



# An integrated fuzzy-based advanced eutrophication simulation model to develop the best management scenarios for a river basin

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Received: 23 October 2017 / Accepted: 2 January 2018 / Published online: 14 January 2018  
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## Abstract

Assessment of water quality status of a river with respect to its discharge has become prerequisite to sustainable river basin management. The present paper develops an integrated model for simulating and evaluating strategies for water quality management in a river basin management by controlling point source pollutant loadings and operations of multi-purpose projects. Water Quality Analysis and Simulation Program (WASP version 8.0) has been used for modeling the transport of pollutant loadings and their impact on water quality in the river. The study presents a novel approach of integrating fuzzy set theory with an “advanced eutrophication” model to simulate the transmission and distribution of several interrelated water quality variables and their bio-physiochemical processes in an effective manner in the Ganges river basin, India. After calibration, simulated values are compared with the observed values to validate the model’s robustness. Fuzzy technique of order preference by similarity to ideal solution (F-TOPSIS) has been used to incorporate the uncertainty associated with the water quality simulation results. The model also simulates five different scenarios for pollution reduction, to determine the maximum pollutant loadings during monsoon and dry periods. The final results clearly indicate how modeled reduction in the rate of wastewater discharge has reduced impacts of pollutants in the downstream. Scenarios suggesting a river discharge rate of 1500 m<sup>3</sup>/s during the lean period, in addition to 25 and 50% reduction in the load rate, are found to be the most effective option to restore quality of river Ganges. Thus, the model serves as an important hydrologic tool to the policy makers by suggesting appropriate remediation action plans.

**Keywords** Eutrophication · Fuzzy decision-making · Modeling and simulation · River basin · Water quality · Wastewater loadings

## Introduction

Depreciating the adverse effects of pollutant loadings and reduced stream flow is one of the primary objectives of river basin planning and management. The designated purpose for which river’s water can be utilized depends heavily on its quality. In addition, water quality has significant impact on human health and biodiversity. Thus, studying the quality aspect of the river water has been the priority of researchers since the last three decades. In this context, water quality

modeling (WQM) of a river has been widely accepted as a reliable tool (Karaouzas et al. 2009; Zhang et al. 2012; Nikoo et al. 2013). The primary purpose of WQM is to study the impact of spatial and temporal variations of the water quality parameters on the river system. Appropriate analyses of the model input parameters and output data are emphatic to the success of modeling, as they allow the decision maker to interpret certain aspects of the water body. Such sophisticated model is supportive in devising suitable management strategies for river basin development (Singh et al. 2015). It is also instrumental in determining the accurate simulation results and water quality assessments (Mannina and Viviani 2010; Chao et al. 2010; Cardona et al. 2011).

In recent times, due to developmental activities, population growth, and economic development, the surface aquatic ecological systems (such as rivers, lakes) are receiving excess of nutrients, which leads to eutrophication. The primary contributing factors of eutrophication in the rivers are fertilizers from agricultural runoffs, effluents from soap and detergent industries, sediment accumulation, and sewage water (Wang et al.

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Responsible editor: Marcus Schulz

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2014; Zhang et al. 2017). Eutrophication poses a serious threat to both the river aquatics and the human population across the major river basins of the world (Conley et al. 2009). It can imbalance the river ecosystem by causing serious problems such as algal blooming, loss of habitat, reduction in self-purifying capacity, and changes in biodiversity (Diaz and Rosenberg 2008). Restoring the water quality from the adverse impacts of eutrophication has been a major challenge to the water authorities, especially due to complex and non-linear cause–effect relationship between the nutrient sources and water quality. Therefore, a proper understanding of the evolvement of eutrophication phenomenon corresponding to varying loads is needed to develop effective management scenarios. In order to establish proper cause–effect relationship between eutrophication parameters and their impact on water quality, WQM has emerged as one of the best scientific initiative (Singh et al. 2007; Zheng and Keller 2008). Water quality models can be classified into different categories such as QUAL, Water Quality Analysis Simulation Program (WASP), BASINS, and Environmental Fluids Dynamics Code (EFDC) models (Wang et al. 2004; Kannel et al. 2007). In the past few decades, many researchers have explained quantitative and qualitative aspects of eutrophication using water quality modeling and simulation. Kuo et al. (2006) simulated the eutrophication process in Te-Chi and Tseng-Wen reservoirs in Taiwan using CE-Qual-W2 model. In this model, after calibration, the best decision scenarios were devised to reduce the nutrient load entering the reservoir. Park et al. (2008) have used AQUATOX to model eutrophication processes for organic toxicants such as chemodynamics of neutral and ionized organic chemicals, bioaccumulation as a function of sorption and bioenergetics, biotransformation to daughter products, and lethal toxicity in rivers, lakes, ponds, and estuaries. Trancoso et al. (2009) used MOHID watershed modeling tool to simulate complex river systems in the aquatic and benthic phases and reproduced the processes occurring in temporary river networks (flush events, pool formation). Hipsey et al. (2006) have developed Computational Aquatic Ecosystem Dynamics Model (CAEDYM v2), which incorporates comprehensive eutrophication processes of the C, N, P, Si, and dissolved oxygen (DO) cycles; several classes of inorganic suspended solids; and phytoplankton dynamics. Wang et al. (2014) have proposed a hydrodynamic three-dimensional modeling approach to develop a sound scientific decision tool for reducing eutrophication in Dianchi Watershed using EFDC. The model incorporates the fate and transport of nutrients, as well as nutrient–algae interactions, and has reproduced the observed spatial and temporal trends in water quality. Yazdi and Moridi (2017) developed an integrated reservoir–watershed modeling framework to evaluate the impact of eutrophication in Gharehsou river. The model uses Soil and Water Assessment Tool (SWAT) for modeling the surface runoff and pollutant

loading transport, and CE-Qual-W2 model is used for simulating the water quality of reservoir. Lai et al. (2013) developed a direct linkage between the river pollution index and suspended solid loadings using WASP for Kaoping river basin in Taiwan. The integrated model shows that suspended solid (SS) and ammonia nitrogen (NH<sub>3</sub>-N) are the primary pollutants causing non-point source (NPS) pollution. Although various models discussed above are advantageous in modeling the eutrophication process of the aquatic systems, there are certain limitations associated with them as listed in Table 1.

Surface water quality modeling using WASP has achieved tremendous success in the last two decades (Xu et al. 2007). WASP model is developed by US Environmental Protection Agency (USEPA) (Geza et al. 2009). It is capable of simulating the impact and transport of pollutants in three dimensions under both the steady-state and dynamic modes (Fan et al. 2009). The model overcomes majority of the limitations of previous models (mentioned in Table 1) by considering the processes and interactions involving detritus, sediments, metals, bacteria compartments, and inorganic pollutants (Lin et al. 2011). In addition, WASP defines kinetic and transport processes separately and thus offers better flexibility in modeling (Wool et al. 2001). It also allows the specification of time–variable exchange coefficients, advective flows, waste loads, and water quality boundary conditions and permits tailored structuring of the kinetic processes, all within its own modeling framework without having to write large sections of computer code. Thus, it enables the decision maker to formulate essential policies by interpreting and predicting the water quality responses to natural phenomena and man-made pollution. Although, WASP can successfully model eutrophication phenomena of several river systems, there is scope to develop an advanced and more flexible eutrophication model (advanced eutrophication model) considering a wide range of water quality variables, their interrelationships, and the biophysiochemical complex processes involved somehow in the aquatic ecosystems such as nutrient cycling (C-N-P), solar radiation, phytoplankton, carbonaceous biochemical oxygen demand (CBOD) process and periphyton kinetics, benthic algae, pH, alkalinity, water temperature, and sediment diagenesis. Another exclusive feature of WASP “advanced eutrophication” model over traditional model is its flexibility which inculcates five classes of phytoplankton and three classes each of CBOD and benthic algae. It also allows the simulation results to be easily linked with various categories of water quality models such as loading models (SWMM, HSPF, LSPC), hydrodynamic models (EFDC, EPD-RIV1), bioaccumulation (BASS, FCM-2), external spreadsheets, and ASCII files. Such flexibility gives a wide scope to the researchers to perform deeper analysis. The complexity of the advanced model can also be adjusted depending on the aquatic and chemical behaviors and management questions. Therefore, the main objectives of this paper are to study the

**Table 1** Classification of water quality simulation models used for modeling eutrophication

Model(s)	Advantages	Limitations
QUAL: QUAL-I, QUAL 2E, QUAL 2K, CE-QUAL-W2	Suitable for modeling phytoplankton, nutrients, benthic compartments, bottom algae, inorganic suspended solids, dissolved oxygen (DO), CBOD (organic nitrogen, ammonia, nitrate, organic phosphate, phosphorus), detritus, and total active metal.	Limited in one-dimensional simulation in rivers; zooplankton and bacteria compartment are not considered.
AQUATOX	Suitable for simulation of phytoplankton, nutrients, DO, plankton and benthic invertebrates, organic sediments and toxic chemicals, and periphyton.	Inorganic pollutants are not considered.
CAEDYM	Suitable for algae, DO, COD, carbon, sediment oxygen demand, zooplankton, benthic oxygen demand, BOD, and silica.	Sediment compartment, metals, and toxins are not considered.
MOHID	In addition to CAEDYM parameters, it also models biogenic silica, pelagic bacteria, benthic bacteria, and benthic-phase organic matter.	Metals are not considered.
EFDC	In addition to CAEDYM parameters, the model is suitable for cyanobacteria, diatoms, green algae, refractory and non-refractory organic carbon, dissolved and biogenic particulate silica, COD, DO, nutrients, and active total metal.	Zooplankton and detritus are not included.
WASP: WASP 6.0, WASP 7.0, WASP 8.0	In addition to CAEDYM parameters, it can model sediments, trace chemicals, fecal coliform, nutrients, heat processes, non-ionic organic toxicants, and C-N-P detritus.	Does not offer flexibility to consider different groups of CBOD; environmental parameters and benthic algae not considered

eutrophication phenomena in a river using advanced eutrophication model and thus to develop a decision support framework for formulating appropriate strategies for a river basin.

Though simulation performed using advanced eutrophication model can estimate many critical parameters through calibration against monitored data, differences exist between values of observed and simulated water quantity and quality variables despite considerable efforts to estimate the optimal values of model output parameters. Such inconsistency is due to the presence of uncertainty in model inputs, parameters, and overall structure (Vrugt et al. 2003). Therefore, completeness of the simulation model depends on incorporating the uncertainties, in order to have a more realistic outlook about the status of water quality. In general, uncertainties pertaining to water quality models are primarily due to randomness and imprecision. Uncertainty due to randomness is caused by the random nature of input variables, such as stream flow, temperature, and water quality parameters. The uncertainty due to imprecision is related with the objectives and prescribed standards given by pollution control agencies, decision makers, and the dischargers (Rehana and Mujumdar 2009). More specifically, methods addressing uncertainties related to a water quality model are divided into four categories (Zhao et al. 2011), namely, the methods addressing (a) structural uncertainties (arising due to basic processes mathematically characterizing changes in variables in the water column), (b) parameter uncertainties (the values of a set of parameters, suitable for a particular model, may change due to different climatic, topographic, and hydrodynamic conditions), (c) input and output uncertainties (due to spatial and temporal variations resulting in over-/underestimation of predicted values of

loadings based on imprecise and inaccurate projections), and (d) measurement and decision uncertainties (due to lack of experience and conflicts in decision-making and imprecision of instruments). Several authors have analyzed structural and parameter uncertainties using various mathematical tools. Zhao et al. (2011) have used environmental fluid dynamics code model package to deal with the uncertainty in predicting dissolved oxygen in the “Three Gorge Reservoir Region.” The study revealed that the processes of nitrification and reaeration are the key sources of uncertainty. Rangel Peraza et al. (2016) developed a parametric optimization model for Aguamilpa reservoir using UNCSIM. The analysis revealed that the wind sheltering coefficient, Chezy bottom friction solution, and coefficient of bottom heat exchange of the CE-QUAL-W2 model significantly influence the prediction of temperature and dissolved oxygen. Abrishamchi et al. (2005) used first-order reliability analysis to consider the uncertainties of model parameters such as total dissolved solids (TDS), DO, and BOD to develop a WQM for Zayandeh-Rood, Iran. Carroll and Warwick (2010) developed an uncertainty model to analyze the transport of mercury in Carson river. The study addresses uncertainty in predicting methylmercury (MeHg) by performing sensitivity analysis, which shows that both the diffusion rate and the methylation/demethylation ratio (M/D) are instrumental in affecting MeHg concentrations. In addition, there has been significant contribution from the researchers to address the uncertainties caused due to model inputs/outputs and measurement and decision-making. Ye et al. (2013) incorporated uncertainties and developed probability distribution functions for water quality indices by applying Monte Carlo simulation to the

model outputs of QUAL2K to assess the water quality of the Liaohe river estuary. Ajami et al. (2006) developed an integrated Bayesian uncertainty estimator methodology, which simultaneously analyzes the uncertainties of both input and output parameters. Shojaei et al. (2015) linked a differential evolution adaptive metropolis uncertainty analysis model with QUAL2K simulation model for Karoon river, Iran, to deal with the uncertainties associated with several inputs and parameters such as headwater quality and quantity, pollutant loadings, and reaeration constants. Reckhow (1994) studied the uncertainty of the results of water quality simulations and declared that limited data and lack of sound scientific knowledge are the primary causes of such incompatibility. Warmink et al. (2011) dealt with uncertainty due to imprecise decision-making by incorporating expert opinion in a case study related to identification and quantification of uncertainties in a hydrodynamic river model. Meeting the challenges associated with sustainable river basin management needs a proper combination of scientific experimentation, analysis using a suitable simulation tool or software, uncertainty analysis, and participation of very sound group of expert stakeholders, who can effectively manage the long-term, complex, uncertain, and imperfectly known risks (Segrave et al. 2014).

Even though various approaches are used for analyzing different types of uncertainties, research is still lacking in simultaneous and integrated analysis of the uncertainties associated with all the outputs of simulation model, while considering the conflicts/imprecisions of the decision makers. Neglecting such analysis may result in considerable bias in model calibration and river water quality simulation. As there is a range of uncertainty associated with input values of simulation model, thus, corresponding uncertainty range would also be associated with outputs. Moreover, the model outcomes are accepted by the decision makers based on degree of uncertainty. Earlier uncertainty models are not able to address the issues concerned with an appropriate aggregation function which incorporates weightages/relative importance to the model outputs according to time, space, and decision maker preferences. Such imprecision in decision-making and model outputs can be simultaneously addressed by integrating fuzzy set theory with simulation model. Another advantage or novel aspect of fuzzy logic techniques is their ability to express the imprecise and incomplete values of inputs in an interval defined over membership functions, which takes care of the variations in the simulation model outputs. In recent times, fuzzy logic has emerged as one of the best tools to deal with the uncertainty associated with water quality management of river basins (Singh et al. 2007; Srinivas and Singh 2017). Zhu et al. (2009) addressed the uncertainties by developing a robust fuzzy non-linear programming model for Guo river, China. Singh et al. (2015)

developed a multi-criteria fuzzy based model to assess the water quality of river Yamuna, India. The model is flexible as it allows addition, deletion, and modification of input variables according to changes with time and space. Srinivas et al. (2017) assessed the impact of trace metals on the water quality of river Ganges, India, by coupling multivariate analysis with fuzzy decision-making approach. The analysis first identifies the critical parameters using principal component analysis and then uses MATLAB fuzzy inference system to deal with the “uncertainty ranges” associated with each parameter. Osmi et al. (2016) addressed the uncertainties involved in water quality management, especially due to the random nature of hydrologic variables and missing data using fuzzy expert system techniques. Srinivas and Singh (2017) dealt with the uncertainties arising due to conflicts among a group of decision makers to analyze the water quality status of industrial wastewater using interval-valued fuzzy AHP technique, where the usage of improved membership functions has increased the credibility of results. Pan et al. (2017) have dealt with the problems of uncertainty, hesitancy, and parametrization associated with water reuse in the city of Penticton. Generalized intuitionistic fuzzy soft set (GIFSS)-based decision-making framework has been developed to provide an effective approach to deal with uncertainty. Although various approaches are used for incorporating uncertainties and complexities by using fuzzy set theory, research is still lagging in integrating/linking the water quality model simulation results with fuzzy approaches, in order to deal with the uncertainty aspects pertaining to model outputs in a more precise manner. Such a novel approach allows the decision maker to have better assessment of the water quality status, and thus, more precise policies can be formulated consequently. The present study links an advanced eutrophication model to fuzzy uncertainty analysis. The integrated model not only deals with essential eutrophication processes which were not dealt effectively by previous models, but also takes care of the uncertainty present in simulation results in an efficient manner. In brief, the present study deals with two novel aspects, viz, (i) advanced eutrophication model considers bio-physiochemical processes and interactions which are not dealt in previous models and (ii) coupling of fuzzy approach with simulation model outcomes gives the scope to the decision maker to deal with uncertainty in the model in a more efficient manner.

According to the above literature review, the study aims to develop a decision support framework to mitigate and control the eutrophication phenomena in the rivers using an integrated fuzzy-based water quality simulation model. The research work contributes towards presenting an advanced eutrophication model coupled with fuzzy technique of order preference by similarity to ideal solution (TOPSIS) approach to evaluate



various load reduction scenarios and to examine the complicated cause-and-effect relationship between watershed loadings, river's discharge, and water quality, which would be helpful in achieving current and future water quality targets. The simulation model has been calibrated and validated against observed historical data (2005–2015), in order to test its robustness and ability to replicate the observed water quality pattern. Fuzzy logic not only addresses the uncertainty aspects of output variables of the simulation model, but also evaluates water quality status at all sampling stations, while taking care of conflicting preferences of decision makers. The comprehensive hydrodynamic model incorporates the impacts of several critical water quality parameters released into river Ganges, India. The simulation model serves as the foundation tool for the policy makers to develop management scenarios for sustainable river basin development.

## Materials and methods

### Model description and application

The modeling framework of WASP consists of a variety of water quality modules such as eutrophication, simple toxicant, non-ionic organic toxicants, organic toxicants, and mercury and heat. As discussed earlier, the *advanced eutrophication* module of WASP software (version 8) is more effective than the traditional eutrophication module, due its ability to incorporate several interacting systems comprising nitrates, phytoplankton, ammonia, phosphates, organic nitrogen, BOD, DO, bacteria, solids, and pH (Zhang et al. 2008). The advanced eutrophication model predicts the water quality with respect to nutrients, plankton, DO, bacteria decay, and reactive pollutants in water column. In addition to biological and chemical interactions occurring within the water column, the model also performs a sediment diagenesis, which couples the water column and sediment bed. This process enables the prediction of benthic nutrient flux and sediment oxygen (SOD), depending on external nutrient loading and water quality dynamics, which helps the decision makers to develop restoration scenarios. The ability of the model to incorporate the

intimate processes mentioned above along with water–sediment interactions makes it easy to overcome the inherent limitations present in many water quality models.

The model determines the hydraulic characteristics of a river, using principles of conservation of mass and momentum (Ambrose et al. 2001). The input data, along with the general mass balance and specific chemical kinetics equations, uniquely define a specific set of water quality equations, which are numerically integrated by the software as the simulation proceeds with time. A mass balance equation for dissolved constituents of the water body accounts for all the material entering and leaving through direct and diffuse loading, advective and dispersive transport, and physical, chemical, and biological transformations. If  $x$  and  $y$  coordinates are in the horizontal plane and the  $z$  coordinate is in the vertical plane, the mass balance (Eq. (1)) around an infinitesimally small fluid volume is

$$\begin{aligned} \frac{\partial C}{\partial t} = & -\frac{\partial}{\partial x}(U_x C) - \frac{\partial}{\partial y}(U_y C) - \frac{\partial}{\partial z}(U_z C) \\ & + \frac{\partial}{\partial x}\left(D_x \frac{\partial C}{\partial x}\right) + \frac{\partial}{\partial y}\left(D_y \frac{\partial C}{\partial y}\right) + \frac{\partial}{\partial z}\left(D_z \frac{\partial C}{\partial z}\right) \\ & + S_L + S_B + S_K \end{aligned} \quad (1)$$

where

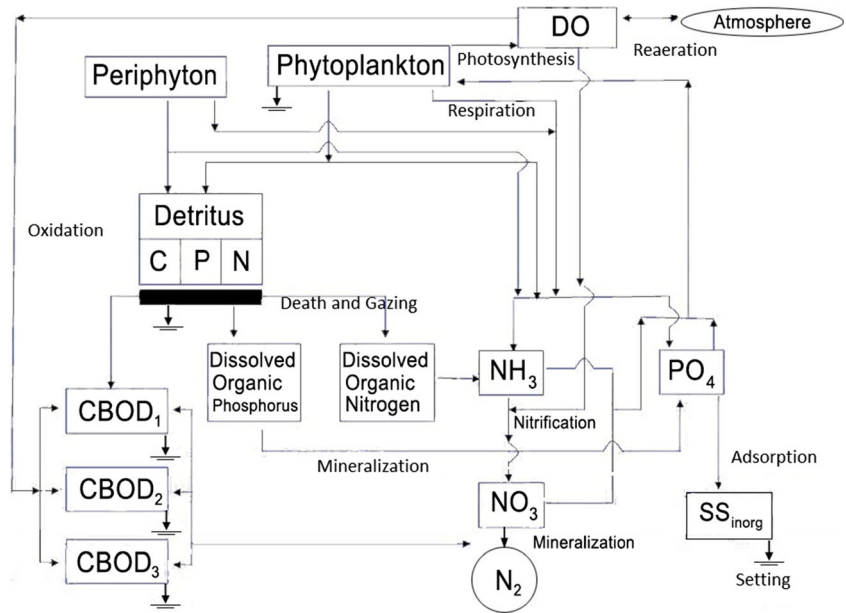
$C$	concentration of the water quality constituent (mg/L or g/m <sup>3</sup> )
$t$	time (days)
$U_x, U_y, U_z$	longitudinal, lateral, and vertical advective velocities (m/day)
$D_x, D_y, D_z$	longitudinal, lateral, and vertical diffusion coefficients (m <sup>2</sup> /day)
$S_L$	direct and diffuse loading rate (g/m <sup>3</sup> day)
$S_B$	boundary loading rate (including upstream, downstream, benthic, and atmospheric, g/m <sup>3</sup> day)
$S_K$	total kinetic transformation rate; positive is source, negative is sink (g/m <sup>3</sup> day)

These infinitesimally small control volumes can be expanded into larger adjoining “segments,” and by specifying appropriate loading, transport, and transformation parameters,

**Table 2** Water quality state variables of advanced-eutrophication WASP model

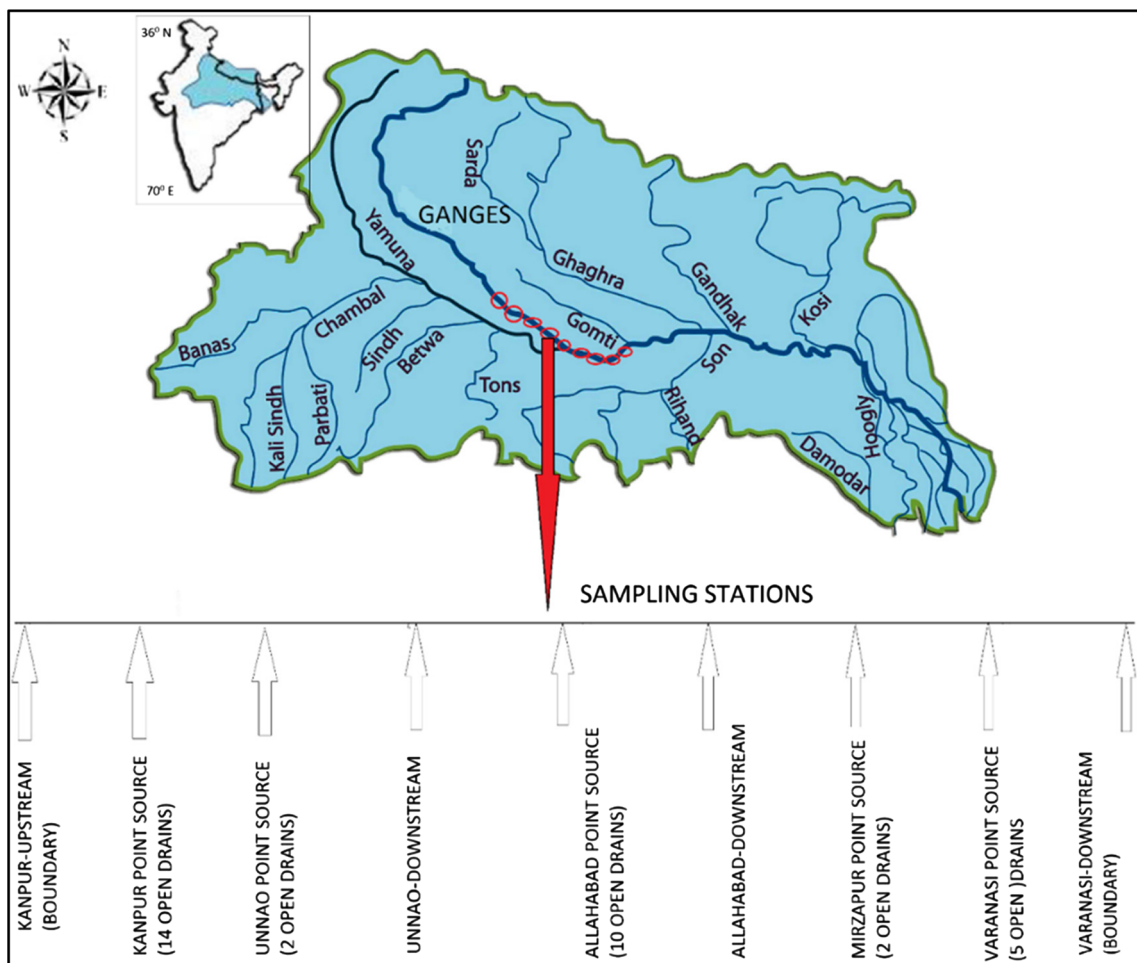
State variables chosen for the study	
1. Nitrogenous ammonia (NH <sub>3</sub> -N), mg/L	7. Total dissolved solids (TDS), mg/L
2. Dissolved oxygen (DO), mg/L	8. Fecal coliform, MPN/100 mL
3. Carbonaceous biochemical oxygen demand (CBOD-1), mg/L	9. Water temperature, °C
4. Carbonaceous biochemical oxygen demand for point source (CBOD-2), mg/L	10. Alkalinity, mg/L
5. pH	11. Nitrate and nitrites (NO <sub>3</sub> -NO <sub>2</sub> ), mg/L
6. <i>Ortho</i> -phosphate (o-PO <sub>4</sub> ), mg/L	12. Chlorophyll-a

**Fig. 1** Schematic diagram representing the interactions between state variables



WASP implements a finite-difference form of Eq. (1). The model assumes vertical and lateral homogeneity (i.e.,

statistical properties of flow remain steady), since the river is long and narrow and exhibits longitudinal and vertical water



**Fig. 2** Map showing sampling stations along the Ganges river basin

**Table 3** List of open drains (pollutant loadings) entering river Ganges in the Kanpur-Varanasi stretch

SL. no.	Drain name	BOD load (kg/day)	Flow (MLD)	SL. no.	Drain name	BOD load (kg/day)	Flow (MLD)
D1	Dabka Nalla-1	15,792	94	D18	Rasulabad-2	5656	20.2
D2	Dabka Nalla-2	3475	25	D19	Rasulabad-3 Drain	1320	14.2
D3	Dabka Nalla-3	10	1.23	D20	Rasulabad-4 Drain	2376	48.5
D4	Shetla Bazar	12,296	29	D21	Nehru Drain	61	7
D5	Wazidpur Nalla	45,522	54	D22	Kodar Drain	1040	20
D6	Satti Chaura	97	1.1	D23	Pongaghat Drain	161	8
D7	Golaghat Nala	114	0.83	D24	Solari Drain	1087	34.8
D8	Bhagwatdas Nala	1144	11	D25	Maviya Drain	3380	65
D9	Sisamau Nala	5,44,980	197	D26	Mugalaha Drain	598	46
D10	Permiya Nala	11,485	186	D27	Ghore Saheed Drain	4121	86.4
D11	Loni Drain	4860	42	D28	Khandwa Drain	5350	62.21
D12	City Jail Drain	7208	35.86	D29	Rajghat Drain	808	16.19
D13	Pandu River	34,900	1396	D30	Nagwa Drain	4060	66.45
D14	Arihari Drain	–	34.25	D31	Ramnagar Drain	963	23.65
D15	Seepage	127	–	D32	Varuna Drain	3776	304.5
D16	NTPC Drain	1121	60.29	D33	Shivala Drain	–	–
D17	Rasulabad-1 Drain	20,264	29.8	–	Total	7,38,152	–

– data not available

quality gradients. For a one-dimensional reach, integrating over  $y$  and  $z$ , Eq. (2) is obtained as follows:

$$\frac{\partial}{\partial t}(AC) = \frac{\partial}{\partial x} \left( -U_x AC + D_x A \frac{\partial C}{\partial x} \right) + A(S_L + S_B) + AS_k \quad (2)$$

where

$A$  cross-sectional area ( $m^2$ )

Equation (2) represents three major classes of the water quality processes. The first, second, and third terms of the right-hand side of the equation represent transport process, loading process, and transformation process, respectively.

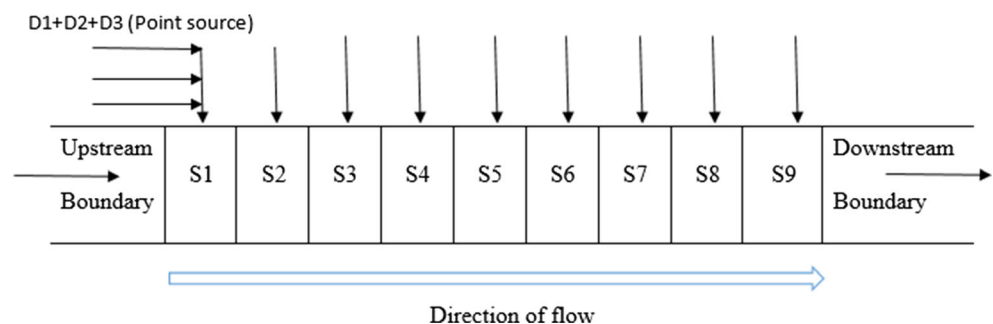
The main steps for conducting simulation using WASP model include defining time step, choosing appropriate state variables, segment generation and preprocessing, input file preparation (defining environmental parameters, kinetic

constants, boundary conditions at water surface, and pollutant loadings), execution and post-processing, result output, and visualization. Step-by-step detailed explanation about the model structure and equations can be found in Ambrose et al. (2001).

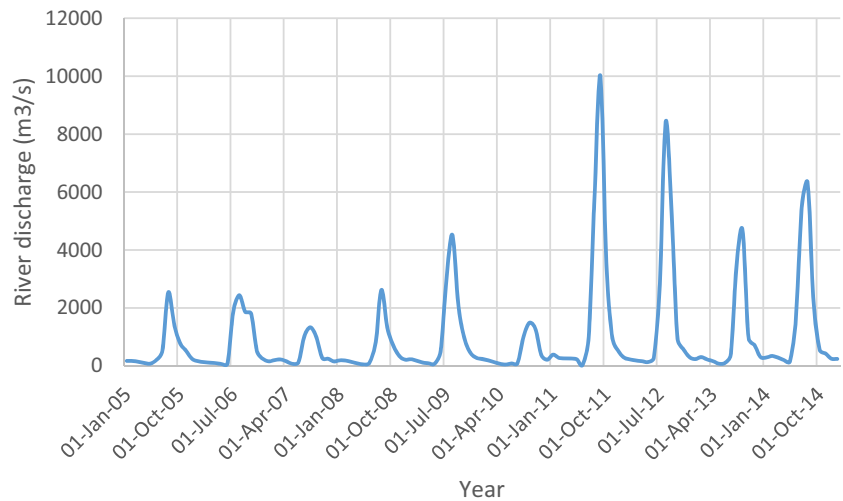
### State variables chosen for the study

Eutrophication in a river body is characterized as the dynamic process, which is taking place between nutrient enrichment and algae growth, resulting from external nutrient loading (e.g., watershed inflows and atmospheric deposition) and recycling within the river system. Within the water column, algae would consume the nutrients in the forms of ammonium, nitrate, and dissolved *ortho*-phosphate for their growth. Meanwhile, the vital life functions of algae such as respiration, predation, and mortality release several forms of carbon, nitrogen, and phosphorous

**Fig. 3** Schematic diagram representing all the nine segments analyzed in the WASP model



**Fig. 4** Discharge of river Ganges in Kanpur-upstream (boundary) on monthly basis from 2005 to 2015



back into the river water (Sagehashi et al. 2000). The aerobic oxidation of organic carbon in the river exerts a carbonaceous oxygen demand, which causes impairment of aquatic ecological system due to depletion in dissolved oxygen. In this study, WASP simulates 12 water column state variables as listed in Table 2. The general interactions between these state variables are illustrated in Fig. 1.

**Case study**

Ganges river basin, located in India, is one of the heavily polluted basins in the world. Ganges river rises in Gangotri (Himalayas) and traverses a total length of 2525 km before entering into the Bay of Bengal. Alarming population growth, barrages and dams, unplanned urbanization, and industrialization have resulted in rising levels of pollutants such as BOD, chromium (Cr), ammonia, fecal coliform, and total dissolved solids. Restoration of water quality of Ganges very much depends on restoring its flow. On the

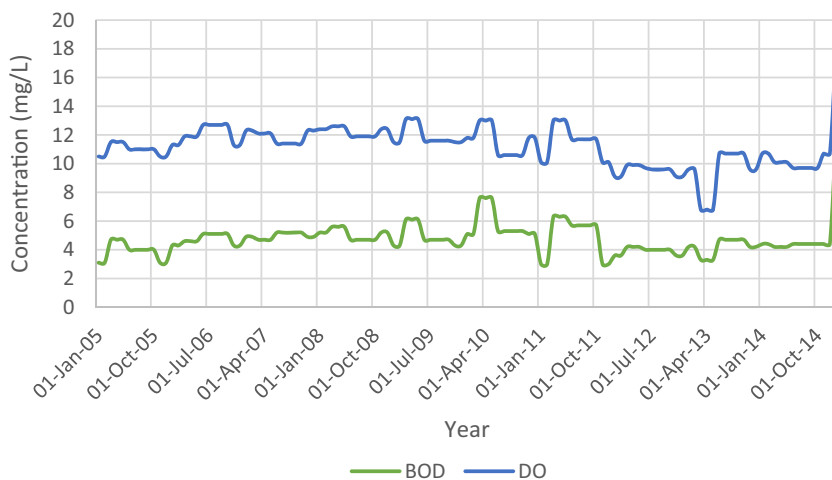
other hand, there have been significant management efforts to reduce the total daily maximum pollution load on the river. Therefore, maintaining adequate flow of river and developing management scenarios to reduce pollutant load should be the main objectives of the decision makers and local governments. One of the heavily polluted stretches of Ganges, starting from Kanpur to Varanasi of about 472 km, has been chosen for developing an advanced eutrophication model (Fig. 2). More than 700 grossly polluting industries, rapid urbanization, and inorganic farming in the agricultural fields have been producing tremendous nutrient loads, causing severe deterioration in the water quality of Ganges. The constructions of roads/highways, sewage treatment plants, garbage collection systems, and urban drainage facilities are not well-equipped as per the prescribed standards. Monthly data of critical water quality state variables has been collected from the Central Water Commission (CWC), non-governmental organizations, and other secondary sources for a period of 10 years (2005–2015) to calibrate and validate the simulation model.

**Table 4** Environmental properties of Kanpur-upstream in the year 2015

Month (2015)	Water temperature (°C)	Wind speed (m/s)	Air temperature (°C)	Dew point (°C)
January	14.8	1.944	14	15
February	14.8	1.944	15	14
March	21.2	1.389	21	19
April	21.2	1.667	26	22
May	21.2	2.222	30	26
June	27.6	1.389	34	20
July	27.6	1.667	30	23
August	27.6	1.389	30	28
September	27.6	1.389	28	23
October	27.6	0.556	24	22
November	14.8	0.278	18	21
December	14.8	0.556	12	18



**Fig. 5** Biochemical oxygen demand (mg/L) and dissolved oxygen (mg/L) observed data at Kanpur-upstream from 2005 to 2015



**Advanced eutrophication model development**

The river stretch of 472 km (Kanpur upstream–Varanasi downstream) has been segmented into a series of nine completely mixed water cells from upstream to downstream. A total of nine regularly monitored sampling stations have been chosen, viz, Kanpur-upstream (S1), Kanpur point source (S2), Unnao point source (S3), Unnao-downstream (S4), Allahabad point source (S5), Allahabad-downstream (S6), Mirzapur point source (S7), Varanasi point source (S8), and Varanasi downstream (S9). These stations are located near the meeting points of the sampling drains. A total of 33 open drains directly or indirectly (by joining other drains) enter into the river system along this stretch (Table 3). For example, drain nos. D1, D2, and D3 together form one drain and enter the first cell (Fig. 3). Similarly, other drains enter the other cells. In total, there are nine meeting points, where these drains discharge their wastewater into the river (Fig. 2). These drains discharge approximately 3000 million L/day (MLD) of wastewater containing 738,152 kg/day of BOD load (Srinivas and Singh 2017). The “completely mixed” assumption ensures that there is no concentration gradient in the vertical and horizontal directions. The concentration of constituents/pollutants is assumed to vary only in the time domain. The assumption also enables an understanding about the gross effects of how a pollutant attains steady-state conditions from an initial state. The assumption is consistent with the river

considered for the study to a good extent as majority of the kinetic constants derived through calibrations by comparing observed and simulated values lie well within the permissible range, though there are some differences. Also, usage of long-term data (10 years) in the simulation model with this assumption has increased the stability of the model. Although this assumption mimics the reality of the river system to a good extent for 10 years, it cannot deal the complete dynamics taking place within the river system. Therefore, it is one of the limitations of WASP software. The results obtained through the model have been compared with the recent works of governmental organizations and research papers which are up to the satisfaction standard as discussed in the “Results and discussion” section. In general, for solving pollutant transformations involving first-order decay rates, completely mixed system has been assumed in most of the water quality modeling software. Thus, “kinematic wave” is chosen as the transport mode as it can be represented simply by a partial differential (Eq. (3)).

The equation contains a single unknown field variable (such as flow or wave height) in terms of two independent variables, namely, time and space, with some parameters containing information about the geometry and physics of the flow.

$$\frac{\partial h}{\partial t} + P \frac{\partial h}{\partial x} = D \frac{\partial^2 h}{\partial x^2} \tag{3}$$

**Table 5** Output variables chosen for simulation

Model output variables		
1. Mass check	7. Nitrate nitrogen	13. Total solids
2. Volume	8. Total CBOD	14. Fecal coliform
3. Flow into the segment	9. Total organic phosphorus	
4. Flow out of the segment	10. Dissolved oxygen	
5. Water temperature	11. pH	
6. Nitrogenous ammonia	12. Alkalinity	

**Table 6** Calibrated values of the crucial water quality parameters for WASP modeling

Kinetic constant	Range	Fixed/estimated by calibration
<b>Nitrification</b>		
Nitrification rate constant at 20 °C (/day)	0.05–0.15	0.1
Nitrification temperature coefficient	1.02–1.08	1.08
Half-saturation constant for nitrification oxygen limit (mg O <sub>2</sub> /L)	0–2.0	0.9
Denitrification temperature coefficient	1.02–1.09	1.045
Denitrification rate constant at 20 °C (L/day)	0–0.09	0.09
Half-saturation constant for denitrification oxygen limit (mg O <sub>2</sub> /L)	0–2.0	0.01
<b>Phytoplankton</b>		
Phytoplankton growth rate at 20 °C (/day)	1.0–3.0	1.9
Phytoplankton rate growth temperature coefficient	0.98–1.072	1.054
Phytoplankton light option	0, 1	1
Phytoplankton death rate constant (/day)	0.02–0.1	0.11
Algal respiration rate constant (/day)	0.05–0.35	0.0075
Algal respiration rate constant temperature constant	1.045–1.1	1.07
Phytoplankton decay rate temperature coefficient	1.0–1.08	1.08
Phytoplankton decay rate in sediments at 20 °C (/day)	0–0.02	0.02
Phosphorus to carbon ratio (mg P/mg C)	0–0.24	0.025
Nitrogen to carbon ratio (mg N/mg C)	0–0.43	0.18
Oxygen to carbon ratio (mg O <sub>2</sub> /mg C)	0–2.67	2.67
<b>BOD and DO</b>		
CBOD decay rate constant at 20 °C (/day)	0.05–0.4	0.25
CBOD decay rate temperature correction	1.0–1.07	1.047
CBOD decay rate in sediments at 20 °C (/day)	0.0004–1.0	1.0
CBOD decay rate in sediments temperature coefficient	1.0–1.08	1.08
CBOD half-saturation oxygen limit	0.5–1.0	0.98
Reaeration rate constant @ 20 °C	0.5–3.0	2.0
Calculation of reaeration option	0 = Covar, 2 = Owens, 3 = Churchill, 4 = Tsvoglou	0
<b>Organic nitrogen</b>		
Dissolved organic N mineralization rate at 20 °C (/day)	0.02–0.075	0.025
Dissolved organic N mineralization temperature coefficient	1.0–1.08	1.045
<b>Organic phosphorus</b>		
Mineralization of dissolved organic P rate constant (/day)	0–0.22	0.05
Mineralization of dissolved organic P temperature constant	1.0–1.08	1.05
<b>Bacteria</b>		
Bacteria death rate (/day)	0–2.5	2.5
Bacteria death rate temperature correction	1.0–1.08	1.07

where  $h$  is the debris flow height,  $t$  is the time,  $x$  is the position of the downstream channel,  $P$  is the pressure gradient, and  $D$  is the flow height and pressure gradient dependent variable diffusion term.

As the simulation time period is long, initial conditions are set to be 0 for all state variables corresponding to each sampling station. During the model simulation, a time step of 1 day has been used. The simulation is run for a time period of 10 years (January 2005 to January 2015).

### Boundary conditions

These are the external driving forces to the modeling system. For the Ganges river, the lateral boundary conditions, such as the flow of river at the upstream boundary, and the pollutant loadings (D1–D33) entering each cell of Fig. 3 have been represented in Fig. 4 and Table 3, respectively. The time-varying surface boundary conditions include environmental properties such as

water temperature, wind speed, air temperature, solar radiation, and dew point. For brevity reasons, only the monitored data values of these environmental parameters for the year 2015 for Kanpur-upstream (S1) are given in Table 4. As the solar radiation depends on the latitude and longitude of the study area, it is automatically calculated by the software. Also, the observed data values of 12 state variables for the entire simulation period are given for the upstream boundary. For illustration, boundary conditions for DO and BOD are represented in Fig. 5. Boundary conditions of other state variables are not presented for brevity reasons.

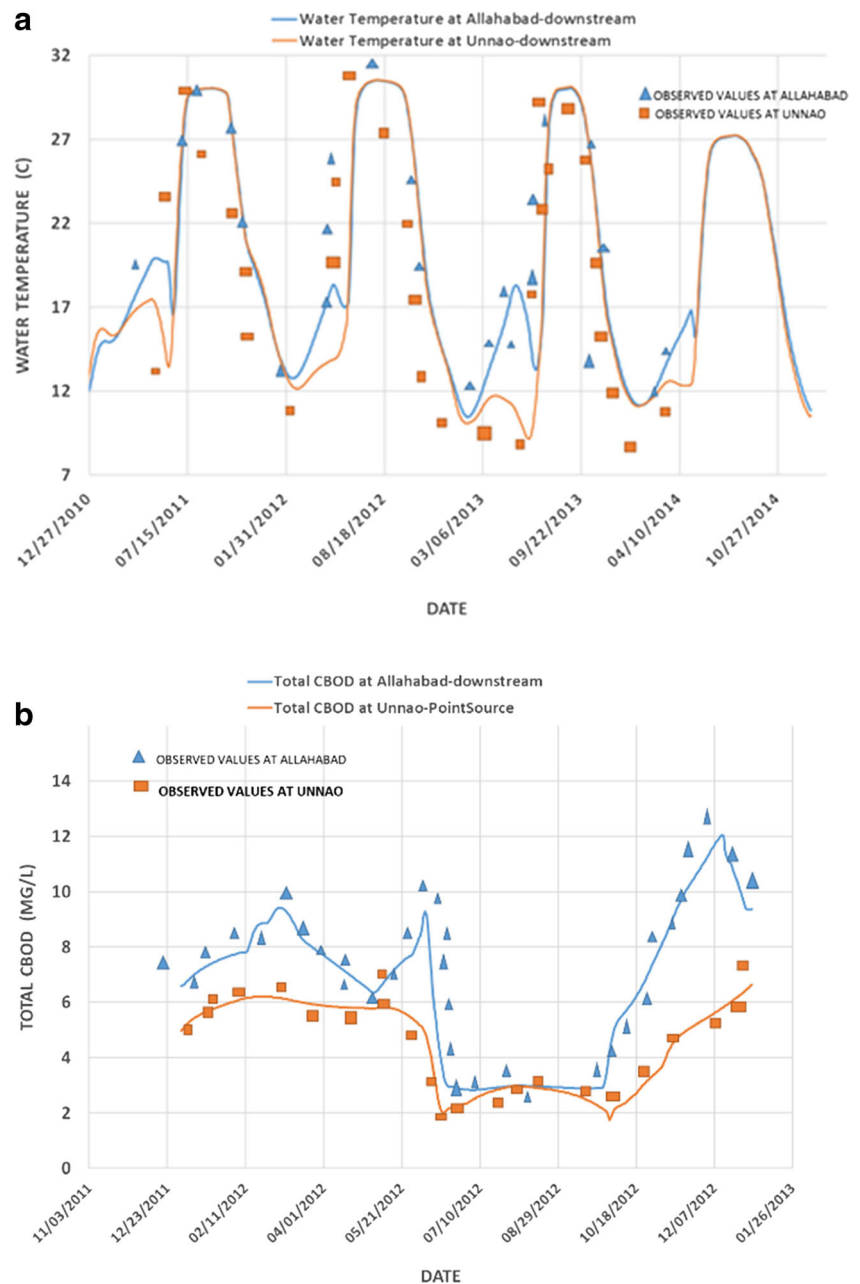
### Selection of output variables

The output variables are chosen based upon the critical pollutants identified by Central Pollution Control Board (CPCB) (2017) in the study area. The variables chosen for the model developed herein are represented in Table 5.

### Model calibration and validation

The primary purpose of the *advanced eutrophication* model developed herein is to provide a decision-making tool to formulate strategies for restoring the water quality

**Fig. 6** Model calibration. **a** Temperature. **b** Total CBOD

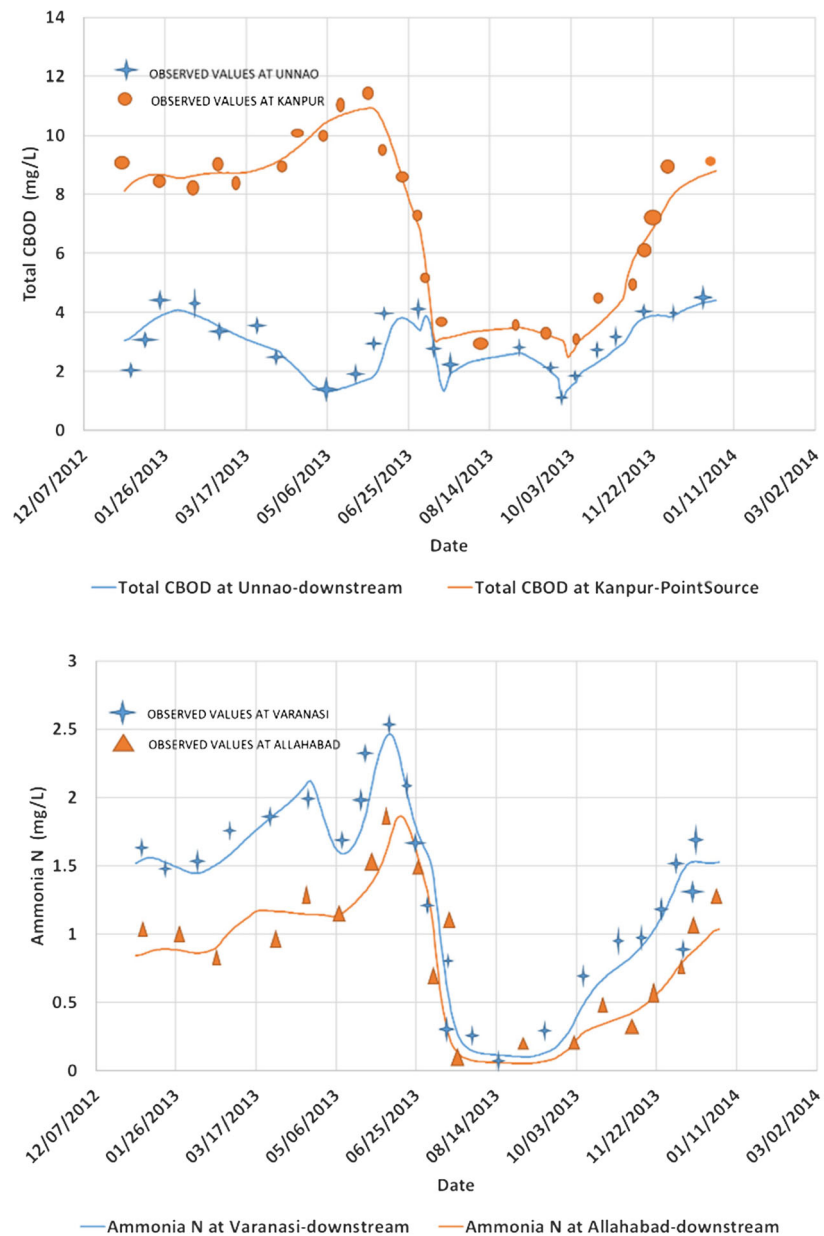


of a river. However, before employing the model for the same, it is essential to assess the effectiveness with which it can represent the relationships between pollutant loadings, river discharge, and water quality of the corresponding segment. This is ensured by subjecting the model through the calibration and validation processes. The process of calibration involves adjusting the values of the kinetic parameters within a certain reasonable and acceptable ranges as defined by controlling agencies, so as to minimize the deviations between the simulated results and the actual monitored data (Singh and Ghosh 2003a, b; Jin et al. 2007). The calibrated model is then validated using a second set of independent data to fur-

ther inspect the model’s ability to represent river body in a realistic and authentic way. In the present study, two independent sets of observed data for the years 2012 and 2013 are used for calibration and validation, respectively.

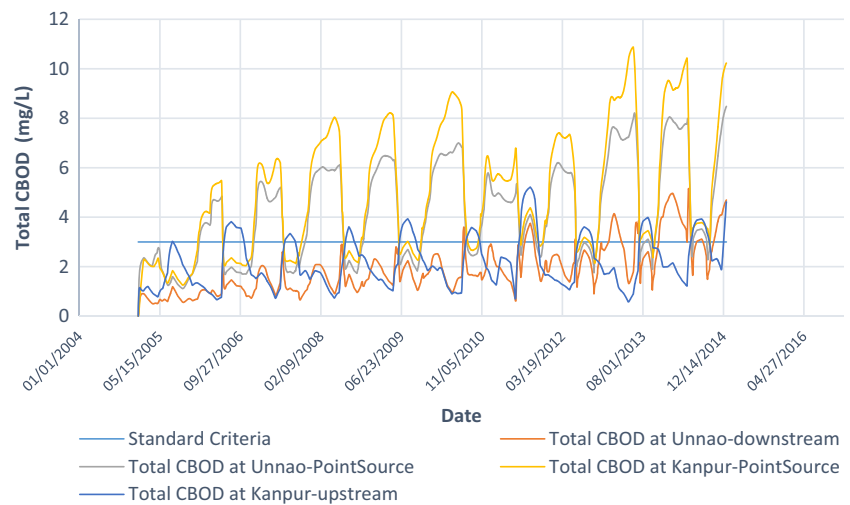
The calibration is performed for the period from January 1, 2012, to December 31, 2012, by comparing the predicted values of the model with the observed data values. The simulated output variables of the model have been compared with observed data, and crucial kinetic parameters listed in Table 6 are adjusted by simulating several trial-and-error runs in order to ensure that the difference between model results and observed data falls within the prescribed error of 10%. The objective function (Eq. (4)),

**Fig. 7** Model validation: observed versus simulated values for the year 2013





**Fig. 8** Simulated values of TCBOD for the first four sampling stations



based on Nash and Sutcliffe (1970) coefficient ( $E_{NS}$ ), has been used for calibration, where the values ranging from 0.5 to 1 are considered reliable and acceptable.

$$E_{NS} = 1 - \frac{\sum_{i=1}^n (O_{a,i} - O_{s,i})^2}{\sum_{i=1}^n (O_{a,i} - \bar{O}_a)^2} \quad (4)$$

where  $O_{a,i}$  is the  $i$ th observed data,  $\bar{O}_a$  is average of observed data,  $O_{s,i}$  is simulated value of the  $i$ th observed data, and  $n$  represents number of data.

It is to be noted that the main objective function has been used to reduce the difference between the observed and modeling values as given by Eq. (4) by ensuring that the error rate is not more than 10%.

Primarily, nutrient parameters are adjusted during the calibration process. The calibration of the hydrodynamic model is conducted in two stages. In the first stage, observed data values of temperature and CBOD are used for calibration. Then, the model is calibrated using the observed data of DO and  $\text{NH}_3\text{-N}$ . For illustration, the calibration process corresponding to temperature and TCBOD, at Unnao and Allahabad, has been shown in Fig. 6a, b, respectively. Thus, the model is able to mimic the temporal variability in the temperature and TCBOD with reasonable accuracy (i.e., less than 10% variation) throughout the year along the various sampling stations. In addition to TCBOD, the temporal and spatial variations of the water temperature are also reproduced by the model with good accuracy, providing a strong foundation for performing further calibration, as all the kinetic processes are a function of temperature. The calibrated results provide the hydraulic parameters and reaction rate constants required for developing the water quality model. Calibrated values are listed in Table 6.

In order to establish the credibility of the WASP model developed herein, an independent set of data of the year 2013 is used for validation, which involves employing the calibrated model without changing values of any variables. The simulated water quality results are again compared against the observed values to evaluate the ability of the model to mimic/represent the real system. Figure 7 shows the graphical representation of simulated values of output variables and observed data values. It can be clearly inferred that the model again mimics the observed water quality well, implying that the parameterization of the model obtained through the calibration process is robust and it can well represent any distinct year.

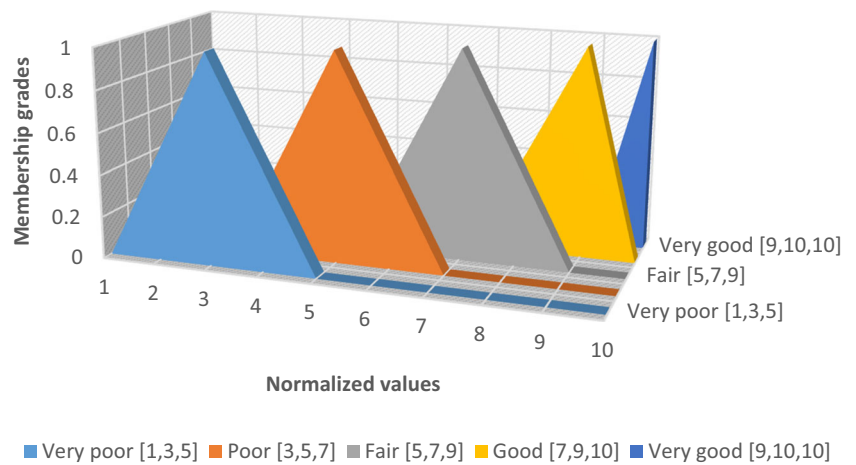
**Execution and post-processing**

The calibrated and validated model is executed, and the entire simulation has been performed on a 64-bit operating system, running 4 Intel Core i5-5200U CPU at 2.20 GHz and 16 GB of RAM. Graphical representation of the simulated values of total carbonaceous biochemical oxygen demand (TCBOD) for the first four segments (S1–S4) is shown in Fig. 8, where blue-colored line in the graph represents the prescribed drinking water standard (3 mg/L) suggested by CWC. Simulation

**Table 7** Linguistic representation of simulated output values (inputs for fuzzy TOPSIS)

Sampling station	pH	DO	BOD	TC
S1	P	F	VP	VP
S2	VP	G	P	VP
S3	P	VG	F	VP
S4	P	G	F	P
S5	P	G	F	P

**Fig. 9** Membership functions of fuzzy linguistic representation



results confirm the deteriorated condition of river at Kanpur and Unnao as values of CBOD are as high as 8 and 10 mg/L during dry seasons. This is primarily due to open defecation, sewage, and industrial and agricultural wastes entering into the river premises (Srinivas and Singh 2017). Comparatively better values (2–4 mg/L) of CBOD at Unnao-downstream and Kanpur-upstream is due to presence of lesser number of industries and urbanization in that area (CPCB 2017). In a similar manner, simulated values of all nine segments have been obtained. Since 14 output variables are simulated, a total of 14 graphs are generated against each segment.

**Uncertainty analysis using fuzzy TOPSIS approach**

Due to the random nature of the state variables (inputs) of the WASP model, they are subjected to change temporally and spatially. Consequently, there is some uncertainty/probability associated with the model outputs. Therefore, the simulated results (outputs) are subjected to uncertainty analysis by using fuzzy TOPSIS approach, in order to enable the decision makers to incorporate the uncertainty due to randomness and imprecision. Linking the fuzzy set theory with the model outputs makes the results more authentic and complete. The main steps involved in fuzzy TOPSIS approach are as follows: (a) linguistic representation and fuzzification of the output variables of the simulation model based on the membership functions, (b) normalization of fuzzy triplets, (c) defuzzification, (d) obtaining positive and negative ideal solutions, and (e) calculating the closeness coefficient. Step-by-step detailed explanation and all equations can be found in Minatour et al. (2015). For illustration, the procedure of incorporating uncertainty, to obtain the total score of water quality status at the first five sampling stations, has been described briefly. For brevity reasons, only four simulated critical output parameters (pH, DO, BOD, and total coliform (TC)) are considered for the year 2015.

The simulated data values of the critical output variables (pH, DO, BOD, and fecal coliform), obtained from WASP,

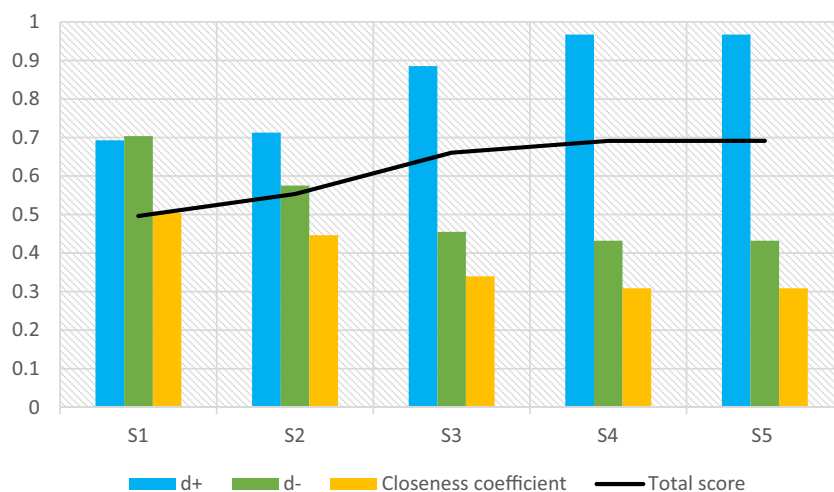
act as the input to the fuzzy TOPSIS framework. These inputs are analyzed and compared with prescribed water quality standards by experts and are assigned a linguistic rating. “Very Poor” (VP), “Poor” (P), “Fair” (F), “Good” (G), and “Very Good” (VG) are linguistic representations of the inputs of various sampling stations. For example, if the value of DO is between 4 and 6 mg/l, it is assigned a linguistic rating “F.” Table 7 represents linguistic (qualitative) assessment for the first five sampling stations along the river. For sampling station S1, the values of pH, DO, BOD, and TC are 8.5, 4 and 9 mg/L, and 150,000 MPN (most probable number)/100 mL in pre-monsoon season of 2015. Thus, DO gets a rating of “Fair.” Linguistic grades are transformed into fuzzy triplets using triangular fuzzy membership functions (Fig. 9).

For example, linguistic representation of DO at S1 is “F” and corresponding fuzzy representation (a, b, c) is (5, 7, 9). By converting range of values into a single fuzzy scale, uncertainty is dealt in an effective manner. These fuzzy triplets, thus, are converted into aggregate rating ( $r_{ij}$ ) using the Hsu and Chen method to obtain normalized scores, which are defuzzified using graded mean formula to obtain a single crisp value. Table 8 presents the fuzzification, aggregated, and crisp values of DO at all five sampling stations. In a similar manner, calculations are performed for other critical variables at each station. The crisp values are then used to determine positive ideal solution (PIS) and negative ideal solution (NIS). The measure of the distance of each parameter from PIS (i.e.,  $d^+$ )

**Table 8** Fuzzy membership ratings and aggregated and crisp values for DO

Sampling station	DO (fuzzy triplet)	Aggregate rating ( $r_{ij}$ )	Crisp value
S1	[5, 7, 9]	[0.56, 0.71, 1.00]	0.74
S2	[7, 9, 10]	[0.50, 0.56, 0.71]	0.57
S3	[9, 10, 10]	[0.50, 0.50, 0.56]	0.51
S4	[7, 9, 10]	[0.50, 0.56, 0.71]	0.57
S5	[7, 9, 10]	[0.50, 0.56, 0.71]	0.57

**Fig. 10** Graphical representation of PIS, NIS, CC, and total water quality score



and NIS (i.e.,  $d^-$ ) is also evaluated, in order to determine the closeness (relative preference) coefficients corresponding to each variable at all sampling stations. Closeness coefficients (CC) are then analyzed to determine the total water quality score on a scale of 0–1. The closer the water quality score of a particular sampling station to 0, the better is its water quality. Figure 10 represents the PIS, NIS, closeness coefficient, and the total score of water quality.

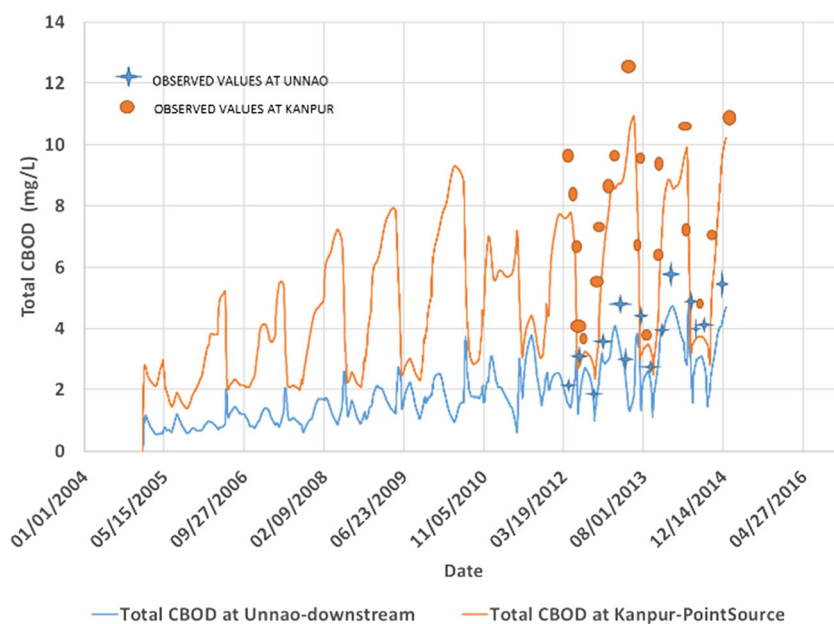
## Results and discussion

### Simulated outcomes of advanced eutrophication model

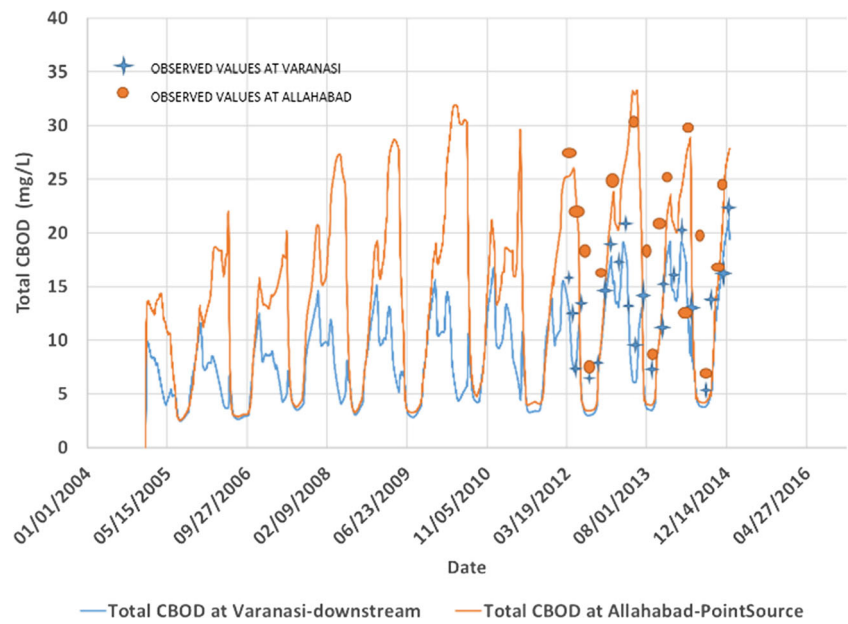
Once the simulation model is calibrated and validated, the interpretation of the results is possible. Figures 11, 12, 13,

14, 15, 16, 17, and 18 represent the simulated values of TCBO<sub>D</sub>, pH, NH<sub>3</sub>-N, DO, TDS, and alkalinity, respectively, for Unnao-downstream, Kanpur point source, Varanasi-downstream, and Allahabad point source. The study reveals the presence of high concentrations of parameters responsible for causing eutrophication such as TCBO<sub>D</sub>, TDS, PO<sub>4</sub><sup>3-</sup>, and NH<sub>3</sub>-N in the river water, especially during the seasons of lean flow (< 1000 m<sup>3</sup>/s). Domestic and industrial sewage and the runoffs from inorganic farms located along the river banks are the primary factors causing algal bloom. The model explains that the increased concentration of organic nitrogenous and phosphorus compounds is due to zooplankton excretion or detritus re-mineralization happening within the water column. As compared to previous models, WASP-based advanced eutrophication model is considered as an invaluable tool to analyze the complex bio-physiochemical processes pertaining to eutrophication phenomena in a riverine

**Fig. 11** TCBO<sub>D</sub> simulated values versus observed data (Unnao and Kanpur)



**Fig. 12** TCBOD simulated values versus observed values (Varanasi and Allahabad)

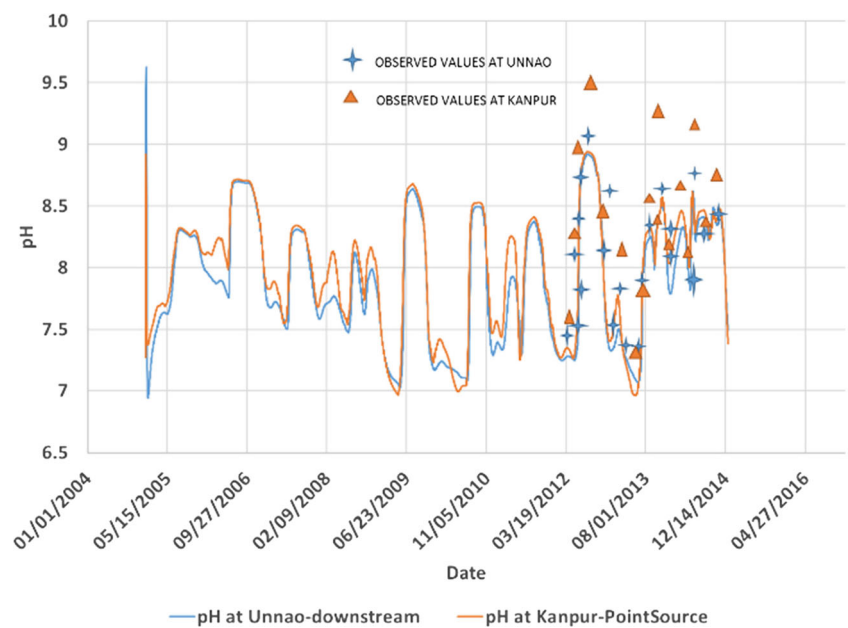


ecosystem. The three-dimensional model very well analyzes the dynamics taking place in an aquatic system such as inter-relationships between dissolved solids, phytoplankton, pH, alkalinity, light, oxygen demand, nitrification, phosphates, bacteria and sediments, which are not dealt simultaneously by previous eutrophication models (Park et al. 2008; Yazdi and Moridi 2017). Also, the flexibility offered by the model provides a latitude to the decision maker to consider different groups of environment parameters and kinetic constants, which enhances the accuracy and precision in prediction (Lai et al. 2013). The simulation results have been validated by comparing them with the recent findings of government agencies (UPJN, UPPCB, and CPCB 2017) and few

secondary sources (Lokgariwar et al. 2014; Chaudhary et al. 2017; Paul 2017; Tare et al. 2017). For example, a recent study conducted by UPJN, UPPCB, and CPCB (2017) on open drains reveal that the river is facing a serious threat as the concentrations of toxins, chemicals, and other dangerous bacteria found in the river are almost 3000 times the safe limit as suggested by the World Health Organization (WHO).

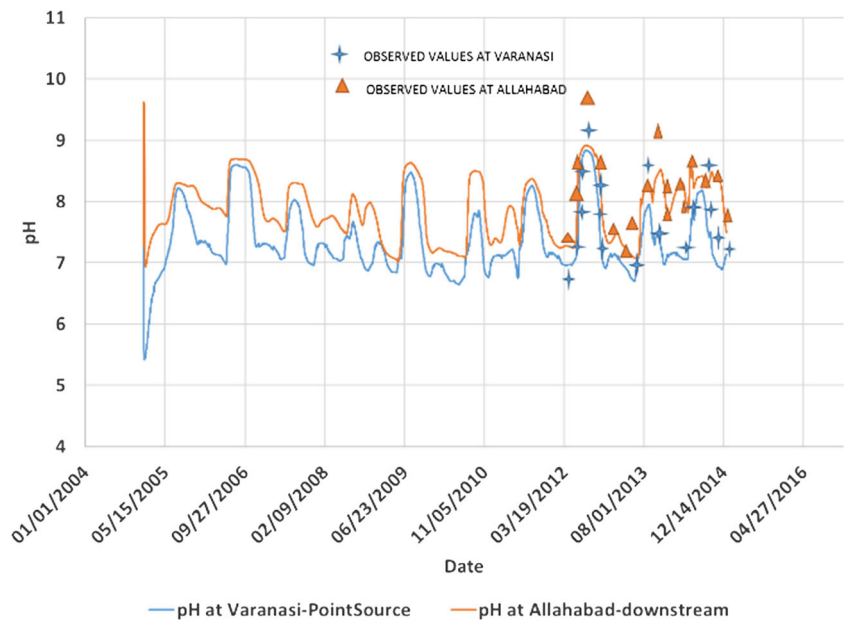
In general, TCBOD shows a decreasing trend during monsoon season (June–October), whereas an increasing trend is observed during dry periods (March–May, November–February), which indicates that the dilution capacity of the river increases during the monsoon due to increase in the flow of the river (MoWR 2016). The values in summer are as high

**Fig. 13** pH simulated values versus observed data (Unnao and Kanpur)





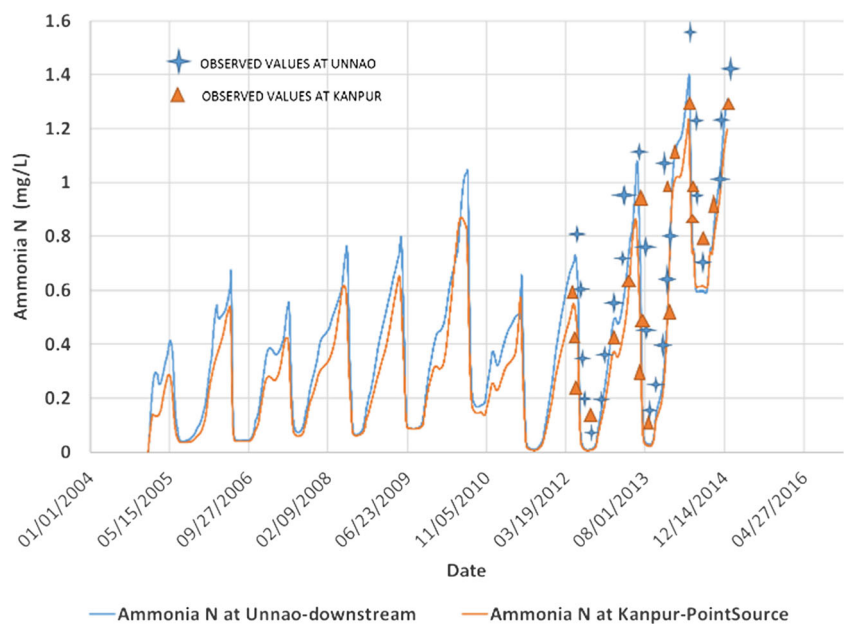
**Fig. 14** pH simulated values versus observed values (Varanasi and Allahabad)



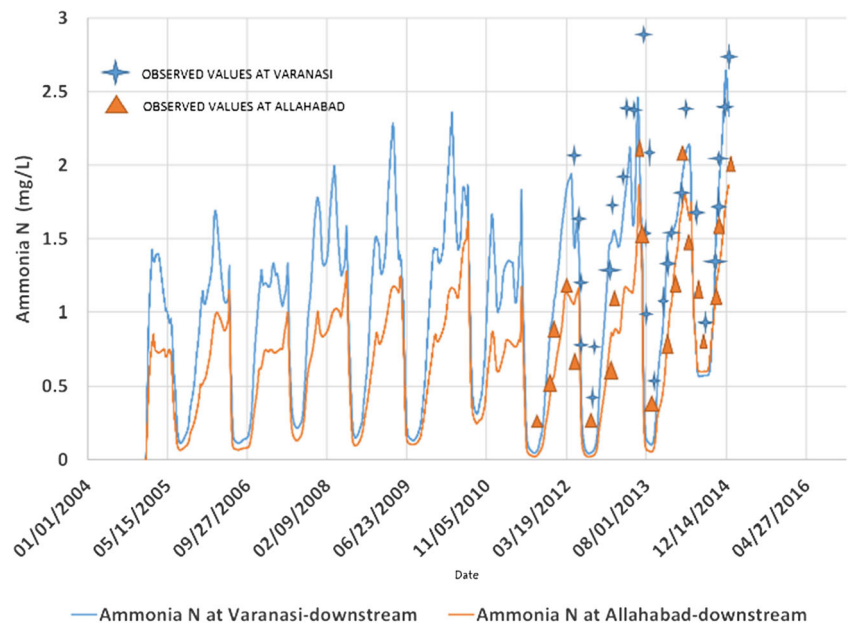
as 11 mg/L at Kanpur as compared to 6 mg/L at Unnao as represented by the peaks in Fig. 11. The higher values at Kanpur is due to the presence of more than 500 industrial sectors such as paper pulp industries, food industry, agricultural industry, textile industries, and tanneries (UPPCB 2013). In addition, municipal sewage of total 700 MLD is discharged into the river at Kanpur and Unnao. Lower values of TCBOD are recorded only during the monsoon when the flow of river is considerably higher ( $> 2000 \text{ m}^3/\text{s}$ ). In Kanpur, even the least values of TCBOD are above the standard prescribed limits and the concentration of TCBOD is rising every year. A similar kind of variation is observed for TCBOD at Varanasi and Allahabad (Fig. 12). The values of TCBOD

range between 20 and 30 mg/L during dry seasons just after the mixing points of drains in the river in Allahabad, where these point sources meet the river. This is mainly because of poor drainage system in the city (UPJN et al. 2017). As compared to Allahabad, concentration of TCBOD is slightly low in Varanasi. The primary problem in Varanasi is poor solid waste management and city sanitation plan. This has resulted in open defecation and increased fecal coliform count (as high as 1,000,000 MPN/100 ml). Raw sewage, effluents from industry, plastic bags and bottles, human waste, chemical from tanneries, discarded idols, partially cremated corpses, flower garlands, human remains, animal carcasses, butcher's offal, chemical dyes from textile factories, and construction

**Fig. 15**  $\text{NH}_3\text{-N}$  simulated values versus observed data (Unnao and Kanpur)



**Fig. 16** NH<sub>3</sub>-N simulated values versus observed data (Varanasi and Allahabad)

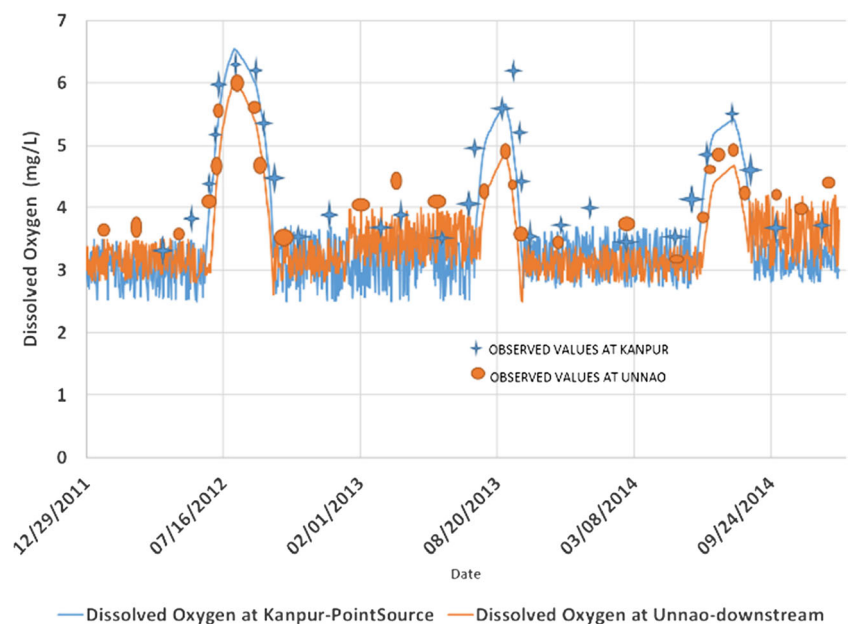


waste end up in river Ganges. The pH (Fig. 13) rises as high as 9 or even 10 in Kanpur and Unnao due to the presence of tanneries and soap industries. In Varanasi and Allahabad, pH (Fig. 14) ranges mostly between 7 and 8.5. Due to implementation of inorganic farming, i.e., frequent usage of pesticides and fertilizers, the agricultural runoff containing high concentration of phosphate, ammonia (Figs. 15 and 16), and nitrates enters the river (MoWR 2016). The increased nutrient concentration results in algal bloom especially in the summer season, which reduces the dissolved oxygen concentration in the river (Paul 2017). The increase in DO (Figs. 17 and 18) during monsoon period is mainly due to the increased discharge of water along with better quality water coming

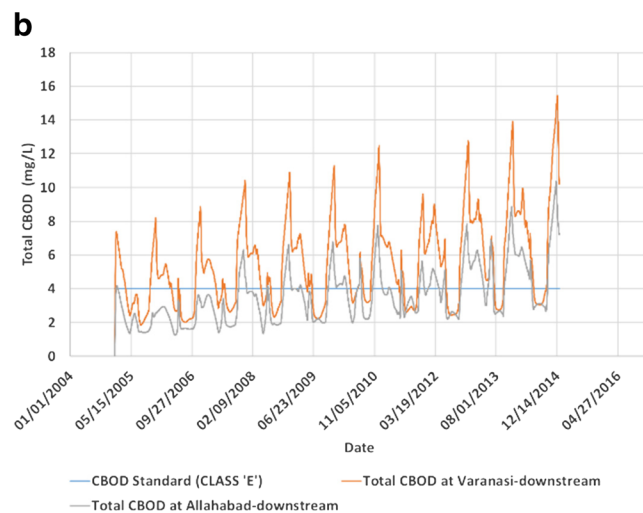
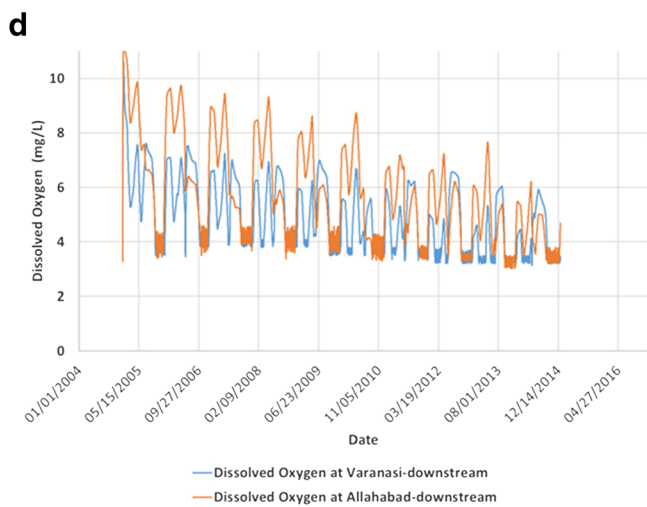
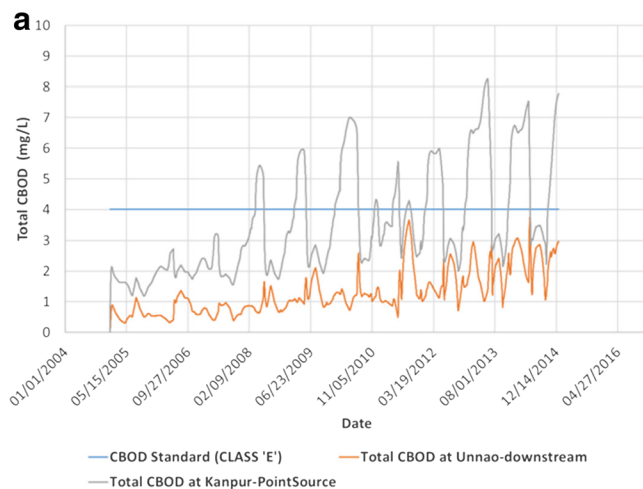
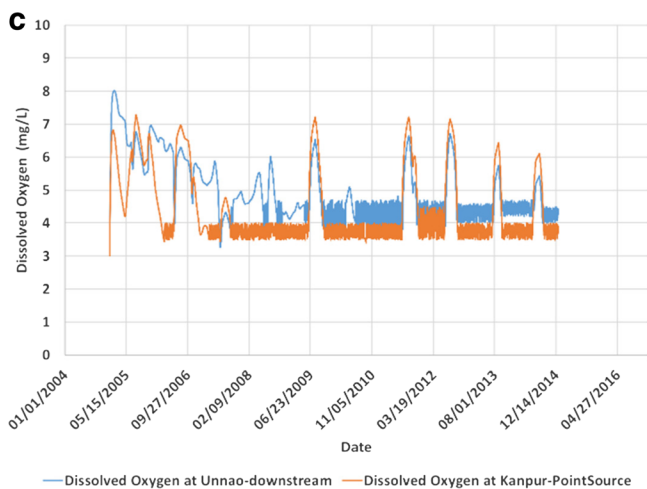
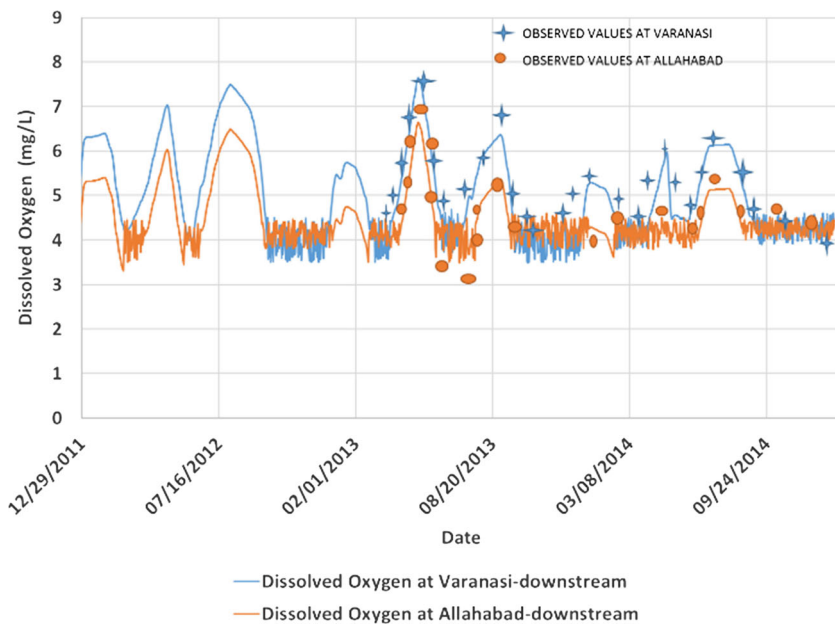
from the upstream of the river. However, the highest value of DO is registered as 6.0 mg/L just upstream of point sources in Kanpur and Unnao and slightly higher (approx. 7.0 mg/L) in Varanasi and Allahabad. Although Allahabad and Varanasi do not have so many industries, still, lower values of DO are recorded due to intensive algal bloom caused by increased nutrient concentration in the river (Chaudhary et al. 2017). Graphical representations of simulation results of fecal coliform, nitrate, and phosphate are omitted for brevity reasons.

The purpose of conducting a long-term simulation is to obtain consistent and stabilized results for comparison. Overall, the model is capable enough to capture both the spatial and temporal variations in the water quality of river

**Fig. 17** DO simulated versus observed values (Kanpur and Unnao)



**Fig. 18** DO simulated versus observed values (Varanasi and Allahabad)



**Fig. 19** Simulation for scenario 1. **a, b** TCOD. **c, d** DO

**Table 9** Results obtained by sensitivity analysis of the fuzzy model

Sampling station	WQS (out of 100) using		
	Triangular MF	Trapezoidal MF	Gaussian MF
S1	49.62	45.34	50.45
S2	55.34	51.78	52.36
S3	66.05	69.32	72.77
S4	69.13	66.15	68.96
S5	69.13	70.34	73.32
S6	68.02	65.09	67.88
S7	69.13	65.34	71.66
S8	61.85	62.22	67.31
S9	61.85	56.67	58.64

Ganges, although a few minor disparities exist between the simulated results and observed data at certain locations and times. However, such disparities are acceptable for decision support purpose as the model can effectively represent the overall dynamics of the river after calibration and validation. The model serves as a foundation tool to predict water quality status of the river with respect to the river’s discharge and pollutant loadings (Fig. 19).

**Uncertainty and sensitivity analyses using fuzzy set theory**

The coupling of simulation results of WASP with the fuzzy approach gives wide scope to the decision maker to deal with the uncertainty associated with the output variables. As the input parameters of the WASP model are subjected to randomness and imprecision due to spatial and temporal changes, hence, model results can be accepted with certainty only when uncertainty aspect is dealt effectively. In addition, fuzzy TOPSIS approach also helps in determining the overall score representing water quality status (WQS) at different sampling stations on a scale of 0–100

with respect to certain critical parameters. Further, a sensitivity analysis is performed by changing the membership functions (MFs) of the input parameters to analyze the robustness of the results obtained using fuzzy approach (Table 9). The outcomes of sensitivity analysis justify the robustness of the fuzzy approach applied for analyzing the uncertainty present in simulation outputs. The similar analysis can also be performed by adding, deleting, and modifying the inputs of the fuzzy model.

As discussed before, lesser score represents better water quality. More than 95% of the values in Table 9 are above 50, indicating the precarious condition of water quality at all sampling stations. Therefore, there is a need to carry out scenario analysis to determine total daily maximum loads and the river discharge, which can restore the river water quality. Also, the policy makers should also try to incorporate and reduce the impact of non-point source pollution in the river water quality modeling.

**Development of scenarios and strategies for sustainable river basin management**

Restoring water quality of Ganges is the primary objective of decision makers, which can be achieved only by proper planning and implementation of appropriate action plans. An effective approach is to analyze the impact of varying pollutant loadings on the water quality of the river, so as to achieve the standard of water quality targets as prescribed by CPCB (Table 10) for five different classes (viz, A to E) (CPCB 2017). The study reveals that the average concentrations of critical parameters such as BOD, DO, TDS, and fecal coliform are very high (very low in case of DO) as compared to the prescribed standards. Therefore, five scenarios are proposed by the experts. An iterative “model scenario” runs are conducted to first achieve the initial objective, i.e., to reach the class E standard. The primary goal is to achieve at least class C standard, so that water can be used for drinking purposes after conventional treatment. The water quality data of 10 years

**Table 10** Classification of water according to the beneficial usage

Classification	Beneficial usage	Prescribed standard
Class A	Drinking water source without conventional treatment but after disinfection	Total coliform 50 MPN/100 mL or less, pH 6.5–8.5, DO 6 mg/L or more, BOD 2 mg/L or less
Class B	Outdoor bathing, swimming, and recreation	Total coliform 500 MPN/100 mL or less, pH 6.5–8.5, DO 5 mg/L or more, BOD 3 mg/L or less
Class C	Drinking water source with conventional treatment followed by disinfection	Total coliform 5000 MPN/100 mL or less, pH 6–9, DO 4 mg/L or more, BOD 3 mg/L or less
Class D	Fish culture and wildlife propagation	pH 6.5–8.5, DO 4 mg/L or more, free ammonia (as N) 1.2 mg/L or less
Class E	Irrigation, industrial cooling, or controlled waste disposal	pH 6–8.5, electrical conductivity 2250 µmhos/cm (max at 25 °C), sodium absorption ratio max 26, boron 2 mg/L (max)

Source: Central Pollution Control Board (2017)



(i.e., 2005 to 2015) and the response of river towards the fractional reduction in pollutant loadings have been studied deeply to formulate different scenarios as given below:

Scenario 1: Reducing loading at Kanpur, Allahabad, and Varanasi by 25%

Scenario 2: Reducing loading at Kanpur, Allahabad, and Varanasi by 50%

Scenario 3: Reducing loading at Kanpur, Allahabad, and Varanasi by 75%

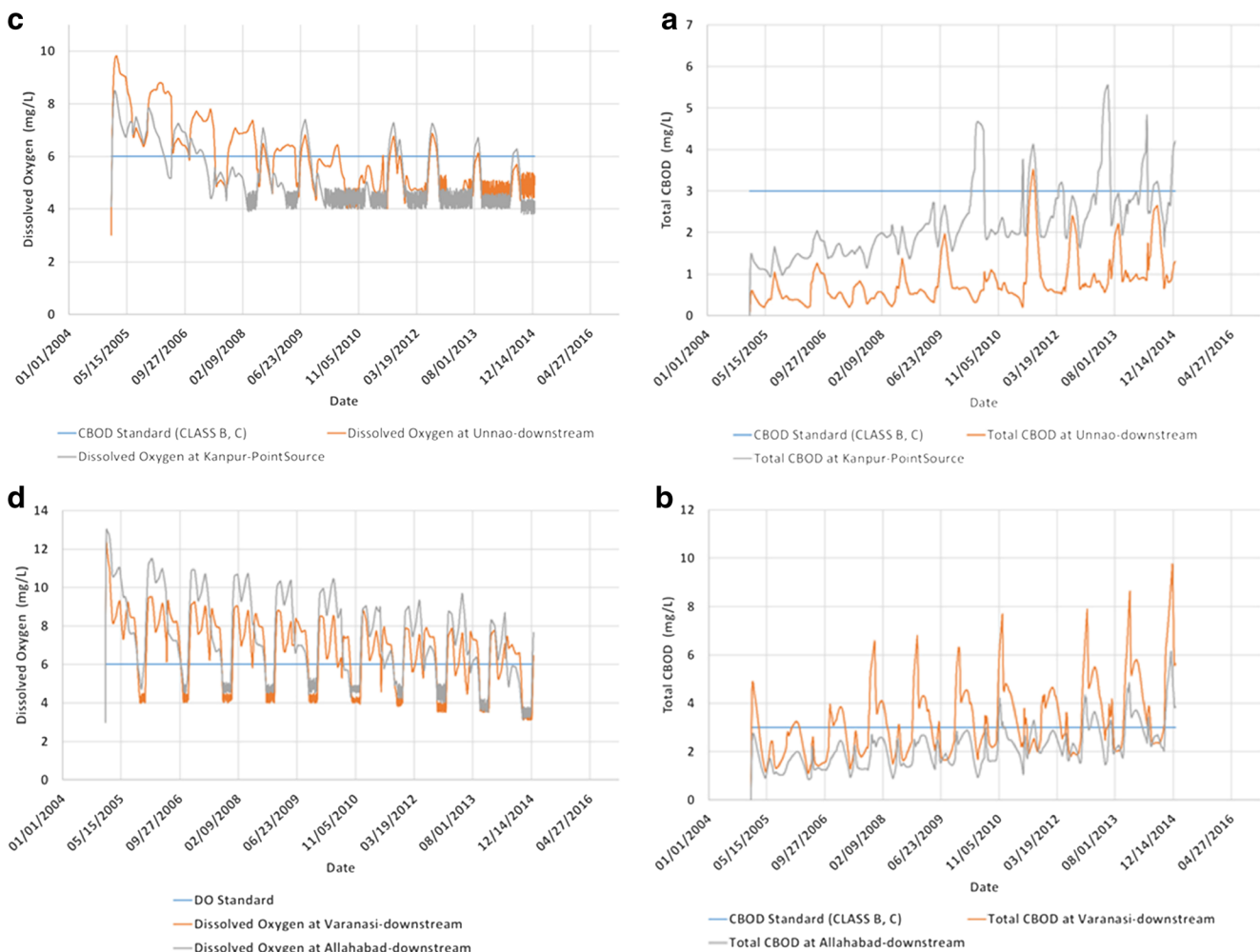
Scenario 4: Reducing loading at Kanpur, Allahabad, and Varanasi by 25% and increasing river flow at Kanpur to at least 1500 m<sup>3</sup>/s during dry seasons

Scenario 5: Reducing loading at Kanpur, Allahabad, and Varanasi by 50% and increasing river flow at Kanpur to at least 1500 m<sup>3</sup>/s during dry seasons

Although pollutant loadings are not uniform at all stations, still, the loads have been reduced fractionally, instead of reducing the same specific to a particular site.

Such decision has been arrived by conducting a simultaneous discussion with all the local governmental authorities.

Figures 19, 20, and 21 give the graphical representation of the simulated results of TCBOD and DO corresponding to all five scenarios. On reducing pollutant loadings of the point sources by 25%, there is a significant improvement in the TCBOD and DO values (Fig. 19). At Kanpur and Unnao, during monsoon seasons, the BOD values are below 4 mg/L and thus suitable for class E purpose. However, most of the BOD values are beyond 4 mg/L for Allahabad and Varanasi, signifying tremendous contribution from heavy untreated wastes. At the same time, dissolved oxygen concentration is below the standard prescribed limit of 6 mg/L, especially during dry periods at all four stations. Allahabad and Varanasi show some improvement in dissolved oxygen due to addition of water from other tributaries at these sampling stations. Thus, fractional reduction of load by 25% can lead to improved water quality, provided that a particular segment has adequate flow. Otherwise, site-specific reduction has to be performed. The results pertaining to TCBOD and DO are



**Fig. 20** Simulation for scenario 2. **a, b** TCBOD. **c, d** DO

further improved for scenario 2, where 50% of the pollutant loadings are reduced. Seventy-five percent of the TCBO values (Fig. 20) for Kanpur, Unnao, and Allahabad are below 3 mg/L, signifying the suitability of the water to be used for class B and class C. During periods of lean flow, a sudden rise in BOD up to 5 and 10 mg/L is observed at Kanpur and Varanasi, respectively. Most of the dissolved oxygen values (Fig. 20) are clustered between 4 and 5 mg/L for all four sampling stations during lean periods, but the values rise up to 6–8 mg/L during monsoon.

About 70–75% of the TCBO values are below 2.5 mg/L for scenario 3, whereas more than 80% of the DO values are above standard prescribed limit of 6 mg/L (Fig. 21). However, the DO values show some decline during the year 2015 due to rapid rise in the industrial and urban sectors leading to increased pollution (Tare et al. 2017). Also, the continuous and increased discharge of dead bodies and poor sanitation system in the Varanasi stretch have further contaminated the river (MoWR 2016). The rise in DO concentration up to 12 mg/L in monsoon season at

Allahabad and Varanasi is due to addition of water from other tributaries.

Although, the development and application of the first three scenarios can be a significant achievement on the part of policy makers, it is not easy to accomplish this goal. As discussed, even to achieve considerably good standard of water quality would require an approximately 75% reduction in the existing pollutant loadings. This would surely demand tremendous effort in terms of planning and management at all levels, which requires huge infrastructure resources along with financial investment and time. Though the primary focus of the state governments demands rapid industrial development to uplift the life of the growing population, balancing the river’s sustainability and the country’s development must be given proper attention. Keeping in view these concerns, the study suggests two more scenarios, which are powerful enough to achieve the desired water quality even without reducing the loading to greater extent. These two scenarios focus on enhancing the assimilative/self-purifying capacity of the river by increasing the river discharge. The 10-year stream

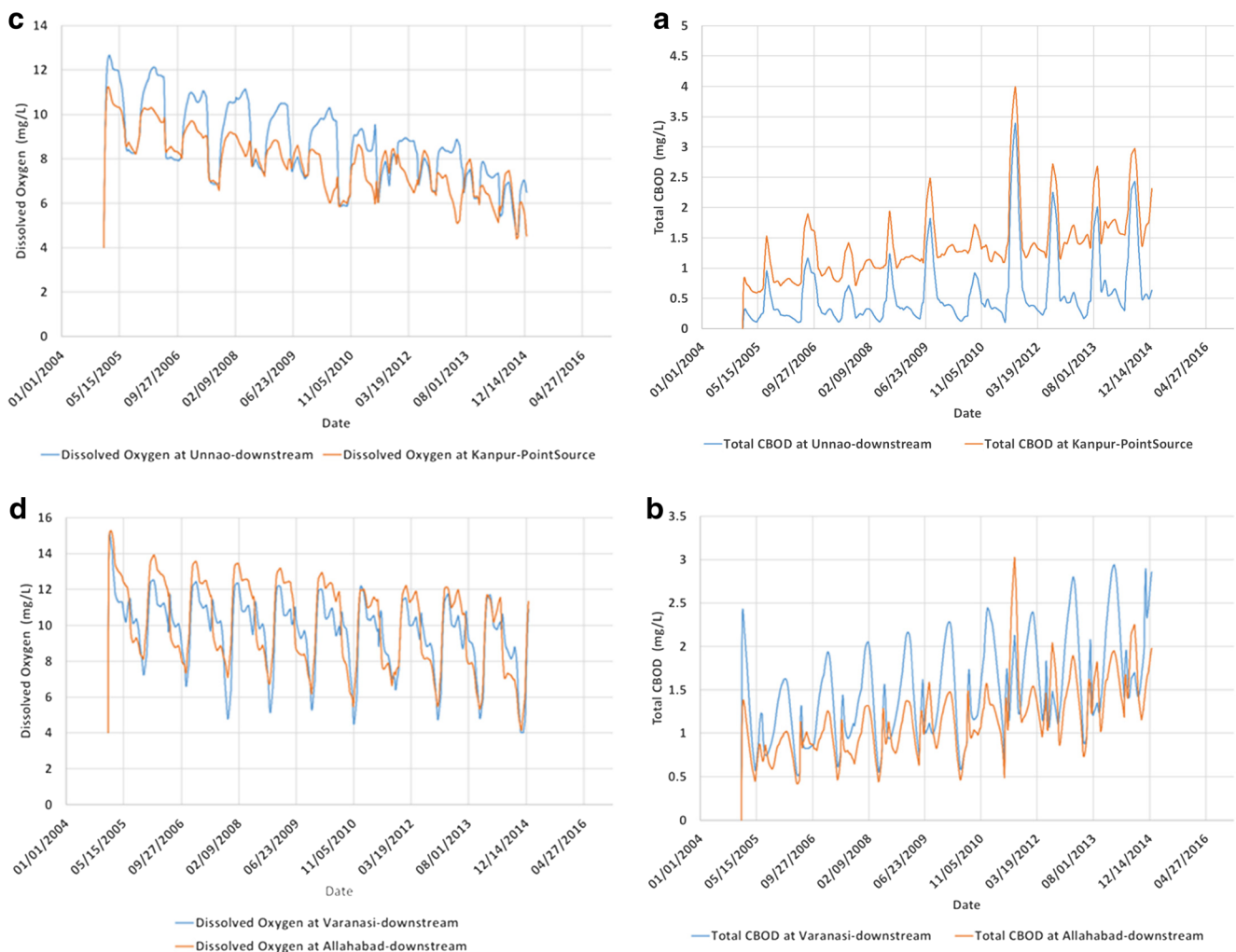
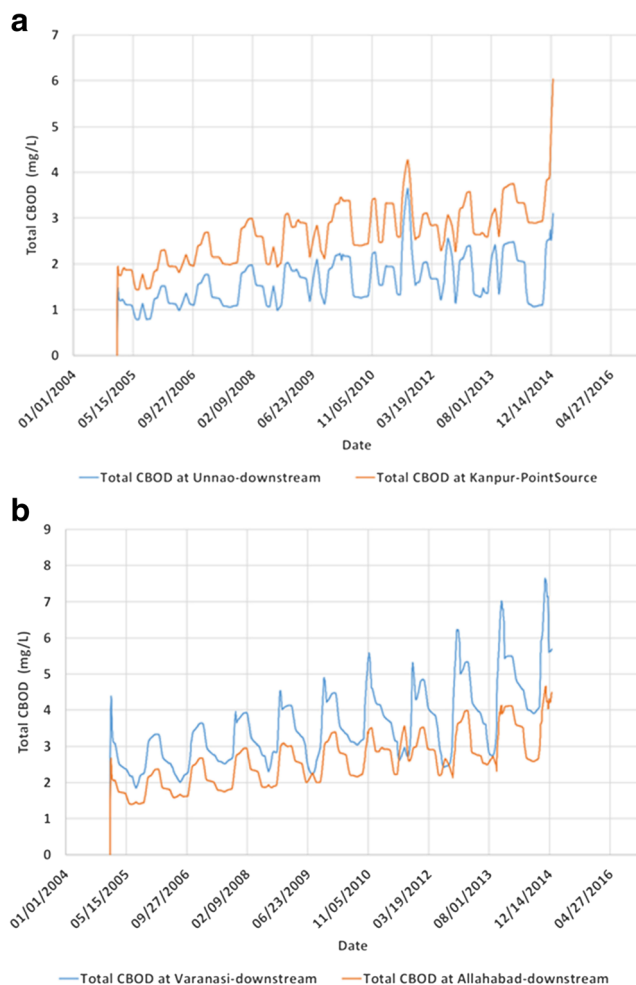


Fig. 21 Simulation for scenario 3. a, b TCBO. c, d DO

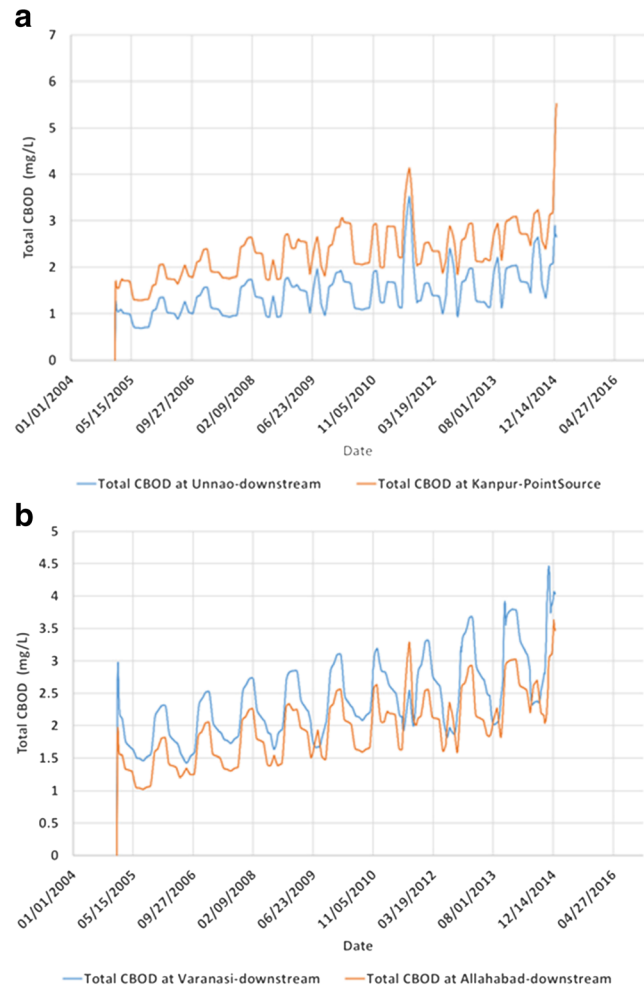
flow data of the river clearly demonstrates that the discharge of river during non-monsoon periods is less than  $1000 \text{ m}^3/\text{s}$  (Srinivas et al. 2017). The model is simulated by increasing the discharge of the river to  $1500 \text{ m}^3/\text{s}$  (Lokgariwar et al. 2014, Tare et al. 2017) at Kanpur during lean seasons along with a load reduction of 25 and 50%, respectively, for scenarios 4 and 5. The results (Figs. 22 and 23) represent a significant improvement in the TCBOB values at all four stations, thus indicating a significant enhancement in the water quality at the downstream as well. The primary objective of these scenarios is to ensure that Ganges has enough water to meet its ecosystem and livelihood needs. The flow is mainly obstructed due to intensive irrigation, multi-purpose projects, and barrages built on the river in recent times. New Delhi water resource bodies' (UPJN, UPPCB, CPCB, 2017) recent report states that more than 80% of water is diverted at Narora barrage before it reaches Kanpur, leading to reduced flow. Most of the hydropower plants built on the Ganges are designed to release either 0 e-flow or at most 10% e-flow in the entire year. Moreover, the Center for Science and Environment (CSE) suggests to provide 30% e-flow for

6 months (May to October) and 50% during dry periods (November to April). Thus, the planning and management of these plants have to be done keeping into consideration the e-flow of the river, sustainability, and competing needs of the society (Lokgariwar et al. 2014). The government must understand that rivers cannot and should not be re-engineered, but these multi-purpose projects certainly need to be re-engineered to optimize the essential parameters. The proposal of CSE would surely reduce the hydropower generation by 7%, but it can significantly improve the water quality not only in the upstream region but also in the downstream of the river. Therefore, scenarios 4 and 5 provide a basic framework to the decision makers for water quality restoration. In addition to TCBOB, all other water quality variables showed significant improvement when simulated for scenarios 4 and 5.

Figures 24, 25, 26, and 27 summarize the overall effect of all five scenarios on critical output variables. The results obtained under different scenarios clearly demonstrate that there is a significant decrease in ammonical nitrogen, nitrate-nitrogen, and organic phosphorus, which are the main sources of eutrophication phenomena. The modeling of eutrophication

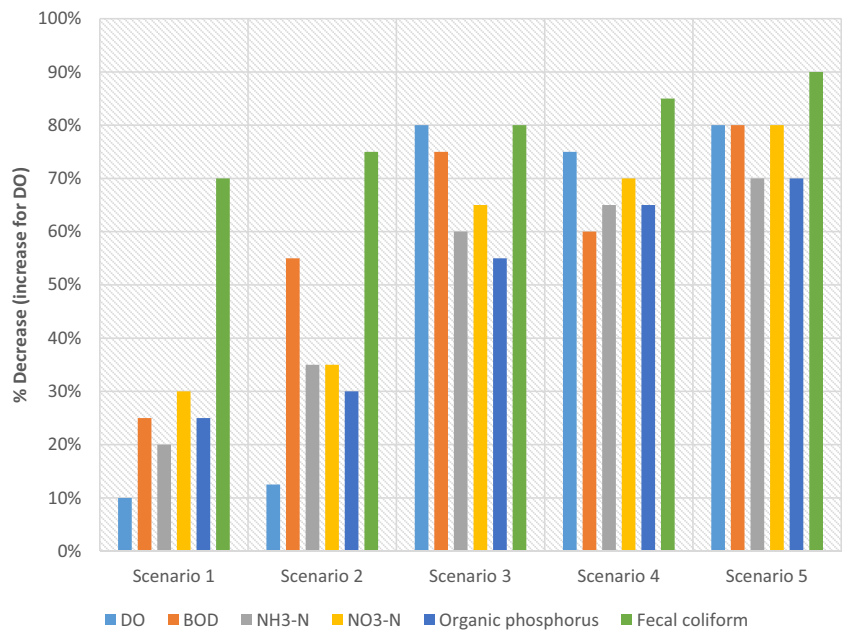


**Fig. 22** Simulation for scenario 4. **a, b** TCBOB



**Fig. 23** Simulation for scenario 5. **a, b** TCBOB

**Fig. 24** Overall effect of different scenarios on the critical output variables at Kanpur



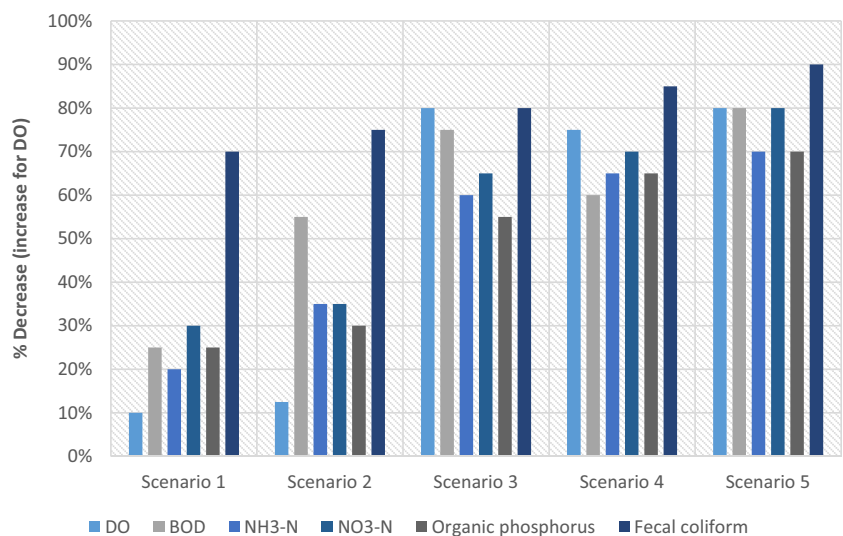
process presented herein thus not only provides an assessment of available concentration of different nutrients/pollutants, but also suggests different scenarios for improving the self-purifying capacity of the river. Along with implementation of scenarios 4 and 5, the study recommends the authorities to focus on modeling and controlling non-point pollution sources, mainly open defecation and agricultural runoff, which lead to eutrophication. Also, a zero-sewage discharge model can be developed by treating the organic pollutants to a particular level, so that they can be used as manure in the agricultural fields. The practice of organic farming can be a significant initiative towards increasing river flow and also controlling eutrophication problems. Organic farming not only reduces non-point pollution, but also increases the water circulation ability of the soil. Such agricultural fields require

less water as compared to the inorganic-based ones, and thus, lesser water will be abstracted from the river (Gomiero et al. 2011). Consequently, the load on the river is reduced both quantitatively and qualitatively.

### Conclusions and recommendations

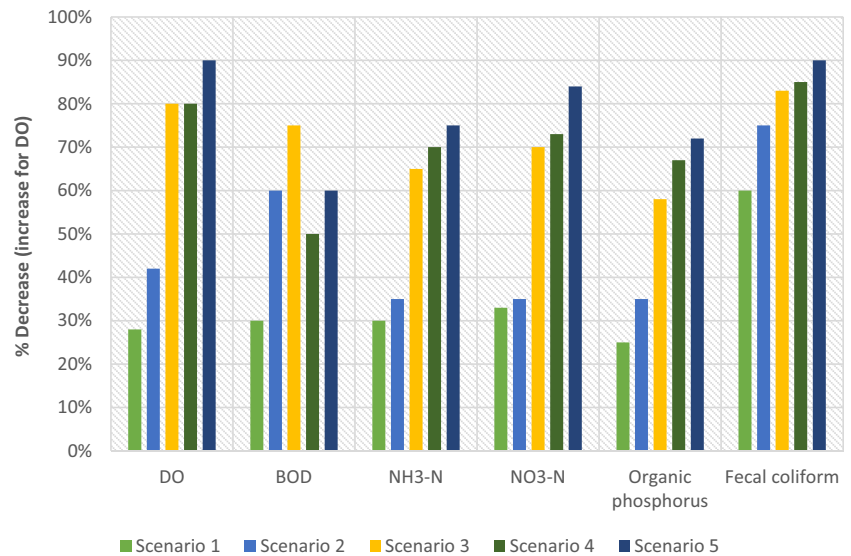
The WASP-based *advanced eutrophication* model developed herein summarizes the water quality at various sampling stations located along the most polluted stretch of river Ganges (Kanpur-Varanasi), India. The model effectively simulates the fate and transport of water quality indicators both spatially and temporally. The advanced eutrophication model overcomes the limitations of the classical models by considering a wide

**Fig. 25** Overall effect of different scenarios on the critical output variables at Unnao





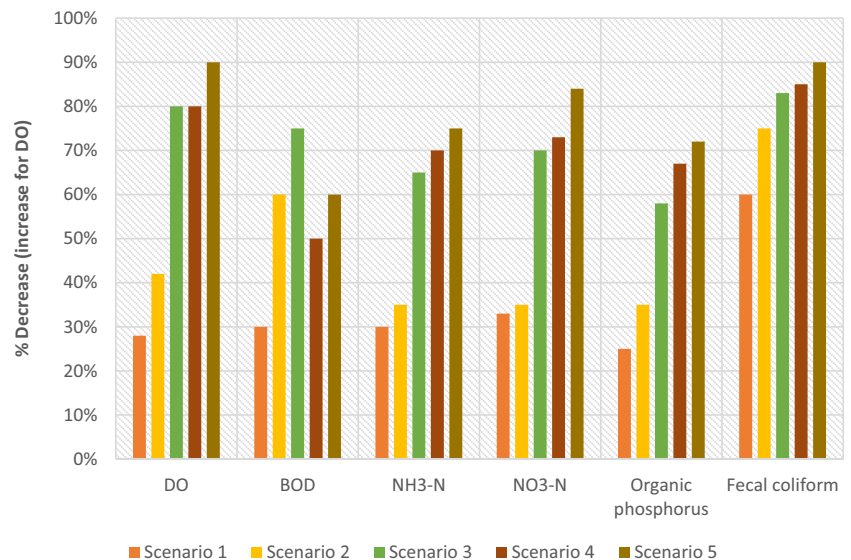
**Fig. 26** Overall effect of different scenarios on the critical output variables at Allahabad



range of interrelated parameters and bio-physicochemical processes contributing towards the dynamic response of the river due to eutrophication. The novelty of the study is to integrate eutrophication model's simulation outcomes to fuzzy methodology to deal with the uncertainty associated with the simulation model in an effective manner. Further, sensitivity analysis also establishes the robustness of the fuzzy TOPSIS approach. The study is quite comprehensive as it takes into account a total of 9 sampling stations, 9 state variables, 33 open drains, and corresponding observed data of 10 years for the simulation. Finally, 14 output variables are simulated, which can effectively predict the water quality for sustainable river basin management. The results and recommendations have been validated by comparing them with previous governmental and non-governmental scientific works. The primary findings and conclusions of the model include the following:

1. The ability of the model to effectively represent the spatial and temporal variation of the observed water quality data clearly indicates that the model is robust and can support the decision makers to study the fluctuations in the riverine ecosystem due to eutrophication. Usage of huge water quality data for a period of 10 years has increased the stability of the model.
2. The model has also been used for developing five important scenarios for pollutant loadings under the guidance of experts and local government organizations. Scenario 3 gives satisfying results; however, it is quite difficult to implement it realistically. Thus, the study proposes an increase in the stream flow of the river during the lean periods to enhance the self-purifying ability of the river. To achieve this objective, two more scenarios (4 and 5) are formulated and regulatory measures for multi-purpose

**Fig. 27** Overall effect of different scenarios on the critical output variables at Varanasi





projects and barrages are suggested. There is a substantial improvement in the water quality of Ganges in the downstream region when the flow in the upstream section is increased.

3. The study firmly recommends organic farming in the agricultural fields with proper justification. The inorganic farming not only leads to non-point source pollution, but also deteriorates the soil's features such as water circulation capacity, which results in intensive irrigation and thus over-abstraction of river water. Organic farming also decreases the amount of water withdrawals from the river (intensive irrigation) by enhancing the capability of soil to circulate water. In addition, the manure and water for the organic farming can be obtained from the sewage treatment plants, which can be an initiative towards developing a "zero-sewage discharge" model. In fact, after some preliminary treatment, sewage water can be used for industrial usages as well.
4. The study emphasizes on sustainable and integrated river basin management. Any developmental activity on the river, especially building of dams and constructing barrages, and widening of roads and highways should be performed without disturbing four interrelated primary survival elements of the river, namely, flow, energy, biodiversity, and sediments. Therefore, a release of 50% of e-flow during dry periods is highly recommended for all multi-purpose projects, and future projects can be designed accordingly.
5. The results obtained from the model can give a comprehensive and focused guidance to the decision makers to achieve sustainable development of river basin. However, the results can be further enhanced and refined by using more accurate data. Usage of fuzzy logic has a tremendous impact on the model outputs by incorporating the intricacies and uncertainties associated with the predicted values. The primary focus of the future research should be to incorporate the effect of non-point sources of pollution, especially agricultural runoff and open defecation, and to link the model with a geo-statistical approach. Accordingly, the model can guide the pollution-controlling agencies to develop strategies for more sophisticated load reduction. The model results can be further enhanced by incorporating the probability associated with random nature of input variables of the simulation. The probabilistic models can be developed to deal with the randomness of input variables at the data source by further enhancing the work using methods such as rank correlation analysis and/or first-order reliability analysis (FORA) to simulate key input variables. Correlation approaches have been found suitable to assess the global importance (i.e., importance of key inputs over a wide range of possible outputs) (Yeh and Tung 1993), whereas FORA can evaluate the best estimate of a specific output using input

variables. In general, if the model is being validated, correlation approaches can be considered of greater importance, as adopted in this study. The model can be further enhanced to reduce uncertainty in prediction by using methods such as FORA and Monte Carlo simulation (Vemula et al. 2004). By identifying key input variables and reducing their uncertainty, model output uncertainty can be reduced. Such simultaneous incorporation of randomness and fuzziness can be taken up as future scope of the study. Overall, the decision support framework presented herein not only has been proved as an effective tool in specific context to river Ganges, but also can equally be applied for analysis, prediction, and management of water quality in any of the selected river basins in an effective and sustainable manner.

**Acknowledgements** The authors are grateful to BITS Pilani, India, for providing necessary facilities to carry out this research work. Authors are also thankful to CWC, Lucknow, and CPCB, New Delhi, for sharing information on river Ganges. The software WASP (version 8.0) used for the entire modeling has been provided by US Environmental Protection Agency. All references cited in the text have provided the detailed insight about the subject matter and therefore are greatly acknowledged. We also express our sincere thanks to the anonymous reviewers and editors for their valuable comments and time.

## References

- Abrishamchi A, Tajrishi M, Shafieian P (2005) Uncertainty analysis in QUAL2E model of Zayandeh-Rood river. *Water Environ Res* 77(3): 279–286
- Ajami NK, Duan Q, Sorooshian S (2006) An integrated hydrologic Bayesian multi-model combination framework: confronting input, parameter and model structural uncertainty in hydrologic prediction. *Water Resour Res* 43. <https://doi.org/10.1029/2005WR004745>
- Ambrose B, Wool TA, Martin JL (2001) The Water Quality Analysis Simulation Program, WASP6, User Manual, US EPA. Athens, GA
- Cardona CM, Martin C, Salterain A, Castro A, San Martín D, Ayesa E (2011) CALHIDRA 3.0—new software application for river water-quality prediction based on RWQM1. *Environ Model Softw* 26: 973–979
- Carroll RWH, Warwick JJ (2010) Evaluating the impacts of uncertainty in geomorphic channel- changes on predicting mercury transport and fate in the Carson river system, Nevada. *Proc. Annual International Conference on Soils, Sediments. Water Energy* 13:266–280
- Chao X, Jia Y, Shields FD Jr, Wang SSY, Cooper CM (2010) Three-dimensional numerical simulation of water quality and sediment-associated processes with application to a Mississippi Delta lake. *J Environ Manag* 91:1456–1466
- Chaudhary M, Mishra S, Kumar A (2017) Estimation of water pollution and probability of health risk due to imbalanced nutrients in River Ganga, India. *Int J River Basin Manag* 15(1):53–60
- Conley DJ, Paerl HW, Howarth RW, Boesch DF, Seitzinger SP, Havens et al (2009) Controlling eutrophication: nitrogen and phosphorus. *Science* 323:1014–1015
- Diaz RJ, Rosenberg R (2008) Spreading dead zones and consequences for marine ecosystems. *Science* 321:926–929
- Fan C, Ko CH, Wang WS (2009) An innovated modeling approach using Qual2K and HEC-RAS integration to assess the impact of

- tidal effect on river water quality simulation. *J Environ Manag* 90:1824–1832
- Geza M, Poeter EP, McCray JE (2009) Quantifying predictive uncertainty for a mountain watershed model. *J Hydrol* 376:170–181
- Gomiero T, Pimentel D, Paoletti MG (2011) Environmental impact of different agricultural management practices: conventional vs. organic agriculture. *Crit Rev Plant Sci* 30(1–2):95–124
- Hipsey MR, Romero JR, Antenucci JP, Hamilton D (2006) Computational aquatic ecosystem dynamics model: CAEDYM v2. Science Manual v2.3. University of Western Australia
- Jin KR, Ji ZG, James RT (2007) Three-dimensional water quality and SAV modeling of a large shallow lake. *J Great Lakes Res* 33(1):28–45
- Kannel PR, Lee S, Lee YS, Kanel SR, Pelletier GJ (2007) Application of automated QUAL2Kw for water quality modeling and management in the Bagmati River, Nepal. *Ecol Model* 202:503–517
- Karaouzas I, Dimitriou E, Skoulikidis N, Gritzalis K, Colombari E (2009) Linking hydrogeological and ecological tools for an integrated river catchment assessment. *Environ Model Assess* 14:677–689
- Kuo JT, Lung WS, Yang CP, Liu WC et al (2006) Eutrophication modeling of reservoirs in Taiwan. *Environ Model Softw* 21:829–844
- Lai YC, Tu YT, Yang CP et al (2013) Development of a water quality modeling system for river pollution index and suspended solid loading evaluation. *J Hydrol* 478:89–101
- Lin CE, Chen CT, Kao CM, Hong A, Wu CY (2011) Development of the sediment and water quality management strategies for the Salt-water River, Taiwan. *Mar Pollut Bull* 63:528–534
- Lokgariwar C, Chopra R, Smakhtin V, Bharati L, O’Keeffe J (2014) Including cultural water requirements in environmental flow assessment: an example from the upper Ganga River India. *Water Int* 39(1):81–96
- Mannina G, Viviani G (2010) Water-quality modelling for ephemeral rivers: model development and parameter assessment. *J Hydrol* 393:186–196
- Minatour Y, Bonakdari H, Zarghami M, Ali BM (2015) Water supply management using an extended group fuzzy decision-making method: a case study in North-Eastern Iran. *Appl Water Sci* 5(3):291–304
- MoWR (2016) River development and Ganga rejuvenation, Ganga basin. Ministry of Water Resources (MoWR), Government of India, New Delhi
- Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models part I—a discussion of principles. *J Hydrol* 10(3):282–290
- Nikoo MR, Kerachian R, Karimi A, Azadnia AA, Jafarzadegan K (2013) Optimal water and waste load allocation in reservoir–river systems: a case study. *Environ Earth Sci* 79(9):4127–4142
- Osmi SFC, Malek MA, Yusoff M et al (2016) Development of river water quality management using fuzzy techniques: a review. *Int J River Basin Manag* 14(2):243–254
- Pan Q, Chhipi-Shrestha G, Zhou D, Zhang K et al (2017) Evaluating water reuse applications under uncertainty: generalized intuitionistic fuzzy-based approach. *Stoch Env Res Risk A*. <https://doi.org/10.1007/s00477-017-1449-1>
- Park RA, Clough JS, Wellman MC (2008) AQUATOX: modeling environmental fate and ecological effects in aquatic ecosystems. *Ecol Model* 213:1–15
- Paul D (2017) Research on heavy metal pollution of river Ganga: a review. *Ann Agrar Sci* 15(2):278–286
- Rangel Peraza JG, Anda JD, Gonzalez Farias FA et al (2016) Sensitivity and uncertainty analysis on water quality modelling of Aguamilpa Reservoir. *J Limnol* 75(1):81–92. <https://doi.org/10.4081/jlimnol.6.1391>
- Reckhow KH (1994) Water quality simulation modeling and uncertainty analysis for risk assessment and decision making. *Ecol Model* 72:1–20
- Rehana S, Mujumdar PP (2009) An imprecise fuzzy risk approach for water quality management of a river system. *J Environ Manag* 90(11):3653–3664
- Sagehashi M, Sakoda A, Suzuki M (2000) A predictive model of long-term stability after biomanipulation of shallow lakes. *Water Res* 34:4014–4028
- Segrave AJ, Vander Zouwen MW, Van Vierssen W (2014) Water planning: from what time perspective? *Technol Forecast Soc Chang* 86:157–167. <https://doi.org/10.1016/j.techfore.2013.08.019>
- Shojaei M, Nazif S, Kerachian R (2015) Joint uncertainty analysis in river water quality simulation: a case study of the Karoon River in Iran. *Environ Earth Sci* 73:3819–3831
- Singh AP, Ghosh SK (2003a) Conceptual modeling and management of water quality in a river basin in recent trends. In: Ramanathan AL, Ramesh (eds) *Hydrogeochemistry*. Capital Books, New Delhi, pp 207–220
- Singh AP, Ghosh SK (2003b) Uncertainty analysis in river basin water quality management. In: Raju KS, Sarkar AK, Dash ML (eds) *Integrated water resources planning and management*. Jain Brothers, New Delhi, pp 260–268
- Singh AP, Ghosh SK, Sharma P (2007) Water quality management of a stretch of river Yamuna: an interactive fuzzy multi-objective approach. *Water Res Manag* 21(2):515–532
- Singh AP, Srinivas R, Kumar S, Chakrabarti S (2015) Water quality assessment of a river basin under fuzzy multi-criteria framework. *Int J Water* 9(3):226–247
- Srinivas R, Singh AP (2017) Impact assessment of industrial wastewater discharge in a river basin using interval-valued fuzzy group decision-making and spatial approach. *Int J Environ Dev Sustain* Springer. <https://doi.org/10.1007/s10668-017-9994-9>
- Srinivas R, Singh AP, Sharma R (2017) A scenario based impact assessment of trace metals on ecosystem of river Ganges using multivariate analysis coupled with fuzzy decision-making approach. *Water Resour Manag* 31(13):4165–4185
- Tare V, Gurjar SK, Mohanta H, Kapoor V et al (2017) Eco-geomorphological approach for environmental flows assessment in monsoon-driven highland rivers: a case study of Upper Ganga, India. *J Hydrol* 13:110–121
- Trancoso AR, Braunschweig F, Leitão PC et al (2009) An advanced modelling tool for simulating complex river systems. *Sci Total Environ* 407:3004–3016
- UPJN, UPPCB, CPCB (2017) Assessment of pollution of drains carrying sewage/industrial effluent joining River Ganga and its tributaries. A joint report by Uttar Pradesh Jal Nigam (UPJN), Uttar Pradesh Pollution Control Board (UPPCB), Lucknow and Central Pollution Control Board (CPCB) New Delhi, India
- UPPCB (2013) Pollution caused by leather tanning industry to the water bodies/ground water in Unnao District of Uttar Pradesh. Uttar Pradesh Pollution Control Board (UPPCB), Lucknow
- Vemula VRS, Mujumdar PP, Ghosh S (2004) Risk evaluation in water quality management of a river system. *J Water Resour Plan Manag* 130(5):411–423
- Vrugt JA, Gupta HV, Bouten W, Sorooshian S (2003) A shuffled complex evolution metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. *Water Resour Res* 39(8):1201. <https://doi.org/10.1029/2002WR001642>
- Wang JQ, Zhong Z, Wu J (2004) Steam water quality models and its development trend. *J Anhui Normal Univ (Nat Sci)* 27(3):243–247
- Wang Z, Zou R, Zhu X et al (2014) Predicting lake water quality responses to load reduction: a three-dimensional modeling approach for total maximum daily load. *Int J Environ Sci Technol* 11:423–436
- Warmink JJ, Klis HV, Booij MJ et al (2011) Identification and quantification of uncertainties in a hydrodynamic river model using expert opinions. *Water Resour Manag* 25:601–622
- Wool TA, Ambrose RB, Martin JL, Comer EA (2001) The water quality analysis simulation program WASP6 draft, users’ manual. US Environmental Protection Agency, GA
- Xu Z, Godrej AN, Grizzard TJ (2007) The hydrological calibration and validation of a complexly-linked watershed–reservoir

- model for the Occoquan watershed, Virginia. *J Hydrol* 345: 167–183
- Yazdi J, Moridi A (2017) Interactive reservoir-watershed modeling framework for integrated water quality management. *Water Resour Manag* 31:2105–2125
- Ye HF, Guo SH, Li FM, Li G (2013) Water quality evaluation in tidal river reaches of Liaohe river estuary, China using a revised QUAL2K model. *Chin Geogr Sci* 23:301–311
- Yeh KC, Tung YK (1993) Uncertainty and sensitivity analyses of pit-migration model. *J Hydraul Eng ASCE* 119(2):262–283
- Zhang ML, Shen YM, Guo Y (2008) Development and application of a eutrophication water quality model for river networks. *J Hydrodyn* 20:719–726
- Zhang RB, Qian X, Li HM, Yuan XC, Ye R (2012) Selection of optimal river water quality improvement programs using QUAL2K: a case study of Taihu lake basin, China. *Sci Total Environ* 431:278–285
- Zhang W, Jin X, Liu D et al (2017) Temporal and spatial variation of nitrogen and phosphorus and eutrophication assessment for a typical arid river—Fuyang River in northern China. *J Environ Sci* 55:41–48
- Zhao X, Shen Z, Xiong M, Qi J (2011) Key uncertainty sources analysis of water quality model using the first order error method. *Int J Environ Sci Technol* 8(1):137–148
- Zheng Y, Keller AA (2008) Stochastic watershed water quality simulation for TMDL development—a case study in the new port bay watershed. *J Am Water Resour Assoc* 44(6):1397–1410
- Zhu H, Huang GH, Guo P, Qin QS (2009) A fuzzy robust nonlinear programming model for stream water quality management. *Water Res Manage* 23:2913–2940