University of Birjand

Water Harvesting Research (2025) Vol. 8, No. 2: 177-186

10.22077/jwhr.2025.10001.1186

ORIGINAL ARTICLE

A Risk-Based Reservoir Health Indicator for Long-Term Water Quality Assessment: Application to Dissolved Oxygen in Minab Dam

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Received: 15 August 2025, **Revised**: 13 September 2025, **Accepted**: 16 September 2025

Abstract

Dissolved oxygen (DO) fluctuations directly affect biological processes and water quality in a reservoir. It can occur gradually or rapidly as a result of a large input load of pollution. This paper proposes the Reservoir Health Indicator (RHI) as a weighted combination of reliability, resiliency, and vulnerability indices. The one-dimensional First-Order Reliability Method (FORM) and the empirical framework are applied to estimate these indices. The analysis uses 50 years of daily DO simulation results, acquired from molding a Minab dam divided into five non-overlapping 10-year periods. An indicator value greater than 0.5 reveals that the dam is healthy and sufficiently reliable in meeting the DO standard. Three weighting scenarios are applied to explore the RHI sensitivity. Results showed that in the first scenario, the approximate range of RHI variation is between 0.6 and 0.2. This indicates that after 20 years, the dam has lost its ability to improve its condition. In the second scenario, the variation is between 0.63 and 0.4, and the dam almost loses its health at 25 years. The third scenario indicates successful performance of the dam such that system has almost ability to recover itself by the end of its life. Therefore, developing such an indicator can effectively help understand the variation of a reservoir water quality by integrating three vital aspects of reliability, resiliency, and vulnerability.

Keywords: Dissolved Oxygen, Reliability, Reservoir Health Indicator, Resiliency, Vulnerability.

1. Introduction

Development and urbanization, industrial growth, increased agricultural production, and rising wastewater and pollutant discharges have intensified reservoir pollution. Eutrophication is a process that occurs when nutrients such as nitrogen and phosphorus promote phytoplankton growth in reservoirs. Excessive algae growth disrupts ecological balance by causing large daily fluctuations in dissolved oxygen (Lukhele and Msagati, 2024). Eutrophication has multiple negative impacts, including oxygen depletion, changes in species composition, unpleasant taste and odor in drinking water, and production of toxins by certain cyanobacteria harmful to animals (Devlin and Brodie, 2023). As nutrient levels rise, these problems intensify. Additional effects include excessive floating plant growth, reduced transparency, water toxicity, foam formation, waterway blockages, and interference with navigation and recreation (Geletu, 2023; Pranta et al., 2023).

Dissolved oxygen (DO) depletion in reservoirs represents one of the most critical water quality challenges facing aquatic ecosystems. This phenomenon, characterized by hypoxic (< 2-3 mg/L) or anoxic (< 1 mg/L) conditions, fundamentally affects reservoir biogeochemistry and threatens ecosystem integrity (Schernewski et al., 2025). For example, hypoxic conditions severely impact fish communities through habitat compression and physiological stress (Nodo et al., 2023; Hughes et al., 2015). In North Texas reservoirs, chronic anoxia from July through September was observed, with dissolved oxygen frequently < 2.0 mg/L throughout the entire water column (Matthews and Marsh-Matthews, 2003). In Iran's Seymareh

Reservoir, low DO led to significant fish mortality (Keyvanshokooh et al., 2009). Anoxic conditions dramatically increase sediment nutrient release. In California reservoirs, anoxic conditions resulted in ammonia fluxes of 82-366 mg-N/m²•d and soluble reactive phosphorus fluxes of 67-122 mg-P/m²•d (Beutel et al., 2008). These rates are extreme compared to typical eutrophic systems (4-60 mg-N/m²•d and 10-53 mg-P/m²•d) (Cortés et al., 2021).

The environmental consequences can extend far beyond simple dissolved oxygen deficiency. It might cause cascading effects that impact biodiversity, water quality, and ecosystem services. Over the years, many studies have aimed to assess reservoir health status and develop several indices. Common parameters include temperature, pH, dissolved oxygen, and nutrients like nitrates and phosphates. For instance, a Mediterranean reservoir study highlighted that WQI deteriorated due to increased urbanization and nutrient runoff (Fadel et al., 2021).

Carlson (1977) introduced the Trophic State Index (TSI), which uses separate regression equations for chlorophyll a, total phosphorus, and Secchi depth to yield values from near zero (oligotrophic) to 100 (eutrophic). Due to eutrophication's complexity, researchers have also developed fuzzy-logic-based and entropy-based indices to better capture uncertainty in trophic level boundaries (Chen et al., 2008; Bharti et al., 2018; Dasgupta et al., 2025). Abdolabadi and NikSokhan (2014) applied both EFEI and TSI to assess Ilam Dam reservoir's epilimnion and hypolimnion over one year, using two weighting scenarios based on chlorophyll a, total phosphorus, and oxygen saturation. Results showed EFEI's reliability in determining trophic levels (Abdolabadi and Niksokhan, 2014).

Risk-based indices such as reliability, resiliency, and vulnerability are widely used to assess sustainability in water-resource systems and have been applied in areas like reservoir operation testing, water supply assessment, TMDL program evaluation, sustainability measurement, and pollution control cost optimization. Given water quality's direct link to public health, long-term assessment is essential. These indices link water quality parameters and ecosystem stability. For instance, resilience indicators can capture the capacity of reservoir ecosystems to absorb disturbances and maintain function (Pelletier et al., 2020; Jaiswal et al., 2021; Guerrero-Jiménez et al., 2024). Diverse resilience indicators include biogeochemical metrics (e.g., hypoxia, nutrient release), ecological community metrics (e.g., species composition, functional groups), and integrated indices such as trophic state and water quality indices (Mi et al., 2023; Toumasis et al., 2024; Xu et al., 2015).

Reviewing literatures reveals that effective reservoir water quality assessment requires not only maintaining standards under normal conditions but also understanding the system's performance under stress and uncertainty. Traditional deterministic indices, which evaluate a system against a single failure threshold, are often insufficient for this task. Probabilistic methods offer a more robust framework. The First-Order Reliability Method (FORM) is a computationally efficient and powerful technique to estimate three critical system performance metrics: Reliability, Vulnerability, and Resiliency (Wei et al., 2023). FORM is applied by many researchers to analyze varied case studies—from urban drainage networks to riverine ecosystems. Azimi et al. (2019) used the FORM to analyze drought recurrence conditions during 1994–2015 from 609 study areas of Iran. They defined reliability based on groundwater resource index. The analysis incorporates geostatistical techniques (Kriging) to map drought risk spatially, providing insight into both the extent and severity of groundwater decline across the country. Thorndahl and Willems (2008) integrated FORM with hydrodynamic urban drainage modeling (MOUSE) to analyze probabilistic overflow events in combined sewer systems. They used multi-year rainfall statistics to derive failure probabilities and return periods for overflows impacting receiving water quality. Hamed and El Beshry (2006) applied FORM in modeling benzene transport in an aquifer, effectively capturing uncertainties in hydrogeological and chemical parameters. They demonstrated that FORM-based exceedance probabilities matched traditional Monte Carlo outputs with far fewer model runs.

This study proposes and applies a Reservoir Health Indicator (RHI), based on reliability, resiliency, and vulnerability, to evaluate long-term dissolved oxygen dynamics in the Minab reservoir. Unlike traditional indices such as TSI, WQI, or fuzzy-based approaches, the RHI explicitly integrates risk-based performance metrics with probabilistic methods (FORM). This provides a dynamic and long-term perspective on reservoir health that captures not only average water quality conditions but also the likelihood, intensity, and persistence of failures. The novelty of this work emphasizes introducing a risk-based framework that enables a evaluation of reservoir water quality dynamics across the entire design life. By focusing on dissolved oxygen as a sentinel parameter, the study demonstrates how RHI can bridge the gap between conventional water quality indices and resilience-based assessment, offering reservoir managers a more robust tool for decision-making under uncertainty.

2. Materials and Methods

When water quality in a reservoir remains standard, from the beginning of the operation to the end of the dam life, the dam has a successful performance and the system is totally reliable. As achieving total reliability in the preliminary designs seems not reasonable (due to excessive expenditure, increased uncertainty, etc.), evaluating reservoir performance in protecting water quality can be useful for managers to avoid encountering challenges like eutrophication and dissolved oxygen depletion.

In this study, we select DO because it directly reflects biological processes (respiration, photosynthesis, decomposition) and indirectly captures the effects of nutrient enrichment, organic loading, and stratification as a primary and integrative indicator. We treat DO as a single random variable and estimate these indices following the conceptual framework of Hashimoto et al. (1982) and Maier et al. (2016), but with a one-dimensional First-Order Reliability Method (FORM) formulation. The analysis uses 50 years of daily DO data from the Minab dam water quality model (Abdolabadi, 2024).

The DO data is divided into five non-overlapping 10-year periods. For each period, indices are computed from the statistical properties of the DO distribution, with the probability calculations performed under the assumption of normality. Finally, RHI is estimated over the operational period under three weighting scenarios. For each period p, the series is denoted as:

$$\{DO_t^{(p)}\}, t = 1, \ldots, T_p \quad (1)$$

where T_p is the final day. The regulatory standard (threshold) was set at $DO_{thr} = 5$ mg/L.

2.1. Reliability

Reliability in water resources is often modeled as the relation between load (system demand/stress) and resistance (system capacity). The random variables influencing load and resistance are denoted by $X = (X_1, X_2, \ldots, X_n)$.

The performance function for such systems is commonly defined as:

$$G(X) = R - L \quad (2)$$

where R is resistance and L is load. Both R and L have physical dimensions which depend on the context and problem definition. The system fails when $G(X) < 0$.

The goal is to estimate the probability of failure:

$$p_f = P(G(X) < 0) = \int_{G(X)<0} f_X(X)dX \quad (3)$$

2.1.1. Empirical reliability

Empirical reliability R_{emp} is defined as the proportion of time steps meeting or exceeding the standard:

$$R_{\text{emp}}^{(p)} = \frac{1}{T_p}\sum_{t=1}^{T_p} I(DO_t^{(p)} \geq DO_{\text{thr}}) \quad (4)$$

where $I()$ is the indicator function. R_{emp} is dimensionless (a probability in [0,1]).

2.1.2. FORM reliability (1-D Case)

The performance function is defined as:

$$G(DO) = DO - DO_{\text{thr}} \quad (5)$$

Assuming DO has a normal distribution $\mathcal{N}(\mu_p, \sigma_p^2)$ for period p, the reliability is:

$$\beta_p = \frac{\mu_p - DO_{\text{thr}}}{\sigma_p} \quad (6)$$

where $\mu_p$is sample mean DO for period p (mg·L^{-1}) and σ_p is standard deviation of DO in period p (mg·L^{-1}). The *FORM* estimate of reliability is then:

$$R_{\text{form}}^{(p)} - \Phi(\beta_p) \tag{7}$$

where *Φ()* is the standard normal cumulative distribution function.

2.2. Vulnerability

Vulnerability is assessed using the failure state severity approach from Maier et al. (2016). The DO domain is partitioned into m states by descending bounds (mg·L⁻¹):

$$DO_{\text{thr}} > b_1 > b_2 > \cdots > b_{m-1} \tag{8}$$

For each failure state j in {1, …, m-1}, a weight *wj* represents the severity of that state (dimensionless). The probability of being in state *j* is:

$$e_j^{(p)} = P(b_j < DO \leq b_{j-1}) = \Phi(\frac{b_{j-1} - \mu_p}{\sigma_p}) - \Phi(\frac{b_j - \mu_p}{\sigma_p}) \tag{9}$$

The vulnerability index is the weighted sum:

$$V^{(p)} = \sum_{j=1}^{m-1} w_j e_j^{(p)} \tag{10}$$

2.3. Resiliency

Resilience is defined as the conditional probability of recovery from a failure state in one time step:

$$\gamma^{(p)} = P(DO_{t+1} \geq DO_{\text{thr}} \mid DO_t < DO_{\text{thr}}) \tag{11}$$

Under the Gaussian assumption, the joint distribution (DO_t, DO_{t+1}) is bivariate normal with: marginal mean μ_p, marginal standard deviation σ_p, and lag-1 autocorrelation ρ_p estimated from the period time series. Failure probability is $P_f = \Phi(a_p)$ where:

$$a_p = \frac{DO_{\text{thr}} - \mu_p}{\sigma_p} \tag{12}$$

Joint failure probability is $P_{ff} = \Phi_2(a_p, a_p; \rho_p)$ where Φ_2 is the bivariate normal CDF with correlation ρ_p (autocorrelation of *DO* in period p, range [-1,1]). Resiliency (dimensionless probability) is then:

$$\gamma^{(p)} = 1 - \frac{P_{ff}}{P_f}, P_f > 0 \tag{13}$$

This formulation accounts for persistence in *DO* excursions due to autocorrelation. Figure 1 presents a conceptual diagram showing how the *DO* domain is partitioned into states and how the indices are computed.

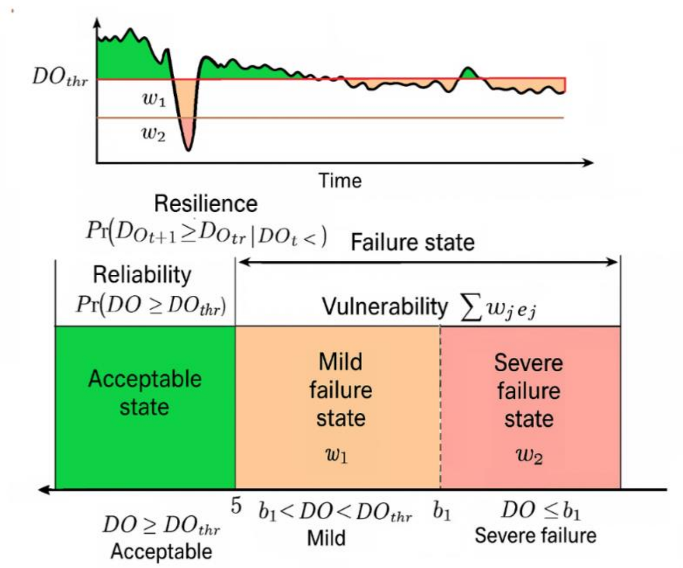

Fig. 1. The schematic diagram of the DO domain in calculating reliability, resiliency, and vulnerability. Reliability refers to how often DO levels meet the standard. Vulnerability evaluates the average seriousness of times when DO levels fall below the threshold. Resiliency reflects the system's capacity to quickly return to acceptable DO levels after a violation.

2.4. Reservoir health index

Based on the explanations provided, the dam reservoir health index can be defined as a weighted combination of the reliability, resiliency, and vulnerability indices of the reservoir. Since reliability and resiliency are probabilistic measures, their values range between zero and one. To maintain consistency, the vulnerability index is also normalized within the same range (0–1), using normalization relative to its maximum value. The relative weights of the three indices take values between zero and one and together sum to unity. Eq. 14 expresses the quantitative value of the reservoir health index as the weighted sum of the three indices:

$$RHI = W_{Rel}(R) + W_{res}(\gamma) + W_{vul}(1 - \delta) \tag{14}$$

where W_{Rel}, W_{Res}, and W_{vul} are the weights assigned to the reliability, resiliency, and vulnerability indices, respectively. To assign weights that reflect the practical importance of each component, three weighting scenarios are considered (Table 1):

- Scenario 1: Reliability is given the highest weight, followed by resiliency, while vulnerability receives the smallest weight. This emphasizes the system's ability to remain functional and recover after disturbances.
- Scenario 2: Equal weights are assigned to all three indices, giving balanced importance to reliability, resiliency, and vulnerability.
- Scenario 3: Reliability again receives the greatest weight, but in this case, vulnerability is given higher importance than resiliency, highlighting the risk associated with severe declines in system condition.

Table 1. The weights corresponding to each index under these three scenarios.

Weights	Reliability	Resiliency	Vulnerability
Scenario 1	0.5	0.4	0.1
Scenario 2	0.33	0.33	0.33
Scenario 3	0.5	0.1	0.4

According to the RHI, values closer to one indicate a better reservoir condition in terms of water quality, characterized by higher reliability and resiliency and lower vulnerability. Conversely, values approaching zero represent a system that frequently fails to meet the standard value of the selected water quality variable (*DO*). In such cases, the system remains failed most of the time. Therefore, a RHI greater than 0.5 can be interpreted as an indication that the reservoir possesses an acceptable level of health with respect to *DO*.

3. Results and Discussion

To study the trend of changes in the health index based on trophic status, the reservoir condition was evaluated over decadal intervals as well as for the overall lifespan. Accordingly, five intervals were defined based on the reservoir's operational history: the first 10 years, 10–20 years, 20–30 years, 30–40 years, and finally 40–50 years. Given the large number of observations (18,250 days) and the potential for computational errors, MATLAB 2012 was used to compute all indicators. Figure 2 presents the time series of dissolved oxygen (DO) concentration in the hypolimnion, along with the values below the standard threshold of 5 mg/L, across the operational life of the Minab reservoir.

As can be seen, from the start of operation until approximately day 5000 (the first 13 years), the system functioned with almost no problems, and DO concentrations on most days were above the standard limit. During this stage, concentrations fluctuated between 4 and 8 mg/L, which is acceptable considering seasonal variations. Between days 5000 and 10,000 (years 13–26), the reservoir entered an intermediate state. While most values were still above the standard limit, DO fluctuations increased in intensity, ranging from 2.5 to 7 mg/L. This indicated a gradual deterioration of system conditions during this period.

From days 10,000 to 15,000 (years 26–39), the DO concentration frequently fell into a critical range, and the reservoir experienced unfavorable conditions. During this interval, fluctuations ranged from 0 to 6 mg/L, reflecting the high vulnerability of the reservoir. In the final 11 years of operation, the decline in DO concentration became more severe, with both variability and intensity of depletion reaching maximum levels.

In this phase, concentration fluctuations remained within 0 to 6 mg/L, signaling the most critical stage of the reservoir's health. Table 2 summarizes the computed values for reliability, resiliency, vulnerability, and RHI, considering the weights assigned under the three defined scenarios.

The probability that the reservoir meets the dissolved oxygen (DO) standard (5 mg/L) decreases over time. In the early years (10–1), reliability is high (0.81–0.98). It indicates that the reservoir has stable conditions. However, in later decades, particularly between years 40–50, reliability drops to 0.59, indicating a gradual decline in system performance.

The ability of the reservoir to recover after failure events remains extremely low throughout the entire lifespan (0.01–0.02). This indicates that once the system falls below the DO threshold, its capacity to return to acceptable conditions is very limited.

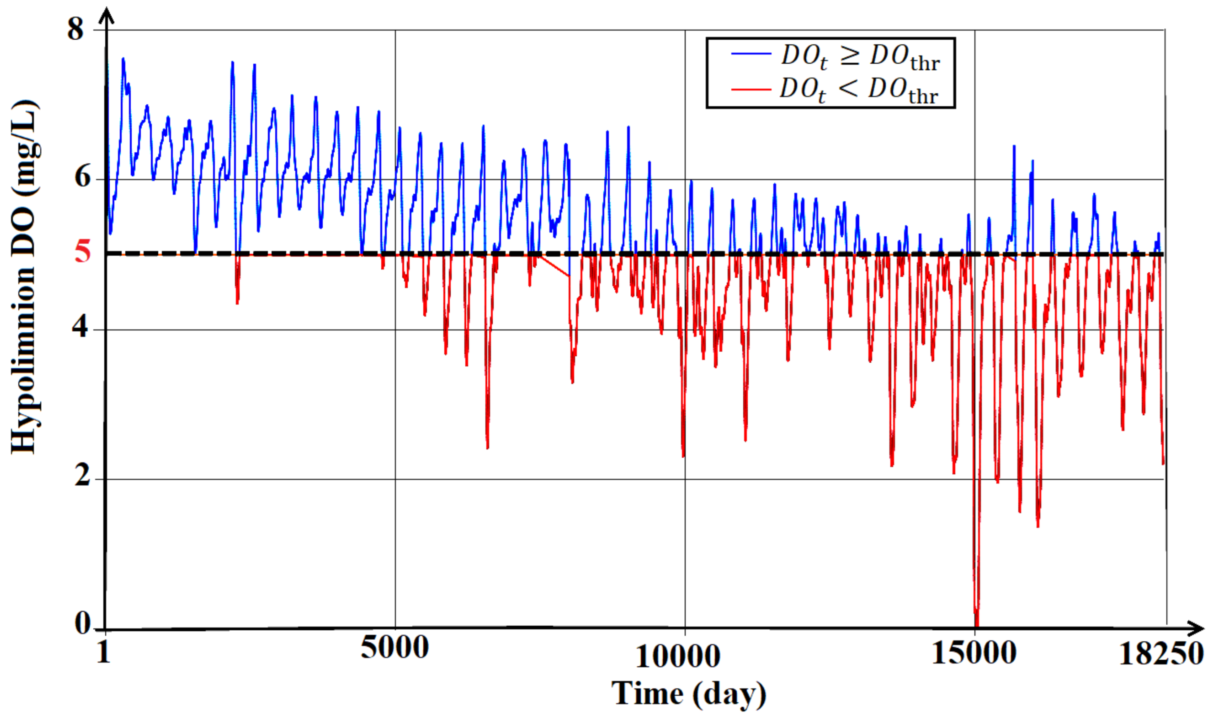

Fig. 2. Dissolved oxygen concentration in the Minab reservoir

Table 2. Reliability, resiliency, vulnerability, and RHI, considering under-weighting scenarios

Index \ Year	10–1	20–10	30–20	40–30	50–40	Lifetime
Reliability	0.982	0.807	0.470	0.412	0.272	0.588
Resiliency	0.016	0.013	0.008	0.009	0.005	0.007
Vulnerability	0.122	0.145	0.138	0.144	0.180	0.115
Average failure days	64	78	128	113	204	45
RHI (Scenario 1)	0.59	0.49	0.32	0.30	0.22	0.39
RHI (Scenario 2)	0.63	0.56	0.45	0.43	0.37	0.50
RHI (Scenario 3)	0.84	0.75	0.58	0.55	0.46	0.65

The severity of failure, when it occurs, fluctuates within 0.11–0.18. The highest vulnerability is observed between years 30–40 (0.18), showing that during this period, failures were more critical. The number of days in which the DO standard is not met varies across intervals. The worst performance is recorded between years 40–30 (204 days on average), while the best condition occurs in the earliest decade (64–78 days). This further confirms the trend of deterioration over time.

In Scenario 1 (reliability prioritized), RHI decreases from 0.59 in the early years to 0.22–0.32 in later decades, reflecting worsening health conditions. In Scenario 2 (equal weights), RHI values are slightly higher (0.37–0.63), but still demonstrate a declining trend over time. In Scenario 3 (vulnerability weighted more heavily), the RHI values are highest (0.46–0.84). However, the same pattern of deterioration is visible, with healthier conditions in the early years and a decline as the reservoir ages. Figure 3 presents fluctuations in the reliability, resiliency, and vulnerability indices of the reservoir over its 50-year operational life.

The reservoir's reliability shows a clear decreasing trend over time, with the decline occurring rapidly and steeply. In the first decade, reliability is high (close to 1). In the second decade, the index decreases by about 18%, yet remains acceptable at around 0.8.

During the third decade, however, the decline becomes more severe, with values dropping from about 0.8 to 0.4, reflecting a marked deterioration in dissolved oxygen conditions. In the fourth decade (years 30–40), the slope of decline lessens, suggesting that while reliability is still poor, fluctuations around the DO threshold are reduced, and concentrations are consistently below the standard level.

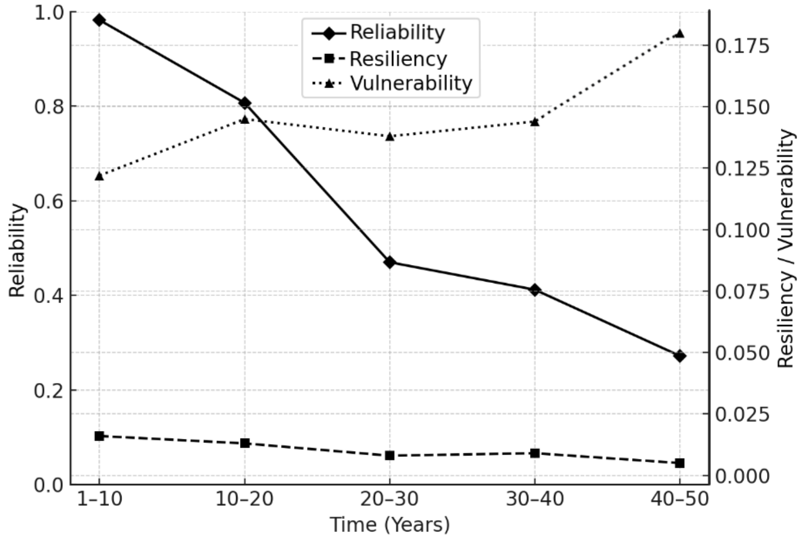

Fig. 3. Reliability, resiliency, and vulnerability in the reservoir

In the final decade, reliability falls further to approximately 0.2, indicating that the system is no longer capable of maintaining DO concentrations above the acceptable standard.

The resiliency index exhibits a trend generally similar to reliability, but its values remain extremely low throughout the reservoir's life (around 0.01–0.02). This indicates that once the reservoir fails (DO < 5 mg/L), the probability of recovery in the next time step is very small. The mean downtime data in Table 2 corroborate this finding. A slight increase in resiliency is observed during the fourth decade, which is attributable to a reduction in the average number of failure days during this period. Nonetheless, the system's overall ability to recover remains negligible.

The vulnerability index increases over time, indicating that the severity of dissolved oxygen depletion events intensifies as the reservoir ages. Since this index is normalized, the maximum possible deviation from the standard (5 mg/L) corresponds to DO values reaching zero, which were observed during some periods (see Figure 1). Interestingly, the vulnerability index shows a temporary decline during the third decade, suggesting that although failures were frequent, their intensity was somewhat reduced. In the fourth decade, the intensity remained comparable, but in the final decade, the vulnerability increased significantly, pointing to more severe oxygen depletion events.

Figure 4 shows the trend of RHI under the three weighting scenarios. Across all scenarios, the RHI follows a logical decreasing trend, reflecting the reservoir's progressive deterioration in water quality. The decline is steep and consistent over time.

Scenario 1 results in the lowest RHI values because reliability is prioritized and vulnerability has minimal weight. Scenario 2 leads to moderate RHI values, as all three indices are equally weighted. Scenario 3 produces the highest RHI values, since greater weight is assigned to vulnerability, which reduces the penalization from poor resiliency and declining reliability.

4. Conclusion

Although water quality monitoring of reservoirs—especially those supplying drinking water—is standard practice, the processes driving water quality changes typically act over the long term. RHI evolves gradually, making it difficult to determine when the system irreversibly loses its ability to maintain acceptable quality without external intervention. To address this challenge, a risk-based indicator of reservoir health was introduced, describing the water quality changes throughout the operational lifetime (design life) of the reservoir.

This indicator evaluates the system's success or failure in meeting desired quality standards over time. In this study, the concept of reservoir health was assessed in relation to dissolved oxygen (DO) level. Three indices—reliability, resiliency, and vulnerability—were quantified and then combined into a single Reservoir Health Index (RHI) using three distinct weighting scenarios. The resulting index was used to analyze the reservoir's water quality across its lifetime.

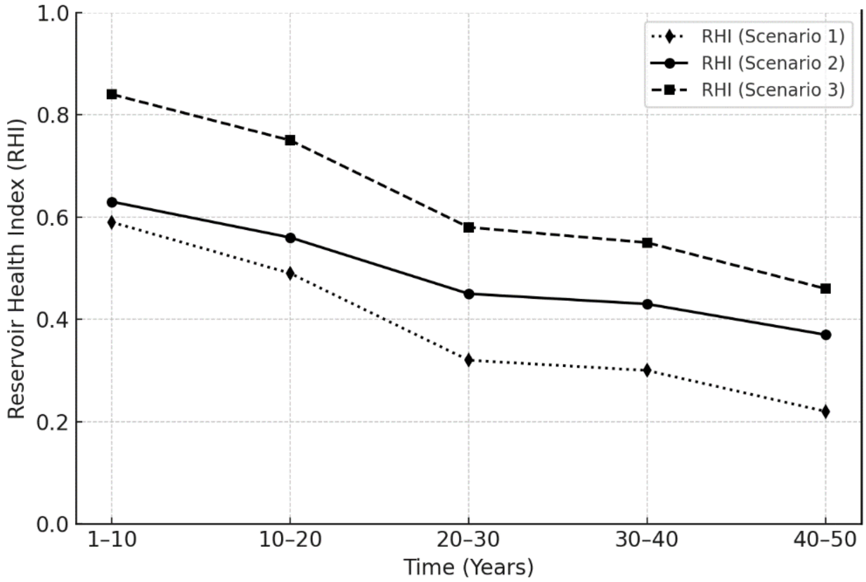

Fig. 4. The RHI under the three weighting scenarios

Scenario 1 demonstrated that the RHI decreased from approximately 0.6 in the first decade to 0.2 in later years. The reservoir fell below the standard threshold by the third decade, suggesting that its ability to improve conditions was largely lost by around 20 years of age. Scenario 2 indicates that the RHI ranged between 0.63 and 0.4. Here, the decline was more gradual, but the reservoir nearly lost acceptable health by around 25 years of age. In scenario 3, although the RHI also declined, the reservoir maintained relatively better performance throughout its lifetime and only lost its recovery capacity near the end of the 50-year period. Given the importance of reliability and resiliency in defining long-term water quality performance, the weighting scheme in Scenario 1 is considered the most reasonable basis for evaluation. Accordingly, it can be concluded that the Minab reservoir gradually lost its health, with a critical decline occurring after 20 years of operation. It is evident that without management interventions such as oxygenation or operational adjustments, the reservoir will continue to experience diminished water quality and reduced ecological resilience in its later stages of life.

This research can provide an early-warning system, enabling managers to anticipate critical phases of water quality decline and to prioritize interventions. By quantifying reliability, resiliency, and vulnerability, the RHI highlights not only when the reservoir is likely to fail in maintaining dissolved oxygen standards but also how severe and persistent these failures may be. This helps shift water quality management from reactive responses to proactive, risk-informed strategies.

5. Conflict of Interest

No potential conflict of interest was reported by the authors.

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