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Reservoir performance under uncertainty in hydrologic impacts of climate change

Deepashree Raje [a], P.P. Mujumdar [a,b,*]

[a] Department of Civil Engineering, Indian Institute of Science, Bangalore, Karnataka 560 012, India
[b] Divecha Center for Climate Change, Indian Institute of Science, Bangalore, Karnataka 560 012, India

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ABSTRACT

Relatively few studies have addressed water management and adaptation measures in the face of changing water balances due to climate change. The current work studies climate change impact on a multipurpose reservoir performance and derives adaptive policies for possible future scenarios. The method developed in this work is illustrated with a case study of Hirakud reservoir on the Mahanadi river in Orissa, India, which is a multipurpose reservoir serving flood control, irrigation and power generation. Climate change effects on annual hydropower generation and four performance indices (reliability with respect to three reservoir functions, viz. hydropower, irrigation and flood control, resiliency, vulnerability and deficit ratio with respect to hydropower) are studied. Outputs from three general circulation models (GCMs) for three scenarios each are downscaled to monsoon streamflow in the Mahanadi river for two future time slices, 2045–65 and 2075–95. Increased irrigation demands, rule curves dictated by increased need for flood storage and downscaled projections of streamflow from the ensemble of GCMs and scenarios are used for projecting future hydrologic scenarios. It is seen that hydropower generation and reliability with respect to hydropower and irrigation are likely to show a decrease in future in most scenarios, whereas the deficit ratio and vulnerability are likely to increase as a result of climate change if the standard operating policy (SOP) using current rule curves for flood protection is employed. An optimal monthly operating policy is then derived using stochastic dynamic programming (SDP) as an adaptive policy for mitigating impacts of climate change on reservoir operation. The objective of this policy is to maximize reliabilities with respect to multiple reservoir functions of hydropower, irrigation and flood control. In variations to this adaptive policy, increasingly more weightage is given to the purpose of maximizing reliability with respect to hydropower for two extreme scenarios. It is seen that by marginally sacrificing reliability with respect to irrigation and flood control, hydropower reliability and generation can be increased for future scenarios. This suggests that reservoir rules for flood control may have to be revised in basins where climate change projects an increasing probability of droughts. However, it is also seen that power generation is unable to be restored to current levels, due in part to the large projected increases in irrigation demand. This suggests that future water balance deficits may limit the success of adaptive policy options.

1. Introduction

The competing demand for water has increased manyfold in developing countries, with high economic growth, change in lifestyles, industrialization, and urbanization. Available supplies are under great stress as a result of population growth, unsustainable consumption patterns and poor management practices. Hydrologic impact of climate change can cause further stress on an already stressed system and needs to be considered in water management. It is important to consider the range of such impacts for adoption of appropriate planning and mitigation measures of water resource systems. A large number of studies have been conducted in recent years on hydrologic impacts of climate change. These studies project changes in regional hydrology such as precipitation, streamflows and floods/droughts due to climate change. Large-scale atmospheric variables output from general circulation models (GCMs) are used to downscale to basin-scale hydrologic variables, through statistical relationships or using a regional climate model (see reviews [16,38,55]). Many studies have also tried to quantify the uncertainty associated with such projections. A typical method of evaluating effects of climate change on flow regime is to use an ensemble of GCMs, scenarios and statistical downscaling/regional climate models to provide inputs to a hydrological model, and examine the range of effects on a statistic of the modeled flows [4,19,39,57].

There are only a few hydrological impact studies which consider applied research to enable informed decision-making, and there is

* Corresponding author. Address: Department of Civil Engineering, Indian Institute of Science, Bangalore, Karnataka 560 012, India. Tel.: +91 80 2293 2669; fax: +91 80 2360 0290.
E-mail addresses: draje@civil.iisc.ernet.in (D. Raje), pradeep@civil.iisc.ernet.in (P.P. Mujumdar).

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little use of Reliability–Resiliency–Vulnerability (RRV) analysis [18]. However, over the last few years the literature on adaptation (not necessarily hydrologic) to climate change has expanded considerably. Some studies have explored conceptual issues such as definitions and classifications [46,47,58], and others have shown the benefits of different adaptation options [11,31,36,51]. Studies such as Schneider et al. [43] have drawn lessons from adaptation to climatic variability or extreme events, whereas others have focused on how adaptation can reduce vulnerability to climate change [24,58]. Vogel et al. [53] showed that the standardized net inflow and the coefficient of variation of net inflow completely characterize the refill properties of storage reservoirs. They compared the resilience, reliability, yield, and vulnerability of individual storage reservoirs under existing scenarios and one future climate scenario. Brekke et al. [5] presented a flexible methodology for conducting climate change risk assessments involving reservoir operations. Using a case study for California's Central Valley Project and State Water Project systems, they showed that assessed risk for a given risk attitude was sensitive to the analytical design choices, namely, the assumption that climate change will influence flood control constraints on water supply operations, and weighting of climate change scenarios. Li et al. [28] investigated potential impacts of future climate change on streamflow and reservoir operation performance in a Northern American Prairie watershed. Lopez et al. [29] used perturbed physics ensembles of climate models for impacts analysis and planning for public water supply in England under climate change. They show that additional information contained in the climate model ensemble provides a better understanding of the possible ranges of future conditions, compared to the use of single model scenarios. Arnell and Delaney [1] examined adaptation to climate change by water supply companies in England and Wales. Fowler et al. [15] studied the impacts of climatic change and variability on water resource reliability, resilience, and vulnerability of the Yorkshire water resource system by modeling changes to weather type frequency, mean rainfall statistics, and potential evapotranspiration. Their results indicated future improvements in water resource reliability due to increased winter rainfall but reductions in resource resilience and an increased vulnerability to drought. Dvorak et al. [13] studied potential impacts of climate change on hydrological system and water resources in four river basins in the Czech Republic. They provided suggestions for adaptation policy options with a preference for nonstructural measures such as water conservation, efficient water demand management and protection of water resources. Buttle et al. [8] studied the impact of changes in the lake levels and flows of the Great Lakes in terms of the hydro-electric power produced. Tanaka et al. [50] examined the ability of California's water supply system to adapt to long-term climatic and demographic changes with population and land use estimates for the year 2100 using an economic-engineering optimization model of water supply management. They found considerable value in including population changes, allowing the system to adapt to changes in conditions, and representing the system in sufficient hydrologic and operational detail to allow significant adaptation. O'Hara and Georgakakos [35] presented a methodology to assess the ability of existing storage to meet urban water demand under present and projected future climatic scenarios, and to determine the effectiveness of storage capacity expansions. Uncertainties in climatic forcing and projected demand scenarios were considered explicitly in the models. Burn and Simonovic [7] studied the potential impacts of climate change on the operational performance of the Shellmouth reservoir in Manitoba, Canada. Using two different 'warm' and 'cool' sets of climatic conditions, synthesized monthly streamflow sequences were input to a reservoir operation model. The impacts from implementation of the reservoir operating policy on the reliability of the reservoir for meeting three purposes, viz. flood control, recreation and water supply were determined. The reservoir performance was determined to be sensitive to the inflow data. Kaczmarek [22] studied the possible impacts of long-term hydrological nonstationarity on the design and operation of water reservoir systems, using a case study of Lake Kariba in the Zambezi river basin. Stochastic storage theory was used to derive the relationship between annual storage capacity, water demand and various performance criteria of reservoir management. This was applied to a number of scenarios, and it was shown that even relatively small changes in the stochastic characteristics of the inflow to the reservoir may be amplified into much larger changes in reliability and other operational criteria. Lettenmaier and Gan [27] analyzed the hydrologic sensitivities of four catchments in the Sacramento and San Joaquin River basins to long-term global warming. Under carbon dioxide doubling scenarios from three GCMs, they showed that winter runoff increased while spring snowmelt runoff decreased in these catchments. The snowmelt and soil moisture accounting models also simulated large increases in the annual flood maxima, with the time of occurrence of many large floods shifting from spring to winter. Klemes [25] developed criteria to determine the suitability of a model for application to the assessment of climate change, which include a sound physical foundation for the model structure, separate validation for each of the structural components and geographic and climatic transferability of the model.

The work presented in this paper deals with studying the impact of climate change on reservoir performance, for the 'business-as-usual' scenario, and with optimal operating policies. Adaptive policies for mitigation of hydrologic impacts in terms of performance criteria are suggested for future scenarios. Climate change effects on monthly power generation and four performance criteria (reliability with respect to three purposes, viz. hydropower, irrigation and flood control, resiliency, vulnerability and deficit ratio with respect to hydropower) are studied initially with the standard operating policy (SOP) using current rule curves for flood protection. Increased irrigation demands, rule curves dictated by increased need for flood storage and downscaled projections of streamflow from three GCMs for three scenarios each are used for projecting future hydrologic scenarios. The results show that using current operations, annual hydropower and reliability with respect to hydropower and irrigation will decrease, while vulnerability and deficit ratio are likely to increase as a result of climate change. A stochastic dynamic programming (SDP) model [30] which addresses the uncertainty associated with inflow is then applied to derive an adaptive optimal monthly operating policy with the objective of maximizing reliabilities with respect to multiple reservoir purposes of hydropower, irrigation and flood control. The adaptive operation shows lower reliability for hydropower but higher reliability for irrigation as compared to the standard operation, while flood control reliability was almost unchanged. Two variations to this adaptive policy are tested for extreme scenarios showing highest decreases in hydropower reliability. The first assigns 1.5 times weightage to hydropower reliability and the second assigns three times weightage to hydropower reliability as compared to other reliabilities. Application of these policies shows that a marginal reduction in irrigation and flood control reliability can achieve an increased hydropower reliability in future. Hence, reservoir rules for flood control may have to be revised in the future. However, it appears that future water balance deficits caused by decreases in streamflows and increased demands may limit the outcome of application of adaptive policies.

2. Case study background

The Hirakud reservoir is a multipurpose project, created by constructing a dam across the river Mahanadi in Sambalpur district,

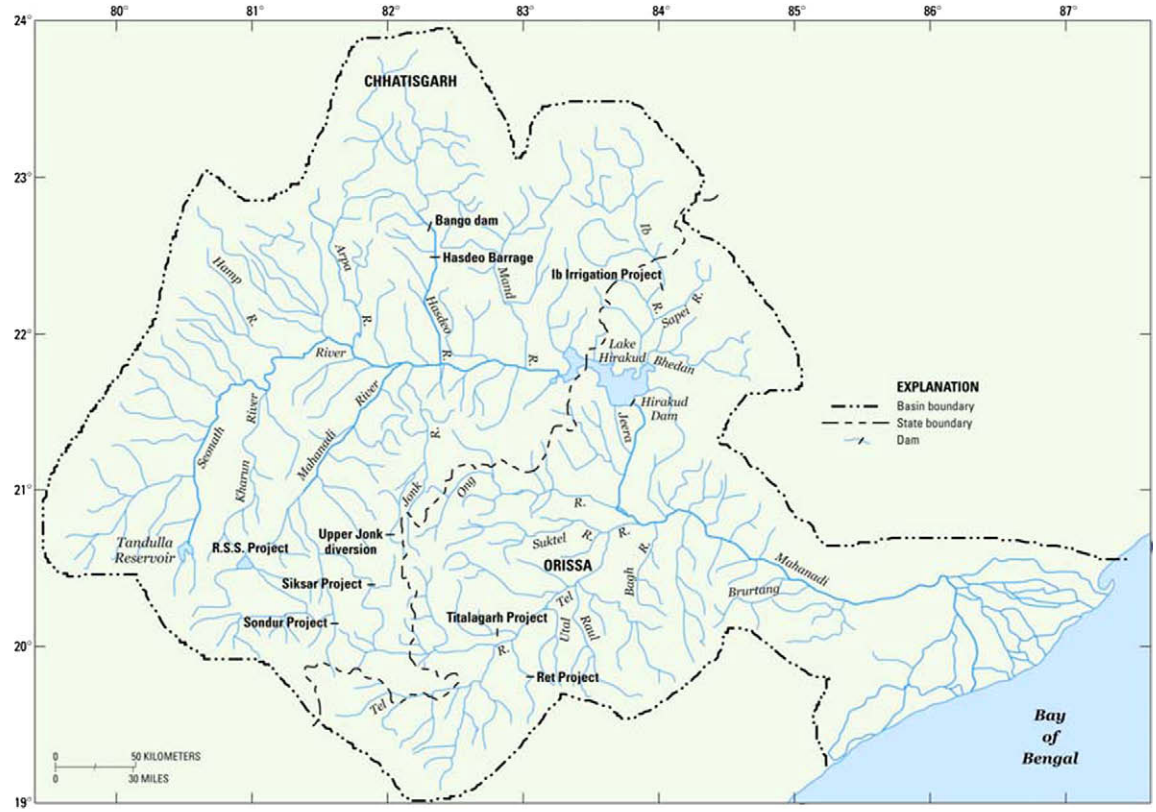


Fig. 1. Mahanadi river basin, including locations of selected diversions and irrigation projects (*Source:* Sengupta et al. [44]).

Orissa state, India. The Mahanadi basin lies in eastern India between 80° 30′E to 86° 50′E longitude and 19° 20′N to 23° 35′N latitude. It has an area of 145,818 km^2 and flows east to the Bay of Bengal. Fig. 1 shows the Mahanadi river basin, along with the location of Hirakud reservoir and dam (21.32° N, 83.45° E). There is no major control structure upstream of the Hirakud reservoir and hence the inflow to the dam is considered as unregulated flow. A major portion of annual rainfall over most parts of India is received during a short span of four months from June to September, which is known as the summer monsoon season. The Mahanadi river is rain-fed with high streamflow during June to September due to monsoon rainfall, with insignificant contribution from groundwater during this season. In the non-monsoon season, low rainfall results in low flow conditions, when baseflow component is significant. Moreover, the monsoon flows are important in Hirakud reservoir to meet the demands during the year. Hence, only monsoon streamflow is downscaled in this study, under climate change conditions. For purposes of this analysis, it is assumed that non-monsoon streamflows remain unchanged in the future. Fig. 2 shows a schematic diagram of the Hirakud project. The reservoir has a catchment area of 83,400 km^2. The Hirakud project is a multipurpose scheme and the storage is used in the following order of priority: flood control, municipal water supply, industrial supply, irrigation and power generation. Water levels begin rising in July with the beginning of monsoon season in the region, and begin declining in October, at the end of the season.

2.1. Projections of future streamflow

Derivation of optimal reservoir operating policy for Hirakud reservoir requires monthly inflows at the reservoir. Previous studies have provided projections of future streamflow through downscaling the monsoon streamflow in Mahanadi river [17,32,42]. In this work also, a statistical downscaling method is used to provide projections of monsoon streamflow. Predictor variables used for downscaling [54,56] should be: (a) reliably simulated by GCMs, (b) readily available from archives of GCM outputs, and (c) strongly correlated with the surface variables of interest. Monsoon streamflow is largely a resultant of rainfall and evaporation. Rainfall is linked to air mass transport and atmospheric water content and thus can be related to atmospheric circulation or pressure patterns and wind velocities [3,20,54], specific humidity [10], geopotential height and temperature [6]. Cannon and Whitfield [9] have used MSLP, 500 hPa geopotential height, 800 hPa specific humidity, and 100–500 hPa thickness field as the predictors for downscaling GCM output to streamflow. Mujumdar and Ghosh [32] and Raje and Mujumdar [42] have used 2 m surface air temperature, MSLP, 500 hPa geopotential height and surface specific humidity as predictor variables for the same case study considered in this paper. Indian monsoon rainfall exhibits large interannual variations which are generally attributed to the slowly varying boundary conditions of sea surface temperature, soil moisture and snow cover over the land surface [45]. Evaporation is mainly influenced by temperature and humidity.

Following Raje and Mujumdar [42], the present study also considers 2 m surface air temperature, MSLP, 500 hPa geopotential height and surface specific humidity as predictors for modeling streamflow in the monsoon season. These variables were found to be significantly correlated with monsoon streamflow at Hirakud. Land use is one of the important factors in generation of streamflow. In the present study, land use pattern is assumed to remain unchanged in the future. Predictor variable data is obtained from the National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis data [23] for a region spanning 15°–25°N and 80°–90°E for years 1959–2005. For future projections, data from the Intergovernmental Panel for

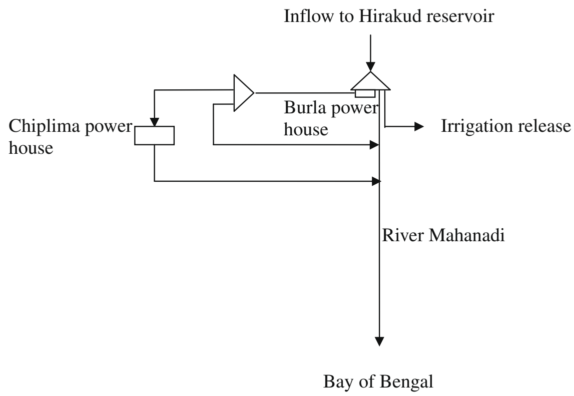


Fig. 2. Schematic diagram of Hirakud project.

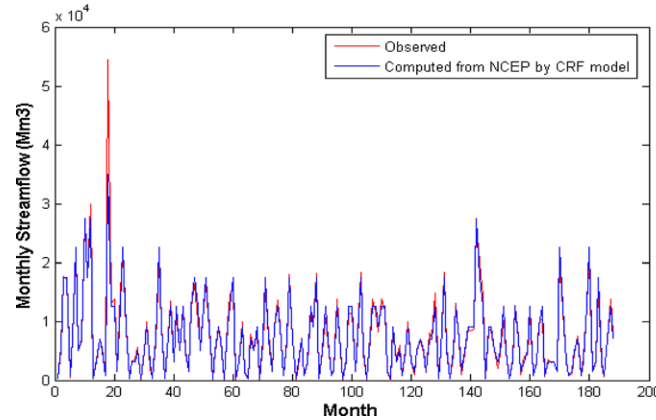


Fig. 3. Training results for CRF downscaling model for monsoon monthly streamflow at Hirakud for years 1959–2005 (*Source*: Raje and Mujumdar [42]).

Climate Change Assessment Report 4 (IPCC AR4) dataset runs for three GCMs for three scenarios each (A2, A1B, B1) is extracted for two time slices of years 2045–65 and 2075–95 from the multi-model dataset of the World Climate Research Programme's Coupled Model Intercomparison Project (WRCP CMIP3). The GCMs used are CGCM2 (Meteorological Research Institute, Japan), MIROC3.2 medium resolution (Center for Climate System Research, Japan) and GISS model E20/Russell (NASA Goddard Institute for Space Studies, USA). These GCMs were found to reproduce statistical properties of current streamflows well, by downscaling from the 20C3M scenario (climate of the 20th century experiment). They are also chosen based on availability of predictor variable data for all scenarios. Monthly mean inflow data of the Hirakud reservoir for years 1959–2005 is obtained from the Department of Irrigation, Government of Orissa, India. Predictor variable data output from the three GCMs for two time slices of years 2046–2065 and 2075–2095 for the A2, A1B and B1 scenarios are used to project future monsoon streamflow. The methodology for downscaling is explained in the following subsection.

2.2. Downscaling model for projections of future streamflow

Conditional random fields (CRFs) belong to a class of stochastic models called undirected discriminative models [26]. CRFs have been applied to a variety of domains, from initial applications in text processing to computer vision, image processing and bioinformatics. A detailed explanation and introductory tutorial of CRFs may be found in Sutton and McCallum [49]. Raje and Mujumdar [41] introduced the CRF model for downscaling to daily precipitation in the Mahanadi basin and provide details of the training and inference methodology. Raje and Mujumdar [42] have downscaled streamflow in the Mahanadi river for uncertainty modeling of hydrologic drought. Following that study, in the current work also, the monsoon mean monthly streamflow is modeled as a conditional random field (CRF). The conditional distribution of the streamflow sequence at a site, given the monthly atmospheric (large-scale) variable sequence, is modeled as a linear-chain CRF. If the monthly streamflow sequence at a site is **y**, and the observed daily atmospheric variable sequence is **x**, then the conditional distribution of the streamflow sequence **y** is:

$$p(\mathbf{y}|\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \exp\left\{\sum_{t=1}^{T}\sum_{k=1}^{K} \lambda_k f_k(y_t, y_{t-1}, \mathbf{x})\right\} \tag{1}$$

where $\{\lambda_k\}$ is a parameter vector, and $\{f_k(y, y', \mathbf{x})\}_{k=1}^{K}$ is a set of real valued feature functions defined on pairs of consecutive streamflow values and the entire sequence of atmospheric data. Various feature functions used in this model are intercept and transition features, raw observation features, difference features and threshold features [42]. Prior to training, bias removal, normalization and principal component analysis is performed on the raw NCEP as well as GCM data. The CRF downscaling model is trained using the first few principal components of atmospheric predictor variables (accounting for more than 95% of the variance) and streamflow. Maximum likelihood training [49] is used, where the regularized log-likelihood (log $p(\mathbf{y}|\mathbf{x}, \lambda)$ as a function of λ) is maximized. A limited-memory version of Broyden–Fletcher–Goldfarb–Shanno (lBFGS) [34] is used for optimization in this model. Using maximum *a posteriori* inference by the Viterbi algorithm [40], the most likely streamflow sequence is computed for testing. Prediction for a future scenario is made using principal components of standardized monthly outputs of atmospheric variables from a GCM to compute the most likely streamflow sequences.

Fig. 3 shows training results for the CRF downscaling model for downscaling to monsoon streamflow in the Mahanadi river. Using the parameters obtained from training, the model is used for future projection of monsoon streamflow for years 2045–65 and 2075–95. Fig. 4 shows the CDFs of projected monsoon monthly streamflow and flow duration curves for 2045–65 and 2075–95 for the range of GCM-scenario combinations. It is seen that for most future scenarios, there is a decrease in middle level flows (equaled or exceeded 20–70% of the time). This decrease becomes more prominent by years 2075–95. High flows increase in most scenarios for 2045–65, but the number of scenarios showing an increase in high flows also decreases by years 2075–95. Low flows show a slight increase for 2045–65 (above 80% flows) but a smaller range of low flows increase for 2075–95 (above 90% flows only).

These projected changes in streamflows affect performance of water resource systems and have direct implications for reservoir operation. The following sections describe the methodology for reservoir management in the case study using current and future downscaled flows.

2.3. Projections for future hydrologic scenarios

Adaptation of multipurpose reservoir operation to offset adverse impacts of climate change calls for capturing all impacts that climate change can have on the operations of the reservoir. In an integrated future hydrologic scenario, it is likely that water demands will change along with changes in inflows to the reservoir. Also, changes in the frequency and severity of flood events need to be incorporated into adaptive policies, through modification of rule curves for the reservoir. Since analysis of flood events requires daily or even hourly simulation of streamflows, projections from other studies in the case study region were used for this purpose. Asokan

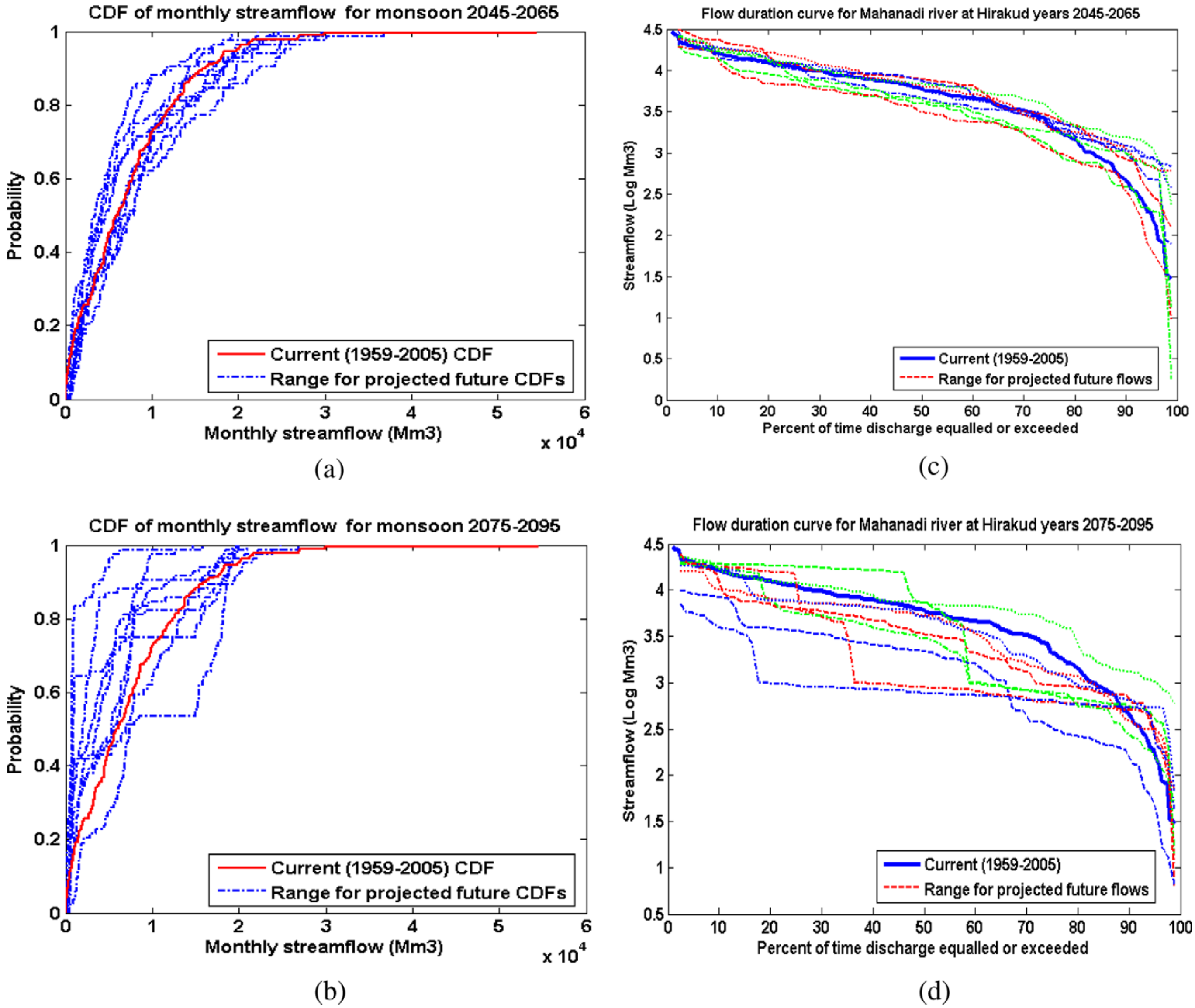


Fig. 4. Range of projected future CDFs ((a) and (b)) and flow duration curves ((c) and (d)) for monsoon inflows at Hirakud for two time slices, 2045–65 and 2075–95, using three GCMs (MIROC, CGCM2, GISS) and three scenarios (A1B, A2, B1).

and Dutta [2] analyzed water resources availability and demand in the Mahanadi River Basin under climate change conditions for years 2000, 2025, 2050, 2075 and 2100 for wet and dry months. They used daily precipitation output from the CGCM2 GCM for the A2 scenario with a physically-based distributed hydrologic model, to project increases in peak runoff in the Mahanadi river for wet months. Fig. 5 shows the percentages of increase in river discharge for wet months for future years, projected from their study. The increases in peak runoff reported in their study are used in the present study to project a correspondingly equal increase in volumetric storage needed at Hirakud dam for flood control.

Irrigation water demands were projected in the same study [2] for future years by incorporating estimated water demands for current and proposed irrigation projects. A change in irrigation intensity was also considered, based on possible changes in land use for future years. Fig. 6 shows projections of absolute irrigation water demand, for all catchments in the Mahanadi basin, reported in that study. The relative increases projected are used in the present study to estimate corresponding equal relative increases in future irrigation demand at Hirakud reservoir. The study also projected

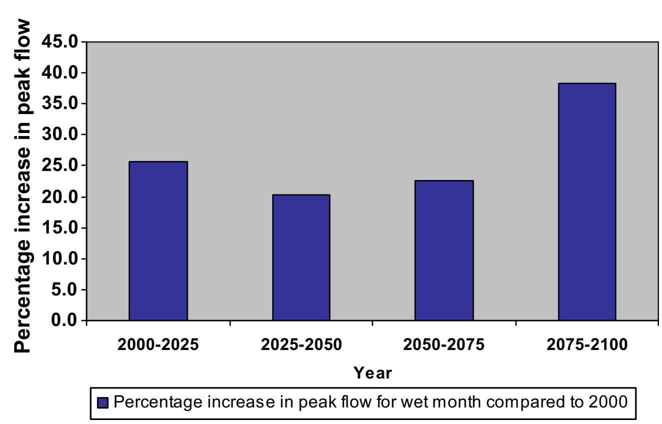


Fig. 5. Percentage variation in peak discharge projected for Mahanadi river (*Source*: Asokan and Dutta [2]).

domestic and industrial water demand for future years, but since

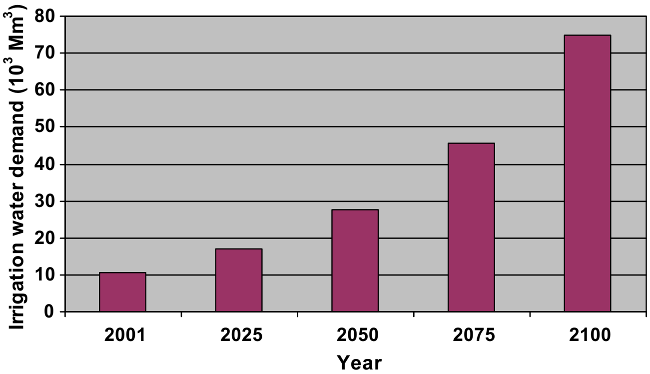


Fig. 6. Projected irrigation water demand for Mahanadi basin catchments (*Source*: Asokan and Dutta [2]).

this demand is currently extremely low for Hirakud, an increase is unlikely to impact operations and was not accounted for, in the present work.

2.4. Reservoir data

The Hirakud reservoir provides irrigation to an area 1554.01 km^2 in the Kharif cropping season (July–October) and 1082.09 km^2 in the Rabi cropping season (November–April). The installed capacity of power generation is 347.5 MW out of which 275.5 MW can be produced from seven units at Burla hydropower station (dam toe power house), and 72 MW from three units at Chiplima hydropower station, located further downstream of Hirakud dam (Fig. 2). The firm power requirement is 134 MW [48]. The water used for power generation at Hirakud, flows from Burla hydropower station to Chiplima hydropower station through a power channel 22.4 km. long. After generating power at Chiplima, water flows back into the river. The revised reservoir storage capacities (year 2000) were reported as 5896 Mm^3 gross storage and 4823 Mm^3 live storage capacity [21]. It should be noted that this report [21] significantly revises the storage capacities as per a remote sensing study by the Central Water Commission, reduced due to sedimentation in the reservoir. The current rule curve followed since 1988 recommends upper and lower limits of levels within which the reservoir is to be maintained at particular periods of the monsoon. During monsoon months, appropriate lower reservoir levels are maintained and a full reservoir level is achieved by the end of September.

The area–capacity curves for the reservoir, which have been modified in 2002 taking into consideration the results of sedimentation survey of the reservoir, and area-elevation curve were obtained [21], and polynomial fits to these curves were derived and used in this study. The municipal water supply demand was reported as 0.411 Mm^3 per month and industrial demand is 51.29 Mm^3 per month. Average monthly pan evaporation rates (1974–1995) and monthly irrigation demands (1959–2006) at Hirakud reservoir were also obtained from the Government of Orissa Water Resources Department [21]. The average monthly power generated in megawatts, P by a turbine of efficiency η is given by

$$P = 9810 \times \frac{R}{30 \times 24 \times 3600} \times H \times \eta = 0.003785R \times H \times \eta \qquad (2)$$

where R is the monthly release in Mm^3 and H is the net head of water available for power generation in meters. Here η is taken as 0.9. The Eq. (2) is used for computation of monthly power generated in this study.

2.5. Performance evaluation

Four performance indices, viz. reliability with respect to hydropower, irrigation and flood control, and resiliency, vulnerability and deficit ratio, all with respect to power generation, are used for performance evaluation in the present study. The definitions for reliability and resiliency, are slightly altered from those given by Hashimoto et al. [18] to incorporate a failure index [14], which incorporates both the frequency and severity of failure. For defining hydropower reliability, a full failure is defined as one when not even 75% of demands are met and smaller failures are measured as:

$$FM_{hp} = \begin{cases} \frac{\Delta_i}{0.25T_i}, & \text{for } \frac{\Delta_i}{0.25T_i} \leqslant 1 \\ 1, & \text{for } \frac{\Delta_i}{0.25T_i} > 1 \end{cases} \qquad (3)$$

where FM_{hp} is the hydropower failure measure, Δ_i is the deficit power in period i, and T_i is the target power (firm power). For defining irrigation reliability, the failure measure is defined as a proportional failure:

$$FM_{irr} = \frac{\Phi_i}{D_i} \qquad (4)$$

where FM_{irr} is the irrigation failure measure, Φ_i is the deficit irrigation in period i, and D_i is the irrigation demand for that period. Similarly, the failure measure for flood control is defined as:

$$FM_{fc} = \frac{\Theta_i}{K_a - FC\max_i} \qquad (5)$$

where FM_{fc} is the flood control failure measure, Θ_i is the excess live storage over maximum storage prescribed by flood control rules for period i, K_a is the live storage capacity of the reservoir and $FC\max_i$ is the maximum storage per flood control rules for that period. The failure index F is then calculated for each failure measure as the ratio of the sum of all failure measures over all periods to the total number (N) of (monthly) operation periods:

$$F = \frac{\sum_{i=1}^{N}(FM)_i}{N} \qquad (6)$$

The corresponding reliability (α) is then defined as $\alpha = 1 - F$. The resiliency (γ) with respect to hydropower is defined as the ratio of the number of transitions from a full failure state ($P_i \leqslant 0.25T_i$) to a satisfactory state ($P_i > 0.25T_i$) to the sum of failure measures:

$$\gamma = \frac{\sum_{i=1}^{N-1}\langle P_i \leqslant 0.25T_i\rangle\langle P_{i+1} > 0.25T_i\rangle}{\sum_{i=1}^{N}(FM)_i} \qquad (7)$$

where P_i is the power generated in period i, and $\langle\cdot\rangle$ is the indicator function (equal to one when the condition is satisfied, else equal to zero). The vulnerability (v) with respect to power is defined here as the expected value of the maximum deficit in any sojourn into failure states. Hence, it is computed as:

$$v = \frac{1}{N_s}\sum_{s=1}^{N_s}\max(T_i - P_i)_s \qquad (8)$$

where N_s are the number of sojourns into failure states.

The deficit ratio (δ) with respect to power is defined in this study as the ratio of total deficit to total demand:

$$\delta = \frac{\sum_{i=1}^{N} D_i}{\sum_{i=1}^{N} T_i} \qquad (9)$$

where $D_i = \begin{cases} T_i - P_i & \text{for } P_i < T_i \\ 0 & \text{for } P_i \geqslant T_i \end{cases} \qquad (10)$

and T_i is the target power (firm power).

Table 1
Current and future flood control storage for monsoon months at Hirakud.

	Minimum required flood control storage (Mm^3)
Current (1959–2005)	
July	4325.3
August	4650.3
September	625.3
October	0
Years 2045–65	
July	4650.3
August	4650.3
September	781.6
October	0
Years 2075–95	
July	4650.3
August	4650.3
September	862.9
October	0

3. Reservoir performance impacts: business-as-usual case

Climate change impacts on future reservoir performance are first quantified for the "business-as-usual" case using the standard operating policy (SOP). SOP aims to best meet the demands in a period given water availability for that period, while meeting the rule curves for flood control in monsoon months. In this study, the total demand in any month is the sum of municipal, industrial, irrigation and power demands. The release as determined by SOP in any time period is equal to the availability or demand, whichever is less. In this study, release is also determined by flood control rules for maximum and minimum storages in monsoon months. Impacts on reservoir performance are determined for nine future hydrologic scenarios. These scenarios incorporate changed streamflows specific to each GCM-emission scenario combination considered, increased irrigation demands common to all scenarios as per Fig. 6 and changes to the rule curve for flood control, again common across scenarios, needed for absorbing increased peak runoff as per Fig. 5. Hence, irrigation demands were increased 2.5 times for years 2045–65 (corresponding to year 2050 from Fig. 6), and 7.5 times for years 2075–95 (corresponding to year 2100 from Fig. 6). Increased flood control storage of 25% and 38% was projected for monsoon months for years 2045–65 (corresponding to years 2050–2075 from Fig. 5) and 2075–95 (corresponding to years 2075–2100 from Fig. 5), respectively. The minimum and maximum values of permitted monsoon storages were decreased by these amounts to allow increased flood control storage. However, they were not allowed to fall below live storage levels. Table 1 shows the current and future projected minimum required flood control storages considered in this study.

4. Adaptive policies for future scenarios

In order to derive adaptive policies for the reservoir as a multipurpose structure, all impacts of climate change on the operations of the reservoir need to be captured. An optimal adaptive policy then needs to be formulated which optimizes impacts on each of these multiple reservoir purposes. For Hirakud reservoir, impacts on hydropower, irrigation and flood control are important, and are hence optimized in this adaptive policy. A stochastic dynamic programming (SDP) model [30] which addresses the uncertainty associated with inflow is applied to derive an optimal monthly operating policy for each future hydrologic scenario with the objective of maximizing reliabilities with respect to multiple purposes of hydropower, irrigation and flood control. In SDP, it is assumed that the inflow to the reservoir constitutes a first-order Markov chain. Assuming that the unconditional steady state probability distributions for monthly streamflows do not change from one year to the next, twelve transition probability matrices are determined for each month, using the available historical streamflow records (1959–2005) for deriving operating policies without climate change effects, and future simulated streamflows for policies with climate change effects considered. In the SDP formulation, time periods are considered as stages. The storage at the beginning of a time period and the inflow during the period represents the state of the system. The decisions to be taken at each stage are the quantities of water to be released. These can be implicitly identified by specifying the storage volumes at the next stage. Here, live storage is discretized into 24 classes, while monthly inflows were discretized into 12–14 classes.

The SDP backward recursive equation for any stage n and period t is

$$f_n^t = \max_{\{feasible\ l\}} \left[B_{kilt} + \sum_j P_{ij}^t f_{n-1}^{t+1}(l,j) \right] \quad \forall k, i \tag{11}$$

subject to reservoir capacity limitations:

$$0 \leqslant S_{kt} \leqslant K_a \text{ and } 0 \leqslant S_{lt+1} \leqslant K_a \tag{12}$$

where B_{kilt} is the system performance measure for period t corresponding to inflow class i, initial storage class k, and final storage class l, P_{ij}^t is the transition probability for streamflow from class i to class j in period t, K_a is the active storage capacity of the reservoir, i and j are class intervals or states of inflow in period t and $(t+1)$ respectively. S_{kt} and S_{lt+1} denote the reservoir storages for storage class k in period t and storage class l in period $(t+1)$, respectively. The performance measure B_{kilt}, used here is the negative sum of normalized deviations below target hydropower, irrigation and flood control:

$$B_{kilt} = -\left(w_1 \frac{(T_t - HP_{kilt})}{T_t} \langle HP_{kilt} < T_t \rangle + w_2 \frac{(D_t - Rirr_{kilt})}{D_t} \langle Rirr_{kilt} < D_t \rangle + w_3 \frac{(S_{kt} - FC\max_t)}{(K_a - FC\max_t)} \langle S_{kt} > FC\max_t \rangle \right) \tag{13}$$

where HP_{kilt} is the power generated in period t corresponding to initial storage class k, inflow class i and final storage class l, T_t is the target power in the same period (firm power), D_t is the irrigation demand in period $t, Rirr_{kilt}$ is the irrigation release in period t corresponding to initial storage class k, inflow class i and final storage class l, K_a is the active (live) storage capacity and $FC\max_t$ is the maximum live storage required at time t for flood control. $\langle \cdot \rangle$ is the indicator function, equal to one when the enclosed condition is satisfied, else equal to zero. w_1, w_2 and w_3 are weights associated with each of the three objectives in this multi-objective optimization formulation, which are all taken here as equal to 1. Since each of the three objective function terms has been normalized between 0 and 1, approximately equal weightages are given to each objective. The objective function essentially minimizes sums of deviations from targets for hydropower, irrigation and flood control. The RHS of Eq. (11) uses only those values of end of-period storages l which are feasible, i.e. lead to non-negative release and satisfy Eq. (12). Eq. (11) is solved recursively till it yields a steady state policy within a few annual cycles [12]. The steady state probabilities of release PR_{kit} corresponding to an inflow i, storage k at time t and l at $(t+1)$ can be obtained from the optimal policy and the marginal probabilities of storage and inflow can also be obtained [30,52]. The SDP optimization is used to derive optimal operating policy for years 1959–2005, as well as each of the nine scenarios (3 GCMs $\times$ 3 scenarios) for two future time slices. Fig. 7 shows a sample optimal policy derived for Hirakud reservoir for current (1959–2005) and a future (MIROC A1B scenario for 2045–65) scenario for the month of October, for various inflow classes. For any given storage value in October and an inflow class (computed from

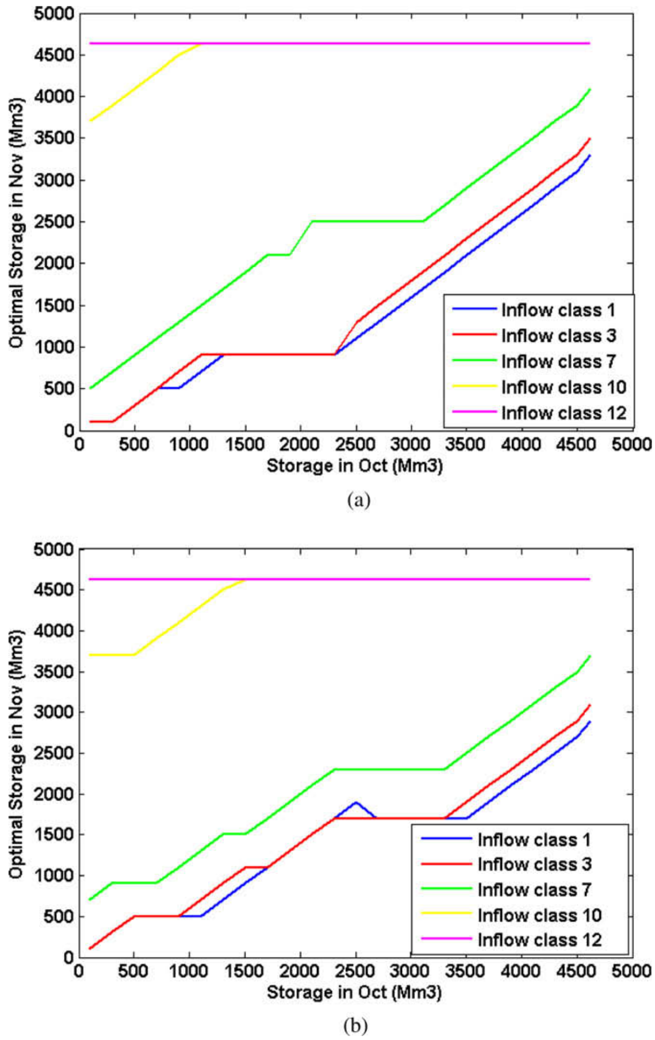


Fig. 7. Optimal SDP policy derived for Hirakud for month October for (a) current period (1959–2005) and (b) a future scenario (MIROC A1B scenario for 2045–65).

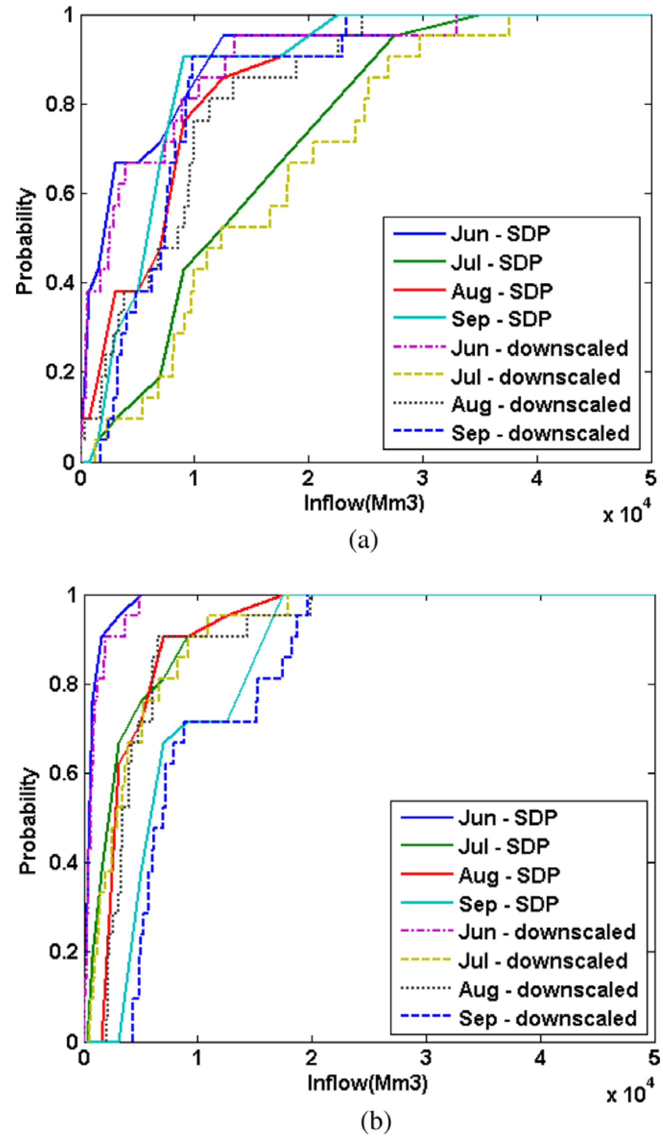


Fig. 8. Future marginal inflow distributions at Hirakud computed from SDP steady policies compared to distributions of downscaled monsoon streamflows for 2045–65 for (a) GCM:MIROC scenario:A1B and (b) GCM:CGCM2 scenario:A1B.

value, lower class has a lower value) for that month, the policy shows the optimal storage value for November, derived as per the policy. It is seen from the figure that the derived future policy changes for mid-level storages. The marginal probabilities of inflow computed from the optimal policies for future projected streamflows should be expected to match the downscaled streamflow CDFs and this was verified for all GCMs and scenarios. Fig. 8 compares CDFs for two scenarios, which show a good fit of marginal distributions with downscaled streamflow distributions.

Because hydropower generation is an important function of Hirakud reservoir, adaptive policies which minimize impacts on power can better mitigate economic impacts of climate change. Hence, in variations to the above adaptive policy, increasingly more weightage is given to the purpose of maximizing reliability with respect to hydropower. Hence, two other SDP policies (referred to as SDP-1 and SDP-2) were derived and tested for two extreme scenarios showing largest decreases in hydropower reliability by varying the weights w_1, w_2 and w_3 in the benefit function given by Eq. (13). In the SDP-1 policy, w_1 was increased to 1.5 while w_2 and w_3 were kept equal to 1. In SDP-2 policy, w_1 was further increased to three while w_2 and w_3 were kept equal to 1. It was expected that SDP-1 policy would increase hydropower reliability as compared to the earlier SDP policy while lowering other reliabilities. An acceptable tradeoff needs to be achieved between the three reliabilities for future scenarios.

Derived policies were applied to the respective streamflow sequences, to get performance measures and monthly power generation and storages. Reliability and deficit ratio can also be obtained theoretically from the steady state release probabilities as

$$\alpha_t = 1 - \sum_k \sum_i PR_{kit} \cdot FM_{kit}, \quad \alpha_{annual} = \sum_{t=1}^{12} \frac{\alpha_t}{12} \tag{14}$$

where PR_{kit} are the steady state probabilities of release corresponding to an inflow i, storage k at time t, α_t are the monthly reliabilities and α_{annual} is the annual reliability. The deficit ratio can be computed as

$$\delta = \frac{E[total\ yearly\ deficit]}{Total\ yearly\ demand} = \frac{\sum_t \sum_k \sum_i PR_{kit} \cdot (Deficit)_{kit}}{12 \times firm\ power} \tag{15}$$

Similarly, resiliency can also be obtained but its theoretical computation is very expensive since it involves pair probabilities. Vulnerability as used in this work also requires probabilities for all combinations of sojourns into failure states to be computed, which is computationally infeasible. The expected value of monthly power generation can be obtained theoretically as

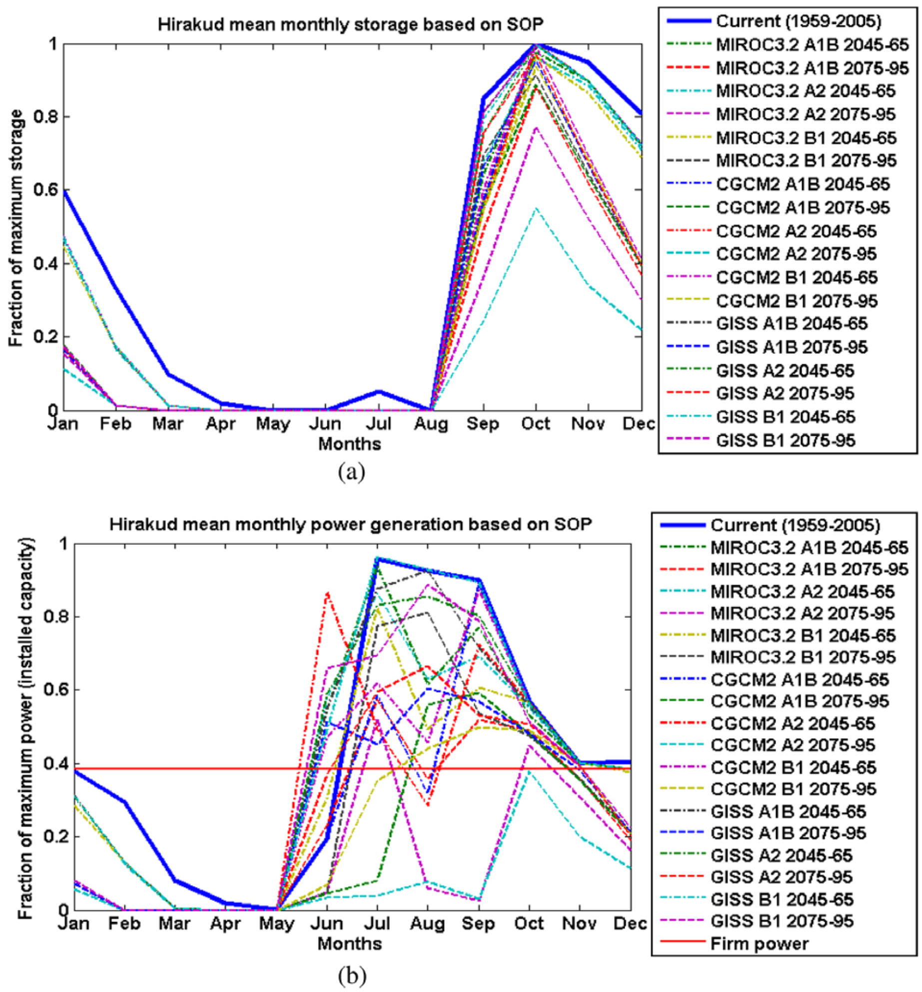


Fig. 9. Impacts on (a) mean monthly live storage and (b) mean monthly power generation (as a fraction of maximum) at Hirakud reservoir for future scenarios, for the 'business-as-usual' case using standard operating policy.

$$E[HP_t] = \sum_k \sum_i PR_{kit} \cdot HP_{R_{kit}} \tag{16}$$

where HP_t is the hydropower generated in month t, and HP_{Rkit} is the hydropower generated from a release R_{kit}.

5. Results and discussion

5.1. Business-as-usual versus adaptive policy

The SOP and SDP optimal policy derived for each scenario are applied to inflows for the current (1959–2005) period, years 2045–65 and years 2075–95 for each GCM-scenario combination. The outputs from each policy are monthly releases, storages, and overflows, from which monthly power generated and performance measures are computed. Fig. 9 shows the mean monthly power generated and monthly live storage (as a fraction of maximum) for SOP, while Fig. 10 shows the values obtained for SDP operation. It is seen that the mean monthly storages are likely to decrease for future scenarios, as a result of hydrologic impacts of climate change. The reservoir is unable to get filled by the end of monsoon in October, for many scenarios in 2075–95. Also, climate change is likely to negatively impact mean monthly power generation, especially in the monsoon months. Since this period is especially important in meeting power demands, this will have a significant impact on annual power generation. Standard operation aims to meet only firm power demands, except in months where flood control rules demand specific end-of-month storages, i.e. the months June–October. Adaptive SDP policy tries to minimize deviations below firm power, while also minimizing deviations below irrigation demand and above flood control storage targets. These are conflicting objectives, since decreasing storage to meet flood control or irrigation demands leads to a reduced head available for power generation. A comparison of annual hydropower production at Hirakud for current and future periods for 'business-as-usual' versus adaptive policy is shown in Fig. 11. For SOP as well as SDP policy, it is seen that for all scenarios in 2045–65, there is a decrease in annual hydropower generation. There is a further decrease in hydropower generation for years 2075–95. It is seen from the figure that the optimized operation (SDP) is able to increase hydropower production above SOP values in most, but not all future scenarios, primarily because it is a multi-objective optimization which achieves a tradeoff between conflicting objectives.

The four performance indices defined in Section 2.5 are computed for SOP and SDP operation and shown in Table 2. It is seen that climate change has an adverse impact on reservoir performance measures for the future hydrologic scenarios considered. For both standard and optimized operation, reliability with respect to hydropower and irrigation show a decrease for 2045–65, while vulnerability and deficit ratio with respect to hydropower increase

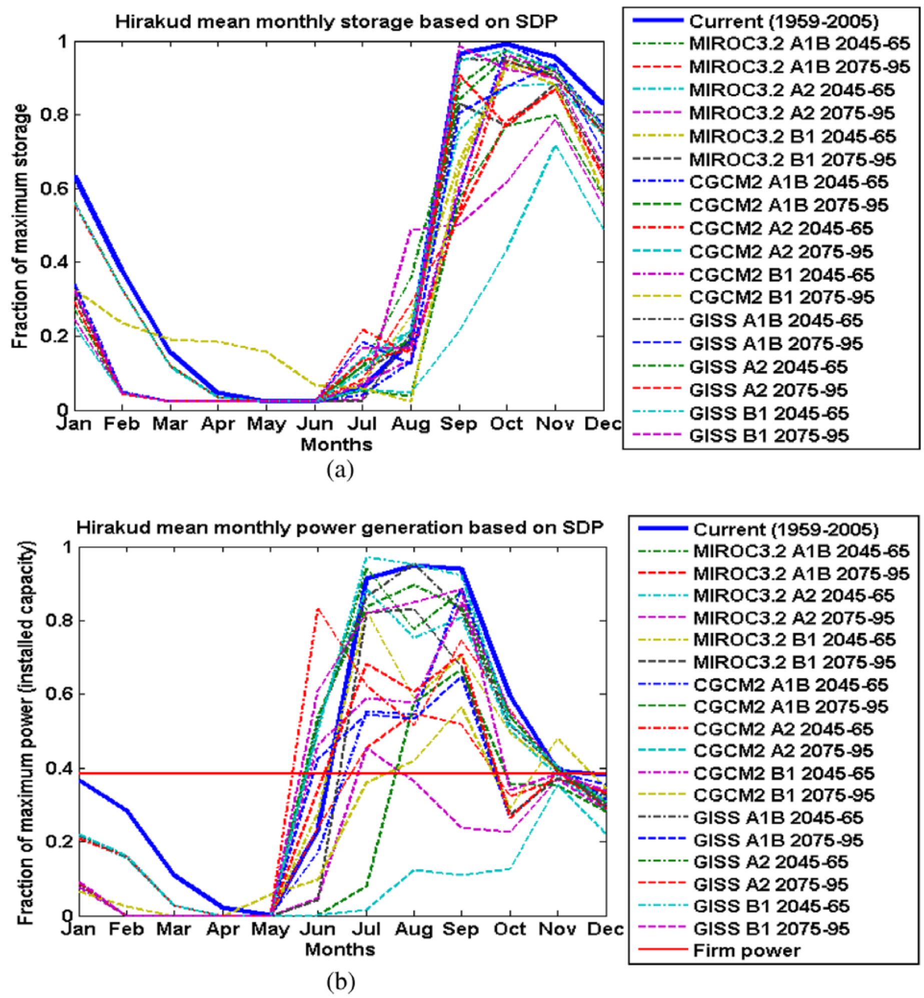


Fig. 10. Impacts on (a) mean monthly live storage and (b) mean monthly power generation (as a fraction of maximum) at Hirakud reservoir for future scenarios, using adaptive optimized SDP policies.

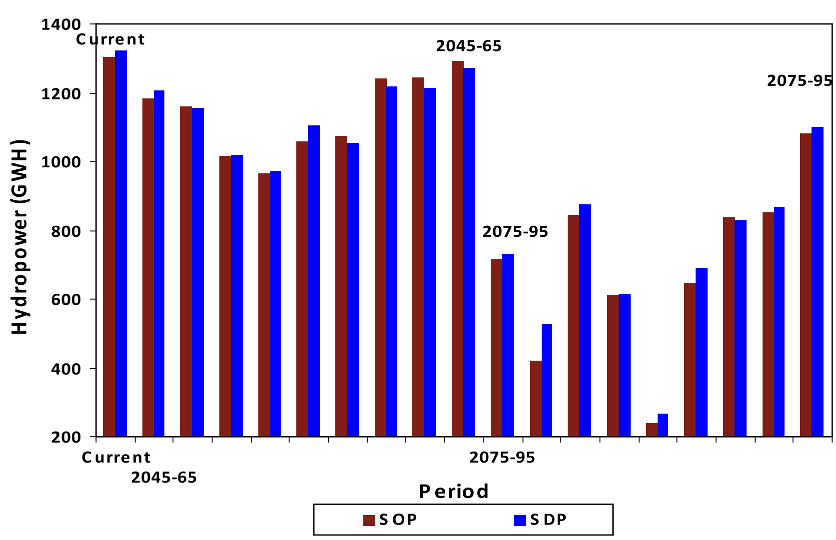


Fig. 11. Annual hydropower production at Hirakud for future scenarios, for 'business-as-usual' case using SOP and adaptive policy using SDP.

for this period. The impact worsens for years 2075–95, with further decreases in reliability and increases in vulnerability and deficit ratios. SOP shows 100% reliability for flood control, for current as well as future scenarios, since by definition the operation has to always meet flood control rule curves. SDP shows a slightly lower flood control reliability as compared to SOP, however it is seen that

Table 2
Impact of climate change on performance of Hirakud reservoir for standard and optimized operation.

	Reliability-power				Resiliency-power				Vulnerability-power			
Standard operating policy												
Current (1959–2005)	0.642				0.239				0.529			
		A1B	A2	B1		A1B	A2	B1		A1B	A2	B1
2045–65	MIROC	0.573	0.553	0.508	MIROC	0.251	0.249	0.250	MIROC	0.739	0.743	0.764
	CGCM2	0.514	0.529	0.538	CGCM2	0.237	0.287	0.241	CGCM2	0.732	0.773	0.737
	GISS	0.588	0.597	0.598	GISS	0.270	0.256	0.237	GISS	0.755	0.696	0.764
		A1B	A2	B1		A1B	A2	B1		A1B	A2	B1
2075–95	MIROC	0.362	0.250	0.386	MIROC	0.193	0.201	0.200	MIROC	0.854	0.967	0.909
	CGCM2	0.306	0.141	0.341	CGCM2	0.160	0.097	0.181	CGCM2	0.846	0.933	0.866
	GISS	0.422	0.422	0.492	GISS	0.240	0.240	0.226	GISS	0.911	0.853	0.778
	Reliability-irrigation				Reliability-flood control				Deficit ratio-power			
Current (1959–2005)	0.785				1.000				0.316			
		A1B	A2	B1		A1B	A2	B1		A1B	A2	B1
2045–65	MIROC	0.713	0.703	0.697	MIROC	1.000	1.000	1.000	MIROC	0.389	0.400	0.436
	CGCM2	0.716	0.725	0.729	CGCM2	1.000	1.000	1.000	CGCM2	0.427	0.406	0.392
	GISS	0.719	0.724	0.731	GISS	1.000	1.000	1.000	GISS	0.363	0.358	0.348
		A1B	A2	B1		A1B	A2	B1		A1B	A2	B1
2075–95	MIROC	0.544	0.424	0.549	MIROC	1.000	1.000	1.000	MIROC	0.603	0.725	0.585
	CGCM2	0.507	0.391	0.540	CGCM2	1.000	1.000	1.000	CGCM2	0.666	0.828	0.629
	GISS	0.553	0.573	0.603	GISS	1.000	1.000	1.000	GISS	0.547	0.534	0.476
	Reliability-power				Resiliency-power				Vulnerability-power			
Adaptive policy using SDP												
Current (1959–2005)	0.604				0.229				0.688			
		A1B	A2	B1		A1B	A2	B1		A1B	A2	B1
2045–65	MIROC	0.500	0.484	0.462	MIROC	0.214	0.215	0.206	MIROC	0.824	0.895	0.931
	CGCM2	0.453	0.523	0.471	CGCM2	0.218	0.224	0.202	CGCM2	0.956	0.750	0.935
	GISS	0.502	0.515	0.514	GISS	0.215	0.221	0.213	GISS	0.911	0.873	0.903
		A1B	A2	B1		A1B	A2	B1		A1B	A2	B1
2075–95	MIROC	0.366	0.286	0.382	MIROC	0.155	0.159	0.177	MIROC	1.000	0.933	0.966
	CGCM2	0.276	0.146	0.294	CGCM2	0.123	0.103	0.255	CGCM2	0.952	1.000	1.000
	GISS	0.403	0.423	0.458	GISS	0.178	0.175	0.180	GISS	0.878	0.883	0.865
	Reliability-irrigation				Reliability-flood control				Deficit ratio-power			
Current (1959–2005)	0.834				0.907				0.311			
		A1B	A2	B1		A1B	A2	B1		A1B	A2	B1
2045–65	MIROC	0.799	0.798	0.795	MIROC	0.906	0.921	0.939	MIROC	0.395	0.410	0.430
	CGCM2	0.796	0.802	0.801	CGCM2	0.961	0.950	0.955	CGCM2	0.429	0.381	0.395
	GISS	0.802	0.801	0.801	GISS	0.899	0.905	0.897	GISS	0.381	0.377	0.371
		A1B	A2	B1		A1B	A2	B1		A1B	A2	B1
2075–95	MIROC	0.592	0.497	0.601	MIROC	0.944	0.930	0.916	MIROC	0.558	0.650	0.571
	CGCM2	0.544	0.447	0.535	CGCM2	0.950	0.988	0.984	CGCM2	0.677	0.800	0.673
	GISS	0.599	0.614	0.634	GISS	0.916	0.902	0.894	GISS	0.525	0.501	0.466

this reliability is not compromised for future scenarios. This is likely due to projected decreases in inflows at the reservoir. For current operation, SDP achieves higher irrigation reliability, but has a lower hydropower reliability than SOP operation. This is again due to the nature of the objective function chosen for SDP, where it achieves a tradeoff between multiple reliabilities. The lower power reliability but higher annual power resulting from SDP policy indicates that SDP increases power generation in months such that the annual total is higher than that resulting from SOP, but it is able to meet firm power demands in fewer months than SOP.

The impact of climate change on monsoon streamflow in Mahanadi river for the majority of future scenarios is a decrease in mid-level flows and an increase in higher flows (Fig. 4). The 50% and 75% flows show a decrease in most scenarios while the 90% flows show an increase in most future scenarios. Projected water demand is also likely to increase by a large factor in future, along with changes in frequencies of flood events. These projected changes will affect the performance of reservoir systems. For the 'business-as-usual' case using SOP, this manifests as a decrease in hydropower generation and reliability and increase in vulnerability of the system for the future. Since uncertainty is an inherent characteristic of water resources systems, it is often inadequate to opt for deterministic decision models, especially when dealing with climate change scenarios with inherent uncertainties. Deterministic optimization can produce sub-optimal policies in such an application since they fail to incorporate adequately the impact of low-probability events [37]. However, the SDP policy has been found to give conservative results as compared to other optimization models. The performance of SDP is found to be lower than reported performance for some deterministic optimization methods used for Hirakud reservoir (ant colony optimization, ~1600 GWH [33]).

5.2. Variations to adaptive policy

Hirakud reservoir is an important multipurpose project and projected decreases for hydropower performance criteria will negatively impact the economy of the region in a significant manner. Variations in the derived adaptive policy are tested for the reservoir for two extreme scenarios showing largest reductions in hydropower generation for years 2045–65, viz. MIROC B1 scenario and CGCM2 A1B scenario. In the SDP-1 policy, the benefit function is modified such that hydropower reliability weightage is 1.5 times the weightage assigned to irrigation and flood control reliability. In SDP-2 policy, the weightage for hydropower reliability is further increased to three times the weightage assigned to irrigation and flood control reliability in the benefit function. The aim of these

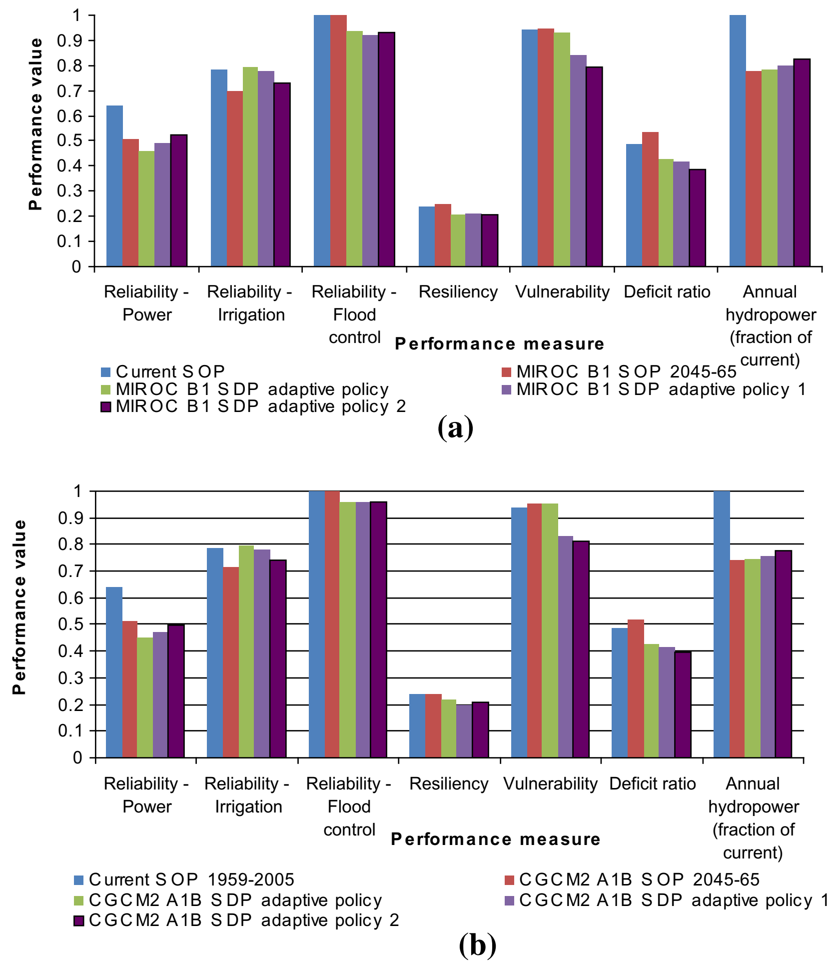


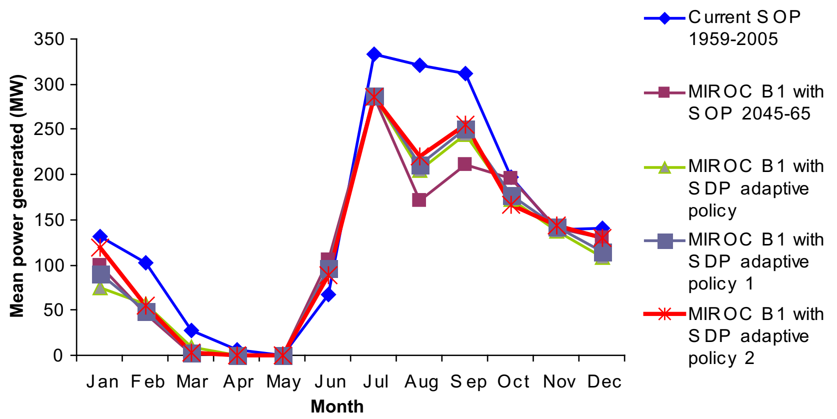
Fig. 12. Effect of applying adaptive SDP policies on performance measures for years 2045–65 for (a) MIROC B1 scenario and (b) CGCM2 A1B scenario. Adaptive policies 1 and 2 have increasing weightage given to hydropower reliability.

policies would be to ideally restore hydropower performance measures to current levels, by achieving a tradeoff with irrigation and flood control performance. For each of these policies, optimal operating policies are derived using SDP. It is seen that Hirakud reservoir has rather constraining flood control rules which dictate an empty reservoir at the beginning of August and a full reservoir on October 1st. Since maximum inflows occur in the monsoon season, sacrificing flood control performance would be expected to appreciably impact power generation.

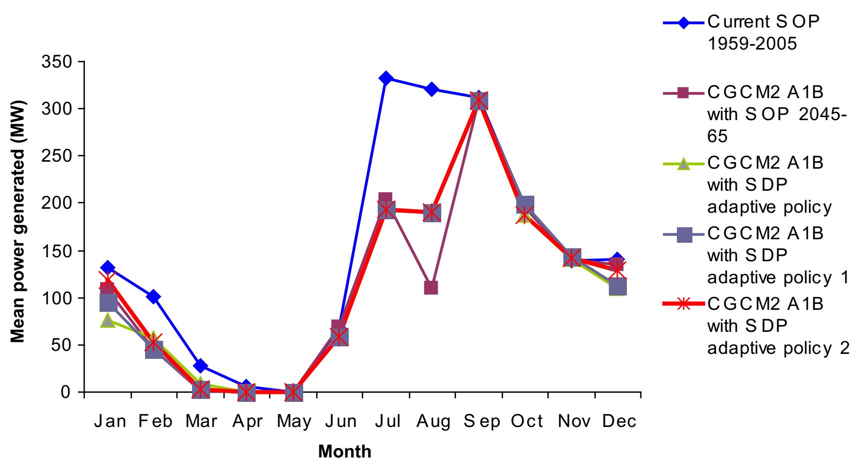
Fig. 12(a) and (b) shows the impact of applying the above three adaptive SDP policies on performance measures for years 2045–65 for MIROC B1 scenario and CGCM2 A1B scenario, respectively. It is seen that SDP-1 and SDP-2 show increasingly higher power reliability at the cost of decreasing irrigation reliability. The vulnerability and deficit ratio with respect to power also show a progressive decrease with increases in the hydropower reliability. Annual hydropower increases for SDP-1 and SDP-2 as compared to SOP and SDP, but is unable to be restored to current levels for these worst-case scenarios. This is due to the combined detrimental effect of decreases in streamflows and increased irrigation demands as well as lowered flood control monsoon maximum storages.

Fig. 13 shows mean monthly power generation obtained by application of adaptive policies for the MIROC B1 scenario and CGCM2 A1B scenario for years 2045–65. It is seen that SDP adaptive policy shows an increase is power generation as compared to SOP for the monsoon months, when flood control rules govern storages. SDP-1 and SDP-2 policies show slightly increased mean power generation as compared to SDP. However, the close overlap between monthly hydropower for SDP-1 and SDP-2 shows that this increase is not substantial even with higher weightages for power reliability. The mean hydropower generation for SDP adaptive policies appears to be limited by the flood control reliability criterion which requires lower maximum storage, especially in the monsoon month of August. Mean hydropower is also limited by available inflows. The computed annual water balances show that maximum current annual demand is 43,626 Mm^3 which increases to ~46,750 Mm^3 for 2045–65, current minimum demand is 18,557 Mm^3 which increases to ~21,670 Mm^3 for 2045–65, current annual average inflow is 34745.8 Mm^3, while annual average projected inflow for MIROC B1 scenario for 2045–65 is 24779.6 Mm^3 and for CGCM2 A1B scenario for 2045–65 it is 23151.9 Mm^3. Thus, annual average inflows are far less than annual maximum demand, but nearer annual minimum demand. Hence, the reliability criterion which uses minimum demand is able to be restored to a larger fraction using adaptive policies; however maximum hydropower obtained for the current period is restored to a much smaller fraction for these future reduced inflow scenarios.

Fig. 14 shows reservoir operation under the CGCM2 A1B scenario. The current and future projected rule curves are compared to the mean elevations obtained for adaptive policies for the MIROC B1 scenario. It can be seen that adaptive policies have a higher reservoir elevation in August than that permitted by the rule curve.



(a)



(b)

Fig. 13. Adaptive policies for (a) MIROC B1 scenario and (b) CGCM2 A1B scenario using SDP optimization show recovery of mean monthly power generated.

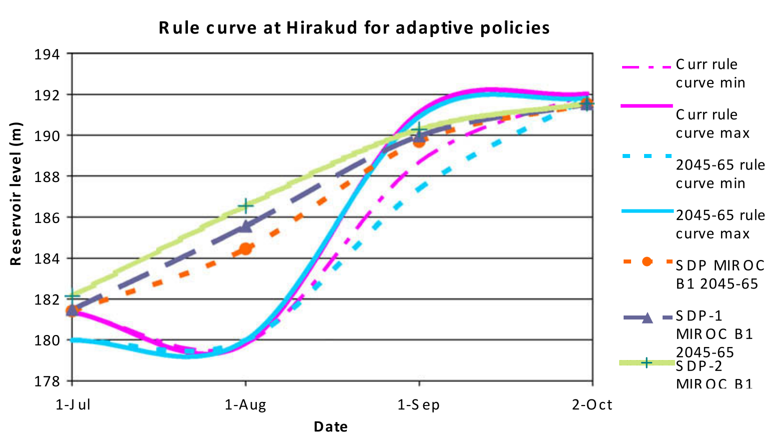


Fig. 14. Reservoir operation under MIROC B1 scenario: current and projected rule curve versus mean elevations obtained for adaptive policies.

Progressively increasing weightage for power reliability in policies SDP-1 and SDP-2 leads to higher elevations, especially in August, for these policies. Hence, a risk assessment strategy where the risk of flooding is weighted against the risk of lower hydropower reliability needs to be formulated. This strategy can be used to derive changes in reservoir operation rules for successful mitigation of climate change impacts.

6. Concluding remarks

This study quantifies the impact of climate change on multipurpose reservoir performance, including annual hydropower and RRV criteria, under GCM and scenario uncertainty. The study shows that the hydrologic impact of climate change is likely to result in decreases in performance criteria and annual hydropower generation for Hirakud reservoir. The standard 'business-as-usual' operation using SOP is shown to result in a decrease in annual hydropower and reliability with respect to power and irrigation for future scenarios. Optimized operation using SDP is also shown to project decreases in these criteria. The study considers uncertainty in future streamflows by using an ensemble of GCMs and emissions scenarios, and selecting those scenarios showing extreme decreases in performance for deriving adaptive policies. Application of adaptive policies is shown to counteract most of the projected performance decreases, even though their success is limited by annual water balance deficits. Future performance of the reservoir depends on the likelihood that adaptive policies will be adopted in practice. Constraints on water managers which keep them aligned with the SOP (e.g. disincentives from changing practices) include the risks involved in changing. Less but smoother hydropower production may be better than more but highly variable production.

A cost analysis which quantifies the economic costs associated with different modes of failure, viz. reliability with respect to each purpose of the reservoir, vulnerability and deficit ratio needs to be performed, which can also estimate tradeoff costs. The implications of relaxing flood control under adaptive policies need to be examined. There is an increased probability of larger floods not being buffered by the reservoir and hence the expected value of damages due to floods must be smaller than the expected value of benefits due to hydropower production for the policies to be economically viable. The final operation rule must be decided based on a probabilistic weighting of the adaptive policies derived under uncertainty in hydrologic scenarios, as well as a risk-benefit analysis for different purposes served by the reservoir. In our approach, we have derived adaptive policies for extreme hydrologic scenarios, which represent worst-case performance impacts and presented suggested mitigation measures. The present work is indicative of necessary changes required in operating policies, and does not include a full economic or risk analysis to recommend a final strategy. For comparison, Fig. 7 presents a sample optimal SDP policy for a future scenario versus current optimal policy. This policy represents real-time operation for a particular scenario; however under uncertainty in hydrologic scenarios a weighted policy has to be derived. Achieving such a weighting of policies to serve desired goals is a topic of further research.

In this study, no weightages are assigned to future scenarios. Streamflow scenarios can be weighted by assigning weights to each GCM and emissions scenario, as per a measure of performance [32,42] with respect to the current period. Further sources of uncertainty such as uncertainty in downscaling can also be considered in such an exercise. Adaptive policies could then be derived for a weighted future streamflow scenario. In this study, a weighted streamflow scenario could not be used because of the optimization method selected (SDP) which is based on transition probabilities. Weighting the transition probabilities will lead to erroneous description of the underlying Markov process, and weighting the streamflow sequences to derive one streamflow sequence will result in loss of variability present in the original sequences. Firm power requirement, municipal and industrial demands are taken as constant in this study, whereas they are almost certainly likely to increase in future. If climate change results in alterations to the fraction of annual precipitation in non-monsoon season, the assumption of unchanged non-monsoon streamflows used in this study will not be valid.

Adaptive policies for water resources systems will play an important role in mitigation of the hydrologic impact of climate change. Reduction of irrigation demand by measures such as growing crops with low crop water requirement will have limited utility for power generation where irrigation demands are low compared to power demands. However, slight changes to reservoir rules for flood control in monsoon or rainy season months may positively impact basins where climate change projects an increasing probability of droughts. Flood control requires storage to absorb the flood for regulated release, whereas power generation and irrigation require the reservoir to be maintained at a higher level. Optimal joint use of the storage space for non-compatible demands needs to be achieved by judicious selection of a modified rule curve as illustrated in this study, to minimize future risk. The annual inflow to reservoir capacity ratio is very high (over five times) for Hirakud reservoir, and spills occur every year during monsoon months. Hence, an increase in storage capacity of the reservoir can also be explored as an adaptive measure. This can help in limiting damage due to floods as well as provide higher storage for supplying demands.

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