ABSTRACT

WANG, HUI. Improved Streamflow in Adaptive Reservoir Operation. (Under the direction of Dr. Sankar Arumugam and Dr. Ranji S Ranjithan).

The main focus of this study is to improve short-term streamflow forecasts and to utilize them in adaptive reservoir operation to enhance sustainability. A combination scheme is developed to integrate reforecasts from a numerical weather model and disaggregated climate forecasts from ECHAM4.5 for developing 15-day ahead precipitation forecasts. Evaluation of the weather-climate information (WCI) based biweekly forecasts under leave-five out cross-validation shows that WCI based forecasts perform better than reforecasts in many grid points over the continental United States. WCI forecasts perform particularly better during summer months when reforecasts have a limited skill. Even though the disaggregated climate forecasts do not perform well at many grid points, the primary reason WCI based forecasts perform better than reforecasts is due to the reduction of the overconfidence of reforecasts. Since the Disaggregated Forecasts (DF) are better dispersed than Reforecasts (RF), combining them with reforecasts results in improved 15-day ahead precipitation forecasts. Improved precipitation and streamflow can be used for adaptive management of water resources system, e.g., reservoir operation.

An adaptive reservoir operation framework is proposed to explicitly incorporate ecological flow requirements. A general optimization-based decision model is presented to consider simultaneously anthropogenic water uses of a reservoir and desirable ecological reservoir releases represented by hydrological alterations parameters that capture the impacts on flow

regime. Multiple uses of the reservoir, including water supply and hydropower generation, are modeled within a mixed integer linear programming model. Investigations based on a model of a reservoir in Virginia demonstrate that compared to standard releases based on the current operational practices, releases simulated using this adaptive framework perform better in mimicking natural flow or pre-impact flows. Perfect streamflow forecasts are used in this analysis. In addition, to understand how the reservoir operation model could benefit when coupled with streamflow forecasts, synthetic Ensemble Streamflow Prediction (ESP) of a month-ahead daily stremflow forecasts is integrated into the adaptive reservoir operation framework. Results demonstrate that synthetic ESP with better skill improves water allocation for intended uses of the reservoir and achieve better flow conditions in the river downstream of the reservoir. The value of updated-ESP in sustaining reservoir operation is also examined as compared to non-updated-ESP. Results show that updating forecasts further improves reservoir operation in term of meeting human needs and ecosystem health.

Improved Streamflow in Adaptive Reservoir Operation

by
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DEDICATION

To my family members, including my wife Nan Qian, my father Xunrong Wang and my mother Yaomei Li.

BIOGRAPHY

Hui Wang was born at a small village of Hunan province, China. He obtained Bachelor degree in civil engineering with specialty in water supply and drainage engineering from Wuhan University in 2003 and he obtained master degree from the same program in 2006. He came to United States for doctoral education, where he spent one and a half years at University of South Carolina. In May 2008, he continued his education at North Carolina State University. Hui Wang enjoys research and will pursuit his career in academia.

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The author thanks to his committee members for providing scientific guidance and mentoring during the graduate study at North Carolina State University. They are Dr. Sankar Arumugam, Dr. Ranji Ranjithan, Dr. Downey Brill and Dr. Anantha Aiyyer. What the author learned from his professors through group meetings and one-to-one research discussions are far more than technical approaches to solve the scientific problems studied in this dissertation, but also the general philosophy of carrying independent research.

The author is in debt to Dr. Kenneth W. Harrison for his mentoring all the time. Sincere appreciation goes to Dr. Zheng Fang and Dr. Qing Shao at Wuhan University. The author appreciates his officemates in Mann 319A, Mann 425 and Daniel's Hall for the wonderful time we spent together.

Finally and the most importantly, this dissertation is to the author's family members. Without their unselfish love, supports and patience, this dissertation cannot be finished.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1 Motivation and Introduction

The focus of this dissertation is to address the following two research questions associated with sustainable water resources management: (1) How to improve short-term precipitation/streamflow forecasts? (2) How to promote sustainable water reservoir operation by utilizing improved precipitation/streamflow forecasts? These two research questions are tightly coupled since the solutions to the first question could help address the second question,. Short-term precipitation/streamflow forecasts, for instance, 15-day precipitation forecasts, can be useful for short-term reservoir operations that consider multiple purposes, including flood control and ecological flow requirements while meeting water supply and hydropower demands. Hence, accurate short-term streamflow forecasts can help enhance sustainable water resources management. Efforts to improve the skill of weather forecasting models could be broadly summarized into three categories: 1) better process representation and parameterization of weather forecasting models; 2) improved estimates of initial conditions through better data assimilation; and 3) recalibration of predicted variables using model output statistics to reduce marginal bias and conditional bias in predictions. With regards to sustainable reservoir operation, it is well recognized that the controlled release from a reservoir has detrimental effects on the health of the downstream ecosystem due to the change in the hydrologic flow regime upon which aquatic systems depend (Petts, 1984; Poff et. al. 1997). Hence, restoring and maintaining the natural flow pattern should be an objective in sustainable reservoir operation. While the current practice common in reservoir operations is to meet a minimum environmental flow release, it is often not optimal for ecological

purposes. Recent studies in the literature (e.g., Shiau and Wu, 2004; Suen and Eheart, 2006; Yang and Cai, in press) suggest incorporating hydrological flow alteration as an evaluation tool in reservoir operations. Most of these studies focus on finding a release pattern using historical data. This can be improved, however, by employing an adaptive release policy based on reservoir inflow.

The research objectives of this dissertation are to: (1) develop an approach to improve short-term precipitation forecasts; and (2) design, implement and test an adaptive sustainable reservoir operation framework to explicitly incorporate anthropogenic water needs and natural flow regime maintenance. There are different ways, as described above, to improve precipitation forecasts. To achieve the first objective of this dissertation, a new approach is considered to integrate climate information and weather information for improving precipitation forecasts. A model combination algorithm is investigated to integrate climate model outputs and weather information to improve short-term precipitation forecasts. To achieve the second objective, an adaptive reservoir operation framework, where anthropogenic water requirements and hydrological flow alterations are explicitly modeled and incorporated, is proposed and studied. Integration of the improved precipitation/streamflow forecasts with the adaptive reservoir operation framework offers a solution to promote sustainable reservoir operation, which is the theme of this dissertation. The rest of the dissertation is organized as follows: Chapter 2 discusses the integration of climate and weather information for improving 15-day ahead accumulated precipitation forecasts. In Chapter 3, a framework for adaptively incorporating ecological releases in

sustainable reservoir operation is described with an illustration using a hydropower reservoir in Virginia. In Chapter 4, improved streamflow forecasts from Chapter 2 are coupled with the proposed reservoir operation framework from Chapter 3 to illustrate the value of improved streamflow forecasts, as well as the value of streamflow forecasts updating. In Chapter 5, the research findings from this dissertation are summarized and future research directions to extend current study are outlined.

The study presented in Chapter 2 employs model combination approach to integrate weather and climate models for improving 15-day ahead accumulative precipitation forecasts. A combination algorithm is proposed to integrate Disaggregated Forecasts (DF) from ECHAM 4.5 and Reforecasts (RF) numerical weather model to obtain a Weather-Climate Information (WCI) based forecasts. The performance of WCI-based model is evaluated over the continental United States. Analyses of the ensemble forecasts of the combination approach reveal that the primary reason WCI-based forecasts perform better than RF is due to the reduction of the overconfidence of reforecasts. Improved medium precipitation forecasts can be used to improve streamflow forecasting skill.

To mitigate hydrological alteration and restore the natural flow regime as much as possible, an adaptive reservoir operation framework is proposed in Chapter 3 to explicitly incorporate ecological flow requirements. A general optimization-based decision model is presented to allocate water for multiple uses and for ecological release that is characterized by a set of flow parameters representing the natural flow regime. Multiple uses of the reservoir,

including releases for water supply, irrigation and hydropower generation are modeled as a mixed integer linear programming problem. Hydropower generation, which is represented by a nonlinear function that usually depends on head and flow, is linearized using a two-dimensional approximation. Investigations using a reservoir in Virginia demonstrate that compared to standard releases based on current operation practice, releases simulated using this adaptive framework perform better in mimicking pre-development flows. Tradeoff among the multiple uses and ecological releases is also investigated. In addition, perfect streamflow forecasts are used to examine whether the proposed approach can effectively balance anthropogenic uses and ecological flow requirements.

Chapter 4 investigates how the framework proposed in Chapter 3 performs when coupled with streamflow forecasts with known forecasting skills, and quantifies the value of improved streamflow forecasts. A synthetic daily streamflow generation scheme is employed to generate ensemble forecasts with a pre-defined skill. Hence, the proposed reservoir operation approach is coupled with Ensemble Streamflow Prediction (ESP) to allocate daily releases in an adaptive mode. Extending the finding from Chapter 3 that long-term distribution of selected flow parameters can be restored using observed inflows, an illustrative study in Chapter 4 using three different forecasts skills reveals that better streamflow forecasts improve the ecosystem health and reliability of meeting hydropower requirements. In addition, this chapter also investigates the value of biweekly updated streamflow forecasts in daily reservoir operation.

Chapter 5 summarizes the research findings from this dissertation and outlines future research directions to extend the study presented in this dissertation.

Chapter 2 Integration of Climate and Weather Information for Improving 15-day Ahead Accumulated Precipitation Forecasts

2. 1 Introduction

Medium-range (7-10 days or sub-monthly time scales) weather forecasting has recently gained more attention owing to its practical importance with regard to water allocation and flood control in large basins. For instance, operation of reservoir systems critically depends on precipitation/streamflow over 2-4 weeks to develop energy and water management plan. Chaotic characteristics of the atmosphere (Lorenz, 1963) known as "butterfly effect" limit the weather predictability resulting in limited skill beyond 10-15 days (Kalnay, 2003). However, comparisons between current generation weather forecasting models and previous generation models show significant improvement in forecasting skill due to improved data collection and assimilation methods (Kalnay, 2003; Gneiting et al. 2005). Efforts to improve the skill of weather forecasting models could be summarized broadly into three categories: 1) Better process representation and parameterization of weather forecasting models; 2) Improved estimates of initial conditions through better data assimilation; and 3) Recalibration of predicted variables using model output statistics to reduce marginal bias and conditional bias in predictions. Over the past several decades, continued efforts to improve parameterization of numerical weather models has resulted in better weather forecasting skills (Kalnay, 2003; Gneiting and Raftery, 2005); Data assimilation approaches such as Sequential Calibration Method (SCM), and Kalman Filter (Kalman, 1960; Bishop et al., 2001; Hamill and Snyder, 2002; Kalnay, 2003) were proposed to obtain better estimates of

initial conditions. Ensemble forecasting techniques have also been pursued to account for uncertainties in initial conditions resulting in improved forecast reliability. Various approaches have been investigated for recalibration of weather forecasts that use the ensemble mean (Wilks and Hamill, 2007) as well as the moments of the forecast probability distribution functions (PDFs) (Wilks and Hamill, 2007; Hamill et al., 2004).

Another approach for improving weather prediction that is gaining popularity is to combine predictions from multiple weather models. Ensembles of a single model suffer from spread-deficiency partly since they tend to be overconfident under a given set of initial conditions (Whitaker et al., 2006). Raftery et al. (2004) applied Bayesian Model Averaging (BMA) to calibrate 48-h forecast ensembles of surface temperature and obtained better predictive PDFS from the raw ensembles. Johnson and Swinbank (2009) combined three individual models from European Centre for Medium-Range Weather Forecasts (ECMWF), Met Office of England and National Centers for Environmental Prediction (NCEP). They developed a global, 15-day multimodel ensemble for temperature, mean-sea-level pressure (MSLP) and 500 hPa height. Results from these studies show that a simple combination of ensembles from different operational centers could result in a significant improvement in the prediction skill. Several other studies (e.g., Krishnamurti et al. 1999; Rajagopalan et al. 2002; Devineni and Sankarasubramanian, 2010a, 2010b) also demonstrate that optimal combination of multiple models result in improved climate forecasts in comparison to the best model. Recently, Weigel (2008) and Weigel and Bowler (2009) carried out a theoretical study based on synthetic forecasts to demonstrate that multimodel combination provides better

forecasting skill than any individual model and can even outperform the single best model if single models are overconfident.

Though the current generation of numeric weather models has good skill in predicting precipitation up to a lead-time of 3-5 days, the skill decreases substantially beyond one week (Kalnay, 2003). In this study, we focus on improving medium-range (15-day ahead) precipitation forecasts by combining 15-day ahead forecasts from a weather model and disaggregated precipitation forecasts over the same period from one-month ahead climate forecast. Precipitation/streamflow forecasts obtained using disaggregation techniques (Valencia and Schaake, 1970; Grygier and Stedinger, 1990; Rajagopalan and Lall, 1999) have been shown to provide better estimates at sub-seasonal time scales. Precipitation forecasts from climate models have also been shown to have good skill in predicting 1-month ahead precipitation (Goddard et al., 2003; Barnston et al., 2003; Sankarasubramanian et al., 2008). Hence, disaggregated forecasts climate models could be utilized to improve the skill of 15-day accumulated precipitation forecasts. Further, most numerical weather models do not employ forecasted Sea Surface Temperature (SST) for obtaining 15-day ahead precipitation forecasts. On the other hand, monthly climate forecasts updated every month use forecasted SSTs as boundary conditions for forcing the atmospheric General Circulation Models (GCMs). Thus, any uncertainty in the initial conditions resulting from SSTs could possibly be reduced by utilizing the disaggregated climate forecasts to develop 15-day ahead accumulative precipitation forecasts.

The main intent of this chapter is to improve medium range precipitation forecasts by combining 15-day ahead precipitation forecasts from reforecast dataset (Hamill et al., 2006) and disaggregated forecasts from one-month ahead precipitation forecasts from ECHAM 4.5 (Li and Goddard, 2005). As shown in the schematic diagram (Figure 2.1), we first disaggregate one-month ahead precipitation forecasts from GCM to obtain 15-day precipitation forecasts. Then, combine the disaggregated precipitation forecasts with 15-day ahead precipitation forecasts from weather models based on the proposed combination scheme. Thus, the objectives of this study are to: (1) develop a combination scheme that uses weather and climate forecasts to improve 15-day ahead accumulated precipitation forecasts; (2) examine the circumstances that make the combination reliable; and (3) investigate why the combination scheme results in improved predictions.

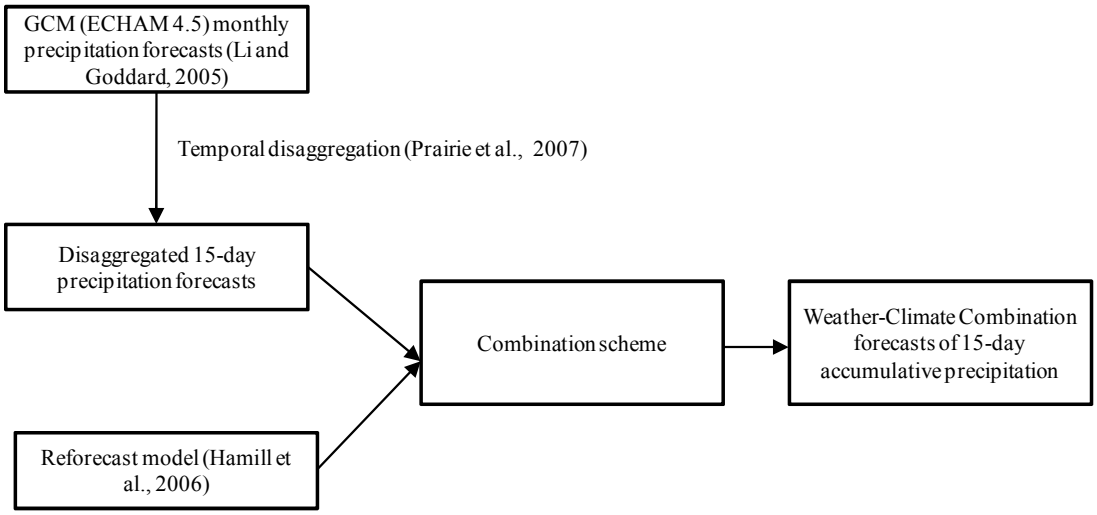

Figure 2.1: Schematic diagram of the combination approach to improve medium-range weather forecasts

This chapter is organized as follows: Section 2 provides detailed information on weather and climate forecasts used in the study along with the motivation behind the proposed combination. The combination algorithm and the disaggregation approach are presented in detail in Section 3. Section 4 discusses results by evaluating the 15-day ahead precipitation forecasts from the combination scheme and also investigates the basis behind the improved performance of the combination scheme. Finally, we conclude with the salient findings arising from the study.

2.2 Datasets

This study employs three datasets for developing WCI-based precipitation forecasts: (a) 15-day ahead precipitation forecasts from numerical weather forecasting model (Hamill et al., 2006); (b) one-month ahead precipitation forecasts from ECHAM 4.5 (Li and Goddard, 2005) and (c) gridded observed daily precipitation for evaluating the developed forecasts (http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCEP/.CPC/.REGIONAL/.US_Mexico/.daily/).

Weather Forecasts: NOAA's reforecasts, which was run with 28 vertical sigma levels (Hamill, 2004) at a T62 resolution (about 200-km grid spacing), is employed in this study. NCEP-NCAR reanalysis (Kistle et al., 2001) is the control initialization, and seven bred pairs of initial conditions (Toth and Kalnay, 1997) are used to develop 15 ensemble members. 15-day ahead retrospective precipitation forecasts are available every day from 1979 to date with forecasts updated every 12 hours at about 2.5° in latitude and longitude over the continental United States. This reforecast data was obtained from the Earth System Research Laboratory

of NOAA (http://www.esrl.noaa.gov/psd/forecasts/reforecast/data.html). For this study, we consider the 15-day accumulated precipitation forecasts issued on the 1st day and 15th day of the month for developing the WCI precipitation forecasts.

Climate Forecasts: For climate forecasts, we consider one-month ahead retrospective precipitation forecasts from ECHAM 4.5 (Roeckner et al. 1996) forced with constructed analogue SSTs (Li and Goddard, 2005). These retrospective forecasts are available for seven months-ahead with the forecasts being updated every month from January 1957 (http://iridl.ldeo.columbia.edu/SOURCES/.IRI/.FD/.ECHAM4p5/.Forecast/.ca_sst/.ensemble24/.MONTHLY/.prec/). We disaggregated the one-month-ahead forecasts into two biweekly precipitation forecasts using the K-Nearest Neighbor (K-NN) disaggregation algorithm of Prairie et al. (2007) (discussed in Section 3.1).

Observed Precipitation: Observed daily precipitation (at 1° in latitude and longitude) was obtained from the International Research Institute for Climate and Society (IRI) data library. Since the spatial resolution of reforecasts and the disaggregated climate model are at 2.5° in latitude and longitude, observed daily precipitation was also spatially averaged over a 2.5°X2.5° grid resulting in a total of 180 grid points over the continental United States. Further, daily time series of precipitation at 180 grid points were temporally aggregated to develop accumulated observed precipitation for the first 15 days and second 15 days of each month for evaluating the skill of the proposed scheme. We consider the data available over the period 1979 to 2004 from these three sources for evaluating the proposed scheme. Both the weather and climate forecasts and observed precipitation were deducted from their respective long-term mean at each grid point to develop anomalous biweekly time series of

precipitation forecasts and observations. This resulted in two candidate biweekly forecasts, disaggregated ECHAM 4.5 forecasts and reforecasts, for developing the weather-climate information combined forecasts. Both the combination scheme and the skill measures for all the forecasts were calculated based on the anomalous biweekly time series of precipitation forecasts and observations.

An initial investigation was carried out to examine the potential benefits in combining disaggregated climate forecasts and weather forecasts. One-month ahead precipitation forecasts from ECHAM 4.5 were disaggregated using the K-NN algorithm proposed by Prairie et al. (2007), and compared with the retrospective 15-day ahead precipitation forecasts from reforecast model. For a given month, we consider two forecasts with one from day 1 to day 15 and another from day 16 to the end of month. For a given grid point, mean square error (MSE) over 26 years (1979-2004) were calculated for both forecasts. MSE for a given forecast is computed by averaging the squared error between the observed biweekly precipitation (O_t) and the ensemble mean of the given forecast (P_t). The performance of both forecasts was compared using Mean Square Skill Score (MSSS) (Equation 1) with MSE_c and MSE_w denoting disaggregated climate forecasts and weather reforecasts, respectively.

$$MSSS = 1 - \frac{MSE_c}{MSE_w} \qquad \ldots\textbf{(2.1)}$$

From Equation 2.1, we infer that for grid points with positive MSSS, disaggregated forecasts perform better than reforecasts in terms of MSE. A comparison of forecast errors in January

based on MSSS for the first fifteen days (Figure 2.2a) and the second fifteen days (Figure 2.2b) clearly shows that for various grid points, particularly over upper Midwest,

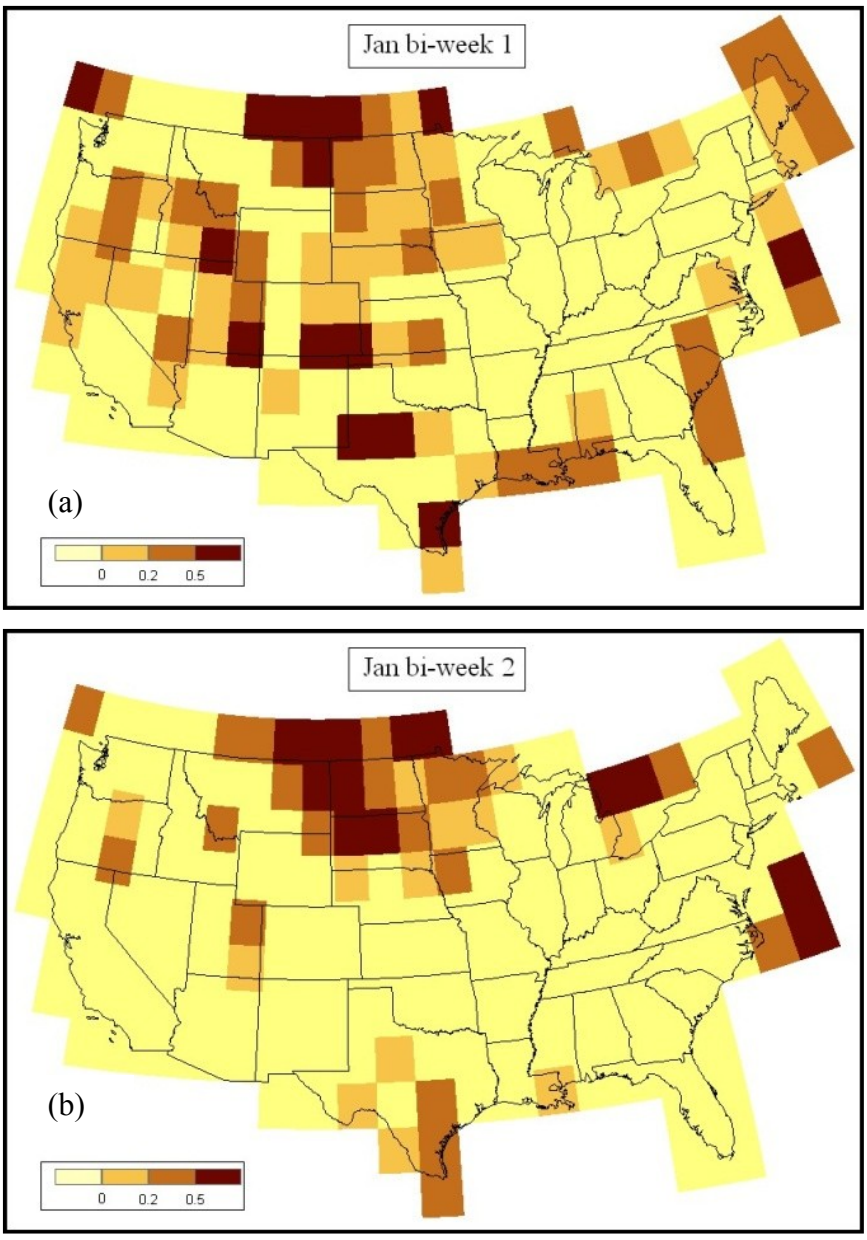

Figure 2.2: MSSS between disaggregated ECHAM4.5 precipitation forecasts and the reforecasts for the first fifteen days (a) and the second fifteen days (b) in January. MSSS>0

indicates MSE of disaggregated biweekly forecasts is lesser than the MSE of the reforecasts indicating potential for the proposed combination scheme (Figure 1).

disaggregated ECHAM 4.5 forecasts have lower MSE values than those of reforecast model. This indicates that a proper combination of disaggregated climate forecasts and weather forecasts could result in improved medium-range forecasts. The next section discusses the methodology for obtaining WCI-based forecasts over the continental United States.

2.3 Methodology

In this section, we briefly describe the disaggregation methodology by Prairie et al. (2007) and the proposed scheme for combining weather and climate forecasts.

2.3.1 Temporal Disaggregation

Disaggregation is the process of dividing a given time series into its constituent parts. Both temporal disaggregation (e.g., from annual streamflow to monthly streamflow) and spatial disaggregation (e.g., from index gauge to upstream gauges) are useful in developing precipitation/streamflow scenarios related to water management. Temporal disaggregation of monthly precipitation forecasts to 15-day accumulative precipitation forecasts is of interest in this study. There are at least two special characteristics of disaggregation problems. First, the summability of the disaggregated precipitation should be maintained. This implies that the monthly precipitation is the sum of the 15-day accumulative precipitations. Second, the disaggregated precipitation series should preserve the statistical properties of the observed time series.

Various stochastic parametric models have been developed for disaggregation. Linear stochastic framework was originally developed by Valencia and Schaake (1973), which was modified by Grygier and Stedinger (1990) to obtain improved parameter estimates. Compared to parametric methods, non-parametric approach has gained more attention for its simplicity and successful application in many hydrological problems (Lall, 1995). The advantage of the non-parametric approach in disaggregation was demonstrated in kernel-based approach by Tarboton et al. (1998). A robust and simple approach based on resampling is proposed to achieve space-time disaggregation (Prairie et al., 2007) to avoid kernel density fitting. Recent works on streamflow disaggregation based on nonparametric approach have shown improvements over traditional parametric schemes (Tarboton et al., 1998; Kumar et al., 2000; Robertson et al., 2004; Lee et al., 2010). In this study, we apply nonparametric disaggregation of Prairie et al. (2007) to disaggregate one-month ahead precipitation forecasts from ECHAM 4.5 to biweekly precipitation forecasts. Daily observed precipitation is summed up from the 1st day to the 15th day and 16th day to the 30th day. We did not include the daily precipitation on the 31st day of relevant months (January, March, May, July, August, October and December). For February, we considered the second forecasting period from the 16th day to the end of the month.

The disaggregation of climate forecasts into biweekly precipitation forecasts was performed in a leave-five out cross-validation mode by leaving out the conditioning year and another four years (randomly) from the training dataset. For the given monthly precipitation forecasts from ECHAM4.5 over the year 1957 to 2006, we identify '*K*' neighbors on the observed

monthly precipitation by computing the Euclidean distance from the conditioning variable (i.e., ECHAM4.5 forecasts) to the observed monthly precipitation. The observed biweekly precipitation for the respective neighbors was resampled to constitute '*N*' ensembles of biweekly disaggregated forecasts. The number of ensembles (*w(k)*N*) that each identified neighbor represents in the conditional PDF (i.e., represented by '*N'* ensembles) is estimated by the kernel weighting function (Equation 2.2) suggested by Lall and Sharma (1995).

$$w(k) = \frac{1}{k\sum_{k=1}^{K}\frac{1}{k}} \quad \ldots \textbf{(2.2)}$$

where $w(k)$ represents the weights of the k^{th} neighbor, and k is the rank of the neighbor out of the total selected *'K'* neighbors.

Leave-five-out cross-validated disaggregated forecasts showed reduced MSE for all the months (figure not shown) for *K*=10 to 12 neighbors. Thus, temporal disaggregation from monthly precipitation to 15-day accumulated precipitation was carried out independently over each grid point for all months by selecting '*K*=10' neighbors under leave-five out cross-validation. A total of 100 ensemble members of 15-day accumulated precipitation were produced to generate probabilistic biweekly precipitation forecasts.

2.3.2 Combination Scheme

The combination algorithm (Figure 2.3) presented here is based on the algorithm of Devineni and Sankarasubramanian (2010a) but was modified for biweekly forecasts combination. We have two different precipitation forecasts over 180 grid points over the continental United States: 15 ensembles of biweekly forecasts from the NOAA reforecast

model issued on the 1st and 16th day of the month and disaggregated biweekly forecasts from ECHAM 4.5 monthly precipitation forecasts. The essence of the combination scheme is to assign weights to each one of the candidate forecasts according to their performance in historical years over the same forecasting period. First, ensembles of both candidate forecasts were converted into tercile probabilities, $PP^{m}_{i,j,t}$,(i=1,2,3 denoting the below-normal, normal and above-normal categories, respectively) based on the 33rd and 67th percentiles of the observed precipitation. We then evaluated the skill of the two candidate models by computing the squared error $SE^{m}_{j,t}$ between the observed precipitation and the conditional mean of the forecasts for all the years from 1979-2004. Then, both the forecasts available for the period 1979-2004 were combined in a leave-five-out cross validation mode. For instance, to develop combined biweekly forecasts for the 1st two weeks of June in the year 1986 (j = 13th biweek in the year), we computed the distance d_l between the ensemble mean of the current forecast $EP^{m}_{13,1985}$ and the rest of the forecasts $EP^{m}_{13,t}$ ($t \neq 1986$ and four additional years). Based on the distance (d_l), we selected '*K*' neighbors and computed the mean square error $\lambda^{m}_{13,1986}$ over '*K*' neighbors (selection of '*K*' is discussed below). Based on the *MSE* value, the weight for an individual model was calculated as:

$$w^{m}_{13,1986} = \frac{1}{\lambda^{m}_{13,1986} \sum_{m=1}^{M} \frac{1}{\lambda^{m}_{13,1986}}} \quad \ldots \textbf{(2.3)}$$

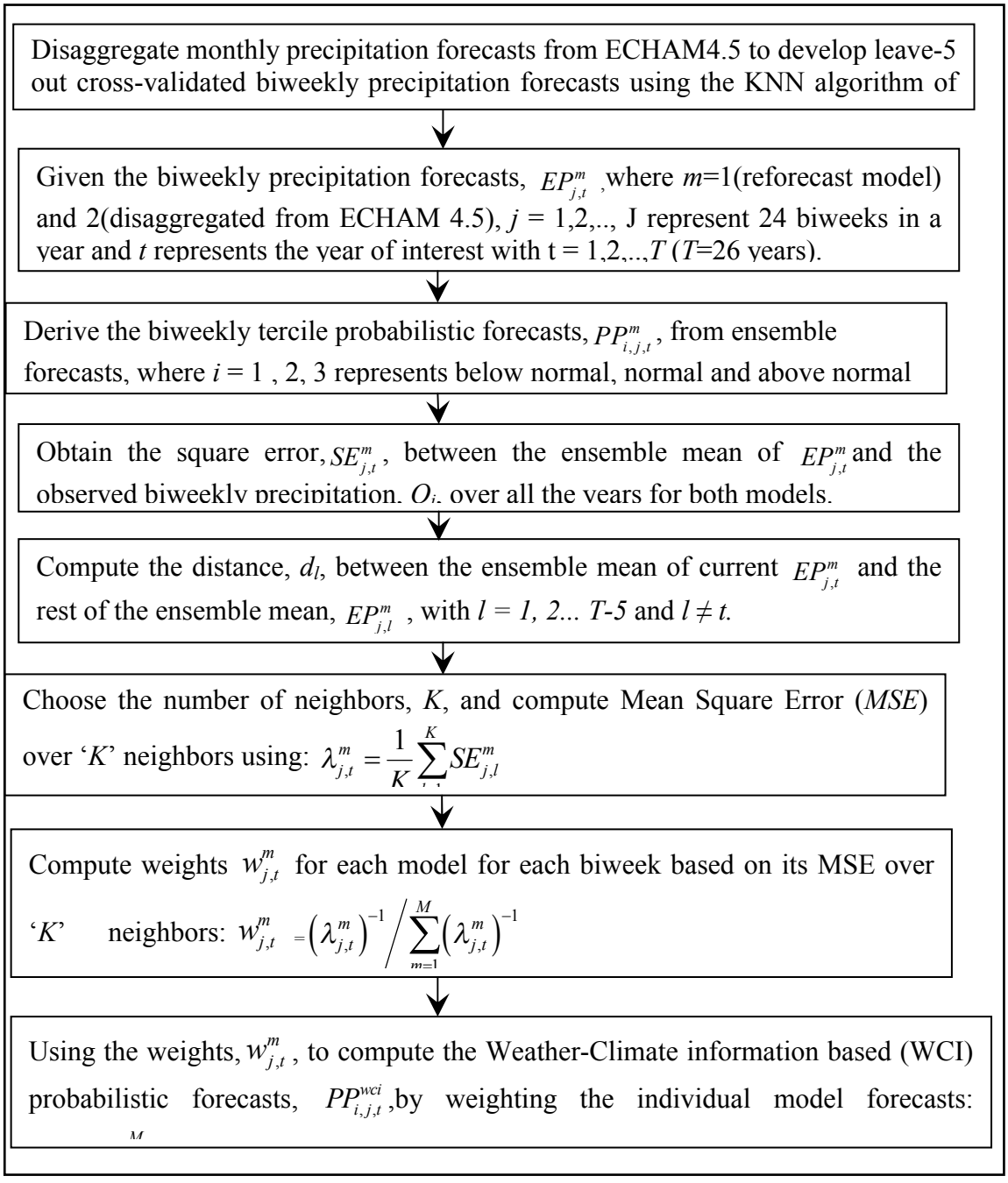

Figure 2.3: Flowchart of the combination algorithm described in Section 2.3.2.

where $w^{m}_{13,1986}$ represents the weight of model *m* for the 1st biweek in June for the year 1986. Once the weights were obtained for both the candidate models, a weighted average of the tercile forecasts were calculated to obtain the weather-climate information combined biweekly tercile forecasts. To find the optimum '*K*' value, we repeated the same procedure (Figure 2.3) and chose the *'K'* neighbors that resulted in the best skill for the WCI-based forecasts for the selected biweek at a given grid point. The optimum number of neighbors '*K*' was found to be 10-15 depending on the biweek (not shown). The skill measure that we employed for selecting the '*K*' neighbors based on leave-five out cross-validation is the average Rank Probability Score (RPS), which computes the mean squared error between the tercile probabilities and the observed category that is represented as 1 (Wilks, 1995). A detailed description of all the steps of the combination scheme is provided in Figure 3. Using this approach, we developed an integrated biweekly precipitation forecasts derived from weather and climate forecasts over the period 1979-2005. The next section presents a detailed evaluation of the skill of the WCI-based biweekly forecasts.

2.4 Results and Analysis

Rank Probability Score (RPS) and Rank Probability Skill Score (RPSS) are used to evaluate the tercile forecasts derived from the weather-climate information-based combination. RPS summarizes the sum of square of errors in the cumulative probabilities of the given categorical forecast and the observed category, which is represented as 1. Similar to MSSS (Equation 2.1), RPSS compares the improvements in RPS of the WCI-based biweekly forecasts with the RPS of the reforecast model. When RPSS is positive (negative), WCI

forecasts (reforecasts) outperforms the reforecasts (WCI forecasts). The RPSS value represents how much of the RPS has been reduced (RPSS > 0) or increased (RPSS < 0) compared to the reference forecasts, which we consider as the reforecasts.

Figure 2.4 shows the RPSS for the two forecasting periods for one month in each of the four seasons. Grid points with light yellow color indicate where reforecast model outperforms WCI combined forecasts, whereas in the rest of the colored grids, the combination scheme reduces the error in probabilistic forecasts. The darker the color, the higher is the RPSS in the specific grid. For most of the grid points when RPSS > 0, combination approach reduces error by 10% to 20% and for a few grids, the improvement is larger than 20% (RPSS > 0.2). It is important to note that for one specific grid, the combination skill is not the same for the two forecasting periods in a given month, since the combination algorithm was carried out independently for the two forecasting periods. Improvements in the combination skill vary both spatially and temporally, partly due to the individual model's performance differing depending on the location and season. There are numerous factors that affect an individual model's skill, such as topography for reforecast model or the strength of climatic teleconnections for ECHAM 4.5. Improved skill in WCI biweekly forecasts is higher for the states of Texas and Utah in January, for the states of Arkansas, Ohio and Pennsylvania in April, and broadly for the western United States in July and October. Notably, both disaggregated climate forecasts and WCI forecasts are obtained under leave-five-out cross-validation.

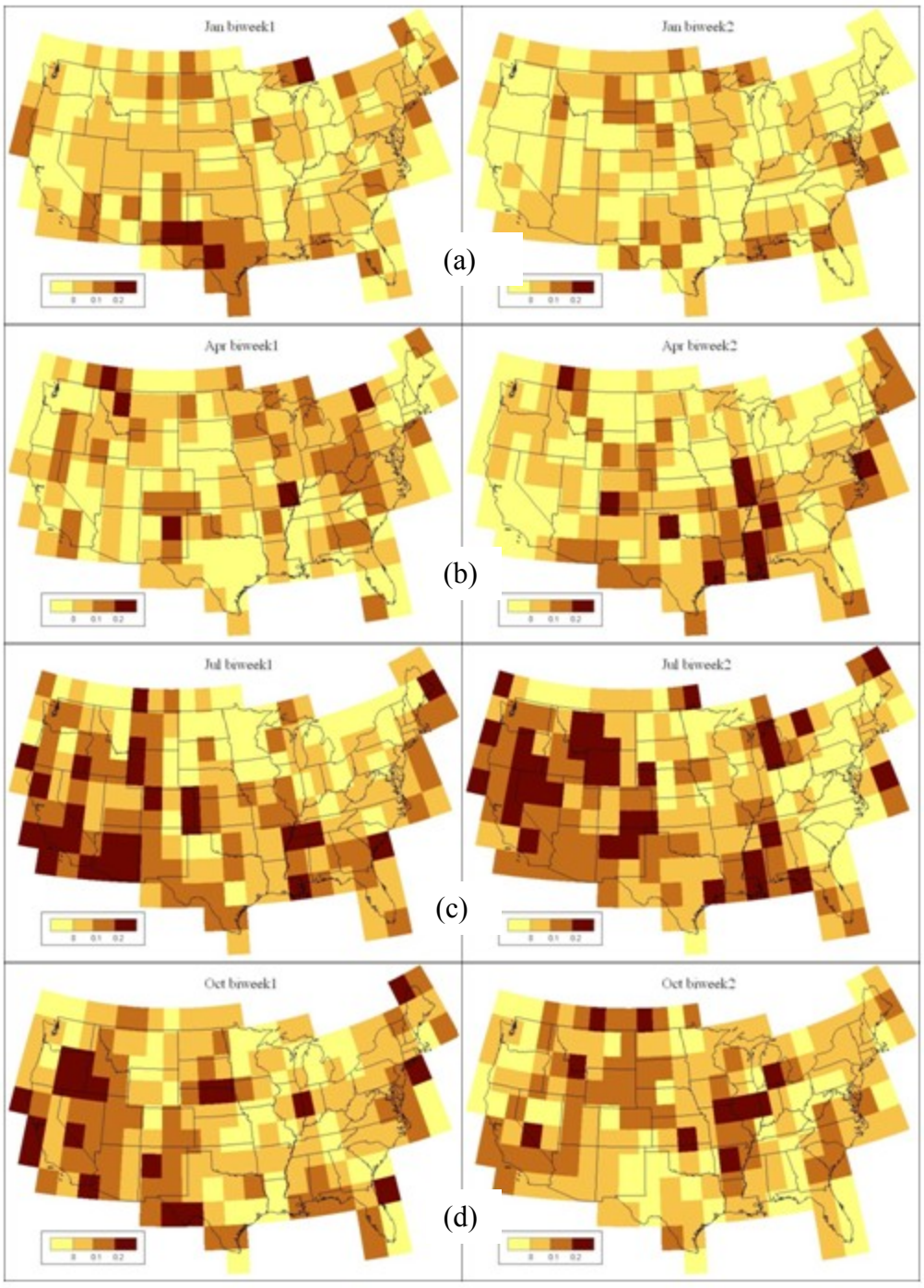

Figure 2.4: RPSS of WCI based forecasts over reforecasts with the left (right) column indicating the first (second) fifteen days for the selected months over four seasons: (a) January; (b) April; (c) July; (d) October.

To understand how the WCI forecasts perform better in each month, we compare the RPS of the combination forecasts and reforecasts for both forecasting periods by pooling the RPS for each month (Figure 2.5) over the 180 grid points. The solid (dashed) boxplots represent RPS for the reforecast model (WCI-based forecasts). Comparing the median RPS of the forecasts from both models, WCI forecasts perform better in all the forecasting periods except in the 1st two weeks of February and in the 2nd two weeks of December. More importantly, the spread (interquartile range) of the RPS of the WCI-based forecasts is also lower than the spread of the RPS of reforecasts. Further, the improvements resulting from the WCI combination are substantial during the summer season compared to the rest of the seasons.

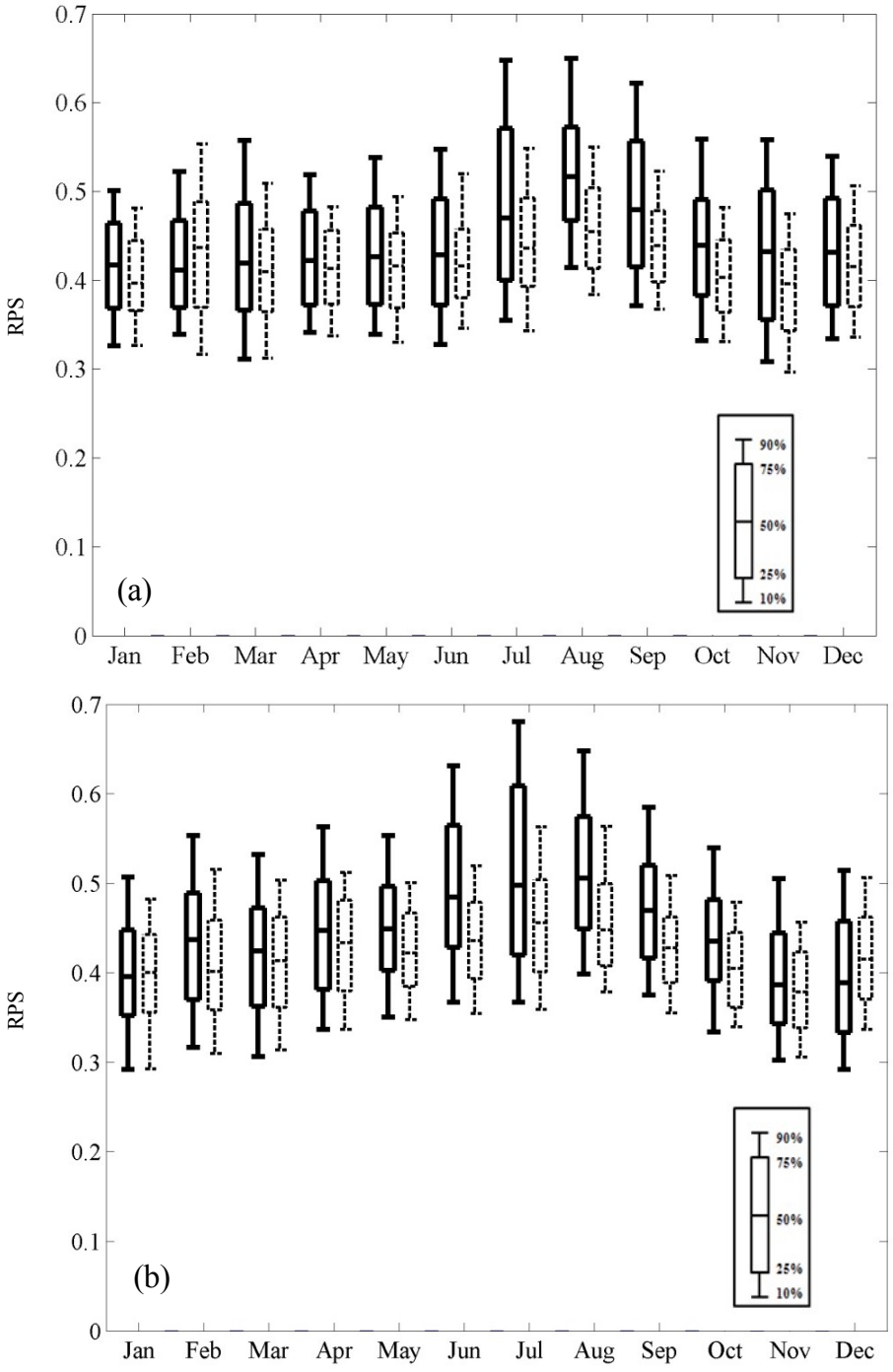

Figure 2.5: Comparison of RPS between reforecast and WCI based forecasts for all months. Panel (a) represents pooled RPS (180 X 26) for the first fifteen days and panel (b) is pooled RPS for the second fifteen days. Solid (Dashed) boxplots represent the RPS of reforecasts (WCI based forecasts).

This is partly due to the relatively poor performance of the reforecast model in summer season (Clark et al., 2004; Hamill et al., 2008). The improvement of the WCI-based forecasts compared to the single reforecast model reveals that there is utility in using disaggregated climate forecasts in improving the 15-day ahead forecasts. Disaggregated climate forecasts utilize the ensemble mean of the climate forecasts and the observed structure of the biweekly precipitation under similar monthly totals to develop biweekly forecasts.

Table 2.1 summarizes the total number of grids in which WCI forecasts outperform the reforecast model (i.e., RPSS > 0). $RPSS_1$ and $RPSS_2$ denote the RPSS for biweek 1 and biweek 2, respectively. From Table 1, March seems to be the month with lowest total number of grid points exhibiting positive RPSS values: 98 (93) for 1^{st} (2^{nd}) fifteen days. The performance of WCI forecasts improves substantially during the spring season, but WCI forecasts perform much better than the reforecasts during the summer season. $RPSS_1$ is positive for 160 out of the 180 grid points and $RPSS_2$ is positive for 153 grid points in August. This improved performance of WCI forecasts is mainly due to the poor performance of the reforecast model during the summer season. Further, when the disaggregated GCM has lower MSE, the combination scheme results in improved forecasts having high RPSS values. Thus, the basis behind the combination scheme is to assign weights to individual models according to their performance in the historical years. The correlation between RPSS of WCI and the MSE of disaggregated ECHAM4.5 is -0.41 for the 1^{st} fifteen days in July. The negative correlation indicates that lower MSE values of the disaggregated forecasts associate with higher values of RPSS. This is true for the other biweekly period forecasts in summer

season (results not shown). We examine the contribution of reforecasts and disaggregated forecasts to the combination scheme by analyzing the weights estimated in the combination scheme.

Table 2.1: Performance of the 15-day ahead precipitation forecasts obtained from the combination of weather and climate information (WCI) expressed as the number of grid points exhibiting RPSS > 0 for the first fifteen days ($RPSS_1$) and the second fifteen days ($RPSS_2$).

	$RPSS_1$>0	**$RPSS_2$>0**
Jan	114	89
Feb	110	105
Mar	98	93
Apr	111	105
May	118	121
Jun	101	168
Jul	135	141
Aug	160	153
Sep	138	148
Oct	138	135
Nov	142	103
Dec	100	102

To understand the importance of both candidate forecasts in reducing the uncertainty in improving 15-day ahead precipitation forecasts, we group the weights for each forecasting scheme into two categories with RPSS > 0 and RPSS < 0 for both biweeks in a selected month (January (Figure 6a), April (Figure 6b), July (Figure 6c) and October (Figure 6d)) for each season. From Figure 2.6, it is clear that weights of the disaggregated forecasts (reforecasts) are higher if the RPSS of the WCI-based forecasts are more (less) than zero in all the four months. Better performance of the disaggregated forecasts in July is also clearly indicated in the boxplot (Figure 2.6c) with the weights distribution of the disaggregated forecasts being positively skewed for RPSS > 0. Thus, the weights analysis shows that the

proposed combination scheme correctly identifies the neighbors in estimating the weights for each candidate model resulting in an improved skill from the WCI-based probabilistic forecasts.

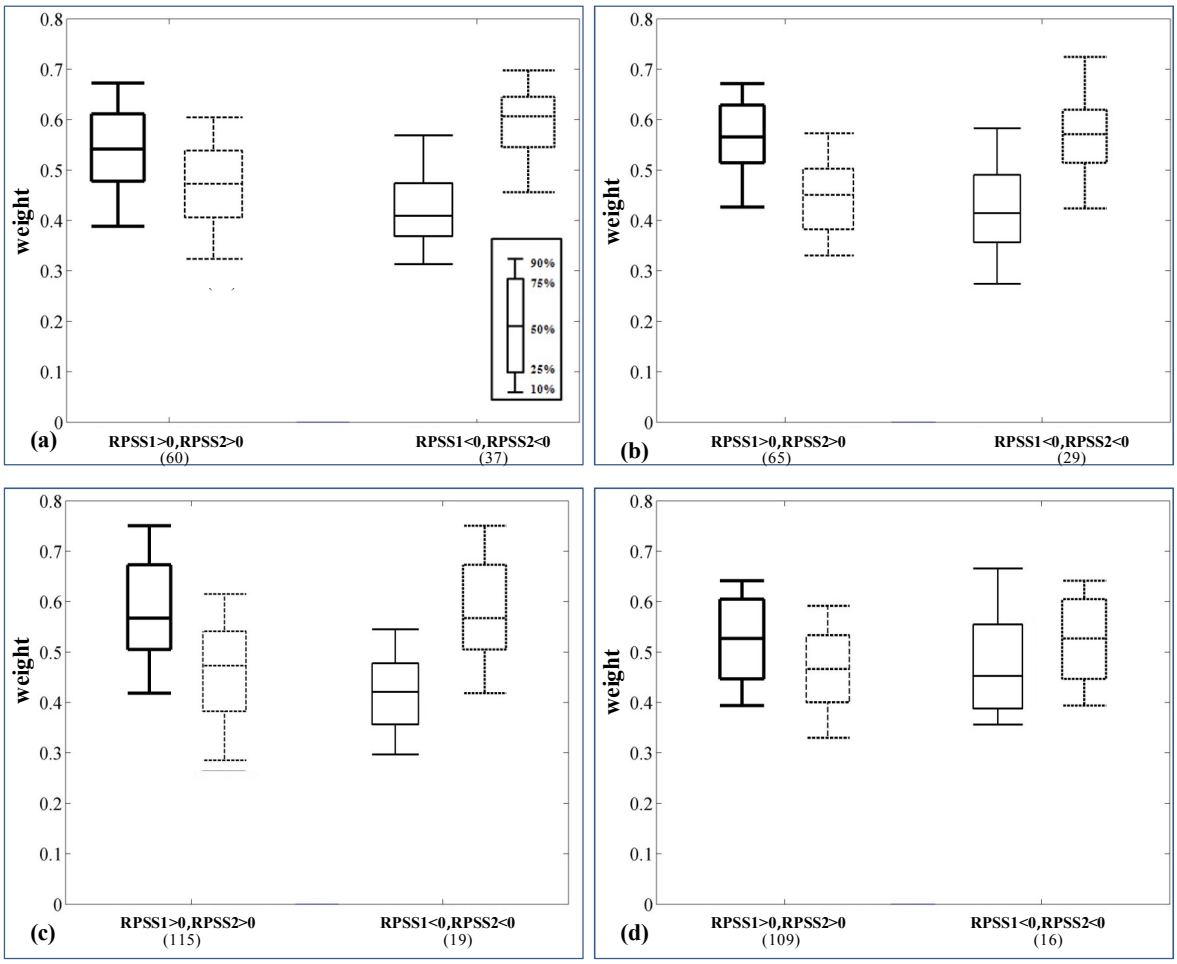

Figure 2.6: Box-plots of weights of the disaggregated GCM forecasts and reforecasts in the proposed combination scheme for different months: (a) January; (b) April; (c) July; (d) October. Weights are grouped by pooling grid points Solid (Dotted) box-plots represent the weights for the disaggregated climate forecasts (reforecasts). Numbers in the parenthesis indicate the number of grid points that have $RPSS_1 > 0$ and $RPSS_2 > 0$ and $RPSS_1 < 0$ and $RPSS_2 < 0$ for the WCI based forecasts.

2.5 Discussion

Results presented in the previous section show that WCI-based combination scheme improves the 15-day ahead precipitation forecasts over the continental United States. We also investigated by relating the improvements in WCI forecasts with various teleconnection indices such as Nino 3.4 (Kaplan et al., 1998) and Pacific-North American Index (Barnston and Livezey, 1987). Our analyses did not provide any firm association between the improved skill in WCI forecasts and any physical mechanism/variability that could be influencing the skill (figures not shown). However, Table 1 and Figures 4-5 clearly show that more than 50% of the grid points result in improved skill from the combination scheme in comparison to the reforecasts. Further, the improvements are particularly significant in forecasting warm-season precipitation (months of July-September), which is primarily due to the relatively lower skill of reforecasts during the summer season. The weights analysis (Figure 6) also shows that the improved skill in WCI forecasts arise from assigning higher weights for the disaggregated biweekly forecasts for conditions under which disaggregated forecasts have lower *MSE* values over '*K*' similar conditions. This brings the discussion to two critical questions: (a) Given the three forecasts including the WCI combined tercile forecasts, which model performs the best for a given grid point? and (b) Given no physical significance with any teleconnection/quasi-oscillatory climatic indices, why does the combination scheme improve the 15-day ahead accumulative precipitation forecasts? Understanding these two issues are critical, since it can provide the basis for selecting the best forecasting model for a given region as well as the reasoning behind the improved skill resulting from the combination scheme.

With regard to the first question, we identified the best model at each grid point based on RPS (Figures 2.7 and 2.8). Figure 7 shows the best model for the two forecasting periods in the selected months over the four seasons, whereas Figure 8 summarizes the total number of grids in which each model has the lowest RPS for each month. From Figures 7 and 8, WCI is the best performing model and reforecasts emerges as the next best model with disaggregated forecasts being the best in only a few grid points for the month of July. Improvements from the combined forecasts is widespread and all over the country during the summer and fall months (Figures 2.7-2.8). During winter and spring months, the improvements from the combination are found predominantly over the Sun Belt during January and April as well as over the upper Mid-West and Mid-Atlantic states in the 1st biweek of April. From Figure 2.8, WCI-based forecasts perform better during all biweeks over the year with the exception being in 1st biweek of February and 2nd biweek of December when reforecasts perform better for many grid points within the continental United States. Thus, it is clear that even though the performance of disaggregated forecasts performs the best in only a few grid points, combining reforecasts and disaggregated ECHAM4.5 forecasts using the proposed combination scheme result in reduced RPS over the continental United States.

To further understand why the combination of reforecasts and disaggregated forecasts perform better, we analyzed the estimated probability distribution of biweekly precipitation

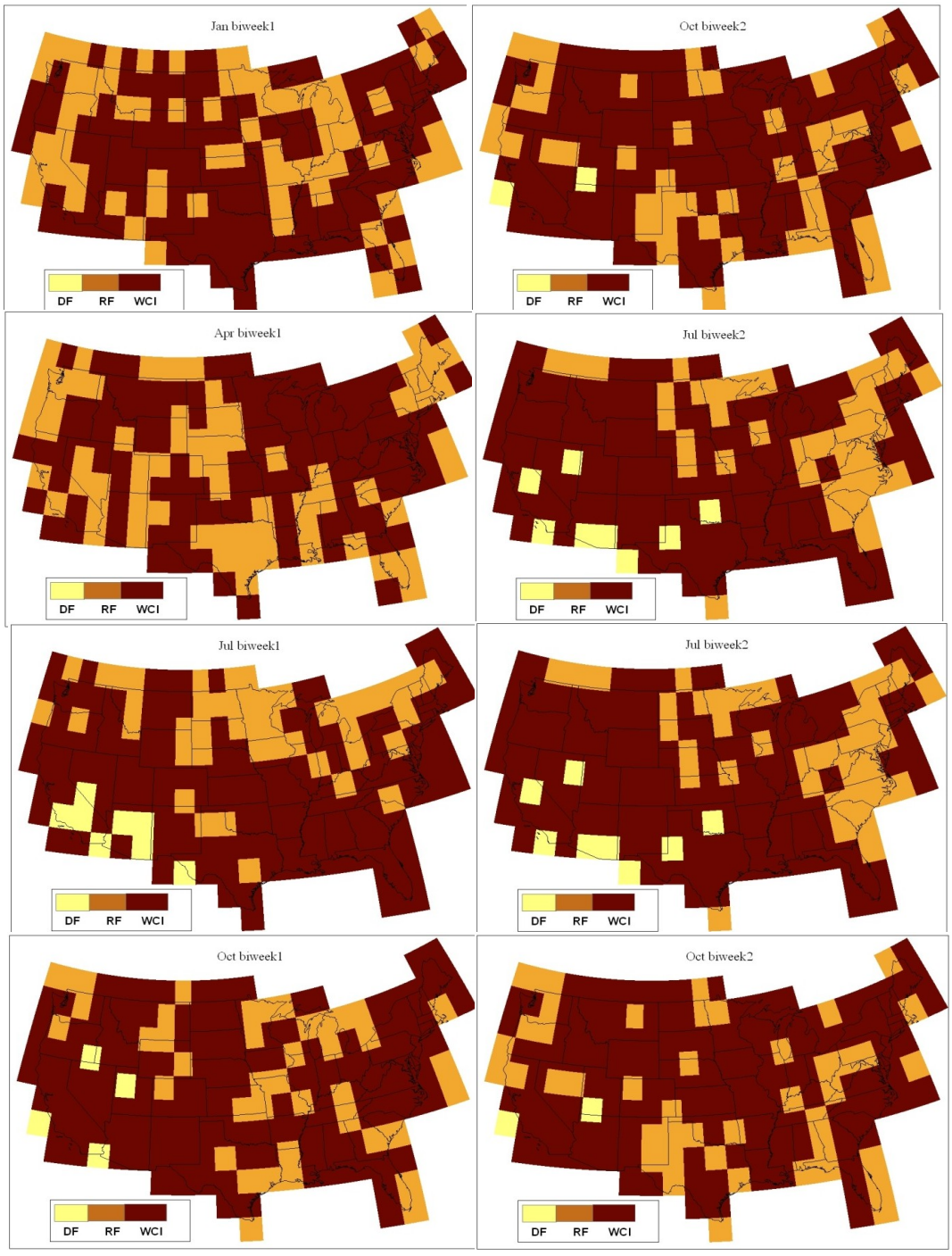

Figure 2.7: Best model for one month under each season over the continental United States based on RPS. DF denotes disaggregated ECHAM4.5 forecasts, RF denotes the reforecasts and WCI denotes weather-climate information based biweekly forecasts.

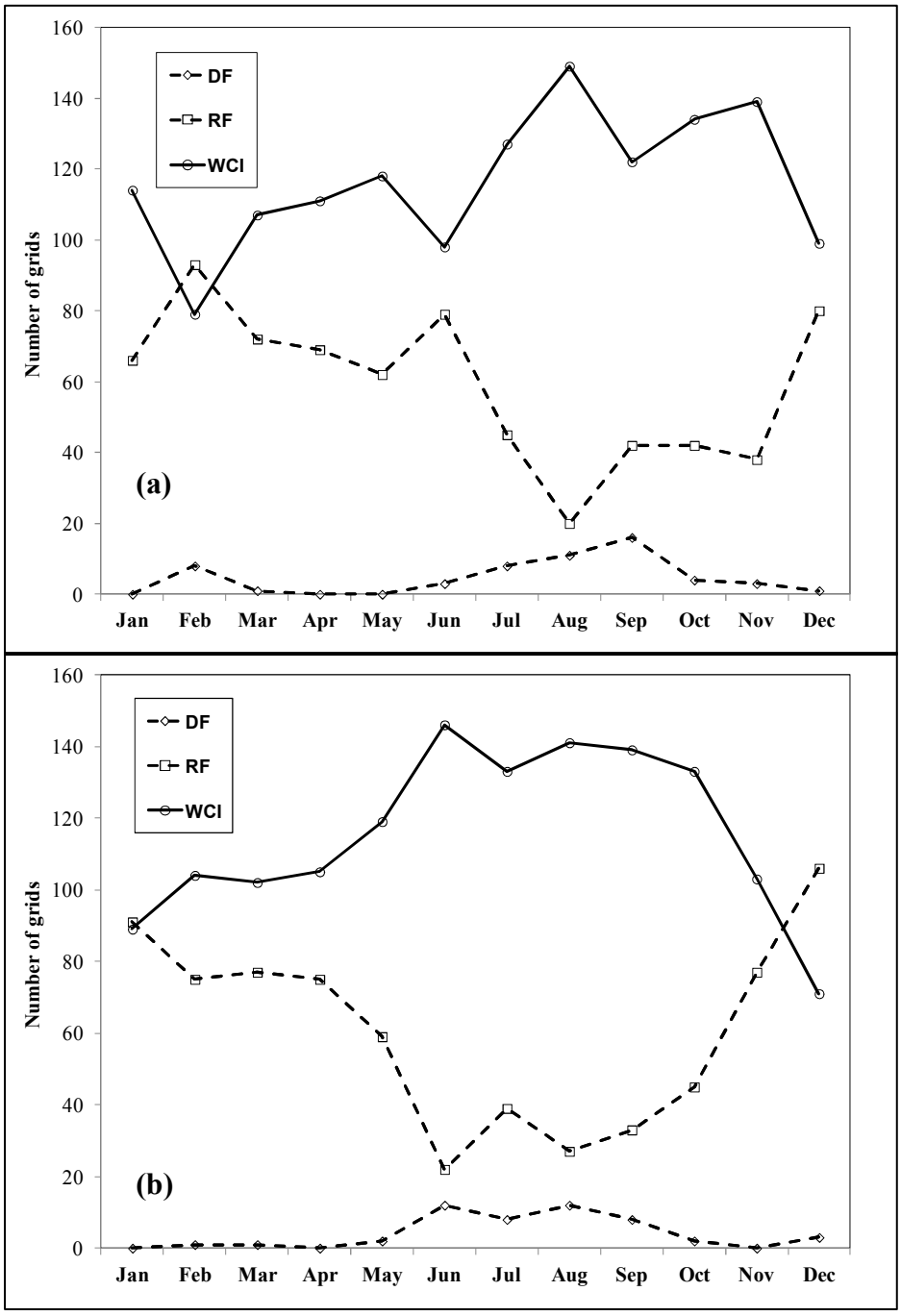

Figure 2.8: Number of grid points under which each forecasts (DF, RF and WCI) during the first fifteen days (a) and the second fifteen days (b) have the lowest RPS for each month over the continental United States.

forecasts. Recently, Weigel et al., (2008) carried a theoretical study to investigate under what situations multi-model combinations can outperform individual models. It was concluded that multimodel combination results in a well-dispersed forecasts by reducing the overconfidence of the individual models. For instance, it is common for forecasts from numerical models to indicate high probability of occurrence of one particular tercile category (e.g., 90% probability of below-normal precipitation). Weigel et al. (2008) suggested methods to estimate the dispersion parameter (β), which ranges from zero to one, based on the forecast ensembles. When β is zero (one), the distribution of forecasts is well-dispersed (overly dispersed). Appendix A provides details on estimating β for a given forecast. For additional details, see Weigel et al. (2008).

Figure 2.9 compares the estimated β between disaggregated GCM forecasts (solid box plots) and reforecasts (dotted box plots) with $RPSS_1$ and $RPSS_2$ of the WCI forecasts being above zero as well as below zero. It is clear that β values of disaggregated GCM forecasts are smaller than that of reforecasts under WCI's RPSS > 0. Thus, by combining a better-dispersed disaggregated GCM forecasts with the overly-dispersed reforecasts, the algorithm in Figure 2.3 produces biweekly precipitation forecasts that are skillful than the reforecasts. We argue that the basic reason why WCI forecasts perform better is due to its better dispersion even though the long-term forecasting skill of disaggregated ECHAM4.5 is worse than that of the reforecast model in most of the grid points. Given that the reforecasts are available only from 1979, we employed leave-five-out cross-validation for evaluating the

WCI forecasts. As the length of reforecasts increases, weather-climate combination forecasts could be evaluated based on split-sample validation as well as by developing real-time experimental forecasts to understand their utility in improving medium-range weather forecasts.

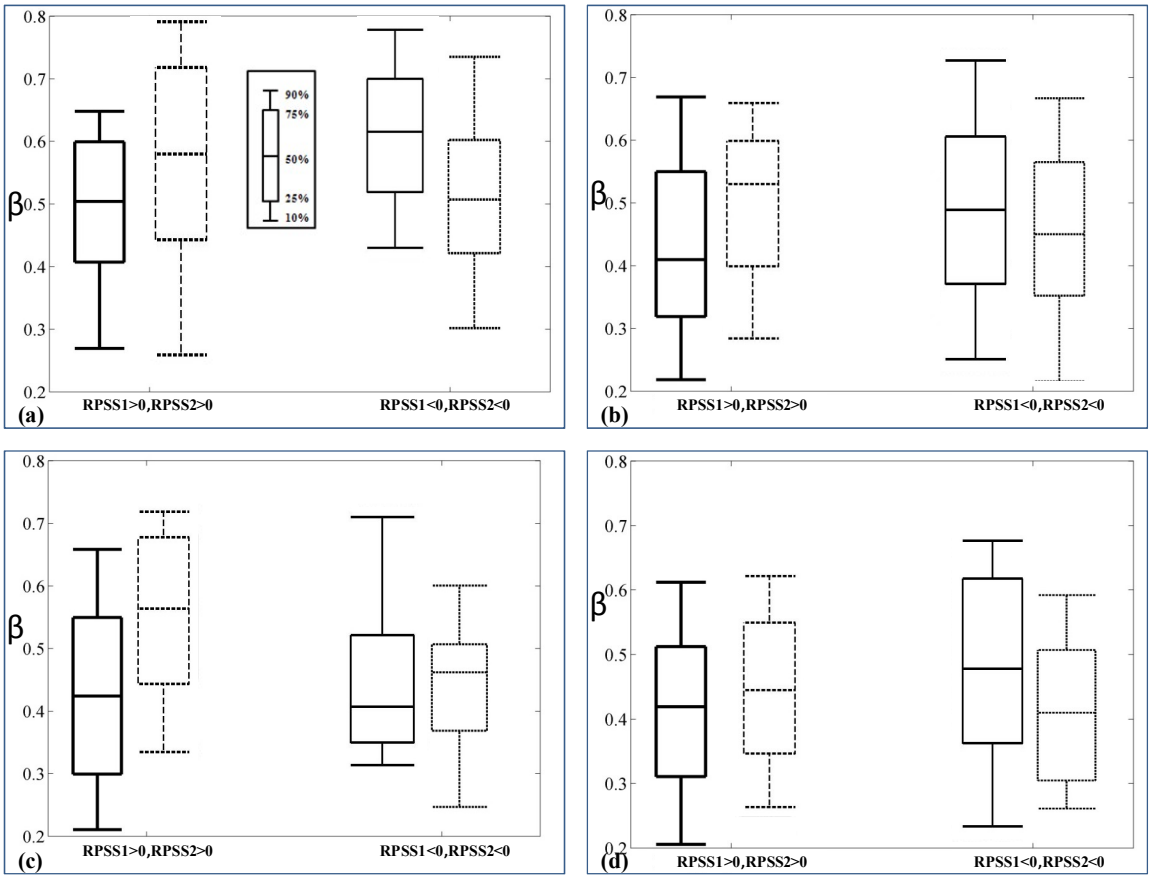

Figure 2.9: Box-plots of dispersion parameter, β , of the disaggregated GCM forecasts (solid box) and reforecast (dotted box) in the proposed combination scheme for different months: (a) January; (b) April; (c) July; (d) October. Dispersion parameter β s are grouped in such a way with $RPSS_1$ and $RPSS_2$ of WCI being greater than and lesser than 0.

2.6 Summary and Conclusions

A combination scheme is proposed to combine reforecasts from a numerical weather model and disaggregated climate forecasts from ECHAM4.5 for developing 15-day ahead precipitation forecasts. The proposed scheme was evaluated by developing biweekly precipitation forecasts for each month in 180 grid points over the continental United States. Evaluation of the weather-climate information (WCI)-based biweekly forecasts under leave-five out cross-validation shows that WCI-based forecasts perform better than reforecasts in many grid points over the continental United States. Correlation between RPSS of WCI forecasts and MSE of the disaggregated forecasts reveals that lower the error in the disaggregated forecasts better the performance of WCI forecasts. Weights analysis also shows that the combination scheme performs better by assigning higher weights to the better performing models. Particularly, WCI forecasts perform better in summer months during which reforecasts have limited skill. Even though the disaggregated climate forecasts do not perform well in many grid points, the primary reason why WCI-based forecasts perform better than reforecasts is due to the reduction of the overconfidence in the reforecasts. Analysis of the dispersion in reforecasts and disaggregated forecasts show that the disaggregated forecasts are better dispersed than reforecasts. Thus, combining the disaggregated climate forecasts with reforecasts results in improved 15-day ahead precipitation forecasts. Our future research will evaluate the utility of these medium-range precipitation forecasts in developing 15-day ahead streamflow forecasts for various selected river basins.

Chapter 3 A Framework for Incorporating Ecological Releases in Sustainable Reservoir Operation

3.1 Introduction

Reservoirs play an important role in balancing temporal variability in water resources availability and in anthropogenic water demands, e.g., flood control, water supply, and hydropower generation. It is well recognized that reservoirs have detrimental effect on the downstream ecosystem health (Petts, 1984; Poff et. al., 1997). One common effect of regulated release from a reservoir is the induced change in the hydrologic flow regime that potentially impairs the aquatic environment by altering the nature flow condition to which the aquatic system is well adapted (Magilligan and Nislow, 2005; Nilsson and Berggren, 2000). Various flow conditions, e.g., high flow and low flow values and times of their occurrences, are critical to some species at specific periods in the year. Mandated release requirements obviously introduce alterations in the natural flow regime, which potentially affects the ecosystem health (Petts, 1984; Poff et. al., 1997). Though the relationship between impaired ecological environment and hydrological flow regime alteration is determined on a case-by-case basis (Poff et. al., 2007), maintaining or mimicking the natural flow pattern is in general important for preserving the ecosystem health. The primary focus of this chapter is to investigate an adaptive reservoir operation framework that explicitly considers simultaneously the anthropogenic water demands and alterations in downstream flows that are affected by the reservoir operation and release.

Explicit consideration of ecological flow regimes is not commonly included in current reservoir operation practice (e.g., Yeh, 1985; Labadie, 2004) that specifies a minimum release, which is determined based on long-term flow conditions and anthropogenic demands. On one hand, due to the competing needs, outflow from the reservoir might not be able to sustain ecological health of the river since minimum environmental flow is usually determined based on agreement among stakeholders, especially downstream communities. On the other hand, water releases for hydropower generation are usually not in conflict with ecological requirements since tail water from turbines typically is returned to the river. Too much water released after hydropower generation would also alter the flow regime that potentially leads to ecological damage. Therefore, it is challenging to explicitly consider ecological flow amount and variation requirements in multi-purpose reservoir operation planning; they are usually considered as hard constraints to meet only a constant minimum release (Jager and Smith, 2008).

Interest in modifying the current reservoir operation practice is getting more attention with the aim of improving downstream ecosystem health. It is important to balance between ecological water demand and anthropogenic needs. The ultimate goal is to maintain the post-impact flow regime to be as similar as possible to that of pre-impact years. When there is no upstream storage and little water extraction for anthropogenic needs, “Run-Of-River” (ROR) operation is a good solution for waterways to generate hydropower and preserve ecosystem at the same time. Some hydropower projects were changed from peaking to ROR operation with the main consideration of protecting downstream aquatic biota (Jager and Smith, 2008).

This operation mode is not practical, however, for a large reservoir that serves multiple purposes, including flood control, domestic water supply, irrigation supply, and hydropower generation. Modified operation rules are needed to meet these anthropogenic demands while minimizing the potential damage to the downstream ecological system.

Flow regime-based ecological consideration in multi-purpose reservoir operation has drawn much attention in the research community (e.g., Cardwell et al., 1996; Richter and Thomas, 2007). Cardwell et al. (1996) proposed a multi-objective optimization model for monthly reservoir operation that considers anthropogenic water demands as well as fish habitats. Jager (2008) suggested three steps to conceptually bring multi-objective reservoir operation closer to meeting the goal of ecological sustainability. Identification of features of flow variation that are essential for river health and quantification of these relationships provide a comprehensive understanding of the river ecosystem. Richter et al. (2007) provided a descriptive framework for modifying reservoir operation to restore ecological flow regime.

Shiau and Wu (2005) simulated various combinations of in-stream flow releases and diversions for a projected diversion weir, and optimized the operation by minimizing the alteration in the distribution of several parameters. Suen and Eheart (2006) proposed a paradigm to incorporate ecological flow regime. A multi-objective optimization model was set up to incorporate hydropower generation and ecological requirements. Reservoir operation was assumed to be the same in each historical year. This does not support, however, an adaptive framework and cannot be easily applied directly for future operations

since historical flows are not necessarily representative of future daily flows. Also, reservoir inflow forecast information is generally not available or reliable beyond a certain time, e.g., one month or one season depending on the inflow forecast model. Recently, Yang and Cai (in press) investigated a multi-objective optimization model that minimizes flood damage and maximizes fish diversity by generating synthetic daily inflow data where the statistical characteristics of historical data was assumed to be preserved.

Restoration of downstream flow regime cannot be assessed based on a short time period; it may take a decade or even longer to know any successful restoration of the ecological environment to that of pre-impact period. Hence, an adaptive framework for reservoir operation is needed to identify daily releases based on inflows for restoring the flow regime in the long term.

The objectives of the study are to: 1) propose an adaptive reservoir operation framework for restoring the flow regime to pre-impact conditions; 2) implement and test the framework using a daily reservoir operation model to incorporate anthropogenic water needs and ecological flow releases; and 3) study the tradeoff between meeting anthropogenic water needs and ecological flow requirements.

Section 3.2 gives a brief introduction to ecological parameters and the Range Variability Approach (RVA). A real-time and adaptive framework to mimic natural flow pattern is proposed and a mixed integer linear programming approach for reservoir operation

optimization is introduced in this section. Results of application of this framework for an illustrative example are discussed in Section 3.3. The assumptions of this work and framework extension are discussed in Section 3.4, followed by concluding remarks in Section 3.5.

3.2 Methodology

3.2.1 Framework Description

A four-step framework (Figure 3.1) for multi-purpose reservoir operation to restore natural flow regime is proposed.

The first step is to identify appropriate flow parameters that represent the flow regime and have significant impact on the ecological system. Numerous hydrological metrics have been proposed in the literature (e.g., Olden and Poff, 2005) to characterize flow regime. No universal metric is accepted in the scientific community. It is challenging to select a few parameters for any specific river system of interest; this requires collaboration between ecologists and water resources planners. Olden and Poff (2005) investigated the overlap present in all hydrological metrics reported in the literature, and presented a framework to identify hydrological flow indices as Indicators of Hydrological Alteration (IHA) that adequately characterize flow regimes. Gao et al. (2009) studied the presence of any potential redundancy in existing IHA parameters and suggested that only a few parameters based on ecodeficit and ecosurplus can sufficiently represent the flow variability; however, IHA parameters are meant to capture flow variability as well as many other factors that affect the health of ecological habitats.

The collection of IHA parameters reflects the magnitude, duration and timing of hydrological variables. Five groups of hydrological variables were proposed and each group corresponds to its own ecological influence. For example, the magnitude of monthly mean flow reflects the habitat availability for aquatic organisms, soil moisture availability for plants and availability of water for terrestrial animals (Ritcher et al., 1996). To determine the relation between hydrological parameters and their possible ecological effects on a river system requires additional site-specific knowledge and cooperation from river managers and ecologists. For example, some species are usually sensitive to low flow and high flow conditions, and mean flow in specific months that may influence fish spawning. Yang et al. (2008) used a data mining approach to identify hydrological indicators related to fish community and generated a quantitative function between an ecological target index and the identified hydrological indicators for upper Illinois River.

For naturally flowing rivers, long term distribution of each hydrological flow parameter reflects the characteristics of the ecological system to which the aquatic system has been adapted. Range of Variability Approach (RVA) (Richter et al., 1998) is employed to evaluate hydrological flow alterations induced by disturbance such as reservoir operation to the natural flow conditions. The 33rd and 67th percentile of the flow parameter distribution in the pre-impact years are used as the critical values to divide the distribution into three categories, namely, low, medium and high categories. In the pre-impact years, about the same number of years falls in each category. Let $N_{i,pre}$ and $N_{i,post}$ represent the number of pre-impact and post-impact years, respectively, for which the value of a hydrological parameter falls within

category i. Then D_i is the difference between $N_{i,pre}$ and $N_{i,post}$. The absolute value of D_i is M_i, which represents the degree of alteration, as represented in Equation 3.1.

$$M_i = | D_i | = | N_{i,post} - N_{i,pre} | \quad i = 1,2,3 \qquad \textbf{… (3.1)}$$

Though D_i is not directly used in RVA analysis, it usually reflects the flow impact of reservoir operation. For example, when a large portion of outflow is needed to meet anthropogenic demand in some months, there will be many years when the monthly average flow parameter falls in the low category for those months. RVA analysis is done for all three categories and for all ecological flow parameters under consideration. Summation of M_i over the three categories of all flow parameters is the total number of mis-hits; its magnitude reflects the degree of flow alteration. RVA aims to compare the distribution of each flow parameter between pre-impact and post-impact period by discretizing the distribution into three categories. Ideally, hydrological alteration over all three categories should be zero, indicating that the reservoir operation has no impact on the hydrological flow regime.

To determine the daily release adaptively, one must know into which category should the next value of each flow parameter fall to best mimic the pre-impact flow pattern. Richter et al. (2007) suggested that if the parameter value in post-impact years falls within a certain range of parameter value distribution in pre-impact years, the ecosystem can be assumed to be similar to that in the pre-impact years. Two approaches, namely, a parametric and a non-parametric approach, for setting a fixed target range for each parameter based on historic flow data were suggested (Richter, 1998; Shiau and Wu, 2004). Setting such a fixed target

range based on past data neglects future inflow condition as well as reduces the flow variability.

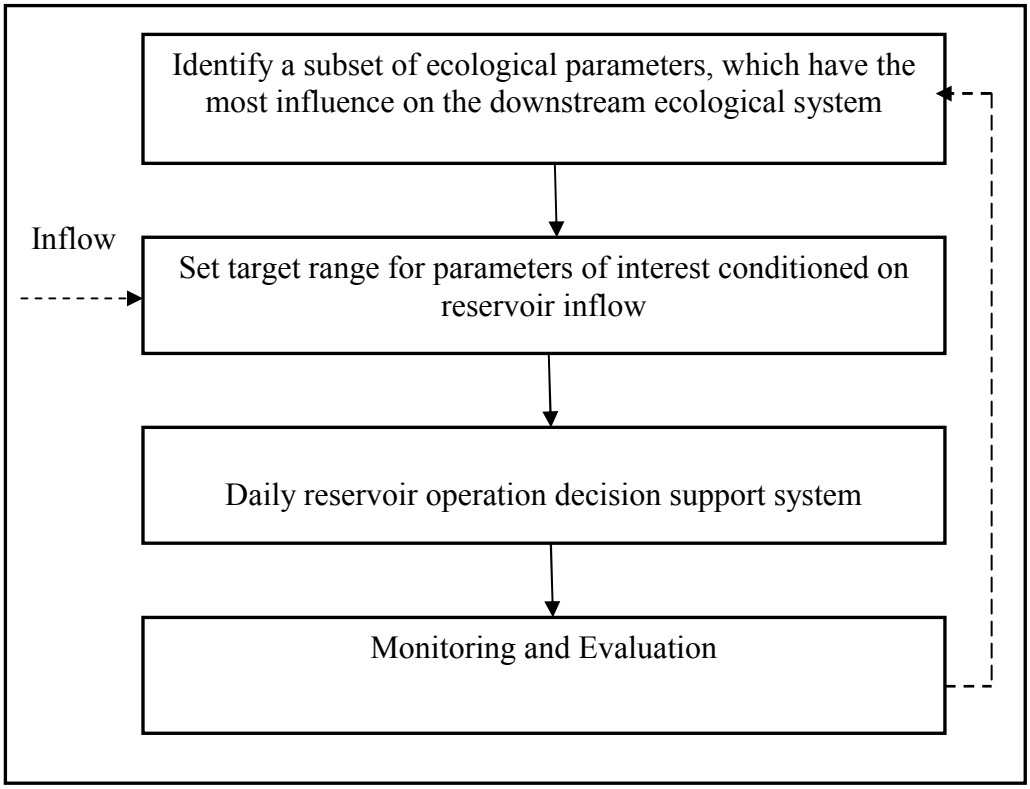

Figure 3.1: An adaptive framework of reservoir operation

To better preserve the flow regime variability, a new approach based on inflow conditions is proposed, which considers all three categories of the flow parameters in pre-impact years. By examining the forecasted inflow condition when deciding the reservoir operation in the decision horizon, the high category of the flow parameter in the pre-impact years is chosen as the target range for the parameter if the inflow is above normal. If the forecasted inflow is below normal, the low category of the flow parameter in the pre-impact years is chosen as

the target range. This approach enables conditional determination of the release instead of using a fixed target range making the reservoir operation framework adaptive.

The third step is to formulate a daily reservoir operation optimization model to determine daily releases that meet different water demands effectively. Various pieces, such as flow balance, ecological mis-hits function, water supply and hydropower generation, of this optimization model are described in Section 3.2.2. A key input to this model is the inflows that are based on streamflow forecasts. Hence, the releases are determined adaptively contingent on the forecasted inflow instead of a static release policy.

Finally, site monitoring and evaluation phase of the framework could provide information on how the river ecosystem responds to the actual ecological releases and help adjust and fine-tune the models and procedures in the framework.

The length of the planning horizon is critical when using the proposed framework. If the horizon is relatively long, e.g., six months to a year, reliable streamflow forecasts are not available. On the other hand, if the horizon is shorter, e.g., one week, the forecasts are usually reliable but are not sufficient to predict seasonal drought conditions. Also, it is hard to estimate ecological parameters such as monthly mean flow if the planning horizon is less than a month. Considering these factors, the following six flow parameters were chosen to reflect the downstream ecosystem: average monthly flow; 1-day minimum flow; 3-day minimum flow; 7-day minimum flow; 3-day maximum flow; and 7-day maximum flow. The

following section presents a daily reservoir operation optimization model to explicitly consider ecological flow requirement and other anthropogenic water demands.

3.2.2 Mathematical Formulation of Reservoir Operation

A multi-purpose reservoir operation optimization model is developed to estimate water releases for the different anthropogenic uses, as well as ecological flow needs. The sets of constraints and necessary expressions for defining the objective function are described below.

Flow balance

Equation 3.2 describes the reservoir flow balance, where s_j is the end-storage on day j, J is total number of days in the decision horizon, I_j is inflow to the reservoir on day j, x_j is ecological release on day j, and R_j is the non-ecological release on day j, e_j and sp_j represent evaporation and spillage, respectively, from the reservoir on day j. Reservoir storage is constrained by Equation 3.2, where $s_{\min}$ is the user-defined acceptable minimum storage and $s_{\max}$ is the user-defined acceptable maximum storage.

$$s_j = s_{j-1} + I_j - R_j - x_j - ws_j - sp_j \quad \forall j \in \{1,2,..,J\} \qquad \textbf{... (3.2)}$$

$$s_{\min} \le s_j \le s_{\max} \quad \forall j \in \{1,2,..,J\} \qquad \textbf{... (3.3)}$$

Mis-hits in ecological flows

The following set of equations is included to represent the six flow parameters considered in this study, and how they are used to calculate the number of mis-hits, i.e., frequency of falling outside of the target range for each parameter.

$$P_1 = \frac{\sum_{j=1}^{J} x_j}{J} \quad \text{… (3.4)}$$

$$P_2 \le x_j \qquad \forall j \in \{1,2,..,J\} \quad \text{… (3.5)}$$

$$P_3 \le \frac{\sum_{t=0}^{2} x_{j+t}}{3} \qquad \forall j \in \{1,2,..,J-2\} \quad \text{… (3.6)}$$

$$P_4 \le \frac{\sum_{t=0}^{6} x_{j+t}}{7} \qquad \forall j \in \{1,2,..,J-6\} \quad \text{… (3.7)}$$

$$P_5 \ge \frac{\sum_{t=0}^{2} x_{j+t}}{3} \qquad \forall j \in \{1,2,..,J-2\} \quad \text{… (3.8)}$$

$$P_6 \ge \frac{\sum_{t=0}^{6} x_{j+t}}{7} \qquad \forall j \in \{1,2,..,J-6\} \quad \text{… (3.9)}$$

$$\frac{P_2 - x_j}{C} \ge h_j^i \qquad \forall j \in \{1,2,..,J\} \quad \text{… (3.10)}$$

$$\frac{P_3 - \sum_{t=0}^{2} x_{j+t} / 3}{C} \ge h_j^i \qquad \forall j \in \{1,2,..,J-2\} \quad \text{… (3.11)}$$

$$\frac{P_4 - \sum_{t=0}^{6} x_{j+t} / 7}{C} \geq h_j^i \qquad \forall j \in \{1,2,..,J-6\} \qquad \textbf{… (3.12)}$$

$$\frac{P_5 - \sum_{t=0}^{2} x_{j+t} / 3}{C} \leq h_j^i \qquad \forall j \in \{1,2,..,J-2\} \qquad \textbf{… (3.13)}$$

$$\frac{P_6 - \sum_{t=0}^{6} x_{j+t} / 7}{C} \leq h_j^i \qquad \forall j \in \{1,2,..,J-6\} \qquad \textbf{… (3.14)}$$

$$\sum_{j=1}^{J} (1 - h_j^i) \geq 1 \qquad \forall j \in \{1,2,..,J\} \quad \forall i = 2,3,...,6 \qquad \textbf{… (3.15)}$$

$$P_i \geq (1 - q_1^i) \times t\arg et_{\min}^i + q_1^i \times t\arg et_{\max}^i \qquad \forall i = 1,2,..,6 \qquad \textbf{… (3.16)}$$

$$P_i \leq q_2^i \times t\arg et_{\min}^i + (1 - q_2^i) \times t\arg et_{\max}^i \qquad \forall i = 1,2,..,6 \qquad \textbf{… (3.17)}$$

$$\sum_{i=1}^{6} (q_1^i + q_2^i) = M_{total} \qquad \textbf{… (3.18)}$$

$$q_1^i, q_2^i, h_j^i \in \{0,1\} \qquad \forall i = 1,2,..,6 \qquad \textbf{… (3.19)}$$

$$h_j^i \in \{0,1\} \qquad \forall i = 2,3,..,6 \quad \forall j \in \{1,2,...J\} \qquad \textbf{… (3.20)}$$

Equation 3.4 represents the monthly mean flow, P_1. x_j is the release in day j, and J is the total number of days in the month. This flow parameter is constrained by Equations 3.16 and 3.17 to fall within the specified target range (defined by $\text{target}_{\min}^1$ and $\text{target}_{\max}^1$.) If the flow parameter fell outside of the target range, then the binary variables q_1^1 and q_2^1 are used to indicate whether P_1 is greater than $\text{target}_{\max}^1$ (q_1^1=1) or less than $\text{target}_{\min}^1$ (q_2^1=1). These

binary variables are used to count the number of mis-hits in Equation 3.18, where M_{total} is total number of mis-hits.

Equations 3.5, 3.10 and 3.15 are collectively used to represent the monthly 1-day minimum flow parameter, P_2. The binary variable h_j^2 is introduced to indicate when the monthly 1-day minimum occurs and to ensure that P_2 is assigned the appropriate value. The constant C in Equations 3.10-3.14 is a large value to ensure the left-hand side expressions remain a fraction.

Similar sets of constraints are included to represent monthly 3-day minimum (P_3), monthly 7-day minimum (P_4), monthly 3-day maximum (P_5), and monthly 7-day maximum (P_6). Corresponding variables q_1^i, q_2^i and h_j^i are introduced to ensure that variable P_i is assigned the appropriate value based on flow values x_j, and all mis-hits are flagged and added in Equation 3.18.

The total count of mis-hits, M_{total}, is then used either as an objective function in scenarios focused on minimizing ecological flow alteration, or as a constraint (Equation 3.21) in scenarios where the flow alteration is limited by some target number (g) of deviations from pre-impact conditions.

$$M_{total} \leq g \qquad \textbf{… (3.21)}$$

Water supply

Equations 3.22 and 3.23 are included to ensure that at least fraction r of water demand is satisfied, where ws_j is the release for water supply on day j, and wd_j is the daily water demand.

$$\sum_{j=1}^{J} ws_j \geq r \times \sum_{j=1}^{J} wd_j \quad \text{… (3.22)}$$

$$ws_j \leq wd_j \qquad \forall j \in \{1,2,..,J\} \quad \text{… (3.23)}$$

Hydropower generation

Hydropower generation is represented usually as a function of water released to turbines and elevation difference between turbines and water level in the reservoir. This depends on the bathymetry of the reservoir and is characterized by storage-elevation curve, which is unique for each reservoir (see an example in Figure 3.2 (a)). For large reservoirs where elevation fluctuation is not a critical factor in hydropower generation or where hydropower generation is mainly flow-dependent, an alternative approach is to assume a constant reservoir water elevation (Loucks et al., 2005), but this is not generally the case. The nonlinear relation between storage and elevation can be explicitly modeled by using a piece-wise linearization approach (D'Ambrosio et. al., 2010; Goor et al., In press).

For day *j,* the daily average storage, $\bar{s}_j$, is calculated as the average of the daily initial storage s_{j-1} and end-of-day storage s_j, as shown in Equation 3.24. The storage axis is divided into *K1*-1 intervals with *K1* break points (Figure 3.2a), and $b_{k,j}$ is a binary variable

associated with interval *k*. At the boundary break points, $b_{0,j}$ is associated with the first break point and $b_{K1,j}$ is associated with the last break point. $\alpha_{k,j}$ is a coefficient in the range of [0,1], and it represents a weight for day *j* associated with break point *k*. To find an estimate of elevation corresponding to $\bar{s}_j$, first the pair of break points adjacent to $\bar{s}_j$ in the storage axis is determined; then the elevation for these break points are weighted to estimate the elevation. The weights are determined based on the relative location of $\bar{s}_j$ compared to the two adjacent break points. Equations 3.27-3.30 are used to find the two adjacent break points. The weights ($\alpha_{k,j}$) corresponding to these two adjacent break points are used to relate (Equations 3.25-3.26) the storage (st_k) at these break points to $\bar{s}_j$. Then the elevations associated with these adjacent break points are combined using the corresponding weights (Equation 3.31) to estimate the elevation h_j^e in day *j*. These equations are shown below.

$$\bar{s}_j = (s_{j-1} + s_j)/2 \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{... (3.24)}$$

$$\bar{s}_j = \sum_{k=1}^{K} \alpha_{k,j} st_k \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{... (3.25)}$$

$$\sum_{k=1}^{K} \alpha_{k,j} = 1 \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{... (3.26)}$$

$$\sum_{k=1}^{K-1} b_{k,j} = 1 \quad \forall j \in \{1,2,..,J\} \quad \forall k \in \{1,2,..,K\} \qquad \textbf{... (3.27)}$$

$$\alpha_{k,j} \le b_{k-1,j} + b_{k,j} \quad \forall j \in \{1,2,..,J\} \quad \forall k \in \{1,2,..,K\} \qquad \textbf{... (3.28)}$$

$$b_{0,j} = 0 \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (3.29)}$$

$$b_{K,j} = 0 \qquad \forall j \in \{1,2,..,J\} \quad \forall k \in \{1,2,..,K\} \qquad \textbf{… (3.30)}$$

$$h_j^e = \sum_{k=1}^{K} \alpha_{k,j} f(st_k) \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (3.31)}$$

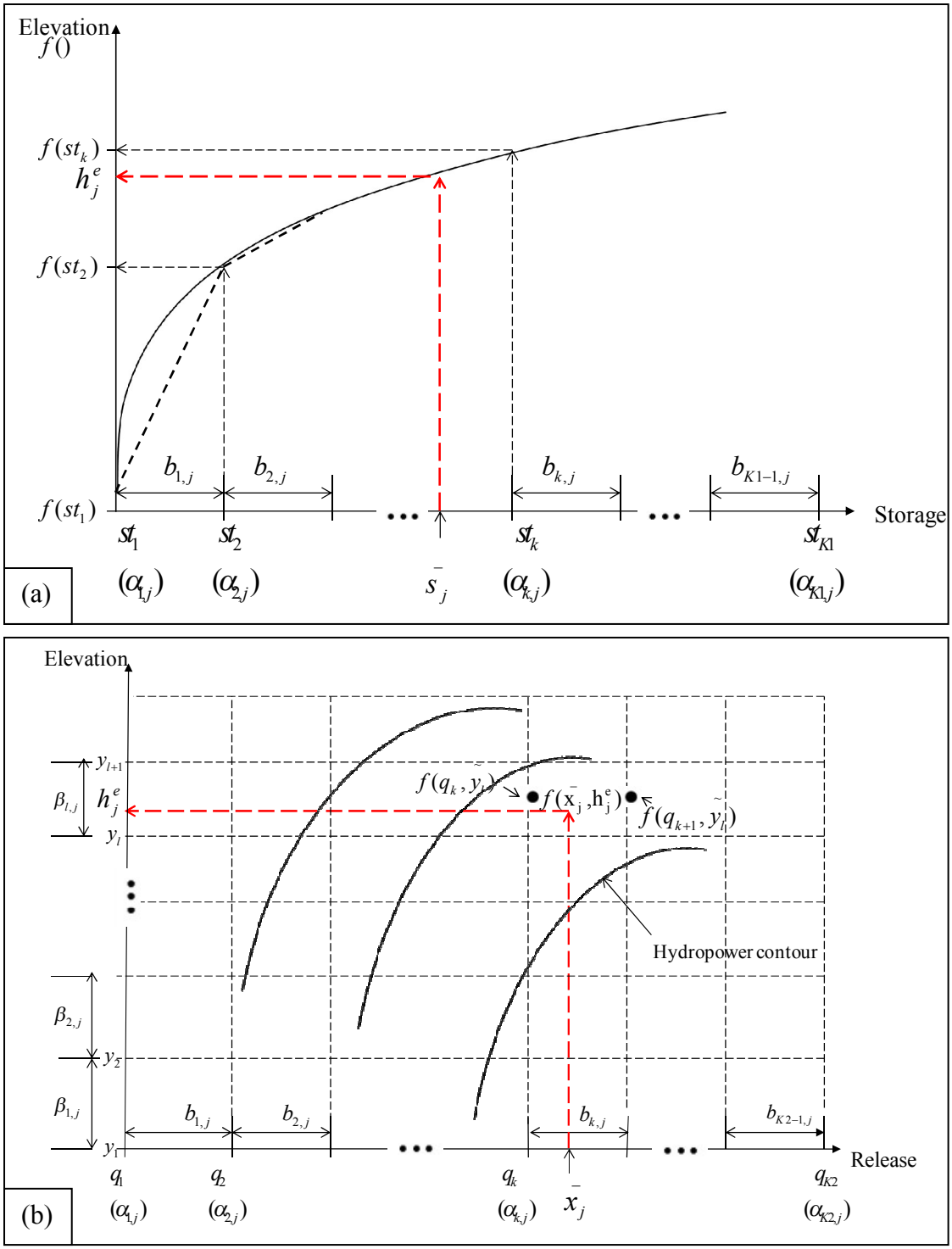

Figure 3.2: (a) Linearization for the storage-elevation curve; (b) Two-dimensional linearization for hydropower generation.

The estimated elevation (h_j^e) corresponding to average daily storage $\bar{s}_j$ on day *j* and daily release $\bar{x}_j$ are combined to estimate the hydropower generated on day *j*, expressed as energy E_j produced on day *j*. The Energy-Elevation-Storage-Release relationship, which is non-linear, is descretized and this non-linear function is represented, as before, using piece-wise-linear approximation. The elevation axis is discretized into *L* intervals with (*L*+1) break points (Figure 3.2b). The variable y_l represents the elevation at break point *l*. A set of binary variables ($\beta_{l,j}$; *l = 1,2,.., L, j=1,2,..,J*) is used to indicate the interval in the elevation axis, and is used to determine the break point closest to h_j^e on day *j* (Equations 3.32-3.35). The release axis is discretized into *K2* intervals with (*K2*+1) break points. $\alpha_{k,j}$ represents the weight on day *j* for break point k; the $\alpha_{k,j}$ weights at the two break points adjacent to $\bar{x}_j$ must be such that the weighted average of the releases q_k at these adjacent break points is equal to $\bar{x}_j$. Equations 3.36 and 3.37 are used to find the energy generated (E_j) on day jas the weighted average (using $\alpha_{k,j}$ weights as corresponding to $\bar{x}_j$) of energy associated with the midpoint $\tilde{y}_l$ for the interval in which h_j^e falls. These constraints are shown below.

$$h_j^e \le \sum_{l=1}^{L-1} \beta_{l,j} y_{l+1} \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (3.32)}$$

$$h_j^e \ge \sum_{l=1}^{L-1} \beta_{l,j} y_l \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (3.33)}$$

$$\beta_{l,j} \in [0,1] \qquad \forall j \in \{1,2,..,J\} \quad \forall l \in \{1,2,..,L-1\} \qquad \textbf{... (3.34)}$$

$$\sum_{l=1}^{L-1} \beta_{l,j} = 1 \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{... (3.35)}$$

$$E_j \le \sum_{k=1}^{K2} \alpha_{k,j} f(q_k, \tilde{y}_l) + M(1-\beta_{l,j}) \qquad \forall l \in \{1,2,..,L-1\} \qquad \textbf{... (3.36)}$$

$$E_j \ge \sum_{k=1}^{K2} \alpha_{k,j} f(q_k, \tilde{y}_l) - M(1-\beta_{l,j}) \qquad \forall l \in \{1,2,..,L-1\} \qquad \textbf{... (3.37)}$$

$$\sum_{j=1}^{J} E_j \ge E_{firm\ \text{yield}} \qquad \textbf{... (3.38)}$$

Optimization models

In this study, four scenarios were investigated. In each scenario, different objective was optimized while others were subjected to target constraints. The combinations of objectives that were optimized and constrained in the four scenarios are tabulated in Table 3.1. The structure of optimization model for each scenario is presented in Figure 3.3.

Table 3.1: Objectives that are optimized and constrained in each scenario.

	Ecological flow	Water supply	Hydropower generation
A		● optimized	× constrained
B	● optimized		
C	● optimized	× constrained	
D	● optimized	× constrained	× constrained

A:

$Maximize \sum_{j=1}^{J} ws_j$ (water supply)

s.t. Flow balance Eqns. 3.2-3.3
Water supply Eqn. 3.23
Hydropower Eqns. 3.24-3.38

B:

$Minimize \sum_{i=1}^{N} (q_1^i + q_2^i)$ (mis-hits)

s.t: Flow balance, Eqns. 3.2-3.3
Mis-hits formulation, Eqns. 3.4-3.20

C:

$Maximize \sum_{i=1}^{N} (q_1^i + q_2^i)$ (mis-hits)

s.t. Flow balance Eqns. 3.2-3.3
Mis-hit formulation, Eqns. 3.4-3.20
Water supply Eqns. 3.22-3.23

D:

$Minimize \sum_{i=1}^{N} (q_1^i + q_2^i)$ (mis-hits)

s.t: Flow balance, Eqns. 3.2-3.3
Mis-hit formulation, Eqns. 3.4-3.20
Water supply Eqns. 3.22-3.23
Hydropower Eqns. 3.24-3.38

E:

$Maximize \sum_{j=1}^{J} E_j$ (hydropower)

s.t. Flow balance Eqns. 3.2-3.3
Water supply Eqns. 3.22-3.23
Hydropower Eqns. 3.24-3.37

F:

$Maximize \sum_{j=1}^{J} E_j$ (hydropower)

s.t: Flow balance, Eqns. 3.2-3.3
Water supply Eqns. 3.22-23
Hydropower Eqns. 3.24-3.38
Mis-hit, Eqns. 3.4-3.20
Allowable mis-hits, $\sum_{i=1}^{6} (q_1^i + q_2^i) \leq 3$

Figure 3.3: Optimization models for the different scenarios investigated in this study.

3.3 Illustrative Study

3.3.1 Site Description

Philoptt dam, which was built during 1948-1952, is located on Smith River in the Roanoke River basin (Figure 3.4). Its main purposes are flood control, recreation and hydropower generation; the powerhouse was built in 1953 with three turbines located at 813 feet above mean sea level. Hydrological alteration in the river downstream of the reservoir due to current reservoir operation was evaluated first. In addition, four scenarios were investigated to examine whether the ecological flow requirements and anthropogenic water use can be met in a more effective manner. The optimization model formulations for the four scenarios are provided in Figure 3.3.

In Scenario A, water supply ratio is optimized while monthly hydropower generation is constrained to meet the firm energy requirement. Ecological flow requirements are not explicitly considered in this scenario; this scenario represents closely the current reservoir operation. In the other three scenarios, the total number of mis-hits is minimized to improve ecological flow conditions. Scenario B represents a hypothetical instance where ecological flow is the only consideration; this scenario is used to set a benchmark (or bound) for the most ecologically friendly operation condition for comparison purposes. Scenario C represents a case that considers ecological flow conditions in conjunction with the current operation; water supply is constrained to be no less than 90% of the demand. Scenario D is built upon Scenario C by adding hydropower generation requirement. The pre-impact duration is based on flows in years 1930 to 1950. The optimization model for each scenario was constructed and optimized one month at a time for the post-impact period of October

1950 to October 1980. The optimization model was implemented using AMPL and was solved using CPLEX 12.2.

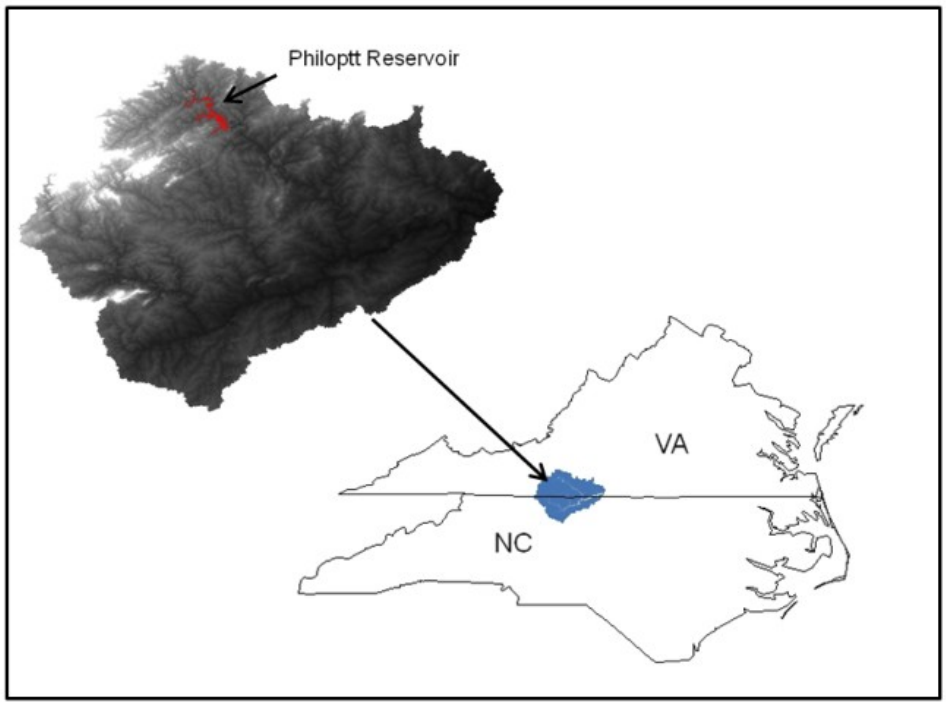

Figure 3.4: Site location of Philoppt reservoir in Virginia.

3.3.2 Result Analysis

Evaluation of current operation

Figure 3.5 (a) shows the comparison of October mean flow between pre-impact period and post-impact period. The two dashed lines correspond to the 33rd percentile and the 67th percentile of the time series in pre-impact period; there are seven years within each of the three categories (low is the 1st 33rd percentile, medium is the 2nd 33rd percentile, and high is the 3rd 33rd percentile) defined by the two critical values (the dashed horizontal lines). The

distribution by categories is different in the post-impact period. For example, only in one year the flow is in the low category, and for six years it is in the high category, resulting in increased number of occurrences (14) in the medium category. The differences in this distribution are represented in terms of mis-hits that reflect the alteration resulting as a consequence of reservoir operation. Figure 3.5 (b) shows the number of mis-hits in each category for the monthly mean flow in each month. The number of mis-hits in the July-August-September (JAS) summer season is relatively higher compared to the other months. This is reflective of the current operations where more water is released in the summer months to meet increased energy demand. As this reservoir is used primarily for hydropower, this deviation in the summer months and the increased flow alterations are consistent with current operation.

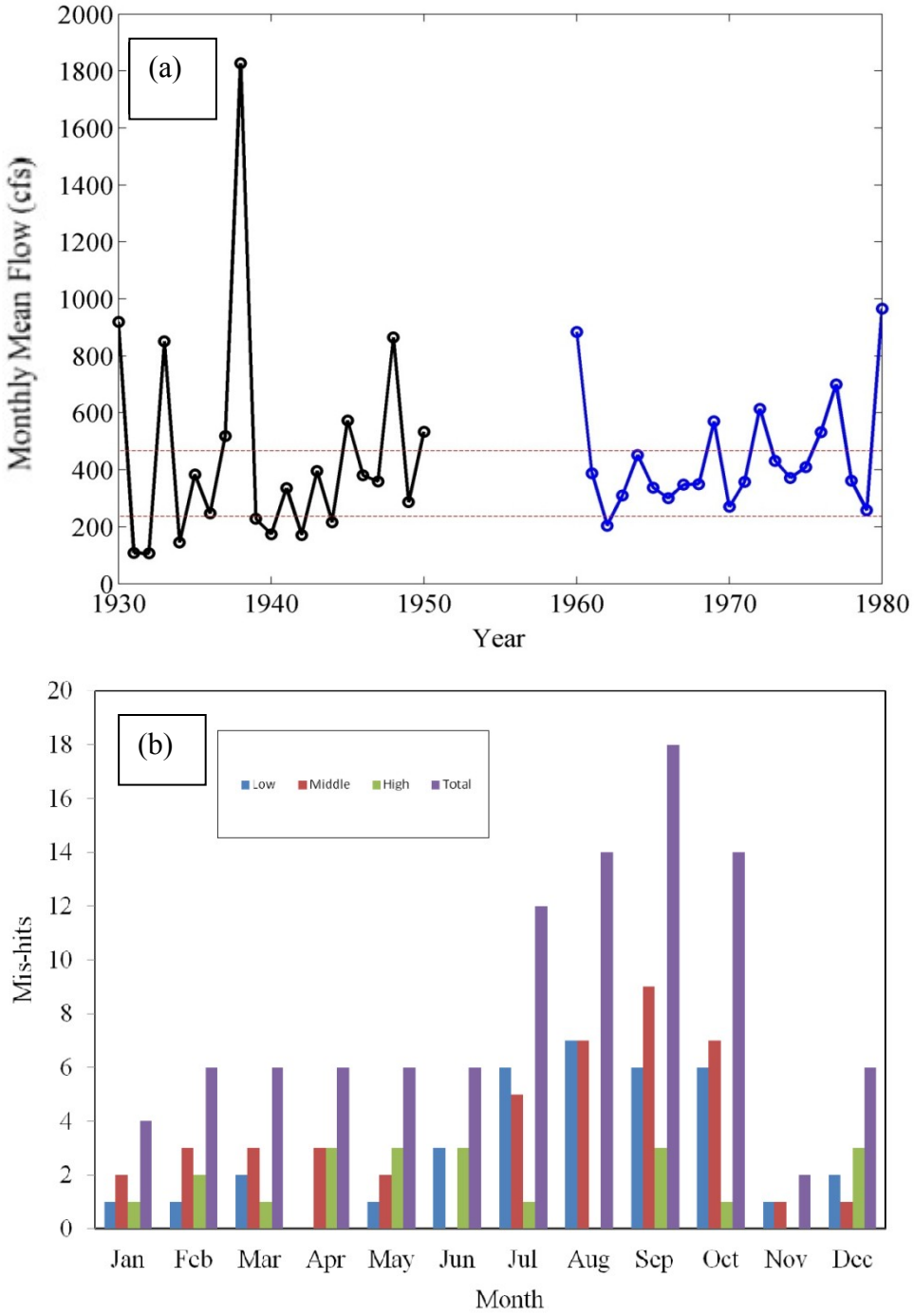

Figure 3.5: Alterations in monthly mean flow under current operation: (a) shows the shift in October mean flow between pre-impact and post-impact years; (b) presents the number of mis-hits in the three categories (low, medium, and high) for mean flow in each month.

Table 3.2 provides a summary of the number of mis-hits for each of the six flow parameters corresponding to the current operations. Compared to monthly average flow, the minimum and maximum flow parameters have higher number of mis-hits. The mis-hits in 1-day minimum flow in JFM season, for example, are all higher than 20, whereas the mis-hits for the monthly average flow parameter are lower than 10. The total number of mis-hits of all six parameters ranges from 50 to 90, with more mis-hits in the summer months.

Table 3. 2: Comparison of the number of mis-hits for the alterations in the six flow parameters due to current operation.

	1-day min	3-day min	7-day min	3-day max	7-day max	Monthly average	Total mis-hits
Jan	24	14	12	10	4	4	68
Feb	22	10	4	4	2	6	48
Mar	24	16	4	4	6	6	60
Apr	26	8	10	6	4	6	60
May	16	10	4	8	4	6	48
Jun	22	8	4	6	8	6	54
Jul	10	10	8	10	12	12	62
Aug	10	10	24	16	18	14	92
Sep	10	4	18	22	16	18	88
Oct	14	4	12	14	14	14	72
Nov	16	6	10	10	8	2	52
Dec	20	8	4	6	6	6	50

Scenarios A, B, C, and D

Scenario A aims to maximize water supply ratio while meeting hydropower generation requirement. Daily water demand was set at 40 cfs and monthly firm energy yield was set at 300 MKWH. This scenario is similar to current reservoir operation in that ecological flow

alteration is not explicitly included. The total number of mis-hits in each month is shown in Figure 3.6. Compared to the number of mis-hits for the current operation, Scenario A has more number of mis-hits, which is expected since water supply deficiency is minimized, resulting in no deficit although the real operation may have had some. Among the six parameters, mis-hits for minimum and maximum flow parameters are higher than that for monthly average flow. In this scenario, ecological flow requirements are not explicitly considered, therefore, it is expected to have increased number of mis-hits.

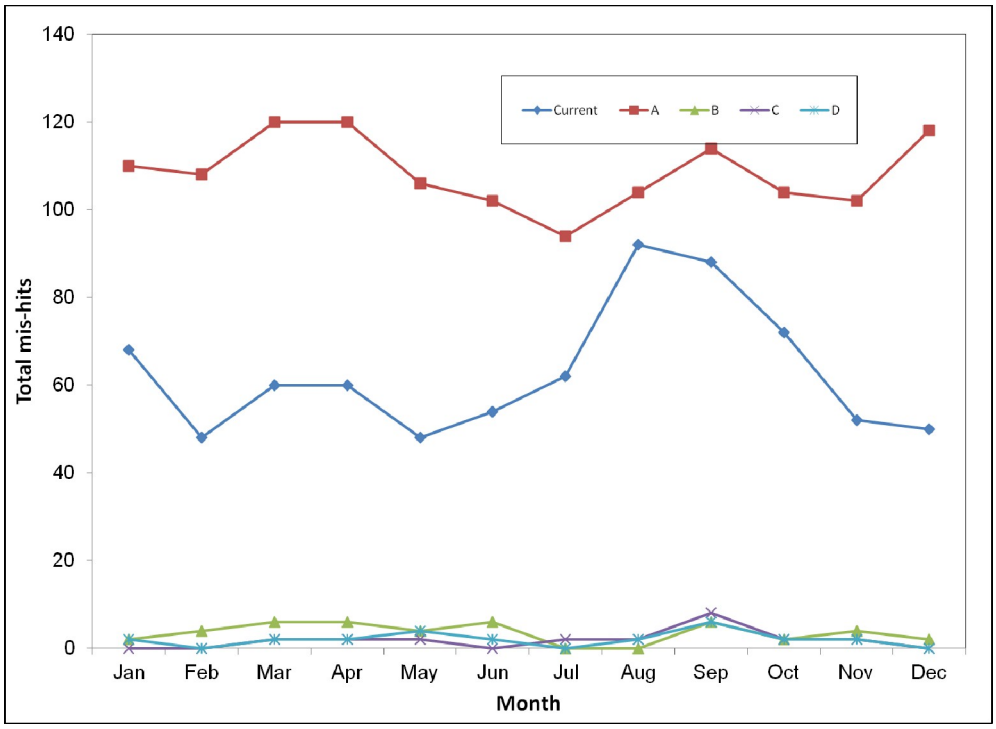

Figure 3.6: Total number of mis-hits for the four scenarios (A, B, C, and D) and current operation.

Scenario B is a hypothetical (or ecologically ideal) case where only ecological flow requirements are optimized and no anthropogenic water demand is considered. To exemplify

the difference in releases between ecologically ideal case and current operation, Figure 3.7 compares the daily releases for the month of October, 1964. The total number of mis-hits in each month is included in Figure 3.6 to enable a comparison with other scenarios where the ecological flow is explicitly optimized, which are discussed below.

The total number of mis-hits for Scenario C is significantly less than that of current operation and Scenario A (Figure 3.6). The water supply satisfaction ratio was 0.9 for Scenario C, which is slightly less that 100% demand satisfaction in Scenario A. Compared to Scenario B (the ecologically ideal case), Scenario C performs similarly while meeting the target water supply satisfaction ratio.

Scenario D captures all anthropogenic uses as well as ecological flow considerations. As shown in Figure 3.6, the total number of mis-hits for this scenario is still much lower than that of current operation, although anthropogenic uses are included to meet the demand satisfaction targets. Although hydropower generation is considered in both Scenarios A and D, Figure 3.8 shows the difference in the monthly hydropower generation, suggesting different downstream releases between the two scenarios.

By modeling and solving the several scenarios, the applicability and the use of the adaptive reservoir operation framework was demonstrated for a realistic case study. Using mis-hits as a surrogate for flow alterations, the comparison and current operation indicate that an improvement in ecological flow impact can be achieved while still meeting the different

anthropogenic water demands by using the proposed framework. Another aspect of natural flow pattern is its variability, which is usually quantified as coefficient of variation *(COV)* of daily flow time series. Shiau and Wu (2010) incorporated this into an optimization problem to study different releases utilizing all historical inflow information. Though this metric is not explicitly quantified and implemented in this framework, formulation of minimum and maximum flow condition indirectly contributes to enhance flow variability. COV of daily flow time series in the pre-impact period is 1.4, while it drops to 0.84 in the post-impact period. The *COV* for scenarios A, B, C, and D is 1.07, 1.14, 1.15 and 1.20, respectively.

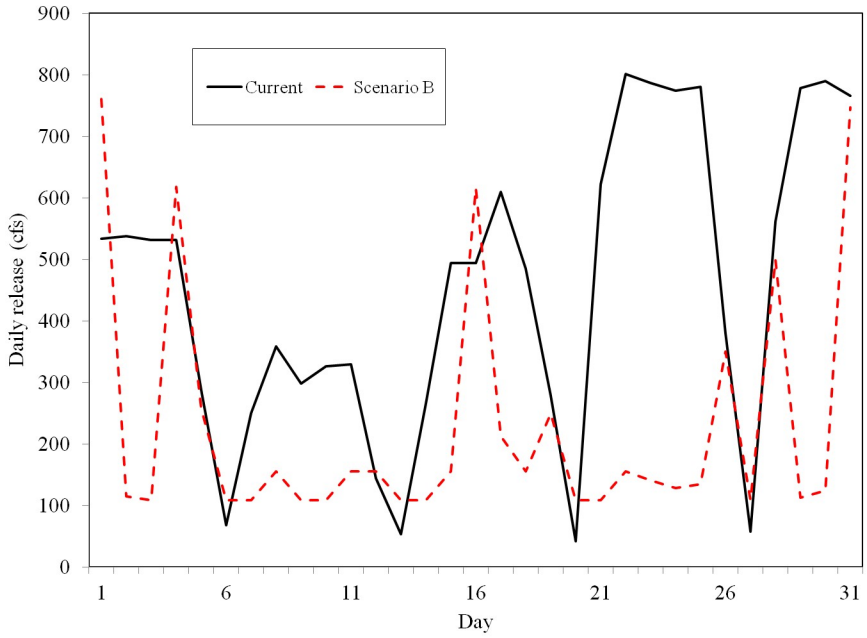

Figure 3.7: The daily reservoir releases in Oct 1964 for current operation and Scenario B for October, 1964.

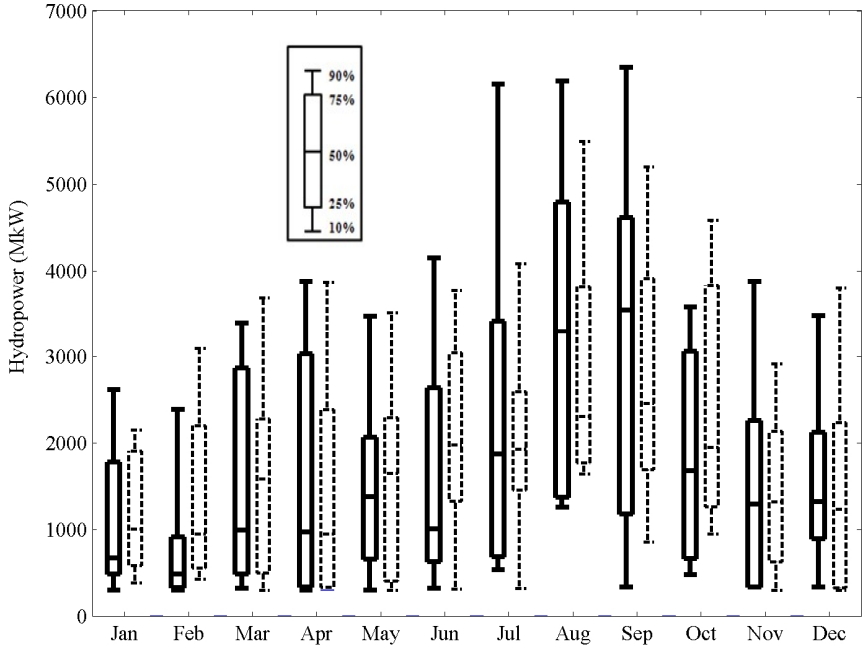

Figure 3.8: Monthly hydropower generation for Scenarios A (solid box-plots) and D (dashed box-plots).

3.3.3 Tradeoff Analysis

To study the tradeoff between hydropower generation and water supply, two new scenarios were developed. Scenario E (Figure 3.3) helps to generate the tradeoff when ecological flow alterations are not considered at all, i.e., the anthropogenic uses are the only objectives optimized. By constraining monthly water supply ratio at discrete values and optimizing for hydropower generation, the non-inferior tradeoff is generated (Figure 3.9). To study the effect of ecological flow considerations on the tradeoff, Scenario F (Figure 3.3) was defined in which a constraint on the total number of mis-hits is included. The mis-hit limit was set to 3, which corresponds to the maximum number of mis-hits for Scenario D. This is to ensure that the resulting number of mis-hits is no worse than those of the solutions obtained using Scenario D, which represents all anthropogenic uses and ecological flow considerations. The

resulting tradeoff is also plotted in Figure 3.8. These plots imply that explicit consideration of ecological flow consideration has little effect (less than 0.2% reduction) on meeting the hydropower and water supply objectives if the releases are accordingly optimized.

3.4 Discussion

One implicit assumption behind restoring natural flow pattern is that natural (or pre-impact) flow pattern is the best for maintaining a healthy downstream ecological system. This assumption is based on the reasoning that aquatic systems in the river downstream of a reservoir are adapted to the pre-impact flow regime. One argument against this is that aquatic systems could adapt to altered flow regime in the post-impact period. Most flow control constructions, e.g., weirs and reservoirs, were usually constructed within the last 100 year, which is short compared to geological time scale. Hence it is reasonable to assume that natural flow regimes are good for sustaining a healthy ecosystem. But whether aquatic systems can partially or well adapt to altered flow regimes remains a research question (Jager and Smith, 2008). Systematic study of the altered flow regime and the ecosystems based on field monitoring is required to test such scientific hypotheses.

Richter et al. (2007) suggested using the 25th and 75th percentile of the flow parameter values in pre-impact years as the low and upper bound for the target range. This fixed target range approach was tested in the preliminary analysis along with an adaptive approach that is dependent on the forecasted inflow. One limitation of using a fixed target range approach is that the flow variability cannot be well preserved because only a few flow values fall below

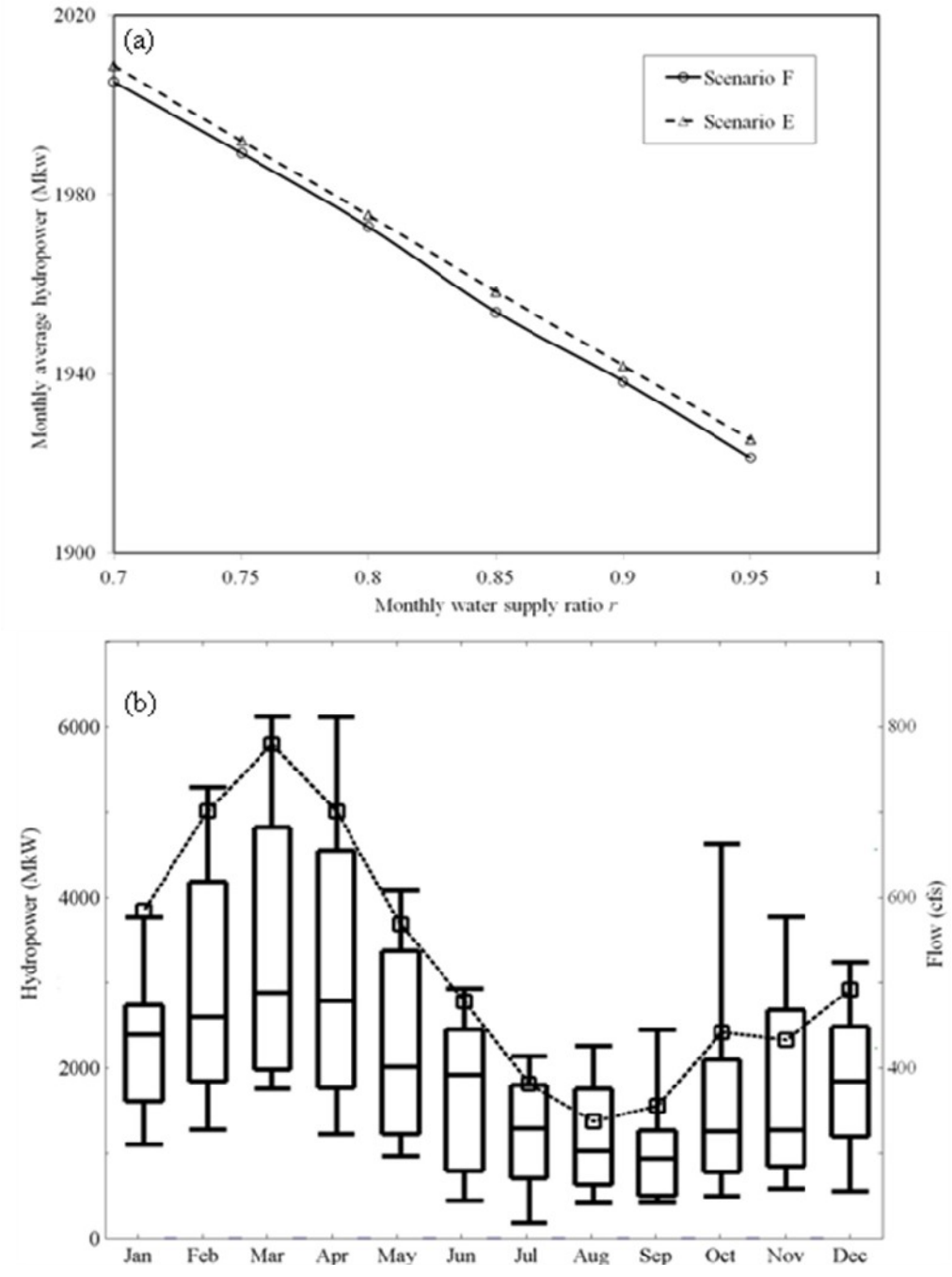

Figure 3.9: (a) The tradeoff between hydropower generation and monthly water supply ratio for Scenarios E and F. (b) Monthly hydropower generation for Scenario E.

the 25th percentile or above the 75th percentile. Preliminary investigation of the correlation between monthly average flow and the other five ecological flow parameters reveal significant correlation (p value < 0.05). As shown in Figure 3.10, the correlation between monthly average flow and 1-day minimum flow in the pre-impact period (252 months) is 0.63. Hence, it is reasonable to assign the target range for the other flow parameters as the same as that of the monthly average flow.

The framework was tested using perfect streamflow forecasts that are available up to a month ahead. Flow forecast information is usually given in one of the following forms: deterministic, probabilistic or Ensemble Streamflow Forecasts (ESP). Deterministic flow information is used in daily reservoir operation model to compare with and demonstrate the effectiveness of the proposed framework. This framework does not preclude other forms of flow information. Many studies reported in the literature (e.g., Maurer and Lettenmaier, 2004; Golembesky et al., 2009) have examined ways to incorporate flow information and uncertainty into optimization of water resources systems. Different forms of flow information could be incorporated in future study to examine the value of streamflow forecasts (see Chapter 4 for such a study).

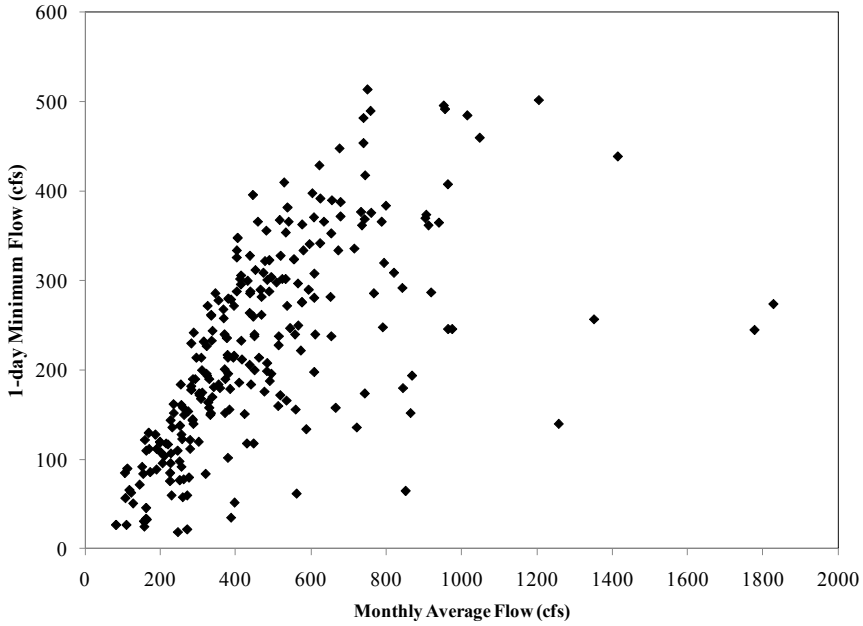

Figure 3.10: Correlation between monthly average flow and 1-day minimum flow over pre-impact years.

The daily reservoir operation model under different scenarios was tested by considering different combinations of mis-hits, monthly water supply and monthly hydropower generation requirements. In addition to monthly anthropogenic water demands, daily requirements can also be modeled. This model also shares the capacity for considering other constraints, such as the maximum number of days to allow violation of water demand requirement or hydropower requirement. Since daily water supply and hydropower were simulated and demonstrated in current formulation, considering such daily requirements would be trivial.

Each step of the proposed framework is critical for achieving natural flow restoration in the long term. Although field monitoring and evaluation was not conducted in this study, its importance cannot be ignored. For adaptively setting the target range for the flow parameters, comprehensive examination of monitoring data could be used in combination with the approach presented in this chapter. This is a clear advantage of the adaptive framework proposed in this study.

3.5 Conclusion

An adaptive framework for sustainable reservoir operation is proposed in this work. Monitoring and data collection is needed to select the site-specific ecological flow parameters. Inflow forecasts at multiple temporal scales, i.e., monthly and daily forecasts, are essential to apply this framework. The target range for ecological flow parameters were based on monthly inflow. This work assumes perfect inflow forecasts are available although inflow uncertainties cannot be neglected.

RVA analysis was applied to evaluate the shift in flow parameter distribution from pre-impact years to post-impact years. Mis-hit was used to quantify the difference between the two distributions over three discretized categories, namely, low, medium and high ranges. The key challenge to matching the release to the natural flow pattern is to determine the releases that mimic natural flow pattern in the short-term. While natural flow pattern may not be restored in a short time period, e.g., one or several years; this approach can minimize alternation in the flow regime over longer periods (e.g., 10-20 years).

An MILP optimization model was formulated to explicitly incorporate ecological flow requirements. To the best knowledge of the author, this is the first time that ecological flow requirement is explicitly incorporated in an adaptive real-time reservoir operation model. Four scenarios of the mathematical model were investigated and the results demonstrate the effectiveness in simultaneously satisfying anthropogenic water demands and ecological releases. Comparisons among these different scenarios show that there is a clear tradeoff between anthropogenic demands and ecological flow requirements. While there is an obvious tradeoff between anthropogenic water demand and ecological flow consideration, the results based on the scenarios analyzed show that flow alterations can be minimized, almost to zero occurrences, by optimizing the daily releases and still meet anthropogenic requirements. Interestingly, the same level of hydropower generation could be achieved while returning the flow regime to pre-impact conditions. Although these observations are specific to the reservoir modeled in this study, the framework is generally applicable and holds premise to enable consideration of ecological flow regime alteration explicitly without sacrificing other benefits through reservoir reoperation using such an adaptive approach. A general reoperation rule is hard to identify based on current study that is limited. But additional studies and results using the proposed framework could shed more light on how to generalize for different types of reservoir operations.

NOTATIONS:

J: Total days in the decision horizon

s_j: End storage on day j

I_j: Reservoir inflow on day j

x_j: Downstream release on day j, it is assumed flowing through turbines

ws_j: Water supply release on day j

sp_j: Spillage on day j

R_j: Release for other purposes on day j

$s_{\min}$: Minimum allowable storage

$s_{\max}$: Maximum allowable storage

P_1: Monthly mean downstream flow

P_2: 1-day minimum flow

P_3: 3-day minimum flow

P_4: 7-day minimum flow

P_5: 3-day maximum flow

P_6: 7-day maximum flow

h_j^i: A binary variable associated with the ith ecological flow parameter on day j

C: A large positive number

q_1^i: A binary variable associated with the ith ecological flow parameter, it is 1 if the ith ecological flow parameter is less than its low boundary, $t \arg et_{\min}^i$

q_2^i: A binary variable associated with the ith ecological flow parameter, it is 1 if the ith ecological flow parameter is larger than its upper boundary, $t \arg et_{\max}^i$

ws_j: Releases for water supply on day j

wd_j: Daily domestic (industrial) water demand

$\bar{s}_j$: Estimated average storage for day j

r: Water supply satisfaction ratio

st_k: Breakpoints on the storage axis in the linearization of storage-head curve

$\alpha_{k,j}$: A real number between 0 and 1 associated with each breakpoint

$b_{k,j}$: A binary variable associated with each interval on storage axis

$b_{0,j}, b_{K1,j}$: Two dummy binary variables associated with the two end points, both are 0

h_j^e: Estimated monthly mean water elevation in the reservoir

E_j: Approximated daily hydropower generation

$f(st_k)$: The water head corresponds to a certain storage, st_k, is provided to piecewise linearize the storage-head curve.

q_k: Break points on the release axis

$\beta_{l,j}$: A binary variable associated with each interval on the elevation axis

$\tilde{y}_l$: Mid points of each interval on the elevation axis

M : A large positive number

K_1 : The number of breaking points (including two end points) in linearization of Storage-Elevation curve

K_2 : The number of breaking points (including two end points) in modeling of Energy-Elevation-Storage-Release relationship

g : Allowable number of mis-hits

$E_{firm\ \text{yield}}$: Monthly firm energy requirement

$f(q_k, \tilde{y}_l)$: Daily hydropower generation corresponds to a break point q_k on the release axis and mid point $\tilde{y}_l$ for the intervals on elevation axis.

Chapter 4 The Value of Ensemble Streamflow Forecasts in Sustainable Reservoir Operation

4.1 Introduction

It is well documented that controlled releases from reservoir have potential damage to downstream ecological systems. Hence, sustainable reservoir operation requires comprehensive consideration of anthropogenic needs and health of downstream ecosystem. Recent studies in the literature investigate reservoir operation rules that focus on restoring or improving river ecological system. For example, Shiau and Wu (2005) simulated various combinations of instream flow release and diversions for a projected diversion weir, optimized the operation by minimizing the alteration in the distribution of a list of flow parameters. Suen and Eheart (2006) proposed a paradigm to incorporate the ecological flow regime by simulating the historical data. Yang and Cai (In press) developed a multi-objective optimization model that minimizes flood damage and maximizes fish diversity by generating synthetic daily inflow data. Yin et al. (2011) proposed an approach to consider water supply reliability and environmental flow requirements by utilizing water level and inflow as two triggers for different environmental flow management rules.

In the previous chapter, a framework for adaptive reservoir operation was developed to help meet anthropogenic needs and restore natural flow pattern. This was demonstrated for a hydropower dam in Virginia. Daily allocations for multiple uses were determined decided for the following month by solving a mixed integer optimization model. While in Chapter 3, the

framework was demonstrated only under perfect streamflow forecasts, this chapter examines how it performs when reservoir inflows are based on streamflow forecasts.

There are different forms of streamflow forecasts, e.g., deterministic forecasts and probabilistic forecasts. Deterministic forecasts are most commonly used in water planning while probabilistic information is under-utilized. With the development of forecasting skill and data assimilation techniques, ensemble streamflow prediction (ESP) that well represents the uncertainties in streamflow forecasts can be coupled with the adaptive approach.

Streamflow forecasts of varying skills at different time scales have been investigated to improve water resources management. Maurer and Lettenmaier (2004) investigated the potential benefit gained from long-term streamflow prediction for Mississippi River Basin and found that improved streamflow predictions have modest economic value, which in general would increase as the size of the reservoir system decreases. Golembesky et al. (2009) investigated the role of improved 3-month-ahead streamflow forecasts in setting up restrictions for drought management for the Falls Lake Reservoir in North Carolina. The ultimate value of streamflow forecasts can be assessed by the economic benefits (Maurer and Lettemaier, 2004) gained by incorporating the corresponding forecasts into water resources management. In practice, it could be challenging and even impractical (Chiew et al., 2003) to provide a comprehensive assessment since there are potentially different users with interests in various aspects of the streamflow forecasts and water resources, as well as the difficulties associated with providing monetary value to different water uses. In this study, the value of

improved streamflow forecasts are evaluated with respect to: increasing water supply satisfaction ratio; enhancing hydropower generation; meeting end-of-month storage requirements; and reducing mis-hits of ecological flow parameters.

An adaptive operation scheme can also benefit by using streamflow forecasts that are updated over time. Eum and Kim (2010) proposed a monthly ensemble streamflow prediction (ESP) forecasting system that can update the ESP in the middle of a month to reflect the meteorological and hydrological variations during that month, and evaluated the value of updating the ESP in reservoir operations. Alemu et al. (2011) studied a decision support system for optimizing reservoir operation using weekly updated ESP and demonstrated the value of weekly updated flow forecasts. The value of updating the streamflow forecasts once every two weeks is investigated and demonstrated in this study.

The objectives of this chapter are to: (1) Extend the original model to utilize ensemble streamflow forecasts; (2) Evaluate the forecasts skill in balancing ecological flow requirements and anthropogenic uses; and (3) Examine the value of biweekly updated streamflow forecasts in sustainable reservoir operation.

The rest of this chapter is arranged as follows: Section 2 provides the synthetic daily streamflow generation scheme and the Mixed Integer Linear Programming (MILP) model to incorporate water supply, hydropower generation and ecological flow requirements. Two schemes for coupling the synthetic streamflow predictions and the optimization model are

presented. Results of daily reservoir operation based on streamflow forecasts with three different skill levels, as well as the value of biweekly updated streamflow forecasts in balancing anthropogenic uses and ecological flow requirements are presented in Section 3. The chapter concludes with summary and discussion of future research in Section 4.

4.2 Reservoir Operation With Synthetic ESP

4.2.1 Synthetic ESP Generation

There are numerous approaches to generate synthetic streamflows with different skills. In Mauler and Letermaier's study (Maurer and Lettenmaier, 2004), a model generating synthetic seasonal forecasts was employed. Weigel et al. (2008) developed a two-parameter synthetic model to investigate multi-model combination of differently skilled streamflow forecasting. For simplicity, slight modification based on Sankarasubramanian et al. (2009) is used in this study, where gamma distributed noise term instead of normal distributed noise is employed to avoid generating negative values. The following equation describes the process for generating synthetic ESP with a certain skill r.

$$Q_{i,j}' = rQ_i + \varepsilon_j \quad \text{… (4.1)}$$

where $Q_{i,j}'$ represents the jth synthetic flow ensemble member for day i; Q_i is the observation for day i. The mean and variance of daily streamflow observation time series is μ_Q and σ^2 respectively. r is the skill indicator which ranges from 0 to 1. ε_j is the noise term that follows gamma distribution with two parameter k and θ.

$$k\theta = \mu_Q(1-r) \quad \text{… (4.2)}$$

$$k\theta^2 = (1-r^2)\theta \quad \text{… (4.3)}$$

As denoted in Equations 4.2 and 4.3, these two parameter k and θ ensure that the mean and variance of the gamma distribution is $\mu_Q(1-r)$ and $(1-r^2)*\sigma^2$ respectively.

The conditional expectation and marginal expectation of $Q_{i,j}'$ can be expressed as:

$$E(Q_{i,j}') = \rho(Q_i - \mu_Q) + \mu_Q \quad \text{… (4.4)}$$

$$E(E(Q_{i,j}')) = \mu_Q \quad \text{… (4.5)}$$

It can be seen from Equation 4.4 that if the skill of synthetic streamflow generation is 1, then the conditional mean of ensemble forecasts will be the same as that of the observation. If r is closer to 0, then the conditional mean will deviate further from that of the observation. Equation 4.5 denotes that the long-term mean of the observation is preserved by the synthetic generation process independent of the skill level. To investigate how well the flow variability is reserved by this synthetic streamflow generation scheme, the variance of conditional expectation of $Q_{i,j}'$ is examined in Equation 4.6.

$$Var(E(Q_{i,j}')) = Var(rQ_j) = r^2\sigma^2 \quad \text{… (4.6)}$$

It can be seen that variation of streamflow explained by ensemble mean is proportional to square of forecasting skill r.

There are two main characteristics of this generation scheme. First, the long-term average flow of observed streamflow is preserved by the ensemble mean under different skills. This does not hold true for most operational forecasting models since they exhibit a long-term bias. For models with bias, the bias can be eliminated after calibration. Second, the variance

of the streamflow observation is partly preserved in synthetic ESP, which is proportional to the square of skill indicator, as shown in Equation 3.6. Figure 4.1 shows the synthetic ESP with two different skills, where the gray area shows the 5% to 95% percentile of ESP, according to a 90% confidence interval. Figure 4.1(a) shows that the ESP with higher skill level preserves the streamflow variance better and exhibits narrower confidence intervals. It has also been shown that the ensemble mean is more skillful than an individual forecast (Toth and Kalnay, 2003) as shown in the study by Alemu et al. (2011). Hence, ensemble mean is used as input to the reservoir operation optimization model in this study. Figure 4.2 shows the boxplot of the correlation between synthetic ESP and observation. Each boxplot is comprised of 100 realization of synthetic ESP.

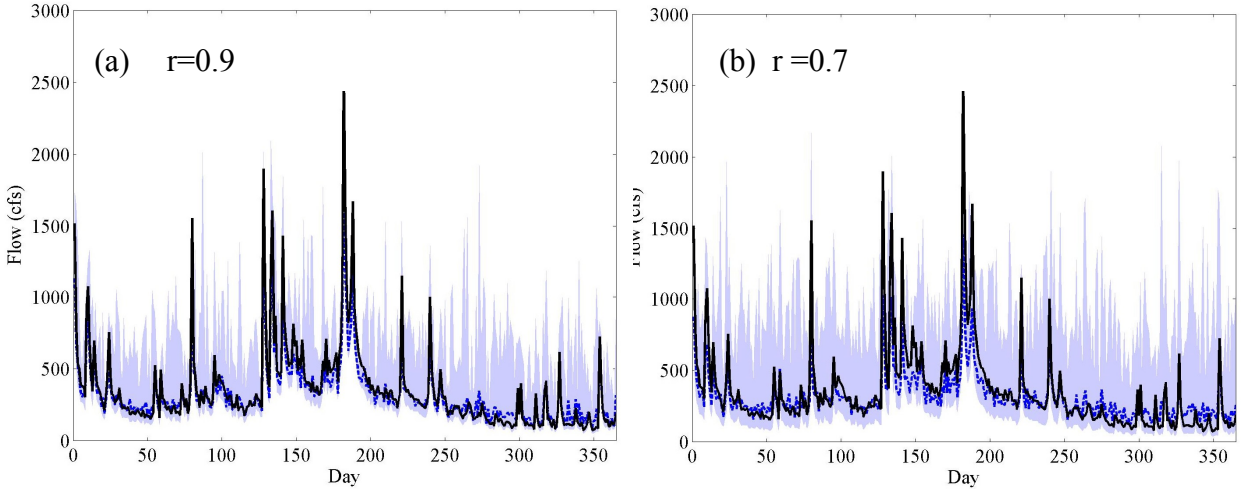

Figure 4.1: An Illustrative example of synthetic ESP with skill indicator r of 0.7 (a) and 0.5 (b).

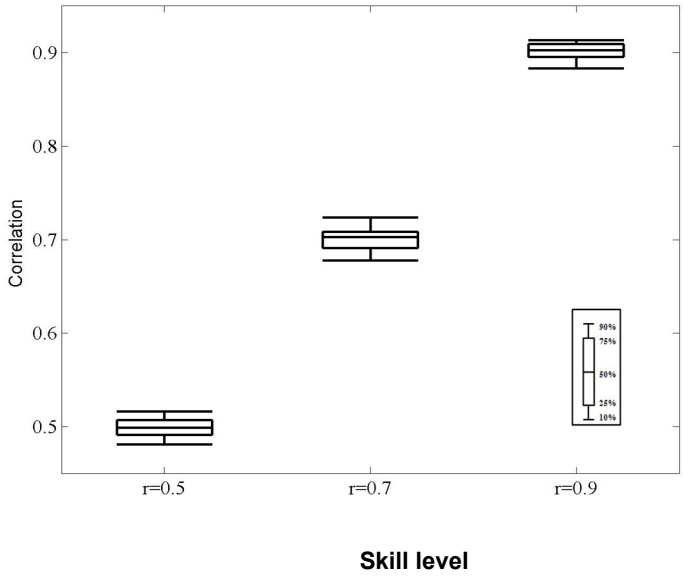

Figure 4.2: Box-plots of correlation between streamflow observation and ensemble member ESP at different skills.

4. 2.2 Reservoir Operation Optimization Model

In the previous chapter, different scenarios of reservoir operation have been examined in detail and it was found that Scenario D has the best performance in balancing anthropogenic uses and ecological flow requirements. Therefore, the same Scenario D in Chapter 3 is employed for analysis in this study. A simple description of the MILP problem is provided and the details of the model formulation are discussed in Chapter 3. The proposed operation mode aims to balance anthropogenic uses and ecological flow requirements. The flow pattern when the reservoir did not exist, i.e., pre-impact years, is assumed to provide the perfect condition for aquatic lives. To preserve a healthy ecological system, the distribution of flow parameters in the post-impact years should be kept similar to that of pre-impact years. Hence, the flow parameter distributions in the pre-impact years are served as a reference; the

measure of mis-hit is introduced to reflect the deviation of the flow parameter distribution in the post-impact years from that of the pre-impact years. To mimic the natural flow pattern, the ecological releases are decided based on forecasted inflow. For example, if the forecasted monthly inflow falls into the low category, the ecological flow parameters are proposed to follow their low categories too. More importantly, this approach can be incorporated into an adaptive operation mode rather than defining a static release policy.

The objective of the MILP formulation is to minimize the total mis-hits of selected flow parameters, whereas anthropogenic uses, e.g., water supply and hydropower generation are provided as constraints. Six flow parameters, as described in the previous chapter, are selected for each month to represent the ecological flow requirements. A mis-hit in each parameter is represented by a binary variable. Water supply ratio is introduced to denote the fraction of monthly water demand being satisfied. A two-dimensional linearlization technique (Ambrosio et.al, 2010) is employed to estimate monthly hydropower generation since it is a nonlinear function of releases through turbines, as well as water head in the reservoir, both of which are affected by the releases. In this study, minimum water supply ratio is set as 0.9 to ensure at least 90% demand satisfaction and the monthly firm hydropower generation is set to at least 300 Million Kilo Watt (MWH). Detailed mathematical formulations of objectives and constraints of the MILP are provided in Chapter 3. The resulting MILP model is as follows:

$$\textbf{Minimize} \quad \sum_{i=1}^{N}(q_1^i + q_2^i) \qquad \textbf{… (4.7)}$$

s.t. $$s_j = s_{j-1} + I_j - R_j - x_j - ws_j - sp_j \quad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.8)}$$

$$s_{\min} \le s_j \le s_{\max} \quad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.9)}$$

$$\sum_{j=1}^{J} ws_j \ge r \times \sum_{j=1}^{J} wd_j \qquad \textbf{… (4.10)}$$

$$ws_j \le wd_j \quad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.11)}$$

$$P_1 = \frac{\sum_{j=1}^{J} x_j}{J} \qquad \textbf{… (4.12)}$$

$$P_2 \le x_j \quad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.13)}$$

$$P_3 \le \frac{\sum_{t=0}^{2} x_{j+t}}{3} \quad \forall j \in \{1,2,..,J-2\} \qquad \textbf{… (4.14)}$$

$$P_4 \le \frac{\sum_{t=0}^{6} x_{j+t}}{7} \quad \forall j \in \{1,2,..,J-6\} \qquad \textbf{… (4.15)}$$

$$P_5 \ge \frac{\sum_{t=0}^{2} x_{j+t}}{3} \quad \forall j \in \{1,2,..,J-2\} \qquad \textbf{… (4.16)}$$

$$P_6 \ge \frac{\sum_{t=0}^{6} x_{j+t}}{7} \quad \forall j \in \{1,2,..,J-6\} \qquad \textbf{… (4.17)}$$

$$\frac{P_2 - x_j}{C} \ge h_j^i \quad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.18)}$$

$$\frac{P_3 - \sum_{t=0}^{2} x_{j+t} / 3}{C} \geq h_j^i \qquad \forall j \in \{1,2,..,J-2\} \qquad \textbf{… (4.19)}$$

$$\frac{P_4 - \sum_{t=0}^{6} x_{j+t} / 7}{C} \geq h_j^i \qquad \forall j \in \{1,2,..,J-6\} \qquad \textbf{… (4.20)}$$

$$\frac{P_5 - \sum_{t=0}^{2} x_{j+t} / 3}{C} \leq h_j^i \qquad \forall j \in \{1,2,..,J-2\} \qquad \textbf{… (4.21)}$$

$$\frac{P_6 - \sum_{t=0}^{6} x_{j+t} / 7}{C} \leq h_j^i \qquad \forall j \in \{1,2,..,J-6\} \qquad \textbf{… (4.22)}$$

$$\sum_{j=1}^{J} (1 - h_j^i) \geq 1 \qquad \forall j \in \{1,2,..,J\} \quad \forall i = 2,3,...,6 \qquad \textbf{… (4.23)}$$

$$P_i \geq (1 - q_1^i) \times t \arg et_{\min}^i + q_1^i \times t \arg et_{\max}^i \qquad \forall i = 1,2,..,6 \qquad \textbf{… (4.24)}$$

$$P_i \leq q_2^i \times t \arg et_{\min}^i + (1 - q_2^i) \times t \arg et_{\max}^i \qquad \forall i = 1,2,..,6 \qquad \textbf{… (4.25)}$$

$$q_1^i, q_2^i, h_j^i \in \{0,1\} \qquad \forall i = 1,2,..,6 \qquad \textbf{… (4.26)}$$

$$h_j^i \in \{0,1\} \qquad \forall i = 2,3,..,6 \quad \forall j \in \{1,2,...J\} \qquad \textbf{… (4.27)}$$

$$\bar{s}_j = (s_{j-1} + s_j) / 2 \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.28)}$$

$$\bar{s}_j = \sum_{k=1}^{K} \alpha_{k,j} st_k \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.29)}$$

$$\sum_{k=1}^{K} \alpha_{k,j} = 1 \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.30)}$$

$$\sum_{k=1}^{K-1} b_{k,j} = 1 \quad \forall j \in \{1,2,..,J\} \quad \forall k \in \{1,2,..,K\} \qquad \textbf{… (4.31)}$$

$$\alpha_{k,j} \le b_{k-1,j} + b_{k,j} \quad \forall j \in \{1,2,..,J\} \quad \forall k \in \{1,2,..,K\} \qquad \textbf{… (4.32)}$$

$$b_{0,j} = 0 \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.33)}$$

$$b_{K,j} = 0 \quad \forall j \in \{1,2,..,J\} \quad \forall k \in \{1,2,..,K\} \qquad \textbf{… (4.34)}$$

$$h_j^e = \sum_{k=1}^{K} \alpha_{k,j} f(st_k) \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.35)}$$

$$h_j^e \le \sum_{l=1}^{L-1} \beta_{l,j} y_{l+1} \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.36)}$$

$$h_j^e \ge \sum_{l=1}^{L-1} \beta_{l,j} y_l \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.37)}$$

$$\beta_{l,j} \in [0,1] \qquad \forall j \in \{1,2,..,J\} \quad \forall l \in \{1,2,..,L-1\} \qquad \textbf{… (4.38)}$$

$$\sum_{l=1}^{L-1} \beta_{l,j} = 1 \qquad \forall j \in \{1,2,..,J\} \qquad \textbf{… (4.39)}$$

$$E_j \le \sum_{k=1}^{K2} \alpha_{k,j} f(q_k, \tilde{y}_l) + M(1-\beta_{l,j}) \qquad \forall l \in \{1,2,..,L-1\} \qquad \textbf{… (4.40)}$$

$$E_j \ge \sum_{k=1}^{K2} \alpha_{k,j} f(q_k, \tilde{y}_l) - M(1-\beta_{l,j}) \qquad \forall l \in \{1,2,..,L-1\} \qquad \textbf{… (4.41)}$$

$$\sum_{j=1}^{J} E_j \ge E_{firm \text{ yield}} \qquad \textbf{… (4.42)}$$

The variables are the same as in previous chapter and the readers are referred to Chapter 3. Daily ESP is coupled with this reservoir operation optimization model in two different ways, as described below.

Coupling Method A:

In this method, the value of using ESP with different skills is investigated. As shown in Figure 4.3 (a), at the beginning, T_0 , of each month, the daily ESP for that month is assumed to be available. Hence, daily releases of the month, from T_0 to T_{end}, are based on the available information at the beginning of that month. To examine the differences in reservoir releases and their efforts on performance, three levels of forecasting skill (r = 0.9, 0.7 and 0.5) were investigated.

Coupling Method B:

In this method, the value of using ESP with updates in the middle of each month is investigated. As shown in Figure 4.3(b), daily ESP of the month is assumed to be first available at the beginning, T_0, for deciding the releases until the end of the month T_{end}. After

first 15 days, updated daily EPS for the rest of the month is assumed to be available. It is presumed that the updated EPS at the middle of the month provides an improved skill for the last two weeks of the month compared to that of the initial ESP. To utilize the updated EPS, observed streamflow for the first 15 days are first used to obtain the initial storage for day 16. Then the updated EPS for the rest of the month combined with releases for the first 15 days are used to run the optimization model to find the daily releases for the rest of the month. Releases of the first 15 days are used because they are needed to compute the ecological flow parameters. ESP with forecasting skill 0.9 is used as the synthetic updated ESP, as compared to un-updated ESP with forecasting skill 0.9 for the first 15 days and 0.7 for the rest of the month.

For both methods, synthetic streamflow of a certain skill was first generated for the whole study period (21 years) and the reservoir release optimization model was solved on a monthly time scale. The mathematical model was built in AMPL and solved by CPLEX. Since synthetic streamflow is influenced by random number, 30 realizations of each synthetic EPS are generated to obtain a better evaluation among different skills.

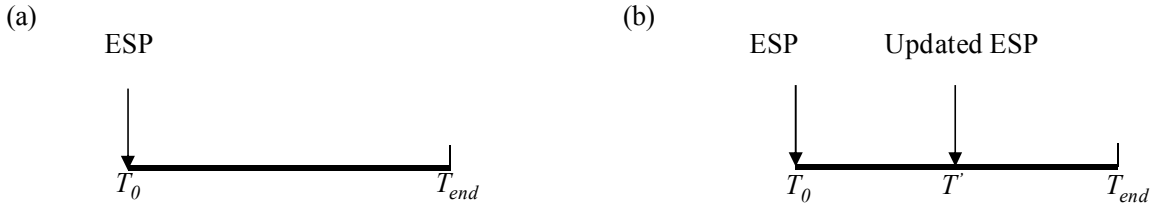

Figure 4.3: (a) Schematic illustration for coupling method A: Daily ESP with a certain skill is used to decide the daily releases for all consumptive purposes; (b) Schematic illustration for coupling method B: Daily ESP available at T_0 is used to decide the first 15 day releases while updated ESP is employed to decide the releases for the rest of the month.

4.3 Results and Discussion

4.3.1 Value of Improved Streamflow Forecasts

Synthetic streamflow with three different levels of skills, representing poor (r =0.5), medium (r =0.7) and good (r =0.9) ESP, were used to compare their effect on finding reservoir releases that are able to meet anthropogenic and ecological flow requirements. For the forecasts with all three skills, the minimum water supply ratio and reliable hydropower generation were satisfied over the post-impact years. But since there is a discrepancy between model simulated hydropower generation using inflow forecasts and observations, the generated hydropower could be less than the firm energy requirement. The end-of-month storage failure rate, f, is defined to quantify the number of times the end-of-month storage is less than the storage requirement, which is defined as follows:

$$f = \frac{m}{M} \qquad \text{... (4.43)}$$

where m is the number of months when end-of-month storage is less than the end-of-month storage requirement; M is the total number of months in post-impact years, which is 252 (21 years) in this study. Table 4.1 lists the f values under different forecasts. These results show better skilled forecasts result in lower violation rate for end-of-month storage. Due to different forecasts, releases for hydropower generation are also different, as Figure 4.4 shows the comparison of monthly hydropower generation two different levels of ESP skills. The variability of monthly hydropower generation is higher for better skilled forecasts, though the difference among long-term average hydropower generation is small.

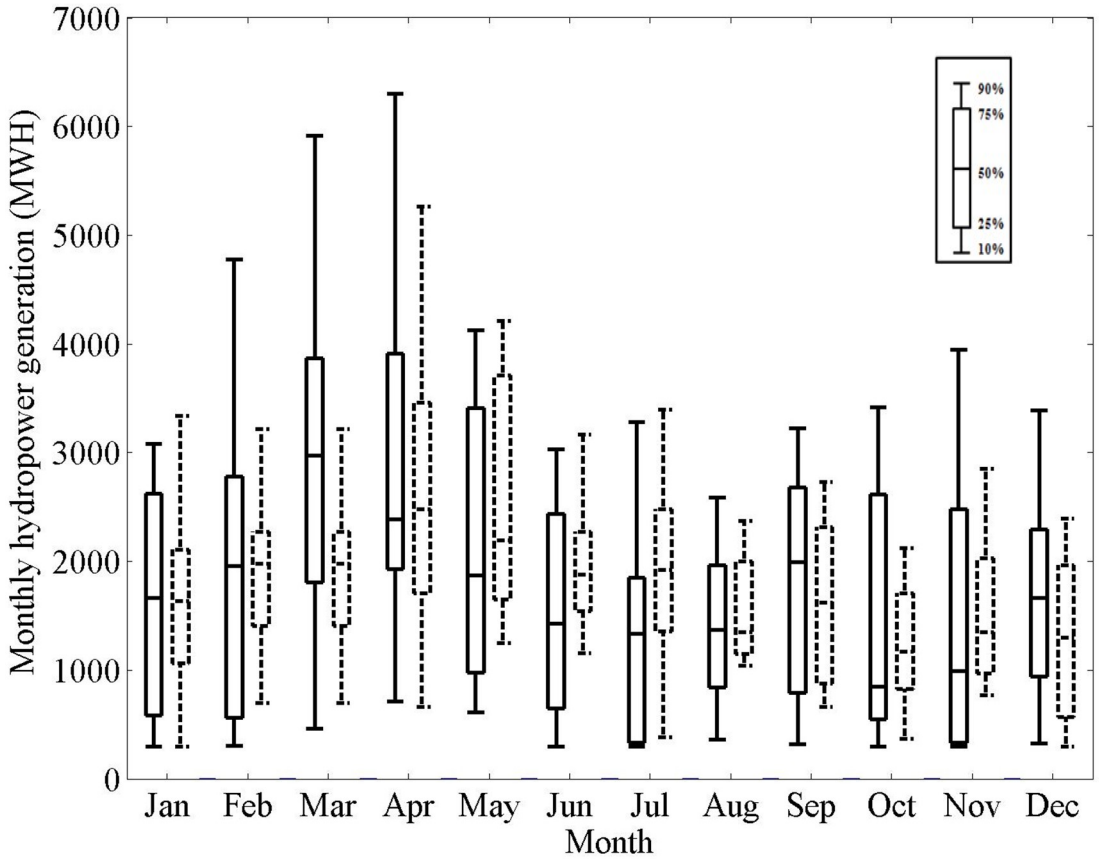

Figure 4.4: Comparison of hydropower generation between two synthetic forecasts. Solid (dotted) box-plots denote skill is 0.9 (0.5).

Table 4.1: Comparison of monthly hydropower generation and end-of-month storage failure rate among all the scenarios investigated in this study.

	Average Hydropower Generation (MWH)	**End-of-Month Storage Failure rate (%)**	**Total Mis-hits**
r=0.5	1922.5 (4.7)	41.25 (1.1)	483.6 (18.4)
r=0.7	1944.1 (5.1)	27.48 (0.9)	379.8 (17.2)
R=0.9	1946.9 (5.3)	12.7 (1.3)	144.8 (16.4)
non-update	1945.8 (4.4)	19.76 (1.4)	244.4 (20.17)
Update	1948.8 (3.3)	11.08 (1.0)	136.6 (15.7)
Historical data	2218	37.1	754

The most notable in performance due to reservoir releases difference resulting from the three sets of forecasts is in the mis-hits for ecological flow parameters. For example, Figure 4.5(a) shows the comparison of daily ecological releases in October 1950 for the three forecasting skills Figure 4.5(b) shows the resulting October average outflows. At skill level of 0.9, the number of times the parameter value falls in each category is the same in the post-impact years. Hence, mis-hits under such circumstance are close to zero. Table 4.2 provides a summary of the number of mis-hits for the six ecological flow parameters in each month. The last column with the total number of mis-hits for all the ecological flow parameters illustrates that smallest number of mis-hits occur when forecasting skill is 0.9.

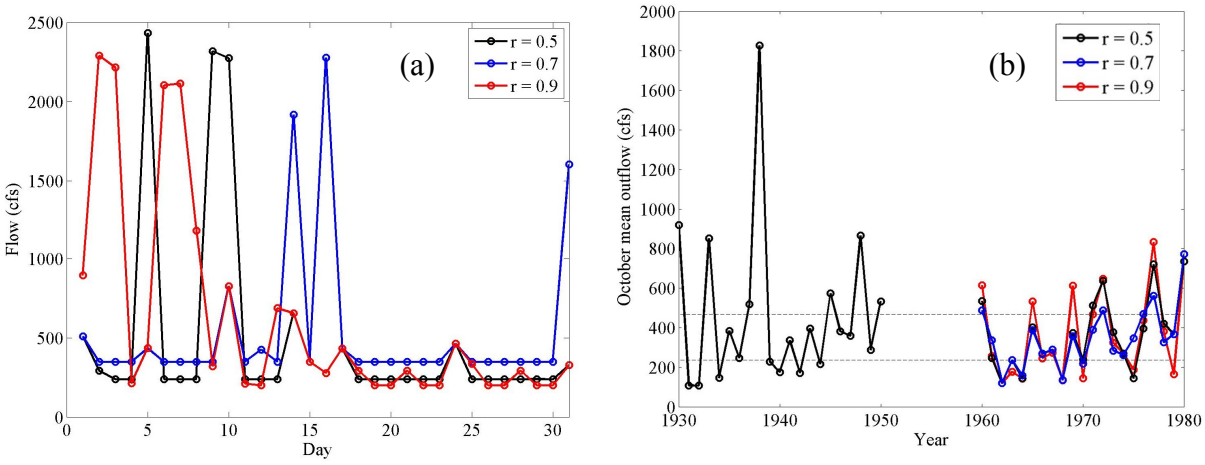

Figure 4.5: (a) Comparison of daily releases in October 1950 for one realization of synthetic ESP with different skills; (b) Comparison of October mean outflow between pre-impact and post-impact years among the three different synthetic ESP.

Table 4.2: Comparison of mis-hits, for each ecological flow parameters, based on releases resulting from different skills.

		1 day min	3 day min	7 day min	3 day max	7 day max	monthly mean	total
Jan	r=0.9	2	2	0	2	2	2	10
	r=0.7	4	4	4	4	4	6	26
	r=0.5	2	2	2	2	4	4	16
Feb	r=0.9	2	2	2	4	4	2	16
	r=0.7	2	2	2	2	2	2	12
	r=0.5	2	2	2	2	2	2	12
Mar	r=0.9	2	2	4	4	4	2	18
	r=0.7	2	2	2	2	2	0	10
	r=0.5	4	4	4	4	4	0	20
Apr	r=0.9	0	0	0	0	0	2	2
	r=0.7	4	4	4	2	4	2	20
	r=0.5	6	6	6	4	6	0	28
May	r=0.9	2	2	4	2	0	0	10
	r=0.7	2	2	2	4	2	2	14
	r=0.5	4	4	4	6	4	4	26
Jun	r=0.9	2	4	2	2	2	2	14
	r=0.7	4	4	4	4	4	4	24
	r=0.5	6	6	6	6	6	6	36
Jul	r=0.9	0	0	0	0	0	2	2
	r=0.7	8	8	8	8	8	8	48
	r=0.5	8	8	8	8	8	6	46
Aug	r=0.9	2	2	2	4	4	2	16
	r=0.7	8	8	8	8	8	8	48
	r=0.5	12	12	10	12	12	10	68
Sep	r=0.9	4	4	0	4	6	2	20
	r=0.7	14	14	14	12	12	6	72
	r=0.5	14	14	14	14	12	8	76
Oct	r=0.9	0	2	2	2	2	0	8
	r=0.7	2	2	2	2	4	6	18
	r=0.5	8	8	8	10	10	14	58
Nov	r=0.9	0	0	2	4	2	2	10
	r=0.7	8	8	8	8	8	8	48
	r=0.5	12	12	12	8	8	2	54
Dec	r=0.9	2	4	2	2	2	2	14
	r=0.7	6	6	6	6	6	6	36
	r=0.5	10	10	10	10	10	8	58

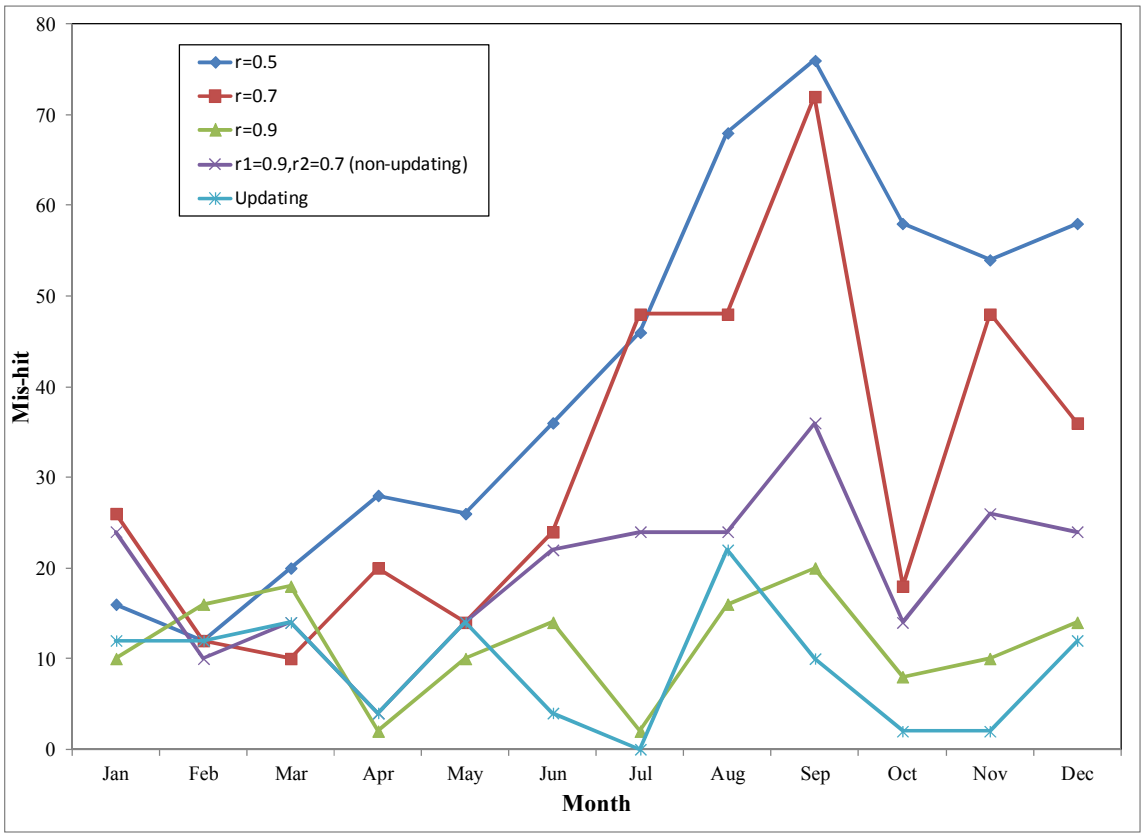

Figure 4.6: Comparison of mis-hits, for all six ecological flow parameters, among different scenarios investigated.

4. 3.2 Value of Streamflow Forecasts Updating

To investigate the value of including updated streamflow in meeting the anthropogenic needs and ecological requirements, two sets of synthetic streamflow data were generated. First set was based on a skill of 0.9 in the first bi-week and 0.7 in the second bi-week, and for the other, forecasting skill is 0.9 for both bi-weeks. Utilizing the first set with the coupling method 1 represents a more realistic case since in reality the skill would be reduced with

increasing forecasting lead. The other set is used in conjunction with coupling method 2, where the first 15 day releases are decided based on streamflow forecasts available at the first day of the month and releases for the rest of the month is based on the updated streamflow information. The comparison between these two cases aims to provide insight of any potential benefits gained by updating streamflow forecasts in the middle of the month with regards to satisfying ecological flow requirements and human uses.

Water supply satisfaction ratio and reliable hydropower generation are posed as hard constraints in the MILP problem. Hence, water supply requirement is satisfied in both methods. As discussed in Section 4.1, though end-of-month storage requirement is satisfied from modeling results, it might be less than storage requirement for some months due to the discrepancy between forecasts and observations. Table 4.1 lists the failure ratio comparison between the two cases, and shows that using updated streamflow reduces the storage failure rate from 19.76% to 11.08% over the 30 realizations of ESP. Figure 4.7(a) illustrates the, for one realization, updated releases for the last two weeks in October 1950 with the updated EPS at day 16. Figure 4.7(b) compares the mis-hits between the two coupling methods for one realization of ESP; coupling method 2 has low mis-hits for most of the months. The mis-hits for all parameters are listed in Table 4.3.

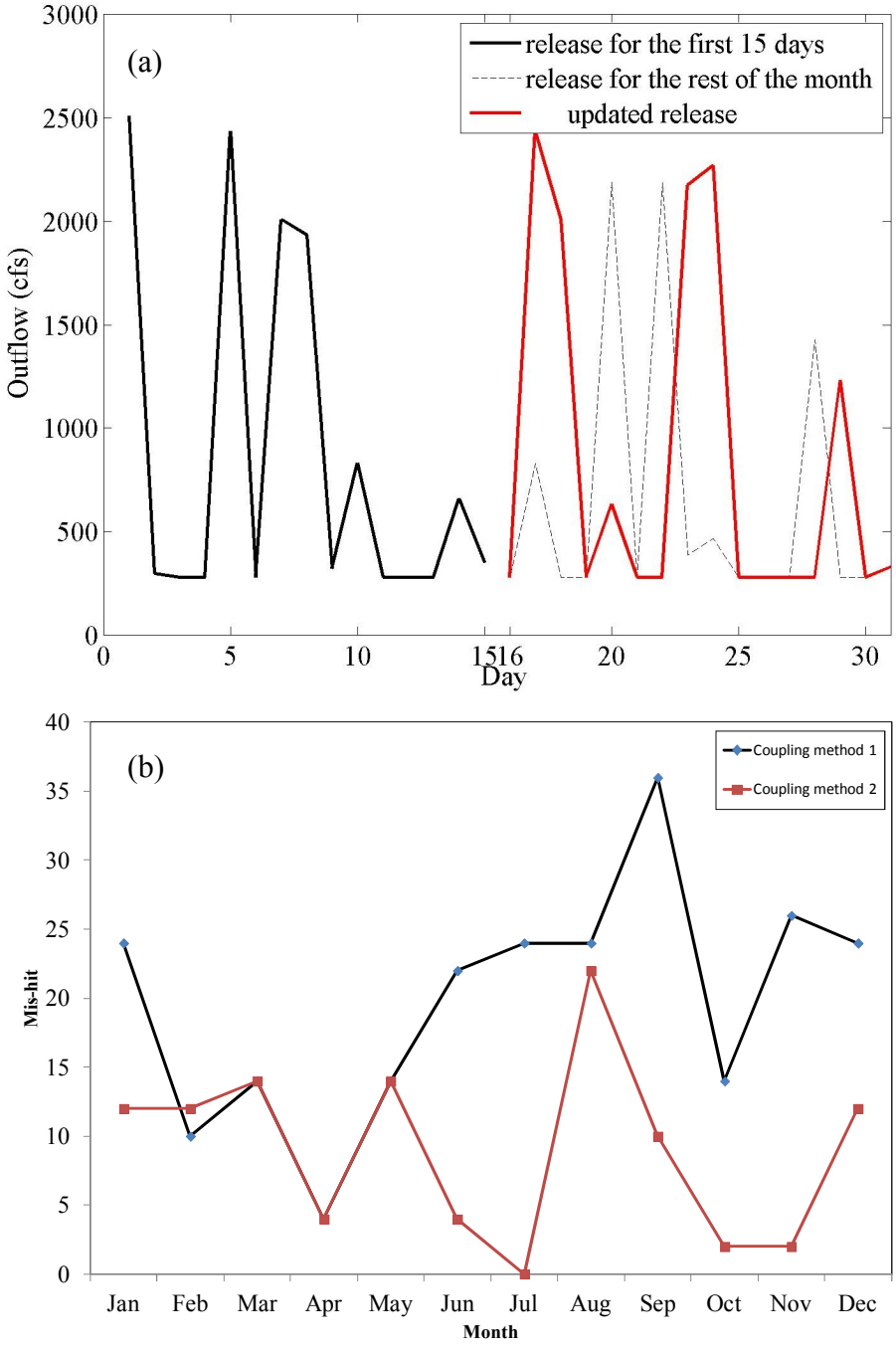

Figure 4.7: (a) An illustrative example of updated releases for the last two weeks in October, 1950. (b) Total mis-hits comparison between updated ESP and non-updated ESP for one realization.

Table 4.3: Mis-hits comparison between non-updated (A) and updated (B) ESP for one realization.

		1 day min	3 day min	7 day min	3 day max	7 day max	monthly mean	total
Jan	A	4	4	4	4	4	4	24
	B	2	2	2	2	2	2	12
Feb	A	2	2	2	2	2	0	10
	B	2	2	2	2	2	2	12
Mar	A	2	2	2	2	2	4	14
	B	2	2	2	2	2	4	14
Apr	A	0	0	0	0	0	4	4
	B	0	0	0	0	0	4	4
May	A	2	2	2	4	2	2	14
	B	2	2	2	4	2	2	14
Jun	A	4	4	4	4	4	2	22
	B	0	0	0	0	0	4	4
Jul	A	4	4	4	4	4	4	24
	B	0	0	0	0	0	0	0
Aug	A	4	4	4	4	4	4	24
	B	4	4	4	4	4	2	22
Sep	A	6	6	6	6	6	6	36
	B	2	2	2	2	0	2	10
Oct	A	2	2	2	2	2	4	14
	B	0	0	0	0	0	2	2
Nov	A	4	4	4	4	4	6	26
	B	0	0	0	0	0	2	2
Dec	A	4	4	4	4	4	4	24
	B	2	2	2	2	2	2	12

4.4 Summary

This chapter demonstrated the applicability of the adaptive reservoir operation framework presented in Chapter 3. By coupling with streamflow forecasting procedures, this study assessed the value of using adaptive reservoir operation aided by stream flow forecasts in meeting the anthropogenic water demands while minimizing the alterations in ecological flow regime. Different skill levels of streamflow forecasts and updating schemes were

investigated and the corresponding improvements in the overall performance were evaluated and compared. For example, when forecasts with better skills were used, the end-of-month storage targets were violated less frequently while the monthly hydropower demand was always met. Further, the number of mis-hits, which was used as a surrogate for ecological flow regime alteration, was reduced more when higher skilled streamflow forecasts were used to determine reservoir releases while meeting the hydropower and water supply demands. When the forecast was updated more frequently, i.e., twice a month versus one a month, these performances improved in a similar manner. These evaluations and comparisons were conducted for ensembles of stream flow predictions to consider the variabilities and their effects of releases and performances.

Additional research is necessary to further demonstrate the applicability of the proposed framework and coupling of forecasts. This should include case studies involving additional reservoirs with different operation conditions and requirements as well as reservoirs in different locations or regions with varying climate and hydrologic conditions. In addition to reservoirs, other engineered structures that affect the downstream flows could be studied using the proposed framework. Through such studies, the results could be collectively investigated to identify relationships among different operating condition, release patterns and performances in meeting the anthropogenic water demands as well as minimizing changes in ecological flow regime.

Chapter 5 Summary and Conclusion

This dissertation focused on improving medium-range (15-day ahead) precipitation forecasts and promoting water resources sustainability. While different approaches to investigate these problems are available, several new research ideas and approaches have been proposed and investigated in this dissertation. A model combination algorithm was proposed and demonstrated to integrate climate and weather information for improving 15-day ahead accumulative precipitation forecasts to improve streamflow forecasts. As streamflow forecasting is not the focus of this dissertation, synthetic Ensemble Streamflow Prediction (ESP) was used to investigate the framework for adaptive reservoir operation to restore as much as possible the natural flow regime while satisfying multiple anthropogenic uses. This framework was first demonstrated using an illustrative real example with perfect streamflow forecasting. It was also investigated under three different levels of forecasting skills and the value of better streamflow forecasting skill was discussed. Further, the value of ESP updating once a month was compared with a non-updated ESP, which was examined using two methods for coupling the synthetic ESP with the proposed reservoir operation optimization model. Figure 5.1 provides a flowchart of analyses conducted in this work.

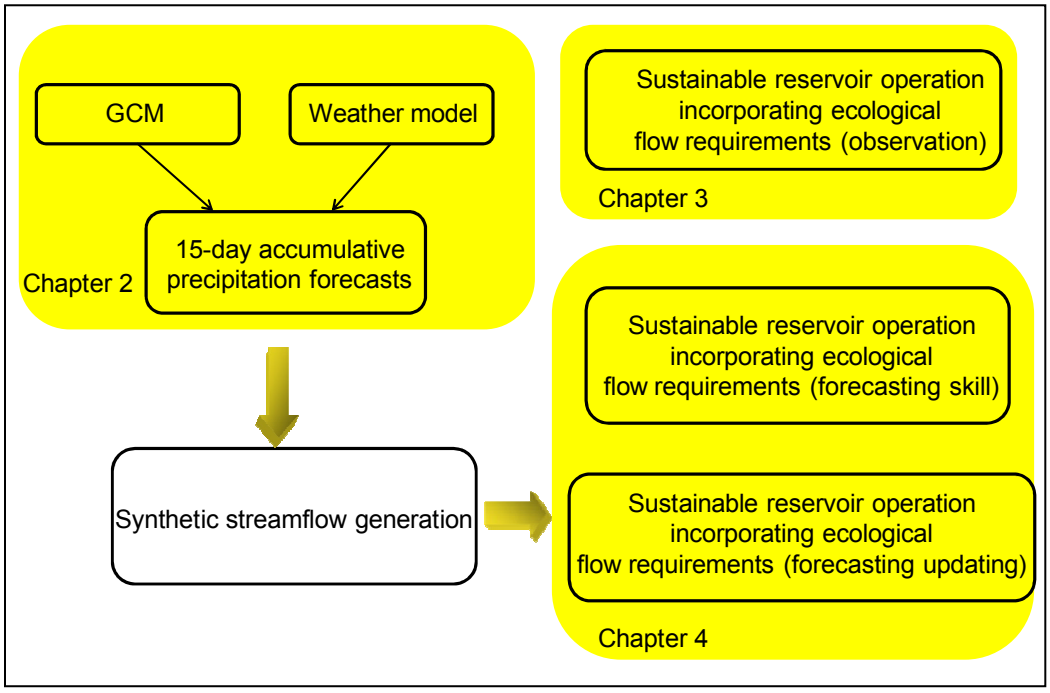

Figure 5.1: Flowchart of analyses conducted in this dissertation. Each highlighted box refers to one chapter.

In Chapter 2, a model combination scheme was developed to combine reforecasts from a numerical weather model (Hamill et al., 2001) and disaggregated climate forecasts from ECHAM4.5 for developing 15-day ahead precipitation forecasts. Evaluation of the weather-climate information (WCI)-based biweekly forecasts under leave-five out cross-validation showed that WCI-based forecasts perform better than reforecasts in many grid points over the continental United States. Correlation between Rank Probability Skill Score (RPSS) and disaggregated ECHAM4.5 forecast errors revealed that lower the error in the disaggregated forecasts, the better the performance of WCI forecasts. Weights analysis from the combination scheme also showed that the biweekly WCI forecasts perform better by

assigning higher weights to the better performing candidate forecasts (reforecasts or disaggregated ECHAM4.5 forecasts). Particularly, WCI-based forecasts perform better during summer months when reforecasts have limited skill. Even though the disaggregated climate forecasts do not perform well over many grid points, the primary reason WCI-based forecasts perform better than reforecasts is due to the reduction in the overconfidence of reforecasts. Since the disaggregated forecasts are better dispersed than reforecasts, combining them with reforecasts results in reduced uncertainty in predicting the 15-day ahead accumulative precipitation.

In Chapter 3, an adaptive reservoir operation framework was proposed to explicitly incorporate ecological flow requirements. A general optimization-based decision model was presented to consider simultaneously the multiple anthropogenic uses of the reservoir and desirable ecological releases characterized by sets of parameters that represent the flow regime. Multiple uses of the reservoir, including for water supply and hydropower generation, were modeled as a MILP–based decision model. Hydropower generation, which is represented by a nonlinear function that usually depends on head and water flow, was linearized using a two-dimensional piece-wise linear function. Investigations using a reservoir in Virginia demonstrated that compared to standard releases based on current operation practice, releases simulated using this adaptive framework perform better in mimicking pre-development flows. It is found that there is little tradeoff between anthropogenic use and ecological releases for the illustrative example.

In Chapter 4, the proposed reservoir operation was examined under streamflow forecasts with various forecasting skills. The value of improved streamflow forecasts with regards to balancing competitive water uses was studies. To achieve this, a synthetic daily streamflow generation scheme was employed to generate ensemble forecasts with a pre-defined skill. An illustrative study using three different forecasts skills revealed that better streamflow forecasts help to improve the ecosystem health and reliability of reservoir storage requirement. In addition, the value of biweekly updated streamflow forecasts in daily reservoir operation compared to non-updated streamflow forecasts were also examined by comparing two methods for coupling synthetic ESP and MILP. Results showed that forecasts updating facilitates reservoir operation to better meet anthropogenic needs and ecosystem health.

Major conclusions from the study are summarized as follows: (1) WCI-based 15-day ahead accumulative precipitation forecasts perform better than reforecasts in many grid points over the continental United States; (2) natural flow pattern of the river can be restored using the adaptive reservoir operation mode which balances ecological flow requirements and anthropogenic uses; for the illustrative example, while there is a tradeoff between water supply and hydropower generation, the tradeoff between mis-hits and hydropower generation is negligible; and (3) improved streamflow forecasts leads to enhanced water sustainability, where lower hydrological flow regime alteration is introduced when operating the reservoir under the adaptive mode.

The key contributions of this dissertation are summarized as follows: (1) integrating climate and weather information provides better probabilistic medium-range precipitation forecasts; (2) an adaptive reservoir operation framework that explicitly incorporates ecological flow requirements is demonstrated to be valuable in achieving improved sustainable reservoir operations; and (3) the value of using streamflow forecasts as well as streamflow forecasts updating with the proposed reservoir operation framework are illustrated.

Recommendations for future research to extend the current study include: (1) conduct additional investigations to assess how the improved medium-range precipitation forecasts can facilitate short-term streamflow forecasts; (2) quantify the relation between flow regime alteration and ecological damage for a specific river system of interest and consider this specific flow regime improvement in reservoir operation; and (3) extend the proposed adaptive reservoir operation framework to incorporate existing operation rules and hedging rules and test it on other river systems where ecological alteration is severe and the allocations between ecological flow and anthropogenic uses are more competitive.

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APPENDICES

Appendix A

Estimation of the dispersion parameter (β)

Weigel et al. (2008) demonstrated that multimodel combination not only depends on individual model's overall skill but also on the dispersion characteristics of the ensembles that represent the conditional probability distribution functions. We employ Weiget et al.'s formulation (2008) estimate the dispersion parameter, β, based on the ensembles of the reforecasts and disaggregated ECHAM4.5 forecasts.

In this study, the number of ensembles (G_m with *m* denoting the models) represented by reforecasts and disaggregated ECHAM4.5 forecasts are 15 and 100 respectively. Given the forecasts, $EP_{j,t}^{m}$ from both models, Weigel et al., (2008) suggested estimation of β for each model *m* based on equation (A1).

$$\hat{\beta}_j^m = \sqrt{\text{var}(\hat{EP}_j^m) - \frac{1}{G_m}\hat{\tau}_{ens,j}^{m\,2} - \hat{\alpha}_j^m} \qquad \text{(A1)}$$

Where $\text{var}(\hat{EP}_j^m)$ denotes the variance of the ensemble mean of the candidate forecasts from the 26 years of data, α denotes the correlation between the ensemble mean and observations over 26 years and $\hat{\tau}_{ens,j}^{m\,2}$ represent the conditional variance or the ensemble spread of each candidate forecasts available in the '*j*' th biweek with G_m denoting the number of ensmebles in each candidate forecasts. For additional details, see Weigel et al., (2008).