Climate change induced risk in water quality control problems

S. Rehana\textsuperscript{a}, P.P. Mujumdar\textsuperscript{a,b,*}

\textsuperscript{a}Department of Civil Engineering, Indian Institute of Science, Bangalore, Karnataka 560 012, India
\textsuperscript{b}Divecha Center for Climate Change, Indian Institute of Science, Bangalore, Karnataka 560 012, India

\begin{abstract}
A modeling framework is presented in this paper, integrating hydrologic scenarios projected from a General Circulation Model (GCM) with a water quality simulation model to quantify the future expected risk. Statistical downscaling with a Canonical Correlation Analysis (CCA) is carried out to develop the future scenarios of hydro-climate variables starting with simulations provided by a GCM. A Multiple Logistic Regression (MLR) is used to quantify the risk of Low Water Quality (LWQ) corresponding to a threshold quality level, by considering the streamflow and water temperature as explanatory variables. An Imprecise Fuzzy Waste Load Allocation Model (IFWLAM) presented in an earlier study is then used to develop adaptive policies to address the projected water quality risks. Application of the proposed methodology is demonstrated with the case study of Tunga–Bhadra river in India. The results showed that the projected changes in the hydro-climate variables tend to diminish DO levels, thus increasing the future risk levels of LWQ.
\end{abstract}

\begin{keywords}
Climate change\hfill Water quality\hfill Risk of low water quality\hfill Statistical downscaling\hfill Fuzzy optimization
\end{keywords}

\section{Introduction}
Climate change includes changes in precipitation, wind speed, incoming solar radiation, and air temperature which directly influence river water quality by altering changes in streamflow and river water temperatures. Increasing concern with potential impacts of climate change on river environmental problems has prompted some researchers to formulate theories and numerical models that simulate lake water quality elements (Stefan et al., 1996; Hassan et al., 1998; Hammond and Pryce, 2007). Most of the chemical and bacteriological processes are dependent on temperature, increasing the growth rates, which motivated some authors to focus on possible effects of global warming on stream temperatures (e.g., Cooter and Cooter, 1990; Mohseni and Stefan, 1999; Morrill et al., 2005). Stefan et al. (2001) projected that under a doubled-CO$_2$ environment, summertime killing of fish in lakes may increase and the habitat for coldwater fish is likely to decrease by up to 30%. Morrill et al. (2005) estimated the future water quality of 43 rivers and stream sites in 13 countries from Global Learning and Observations to Benefit the Environment (GLOBE), by considering a nonlinear regression equation developed by Mohseni et al. (1998) between air temperature and water temperature, using the Hadley Centre Coupled Model, version 3 (HadCM3) GCM output directly. Cox and Whitehead (2009) showed that, under a range of UKCIP (United Kingdom Climate Impacts Programme) scenarios, DO in the river Thames will be affected in the 2080s by enhanced Biochemical Oxygen Demand (BOD), and by the direct effects of temperature which reduces the saturation concentration of DO. Among the hydro-climatic variables influencing the water quality of a river, streamflow and water temperatures are the most significant ones, as most of the water quality indicators (e.g., DO, BOD, turbidity, pH, etc.) are functions of these two variables. Efforts were made in Rehana and Mujumdar (2011) to quantify the possible changes in water quality indicators (e.g., DO, BOD, water temperature, pH) using the water quality simulation model, QUAL2K, under six hypothetical scenarios of increase in water temperature (+1°C, +2°C) and decrease (−20%, −10%, 0%) in river flow. The river water temperature is estimated based on air temperature only using a linear regression, whereas the water temperature is also governed by other meteorological variables such as solar radiation, wind speed and relative humidity, which are likely to be affected by climate change. Further river water temperature is influenced by the net heat inputs and outputs under specific hydrological/hydraulic conditions (through instream flow rate, inflow temperature, river width and length, bottom slope and bed roughness) and meteorological conditions (through air temperature, solar radiation, wind, and humidity). According to Edinger et al. (1974) river temperature is mainly controlled by ambient atmospheric conditions. Therefore...
not only streamflow but all other meteorological variables which influence river water temperature must be modeled under climate change scenarios in the river water quality impact studies.

Quantification of variability of water quantity and the resulting water quality will itself be not adequate to understand the risks and to develop adaptive responses. Translating the projections to predictions of water quality threshold exceedence will be necessary. Logistic regression models are useful for predicting the probability of the river water quality exceeding a threshold. Smith et al. (2001) employed logistic regression to show that watersheds with large proportions of urban land cover or agriculture on steep slopes had a very high probability of being impaired by pathogens. Towler et al. (2010) developed a local logistic regression based approach to estimate threshold exceedances of turbidity, conditioned on seasonal climate forecast of streamflow in the Pacific Northwest.

In this paper, an integrated river water quality management modeling framework is presented with the use of GCM projections of hydro-climate variables modeled by a downscaling method. The flowchart of the modeling framework is shown in Fig. 1.

In the first part of the framework GCM outputs of large-scale climate variables are downscaled to local or regional scales to provide projections of hydro-climatic variables using Canonical Correlation Analysis (CCA). These projections can be further utilized into any water quality simulation model to predict the river water quality. The water quality simulation model used in this work is QUAL2K, developed by the United States Environmental Protection Agency (USEPA). In the present work, the river water quality variable of interest is DO which is a function of not only streamflow but also of the water temperature. The situation when the DO level is less than a specified value is termed as low water quality (LWQ) event and is represented as a failure of the river system. A Multiple Logistic Regression (MLR) is used for the evaluation of LWQ occurrence corresponding to a specified threshold based on the joint behavior of streamflow and temperature. The Imprecise Fuzzy Waste Load Allocation Model (IFWLAM) developed by Rehana and Mujumdar (2009) is modified to develop the optimal decision policies for the dischargers accounting for the projected changes of river water quality variables. The main goal of this study is to integrate the hydrologic scenarios projected from a GCM with a river water quality control model to quantify the future expected risk of low water quality. A regional river water quality management model is used with climate information to derive the adaptive policies by considering the projected water quality risks. The proposed model is a generalized approach to study the climate change impacts on river water quality that result from climate change impacts on the hydrological variables.

2. Case study description

Tunga–Bhadra river is formed by the confluence of Tunga and Bhadra, the two tributaries of river Krishna, located in Karnataka, India (Fig. 2, which also includes grid points of National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis data and GCM grid points used in downscaling). The river has two other tributaries, Kumudavati and Haridra. They join Tunga–Bhadra river from west and east directions at a distance of 84 km and 124 km downstream of the junction, respectively. The schematic diagram of the Tunga–Bhadra river is shown in Fig. 3. The river stretch considered starts from Lakkavalli station along Bhadra river and ends with Harlahalli station along Tunga–Bhadra river. The total length of the river stretch considered is about 200 km. The river receives the waste loads from eight major effluent points, which include five industrial effluents and three municipal effluents (Fig. 3), apart from the non-point sources of pollution.

In the case study, there is a convincing evidence of increase in air temperature and decrease in streamflow over the historical period (Rehana and Mujumdar, 2011). The mean streamflow decrease is about 3.1% at Shimoga along Tunga river compared from the period of 1971–1991 to 1992–2006. Similarly about 24.16% reduction in mean streamflow is observed at Byladenahalli along Haridra river from period 1985–1995 to 1996–2005. The motivation behind such comparison is to show the range of reduction in the mean streamflow as 3.1–24.16% for the considered river stretch. The reduced annual mean flows produced similarly large reductions in low flows in terms of 7Q10 values. A 7Q10 value is the 7-day low flow with a 10-year return period using daily data. The 7Q10 values for the periods of 1971–1991 and 1992–2006 at Shimoga along Tunga–Bhadra river are 0.052 and 0.00, respectively.

![Flowchart of the proposed methodology](image-url)
Fig. 2. Location of Tunga–Bhadra river basin, showing NCEP and MIROC3.2 GCM grids superimposed.

Fig. 3. Schematic diagram of Tunga–Bhadra River.
Similarly the 7Q10 values for the periods of 1985–1995 and 1996–2005 at Byladahalli along Haridra river are 0.027 and 0.00, respectively. Increase in air temperature is about 0.215 °C (at Shimoga in the interval 1988–1999 to 2000–2006) to 1.39 °C (at Kuppelur in the interval 1991–2000 to 2001–2006) and the corresponding (estimated) increase in water temperature is about 0.6 °C (Shimoga) to 3.34 °C (Honnali). A maximum reduction of 2.1 mg/L of DO is observed during the period 1988–1999 and 2000–2006 along the river stretch considered (Rehana and Mujumdar, 2011). This observed change in water quality may be due to several reasons, including increase in pollutant loads, decrease in streamflow and increase in temperatures.

The daily streamflow data of Tunga river, Bhadra river, Kumudavathi river, Haridra river are obtained from Central Water Commission (CWC). The meteorological variables, maximum temperature, minimum temperature, wind speed and relative humidity, from 1969 to 2005, are obtained from the India Meteorological Department (IMD), Pune. The period of availability of data on streamflow and other meteorological variables considered in the statistical downscaling are given in Table 1. The table also gives the periods considered for training and testing, in the statistical downscaling. Further an area from 10°-20°N to 70–80°E over the target region where hydro-climate variables of a water quality simulation model are to be downscaled is chosen for large-scale climate variables as predictors data collection. The monthly values of the predictors are obtained from the NCEP/NCAR reanalysis data (Kalnay et al., 1996) (available at http://www.cdc.noaa.gov/cdc/data.ncep.reanalysis.html) are used for training the statistical downscaling model. Large-scale monthly atmospheric variables output from the Model for Interdisciplinary Research on Climate, version 3.2 (MIROC 3.2) GCM for the A1B scenario (720 ppm CO2 stabilization experiment) are extracted from the multimodal data set of the World Climate Research Programme’s Coupled Model Intercomparison Project (WCRP/CMIP3) (available at https://esg.llnl.gov:8443/about/ftp.do). The simulations for A1B scenario of the Intergovernmental Panel on Climate Change (IPCC) AR4 (IPCC, 2007) provided by MIROC 3.2 GCM (medium-resolution of 1.125° × 1.125°, GCM from the Center for Climate System Research, CCSR, Japan) are used for impact assessment.

3. Statistical downscaling

The statistical techniques used to bridge the spatial and temporal resolution gaps between what GCMs are currently able to provide and what impact assessment studies require is called as statistical downscaling methods. Generally these methods involve deriving empirical relationships that transform large scale simulations provided by a GCM (climate variables as predictors) to regional scale variables (hydrological variables as predictands). As an initial step the predictands to be downscaled to study the climate change impacts on river water quality must be selected depending on the input variables required to a water quality model.

Among the meteorological variables considered in this study, solar radiation could not be directly downscaled due to the nonexistence of observed solar radiation data for the study region. Most of the methods to estimate solar radiation (e.g., Angstrom, 1924; Hargreaves, 1994) include the information of cloud cover, maximum and minimum temperatures, sunshine hours, relative humidity and site-specific coefficients. As the observations of maximum and minimum temperatures are available for the study region, the future projections of solar radiation can be computed based on the downscaled variables of maximum and minimum temperatures based on Hargreaves and Samani (1982). Hence the maximum and minimum temperatures are also included in the predictand set. Therefore the predictands considered for downsampling to assess the climate change impacts on river water quality are streamflow, average air temperature, maximum and minimum air temperatures, average wind speed and relative humidity.

The next step in statistical downscaling is the selection of atmospheric predictor variables. The predictors used for downsampling (Wilby et al., 1999; Wetterhall et al., 2005) should be (1) reliably simulated by GCMs, (2) readily available from archives of GCM outputs, and (3) strongly correlated with the surface variables of interest. Cannon and Whitfield (2002) used Mean Sea Level Pressure (MSLP), 500 hPa geopotential height, 800 hPa specific humidity, and 100–500 hPa thickness field as the predictors for downsampling GCM output to streamflow. Ghosh and Mujumdar (2008) considered 2 m surface air temperature, MSLP, 500 hPa geopotential height and surface specific humidity as the predictors for modeling Mahanadi streamflow in monsoon season. Anandhi et al. (2009) considered air temperature, zonal and meridional wind velocities at 925 mb, surface flux variables such as latent heat, sensible heat, shortwave radiation and long wave radiation fluxes as predictors to downscale monthly mean maximum and minimum temperatures. Davy et al. (2010) considered 16 meteorological variables including geopotential height, air temperature, U- wind and V-wind speed, relative humidity, vertical velocity, absolute vorticity as multilevel quantities evaluated at 1000 hPa height to downscale the wind variability. Huth (2005) downscaled relative humidity, water vapor pressure, dew-point temperature, and dew-point deficit by considering geopotential height at 500, 850 and 1000 hPa, wind speed and vorticity at 500, 850 hPa, temperature at 850 hPa, humidity variables (relative humidity, specific humidity, water vapor pressure, dew-point temperature, dew point deficit at 850 hPa) as predictors. Following this literature and the availability of the predictors from the GCM, in this study, eleven large-scale atmospheric predictors are selected as given in Table 2.

After the selection of predictor variables to be used to model the predictands, a mathematical transfer function is to be adopted to derive predictor–predictand relationship. For this purpose an appropriate statistical technique must be adopted which can account for the multivariate predictands. The most commonly used statistical technique for the multivariate data sets is CCA (Glahn, 1968). CCA can be used as a downsampling technique for relating surface-based observations and free-atmosphere variables when simultaneous projection of predictands is of interest (e.g., Barnett and Preisendorfer, 1987; Karl et al., 1990; Mpelasoka et al., 2001; Juneng and Tangang, 2008). CCA has found wide application in

<table>
<thead>
<tr>
<th>Hydro-climate predictand variable</th>
<th>Period of available data</th>
<th>Training period</th>
<th>Testing period</th>
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</table>
Table 2
Predictors selected for CCA downscaling.

<table>
<thead>
<tr>
<th>Predictand</th>
<th>Predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Streamflow, average air temperature, maximum air temperature, minimum air temperature, wind speed, relative humidity</td>
<td>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</td>
</tr>
</tbody>
</table>

modeling precipitation and meteorological variables (e.g., Von Storch et al., 1993; Busuioc and von Storch, 1996). The methodology involves training the surface observed predictands and NCEP atmospheric predictor data with the CCA analysis after data preprocessing with standardization and PCA. The principal component scores obtained based on NCEP data are used as reference to develop the GCM principal components to eliminate the computation of principal component scores separately for GCM output also. Statistical relationship in terms of canonical regression equations are obtained for each of the hydro-climate predictand based on NCEP data and surface observations using CCA. The developed regression equations are applied to the interpolated NCEP gridded GCM output to model future projections of hydro-climate predictands. These steps are discussed in detail in the following sub-sections.

3.1. Data preprocessing

The large-scale atmospheric data have to be preprocessed before they are used for training the CCA loadings. The first step involved in the data preprocessing is standardization to reduce systematic biases in the mean and variances of GCM predictors relative to the observations or NCEP/NCAR data. Standardization involves subtraction of mean and division by standard deviation of the predictor variable for a predefined baseline period for both NCEP and GCM outputs. In this study the period 1961–1990 is considered as baseline based on literature (Wilby et al., 2004; Ghosh and Mujumdar, 2007). Data from the twentieth-century experiment of MIROC3.2 GCM from 1960 to 1990 are used to calculate the mean and standard deviation of each variable at each grid point for this period. Similarly, the mean and standard deviation of NCEP variables is computed. The bias corrected value for the kth predictor variable \( p \) is then computed as

\[
p_{\text{std}}^k(q) = \frac{p_k(q) - \bar{p}_{1960-1990}(q)}{\sigma_{p_{1960-1990}}(q)}
\]

where \( p_{\text{std}}^k(q) \) is the standardized value of the variable \( p_k \) at time \( t \), \( p_k(t) \) is the original value at time \( t \), \( \bar{p}_{1960-1990}(q) \) is the mean value of \( p_k \) for the period 1960–1990, and \( \sigma_{p_{1960-1990}}(q) \) is the standard deviation for this period. Each standardized variable is further normalized by subtracting its mean and dividing the result by its standard deviation to produce a new data set having zero mean and unit standard deviation. The normalization is done before applying PCA for each predictor variable both in NCEP and MIROC3.2 data. The number of predictor variables is 25/30/42 (number of NCEP grid points for surface flux, surface/pressure and radiation flux variables, respectively) \( \times 11 \) (total number of predictors), which is very large, and working out the model with this large number would be computationally very expensive. Therefore PCA is applied on the large data set to reduce the dimensionality and to effectively summarize the spatial information from the 25/30/42 grid points. It was found that 95% of the variability of original set is explained by the first ten principal components, and therefore only the first ten principal components are used as predictor set in the further analysis. The eigen vectors or coefficients obtained from NCEP data were applied to the standardized MIROC3.2 data to get the projections in the principal directions. Interpolation is performed before standardization to obtain the GCM output at NCEP grid points as the location of NCEP/NCAR grid points and MIROC grid points do not match. A Mercator projection (conformal cylindrical map projection) is first performed and then a linear interpolation is performed between the projected points. This method is suitable for tropical regions where there is minimum distortion (Mulcahy and Clarke, 1995). CCA is used to model the monthly hydro-climate variables in the Tunga–Bhadra river basin using the data set constituting the first ten principal components obtained from PCA as the predictor set.

3.2. Canonical Correlation Analysis (CCA)

The variables to be modeled by GCM for the river water quality impact study under climate change are multiple and therefore the downscaling technique should accommodate the selected vector of predictands. CCA is a very powerful multivariate method that has been used to develop numerous optimally coupled anomaly patterns of a climate based predictor set and surface based predictand set. An advantage of the CCA in the context of downscaling is that the relationships between climate variables and the surface hydrologic variables are simultaneously expressed, as occurs in nature by retaining the explained variance between the two sets. CCA method of downscaling is a better choice when a strong relationship between large scale climate variables and regional scale surface variables exists. CCA finds pairs of linear combinations between the N-dimensional climate variables, \( X \), and \( M \)-dimensional surface variables, \( Y \), which can be expressed as follows:

\[
U_m = a^T X, \quad m = 1, \ldots, \min(N, M)
\]

\[
V_m = b^T Y, \quad m = 1, \ldots, \min(N, M)
\]

where \( U_m \) and \( V_m \) are called predictor and predictand canonical variables respectively, \( a = [a_1, a_2, \ldots, a_N]^T \) and \( b = [b_1, b_2, \ldots, b_M]^T \) are canonical loadings. The objective of canonical correlation is to identify \( m \) sets of canonical variables such that the correlation, \( \rho \), between predictor canonical variable, \( U_m \) and predictand canonical variable, \( V_m \) is maximum. This way \( N \)-dimensional predictor set and \( M \)-dimensional predictand set is reduced to \( m \)-dimensional canonical variables which will be further useful in developing the regression equations for each predictand. Further details on the evaluation of canonical correlation and the canonical loadings are available in Anderson (1958) and Wilks (2008). After the estimation of canonical variables, regression relation is established for each of the predictand as discussed in the following sub-section.

3.3. Linear regression using CCA

A separate regression equation is derived for each hydro-climate predictand variable from the canonical variable coefficients or scores and correlations computed from the observed data. The truncated principal components extracted from the NCEP data are considered as predictor set to perform CCA to fit the regression relation between the climate variables and surface based observations. The observed predictor canonical variable, \( U_{\text{obs},m} \), is computed from Eq. 2 with the NCEP Principal Components (PCs) as follows:

\[
U_{\text{obs},m} = a^T X_{\text{NCEP,PCS}}
\]

In above expression, \( q \) represents the minimum of the number of PCs considered and the number of predictands considered. As the number of PCs considered is ten in this case, to account for 95% variability and the number of predictands considered is seven,
CCA will yield seven predictor and predictand canonical variables and seven canonical correlations between them. The predictand canonical variable, $V_{predicted,q}$, can be evaluated from the predictor canonical variable, $U_{obsq}$, from Eq. (4) as follows:

$$V_{predicted,q} = \rho_{Cq} \times U_{obsq}$$ (5)

In above expression $\rho_{Cq}$ is the canonical correlation coefficient and represents the percent of variance in the predictand canonical variable explained by the predictor canonical variable and it is a diagonal matrix. The downscaled scenario for each of the predictand can be derived according to:

$$Y_{predicted} = [b^{-1}] \times V_{predicted,q}$$ (6)

Prediction of future scenario is made using the principal components of atmospheric variable monthly outputs from the GCM in place of NCEP Principal Components in Eq. (4). Further, first few significant canonical variables are selected with Bartlett (1947) test based on Wilk’s value ($A$), to reduce the computational effort. Such truncation of significant canonical variables makes it easier to perform the canonical regression. MATLAB (2004) has been used for CCA and the statistical tests mentioned.

3.4. Training and testing

The downscaling methodology CCA is applied to downscale the hydro-climate variables at four locations, which includes Shimoga along Tunga river, Lakkavalli along Bhadra river, Kuppelur along Kumudavathi river, Byladahalli along Haridra river (Fig. 2). The statistical downscaling model is trained using the past records of atmospheric and hydro-climate data to estimate the canonical scores which can be applied for the future predictions. The model is trained on a subset of the available data and tested on the remaining part of the data (see Table 1).

The CCA model is trained using the sets of PCs of atmospheric variables and monthly surface hydro-climate variable data for each station using monthly training datasets. The first ten PCs and the seven hydro-climate variables are considered as independent and dependent data sets respectively in CCA analysis. The resulting seven canonical variables are further tested to select the first few significant canonical correlations. Table 3 gives results of the CCA, along with the Chi-square and the Wilk’s $A$, used for testing the significance of the canonical correlations. The 5% significance critical Chi-square values are given in the brackets in Table 3, with the corresponding degrees of freedom. The first three canonical correlations are significant at 5% significance level therefore first three canonical modes can be selected in the development of regression relationship for each of the predictand. Further Wilk’s $A$ value represents the variance unexplained by the model, $(1 - A)$ yields the variance shared between the variable sets. Only the first three canonical correlations were considered in the context of this study (96%, 80.4% and 35.7% of shared variance, respectively). For all stations only first three canonical variables are sufficient to represent most of the variance that could be explained by the predictor variables on the predictands. Independent data sets are used (Table 1), to test how well the downscaling from NCEP large-scale variables reproduced the observed local climate statistics. The mean, standard deviation and $R^2$-value between the modeled value of each diagnostic statistic and its observed value over the validation data set were used as the indices of performance of a model. For the training datasets, the CCA downscaled results matched the monthly means, and also the standard deviations with the observed statistics, reasonably well, as shown in Table 4.

Monthly mean streamflow values for all the stations along Tunga–Bhadra river are well reproduced by CCA downscaling. The variability in streamflow is slightly under predicted by CCA downscaling. A reason for this may be the inability of the method to capture large variabilities in the data sets by CCA regression, streamflow data shows a large variance. However meteorological variables are well predicted by CCA downscaling as the statistics of mean and standard deviations are well matched. It is worth noting here that CCA demands large sample sizes while modeling the canonical loadings which finally affect the overall performance of the model. The projected hydrologic and climate variables are used in the water quality simulation model to examine the impact on the river water quality.

4. Water quality simulation model

In this study, the water quality model, QUAL2K is adopted for the future water quality assessment of the Tunga–Bhadra river. QUAL2K is a river and stream water quality model applied extensively for the evaluation of surface water quality and to estimate the impacts of pollutants on water quality indicators, such as DO. Detailed information about QUAL2K can be obtained from Chapra and Pelletier (2003). There are a number of earlier studies on the application of QUAL2K (e.g., Fang et al., 2008; Fan et al., 2009). The reason to select QUAL2K as water quality simulation model is it can include climate variables of dew point temperature, wind speed, cloud and solar radiation to analyze surface water quality variables, and is available in a freely downloadable form (http://www.epa.gov/athens/wwqtsc/html/qual2k.html) along with a user manual. As the downscaling model CCA predicts the future projections of streamflows as well as other climate variables, QUAL2K can be used to simulate the temporal changes in water quality elements using the meteorological variables. The QUAL2K model uses climate variables of dew and wet point temperatures, wind speed, air pressure, cloud, and solar radiation to analyze surface water temperature variations using linear empirical relationship for evaporation estimates. Even though the temperature model of QUAL2K includes all meteorological variables, it cannot account for the future flow variability. Therefore to include all the hydro-climate variables and also to have a better understanding over the resulting temperature, an analytical river temperature model is used following Gu and Li (2002), Thomann and Mueller (1987). The temperature model predicts the river water temperature projections by accommodating all the downscaled hydro-climatic

<table>
<thead>
<tr>
<th>No. of canonical correlation</th>
<th>Canonical correlation ($\rho$)</th>
<th>Chi-square value ($\chi^2$)</th>
<th>Degrees of freedom</th>
<th>Wilk’s value ($A$)</th>
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</thead>
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<tr>
<td>1</td>
<td>0.892</td>
<td>697.54 (90.53)</td>
<td>70</td>
<td>0.040</td>
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<tr>
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<td>54</td>
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</tr>
<tr>
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<td>0.489</td>
<td>96.26 (55.76)</td>
<td>40</td>
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</tr>
<tr>
<td>4</td>
<td>0.262</td>
<td>37.13 (41.34)</td>
<td>28</td>
<td>0.845</td>
</tr>
<tr>
<td>5</td>
<td>0.219</td>
<td>22.81 (28.87)</td>
<td>18</td>
<td>0.907</td>
</tr>
<tr>
<td>6</td>
<td>0.169</td>
<td>12.28 (18.31)</td>
<td>10</td>
<td>0.953</td>
</tr>
<tr>
<td>7</td>
<td>0.138</td>
<td>5.53 (9.49)</td>
<td>4</td>
<td>0.981</td>
</tr>
</tbody>
</table>
variables. In this study the monthly mean values of flow rate (Q), average air temperature ($T_a$), wind speed ($U_w$), solar radiation ($H_s$), relative humidity ($r_h$) projections developed using the CCA downscaling method are used as inputs to the river temperature model to evaluate the projections of river water temperature. The computed future projection of river water temperature for each reach is a function of all the meteorological variables as well as streamflow while keeping other river geometric characteristics and effluent loadings as constant.

There is no control in QUAL2K to correct the reaction rates to account for the future changes of streamflows and water temperatures. The implication of an analytical temperature model will be useful as the computed river temperature for each reach can be linked with reaction rate computation steps. The coefficients of reaeration and deoxygenation should be corrected for the changed scenarios of streamflow and water temperature, which can be done by using the relationships provided by O’Corner–Dobbin (1956) and Maidment (1993) respectively for each reach. The functional relationships of deoxygenation and reaeration are taken from Rehana and Mujumdar (2011), which are dependent on streamflow, water temperature and effluent flow, if river geometry is assumed to be unchanged. This study is aimed to quantify the future river water quality levels for the altered streamflow and the water temperatures. Therefore the rates are computed for the changed scenarios of streamflow and water temperature only, for each reach, which is given as input to the water quality simulation model. The water temperature affected drivers are not only reaeration and BOD decay; in general, the impact will also be on photosynthesis and Sediment Oxygen Demand (SOD). However due to data limitations, this study is limited to BOD decay and reaeration coefficients.

To account for non-point source pollution, a high value of 30 mg/L for BOD and a low value of 4 mg/L for DO are used for the incremental flow in the analysis. The value of incremental flow is calculated based on the gauge stations located at Bhadra (Reach 1), Tunga (Reach 4) and Tunga–Bhadra (Reach 7) rivers. The difference between the sum of the flows at the Bhadra (Lakkavalli) and Tunga (Shimoga) gauge stations and Tunga–Bhadra (Honnali) gauge stations are used to obtain the distributed load per unit distance. This value is used as incremental flow throughout the river stretch, to account for non-point source pollution due to runoff (Subbarao et al., 2004; Rehana and Mujumdar, 2009). The incremental flow computation is based on the streamflows at locations Lakkavalli, Shimoga and Honnali. Therefore the streamflows downscaled at these locations are used to compute the incremental flow for the future scenarios by keeping the effluent discharges as constant.

Further it is assumed that industries and their effluents will remain unchanged in future as it is difficult to understand and predict the future pollution levels. However PCBs maintain river water quality by setting some safe permissible limits for the industries. For example, the standard on effluent discharges requires that the effluent BOD should not exceed 15 mg/L which can be considered as the constant effluent loading for the industries and municipal effluents for the future scenarios. The projections of river water quality indicators and the optimal decision policies are studied when the dischargers are at safe permissible limits.

5. Low water quality risk quantification

A functional approach is developed to translate the projections of river water quality variables (streamflow and water temperature) to the predictions of the probability of failure of a river system in terms of occurrence of LWQ. The conventional definition of LWQ is any concentration of the water quality indicator less than a specified value, say, $c^{min}$, the minimum permissible level at check point, $l$, corresponds to a LWQ. In this study the river water quality indicator of interest is DO, which can be described by streamflow and water temperature as predictor variables. As the predictor variables considered are multiple, the MLR is adopted to model the probability of DO level being less than a specified threshold. The threshold value used in this study is the permissible level of DO at a check point. The crisp definition of risk of LWQ, with water quality indicator as DO (e.g., Mujumdar and Sasikumar, 2002) is given as:

$$r_l = p(c_l < c^{min})$$  \hspace{1cm} (7)

where $r_l$ is the risk of low water quality at check point, $l$; $c_l$ is the DO level at check point, $l$; $c^{min}$ is the minimum permissible level of DO at check point, $l$; $p(c_l < c^{min})$ is the probability associated with the occurrence of the LWQ event. The permissible level of DO is set based on the standards of the water supply in the river. In earlier works (e.g., Ghosh and Mujumdar, 2006; Rehana and Mujumdar, 2009) the $p(c_l < c^{min})$, the Probability Density Function (PDF) of the water quality indicator is derived using the Monte–Carlo Simulation (MCS) along with a water quality simulation model. This method may not be appropriate to evaluate the future risk of LWQ accounting for projected stream flow and temperature due to climate change. Therefore a functional approach is developed based on MLR that uses the projections from statistical downscaling to predict the future likelihood of risk levels. The predicted future risk levels can be further used into IFWLAM to obtain the optimal decision policies.

5.1. Multiple Logistic Regression

A generalized approach of MLR is adopted to predict the future risk of LWQ for a given threshold. In this study the historical

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Tunga streamflow (cumecs)</th>
<th>Bhadra streamflow (cumecs)</th>
<th>Kumudavathi streamflow (cumecs)</th>
<th>Haridra streamflow (cumecs)</th>
<th>Honnali streamflow (cumecs)</th>
<th>Average temperature (°C)</th>
<th>Maximum temperature (°C)</th>
<th>Minimum temperature (°C)</th>
<th>Relative humidity (%)</th>
<th>Wind speed (kmph)</th>
</tr>
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<tbody>
<tr>
<td>Observed</td>
<td>160.54</td>
<td>83.18</td>
<td>12.58</td>
<td>12.71</td>
<td>206.41</td>
<td>25.35</td>
<td>31.25</td>
<td>19.44</td>
<td>70.78</td>
<td>3.73</td>
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<td>210.04</td>
<td>25.55</td>
<td>31.48</td>
<td>19.57</td>
<td>69.95</td>
<td>3.74</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>256.34</td>
<td>119.31</td>
<td>21.71</td>
<td>15.10</td>
<td>295.55</td>
<td>1.88</td>
<td>2.77</td>
<td>2.32</td>
<td>10.03</td>
<td>1.26</td>
</tr>
<tr>
<td>Observed</td>
<td>221.36</td>
<td>107.87</td>
<td>15.46</td>
<td>9.74</td>
<td>250.93</td>
<td>1.65</td>
<td>2.40</td>
<td>1.82</td>
<td>7.72</td>
<td>1.17</td>
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</tr>
<tr>
<td>R-square</td>
<td>0.89</td>
<td>0.91</td>
<td>0.81</td>
<td>0.81</td>
<td>0.88</td>
<td>0.92</td>
<td>0.93</td>
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<td>0.96</td>
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</table>

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Kumudavathi streamflow (cumecs)</th>
<th>Haridra streamflow (cumecs)</th>
<th>Average precipitation (mm)</th>
<th>Maximum temperature (°C)</th>
<th>Minimum temperature (°C)</th>
<th>Relative humidity (%)</th>
<th>Wind speed (kmph)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td>160.54</td>
<td>83.18</td>
<td>256.34</td>
<td>1.88</td>
<td>2.77</td>
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<tr>
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<td>0.88</td>
<td>0.92</td>
<td>0.96</td>
</tr>
</tbody>
</table>
monthly streamflow and water temperature and the corresponding DO levels are used to estimate the conditional threshold exceedance probability. Historical monthly data of streamflow and water temperature data for a period of 1988 to 2006 at station Shimoga is used to estimate the conditional threshold probability of DO. Due to the absence of historical data of DO for a long period of 1988–2006, the DO values are simulated using UQA2K for which the model is calibrated with the available data of 2000–2006. The simulated DO values along with the historical streamflow and water temperature are used to fit the logistic regression model. The response variable (i.e., DO) takes on a value of 1 if the value of DO is less than the prescribed threshold and 0 if the value of DO is greater than the prescribed threshold. Logistic regression transforms the estimated probabilities of a binary variable into a continuous response variable. The transformed response is predicted from one or more explanatory variables, and subsequently retransformed back to a value between 0 and 1. The general form of MLR with two explanatory variables to obtain the predicted value of the response is given as (adopted from Helsel and Hirsch, 1995, chapter 15)

$$p(LWQ/(S, WT)) = \frac{\exp(\beta_0 + \beta_1 S + \beta_2 WT)}{1 + \exp(\beta_0 + \beta_1 S + \beta_2 WT)}$$

where \(p(LWQ(S, WT))\) is the probability of occurrence of LWQ, conditioned on streamflow, \(S\) and water temperature, \(WT\). The \(\beta\) coefficients are estimated from the historical data by maximizing the log likelihood function \((L)\) which can be written as:

$$L = \sum_{j=1}^{J} y_j \ln(\hat{p}_j) + (1 - y_j) \ln(1 - \hat{p}_j)$$

where \(y_j\) is the binary observations and \(\hat{p}_j\) is the predicted probabilities for observations \(j = 1, J\). The log of either \(p\) or \(1 - p\) will be negative and therefore \(L\) is a negative number which is maximized to obtain the \(\beta\) coefficients. The log likelihood function, \(L\), is useful to examine whether the logistic model fits the observed data or to estimate the amount of uncertainty explained by the logistic model. This can be done by McFadden’s – \(R^2\) or likelihood – \(R^2\) which is given by

$$R^2 = 1 - \frac{L}{L_0}$$

where \(L_0\) is the log likelihood of the ‘intercept only’ model i.e. the slope coefficients are set to zero. In this application the water quality variable considered is DO which is sufficiently defined by the two predictor variables streamflow (\(S\)) and water temperature (\(WT\)). However this approach may be applied for any other water quality indicator which may need multiple predictors for which a MLR can be adopted.

5.2. Likelihood of low water quality

The likelihood of low water quality for a given forecast of streamflow and water temperature has to be determined. As such, the theorem of total probability (Ang and Tang, 2007; Towler et al., 2010) in its continuous form with conditional variable as streamflow can be written as

$$p(LWQ) = \int_0^\infty p(LWQ/S\), p(S) \, dS$$

Similarly the theorem of total probability in its summation form with conditional variable as streamflow can be written as

$$p(LWQ) = \sum_{i=1}^{n} p(LWQ/S_i), p(S_i)$$

The above expression can be modified with conditional variables as streamflow (\(S_i\)) and water temperature (\(WT_i\)) as follows:

$$p(LWQ) = \sum_{i=1}^{n} \sum_{j=1}^{n} p(LWQ/S_i, WT_j) p(S_i, WT_j)$$

where \(p(LWQ)\) is the total likelihood of LWQ threshold occurrence for a given forecast of \(S_i\) and \(WT_j\); \(p(LWQ/S_i, WT_j)\) is the conditional probability obtained from Eq. (8); \(p(S_i, WT_j)\) is the joint PDF of flow and temperature. The empirical joint PDF of \(S_i\) and \(WT_j\) is computed from the historical data of streamflow and temperatures (Fig. 4). For the quantification of future risk levels the developed logistic model can be applied with the forecasted results of \(S\) and the evaluated \(WT\). The predicted future likelihood of risk levels further can be included in IFWLAM to provide the optimal decision policies for forecasted scenarios. Further adaptation of MLR offers flexibility in assessing the impacts of changing thresholds. For instance, decision makers can choose thresholds based on the water quality requirements to compute the exceedance probabilities of a prescribed water quality indicator. This facilitates fixing the bounds of probabilities of LWQ by choosing the thresholds as minimum and desirable levels of DO.

6. Optimal decision policies for future scenarios

The expression for risk of low water quality, Eq. (13) for future scenarios, is used in a fuzzy optimization model to derive optimal fractional removal levels for the dischargers to minimize the risk of low water quality under projected scenarios. The fuzzy optimization model adopted to study the changes in the resulting optimal decision policies due to changes in the hydro-climate variables accounting for climate change is an IFWLAM developed by Rehana and Mujumdar (2009). The IFWLAM is developed to address various types of uncertainties including randomness (due to the random nature of input variables), imprecision (in specifying the goals of dischargers and PCBs) and partial ignorance (due to missing data in the input variables). The formulation of IFWLAM is given by

$$\text{Max } \lambda$$

$$\frac{x_{m} - x_{m}}{x_{m} - x_{m}} \geq \lambda \quad \forall m$$

$$\frac{r_{l} - r_{l}}{r_{l} - r_{l}} \geq \lambda \quad \forall l$$

$$\frac{r_{l} - r_{l}}{r_{l} - r_{l}} \geq \beta \quad \forall l$$

$$\frac{\alpha + \beta}{2} \geq \lambda$$

$$r_{l} \leq r_{l} \leq r_{l} \leq r_{l} \quad \forall l$$

$$x_{m} \leq x_{m} \leq x_{m} \quad \forall m$$

$$0 \leq \alpha \leq 1$$

$$0 \leq \beta \leq 1$$

$$0 \leq \lambda \leq 1$$

where \(\lambda\) is the minimum satisfaction level of PCBs and dischargers and is to be maximized in the optimization model. \(x_{m}\) and \(x_{m}\) are the minimum aspiration level and maximum acceptable fractional
removal levels for the discharger, $m$. The minimum aspiration level, $x_{Lm}$, and maximum permissible level, $x_{Um}$, of the dischargers are set to 35% and 90%, respectively. $x_m$ is the fractional removal level of the discharger $m$ and is a decision variable in the optimization model for each $m$; $r^l$ and $r^u$ are the minimum acceptable and maximum permissible risk levels. A minimum acceptable risk level, $r^l$, of 0.00 and a maximum permissible risk level, $r^u$, of 1.00 are assumed for the risk levels. $r^l$ and $r^u$ are the upper and lower bounds of imprecise fuzzy risk at check point $l$. $\alpha$ and $\beta$ are the minimum goal fulfillment levels of PCBs, when lower and upper bounds of imprecise fuzzy risks are involved respectively. Generally in any FWLAM the key parameters which define the LWQ are membership parameters of the fuzzy set of low water quality given as the minimum permissible and desirable levels at a check point. If the water quality indicator under consideration is DO, then the minimum and desirable levels of DO at a check point can be considered as lower and upper thresholds to derive the lower and upper bounds of risk levels. The lower threshold as 6.00 mg/L and an upper threshold as 7.43 mg/L (Rehana and Mujumdar, 2009) can be considered in the MLR (Eq. (13)) to evaluate the lower and upper bounds of likelihood of future risk levels which can be utilized in IFWLAM. First MLR is applied with the threshold of 6.00 mg/L and then with 7.43 mg/L to compute the lower and upper conditional threshold exceedance probabilities, $p^{-1}(LWQ)/(S, WT)$ (Eq. (8)). The next step is to compute the future likelihood of risk levels as, $p^l(LWQ)$ (Eq. (13)). In this analysis the fuzzy risk is not considered, only crisp risk with an upper possibility $p^u(LWQ)$ and a lower possibility $p^l(LWQ)$, computed from total likelihood of risk by changing the thresholds, are considered. With this the IFWLAM is modified to incorporate the future probability of failure of the river system. The goal of PCBs is considered as minimization of both the possibilities of future likelihood of risk levels for which the formulation of IFWLAM needs some modifications. The goal of PCBs (Eqs. (16) and (17)) are modified as follows:

$$\frac{r^u - p^{-1}(LWQ)}{r^u - r^l} \geq \alpha \quad \forall l$$

$$\frac{r^u - p^l(LWQ)}{r^u - r^l} \geq \beta \quad \forall l$$

The constraint related to risk bounds (Eq. (19)) is also modified as follows:

$$r^l \leq p^{-1}(LWQ) \leq p^l(LWQ) \leq r^u \quad \forall l$$

The goals of dischargers and the remaining constraints are kept unchanged in the IFWLAM. Further the likelihood of risk values computed in this study is at the location Shimoga along Tunga river, based on the availability of observed data, which have been considered as same for other check points also throughout the river stretch considered. The reaction rates are corrected with the projections of streamflow and the simulated river water temperature for each reach. IFWLAM is run by including the future projections of streamflow, water temperature, the corrected reaction rates and the bounds of future likelihood of risk levels to obtain the optimal fractional removal levels for the future scenarios.

7. Results and discussion

7.1. Future projections from downscaling

CCA downscaling model is used to derive the changes in monthly mean hydro-climate variables the outputs of MIROC 3.2 GCM variables for 30-year time slices with periods 2010–2040, 2040–2070 and 2070–2100 as shown in Figs. 5 and 6 and Table 5. Fig. 5 presents box plots of the observed and predicted streamflows by GCM for the MIROC 3.2 GCM with A1B scenario, for the periods 2010–2040, 2040–2070 and 2070–2100. A significant decreasing trend is observed in streamflow at various locations along Tunga–Bhadra river basin. The results show that although there is no significant change in the mean values for each of the period as shown in the box plots with a horizontal line connecting the mean values represented as stars. The change in streamflow will have a significant effect on the incremental flow volume, used for estimation of non-point source pollution. Therefore the incremental flow projections are computed from the streamflow projections obtained from CCA downscaling for the locations Lakkavalli, Shimoga and Honnali. There is an increase in the incremental flow volume for the future scenarios. The historical value is 0.79 cumecs/km whereas for 2010–2040 it is 0.85 cumecs/km, for 2040–2070 it is 0.93 cumecs/km and for 2070–2100 it is 1.01 cumecs/km. The incremental flow mainly depends on the difference in the flow volume between the gauge stations of Lakkavalli, Shimoga and Honnali as the effluent flows are assumed as constant for the future scenarios. Such incremental flows computed for each 30 year time slices are used in the water quality model as non-point source pollution due to runoff.

GCC predicted meteorological variables also resemble well with the observed data (A) in Figs. 6(i)–(v)) with increasing trends in temperature variables and minor changes of wind speed and relative humidity along the Tunga–Bhadra river basin ((B) in Figs. 6(i)–(v)). Temperature variables (average, maximum and minimum) are well simulated by GCM with CCA downscaling. The climate variables are downscaled at Shimoga along Tunga river due to the availability of observed data at this location. The projected climate variables are pooled from a large spatial scale data which represent the average variability of the entire basin. Therefore the GCM derived projections of climate variables at Shimoga station is considered as the variability of the metrological variables for the entire river stretch considered for river quality assessment.

As CCA is a linear prediction model, the change in the mean values only can be captured well having small variability in the data sets. A major limitation in CCA model is the relation between the climate predictor variables and surface predictand variables is constrained to be linear, which may not reflect accurate relationship between two data sets. In addition to this the performance of this
The statistical downscaling method is dependent on the number of PCs retained, the number of CCA components used in the regression model and also on the training data sets. Particularly CCA uses dominant features in the predictor fields based on the PCs retained, and leads to ignore the less dominant but important local and regional features in the predictor fields. However, downscaled results

![Box plots of observed and predicted streamflow](image)

**Fig. 5.** Results of observed and CCA predicted from MIROC 3.2 GCM (A1B) for Streamflow using box plots at various locations along the Tunga–Bhadra river, (i) Shimoga along Tunga river, (ii) Lakkavalli along Bhadra river, (iii) Koppelur along Kumudavathi river, (iv) Byladahalli along Haridra river, (v) Honnali along Tunga-Bhadra river. The horizontal line in the middle of the box represents median. The star denotes the mean value of the period under consideration while the line connecting the stars depicts the mean trend of streamflow projected by GCM. In these figures, (A) gives the validation of the GCM predicted data with the observed data for periods given in Table 1 and (B) gives the future projections with the GCM.
can be substantially improved by including longer training data series as accuracy may be limited by representativeness of the training data for the current situation.

7.2. Future projections of water quality

The observed and computed river temperature at Shimoga along Tunga river is shown in Fig. 7. The analytical water temperature model is calibrated with 10 years (1988–1997) observed data and validated with 9 years (1998–2006) data. Even though the resulting river water temperature dependents on many factors including human modifications such as impoundments and waste water inputs or by ground water inflows, this study includes only ambient climate variables affected by climate change. The calibrated QUAL2K model using 6-years monthly data is used to simulate the river water quality for the present and future.
Table 5
Comparison of observed and GCM simulated mean values of predictands.

<table>
<thead>
<tr>
<th>Hydro-climate variable</th>
<th>Observed</th>
<th>GCM simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2010–2040</td>
</tr>
<tr>
<td>Tunga streamflow (cumecs)</td>
<td>160.54</td>
<td>151.67</td>
</tr>
<tr>
<td>Bhadra streamflow (cumecs)</td>
<td>83.18</td>
<td>81.99</td>
</tr>
<tr>
<td>Kumudavathi streamflow (cumecs)</td>
<td>12.58</td>
<td>9.69</td>
</tr>
<tr>
<td>Haridra streamflow (cumecs)</td>
<td>12.71</td>
<td>11.94</td>
</tr>
<tr>
<td>Honnali streamflow (cumecs)</td>
<td>206.41</td>
<td>198.45</td>
</tr>
<tr>
<td>Average temperature (°C)</td>
<td>25.35</td>
<td>25.79</td>
</tr>
<tr>
<td>Maximum temperature (°C)</td>
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<td>Minimum temperature (°C)</td>
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<td>19.55</td>
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<td>Relative humidity (%)</td>
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<tr>
<td>Wind speed (kmph)</td>
<td>3.73</td>
<td>3.72</td>
</tr>
</tbody>
</table>

![Fig. 7](image-url)

Fig. 7. Observed and predicted river water temperature projections at Shimoga, computed from analytical river temperature model. (A) gives the validation of the simulated data with the observed data for period of 1988–2006 and (B) gives the future projections.

conditions. For future assessments the monthly average values of downscaled hydro-climate projections of MIROC 3.2 GCM climate scenarios with 30-year time slice data (Table 5) are considered as steady state values in water quality simulation model, QUAL2K to quantify the future changes in DO levels. Fig. 8 shows the observed and future simulated DO levels for 30-year time slices (2010–2040, 2040–2070 and 2070–2100) at various check points along the river stretch. These critical check points (1, 2, and 11) are the locations immediately downstream of the effluents, where the quality levels may go down drastically. The other critical check points considered for the analysis are check point 5 (confluence point of Tunga and Bhadra rivers), 10 (upstream of a discharger) and 14 (last check point of the considered river stretch). At check point 5 where the current DO level is at 6.80 mg/L it may go down to 5.60 mg/L in 2080s. It should be noted that even though this check point is not immediately downstream of a discharger, the DO levels show a significant decrease. The DO levels obtained for the future scenarios will give an idea of the future impairment of river water quality.

7.3. Low water quality risk quantification

The future projections of river water quality have been included into a probabilistic approach to quantify the future risk levels. The MLR is applied by changing the thresholds of minimum (6.0 mg/L) and desirable level (7.43 mg/L) of DO to compute the lower and upper possibilities of LWQ, conditioned on streamflow, S and water temperature, WT. Using the estimates (Table 6) produced by the maximum likelihood estimation procedure for S and WT (Eq. (8)), we write the following equations for the estimation of the upper and lower bounds of probability of occurrence of LWQ, conditioned on streamflow, $S$ and water temperature, $WT$.

$$p^+(LWQ/(S, WT)) = \frac{\exp(5.82 + (-0.07) \times S + (0.1) \times WT)}{1 + \exp(5.82 + (-0.07) \times S + (0.1) \times WT)}$$ (27)

$$p^-(LWQ/(S, WT)) = \frac{\exp(4.94 + (-0.03) \times S + (0.12) \times WT)}{1 + \exp(4.94 + (-0.03) \times S + (0.12) \times WT)}$$ (28)

The MLR showed that logistic model performed better in terms of McFadden’s $−R^2$ (Table 6) for both lower and upper bounds of conditional probabilities computation. Further the $\beta$ coefficients represent the changes in the response variable (DO, in this case) associated with changes in the independent variables. A positive $\beta$ coefficient represents that an increase in the independent variable is associated with an increase in the predicted probability, and vice versa. The negative $\beta$ coefficients for $S$ indicate there will be negative impact of $S$ on LWQ as decrease in streamflow decreases DO levels and therefore consequent increase in the probability of occurrence of LWQ. Similarly positive $\beta$ coefficients for $WT$ is due to the positive impact of $WT$ with LWQ, as increase in $WT$ decreases DO levels and therefore consequent increase in the probability of occurrence of LWQ. The resulting conditional probability functions (Eqs. (27) and (28)) obtained from MLR based on historical monthly streamflow and water temperatures are used in the computation of future likelihood of risk levels.

Fig. 9 shows the likelihood of low water quality by varying the thresholds. The $P(LWQ)$ with a threshold of 6.0 mg/L represents the
The lower bound of the future likelihood of risk level and upper bound of risk level with threshold of 7.43 mg/L. The values of \( P(LWQ) \) with 6.0 mg/L as threshold are less than the values of \( P(LWQ) \) with 7.43 mg/L as threshold as there is a more chance of occurrence of LWQ event with the threshold of 7.43 mg/L. Both the bounds of risk of occurrence of LWQ are increasing in the future (Fig. 9). The quantified bounds of future risk levels were included in the optimization model to obtain the optimal fractional removal levels by minimizing both the bounds of future likelihood of risk levels.

---

**Table 6**

<table>
<thead>
<tr>
<th>Logistic model</th>
<th>Coefficients</th>
<th>Goodness-of-fit statistics</th>
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</thead>
<tbody>
<tr>
<td>( b_0 )</td>
<td>( b_1 )</td>
<td>( b_2 )</td>
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<tr>
<td>Lower bound, ( P^-(LWQ) )</td>
<td>5.82</td>
<td>-0.07</td>
</tr>
<tr>
<td>Upper bound, ( P^+(LWQ) )</td>
<td>4.94</td>
<td>-0.03</td>
</tr>
</tbody>
</table>

**Fig. 8.** Present and future estimates of DO levels at various check points along Tunga–Bhadra river.

**Fig. 9.** Likelihood of low water quality, \( p(LWQ) \), for two DO thresholds.

**Fig. 10.** Optimal fractional removal levels under MIROC 3.2 GCM with A1B scenario: current and projected treatment policy.
7.4. Decision policies the projected scenarios

The predicted lower and upper likelihood of future risk values along with the projected scenarios of hydro-climate variables are used in the IFWLAM to evaluate the future decision policies for each of the Discharger. Under MIROC 3.2, A1B scenario, the optimal fractional removal levels may reach up to 90% during the period 2070–2100 (Fig. 10), which is not desirable. It may be noted that the maximum fractional removal level assigned to each of the discharger in the fuzzy optimization model is also 90%. The adaptive treatment policies are developed when the effluents are at safe permissible levels. The results suggest that the dischargers have to improve their treatment levels even if they preserve the current standards, in accordance to changes in the hydrological and climate variables. Therefore to achieve better river water quality levels in the future the current standards have to be improved significantly. A substantial modification in the current river water quality standards may be necessary to account for the future vulnerabilities of river water quality.

The future projections of river water quality indicators and the decision policies to be adopted are due to a single GCM using a single scenario. It is widely acknowledged that the mismatch between different GCMs over regional climate change projections represents a significant source of uncertainty (e.g., New and Hulme, 2000; Simonovic and Li, 2004; Wilby and Harris, 2006; Ghosh and Mujumdar, 2007). Therefore future decision making should include all the GCMs with scenarios to model the underlying GCM and scenario uncertainty.

8. Concluding remarks

The modeling framework of risk assessment proposed in this paper integrates climate change projections with a river water quality management model. The MIROC 3.2 GCM with A1B scenario, when applied to the case study of the Tunga–Bhadra river, projects a decreasing trend in future streamflow for tributaries of Tunga, Bhadra, Kumudavathi, and Haridra. The air temperature shows an increasing trend, with minor changes of relative humidity and wind speed observed. Increase in air temperature variables (daily maximum and minimum) are also observed along Tunga–Bhadra river with HADCM3 GCM under A2 and B2 scenarios in the study of Meenu et al. (2011). They found the maximum daily temperature in Tunga–Bhadra river basin with HADCM3 GCM under A2 scenario is increasing by 1, 2.1 and 3.4 °C, respectively, in the 2020s, 2050s and 2080s. These results are comparable with the downscaled results of monthly maximum temperature with MIROC 3.2 GCM with A1B scenario, with increasing by 0.13, 1.18, 2.16 °C respectively, in the 2010–2040, 2040–2070, 2070–2100. Steady state DO levels were simulated for the present and for the future time slices of 2010–2040, 2040–2070 and 2070–2100 by using QUAL2K. Significant impairment of water quality has been observed with the decrease in DO levels. This is due to the reduced dilution capacity and low water velocities derived from the reduced streamflows and also due to the changes in reaction rates derived from the increase in water temperature. Future estimates show that the DO levels may go down up to 3.56 mg/L (at the most critical check point, 2, for the period 2070–2100) along the considered river stretch, for the same current conditions of effluent discharges and river geometry. Such degradation of DO levels are also observed along Tunga–Bhadra river with hypothetical scenarios of streamflow and temperatures in the study of Rehana and Mujumdar (2011). The water quality degradation with the GCM simulated outputs has been found to be more (with a decrease of DO as 3.56 mg/L) than with the hypothetical scenarios (with decrease in DO as 1.02 mg/L) when compared with the current DO levels. However the increase in air temperature for the future scenarios with the GCM modeled outputs of the present study (2.16 °C) is comparable with the hypothetical scenario of 2 °C increase in air temperature used in Rehana and Mujumdar (2011). The lower and upper possibilities of future likelihood of risk levels are quantified by varying the DO thresholds. This approach revealed the increasing tendency of risk levels of LWQ in future. The IFWLAM considers the downscaled projections of streamflow, simulated river water temperature and the predicted lower and upper likelihood of future risk values to evaluate the future decision policies for each of the Discharger. This way the utility managers can incorporate climate change projections in their decision policies. The results indicate that the optimal fractional removal levels required for the future scenarios will be higher compared to the present levels, even if the effluent loadings remain unchanged. With this one can conclude that the current standards for the dischargers have to be modified to account for the future variability of water quality levels. The methodology developed can be used to project the hydro-climate indices for other GCMs and scenarios also and there is a possibility of mismatch in the projections resulting GCM and scenario uncertainty. Although such uncertainties are important for studies requiring detailed hydrological inputs, analyses based on the more stable GCM hydro-climate estimates can still address many crucial water quality issues.

References
