HYDROLOGIC ENSEMBLE PREDICTION FOR RISK-BASED WATER RESOURCES MANGEMENT AND HAZARD MITIGATION

Dong-Jun Seo, Project Scientist, National Weather Service Office of Hydrologic Development (NWS/OHD) & University Corporation for Atmospheric Research (UCAR), Silver Spring, MD, dongjun.seo@noaa.gov; Julie Demargne, Project Scientist, NWS/OHD & UCAR, Silver Spring, MD, Julie.demargne@noaa.gov; Limin Wu, ????, NWS/OHD & Wyle Information Systems, Silver Spring, MD, limin.wu@noaa.gov; Yuqiong Liu, Research Hydrologist, NWS/OHD & Riverside Technology, inc. (RTi), Silver Spring, MD, yuqiong.liu@noaa.gov; James D. Brown, NWS/OHD & UCAR, Project Scientist, Silver Spring, MD, james.d.brown@noaa.gov; Satish Regonda, Research Hydrologist, NWS/OHD & RTi, Silver Spring, MD, satish.regonda@noaa.gov; Haksu Lee, Associate Scientist, NWS/OHD & UCAR, Silver Spring, MD, haksu.lee@noaa.gov

Abstract: Hydrologic predictions are subject to various sources of error due to uncertainties in the atmospheric forcing observations and predictions, hydrologic model initial conditions, parameters and structures, and streamflow regulations. To allow risk-based decision making in water resources and emergency management, quantification of predictive uncertainty in streamflow forecasts across short, medium and long ranges is necessary. To obtain reliable predictive uncertainty, it is necessary to account for both input (i.e. atmospheric) and hydrologic uncertainties accurately. To provide uncertainty-quantified streamflow forecast products operationally, the National Weather Service (NWS) Office of Hydrologic Development (OHD) and its partners have been developing a prototype hydrologic ensemble forecast system, the EXperimental Ensemble Forecast System (XEFS). The principal components of the prototype system are currently implemented in the Community Hydrologic Prediction System (CHPS). Testing and experimental operation of the XEFS components have begun in late 2009 at selected NWS River Forecast Centers (RFC). In this paper, we describe the progress and plans, evaluation results from hindcasting experiments, and challenges ahead.

INTRODUCTION

Uncertainty-quantified water resources and flood forecast products from short to long ranges are one of the most pressing needs in operational hydrologic forecasting today. The National Weather Service (NWS) Office of Hydrologic Development (OHD), in collaboration with the NWS River Forecast Centers (RFC), Deltares and other partners, has been developing the EXperimental Ensemble Forecast System (XEFS) to meet this need. The principal components of XEFS are currently being implemented in the NWS's Community Hydrologic Prediction System (CHPS). The CHPS-XEFS also includes ensemble hindcasting capability that allows systematic validation of the ensemble forecast system, large-sample verification of the ensemble products, and cost-effective collaborative research and development and research-to-operations transition of new or improved scientific components. In this paper, we describe the progress and plans, evaluation results from hindcasting experiments, and challenges for operational hydrologic ensemble forecasting.

WHY HYDROLOGIC ENSEMBLE PREDICTION?

Though various stochastic methods have been used widely in a wide array of hydrology and water resources applications, hydrologic ensemble prediction is relatively new. Below we describe the motivations from the perspective of operational hydrologic forecasting:

- Provide estimates of predictive uncertainty - For the forecasters, such uncertainty information provides an objective guidance for the level of confidence that they may place in the raw model forecasts. For the users, predictive uncertainty allows risk-based decision making specific to their applications.
- Improve the absolute accuracy of the forecast – This may be achieved by optimally merging or combining multiple forecasts in the single-valued or ensemble sense, respectively (Geogakakos et al. 2004).
- Extend forecast lead time - Weather and climate forecasts are generally highly uncertain and noisy. As such, inputting single-valued forecasts beyond a certain lead time can produce river stage or discharge forecast with an unacceptably large error. For this reason, in the single-valued forecast process, the RFCs input single-valued quantitative precipitation forecast (QPF) into hydrologic models only out to a very limited lead time, beyond which zero precipitation is assumed. This practice reduces certain types of errors in the single-valued river forecast, but does not capitalize on the positive skill that exists in the forcing forecasts well beyond the capped lead time (see Fig 3).
- Improve the forecast systems, science and process cost-effectively - Ensemble prediction requires quantification of major uncertainties in the forecast process. As such, it allows quantitative assessment of relative importance among them as a function of lead time and other attributes.

EXPERIMENTAL ENSEMBLE FORECAST SYSTEM (XEFS)

The XEFS is a prototype end-to-end hydrologic ensemble forecast system currently under development by NWS. It is based on the comprehensive plan developed in 2007 (http://www.weather.gov/oh/rfcdev/docs/XEFS_design_gap_analysis_report_final.pdf). The NWS/OHD is collaborating with the RFCs, Deltares, the National Centers for Environmental Prediction (NCEP), NOAA Office of Atmospheric Research (OAR), and universities for research and development, and research-to-operations transition of XEFS. It is to be deployed at the RFCs via CHPS. The prototype components of XEFS are currently under testing and evaluation at selected RFCs. Additional prototypes will be deployed during the next 2 years.

The XEFS consists of the following 5 principal components and the Hydrologic Model Output Statistics (HMOS) processor (see Fig 1):

- Ensemble Pre-Processor (EPP): The EPP (Schaake et al. 2007, Wu et al. 2009) generates short- to long-range ensemble forecasts of precipitation and temperature based on the single-valued QPF and quantitative temperature forecast (QTF) from NCEP's Hydrometeorological Prediction Center (HPC), the ensemble mean forecast of precipitation and temperature from the frozen version of the NCEP's Global Forecast System (GFS, Hamill et al. 2006) and Climate Forecast System (CFS, Saha et al. 2006).
- Ensemble Streamflow Prediction (ESP) Subsystem: The ESP inputs forcing ensembles, runs the necessary hydrologic models, and produces streamflow ensembles.

- Ensemble Post-Processor (EnsPost): EnsPost post-processes the ESP-produced streamflow ensembles statistically to bias-correct and to add hydrologic uncertainty (Seo et al. 2006). The streamflow ensembles obtained from the EPP, ESP and EnsPost operations reflect both the input and hydrologic uncertainties (see below).
- Ensemble Verification System (EVS): The EVS is a prototype tool for verification of hydrometeorological and hydrologic ensemble forecasts such as streamflow, river stage, precipitation and temperature (Brown et al. 2009). It is intended for use by the RFC forecasters, researchers and developers at OHD, and collaborators elsewhere.
- Graphics Generator (GG): The GG is a generic software tool for CHPS, and is responsible for building products for use in the forecasting process or to be disseminated to external users. The initial version of the software replicates the functionality in the Ensemble Streamflow Prediction Analysis and Display Program (ESPADP). The GG software is plug-in oriented for extensibility. The GG software components include Time series plug-ins, Aggregation tools, Chart appearance plug-ins, Graphics Generator engine and Graphics Generator user interfaces.
- Hydrologic Model Output Statistics (HMOS): Streamflow ensemble generation via EPP, ESP and EnsPost is based on separate modeling of input and hydrologic uncertainties (see below). In certain situations, direct modeling of the total uncertainty may provide a simpler alternative. The HMOS directly models the total uncertainty associated with the operationally-produced single-valued streamflow forecast and generates an ensemble streamflow forecast via conditional simulation (Regonda et al. 2009).

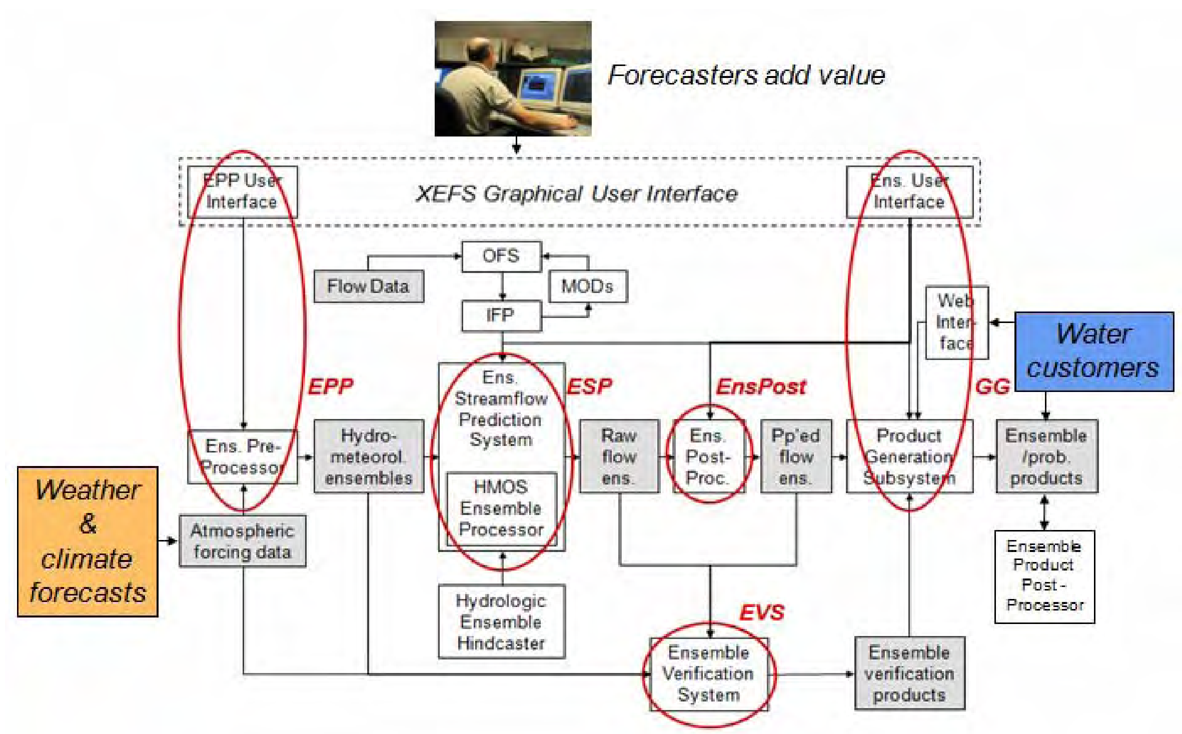

Figure 1 Schematic of the Experimental Ensemble Forecast System (XEFS).

METHODOLOGY

Hydrologic ensemble forecasting with XEFS is based on source-specific modeling of major uncertainties, and Monte-Carlo integration of them via the total probability law (Krzysztofowicz 1999, Seo et al. 2006):

$$f_1(q_f \mid q_o) = \int f_2(q_f \mid q_o, s_f)\ \ f_3(s_f \mid q_o)\ \ ds_f \qquad (1)$$

where f_i's denote probability density functions (PDF), and q_f, q_o and s_f denote the streamflow at some future times, the observed flow up to and including the current time, and the model-predicted streamflow at the future times, respectively. The PDF's in the integrand in Eq.(1) may be rewritten as:

$$f_3(s_f \mid q_o) = \iiint f_4(s_f \mid b_f, i, p)\ \ f_5(b_f)\ \ f_6(p)\ \ f_7(i)\ \ db_f\ \ di\ \ dp \qquad (2)$$

$$f_2(q_f \mid q_o, s_f) = \frac{\partial \varepsilon(q_f, q_o, s_f)}{\partial q_f}\ f_8(\varepsilon(q_f, q_o, s_f) \mid q_o, s_f) \qquad (3)$$

where b_f denotes the boundary conditions of precipitation and temperature at the future times, i denotes the model initial conditions, p denotes the model parameters, and $\varepsilon(\cdot)$ denotes the error in predicting q_f given q_o and s_f. The error function $\varepsilon(\cdot)$ is obtained by inverting the prediction model for q_f. In rewriting Eq.(2), we assumed for simplicity but without loss of generality that there is no updating of model states based on observed streamflow. The PDF's $f_5(b_f)$, $f_6(p)$ and $f_7(i)$ in Eq.(2) correspond to the EPP, the parametric uncertainty processor, and the initial condition uncertainty processor, respectively, the latter two of which will be implemented in the future. Currently, all hydrologic uncertainties are modeled by the single term $\varepsilon(q_f, q_o, s_f)$ in EnsPost. In the following two sections, we describe how $f_5(b_f)$ and $f_2(q_f \mid q_o, s_f)$ in Eqs.(2) and (3) are obtained by EPP and EnsPost, respectively.

As noted in the previous section, HMOS models the total uncertainty directly (Regonda et al. 2009). Within the above mathematical description, streamflow ensemble generation using HMOS amounts to the following special case:

$$f_3(s_f \mid q_o) = \delta(s_f) \qquad (4)$$

Note that Eq.(4) zeroes out the input uncertainty in $f_3(s_f \mid q_o)$ and moves the uncertainty to $f_2(q_f \mid q_o, s_f)$ (see Eq.(1)).

INPUT UNCERTAINTY

The input certainty, $f_5(b_f)$ in Eq.(2), is modeled numerically by the EPP (Schaake et al. 2007, Wu et al. 2009). It is well known that, in general, raw precipitation ensemble forecasts from the numerical weather prediction (NWP) models are not very reliable (i.e. biased in the probabilistic sense), that most of the information content is in the ensemble mean, and that, for short-range prediction, human forecasters add significant skill to the NWP-generated single-valued forecasts. The EPP uses a statistical procedure to generate ensemble forecasts of precipitation and temperature from single-valued QPF and QTF, respectively. The procedure models bivariate distributions of precipitation and temperature between the observed and forecast values. The precipitation and temperature forecasts used in EPP come from NCEP/HPC up to Day 5, the frozen version of GFS up to Day 14 and CFS up to Month 9, beyond which historical observations are used as forecasts.

Statistical modeling of precipitation is particularly challenging due to intermittency, large variability, and relative small predictive skill. Since the initial development (Schaake et al. 2007), significant improvement has been made to precipitation ensemble generation (Wu et al. 2009). Fig 2 shows the mean continuous ranked probability score (CRPS, Hersbach 2000) of EPP-generated 6-hr precipitation ensembles for Day 1 for the North Fork of the American River basin (NFDC1, 875 km^2) near Sacramento, CA. In the figure, Methods 1 and 2 represent the old and new versions of the technique used for precipitation ensemble generation, respectively. Method 3 adds parameter optimization to Method 2 (see Wu et al. 2009 for details). In the figure, DV and CV indicate that the results are from dependent validation, i.e. parameter estimation, and independent validation based on leave-one-year-out cross validation, respectively. SVF indicates the mean absolute error of the conditioning single-value QPF. Recall that, for single-valued forecasts, the mean CRPS collapses to the mean absolute error, which allows comparison between ensemble and single-valued forecasts. Fig 2 indicates that the quality of EPP-generated precipitation ensembles has improved significantly since the initial development, and that the technique captures the skill in the conditioning single-valued QPF very well.

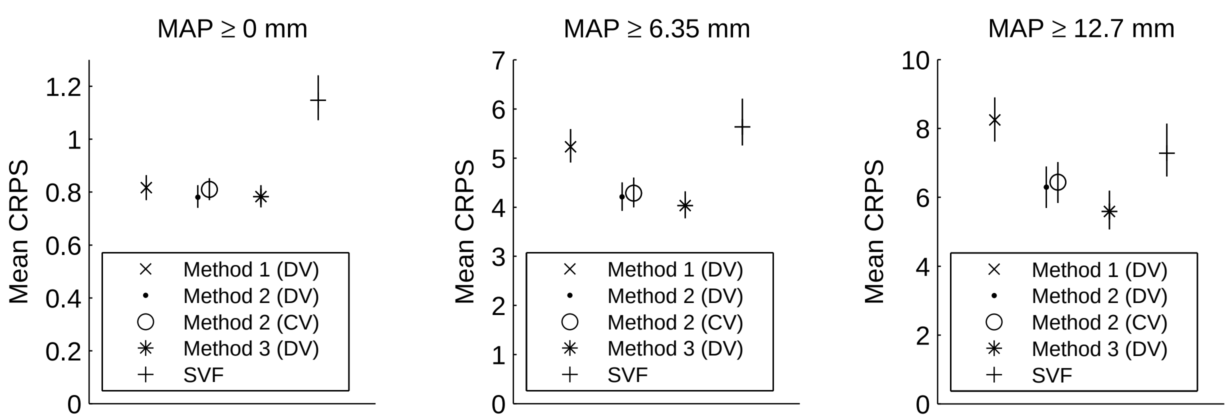

Figure 2 Mean CRPS of ensemble hindcasts of 6-hr precipitation for all four 6-hr periods in Day 1 from Oct. through May. The results are for NFDC1 with upper and lower areas combined. The

vertical bars denote the 95% confidence intervals. The mean CRPS values are conditioned on mean areal precipitation (MAP) ≥ 0, 6.35 and 12.7 mm. (From Wu et al. 2009)

Fig 3 shows the unconditional and conditional mean CRPS (left plot) and continuous rank probability skill score (CRPSS, right plot) of EPP-generated precipitation ensemble hindcasts for NFDC1. The single-valued QPF used is the ensemble mean precipitation hindcasts from the frozen version of GFS. The hindcast period is from Jan 1, 1979, through Sep 30, 2002, and each hindcast from EPP has 55 members. The reference forecast used in the skill score calculation is the climatological ensembles made of 55 historical traces of observed daily precipitation. Note in the CRPSS plot the varying levels of significant skill in the ensemble precipitation forecasts multiple days into the future.

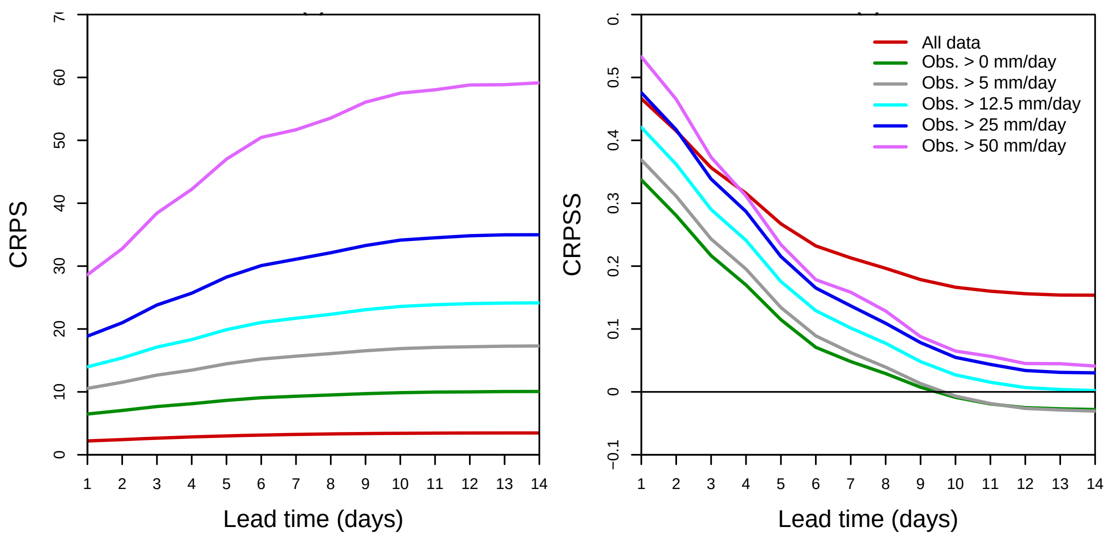

Figure 3 Unconditional and conditional mean CRPS (left) and CRPSS (right) of EPP-generated precipitation ensemble hindcasts for NFDC1. The conditioning single-valued QPF used is the ensemble mean precipitation hindcasts from the frozen version of GFS. The reference forecast is the climatological ensembles. (From Demargne et al. 2009)

HYDROLOGIC UNCERTAINTY

Hydrologic uncertainty comes from multiple sources: model structural errors, model parametric errors, errors in model initial conditions, errors in the observed forcing, human regulations of flow that are not known or could not be accounted for, etc. Depending on the goodness of the models being used, quality of model calibration, quality of observed forcing, and presence or absence of flow regulations, hydrologic uncertainty impacts the quality of streamflow ensemble forecast with varying degrees. The left plot in Fig 4 shows the unconditional and conditional mean CRPS of streamflow ensemble hindcasts for NFDC1 forced by the EPP-generated precipitation and temperature ensemble forecasts as conditioned by the ensemble mean forecasts from the frozen version of GFS. The right plot of Fig 4 shows the reliability component only of mean CRPS following its decomposition (Hersbach 2000). In the plots, the solid and dashed lines represent the verification results against the observed and the model-simulated flows, respectively. As such, the solid line reflects the total (input plus hydrologic) uncertainty whereas the dashed reflects the input uncertainty only. The figure indicates that, even though the hydrologic modeling for this basin is of very high quality particularly for high flows, hydrologic uncertainty has significant negative impact on mean CRPS particularly at short lead times and for larger amounts of flow, and that the loss of skill is due largely to reduced reliability. The purpose of EnsPost is to account for the hydrologic uncertainty so that the post-processed streamflow ensembles are reliable (i.e. unbiased in the probabilistic sense).

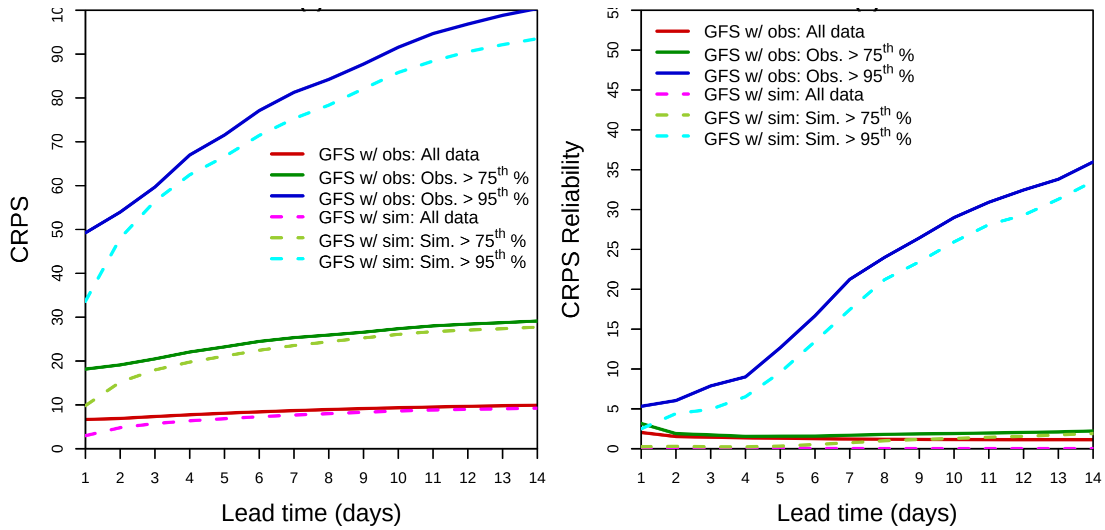

Figure 4 (Left) Unconditional and conditional mean CRPS of streamflow hindcasts for NFDC1. The hydrologic model is forced by the EPP-generated precipitation ensemble hindcasts shown in Fig 3. (Right) Same as the left plot but reliability component only (From Demargne et al. 2009)

In XEFS, hydrologic uncertainty is modeled numerically via $f_2(q_f \mid q_o, s_f)$ in Eq.(3). In the current version of EnsPost, all hydrologic uncertainties are aggregated into a single error term, $\varepsilon(q_f, q_o, s_f)$ in Eq.(3). Following normal quantile transformation (NQT) of simulated and observed streamflow, the above error is modeled as AR(1) (Seo et al. 2006). Recently, this model has been modified to account for serial correlation in the error approximately while maintaining parsimony. One may assess the performance of ensemble post processing without being masked by input uncertainty by assuming perfectly known future forcing. Due to space limitations, we only show a pair of examples in Fig 5 of the reliability diagram and the relative operating characteristic (ROC) curves for ensemble hindcasts under the assumption of perfectly known future forcing. The hindcasts are for daily flow at Kremmling (KRMC2, 6167 km^2) in the upper Colorado River basin. The verification statistics are at a threshold of 95th-percentile flow. These and other results indicate that, in general, the post-processed streamflow ensembles are reliable (left plot in Fig 5) and capture the discriminatory skill (right plot in Fig 5) in the single-valued model results very well, but that, if the flow is heavily regulated, the current version of EnsPost has limited positive impact.

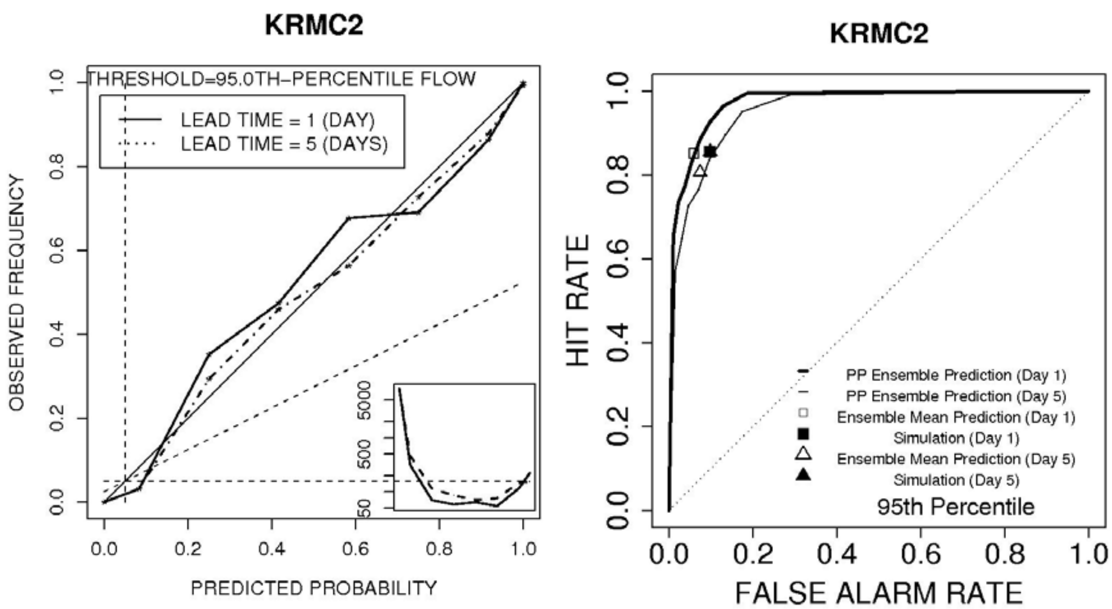

Figure 5 Examples of the reliability diagram (left) and the relative operating characteristic (ROC) curves (right) for ensemble hindcasts of daily from at KRMC2 in the upper Colorado River basin under the assumption of perfectly known future forcing.

CONCLUSIONS AND CHALLENGES

To provide uncertainty-quantified hydrologic forecast products, the National Weather Service (NWS) Office of Hydrologic Development (OHD) with its partners has been developing a prototype hydrologic ensemble forecast system, the EXperimental Ensemble Forecast System (XEFS). The principal components of the prototype system are currently implemented in the Community Hydrologic Prediction System (CHPS). Testing and experimental operation of the XEFS components have begun in late 2009 at selected NWS River Forecast Centers (RFC) and will continue at other RFCs in the next two years. Evaluation based on hindcasting experiments indicates that, in general, the XEFS components are capable of generating reliable forcing ensembles that very well reflect the skill in the conditioning single-valued forcing forecasts and reliable streamflow ensembles that possess comparable skill, in the single-valued sense, as the operational single-valued forecasts. End-to-end evaluation of XEFS will be carried out in FY10 using the hindcasting capabilities of XEFS in the CHPS environment.

To translate skill in weather and climate predictions into uncertainty-quantified and actionable water information across scale, ensemble streamflow prediction must be seamless across short, medium, to long ranges, the forcing ensembles must be reliable, and hydrologic uncertainties in model initial conditions, parameters and structures as well as those due to human influences must be accounted for and reduced. Concerted and focused efforts are necessary by the scientific, operational and user communities to address the many challenges therein (adapted from Hartman 2007):

- Appropriately model and integrate uncertainties introduced from data, model, and human sources,
- Combine ensemble forcings for short, medium and long ranges from multiple sources,

- Maintain spatial and temporal relationships across different scales,
- Include forecaster skill in short-term forcing forecasts,
- Allow forecaster guidance for hydrologic model operations through run-time modifications,
- Maintain coherence between deterministic and ensemble forecasts,
- Provide uncertainty information in a form and context that is easily understandable and useful to the customers,
- Reduce the cone of uncertainty for effective decision support,
- Improve accuracy of both meteorological and hydrologic models,
- Improve uncertainty modeling of rare and extreme events (e.g. record flooding, drought) as extreme conditions may be outside of model limits and without historical analog, and
- Greatly improve computing power, database and data storage.

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