Environmental Science and Pollution Research (2024) 31:37732–37745
https://doi.org/10.1007/s11356-024-33695-y

RESEARCH ARTICLE

A novel integration of regret-based methodology and bankruptcy theory for waste load allocation

Alireza Nouri[1] · Masoud Montazeri Namin[2] · Ershad Oftadeh[1]

Received: 19 January 2024 / Accepted: 12 May 2024 / Published online: 24 May 2024

Abstract

Developing a suitable index for Waste Load Allocation (WLA) is essential for both industrial polluters and environmental organizations. Identifying the index that best describes the quality conditions of the river is the main concern of this study. To achieve this purpose, a novel framework incorporating a regret-based index and a bankruptcy-based approach to address the impacts of low water quality and pollutant locations within the WLA are introduced. The framework includes a simulation–optimization model to minimize river quality regret for environmental organizations and total treatment cost for industrial polluters, employing Nash bargaining theory for conflict resolution. Additionally, a new bankruptcy approach, the Namin's rule, is proposed for redistributing the River Quality Regret Index among industrial polluters. Applying this methodology to data from the KhoramAbad River, a sensitivity analysis reveals that while there is no significant difference between the methodology and fuzzy risk when polluters are close, the methodology provides more accurate results as the distance between polluters increases. When the distance between two pollutants was 20 km, the sum of WLA was evaluated to be 300 kg per day higher than that in the compared method, potentially enhancing environmental justice.

Keywords Regret approach · Bankruptcy · Nash bargaining · NSGA-II · KhoramAbad River

Introduction

With the industrial development of cities and the large-scale discharge of wastewater into water resources, the concerns of water resource managers have shifted toward managing both the quantity and quality of resources. If we consider Liebman and Lynn (1966) pioneering research as one of the primary explorations into river quality management, numerous frameworks and methodologies have been introduced since then. In the meantime, given the inherent uncertainties of qualitative systems (Jolma 1995), uncertain models are increasingly preferred (Nouri et al. 2023). The two primary categories of management criteria, serving as the basis for the development of uncertain models, include regret-based models and risk-based models.

While the concept of regret is familiar in management, and everyone may have experienced it (Loomes and Sugden 1982), the Min–Max regret approach to river quality management was introduced by Burn and Lence (1992). Building on the Min–Max Regret concept (Ellis 1988), it minimizes the maximum regret across several scenarios encompassing hydrological, hydraulic, and qualitative uncertainties. This research presented multiple implementations, demonstrating a quasi-trade-off between budget and quality criteria, though dominated solutions appear in most outputs. Subsequently, this approach was adopted in other studies on river quality management (e.g., Jolma (1995) and Faraji et al. (2015)). Other areas of water resources management, such as Li et al. (2009), Poorsepahy-Samian et al. (2012), and Eyni et al. (2021), also drew inspiration from this view, but its wider adoption remained limited. Notable adjustments include the conversion of minimum the maximum regret to minimum the average regret in groundwater quality management (Bashi-Azghadi et al. 2016). Following the development of regret-based models, the research focus shifted toward risk-based models that incorporating uncertainty

Responsible Editor: Marcus Schulz

Alireza Nouri
m_alireza_nouri@yahoo.com

[1] Islamic Azad University Science and Research Branch, Tehran, Iran

[2] School of Civil Engineering, College of Engineering, University of Tehran, Tehran, Iran

more effectively. The fuzzy theory proved particularly suitable for this purpose, as it goes beyond the limited set of scenarios considered in regret-based models, each treated with equal probability (Burn and Lence 1992), and offers a more comprehensive approach to the state space.

The risk of an event, as discussed in most research, is calculated by multiplying the probability of that event by its impact (Sadiq et al. 2007; Deng et al. 2011). In river quality management spatially Waste Load Allocation (WLA) determination, a threshold for the low water quality of a water quality indicator such as dissolved oxygen (DO) is traditionally considered. Using Monte Carlo Simulations (MCS), the probability distribution function (PDF) of the occurrence of that threshold is calculated, which allows for the estimation of the risk of the river's low quality (Vemula et al. 2004; Ghosh and Mujumdar 2006; Jha and Gu 2010).

It is noteworthy that some researchers have proposed fuzzy risk to address the limitations of the strict probabilistic definition (Sasikumar and Mujumdar 2000; Mujumdar and Sasikumar 2002). While they agree that if, in any simulated scenario, the qualitative indicator's value falls below the defined threshold, such as that set by environmental organizations in governments and states, that scenario should be considered a failure. However, they argue that values slightly higher than the threshold should not be considered entirely acceptable, although not complete failures. Therefore, based on Fuzzy logic, they developed fuzzy risk by determining acceptable low and high thresholds and incorporating the fuzzy membership function of low water quality between these two thresholds (Mujumdar and Sasikumar 2002). Despite these efforts, the mentioned indicators do not fully capture the severity of the impact.

By examining the research conducted on the issue of determining WLA, it is evident that in most of the developed frameworks, a model has been placed as an allocator and less than the same optimization outputs have been used as WLA (Nouri et al. 2023). Each of these studies has its strengths, including the variety of conflict resolution methods at different levels and contexts. For example, Hung and show (2005) and Farrow et al. (2005) came up with the idea of pollution load trading to minimize the cost of the whole system. Niksokhan et al. (2009a, b) and Nikoo et al. (2011) presented the idea of game theory to fairly and efficiently allocated the waste load based on the polluters' cooperation. Farjoudi et al. (2021), Nouri et al. (2023), and Babamiri and Dinpashoh (2024) discussed the use of bankruptcy theory in order to redress the justice in complicated environmental conflicts. Despite individual strengths, each study exhibits weaknesses. These include identifying the primary WLA and pollutant rights trading based on linear simulation assumptions in qualitative-quantitative simulation process of the river (e.g., Mesbah et al. 2009). A further weakness in past research is neglecting the impact of pollution discharge location on simulations when determining WLA was based on bankruptcy theory (Farjoudi et al. (2021) and Nouri et al. (2023)). While bankruptcy laws, relying on ethical, equitable, and reasonably efficient principles, provide a framework for fair asset distribution (Herrero and Villar (2001), Sheikhmohammady and Madani (2008), Li et al., (2020)), but other than them, the criteria that may depend on the nature of the problem under consideration should be taken into consideration. (Herrero and Villar (2001)). Therefore, attention should be paid to the nature of what is considered "assets" (which is a function of the river's self-purification in the water quality management), because it is possible that neglecting this, the developed law is not a fair interpretation from the point of view of some representatives (which here means the polluters).

In this study, a novel framework to address the limitations of existing risk indicators and regret-based indices has been proposed using two innovative approaches: a novel regret-based index termed the River Quality Regret Index (RQRI) and the Namin rule. RQRI aims to provide a more comprehensive insight into river pollution by assessing the acceptable fuzzy level of pollution along the river. Unlike traditional risk indicators (such as Sasikumar and Mujumdar 2000). RQRI accounts for the intensity of pollution violations, filling a critical gap in current methodologies. The Namin rule addresses the oversight of bankruptcy rules regarding the location of pollution discharge. This novel approach, unlike other laws that do not consider this issue (such as Nouri et al. (2023) and Babamiri and Dinpashoh (2024)), considers the contribution of each pollutant relative to its impact on degrading water quality in the river, thereby enhancing the precision of assessment. This ensues from the recognized shortcomings of existing methodologies in accurately assessing and managing the impact of point pollution discharge on river quality. While current risk indicators lack the capability to indicate the intensity of violations, regret-based indices fail to address uncertainty effectively. By proposing the RQRI and the Namin rule, the aim is to overcome these limitations and provide more robust tools for environmental assessment and management.

The purpose of this study is twofold. Firstly, to investigate whether estimating the intensity of low water quality using the RQRI will lead to a change in the WLA of the pollutant. Secondly, to explore whether introducing sensitivity to the location of the pollutant through the Namin rule induces a significant change in WLA. By addressing these questions, and the proposed methodology can contribute to the advancement of environmental assessment and management practices.

The advantage of this approach lies in its ability to provide more accurate and precise assessments of river quality and pollution impact. By incorporating the intensity of violations and considering the spatial distribution of pollutants, the proposed methodology offers a more nuanced understanding of environmental risks and opportunities for more effective pollution management strategies.

This study presents a novel framework integrating a regret-based index for WLA, providing a systematic approach to water quality assessment and management. The proposed Namin rule enhances fairness and efficiency in pollution management strategies. Comparative analysis demonstrates the superiority of our methodology over the fuzzy risk assessment methods, particularly in scenarios involving varying distances between polluters. These contributions advance the understanding and practice of sustainable water resource management, offering valuable insights for policymakers, environmental practitioners, and industrial stakeholders alike.

To achieve these objectives, this paper is structured into seven sections. In the "Methodology" section, the models and implementation of them using case study data are introduced. The "Case study" section presents the details of the case study data utilized. Following this, the "Result" section reports on the results obtained from our analysis. Subsequently, in the "Analyses" section, we delve into an in-depth analysis of the obtained results. The "Discussion" section involves a comparative analysis between the methodology presented in this research and the methodology proposed by Nouri et al. (2023). Finally, the " Conclusion" section provides a comprehensive summary and conclusion of the research, highlighting the key findings and their implications.

Methodology

The purpose of this research is to establish a methodology for determining the WLA using the bankruptcy approach and the Regret approach. The various steps involved in developing this methodology are illustrated in Fig. 1. As shown in the figure, following the collection of quantitative and qualitative data on the river, economic data on the polluting units, and conflict-related goals, a quantitative–qualitative simulation model of the river is constructed. This simulation model is then linked and executed with a multi-objective optimization model (NSGA-II) to generate non-dominant options. Subsequently, the Nash bargaining approach is employed to determine the point of agreement among the main stakeholder groups for these non-dominant options. Finally, a new law is developed based on the bankruptcy theory approach to determine the WLA for each polluting unit.

Water quality simulation model

The transfer of pollution in the river system occurs via two processes: diffusion and advection (Thomann and Mueller 1987). In a simplified one-dimensional flow scenario, these two processes can be modeled by assuming the spreading coefficient, flow intensity, and cross-sectional area of the river to be constant as Eq. 1 (Mannina and Viviani 2010).

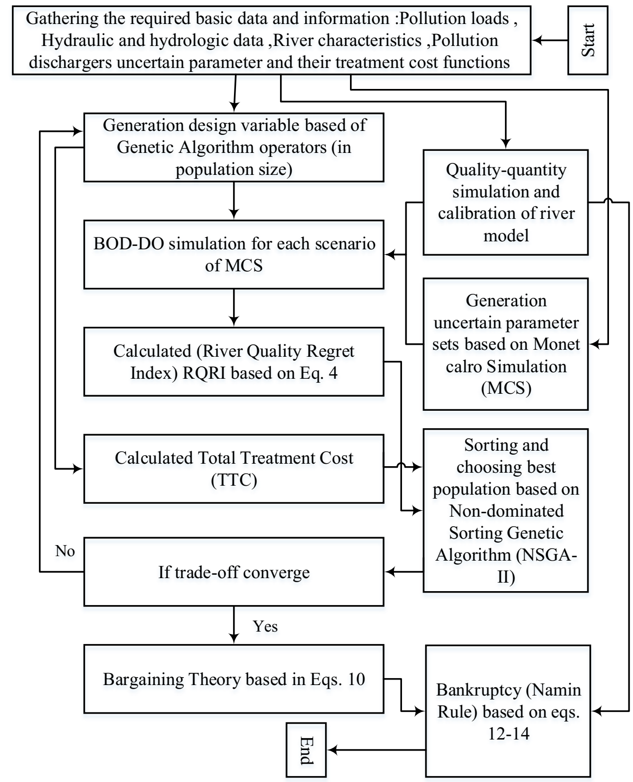


Fig. 1 Flowchart of proposed methodology

$$\frac{\partial C}{\partial t} + u\frac{\partial C}{\partial x} = D_L\frac{\partial^2 C}{\partial x^2} - f(C) \quad (1)$$

where C is the general form of pollutant concentration. Biochemical oxygen demand (BOD) is a crucial qualitative indicator in river quality management due to its interactions with various other qualitative parameters (Nouri et al. 2023). Accordingly, the quantitative–qualitative simulation of the river in this study is based on BOD-DO simulation. The Streeter-Phelps Eqs. (1925) represent one of the most widely recognized BOD-DO simulation models for rivers and have been extensively employed for quantitative–qualitative river simulations in various research studies (Nouri et al. 2023). Streeter and Phelps (1925) derived the well-known Eqs. 2 and 3 by applying simplifying assumptions to the one-dimensional equation of DO mass balance. The items in all equations are introduced in Appendix A Table A1.

$$D = \frac{k_c \cdot L_{C_0}}{k_2 - k_c}\left(e^{-k_c \cdot t} - e^{-k_2 \cdot t}\right) + D_0 \cdot e^{-k_2 \cdot t} \quad (2)$$

Table 1 The results of Eqs. 12, 13, 14 for a numerical example

Steps	G_i		ΔBOD_i^m(kg)		BOD_i^{new}(kg)	
	Unit 1	Unit 2	Unit 1	Unit 2	Unit 1	Unit 2
1	0.0007	0.0033	0.82	0.18	81.81	18.19
2	0.0025	0.0039	0.61	0.39	143.03	56.97
3	0.0052	0.0077	0.60	0.40	202.71	97.29

Table 2 Qualitative and hydraulic attributes for the river reaches (Ahour 2006)

Check point	DO (mg/L)	BOD5 (mg/L)	*V* (m/s)	*Q* (m^3/s)
1	4.20	9.47	2.59	3.8
2	4.00	9.88	2.50	3.85
3	3.80	9.88	2.60	3.9
4	3.50	9.26	2.10	3.6
5	4.50	7.82	2.24	3.65
6	4.70	9.88	2.31	3.7
7	4.80	11.93	2.46	3.75
8	4.70	11.94	2.67	3.95
9	4.40	12.61	2.70	4

$$L_C = L_{C_0} \cdot e^{-k_c \cdot t} \tag{3}$$

River Quality Regret Index (RQRI)

As stated in the introduction, risk-based indicators have weak points. For more clarity, refer to Fig. 2 that illustrates two scenarios of river DO simulation. In scenario 2, the length of the river below the acceptable lower threshold is nearly twice as long as in scenario 1. Conversely, DO values in scenario 2 are significantly lower than in scenario 1. Nevertheless, both scenarios, in terms of both the traditional and fuzzy risk definitions, indicate a consequence. In contrast, regret theory, which is often used to estimate deep uncertainties in economic systems (Bashi-Azghadi et al. 2016), is a better alternative to risk due to attention to details. In this regard, based on the regret approach and inspired by the correction that Bashi-Azghadi et al. (2016) made on Max–Min Regret approach, we introduce the uncertain and fuzzy, RQRI, which equals the average level below the DO profile relative to the acceptable threshold in the average river level in that interval, as shown in Eq. 4.

$$RQRI = \frac{\sum_{n=1}^{N} \int_0^{l_d} Regret_n(l)dx}{N} \cdot \overline{A} \tag{4}$$

RQRI with a dimension equal to M represents the oxygen deficiency of the entire reach. The $Regret_n$ is the regret value of the nth scenario of MCS based on the definition provided by (Sasikumar and Mujumdar 2000; Mujumdar and Sasikumar 2002). It is calculated in Eq. 5.

$$Regret_n(l) = \begin{cases} 0 & DO_{l,n} \geq DO^U \\ \left(DO^U - DO_{l,n}\right) * \mu_{LWQ} & DO^L < DO_{l,n} < DO^U \forall l, n \\ DO^L - DO_{l,n} & DO_{l,n} \leq DO^L \end{cases} \tag{5}$$

While μ_{LWQ} represents the function of the change in the river's low water quality, which can be calculated using Eq. 6.

It should be noted that the acceptable lower limit and upper limit in Eq. 6 are considered 4 and 5 mg/L, respectively.

Table 3 Economic qualitative and quantitative data for the polluting units (Ahour 2006)

Units	*Q* (m^3/day)	BOD_5 (mg/L)	Temperature °C	Classified treatment cost (US$/Mon)		
				30%	60%	90%
1	775	129	21	538	900	1750
2	200	195	19	113	225	338
3	1.5	165	19	100	200	350
4	36	362	21	163	363	525
5	250	89	20	538	950	1300
6	37	89	20	438	825	1075
7	150	42,000	51	1138	1700	2650
8	110	95	17	325	400	663
9	45	42,000	51	285	425	663

Table 4 Nash bargaining results and Namin and CEA rules for RQRI and fuzzy risk approaches

Fuzzy risk		RQRI			Items
CEA	Nash	CEA	Namin	Nash	
0.12	0.12	0.21	0.21	0.20	RQRI (kg)
15.26	15.22	24.12	24.12	23.64	Risk (%)
26.6	26.59	25.69	25.70	26.14	TTC *
99.98	98.29	99.98	99.98	99.94	Unit 1 (%)
39	38.32	39	39	32.24	Unit 2 (%)
0.25	0.24	0.25	0.25	0.25	Unit 3 (%)
13.03	12.88	13.03	13.03	12.95	Unit 4 (%)
22.25	22.21	22.25	22.25	22.15	Unit 5 (%)
3.29	3.29	3.29	3.29	3.29	Unit 6 (%)
420.28	597.98	509.16	505.26	669.27	Unit 7 (%)
10.45	10.40	10.45	10.45	10.40	Unit 8 (%)
420.28	241.34	509.16	513.22	344.34	Unit 9 (%)

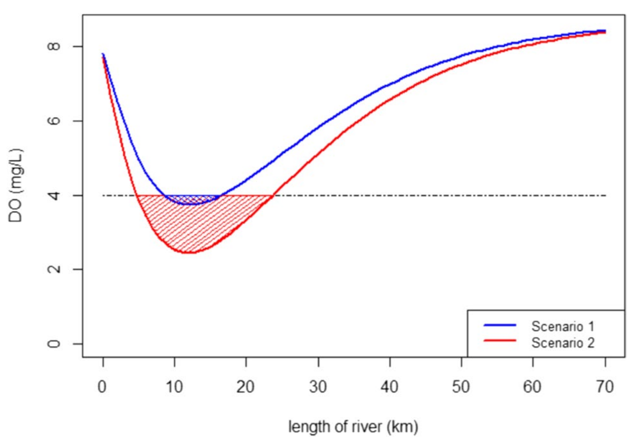


Fig. 2 Compare two scenarios of river DO simulation

$$\mu_{LWQ}(DO) = \left[\frac{DO^U - DO}{DO^U - DO^L}\right] \tag{6}$$

Multi-objective optimization model

River quality management, particularly the determination of WLA, is inherently a multi-objective issue. Environmental organizations and advocates strive to improve river quality, while polluters aim to reduce their treatment costs (Nouri et al. 2023). If stakeholders seeking to minimize their treatment costs can be grouped due to the commonality and alignment of their goals, the WLA determination problem can be modeled as a multi-objective optimization problem (Mahjouri and Abbasi, (2015); Andik and Niksokhan, (2020)). In this research, the objective function of Iran's Department of Environment for maintaining river quality is to minimize the RQRI (presented in the "River Quality Regret Index (RQRI)" section). Similar to many other studies (such as Niksokhan et al. (2009a, b a and b)), the objective function of point pollutants in the river, which are industries, is considered to be minimizing the Total Treatment Cost (TTC) in the form of Eq. 8.

$$O_1 = min\ RQRI \tag{7}$$

$$O_2 = minTTC = min\sum_{i=1}^{m} TC_i\left(x_i\right) \tag{8}$$

x_i represents the wastewater treatment percentage of each pollutant and serves as the optimization decision variable in the bi-objective optimization problem, ranged between 0 and 100 with no further constraints in this optimization system. In this research, the calculation of the trade-off between O_1 and O_2 is done by NSGA-II (Deb et al. 2000). NSGA-II is a powerful and efficient algorithm for solving multi-objective optimization problems, and it has been successfully applied in various fields of water resources management (Nouri et al. 2022). NSGA-II integrates non-dominated sorting and crowding distance calculation with other Genetic Algorithm operators (such as crossover and mutation) to assess the Pareto front in the Rn space (Deb et al. 2000). For further insights, refer to Niksokhan et al. (2009a).

Conflict resolution models

The conflicting objectives presented in Eqs. 7 and 8 lead to disputes at two levels. Firstly, the Department of Environment and polluters disagree on the selection of RQRI and TTC from among the non-dominated options generated by NSGA-II. Secondly, polluters themselves clash over the allocation of pollution discharge limits to achieve the agreed-upon RQRI (Nouri et al. 2023). Despite these conflicts, there is evidence of collaboration between the parties, for example, Nash bargaining, a common method for resolving conflicts, is frequently employed in river quality management and WLA determination (Nouri et al. 2023).

Let us suppose there are m decision makers involved in a scenario, each capable of influencing the decision space, X. f_i: $X \rightarrow R$ represent the objective function of decision maker i, and the payoff set is defined by Eq. 9 (Saadatpour et al. 2020).

$$H = \left\{\overline{u}\middle|\overline{u} \in R^m, \overline{u} = \left(u_i\right), u_i = f_i(x)\ with\ some\ x \in X\right\} \tag{9}$$

where $\overline{u}$ is the payoff space and ui is the payoff of player i. Nash solution, derived from the principles outlined by Nash (1953), requires a closed, convex, and bounded decision space, ensuring that no party receives less than their point of disagreement. It is calculated using a set of mathematical expressions (Kerachian et al. 2012).

$$
\begin{array}{ll}
Maximazation \ \sum_{i=1}^{m} \left(f_{ij} - d_i\right) & \\
\quad Subject\ to: & \\
\quad\quad f_{ij} \geq d_i \qquad \forall i,j & \\
\quad\quad f_{ij} \in H \qquad \forall i,j &
\end{array} \tag{10}
$$

However, as the determination of treatment percentages for each polluting unit (WLA) is not inherently equitable, various methodologies, such as bankruptcy-based strategies, have been proposed to rectify this and rebalance risk and responsibilities (Nouri et al. 2023). For example, one of the bankruptcy-based rules is the Constrained Equal Awards (CEA) Rule.

The CEA rule allocates a system's assets (in this case, the total allowable pollution load that can be discharged into the river without exceeding the acceptable threshold) among claimants (here, the maximum allowable pollution load for each pollutant). As denoted by Eq. 11, the minimal claim and λ are apportioned among stakeholders, ensuring that the sum of allocations equals the total wealth (Madani & Zarezadeh 2012).

$$
\begin{array}{c}
CEA_i(Acceptable\ threshold,\ BOD^{max}) = min\left\{BOD_i^{max}, \lambda\right\} \\
Subject\ to: \\
To\ apply\ (CEA) \xrightarrow{Consequence} Acceptable\ threshold
\end{array} \tag{11}
$$

In the CEA rule, the modified claim of each claimant increases from zero until either the claimants reach their maximum claim or the sum of the modified claims equals the available assets. This approach prioritizes satisfying the demands of smaller claimants, thereby reducing the overall number of unsatisfied parties (Herrero and Villar 2001).

It seems reasonable the impact of each pollutant's BOD unit on the RQRI of the entire river is a fair approach to determining WLA. The pollutant with the most significant impact on raising the RQRI should contribute more to its own wastewater treatment to maintain a low RQRI. Based on this principle, we expanded the Namin rule using the bankruptcy approach to enhance the environmental justice. First, the partial RQRI per the partial BOD of the i^{th} pollutant are calculated, considering the pollution discharge of all pollutants except pollutant i (represented as i^- in Eq. 12). Next the ratio of the calculated partials of each pollutant per total partials of all pollutants is determined. By multiplying this ratio by the delta BOD changes calculated in Eq. 12, the contribution of each pollutant to increasing the RQRI in that step is determined (Eq. 13). The BOD value for pollutant i in this step is calculated by adding this contribution to the BOD calculated previously (Eq. 14). This process (execution of Eqs. 11 and 14) is repeated until the RQRI value reaches the RQRI* value (the value obtained from Nash bargaining). The resulting BODs represent the creation of the RQRI agreed upon in the Nash bargaining between industrial polluters and the environmental organization. These calculated BODs are considered the WLA for each pollutant.

$$
G_i = \frac{\partial RQRI}{\partial BOD_i} \forall i | cons\tan t\ i^- \tag{12}
$$

$$
\triangle BOD_i^m = \left(\frac{\frac{1}{G_i}}{\sum_i \frac{1}{G_i}} \right) \cdot \triangle BOD_i \tag{13}
$$

$$
BOD_i^{new} = BOD_i^{last} + \triangle BOD_i^m \tag{14}
$$

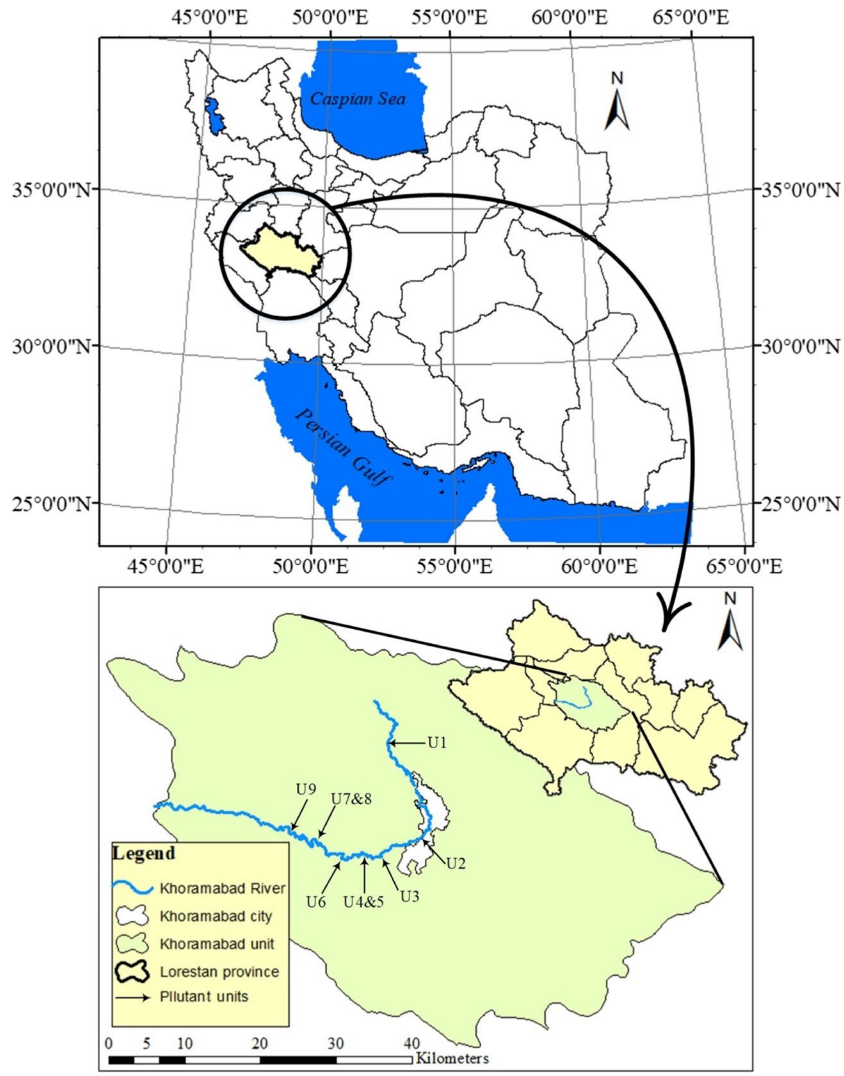
For further elucidation, the specified procedures are examined with the help of a numerical example in three steps and the results are presented in Table 4. Equation 12 is utilized to calculate the impact share of BOD changes of i^{th} pollutant on RQRI. G_2 is nearly five times more than G_1 that means unit 2 has a greater share in raising RQRI. Next, we need to determine the ratio of each pollutant's impact on RQRI to all pollutants, so Eq. 13 is used to calculate the increasing BOD share of i pollutant. According to Table 1, unit 2 that has a grater share in increasing RQRI, has less $\triangle BOD_i^m$ compared to unit 1. Finally, The BOD calculated in this step $\left(\triangle BOD_i^m\right)$ is added to the BOD calculated in the previous step $\left(BOD_i^{last}\right)$ and steps are repeated. After three steps, the permitted BOD for unit 1 is equal to 202.71 kg/day while this value is 97.29 for unit 2. If there are equal BOD shares for two units, the values are the same and equal to 150 kg/day.

Case study

The methodology presented in this article was implemented by of the quantitative and qualitative data of the KhoramAbad River. KhoramAbad City, having a share of 28% of the total industries in Lorestan Province, is considered a semi-industrial city. This has led to many industrial units being put into operation near the KhoramAbad River. The passage of several kilometers of this river through the city of KhoramAbad, along with the pollution and discharge of industrial effluents into it, has caused the increasing sensitivity of the quality conditions of this river-factory system. The location of the research area and the quantitative and qualitative data of the river and its adjacent pollutants are presented in Fig. 3, Tables 2 and 3, respectively.

According to Fig. 3, our research area encompasses nine distinct industrial pollutants, each impacting to the overall environmental landscape. These pollutants have been systematically categorized into groups of minor and major polluters, a classification meticulously detailed in Table 3.

Fig. 3 Case study area



Notably, units 7 and 9 emerge as major polluters, characterized by their significantly elevated BOD concentration of 4200 mg/L. The remaining pollutants are classified within the minor group. This stratification not only delineates the varying degrees of impact exerted by each pollutant but also underscores the robustness of our methodology in accurately assessing and categorizing pollutants for the purpose of determining WLA.

Result

Optimization-simulation model running

The methodology developed in this project was applied to the quantitative and qualitative data of the study area, as described in the "Case study" section. The first step involved simulating the desired river both quantitatively and qualitatively. This was achieved using a calibrated qualitative-quantitative simulation model of the KhoramAbad River (Nouri et al. 2023), based on Eqs. 2 and 3. Since the aim of this research was to present an uncertain model, MCS was used to generate the required scenarios of uncertain parameters after collecting the necessary quantitative and qualitative data. The scenarios presented by Nouri et al. (2023) were used for the MCS.

Next, the simulator model and MCS scenarios were linked with NSGA-II, a multi-objective optimizer model. This resulted in a simulator-optimizer model with the objectives presented in Eqs. 7 and 8, which was ready for implementation. In this research, a population of 50 chromosomes was selected. The probability of mutation and crossover was set to 0.01% and 80%, respectively. The evaluation process of non-dominated procedure was subjected to sensitivity analysis with respect to the number of generations. No change was observed from the 100th generation onwards. Therefore, the 100th generation, presented in Fig. 4 with the legend "RQRI-TTC," was set as the criterion for continuing the research.

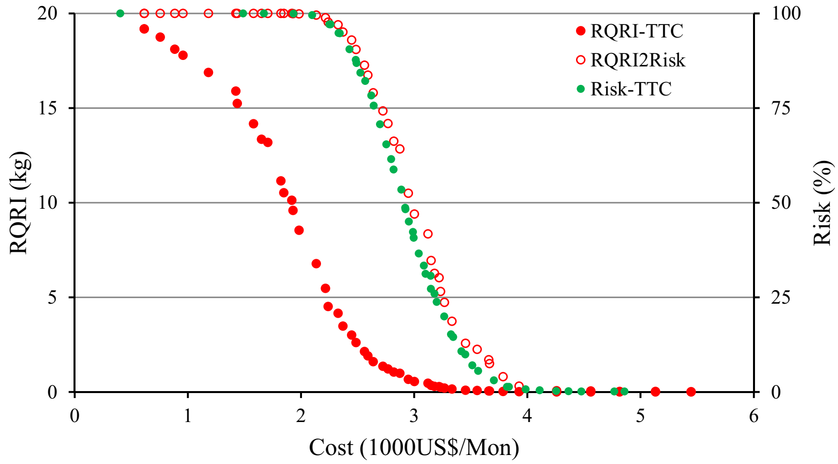


Fig. 4 The trade-off between objectives, output of multi-objective optimizer model (RQRI-TTC represent trade-off between RQRI and TTC, Risk-TTC represent trade-off between fuzzy risk and TTC and RQRI2Risk represent trade-off between the fuzzy risk corresponding to RQRI and TTC)

Conflict resolution result

Based on the considerations presented in the "Conflict Resolution Models" sections, the Nash bargaining model was employed to resolve the conflicts between the Department of Environment and the polluters. The model was implemented using the set of Eqs. 10, and the results are presented in Table 4. The Nash bargaining application yielded RQRI* and TTC*, which are functions of nine pollutant treatment percentage, a decision variable.

After determining the RQRI* agreed upon by the polluters and the Department of Environment, the WLA was determined using the rule developed in this research (Namin's rule). Formulations 10 to 12 were used in an iterative process with an initial value of zero. The process continued until the pollution permit value calculated in Eq. 13 did not cause the RQRI of the river to exceed 0.2 kg (RQRI*). The amount of pollution that led to the closest RQRI to RQRI* was introduced as WLA. This value for nine pollutants is presented in Table 4.

Analyses

This research introduces a novel uncertain index for measuring river quality and a groundbreaking bankruptcy-based approach for allocating the waste load of pollutants. To further examine and analyze these methodologies, fuzzy risk (for comparison with RQRI) and CEA rule (for comparison with Namin's rule) were also applied using the developed data. These methods will be compared and contrasted in the following section.

This advantage, which incorporates the fuzzy risk of the river's low water quality as a fuzzy membership function, removes the obtained index from the rigid state and makes it a more accurate measure than the conventional risk for low water quality. To determine the fuzzy risk in this study, the PDF of the river quality index was required, which was obtained from the MCS and the dataset used to calculate the RQRI. For more information on fuzzy risk, refer to Niksokhan et al. (2009a). Based on this, the output trade-off from running the simulator-optimizer model with the objectives of minimizing fuzzy risk and TTC is presented in Fig. 4 with the legend "Risk-Cost." To better compare the trade-off of "RQRI-TTC" with "Risk-TTC," the fuzzy risk values corresponding to RQRI, which can be calculated using the percentage of nine pollutant treatments (as a decision variable), are shown in Fig. 4 with the legend "RQRI2Risk".

Upon examining Fig. 4, it is evident that the overall forms of the two graphs exhibit remarkable similarity. Notably, the values of "RQRI2Risk" closely align with those of "Risk-TTC". This implies that the pollutant treatment percentages associated with the non-dominated "RQRI-TTC" options are nearly identical to those that comprise "Risk-TTC". The primary distinction between the trade-offs of "RQRI2Risk" and "Risk-TTC" lies in the vicinity of fuzzy risk = 100, where the number of the former's options is several times greater than that of the latter. This disparity arises from the fact that in fuzzy risk, a failure is calculated as one unit if the critical point of the DO profile in each MCS scenario falls below the standard limit (in this case, 4 mg/L).

In contrast, RQRI considers all scenarios where the DO level falls below the standard limit. Consequently, at a specific threshold (precisely located on the "RQRI-TTC" trade-off point), all MCS scenarios fall below the standard line, resulting in a corresponding risk of 100. Meanwhile, RQRI remains sensitive to increasing pollution levels, enabling it to calculate and consider higher values than RQRI*.

To further compare the two approaches, the Nash bargaining outcomes for the "Risk = TTC" trade-off was evaluated against those for the "RQRI-TTC" trade-off (presented in Table 4). Based on this comparison, it can be concluded that under the conditions of this study, the risk-based approach is somewhat stricter than the regret-based approach, as the risk associated with RQRI* is lower than the Risk* corresponding to "Risk-TTC."

Another approach to comparing RQRI with fuzzy risk is to utilize Sensitivity Analysis (SA). This method allows us to understand how changes in input parameters affect the outcomes of both indices, providing insights into their robustness and reliability in evaluating river quality. In this research, we employed the one-at-a-time method to conduct SA for both RQRI and fuzzy risk. Apart from simplicity, another significant advantage of this method is that any observed changes can be attributed to the alterations in that single factor, whereas statistical methods necessitate some kind of formal analysis (Ferretti et al. 2016).

Inputs such as upstream flow, upstream DO, upstream BOD, and pollution discharge of units were incorporated into MCS to assess their uncertainty. The remaining parameters, including k_2, k_c, and the level of treatment of BOD of each unit, were selected for SA. The sensitivity analysis for determining parameters was assessed using Equation B1 for both indices, and the outputs are reported in Fig. 5. As shown in Fig. 5, units 7 and 9 exhibited high sensitivity, while sensitivity for other units was close to zero. However, these sensitivity values were higher for unit 7 in the case of RQRI, primarily due to BOD levels of the units. Only k_c for RQRI showed minimal sensitivity in comparison.

Subsequent analysis using the CEA rule revealed similar WLA values for pollutants compared to the method proposed by Nouri et al. (2023). The claimants' WLA values resulting from CEA implementation are presented in Table 4. As anticipated, the small polluters received their maximum claims, while the two macropollutants received equal shares of 509 kg/day. This value closely resembles the results obtained using the Namin rule methodology presented in this research.

Discussion

The method presented in this research bears a close resemblance to the corresponding methods, fuzzy risk and CEA rule, introduced by Nouri et al. (2023). However, due to the enhanced accuracy of RQRI calculations compared to popular methods, it emerges as a more reliable measure than fuzzy risk. On the other hand, the mechanism for determining creditor shares in CEA rule, like many other bankruptcy approach laws, adheres to the equality procedure. While this approach is appropriate in many situations, it may not be suitable in cases where the impact of increasing a creditor's claim on the property value is variable. One such instance is the determination of WLA in the river-pollutant system, where the river's self-purification capability influences the pollutant discharge sites differently. In other words, the assumption of linearity in the qualitative simulation of the river within the CEA rule may lead to WLA values that diverge from those obtained from the non-linear simulation of the river in the Namin rule.

To discuss the developed methods, we assume that the studied river has only two pollutant sources. The first source discharges at point 1 of the main case, while the second source discharges in four scenarios at distances of 2, 5, 10, and 20 km from the first pollutant. In these four scenarios, the CEA rule and Namin rule were applied to achieve an RQRI of 0.2 kg per day. The results of the WLA for two hypothetical pollutants and the corresponding fuzzy risk for each scenario are depicted in Fig. 6. As the distance between the two sources increases, the WLA assigned to the two pollutants in the Namin rule diverges, while according to the CEA rule, the WLA remains constant for both sources. On the other hand, the river's overall pollution acceptance

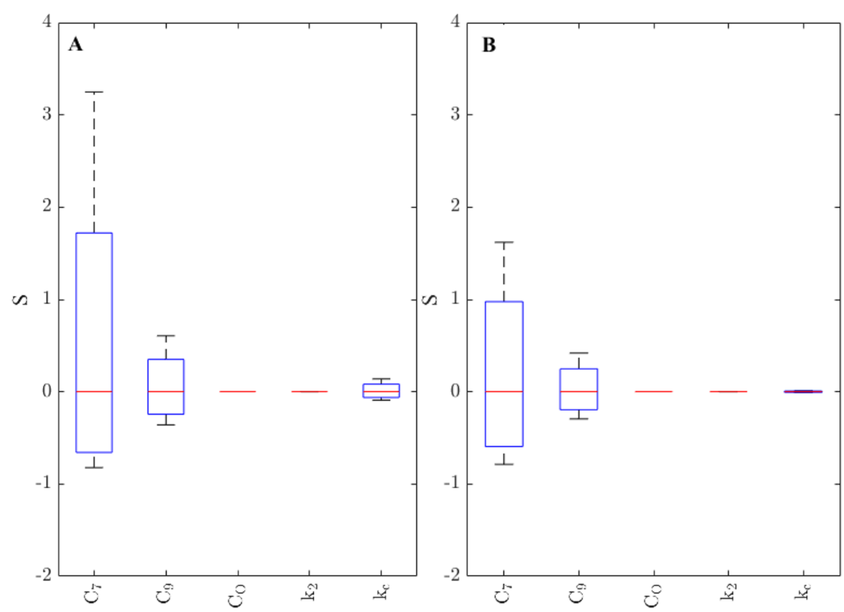


Fig. 5 Results of SA: **A** RQRI, **B** fuzzy risk. C_i is the concentration of pollutant i and C_o represented other units

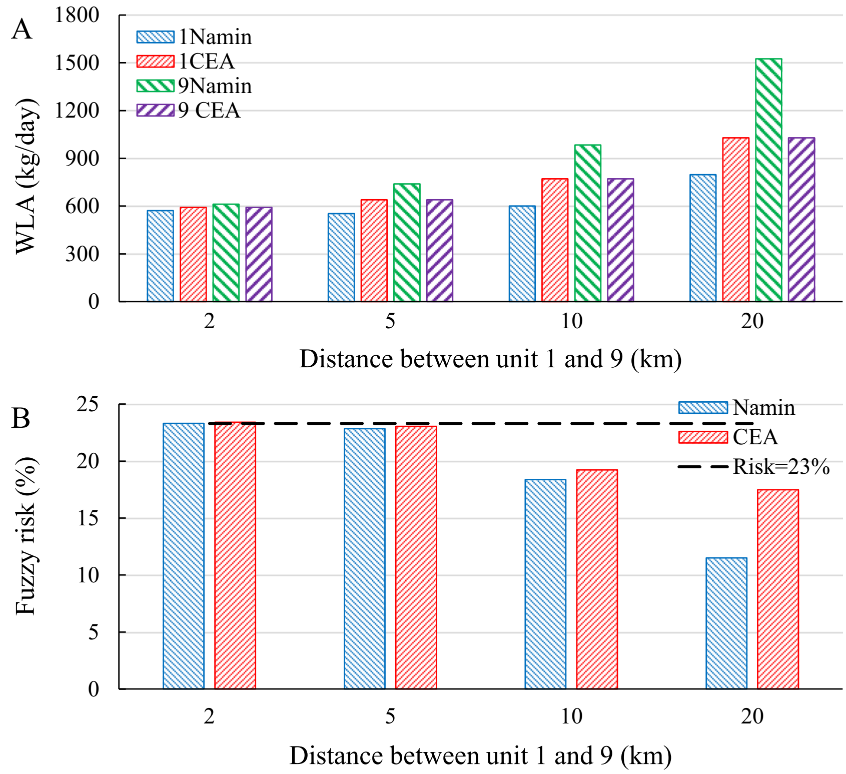


Fig. 6 Compare distance between two pollutants of virtual case, **A** WLA for Namin and CEA rules, **B** fuzzy risk for Namin and CEA rules

capacity generally increases with the distance between the two pollution sources. However, the Namin rule utilizes the pollution acceptance capacity more extensively than the CEA rule. Consequently, the total WLA in the scenario with a distance of 20 km between the two pollution sources was approximately 2000 kg per day for the CEA rule, while the Namin rule calculated a total WLA of approximately 2,300 kg per day. This increases environmental justice with the help of a mechanism based on the method, while in some studies, they have intended to achieve it with the help of an objective function similar to inequity (e.g., Andik and Niksokhan (2020) and Haghdoost et al. (2023)).

Meanwhile, in the realm of research literature concerning the determination of WLA through bankruptcy approaches, notable studies include Babamiri and Dinpashoh (2024), who conducted a case study involving three major pollutants with significant spatial dispersion, one situated more than 30 km away from the other two. Similarly, Moridi (2019) and Farjoudi et al. (2021) undertook studies in analogous areas where pollutant sources were spread over distances exceeding 15 km. In all instances, WLA was determined solely by traditional bankruptcy approaches, yielding results comparable to those of this research. It is worth mentioning that implementing the Nemin rule in these cases could potentially enhance the river's self-purification capacity, akin to the findings of this study.

Another aspect to consider is the variation in fuzzy risk across the scenarios. Figure 6b depicts the fuzzy risk associated with various pollution discharge distances. Despite having the same RQRI and a corresponding real-world risk of 23%, increasing the distance resulted in an underestimation of the fuzzy risk. In other words, if fuzzy risk criteria were used for WLA allocation, the self-purification of the river's upper reaches would be taken into account as the distance increases, leading to an RQRI greater than 0.2 kg per day and placing the river in a critical quality state. Therefore, due to its finer details, RQRI provides a more accurate assessment of fuzzy risk.

To elucidate the underlying mechanism, Fig. 7 presents the frequency diagram of MCS for four scenarios representing the distance between two pollution sources and the two aforementioned methods, both with an RQRI of 0.2 kg. The shape of graphs a to d, associated with the 2 and 5 km scenarios, closely resembles that reported by Nouri et al. (2023) for the simulation of a river with nine pollutants located in close proximity and with the minimum occurring approximately 10 km from the first source. However, as the distance increases (graphs e to h), the graphs exhibit two local minima. RQRI exhibits greater differentiation than risk, as a wider range of MCS scenarios falls within the non-standard Fuzzy area.

On the other hand, since the CEA rule allows for equal pollution discharge from the two sources, once the RQRI reaches the $RQRI^*$ (here due to the increase in pollution to 0.2), it ceases to increase the share allocated to the second source. Between the first and second sources, the river's self-purification process will lead to a relative improvement in the river's condition, and the downstream of the second source still possesses the potential to

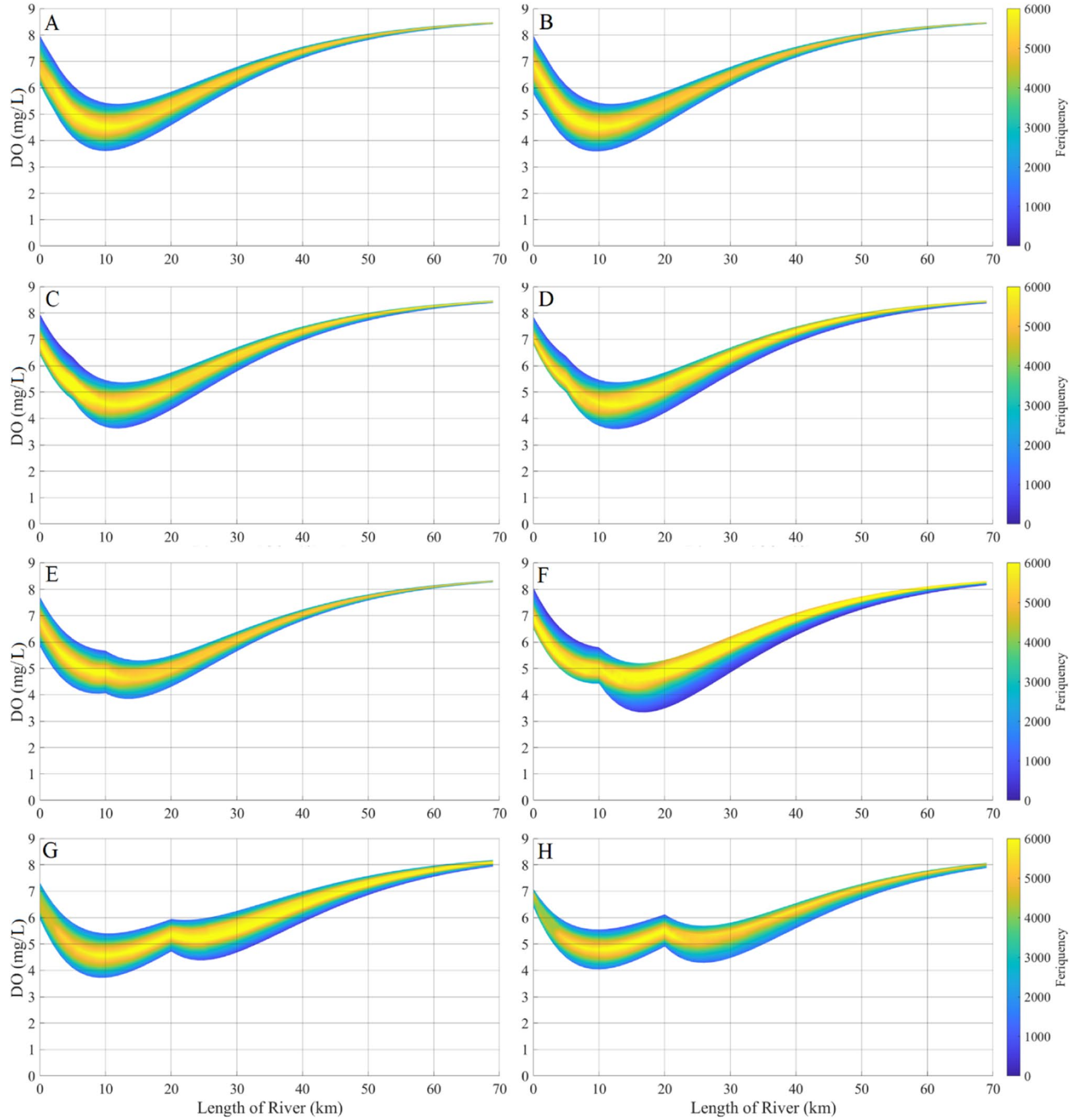


Fig. 7 MCS scenario frequency for different distance for apply WLA based on Namin and CEA rules. Note: **A**, **C**, **E**, and **G** for CEA rule and **B**, **D**, **F**, and **H** for Namin rule, distance between two virtual pollutants in **A** and **B** is 2 km, in **C** and **D** is 5 km, in **E** and **F** is 10 km, and **G** and **H** is 20 km

absorb pollution. Based on this, graphs f and h clearly demonstrate that the Namin rule, adhering to its principle of allocating pollutant shares proportionally to the changes they induce in the river's WLA state, slightly adjusts the pollution from the first source while simultaneously augmenting the amount of pollution discharged by the second source. It is worth noting that because the river's qualitative simulation process is not linear, the amount subtracted from source 1 is not exactly equal to what is added to the second source. However, the self-purification effect of the river in the reach between the first and second sources results in an overall increase in pollution capacity greater than the amount taken from source 1 and added to source 2.

Conclusion

The main achievement of this research is the development of a novel methodology encompassing two key methods: one for establishing an uncertain river quality index, RQRI, using the regret approach, and another for determining the WLA of point-source polluting units through an environmentally just approach based on the bankruptcy approach, referred to as Namin. This methodology integrates Streeter-Phelps Eqs. (1925) and a multi-objective optimization model such as NSGA-II to achieve a minimal trade-off between environmental and polluter perspectives. RQRI captures the environmental organization's viewpoint, while minimizing total treatment cost (TTC) serves as a proxy for the polluter's opinion. The methodology, implemented using data from the KhoramAbad River in Iran, aligns with previous models, including that of Nouri et al. (2023), and is analyzed from two perspectives: fuzzy risk versus RQRI and CEA rule versus Namin's rule.

Initially, when comparing the outcomes of the methodology presented in this study and the methodology of Nouri et al. (2023), no significant divergence is observed in terms of the Nash-agreed solution and WLA. The primary cause for this lack of distinction is the extremely short distance between the two major river pollutants (pollutants 7 and 9) – less than one kilometer. As a result, RQRI and Namin do not have sufficient space to showcase their abilities. To address this, a hypothetical scenario was developed based on the characteristics of the main case, involving two polluting sources: the first source positioned at the location of the first pollutant in the main case and the second source situated in four scenarios at distances of 2, 5, 10, and 20 km from the first pollution source. The analysis showed that when comparing the RQRI values for the fuzzy risk, the method proposed by Nouri et al. (2023) tended to yield slightly more cautious results than the approach used in this study.

Additionally, it was observed that as the distance increased, the fuzzy risk values calculated using identical RQRIs exhibited a diminishing increase across four different scenarios. This indicates that when the pollutants are close together and the DO profile along the canal exhibits only one concave area, the method of Nouri et al. (2023) holds true. However, for cases involving large distances between pollutant sources, RQRI is a more reliable indicator of river quality status.

This argument held true for WLAs as well. In the instance of WLA allocation based on the CEA rule, there was little distinction from Namin's rule. However, with the increase in the distance between the two pollution sources in the hypothetical case, significant discrepancies emerged between the WLAs assigned from the two standpoints. As the distance between the two sources increased, the amount of self-purification potential taken into account by Namin's rule was more substantial than in the CEA rule. Therefore, this methodology impacts stakeholders in two significant ways: providing a clearer interpretation of the river's quality situation, which persuades environmental organizations, and reducing TTC by increasing the WLA for the entire system, thereby persuading polluters and effectively implementing environmental justice.

Nevertheless, a rule grounded on the bankruptcy approach should not only be logical and understandable but also simple. Although Namin's rule adheres to environmental justice and avoids making linear assumptions, its main limitation lies in its complexity compared to other fair rules. Another limitation is that RQRI significantly increases the computational costs. In this research, Namin's rule is only compared to CEA. Future research could explore comparisons with other significant bankruptcy rules. Additionally, alternative water quality parameters such as electrical conductivity could be considered.

Appendix A.

Table A1 Nominations used in equations

Items	*Description*
L_c	BOD at the end of the reach
k_c	BOD at the end of the reach
k_2	The Reaeration coefficient (1/day)
DO	Dissolve Oxygen (DO)
D	Dissolve Oxygen (DO) Deficiency (mg/L)
D_0	DO deficiency at the entry reach
L_{c_0}	BOD at the entry of the reach
N	Monte Carlo Simulations scenario number
$\overline{A}$	Average cross section of the river
l_d	A length of the river that is in state low water quality
μ_{LWQ}	Low water quality membership function
DO^U	Upper limit of unacceptable DO
DO^L	Lower limit of unacceptable DO
O_i	Objective function i^{th}
TC_i	Treatment cost of pollutant i
f_{ij}	Target function for stakeholder i
d_i	The disagreement points for stakeholder i
H	Solution space
G_i	The ratio of RQRI partial to BOD of pollutant i partial
$\bar{i}$	All pollutant except pollutant i
ΔBOD_i^m	Increasing the BOD share of i pollutant
BOD_i^{last}	BOD share of i pollutant in the previous step
BOD_i^{new}	BOD share of i pollutant in the current step

Appendix B. Sensitivity analysis

Sensitivity analysis (SA) is an essential tool in mathematical modeling, aiming to understand how changes in input parameters impact model outcomes. It assesses the extent to which variations in inputs lead to changes in outputs, helping to identify sources of errors and key parameters (Ma et al. 2000). SA evaluates the significance of uncertainties or inaccuracies in model inputs, crucial for assessing model reliability and precision (Andik and Niksokhan 2020). There are two main categories of SA methods: local, such as one-at-a-time (OAT) (Chang et al. 2020; Wang et al. 2023; Xu et al. 2024), and global, such as MCS (Nakane and Heydari 2010; Dehghani et al. 2024). Local methods examine the effect of individual variables on the output, while global methods consider the influence of all parameters simultaneously (Yong et al. 2023). Conducting sensitivity analysis is critical for assessing a model's behavior, determining its utility, and identifying areas for improvement in the model development process (Ma et al. 2000; Wagener and Kollat 2007). These methods are characterized by their ease of operation, interpretability, and low computational cost.

One way to accomplish this assessment is through the OAT method, widely employed in the sensitivity analysis of water quality models due to its high computational efficiency and simplicity (Timalsina et al. 2023). In the OAT method, each parameter is perturbed one-at-a-time to a constant proportion (e.g., 90 to 110%) of its calibrated value, the sensitivity index (S_i) is calculated as Eq. B1 (Sun et al. 2012).

$$S_i = \frac{x_i\left(y_i - y_o\right)}{\delta x_i y_o} \tag{B1}$$

where y_i is the perturbed output; y_o is the reference output; x_i is the parameter value and δx_i is the perturbation of the i^{th} parameter.

Acknowledgements We would like to express our deepest appreciation to Dr Mohammadreza Bazargan-Lari for the invaluable assistance and guidance he gave us throughout the process of this research. His expertise and encouragement have been instrumental in shaping the direction and focus of this work.

Author contribution Dr. Alireza Nouri (Ph.D.), the first author, spearheaded the research, driving both its innovative title and design. Prof. Masoud Montazeri Namin (Assoc) offered crucial consultations throughout the project, both initially and for the final draft. Mr. Ershad Oftadeh (M.Sc.) provided valuable expertise on the bankruptcy sections, going above and beyond to draft the final manuscript.

Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval Prioritizing ethics, the research received approval from the relevant board. We meticulously examined participant welfare, confidentiality, and study integrity throughout the design, methodology, and impact assessment.

Consent to participate After receiving detailed information about the study's aims, procedures, potential risks, and potential benefits, all participants provided their voluntary informed consent to participate.

Consent for publication We authors grant our voluntary consent for the publication of the findings derived from our participation in this study.

Competing interests The authors declare no competing interests.

References

Ahour M (2006) Pollution management and monitoring of the KhoramAbad River. Iran's Department of Environment

Andik B, Niksokhan MH (2020) Waste load allocation under uncertainty using game theory approach and simulation-optimization process. J Hydroinf 22(4):815–841

Babamiri O, Dinpashoh Y (2024) River water quality management using an integrated multi-objective optimization-simulation approach based on bankruptcy rules. Environ Sci Pollut Res 31(4):6160–6175

Bashi-Azghadi SN, Kerachian R, Bazargan-Lari MR, Nikoo MR (2016) Pollution source identification in groundwater systems: application of regret theory and Bayesian networks. Iran. J Sci Technol - Trans Civ Eng 40:241–249

Burn DH, Lence BJ (1992) Comparison of optimization formulations for waste-load allocations. J Environ Eng 118(4):597–612

Chang N, Luo L, Wang XC, Song J, Han J, Ao D (2020) A novel index for assessing the water quality of urban landscape lakes based on water transparency. Sci Total Environ 735:139351

Deb K, Agrawal S, Pratap A, Meyarivan T (2000) A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II. In: Schoenauer M et al (eds) Parallel Problem Solving from Nature PPSN VI. PPSN 2000. Lecture Notes in Computer Science, vol 1917. Springer, Berlin, Heidelberg. https://doi.org/10.1007/3-540-45356-3_83

Dehghani M, Rezaie Rahimi N, Zarei M, Parseh I, Soleimani H, Keshtkar M, Khaksefidi R (2024) Chemical and radiological human health risk assessment from uranium and fluoride concentrations in tap water samples collected from Shiraz, Iran; Monte-Carlo simulation and sensitivity analysis. Int J Environ Anal Chem 104(6):1349–1364. https://doi.org/10.1080/03067319.2022.2038145

Deng Y, Sadiq R, Jiang W, Tesfamariam S (2011) Risk analysis in a linguistic environment: a fuzzy evidential reasoning-based approach. Expert Syst Appl 38(12):15438–15446

Ellis JH (1988) Acid rain control strategies. Environ Sci Technol 22(11):1248–1255

Eyni A, Skardi MJE, Kerachian R (2021) A regret-based behavioral model for shared water resources management: application of the correlated equilibrium concept. Sci Total Environ 759:143892

Faraji E, Afshar A, Rasekh A (2015) Regret-based TMDL optimization under climate change with charged system search algorithm. In World Environmental and Water Resources Congress 2015. pp 2449–2458. https://doi.org/10.1061/9780784479162.240

Farjoudi SZ, Moridi A, Sarang A, Lence BJ (2021) Application of probabilistic bankruptcy method in river water quality management. Int J Environ Sci Technol 18:3043–3060. https://doi.org/10.1007/s13762-020-03046-8

Farrow RS, Schultz MT, Celikkol P, Van Houtven GL (2005) Pollution trading in water quality limited areas: use of benefits assessment and cost-effective trading ratios. Land Econ 81(2):191–205

Ferretti F, Saltelli A, Tarantola S (2016) Trends in sensitivity analysis practice in the last decade. Sci Total Environ 568:666–670
Ghosh S, Mujumdar PP (2006) Risk minimization in water quality control problems of a river system. Adv Water Resour 29(3):458–470
Haghdoost S, Niksokhan MH, Zamani MG, Nikoo MR (2023) Optimal waste load allocation in river systems based on a new multi-objective cuckoo optimization algorithm. Environ Sci Pollut Res 30(60):126116–126131
Herrero C, Villar A (2001) The three musketeers: four classical solutions to bankruptcy problems. Math Soc Sci 42(3):307–328
Hung M-F, Shaw D (2005) A trading-ratio system for trading water pollution discharge permits. J Environ Econ Manag 49:83–102
Jha M, Gu R (2010) Risk analysis of seasonal stream water quality management. Water Sci Technol 62(9):2075–2082
Jolma A (1995) 'Regret analysis for river water quality management' IIASA Working Paper, no. WP-95–4, Austria
Kerachian R, Karamouz M, Naseri AV (2012) River water quality management: application of stochastic genetic algorithm. In Impacts of Global Climate Change. pp 1–12. https://ascelibrary.org/doi/abs/10.1061/40792%28173%29437
Li S, He Y, Chen X, Zheng Y (2020) The improved bankruptcy method and its application in regional water resource allocation. J Hydro-Environ Res 28:48–56
Li YP, Huang GH, Nie SL (2009) A robust interval-based minimax-regret analysis approach for the identification of optimal water-resources-allocation strategies under uncertainty. Resour Conserv Recycl 54(2):86–96
Liebman JC, Lynn WR (1966) The optimal allocation of stream dissolved oxygen. Water Resour Res 2(3):581–591
Loomes G, Sugden R (1982) Regret theory: an alternative theory of rational choice under uncertainty. Econ J 92(368):805–824
Ma L, Ascough Ii JC, Ahuja LR, Shaffer MJ, Hanson JD, Rojas KW (2000) Root zone water quality model sensitivity analysis using Monte Carlo simulation. Trans ASAE 43(4):883–895
Madani K, Zarezadeh M (2012) Bankruptcy methods for resolving water resources conflicts. In World environmental and water resources congress 2012: Crossing boundaries. pp 2247–2252. https://doi.org/10.1061/9780784412312.226
Mahjouri N, Abbasi MR (2015) Waste load allocation in rivers under uncertainty: application of social choice procedures. Environ Monit Assess 187:1–15
Mannina G, Viviani G (2010) Water quality modelling for ephemeral rivers: model development and parameter assessment. J Hydrol 393(3–4):186–196
Mesbah SM, Kerachian R, Nikoo MR (2009) Developing real time operating rules for trading discharge permits in rivers: application of Bayesian Networks. Environ Model Softw 24(2):238–246
Moridi A (2019) A bankruptcy method for pollution load reallocation in river systems. J Hydroinf 21(1):45–55
Mujumdar PP, Sasikumar K (2002) A fuzzy risk approach for seasonal water quality management of a river system. Water Resour Res 38(1):5–1
Nakane K, Heydari A (2010) Sensitivity analysis of stream water quality and land cover linkage models using Monte Carlo method. Int J Environ Res 4:121–130
Nash J (1953) Two-Person Cooperative Games. Econometrica 21(1):128–140. https://doi.org/10.2307/1906951
Nikoo MR, Kerachian R, Niksokhan MH, Beiglou PHB (2011) A game theoretic model for trading pollution discharge permits in river systems. Int J Environ Sci Dev 2(2):162–166
Niksokhan MH, Kerachian R, Amin P (2009a) A stochastic conflict resolution model for trading pollutant discharge permits in river systems. Environ Monit Assess 154:219–232
Niksokhan MH, Kerachian R, Karamouz M (2009b) A game theoretic approach for trading discharge permits in rivers. Water Sci Technol 60(3):793–804
Nouri A, Bazargan-Lari M, Oftadeh E (2023) A new fuzzy approach and bankruptcy theory in risk estimation in Waste Load Allocation. Environ Monit Assess 195(10):1254
Nouri A, Saghafian B, Bazargan-Lari MR, Delavar M (2022) Local water market development based on multi-agent based simulation approach. Groundw Sustain Dev 19:100826
Poorsepahy-Samian H, Kerachian R, Nikoo MR (2012) Water and pollution discharge permit allocation to agricultural zones: application of game theory and min-max regret analysis. Water Resour Manage 26:4241–4257
Saadatpour M, Afshar A, Khoshkam H, Prakash S (2020) Equilibrium strategy based waste load allocation using simulated annealing optimization algorithm. Environ Monit Assess 192(9):612
Sadiq R, Kleiner Y, Rajani B (2007) Water quality failures in distribution networks—risk analysis using fuzzy logic and evidential reasoning. Risk Analysis: Int J 27(5):1381–1394
Sasikumar K, Mujumdar PP (2000) Application of fuzzy probability in water quality management of a river system. Int J Syst Sci 31(5):575–591
Sheikhmohammady M, Madani K (2008) Sharing a multi-national resource through bankruptcy procedures. In World Environmental and Water Resources Congress 2008: Ahupua'A. pp 1–9. https://doi.org/10.1061/40976(316)556
Sun XY, Newham LT, Croke BF, Norton JP (2012) Three complementary methods for sensitivity analysis of a water quality model. Environ Model Softw 37:19–29
Thomann RV, Mueller JA (1987) Principles of surface water quality modeling and control. Harper & Row, New York, p 644
Timalsina H, Hwang S, Cooke RA, Bhattarai R (2023) Comparative sensitivity analysis of hydrology and relative corn yield under different subsurface drainage design using DRAINMOD. Appl Sci 13(16):9252
Vemula VS, Mujumdar PP, Ghosh S (2004) Risk evaluation in water quality management of a river system. J Water Resour Plan Manag 130(5):411–423
Wagener T, Kollat J (2007) Numerical and visual evaluation of hydrological and environmental models using the Monte Carlo analysis toolbox. Environ Model Softw 22(7):1021–1033
Wang P, Deng H, Peng T, Pan Z (2023) Measurement and analysis of water ecological carrying capacity in the Yangtze River Economic Belt, China. Environ Sci Pollut Res 30(42):95507–95524
Xu M, Bravo de Guenni L, Córdova JR (2024) Climate change impacts on rainfall intensity–duration–frequency curves in local scale catchments. Environ Monit Assess 196(4):372
Yong SLS, Ng JL, Huang YF, Ang CK, Mirzaei M, Ahmed AN (2023) Local and global sensitivity analysis and its contributing factors in reference crop evapotranspiration. Water Supply 23(4):1672–1683