Improved water allocation utilizing probabilistic climate forecasts: Short-term water contracts in a risk management framework

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[1] Probabilistic, seasonal to interannual streamflow forecasts are becoming increasingly available as the ability to model climate teleconnections is improving. However, water managers and practitioners have been slow to adopt such products, citing concerns with forecast skill. Essentially, a management risk is perceived in "gambling" with operations using a probabilistic forecast, while a system failure upon following existing operating policies is "protected" by the official rules or guidebook. In the presence of a prescribed system of prior allocation of releases under different storage or water availability conditions, the manager has little incentive to change. Innovation in allocation and operation is hence key to improved risk management using such forecasts. A participatory water allocation process that can effectively use probabilistic forecasts as part of an adaptive management strategy is introduced here. Users can express their demand for water through statements that cover the quantity needed at a particular reliability, the temporal distribution of the "allocation," the associated willingness to pay, and compensation in the event of contract nonperformance. The water manager then assesses feasible allocations using the probabilistic forecast that try to meet these criteria across all users. An iterative process between users and water manager could be used to formalize a set of short-term contracts that represent the resulting prioritized water allocation strategy over the operating period for which the forecast was issued. These contracts can be used to allocate water each year/season beyond long-term contracts that may have precedence. Thus, integrated supply and demand management can be achieved. In this paper, a single period multiuser optimization model that can support such an allocation process is presented. The application of this conceptual model is explored using data for the Jaguaribe Metropolitan Hydro System in Ceara, Brazil. The performance relative to the current allocation process is assessed in the context of whether such a model could support the proposed short-term contract based participatory process. A synthetic forecasting example is also used to explore the relative roles of forecast skill and reservoir storage in this framework.

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1. Introduction

[2] Considerable improvement in the skill of seasonal climate forecasts over the last decade has been achieved using the slowly evolving boundary conditions such as SSTs in the tropical oceans [*Goddard et al.*, 2003]. Efforts linking these climate forecasts to antecedent land surface conditions have resulted in water supply forecasts [*Wood et al.*, 2002]. Despite these and related advances in downscaling [*Wood et al.*, 2005; *Sankarasubramanian et al.*, 2008] climate forecasts to operational streamflow forecasts, water managers find their use in the current policy/allocation framework to be a challenge [*Pagano et al.*, 2001, 2002].

[3] These challenges relate both to the form of the information and the associated uncertainty. For instance, forecast producers typically express the forecasts in the form of an ensemble or as tercile probabilities indicating the uncertainty in the relevant hydroclimatological attributes. On the other hand, forecast consumers, water managers and reservoir operators, have difficulty interpreting such products for their direct use [*Pagano et al.*, 2002]. Traditionally, reservoir operation rule curves were developed specifically to address situations where shortages/spills could occur considering the uncertainty of flows over the entire period of record. It is unclear to the operator whether there is much to be gained in modifying the rule curve given an inflow

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forecast of uncertain skill, when the contingency may already be addressed by the rule curve which is developed considering long-term operation. Thus, a "proactive" change in the operating policy given a probabilistic forecast could expose the manager to additional risk relative to following the existing rule curve, while it may not promise the manager a commensurate reward [*Pagano et al.*, 2001].

[4] There is a recognition that innovation in the water system operation and policy setting may be needed to facilitate the use of probabilistic forecasts. Here, we argue that one way to make probabilistic inflow forecasts useful in reservoir operation and water allocation is to identify the amount of water that can be provided with a specified reliability to a certain user group, rather than focusing on the communication of the raw inflow forecast. This quantity will vary from year to year, and season to season, recognizing the desired end of period reservoir storage for future operations, the initial reservoir storage, and the probabilistic inflow forecast over the operating period. Given heterogeneous users, the desired reliability and the value assigned to a certain quantity of water over the upcoming season will vary by user class. Thus, multiple short-term contracts at different levels of reliability (or probability of failure) over the contract period could in principle be arrived at through a negotiation by the users. Since the reliability of each contract has been estimated as part of the allocation process, the contract is potentially insurable. Thus, we propose to directly address the supply risk as described by a probabilistic inflow forecast through allocation, and manage the residual risk of failure through insurance like mechanism. An assumption is that the probabilistic forecast uncertainty can be well calibrated thus allowing a simulation based assessment of the potential amount of water that can be allocated using multiple contracts with different levels of reliability. Existing long-term contracts or water rights and their potential short-term trading could also be considered in the same framework.

[5] The key elements of the proposed scheme are: (a) a contract structure developed and implemented prior to the season that incorporates the reliability for a user specified release, (b) a strategy for restrictions and penalties if conditions in the actual operation period are adverse, and contract failure is imminent; (c) a probabilistic constraint on end of the season target storages to ensure water for allocation during the next season and (d) the maximization of a composite user specified benefit function from the bulk sectoral allocation based on stakeholders-specified contract terms. An example using streamflow forecasts developed using climate information for an arid basin in the state of Ceara, North East Brazil, which has been shown to have significant skill in predicting seasonal to interannual variability in climate is provided [*Moura and Shukla*, 1981; *Souza Filho and Lall*, 2003]. Synthetic experiments to examine aspects related to forecast skill and reservoir storage to annual water demand ratio are then explored to develop insights as to situations in which the proposed strategy may be most effective.

[6] A brief overview of the literature related to climate and water management is presented in Section 2. Section 3 details the components of the water allocation framework proposed in this study. Following that, we provide details on the skill of the climate information based probabilistic streamflow forecasts along with the experimental design employed in the study to evaluate these forecasts against climatology. Section 5 shows the utility of framework in improving water allocation from the Oros reservoir in Ceara. Section 6 evaluates the framework under synthetic forecasts having different skills and with different system configurations. Finally, we conclude with the summary and conclusions arising from the study.

2. Ensemble Streamflow Forecasts and Their Utility in Water Management

[7] Recent investigations focusing on the teleconnection between Sea Surface Temperature (SST) conditions and land surface fluxes show that interannual and interdecadal variability in exogenous climatic indices modulate rainfall [*Trenberth and Guillemot*, 1996; *Cayan et al.*, 1999] and streamflow patterns at both global and hemispheric scales [*Dettinger and Diaz*, 2000] as well as at regional scales [e.g., *Guetter and Georgakakos*, 1996; *Piechota and Dracup*, 1996]. Seasonal streamflow forecasts based on exogenous climate indices can be obtained using both dynamical and statistical modeling approaches. The dynamical modeling involves coupling of a hydrological model with a Regional Climate Model (RCM) that preserves the boundary conditions specified by the General Circulation Model (GCM) outputs considering the topography of the region [e.g., *Leung et al.*, 1999; *Nijssen et al.*, 2001]. The alternative of developing a statistical model has been successfully pursued by many investigators focusing on the estimation of conditional distributions/expectations of streamflow based on current conditions of snowpack, streamflow volume and SST anomalies to issue seasonal and long-lead (3–12 months) streamflow forecasts [*Maurer and Lettenmaier*, 2004; *Piechota et al.*, 2001; *Sicard et al.*, 2002; *Souza Filho and Lall*, 2003; *Devineni et al.*, 2008]. Studies have also employed Model Output Statistics for statistically downscaling GCM climate forecasts to develop real-time streamflow forecasts [*Landman and Goddard*, 2002; *Sankarasubramanian et al.*, 2008].

[8] Recent studies have also focused on demonstrating the utility of climate forecasts for improving water management [*Yao and Georgakakos*, 2001; *Hamlet et al.*, 2002; *Maurer and Lettenmaier*, 2004; *Voisin et al.*, 2006; *Georgakakos and Graham*, 2008; *Golembesky et al.*, 2009]. Using retrospective streamflow forecasts for the Columbia River, *Hamlet et al.* [2002] show that the long-lead streamflow forecasts can be effectively utilized in operating reservoirs to obtain increased annual average hydropower. *Georgakakos et al.* [1998] showed that using coupled hydraulic-hydrologic prediction models along with robust forecast control methodologies can increase resilience of the reservoir systems to climate variability and change. *Golembesky et al.* [2009] utilize probabilistic multimodel streamflow forecasts to invoke water withdrawal restrictions for improving the operation of Falls Lake reservoir, Neuse basin during below-normal inflow years. To summarize, application of climate information for water management has been shown to result in improved benefits over the long term in comparison to the benefits that would be obtainable under no-forecasts (climatology) based operation.

[9] Studies have shown that promoting water allocation using water contracts in water-stressed regions and allowing

water trading during droughts can increase the water use efficiency resulting in increased net benefits [*Characklis et al.*, 1999; *Pulido-Velazquez et al.*, 2004]. Most of the proposed contracts and allocation mechanisms focus on time scales longer than 5–10 years and do not have the flexibility to deal with short-term (3 months to 12 months) probabilistic inflow forecasts. The following section discusses the water allocation model and the associated risk management framework that we propose to address this situation.

3. Dynamic Water Allocation Framework for Multiple Uses

[10] A new strategy for adaptively allocating water resources using short-term probabilistic streamflow forecasts is presented here. A participatory process is envisaged for state/basin scale decision making on water allocation using existing water infrastructure. Incentives, equity, economic efficiency, contract reliability, a self-insurance mechanism, and uncertainty in short-term forecasts are considered in the water allocation framework. The proposed framework encompasses (a) a structure for water contracts, and (b) a water allocation model that can be used for decisions on which contracts to be issued for multiple uses, conditional on reservoir levels and streamflow forecasts. The water allocation model presented here is a single site, multi purpose reservoir optimization model that maximizes a user specified utility function given a policy structure for desired yield reliabilities, sectoral water allocation constraints and preferences. The net benefit from all releases of specified reliability of supply is maximized by meeting policy and physical constraints contingent upon the given ensemble streamflow forecasts.

[11] The model is similar to previous formulations of a yield model for reservoir sizing and operation [*Lall and Miller*, 1988; *Lall*, 1995; *Sinha et al.*, 1999; *Stedinger et al.*, 1984]. In the traditional yield model, firm and secondary yields from the reservoir corresponding to a high and a low reliability are considered through simulation or a stochastic analysis of the long-term performance of the reservoir given uncertain inflows. The objective is often to maximize net benefits from the firm and secondary yield for each of the designated uses of the water to be released as per a specified monthly demand pattern. We extend this paradigm by considering that if forecasts are available, then one may be able to identify conditions under which the secondary yield (e.g., with a long-term reliability of 50%) may be available in the upcoming season with a much higher reliability (e.g., 90%) without compromising the long-term performance of the system. If this is possible, then higher value uses could be met during the upcoming season, thus increasing the benefits from system operation. Short-term contracts that guarantee this secondary yield at the desired reliability could then be issued or traded as the mechanism for implementing the allocation.

[12] As indicated earlier, the model is intended to be used by the reservoir system operator as part of an iterative process with user groups. In a given iteration, each user group will declare certain preferences consistent with the structure of the model. An optimal solution for the allocation or contract specification is then derived using the probabilistic forecast and the model described in this section. The user groups respond to the model derived proposal from the operator with revised offers as to their proposed terms regarding price, quantity and reliability. This leads to the next iteration of the model. The iterative transactions could occur as part of reservoir or river basin committee meetings that already exist in the setting in Brazil which we use for our example.

3.1. Water Contracts Structure

[13] Consider that initial discussion among the water users has led to a total of ‘n’ users (these could be irrigation districts or a municipal wholesaler, rather than thousands of individual consumers). Then, a water supply contract for ith use can be described by: (a) contract duration, T; (e.g., seasonal (T = 3) or annual (T = 12)) (b) total volume of water, R_i, to be delivered over period; (c) within period demand fraction, β_{ti}; (d) amount, φ_i, to be paid for the water if all contract terms are met; (e) target reliability, $(1-p_{fi})$, where p_{fi} is the probability of failure of the ith contract; (f) Restriction volume, w_i^*, that the supplier can impose as part of the contract if the inflows are lesser than the forecast during the period of contract operation; (g) Restriction fraction, α_{il}, signifying the reduced supply under restriction level ‘l’ (where l l = 1, . . ., n_r with n_r is the total number of restriction levels agreed by the water users and the agency) (h) Compensation amount, γ_{il}, for the contract holder if restriction level ‘l’ is imposed; (i) Compensation schedule, ν_i, for the contract holder in the event of contract failure (i.e., if the total possible restriction is inadequate to meet the shortfall in the forecasted streamflow).

[14] It is important to note that these contract terms consider both the quantity of the water to be supplied with certain reliability, as well as contingencies for what happens during the actual operation period, in case the contracted amount of water cannot be supplied. These contingencies prescribe how much failure of the contracted water can be allowed under different emergency conditions (or restriction levels) that the operator would need to announce under a predefined scheme, and the associated compensation due to the user. In effect an insurance policy is being prescribed through these contingencies. The precise terms would need to be negotiated, and a formal numerical analysis can be used to assist the establishment of a fair system of compensation under failure that is related directly to the specified reliability (or probability of failure) and the associated levels of failure. For the operator, a procedure for how different contracts are honored (e.g., prioritized reduction or proportional reduction for all users) would also be needed.

[15] It might be useful to develop generic contracts for each category of use (e.g., municipal or agricultural use) adhering to the guidelines set by the local water Committee/agency in the region. These contracts could then also become the instruments on which water trading can take place with clear knowledge of the terms including the reliability of supply and the restriction/compensation pattern. Water that is needed for basic services like domestic water supply and ecosystem services could also be allocated separately by assigning high priorities or longer term contracts that take precedence over the forecast based short-term contracts.

[16] Often drought management rules in many areas consider the declaration of a drought watch, warning or

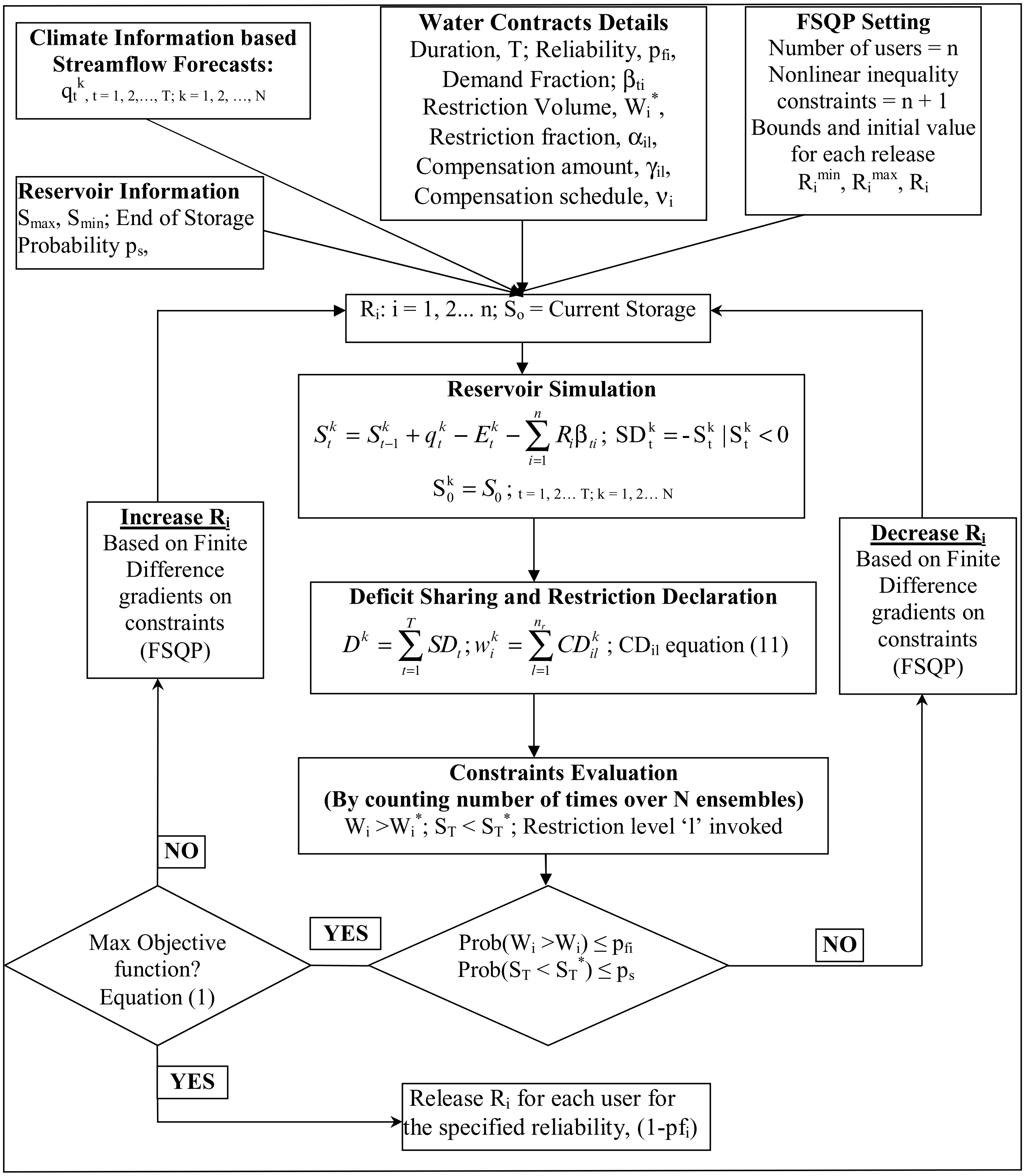

Figure 1. Water Allocation Framework embedded in a simulation-optimization model with water contracts and probabilistic constraints on reservoir storage.

emergency denoting the possibility of progressive severity of potential failure of supply. Specific restrictions on use and curtailment of supply are then placed on water use. Here, we consider a similar strategy, where the operator may declare different restriction levels, not just related to drought, but to inflow conditions being relatively drier than assumed in deriving the amount of water that could be allocated with the prescribed degree of reliability using the forecasts. If a restriction is imposed, then a contract 'i' would receive a reduced supply of water, by an amount, α_{il} R_i, under restriction level 'l'. Each contract could potentially have a different restriction fraction under a particular restriction level. Figure 1 provides a schematic of the water allocation framework by combining this water contract structure with the simulation-optimization model, which is described in detail in the next section.

3.2. Water Allocation Model for Bulk Sector Contracts Using Ensemble Forecasts

[17] The model (Figure 1) developed here seeks to maximize the utility associated with water allocation for the upcoming period of allocation from the reservoir, given the contract structure described above and an ensemble forecast of monthly flows over the season. Here the term utility is used rather broadly. It could refer to a measure that relates to the expected net revenue from operations accounting for the water price defined for each contract, and the penalties that could be paid with some probability if the terms or not met. Alternately, utility could be defined by any other measure that relates to social/community or organizational goals. The idea is that given certain values assigned to different levels of reliability for different uses, we need criteria to decide how much water we can allocate to those uses given the forecasts and the desired reliability levels.

[18] The feasible releases, R_i, with reliability $(1-p_{fi})$ for the ith contract are determined considering the following factors.

[19] 1. A T month lead ensemble reservoir inflow forecast, q_t^k, where t = 1, 2, ..., T denotes the period of operation (usually t is in months), k = 1, 2, ..., N is the index representing one of 'N' forecast ensemble members.

[20] 2. The current reservoir storage, S_{0*}, at the beginning of the allocation period.

[21] 3. An end of season target storage, S_{T*}, with failure probability p_s. The end of the year (period) target storage S_{T*} could be prescribed by policy to meet a target demand, or obtained based on the long-term water rights.

3.2.1. Objective Function

[22] The goal is to maximize the utility (taken in our application to be the net expected revenue from the allocation)

$$O = E\left\{\sum_{i=1}^{n}\phi_i(R_i) - \left[\sum_{i=1}^{n}\sum_{j=1}^{n_l}\gamma_{il}W_{il} + \sum_{i=1}^{n}\nu_i\delta\left(W_i - W_i^*\right)\right]\right\} \tag{1}$$

where $\varphi_i(R_i)$ denotes the benefit/tariff associated with releasing R_i and $\delta(x) = \begin{cases} 1 & if \quad x > 0 \\ 0 & Otherwise \end{cases}$. The operator E{} denotes the expectation and the term in the squared brackets within the expectation operator denotes the associated compensation (γ_{il}) for the restriction volume (W_{il}) and penalty (ν_i) under contract failure (if $W_i > W_i^*$).

3.2.2. Constraints

[23] The constraints in the proposed water allocation model can be grouped into two categories: (a) contract level constraints (b) reservoir level constraints. Contract level constraints prescribe the minimum and maximum release and the target reliability for each use that enforces the probability of supplying the contracted volume, R_i, without imposing the user specified restriction, w_i^*. Reservoir level constraints specify the end of the season target storage as well as the minimum and maximum storage constraints.

[24] In the operation of most water supply systems, water for human and animal consumption is assigned high priority (accordingly target reliability is high) with a specified lower bound. Similarly, water necessary to maintain prescribed water quality characteristics for the sustenance of aquatic life could be expressed, as the sum of releases from all contracts along the river reach should be above the minimum prescribed amount. These policy or physical considerations may enforce the release for each contract to be constrained between an upper and lower bound, which could be expressed as

$$R_{i,min} \leq R_i \leq R_{i,max} \tag{2}$$

[25] The target reliability $(1-p_{fi})$ of supply of the contracted quantity, R_i is enforced by specifying that the likelihood of actual restrictions, w_i, for each contract being greater than maximum allowed restriction volume, w_i^*, should be lesser than the contract failure probability, p_{fi}. The maximum allowed restriction volume, w_i^* and the contract reliability $(1-p_{fi})$ act together to provide a safety mechanism for both the user as well as the supply agency.

$$\text{Prob}\left(w_i \geq w_i^*\right) \leq p_{fi} \tag{3}$$

The end of the season target storage constraint binds all contracts allocation. The end of the season storage, S_{T*}, prescribes the minimum quantity of water to be maintained in the reservoir at the end of the contract period considering various issues including the minimum quantity needed for basic human need in the ensuing year/season as well as water that needs to be stored to meet long-term water contracts. To ensure this, a probability constraint on the end of the season storage could be introduced as in (4).

$$\text{Prob}\left(S_T \leq S_{T*}\right) \leq p_s \tag{4}$$

It is important to note that S_T and w_i are not decision variables. These state variables expressed as functions of the release, R_i, are evaluated during each iteration of the optimization model using the reservoir simulation described below. Probability constraints (3) and (4) are evaluated by counting the number of times the respective inequalities are satisfied.

3.2.3. Reservoir Simulation

[26] Most reservoir optimization models consider all state variables as explicit decision variables, thereby increasing the dimensionality of the problem and computation time. This could be avoided by embedding a simulation module inside the optimization scheme [*Lall and Miller*, 1988; *Lall*, 1995]. Essentially, the simulation module obtains the reservoir storages using basic continuity equations for the current value of the decision variable, R_i, in the optimization scheme. For a recent discussion of the merits of the combined simulation-optimization approach, see *Koutsoyiannis and Economou* [2003].

[27] For each trace 'k' (k = 1, 2, ..., N) in the ensemble, we compute the reservoir storages given the initial reservoir

storage, $S_0 = S_{0*}$ and the release, R_i. Using the continuity equation, the monthly storage equations could be expressed using equations (5) and (6).

$$S_t = S_{t-1} + q_t - E_t - \sum_{i=1}^{n} R_{ti} - SP_t + SD_t, t = 1, 2, \ldots, T \quad (5)$$

$$SD_t = (S_{min} - S_t)|S_t < S_{min}; SP_t = (S_{max} - S_t)|S_t > S_{max} \quad (6)$$

Equation (6) evaluates the shortfall (SD_t) and spill (SP_t) if the end of the month storage (S_t) violates the minimum (i.e., dead storage) and maximum possible storage respectively. Monthly storage equations are constrained so that the storage is between the dead storage, S_{min}, and maximum possible storage, S_{max}. Monthly releases, R_{ti}, are computed using monthly demand fractions in equation (8).

$$S_t = \min(S_t, S_{max}), S_t = \max(S_t, S_{min}) \quad (7)$$

$$R_{ti} = \beta_{ti} R_i \quad (8)$$

Evaporation, E_t, at each month is computed implicitly as a function of average storage during the month using the area-storage relationship of the reservoir.

$$E_t = \psi_t \delta_1 ((S_t + S_{t-1})/2)^{\delta_2} \quad (9)$$

where ψ_t is the monthly evaporation rate, δ_1 and δ_2 are coefficients describing the area-storage relationship.

[28] To evaluate the reliability constraint in (3), it is important to distribute the deficit SD_t to each user 'i' using the agreed restriction levels and the corresponding restriction fraction. Computing the total deficit, D, in trace 'k'

$$D = \sum_{t=1}^{T} SD_t \quad (10)$$

If D = 0, then $S_t > S_{min}$ over all months implying $w_i = 0$. On the other hand, if D > 0, compute CD_{il}, the total restriction received by user 'i' in the restriction level 'l' to account shortfall/deficit 'D' in trace 'k' using (11).

$$CD_{il} = \min(\lambda_{il}(D - AD_{l-1})/\lambda_l, \lambda_{il}); AD_{l-1} = \sum_{l=1}^{j-1} \sum_{i=1}^{n} CD_{il};$$
$$AD_0 = 0 \quad (11)$$

where AD_{l-1} is the total deficit accounted up to restriction level 'l−1', $\lambda_{il} = \alpha_{il} R_i$ is the maximum amount of restriction that can be placed on user 'i' under restriction level 'l' and $\lambda_l = \sum_{i=1}^{n} \lambda_{il}$ is the maximum amount of restriction that can be accounted under restriction level 'l' considering all the contracts. Both λ_{il}, λ_l can be calculated upfront based on the current value of R_i and they do not change for each trace. Based on this information, w_i for each use can be expressed as

$$w_i = \sum_{l=1}^{n_r} CD_{il} \quad (12)$$

Looking across all the traces in the ensemble, compute the following probabilities.

[29] 1. Prob ($w_i > w_i^*$) as the number of traces in which ($w_i > w_i^*$)/total number of traces, N.

[30] 2. Prob($S_T \leq S_{T*}$) as the number of traces in which $S_T \leq S_{T*}$/total number of traces, N.

[31] We consider N = 1000 traces that contains monthly streamflow forecasts and the above probabilities are computed across the ensemble to evaluate constraints in equations (3) and (4). The optimization solver, Fortran Feasible Sequential Quadratic Programming (FFSQP) developed at the University of Maryland [*Zhou et al.*, 1997], maximizes the net value, O, from the reservoir by satisfying the constraints in Section 3.2.2 and using the reservoir simulation details listed in (5)–(12).

4. Brazil Application: Streamflow Forecast Development and Experiment Design

[32] The utility of the proposed allocation model as part of the contract based allocation system is evaluated by considering an application for the multipurpose Oros reservoir, which is the biggest reservoir in the Jaguaribe-Metropolitan Hydro (JMH) System, Ceara, North East Brazil. The performance of the system in making firm commitments of allocation through contracts at the desired level of reliability and reduced system losses (spill and evaporation) utilizing 12 month ahead streamflow forecasts is compared with same metrics under a) a climatological forecast (i.e., each year of the historical record is drawn with equal probability to form an ensemble), and b) a zero inflow forecast, which is currently used by the local water agency as a "conservative" forecast basis for water allocation. Inflows into the Oros reservoir occur typically during January–June with literally zero flow during July–December. Subsequently, the irrigation needs for agriculture are mainly during August–November, whereas release for human and industrial demands is constant all through the year. For additional details, see *Souza Filho and Lall* [2003]. Figure 2 shows the location of the Oros reservoir in the JMH system in the state of Ceara, North East Brazil. A water allocation year (e.g., 1949 water allocation year implies July 1949 to June 1950) in Ceara typically spans from July to June of the calendar year with the allocation for different uses decided through water committee meeting July. The next section briefly describes the development of 12 month lead retrospective streamflow forecasts developed for the Oros reservoir using the semiparametric K-nearest neighbor (K-NN) algorithm of *Souza Filho and Lall* [2003].

4.1. Retrospective Streamflow Forecast Generation

[33] Using the semiparametric K-nearest neighbor resampling algorithm of *Souza Filho and Lall* [2003], 1000 traces of retrospective monthly streamflow forecasts are developed using the following two predictors: April–June average of East Atlantic Dipole (EAD) and NINO3.4. *Souza Filho and*

Figure 2. Location of Ceara, Brazil, and the Reservoir Inflow Locations. Here 1, Oros; 2, Banabuiu; 3, Pedras Branca; 4, Pacajus; 5, Pacoti Riachao; 6, Gaviao. The major irrigation demand areas are indicated by squares, and the municipal and industrial demand areas served are indicated by filled circles. Only features of the Jaguaribe and Metropolitan basins are filled in. Other basin boundaries are marked.

Lall [2003] show the correlations between the annual flows at Oros reservoir and these two predictors are statistically significant. NINO3.4, the most commonly used index to represent ENSO condition in the tropical Pacific, is defined as the average SST anomaly in the region bounded by the eastern equatorial Pacific 170 degrees W to 120 degrees W and 5 degrees S to 5 degrees N. The other climatic index, East Atlantic SST Gradient (EAG), is defined as the difference in the monthly average of the SST anomaly in the region bounded by North Atlantic (5–20N, 60–30W) and the monthly average of the region bounded by South Atlantic (0–20S, 30W–10E). The monthly time series for these indices were derived from the gridded SST anomaly data sets developed by *Kaplan et al.* [1998] available at http://ingrid.ldeo.columbia.edu/SOURCES/.KAPLAN/.EXTENDED/. For additional details, see *Souza Filho and Lall* [2003].

[34] Figure 3a shows the conditional distribution of 12 month ahead retrospective forecasts for water allocation years 1970–1995 obtained in a leave-one-out cross validation mode using the K-NN resampling algorithm. The correlation between the observed flows and the average of the ensemble is 0.73. Figure 3b shows the adaptive forecasts for the water allocation years 1990–1999 which is developed by fitting the model using the data available for the period July 1949 to June 1990. The correlation between the observed annual flows and the ensemble average of the forecasted annual flows obtained is 0.7 for the period July 1990 to June 2000. Both Figure 3 and the forecast verification shown by *Souza Filho and Lall* [2003] show that the annual flows in Oros could be predicted quite well using the two predictors (NINO3.4 and EAG). We employ the adaptive streamflow forecasts shown in Figure 3b to show the utility of the water allocation framework discussed in Section 3.

4.2. Climatological Forecasts of Streamflow (Null Forecast)

[35] The lag-one correlation between the annual flows of the Oros reservoir is near zero. Hence, to develop climatological ensembles of streamflow, we simply bootstrap the observed annual flows to form 1000 ensembles every year. The monthly streamflow sequence corresponding to the bootstrapped annual flow would form the respective monthly flows in that trace.

4.3. Zero Inflow Policy

[36] Since about 10% of the historical years have no flow in the wet season, the state water allocation agency for the JMH System assumes zero inflow for the next twelve months (July–June) for the short-term allocation of water for different uses. In other words, water is allocated purely based on the currently available storage with the goal of keeping a certain amount of water in storage at the end of the period to cover the anticipated demands for the next 18 months. This is claimed to be a conservative approach that ensures the reliability of supply being equal to nearly 100% over the allocation period since it only allocates the stock in the reservoir at the beginning of the dry season. However, this approach may lead to periodic spills and excess evaporation from the reservoir due to under-allocation.

4.4. Experimental Design

[37] The utility of climate information based streamflow forecasts is assessed for multipurpose water allocation from

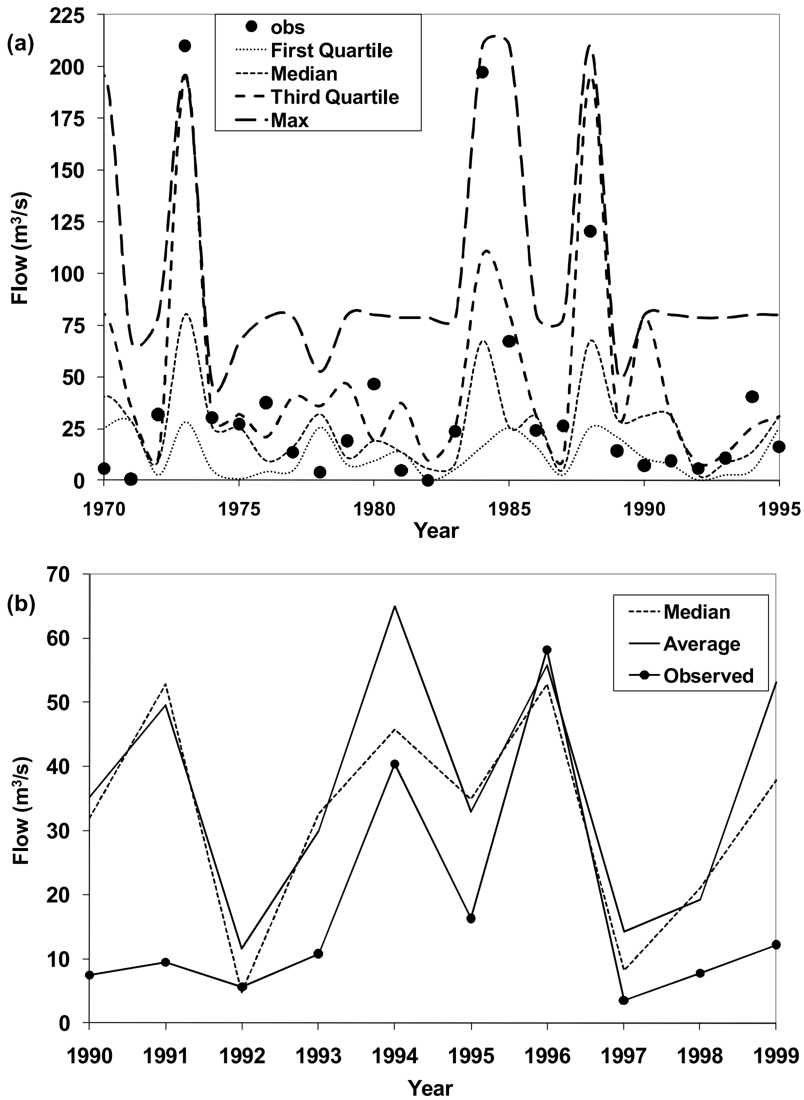

Figure 3. Performance of the K-nearest neighbor resampling algorithm in predicting the observed flows at the Oros reservoir. (a) Conditional distribution of leave-one-out cross-validated annual flows for 1970–1995. (b) Adaptive forecasts for the period 1990–1999 obtained using the flow values and predictors available for the period 1949–1989.

the Oros reservoir by maximizing the net benefits function in (1) for the period July 1990 to June 2000 (T = 12 months). The water allocation experiment is run for 90% reliability ($1-pf_i$) for each use. We make an ad hoc assumption that the target year-end storage probability, p_s is equal to the contract failure probability, p_{fi}. We assumed two restriction ($n_r = 2$) levels with the restriction fraction for each user being $\alpha_{il} = 0.5$ and 0.9 for l = 1 and 2 and the restriction volume $w_i^* = 0$; $\forall i$ (i = 1, 2 and 3). The tariffs for municipal, industrial and agricultural uses are R$ 87, 33 and 8 respectively for 1000 m^3 of supply (Source: COGERH, the JMH water allocation agency). Thus, the benefit function ($\phi_i(R_i)$) in equation (1) becomes a linear function of the tariff to the supplied release. The compensation (γ_{il}) under both restriction levels and the penalty (ν_i) under contract failure are assumed to be 30% and 60% of the tariff respectively of each use.

Table 1. Monthly Evaporation Rate and the Within-Year Demand Fraction for the Oros Reservoir Used for Simulation[a]

	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
ψ_t	0.151	0.174	0.175	0.189	0.172	0.170	0.129	0.091	0.072	0.069	0.081	0.118
β_{ti} (i = 3) (Irrigation)	0.0	0.2	0.4	0.3	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0

[a]Monthly evaporation rate, ψt, is in meters. Within-year demand fraction, β_{ti}. The total annual evaporation is 1.590 m with the area-storage coefficients assumed to be $\delta_1 = 0.338$ and $\delta_2 = 0.842$. The maximum storage capacity (S_{max}) of the Oros reservoir is 1940 hm^3. Within-year demand fraction for municipal and industrial use ($\beta_{ti} = 1/12$; i = 1 and 2) is assumed to be uniform throughout the year.

Table 2. Utility of Reservoir Inflow Forecasts Toward Improving Bulk Sector Water Allocation and in Reducing System Losses With 90% Reliability for Each Use[a]

	K-NN Forecast		Zero Inflow		
	Mean	Standard Deviation	Mean	Standard Deviation	Annual Demand
Yield (Human)	130.0	0.0	130.0	0.0	130.0
Yield (Industry)	81.0	28.5	81.0	28.5	90.0
Yield (Agriculture)	130.5	45.9	120.2	53.3	145.0
Deficit/Shortfall (SF)	0.0	0.0	0.0	0.0	-
Evaporation	239.6	98.6	245.6	92.8	-
Spill (SP)	46.2	146.2	50.5	159.7	-

[a]The end of year target storage was assumed to be 260 hm^3 to supply 18 months of municipal demand even if zero inflow occurs during that period. All values are in hm^3.

[38] Table 1 gives the monthly evaporation rate for the Oros reservoir, North East Brazil along with the within-year demand fraction (β_{ti}) for all the uses. The average annual evaporation for the Oros reservoir is 1.590 m (Table 1) and the coefficients of the area-storage relationship δ_1 and δ_2 are 0.338 and 0.842 respectively. Since Ceara is a semiarid region experiencing multiyear droughts, the currently adopted strategy is to fix the end of the year storage so that the resulting storage can supply 18 months of municipal demand (including evaporation losses) even if zero inflow occurs during the period of allocation (i.e., 12 months). By assuming such a high target end of year storage, the system is protected from failure to supply municipal demand for almost 30 months even if no flow occurs. However, this severely limits the flexibility in annual allocation through contracts for each scenario. For the annual municipal demand given in Table 2, the end of year target storage to supply 18 months of municipal demand under zero inflow assumption including evaporation losses is 260 hm^3 (1 hm^3 = 1 million m^3). The maximum storage (S_{max}) and the dead storage (S_{min}) of the Oros reservoir are 1940 hm^3 and 20 hm^3 respectively.

[39] Based on the schematic diagram in Figure 4, the multipurpose water allocation experiment is run using the adaptive forecasts developed for the period July 1990 to June 2000. The actual recorded volume in Oros reservoir on July 1, 1990 was 1914.17 hm^3. Using this initial storage (S_0) for year 1990, the reliability for each use and end of the year target storage constraints, we obtain annual reservoir yields (R_{ij} – j denotes the year) for each use using the adaptive forecasts developed for the period July 1990 to June 1991. The performance of the reservoir under the forecast-suggested allocation policy was simulated by combining the forecasts-suggested releases with the observed monthly flows ($Q_{t,j}$) during that year. Under this simulation with observed flows, we also note the shortfall, spill and evaporation and actual releases that would have occurred if one employed the forecasts. The resulting end of year storage based on this simulation was assumed to be initial storage for the next year (July 1991 to June 1992). This procedure was repeated for all the 10 years (July 1990 to June 2000) for both zero inflow forecasts and for climatology.

[40] Let us denote the storages in the reservoir at each month by releasing the target monthly yield ($\beta_{ti}R_{ij}$) using the observed inflows ($Q_{t,j}$) as $S_{t,j}$, where R_{ij} is the release suggested by the one of the candidate forecasts (discussed in Sections 4.1–4.3) obtained for use 'i' in year 'j'. Then, the annual spill (SP_j) and shortfall (SF_j) volumes (T = 12 months) can be expressed as

$$SP_j = \sum_{t=1}^{T} \left(S_{t,j} - S_{\max}\right) \big| S_{t,j} > S_{\max} \tag{13}$$

$$SF_{ij} = \sum_{t=1}^{T} \left(\beta_{ti}R_{ij} - R'_{tij}\right) \Big| \left(\beta_{ti}R_{ij} - R'_{tij}\right) > 0 \tag{14}$$

where R'_{tij} is the actual release that was made in the month 't' in year 'j' for use 'i' using the observed monthly flows. The actual release R'_{tij} would be lesser than the target yield ($\beta_{ti}R_{ij}$) if the observed flows were drier than the forecasted flows. The end of the year storage ($S_{T,j}$) obtained from

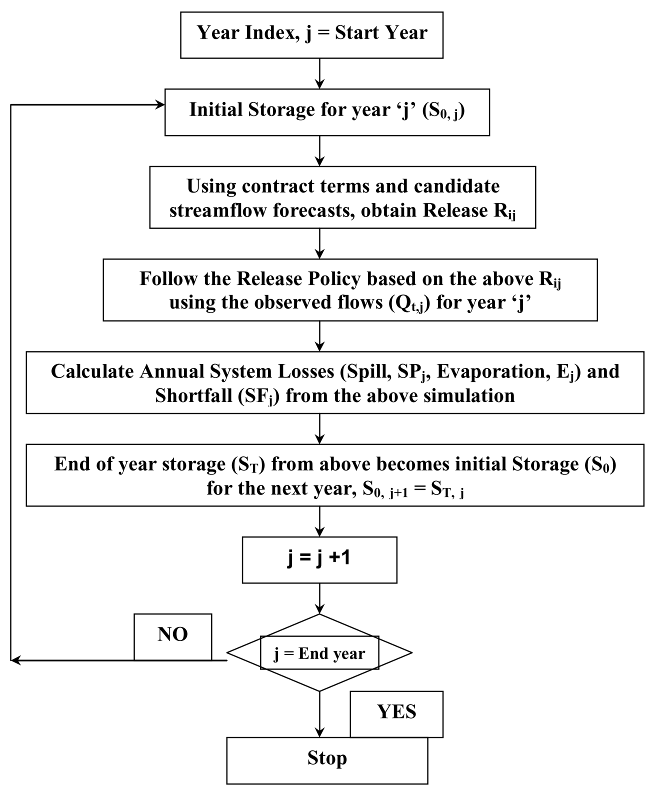

Figure 4. Schematic diagram of the experimental design adopted to validate the utility of climate information based retrospective forecasts.

reservoir simulation using (5)–(12) would be assumed to be the beginning of the year storage for the year ‘j + 1’. This entire procedure is repeated from July 1990 to June 2000 to obtain maximum reservoir yields (R_{ij}) and the corresponding annual spills (SP_j), annual shortfalls (SF_{ij}) and monthly evaporation (E_{tj}) are noted. To summarize, this experiment actually walks through the entire water allocation procedure from July 1990 to June 2000 and records the releases, spills, shortfalls, storages and evaporation that would have happened if these 12 month lead retrospective forecasts of streamflow were utilized for determining the annual yields from the reservoir. Using the same experimental design in Figure 4, we also obtain the releases, spills, shortfalls, storages and evaporation that would have occurred if one adopted the zero inflow policy and the climatological forecasts of streamflows for water allocation from the Oros reservoir.

4.5. Performance Measures

[41] *Hashimoto et al.* [1982] define three criteria namely resilience, reliability and vulnerability for evaluating the reservoir performance over the long term. We evaluate the vulnerability of the reservoir based on its ability to reduce evaporation (E_j), shortfalls (SF_j) and spills (SP_j) obtained for each year using the three streamflow forecast ensembles (KNN, Climatology/Null, and Zero Inflow Policy) over 10 (M = 10) years of allocation.

$$\hat{\mu}_{SF} = \frac{1}{M}\sum_{j=1}^{M} SF_j; SF_j = \sum_{i=1}^{n} SF_{ij} \tag{15}$$

$$\hat{\sigma}_{SF} = \sqrt{\frac{1}{(M-1)}\sum_{j=1}^{M}\left(SF_j - \hat{\mu}_{SF}\right)^2} \tag{16}$$

$$\hat{\mu}_{SP} = \frac{1}{M}\sum_{j=1}^{M} SP_j \tag{17}$$

$$\hat{\sigma}_{SP} = \sqrt{\frac{1}{(M-1)}\sum_{j=1}^{M}\left(SP_j - \hat{\mu}_{SP}\right)^2} \tag{18}$$

The mean and standard deviation of annual evaporation ($\hat{\mu}_E$, $\hat{\sigma}_E$) from the reservoir is also calculated using the simulated storages ($S_{t,j}$) obtained from the evaporation equation in (9).

5. Assessment of the Utility of Climate Information Based Streamflow Forecasts

[42] In this section, we assess the utility of retrospective reservoir inflow forecasts (developed in Section 4.1) toward potential improvement in annual water allocation for multipurpose use in the JMH basin, Ceara for the period July 1990 to June 2000. First, we briefly demonstrate the utility of the proposed risk management framework using a simple illustration.

5.1. Dynamic Water Allocation Framework: An Illustration

[43] Annual reservoir yields obtained using the water allocation framework in Section 3 varies according to the shift in the conditional distribution of flows. To illustrate this, we show the reliability yield curve (Figure 5a) for a high flow year (1988) and low flow year (1992) obtained using the leave-one-out cross-validated forecasts (Figure 3a) as well as the yields obtained using climatological ensemble. The reliability yield curves shown in Figure 5a are obtained by assuming the storage in the reservoir in the beginning of July 1988 and July 1992 to be 50 hm^3. From Figure 3, it can be seen that the flow in 1988 is among the largest flows that often occurs if La Nina conditions persist in the tropical Pacific. On the other hand, flow in 1992 corresponds to a low flow year that typically occurs during El Nino events. Reservoir yields obtained using the climate information based streamflow forecasts reflect this with the yield being higher in 1988 and lower in 1992, whereas reservoir yields obtained from climatological ensemble do not vary from year to year. Figure 5b shows the median of the simulated storages (out of 1000 ensemble of simulated storages) for supplying the specified yield at 90% reliability for years 1988 and 1992. To supply the higher annual target in 1988, the median of the simulated storages for 1988 is higher than the median of the simulated storages for 1992. The simulated storages obtained based on climatological yields do not change, since the information in the ensemble remain the same every year. This shows that both the annual yields and the simulated storages vary according to the change in inflow potential indicated by the streamflow forecasts.

5.2. Utility of Long-Lead Forecasts in Improving Bulk Sector Water Allocation

[44] The results presented under this section focus on quantifying the utility of 12 month ahead streamflow forecasts in improving bulk sector water allocation using the experimental design in Section 4 for the period July 1990 to June 2000. Table 2 gives the annual average yields for human, industrial and municipal use using the K-NN forecasts and the zero inflow assumption along with the maximum annual demand for each use. Table 2 also summarizes the annual average shortfall, spill and evaporation in meeting the target yield obtained using both the approaches. As we can see from Table 2, there is no difference in annual allocation for municipal and industrial use using either of the two approaches, since their tariffs are higher than irrigation. But, average annual yield for agriculture could be considerably increased using the K-NN forecasts, which is mainly obtained by reduction in spill and evaporation. Table 2 also quantifies the variability in annual yields, evaporation and spill from the reservoir.

[45] Figure 6a shows the difference between yields obtained using K-NN forecasts and yields obtained using zero inflow assumption for all the three uses along with the observed annual flows in that particular year. Since the municipal use has the highest tariff, the entire annual demand for municipal use was allocated in each year during the period July 1990 to June 2000 under both K-NN forecast and zero inflows. For industrial use, except in 1994, the net annual demand was allocated in all the years

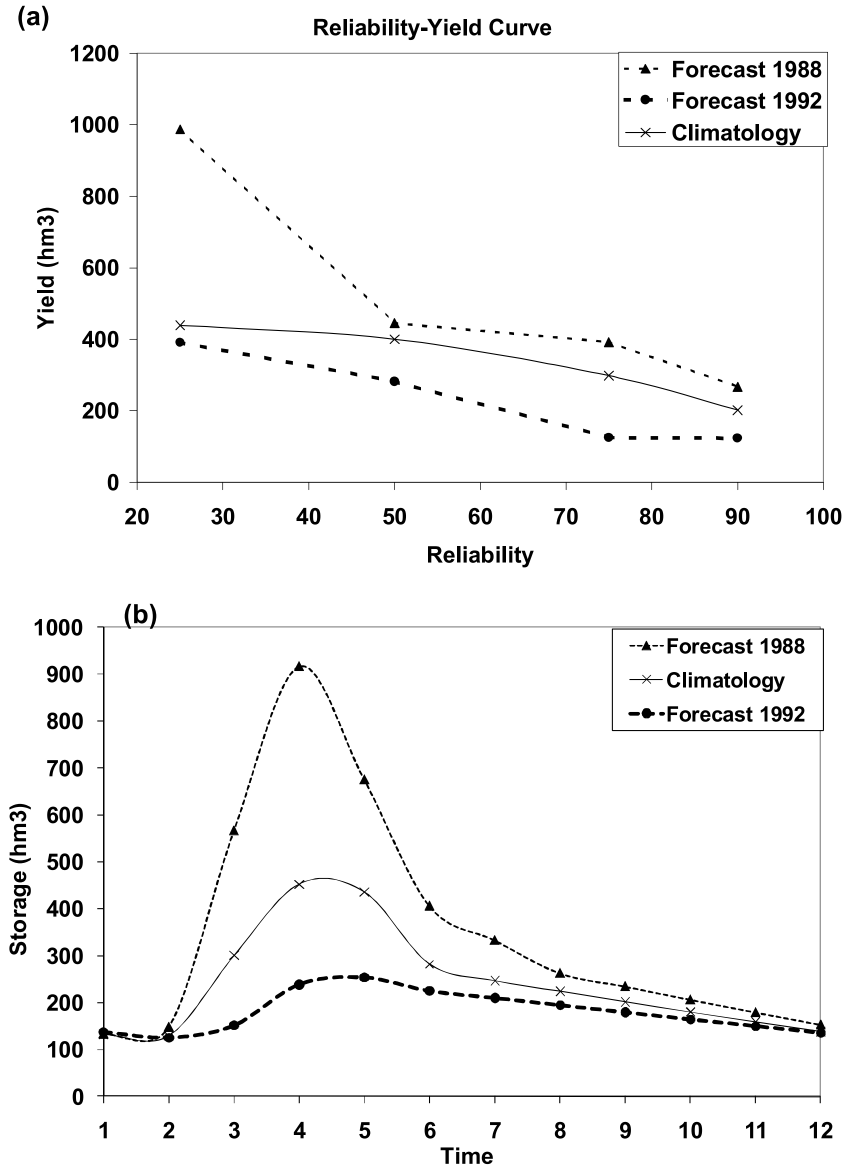

Figure 5. Bulk Sector Water allocation for years 1988 and 1992 for the Oros reservoir using the 12 month lead semiparametric K-NN forecast and using the climatological ensembles: (a) Reliability Yield Curve and (b) median of the simulated storages for supplying 90% reliability.

by both K-NN forecast and zero inflow. However, in 1994, the difference in yield between K-NN forecast and zero inflow (in Figure 6a) is zero for both industrial and agriculture uses, since the net allocation was zero by both schemes due to low initial storage conditions. For agriculture, the difference in yield between forecasts and zero inflow is positive only in 1993 indicating the increased yield (145 hm^3) under K-NN forecasts in comparison to the yield (42 hm^3) suggested by the zero inflow.

[46] To understand why K-NN forecasts suggest additional allocation for agriculture in 1993, we plot the simulated reliability of supply and the corresponding simulated initial storage available for allocation in Figure 6b. During the period 1990–1992, the observed flow was below normal which forced the storage in the reservoir to continuously deplete. Thus, in 1993, the available initial storage (657 hm^3) cannot guarantee allocation of the entire demand for agriculture use under the zero inflow assumption, which results in a reduced allocation of only 42 hm^3 for agriculture. However, the forecasts having the ability to predict the change in flow potential suggests allocation of entire agriculture demand in 1993. But, in 1994, with the simulated initial storage being at the lowest in 10 years, the simulated reliability of supply using K-NN forecasts for municipal use is reduced to 90%. Thus, the utility of climate forecasts is more pronounced during critical drought periods when the initial storage is lesser than the total demand for all the uses.

[47] Figure 7 shows the system losses in terms of evaporation and spill for water allocation years 1990–1999. Figure 7a shows that the evaporation using K-NN forecasts is lower than the zero inflow assumption, since K-NN forecasts suggest additional releases in year 1993 which results in reduced storage for evaporation. Figure 7b shows the reduction in spill (around 40 hm^3) that was achieved in 1996 using K-NN forecasts over the zero inflow assump-

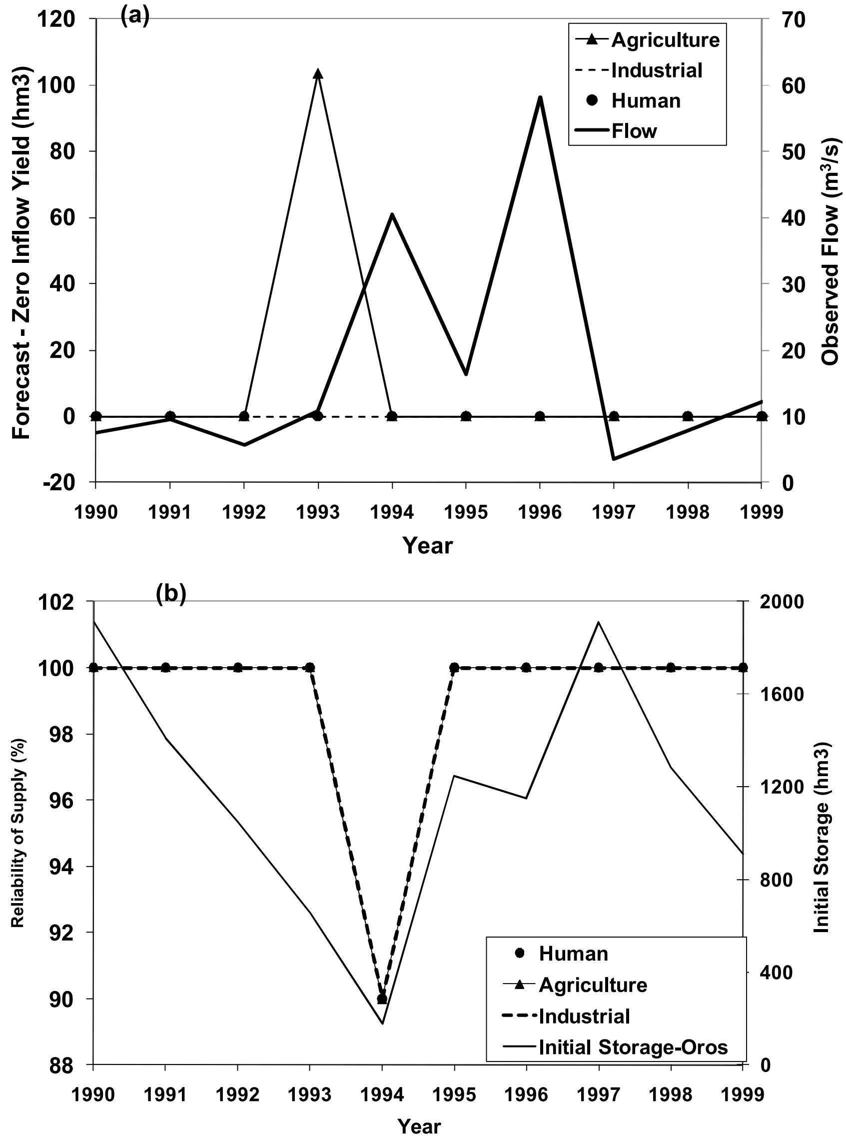

Figure 6. Performance of adaptive K-NN forecasts in improving multipurpose water allocation. (a) Difference in Forecasted Yield and Zero Inflow Yield for three uses. (b) Simulated reliability of supply using the K-NN forecast ensembles for each use.

tion. The tropical Pacific was going through a La Nina phase in year 1996–1997 that usually leads to above normal inflows into the Oros reservoir. Once the reservoir builds up sufficiently with high initial storage conditions, there is no difference in reservoir yields using climate information based reservoir inflow forecasts and zero inflow assumption. From this view point, if ENSO cycle enters into La Nina conditions first followed by El Nino conditions, then water management during drought periods (during El Nino conditions) becomes relatively easy since sufficient storage is built up during La Nina conditions. Reversal of this scenario (with El Nino first followed by La Nina conditions) would be difficult from short-term water management point of view. The worst situation would be if two consecutive ENSO cycles were diametrically opposite (i.e., La Nina to El Nino to neutral to El Nino to La Nina).

[48] Results from this exercise show that the utility of climate forecasts for multipurpose water allocation from the Oros reservoir is more pronounced during above-normal and below-normal inflow years. Since Oros is a multiyear storage reservoir that ensures sufficient initial storage conditions in July, the reservoir yields obtained using both K-NN forecasts and zero inflow assumption do not differ during normal conditions. The currently pursued strategy of zero inflow assumption only leads to increased losses from the system. Important information from Table 2 is that the improvements obtained using these forecasts are very small for the Oros system, since the storage to annual inflow volume ratio for Oros ratio is 4.23. Studies have shown that as the storage to annual inflow volume ratio increases the utility of forecasts decreases [*Maurer and Lettenmaier*, 2004]. However, a more appropriate metric to evaluate the utility of forecasts is the storage to annual demand ratio, since it incorporates the demand the system need to supply over the period of allocation. In the next section, we perform detailed analyses in understanding the utility of

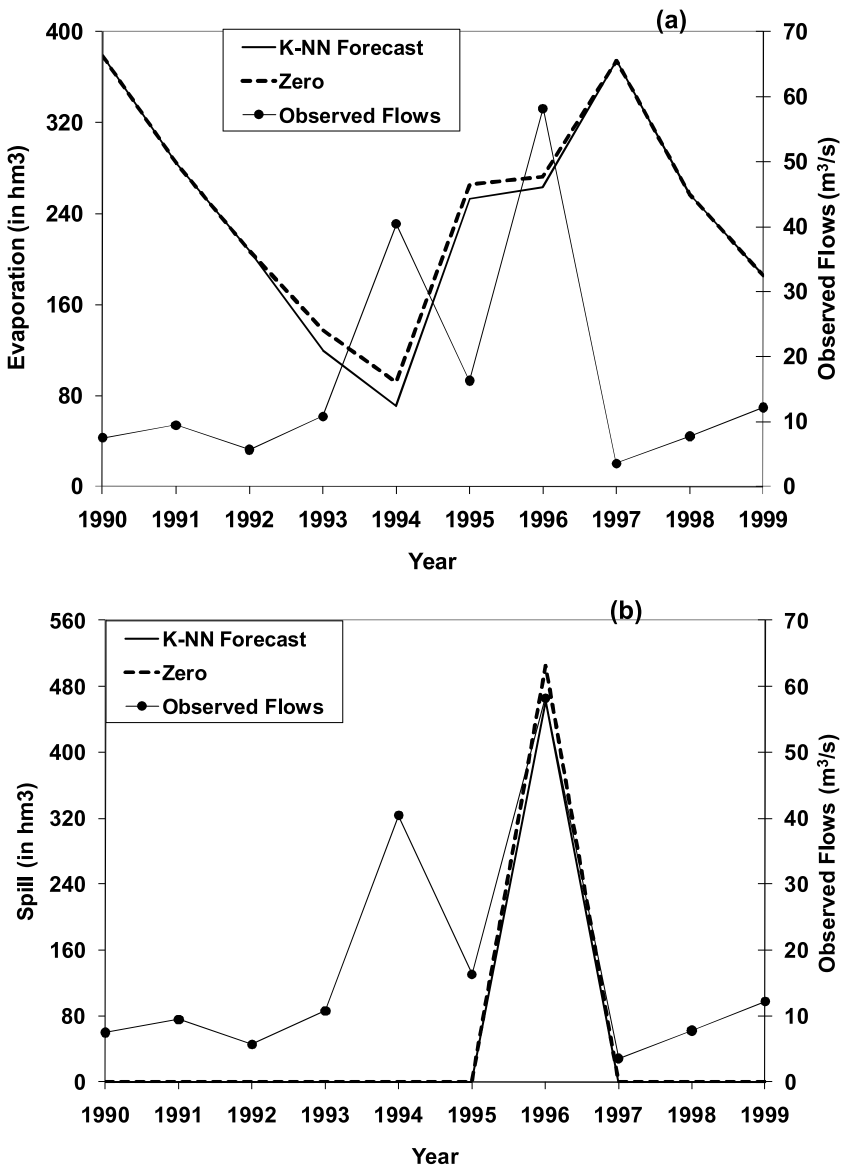

Figure 7. System Losses from Oros reservoir utilizing K-NN forecasts and based on Zero Inflow assumption: (a) evaporation and (b) spill. The end of the year target storage was assumed to be 260 hm^3 which would ensure municipal supply for an additional 18 months. The reliability of supply for each use is 90%.

streamflow forecasts having different skill in improving water allocation under various system configurations.

6. Utility of Streamflow Forecasts Under Various System Configurations

[49] The analysis in the previous section showed that the utility of streamflow forecasts is limited if the reservoir storage is considerably larger in comparison to its annual demand. Given that the state of Ceara is undergoing rapid industrialization and development, the demand is expected to increase substantially in the near future [*Broad et al.*, 2007]. One could anticipate that under those conditions, the increased demand will constrain the storage in the reservoir thereby increasing the utility of streamflow forecasts. In this section, we systematically show that the utility of streamflow forecasts increases if the storage to demand ratio decreases.

6.1. Reservoir Inflow Forecasts of Known Predictive Skill

[50] To develop synthetic streamflow forecasts exhibiting different skill with observed flows, we generate ensemble of synthetic streamflows for the Oros reservoir using a parametric periodic gamma autoregressive model [*Fernandez and Salas*, 1986]. We basically add noise to the observed historical flow sequence such that the synthetic streamflow preserves the monthly mean, variance and month-to-month correlation structure recorded at the Oros reservoir. Since the observed streamflows exhibit significant skewness [*Souza Filho and Lall*, 2003], we generate errors from a periodic gamma autoregressive model. By choosing a particular forecast skill, $\rho_{Q,Q_t'}$ we generate synthetic forecasts

Table 3. Comparison of Monthly Statistics of Simulated Flows Using (19) Defined in Section 6.1[a]

	Statistic	January	February	March	April	May	June
Observed	$\hat{\mu}_Q$	4.37	28.43	103.08	184.74	56.57	9.81
$\rho_{Q_t}Q'_t \approx 1.0$	$\hat{\mu}_Q'$	4.37	28.43	103.09	184.73	56.57	9.81
$\rho_{Q_t}Q'_t = 0.75$	$\hat{\mu}_Q'$	4.36	28.43	103.09	184.73	56.57	9.81
$\rho_{Q_t}Q'_t = 0.5$	$\hat{\mu}_Q'$	4.37	28.43	103.08	184.73	56.57	9.81
Observed	$\hat{\sigma}_Q$	7.97	54.63	151.66	279.02	100.86	21.07
$\rho_{Q_t}Q'_t \approx 1.0$	$\hat{\sigma}_Q'$	7.25	51.65	148.63	271.25	97.67	19.48
$\rho_{Q_t}Q'_t = 0.75$	$\hat{\sigma}_Q'$	7.17	49.45	146.46	270.38	96.45	19.01
$\rho_{Q_t}Q'_t = 0.5$	$\hat{\sigma}_Q'$	7.01	48.47	145.84	268.10	94.12	18.57
Observed	$\hat{\phi}$	0.68	0.29	0.46	0.57	0.85	0.67
$\rho_{Q_t}Q'_t \approx 1.0$	$\hat{\phi}$	0.67	0.29	0.46	0.57	0.85	0.65
$\rho_{Q_t}Q'_t = 0.75$	$\hat{\phi}$	0.69	0.30	0.50	0.59	0.87	0.71
$\rho_{Q_t}Q'_t = 0.5$	$\hat{\phi}$	0.71	0.32	0.53	0.61	0.91	0.74

[a]All the statistics are given in m^3/s. Monthly statistics $\hat{\mu}_Q$, $\hat{\sigma}_Q$, and $\hat{\phi}$ denote the observed monthly mean, standard deviation, and lag-one monthly correlation, respectively. The statistics for the period July–December is not presented since the average inflow into the Oros reservoir is almost zero.

based on (19) with the errors being generated from a periodic gamma autoregressive model.

$$Q'_{t,j} = \rho_{Q_tQ'_t}Q_{t,j} + \varepsilon_t \tag{19}$$

where $Q'_{t,j}$ and $Q_{t,j}$ are the generated and observed flows in month 't' in year 'j' respectively and ε_t follows a periodic gamma autoregressive model having $\mu_{Q_t}(1-\rho_{Q_tQ'_t})$, standard deviation $\hat{\sigma}_t\sqrt{1-\rho^2_{Q'_t,Q_t}}$ and skewness $\hat{\gamma}_t$ with the autoregressive structure preserving the observed lag-one monthly correlation($\hat{\phi}_t$) given in Table 3. The skewness $\hat{\gamma}_t$ employed for simulation is estimated using the bias correction factors suggested by *Bobee and Robitaille* [1977]. *Fernandez and Salas* [1986] give the feasible parameter space for the periodic gamma autoregressive model as $\hat{\rho}_t \leq \hat{\gamma}_t/\hat{\gamma}_{t-1} \leq 1/\hat{\rho}_t$. Because of this constraint, periodic gamma autoregressive model cannot be employed for generating inflows into the Oros reservoir from July to December. Since the flows during those months were near to zero in the past 47 years (1949–1995), we assume that the generated flows during those months as zero. The advantage of using the periodic gamma autoregressive model is that it directly preserves the observed monthly skewness and correlation structure without any transformation to normality. It is important to note that the lag-one monthly correlation ($\hat{\rho}_t$) does not change by perturbing the monthly noise variance. Varying $\rho_{Q'_tQ_t}$ in (19) changes $\sigma^2_{\varepsilon_t}$ and covariance between the generated flow, $Q'_{t,j}$, and the observed flow, thereby producing ensembles of streamflows with different skill with observed flows.

[51] Using the above procedure, synthetic inflow ensembles are generated for the period 1949 July to 2000 June. Table 3 compares the monthly statistics of generated flows, mean, standard deviation, lag-one correlation for three predictive skills $\rho_{Q_tQ'_t}$ = 0.98 (≈1.0), 0.75 and 0.5 along with the observed flow statistics. The monthly statistics of generated flows are obtained by averaging across the 1000 traces. As one can see from Table 3, the mean monthly flows and the lag-one monthly correlation are preserved for the three predictive skills considered. Similarly, Table 3 also shows the average of monthly standard deviation across the traces, which increases according to the predictive skill chosen.

6.2. Improvements in Bulk Water Allocation: An Assessment From System Perspective

[52] In this section, we investigate the level of forecasting skill required to make substantial improvements in bulk sector water allocation utilizing probabilistic streamflow forecasts under different reservoir system configurations and demand scenarios. To assess this, we consider different storage to annual demand ratios (in Table 4) for the Oros system by reducing the current storage capacity and by increasing the annual demand to be supplied by the Oros system. For these storage to demand ratios, the water allocation model presented in Section 3 was run using synthetic streamflow ensembles developed in Section 6.1 ($\rho_{Q_tQ'_t}$ = 1,0, 0.75 and 0.5) and with the climatological ensemble. We consider bulk sector water allocation for all the three major uses, municipal, industrial and agricultural from the Oros reservoir. The reservoir yields corresponding to 90% reliability were obtained for each year for each use for the assumed (Table 4) storage to demand ratios. The net annual yield for all the three uses over the period 1949–2000 was calculated for various storage to demand ratio under both synthetic and climatological ensembles. Using the net annual yield, the percentage improvement in water allocation using synthetic ensembles having skill, $\rho_{Q_tQ'_t}$, in comparison the climatological ensemble was calculated based on equation (20) for each set of storage/demand ratio.

$$\%\ Improvement = \left(1 - \frac{\sum_{j=1}^{M}\sum_{i=1}^{3} R_{ij}\Big|\rho_{Q_tQ'_t}}{\sum_{j=1}^{M}\sum_{i=1}^{3} R_{ij}\Big|\rho_{Q_tQ'_t} = 0}\right)*100 \tag{20}$$

Figure 8 shows the % improvement in water allocation for different reservoir system configurations using synthetic inflow forecasts exhibiting different skills. From Figure 8, we can see clearly that as forecasting skill increases, % improvement in water allocation relative to the climatological approach increases. However, the % improvement is much higher for systems having low storage to demand ratio. This is mainly because systems having large storage to demand ratio have the ability to supply the annual demand

Table 4. Storage to Demand Ratios Considered for Analyzing the Utility of Streamflow Forecasts in Improving Bulk Sector Water Allocation Using Synthetic Streamflow Forecasts Having Different Skills[a]

Storage (hm^3)	Demand (hm^3)	Storage/Demand Ratio
1940	365	5.32
1455	365	3.99
970	365	2.66
1940	730	2.66
1455	730	1.99
970	730	1.33
1940	1095	1.77
1455	1095	1.33
970	1095	0.89

[a]Current capacity of Oros reservoir is 1940 hm^3, and the annual demand to be supplied by Oros for the JMH system is 365 hm^3.

(including evaporation losses) purely based on the initial storage, S_o, in many years thereby nullifying the utility of probabilistic streamflow forecasts. On the other hand, streamflow forecasts are much more useful in systems having low storage to demand ratio, since the initial storages at the beginning of the year always constrain the system allocation. We explain this in detail using Figure 9.

[53] Under the current system configuration (Figure 9a; storage to demand Ratio = 5.32), the difference in annual yield (expressed as $R_j(\rho_{Q_tQ_t'}) - R_j(\rho_{Q_tQ_t'} = 0)$ where $R_j = \sum_{i=1}^{3} R_{ij}$ with 'i' denoting each uses and 'j' denoting the year) between streamflow forecasts having a particular skill and the climatological approach is zero in many years, since the entire annual yield was met purely based on the initial storage available at the end of June. On the other hand, for systems having low storage to demand ratio (Figure 9b), the difference in annual yield varies according to the nature of flows. During above normal inflow years, the difference in annual yield is positive indicating yield obtained using the forecast is much higher than the climatological approach and vice versa during below normal inflow years. The difference in annual yield shown in Figure 9b increases as the forecast skill increases, which is also reflected in Figure 8. Our recent study for a system with small storage to demand ratio for Angat reservoir system in the Philippines showed that substantial improvement in hydropower production could be achieved by utilizing the monthly updated climate forecasts available throughout the season [*Sankarasubramanian et al.*, 2009].

[54] It is important to note that % improvement given in Figure 8 quantifies only the improvements in annual yield, not the increased utility/net benefits using probabilistic streamflow forecasts. Increased net benefits depend on the purpose for which the release is put into use. For instance, if the increased yield is utilized for power generation for which the shadow price of water is relatively high in comparison to other uses, then increased revenue could be expected from application of climate forecasts. *Maurer and Lettenmaier* [2004] show that just 1% improvement in releases from the upper Missouri system hydropower generation using the climate information based streamflow forecasts could result in increased net benefits as high as $11million. Thus, climate information based streamflow forecasts have higher utility in systems with multiple uses constraining the allocation process as well as in systems having very low storage to demand ratio.

7. Summary and Conclusions

[55] The goal of the work presented here was to introduce an adaptive and participatory water allocation framework that can be used in conjunction with probabilistic streamflow forecasts. A key design goal of the allocation process was to remove or reduce the impact of the uncertainty associated with probabilistic forecasts (even if they have a skill no better than that of climatology) by developing estimates of the "best" way to allocate water over the coming operation cycle based on short-term forecasts using demand and value parameter, including the value attached by each user to the water quantity to be supplied, and the associated reliability of the supply over the operating period. The formulation of contracts with an insurance proviso in the event of failure of the contract could in concept promote effective adaptive management by permitting reallocation through the specification of different economic values assigned to water and to reliability depending on the water in stock in the reservoir and the forecast for the upcoming season or year. In practice, one could have long-term and short-term contracts for the reservoir water, thus separating critical nonreallocable use and uses that can be reallocated during drought/surplus periods. The paradigm thus invoked is one which leads to a more active management than the traditional approach that focuses on long-term water allocation with drought stresses managed by the reduction of supply to lower priority uses, but limited or no reallocation across use areas (i.e., changing priorities for use are not recognized as they could be in our proposal). In this paper, to keep the formulations simpler and communicate the key points we assumed that all the water in the reservoir could be allocated through short-term contracts, and focused on the development and testing of a simulation-optimization model that the water manager could use to derive feasible and optimal contracts given forecasts and other parameters, as part of a participatory and adaptive allocation process. The details of the participatory allocation

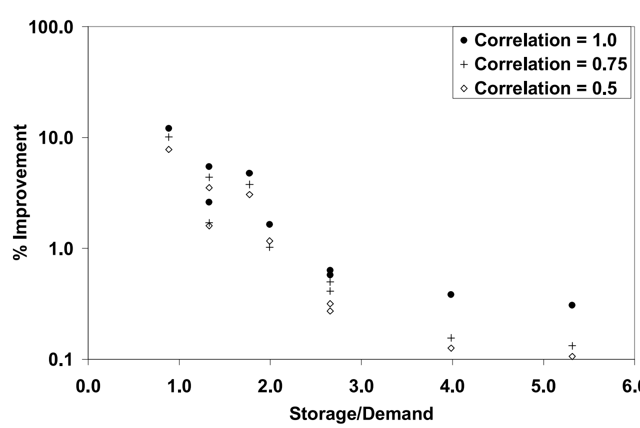

Figure 8. Utility of Streamflow forecasts in improving water allocation under different reservoir system configurations. Net annual yield corresponding to 90% reliability is obtained for each use using the within year demand fractions given in Table 1.

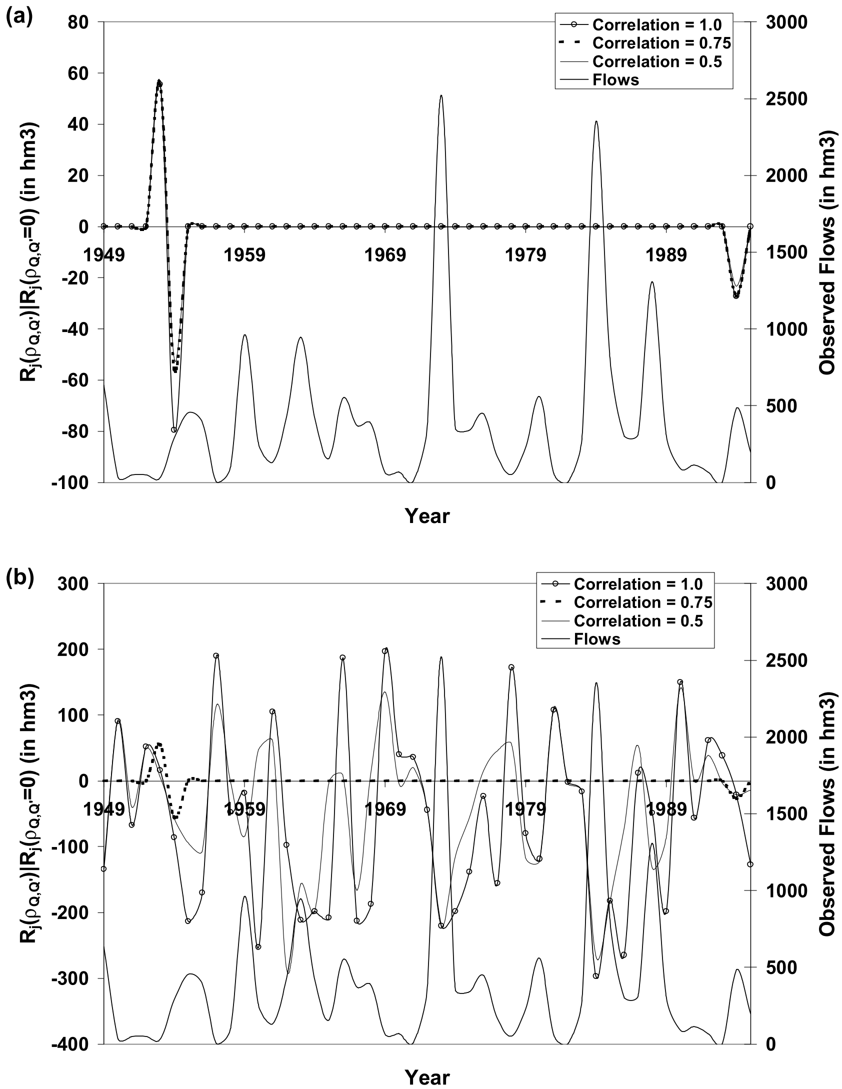

Figure 9. Difference in annual yield using the synthetic streamflow forecasts having a particular skill and using climatology for two different system configurations. (a) Current system configuration (Storage = 1940 hm^3; Annual Demand = 365 hm^3). (b) Modified System Configuration (Storage = 970 hm^3; Annual Demand = 1095 hm^3).

framework, its comparative analysis relative to other allocation systems, its operational application and reactions of users and water managers to the proposal from experimental applications in Northeast Brazil will be presented in a separate paper. Here, the basic ideas were discussed and the focus was on the potential utility of the simulation-optimization model and the probabilistic forecasts.

[56] The single site, multipurpose reservoir optimization model considers a water contract structure with specified reliability, restriction volume, and compensation in the event of failure. The allocation is achieved by maximizing a utility function (net revenue in the examples used considering the contract revenue and the expected value of compensation in the event of failure) given specified yield reliabilities, sectoral water allocation constraints, mass balances given a streamflow forecast ensemble. The use of this model with data from Northeast Brazil, and with a synthetic data set was pursued to assess potential conditions under which probabilistic forecasts could be useful under this framework.

[57] The potential utility of climate forecasts in improving bulk water allocation was assessed toward multipurpose water allocation from Oros reservoir over the period July 1990 to June 2000 using the 12 month ahead streamflow forecasts developed based on the work by *Souza Filho and Lall* [2003]. The performance of the reservoir is assessed in its ability to allocate the demand for all the uses under the forecasts and under the currently pursued zero inflow assumption. The analysis shows that the initial storage available in July of every year was adequate to supply water for all the uses even under a zero inflow assumption since Oros is designed with storage equal to approximately 2.5 years of mean annual flow. So, in this setting, the forecast based allocation is effective in increasing the firm allocation for agriculture during critical droughts. This is significant since a preseason declaration of the availability of a reliable yield or contract for agriculture has high value

given that it will directly influence the crop area that can be reliably brought under irrigation that year. Thus, such an allocation could be considerably beneficial relative to the current situation where farmers will have no prior knowledge that water may be available as a consequence of uncontrolled spills from the reservoir in that year.

[58] To assess the utility of streamflow forecasts increased demand scenarios as well as with improved forecasting skills in the future (as discussed by *Souza Filho and Lall* [2003] and *Broad et al.* [2007]), we assessed potential improvements that could be obtainable toward multipurpose water allocation utilizing synthetic inflow forecasts having three different skills. Totally, nine different storage to demand scenarios is considered and the improvement in water allocation under each system configuration is summarized in terms of percentage improvement in net annual yield in comparison to the climatological approach using the streamflow forecasts exhibiting a particular skill. The analyses show that reservoir systems with smaller storage to demand ratio could benefit substantially even with streamflow forecasts having modest skill. The percentage improvement using the streamflow forecasts is much smaller even utilizing perfect forecasts for systems that have large storage to demand ratios, such as the Oros reservoir. Thus, our findings suggest that the climate information based streamflow forecasts have higher utility in systems with multiple uses constraining the allocation process as well as in systems having very low storage to demand ratio.

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