Hydrol. Earth Syst. Sci. Discuss., 7, 3765–3802, 2010
www.hydrol-earth-syst-sci-discuss.net/7/3765/2010/
doi:10.5194/hessd-7-3765-2010
© Author(s) 2010. CC Attribution 3.0 License.

Hydrology and
Earth System
Sciences
Discussions

This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

Tailoring seasonal climate forecasts for hydropower operations in Ethiopia's upper Blue Nile basin

P. Block

International Research Institute for Climate and Society, Columbia University, Palisades, New York, USA

Received: 1 June 2010 – Accepted: 7 June 2010 – Published: 24 June 2010

Correspondence to: P. Block (pblock@iri.columbia.edu)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Explicit integration of seasonal precipitation forecasts into water resources operations and planning is practically nonexistent, even in regions of scarcity. This is often attributable to water manager's tendency to act in a risk averse manner, preferring to avoid consequences of poor forecasts, at the expense of unrealized benefits. Convincing demonstrations of forecast value are therefore desirable to support assimilation into practice. A dynamic coupled system, including forecast, rainfall-runoff, and hydropower models, is applied to the upper Blue Nile basin in Ethiopia to compare benefits and reliability generated by actual forecasts against a climatology-based approach, commonly practiced in most water resources systems. Processing one hundred decadal sequences demonstrates superior forecast-based benefits in 68 cases, a respectable advancement, however benefits in a few forecast-based sequences are noticeably low, likely to dissuade manager's adoption. A hydropower sensitivity test reveals a propensity toward poor-decision making when forecasts over-predict wet conditions. Tailoring the precipitation forecast to highlight critical dry predictions minimizes this inclination, resulting in 97% of the sequences favoring the forecast-based approach. Considering managerial risk preferences for the system, even risk-averse actions, if coupled with forecasts, exhibits superior benefits and reliability compared with risk-taking tendencies relying on climatology.

1 Introduction

Seasonal climate forecasting capabilities continue to advance, attributable predominantly to enhanced observations, computing power, better physical understanding of the climate system, and experience (Barnston et al., 1994; Goddard et al., 2003; Barnston el al., 2005). Their principle goal is to reduce climate-related risks, providing advance information to potentially improve decision-making and increase societal benefits, especially over the long term. Currently, however, there exists little evidence of explicit forecast use in operations, especially in water resources management, even in regions of scarcity. This is often ascribed to water managers tendency to act in a risk averse manner, "poor" forecast skill or scale, difficulty in integrating forecasts into existing decision support systems, lack of focus on specific user needs, anticipated shifts in the water sector, management and political disincentives, individual and institutional inflexibility, behavioral effects, and informational constraints (Pulwarty and Redmond, 1997; Hamlet et al., 2002; Ritchie et al., 2004; Rayner et al., 2005; Broad et al., 2007; Johnston et al., 2007; Lemos, 2008; Millner, 2009; Ziervogel et al., 2010).

The abundance of research and literature over the past decade identifying challenges and impediments should act as a stimulus for case studies evaluating potential economic benefits and improved reliability through forecast inclusion. These two determinants are powerful motivators for water resources managers and policy makers, and forecast-induced positive outcomes may provide incentive to address other barriers. Previous research studies have advocated for demonstrations of such effective forecast use (e.g., Pagano et al., 2001). Minimal applications within the water resources community, however, seek to quantify the actual monetary and reliability gains or losses of including a forecast in comparison to commonly accepted climatology-based operations, and most of those examples refer only to perfect forecasts, excepting a few (e.g., Yeh et al., 1982; Yao and Georgakakos, 2001; Hamlet et al., 2002; Chiew et al., 2002; Maurer and Lettenmaier, 2004; Axel and Céron, 2007; Sankarasubramanian et al., 2009). An absence in forecast adoption is unmistakable (Rayner et al., 2005), and further exaggerated in developing countries with limited hydrologic observations (Patt et al., 2007; Ziervogel, 2010).

This motivates the current research to demonstrate the improved economic value and reliability resulting from a flexible seasonal climate forecast – hydropower system, given biophysical, policy, and economic constraints, by mitigating losses and capitalizing on opportune conditions (Hellmuth et al., 2007). Gaining an understanding of expectations from a realistic, imperfect forecast imbedded in a dynamic operational system could prove enticing for water managers to adopt forecast inclusion, or justifi-

cc BY

cation for rejecting. Appreciating benefits and reliability in a context of climate variability begins to address a number of the aforementioned impediments (summarized well in Ziervogel et al., 2010).

This paper commences with a description of the application site, the Blue Nile basin in Ethiopia's highlands, followed by an outline of the coupled forecast-hydropower system model. The economic value and reliability produced from the seasonal climate forecast driven system are then compared with a non-forecast approach, ending with a discussion and conclusion.

2 Description of application site

Ethiopia possess abundant water resources and hydropower potential, second only to the Democratic Republic of Congo in all of Africa, yet only 2% of this potential has been developed (World Energy Council, 2007). Currently, 83% of Ethiopia's population lacks access to electricity, with 94% still relying on fuel wood for daily cooking and heating (Tegenu, 2006). The Ethiopian government is therefore pursuing ambitious plans and programs to develop hydropower in an effort to substantially reduce poverty and create an atmosphere for social change. It has been shown that access to electricity, including rural electrification, is a key to poverty reduction in Ethiopia (MoFED, 2006). Implementation, however, is not trivial, especially due to the large financing and investment challenges, as well as required institutional capacity.

The Blue Nile headwaters emanate at the outlet of Lake Tana in the Ethiopian highlands, and is joined by many important tributaries, draining 180 000 km^2 in the Central and Southwestern Ethiopian highlands (Steenhuis et al., 2008), becoming a mighty river long before it reaches the lowlands and crosses into Sudan (Fig. 1). It stretches nearly 850 km between Lake Tana and the Sudan-Ethiopia border, with a fall of 1300 m; the grades are steeper in the plateau region, and flatter along the low lands. Very few stream gauges exist along the Blue Nile River within Ethiopia, and those that do tend to have spotty or limited records, and are often not publicly available. Roseires dam in

CC BY

Sudan presents the first streamflow record of sufficient length; monthly averages are illustrated in Fig. 2.

The climate in the Blue Nile River basin varies between its inception in the wet, moderate highlands of Ethiopia and its confluence with the White Nile River in a drier, warmer region. Monthly precipitation records indicate a summer monsoon season, with highest totals in the June–September months (Block and Rajagopalan, 2007); seasonal precipitation averages in excess of 1000 mm in the highlands but only 500 mm near the Sudan border (Shahin, 1985; Sutcliffe and Parks, 1999), with significant interannual variability throughout as illustrated in Fig. 3a (solid line). Near the border, rains during this season account for nearly 90% of total annual precipitation, while in the highlands, approximately 75% of the annual precipitation falls during the monsoon season. The El Niño–Southern Oscillation (ENSO) phenomenon is a main driver of the interannual variability in seasonal precipitation in the basin, with El Niño (La Niña) events generally producing drier (wetter) than normal conditions (Block and Rajagopalan, 2007). Evaporation in the basin varies inversely with precipitation, favoring lesser annual rates in the highlands (∼1150 mm) compared with excessive rates (∼2500 mm) near the Sudan-Ethiopia border (Shahin, 1985; Sutcliffe and Parks, 1999).

In 1964, the United States Bureau of Reclamation (USBR), upon invitation from the Ethiopian government, performed a thorough investigation and study of the hydrology of the upper Blue Nile basin. Included in the USBR's study was an optimistic list of potential projects within Ethiopia, including preliminary designs of dams for irrigation and hydroelectric power along the main Blue Nile stem. The four major hydroelectric dams along the Blue Nile, as proposed by the USBR, are presented in Fig. 1. Operating in series, these four dams could impound a total of 73 billion cubic meters, which is equivalent to approximately 1.5 times the average annual runoff in the basin. The total installed capacity at design head would be 5570 megawatts (MW) of power, about 2.5 times the potential of the Aswan High Dam in Egypt, and capable of providing electricity to millions of homes. This would be an impressive upgrade over the existing 529 MW of hydroelectric power within Ethiopia as of 2001 (Thomson Gale, 2006). Initial construction costs range from $1.8–$2.2 billion per dam; annual costs (operation and maintenance, scheduled replacement, and insurance) begin in the first year post-construction and range from $12.5–$17.9 million (Bureau of Reclamation, 1964). While none of these dams have actually been constructed, chiefly due to financial constraints, the Ethiopian Government still has intentions for their full development. For demonstration purposes, however, the dams are assumed online and functional, which is analogous to an operational-level planning study, ideally providing insight into additional expected benefits with forecast inclusion.

3 Coupled modeling system

To evaluate the expected benefits of forecast inclusion, in comparison to climatology-based operations, a coupled modeling system approach is adopted. This allows processing and transformation of the *Kiremt* (June–September) monthly precipitation into streamflow for hydropower optimization along the Blue Nile River. The framework is structured by linking previously developed, independent models.

3.1 Structure and components

Three major modeling components are required: precipitation forecast, rainfall-runoff, and hydropower/water systems optimization. The forecast model (Block and Rajagopalan, 2007) predicts total seasonal (June–September) precipitation over the Blue Nile basin. One-season lead (March–May) predictors include sea level pressures, sea surface temperatures, geopotential height, air temperature, and the Palmer Drought Severity Index (PDSI), identified through correlation mapping with seasonal precipitation (e.g., Singhrattna et al., 2005; Grantz et al., 2007). The correlation patterns in sea surface temperatures and sea level pressures resemble ENSO features, yet are more skillful than common ENSO indices. The remaining three predictors capture regional characteristics, with PDSI acting as a soil moisture surrogate.

A nonparametric forecast model based on local polynomial regression (Loader, 1999) is adopted to address various shortcomings common with linear regression, including artificially high skill scores stemming from limited data length and multicollinearity among predictors, regression coefficients being greatly influenced by a small number of outliers, often leading to a poor fit, and the inability to capture nonlinear relationships. In the nonparametric approach, estimation of the model function is performed "locally" at the point to be estimated; therefore no global mathematical function exists. This "local" estimation provides the ability to capture features (i.e. nonlinearities) that might be present locally, without granting outliers any undue influence in the overall fit. Optimal model parameters and predictors (the five previously mentioned) are selected via the generalized cross validation score function (Craven and Wahba, 1979). A detailed implementation algorithm is available in Block and Rajagopalan (2007).

Forecast ensembles are created by adding normal random deviates (mean zero and standard deviation of the global predictive error) to the predicted precipitation value (Helsel and Hirsch, 1995). Ensembles contain 500 members, capture a portion of the forecasting uncertainty, and are normally distributed. Ensemble medians demonstrate a correlation coefficient of 0.69 with observations, and a rank probability skill score (using the full distribution) of 0.39, a marked improvement over climatology alone. Figure 3 illustrates the observed and modeled time-series for 1961–2000. Seasonal precipitation forecasts are disaggregated into monthly forecasts through a proportion vector calibrated on historic data.

The rainfall-runoff model employed is a derivative of the Watbal model (Yates, 1996; Yates and Strzepek, 1998), specifically calibrated to the Blue Nile basin. It is a semi-distributed, average-monthly model, with lumped soil and vegetation type and distributed climatic inputs, applied to gridded data ($0.5^{\circ} \times 0.5^{\circ}$ for this study). The model simulates changes in soil moisture and runoff, and is essentially an accounting scheme based on a conceptualized, one-dimensional bucket that lumps both the root and upper soil layer. The model comprises two elements: the first is a water balance component that describes water movement into and out of a conceptualized basin; the second is the calculation of potential evapotranspiration, which is computed using the FAO Penman-Monteith approach (FAO, 1998). The water balance component of the model comprises three parameters: surface runoff, sub-surface runoff, and maximum catchment water-holding capacity. The simplified representation of soil moisture dynamics has been shown to adequately represent runoff changes due to climate fluctuations (Yates, 1996; Yates and Strzepek, 1998). A final module translates runoff into Blue Nile River streamflow for critical points throughout the basin.

The hydropower model selected is IMPEND, the Investment Model for Planning Ethiopian Nile Development (Block and Strzepek, 2010). It is classified as a planning tool with operational-level detail to help define feasibility and expectations of project choice. IMPEND is a deterministic water resources system model requiring a single input file of monthly streamflow and net evaporation at the four proposed Ethiopian dam locations and at the existing Roseires dam in Southeastern Sudan (all in series). The model thus encompasses the Blue Nile River from its inception at Lake Tana to the Roseires dam, just beyond the Sudan-Ethiopian border. The current version values hydropower at 8-cents per kilowatt-hour; reservoir head represents the decision variable and net present benefits constitutes the objective value. Specific model equations and details are provided in the Appendix.

A key attribute of the model is its ability to accept monthly input data varying from year to year, which is critical for proper performance assessment. Analysis based solely on a climatological perspective may well misjudge long-term project benefits (Block et al., 2008). IMPEND is also capable of assessment over various interest (or discount) rates; for the purposes of this study, this rate has been restricted to 10%. This social rate of discounting has been used by others (e.g., Jabbar et al., 2000) and falls within the range of discount rates experienced by Ethiopia within the last five years (Central Intelligence Agency, 2006). A final noteworthy characteristic is the flexibility of downstream flow policies, modulated by the downstream flow constraint established at the entrance to Roseires dam. The policy employed here allows for up to 5% of the annual flow passing the border to be impounded within Ethiopia.

IMPEND may be configured to account for transient (filling) conditions for dams coming online, however for this analysis, all reservoirs are assumed initially filled to design height to mimic operational aspects. Reservoir operations are not restricted to explicitly following established rule curves, but rather are flexible, optimizing operations based on expected future streamflow. Benefits attributable to climate forecasts in hydropower optimization are an aspect not often considered. For a climatology-based operation, however, for which future streamflows are simply historical monthly means, this approach essentially collapses to a process analogous to following a rule curve.

3.2 Data

For the forecast model, global atmospheric and oceanic variables, including sea surface temperature, sea level pressure, geopotential height, and air temperature, were obtained from the National Oceanic and Atmospheric Administration's (NOAA's) Climate Diagnostics Center (CDC), based on National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis data (Kalnay et al., 1996). These are monthly average values on a $2.5^\circ \times 2.5^\circ$ grid for 1949 to the present. PDSI values (Dai et al., 2004), also at monthly time scales and on a $2.5^\circ \times 2.5^\circ$ grid, for 1870–2003, were provided by NCAR's Climate and Global Dynamics Division. Observed precipitation data (the predictand) are part of the Climatic Research Unit (CRU) time series 2.0 dataset, obtained from the University of East Anglia, Norwich, United Kingdom (Mitchell and Jones, 2005).

In addition to the June–September monthly precipitation produced by the forecast model, the rainfall-runoff model requires inputs of mean daily temperature and the diurnal temperature range, acquired from the CRU dataset (Mitchell and Jones, 2005). Precipitation for months other than June–September represents climatology based on the same dataset. Monthly streamflow and net evaporation outputs are produced monthly.

Physical, hydrologic, and climatic data required for building and running IMPEND were acquired from a number of sources. Dam, reservoir, and power characteristics are provided in the USBR preliminary study (Bureau of Reclamation, 1964). Historical

CC BY

streamflow records for calibration and validation in the upper Blue Nile basin are publicly available through numerous sources, including NCAR's ds552.1 dataset (Bodo, 2001). The rainfall-runoff model provides streamflow and net evaporation. IMPEND outputs include project benefits or net benefits (discounted back to the simulation start year), energy production, and reservoir levels at monthly intervals.

3.3 Forecast modes and evaluation

To quantify the value of a seasonal precipitation forecast carried through the coupled system, three types of forecasts are evaluated: perfect, actual (imperfect), and monitoring (based on climatology), with 12 month foresight. In the perfect forecast case, observed precipitation and temperature are fed into the rainfall-runoff model to generate a streamflow and net evaporation sequence. For each time-step in the sequence, the hydropower model is privy to 12 subsequent months of "observed" streamflow and net evaporation, optimizing operations in the current step reflective of expected future conditions, given constraints. Marching forward one month to the next, the hydropower model receives new information regarding the time-step 12 months out, and adjusts reservoir decisions accordingly to maximize benefits.

The actual forecast approach follows a similar overall progression, excepting application of predicted precipitation for June–September, with climatological precipitation in other months, as inputs into the rainfall-runoff model. (Observed temperatures are also applied. Minimal difference in the final results were noted between substituting climatological temperature for observed temperature, therefore observations were chosen to isolate the pure value of a precipitation forecast). Using the streamflow and net evaporation sequence, the hydropower model optimizes over the subsequent 12 months, as in the perfect forecast case, however prior to May, when the forecast is issued, only climatological values are assumed. Thus in May of every year, streamflow and net evaporation for each of the subsequent 12 months of the sequence change from climatology to forecasted values. Following monthly forecast-based reservoir management operations, actual reservoir storage, based on the difference between forecasted and observed conditions, is updated.

Decision-making for the monitoring approach is simply based on reacting to current reservoir conditions and planning based on climatological expectations, the common approach for most water managers. It is nearly identical to the forecast approach devoid of predictions, except for the use of climatological streamflow and net evaporation values based on observed precipitation (as opposed to climatological precipitation.)

Forecast modes are evaluated by comparing the sum of monthly hydropower benefits, aggregated to decadal totals, using the historical 1961–2000 record. The decadal time-series length allows for examination of compounding effects and tends to smooth out noisy monthly optimization behavior. For the actual forecast approach, initial comparisons use forecast medians, however to appreciate a range of feasible outcomes, sampling by random draws from the normal forecast distributions and random year sequencing are also assessed. Initial comparisons include approaches with all four proposed dams online; latter comparisons include only Karadobi, the furthest upstream dam site.

Two performance metrics, analogous to reliability and resilience, are created for further comparison between actual forecast and monitoring benefits. Reliability is represented as:

$$\text{If} \quad \mathrm{FB}_t > \mathrm{MB}_t, \text{then } z_t = 1, \quad \text{else} \quad z_t = 0 \tag{1}$$

$$\text{Reliability} = (\Sigma_t z)/n \tag{2}$$

where FB_t represents hydropower benefits from the actual forecast model system at time-step t, MB are the monitoring approach system benefits, z is a counting scalar, and n equals the total number of time-steps. This comparative reliability may therefore vary from 0–1; values less than 0.5 infer higher overall reliability by the monitoring methodology, while values greater than 0.5 indicate higher overall reliability by the actual forecast approach. Resilience measures the ability of the actual forecast system to respond to years with benefits lower than the monitoring approach with greater benefits in the following year.

$$\begin{array}{lll} \text{If} \quad \mathrm{FB}_t < \mathrm{MB}_t & y_t = 1 & \text{if} \quad \mathrm{FB}_{t+1} >= \mathrm{MB}_{t+1} \\ \qquad\quad\ \text{else} & y_t = 0 & \end{array} \tag{3}$$

$$\text{Resilience} = \left(\sum{}_{t-1} y\right)/m \tag{4}$$

where y is a counting scalar, and m equals the total number of occurrences. Resilience varies from 0–1 with larger values signifying greater actual forecast system resilience.

Tailored seasonal precipitation forecasts are also assessed through the coupled-model system. For the context of this paper, tailoring refers to restricting or dampening precipitation forecasts in response to identified sensitivities of the hydropower model (e.g. extreme wet or dry conditions), to address risk-averse behavior.

4 Economic value and reliability of seasonal climate forecasts

The benefits of the coupled model system drawing on the three forecasting approaches, reliabilities between the actual forecasting and monitoring approaches, and application of a tailored actual forecast to address water manager's risk-aversion are presented in the following section.

4.1 Chronological historical analysis

Using the four decades from the historical record, decadal hydropower benefits of the coupled model system from the perfect, actual forecast (medians), and monitoring approaches are presented in Fig. 4. Dams are assumed to be online from the onset. Only the 4-reservoir scheme is displayed, as the single-reservoir (Karadobi only) scheme behaves quite similarly. As expected, the perfect forecast outperforms both the actual and monitoring forecasts; with the exception of the first decade, the actual forecast system benefits are on par or surpass those of the monitoring system. Poor forecasts in the early years, especially 1962–1963, for which notably wetter than observed conditions are predicted, contribute to the slightly inferior actual forecast system performance of that decade. The third decade, for which the actual forecast approach benefits far exceed those of the monitoring approach, is a relatively dry period with two exceptionally dry years (1982, 1987). The actual forecast model does predict drier than normal conditions for those years, but not to the extreme observed. From this preliminary analysis, it would appear there is value in using an actual seasonal forecast compared with climatology.

4.2 Sampling from the historical record

Clearly evaluating the historical record in chronological order only represents one plausible sequence. To augment the ensemble size of decades and better capture potential variability (i.e. climate and model uncertainty), random sampling from all available years (1961–2000) was performed to generate 100 decadal sequences. In addition, for each of the ten years within the 100 sequences, the actual precipitation forecast was randomly selected from that year's forecast distribution (as opposed to using forecasted means) to represent model uncertainty. Although minimal temporal structure is evident, no attempt was made to preserve interannual (or longer time-scale) autocorrelation at this stage.

Figure 5 is a comparison of decadal benefits between the actual forecast and monitoring system approaches for the 100 sequences. Both the 4-reservoir and single-reservoir (Karadobi only) schemes are displayed. Points above the 1-to-1 line represent sequences for which the actual forecast method's cumulative benefits surpass those of the monitoring method; similarly, points below the line favor the monitoring method. For both the multi and single reservoir schemes, the majority of points are bundled around the 1-to-1 line at the higher benefit end, not clearly favoring either forecasting approach. For sequences resulting in lower benefits, the actual forecast method tends to fare better. Negative benefits are possible due to a penalty function applied to low reservoir levels/low outlet flows. Reliability for the single reservoir scheme, as computed by Eq. (2) and presented in Table 1, is 0.68 and 0.58 for decadal and annual (1000 years) series, respectively, indicating added value for actual forecast inclusion. Resilience, based on Eq. (4) and reported in Table 1, is 0.48 for the annual assessment, indicating an immediate rebound for approximately half the occurrences. Lack of resilience may be explained by multiple sequential poor forecasts, or the inability of the system to respond timely to a poor forecast, even if the subsequent year's forecast is adequate. The multi-reservoir scheme reliability and resilience (not reported) is almost identical.

Although the overall results are generally positive, specific sequences, such as decades labeled *A* and *B* on Fig. 5, may be severe enough to dissuade managers from accepting an actual forecasting approach. Even though the likelihood of these events occurring is small, the risk may still be sufficient. Examining these specific sequences in detail is enlightening. Annual streamflow and benefits for decade *A* from the actual and monitoring forecast approaches, for the single-reservoir scheme, are illustrated in Fig. 6. Most notably from the streamflow series is the over-prediction by the actual forecast system in years 2–3 and 5. The ramifications of this are evident in the annual benefits figure: in years following a poor forecast, benefits drop noticeably in comparison to the monitoring approach, especially when forecasting greater than observed "wet" conditions. (The figure illustrates discounted benefits, so a general downward trend is not unexpected). This phenomenon is also apparent upon inspection of decade *B*, presented in Fig. 7, in which years 3 and 5–7 all represent forecasts greater than observed. Similar findings explain the poor performance of the actual forecast for decades *A* and *B* under the multi-reservoir scheme (not shown.)

4.3 Tailoring the seasonal forecast

Undeniably, water managers considering implementation of a seasonal forecast into operations would prefer the vast majority (perhaps all!) of the project benefits reside

cc BY

above the 1-to-1 line. While the results of the actual forecast system demonstrated thus far indicate potentially greater benefit value versus a monitoring approach, tailoring the forecast in response to hydropower model sensitivities is worth exploring.

Examining the actual forecast errors (1961–2000) by terciles (i.e. below normal, near normal, above normal) reveals approximately equal error means and standard deviations across each category, implying no inherent bias in the forecast. Hydropower response to forecast errors in the above and below terciles, however, is less even. A simple test using the historical record and prescribed errors to construct four ten-year time-series, demonstrates significantly higher hydropower model sensitivity to above normal versus below normal conditions. To test, two "observed" series are created: June–September precipitation for each year is set at the 75 percentile (25 percentile) of the historical record to represent consistently above (below) normal conditions; remaining months are set to climatology. To mimic a forecast error, two additional series are created by adding (subtracting) 25 mm of monthly precipitation from each of the June–September months to the above (below) normal "observed" series. Results are displayed in Table 2. Comparison of differences between "observed" and "observed with error" series clearly exhibits greater hydropower model sensitivity to above normal forecast errors. Thus, for this coupled model system, errantly predicting wetter than observed conditions in the above normal category appears to be more detrimental to hydropower operations and ensuing benefits than errantly predicting drier than observed conditions in the below normal category. This stems from the aggressive actions (significant release from storage) following a wet forecast as opposed to conservative actions (maintain storage) following a dry forecast. Therefore dampening "wet" forecasts and retaining "dry" forecasts is a reasonable option in light of this sensitivity.

To this end, the precipitation forecast is tailored such that all actual forecasts in the above normal and near normal terciles are modulated to reflect climatology. (Little is gained from a near normal forecast in comparison to climatology.) This procedure effectively eliminates prediction of wet forecasts; some opportunities are clearly lost, however damages due to poor wet forecasts deem them worthy of disregarding. Ac-

CC BY

tual forecasts in the below normal category remain unchanged. This modification has no effect on the perfect or monitoring forecast system approaches. Figure 8 illustrates the product of this tailored forecast for the single-reservoir scheme in comparison to the monitoring approach, updating Fig. 5a. The effect is quite drastic: decadal sequence benefits from the actual forecast approach nearly always outpace those of the monitoring approach, with the few actually favoring the monitoring approach in close proximity to the 1-to-1 line. The elimination of low or negative decadal benefits from the actual forecast system is promising, and may begin to entice managers to incorporate such methodologies into their practices. Decadal and annual reliability and resilience scores, presented in Table 1, indicate a marked improvement over the original actual forecast approach. The relatively low annual reliability may be deceiving, and is best understood in context. To take an example, in a dry year, benefits from the monitoring approach may outpace the actual forecast approach, as it prescribes the release of more water through the turbines that year, however repercussions to benefits in the following year are likely to be more severe for the monitoring case. The resilience metric addresses this issue, indicating a rebound by the actual forecast approach in the following year for more than two-thirds of the occurrences.

While tailoring the actual forecast to this stage is clearly beneficial, incentives to improve the forecast model to potentially draw even greater returns is evident through comparison with the perfect forecast output (Fig. 9). Attaining a perfect forecast may be unrealistic due to inherent climate uncertainty, however the potential for further advancement plainly exists.

4.4 Assessing behavioral risk outcomes

The level of risk a water manager is willing to accept is intrinsically tied to institutional requirements, user demands, the flexibility of the system, and personal experiences, among other influences. This level implies consequent effects on system reliability and benefits. Two tendencies are addressed here through the use of a penalty function: one toward risk-taking (RT), one toward risk-aversion (RA). Figure 10 graphically demonstrates the simple linear functions adopted to impose a penalty (represented by energy loss but effectively financial loss) in the event of a predetermined energy threshold not being exceeded. To simulate RA (RT) behavior, a steep (moderate) sloped penalty function is employed. Lowering monthly energy production below the threshold results in larger penalties.

Assessment of the two risk levels for both the monitoring and forecast approaches is undertaken for four minimum energy thresholds, selected to span conceivably acceptable levels of reliability. The identical 100 decadal simulations from the prior evaluation are utilized. Figure 11a illustrates the monthly threshold – reliability relationship, and Fig. 11b the decadal threshold – benefits relationship. (Reliability here in the traditional sense refers to the number of months the threshold was exceeded over the 12 000 months evaluated.) Reliability and benefits substantially work in contrast to one another: higher (lower) reliability implies a reduction (increase) in benefits. Also, as the threshold level drops, the difference between levels of risk diminishes, becoming less of a factor when thresholds are easily surpassed. Of notable interest is the clear separation not simply between the monitoring and forecast approaches, but specifically between the RT monitoring and RA forecast. The RA forecast appears more stable, providing greater benefits and higher reliability over the course of thresholds evaluated. Even this conservative behavior produces superior performance when climate information is exploited, perhaps enticing mangers to consider forecast inclusion for improvements in reliability and benefits.

5 Discussion and conclusions

The modeling system is necessarily multi-disciplinary, linking climate, hydrology, and water management, an approach to valuing climate information that is often neglected due to its challenges and time consuming nature (Mjelde, 2002). The independent models themselves do not constitute new methodology; the uniqueness of the contribution comes in model integration, the exploitation of sensitivities between integrated models, and ultimately a clear demonstration of economic value through actual forecast inclusion. Ritchie et al. (2004) assert that a forecast system may be considered useful if the forecast is statistically valid (verified) and demonstrates a positive value of information, both of which appear true for this study.

The realization of added value and reliability through forecast inclusion, specifically addressed by dynamic management and decision-making through tailored climate information, is an important outcome. The retention of dry state forecasts adds quality information without subjecting the hydropower model to unreasonable levels of operational risk. Dry forecasts typically prescribe conservative reservoir action, and even if in error, will only forfeit minimal benefits (a higher than expected rainfall will still deliver streamflow to the reservoir for use in later months.) Although only exploiting a subset of the forecast range, and likely sacrificing benefits in wet years, a water manager may be inclined to adopt a mechanism that focuses more on reducing risk and potentially lost benefits than lost opportunities. This begins to address one historical impediment to forecast inclusion of not focusing sufficiently on user needs and applications (Ziervogel et al., 2010).

Equally informative is the recognition of forecast benefit from a risk perspective. Risk-averse managers typically face constraints coercing conservative action, whereas risk-takers have more latitude to absorb a low-output time-step in exchange for a substantial payoff later, typically leading toward greater aggregate benefits. Given the success of forecast inclusion demonstrated, it is rather expected that for a specified level of risk, utilizing a forecast produces benefits and reliability in excess of simply depending on climatology. More enlightening is how even conservative action bolstered by a forecast regularly outperforms a risk-taking approach conditioned on climatology, for equivalent energy threshold requirements. This addresses one of the cardinal impediments (risk-aversion) by theoretically allowing managers to remain risk-averse and realize considerable gains.

While the tailored approach demonstrated in this study is effective, it is errant to assume an identical procedure conducted for other regions or project types will necessitate improved benefits, however given success here, exploration is warranted. Locations susceptible to climate variability where forecast skill is apparent are ripe for investigation. As in this instance, it is also conceivable that decisions in other sectors (agriculture and food security, flood early warning, health, etc.) may likewise tend toward emphasis on one end of the forecast spectrum, although minimal evidence of demonstration currently exists.

In addition to climate, sensitivity to coincident drivers (policy, economics, demand, etc.) may also exhibit significant influence. A reassessment of hydropower model sensitivities subjected to different circumstances may be warranted. Other integrated and social factors may also be equally relevant and worthy of inclusion, beyond hydropower simulation, as advocated by the World Commission on Dams (WCD, 2000). The interrelationship of all these aspects is not trivial or currently well understood, however, potentially complicating decision-making (McCartney, 2007).

The forecast model presented here is generally founded on stationary climate principles. Multi-decadal effects or climate change are not explicitly addressed. A recent study by O'Connor et al. (2005) reveals the strongest determinant of forecast use is risk perception; if extreme climate conditions are anticipated in the near future, the uptake of a forecast is more likely. Climate change may pose such a perception. Integrating an adaptive forecast model into the coupled system to explore implications of changing precipitation trends and variability and increasing temperature warrants future attention.

Appendix A

The objective function for IMPEND consists of maximizing net benefits:

$$\mathrm{OBJ} = \max \sum_{y} \sum_{s} \left(\mathrm{NB}_{y,s}^{\mathrm{HP}} \right) \tag{A1}$$

where y=year, s=dam/reservoir site (Karadobi, Mabil, Mendaia, Border), NB=net benefit (HP=hydropower), \$$10^9$, and

$$\mathrm{NB}^{\mathrm{HP}}_{y,s}=\sum_{y}\sum_{s}\left(E_{y,s}-\mathrm{Pen}^{\mathrm{T}}_{y,s}\right)\times P^{\mathrm{HP}}\times D-\sum_{y}\sum_{s}\left(\mathrm{Pen}^{\mathrm{LF}}_{y,s}\times f_s\right) \tag{A2}$$

where E=energy generated from hydropower, GW h/mo, $\mathrm{Pen}^{\mathrm{T}}$=threshold penalty, GW h/mo (described later), P=price (HP=kWh), \$, D=discount rate, $\mathrm{Pen}^{\mathrm{LF}}$=low flow penalty, \$, f=low flow penalty function, and

$$E_{y,s}=\sum_{m*}E_{m,s} \tag{A3}$$

where: m=month (1–120 for a 10-year simulation), m^*=months in corresponding year (i.e., for year 3, m^*=25–36).

The threshold penalty function, $\mathrm{Pen}^{\mathrm{T}}$, is only enacted for the final piece of analysis considering risk, and outlined in detail in the *Assessing Behavioral Risk Outcomes* section. For all other analysis, this penalty is zero.

Electric energy is formulated around the head level in each reservoir. All operational aspects are nonlinear functions of head, including the reservoir storage, reservoir surface area for determining evaporative losses, the quantity of water released through the turbines, turbine efficiency, and reservoir spilling. These functions have been derived from either relationship curves in the preliminary USBR report, or typical relationships based on site-specific characteristics. Equations (A4) and (A5) present the monthly reservoir storage balance and monthly energy production equations, respectively.

$$S_{s,m+1}=S_{s,m}+Q^{\mathrm{RO}}_{s,m}+Q^{\mathrm{US}}_{s,m}-\mathrm{NE}_{s,m}\times\mathrm{RA}_{s,m}-\beta_s\times\mathrm{CE}_{s,m}-Q^{\mathrm{P}}_{s,m}-Q^{\mathrm{SP}}_{s,m} \tag{A4}$$

$$E_{s,m}\leq Q^{\mathrm{P}}_{s,m}\times H_{s,m}\times e_{s,m}\times\alpha \tag{A5}$$

where: S=reservoir storage, m^3, Q^{RO}=inflow to reservoir from basin runoff, m^3/mo, Q^{US}=inflow to reservoir from upstream, $=Q^{\mathrm{P}}+Q^{\mathrm{SP}}$ of u/s dam, m^3/mo, NE=net evaporation (potential evapotranspiration minus effective precipitation), m^3/mo, RA=reservoir area, m^2, β=channel properties factor, CE=channel evaporation, m^3/mo, Q^{P}=flow for power, released through turbines, m^3/mo, Q^{SP}=flow over the spillway, m^3/mo, H=reservoir head, m^3, e=turbine and generator efficiency, α=conversion factor.

Rated (or installed) power, according to the USBR preliminary report, is assumed to be at design head, and increases linearly to the ultimate head (Bureau of Reclamation, 1976). The head level must be at the minimum operating level before power generation may commence.

The downstream flow constraint illustrating allowable annual flow based on the flow policy at Rosieres dam is presented in Eq. (A6).

$$Q_y^{\mathrm{R}} \ge \sum_s \sum_{m*} \left(Q_{m,s}^{\mathrm{IN}}\right) * (1 - \mathrm{FP}) \qquad \text{(A6)}$$

where Q^{R}=flow at Roseires (furthest point modeled downstream), m^3/mo, Q^{IN}=inflow to Roseires from basin runoff and upstream, m^3/mo, FP=flow policy (fraction retained in Ethiopia).

Net evaporation from the free water surface is computed monthly for the four reservoirs and channel lengths in-between. The NE value is multiplied by the dynamic reservoir area to determine losses or gains. For computation of net channel evaporation, which is comparably quite small, channel lengths and widths are assumed constant.

Acknowledgements. This paper is funded by a grant/cooperative agreement from the National Oceanic and Atmospheric Administration, NA0OAR4311004. The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its subagencies. Special thanks are given to Alessandra Giannini and Michael Tippet of IRI for their guidance and advice.

References

Axel, J. and Céron, J. P.: Elements for Life, edited by: Griffiths, J., Tudor Rose, London, 70–71, 2007.

Barnston, A. G., van den Dool, H. M., Rodenhuis, D. R., Ropelewski, C. R., Kousky, V. E., O'Lenic, E. A., Livezey, R. E., Zebiak, S. E., Cane, M. A., Barnett, T. P., Graham, N. E., Ji, M., and Leetmaa, A.: Long-lead seasonal forecasts – where do we stand? B. Am. Meteor. Soc., 75, 2097–2114, 1994.

Barnston, A. G., Kumar, A., Goddard, L., and Hoerling, M. P.: Improving seasonal prediction practices through attribution of climate variability, B. Am. Meteorol. Soc., 86(1), 59–72, 2005.

Block, P. and Rajagopalan, B.: Interannual variability and ensemble forecast of upper Blue Nile basin kiremt season precipitation, J. Hydrometeorol., 8(3), 327–343, 2007.

Block, P., Strzepek, K., Rosegrant, M., and Diao, X.: Impacts of considering climate variability on investment decisions in Ethiopia, J. Agr. Econ., 39, 171–181, 2008.

Block, P. and Strzepek, K.: Economic analysis of large-scale upstream river basin development on the Blue Nile in Ethiopia considering transient conditions, climate variability, and climate change, J. Water Res. Pl-ASCE, 136(2), 156–166, 2010.

Bodo, B.: Monthly discharge data for world rivers, CISL research data archive, available at: dss.ucar.edu/datasets/ds552.1, (accessed June 2005), 2001.

Broad, K., Pfaff, A., Taddei, R., Sankarasubramanian, A., Lall, U., and Souza Filho, F. A.: Climate, stream flow prediction and water management in northeast Brazil: societal trends and forecast value, Climatic Change, 84(2), 217–239, 2007.

Bureau of Reclamation, US Department of Interior, Land and Water Resources of Blue Nile Basin: Ethiopia. Main Report and Appendices I–V, Government Printing Office, Washington, DC, 1964.

Central Intelligence Agency (CIA): The World Factbook, CIA, Washington, DC, 2006.

Chiew, F. H. S., Zhou, S. L., and McMahon, T. A.: Use of seasonal streamflow forecasts in water resources management, J. Hydrol., 270(1–2), 135–144, 2003.

Craven, P. and Wahba, G.: Smoothing noisy data with spline functions, J. Numer. Math., 31, 377–403, 1979.

Dai, A., Trenberth, K., and Qian, T.: A global data set of Palmer Drought Severity Index for 1870–2002: relationship with soil moisture and effects of surface warming, J. Hydrometeorol., 5, 1117–1130, 2004.

FAO (Food and Agriculture Oranization of the UN), Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements, FAO Irrigation and Drainage Paper No. 56, 300pp., Food and Agriculture Organization of the United Nations, Rome, 1998.

Hamlet, A. F., Huppert, D., and Lettenmaier, D. P.: Economic value of long-lead streamflow forecasts for Columbia River hydropower, J. Water Res. Pl.-ASCE, 128(2), 91–101, 2002.

Hellmuth, M. E., Moorhead, A., Thomson, M. C., and Williams, J. (Eds.): Climate Risk Management in Africa: Learning from Practice, 104 pp., International Research Institute for Climate and Society (IRI), Columbia University, New York, 2007.

Helsel, D. and Hirsch, R.: Statistical methods in water resources, Elsevier Science, Amsterdam, 1995.

Goddard, L., Barnston, A. G., and Mason, S. J.: Evaluation of the IRI's "net assessment" seasonal climate forecasts: 1997–2001, B. Am. Meteorol. Soc., 84, 1761– 1781, doi:10.1175/BAMS-84–12-1761, 2003.

Grantz, K., Rajagopalan, B., Clark, M., and Zagona, E.: Seasonal shifts in the north american Monsoon, J. Climate, 20(9), 1923–1935, 2005.

Jabbar, M., Pender, J., and Ehui, S.: Policies for sustainable land management in the highlands of Ethiopia: Summary of papers and proceedings of a seminar held at ILRI, Addis Ababa, Ethiopia, 22–23 May 2000, Socio-economics and Policy Research Working Paper 30, ILRI (International Livestock Research Institute), Nairobi, Kenya, 2000.

Johnston P. A., Ziervogel, G., and Matthew, M.: The uptake and usefulness of weather and climate information among water resource managers, Papers Appl. Geog. Conf., 30, 380–389, 2007.

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J., Mo, K. C., Ropelewski, C., Wang, J., Leetmaa, A., Reynolds, R., Jenne, R., and Joseph, D.: The NCEP/NCAR reanalysis 40-year project, B. Am. Meteorol. Soc., 77, 437–471, 1996.

Lemos, M. C.: What influences innovation adoption by water managers? climate information use in Brazil and the United States, J. Am. Water Res. Assoc., 44(6), 1388–1396, 2008.

Loader, C.: Local Regression Likelihood, Springer, New York, 1999.

Maurer, E. P. and Lettenmaier, D. P.: Potential effects of long-lead hydrologic predictability on Missouri river main-stem reservoirs, J. Climate, 17, 174–186, 2004.

McCartney, M. P.: Decision support systems for large dam planning and operations in Africa, IWMI Working Paper 119, 47 pp., International Water Management Institute, Colombo, Sri

cc BY

Lanka, 2007.

Millner, A.: What is the true value of Forecasts? Weather Clim. Soc., 1, 22–37, 2009.

Mitchell, T. and Jones, P.: An improved method of constructing a database of monthly climate observations and associated high-resolution grids, Int. J. Climatol., 25, 693–712, 2005.

Mjelde, J.: Value of Improved Information in Agriculture: Weather and Climate Forecasts, Paper for the Southern Region Information Exchange Group-10 annual meeting, Huntsville, AL, 20–21 May, 32 pp., 1999.

MoFED (Ministry of Finance and Economic Development), Ethiopia: Status Report on the Brussels Programme of Action for Least Developed Countries, Addis Ababa, Ethiopia, www.un.org/special-rep/ohrlls/ldc/MTR/Ethiopia.pdf, 2006.

O'Connor, R. E., Yarna, B., Dow, K., Jocoy, C., and Carbone, G.: Feeling at risk matters: water managers and the decision to use forecasts, Risk Anal., 25(5), 1265–1275, 2005.

Pagano, T., Hartmann, H., and Sorooshian, S.: Using climate forecasts for water management: Arizona and the 1997–1998 El Niño, J. Am. Water Resour. Assoc., 37(5), 1139–1153, 2001.

Patt, A. G., Ogallo, L., and Hellmuth, M.: Learning from ten years of climate outlook forums in Africa, Science 318, 49–50, 2007.

Pulwarty, R. and Redmond, K.: Climate and salmon restoration in the Columbia river basin: the role and usability of seasonal forecasts, B. Am. Meteorol. Soc., 78(3), 381–397, 1997.

Rayner, S., Lach, D., and Ingram, H.: Weather forecasts are for wimps: Why water resource managers do not use climate forecasts, Climatic Change, 69(2–3), 197–227, 2005.

Ritchie, J. W., Zammit, C., and Beal, D.: Can seasonal climate forecasting assist in catchment water management decision-making?: A case study of the Border rivers catchment in Australia, Agr. Ecosyst. Environ., 104(3), 553–565, 2004.

Sankarasubramanian, A., Lall, U., Souza Filho, F. A., and Sharma, A.: Improved water allocation utilizing probabilistic climate forecasts: short-term water contracts in a risk management framework, Water Resour. Res., 45, W11409, doi:10.1029/2009WR007821, 2009.

Shahin, M.: Hydrology of the Nile Basin, Elsevier Science, Amsterdam, 1985.

Singhrattna, N., Rajagopalan, B., Clark, M., and Krishna Kumar, K.: Forecasting Thailand summer monsoon rainfall, Int. J. Climatol., 25, 649–664, 2005.

Steenhuis, T. S., Collick, A. S., Easton, Z. M., Leggesse, E. S., Bayabil, H. K., White, E. D., Awulachew, S. B., Adgo, E., and Ahmed, A. A.: Predicting discharge and sediment for the Abay (Blue Nile) with a simple model, Hydrol. Process., 23, 3728–3737, 2009.

Sutcliffe, J. and Parks, Y.: The hydrology of the Nile, IAHS Press, Wallingford, Oxfordshire, UK, 1999.

Tegenu, A.: Statement at the Fourteenth Commission on Sustainable Development, United Nations, New York, www.un.org/esa/sustdev/csd/csd14/statements/ethiopia_11may.pdf, 2006.

Thomson Gale, Encyclopedia of the Nations–Africa, Thomson Corporation, Farmington Hills, MI, USA, 2006.

World Commission on Dams (WCD), Dams and Development: A New Framework for Decision-making, 404 pp., Earthscan Publications Ltd., London, 2000.

World Energy Council: 2007 Survey of Energy Resources, 586 pp., World Energy Council, London, 2007.

Yao, H. and Georgakakos, A.: Assessment of Folsom Lake response to historical and potential future climate scenarios: 2. reservoir management, J. Hydrol., 249(1–4), 176–196, 2001.

Yates, D.: WatBal: an integrated water balance model for climate impact assessment of river basin runoff, Int. J. Water Resour. D., 12(2), 121–139, 1996.

Yates, D. and Strzepek, K.: Modeling the Nile basin under climate change, J. Hydrol. Eng., 3, 98–108, 1998.

Yeh, W. W.-G., Becker, L., and Zettlemoyer, R.: Worth of inflow forecast for reservoir operation, J. Water Resour. Pl.-ASCE, 108(3), 257–269, 1982.

Table 1. Decadal and annual reliability and resilience for two forecasting approaches in comparison to monitoring (climatology). Single-reservoir scheme only.

Scenario	Reliability		Resilience
(single reservoir scheme)	Decadal	Annual	Annual
Full forecast	0.68	0.58	0.48
BN tercile forecast only	0.97	0.72	0.69

Note: BN=below normal precipitation.

Table 2. Results of hydropower sensitivity test to forecast errors in above and below normal terciles. Single-reservoir scheme only.

Scenario (single reservoir scheme)	Aggregated benefits (million $) Observed	 Observed with error	Difference
AN series (75 percentile)	3682	2272	1410, 38.3%
BN series (25 percentile)	2975	2745	230, 7.8%

Notes: AN=above normal precipitation, BN=below normal precipitation. Percentile based on historical 1961–2000 record. Error is +25 mm/mo for Jun–Sep for AN, −25 mm/mo for BN.

CC BY

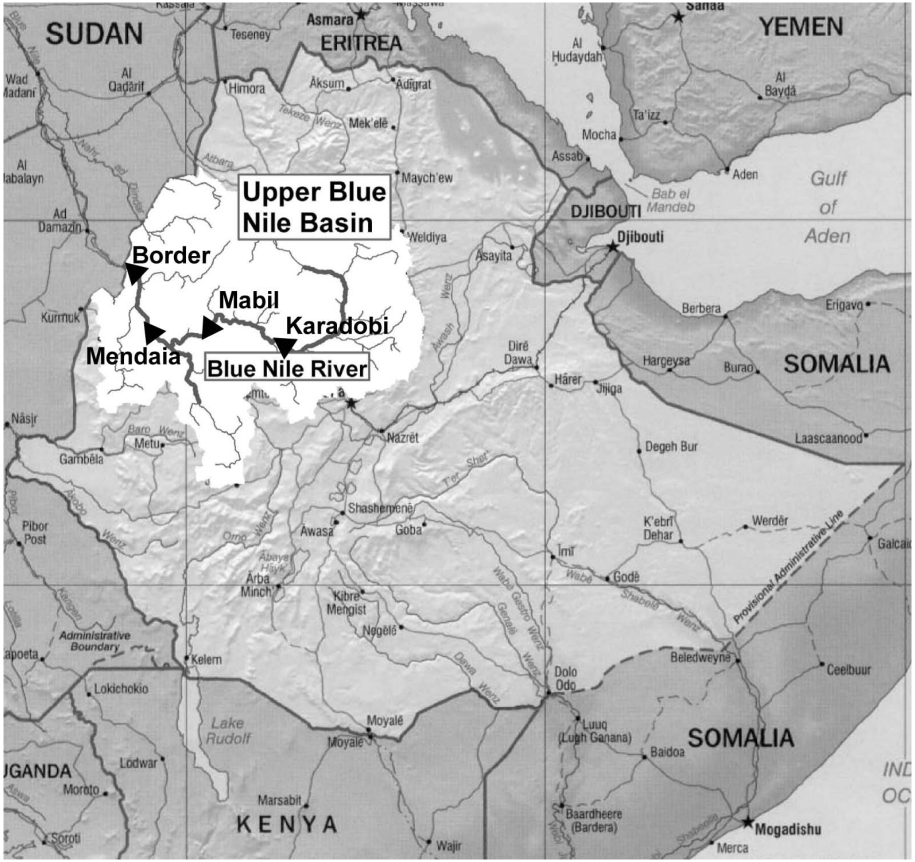

Fig. 1. The upper Blue Nile basin, Ethiopia, including proposed large-scale hydropower dams. Base map courtesy of the Perry-Castañeda Library map collection, University of Texas.

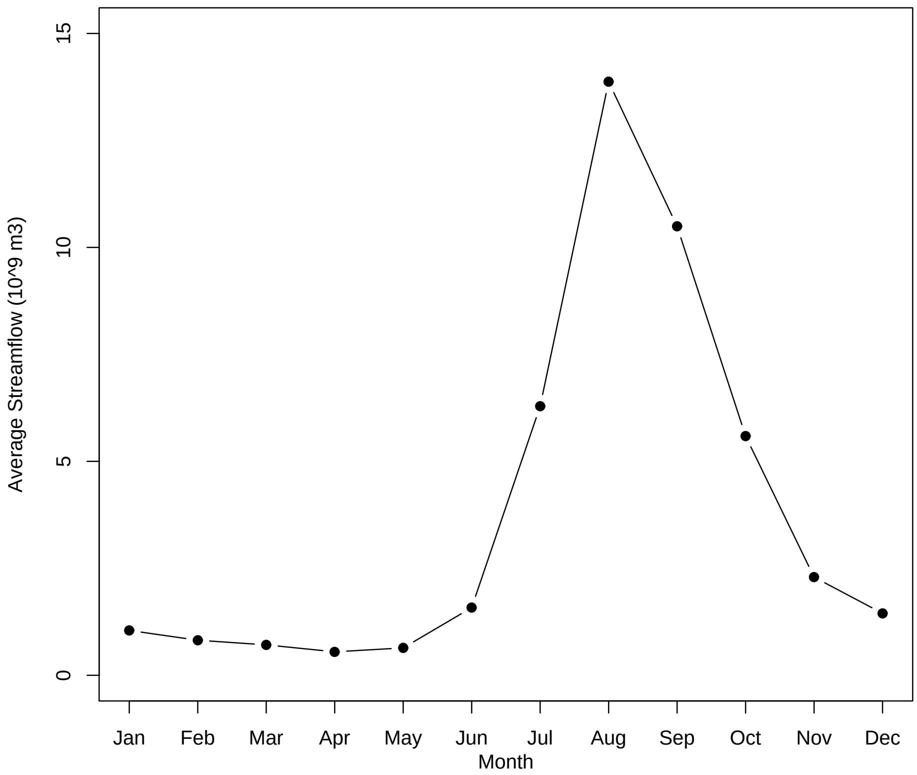

Fig. 2. Mean monthly streamflow at Roseires, Sudan, 1961–1990. Same as Fig. 1 in Block and Strzepek (2010).

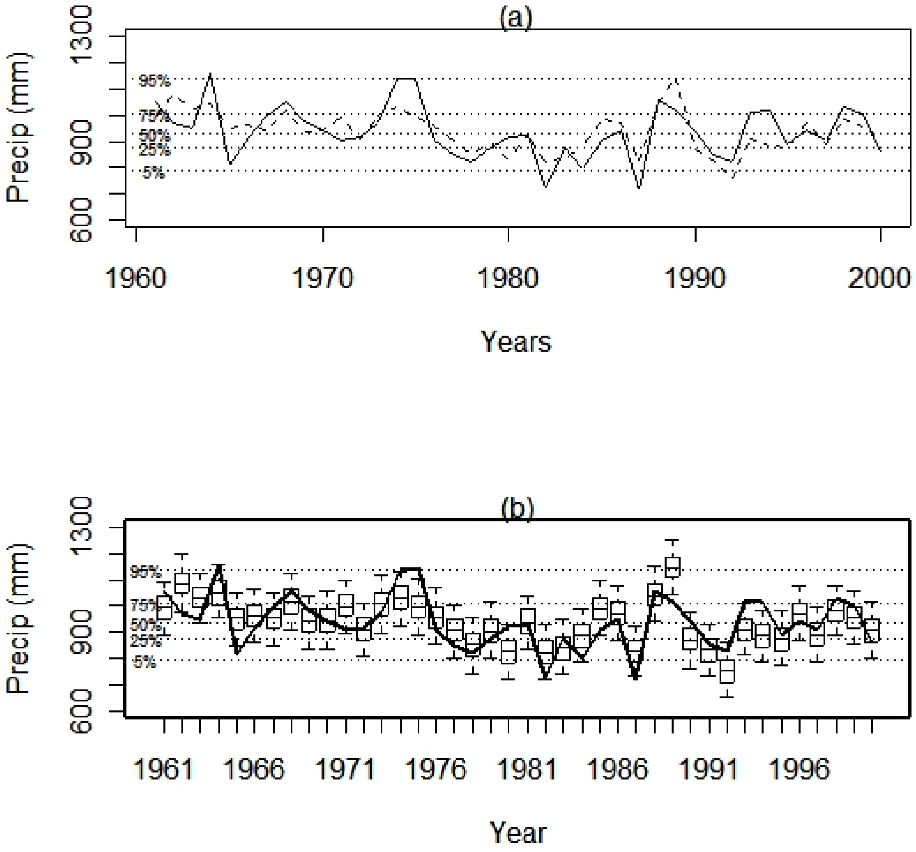

Fig. 3. Local polynomial June–September precipitation forecast modeling approach results. **(a)** Observed and cross-validated estimates with horizontal lines at percentiles from the observed seasonal precipitation. **(b)** Box plots of cross-validated ensembles with horizontal lines at percentiles from the observed seasonal precipitation. Observed data shown as solid line; cross-validated model estimates shown as dashed line in **(a)** and boxes in **(b)**. Same as Fig. 11 in Block and Rajagopalan (2007).

CC BY

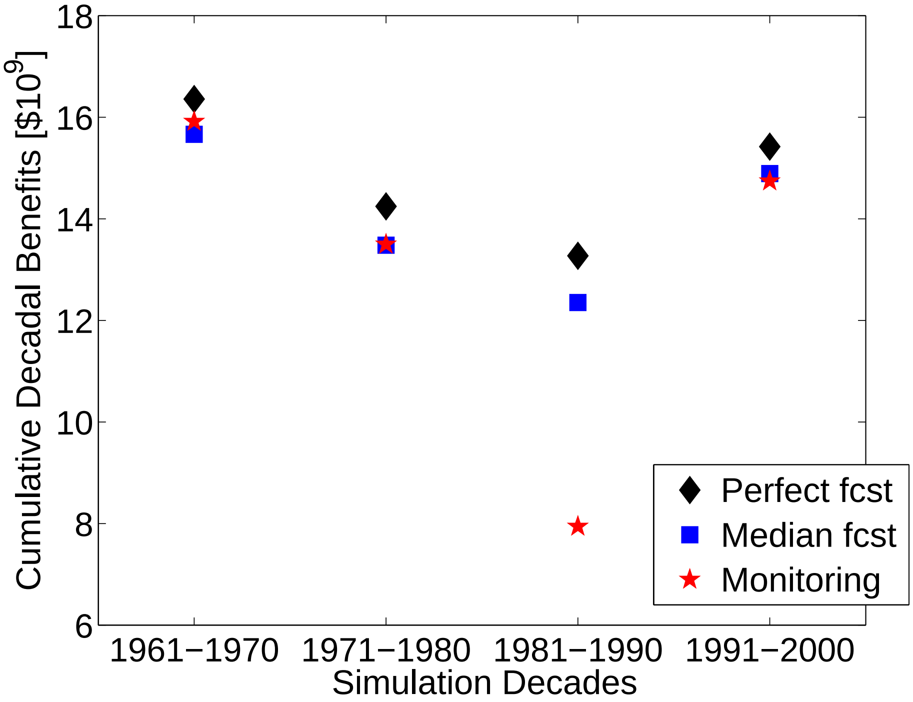

Fig. 4. Cumulative decadal hydropower benefits for historical decades using the perfect (diamond), actual (median, square), and monitoring (climatology, star) precipitation forecasts to drive the coupled model system.

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
◂◂ ▸▸ ◂ ▸
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

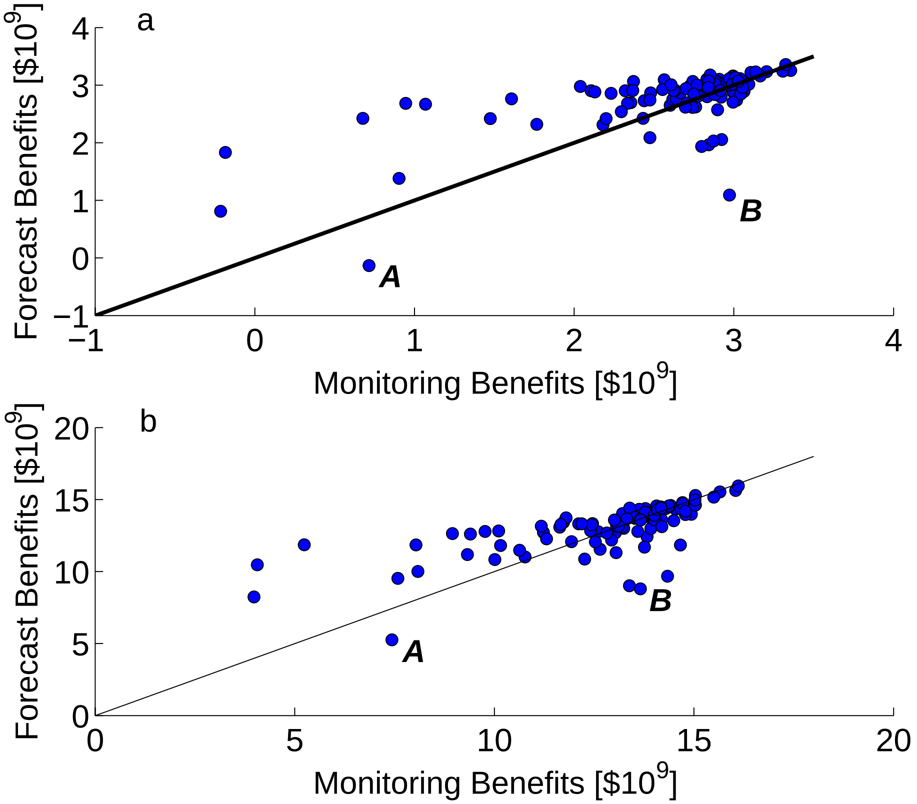

Fig. 5. Comparison of hydropower benefits between monitoring and actual forecast coupled model approaches for **(a)** single-reservoir (Karadobi), and **(b)** 4-reservoir schemes.

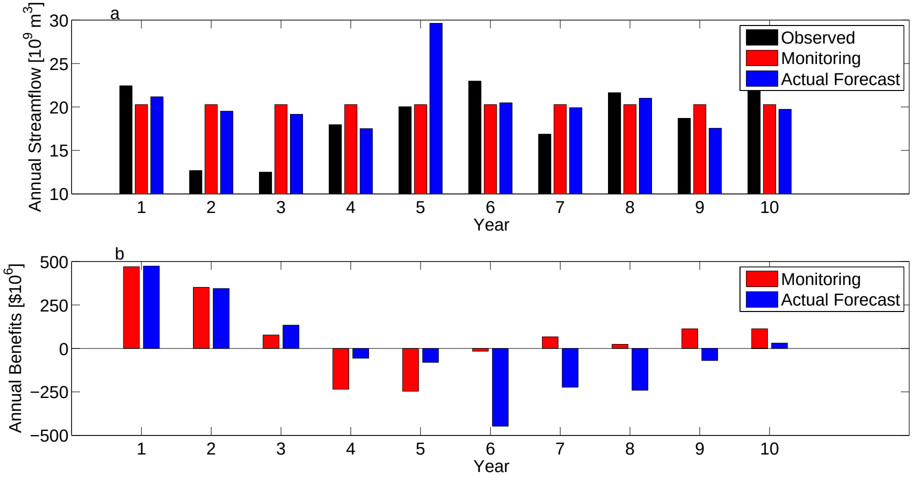

Fig. 6. Annual analysis of decadal time-series *A* as identified in Fig. 5. **(a)** annual streamflow based on observed (black), monitoring (climatology, red), and actual forecast (blue) precipitation. **(b)** annual discounted hydropower benefits based on monitoring (red) and actual forecast (blue) coupled model approaches.

CC BY

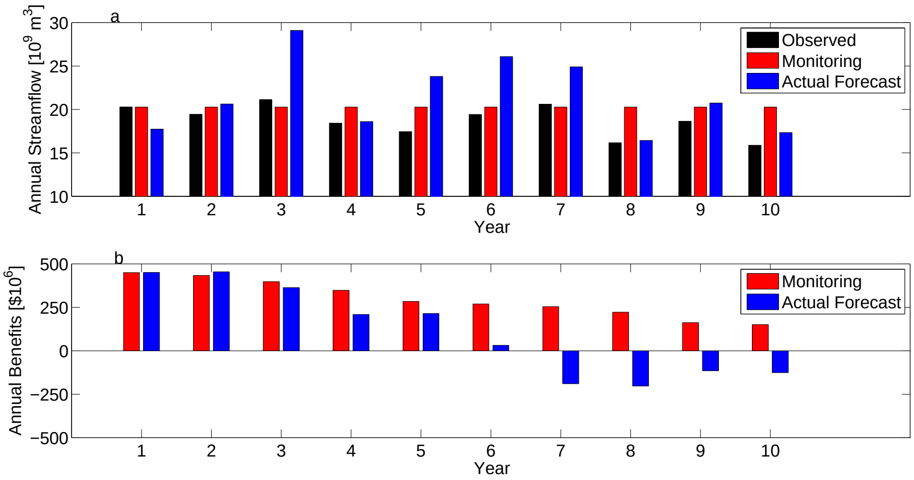

Fig. 7. Same as Fig. 6, except using time-series *B* from Fig. 5.

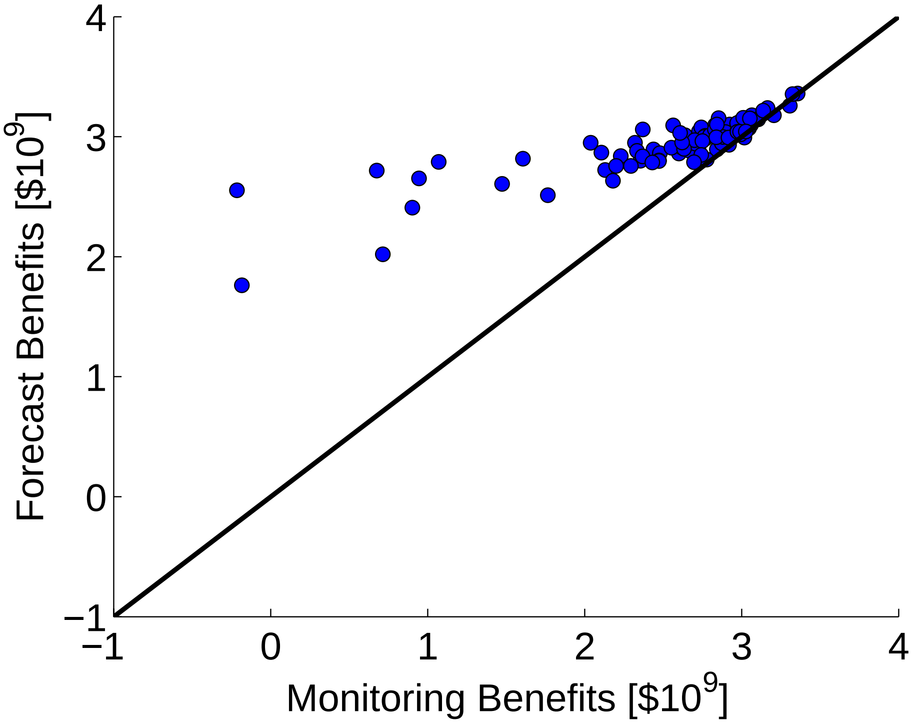

Fig. 8. Comparison of hydropower benefits between monitoring and actual tailored forecast coupled model approaches for the single-reservoir (Karadobi) scheme. Tailored approach includes dampening of above and near normal precipitation forecasts.

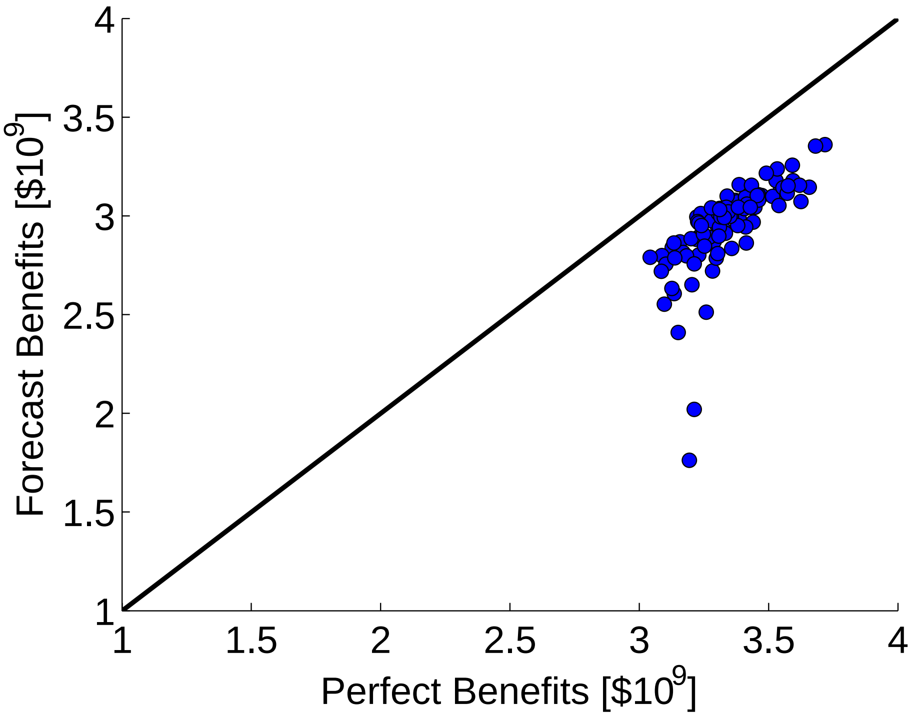

Fig. 9. Comparison of hydropower benefits between perfect and actual tailored forecast coupled model approaches for the single-reservoir (Karadobi) scheme.

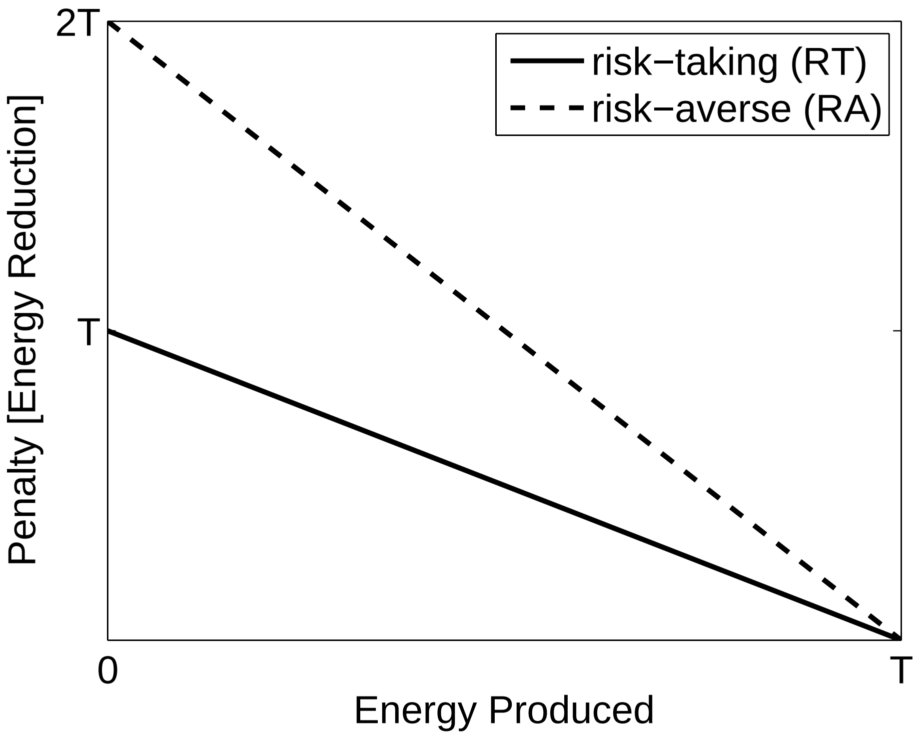

Fig. 10. Penalty functions for risk-taking (RT) and risk-averse (RA) behaviors. *T* =energy threshold. Units for Energy Produced and Penalty are GW h/mo.

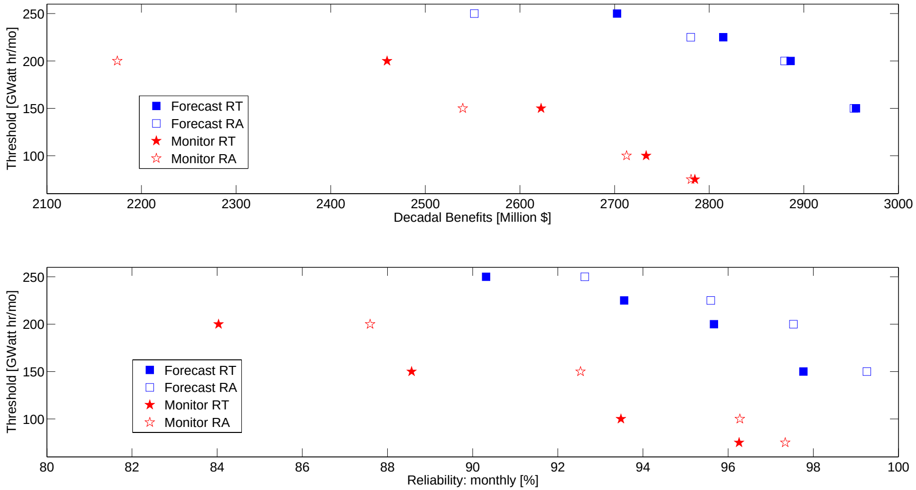

Fig. 11. Comparison of monitoring and forecast approaches under risk-taking (RT) and risk-averse (RA) behavior for **(a)** threshold – reliability and **(b)** threshold – benefit relationships.