Modeling of extreme risk in river water quality under climate change

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ABSTRACT

A river water quality management model under average climatic conditions may not be able to account for the extreme risk of low water quality which is more prominent under an increase in river water temperature and altered river flows. A modeling framework is developed to assess the risk of river low water quality extremes by integrating a statistical downscaling model based on Canonical Correlation Analysis, risk quantification model based on Frank Archimedean Copula function and multiple logistic regression model integrated with a river water quality simulation model, QUAL2 K. The results reveal that the combination of predicted decrease in low flows of approximately 57% and increase in maximum river water temperatures of approximately 1.2°C has shown an increase of about 46% in risk of low water quality conditions for the future scenarios along Tunga-Bhadra River, India. The extreme risk of low water quality is observed to increase by 50.6% for the period 2020–2040 when compared with the current extreme conditions of 4.5% and average risk conditions of about 3% for the period 1988–2005. The study captured the occurrence of extremes of low water quality with evidence of a strong link between climate and water quality impairment events.

Key words | Canonical Correlation Analysis, Copula, multiple logistic regression model, QUAL2 K, statistical downscaling

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INTRODUCTION

River water quality parameters are directly affected by any changes in climate, which in turn increases the risk of deterioration of the river ecosystem. Higher water temperatures and changes in extremes, including floods and droughts in the future, are projected to influence water quality and exacerbate many forms of water pollution (Bates *et al.* 2008). An increase in river water temperature due to an increase in air temperature under climate change has been the subject of several studies (e.g. Mohseni *et al.* 2003; Morrill *et al.* 2005; van Vliet *et al.* 2011; Li *et al.* 2014), questions investigating how climate change will affect river water quality extremes has obtained limited attention.

In this context, the use of logistic regression models for predicting the probability of river water quality parameters exceeding a threshold is a recent development in river water quality management (e.g. Smith *et al.* 2001; Towler *et al.* 2010; Rehana & Mujumdar 2012) and climate variability and related health implications studies (e.g. Baguma *et al.* 2014). Towler *et al.* (2010) developed a methodology based on the generalized extreme value model to quantify maximum flow distributions which is further used to calculate the risk of water quality for a given threshold of turbidity using a logistic regression method. Rehana & Mujumdar (2012) developed a multiple logistic regression model (MLRM) with streamflow and river water temperatures as explanatory variables to model the threshold exceedance of dissolved oxygen (DO) under long term climatic averages of river water quality conditions and climate change. Climatic averages are important, however, the river water quality extremes can be expected to be more sensitive than

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average conditions, in response to climate change. Rehana & Mujumdar (2012) studied the monthly average streamflow and river water temperatures influence on river water quality under climate change; however, the critical combination of maximum river water temperatures and minimum flow conditions was not considered. An extreme scenario of river water quality can be expected when the river water temperature is at its maximum and when streamflow is at its minimum (i.e. low flow conditions), which can be expected during non-monsoon periods for most of the Indian rivers. Hence, the minimum streamflow and maximum river water temperature at a particular river location will be the worst case scenario with respect to river water quality. Knowing this, another related question that arises is how to assess the river water quality extremes under such critical combinations of maximum river water temperatures and minimum flows. Most of the studies consider the 7Q10 flow as the design flow, which is the minimum average 7-day flow that would be expected to occur once in every 10 years (Thomann & Mueller 1987). This is the smallest flow that would be expected to occur for seven consecutive days and is generally considered as the minimum design flow in river water quality modeling. The present study utilizes the minimum 7-day average consecutive flow values over a particular month as the extreme flow in the assessment of risk of river water quality under climate change.

In order to model the maximum river water temperature, a statistical model is needed which can relate both air and water temperatures. Several authors adopted different statistical methods such as linear regression models to predict river water temperature, with air temperature as a predictor variable, due to the ease of implementation (e.g. Neumann *et al.* 2003; Caissie 2006; Rehana & Mujumdar 2011, 2012). However, as the air temperature increases, the moisture holding capacity of the atmosphere increases and the rate of evaporative cooling often increases, and therefore the stream temperature no longer increases linearly with air temperature (Mohseni *et al.* 1998; Bogan *et al.* 2003). As the air and water temperature linear regression models may not be preferable at higher temperatures, the present study adopted a non-linear logistic regression model developed by Mohseni *et al.* (1998) to predict the monthly maximum river water temperature. To estimate the threshold exceedance probability of a water quality indicator, a multiple logistic regression (MLR) model is adopted, with streamflow and water temperature as the predictor variables and water quality parameter threshold exceedance as the predictand variable.

To quantify the extreme risk of river water quality in terms of any water quality indicator (DO, biochemical oxygen demand (BOD)), the joint behavior of minimum streamflow and maximum river water temperatures has to be estimated. The study of Rehana & Mujumdar (2012) used an empirical joint probability distribution of monthly average streamflow and river water temperatures to estimate the risk of low water quality for a given DO threshold. The joint distribution as estimated by previous studies had (i) not taken into account the dependency between the variables and (ii) assumed the same marginal probability distribution for all variables. Hence, in order to rectify these, a Copula-based function was adopted in the present study to estimate the joint probability distribution function of the calculated monthly minimum 7-day average consecutive low flows and daily maximum river water temperature. The occurrence of risk of river water quality extremes was then studied considering the projections of streamflow and the modeled river water temperatures for the current and future scenarios. The specific research contributions of the present study, when compared to the past studies are: (i) estimation of risk of low water quality for the critical combinations of maximum river water temperature (using a non-linear regression river temperature model) and minimum streamflows (using 7Q10 values); and (ii) estimation of combined behavior of maximum river water temperature and minimum streamflows (using Copula function). To accomplish these, the objectives of the work are set as: (i) downscaling the future projections of streamflow and air temperatures from the large-scale climate variables from the global circulation model (GCM) outputs; (ii) modeling the monthly maximum river water temperature using a non-linear logistic regression model; (iii) modeling the river water quality extremes for current and future scenarios using a river water quality simulation model; (iv) quantification of extreme water quality threshold using a MLRM; (v) using Copula to model the joint distribution of low flow and maximum river water temperatures; and (vi) assessing the extreme risk of low water quality for current and future scenarios.

METHODOLOGY

Study area

The Tungabhadra River, one of the main tributaries of the Krishna River, is highly polluted due to the rapid growth of urban industries located along it. The majority of the river stretch is polluted due to effluents from paper, pulp, rayon and steel industries such as Mysore paper mill and Harihar polyfibre. Tunga River (147 km long) and Bhadra River (178 km long), join at Kudli, which is about 14.5 km from Shimoga city, to form the Tungabhadra River (Figure 1). The river location considered for the quantification of extreme risk of low water quality is Shimoga, along the Tunga River. The river location receives the waste load from Shimoga city municipal effluent. The potential effects of climate change on the Tungabhadra River's water quality have been identified in earlier studies. For instance, a significant increase in air temperature and decrease in streamflow (about 3.1% at Shimoga) along Tunga River were reported (Rehana & Mujumdar 2011). Furthermore, the streamflow along the Tungabhadra River was projected to decrease by 21% and air temperature was projected to increase approximately 1.66 °C for the period from 2070 to 2100 according to MIROC 3.2 GCM (Rehana & Mujumdar 2012).

Data

The daily streamflow and river water temperature data from 1988 to 2005 recorded at Shimoga station were obtained from the Central Water Commission (CWC), Karnataka, India. Large-scale climate predictor variables considered were air temperature, mean sea level pressure, specific humidity, U-wind, V-wind and zeopotential height, based on earlier studies on the region of interest (Rehana & Mujumdar 2012). The National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis data (Kalnay *et al.* 1996) is generally considered as a surrogate of observed data sets of predictor variables. The NCEP/NCAR reanalysis data for the considered predictors with a resolution of $2.5 \times 2.5^\circ$ was extracted for a region of 10–20° N to 70–80° E, for the period of January 1948 to December 2005. Six NCEP grid points fell over the region considered, i.e. 10–20° N to 70–80° E. The daily streamflow, air temperature data and predictor set for a period of 10 years (1988–1998) were used for calibrating the downscaling model and the data from 1999 to 2005 were used for validation. The future climate variables were obtained from the simulations of the Beijing Climate Center (BCC-CSM1-1) model output by the Beijing Climate Center, China Meteorological Administration, considered in CMIP5 (Coupled Model Intercomparison Project 5). The BCC-CSM1-1 model was selected based on the availability of CMIP5 projections of predictor variables to demonstrate the modeling of extreme risk of river water quality. In this study, we restricted our analyses by considering only one GCM, i.e. the BCC-CSM1-1 model. The different future scenarios are available in the form Representative Concentration Pathways (RCPs). Among these, RCP 8.5 represents the high concentration mitigation pathway, which continues to rise throughout the 21st century, and RCP 2.5 represents the mildest scenario. In this study, for demonstration purposes, we have only considered the RCP 8.5 scenario. The daily GCM projections for historical scenario and future RCPs were obtained from http://cmip-pcmdi.llnl.gov/cmip5/data_portal.html. Predictor variables were extracted for historical scenarios for the period 1950–2012 and for RCPs for the period 2006–2099, from the BCC-CSM1-1 model, for a spatial resolution of $2.8 \times 2.8^\circ$.

Model framework for risk quantification

The modeling framework to assess the river water quality extremes under climate change included a statistical downscaling model based on a Canonical Correlation Analysis (CCA) statistical downscaling model, a non-linear river water temperature model, a river water quality simulation model, MLRM and Copula based joint distribution (Bardossy & Pegram 2009; Shi & Xia 2017) of streamflow and water temperature, as shown in Figure 2. First, the climate change induced projections of streamflow and air temperatures were obtained from the CCA statistical downscaling model. The air temperature projections were used as independent variables in a non-linear regression model to predict the daily river water temperature. The river water quality simulation model QUAL2 K was used to simulate the DO levels under the scenario of maximum river water

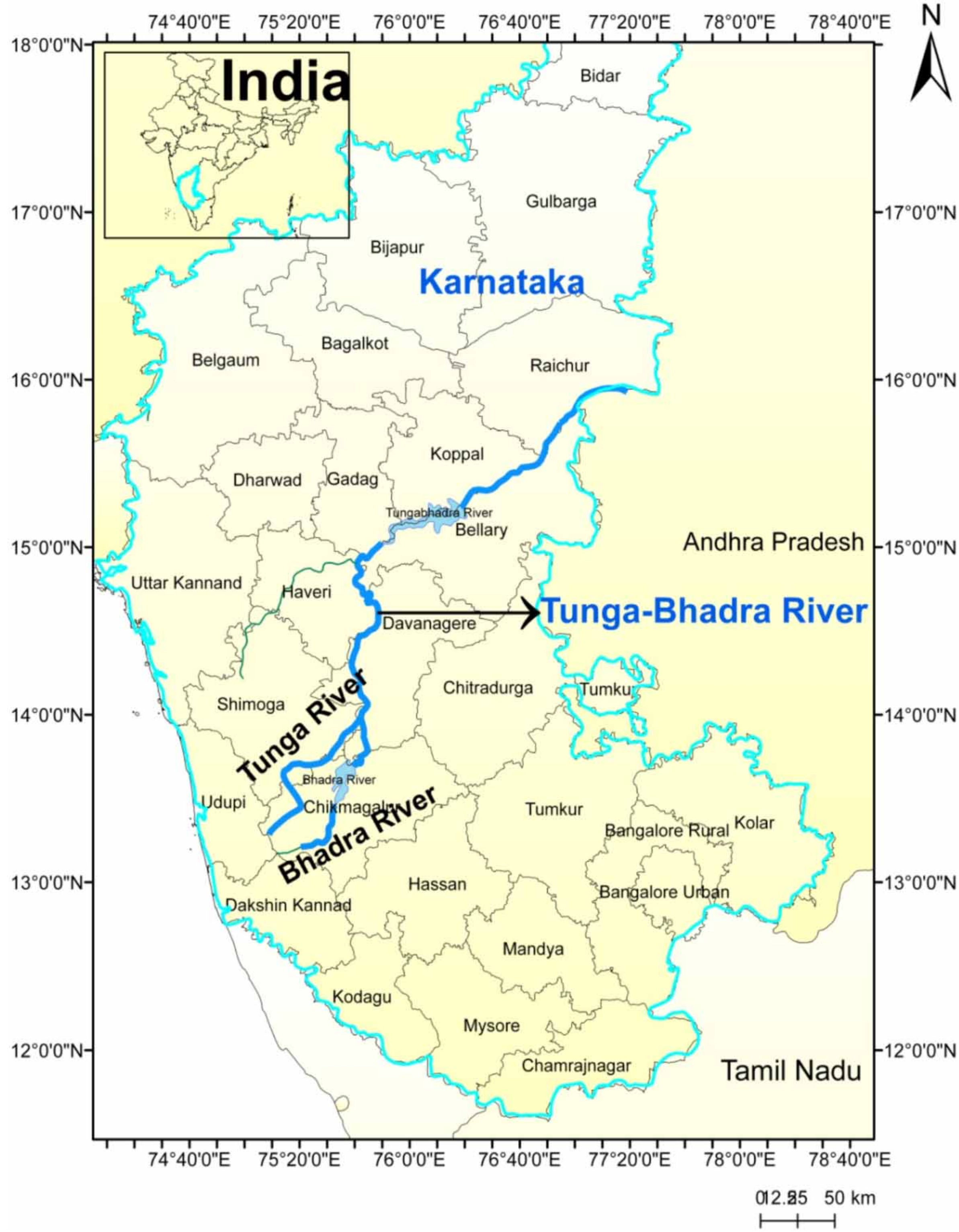

Figure 1 | Location map of Tunga-Bhadra River, India.

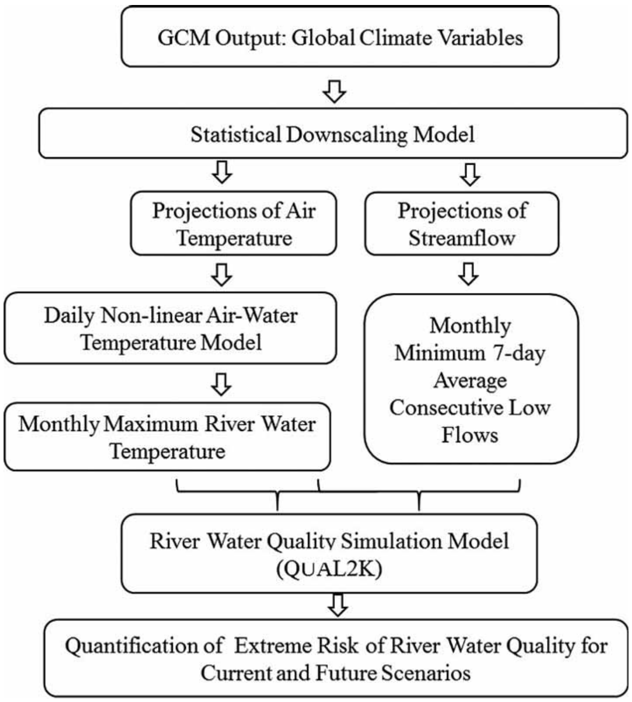

Figure 2 | Overview of the quantification of river water quality extremes under climate change.

temperatures and minimum 7-day average consecutive low flows. The extreme risk of low water quality levels were estimated for current and future scenarios for the given thresholds of DO levels using a MLRM.

CCA statistical downscaling model

To develop the climate change projections of streamflow and air temperatures at a river location, a multivariable statistical downscaling methodology based on CCA, developed by Rehana & Mujumdar (2012), was deployed. The performance of the downscaling model on a monthly scale is explained in detail in Rehana & Mujumdar (2012). CCA is a multivariable linear prediction model used for simultaneous projection of regional variables from large scale climate variables. The predictor variables extracted from NCEP/NCAR reanalysis data were used for removing the bias in GCM predictor variables. A linear interpolation is performed to re-grid the GCM projections to NCEP grid points. The base line period was considered as 1960–1990. Data was preprocessed to reduce systematic biases in the mean and variances of GCM predictors relative to the observed or NCEP/NCAR data, by normalization. Principal component analysis (PCA) was then performed in this normalized predictor dataset, to reduce the dimension of predictor dataset. A few principal components (PCs), which capture maximum variance, were then retained. These PCs were then considered as the predictor canonical variables, while daily streamflow and average air temperature served as predictand canonical variables in the CCA model (Equations (1) and (2)):

$$U_m = a^T X, q = 1, \; \ldots . \min(N, M) \tag{1}$$

$$V_m = b^T Y, q = 1, \; \ldots . \min(N, M) \tag{2}$$

where U_m and V_m are predictor and predictand canonical variables respectively, $a = [a_1, a_2, \ldots a_N]^T$ and $b = [b_1, b_2, \ldots b_N]^T$ are canonical loadings or weights. The canonical correlation, ρ_{c_q}, between predictors canonical variable, U_q and predictand canonical variable, V_q is maximum.

The canonical coefficients or loadings of the predictor and predictand variables were estimated for a given training period from 1988 to 1998 and the estimated loadings were used for the testing period from 1999 to 2005. Optimally correlated patterns between large scale climate variables and surface based observations were identified in terms of canonical regression equations which were back transformed to develop streamflow and air temperature predictions. Statistical relationships developed based on observed data were driven with GCM projected climate variables to obtain the future projections of streamflow and air temperatures.

Non-linear stream temperature regression model

A non-linear regression model representing the S-shaped function between weekly air and water temperatures based on the approach of Mohseni *et al.* (1998) was adopted in the present study to estimate the daily river water temperature. The four parameter non-linear daily stream temperature model (T_s), which considers the daily air temperature (T_a) as an independent variable, is given as follows:

$$T_s = \mu + \frac{\alpha - \mu}{1 + e^{\gamma(\beta - T_a)}} \tag{3}$$

$$\gamma = \frac{4 \tan\theta}{\alpha - \mu} \tag{4}$$

where α is the upper bound of stream water temperature, μ is the lower bound of stream temperature, γ is the measure of the slope at the inflection point of the function, β is the air temperature at the inflection point, and $\tan\theta$ is the slope at the inflection point. The values of α, β, γ and μ can be determined by a least square regression method. The developed stream temperature model was then driven with the downscaled future projections of air temperature to obtain the future daily river water temperature along the Tungabhadra River. The monthly maximum river water temperatures were extracted from the daily water temperatures obtained.

Water quality simulation model

A surface river water quality model is a useful tool to simulate and predict the risk of biological and chemical pollutants for a given river stretch. A stream water quality simulation model, QUAL2 K, was used to simulate the river water quality indicator responses for the given streamflow and river water temperature scenarios. QUAL2 K is a widely accepted river water quality simulation model developed by Chapra & Pelletier (2003) for the evaluation of impacts of pollutants on quality indicators (e.g. Park & Lee 2002; Fan *et al.* 2009; Chaudhary *et al.* 2017). QUAL2 K is programmed in the Windows macro language, Visual Basic for Applications (VBA) with Excel as the graphical user interface. The United States Environmental Protection Agency (USEPA) provides the downloadable version (http://epa.gov/athens/wwqtsc/html/qual2 k.html) along with the user manual for the execution of QUAL2 K. Although water temperature can be simulated with QUAL2 K by including various meteorological variables, it cannot be used for the evaluation of maximum river water temperatures from changes in the air temperature as the predictor variable. Therefore, the present study used the monthly maximum river water temperatures estimated from the non-linear stream temperature regression model and the 7-day average consecutive low flow of a month as inputs in QUAL2 K to simulate the river water quality indicators. DO is one of the important river water quality indicators, which defines the extent of pollution levels in rivers. In general, the calibration of any water quality model involves calibration of reaeration and deoxygenation coefficients. QUAL2 K model was calibrated with observed data for the period 2000–2006, to simulate the DO responses. Furthermore, the deoxygenation coefficient depends mainly on river water temperature and streamflow and effluent flow (Maidment 1993) and the reaeration coefficient depends on diffusivity coefficient of oxygen, stream velocity and average depth of flow (O'Connor & Dobbins 1956). Therefore, the reaction rates were corrected for the changes in streamflow and stream water temperatures following the functional relationships of deoxygenation and reaeration according to Maidment (1993) and O'Connor & Dobbins (1956). Once calibrated, the QUAL2 K model was run to simulate the DO for the historical and future scenarios of streamflow and river water temperatures. For repeated simulations, the QUAL2 K model was coupled to the MATLAB (2014) platform externally (Chaudhary *et al.* 2017).

Multiple logistic regression model

The MLRM model was used to explain how the river water quality variable projections can be used to predict the failure of a river system in terms of the possible occurrence of a low water quality event for a given threshold value of a water quality indicator. The historical monthly streamflows, water temperatures and corresponding DO levels were used to estimate the conditional threshold exceedance probability. In this context, if the simulated DO level is less than the minimum permissible level for a given streamflow and water temperature condition, then it was considered as a low water quality event. Generally, the minimum permissible value can be assigned based on the standards of the water supply in the river. In this study, a minimum permissible level of 4.00 mg/L was considered based on the Central Pollution Control Board (CPCB) (www.cpcb.nic.in/Water_Quality_Criteria.php) recommendation to maintain ecological stability of a river and the propagation of wildlife and fisheries. The simulated DO values for the period from 1988 to 2005, along with the historical streamflow and water temperature, were used to fit the logistic regression model as given in Equation (5) (Helsel & Hirsch 1995):

$$P(LWQ/(S, WT)) = \frac{\exp(\beta_0 + \beta_1 \times S + \beta_2 \times WT)}{1 + \exp(\beta_0 + \beta_1 \times S + \beta_2 \times WT)} \qquad (5)$$

where $P(LWQ/(S, WT))$ is the probability of occurrence of low water quality (LWQ), conditioned on streamflow (S)

and water temperature (WT). The predictor variables of MLRM were monthly maximum river water temperature and monthly minimum 7-day average consecutive low flow, whereas the dependent variable takes on categorical values of '1' if the value of DO is less than the threshold and '0' if the value of DO is greater than the prescribed threshold. The logistic regression coefficients β_0, β_1 and β_2 can be estimated from the historical data by maximizing the log likelihood function. The probability of occurrence of extreme low water quality can be estimated using the total probability theorem (Ang & Tang 2007; Towler *et al.* 2010). Here, the conditional probability of extreme low water quality estimated from MLRM were combined with the joint probability density function (PDF) of monthly low flows and maximum river water temperatures (Rehana & Mujumdar 2012), as follows:

$$P(LWQ) = \sum_{i=1}^{n}\sum_{j=1}^{n} P(LWQ/S_i, WT_j)P(S_i, WT_j) \tag{6}$$

where $P(LWQ)$ is the probability of occurrence of extreme LWQ for a given projections of S_i and WT_j; $P(LWQ/S_i, WT_j)$ is the conditional probability of LWQ for a given S_i and WT_j obtained from Equation (5); $P(S_i, WT_j)$ is the joint PDF of minimum monthly low flows and maximum river water temperatures. The logistic regression model fitted with the observed data was then driven with future projections of streamflows, water temperatures and DO levels, to predict the possibilities of occurrence of risk of low water quality for future scenarios.

Copula function

The Archimedean family of Copulas were investigated to find a best fit joint PDF monthly low flows and maximum river water temperatures. The Archimedean Copula is also found to be more suitable for hydrologic event analysis and it can be applicable for both positive or negative correlations (Nelsen 1999). More details of Copula and different families can be found in Nelsen (1999). In order to fit marginal distribution, each variable was fitted into an empirical cumulative distribution function (ECDF). Subsequently, the dependence between variables was calculated using Kendall's Tau, ζ_k. Kendall's Tau can be defined as the difference between the probability of concordance and probability of discordance. In particular, for the Archimedean case, Kendall's Tau can be expressed as a function of generator γ of Copula 'C' between two variables as follows:

$$\zeta_k = 1 + 4\int_0^1 \frac{\gamma(t)}{\gamma^!(t)} dt \tag{7}$$

The sample version t of Kendall's (ζ_k) can be computed as follows:

$$t = \frac{c-d}{c+d} \tag{8}$$

where c is the number of concordant pairs and d is the number of discordant pairs in sample size 'n'. A suitable Copula family is hence chosen based on the ζ_k value, which lies in the range of -1 to $+1$. The ECDF was then fitted using the selected Copula function.

RESULTS AND DISCUSSION

CCA statistical downscaling model

The statistical downscaling model based on CCA is used to predict the changes in daily streamflow and air temperature projections from BCC-CSM 1-1 GCM for the period from 2006 to 2099. PCA is applied on the large climate data sets extracted from NCEP/NCAR reanalysis data to reduce the dimensionality and to effectively summarize the spatial information. It was found that 95% of the variability of the NCEP/NCAR reanalysis predictors data set can be explained by the first 15 principal components, and therefore only the first 15 principal components were used as a predictor set in the further analysis. The root mean square error (RMSE) values for the training and testing periods for streamflow were obtained as 403.61 and 419.77, respectively. Similarly, for air temperature, RMSE values were 3.41 and 3.92 for the training and testing periods, respectively. The performance of the downscaling model for streamflow was further assessed using Nash–Sutcliffe coefficients of 0.73 and 0.21 for the training and testing period, respectively. Similarly, Nash–Sutcliffe coefficients for air temperature were 1.00 and 0.56 for the training and testing period, respectively. Since the downscaling model adopted was a linear prediction model, the mean variability can be captured very well with a small variance in the data sets. The daily time scale data of streamflow will generally have high standard deviations and the linear prediction model adopted is able to model the variability in the mean values only.

The projected daily streamflow values were used to estimate the monthly minimum 7-day average consecutive low flows for future scenarios. Figure 3(a) shows the annual 7-day average consecutive low flows for the observed period from 1988 to 2005 and for the future scenarios of the 2020s and 2040s. Figure 3(b) shows annual low flow values, which indicates a linear decreasing trend in the future low flow for Tungabhadra River at Shimoga and the decrease in annual low flows per decade is observed as 7% for the projected period of 2040, while the decrease in 7Q10 values has been reduced from 0.052 to 0.002 cumecs for the period from 1971–1991 to 1992–2006 (Rehana & Mujumdar 2011). Overall, a significant decrease in daily streamflow values and consequent decrease in annual low flow values have been observed for Tunga river at station Shimoga for current and projected scenarios. The findings of the climate change projections obtained in the present study were consistent with the earlier studies on the Tunga-Bhadra case study (Rehana & Mujumdar 2012).

Non-linear stream temperature regression model

The daily average air temperature values were used to estimate the daily average river water temperature using the non-linear river water temperature model. The relationship and variation of air and water temperatures at Shimoga are shown in Figure 4. The river water temperature follows the same daily variation as air temperature. Therefore, for the present case study the river water temperature can be reasonably predicted by considering the average air temperature as the independent variable. However, it should be noted that there are several anthropogenic heat sources such as emission of industrial cooling water, outfalls from a sewage treatment plant, downstream of a thermal plant, net exchange from ground water temperature etc., which may cause higher water temperature at any particular river location. This can be observed from Figure 4, where river water temperature is approximately 4 °C higher than air temperature.

Due to the unavailability of such information for the present case study, the modeling framework has not accounted for such heat input sources in the modeling framework. As air temperature and streamflow are more readily available data sets, the present study was mainly focused on predicting the river water quality levels under climate change, under the influence of temperature and streamflows. The river water temperature at Shimoga was predicted for the current period from 1988 to 2005 using a non-linear river water temperature model. The parameters of non-linear regression model estimated from the observed data are given in Table 1. The performance of the non-linear river water temperature prediction model in terms of the percentage of absolute error (difference between each observed water temperature value and corresponding predicted value) is about 5.18% and the sum of squared errors is about 21036.58. The non-linear regression river water

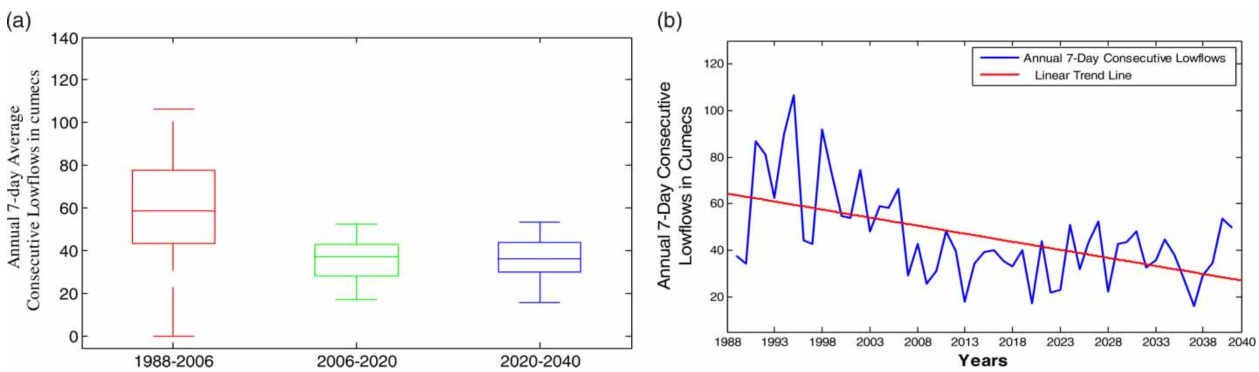

Figure 3 | (a) Annual 7-day average consecutive low flows for the observed period of 1988 to 2006 and for the future scenarios of the 2020s and 2040s. (b) Annual low flows from the period 1988–2040.

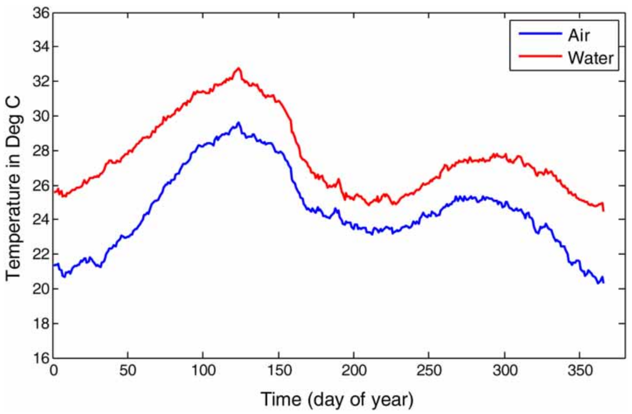

Figure 4 | Long term average of daily air and water temperatures for the period 1988–2005 at Shimoga.

Table 1 | Parameters of non-linear river water temperature model

Parameter	Value
Lower bound of stream temperature, μ	0.00
Upper bound of stream temperature, α	208.36
Slope at inflection point, γ	0.029
Air temperature at inflection point, β	88.87

temperature has improved the predictability compared to linear regression models with air temperature as the predictor variable (Rehana & Mujumdar 2011). The findings of the study emphasize how centrally important it is to adopt a non-linear regression water temperature model to predict projected changes in river water temperature.

The air temperature from BCC-CSM1-1 is projected to increase for the future scenarios, as shown in Figure 5. A subsequent increase is also seen in the water temperature for the current and near-future time windows of 2006–2020 and 2020–2040. The river water temperature was modeled as 23.5 °C for the period 1988–2005 with an increase to 24.7 °C for the period 2020–2040.

The findings of the study stress have shown a projected increase in river water temperature under climate change which may have an adverse effect on river water quality.

Water quality simulation model

The future monthly minimum 7-day average consecutive low flows and monthly maximum river water temperatures were used to predict the probability of occurrence of risk of low water quality events for current and future scenarios. The DO levels simulated using QUAL2 K for the observed and projected monthly low flows and maximum river water temperatures were used to estimate the low water quality events. The low water quality events were identified for different thresholds, starting with the minimum DO level of 4–7 mg/L, as shown in Figure 6. It is evident that the number of low water quality events are predicted to increase for future scenarios under the projected changes in the low flows and river water temperatures. Quite evidently, the number of low water quality events is higher for higher DO thresholds adopted.

Copula function for joint PDF

Joint PDF of low flows and high water temperatures is fitted by identifying a suitable Copula function, chosen based on Kendall's Tau value. The Frank Archimedean Family is found to better represent the relation between streamflow and water temperature (Kendall's Tau value was obtained as -0.46). Figure 7 shows the joint PDF of streamflow and water temperatures with an Archimedean Copula function fitted with the observed data. The estimated joint PDF will be further used in the MLRM to estimate the extreme risk of low water quality. The empirical joint PDF, which was estimated based on the mean streamflows and river water temperatures, as employed in Rehana & Mujumdar (2012), may not be adequate to estimate the extreme risk of low water quality with higher river water temperatures and lower streamflows. The research findings of the study were able to capture the extreme behavior of low flows and maximum river water temperatures to centrally model the extreme risk of low water quality.

Quantification of extreme risk of river water quality using MLRM

The probability of occurrence of a low water quality event for a given streamflow, water temperature and the corresponding DO levels (Equation (6)) was calculated by combining the joint PDF generated from Copula function and the conditional probability of low water quality from MLRM. The probability of low water quality or risk of low

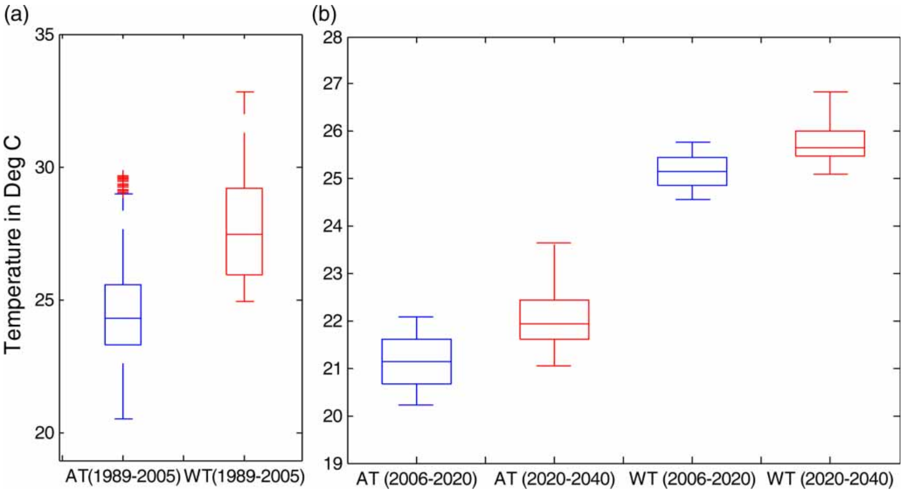

Figure 5 | Annual observed air temperature (AT) and water temperature (WT) for (a) observed period of 1989–2005 and (b) future projections for the periods of 2006–2020 and 2020–2040.

water quality was calculated for current and future scenarios using streamflow and water temperature projections. Figure 8(a) and 8(b) map the risk in terms of probability of low water quality for a given streamflow and water temperature for current (1988–2005) and future (2020–2040) scenarios respectively. It can be observed from Figure 8 that the probability of low water quality values are more sensitive to low flows and maximum water temperatures for current and future scenarios. To compare the risk associated with current average conditions (with average monthly streamflows and water temperatures) and current extreme conditions (with monthly maximum water temperatures and minimum 7-day average consecutive low flows) of risk of low water quality, a comparison of streamflow, temperature and associated risks are given in Table 2. The minimum monthly streamflow and water temperature for the current extreme scenario for a period of 1988 to 2005 were 0.021 m^3/s and 23.5 °C respectively, with associated probability of low water quality of 0.045. The minimum monthly streamflow and water temperatures for the time period 2020–2040 were about 0.049 m^3/s and 24.67 °C respectively, with associated probability of low water quality of 0.506, which indicates the possibility of increasing low water quality events in the river for future scenarios. The findings of the present study reveal that the combination of predicted decrease in low flows of about 57% and increase in maximum river water temperatures of about

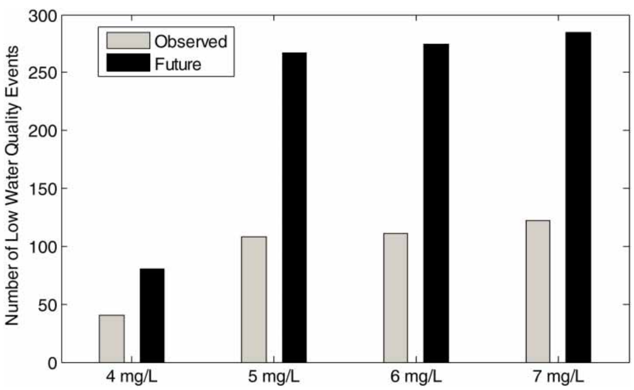

Figure 6 | Observed and future number of low water quality events for different thresholds of DO levels.

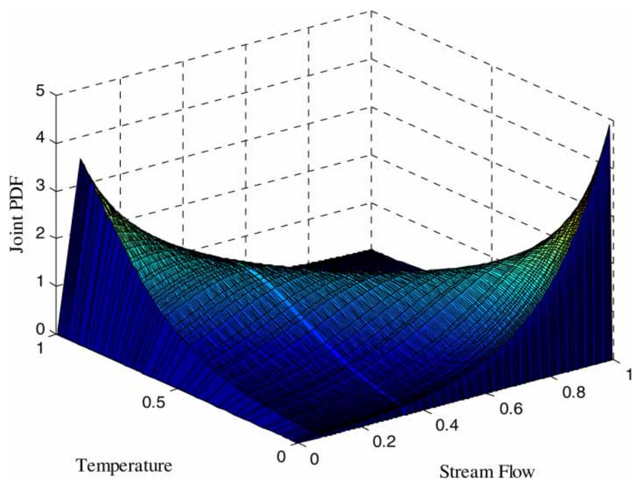

Figure 7 | Empirical joint PDF of streamflow and water temperatures Archimedean Copula function with observed data.

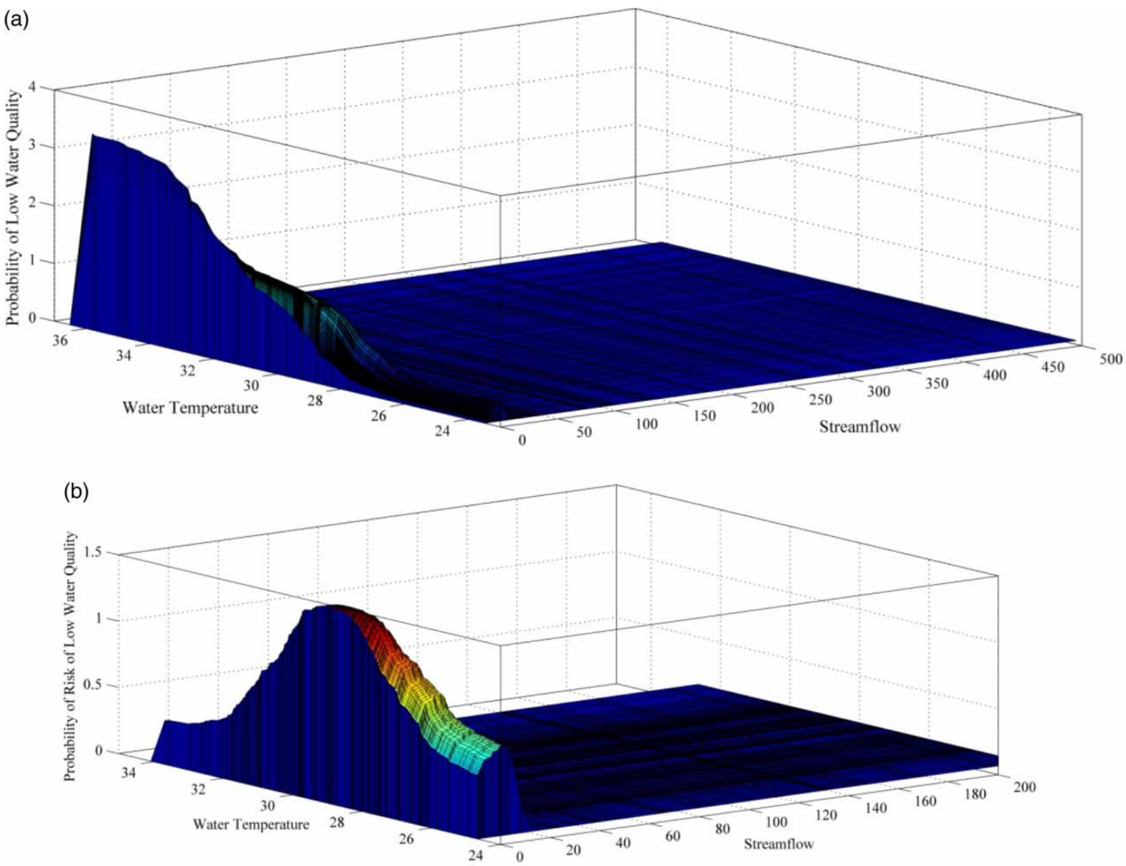

Figure 8 | The probability of low water quality for (a) current (1988–2005) and (b) future scenario (2020–2040).

1.2 °C have a consequent increase of about 46% in risk of low water quality conditions for the future scenarios along Tunga-Bhadra River. Overall, the extreme risk of low water quality is observed to increase by 50.6% for the period of 2020–2040 when compared with the current extreme conditions of 4.5% and average risk conditions of about 3% for the period of 1988–2005.

Table 2 | Comparison of risk of low water quality for current average, current extreme and future extreme scenarios

Scenario	River water temperature (°C)	Streamflow (m^3/s)	Risk of low water quality
Current average (1988–2005)	20.88	0.19	0.03
Current extreme (1988–2005)	23.50	0.049	0.045
Future extreme (2020–2040)	24.67	0.021	0.506

The findings related to the study of risk of low water quality values estimated for current and future scenarios can be used in river water quality management, considering the conflicting goals of pollution control boards and dischargers. The probability of low water quality estimated for a DO threshold of 4 mg/L and risk values can also be estimated for various threshold values of DO. Specifically, the associated risk values can be implemented for lower and higher threshold values to estimate bounds of risk values, which can be further used in a river water quality management model to estimate the fractional removal levels for each of the discharges in terms of lower and upper bounds, using an imprecise fuzzy waste load allocation model (Rehana & Mujumdar 2009). The findings related to the work of risk maps developed in the present study will be useful for the assessment of the possibility of risk of low water quality events for future scenarios and river water quality management under climate change.

CONCLUSIONS

The present study proposes a modeling framework for the assessment of extreme risk of low water quality, integrating climate change projections of river water quality responses, considering a threshold of water quality indicator, with a risk quantification model, to predict the probability of occurrence of low water quality events for a given river system. Air temperature and precipitation extracted from the GCMs BCC-CSM1-1 climate model for RCP 8.5 is downscaled for Tungabhadra River with a CCA downscaling model. Overall, the combination of decrease in low flows and increase in maximum river water temperatures proves to be the worst, which results in extreme river water quality risk conditions for current and future scenarios along Tungabhadra River. The results reveal that the combination of projected decrease in low flows of about 57% and increase in maximum river water temperatures of about 1.2 °C has shown an increase of about 46% in risk of low water quality conditions for future scenarios along Tunga-Bhadra River, India. The results reveal that the river system is more sensitive to extremes of streamflows and water temperatures when compared with the average conditions in terms of extreme risk of low water quality. The extreme risk of low water quality is observed to increase by 50.6% for the period of 2020–2040 when compared with the current extreme conditions of 4.5% and average risk conditions of about 3% for the period of 1988–2005. The risk is expected to increase for more stringent water quality criteria. The study highlights the importance of considering the possible impact of climate change in water quality conditions, of any river stretch.

Due to the availability of observed data of air and water temperatures for sufficiently long time periods, the present study of a risk quantification model is demonstrated with one river location in the considered river stretch. However, the proposed methodology can be applied for various water quality check points along a river system with sufficient data availability with varying spatial and temporal scales. It is worthwhile pointing out that while climate change is one dominant factor, as established by the present study, in impairing the water quality of river stretches, human activities in the system, which will be yet another dominant factor, should also be considered. Any scrupulous diversions in the upstream sections, which in turn further reduce the downstream discharge and release of industrial water with high temperatures, will certainly diminish the downstream water quality. All these factors need to be incorporated, along with climate change, in the risk assessment of water quality conditions.

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