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Assessing climate change impacts on operation and planning characteristics of Pong Reservoir, Beas (India)

B. SOUNDHARAJAN[1], ADEBAYO J. ADELOYE[1] & RENJI REMESAN[2]

1 School of the Built Environment, Heriot-Watt University, Edinburgh, UK
b.soundharajan@hw.ac.uk
2 School of Applied Sciences, Cranfield University, Cranfield, UK

Abstract In India, there is a considerable change in both spatial and temporal patterns of the monsoon rainfall, resulting in reduced crop yields and increasing uncertainty in the agriculture-based livelihoods of the rural population. Changes in rainfall, temperature and evapotranspiration are affecting water resources availability and demands, and hence the performance of irrigation water supply facilities such as reservoirs and canal diversions. In order to accommodate these changes in the water resources situation, there must be substantial improvement in water use and management efficiency but this can only be meaningfully done if the impact of climate change and variability is quantified. Consequently, this work has investigated the effects of climate change and variability on irrigation water security in Beas River basin in India by characterising the yield and performance (reliability, resilience and vulnerability) of the associated Pong Reservoir for current (baseline) and climate-change perturbed future horizons. Climate change perturbations based on CGCM3.1 (third generation coupled GCM) for the A1B and B2A IPCC SRES socio-economic scenarios, appropriately downscaled to basin scale were used. The whole analysis was conducted within a Monte Carlo simulation framework, thus enabling the variability and uncertainty associated with each of these variables to also be quantified. The results show that future inflow series to the Pong will exhibit higher inter-annual variability than the baseline, necessitating increased reservoir capacity to meet existing irrigation water demands. In terms of overall performance, while the reliability (both volume- and time-based) was largely unaffected by climate change, the resilience significantly deteriorated especially for the A1B scenario. There were also noticeable changes in the rule curves as a result of climate change.

Key words rule curves; reservoir operation; climate change

INTRODUCTION

Reservoir operation planning is an essential aspect of reservoir management in that by showing target storage levels in different months, the reservoir operation can be guided to ensure improved overall performance of the reservoir in terms of its reliability and vulnerability. Derivation of an operating policy often involves more complex analysis and requires specialist expertise (Adeloye *et al.*, 2003). Reservoir rule curves, which are a basic guidance for reservoir operating policy, however, are not as complex to derive and use but, unlike operating policies, they do not prescribe the amount of water to be released.

Changes in rainfall, temperature and evapotranspiration are affecting water resources availability and demands, and hence the performance of reservoir-based irrigation systems. In order to accommodate these changes in the water resources situation, there must be substantial improvement in reservoir operating policy and water use and management efficiency, but this can only be meaningfully done if the impact of climate change and variability is quantified. The assessment of these impacts of climate change on water resources systems is based on the downscaled GCM future climate scenarios.

This work has investigated the effects of climate change and variability on irrigation water security in the Beas River basin in India by characterising the performance (reliability, resilience and vulnerability) and rule curves of the associated Pong Reservoir for current (baseline) and climate-change perturbed future horizons. Climate change perturbations based on GCM for different two IPCC SRES socio-economic scenarios, i.e. A1B and B2A, and appropriately downscaled to basin scale, were used. To characterise the uncertainty, the whole analysis was conducted within a Monte Carlo simulation framework, thus enabling the variability and uncertainty associated with each of these variables to also be quantified. In the next section, more details about the methodology are given. This is then followed by a description of the case study basin and available data. Then the results are presented and discussed, and finally the conclusions are given.

METHODOLOGY

Rule curve design using sequent peak algorithm (SPA)

The Sequent Peak Algorithm (Thomas & Burden, 1963) is a critical period technique for failure-free reservoir planning analysis and produces an estimate of the reservoir capacity, K_a, as well as the time series of the sequential deficit, K_t, obtainable using:

$$K_{t+1} = \max(0, K_t + D_t - I_t); t \in N \tag{1a}$$

$$K_a = \max(K_{t+1}) \tag{1b}$$

where, K_{t+1} and K_t are the sequential deficits at the end and start of time t, D_t is the demand during t, I_t is the inflow during t and N is the total number of time periods in the simulation. The analysis assumes that the reservoir is initially full, i.e. $K_o = 0$. Where system failures and secondary processes such as evaporation loss must be accommodated, the modified form of the SPA (see Adeloye *et al.*, 2001; Adeloye, 2012) can be used. Once the time series of K_t are available, the rule curve ordinates for each month of the year are then obtained as:

$$URC_j = max(K_{i,j}),\ 1 = 1,\ N;\ j = 1, 12 \tag{2a}$$

$$LRC_j = min(K_{i,j}),\ 1 = 1,\ N;\ j = 1,12 \tag{2b}$$

where $K_{i,j}$ is the sequential deficit in year i, month j, and URC and LRC are the upper and lower rule curve ordinates, respectively. The above analysis uses the single historic record of flow series at the site assuming that future flows will be same as historic. However, this is unlikely to be the case, thus future flow series were derived from the downscaled GCM model parameters (precipitation, temperature and evapotranspiration) for different SRES scenarios of the IPCC using HyMOD (discussed in the subsequent section). To improve the efficiency of the rule curves, a Monte Carlo framework was employed to generate the 1000 replicates of the future monthly flows of the different SRES scenarios, using the parameters estimated from the series (mean, standard deviation and correlation between subsequent time periods) and the Thomas-Fiering model (McMahon & Adeloye, 2005). Each generated replicate was then used in the SPA to obtain the time series of sequential deficits, K_t, as described here. For the Monte Carlo experiment, a slightly different approach was used in deriving the upper and lower rules curves. Here, only the maximum K_t for each month was extracted from the time series of K_t; this gave 1000 replicates for each of the 12 months. The lower and upper rule curves were then determined using:

$$URC(or\ LRC) = \bar{x}(1 \pm 1.96CV) \tag{3}$$

where, $\bar{x}$ is the mean of the K_t for the month under consideration and CV is the corresponding coefficient of variation (= σ/$\bar{x}$, where σ is the standard deviation). Equation (3) assumes that the population of the monthly sequential deficits, K_t, follows the normal distribution.

Hydrological Model (HyMOD)

The five-parameter Hydrological MODel (HyMOD) was originally proposed by Boyle (2001) based on the general concept by Moore (1985) describing an extension of the Probability Distributed Moisture (PDM) lumped storage model. The HyMOD concept consists of a simple, probabilistic, rainfall excess representation connected to two series of linear reservoirs (three identical reservoirs for quick flow response and a single reservoir for the slow flow, groundwater response). Each point in the catchment is assumed to have a capacity, C, of which a portion is filled up as water storage. When the water storage capacity is exceeded, excess water drains out of the catchment as runoff. The model further assumes a distribution function for this varying water storage capacity of the catchment as follows:

$$F(C) = 1 - \left(1 - \frac{C}{C_{\max}}\right)^{b_{\exp}}; 0 \le C \le C_{\max} \tag{4}$$

where $F(C)$ is the cumulative probability of a given water storage capacity, C. The five model parameters are C_{max}, b_{exp}, $Alpha$, R_q and R_s, respectively, representing the maximum storage capacity within the watershed, the degree of spatial variability of the soil moisture capacity within the watershed, a factor partitioning the flow between the two series of linear reservoir tanks, the residence time parameters of quick-flow tanks and the residence time parameters of slow-flow tanks, respectively. These parameters must be optimized with respect to observed streamflow data. The model has been widely applied in hydrology with encouraging results (e.g. Wagener *et al.*, 2001; Remesan *et al.*, 2011).

CASE STUDY RIVER BASIN AND DATA

The Beas River, on which the Pong dam is located, is one of the five major rivers of the Indus basin, India. The reservoir drains a catchment area of 12 561 km^2, of which the permanent snow catchment is 780 km^2 (Jain *et al.*, 2007). Active storage capacity of the reservoir is 7051 Mm^3. Monsoon rainfall between July and September is a major source of water inflow into the reservoir, apart from snow and glacier melt. The dam acts as a sponge for flood flows, and reservoir regulation prevents the inundation of surrounding upland areas from routine flooding during the monsoon season. Monthly reservoir inflow and release from January 2000 to December 2009 (10 years) were used in this study. Apart from its use for generating hydropower, the Pong meets irrigation water demands of 8896 Mm^3/year, which are spread relatively uniformly throughout the year. Indeed, all the water that passes through the hydropower turbines is eventually used for irrigation, and on occasions when this is not sufficient, additional water is released directly from the dam for irrigation purposes (Jain *et al.*, 2007). Downscaled third generation couples GCM data from the Canadian Centre for Climate Modelling and Analysis (CGCM 3.1) of precipitation and temperature for Beas basin were used to derive the runoff at Pong Dam site for the future 2030–2039 time slice for the A1B and B2A SRES scenarios.

RESULTS

Calibration of the HyMOD

The five parameters of the HyMOD were estimated using a genetic algorithm optimiser with the monthly precipitation, evapotranspiration and runoff from January 1998 to December 2002. The result of the model calibration is shown in Fig. 1. As can be seen in Fig. 1, the model reasonably simulates the low flows compared to the high flows during the monsoon periods. Since low flows are important for this study dealing with reservoir planning and operation, the HyMOD's under estimation of high flows is not seen as so much of an immediate problem. Nonetheless, efforts are being made to improve the model's performance for high flows as part of the next stage of this work.

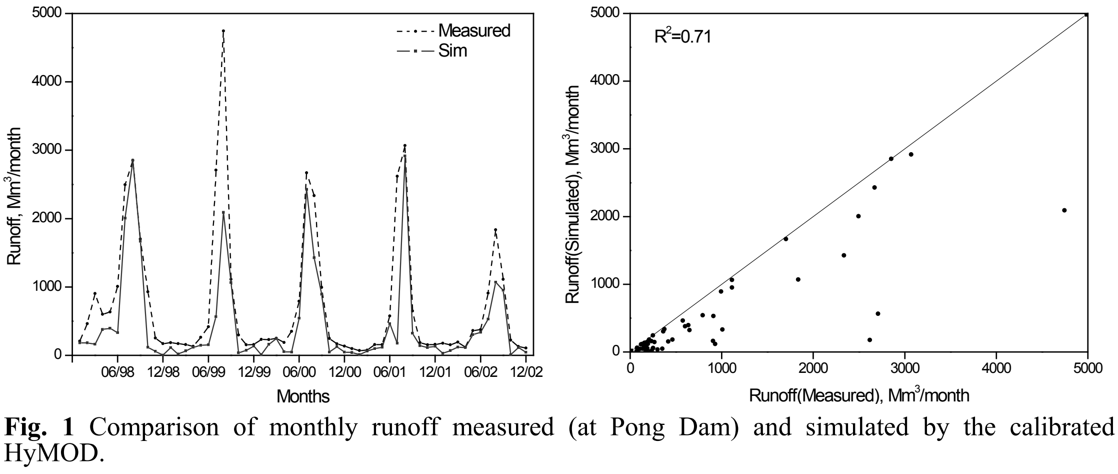

Fig. 1 Comparison of monthly runoff measured (at Pong Dam) and simulated by the calibrated HyMOD.

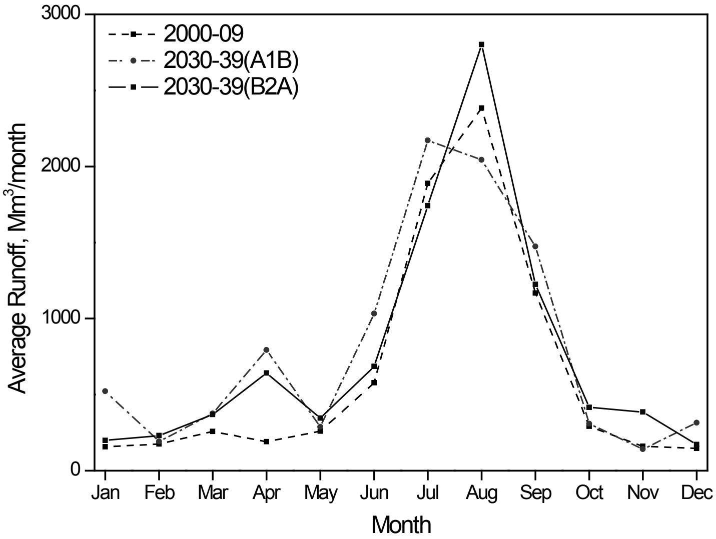

Fig. 2 Monthly average Beas basin runoff (at Pong Dam) of historical and future time periods.

Table 1 Annual runoff characteristics of historic and HyMOD simulated future flows.

Parameter	Historic (2000–2009)	Future flows (2030–2039)	
		A1B	B2A
Mean	7655	9656	9213
Standard deviation	1392	2883	3252
Coefficient of variation(CV)	0.18	0.29	0.35

Climate change impacts on runoff

The calibrated HyMOD was used to simulate the Beas basin runoff under A1B and B2A SRES scenarios for a period of 10 years (2030–2039). The average monthly simulated runoff under both scenarios along with historical data (2000–2009) is shown in Fig. 2. The runoff under both scenarios was not significantly different from the historical flows. In the A1B scenario, runoff during the summer months (April–May) is increasing, but during the monsoon period (August) it is decreasing. In B2A scenario, the runoff will increase both in the summer and monsoon period. Summer months runoff increase due to excessive snowmelts in the Himalayan catchment were reported by many studies.

From the annual flow characteristics (Table 1), while the mean annual runoff will be more in the future, the interannual variability in the runoff, as characterised by the annual CV, will however be higher in the future. Since in general the reservoir capacity will vary as the square of the CV (see Adeloye, 2012), this is an indication that the existing Pong Reservoir capacity may prove small for the future hydrological situation in the basin. Indeed, while the SPA capacity estimate based on the historic was 7210 Mm^3, the corresponding capacity requirements for meeting the same historical demands were 7368 Mm^3 and 7886 Mm^3 for the A1B and B2A scenarios, respectively.

Climate change impacts on rule curves and reservoir performance

The rule curves developed using the historical flow data from 2000 to 2009 with the SPA, as described earlier, are shown in Fig. 3. Similarly, the 1000 rule curves developed using the ensembles by Monte Carlo simulation for the A1B and B2A scenarios future runoff. The average of the 1000 rule curves, as shown in Fig. 4. The URC and LRC are estimated from the mean rule curves using equation (3). For developing the rule curves for future flows, the demand is assumed to be the same as the historic, to compare the reservoir performances under historic and future flow conditions, to meet the same level of demand.

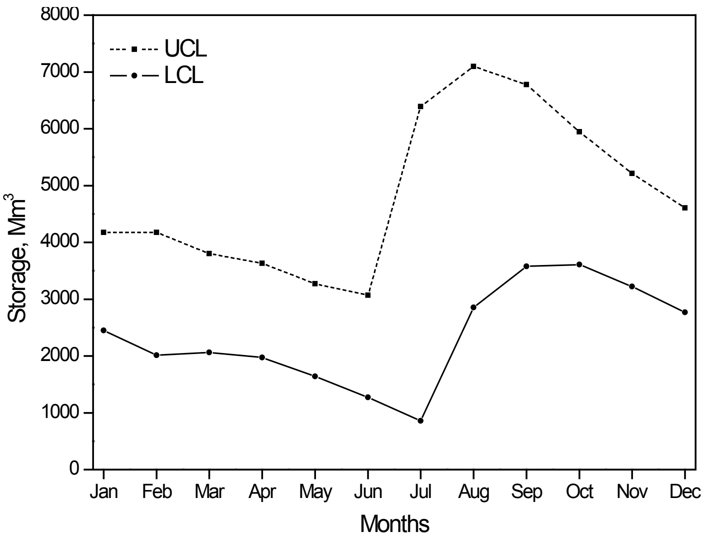

Fig. 3 Rule curves developed using the historical data.

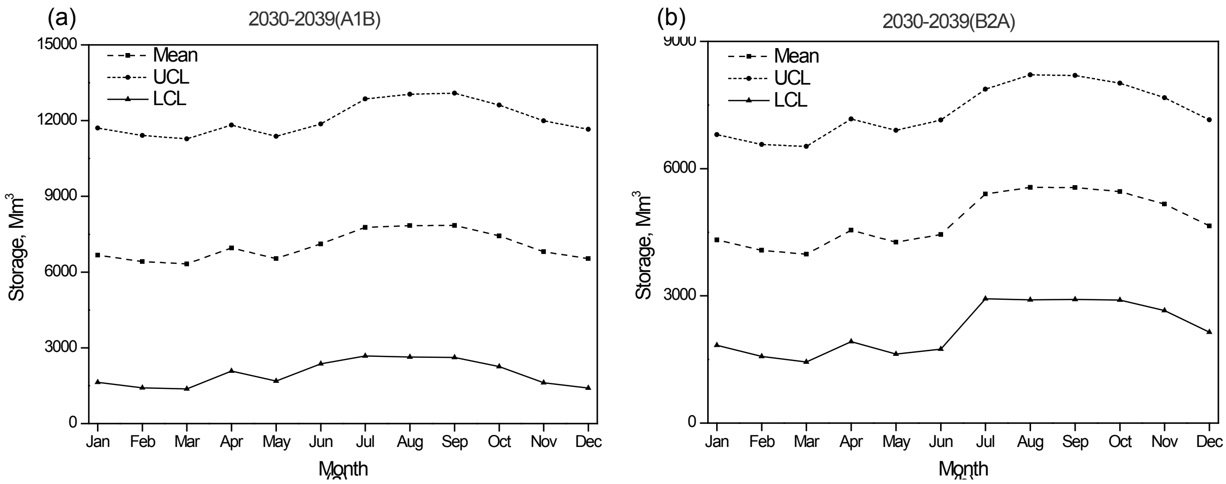

Fig. 4 Rule curves for future flows (2030–2039) of Pong Dam under A1B and B2A scenarios.

A juxtaposition of Figs 3 and 4 will reveal that the rule curves developed for future flows are significantly changed from the historic. In particular, the storage levels required to be maintained for both A1B and B2A are higher than those for the historic, a situation that has arisen because of high interannual flows variability in the future, as indicated by the annual CV (see Table 1).

Estimates of the commonly used reservoir performance measures are given in Table 2. The details of the performance measures are available in McMahon & Adeloye (2005). As seen in Table 2, for the reservoir reliability (both volumetric- and time-based) there is no significant change between the historic and future flow scenarios. However, in resilience, there is a significant difference, with the future flow scenarios exhibiting lesser resilience than the historic system. Since resilience measures the ability of the system to recover from a failure, the low resilience for the future systems is an indication that, in the future, longer continuous failure periods are likely which is not good for a system serving irrigation water needs. Extended periods of water scarcity that may result from a low resilience system will mean that crops are likely to experience longer periods of water stress, with implications for crop yields. In such situations, better operational practices that manage the available through improved hedging and irrigation water scheduling will be required. The intervention may also need larger reservoir capacity to meet the demands in future.

Table 2 Performance of the reservoir system under historic and future scenarios.

Performance indicators	Historic (2000–2009)	Future flows (2030–2039)	
		A1B	B2A
Reliability (volume)	0.98	0.97	0.97
Reliability (time)	0.95	0.95	0.94
Resilience	0.83	0.16	0.42
Vulnerability	0.41	0.57	0.50

CONCLUSION

The utility of the historic rule curves will be limited in the future because of the significant changes in the future flows. The future river inflows at Pong Dam simulated by HyMOD show that flows during summer months and monsoon months will be higher than the historic records, leading to an overall increase in the mean annual runoff for the future in comparison with the historic. However, this masks the highly variable nature of the future inflows, with the annual CV for the two SRES scenarios being much higher than the corresponding value for the historic. Since reservoir planning characteristics, e.g. capacity, yield, etc., are more sensitive to the inter-annual variability than the mean annual runoff, larger reservoir storage capacity is needed due to the high future inter-annual fluctuations in flow. Additionally, the analysis has shown that the system is less resilient under future flow conditions, i.e. there will be possibilities for longer continuous failure periods. The observed changes in the flow pattern will also influence the reservoir operating policy in the future, even under the assumption that historic demand patterns will repeat in future. So, rule curves will need to be updated to accommodate these changes in the runoff characteristics.

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