Mahanadi streamflow: climate change impact assessment and adaptive strategies

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Impacts of climate change on hydrology are assessed by downscaling large scale general circulation model (GCM) outputs of climate variables to local scale hydrologic variables. This modelling approach is characterized by uncertainties resulting from the use of different models, different scenarios, etc. Modelling uncertainty in climate change impact assessment includes assigning weights to GCMs and scenarios, based on their performances, and providing weighted mean projection for the future. This projection is further used for water resources planning and adaptation to combat the adverse impacts of climate change. The present article summarizes the recent published work of the authors on uncertainty modelling and development of adaptation strategies to climate change for the Mahanadi river in India.

Keywords: Adaptation, climate change, hydrologic impact, uncertainty.

Introduction

GENERAL circulation models (GCMs) are tools designed to simulate time series of climate variables globally, accounting for effects of greenhouse gases in the atmosphere. They attempt to represent the physical processes in the atmosphere, ocean, cryosphere and land surface. They are currently the most credible tools available for simulating the response of the global climate system to increasing greenhouse gas concentrations, and to provide estimates of climate variables (e.g. air temperature, precipitation, wind speed, pressure, etc.) on a global scale. GCMs demonstrate a significant skill at the continental and hemispheric spatial scales and incorporate a large proportion of the complexity of the global system; they are, however, inherently unable to represent local subgrid-scale features and dynamics, which are of interest to a hydrologist. Accuracy of GCMs in general decreases from climate-related variables such as wind, temperature, humidity and air pressure to hydrologic variables such as precipitation, evapotranspiration, runoff and soil moisture, which are also simulated by GCMs. These limitations of the GCMs restrict the direct use of their output in hydrology.

Downscaling in the context of hydrology is a method to project the hydrologic variables (e.g. rainfall and streamflow) at a smaller scale based on large scale climatological variables (e.g. mean sea level pressure) simulated by a GCM. Poor performances of GCMs at local and regional scales have led to the development of limited area models (LAMs) in which a fine computational grid over a limited domain is nested within the coarse grid of a GCM. This procedure is also known as dynamic downscaling. A major drawback of dynamic downscaling, which restricts its use in climate change impact studies, is its complicated design and high computational cost. Moreover, dynamic downscaling is inflexible in the sense that expanding the region or moving to a slightly different region requires redoing the entire experiment[1]. Another approach to downscaling is statistical downscaling, in which, regional or local information about a hydrologic variable is derived by first determining a statistical model which relates large scale climate variables (or predictors) to regional or local scale hydrologic variables (or predictands). Then the large scale output of a GCM simulation is fed into this statistical model to estimate the corresponding local or regional hydrologic characteristics. There are three implicit assumptions involved in statistical downscaling: first, the predictors are variables of relevance and are realistically modelled by the GCM; second, the empirical relationship is also valid under altered climatic conditions and third, the predictors employed fully represent the climate change signal. Statistical downscaling methods can be further classified into weather generators, weather typing and transfer functions based on the use of different statistical tools.

Weather generators are statistical models of sequences of weather variables. They can also be regarded as complex number generators, the output of which resembles daily weather data at a particular location. There are two fundamental types of daily weather generators, based on the approach to model daily precipitation occurrence: the Markov chain approach[2] and the spell-length approach[3]. In the Markov chain approach, a random process is constructed which determines a day at a station as rainy or dry, conditional upon the state of the previous day,

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following given probabilities. In case of spell-length approach, instead of simulating rainfall occurrences day by day, spell-length models operate by fitting probability distribution to observed relative frequencies of wet and dry spell lengths. In either case, the statistical parameters extracted from observed data are used along with some random components to generate a similar time series of any length. In statistical downscaling, the parameters of the weather generators are conditioned upon a large-scale state, or the relationships between daily weather generator parameters and climatic averages can be used to characterize the nature of future days statistics on the basis of more readily available time-averaged climate change information[4]. Weather typing approaches involve grouping local, meteorological variables in relation to different classes of atmospheric circulation. Future regional climate scenarios are constructed, either by resampling from the observed variable distribution (conditional on circulation patterns produced by a GCM), or by first generating synthetic sequences of weather patterns using Monte Carlo techniques and resampling from the generated data. The mean or frequency distribution of the local climate is then derived by weighting the local climate states with the relative frequencies of the weather classes. Climate change is then estimated by determining the change of the frequency of weather classes. The most popular approach of statistical downscaling is the use of transfer function which is a regression-based downscaling method that relies on direct quantitative relationship between the local scale climate variable (predictand) and the variables containing the large scale climate information (predictors) through some form of regression. Individual downscaling schemes differ according to the choice of mathematical transfer function, predictor variables or statistical fitting procedure. To date, linear and nonlinear regression[5], artificial neural network (ANN)[1] and canonical correlation[6] have been used to derive the predictor–predictand relationship.

Assessing the hydrologic impacts of climate change using downscaling technique is characterized by uncertainties associated with use of multiple GCMs, use of multiple scenarios, intramodel uncertainty resulting from parameterization of GCMs and use of multiple downscaling techniques. Use of multiple models with multiple scenarios leads to a number of realizations and may not be useful for deriving water resources planning and adaptation strategies. Therefore, there is a need to model uncertainty which assigns weights to GCMs and results in a weighted mean projection, useful in water resources management systems. Possibilistic approach[7] used for uncertainty modelling is discussed with the case study of monsoon streamflow forecasting of Mahanadi river, upstream to Hirakud dam. Use of projections of inflow for Hirakud dam in water resources management and adaptation is discussed in detail. The next section presents the details of possibilistic approach used for uncertainty modelling in prediction of Mahanadi inflow to Hirakud dam.

Uncertainty modelling

The Hirakud dam is located on the Mahanadi river in Orissa. Figure 1 shows the location of the river stretch considered, along with the corresponding National Centres for Environmental Prediction (NCEP) grid points. The latitude and the longitude of the dam location are 21.32°N and 83.45°E respectively. The monthly streamflow at Hirakud dam, for the period 1961 to 2005 is obtained from the Department of Irrigation, Government of Orissa, India. A subset of the data set, viz. streamflow data from 1961 to 1990 is used for statistical downscaling and the rest of the data is used for modelling GCM and scenario uncertainty (with Third Assessment Report (TAR) projections) with possibility distribution.

Following IPCC storylines and TAR, it is argued in the possibilistic approach[7], that the signals of climate forcing would be visible after the year 1990. For appropriate planning and adaptation responses, with the passage of time, it is relevant to assess the effectiveness of GCMs in modelling climate change and also to judge which of the scenarios represent the present situation best under climate forcing. A methodology based on possibility distribution has been developed by Mujumdar and Ghosh[7] to model GCM and scenario uncertainty with an objective of assignment of possibility values to GCMs and scenarios depending on their performance in modelling signals of climate forcing in the recent past (1991–2005). The possibilities thus obtained are used as weights in deriving the possibilistic mean CDF (weighted cumulative distribution function) for standard time slices of 2020s, 2050s and 2080s.

Figure 2 presents an overview of the possibilistic approach in modelling GCM and scenario uncertainty. The approach typically involves statistical downscaling with bias correction and assignment of possibilities to all GCMs and scenarios based on performance during recent past. Application of the possibilistic model is demonstrated with the monsoon streamflow of Mahanadi at Hirakud dam. A statistical downscaling model based on PCA, fuzzy clustering and relevance vector machine (RVM)[8] is developed to predict the monsoon streamflow of Mahanadi river at Hirakud reservoir, from GCM projections of large scale climatological data. Surface air temperature at 2 m, mean sea level pressure (MSLP), geopotential height at a pressure level of 500 hecto Pascal (hPa) and surface specific humidity are considered as the predictors for modelling Mahanadi streamflow in monsoon season. Three GCMs, Centre for Climate System Research/National Institute for Environmental Studies (CCSR/NIES), Hadley Climate Model 3 (HadCM3) and Coupled Global Climate Model 2 (CGCM2) with two

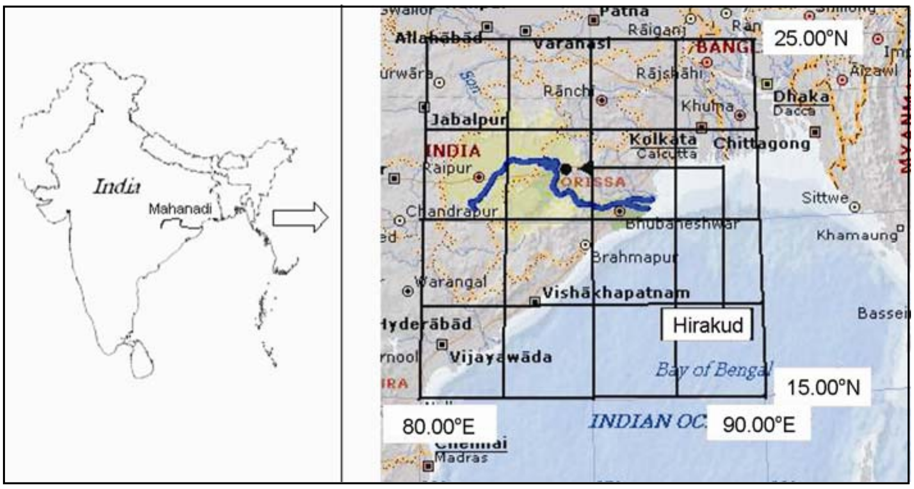

Figure 1. Mahanadi River basin (Mujumdar and Ghosh[7]).

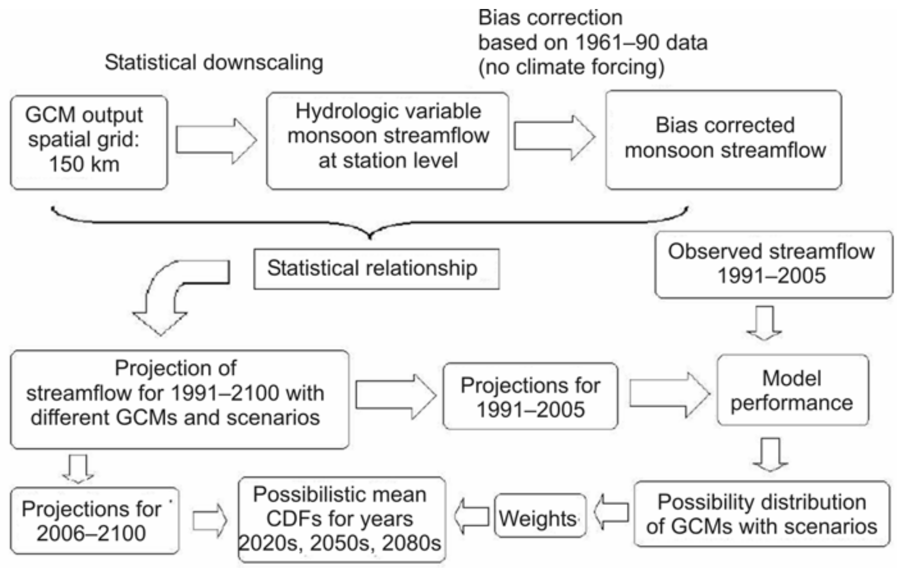

Figure 2. Possibilistic approach for modelling GCM and scenario uncertainty (Mujumdar and Ghosh[7]).

scenarios, A2 and B2, are used for the purpose. Because of the unavailability of the predictor variables from other GCMs and scenarios, the analysis is limited only to the three GCMs (CCSR/NIES, Japan; CGCM2, Canada and HadCM3, UK) and the two scenarios (IPCC scenarios A2 and B2). The CDFs of the future streamflow derived with multiple GCMs and scenarios are presented in Figure 3. The figure shows that the uncertainty bandwidth for 1990–2005 for probabilities in the range 0.2–0.5 is high and become smaller at lower or higher probabilities. This points to higher disagreement between the simulations of GCMs for medium flow in the observed period.

Figure 3 reveals significant dissimilarity among the projections of GCMs and scenarios. To model the resulting uncertainty, possibilities are assigned to GCMs and scenarios based on their performances in predicting the streamflow during years 1991–2005, when signals of climate forcing are visible. ‘Possibility assigned to a GCM’ is interpreted here as the possibility with which the future hydrologic variable of interest is modelled best by the downscaled output of the GCM. Similarly, ‘possibility assigned to a scenario’ denotes the possibility with which the scenario best represents the climate forcing resulting in a change in the hydrologic variable. The possibility values computed for GCMs and scenarios are presented in Figure 4. It is worth mentioning that a large difference is not observed between the possibilities for the two scenarios considered. This is because of the fact that the signal of climate forcing is not very pronounced in the initial time (1991–2005) and therefore the results obtained by modelling climate forcing by GCMs are not significantly different from each other. With the passage of time, and with a stronger signal of climate change, the possibility distribution information will be more useful in assessing which of the GCMs is able to model the climate change the best and which of the scenarios the regional or local climate is actually following.

The possibilities are used as weights for deriving the possibilistic mean CDF for the three standard time slices of 2020s, 2050s and 2080s. An advantage of possibilistic approach over probabilistic approach[9] is that, it not only projects the hydrologic variable for the future considering GCM and scenario uncertainty, but also assigns possibilities to the GCMs and scenarios to determine how effectively the GCMs model climate change and which of the scenarios best represent the present situation under the threat of global-warming induced climate forcing. Possibilistic mean CDF derived with the possibilities assigned to GCMs and scenarios, and the most possible CDF are presented in Figure 5 for 1961–1990, 2020s, 2050s and 2080s. All of them present a decreasing trend in the monsoon flows of Mahanadi river at Hirakud dam. An earlier study[10] on Mahanadi river also observed a decrease in monsoon streamflow for the historic period. One possible reason for such a decreasing trend is the significant increase in temperature due to climate warming. Analysis of instrumental climate data has revealed that the mean surface temperature over India has increased at a rate of about 0.4°C per century[10], which is statistically significant. The increasing trend of temperature in Mahanadi river basin due to climate change is even more severe. The surface air temperature over this basin is increasing at a rate of 1.1°C per century, which is more than double the rate of increase for entire India. Increase of temperature at such a high rate may increase the evaporation and thus reduce the effective rainfall which is reflected in the streamflow predictions. An increasing trend of extreme drought is also observed by Ghosh and Mujumdar[9], due to high surface warming which is consistent with the predictions of Mahanadi streamflow obtained by Mujumdar and Ghosh[7]. Although the future predictions present a favourable condition in Hirakud dam for flood control operation, simultaneous occurrence of reduction in Mahanadi streamflow and increase in extreme drought is likely to pose a major challenge for water resources engineers in meeting water demands in future.

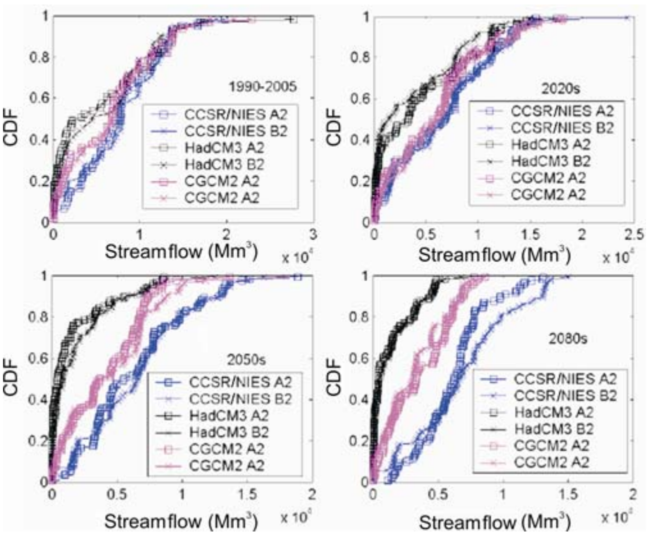

Figure 3. Predicted streamflow with different GCMs and scenarios (Mujumdar and Ghosh)[7].

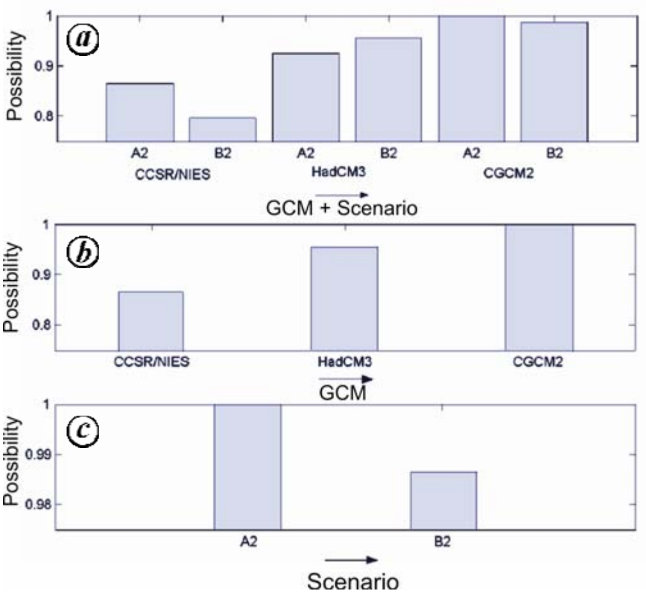

Figure 4. Possibility values assigned to GCMs and scenarios (Mujumdar and Ghosh)[7].

Adaptive policies for climate change

Over the last few years, the literature on adaptation to climate change has expanded considerably. Some studies have explored conceptual issues such as definitions and classifications[11–13], and others have shown the benefits of different adaptation options[14–17]. Studies such as Schneider *et al.*[18] have drawn lessons from adaptation to climatic variability or extreme events, whereas others have focused on how adaptation can reduce vulnerability to climate change[13,19]. Brekke *et al.*[20] presented a flexible methodology for conducting climate change risk assessments involving reservoir operations. 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.*[21] investigated potential impacts of future climate change on streamflow and reservoir operation performance in a Northern American Prairie watershed. Lopez *et al.*[22] used perturbed physics ensembles of climate models for impacts analysis and planning for public water supply in England under climate change. Arnell and Delaney[23] examined adaptation to climate change by water supply companies in England and

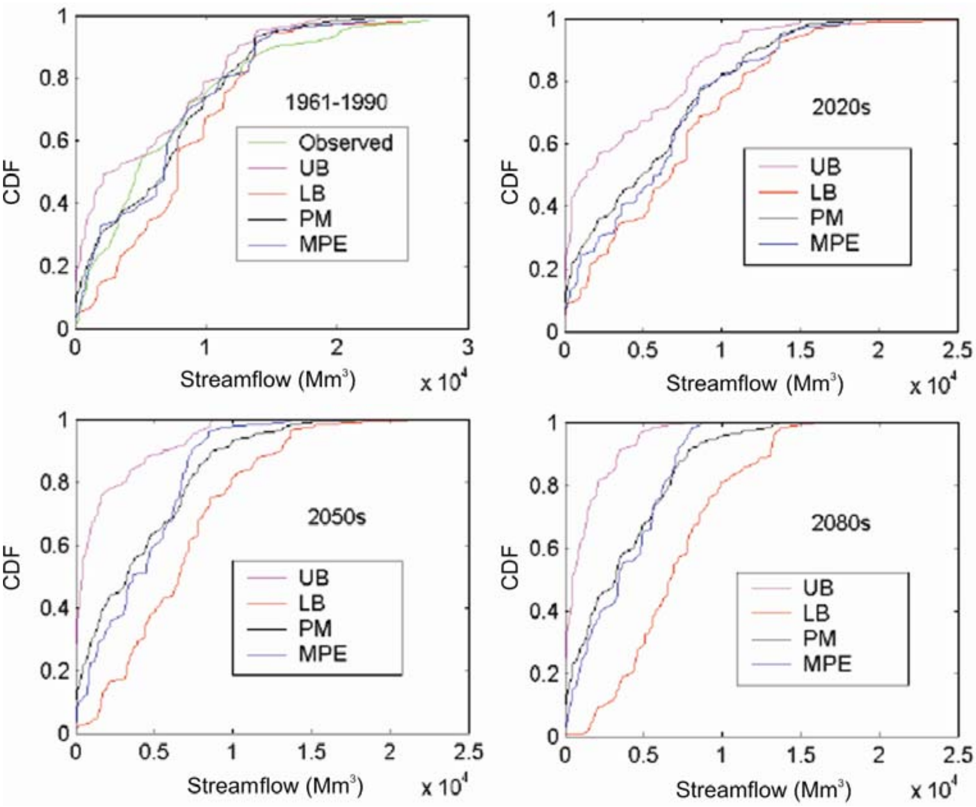

Figure 5. Upper bound (UB), lower bound (LB) and possibilistic mean CDF. PM, possibilistic mean; MPE, most possible experiment.

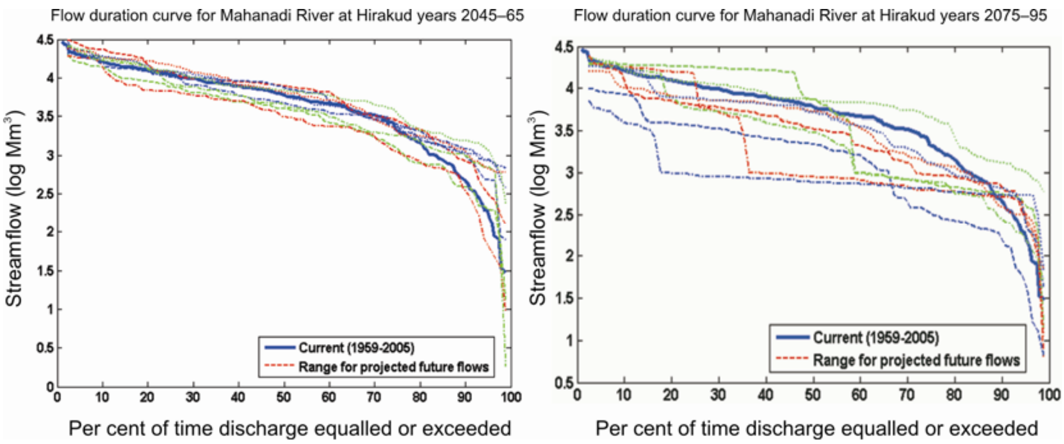

Figure 6. Range of projected future flow duration curves for monsoon inflows at Hirakud for two time slices, 2045–65 and 2075–95.

Wales. Fowler *et al.*[24] studied the impacts of climatic change and variability on water resource reliability, resilience and vulnerability of the Yorkshire water resource system.

In this work, the impact of climate change on reservoir performance is studied for the 'business-as-usual' case as well as 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, resiliency, vulnerability and deficit ratio) are studied initially with the standard operating policy (SOP) using current rule curves for flood protection. The results show that using current operations, annual hydropower and reliability will decrease and vulnerability will increase as a result of climate change for future scenarios. A stochastic dynamic programming (SDP) model[25] which addresses the uncertainty associated with inflow is then applied to derive optimal monthly operating policy with the objective of maximizing annual power generation. The optimal operation also shows a decrease in hydropower and increase in vulnerability for the future. Adaptive policies are tested for two extreme cases from future scenarios.

Projections of future streamflow

Figure 6 shows the flow duration curves for monsoon streamflows projected using the conditional random field (CRF)-downscaling model[26,27] for 2045–65 and 2075–95 for the range of GCM-scenario combinations with Fourth Assessment Report (AR4) projections. 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). It is seen that for most future scenarios, there is a decrease in middle level flows (equalled or exceeded 20–70% of the time). This decrease becomes more prominent by 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 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).

The effect of changes in streamflow on future reservoir performance is quantified for the 'business-as-usual' case using current rule curves and SOP, and the optimized case using SDP[25].

Another SDP optimization (referred to as SDP-1) with penalization for monthly hydropower deviations below firm power was also used to derive optimal operating policy. The optimal SOP and SDP derived for each scenario are applied to inflows for current (1959–2005) years, 2045–65 and 2075–95 for each GCM–scenario combination. For both SOP as well as both SDP formulations, in most (six out of nine) scenarios in 2045–65, there is a decrease in annual hydropower. There is further decrease in hydropower generation for 2075–95 (eight out of nine scenarios). This decrease is due to the decrease in mid-level flows. Penalized SDP (SDP-1) policy has an intermediate hydropower generation between SOP and SDP, since it has to achieve a tradeoff between optimizing hydropower and reliability.

Adaptive policies are tested for the reservoir for two extreme scenarios showing largest reductions in hydropower generation for the period 2045–65, viz. MIROC B1 scenario and CGCM2 A1B scenario. The first policy aims to restore performance with respect to power generation by decreasing other demands – in this study, irrigation demands. Hence, in this policy (adaptive policy 1), irrigation demands are reduced to half the current monthly values. For the same total release, this policy would increase release for power generation since the irrigation release is halved. The second policy explores how changes in flood control rules could be used to restore performance. Since maximum inflows occur in the monsoon season, changes in these rules would be expected to appreciably impact power generation. In this policy (adaptive policy 2), irrigation demands are reduced to half while also simultaneously relaxing flood control rules marginally. Hence, storage deviations from flood control defined storages up to 2000 Mm^3 are allowed in this policy (the live storage capacity of the reservoir is 4650 Mm^3). The third policy extends the limits of changes in flood control rules. In this policy (adaptive policy 3), irrigation demands are reduced to half while flood control rules are further relaxed from policy 2 up to 3000 Mm^3.

Figure 7 *a* and *b* shows the impact of applying the above three adaptive SDP policies on performance measures[28] during 2045–65 for MIROC B1 scenario and CGCM2 A1B scenario respectively. Adaptive policy 1 decreases the vulnerability and deficit ratio and increases resiliency, but does little to increase hydropower or reliability. This can be expected, since irrigation demands are a small fraction of minimum power demands for Hirakud. Hence, reduced irrigation demands lead to only small increases in power releases, and power generation is not increased substantially. Adaptive policy 2 is able to restore reliability and deficit ratios to current values, though vulnerability is increased as compared to policy 1. This policy is also able to significantly increase annual hydropower as compared to policy 1. Application of adaptive policy 3 increases reliability, and decreases the deficit ratio and vulnerability as compared to policy 2 for one of the two extreme scenarios (MIROC B1), but they remain constant for the other extreme scenario considered (CGCM2 A1B). It increases hydropower generation as compared to policy 2, but is unable to restore it to current levels.

Figure 8 shows reservoir operation under the CGCM2 A1B scenario. The current rule curve is compared to the mean elevations obtained for future projections using SDP (without adaptive policies) and for each of the adaptive policies. It can be seen that the optimal rule curve without adaptive policies for 2045–65 is identical to that obtained for adaptive policy 1. However, adaptive policies 2 and 3 have higher reservoir elevations in August and lower elevations in September. It can be concluded that changes in reservoir operation rules are required for successful mitigation of decreases in streamflow due to climate change.

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

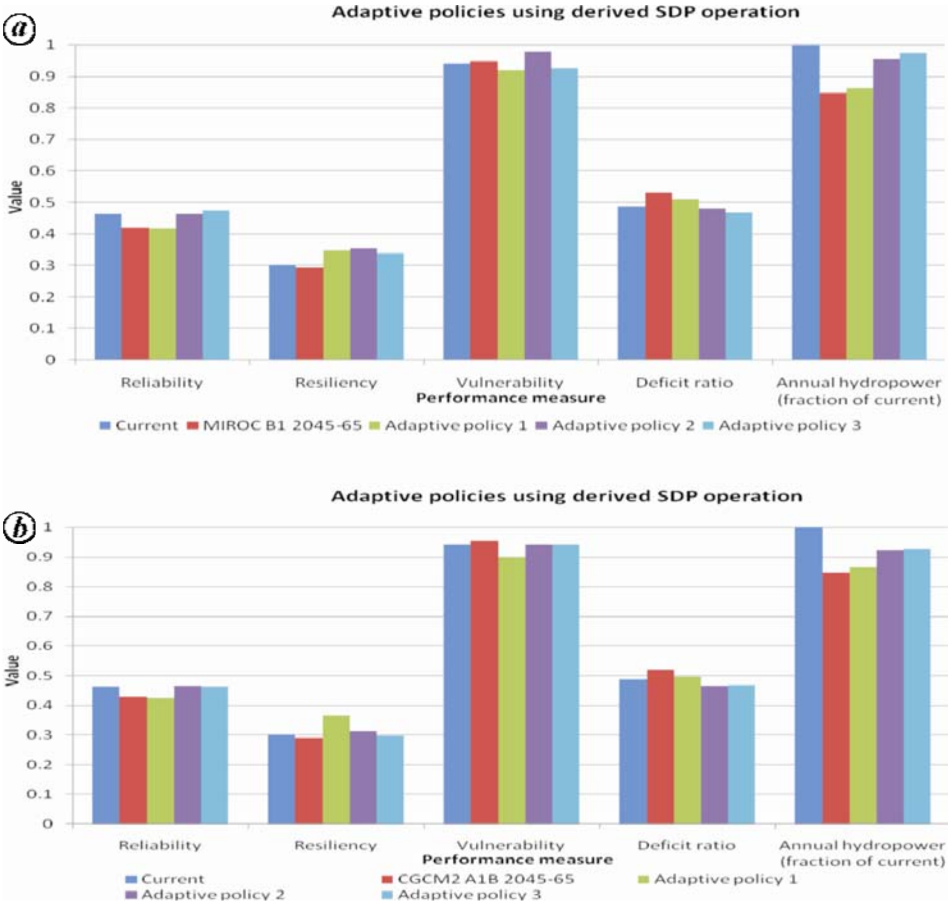

Figure 7. Effect of applying adaptive SDP policies on performance measures for 2045–65 for ***a***, MIROC B1 scenario; ***b***, CGCM2 A1B scenario.

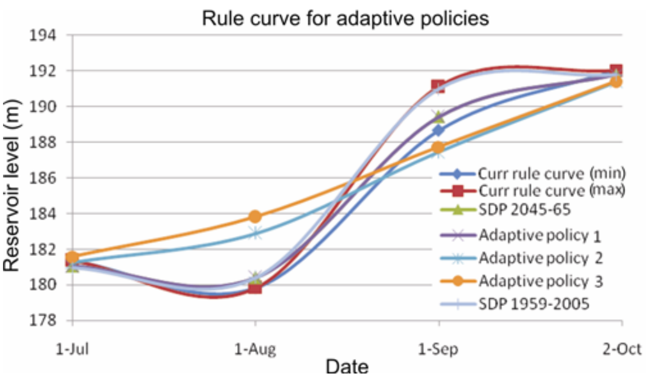

Figure 8. Reservoir operation under CGCM2 A1B scenario: current rule curve versus mean elevations obtained for adaptive policies.

demands. However, slight changes in reservoir rules for flood control in monsoon or rainy season months may positively impact basins where climate change projects an increasing probability of droughts. The reservoir 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 policy. This can help in limiting damage due to floods as well as provide higher storage for supplying demands. Desilting the reservoir to increase reservoir capacity to its original value can serve this purpose. However, given the increasing deficits in annual water balances for future scenarios, this policy may be limited in its success. Instead of halving irrigation demands for all months, the demands could have been reduced in selected months (non-monsoon) to the extent that hydropower production does not fall below firm power in these months. For cases where irrigation demands are substantial, this would lead to increase in reliability. However, since irrigation demands are small compared to power generation demands in this case study, this policy would be expected to have limited impact on hydropower.

Concluding remarks

Impact of global climate change on hydrology and water resources needs to be assessed at river basin scales. The most credible tools of climate projections available today, viz. the GCMs however provide the projections at much larger spatial scales. Downscaling of GCM projections of climate variables is therefore necessary. In such an accepted methodology of assessing climate change impacts, inevitably, a large number of uncertainties are introduced. Some sources of the uncertainties are due to the way climate system is modelled by different GCMs (leading to the GCM uncertainties), uncertainties due to how the future socio-economic scenario – that has implications on carbon emission, and hence on the climate – might really unfold (leading to scenario uncertainties), downscaling methods and identification of climate variables, among many other sources. Weighted projection resulting from the uncertainty models can be used for adaptation. The paper discusses recent studies carried out for climate change impact assessment and adaptation for Mahanadi river basin. Uncertainty modelling of climate change impacts on water availability needs to be utilized in risk assessment and planning of mitigation measures for reservoir systems. Results from hydrological impact assessment studies can thus enable policy makers to identify adaptation and mitigation strategies that are robust to future uncertainties.

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