Water Resources Research Institute of The University of North Carolina

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SEASONAL STREAMFLOW FORECASTS FOR THE HYDROLOGIC UNIT CODE (HUC-8) BASINS IN NORTH CAROLINA UTILIZING MULTIMODAL CLIMATE FORECASTS

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Abstract

Despite the relative abundance of water in North Carolina (NC), increasing demand at major metropolitans make the local and regional water supply systems vulnerable to even moderate drought conditions. Thus, information about the precipitation/streamflow over the upcoming season would be beneficial in developing a proactive water management plan that includes restrictions and early draw-down of reservoirs. In this study, we propose to downscale the large-scale climate forecasts issued by various national agencies and centers to develop seasonal streamflow forecasts for four reservoirs and two streamflow gauging stations in the Catawba River to support various ongoing drought management activities in NC.

Given the uncertainties in seasonal to interannual climate forecasts, recent studies have focused on developing multimodel forecasts which considerably reduces the uncertainty in climate forecasts. Before developing reservoir inflow forecasts from multiple climate models, the study focused on a fundamental research question related to multimodel forecasts development: Given that we have climate forecasts from multiple climate models, which could be ingested with multiple watershed models, what is the best strategy to develop multimodel streamflow forecasts? To answer this question, we consider two possible strategies: (a) reduce the input uncertainty first by combining climate models and then use the multimodel climate predictions with multiple watershed models, which again could be combined to develop multimodel streamflow predictions (b) ingest the individual climate forecasts (without multimodel combination) with individual watershed models and then combine the streamflow predictions that arise from all possible combinations of climate and watershed models. To investigate this, we consider a synthetic streamflow and climate forecasting scheme, so that we will be able to compare all the performance of candidate strategies with the true flows. The study clearly shows that the first strategy of reducing the input first results in better multimodel climate forecasts.

The study also has developed retrospective inflow forecasts for four reservoir sites and two USGS gauging stations from the Catawba River basin. Inflow forecasts available for six sites in the NC-CRONOS database are developed based on principal components regression using ECHAM4.5 climate forecasts and the previous month streamflow as the predictors. The developed reservoir inflow forecasts portal is also customized so that inflow forecasts for any site could be uploaded into the NC-CRONOS database. Developed streamflow forecasts could be effectively combined with the reservoir model to support water allocation for these selected basins.

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1. Introduction and Objectives

Despite the relative abundance of water in North Carolina (NC) (Moreau, 2006), increasing demand at major metropolitans make the local and regional water supply systems vulnerable to even moderate drought conditions (Weaver, 2005). For instance, in the Triangle Area in NC, the demand has grown by about 20%-62% from 1995-2000 resulting in three severe droughts/shortages (summers of 2002, 2005 and 2007) in the past five years. But, the reservoir systems in humid regions are typically designed as within-year storage systems with an intent to capture only the seasonal variability in streamflow, but do not carry over the deficit/surplus from year to year (e.g., reservoirs in the western US are over-year). Thus, the low storage (typically expressed as % of annual streamflow volume) and increasing urban demand necessitate the importance of utilizing climate-information based streamflow forecasts to develop strategies for water management. Unfortunately, the climate (precipitation and temperature) forecasts from General Circulation Models (GCMs) that are issued by the National Center for Environmental Prediction (NCEP) are typically available at large spatial scales (2.5°×2.5°) and also do not have streamflow forecasts. Though rainfall in NC has been shown to have significant predictability in response to various climatic signals such as El-Nino Southern Oscillation and Atlantic Dipole (Devineni et al., 2008; Roswintiarti et al., 1998), limited effort has been undertaken in developing seasonal streamflow forecasts (Rhome et al., 2000; Golembesky et al., 2009). In this study, we propose to downscale the large-scale climate forecasts issued by various national agencies and centers to develop seasonal streamflow forecasts to support various ongoing drought management activities in NC. Though we proposed to develop streamflow forecasts over the HUC, the project team realized that this first effort could focus on developing streamflow forecasts for four reservoir sites (Lake Jordan, Falls Lake, Kerr Scott Lake, and Philpot Lake) and for two USGS gaging stations in the Catawba River basin.

Three objectives are proposed under this project.

Objective 1: *Assemble precipitation forecasts from multiple General Circulation Models (GCMs) available from various research and national agencies and analyze their potential ability to predict seasonal streamflow variability in HUC-8 basins.*

Objective 2: *Statistically downscale the precipitation forecasts available from GCMs and RCMs and optimally combine them to develop seasonal streamflow forecasts for the HUC-8 basins.*

Objective 3: *Disseminate both retrospective and real-time streamflow forecasts developed for the winter and summer seasons through the NC CRONOS database.*

The findings under each of these objectives are summarized over the next three sections.

2. Multimodel Streamflow Forecasts Development (Objective 1)

Before developing multimodel streamflow forecasts, the study team focused on a fundamental research question: Given that we have climate forecasts from multiple climate models, which could be ingested with multiple watershed models, what is the best strategy to develop multimodel streamflow forecasts? *To answer this question, we consider the two possible strategies: (a) reduce the input uncertainty first by combining climate models and then use the multimodel climate predictions with multiple watershed models, which again could be combined to develop multimodel streamflow predictions (b) ingest the individual climate forecasts (without* *multimodel combination) with individual watershed models and then combine the streamflow predictions that arise from all possible combinations of climate and watershed models.* To investigate this, we consider a synthetic streamflow and climate forecasting scheme, so that we will be able to compare the performance of candidate strategies with the true flows.

Climate Forecasts Generation: The generation model for developing synthetic climate forecasts follow the scheme suggested by Weigel *et al.* (2008). The skill of the forecasts is controlled by two parameters α and β, which denote the correlation between the forecasted precipitation and the true precipitation and the overconfidence of the forecasted precipitation respectively. We consider the observed winter (January-March) precipitation (P_t) at Tar River at Tarboro over the period 1951-1990 as the true precipitation with winter climatology represented by mean (μ_P) and standard deviation (σ_P).

$$\overline{P}_t = \overline{X}_t \cdot \sigma_P + \mu_P \qquad \text{...(1)}$$

$$X_{t,m} = \alpha \cdot x_t + \varepsilon_{\beta,t} + \varepsilon_m \qquad \text{...(2)}$$

$$\overline{X}_t = \sum_{m=1}^{M} X_{t,m} \qquad \text{...(3)}$$

$$x_t = \frac{P_t - \mu_P}{\sigma_P} \qquad \text{...(4)}$$

$$\varepsilon_\beta \sim N(0, \beta) \qquad \text{...(5)}$$

$$\varepsilon_m \sim N(0, \sqrt{1-\alpha^2-\beta^2}) \qquad \text{...(6)}$$

We assume the precipitation forecasts for each winter season, *t*, to constitute 100 ensembles (M=100) following Gaussian distribution. It is important to note that the noise term ε_β which denotes the overconfidence of the forecasts is fixed for a given year. The parameter β is used to control the conditional mean by generating the overconfidence with Gaussian noise term with zero mean and standard deviation β. The parameter α is used to control the average correlation between the observed precipitation and the precipitation ensembles. Since α is a correlation coefficient, its value should be less than or equal to one. By adjusting these two parameters the center and the spread of the precipitation ensembles can be controlled. The forecasted precipitation will equal the observed precipitation if $\alpha = 1$ and $\beta = 0$. By assuming different α and β, we generate climate forecasts having different skill for the Tarboro site.

Streamflow Models: Using the generated ensemble mean, we obtain the predicted streamflow using any of the three watershed models: (a) Simple linear model (b) Log-linear model and (c) Non-linear 'abcd' model. Suppose if we have two climate forecasts, then we can obtain a total of six streamflow predictions, which could be combined to develop a multimodel streamflow prediction for the site (Strategy 2). On the other hand, if one combines the precipitation forecasts first, then we will have only three streamflow predictions, which could be combined to develop one prediction (Strategy 1). In this study, we consider a total of three watershed models and two sets of candidate forecasts for our analyses with the true streamflow being generated by one of the candidate models. To obtain the true flows, we fit the watershed model between observed flows and precipitation at the site and estimate the parameters (θ). These estimated parameters are used to generate 40 years of streamflows and the performance of the multimodel strategies are compared in predicting these true flows using mean square error. We evaluate these two strategies by comparing over 1000 sets of Mean Square Error (MSE) computed by generating 1000 sets of 40 years of flows. For this report, we present the results under just one watershed model (linear case) with three sets of climate forecasts. However, important findings from the study are summarized at the end of this section. A manuscript is currently under preparation for potential publication in water resources research.

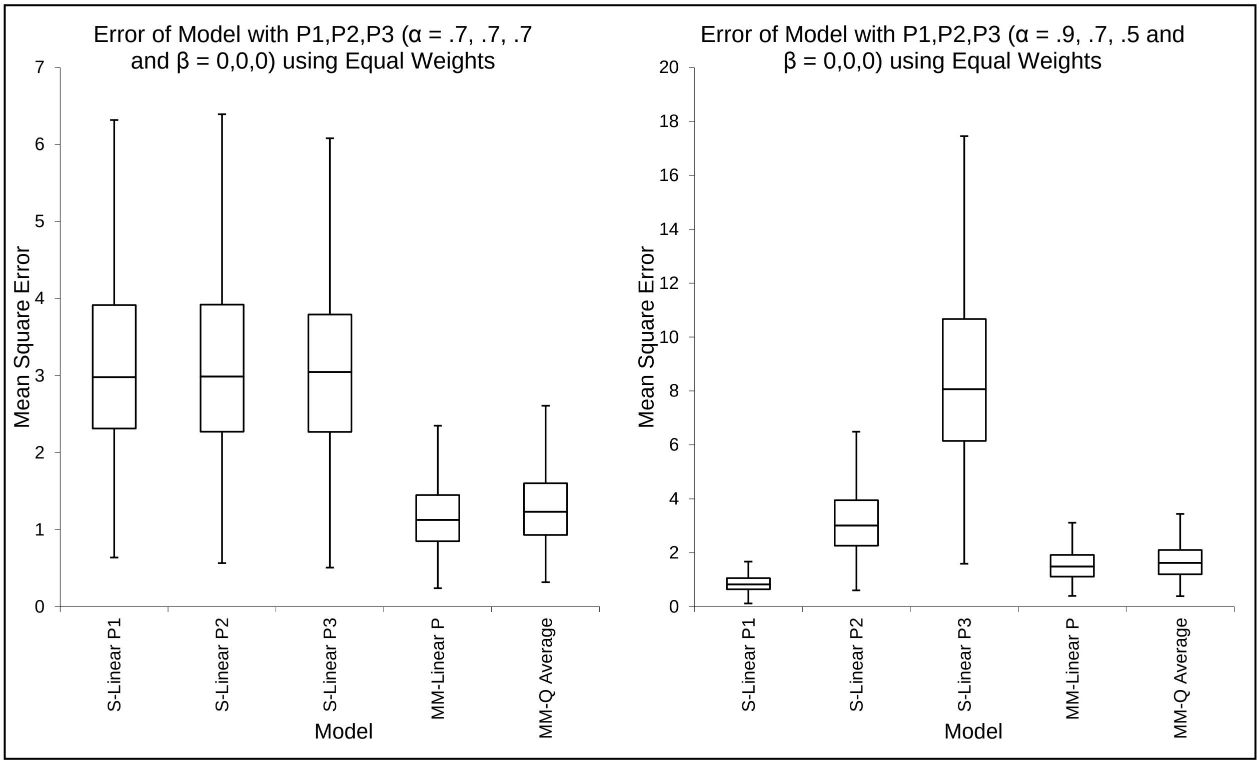

Figure 1: Box-plots of Mean Square error from fitting of 1000 sets of 40 years of synthetic streamflows generated from a linear model. Three climate forecasts are generated with all models having b =0, but with a = 0.7 for all the models (left) and having different a = 0.9, 0.7 and 0.5 (right). The performances of six predictions are summarized with single model (S). Two multimodel strategies (MM) are summarized next with the first strategy (MM-Linear P) – reducing input uncertainty first – followed by the second strategy (MM-Q Average) – combining the individual model predictions to develop multimodel predictions.

Analyses from Figure 1 clearly show that reducing input uncertainty first results in reduced MSE (MM-Linear P) compared to multimodel combinations developed from the combinations of individual model forecasts and watershed models (MM-Q Average). This is mainly because reduced uncertainty in the watershed model inputs results in better correspondence towards both model fitting and prediction. It is important to note the skill of the climate forecasts could be improved by combining multiple models that primarily arise from reducing the overconfidence of the individual models. Further, the single model performs better than the multimodel in the second case, since the multimodel combination is performed with equal weights on the individual models. These limitations on multimodel combination could be overcome by combining models based on their optimal combination (Devineni et al., 2008).

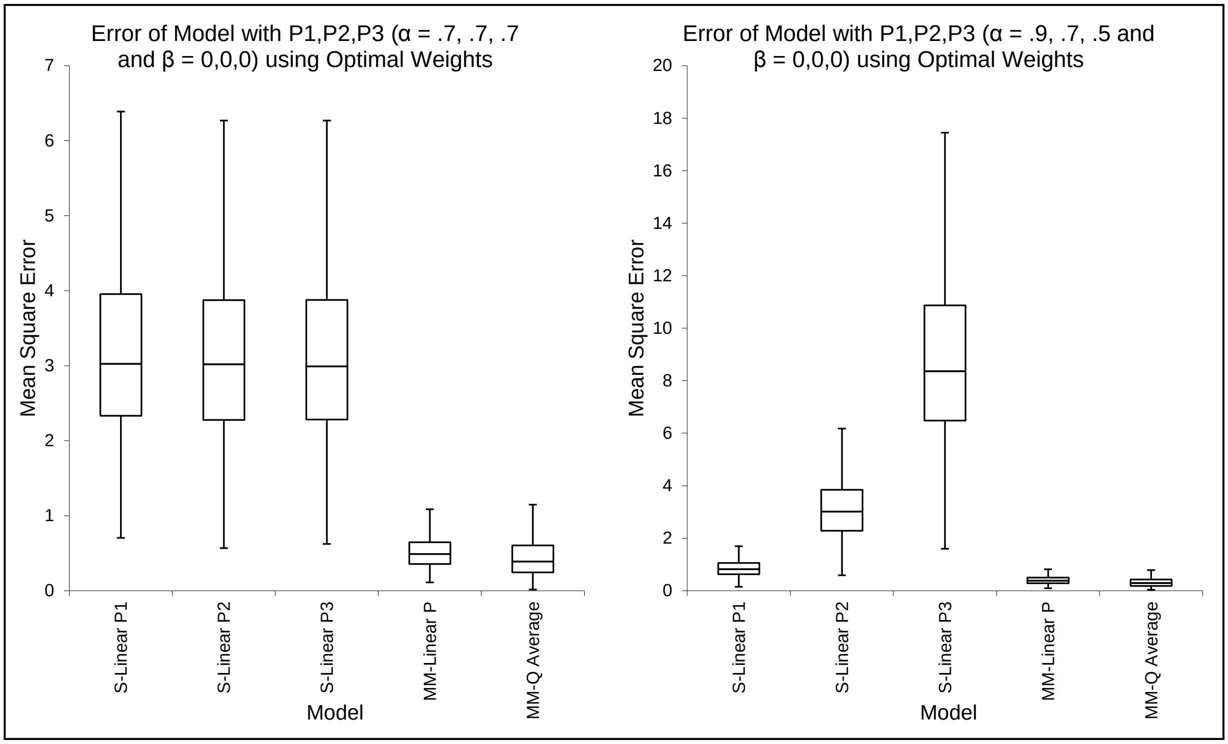

Figure 2: Same as Figure 1, but multimodel predictions are obtained based on optimal combinations of the individual models based on the algorithm of Devineni et al., (2008).

Figure 2 shows the similar analyses as Figure 1, but here the multimodel predictions are obtained based on optimal combinations. Under this case, the poorly (better) performing models during the calibration period are given lesser (higher) weights resulting in improved predictions. From Figure 2, when all the models have the same skill, optimal combinations distribute the weights equally (box-plots on the left), whereas with models having different skills (box-plots on the right), we clearly see multimodel predictions (MM-Linear P and MM-Q average) have the lowest MSE compared to the individual models. Among the multimodels, though it is difficult to see, MM-Linear P performs better than the MM-Q Average. Thus, given the hydrologic model, we reach the following conclusions for developing multimodel predictions (Figures 1 and 2):

(a) Multimodel streamflow predictions perform better than the streamflow predictions obtained from individual models even if we employ the individual models having the true model form.
(b) Reducing the input certainty – precipitation and temperature forecasts – through multimodel combinations on climate outputs is more critical than developing multimodel combinations without reducing uncertainty.
(c) Multimodel predictions obtained through optimal combinations perform better than the streamflow predictions obtained from the best single model as well as over the multimodel predictions obtained based on equal weights approach.

Similar analysis was performed with multiple hydrologic models with multimodel combinations obtained based on equal and optimal combinations. The above conclusions are true even under the case with unknown hydrologic model form. Thus, to reduce the uncertainty in streamflow predictions, it is important to first reduce the input uncertainty, which needs to be followed with reduction in hydrologic model uncertainty (Results under this case is not presented here). A manuscript based on these findings is under preparation to Water Resources Research:
Singh, H., and A. Sankarasubramanian, Systematic uncertainty reduction in streamflow forecasts development: Importance of Input and Hydrologic Model Uncertainty, Water Resources Research, 2011.

3. Reservoir Inflow Forecasts Development over Target Basins in NC (Objective 2)

For this purpose, we have focused on developing inflow forecasts over four target basins and two USGS gauging stations because of their significance to water management and hydropower generation. The four reservoir sites are: Falls Lake, Lake Jordan, Kerr-Scott Lake and Philpot Lake in Virginia. The two USGS gauging stations selected from the Catawba River system are South Fork Catawba River at Lowell, NC and Rocky Creek at Great Falls, SC.

Forecast Development Overview: Retrospective and real-time streamflow forecasts for the above six sites are currently available (http://www.nc-climate.ncsu.edu/inflowforecast) for the winter season over the period 1990 to date. The approach we employ for developing streamflow forecasts is principal components regression, which is one of the commonly employed methodologies for statistical downscaling [Sankarasubramanian et al., 2008]. Given that the precipitation fields obtained from GCMs and SSTs are spatially correlated, application of Principal Components Analysis (PCA) rotates the original GCM fields into orthogonal components with the first mode representing the maximum variance of the original GCM fields. PCA, also known as empirical orthogonal function (EOF) analysis, on the predictors (GCM and SST fields) could also be performed by singular value decomposition on the spatial correlation matrix or covariance matrix of the predictors. Since PCA is scale dependent, loadings (eigenvectors or EOF patterns) obtained from the covariance matrix and the correlation matrix are different. Importance of each EOF pattern is quantified by the fraction of the variance the principal component represents with reference to the original predictor variance. In the case of PCA performed using correlation matrix approach, the sum of all eigenvalues is equal to the total number of elements in the data.

Dimension Reduction and Predictor Selection: For developing streamflow forecasts for various basins, we consider two candidate predictors for statistical downscaling: (a) precipitation forecasts from ECHAM4.5 forced with constructed analogue SST forecasts over the Southeast US (23-40N; 92-73W) (b) observed monthly streamflow at the site. The grid points of precipitation forecasts that correlate well with the observed streamflow are identified based on Spearman rank correlation. These grid points of precipitation forecasts together with observed streamflow provide the predictor set for predicting streamflow for each basin. Since these predictors are correlated, it is better to employ principal components regression than multiple linear regression.

Principal Components Regression (PCR), otherwise known as Model Output Statistics (MOS) when employed with gridded predictors, primarily recalibrates large-scale GCM fields or the principal components of the GCM fields to the observed smaller spatial scale hydroclimatic variable of interest using regression analyses. The predictand could be either streamflow (Q_t) or observed rainfall over a region. PCR not only relates large-scale climatic information to the smaller spatial scale variable of interest, but also eliminates systematic errors and biases in GCM fields by regressing with the predictand fields. Expressing PCR in equation (7):

$$\ln(Q_t) = \beta_0 + \sum_{k=1}^{K} \beta_k * PC_{k,t} + \varepsilon_t \qquad \ldots (7)$$

where Q_t denotes the seasonal streamflow in year't', PC_t^k denotes the 'k'th PCs from the retained 'K' PCs of precipitation forecasts and $\hat{\beta}$ s denote the regression coefficients whose estimates are obtained by minimizing the sum of squares of error. We consider the logarithm of the streamflow as predictand to eliminate the possibility of estimating negative flows. To select 'K' PCs from the predictor set (gridded precipitation forecasts and streamflow), we employ step-wise regression that maximizes the correlation between the observed streamflow and predicted streamflow for the chosen validation scheme.

We present the model performance under two types of validation: Leave-one out cross-validation (L1CV) (displayed under Retrospective Forecasts) and Split-sample validation (displayed under Individual Year forecasts). L1CV is a rigorous model validation procedure in which the prediction for *t*' th year is obtained based on the PCR model developed using the predictand and predictor(s) available over the remaining '*n-1*' years. In essence, L1CV develops '*n*' PCR models to obtain seasonal streamflow conditioned on the PCs. Under split-sampling validation (SSV), a predictive model is developed using the Q_t and *PCs* over the calibration period (1957-1989) and the developed PCR model is employed for predicting the loadings over the validation period (1991- till date). We also obtain the conditional variance for each year (otherwise known as point forecast error in regression model) to develop ensembles of streamflow by assuming the flows follow lognormal distribution. The performance of the PCR model is summarized based on both deterministic and probabilistic verification measures, which are detailed next.

Forecast Verification Measures: Ensembles of streamflow forecasts developed under L1CV and SSV for each year are summarized using box-plots. The box-plot gives the various percentiles (to be selected by the user) of the forecasts obtained from the conditional mean and variance of the PCR model. The background of the box-plot also gives the streamflow corresponding to the chosen climatological probabilities. The forecast probability distribution table gives the probability of the forecasted flow occurring under different flow ranges that correspond to different climatological probabilities. For a reliable forecast, the number of times the observed flow exceeded the flow corresponding to a given climatological percentile (*p*) should be approximately equal to 'p' times the number of years of forecasts considered for verification. For instance, for flow corresponding to the below-normal category (33^{rd} percentile of climatological probability), the observed flow should exceed 67% of the time the flow corresponding to the forecasted 33^{rd} percentile.

The performance of the forecast is also summarized by comparing the conditional mean of the forecast with the observed flows using three different measures: (a) Correlation (b) Relative root mean square error (R-RMSE) (c) Mean Square Skill Score (MSSS). The correlation is computed as Pearson correlation between the observed and the predicted flows (conditional mean, $\hat{Q}_t$) from the PCR. A good forecast is expected to have a correlation around 1. However, for the correlation to be statistically significant, the computed correlation should be greater than 1.96/ (n-3) ^0.5 where '*n*' denotes the number of years of data used for computing correlation. Relative-RMSE denotes the average error in the conditional mean of the forecasts compared to the observed flows and it is computed using the following equation:

$$R-RMSE = \sqrt{n^{-1}\sum_{t=1}^{n}(1-\hat{Q}_t/Q_t)^2} \qquad \dots (8)$$

A good forecast is expected to have R-RMSE closer to zero. Another way to summarize the performance of the mean of the forecast is using MSSS. Basically, MSSS is similar to R-RMSE but it compares the mean square error of the candidate forecast with the mean square error of the climatological forecast (which is just the mean monthly/seasonal streamflow ($\overline{Q}$). The expression for MSE of the forecast and climatology could be written as follows:

$$MSE(\hat{Q}_t) = \sqrt{n^{-1}\sum_{t=1}^{n}(Q_t-\hat{Q}_t)^2}\ ;\ MSE(\overline{Q}) = \sqrt{n^{-1}\sum_{t=1}^{n}(Q_t-\overline{Q})^2} \qquad \dots (9)$$

Based on these two expressions, MSSS could be written as:

$$MSSS = 1 - MSE(\hat{Q}_t)/MSE(\overline{Q}) \qquad \dots (10)$$

For a good forecast, we would expect MSSS should be closer to one. A forecast is considered to be poorer than climatology if MSSS is lesser than zero.

Given that seasonal forecasts are better represented probabilistically using ensembles, expressing the skill of the forecasts using correlation requires summarizing the forecasts using some measures of central tendency such as mean or median of the conditional distribution, which does not give any credit to the probabilistic information in the forecast. Rank Probabilistic Skill Score (RPSS) computes the cumulative squared error between the categorical forecast probabilities and the observed category in relevance to a reference forecast (Wilks, 1995). In general, the correlation of the retrospective forecasts for all the above six sites are statistically significant for the winter season and it ranges from 0.5-0.8. For details on the skill evaluation of these forecasts, see http://www.nc-climate.ncsu.edu/inflowforecast.

4. Reservoir Inflow Forecasts Portal Development (Objective 3)

A nice web portal that can both upload and disseminate the streamflow forecasts from the NC-CRONOS database has been developed (http://hatteras.meas.ncsu.edu/ajmcnama/). The portal can display both retrospective forecasts and individual year forecasts along with detailed info on the forecast skill summary. Under individual year forecasts, the user has been provided with the option to download the forecast files under various file formats. Under retrospective forecasts, the skill of the forecasts are summarized using simple correlation, relative root mean square error, mean squared skill score and rank probability skill score. Details regarding the skill measures have also been provided in the website. Both these forecasts and web portal was developed by two graduate students, Harminder Singh and Andrew McNamara, from the Department of Civil, Construction and Environmental Engineering at NC State University. We have submitted a proposal to the NC-urban water consortium for a continuation project that focuses on the automation of seasonal to interannual streamflow forecasts for these target reservoirs. A manuscript based on the importance of disseminating seasonal inflow forecasts to water managers and their skill over NC will be prepared and submitted to the Journal of American Water Resources Association or to the Bulletin of American Meteorological Society.

5. Summary and Conclusions

Seasonal to interannual climate forecasts are beneficial in developing reservoir inflow forecasts which could be utilized in setting up water allocation strategies and contingency measures during droughts. This study focused on developing a portal (http://www.nc-climate.ncsu.edu/inflowforecast) for disseminating reservoir inflow forecasts which is downscaled from climate forecasts and previous month streamflow. The developed forecasts are currently archived in the NC-CRONOS database and a continuation project is currently under development by coordinating with the NC Urban Water Consortium members that can automate the entire portal for developing inflow forecasts.

The study also focused on answering a fundamental research question related to multimodel streamflow forecasts development. Given that we have climate forecasts from multiple climate models, which could be ingested with multiple watershed models, what is the best strategy to develop multimodel streamflow forecasts? To answer this question, we consider two possible strategies: (a) reduce the input uncertainty first by combining climate models and then use the multimodel climate predictions with multiple watershed models, which again could be combined to develop multimodel streamflow predictions (b) ingest the individual climate forecasts (without multimodel combination) with individual watershed models and then combine the streamflow predictions that arise from all possible combinations of climate and watershed models. For answering this question, we consider synthetic streamflow and climate forecasting schemes, so that we will be able to compare all the performance of candidate strategies with the true flows. The study clearly shows that the first strategy of reducing the input first results in better multimodel climate forecasts. Thus, for developing streamflow forecasts, the effort should first focus on reducing the input uncertainty (i.e., uncertainty in climate forecasts) before ingesting the climatic inputs into the watershed models. The study also shows clearly that developing multimodel climate forecasts using optimal combination methods result in improved forecasts as opposed to combining climate forecasts by equal weighting approach. As part of future effort, we intend to develop multimodel streamflow forecasts and archive them in the developed reservoir inflow forecasts portal.

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Appendix I

Notations are self-contained in the report

Appendix II

Two graduate students, Harminder Singh and Andrew McNamara (part-time), worked on this project.

Harminder Singh received third prize in the Annual NC WRRI conference for his poster presentation:
Singh, H., McNamara, A., Boyles, R. and Arumugam, Experimental Reservoir Inflow Forecast, NC Annual Water Conference, March 22-23, Raleigh, NC.

Journal Publication (in preparation):
Singh, H., and A. Sankarasubramanian, Systematic uncertainty reduction in streamflow forecasts development: Importance of Input and Hydrologic Model Uncertainty, Water Resources Research, 2011, to be submitted, 2011.