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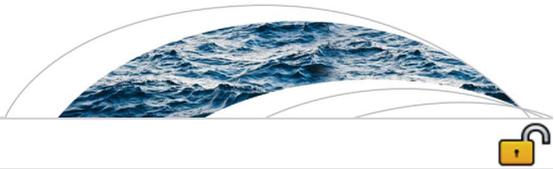
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- Climate forecasts promote interbasin transfer
- Spatial correlation between inflows and initial storage control the transfers
- Low spatial correlation between inflows and/or initial storage promote IBT

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Improved regional water management utilizing climate forecasts: An interbasin transfer model with a risk management framework

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Abstract

Regional water supply systems undergo surplus and deficit conditions due to differences in inflow characteristics as well as due to their seasonal demand patterns. This study proposes a framework for regional water management by proposing an interbasin transfer (IBT) model that uses climate-information-based inflow forecast for minimizing the deviations from the end-of-season target storage across the participating pools. Using the ensemble streamflow forecast, the IBT water allocation model was applied for two reservoir systems in the North Carolina Triangle Area. Results show that interbasin transfers initiated by the ensemble streamflow forecast could potentially improve the overall water supply reliability as the demand continues to grow in the Triangle Area. To further understand the utility of climate forecasts in facilitating IBT under different spatial correlation structures between inflows and between the initial storages of the two systems, a synthetic experiment was designed to evaluate the framework under inflow forecast having different skills. Findings from the synthetic study can be summarized as follows: (a) inflow forecasts combined with the proposed IBT optimization model provide improved allocation in comparison to the allocations obtained under the no-transfer scenario as well as under transfers obtained with climatology; (b) spatial correlations between inflows and between initial storages among participating reservoirs could also influence the potential benefits that could be achieved through IBT; (c) IBT is particularly beneficial for systems that experience low correlations between inflows or between initial storages or on both attributes of the regional water supply system. Thus, if both infrastructure and permitting structures exist for promoting interbasin transfers, season-ahead inflow forecasts could provide added benefits in forecasting surplus/deficit conditions among the participating pools in the regional water supply system.

1. Introduction

Regional water management aims to balance water supply, which critically depends on the regional hydroclimate, and demand that is driven by the urbanization and growth in the region. Given the limited opportunities for developing new water supply systems, efforts have focused on identifying strategies for both supply augmentation and demand reduction on existing systems. For instance, the most commonly employed supply augmentation strategies are reallocation of existing storages in the reservoir, developing wastewater reuse infrastructure and promoting interbasin transfers [Postel et al., 1996; Gleick, 1998]. Similarly, the popular demand reduction approaches include imposing restrictions for tertiary uses (e.g., watering lawns), lawn buyback programs, and water pricing. Recent studies have shown that the imbalance between supply and demand at seasonal to interannual time scales could be offset by an adaptive approach that changes the allocation conditioned on the inflow forecasts derived using climate information [Sankarasubramanian et al., 2009a, 2009b; Voisin et al., 2006; Zhao et al., 2012]. Most of the studies on utilizing climate information have primarily focused on the application of streamflow forecasts to a single/multiple reservoir system [Golembesky et al., 2009; Georgakakos and Graham, 2008] in a single river basin [Maurer et al., 2002]. Given that the association between climatic conditions and the basin hydroclimatology is usually exhibited at the regional level, it is prudent to utilize the climate-information-based streamflow forecasts for basins that have interbasin transfer (IBT) protocols. Studies have emphasized the importance of IBT in improving regional water management [Cai and Rosengrant, 2004] and also support the transfers with appropriate financial instruments [Characklis et al., 2006]. However, these studies have primarily used

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observed inflows that do not consider inflow uncertainty for setting up the IBT. Thus, the main focus of this study is to: (a) propose a stochastic IBT model that uses probabilistic inflow forecasts for improving regional seasonal water management and (b) generalize the conditions under which the IBT can improve regional water management utilizing seasonal forecasts derived using climate information.

Recent studies show that seasonal inflow over a region is partly influenced by variations in climatic conditions such as sea surface temperatures (SST) [Piechota *et al.*, 2001; Sicard *et al.*, 2002] and partly due to the chaotic nature of the atmosphere and initial land surface conditions [Maurer and Lettenmaier, 2004; Mahanama *et al.*, 2012; Sinha and Sankarasubramanian, 2012]. Hence, considerable effort has been focused on improving the skill of seasonal climate forecasts by reducing uncertainty of climate models [Rajagopalan *et al.*, 2002; Weigel *et al.*, 2008; Devineni and Sankarasubramanian, 2010a, b], by estimating better initial land surface conditions [Koster *et al.*, 2002] and by reducing hydrologic model uncertainty [Ajami *et al.*, 2006; Li and Sankarasubramanian, 2012]. Despite these improvements in streamflow forecast development, application of climate information for water management has faced serious challenges in interpreting probabilistic information in the forecasts and in translating that information into relevant water management attributes [Pagano *et al.*, 2002; Sankarasubramanian *et al.*, 2009a, b].

Most of the studies on IBT have commonly evaluated the allocation under perfect inflow assumption [Cai and Rosengrant, 2004; Pulido-Velazquez *et al.*, 2004; Palmer and Characklis, 2009]. However, assuming perfect inflow information ignores the inflow uncertainty which can critically influence IBT allocations at seasonal to interannual time scales. Recent studies [Yao and Georgakakos, 2001; Hamlet *et al.*, 2002; Georgakakos and Graham, 2008; Golembesky *et al.*, 2009] have clearly demonstrated that seasonal streamflow forecasts could be effectively utilized for improving regional water management. Sankarasubramanian *et al.* [2009a, b] have demonstrated that monthly updated season-ahead inflow forecasts could be utilized adaptively to increase/decrease release for each use. Yao and Georgakakos [2001] demonstrated that reliable inflow forecasts and adaptive decision systems can substantially benefit reservoir performance. However, the utility of climate forecasts in reservoir management is sensitive to prediction skill, system characteristics, and management objectives [Georgakakos and Graham, 2008; Sankarasubramanian *et al.*, 2009a, b]. Given that IBT reduces the cost and increases the reliability in water allocation [Characklis *et al.*, 2006], it is critical to evaluate the potential benefits of climate-information-based forecasts for facilitating IBT. For instance, if two basins exhibit significantly different initial storage conditions at the beginning of a season, then streamflow forecasts could be utilized to facilitate IBT based on the agreed protocols for improving regional water sustainability. This study mainly focuses on investigating three aspects related to IBT across multiple pools/reservoirs: (a) role of inflow forecast skill, (b) importance of spatial correlation between inflows across the multiple systems, and (c) role of spatial correlation between the initial storages across the pools. For this purpose, the study considers IBT between Falls Lake and Jordan Lake in the Research Triangle Area of North Carolina (NC), which has been experiencing frequent demand-induced droughts due to rapid growth in population and development.

In this paper, section 2 discusses the regional water management issues in the study region in NC and provides the data sources related to the development of forecasts and reservoir models. Section 3 proposes an IBT optimization model and demonstrates the utility of seasonal climate forecast in promoting IBT in the study area. Section 4 utilizes a synthetic streamflow forecasting model to generalize the findings on the utility of climate forecasts in facilitating IBT. Finally, we summarize the findings and conclusions arising from the study.

2. Study Region and Data Sources

2.1. Water Management in the Research Triangle Park (RTP) Area and Potential for IBT

Two major water supply systems, Falls Lake reservoir in the Neuse River basin and the Jordan Lake reservoir in the Cape Fear River basin, primarily serve the municipalities (Raleigh, Cary, Apex, and Morrisville) in the RTP region. Figure 1 shows the water supply and demand nodes in the area. Falls Lake, which primarily supplies the City of Raleigh withdrawing 70 MGD-million gallon per day (MGD), whereas Jordan Lake supplies water to three municipalities, Cary, Apex, and Morrisville, with a daily withdrawal of 16 MGD.

Apart from supplying water to the municipalities, both reservoirs also have to maintain required water quality releases to sustain healthy downstream ecology. The mandated water quality releases during the

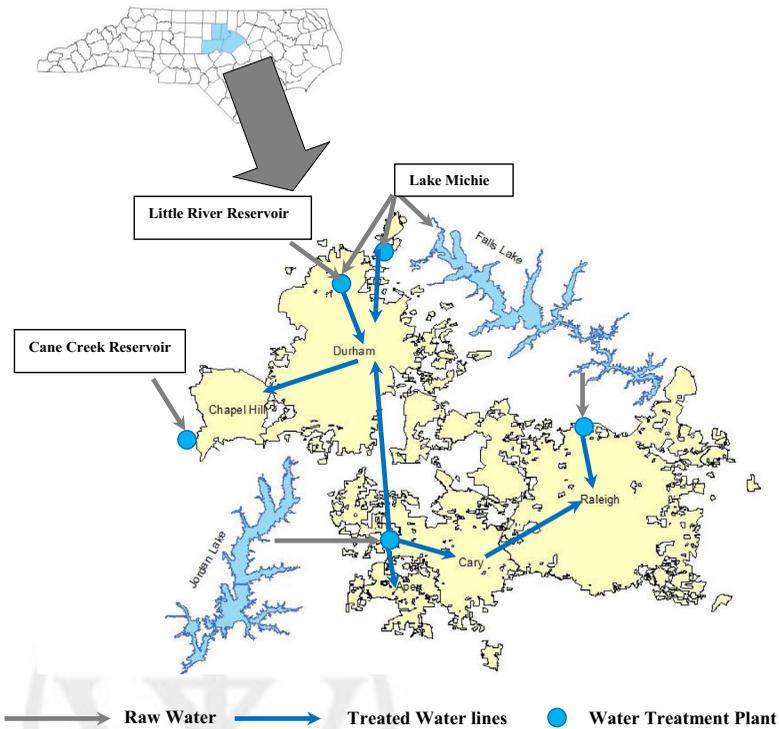


Figure 1. Infrastructure for interbasin transfer across Cape Fear River basin and Neuse River basin, North Carolina. Two Reservoirs (Falls Lake and Jordan Lake) and the demand nodes (Cary, Apex, Durham, Chapel Hill, and Raleigh) are also presented.

summer (July–August–September) season are 255 cfs (cubic feet per second) for Falls Lake and 600 cfs for Jordan Lake. To manage the reservoir for water supply and water quality purposes, the US Army Corps of Engineers (USACE) has two storage units within the conservation pool of each reservoir (Table 1). Both the inflows and evaporation of the lakes are also apportioned in the same ratio as specified for water supply and water quality pools in both systems (Table 1).

2.2. Proposed IBT Between Cape Fear River Basin and Neuse River Basin

Palmer and Characklis [2009] explored the potential for reducing the cost of meeting continually increasing water demand through IBT. They proposed to utilize the existing IBT for Chapel Hill and Durham (partly in the Neuse River basin) from Jordan Lake by distributing the water from the Cary Water Treatment Plant, so that future increased demand at Durham and Chapel Hill could be met with desired reliability. The motivation behind their proposal is to eliminate the investment cost for a new water treatment plant for distributing the water from Jordan Lake to Chapel Hill and Durham. The proposal suggested to treat the allocated water for the two cities at the Cary Water Treatment Plant and to distribute the treated water through the existing infrastructure between Cary and Durham.

The existing IBT plan between Upper Neuse River basin and Haw River basin (that feeds into Jordan Lake) allows a transfer of up to 24 million gallons per day (MGD) from Jordan Lake to Neuse River basin. Given that the physical infrastructure (i.e., distribution networks) exists to distribute the treated water across the region, recent studies have also emphasized the need for regional water management plans to meet future

Table 1. Water Supply and Water Quality Storages Within Conservation Storage of Falls Lake and Jordan Lake Reservoir (All Values Are in Acre-Feet)

	Dead Storage	Conservation Storage		Releases (R_i)		Flood Control Storage
		Water Supply	Water Quality	Water Supply	Water Quality	
Falls Lake	25,073	45,000 (42.3%)	61,322 (57.7%)	22,497	45,520	221,182
Jordan Lake	74,730	45,800 (32.62%)	94,600 (67.3%)	5142	107,108	538,400

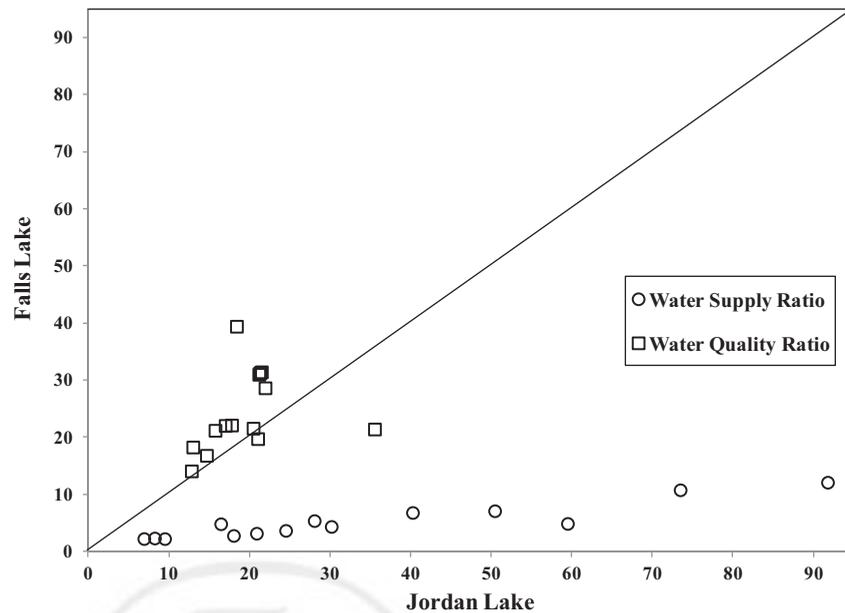


Figure 2. Water availability (inflow + initial storage) to demand ratio for water supply pool and water quality pool for Falls Lake and Jordan Lake, NC. WAD ratio for water quality pool is multiplied by a factor of 10 to match the scale of the figure.

demand (Triangle Journal of Governments, 2013). Since Falls Lake and Jordan Lake are the two major systems in the region, we propose an IBT framework to manage these two systems for ensuring regional water sustainability. For instance, under extreme low storage conditions in Falls Lake, additional water could be released from Lake Michie to downstream of Falls Lake and this additional downstream release could be offset by an equivalent transfer from Jordan Lake to Durham and Chapel Hill using the existing distribution networks. Another option is to release the water directly from Cary Water Treatment Plant to Raleigh through the existing distribution network between Cary and Raleigh. Similarly, if Jordan Lake experiences severe drought conditions, water from the Falls Lake system could be transferred to Cary to offset the reduced availability in Jordan Lake. Since Lake Michie, Little River Reservoir, and Cane Creek Reservoir supply water only to Durham and Chapel Hill and do not have any agreed IBT protocols, transfer among them are not considered as part of the IBT framework proposed here. Further, since the storage capacities of Falls Lake and Jordan Lake are much larger than that of the other Lakes (Michie, Cane Creek Reservoir, and Little River Reservoir) that supply water to these municipalities, we are not considering them as part of the IBT framework.

Before we investigate the added benefits of IBT in improving regional water sustainability, we first explore the scope for IBT by looking at water availability to demand during the summer in water quality and water supply pools in both reservoirs. Given that both reservoirs are within-year systems (i.e., do not carry a surplus/deficit from 1 year to next), it is desired that the storage in each pool needs to be at the operational rule curve, which is the top of the conservation storage by 1 July to deliver the summer demand and to have enough space for flood control. Any deviation above that storage will increase the flood risk and substantial deviations below the target storage will exacerbate the failure to supply the summer and fall demand. Figure 2 shows the water availability to demand (WAD) ratio as $\psi_t = \frac{S_0 + I_t}{O_t}$ during the summer (July–September, JAS) season where S_0 denotes the storage for water supply/quality on 1 July in year t , I_t denotes the JAS inflow for water supply/quality purpose and O_t denotes the water supply/quality release for the year t .

From Figure 2, we can infer that the WAD ratio in the water supply pool of Jordan Lake is abundant compared to the WAD ratio in the water supply pool of Falls Lake indicating the potential for significant benefits from IBT. On the other hand, WAD ratio for water quality purpose is similar for both systems. The intent of this research is to develop an IBT framework for these four pools within the two reservoir systems so that the total-end-of-the-season deviation from the target storage across the four systems could be minimized conditioned on the climate-information-based seasonal forecasts.

2.3. Data Sources and Inflow Forecasts Development

Historical monthly inflows (1957–2008) and outflows (1991–2008) for both Falls Lake and Jordan Lake were collected from the US Army Corps of Engineers (USACE), Wilmington district (<http://epec.saw.usace.army.mil/>) along with the storage information. The operating rule curves for Falls Lake and Jordan Lake are 251.5 feet (ft) above the mean sea level (m.s.l.) and 216.0 ft m.s.l, respectively. For Falls (Jordan) Lake, the conservation storage levels for water supply and water quality purposes range between 236.5 and 251.5 ft (150–216 ft) and the controlled flood storage levels range between 251.5 and 264.8 ft (216–240 ft). Any storage below the conservation storage is assumed as dead storage for modeling purposes. Since the summer season is the challenging period for meeting water quality and water supply demands, we consider 1991–2008 July–August–September (JAS) months for demonstrating the utility of inflow forecasts in facilitating IBT between the two systems.

Given the main interest is in utilizing climate-information-based streamflow forecasts in initiating IBT, we developed inflow forecasts for both Falls Lake and Jordan Lake using the historical monthly inflows available for the period 1957–2008. For this purpose, we considered 3 month ahead precipitation forecasts issued on 1 July from the ECHAM4.5 atmospheric General Circulation Model (GCM) (http://iridl.ideo.columbia.edu/SOURCES/.IRI/.FD/.ECHAM4p5/.Forecast/.ca_sst/) forced with constructed analog sea surface temperature (SSTs) forecasts available for the period 1957–2008. Given that the two reservoirs are near each other (within 30 miles) and both basins have similar hydroclimatology, the correlation between JAS inflows into both lakes is 0.92. Hence, we considered the first principal component of the JAS inflow, which accounts for 86% of the total variance in JAS inflows for developing an inflow forecasting model. The first principal component of JAS inflows was correlated with JAS precipitation forecasts (issued in 1 July) available over four grid points around the region. Apart from these four grid points of precipitation forecasts, we also considered the June streamflow into each lake as predictors for developing inflow forecasts.

Principal Component Regression (PCR) model was developed using the JAS precipitation forecasts from four grid points and the June streamflow into each lake as predictors and the first principal component of JAS inflow into each lake as predictand for the period 1957–1990. For additional details on developing a PCR model, see *Sankarasubramanian et al.* [2009a, b]. The PCR model was then employed to develop a retrospective forecast for the period 1991–2008 using the predictors available over that period. *Devineni et al.* [2008] combined two different inflow forecasting models namely a PCR model and a semiparametric resampling model, to develop improved multimodel streamflow forecasts for JAS into Falls Lake. *Golembesky et al.* [2009] utilized these multimodel forecast for invoking restrictions during the summer in Falls Lake. It is well known that streamflow forecasts with better skill result in increased yields from reservoir systems [*Maurer and Lettenmaier, 2004; Sankarasubramanian et al., 2009a, 2009b*]. Given that the focus of this study is to demonstrate the utility of inflow forecast in improving IBT, we primarily employed a simple PCR model for forecasting inflows into each lake. Thus, the retrospective forecasts for the period 1991–2008 estimated the conditional mean and variance of the first PC of the inflow into each lake, which were back transformed to their original flow space using the inverse of the matrix of the eigenvectors. The correlations between the conditional mean of inflow forecasts and the observed JAS inflows for Falls Lake (Figure 3a) and Jordan Lake (Figure 3b) were 0.55 and 0.54, respectively, which were statistically significant at the 95% confidence interval. Figure 3 also shows the climatological thresholds for below-normal (33rd percentile) and for above-normal (67th percentile) inflow conditions along with the forecasted and observed JAS inflows for each year. From Figure 3, inflow forecasts overall capture the variability in observed summer flows. For instance, in year 1999 (1993), an above-normal (below-normal) inflow year, the conditional density is shifted toward the upper (lower) tails of the climatological percentiles. Most of the evaluation on seasonal forecasting over the Southeast US using a physically distributed model have reported a correlation of around 0.6–0.7 for the summer season [*Sinha and Sankarasubramanian, 2014; Li et al., 2009*]. Forecasts are also incorrect in few years (e.g., 1997—an above-normal inflow year; 2007—a below-normal inflow year) with the conditional density being incorrectly estimated in the inflow forecast. Thus, by using the conditional mean and point forecast error of JAS inflows into each lake and by assuming the flows follow log-normal distribution, we obtained 1000 realizations of inflows that were forced into the IBT model, which is discussed in the next section.

3. IBT Based on Climate Forecasts: Formulation and Application

3.1. InterBasin Transfer Water Allocation Model

This section describes the water allocation model for transferring water across multiple pools/reservoirs such that the sum of the deviations from the end-of-season target storage across the considered pools/

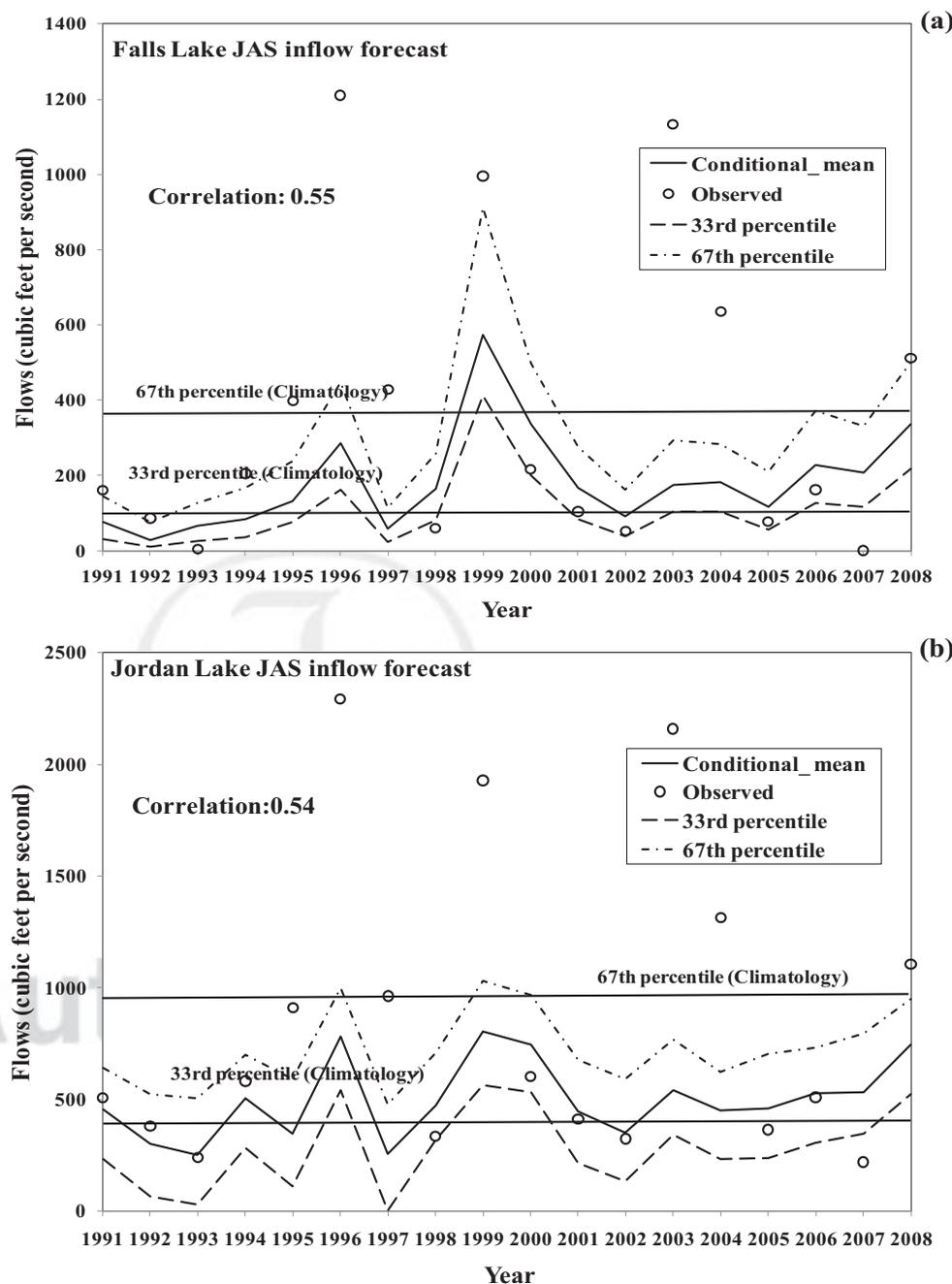


Figure 3. Downscaled JAS inflow forecasts for the (a) Falls Lake and (b) Jordan Lake using ECHAM4.5 precipitation forecasts and June inflow for the period 1991–2008. Horizontal lines indicate the below-normal (33rd percentile) and above-normal (67th percentile) climatological thresholds.

reservoirs is at its minimum. The novelty of the proposed framework lies in developing a stochastic linear programming model that promotes interbasin transfer by minimizing the total deviation from the target storage for all the users in by utilizing ensembles of inflows developed using climate information. Thus, the objective for a given summer season is to minimize the expected sum of the normalized deviations:

$$E \left[\sum_{i=1}^n \left(\frac{|S_i - S_i^*|}{S_i^*} \right) \right] \quad (1)$$

where S_i is the forecasted end-of-season storage and S_i^* is the target storage in the i th pool out of the total “ n ” pools/reservoirs. The expected sum (equation (1)) is minimized by changing the decision variables, x ,

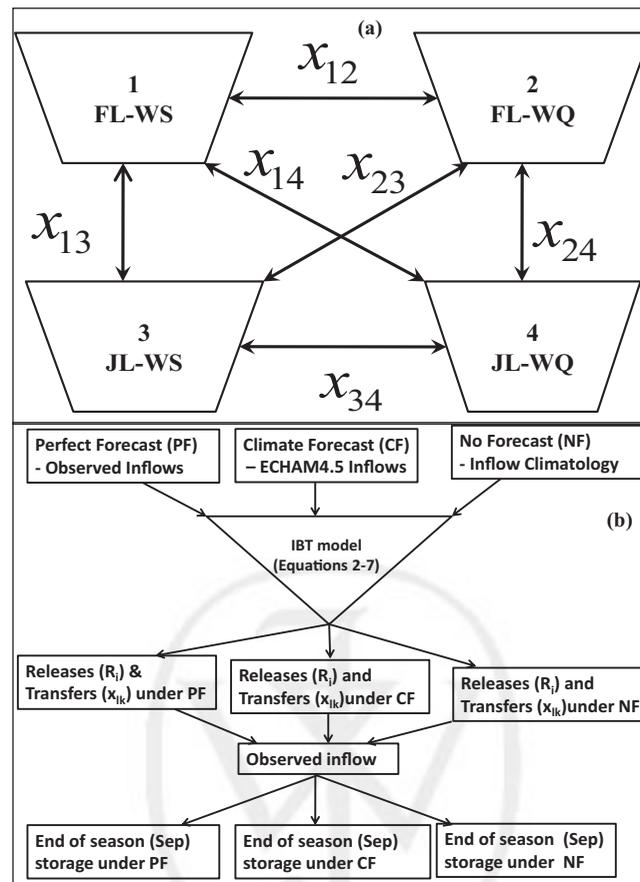


Figure 4. (a) Proposed interbasin transfer scheme and (b) the experimental design for validating IBT model under three inflow scenarios for meeting the end of the season target storage (September) across four pools in two reservoirs, Falls Lake and Lake Jordan, in the Triangle Area. Pools 1 (3) and 2 (4) denote the water supply and water quality storages in the Falls (Jordan) Lake and the arrows indicate the potential for transfers in Figure 4a.

pool i , and x_{lk} is the transferred water between user/pool l to the user/pool k . The primary purpose behind this IBT model is to find reliable delivery of water during droughts and to reduce the vulnerability of not having enough storage to meet the future demand without compromising the downstream needs of each basin. Thus, the decision variables, x_{lk} , can be positive (negative) if water is transferred from $l(k)$ to $k(l)$. Finally, the lower bound and upper bound for each x_{lk} are specified based on equation (4) as the sum of maximum storages between the two uses “ l ” and “ k ” and maximum required release between the two users “ l ” and “ k ”

$$-(\max(S_l, S_k) + \max(R_l, R_k)) \leq x_{lk} \leq \max(S_l, S_k) + \max(R_l, R_k) \quad (4)$$

Figure 4a shows the potential transfers across the four pools in the Falls Lake and Jordan Lake system. Equation (2) implies that each pool in the regional water system should deliver the desired release R_i . The potential transfers, x_{lk} , are the decision variables which guarantee the target release, R_i , being delivered and ensure the total deviation from the target storage across all the pools is at its minimum. The values of R_i (Table 1) and x_{lk} do not vary under each realization j . Thus, given “ n ” users, the total number of decision variables (x_{lk}), i.e., the potential transfers is $n * (n - 1)/2$. For Falls Lake and Jordan Lake, there are four pools. So, the number of potential transfers is six.

Since all the constraints in the above model (equations (2–4)) are linear except for the objective function (equation (1)), we introduce two surrogate variables S_{ij}^+ and S_{ij}^- , for solving the formulation as a linear programming (LP) model. Reformulating the above model, the objective function (equation (1)) can be written as:

that denotes the transfers between the pools and the expectation is obtained based on M ($M = 1000$) realizations of storage obtained from the M realizations of apportioned inflows available for each pool. For each realization, j ($j = 1, 2, \dots, M$) of apportioned inflows, Q_{ij} , the mass balance for each pool/reservoir i can be written as:

$$S_{i,j} = S_i^0 + Q_{i,j} - E_{i,j} - \left(R_i + \sum_{k=1}^n \sum_{l=k+1}^n x_{lk} \right) \quad \forall i=1, 2, \dots, n; \quad j=1, 2, \dots, M \quad (2)$$

$$S_i^{\min} \leq S_{i,j} \leq S_i^{\max}, \quad \forall i=1, 2, \dots, n; \quad j=1, 2, \dots, M \quad (3)$$

S_i^{\min} is the minimum storage for reservoir i , S_i^{\max} is the maximum storage for reservoir i , $S_{i,j}$ is the end-of-season storage at reservoir i for the realization j , S_i^0 is the beginning of season storage at reservoir i , $Q_{i,j}$ and $E_{i,j}$ denote the apportioned inflow and evaporation under realization j for user i , R_i is the required water supply release from the

$$\text{Minimize } \frac{1}{M} \sum_{j=1}^M \left[\sum_{i=1}^n (S_{ij}^+ + S_{ij}^-) / S_i^* \right] \quad (5)$$

where 243
 S_{ij}^+ denotes the excess storage above target storage (S_i^*) for pool i in realization j ; 244
 S_{ij}^- denotes the shortfall below target storage (S_i^*) for pool i in realization j ; 245
 and 246

$$S_{ij}^+ - S_{ij}^- = S_{ij} - S_i^* \quad \forall i = 1, 2, \dots, n; j = 1, 2, \dots, M \quad (6)$$

$$S_{ij}^+ \geq 0, S_{ij}^- \geq 0 \quad \forall i = 1, 2, \dots, n; j = 1, 2, \dots, M \quad (7)$$

Thus, the expectation in equation (5) is across all 1000 realizations. The above LP model with the objective 247
 function in equation (5) and constraints in equations (2), (3), (4), (6), and (7) was solved in the IBM ILOG 248
 CPLEX optimization studio to obtain different transfer scenarios. 249

3.2. IBT Based on Climate-Information-Based Streamflow Forecasts: Application 250

Based on the formulation presented in section 3.1, climate-information-based streamflow forecasts were 251
 employed for initiating the IBT framework for the Triangle Region in NC. The IBT model was set for initiating 252
 the water transfer at the beginning of the summer season (1 July) between the four pools in the two reser- 253
 voirs (Figure 4a), Falls Lake and Jordan Lake. Six potential transfers (Figure 4a) are possible among the four 254
 pools (FL-WS: Falls Lake water supply; FL-WQ: Falls Lake water quality; JL-WS: Jordan Lake water supply; JL- 255
 WQ: Jordan Lake water quality). For this purpose, each realization j in the JAS inflow forecast into each reser- 256
 voir (Figure 3) was simply apportioned into respective inflows (Q_{ij}) to each pool based on the percentages 257
 shown in Table 1 for water quality and water supply storages. Since the JAS evaporation for each lake did 258
 not exhibit much year-to-year variability, we assumed them to be constant with 3500 and 4998 acre-feet for 259
 Falls Lake and Jordan Lake, respectively. Evaporation from each lake was also similarly apportioned to 260
 obtain the evaporation (E_{ij}) for water supply and water quality pools. In this section, we discuss the perform- 261
 ance of the JAS inflow forecasts in estimating the potential transfers between the four pools across the two 262
 river basins over the period 1991–2008. For this purpose, we consider four different inflow scenarios (Figure 263
 4b) for initiating the transfer between the four pools. 264

1. *Perfect Forecast (PF)*: Force the IBT model with observed inflow, and obtain the optimal transfers that min- 265
 imize the total deviation from the target storage in the four pools. 266

2. *Climate-information-based-inflow Forecast (CF)*: Force the IBT model with downscaled inflow from 267
 ECHAM4.5 (Figure 3), and obtain the optimal transfers, which denote the transfers based on existing skill in 268
 predicting streamflow for the region. Inflow forecasts were obtained using PCR by downscaling ECHAM4.5 269
 forecasts with June inflows. 270

3. *No Forecast (NF)*: Force the IBT model with climatological inflows, and obtain the optimal transfer. Given 271
 that the lag-1 correlation between summer flows is insignificant, we obtained climatological inflow ensem- 272
 ble with M realizations, which were generated from the log-normal distribution using the observed mean 273
 and variance of JAS inflows into each lake. Thus, the ensemble characteristics obtained under NF remains 274
 the same with no potential to forecast the inflows in a given year. 275

4. *No IBT*: Under this scenario, there is no-transfer between the lakes and the summer demand is purely allo- 276
 cated based on the observed JAS inflows and the initial storage. Hence, there is no optimized allocation 277
 with both systems being operated independently. 278

The performance of these three forecast scenarios was evaluated by simulating the reservoir with the 279
 observed inflows to obtain the end-of-season storages ($S_{i,t}$) for each pool over the period 1991–2008 using 280
 the IBT model-suggested transfers and releases under the above four scenarios. Given the performance of 281
 the releases suggested by the inflow forecasts are evaluated with observed flows, we just get one 282
 storage ($S_{i,t}$) for each pool i . ~~the Based~~ Based on S_i^* , the deviation from the target storage, $\lambda_{i,t} = \frac{S_{i,t} - S_i^*}{S_i^*}$, was 283
 computed for each pool i in year t . For instance, a value of $\lambda_{i,t} = 0.5$ means that pool has 50% excess storage 284
 than its allocated storage. Difference in the performance ($\lambda_{i,t}$) between scenarios (2) and (3) quantifies the 285
 improvements obtained using climate forecast alone. Difference in the performance ($\lambda_{i,t}$) between scenarios 286

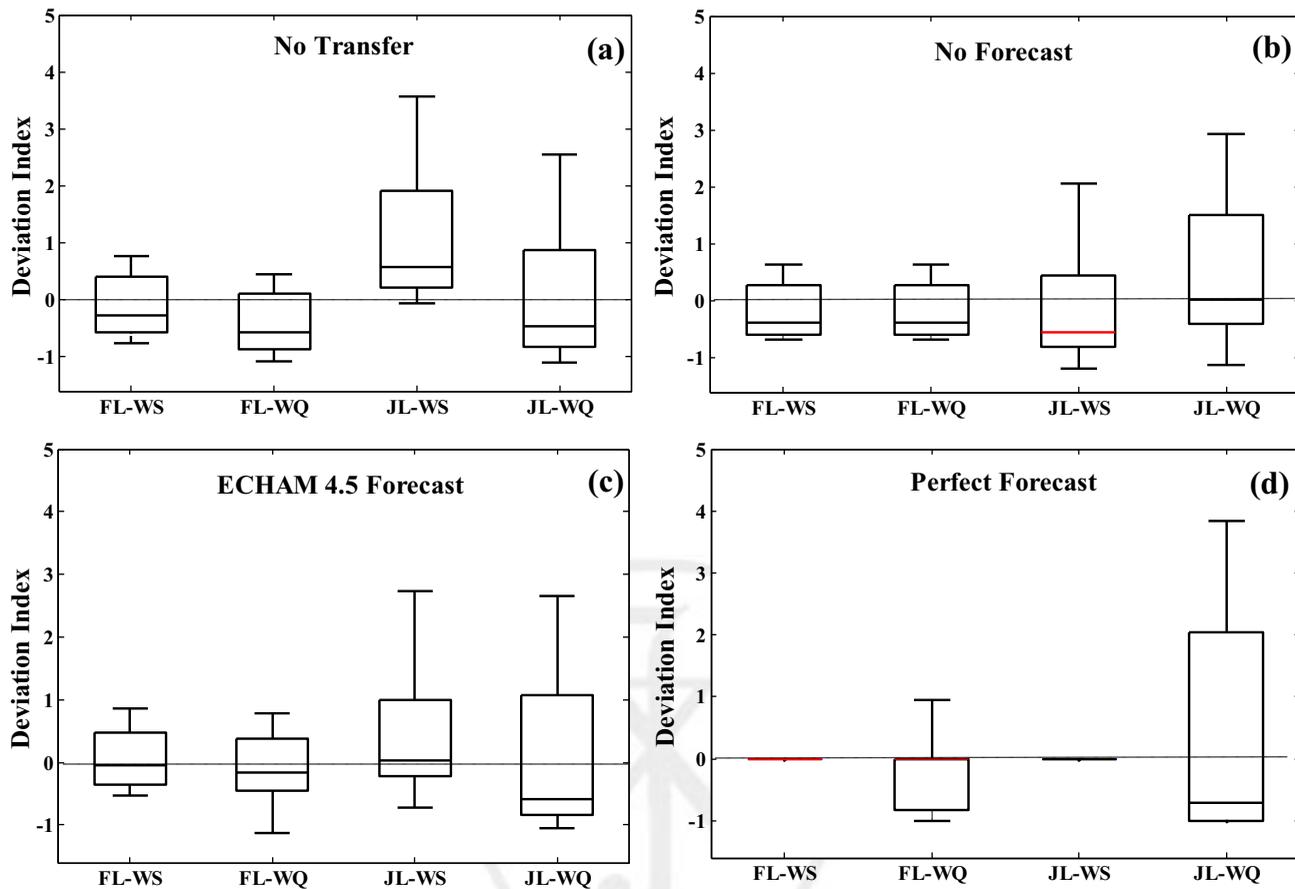


Figure 5. Normalized end-of-season storage deviations, $\lambda_{i,t}$, for pools in Falls Lake and Jordan Lake under four different scenarios: (a) no-transfer; (b) climatology-based transfer; (c) seasonal forecast-based transfer; and (d) perfect forecast-based transfer. Positive (negative) deviation indicates surplus (deficit) storage condition.

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(1) and (2) quantifies the maximum possible improvement that is obtainable using the climate forecast. Difference in the performance ($\lambda_{i,t}$) between scenarios (1) and (4) show the improvements obtained using optimization alone from IBT with perfect information. 287
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Figure 5 shows the boxplot of the normalized deviations, $\lambda_{i,t}$, for each pool during the period 1991–2008 for three inflow forecasts. Each box represents the 10th, 25th, 50th, 75th, and 90th percentiles of the deviation index ($\lambda_{i,t}$). We also include a baseline scenario (Figure 5a), which indicates $\lambda_{i,t}$ obtained through observed inflows without any transfer. In Figure 5a, for the no-transfer scenario, the end-of-season (September) storage obtained by combining the observed inflow shows a large deviations across the four pools. For optimal transfers obtained using climatological inflow (Figure 5b), which has no skill, the storage deviation is reduced for the water supply pools from the no-transfer scenario that used actual observed inflows. This demonstrates that IBT could be effectively employed even with limited/no skill in forecasting the seasonal inflows. With ECHAM 4.5 forecast (Figure 5c), the resulting deviation is further reduced compared to the climatology scenario and the no-transfer scenario. Finally, the normalized deviations, $\lambda_{i,t}$, is the lowest across the four pools under perfect inflow information (Figure 5d). As seen in Figure 5d, both water supply pools in Falls Lake and Jordan Lake are able to meet their target storages whereas the water quality pools in both Lakes are exhibiting increased deviations. This indicates that water quality pools transfer water to the water supply pools in both systems for meeting the September end target storage. This happens primarily because the normalized deviations (see equation (1)—objective function) are higher for water supply pools, thereby initiating the transfers from water quality pools to obtain the minimum total deviation in a given season. This issue is discussed in detail in the next paragraph (Figure 6). Comparing Figure 5a with Figures 5b–5d, it is evident that the end-of-season storage deviation under each pool is reduced under IBT even 290
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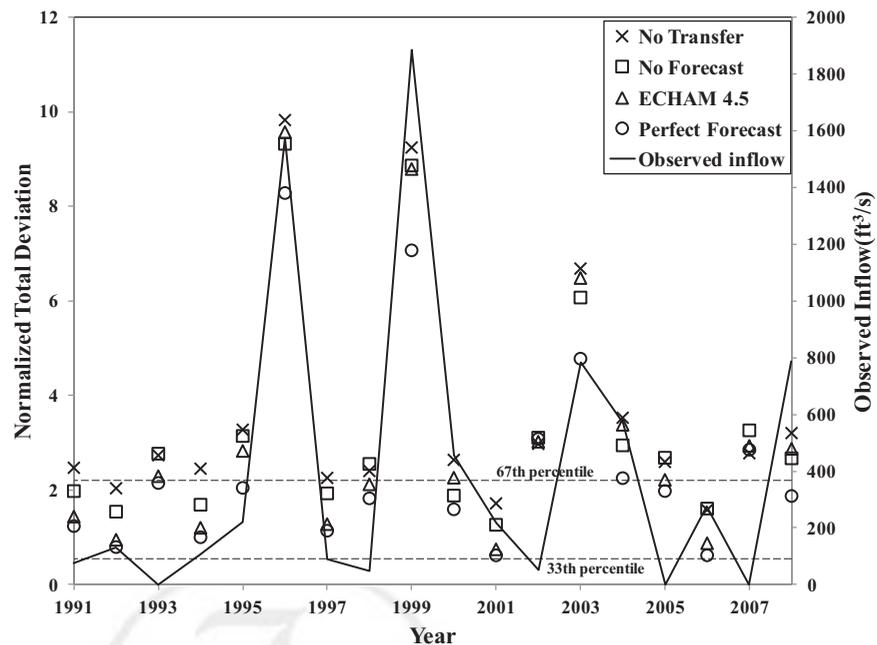


Figure 6. Total normalized deviations, TD_t , across the four pools resulting from IBT under three inflow forecast scenarios as well as under no-transfer between the four pools in Falls Lake and Jordan Lake for the period 1991–2008.

with the transfer initiated by climatological inflows (no forecast), which implies that IBT is beneficial in meeting target storages even under a low/no skill in forecasting. Furthermore, Figures 5b and 5c show that as the skill of the forecast increases, the normalized deviation further reduces indicating the potential for improving the storage conditions in both Lakes based on IBT initiated using either climatological inflows (Figure 5b) or ECHAM4.5-GCM-based inflow forecasts (Figure 5c).

We also quantify the total absolute deviations (Figure 6), $TD_t = \sum_{i=1}^4 \left| \frac{S_{i,t} - S_i^*}{S_i^*} \right|$, by computing the sum of relative absolute deviations from the target storage across the four pools for each year under different inflow scenarios and under no-transfer scenario. It is important to note that these total absolute deviations shown in Figure 6 are not obtained directly from the objective function (equation (1)). Instead, the transfers suggested by the IBT are combined with the observed inflows into each lake to obtain the end-of-season target storage (see Figure 4b). Thus, any error in the forecast (climatology or ECHAM4.5 forecasts) would be reflected in obtaining the end-of-season target storage. In Figure 6, the primary y axis shows the total absolute deviations over four pools in two reservoirs during the period 1991–2008 with the secondary y axis showing the observed inflow for Falls Lake. We can infer from Figure 6 that the total storage deviation is reduced through IBT compared with no-transfer scenario. Furthermore, comparing the performance between ECHAM4.5 forecast and no forecast, the total absolute deviation decreases across the system indicating that the reduced uncertainty in inflows further facilitates IBT. It is also clear that no-transfer-based total deviations, which are obtained using observed JAS inflows in both lakes, are higher than the total deviations obtained under climatological inflows and ECHAM4.5-based inflow forecasts in every year with the only exception being 2007 summer. As expected, total absolute deviations obtained under IBT using perfect forecast (i.e., observed inflows) are the smallest over the entire period of study. It is important to note that these transfers (summarized in Figures 5 and 6) are obtained without compromising the downstream needs as well as by not increasing the downstream flood control risk.

Thus, results shown in Figures 5 and 6 clearly emphasize the two critical findings related to interbasin transfer between Falls lake and Jordan Lake in the NC Triangle Area: (1) interbasin transfers between these two systems utilizing inflows from no forecast (climatology) or climate forecast scenarios provide better ability to meet the end-of-season target storage conditions in comparison to the September storage conditions obtained by operating these two systems independently (i.e., no-transfers) using observed inflows; (2)

reduced uncertainty in inflows arising from climate forecasts are more beneficial than no-forecast in meeting the target storages across the four pools based on IBT. Though we infer IBT improves regional water management, the difference in deviations in individual pools (Figure 5) and over the four pools (Figure 6) under different inflow scenarios is relatively small particularly between ECHAM4.5 forecast and No forecast. This is primarily because the similarity between summer inflow conditions (correlation 0.92) between the two lakes and high correlation (0.82) between the initial conditions on the two systems. This results in both lakes experiencing deficit/surplus conditions resulting in limited scope for IBT over four pools. Hence, it is important to understand how climate forecast with IBT can improve regional water management by generalizing the findings for basins experiencing different hydroclimatic settings and release patterns.

4. Role of Spatial Correlations Between Inflows and Initial Conditions in Promoting IBT

Recent studies on the role of climate forecasts in improving seasonal to annual water allocation show that reservoir systems with low storage-to-demand ratio provide increased yields through reduced system losses (spill and evaporation) as the forecast skill increases [Maurer *et al.*, 2004; Sankarasubramanian *et al.*, 2009a, b]. Thus, any improvements in the inflow forecasts used in this study (Figure 3) is expected to reduce the total absolute deviations (Figure 6) further under IBT with the reduction on total normalized deviations being bounded by the deviations obtained using observed inflows (i.e., perfect forecast) into both systems. Given that both Falls Lake and Jordan Lake are close to each other and the initial storage conditions (S_i^0) are similar, strong spatial correlations exist between inflows and initial storage conditions. This indicates that if one basin experiences drier/wetter conditions, then the other basin also experiences similar conditions, thereby limiting the potential for IBT. On the other hand, even if the reservoirs experience similar inflow conditions, initial storage conditions are predominantly determined by the demand patterns in the previous season for each system. Apart from the storage-to-demand ratio and inflow forecasting skill, we hypothesize that two additional factors, spatial correlation between observed inflows (γ_Q) and spatial correlation between initial storage conditions (γ_{S_0}), determine the utility of inflow forecasts in promoting IBT for meeting the end-of-season target storage conditions. To understand how these two spatial correlations could impact IBT, we performed a synthetic experiment that systematically analyzes the utility of IBT under various spatial correlation patterns and inflow forecasting skill. For this purpose, we assumed that IBT occurs between two river basins with four pools (similar to Figure 4a) across two river basins, but the inflow and initial storage conditions will be perturbed to generate different spatial correlation scenarios.

4.1. Synthetic Inflow and Initial Storage Generation Schemes

To obtain the time series of inflows or initial storages with a specified spatial correlation, we assumed that the selected variable (i.e., inflows or initial storages) follows bivariate lognormal distribution and then synthetically generated 100 years of records (inflows or initial storages) for the summer season. The following procedure outlines the detailed steps for generating the spatially correlated variables for the two systems.

1. Log-transform the observed JAS historical inflows or initial storages (1 July) for Falls Lake and Jordan Lake as $Y = \log X$, where X denotes observed inflows or initial storage.
2. Obtain the mean (μ_Y^k) and standard deviation (σ_Y^k) of these log-transformed variables, where k denotes the system with $k = 1$ denoting Falls Lake and $k = 2$ denoting Jordan Lake.
3. Given the spatial correlation γ , express the covariance matrix for generating log-normal variates as

$$\Sigma_Y = \begin{bmatrix} \sigma_{Y^1}^2 & \gamma \cdot \sigma_{Y^1} \cdot \sigma_{Y^2} \\ \gamma \cdot \sigma_{Y^1} \cdot \sigma_{Y^2} & \sigma_{Y^2}^2 \end{bmatrix}.$$
4. Generate 100 bivariate lognormal random values using the mean and covariance matrix estimated in steps (2) and (3) to obtain the inflow or initial storage time series.
5. Transform the log values to the original space (inflows or initial storages) for each system and consider this as the synthetic inflows ($Q_{S_{t,k}}$) for the two systems.

6. Apportion the initial storage or the inflow into assigned quantities for water supply and water quality pools using the ratios given in Table 1 and obtain the time series of initial storages and inflows for the four pools to solve the IBT model provided in section 3.

7. We generated 100 years of inflows and initial storages for two hypothetical reservoirs utilizing the mean and variance of the inflows and initial storage characteristics of Falls Lake and Jordan Lake under different spatial correlation scenarios. For inflows, we consider two spatial correlations, $\gamma_Q = 0.9$ and 0.1 , indicating two distinct conditions for representing spatial pattern in inflows. High spatial correlation in inflows could be thought of conditions similar to Jordan Lake and Falls Lake with basins experiencing similar hydroclimatic conditions. Low spatial correlations between inflows could be interpreted as basins experience different seasonality in hydroclimate owing to topography (e.g., two basins with one on windward side and another leeward side). Spatial correlation in initial storage conditions (γ_{S_0}) is primarily influenced by the demand patterns in the previous season for both systems; we considered two cases: $\gamma_{S_0} = 0.8$ and 0.1 with the high spatial correlation indicating that both basins experience similar demand pattern. Low spatial correlations in initial storage could be interpreted as one basin experiencing increased demand (e.g., irrigation) in the spring season while the other basin having limited/no irrigation in the previous season. This resulted in a total of four scenarios: (a) $\gamma_{S_0} = 0.8$ and $\gamma_Q = 0.9$; (b) $\gamma_{S_0} = 0.8$ and $\gamma_Q = 0.1$; (c) $\gamma_{S_0} = 0.1$; and $\gamma_Q = 0.9$; and (d) $\gamma_{S_0} = 0.1$ and $\gamma_Q = 0.9$. In the next section, we briefly discuss an approach for generating inflow forecasts having the skill of the candidate forecast that is shown in Figure 3.

4.2. Synthetic Inflow Forecasts of Different Skill

Given that we specified different spatial correlation patterns for inflows and S_0 , we needed to ensure that synthetic inflow forecasts have a skill similar to the skill shown in Figure 3 ($\rho \cong 0.56$) so that the synthetic experiment could also be evaluated under three inflow forecasting scenarios (Figure 4b). We did not consider any inflow forecast skill higher than the reported skill in Figure 3, since previous studies have clearly shown that reduction in inflow forecast uncertainty result in improved water allocation [Sankarasubramanian et al., 2009a, b]. Sankarasubramanian et al. [2009a, b] generated inflow forecasts with specified skill using a parametric periodic gamma autoregressive model [Fernandez and Salas, 1986] to demonstrate the utility of inflow forecasts in improving water allocation under different system characteristics (storage to demand ratios). Given the synthetically generated JAS inflow, $Q_{S_{t,k}}$ with $t = 1, 2, \dots, 100$ denoting number of years of summer inflows and k denoting the reservoir, we generated Gaussian noise to each of these flows such that the inflow forecasts with the specified skill preserves the mean and variance of generated flows at each site. For a specified correlation that denotes the forecast skill, ρ , the noise ε_t follows normal distribution with a mean $\mu_{Q_{S_k}}(1 - \rho_k)$ and a standard deviation $\sigma_{Q_{S_k}} \sqrt{1 - \rho_k^2}$, where $\mu_{Q_{S_k}}$ and $\sigma_{Q_{S_k}}$ were obtained from the synthetic series. Thus, the synthetic inflow forecasts, $Q_{S'_{t,k}}$ with M realizations for each time step t could be generated using the Gaussian error term:

$$Q_{S'_{t,k}} = \rho * Q_{S_{t,k}} + \varepsilon_{t,k} \quad (8)$$

Using the method discussed above, synthetic inflow forecasts under two different spatial correlation scenarios ($\gamma_Q = 0.9$ and 0.1) were generated for a predictive skill $\rho = 0.56$, which approximately corresponds to the skill of the downscaled inflow forecasts shown in Figure 3. Thus, the synthetic inflow forecast, $Q_{S'_{t,k}}$ with M realizations were used as the climate-information-based inflow forecast for evaluating the utility of IBT in improving water allocation under different spatial correlations of γ_Q and γ_{S_0} .

4.3. Results and Discussion: IBT Under Various System Characteristics

Using the synthetic generation schemes described above for generating different spatial correlations between inflows and storages with a specified skill, four different IBT scenarios were considered: (a) high spatial correlation between inflows and initial storages (i.e., similar to the Falls Lake and Jordan Lake system) (HH); (b) high spatial correlation between inflows and low spatial correlation between initial storages (i.e., systems experience similar hydrology, but completely different demand patterns in the previous season) (HL); (c) low spatial correlation between inflows and high spatial correlation between initial storages (i.e., basins experience different hydroclimatology due to orography or due to the nature of precipitation (e.g., rain versus snow)) (LH); (d) low spatial correlations between inflows and low spatial correlation between initial storages (i.e., basins experience different hydroclimatology as well as different demand patterns in the previous season) (LL). In the following discussion, we will denote the four pools (1–4) in the two

hypothetical reservoirs (similar to Figure 4a) in which four pools transfer water across the basins. The IBT model outlined in section 3 was run for each spatial correlation scenario with three inflow scenarios obtained from the 100 years of synthetic flows, $(Q_{s,t,k})$ namely: (a) no forecast, whose ensemble was obtained using the mean and variance of the synthetic inflows $(Q_{s,t,k})$, (b) synthetic inflow forecast $(Q'_{s,t,k})$ with $\rho = 0.56$ as discussed in the previous section; and (c) perfect forecast with the transfers being obtained using the synthetic flows $(Q_{s,t,k})$. These three scenarios were also compared against the no-transfer scenario in which the releases (R_i) in Table 1 were provided for the four pools using the synthetic inflows $(Q_{s,t,k})$ without any transfers. All the four scenarios were run with the storages, fractions for partitioning the inflows and storages and releases given in Table 1. Thus, this synthetic experiment is similar to the analyses presented in section 3, but the generated synthetic inflows and initial storage conditions between the two hypothetical systems exhibit four different correlation structures. Since HL spatial correlation case is the most common case, we present detailed analyses for the spatial correlation case of HL (Figures 7 and 8) and then summarize how inflow forecasts with a specified skill improve IBT under all the four spatial correlation scenarios.

4.4. High Spatial Correlation on Inflows and Low Spatial Correlation With Initial Storages (HL)

Perhaps spatial correlation scenario HL is the most common situation, which indicates basin experience similar hydroclimatology, but they undergo a completely different demand patterns in the previous season. Figure 7 shows the boxplot of the normalized end of the season target storage deviation, $\lambda_{i,t}$, for all the four pools under three different IBT scenarios and under no-transfer scenario with the synthetically generated inflows $(Q_{s,t,k})$. We can see clearly from Figure 7 that IBT (Figures 7b–7d) could reduce the end of the season target storage deviation over the no-transfer scenario (7a). Particularly, when IBT is initiated using no forecast (i.e., climatology), we can see that the normalized target storage deviation for the four pools are reduced and more uniform in comparison to the no-transfer scenario. Under inflow forecasts exhibiting significant skill in predicting observed flows, the end-of-season storage deviation is further decreased showing the utility of inflow forecasts in developing improved IBT strategies. We can also see that the target storage deviation goes down to almost zero for three of the pools (1–3) under perfect forecasts indicating these three pools reach their target storage at the end of the season by getting the water from the fourth pool (analogously water quality pool in Jordan Lake) over 100 years of evaluation. Comparing the results from Figure 7 with Figure 5, we can infer that the overall distribution of the deviation index for all the four pools is narrower and closer to the target storage. This indicates that low spatial correlation between initial storages warrant IBTs more than with systems experiencing high correlation on initial storages of the two systems, since under the latter case both systems simultaneously experience surplus or deficit storage conditions.

Though the overall potential for IBT depends on the spatial correlation in inflows and initial storages of the two systems over the long term, the ability to transfer water in a given season primarily depends on the differences in the inflows or initial conditions among the transferring pools. The potential for transfer in a given season, ω_t (equation (9)), across the four pools is quantified by the sum of deviations in inflows or initial storages to their respective climatological values during year t . Expressing ω_t over the entire system,

$$\omega_t = \sum_{i=1}^4 (V_i^t - V_i^{ave}) \quad (9)$$

where V_i^t is the initial storage (S_o^*) or inflow ($Q_{s,t,i}$) of a particular pool ($i = 1, 2, 3, 4$) for year t over the 100 year period and V_i^{ave} is the climatological values of inflows or initial storages for the four pools. Larger the deviation from climatology on the inflows (ω_t^Q) or initial storage ($\omega_t^{S_0}$) over all the four pools, lesser is the potential for transfer value of transfer. For instance, if in a given season inflows or initial storages for all four pools are above (below) their climatology, this indicates that all pools experience surplus (deficit) conditions yielding no potential for transfer. On the other hand, if inflows or initial storages exhibit surplus and deficit conditions among the four pools, then ω_t will be near zero indicating potential for transfer from surplus pools to deficit pools. For the HL scenario, we computed ω_t^Q , $\omega_t^{S_0}$, and normalized total deviations (similar to

Figure 6), $TD_t = \sum_{i=1}^4 \left| \frac{S_{i,t} - S_i^*}{S_i^*} \right|$ for each year over the 100 years of synthetic simulation under four scenarios of transfer.

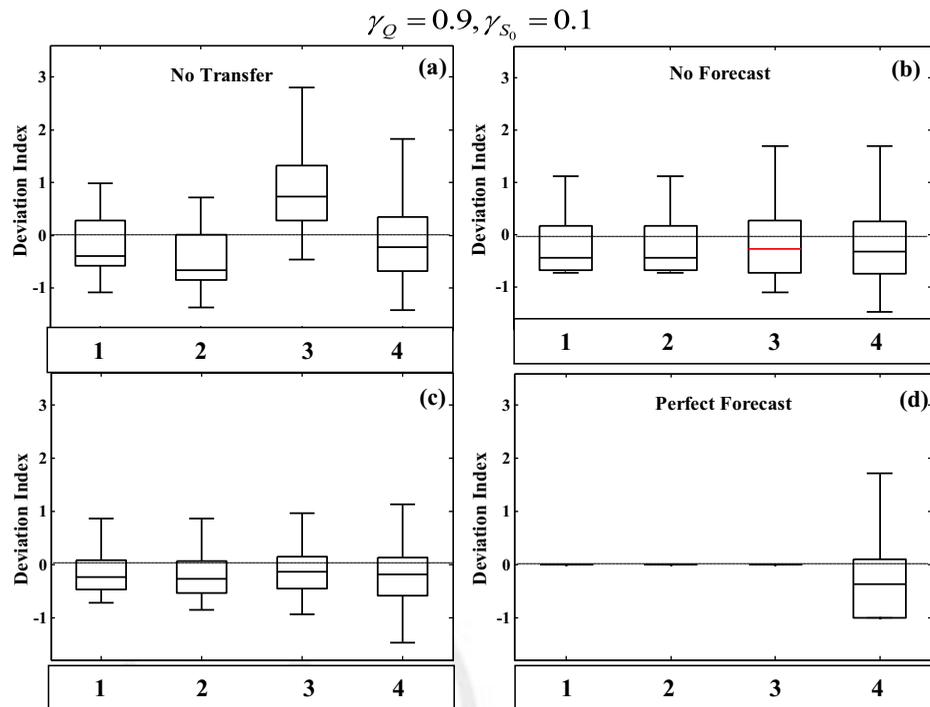


Figure 7. Same as Figure 5, the normalized end-of-season storage deviation, $\lambda_{i,t}$, but for four hypothetical pools exhibiting high spatial correlation between inflows and low spatial correlation between initial storages. Pools 1–4 could be interpreted as pools as shown in Figure 4a.

Each circle in the figure represents the normalized total deviation of the four pools for every year with bigger circles indicating larger TD_t . It is clear that the size of the circles decreases from Figures 8a–8d indicating transfers based on inflow forecasts being better than no-transfer and the climatology inflow options with TD_t being the smallest under perfect forecast. We also infer that the total deviation is smaller in regions where $\omega_t^{S_0}$ and ω_t^Q are close to zero for scenarios (1)–(4), which implies that the utility of IBTs is more in these conditions/seasons. On the other hand, if $\omega_t^{S_0}$ and ω_t^Q are far away from zero, we understand that the size of the circle increases denoting a larger TD_t . This implies that if surpluses and deficits exist simultaneously across the four pools, then the potential for transfer is low resulting in larger TD_t . Therefore, both overall deviations of inflows and initial storage conditions from their respective climatologies should be closer to zero, so that water could be transferred from surplus pools to deficit pools. If such conditions do not exist (i.e., $\omega_t^{S_0}$ and ω_t^Q being large), even if we have inflow forecasts with perfect skill, the potential for IBT does not exist. Thus, greater the disparity in deviations on initial storage and inflow from their climatologies, larger the benefits of inflow forecasts in facilitating IBTs.

4.5. Role of Spatial Correlations Between Inflows and Initial Storages of Participating Pools

Based on the discussion from Figures 7 and 8, we understand that inflow forecasts with skill above climatology (no forecast) is especially beneficial in initiating IBT reducing the total deviations from the target storage across the participating pools with regard to systems having high spatial correlation between inflows and low spatial correlation between initial storages. We investigate the total deviations from the target storage, TD_t , under four different combinations of spatial correlation between the inflows and spatial correlation between the initial storages of the two systems ((a) High-High (HH), (b) High-Low (HL), (c) Low-High (LH), and (d) Low-Low (LL)) under four different scenarios of interbasin transfers based on the 100 years of synthetically generated inflows and initial storages. It is important to note that, similar to Figure 4b, each transfer scenario obtained from the IBT model was combined with the perfect forecast (i.e., the synthetically generated flows $Q_{S_{t,k}}$) to obtain the end-of-season target storage for calculating TD_t .

Figure 9 shows the median of TD_t is higher under no-transfer scenario under the four different cases of spatial correlations. Considering IBT as a management option, it is clear that as the inflow forecast uncertainty reduces (i.e., no forecast to perfect forecast), the spread of TD_t in general decreases for the four cases of

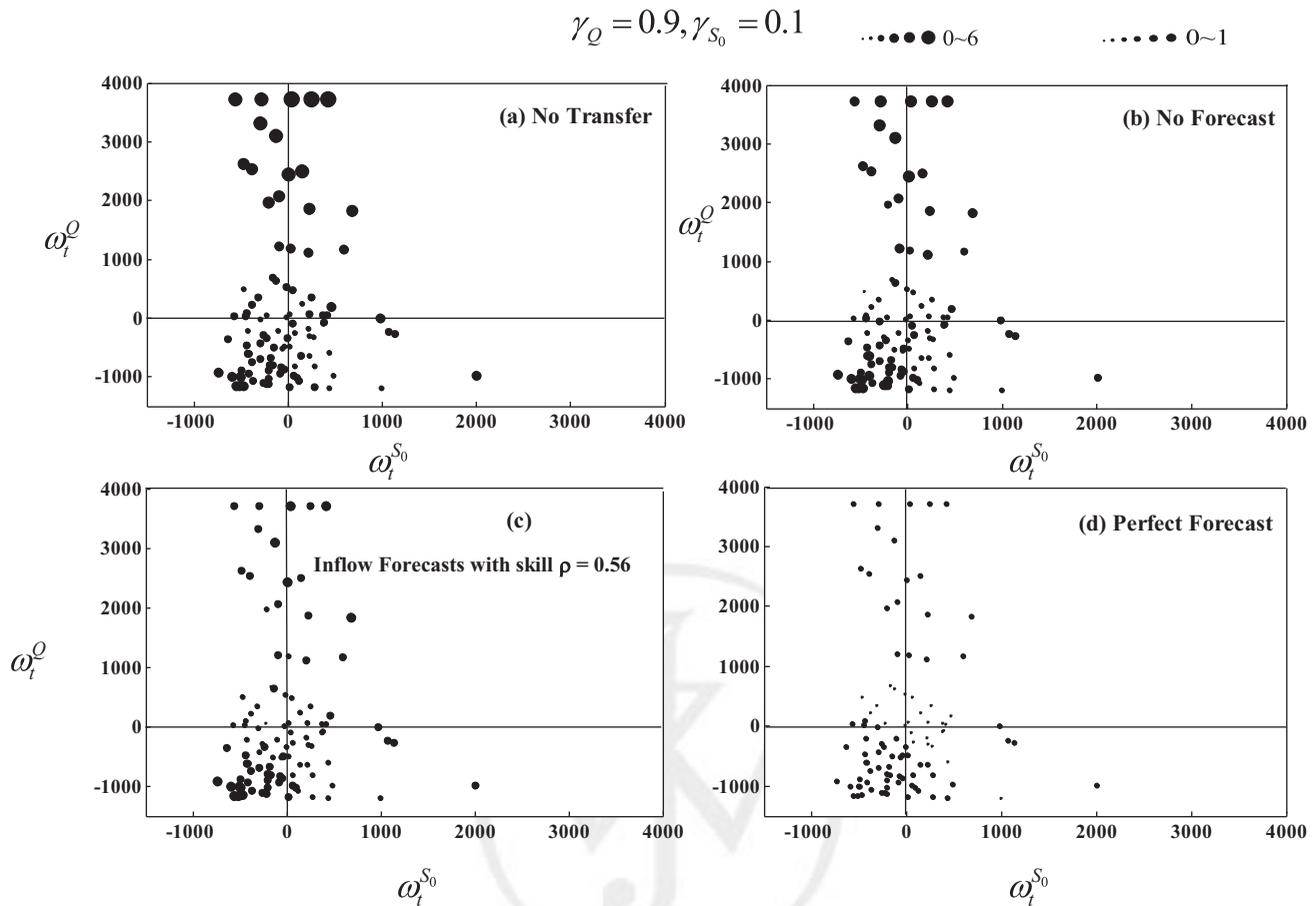


Figure 8. Scatter plot of the normalized total deviations (TD_t) with transfer potential for each year, $\omega_t^{S_0}$ and ω_t^Q , under four scenarios of transfer: (a) no-transfer; (b) no forecast; (c) $\rho_{Q,Q'} = 0.56$; (d) perfect forecast. Each circle in the figure represents the normalized total deviation of the four pools for every year with bigger circles indicating larger TD_t .

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spatial correlations. Comparing across the four cases of spatial correlations that indicate the basin hydroclimatology and the demand patterns between the two systems, we infer that IBT is least beneficial in reducing TD_t under HH, which implies both systems experience surplus or deficit simultaneously, thereby limiting the scope for transfer across the participating pools. It is important to note that even under HH, IBT is more beneficial than no-transfer scenario. Further, if the spatial correlation between inflows or initial storages is lower, IBT is more beneficial indicating the opportunity for transfer that occurs due to not having inflows/storage in one of the basins. Thus, IBT is most beneficial when basins experience low correlations on both inflows as well as initial storages between the two systems. Comparing the distribution of TD_t between climatology (no forecast) and inflow forecasts with the specified skill, the distribution of TD_t is narrower in the latter case indicating the utility of season-ahead inflow forecasts in facilitating the transfer. To recapitulate, if both infrastructure and interbasin transfer permits exist, IBT obtained using inflow forecasts is beneficial in promoting regional water sustainability by ensuring that individual users' demands and target storages for each pool are met.

4.6. Discussion

Application of season-ahead climate forecasts on Falls Lake and Jordan Lake over the Triangle Area showed that there is potential for promoting interbasin transfer across the four lakes in the two systems. However, the improvements across the system is limited since there is a high correlation between inflows and also between the initial storages across the system. This motivated us to investigate a synthetic case study that considers different correlation patterns (high, low) between the inflows and between the initial conditions of the four lakes. Most studies [Cai and Rosengrant, 2004; Characklis et al., 2006] that emphasized the

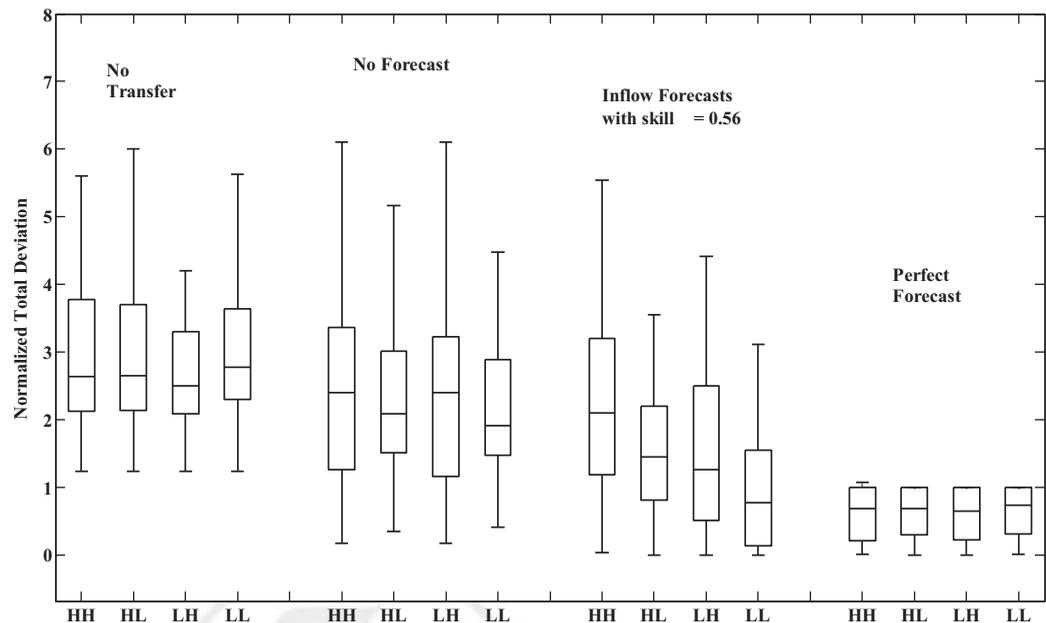


Figure 9. Total normalized storage deviation, TD_n , under different cases of spatial correlation of inflows and initial storages for four different scenarios of water transfers in the synthetic study.

importance of IBT have utilized observed inflows for supporting regional water management. Though this study utilizes climate forecasts for improving IBT, the primary contribution is in developing a stochastic IBT model for utilizing probabilistic streamflow forecasts and also to understand the hydroclimatic settings and reservoir storage conditions that could benefit from IBT for improving regional water management. For this purpose, we considered the Triangle Area reservoirs, Falls Lake and Jordan Lake, for transferring the water between the Neuse and Cape Fear River basins. The IBT considered minimizing the total absolute fractional deviations from the target storage over the four pools using linear programming. The primary reason we consider the end-of-the-season target storage in the objective function is because initial storages in most reservoirs guarantee the entire seasonal demand thereby limiting the potential to use forecasts. In the case of Falls Lake and Jordan Lake, there is no priority in allocating the water across the four pools. However, the proposed IBT could be modified to incorporate appropriate penalty function that could be related to relevant financial instruments [Characklis et al., 2006; Palmer and Characklis, 2009]. For instance, if maintaining downstream ecology and water quality during the fall season (i.e., September storage) is more critical, then one could give assign a function that translates the deviation from the target storage into appropriate penalties. Similarly, the penalty function could also vary depending on the importance of maintaining the target storage in a given season. For example, in the spring and summer (winter and summer) seasons, one could assign higher penalty for maintaining the target storage for irrigation (hydropower) pool in a given reservoir for promoting transfer into the irrigation (hydropower) pool. Thus, the proposed IBT model could be modified to accommodate the basins' priorities and tariff system for meeting the target storages in the pools over the participating reservoirs.

Though this study has primarily focused on initiating the transfers to meet the target storage, studies have showed that even a small improvement in reservoir yields utilizing climate forecast could result in substantial increase in the revenue generation depending on the intended use [Maurer and Lettenmaier, 2004; Voisin et al., 2006; Oludhe et al., 2013]. For instance, Maurer and Lettenmaier [2004] show that even 1% improvement in hydropower releases by reducing the spill from the Missouri system could result in significant increase in revenue from hydropower generation. Further, the utility of forecasts to initiate transfers is bound to improve as the demand in the regional water supply system continues to increase. Sankarasubramanian et al. [2009a, 2009b] show that even climate forecast with moderate skill is more (less) beneficial for systems with smaller (larger) storage-to-demand ratio as the initial storage constraints (guarantees) the entire seasonal demand. Hence, as the demand increases in the Triangle Area, the utility of forecast is bound to improve. That is, even with the current level of skill, the forecast will become more valuable to

decision making as the urban demand increases. Hence, the relevance of forecast to decision making does not depend on the skill alone, but also on reservoir system characteristics.

Efforts to improve forecasting skill using multimodel combination could also improve the confidence in using the forecasts [Devineni et al., 2008; Singh and Sankarasubramanian, 2014]. Thus, improvements in streamflow forecasting skill and the increased water demand due to population growth will provide increased reliability and need for IBT across the participating systems/pools. As demonstrated in this study, the utility of streamflow forecasts will further increase if the basins experience low correlation between the inflows and low correlations between the initial storages across the participating pools. Our hydroclimatology research group in collaboration with the State Climate Office of NC has developed an online portal (<http://www.nc-climate.ncsu.edu/inflowforecast>) for disseminating both the inflow forecasts from multiple models and the storage forecasts for the user-specified releases from Falls Lake and Jordan Lake. We believe that as the water demand continues to increase in the Triangle Area, providing online access to both inflow and storage forecasts along with potential interbasin transfer scenarios on an experimental basis will result in real-time evaluation and application of climate-information-based streamflow forecasts for promoting IBT to improve regional water supply management.

5. Summary and Conclusions

Regional water supply systems undergo surplus and deficit conditions due to differences in inflow characteristics as well as due to their seasonal demand patterns. This study proposes a framework for regional water management by proposing an interbasin transfer model that uses climate-information-based inflow forecasts for minimizing the deviations from end-of-season target storage across the participating pools. Using the ensemble streamflow forecast, the IBT water allocation model was applied for two reservoir systems in the Triangle Area in NC. Results show that interbasin transfer initiated by ensemble streamflow forecast could potentially improve the overall water supply reliability of the region as the demand continues to increase. To further understand the utility of climate forecasts in facilitating the IBT under different spatial correlation structures between inflows and between initial storages of the two systems, a synthetic experiment was designed to evaluate the framework under three different scenarios of inflows. Findings from the synthetic study could be summarized as follows:

1. Interbasin transfer is an efficient way to reduce uncertainty in water allocation and favors improved storage conditions at the end of the season. Inflow forecasts combined with the proposed IBT optimization model provide improved allocation in comparison to the allocations obtained under no-transfer scenario as well as under climatology-based transfers.

2. Spatial correlations between inflows and between initial storages among participating reservoirs could also influence the potential benefits that could be achieved through IBT. IBT is particularly beneficial for systems that experience low spatial correlations between inflows or between initial storages or on both attributes of the considered regional water supply system.

Thus, if both infrastructure and permitting structures exist for promoting interbasin transfers, season-ahead inflow forecasts provide added benefits in forecasting surplus/deficit conditions among the participating pools in the regional water supply system.

Acknowledgments

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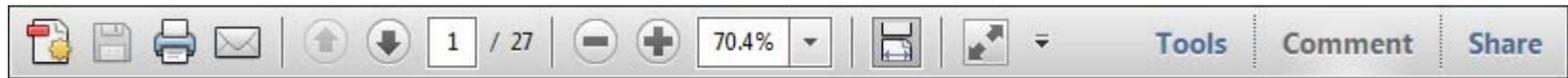
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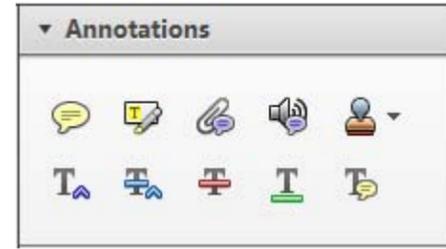
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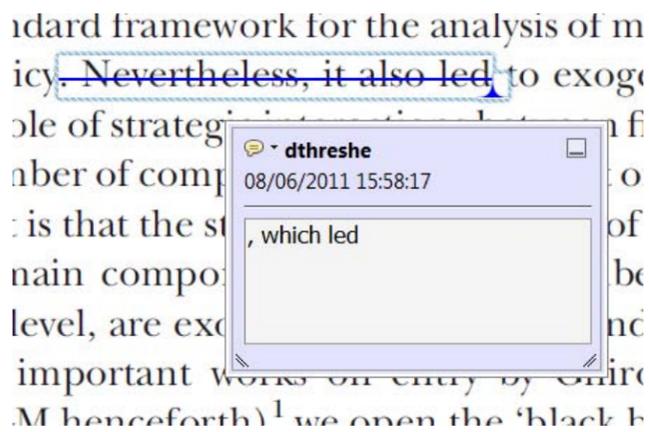
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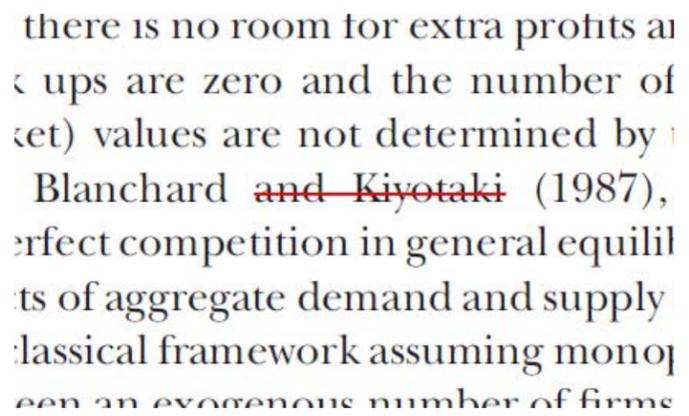
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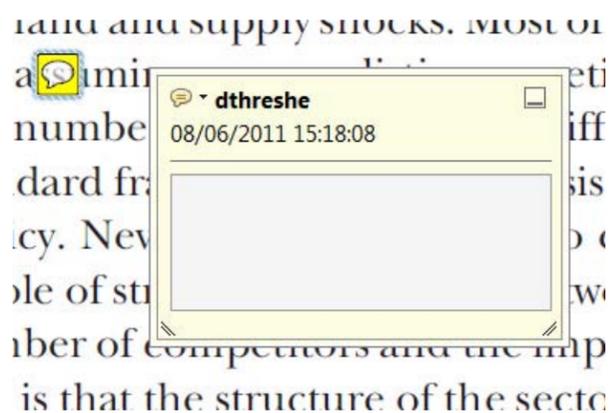
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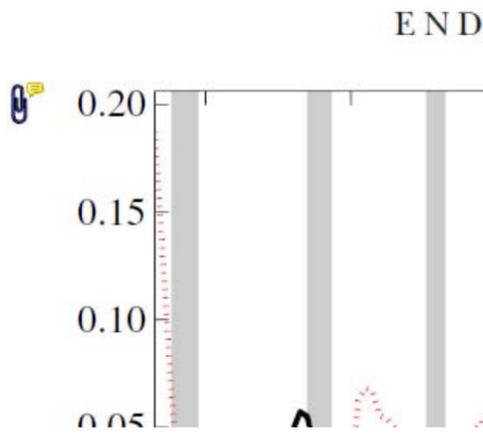
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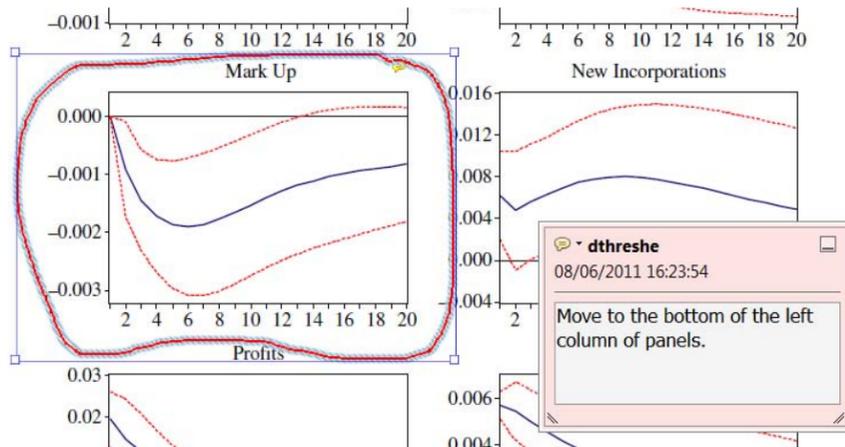


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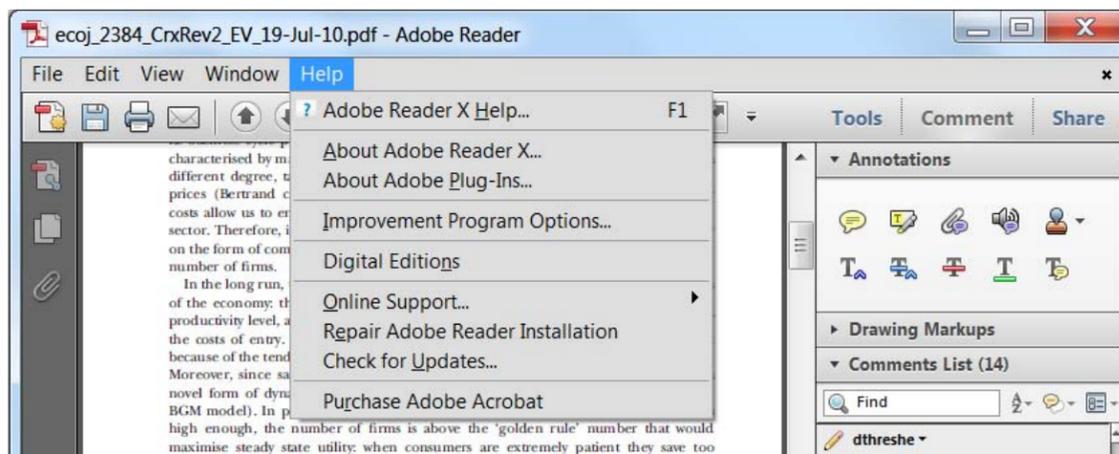
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