- Decomposing the CRPS into reliability and potential component, we observed that the scenario that combines preprocessing and postprocessing results in slightly lower CRPS than the other scenarios. We found that the scenario involving only postprocessing tends to demonstrate similar reliability to the scenario consisting of both preprocessing and postprocessing across most ~~all~~ of the lead times, basins and seasons. We also found that in several cases~~However~~ the postprocessing alone scenario displays improved reliability relative to the preprocessing alone scenario.~~, the scenario that combines preprocessing and postprocessing results in slightly lower CRPS than other scenario.~~

These conclusions are specific to the RHEPS forecasting system, which is mostly relevant to the U.S. research and operational communities as it relies on a weather and a hydrological model that are used in this domain. However, the use of a global weather forecasting system illustrates the potential of applying the statistical techniques tested here in other regions worldwide.

The emphasis of this study has been on benchmarking the contributions of statistical processing to the RHEPS. To accomplish this, our approach required that the quality of ensemble ~~flood~~ streamflow forecasts be verified over multiple years (i.e., across many ~~flood~~ flood cases) to obtain robust verification statistics. Future research, however, could be focused on studying how distinct hydrological processes contribute or constrain forecast quality. This effort could be centered around specific flood events rather than in the statistical, many-cases approach taken here. To further assess the relative importance of the various components of the RHEPS, additional tests involving the uncertainty to initial hydrologic conditions and hydrological parameters could be performed. For instance, the combined use of data assimilation and postprocessing has been shown to produce more reliable and sharper streamflow forecasts (Bourgin et al., 2014). The potential for the interaction of preprocessing and postprocessing with data assimilation to significantly enhance streamflow predictions, however, has not been investigated. This could be investigated in the future with the RHEPS, as the pairing of data assimilation with preprocessing and postprocessing could facilitate translating the improvements in the preprocessed meteorological forcing down the hydrological forecasting chain.

Data availability: Daily streamflow observation data for the selected forecast stations can be obtained from the USGS website (https://waterdata.usgs.gov/nwis/). Multisensor precipitation estimates are obtained from the NOAA's Middle Atlantic River Forecast Center. Precipitation and temperature forecast datasets can be obtained from the NOAA Earth System Research Laboratory website (https://www.esrl.noaa.gov/psd/forecasts/reforecast2/download.html).

Appendix A: Verification metrics

Modified correlation coefficient (R$_m$): The modified version of the correlation coefficient, called as modified correlation coefficient R_m, compare event specific observed and simulated hydrographs (McCuen and Snyder, 1975). In the modified version, an adjustment factor based on the ratio of the observed and simulated flow is introduced to refine the conventional correlation coefficient R. The modified correlation coefficient R_m is defined as:

$$R_m = \mathrm{R}\frac{min\{\sigma_s,\sigma_q\}}{max\{\sigma_s,\sigma_q\}}, \quad \text{(A1)}$$

where σ_s and, σ_q denote the standard deviation of the simulated and observed flows, respectively.

Percent bias (PB): PB measures the average tendency of the simulated flows to be larger or smaller than their observed counterparts. Its optimal value is 0.0 where positive values indicate model overestimation bias, and negative values indicate model underestimation bias. The PB is estimated as follows:

$$PB = \frac{\sum_{i=1}^{N}(s_i - q_i)}{\sum_{i=1}^{N} q_i} \times 100, \quad \text{(A2)}$$

where s_i and q_i denote the simulated and observed flow, respectively, at time i.

Nash-Sutcliffe efficiency (NSE): The NSE (Nash and Sutcliffe, 1970) is defined as the ratio of the residual variance to the initial variance. It is widely used to indicate how well the simulated flows fit the observations. The range of NSE can vary between negative infinity to 1.0, with 1.0 representing the optimal value and values should be larger than 0.0 to indicate minimally acceptable performance. The NSE is computed as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{N}(s_i - q_i)^2}{\sum_{i=1}^{N}(q_i - \bar{q}_i)^2}, \quad \text{(A3)}$$

where s_i, q_i, and $\bar{q}_i$ are the simulated, observed, and mean observed flow, respectively, at time i .

~~**Relative mean error (RME):** RME quantifies the average error between the ensemble mean forecast and their corresponding observation as a fraction of the averaged observed value. RME gives an indication how good the forecast is relative to the observation. RME is expressed as follows:~~

~~$RME = \frac{\sum_{i=1}^{n}(\bar{f}_i - q_i)}{\sum_{i=1}^{N} q_i}$,~~

~~(A4)~~

~~where $\bar{f}_i = \frac{1}{m}\sum_{k=1}^{m} f_{i,k}$, m is the number of ensemble members, $f_{i,k}$ is the forecast for member k and time i, q_i denotes the corresponding observation at time i, and n denotes the total number of pairs of forecasts and observed values.~~

Brier Skill Score (BSS): The Brier score (BS; Brier, 1950) is analogous to the mean squared error, but where the forecast is a probability and the observation is either a 0.0 or 1.0. The BS is given by

$$BS = \frac{1}{n}\sum_{i=1}^{n}\left[F_{f_i}(z) - F_{q_i}(z)\right]^2,$$

(A4~~5~~)

where the probability of f_i to exceed a fixed threshold z is

$$F_{f_i}(z) = P_r[f_i > z],$$

(A5~~6~~)

n is again the total number of forecast-observation pairs, and

$$F_{q_i}(z) = \begin{cases} 1, & q_i > z \\ 0, & otherwise. \end{cases}$$

(A6~~7~~)

In order to compare the skill score of the main forecast system with respect to the reference forecast, it is convenient to define the Brier Skill Score (BSS):

$$BSS = 1 - \frac{BS_{main}}{BS_{reference}},$$

(A7~~8~~)

where BS_{main} and $BS_{reference}$ are the BS values for the main forecast system (i.e. the system to be evaluated) and reference forecast system, respectively. Any positive values of the BSS, from 0 to 1, indicate that the main forecast system performs better than the reference forecast system. Thus, a BSS of 0 indicates no skill and a BSS of 1 indicates perfect skill.

Mean Continuous Ranked Probability Skill Score (CRPSS): Continuous Ranked Probability Score (CRPS) quantifies the integrated square difference between the cumulative distribution function (cdf) of a forecast, $F_f(z)$, and the corresponding cdf of the observation, $F_q(z)$. The CRPS is given by

$$CRPS = \int_{-\infty}^{\infty}\left[F_f(z) - F_q(z)\right]^2 dz.$$

(A8~~9~~)

To evaluate the skill of the main forecast system relative to the reference forecast system, the associated skill score, the mean Continuous Ranked Probability Skill Score (CRPSS), is defined as:

$$CRPSS = 1 - \frac{CRPS_{main}}{CRPS_{reference}},$$

(A9~~10~~)

where the CRPS is averaged across *n* pairs of forecasts and observations to calculate the mean CRPS of the main forecast system ($CRPS_{main}$) and reference forecast system ($CRPS_{reference}$). The CRPSS varies from -∞ to 1. Any positive values of the CRPSS, from 0 to 1, indicate that the main forecast system performs better than the reference forecast system.

To further explore the forecast skill, the $CRPS_{main}$ is decomposed into the CRPS reliability ($CRPS_{rel}$) and potential($CRPS_{pot}$) such that Hersbach (2000)

$$CRPS_{main} = CRPS_{rel} + CRPS_{pot}.$$

(A10~~1~~)

The $CRPS_{rel}$ measures the average reliability of the precipitation ensembles similarly to the rank histogram, which shows whether the frequency that the verifying analysis was found in a given bin is equal for all bins (Hersbach 2000). The $CRPS_{pot}$ measures the CRPS that one would obtain for a perfect reliable system. It is sensitive to the average ensemble spread and outliers.

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Table 1. Main characteristics of the four study basins.

Location of outlet	Cincinnatus, New York	Chenango Forks, New York	Conklin, New York	Waverly, New York
NWS id	CINN6	CNON6	CKLN6	WVYN6
USGS id	01510000	01512500	01503000	01515000
Area [km^2]	381	3841	5781	12362
Latitude	$42^0$32’28”	$42^0$13’05”	$42^0$02’07”	$41^0$59’05”
Longitude	$75^0$53’59”	$75^0$50’54”	$75^0$48’11”	$76^0$30’04”
Minimum daily flow* [m^3/s]	0.31 (0.11)	4.05 (2.49)	6.80 (5.32)	13.08 (6.71)
Maximum daily flow* [m^3/s]	172.73 (273.54)	1248.77 (1401.68)	2041.64 (2174.734)	4417.42 (4417.42)
Mean daily flow* [m^3/s]	8.89 (9.17)	82.36 (81.66)	122.93 (121.99)	277.35 (215.01)
Climatological flow (Pr=0.95)** [m^3/s]	29.45	266.18	382.28	843.84

*The number in parenthesis is the historical (based on entire available record, as opposed to the period 2004-2012 used in this study) daily minimum, maximum, or mean recorded flow.

**Pr=0.95 indicates flows with exceedance probability of 0.05.

Table 2. Summary and description of the verification scenarios.

Scenario	Description
S1	Verification of the raw ensemble precipitation forecasts from the GEFSRv2
S2	Verification of the preprocessed ensemble precipitation forecasts from the GEFSRv2: GEFSRv2+HCLR
S3	Verification of the raw ensemble flood forecasts: GEFSRv2+HL-RDHM
S4	Verification of the preprocessed ensemble flood forecasts: GEFSRv2+HCLR+HL-RDHM
S5	Verification of the postprocessed ensemble flood forecasts: GEFSRv2+HL-RDHM+QR
S6	Verification of the preprocessed and postprocessed ensemble flood forecasts: GEFSRv2+HCLR+HL-RDHM+QR

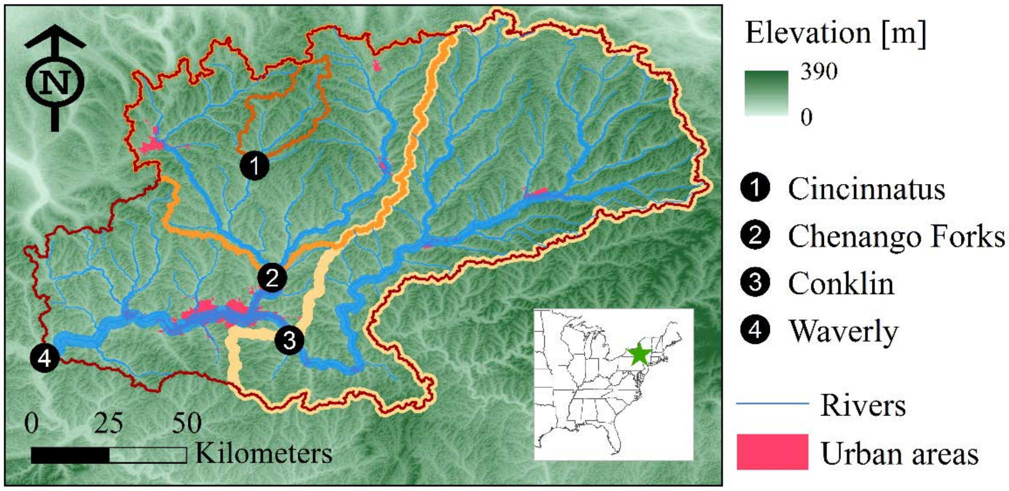


Figure 1: Map illustrating the location of the four selected river basins in the U.S. middle Atlantic region.

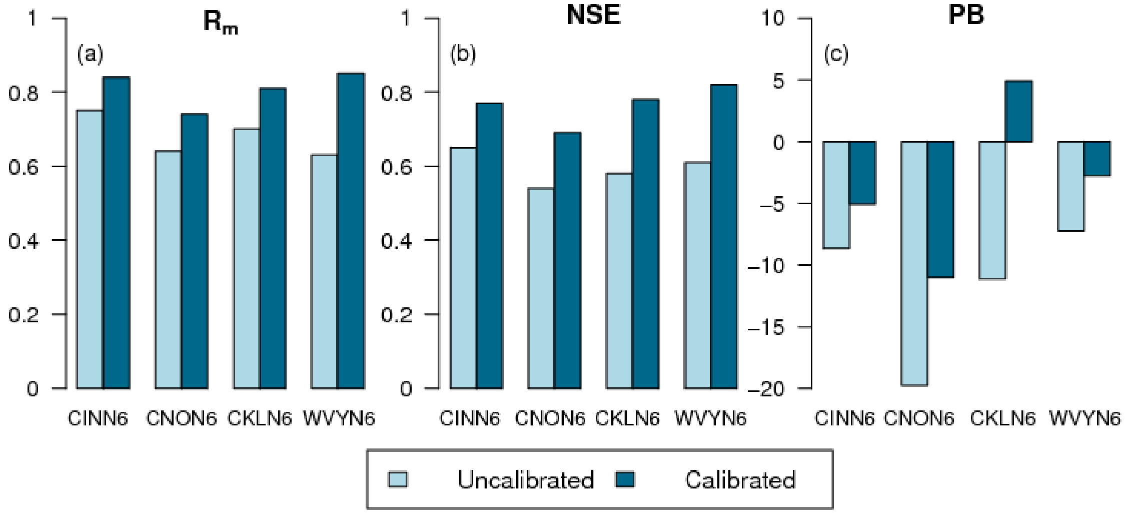
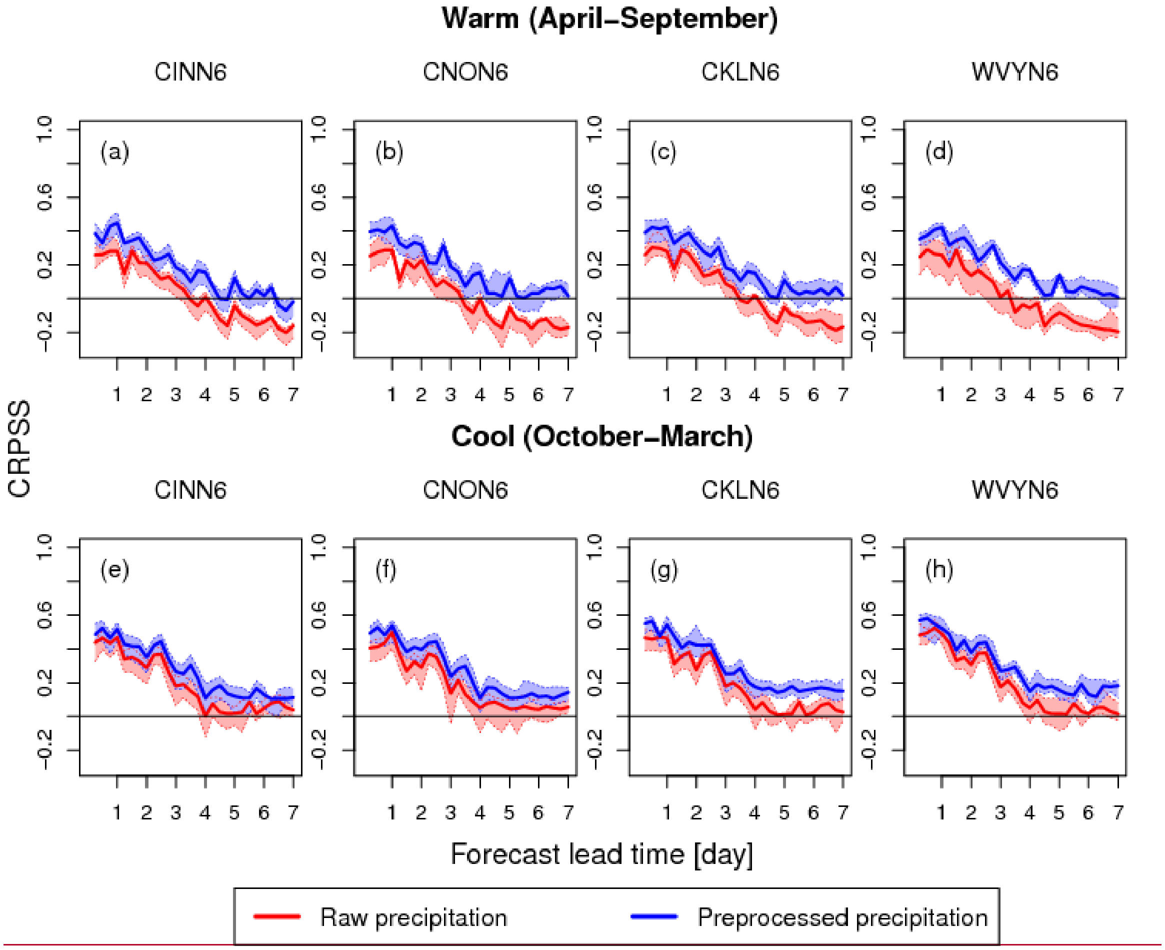


Figure 2: Performance statistics for the uncalibrated and calibrated simulation runs for the entire period of analysis (years 2004-2012): (a) R_m, (b) NSE, and (c) PB.


Warm (April–September)
CINN6
CNON6
CKLN6
WVYN6
(a)
(b)
(c)
(d)
Cool (October–March)
(e)
(f)
(g)
(h)
CRPSS
1.0
0.6
0.2
-0.2
1 2 3 4 5 6 7
Forecast lead time [day]
Raw precipitation
Preprocessed precipitation

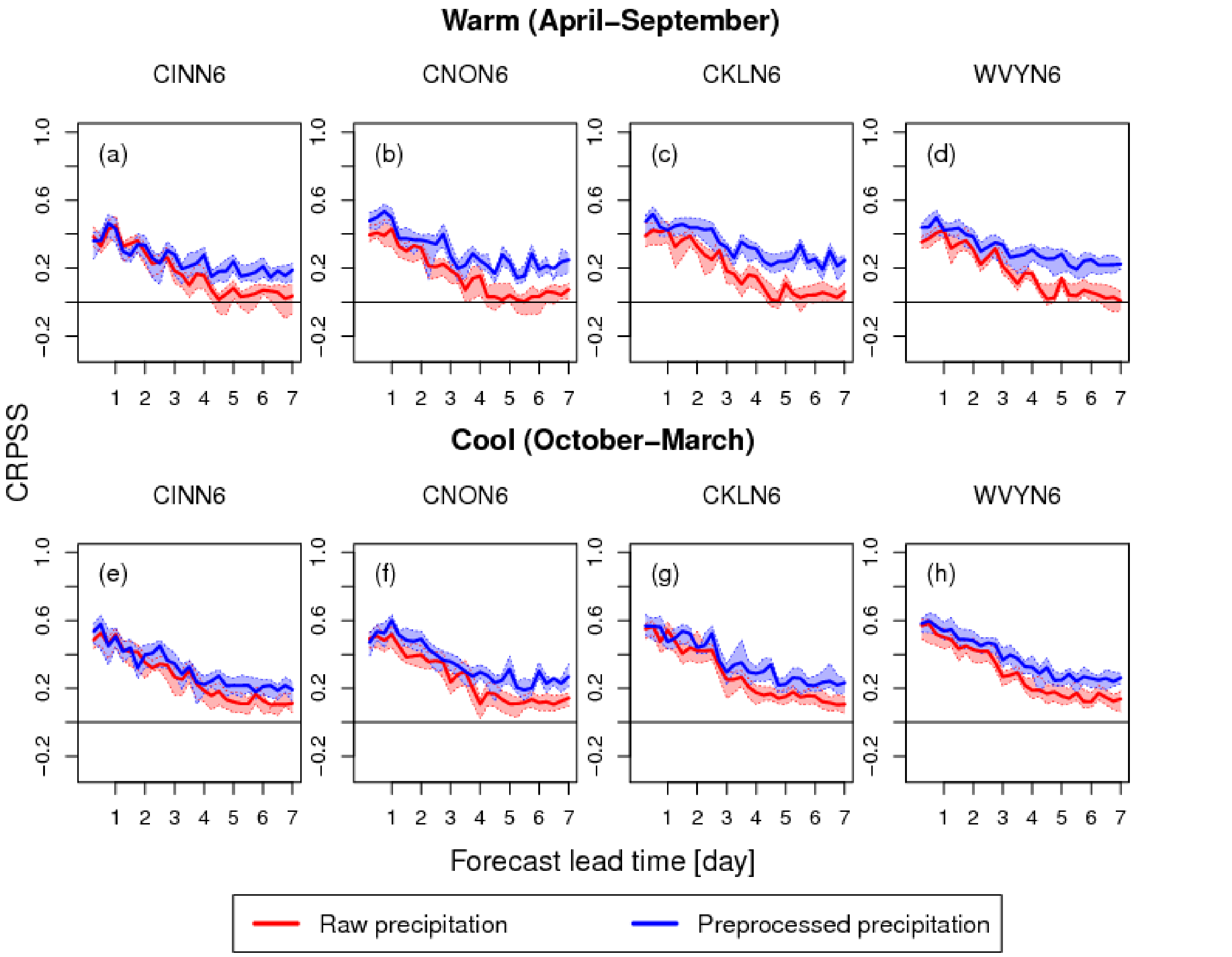
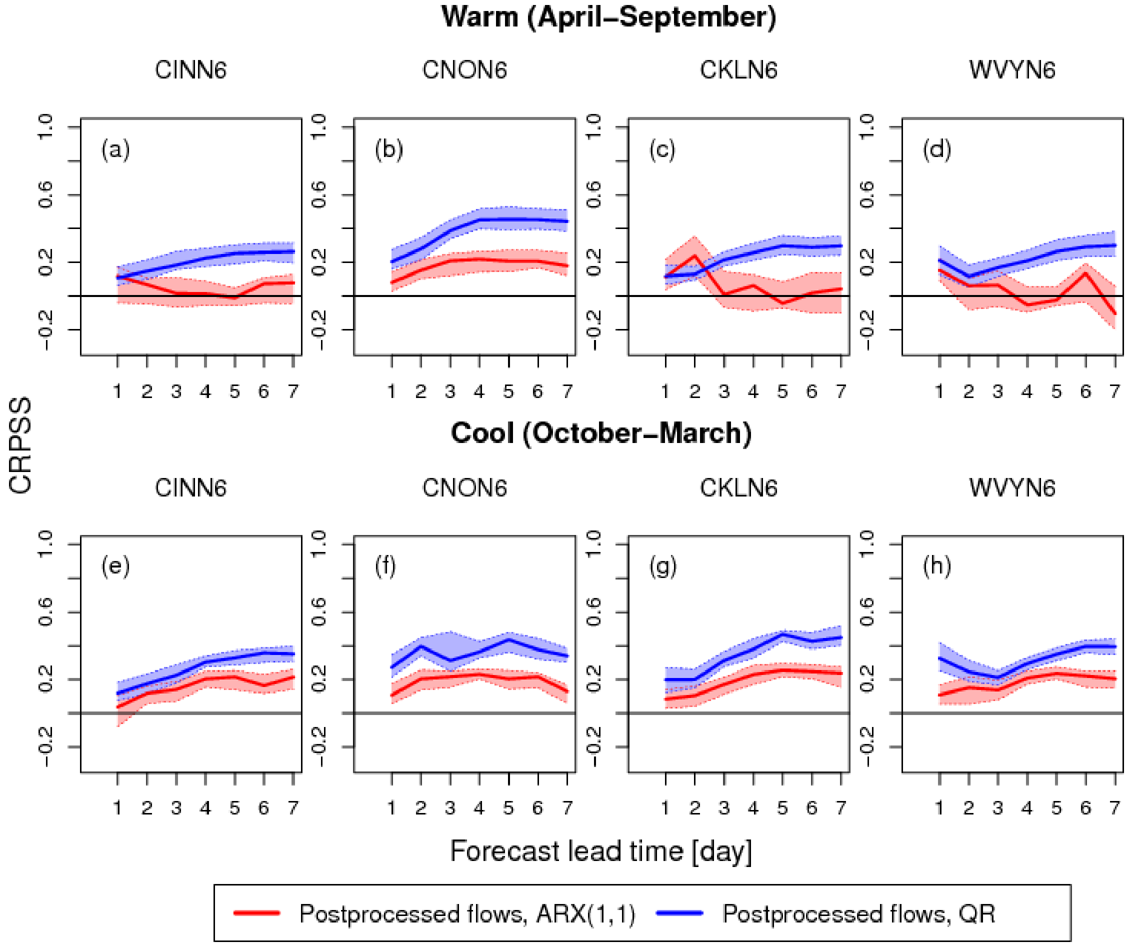


Figure 3: CRPSS (relative to sampled climatology) of the raw (red curves) and preprocessed (blue curves) ensemble precipitation forecasts from the GEFSRv2 vs the forecast lead time during the (a)-(d) warm (April-September) and (e)-(h) cool season (October-March) for the selected basins.


Warm (April–September)
CINN6
CNON6
CKLN6
WVYN6
(a)
(b)
(c)
(d)
Cool (October–March)
(e)
(f)
(g)
(h)
CRPSS
−0.2
0.2
0.6
1.0
1 2 3 4 5 6 7
Forecast lead time [day]
Postprocessed flows, ARX(1,1)
Postprocessed flows, QR

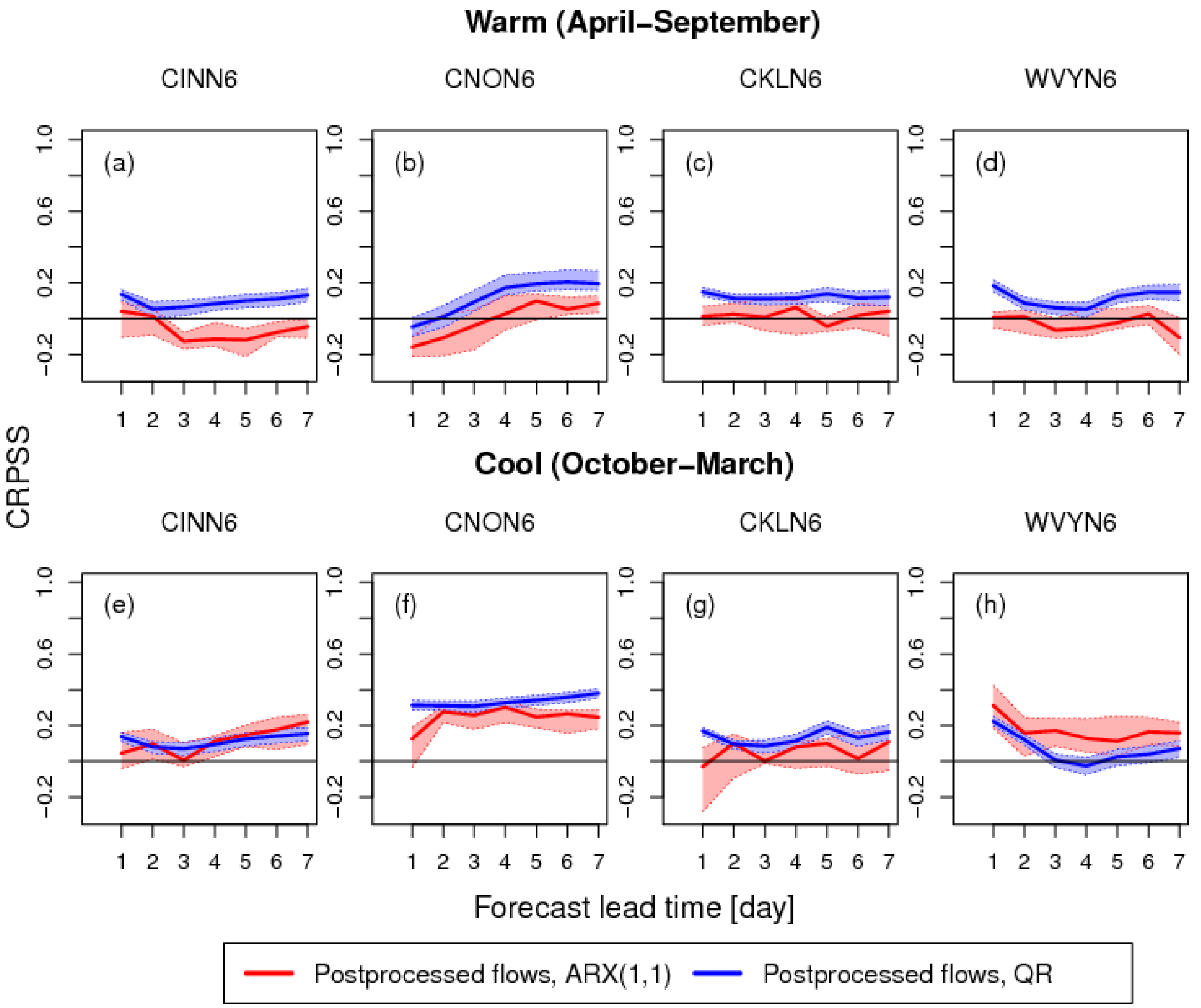
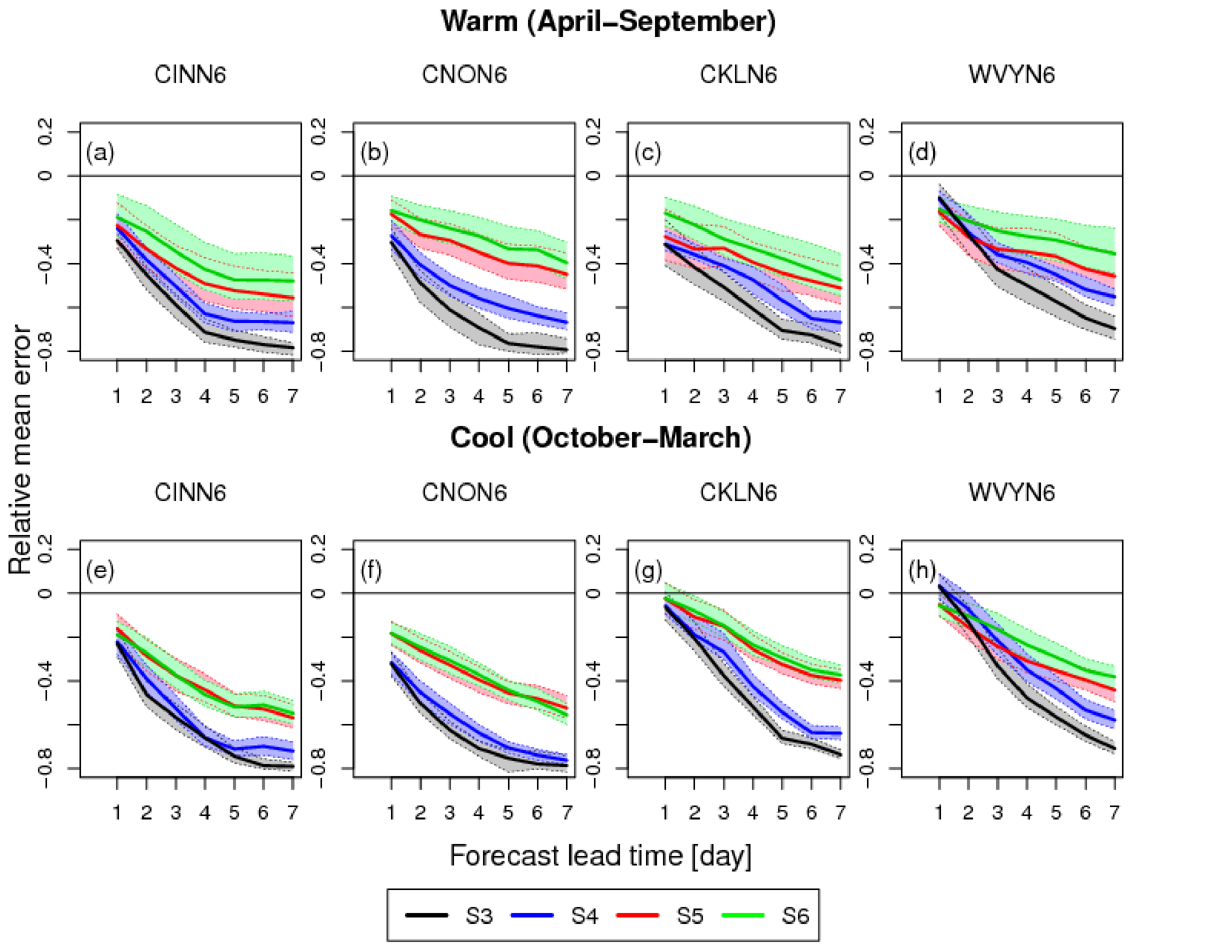
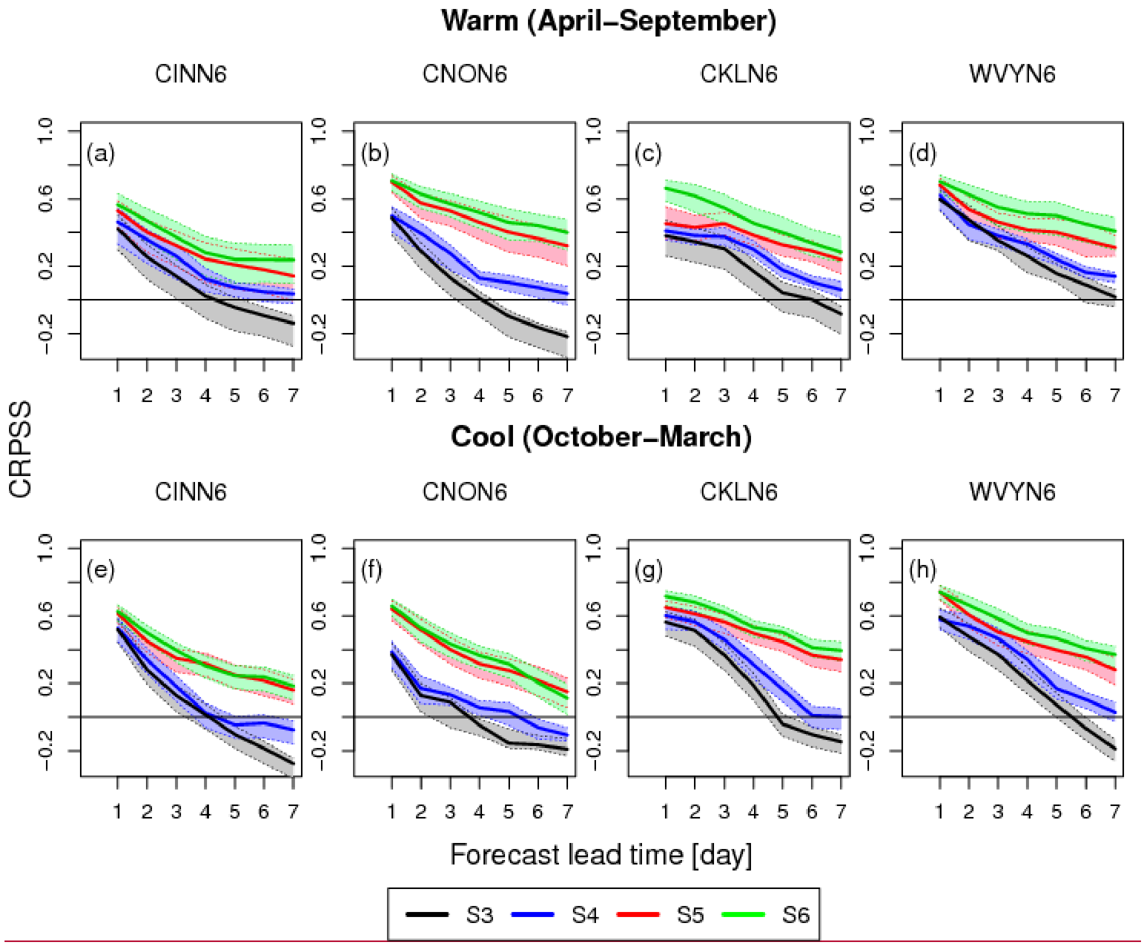


Figure 4: CRPSS (relative to the raw forecasts) of the ARX(1,1) (red curves) and QR (blue curves) postprocessed ensemble flood forecasts vs the forecast lead time during the (a)-(d) warm (April-September) and (e)-(h) cool season (October-March) for the selected basins.

5



~~Figure 5: Relative mean error (RME) of the mean ensemble flood forecasts vs the forecast lead time during the (a)-(d) warm (April-September) and (e)-(h) cool season (October-March) for the selected basins. The curves represent the different forecasting scenarios S3-S6. Note that S3 consists of GEFSRv2+HL-RDHM, S4 of GEFSRv2+HCLR+HL-RDHM, S5 of GEFSRv2+HL-RDHM+QR, and S6 of GEFSRv2+HCLR+HL-RDHM+QR.~~


Warm (April–September)
CINN6
CNON6
CKLN6
WVYN6
(a)
(b)
(c)
(d)
Cool (October–March)
(e)
(f)
(g)
(h)
CRPSS
−0.2
0.2
0.6
1.0
1
2
3
4
5
6
7
Forecast lead time [day]
S3
S4
S5
S6

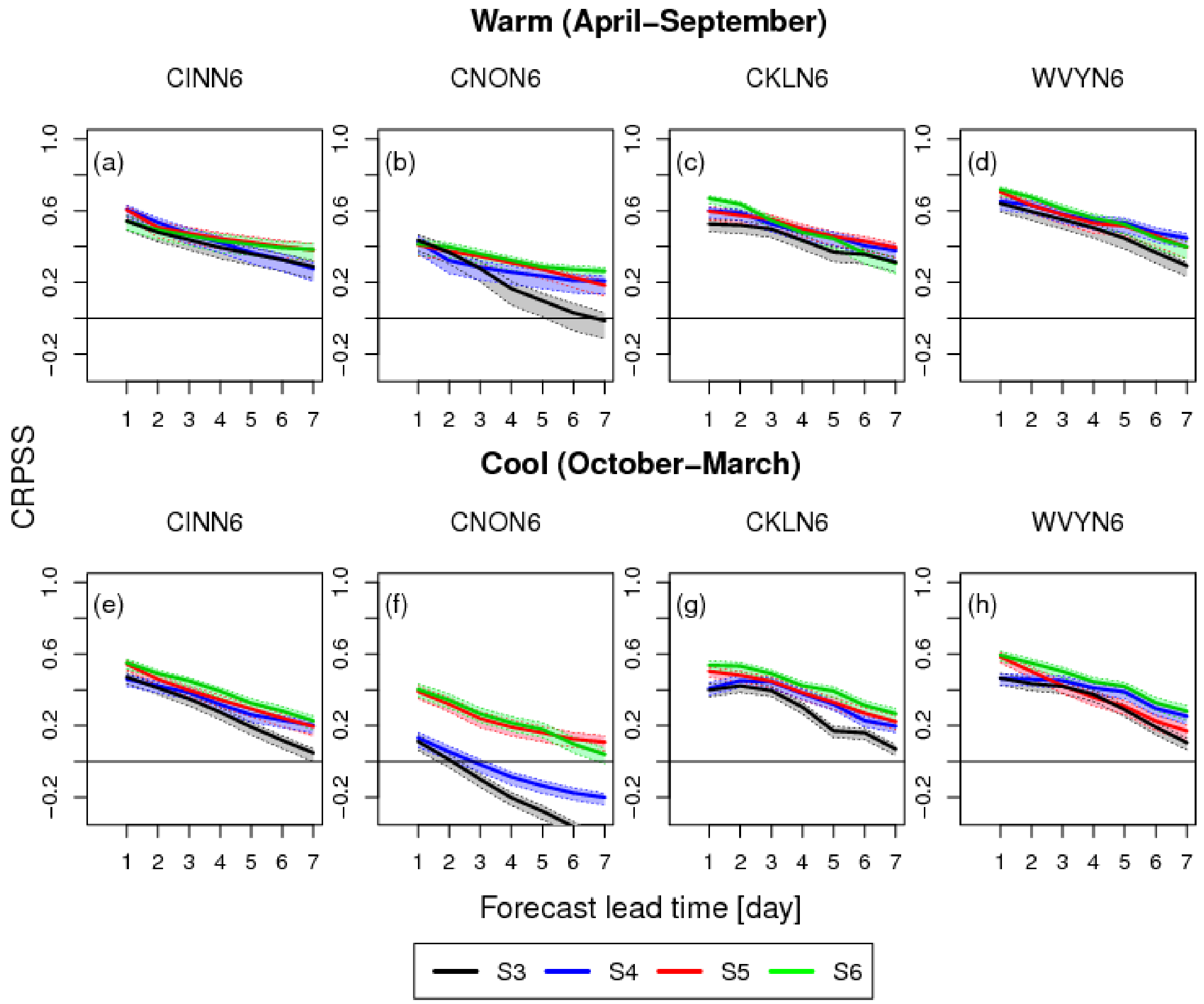
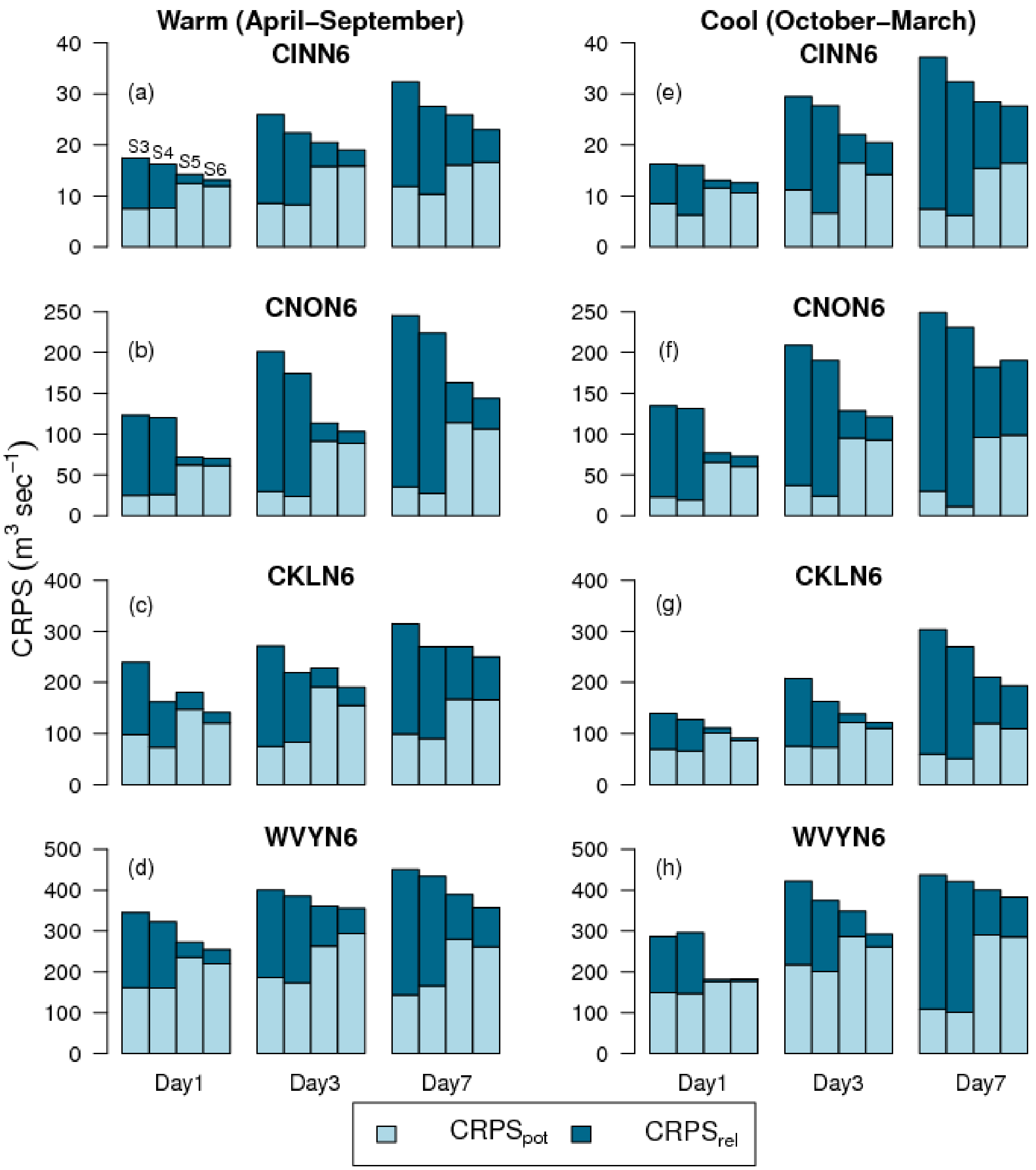


Figure ~~5~~6: Continuous ranked probability skill score (CRPSS) of the mean ensemble flood forecasts vs the forecast lead time during the (a)-(d) warm (April-September) and (e)-(h) cool season (October-March) for the selected basins. The curves represent the different forecasting scenarios S3-S6. Note that S3 consists of GEFSRv2+HL-RDHM, S4 of GEFSRv2+HCLR+HL-RDHM, S5 of GEFSRv2+HL-
5 RDHM+QR, and S6 of GEFSRv2+HCLR+HL-RDHM+QR.

~~As in Fig. 5, but for the CRPSS (relative to sampled climatology) of the ensemble flood forecasts vs the forecast lead time.~~


Warm (April–September)
Cool (October–March)
CINN6
CNON6
CKLN6
WVYN6
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
S3
S4
S5
S6
0
10
20
30
40
0
50
100
150
200
250
0
100
200
300
400
0
100
200
300
400
500
CRPS (m^3 sec^{-1})
Day1
Day3
Day7
▢ $CRPS_{pot}$
■ $CRPS_{rel}$

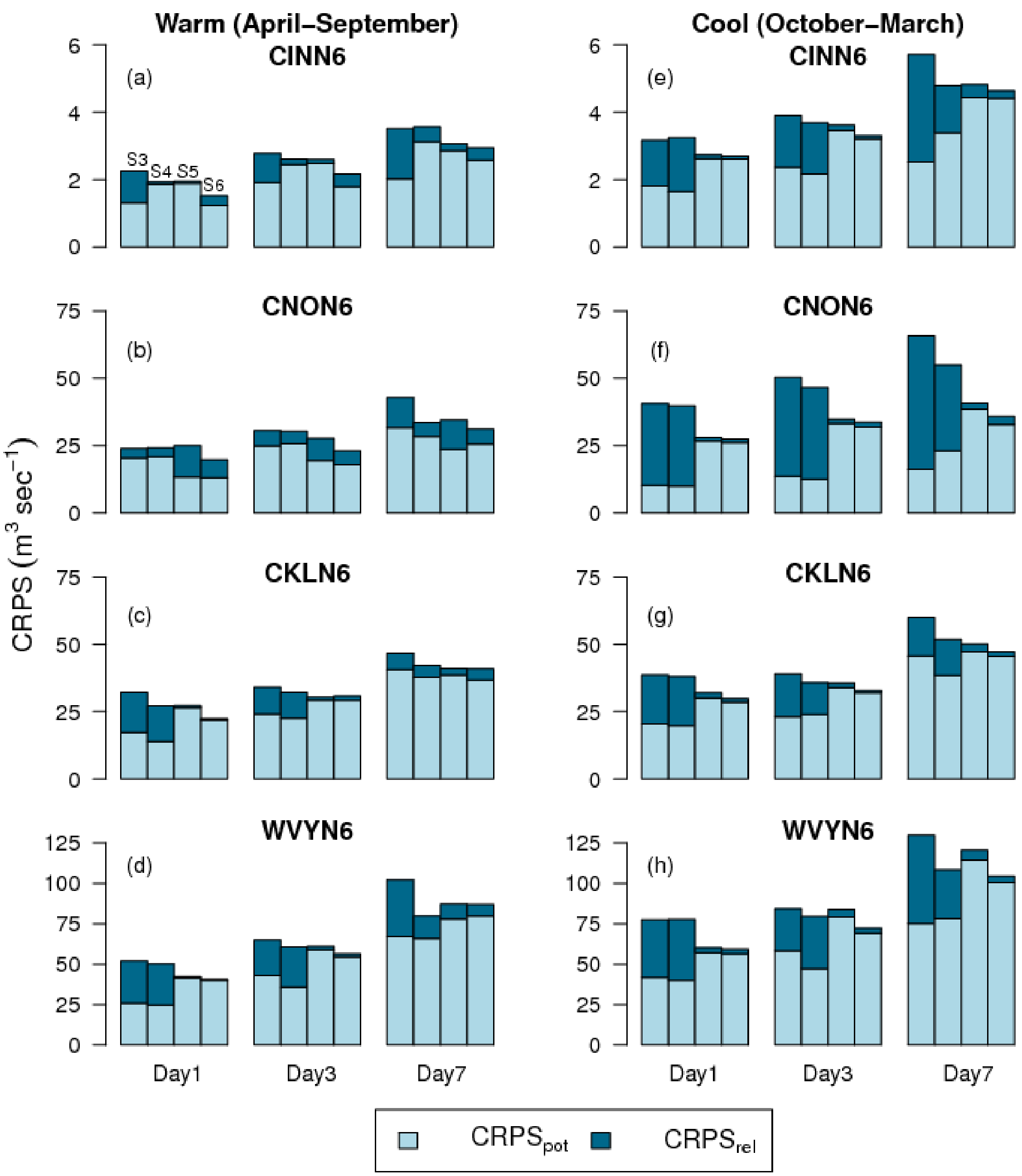


Figure 6~~7~~: Decomposition of the CRPS into CRPS potential (CRPS$_{pot}$) and CRPS reliability (CRPS$_{rel}$) for forecasts lead times of 1, 3, and 7 days during the warm (a)-(d) (April-September) and cool season (e)-(h) (October-March) for the selected basins. The four columns associated with each forecast lead time represent the forecasting scenarios S3-S6 (from left to right). Note that S3 consists of GEFSRv2+HL-RDHM, S4 of GEFSRv2+HCLR+HL-RDHM, S5 of GEFSRv2+HL-RDHM+QR, and S6 of GEFSRv2+HCLR+HL-RDHM+QR.

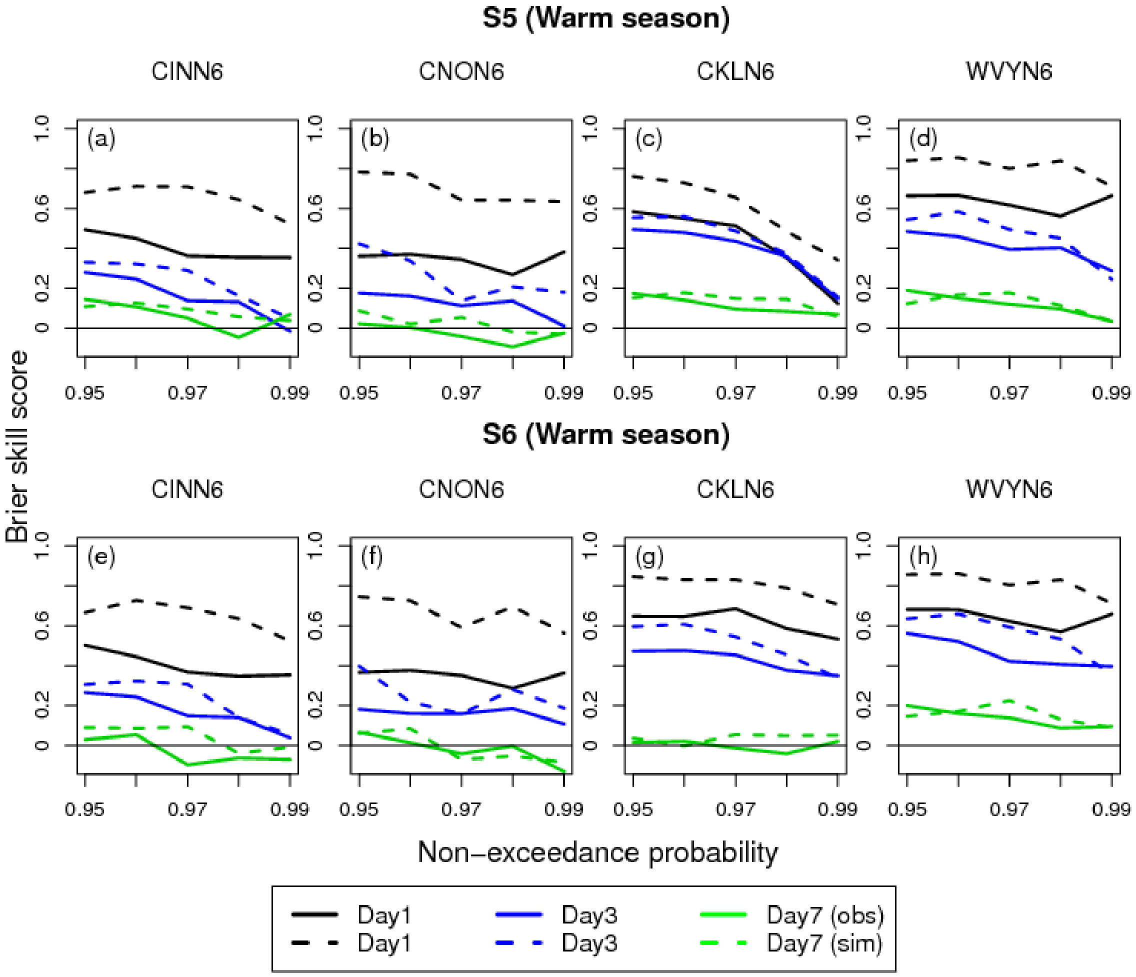


Figure 78: Brier skill score (BSS) of the mean ensemble flood forecasts for S5 (a-d) and S6 (e-h) vs the flood threshold for forecast lead times of 1, 3, and 7 days during the warm (April-September) season for the selected basins. The BSS is shown relative to both observed (solid lines) and simulated floods (dashed lines).