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Basin Scale Water Resources Systems Modeling Under Cascading Uncertainties

S. Rehana · P. P. Mujumdar

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Abstract Global change in climate and consequent large impacts on regional hydrologic systems have, in recent years, motivated significant research efforts in water resources modeling under climate change. In an integrated future hydrologic scenario, it is likely that water availability and demands will change significantly due to modifications in hydro-climatic variables such as rainfall, reservoir inflows, temperature, net radiation, wind speed and humidity. An integrated regional water resources management model should capture the likely impacts of climate change on water demands and water availability along with uncertainties associated with climate change impacts and with management goals and objectives under non-stationary conditions. Uncertainties in an integrated regional water resources management model, accumulating from various stages of decision making include climate model and scenario uncertainty in the hydro-climatic impact assessment, uncertainty due to conflicting interests of the water users and uncertainty due to inherent variability of the reservoir inflows. This paper presents an integrated regional water resources management modeling approach considering uncertainties at various stages of decision making by an integration of a hydro-climatic variable projection model, a water demand quantification model, a water quantity management model and a water quality control model. Modeling tools of canonical correlation analysis, stochastic dynamic programming and fuzzy optimization are used in an integrated framework, in the approach presented here. The proposed modeling approach is demonstrated with the case study of the Bhadra Reservoir system in Karnataka, India.

Keywords Climate change · Statistical downscaling · Reservoir rule curves · Stochastic dynamic programming · Fuzzy optimization

S. Rehana
Department of Civil Engineering, Malla Reddy Institute of Technology and Science, Hyderabad, Andhra Pradesh 500014, India

P. P. Mujumdar
Department of Civil Engineering, Indian Institute of Science, Bangalore, Karnataka 560 012, India

P. P. Mujumdar (✉)
Divecha Center for Climate Change, Indian Institute of Science, Bangalore, Karnataka 560 012, India
e-mail: pradeep@civil.iisc.ernet.in
URL: http://civil.iisc.ernet.in/~pradeep

1 Introduction

Climate change is likely to affect various components of a water resources system such as water availability, water quality, agricultural water demands and consequently the regional water resources management policies due to increase in temperature and change in precipitation and other climatic variables. Figure 1 shows typical regional water resource system components likely to be affected by climate change. In modeling a water resource system under climate change impacts, three steps are generally involved: first, General Circulation Models (GCMs) outputs are downscaled to obtain climate change projections at regional scale, second, climate change projections are input into hydrologic models to simulate future water resources scenarios, and third, to formulate long-term decisions according to the predicted hydrological conditions and variability. Generally, such hydrological impact assessment studies of climate change based on downscaling of GCM outputs are subjected to a range of uncertainties including GCM and scenario uncertainty (Arnell 2004; Prudhomme and Davies 2009), uncertainty due to downscaling methods (Khan et al. 2006; Dibike and Coulibaly 2005; King et al. 2012) and uncertainty due to the hydrological models (Teutschbein et al. 2011; Chen et al. 2011) used for impact assessment. A large number of studies have been conducted in recent years on hydrologic impacts on water resources management and operating policies by combining statistical downscaling models/Regional Climate Models (RCMs) and climate scenarios (e.g. Burn and Simonovic 1996; Eum and Simonovic 2010; Vicuna et al. 2010; Raje and Mujumdar 2010; Davies and Simonovic 2011; Majone et al. 2012).

An integrated regional water resources management operation under climate change should capture all impacts that climate change can have on the demands and operations of the reservoir. There are only a few studies with implications on water resources management in response to the anticipated demands under hydrologic impacts of climate change (Asokan and Dutta 2008; Davies and Simonovic 2010; Raje and Mujumdar 2010; Eum et al. 2012). Particularly, analysis of operating rules of a reservoir system accounting for the various

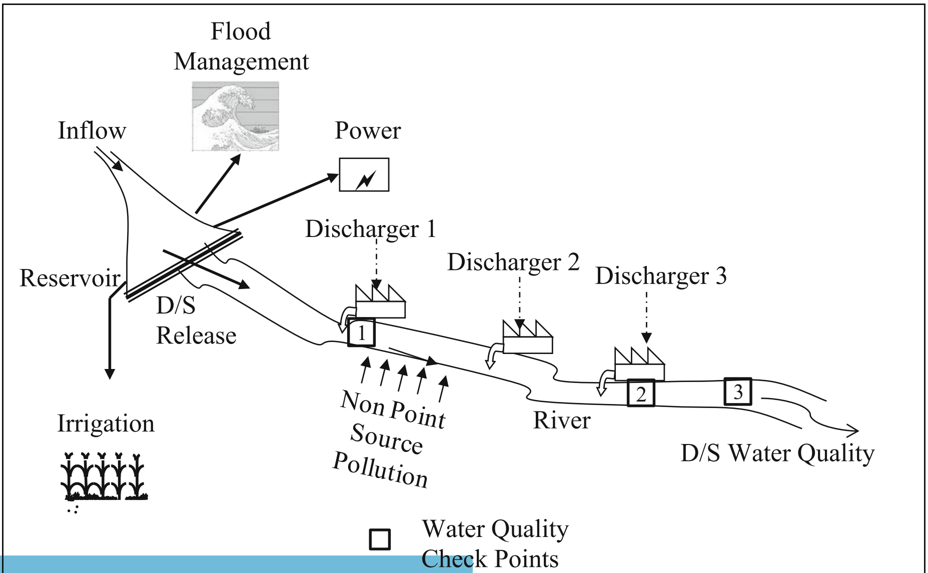


Fig. 1 A typical water resource system with components impacted by climate change

projected demands of a reservoir in a changed climate is rarely addressed in the climate change impact studies. The present study proposes an integrated regional water resources management model with an integration of multiple components including a hydro-climatic variable projection model, projected demand quantification model, and a water quantity-quality management model to represent complex relationships in the integration of climate-hydrology-water availability/demands/quality-reservoir policies. An overview of the modeling framework adopted in this study is shown in Fig. 2. In the first part of the framework, a hydro-climatic projection model is applied to downscale the surface hydrologic variables, from GCM outputs of large-scale climate variables. A multivariable downscaling methodology based on Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA) is used to downscale the hydro-climatic (inflow, rainfall, maximum and minimum temperatures, relative humidity and wind speed) projections which govern the supply and demands and therefore affect the reservoir operation.

Uncertainty in the future climate in terms of GCM and scenario, combinedly represented as climate model uncertainty, stems as a first level of uncertainty in the integrated regional water resources management modeling. Research on climate model uncertainty in climate change impact assessment studies has advanced on several fronts (e.g., Tebaldi et al. 2004; Simonovic and Li 2004; Ghosh and Mujumdar 2009; Simonovic 2010). In this study, the weights are assigned to each GCM and scenario to derive Multimodel Weighted Mean (MWM) based on their performance in reproducing the present climatology and deviation of each of the projection provided by the GCM-scenario combination from the projected ensemble average following to earlier studies of Ghosh and Mujumdar (2009) and Giorgi and Mearns (2002). The uncertain hydro-climatic variables are used to quantify the irrigation, water quality, and hydropower demands for Bhadra reservoir. Several studies have emphasized on integrated management of water quality and quantity (e.g. Nikoo et al. 2013) and some studies have dealt with reservoir water quality through optimal releases (e.g. Chaves et al. 2003). Efforts are

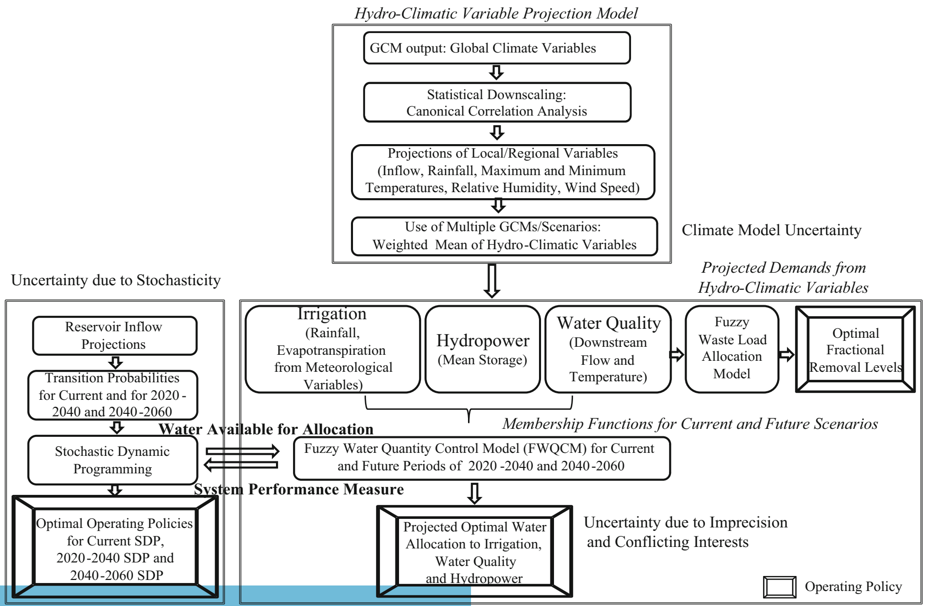


Fig. 2 Overview the proposed model for a multi-purpose reservoir under climate change

made in this study to assess the impact of climate change on downstream water quality due to changes in river flow and river water temperature.

The uncertainty introduced by imprecise/fuzzy description of the conflicting goals forms the second level of uncertainty in the integrated regional water resources management model. Fuzzy set theory (Zadeh 1965) is used to address such uncertainty by membership functions through varying degrees of acceptability (or satisfaction) of reservoir users to water allocation (e.g. Orlob and Simonovic 1982; Teegavarapu and Simonovic 1999; Akter and Simonovic 2004). A reservoir with randomly varying inflow leads to third level of uncertainty known as stochastic or aleatory uncertainty in an integrated regional water resources management model. To address the inherent variability of the reservoir inflow, the fuzzy water allocation model is integrated with a reservoir operation model such as a Stochastic Dynamic Programming (SDP) (e.g., Loucks et al. 1981; Lee and Labadie 2007) to develop a fuzzy-SDP model to derive the long-term reservoir operating policies for the current and for the future scenarios. The proposed methodology is applied to the Bhadra reservoir in India.

The objectives of the work include (i) downscaling the projections of various surface hydrologic variables from GCM outputs of large-scale climate variables, (ii) addressing GCM/scenario uncertainty using ensemble averaging approach (iii) quantifying the projected demands of irrigation, water quality and hydropower demands under climate change uncertainties (iv) quantifying the current and projected water allocations using an integrated regional water resources management model (v) analyzing the operating policies in terms of rule curves and associated pollutant treatment levels under climate change.

2 Case Study Details

The Bhadra Reservoir is an integrated regional water resources system located on Bhadra River, Karnataka, India (Fig. 3). The Bhadra command area spreads over the districts of Chitradurga, Shimoga, Chickmagalur and Bellary as shown in Fig. 3. The gross command area under the Bhadra canal system is 162,818 ha with a culturable command area of 121,500 ha out of which 105,570 ha have been earmarked for irrigation. The reservoir also generates hydropower to a minor extent.

The Bhadra River flows through nearly 190 km from its origin and joins River Tunga to form the River Tunga-Bhadra. The river receives the waste loads from three major effluent points, which include two industrial effluents (MPM: Mysore Paper Mill; VISL: Visvesvaraya Iron and Steel Limited) and one municipal effluent (Bhadravathi City) (Fig. 1). The considered river stretch of about 27 km is divided into three reaches of varying lengths based on river morphology, each one of which is further discretized into computational elements of 1 km in length to estimate the water quality parameters at prescribed check points as shown in Fig. 1. The high-resolution gridded daily precipitation data from 1971 to 2005 at 0.5×0.5° grid interpolated from station data are obtained from the India Meteorological Department (IMD), Pune and is used as observed rainfall data.

The potential effects of climate change on Bhadra River have already been discussed from a variety of perspectives: water quality (Rehana and Mujumdar 2011, 2012); irrigation demands (Rehana and Mujumdar 2013); hydrological impacts (Meenu et al. 2013). This work provides the most robust estimates of future climate change to date for water resources in an uncertain environment in this region.

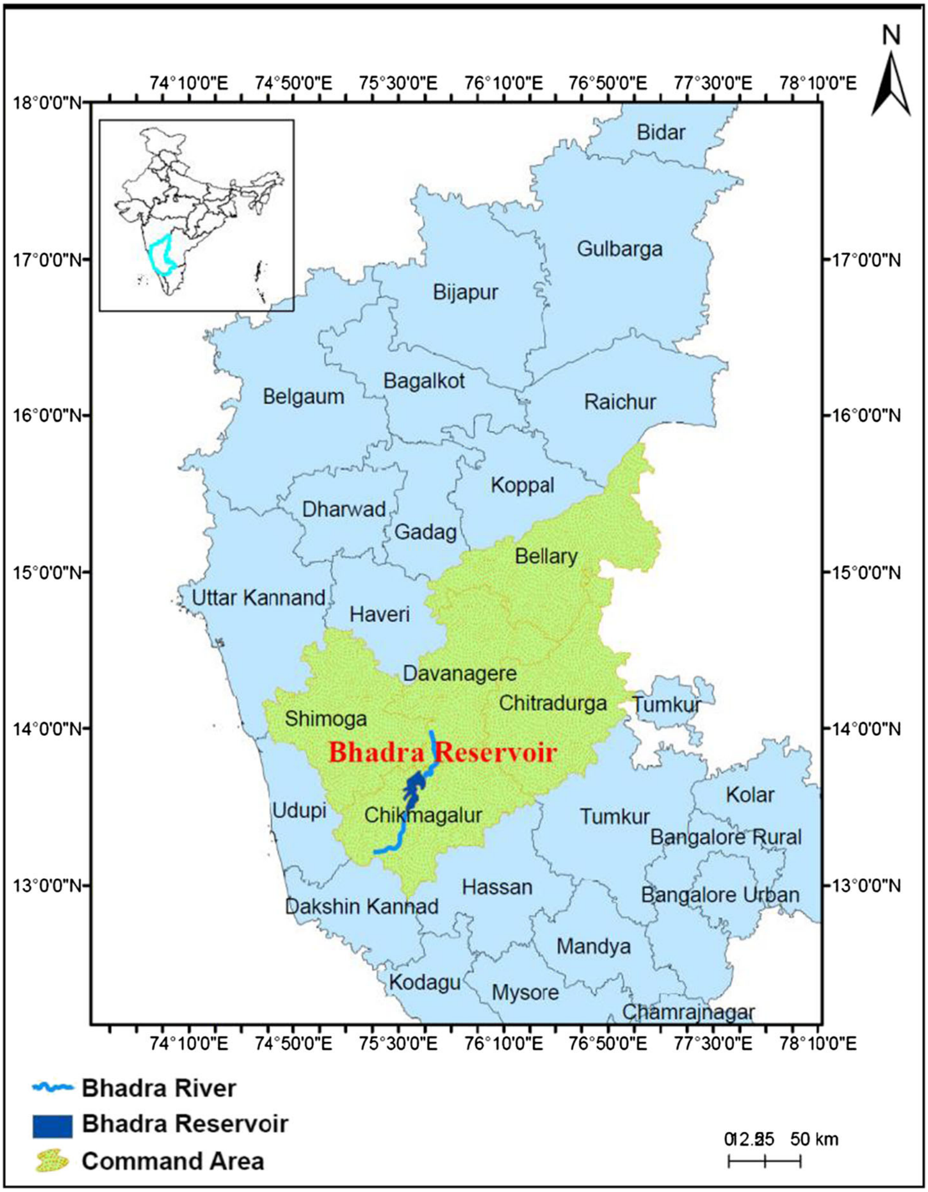


Fig. 3 Location Map of Bhadra River Basin

3 Integrating Uncertainties from Climate Projections

The uncertain future hydro-climatic variables which influence water availability and various water demands of the reservoir are to be identified as predictands to model the future hydrologic scenario. Climate change is likely to impact the agricultural sector directly with changes in rainfall and evapotranspiration. The reference evapotranspiration is more complex form of various climate variables such as air temperature, wind speed, relative humidity, and solar radiation etc. Therefore, reference evapotranspiration cannot be quantified directly through downscaling. Hence, various surface based variables included in the hydro-climatic projection model are streamflow, rainfall, air temperature, wind speed, and relative humidity.

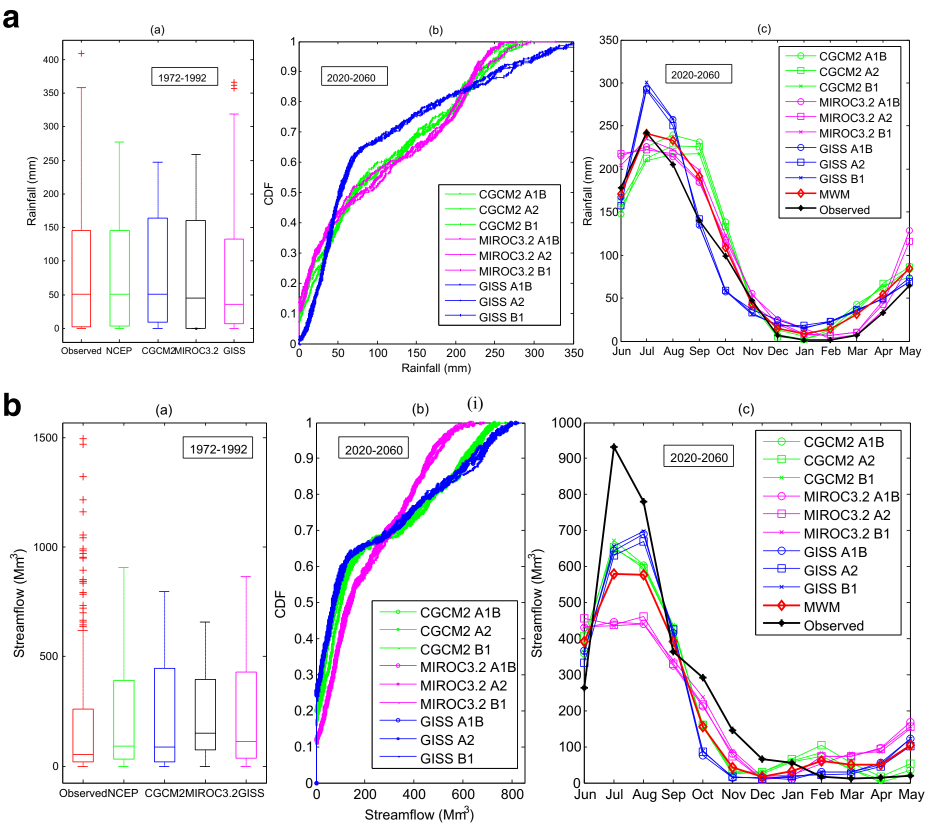
The large scale predictors used to downscale the selected hydro-climatic variables are from Rehana and Mujumdar (2012, 2013). The predictor variable data is collected from National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis data (Kalnay et al. 1996) over a region of 10–20° N to 70–80° E. The GCMs considered 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) with three scenarios A1B, A2 and B1 from Intergovernmental Panel on Climate Change (IPCC) AR4 runs for obtaining the projections of hydro-climatic variables. The selection of three GCMs and three emission scenarios for the ensemble approach is based on the availability of the large number of predictors. The present study deals with about thirteen large scale predictors (precipitation flux, precipitable water, surface air temperature at 2 m, mean sea level pressure, geopotential height at 500 mb, surface U-wind, surface V-wind, specific humidity at 2 m, surface relative humidity, surface latent heat flux, sensible heat flux, surface short wave radiation flux, surface long wave radiation flux, etc.) and the selected GCM and scenario should comprise of these selected predictors. Based on these restrictions the present study considers three GCMs with three scenarios for the ensemble approach. The methodology for downscaling of hydro-climatic variables and the corresponding climate model uncertainty is explained in the following subsection.

3.1 Hydro-Climatic Variable Projection Model

To develop the projections of the multivariate predictands of hydro-climatic variables (streamflow, average, maximum and minimum air temperatures, relative humidity and wind speed) a multivariable statistical downscaling methodology based on CCA developed by Rehana and Mujumdar (2012) is employed. The potential of CCA downscaling model in simulating the observed and future projections of various predictands over Bhadra command area is evaluated as shown in Fig. 4. In Fig. 4, figures (a) represent the box plots of observed and simulated projections from NCEP and three GCMs for the period 1972–1992. These figures show the hydro-climatic predictions for the training data set simulated with NCEP/NCAR and with three GCMs and represent CCA model reproduced observed data reasonably well in terms of R- square values.

3.2 Uncertainties: Climate Change Projections

The figures (b) in Fig. 4 provide the Cumulative Distribution Functions (CDFs) of hydro-climatic projections for GCMs CGCM2, MIROC3.2 and GISS under A1B, A2 and B1 scenarios for period 2020–2060. The CDFs of hydro-climatic projections downscaled from one GCM is entirely different from that of another. The dissimilarity can also be observed among two scenarios of any particular GCM, although they show a similar trend in the projections. The difference between the CDFs from one GCM to other is more compared to that from one scenario to another for the same GCM, which indicates that GCM uncertainty is greater than scenario uncertainty which supports some of the earlier findings on GCM and scenario uncertainty modeling (Mujumdar and Ghosh 2008; Chen et al. 2011). Climate change impacts are evaluated by comparing the observed hydro-climatic variables for a time period of 1972–1992 along with the MWM ensemble derived from multimodels and scenarios for future time period of 2020–2060 time slices (figures (c) in Fig. 4, (i) to (vi)). All climate change



(ii)

Fig. 4 Observed and downscaled monthly GCM projections for various hydro-climatic variables. In above figures (i) to (vi) the figure *a* represents observed, NCEP/NCAR, CGCM2, MIROC3.2 and GISS simulated hydro-climatic variables for the period 1972–1992 and figures, **b** represents the CDF of downscaled GCM projections for various hydro-climatic variables for the period 2020–2060, **c** represents the monthly mean projections for a period of 2020–2060 compared with the observed ones for a period of 1972–1992

scenarios project a significant reduction of monthly streamflow for 2020–2060 with respect to 1972–1992, with CCA downscaling (figure (c) of Fig. 4i).

4 Optimal Reservoir Operation

4.1 Operating Policy Model: Stochastic Dynamic Programming

A SDP model is used to derive the optimal monthly steady state operating policy for future hydrologic scenarios. In period t, for known class intervals of storage at the beginning of the period, k, storage at the end of the period, l, and inflow, i, the release, R_{kilt}, is considered as the water available for allocation among the users of the reservoir in period, t. The release, R_{kilt} is used in the fuzzy water allocation model, WQCM, described in Section 4.2, for obtaining the optimal allocations among the users and the system performance measure required in SDP. Figure 5 shows the link between SDP and WQCM.

The optimal satisfaction level, λ^*, obtained from WQCM can be considered as the system performance measure, λ_{kilt}, in SDP for a release of R_{kilt}. The objective of the SDP model is to maximize the expected value of λ_{kilt} and the backward recursive equation for any stage n and period t is given by

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

where λ_{kilt} is system performance associated with the reservoir storage at the beginning of the period, t, S_k^t, inflow during the period, t, Q_i^t, release of R_{kilt}, and reservoir storage at the end of period, t, S_l^{t+1}, obtained from WQCM; P_{ij}^t is the transition probability for streamflow from class i to class j in period t.

The optimal final storage state, l^*, in a period t is thus obtained for a given storage state at the beginning of the period, k and inflow state i by solving the SDP model formulation. The following section discusses the fuzzy water allocation model, WQCM, which is used to compute the system performance λ_{kilt}.

4.2 Operating Policy Model: Water Quantity Control Model

4.2.1 Irrigation Demands Under Climate Change

The irrigation demand of the command area is computed based on the precipitation contribution and potential evapotranspiration of the crops grown in that command area following Rehana and Mujumdar (2013). The projected rainfall and other meteorological variables obtained from the uncertainty analysis of hydro-climatic variable projection model (Section 3.2) are used to quantify the irrigation demands for the future scenarios. The details of the computation of irrigation demands can be obtained from Rehana and Mujumdar (2013). The projected monthly irrigation water requirement for sugarcane, paddy, permanent garden and semidry crops over Bhadra command area for current and for two future time slices of

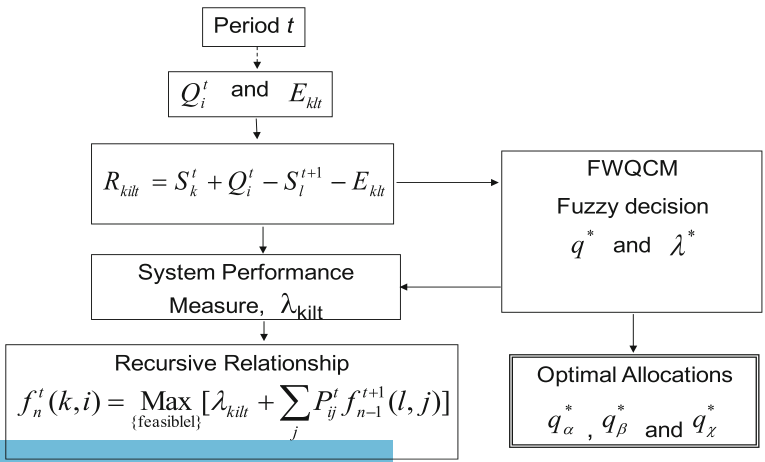


Fig. 5 Link between SDP and WQCM

2020–2040 and 2040–2060 are quantified. Figure 6a shows projected monthly percentage changes in rainfall, evapotranspiration for 2020–2060 period compared with those for 1984 to 2004, whereas, Fig. 6b shows the projected monthly difference in irrigation demands for 2020–2060 period compared with those for 1984–2004. It can be observed that the increase in evapotranspiration offsets the increasing effect of rainfall indicating pronounced changes in irrigation demands. For example, the irrigation demand for the month of October is entirely due to increase in evapotranspiration with a decrease in rainfall.

The quantified monthly irrigation water demands for current and for two future time slices of 2020–2040 and 2040–2060 are used as membership functions for irrigation user (q_α^D). The allowable water deficit for irrigation user is considered subjectively as fifteen percent of the desirable quantity, q_α^D, to define the minimum irrigation requirement, q_α^{Min}. The linear membership functions for irrigation user for current and two future scenarios of 2020–2040 and 2040–2060 are shown in Fig. 7a. Further, this forms the basis to modify the membership function of the irrigation user accounting for the projected irrigation demands in the water allocation model.

4.2.2 Downstream Water Quality Under Climate Change

The optimal treatment levels and the corresponding degree of acceptability for a given flow can be determined using a Waste Load Allocation Model (WLAM). For this purpose, a Fuzzy Waste Load Allocation Model (FWLAM) developed by Sasikumar and Mujumdar (1998) is adopted to assess the impact of climate change on downstream water quality due to changes in river flow and river water temperature. The FWLAM can be solved for different values of flow between a minimum prescribed downstream release, q_β^{Min}, (generally specified by Pollution Control Boards, PCBs), and maximum possible flow, q_β^D,(considered, based on several trial runs of the FWLAM, as the average of all possible release values in the SDP) of the reservoir to obtain a functional relation between the flow, q_β, and quality control decision maker's satisfaction, λ_1^* (Fig. 7b). The functional relation, $f(q_\beta)$, indicates the degree of acceptability of the decision maker for water quality control in the river for a given downstream water

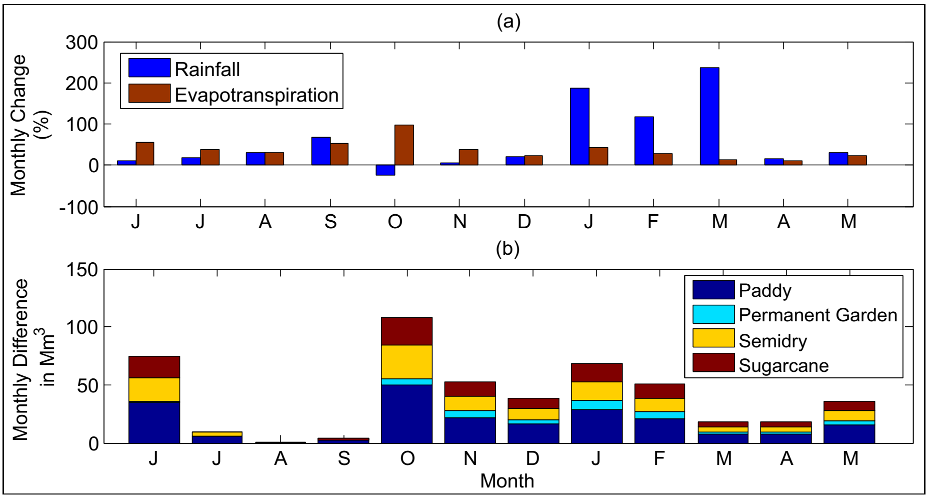
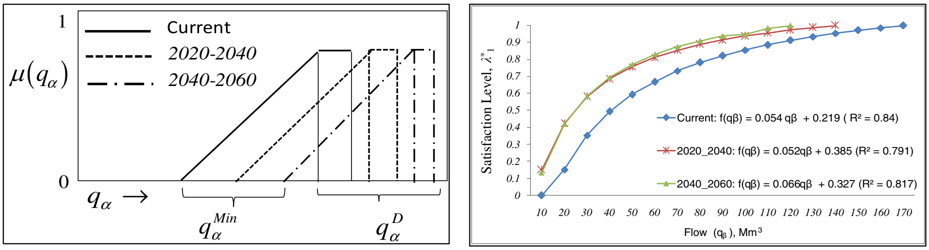


Fig. 6 Change in **a** rainfall and evapotranspiration in terms of monthly percentage change for 2020–2060 corresponding to period of the 1984–2004, **b** in irrigation demands for various crops in terms of monthly difference for 2020–2060 corresponding to period 1984–2004



(a) (b)

Fig. 7 Membership functions for **a** irrigation and **b** water quality

allocation, q_β. The typical membership function for downstream water quality, $\mu(q_\beta)$, which can be used into the WQCM to obtain the water allocations is given as follows,

$$\mu(q_\beta) = \begin{cases} 0 & q_\beta < q_\beta^{Min} \\ f(q_\beta) & q_\beta^{Min} \le q_\beta \le q_\beta^{D} \\ 1 & q_\beta \ge q_\beta^{D} \end{cases} \tag{2}$$

The projected changes of reservoir inflows and water temperature (due to change in air temperature) are incorporated into the river water quality management model (following Rehana and Mujumdar 2011) to examine the downstream river water quality response. A regression model is applied with the uncertain projected air temperature resulting from uncertainty analysis of hydro-climatic projection model (Section 3.2) to evaluate the future water temperature. Further, the non-point source pollution is accounted in the water quality simulation model by adopting a backward finite difference formulation (Chapra 1998), where the incremental flow is divided equally among the element of a reach for the river stretch under consideration following to Rehana and Mujumdar (2009).

4.2.3 Hydropower Demand

The water requirement for hydropower generation depends on the head available, which in turn depends on the reservoir storage. The release required, for power production, Q_p, is considered as the desirable release, q_χ^D, for a given head. For a given state in SDP the q_χ^D is worked out for the mean storage, which is the average of storages at the beginning and end of a period, with the corresponding net head determined from the storage-elevation relationship of the reservoir. The storage-elevation relationship derived based on historical data is assumed to remain unchanged for the future scenarios. Therefore, the membership function for hydropower demand remains unchanged for the future scenarios. The linear membership function for hydropower demand, is then given as:

$$\mu\left(q_\chi\right) = \begin{cases} 0 & q_\chi \le q_\chi^{Min} \\ \left(\dfrac{q_\chi - q_\chi^{Min}}{q_\chi^D - q_\chi^{Min}}\right) & q_\chi^{Min} \le q_\chi \le q_\chi^D \\ 1 & q_\chi \ge q_\chi^D \end{cases} \tag{3}$$

where q_χ^{Min} is the minimum specified power at a given head; q_χ is the hydropower water allocation. The derived membership functions for current and for future scenarios for each of the reservoir user, accounting for the projected water demands of the reservoir, are used in the WQCM to obtain the water allocations among the reservoir users under climate change.

Further, the present study considers linear membership functions for each of the water user generated based on subjective perception of membership degree for a given water allocation. The essential approach in real conditions is to carry out field surveys of water managers, users, and experts, to describe their interpretation of how well an allocation meets the goals for various purposes and then to fit the response to suitable membership functions. The common approach is to fit a least square fitting between survey data and suitable parameterized family of membership functions. In some situations the limitation of linear membership function can be eliminated by employing some data-driven methods (e.g. probability, possibility, neural networks, nearest neighbor) to generate non-linear membership functions such as Gaussian and sigmoid functions which may be more suitable for realistic situations.

4.2.4 Formulation of WQCM

The WQCM maximizes the minimum satisfaction level, λ, in the system, (Binoy Alias 2005) by considering the membership functions of all the users to determine the water allocations for current and for future scenarios. The model is expressed as follows:

$$\text{Maximize } \lambda \tag{4}$$

Subject to

$$\left[\frac{q_\alpha - q_\alpha^{Min}}{q_\alpha^D - q_\alpha^{Min}}\right] \geq \lambda \tag{5}$$

$$f(q_\beta) \geq \lambda \tag{6}$$

$$\left[\frac{q_\chi - q_\chi^{Min}}{q_\chi^D - q_\chi^{Min}}\right] \geq \lambda \tag{7}$$

$$q_\alpha^{Min} \leq q_\alpha \leq q_\alpha^D \tag{8}$$

$$q_\beta^{Min} \leq q_\beta \leq q_\beta^D \tag{9}$$

$$q_\chi^{Min} \leq q_\chi \leq q_\chi^D \tag{10}$$

$$q_\chi + q_\beta + q_\chi \leq W_A \tag{11}$$

$$0 \leq \lambda \leq 1 \tag{12}$$

where W_A is the amount of water available for allocation, which is the reservoir release, R_{kilt}, for a given k, i, l and t in SDP. The solution of the resulting optimization problem will be q^* and λ^* where $q^* = \{q^*_\alpha, q^*_\beta, q^*_\chi\}$ corresponds to optimum water allocation among the three water users; viz., irrigation, water quality and hydropower, and λ^* is the maximized minimum satisfaction level in the system. The recursive equation (Eq. (1)) is solved together with WQCM till the steady state is reached, defining the steady state policy $l^*(k,i,t)$ separately for current and for future scenarios.

The irrigation demand model (Section 4.2.1), water quality model (Section 4.2.2), hydropower demand model (Section 4.2.3), water allocation model (Eqs. (4) to (12)) and steady state operating policy model (Eq. (1)) are solved together with the membership functions evaluated for irrigation (Fig. 7a), water quality control (Fig. 7b) and hydropower (Eq. (3)) to derive the optimal operating policies. The steady state operating policies are derived for current (1967–2000) period and for each GCM-scenario combination and for the weighted mean hydro-climatology for a 30-year future time slice (2020–2050) for Bhadra reservoir system. In each operating policy the WQCM is solved for water allocation for all states in a stage of SDP. Twelve transition probability matrices are determined, one for each month, using the available historical streamflow records (1967–2000) for current period and using the projected inflows for future period of 2020–2050. The outputs from each policy are monthly releases, water allocations for each reservoir user and storages, from which monthly operating policies are generated for the current and for future scenarios.

4.3 Impact on Optimal Water Allocations

The monthly water allocations are derived from WQCM for each reservoir user in conjunction with the projected demands computed accounting for the climate model uncertainty of hydro-climatic variables. The resulting irrigation water allocations are projected to increase throughout most of the year to compensate the projected irrigation demands. For instance, the irrigation demand for the month of April for current and for future time slices of 2020–2040 and 2040–2060 is obtained as 268.20, 280.80 and 294.07 Mm^3 respectively and the quantified water allocations are 242.43, 250.04 and 263.73 Mm^3. The derived allocations are able to fulfill the demands for the monsoon months starting from June to October for current as well as for future scenarios. However, significant water deficits are observed for the non-monsoon months starting from November to May for current as well as for future periods. The negligible amount of rainfall in these months necessitates higher irrigation demands and therefore consequent occurrence of water deficits, which are more pronounced for the future scenarios.

The total downstream allocations depend on the hydropower and water quality allocations. The FWLAM is solved for a particular downstream allocation to obtain the optimal fraction removal levels for the dischargers and the resulting Dissolved Oxygen (DO) levels at various checkpoints along the river stretch. Sample results of the FWLAM for a given downstream allocation, resulting fractional removal levels for three dischargers, and the DO levels in mg/l at three check points are given in Table 1. From Table 1 it is clear that downstream allocations are projected to decrease due to change in response to the water quality according to the future projected changes of reservoir inflows and water temperature. In addition, the projected irrigation water allocations (to compensate the projected irrigation demands) also affect the downstream water allocations. It may be noted that higher downstream allocation for water quality control leads to lower effluent treatment levels leading a healthy downstream environment, particularly for monsoon months. The downstream river stretch of Bhadra reservoir may experience deterioration conditions with decrease in DO levels for the non-monsoon months with a minimum downstream allocation of 9 Mm^3 and consequent increase in higher treatment

Table 1 Sample results of waste load allocation model: for a given downstream allocated flow, the resulting fractional removal levels for three dischargers (MPM, Bhadravathi City and VISL) and the DO levels at three check points (Checkpoints 1, 2 and 3) (Fig. 1)

Month	Downstream water quality response from FWLAM									
	Property	Current			2020–2040			2040–2060		
Jun	Downstream allocation (Mm^3)	464.88			377.91			362.50		
	Fractional removal level (%)	51	49	51	53	53	53	53	53	53
	DO levels at 3 check points (mg/l)	6.57	6.72	6.44	6.56	6.70	6.34	6.55	6.69	6.31
Jul	Downstream allocation (Mm^3)	461.73			427.56			394.83		
	Fractional removal level (%)	51	51	51	52	52	49	52	52	52
	DO levels at 3 check points (mg/l)	6.57	6.72	6.44	6.56	6.72	6.40	6.56	6.70	6.36
Mar	Downstream allocation (Mm^3)	9.00			9.00			9.00		
	Fractional removal level (%)	90	90	90	90	90	90	90	90	90
	DO levels at 3 check points (mg/l)	5.15	4.63	2.02	5.15	4.63	2.02	5.15	4.63	2.02
Apr	Downstream allocation (Mm^3)	83.02			53.36			62.51		
	Fractional removal level (%)	74	61	75	83	77	83	79	79	79
	DO levels at 3 check points (mg/l)	6.35	6.30	4.96	6.24	6.11	4.44	6.28	6.18	4.63

levels of about 90 % (Table 1). Therefore, the minimum release of 9 Mm^3 may not be adequate due to a decrease in DO level up to 2.02 mg/l, particularly in the low flow months of January, February and March. Such minimum releases can be revised to avoid eutrophication conditions and to maintain a healthy downstream river environment. Further, the environmental flow rates play an important role over Bhadra river stretch due to the presence of high effluent dischargers within a short river stretch and require considerable attention towards the downstream releases of the Bhadra reservoir.

4.4 Impact on Operating Policies

There is a large uncertainty in the regional impacts of climate change in the Bhadra river basin. Figure 8 depicts the uncertainties at various stages of the regional impact assessment of climate change, representing: uncertainty in reservoir inflows from hydro-climatic projection model (Fig. 8a); uncertainty in demand quantification from irrigation demand projection model (Fig. 8b); uncertainty in the satisfaction level of the reservoir system for a given water allocation from water quantity model (Fig. 8c), and uncertainty in the operating rule curves for the steady state policies (Fig. 8d). Since uncertainties accumulate from various levels, their propagation up to the regional or local level leads to large uncertainty ranges at such scales (Wilby 2005) resulting in more complexity in the selection of appropriate rule curves. From Fig. 8, it is clear that the projected decrease in reservoir inflows and increase in water demands will have serious negative consequences on satisfaction level of the reservoir system. The reduced amount of inflows reduces the releases/water available for allocation and consequently the satisfaction level of the reservoir system, λ*, under climate change conditions. Figure 8d shows the current and future projected rule curves for all GCM-scenario projections, thus derived. There is a significant uncertainty in the derived operating policies for the Bhadra reservoir. The required storages to be maintained in the reservoir are seen to be increasing for the future scenarios under various climate change projections to compensate the projected water demands and reduced water availability for the monsoon months. For non-monsoon

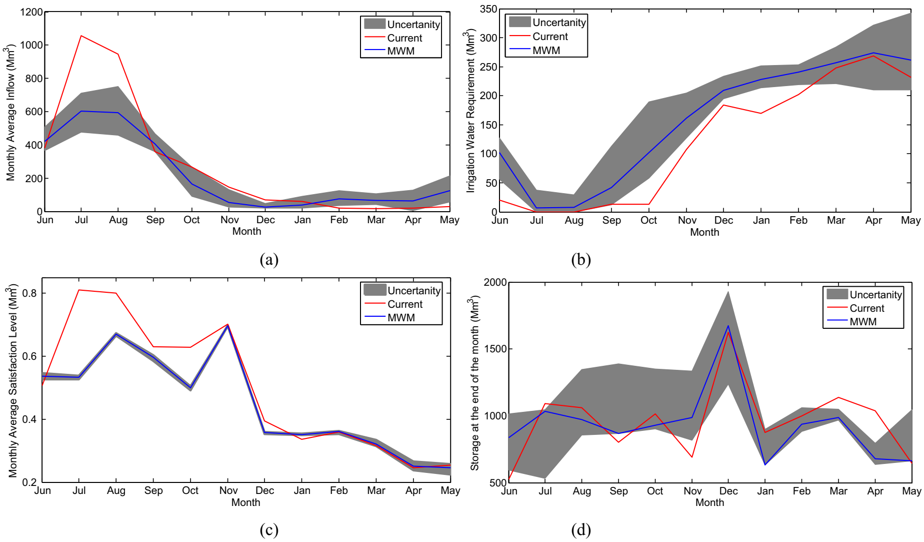


Fig. 8 Various levels of uncertainties in the regional impacts of climate change in the Bhadra river basin showing the maximum and minimum values, along with the MWM hydro-climatology for the 2020–2050 period reflecting uncertainty in **a** the reservoir inflows from hydro-climatic projection model, **b** the demand quantification from irrigation demand model, **c** the satisfaction level of the reservoir system for a given water allocation from water quantity model and **d** the operating rule curves for the steady state policies

months, even though the projected water demands are higher, the increased water availability compared to current conditions results in reduced storages to be maintained. This perhaps needs efforts towards optimal investment in water storage capacity (Fisher and Rubio 1997) considering the uncertainty in water supply and demands due to the variability in hydrological cycle due to climate change.

5 Concluding Remarks

A modeling framework is presented in this paper addressing various levels of uncertainties in an integrated regional water resource system to develop long term operating policy considering three water users: irrigation, water quality and hydropower. The main focus of the proposed methodology is on the interconnections between climate change scenarios, water resources supply, demand, allocations and long term operating policies. Uncertainties due to climate change impacts arising from choice of specific models and scenarios, conflicting interests among the water users and random nature of reservoir inflows are all modeled and integrated to provide reservoir rule curves and associated pollutant treatment levels. The water allocation model developed in this study facilitates explicit inclusion of downstream water quality. The application is demonstrated with outputs from three GCMs of the CMIP3 ensemble for AR4 scenarios. Simulations of CMIP5 ensemble of models are now available for the AR5 scenarios. Use of these simulations may produce different sets of results. Further, the operating policies derived for climate change scenarios from classical optimization methods such as SDP should be interpreted with caution. Classical SDP cannot accommodate non-stationarity in the inflow process, and thus the information on future variability of inflows due to climate change cannot be addressed in the SDP. Further, the methodology and modeling tools developed in the present work discus the projections of future water demand mostly as a physically – based problem caused by the impact of climate change on the hydrologic cycle. Human impact and population changes must be considered which have much more important role to play in the projections of future water demand (e.g. Vörösmarty et al. 2000).

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