ABSTRACT

SINGH, HARMINDER. Systematic Uncertainty Reduction Strategies for Developing Streamflow Forecasts Utilizing Multiple Climate Models and Hydrologic Models. (Under the direction of Sankarasubramanian Arumugam).

Skillful streamflow forecasts are important for planners and water managers to inform the public about seasonal water availability and its allocation. Typically, streamflow forecasts are obtained by forcing downscaled precipitation and temperature forecasts from atmospheric general circulation models (AGCMs) into hydrologic models. But, the skill of these streamflow forecasts depends on the type of AGCM, hydrologic model as well as the season and the location of interest. Recent studies show that combining multiple models improves the hydroclimatic predictions by reducing model uncertainty. Given that we have precipitation and temperature forecasts from multiple climate models, which could be ingested with multiple watershed models, what is the best strategy to reduce the uncertainty in streamflow forecasts? *To answer this, we consider three possible strategies: (1) reduce the input uncertainty first by combining climate models and then use the multimodel climate forecasts with multiple watershed models (2) ingest the individual climate forecasts (without multimodel combination) with various watershed models and then combine the streamflow predictions that arise from all possible combinations of climate and watershed models (3) combine the streamflow forecasts obtained from multiple watershed models based on strategy (1) to develop a single streamflow prediction that reduces uncertainty in both climate forecasts and watershed models.* To address this question, we consider synthetic schemes that generate streamflow and climate forecasts, so that we can compare the performance of both strategies with the true flows. Results from the study shows that reducing input uncertainty first by combining climate forecasts results in reduced error in

predicting the true streamflow compared to the error of multimodel streamflow forecasts obtained by combining streamflow forecasts from all-possible combination of individual climate model with various hydrologic models. The findings are also consistent on application to a real watershed, Tar River at Tarboro, for which the ability to predict the observed streamflow is evaluated by developing multimodel streamflow forecasts based on both strategies based on five climate models, two stochastic streamflow models and one water balance model.

Systematic Uncertainty Reduction Strategies for Developing Streamflow Forecasts Utilizing Multiple Climate Models and Hydrologic Models

by
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BIOGRAPHY

Harminder Singh was born in the village of Manuke, Jagraon in Ludhiana District of Punjab, India on Wednesday, February 25, 1987. At the age of 12 in 1999 Harminder moved to the United States with his family. After spending two months in New York City, his family decided to move to Greensboro, NC where he attended Grimsley High School and graduated in 2005. Harminder obtained a B.S. in Civil Engineering with a concentration in Water Resources at North Carolina State University.

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CHAPTER 1 Introduction

Skillful seasonal streamflow forecasts are useful to planners and managers making decisions regarding water availability and allocation. Seasonal streamflow forecasts are typically obtained either by statistical relationships between the climate forecasts and initial land surface conditions and the observed streamflow (Sankarasubramanian et al., 2008) or by downscaling the precipitation and temperature forecasts into watershed model's grid scale, so that downscaled forcings could be ingested into a land surface model (Wood et al., 2002; Luo et al., 2008; Mahanama et al., 2011, Sinha and Sankarasubramanian, 2012). To obtain streamflow forecasts using the latter method, a skillful seasonal climate forecasts along with a good hydrologic model is required. Since the skill of the climate forecasts from general circulation models (GCMs) varies enormously across the season (Goddard et al., 2003) as well as across the models (Devineni and Sankarasubramanian, 2010), research institutes and operational agencies issue forecasts from multiple GCMs. Similarly, there are many hydrologic models available but each model has its own strengths and applications under different conditions and regions (Xu and Singh, 2004; Overgaard et al., 2006). Thus, the availability of multiple models provides options to develop streamflow forecasts based on various combinations of climate and hydrologic models.

Recent studies have shown that combining multiple models reduces the uncertainty in climate forecasts (Rajagopalan et al., 2002; Devineni and Sankarasubramanian, 2010). For instance, real-time climate forecasts are these days issued based on net assessment by combining multiple climate models (Goddard et al., 2003; Barnston et al., 2003). Devineni et al., (2010) improved the skill in predicting winter precipitation and temperature over the United States by optimally combining multiple general circulation models (GCMs) using an algorithm by assessing the models' skill conditioned on El Nino Southern Oscillation (ENSO) state. Weigel et al. (2008) demonstrated using a synthetic model setup that multimodel forecasts were able to outperform the best single model by reducing the overconfidence of the single models.

Similarly, on the streamflow predictions, studies have investigated about the utility of combining hydrologic models in order to improve streamflow predictions (Georgakakos et al. 2004; Ajami et al., 2007; Marshall et al., 2005; Marshall et al., 2006; Oudin et al., 2006; Devineni et al., 2008). Since no hydrologic model can perfectly replicate the conditions of the real world processes, it is advantageous to combine the strengths of individual hydrologic models to improve predictions (Vrugt et al., 2006; Duan et al. 2007; Marshall et al., 2007; Vrugt and Robinson, 2007; Chowdhury and Sharma, 2009). For developing streamflow forecasts using statistical models too, it has been shown that multimodel forecasts seem to outperform individual model forecasts (Regonda et al., 2005; Devineni et al. 2008). Recently, Li and Sankarasubramanian showed using a synthetic study that multimodel streamflow predictions perform better than individual model predictions as model uncertainty increases. While these multimodel combination studies focus exclusively on reducing the uncertainty on climate forecasts or on uncertainty in hydrologic models, there is no unified approach available on how to reduce the uncertainty in seasonal streamflow forecasts given the plethora of climate forecasts and hydrological models.

The main objective of this study is to find the best strategy to reduce the uncertainty in the streamflow forecasts using a hydrological model. Given the climate forecasts from multiple GCMs are better than individual model GCMs, which one should one employ in developing streamflow forecasts? Towards this, we consider three possible strategies: *(1) reduce the input uncertainty first by combining climate models and then use the multimodel climate forecasts with multiple watershed models (2) ingest the individual climate forecasts (without multimodel combination) with various watershed models and then combine the streamflow predictions that arise from all possible combinations of climate and watershed models (3) combine the streamflow forecasts obtained from multiple watershed models based on strategy (1) to develop a single streamflow prediction that reduces uncertainty in both climate forecasts and watershed models.* Evaluating the above three strategies can provide a systematic approach that can reduce uncertainty in streamflow forecasts. We evaluate these three strategies based on a synthetic streamflow forecasting scheme by their ability to predict a known “true flow” as well as by applying for a watershed in NC.

This paper is organized as follows: Chapter 2 describes the experimental design as well as evaluation methodology for evaluating the performance of streamflow forecasts under the proposed multimodel combination strategies. Chapter 3 presents the results and analysis of the various multimodel strategies by evaluating the skill of the streamflow forecasts. Finally, the application and conclusions from the study are presented in Chapter 4 and 5.

CHAPTER 2 Multimodel Combination Methodology

This chapter describes the experimental design that is involved in developing synthetic streamflow. The primary idea behind developing synthetic streamflow is that the "true flow" under a given forecast skill is known, so that the performance of candidate modeling strategies could be compared. To understand why multimodel climate forecasts perform better than individual model forecasts, Wiegel et al., (2008) employed a toy model setup under which the true value of the climatic attribute was corrupted to develop a climate forecast with a specified correlation with the true value. Similarly, in evaluating how streamflow predictions from combining multiple hydrologic models perform better than individual models, Li and Sankarasubramanian (2011) employed a streamflow generation scheme that evaluated the performance of candidate models and multimodel schemes under a specified model errors.

In this study, we consider the observed precipitation, potential evapotranspiration and streamflow at Tar River at Tarboro as the true hydroclimatic attributes for which the precipitation forecast with a specified skill and streamflow with a specified error characteristic is obtained. Observed monthly and seasonal time-scale precipitation, streamflow and potential evapotranspiration are obtained for 35 years at the Tar River Site from the national hydroclimatic database available for the continental United States (Vogel and Sankarasubramanian, 1999; Vogel and Sankarasubramanian, 2005). The first section of the experimental design describes a scheme to create synthetic precipitation forecasts from the observed monthly precipitation. The synthetic climate forecasts can be thought of as climate forecasts obtained from a GCM having a specified skill over the watershed. The second section describes the population model setup where we consider multiple watershed models as the true underlying models. The climate forecasts and hydrologic models are used to evaluate the performance of various multimodel combinations that could reduce the uncertainty in the estimated streamflow. As discussed in the introduction, we evaluate three strategies of multimodel combination in developing streamflow forecasts: *(1) reduce the input uncertainty first by combining climate models and then use the multimodel climate forecasts with multiple watershed models (2) ingest the individual climate forecasts (without multimodel combination) with various watershed models and then combine the streamflow predictions that arise from all possible combinations of climate and watershed models (3) combine the streamflow forecasts obtained from multiple watershed models based on strategy (1) to develop a single streamflow prediction that reduces uncertainty in both climate forecasts and watershed models.* For simplicity, we refer to these three multimodel combination strategies as *MM-P*, *MM-Q* and *MM-PQ* respectively.

2.1 Precipitation Forecast Generation Scheme

The synthetic climate forecasts, P_m^i, where $m=1,2,\ldots,M$ denote the number of members in the ensemble and $i=1,2,\ldots,n_m$ represent the number climate models issuing forecasts, are generated based on the toy model suggested by Weigel *et al.* (2008). The skill of the synthetic climate 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 1952-1986 as the true precipitation with winter climatology represented by mean (μ_P) and standard deviation (σ_P). Using the winter climatology, the observed precipitation is standardized to obtain x_t (Equation 1). Two noise terms ε_β and ε_m are generated from the normal distribution with zero mean and the respective standard deviations as specified in equations 2 and 3. The noise term, ε_β, specifies the overconfidence of the forecast, which forces all the members of ensemble to be far away from the true precipitation (P_t). It is important to note that the noise term ε_β which denotes the overconfidence of the forecasts is fixed for a given year. Thus, the parameter β is used to control the relocation of the conditional mean by generating the overconfidence forecasts with Gaussian noise term with zero mean and standard deviation β. The parameter α is used to control the correlation between the observed precipitation and the precipitation forecasts. Since α represents correlation coefficient, its value ranges between 0 and 1. Thus, the noise term, ε_m, controls the correlation between the observed precipitation (P) and the issued forecast over the period 1952-1986. For further details on the analytical derivation of how α and β control the correlation and forecast overconfidence, see Weigel et al., (2008).

$$x_t = \frac{P_t - \mu_P}{\sigma_P} \qquad \text{...(1)}$$

$$\varepsilon_\beta^i \sim N(0, \beta^i) \qquad \text{...(2)}$$

$$\varepsilon_m^i \sim N(0, \sqrt{1-(\alpha^i)^2-(\beta^i)^2}) \qquad \text{...(3)}$$

The two noise terms ε_β and ε_m are added to the standardized precipitation adjusted to the specified skill parameter α (equation 4). The members of the ensemble, $X_{t,m}{}^{i}$, are then averaged to obtain X_t^i (equation 5) and are transformed back using the observed winter climatology of precipitation (equation 6). We assume the precipitation forecast ensemble for each winter season, *t*, to constitute 100 members (*M=100*) following Gaussian distribution. The conditional mean of the forecasted precipitation is equal to the observed precipitation if $\alpha = 1$ and $\beta = 0$. Thus, by adjusting these two parameters, α and β, the center and the spread of the precipitation forecast ensemble are controlled. For example, a precipitation forecast with $\alpha = 0.9$ and $\beta = 0$ represents a well-dispersed high skill forecast while $\alpha = 0.5$ and $\beta = 0.85$ represents an overconfident low skill forecast. By assuming different α and β**,** we generate climate forecasts having different skills for the Tarboro site.

$$X^i_{t,m} = \alpha^i \cdot x_t + \varepsilon^i_{\beta,t} + \varepsilon^i_m \qquad ...(4)$$

$$\overline{X}^i_t = \sum_{m=1}^{M} X_{t,m} \qquad ...(5)$$

$$P^i_t = \overline{X}^i_t \cdot \sigma_P + \mu_P \qquad ...(6)$$

2.2 True Streamflow Generation for a given Hydrological Model

To generate streamflow forecast conditional on the precipitation forecasts from Section 2.1, we consider two stochastic streamflow generation models and one conceptual water balance model. The streamflow generation scheme is similar to that of the scheme employed by Li and Sankarasubramanian (2012) for understanding why multimodel streamflow estimates perform better than the individual model estimates. Table 1 provides the structure of linear, log-linear and 'abcd' model. The true streamflow is generated using one of these watershed models based on the observed precipitation and potential evapotranspiration available for the Tarboro site. We use the observed winter precipitation (P_t), streamflow (Q_t) and potential evapotranspiration (PET_t) for the Tar River at Tarboro to estimate the population parameters by minimizing the sum of squares of errors between the observed streamflow and the model predicted streamflow.

Table 1: Summary of candidate stochastic streamflow generation models used in the synthetic study as well as for individual model evaluations

Models	Population model	Population parameters	Model/output error
Linear	$Q_t^1 = \hat{a}_1 + \hat{b}_1 * P_t + \hat{c}_1 * PET_t + \varepsilon_t^1$	θ_1 = 41.15, 0.58, -0.77	$\varepsilon_t^1 \sim \mathrm{N}\left(0, f * \hat{\sigma}_\varepsilon^1\right)$
Log-Linear	$Y_t = \hat{a}_2 + \hat{b}_2 * \log(P_t) + \hat{c}_2 * \log(PET_t) + \varepsilon_t^2$ $Q_t^2 = 10^{Y_t}$	θ_2 = .99, 1.08, -0.80	$\varepsilon_t^2 \sim \mathrm{N}\left(0, f * \hat{\sigma}_\varepsilon^2\right)$
'abcd'	Conceptual model with G_{t-1}, S_{t-1}, PET_t, P_t as inputs and Q_t^3 as output	θ_3 = 0, 148.60, .48, 0	$\varepsilon_t^3 \sim \mathrm{N}\left(0, f * \hat{\sigma}_\varepsilon^3\right)$

Using the population parameters specified in Table 1, we generate true streamflow, Q_t^j where j denotes the hydrologic model index, from each watershed model using the observed precipitation and PET. It is important to note that the true flows also contain a model or output error (ε_t^j), which follows Gaussian noise with zero mean and standard deviation, $f * \hat{\sigma}_\varepsilon^j$, where '$f$' denotes a factor that control the residual standard deviation ($\hat{\sigma}_\varepsilon^j$) for model '$j$'. The residual standard deviation ($\hat{\sigma}_\varepsilon^j$) for a given model is estimated based on the residuals between the observed winter streamflow and the model-estimated flow. For *f=0*, the generated flow does not have any model error resulting in flows being exactly as that of model estimates for the Tar River at Tarboro. The model error is added explicitly to the model-estimated flow to generate many realizations of true flows. The true flows from the population models allow us to compare between single model streamflow predictions and various streamflow multimodel schemes developed using the precipitation forecasts. The next section describes the candidate single models and multimodels that are available for inter-comparison.

2.3 Single Model Forecasts Development and Evaluation Methodology

Based on the details given in Sections 2.2 and 2.3, we generate 35 years of synthetic climate forecasts based on the chosen α and β and then force it with a candidate model, j, in Table 1 to develop 35 years of synthetic streamflow forecasts. We also obtain the true streamflow, Q_t^j, by using the observed precipitation and PET for the 35 year period using the population parameters given in Table 1. Figure 1 shows the evaluation methodology for a single model. The generated streamflow, Q_t^j, is split into two sets with the first 20 years ($t=1, 2,\ldots n_c$; n_c denotes the number of years of calibration)of flow being used for calibration and the remaining 15 years ($t=n_c+1, n_c+2,\ldots n$; n denotes the number of years of evaluation)for validation. Considering the generated streamflow as the flow available for calibration, we estimate the model parameters, $\hat{\theta}_j$, using Q_t^j, precipitation forecasts (P_t^i) and PET_t by minimizing the sum of squares of errors between Q_t^j and the calibrated flow $\hat{Q}_t^j$ over the 20-year calibration period. The calibrated parameters, $\hat{\theta}_j$, are subsequently used with precipitation forecasts (P_t^i) and PET_t to estimate the forecasted streamflow, $Q_{SM-t}^{i,j}$, by the individual model for the validation period. It is important to note that the forecasted streamflow by a given model, j, could vary depending on the skill of precipitation forecasts, P_t^i, which is determined by α and β equations (1)-(6)).

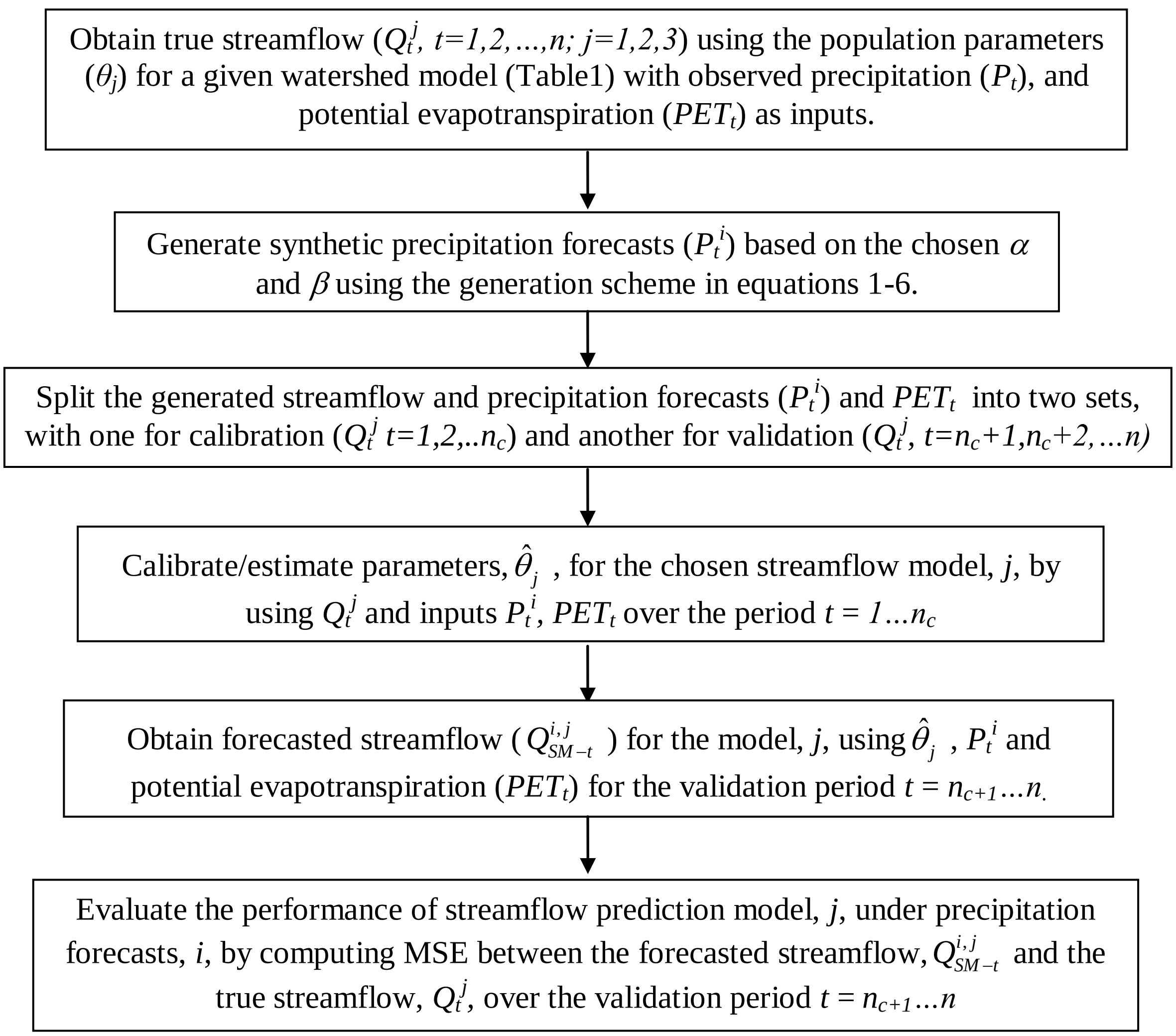

Figure 1: Flow chart for the generation of synthetic streamflow forecasts under a given climate forecasting scheme and hydrologic model

We also consider a conceptual watershed model, *abcd*, for estimating the single model forecasts of streamflow. The 'abcd' model originally suggested by Thomas (1981) has been employed by various monthly and annual water balance studies (Vogel and Sankarasubramanian, 2000; Sankarasubramanian and Vogel, 2002a). For details, see Sankarasubramanian and Vogel (2002b). For forecasting the winter streamflow using '*abcd*' model, apart from P_t^i and PET_t, the model also requires initial soil moisture and groundwater states, S_{t-1} and G_{t-1}, over the calibration and validation period. We upfront develop these estimates, S_{t-1} and G_{t-1}, over the entire 35 year period by simulating the '*abcd*' model at seasonal time scale using observed precipitation and potential evapotranspiration and the model parameters (shown in Table 1) over the entire 35 years of record. Thus, for forecasting each year winter streamflow, we use the simulated initial soil moisture and groundwater states along with P_t^i and PET_t for performing calibration and validation. Given the single model streamflow forecasts, we combine them next to develop multimodel streamflow forecasts.

2.4 Multimodel Precipitation and Streamflow Forecasts Development

Models invariably contain model errors due to different sources including quality of input data, initial states of the model, parameter estimation and the inability of the model to perfectly replicate the actual physical process (Feyen et al., 2001). In recent years, multimodel combinations have emerged as a way to reduce these model errors by combining multiple models to obtain improved predictions. (Georgakakos et al. 2004; Ajami et al., 2007; Devineni et al., 2008; Devineni and Sankarasubramanian, 2010) have shown that combining different competing single models result in improved predictions. Multimodel predictions are also able to capture the strength of the single models which results in improved predictability (Ajami et al., 2007; Duan et al., 2007; Devineni et al., 2008).

When considering multimodel combination there are various methods available using weighted averages, including simple or weighted average of single model predictions (Georgakakos et al., 2004; Shamseldin et al., 1997; Xiong et al., 2001). Other studies have explored statistical techniques such as multiple linear regression (Krishnamurthi et al., 1999) and Bayesian model averaging (Duan, et al., 2007) for multimodel combinations. In this study, multimodel combinations are obtained from single models by using weights which are obtained based on the performance of the single model over the calibration period.

For combining different synthetic precipitation/streamflow forecasts to develop multimodel forecasts, we combine models based on their ability to predict during the calibration period. Given the precipitation forecasts, P_t^i, over the calibration period (20 years), we compute the skill of the issued precipitation forecast by computing the mean square error between the forecasted mean, P_t^i, and the observed precipitation, P_t, using equation (7). Given that we have n_m climate forecasts from the synthetic scheme in Section 2.1, we obtain weights for individual models by giving higher weights for the best-performing model (equation 8). Using the weights, W_i, obtained for each model, we obtain multimodel precipitation forecasts, P_{MM-t}, over the validation period. One could obtain further improvements in multimodel precipitation forecasts by pursuing optimal model combination (Rajagopalan et al., 2002) or optimal model combination conditioned on the predictor state (Devineni and Sankarasubramanian, 2010). Those approaches are not pursued here, since the focus is to compare the three strategies proposed in the introduction. Application of such methods will only result in further improvements in multimodel predictions.

$$MSE_i = \sum_{t=1}^{n_c} (P_t - P_t^i)^2 \qquad ...(7)$$

$$W_i = \frac{MSE_i^{-1}}{\sum_{i=1}^{n_m} MSE_i^{-1}} \qquad ...(8)$$

$$P_{MM-t} = \sum_{i=1}^{n_m} P_t^i * W_i \qquad t = n_c + 1,\ n_c + 2,\ ...,\ n \qquad ...(9)$$

Similar to multimodel combination on precipitation forecasts, we also combine the streamflow forecasts, $Q_{SM-t}^{i,j} \quad (i = 1, 2..., n_m;\ j = 1, 2, 3)$, developed from individual models with different synthetic precipitation forecasts. To begin with, we first compute mean square error between the single model prediction, $Q_{SM-t}^{i,j}$ and the true flow for the model, Q_t^j, over the calibration period ($t=1,2,..n_c$). This results in a total of n_m*3 MSE estimates from different combinations of precipitation forecasts forced with various streamflow prediction models. These MSE estimates (equation 10) are converted into weights (equation 11) for each forecast by giving higher weights for the forecasts that perform the best. Given the weights, $W_{i,j}$, the individual model predictions are converted into multimodel forecasts using equation

(12) over the validation period. This basically gives the multimodel forecasts corresponding to the second strategy *MM-Q*.

$$MSE_{i,j} = \sum_{t=1}^{n_c} (Q_t^j - Q_{SM-t}^{i,j})^2 \qquad ...(10)$$

$$W_{i,j} = \frac{MSE_{i,j}^{-1}}{\sum_{\forall i,j} MSE_{i,j}^{-1}} \qquad ...(11)$$

$$Q_{MM-Q-t} = \sum_{\forall i,j} Q_{SM-t}^{i,j} * W_{i,j} \qquad t = n_c + 1,\ n_c + 2,\ ...,\ n \qquad ...(12)$$

2.5 Streamflow Predictions – Candidate Single Models and Multimodels

To evaluate the three strategies proposed in the introduction for reducing the uncertainty in streamflow predictions, we also need candidate streamflow prediction models that estimate the streamflow forecasts for the given precipitation forecasts. Synthetic precipitation forecasts with different skills could be generated using equations (1) - (6) for the 35-year period with each year forecast being represented with 100 realizations. The ensemble mean is used as the forecast inputs for the streamflow prediction models. The first model is the single model setup in which the individual synthetic precipitation forecasts (P_t^i) is be used with one of the streamflow prediction models (Table 1) to obtain the modeled streamflow ($Q_{SM-t}^{i,j}$). Thus, in the individual model streamflow predictions denoted as $Q_{SM-t}^{i,j}$ (Table 2), there is no combination of precipitation or streamflow forecasts from multiple models.

Table 2: Summary of streamflow forecasts developed from different climate and hydrology model combinations

Model Indices-Schemes	**Brief Description**
$Q^{i,j}_{SM-t}$	Streamflow is obtained by forcing individual streamflow model 'j' with a single climate model input 'i'.
Q^{j}_{MM-P-t}	Streamflow is obtained by forcing individual watershed model 'j' with the combined P_{MM-t} as the input
Q_{MM-Q-t}	Streamflow is obtained by combining all $Q^{i,j}_{SM-t}$
$Q_{MM-PQ-t}$	Streamflow is obtained by combining all Q^{j}_{MM-P-t}

The first strategy, MM-P, reduces the input uncertainty first by combining the synthetic precipitation forecasts to develop multimodel precipitation forecasts, P_{MM-t}, which are then used as an input with the streamflow prediction model (Table 1), *j*, to obtain streamflow (Q^{j}_{MM-P-t}). Details and steps involved in multimodel combination of precipitation and streamflow are given in the previous section. The second strategy, *MM-Q*, reduces the uncertainty in streamflow prediction by first ingesting the individual synthetic climate forecasts (without multimodel combination) with the individual watershed models and then combines the individual streamflow ($Q^{i,j}_{SM-t}$) to obtain a multimodel streamflow which is denoted by Q_{MM-Q-t}. Thus, the strategy, *MM-P*, uses multimodel precipitation forecasts to obtain streamflow, while the *MM-Q* method combines the streamflow forecasts obtained from various individual models. The third strategy, MM-PQ, combines all Q^{j}_{MM-P-t} obtained from the strategy MM-P to obtain $Q_{MM-PQ-t}$. The multimodel modeled streamflow, Q^{j}_{MM-P-t} from the *MM-P*, are combined to give a single streamflow denoted by $Q_{MM-PQ-t}$.

In summary, we have streamflow predictions from single models, $Q_{SM}^{i,j}$ and three multimodel combinations Q_{MM-P}^{j}, Q_{MM-Q} and Q_{MM-PQ} as shown in Table 2. The performance of these streamflow predictions is evaluated using mean square error, which is computed based on the streamflow predictions and the true model streamflow Q_t^j during the validation period $t = n_{c+1} \ldots n$. For each climate model precipitation i and model index j, the evaluation of streamflow predictions $Q_{SM}^{i,j}$ gives a single value of mean square error. The first multimodel combination, MM-P, denoted by Q_{MM-P}^{j} yields a single value of mean square error for each model index, j. The second and third multimodel combinations denoted by Q_{MM-Q} and Q_{MM-PQ} each yield a single value of mean square error. For the results, the evaluation methodology as outlined in Figure 1 is repeated 1000 times for all single and multimodel combinations to yield 1000 mean square error values for each model. A box plot is used to evaluate the performance of each model by plotting the 1000 mean square error values.

CHAPTER 3 Results

In this chapter, we compare the performance of single models and the three multimodel strategies based on the estimated mean square error from 1000 realizations. The first section presents results from three precipitation forecasts forced with the linear streamflow prediction model (Table 1). The true flows, Q_t^1, are also generated from the linear model. Given that we have only one streamflow prediction model, the third strategy, *MM-PQ,* is non-existent resulting in comparison between *MM-P* and *MM-Q*. The primary question that we address under this analysis is: Given no hydrologic model uncertainty, what is the best way to reduce uncertainty in streamflow forecasts using precipitation forecasts available from multiple models?

In the second section, we consider three streamflow prediction models (Table 1) with the true streamflow being generated from one of the hydrologic model. Thus, under this case, we explicitly consider uncertainties across climate models and hydrologic models by analyzing the proposed three strategies, *MM-P*, *MM-Q* and *MM-PQ*, for reducing the uncertainty in streamflow forecasts based on MSEs from 1000 realizations. This helps us to pick the right strategy that will reduce uncertainty in streamflow predictions by considering both input (precipitation) uncertainty and output (streamflow) uncertainty.

3.1 Streamflow Predictions – Candidate Single Models and Multimodels

Under this analysis, we consider the linear streamflow prediction model (Table 1) to be the population model as well as the candidate watershed model. We generate three precipitation forecasts with different skills by varying α and β. Each precipitation forecast is used with the candidate model – linear streamflow prediction model – to estimate three single model streamflows denoted by Q_{SM}^{i}. The first multimodel combination streamflow, Q_{MM-P}, is derived by combining the three precipitation forecasts and then the combined precipitation forecasts, P_{MM}, is used with the linear model. The second multimodel combination streamflow, Q_{MM-Q}, is derived by combining the streamflow from the single models (Q_{SM}^{i}; $i=1,2,3$). We basically repeat the procedure in Figure 1 1000 times to develop 1000 estimates of MSEs. Similarly, we also obtain MSEs, Q_{MM-P} and Q_{MM-Q}, by repeating the procedure in Section 2.4.

To begin with (Figure 2), we consider precipitation forecasts with varying skills by adjusting values for α and also by allowing the forecasts to be well-dispersed (Figure 2a) or overconfident (Figure 2b) based on β. It is important to note that in evaluating the precipitation forecasting schemes, we compare their ability to predict the true streamflow arising from the same population model. It is obvious from Figure 2a, skillful forecasts have lesser MSEs compared to the streamflow estimated by using lower skillful forecasts. Comparing Figures 2a and 2b, MSEs produced by a well-dispersed forecast have a lower MSE values compared to the overconfident forecasts. This is due to the ensemble spread of the forecasts becoming narrower due to the increase in the value of β.

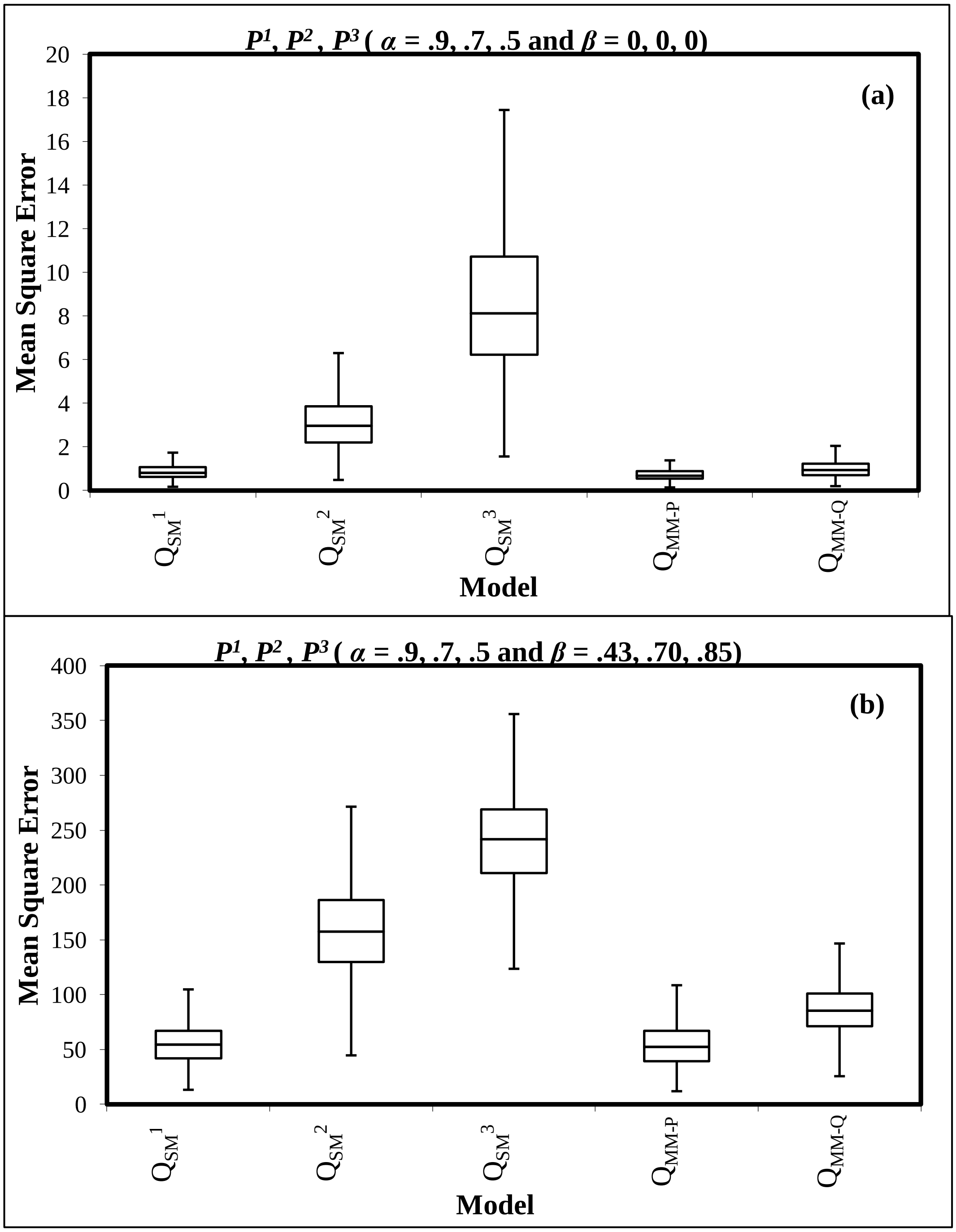

Figure 2: Box-plots of MSEs in predicting streamflow estimated by a linear model for (a) well-dispersed ($\beta = 0$) precipitation forecasts having different correlations ($\alpha = .9, .7, .5$) and (b) over-dispersed ($\beta \neq 0$) precipitation forecasts having different correlations ($\alpha = .9, .7, .5$)

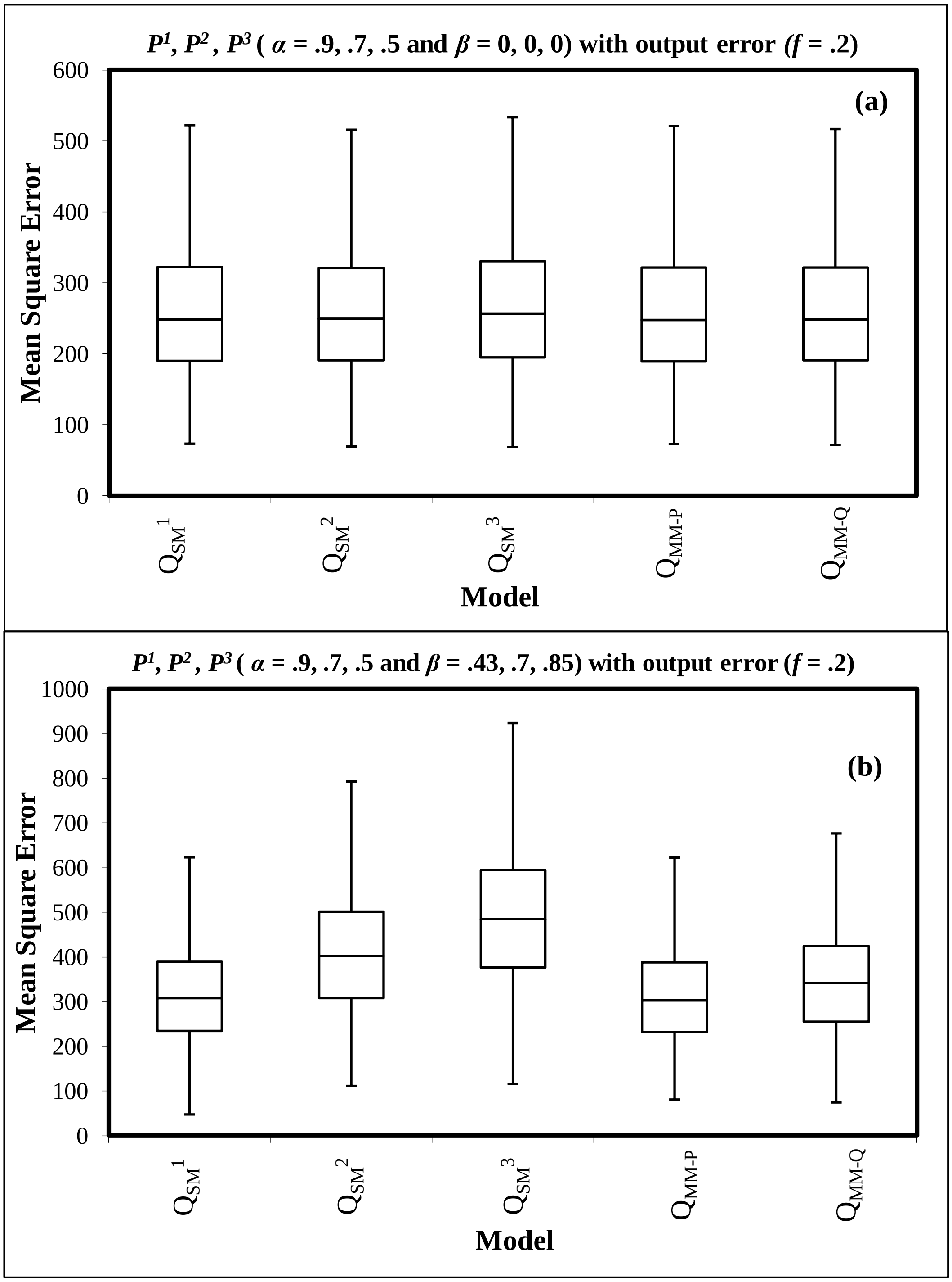

Figure 3: Box-plots of MSEs in predicting streamflow estimated by a linear model with the true streamflow generated with output error (*f=0.2*) for (a) well-dispersed ($\beta = 0$) precipitation forecasts having different correlations ($\alpha = .9, .7, .5$) and (b) over-dispersed ($\beta \neq 0$) precipitation forecasts having different correlations ($\alpha = .9, .7, .5$)

The single models perform better as the skill of the precipitation increases. We also see that the two multimodels (*MM-P* and *MM-Q*) perform better due to reduction in climate model uncertainty. Both multimodel combinations improve performance by reducing uncertainty. It is important to note that MM-P performs very close to the best-performing individual model. Since the skill of the precipitation forecast is not the same (varying values for α), we have used varying weights to combine the precipitation and streamflow used in the multimodels. Due to the varying weights we can observe that the multimodel combinations can perform better than the best single model (model with the highest value of α) as shown in Figure 2(a). The multimodel combination Q_{MM-P} (reducing input uncertainty) performs better than the best single model and the Q_{MM-Q} (reducing output uncertainty) multimodel. This implies that for systematic uncertainty reduction in streamflow, we need to reduce input (precipitation) uncertainty first, so that the estimated streamflow using multimodel climate forecast performs better than streamflow forecasts derived without any reduction in input uncertainty. This is mainly because reduced uncertainty in the inputs to the watershed model results in better accuracy in predicting the true streamflow arising from the same model. So regardless of the whether the precipitation forecast is well-dispersed or overconfident, the improvement in performance is better if one reduces the input uncertainty rather than the output uncertainty. Furthermore, both multimodel combinations provide improvements in performance. From this analysis, we infer that given no hydrologic model uncertainty, forcing the hydrologic models with reduced input uncertainty result in improved streamflow forecasts.

In Figure 2, we did not consider the hydrologic model error or output error by forcing the term *f=0* in synthetic streamflow generation. By selecting *f=0.2*, Figure 3 shows the performance of different models under a well-dispersed and over-confident precipitation forecasts with varying β. Figure 3a shows that the performance of the multimodel, MM-P, is just as good as the best-performing streamflow prediction scheme forced with a highly skillful well-dispersed precipitation forecast. From Figure 3b, we see that as the forecasts become overconfident, MM-P performs better than MM-Q as well as the best-performing single model predictions. These findings are completely in line with Weigel et al. (2008) who showed that multimodel combinations result in better predictions as the model dispersion increases. In the case of well-dispersed forecasts, the performance of multimodel predictions is just as good as the best-performing individual model predictions.

3.2 Source of Model Uncertainty - Climate Models and Hydrologic Models

In the previous section we considered only the linear model to be the candidate and the population hydrologic model. In this section we consider all three models (in Table 1) to be candidate models with the true streamflow being generated by either linear model or 'abcd' watershed model. Similar to the previous section, we consider three precipitation forecasts having different skills. Each precipitation forecast is forced with the three streamflow prediction models to develop nine streamflow forecasts, $Q_{SM}^{i,j}$ where $i = 1,2,3$ and $j = 1,2,3$. We also combine the three precipitation forecasts (using equations (7) – (9)) and use the combined precipitation forecast with each candidate model to develop three multimodel combination streamflows (Q^{j}_{MM-P} with j = *1,2,3*). The streamflow from nine single models $Q^{i,j}_{SM}$ is combined using equations (10)-(12) to develop multimodel Q_{MM-Q}. Similarly, streamflow forecasts from three multimodel Q^{j}_{MM-P} is combined separately (using equations (10)-(12)) to develop multimodel streamflow forecasts, Q_{MM-PQ}, which reduces first the input uncertainty followed by output uncertainty. Thus, in this section, we present MSEs from 14 models that include nine single models and five multimodels. All the multimodel combinations on precipitation/ streamflow are obtained using weights dependent upon the skill of the forecast during the calibration period.

Figure 4 presents the box-plots of MSEs for 14 models with the linear model as the population model having no output error (*f*=0). From Figure 4, we can see that the Q^{abcd}_{SM} and Q^{abcd}_{MM-P} perform the worst across all the models. This is partly because the assumed watershed model is linear and the 'abcd' model is a nonlinear water balance model. The multimodel combinations, Q_{MM-P}, that reduces first the input uncertainty performs better than their counterpart forced with individual model precipitation forecasts. We can see that in the case of the linear candidate model, Q^{Linear}_{MM-P} performs better than the best single model $Q^{1,Linear}_{SM}$. Similarly, log-linear and 'abcd' candidate model forced with multimodel precipitation forecast, Q_{MM-P}, perform better than their respective counterpart in the single model. Since we are using varying weights during combination we assign more weight to the precipitation or streamflow forecast with good skill. The multimodel combination Q_{MM-Q}, which reduced the output uncertainty by combining the streamflow all the six single models, performs worse than the multimodel combination Q_{MM-PQ}. This is to be expected since Q_{MM-PQ} reduces input and output uncertainty by combining the streamflow from the multi-modes combination Q_{MM-P} rather than the single models.

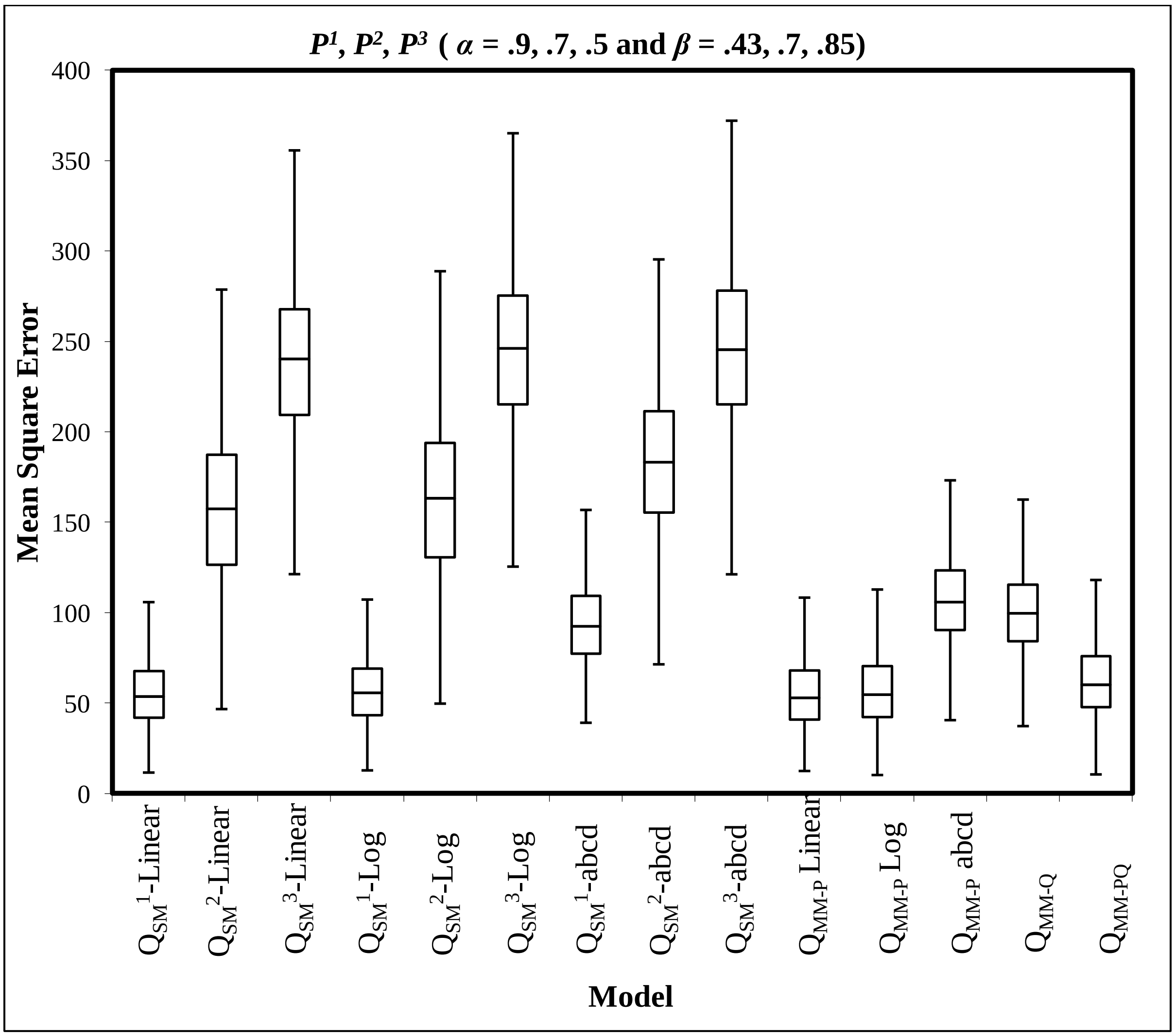

Figure 4: Box-plots of MSEs for 1000 realization for three candidate streamflow prediction models with the true streamflow arising from linear model (f=0) and the precipitation forecasts having different skill (α = .9, .7, .5) and dispersiveness (β = .43, .7, .85)

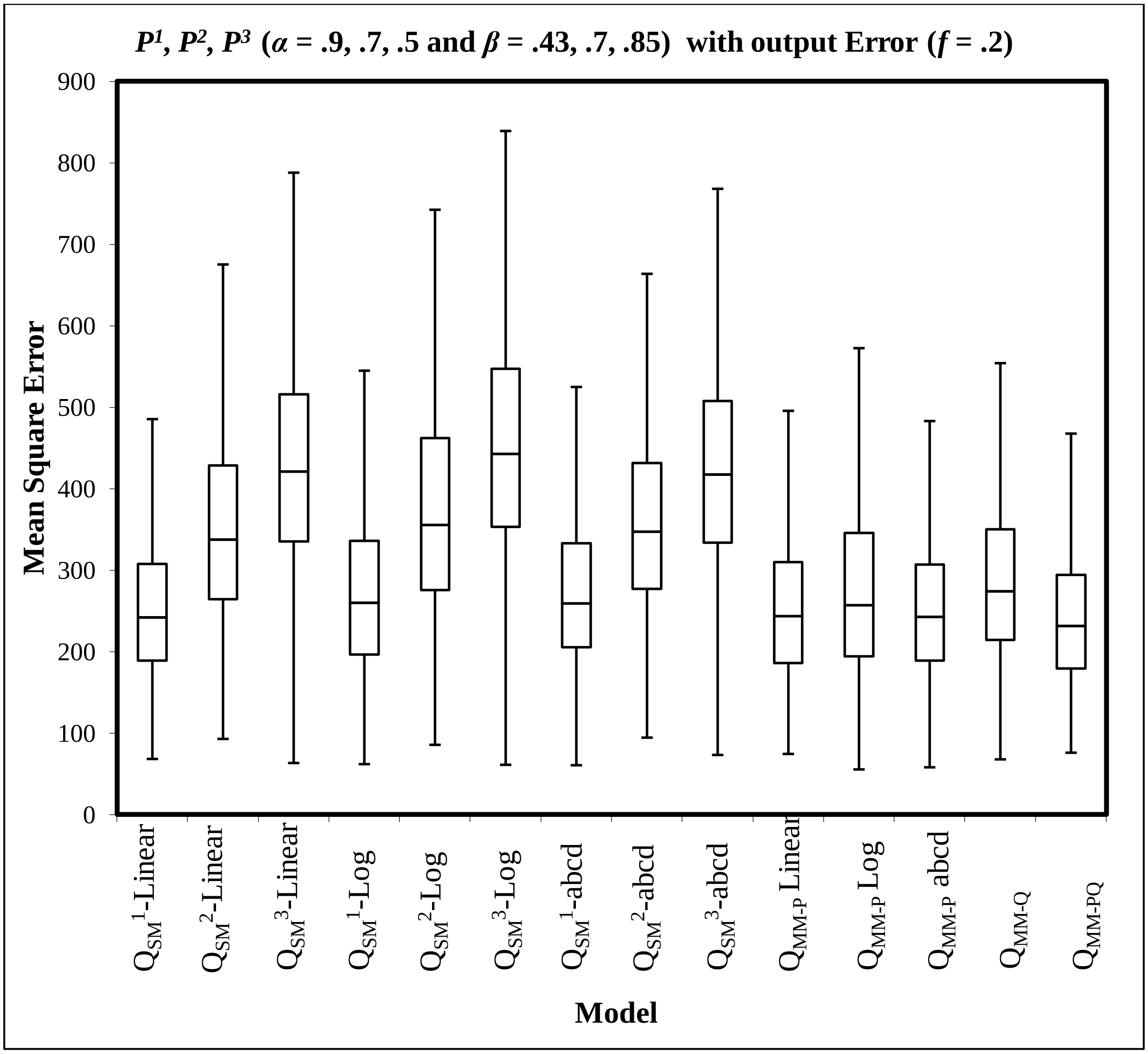

Figure 5: Same as Figure (4) but with streamflow output error (*f* =.2)

The mean square error of all models has increased in Figure 5 primarily due to the noise added to the true model streamflow (*f* = .2). But the relative performance of the single and multimodel combinations has remained the same. Forcing the candidate watershed model with multimodel precipitation forecasts, *MM-P*, improves the performance of three candidate models. Similarly, streamflow forecasts developed based on the strategy, *MM-PQ*, perform better than MM-P and MM-Q when output error is present. Thus, to reduce the uncertainty in streamflow prediction, it is important to first reduce the input uncertainty, which needs to be followed with reduction in hydrologic model uncertainty.

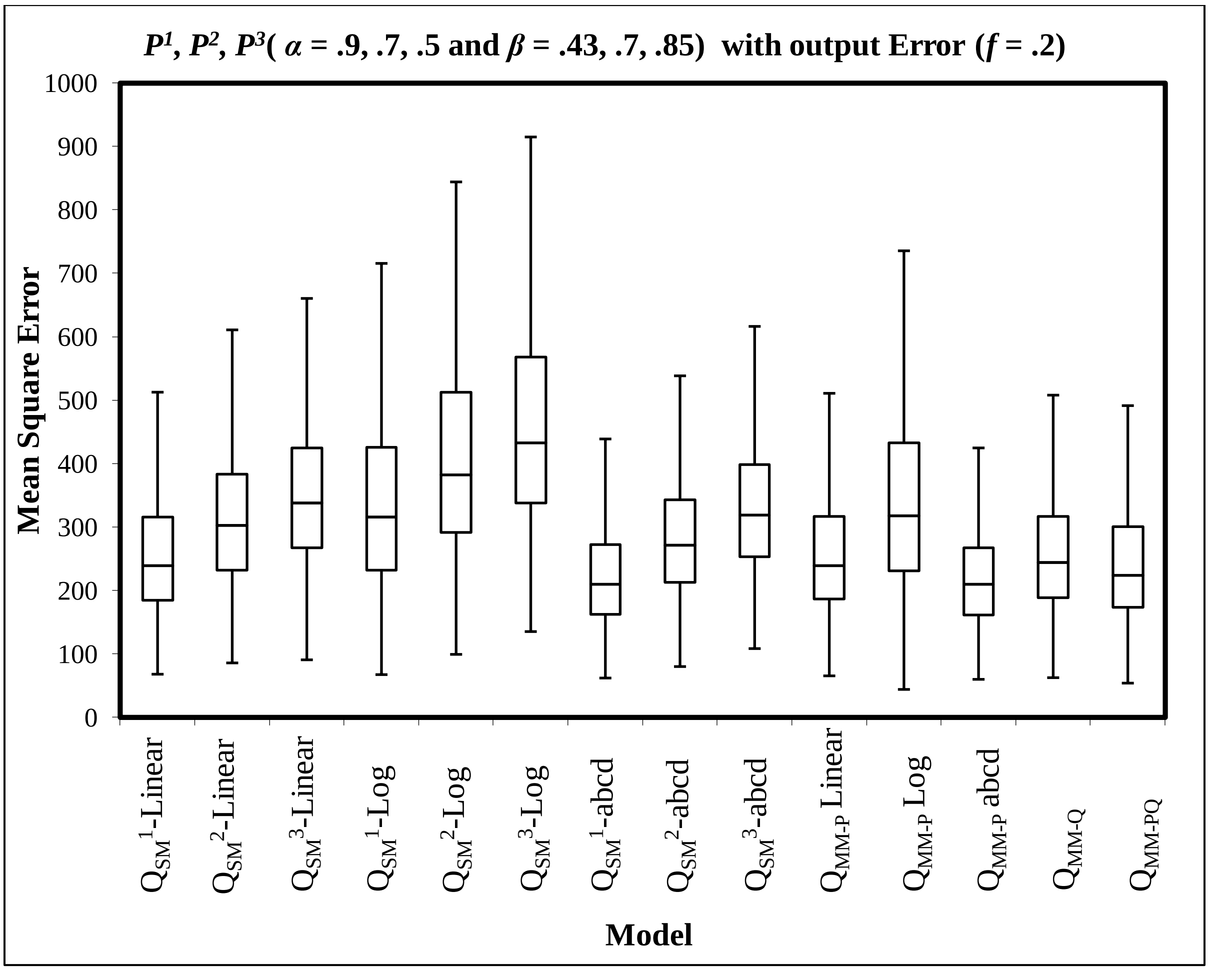

Figure 6: Same as Figure 5, but the true flows arise from 'abcd' model with output error (f =.2)

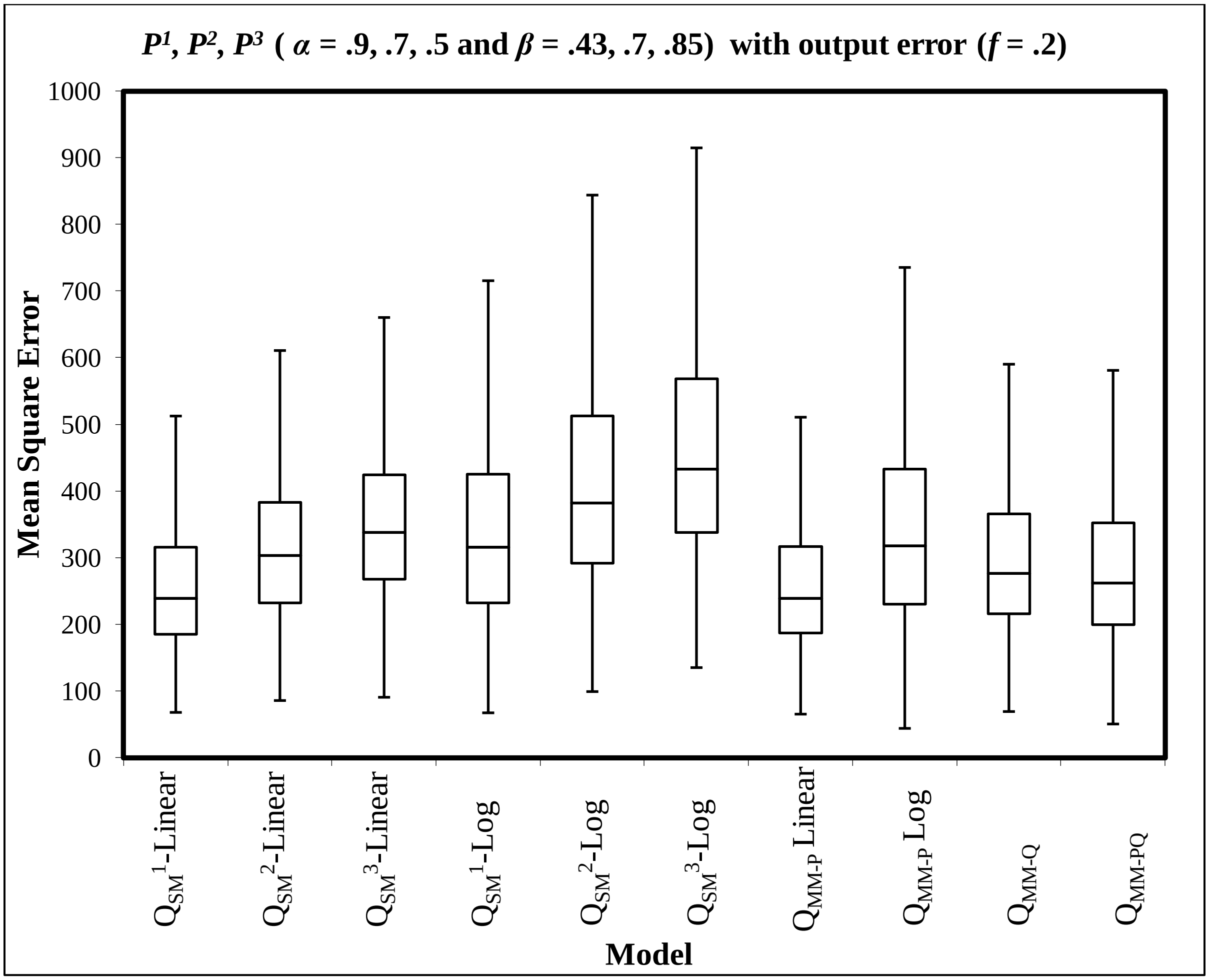

Figure 7: Same as Figure 6, but without 'abcd' model among the candidate models

In all previous results we have considered the true streamflow generation model along with the candidate model available for developing streamflow forecasts. We also considered how various candidate single models and multimodels perform when the true streamflow arises from a population model that is not part of the candidate models. In Figure 7, we perform the same analysis by excluding 'abcd' model from the candidate model. Thus, we consider the linear and log-linear to be the candidate models. Thus, we have a total of six single model forecasts ($Q_{SM}^{i,j}$), two single model predictions forced with multimodel precipitation forecast (Q_{MM-P}^{j}), one multimodel predictions (Q_{MM-Q}) from $Q_{SM}^{i,j}$ and one multimodel predictions (Q_{MM-PQ}) based on Q_{MM-P}^{j}. This results in a total of 10 prediction schemes available for evaluation. Based on Figure 7, the best-performing models are Q_{MM-P}^{Linear} and Q_{MM-PQ}. Though the median of Q_{MM-PQ} is slightly higher than that of Q_{MM-P}^{Linear}, the difference in the MSE between the two schemes is very marginal.

In this chapter we have considered reducing only climate model uncertainty and both climate and hydrological model uncertainty as a means of reducing uncertainty in the streamflow predictions by analyzing three proposed strategies, *MM-P, MM-Q* and *MM-PQ*. When considering no hydrological model uncertainty, reducing input uncertainty by using *MM-P* strategy performs better than reducing output by using *MM-Q* regardless of whether the precipitation forecasts is well-dispersed or overconfident. We can attribute this to the fact that reduced uncertainty in the inputs of the watershed model results in better accuracy in predicting the true streamflow arising from the same model. While we only consider the linear model to be the population and candidate model in Section 3.1, the same conclusions can be reached if one uses other model, log or ‘abcd’ model, for either population or candidate model. In Section 3.2 we consider multiple candidate models thus incorporating both climate and hydrological model uncertainty which allows us to evaluate the streamflow predictions from all three proposed strategies *MM-P, MM-Q* and *MM-PQ*. We find that regardless of the candidate models it is important to first reduce the input uncertainty, which needs to be followed with reduction in hydrologic model uncertainty in order to obtain the best streamflow prediction given that we do not know the true watershed. In the next section we will evaluate performance of three multimodel combination strategies in predicting the observed streamflow at Tar River at Tarboro using five coupled GCMs.

CHAPTER 4 Application

The results discussed so far have been based on a synthetic model. In this section, we investigate how the proposed multimodel combination strategies perform in predicting the observed streamflow at Tar River at Tarboro (Figure 8). The observed winter seasonal streamflow and potential evapotranspiration are obtained for the Tar River at Tarboro site (02083500) from the HCDN database of Vogel and Sankarasubramanian (2005). The precipitation forecasts for Tar River at Tarboro are obtained from five coupled GCMs (Table 3) developed as part of the ENSEMBLES project (Devineni, N., and A. Sankarasubramanian 2010). The precipitation forecasts from eight grid points over the domain (longitude -80W to 75W; latitude-32.5N to 37.5N) available at a monthly time step from 1981 to 1999 are considered for developing winter streamflow forecasts. The monthly precipitation forecasts issued in November from each GCM are converted into seasonal precipitation forecasts over the period January-March for further analysis.

Table 3: List of coupled GCMs used in the application for Tar River at Tarboro

Ocean Model	Atmospheric Model	Institution	Reference
HOPE	IFS CY31R1	ECMWF	Balmaseda et al. [2008]
HadGEM2-O	HadGEM2-A	UKMO	Collins et al. [2008]
OPA8.2	ARPEGE4.6	MF	Daget et al. [2009]
MPI-OMI	ECHAM5	IFM-GEOMAR	Keenlyside et al. [2005]
OPA8.2	ECHAM5	CMCC-INGV	

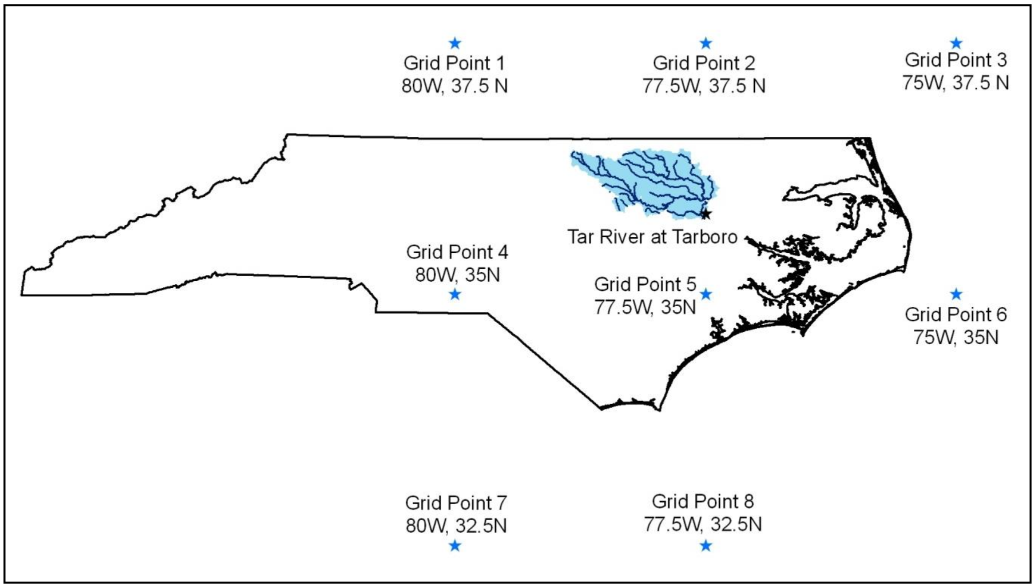

Figure 8: Location of the Tar River at Tarboro along with the latitude and longitude of the eight grid points used for the analysis

The precipitation from the five GCMs (Table 3) ($i = 1 \ldots 5$) is used with the candidate models ($j = 1 \ldots 3$) to obtain the single model streamflow $Q_{SM}^{i,j}$. There are fifteen single models which are combined to obtain the multimodel streamflow denoted by Q_{MM-Q}. The multimodel precipitation data is based on the algorithm developed by *Devineni and Sankarasubramanian* (2010) which considers the forecasted Nino3.4 from each GCM as the conditioning variable. The multimodel streamflow Q_{MM-P}^{j} is obtained by using the multimodel precipitation with the candidate model *j*. The final multimodel combination Q_{MM-PQ} is obtained by combining the three Q_{MM-P}^{j} streamflow. The winter precipitation forecasts from the above five GCMs (Table 3) and the multimodel algorithm are statistically downscaled using principal component regression before the precipitation data can be used with the candidate models. Since the precipitation data from the eight grid points (Figure 8) of each GCM is spatially correlated, we can use Principal Component Analysis to obtain a single time series which explains the maximum variance of the original eight grids of the GCM. Generally the downscaled precipitation has better correlation than the eight grid points.

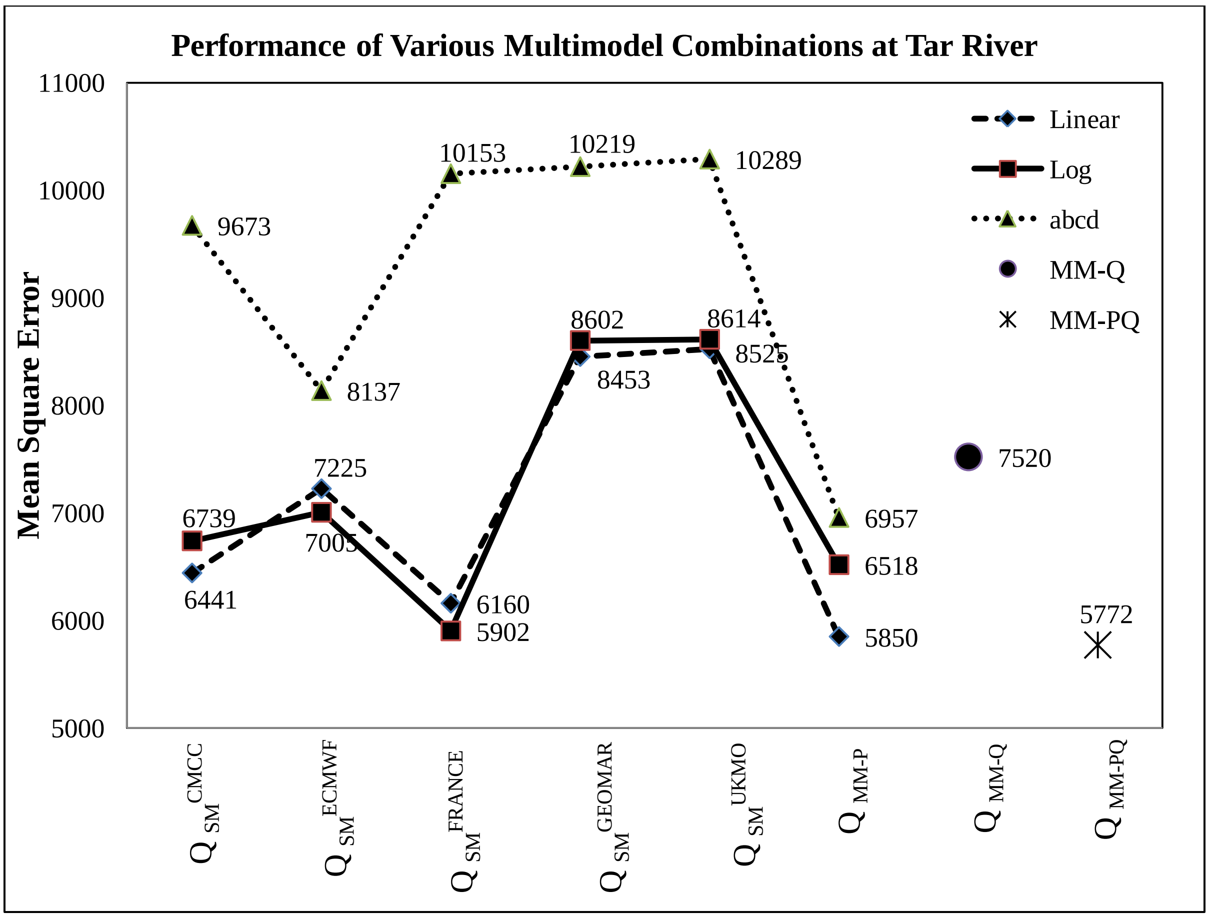

Figure 9: Mean square error of individual GCMs and multimodel combination schemes in predicting the observed streamflow for the Tar River at Tarboro. The analysis considers three hydrological models linear, log-linear and 'abcd' model

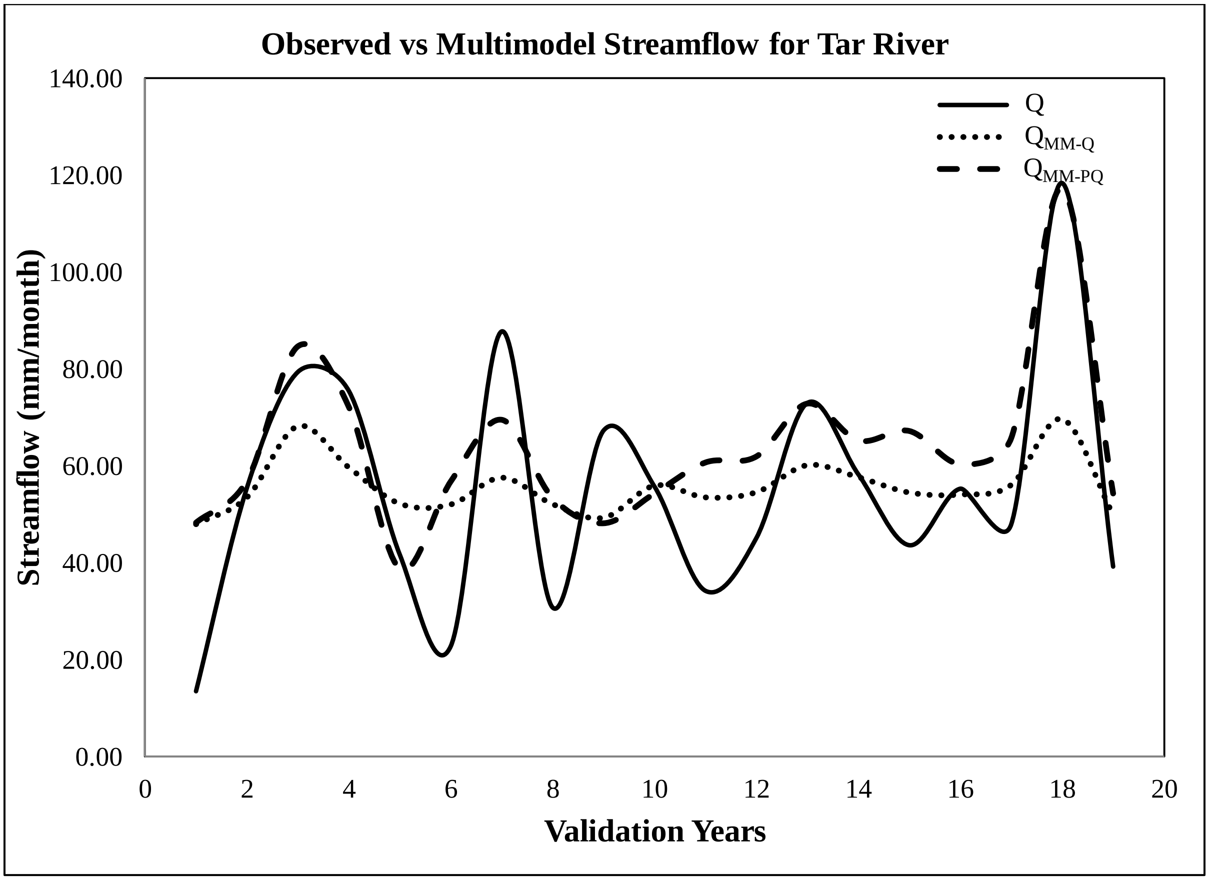

Figure 10: Multimodel streamflows plotted with the observed streamflow at Tar River

In order to evaluate the performance of the various multimodel methods, we use a calibration and validation approach as described in the experimental design section with mean square error as the performance metric. The first 20 years of data (1961-1980) are used to calibrate the various hydrological models while the last 19 years (1981-1999) are used for validation. The models are calibrated and validated using the observed streamflow, potential evapotranspiration and precipitation data from the five single GCMs and multimodel algorithm. The results from the application are presented in Figure 9 during the validation period (1981-1999).

Multimodel and observed streamflow are plotted in Figure 10. The results obtained in this analysis verify the results obtained through the synthetic model setup. It is clear that employing multimodel combination improves performance over single models. We also see that reducing the input uncertainty (climate models) through multimodel combinations is more critical than reducing output uncertainty (hydrological models) (the results for MM-Q for each candidate model are not shown in Figure 9). The overall best performance is obtained by reducing input uncertainty followed by reducing output uncertainty as shown by model MM-PQ. Thus, application to actual watershed confirms the synthetic study that MM-PQ is the overall best strategy to reduce the uncertainty in streamflow forecasts.

CHAPTER 5 Conclusions

Given that we have climate forecasts from multiple climate models, which could be ingested with multiple watershed models, a systematic analysis is performed for identifying the right strategy to reduce the uncertainty in streamflow forecasts. The methodology considers reducing the input uncertainty first by combining climate forecasts and then uses those multimodel climate forecasts as inputs with multiple watershed models. We further combined the streamflow predictions obtained using multimodel climate forecasts to develop a forecast that reduces uncertainties in climate models and hydrologic models. We also considered combining streamflow predictions developed by forcing individual climate models with individual watershed models. Considering the synthetic precipitation forecast scheme suggested by Weigel *et al.* to generate climate forecast, the study considers three streamflow prediction models linear, log-linear and 'abcd' model as candidate models. Based on the synthetic models and application for Tar River, we reach the following conclusions:

(a) Multimodel streamflow obtained either by reducing input (climate forecast) or output (hydrologic model) uncertainty performs better than the streamflow predictions obtained from single models even if we employ the single models having the true model form.

(b) Reducing the input (climate forecast) uncertainty through multimodel combinations is more critical than reducing output (hydrologic model) uncertainty.

(c) Multimodel streamflow obtained by giving higher weights for the best-performing model during the calibration period results in improved predictions during the validation period even compared to the streamflow predictions obtained from the best single model.

(d) When considering multiple candidate models, reducing input (climate forecast) uncertainty followed by reducing output (hydrologic model) uncertainty will provide better results than only reducing output (hydrologic model) uncertainty.

(e) Of all the multimodels, MM-PQ, performed the best in most situations. Given that we don’t know the true watershed model, it is imperative to reduce model uncertainties in both sources – climate model and hydrologic model – for improving the streamflow predictions.

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