



# OPEN Enhancing water security through integrated decision-making and selective withdrawal for sustainable reservoir management

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Effective management of water quantity and quality in reservoir systems is vital for strengthening regional water security. Selective Withdrawal Systems (SWSs) contribute to this goal by allowing the precise extraction of water from specific layers in stratified reservoirs, where water quality and other properties differ across depths. Climate change and management policies further influence the hydrodynamics of SWSs, significantly impacting reservoir water quantity and quality. This study presents a multi-stage framework to identify optimal SWSs as solutions for the Wadi Dayqah reservoir in Oman, using both quantitative and qualitative approaches. The framework begins with optimizing SWS operations to ensure adequate water supply, improve the quality of released water, and enhance overall reservoir conditions. In the next phase, a robust decision-making (RDM) framework addresses uncertainties associated with climate change. This framework evaluates generated states of the world (SOWs) using sustainability indices by combining optimized responses with climate uncertainties. Additionally, a cellular automata (CA) model assesses three critical approaches in sustainable reservoir management: water deficit, undesirable water quality, and eutrophic conditions. The optimization results revealed that the proposed SWS strategies consistently outperformed the current operational state across all objectives. Notably, the lower gate (Gate 1) played a pivotal role in meeting agricultural and environmental water demands, significantly contributing to water withdrawals. Sustainability indices (SIs) for the SOWs in the RDM framework were computed based on stakeholder-defined thresholds. The SI values for the first, second, and third approaches were 0.898, 0.709, and 0.533, respectively, demonstrating the effectiveness of the optimized strategies in mitigating water deficits, improving water quality, and reducing eutrophic conditions.

**Keywords** Climate change, Selective withdrawal, Robustness, Multi-objective optimization, Sustainability index, Cellular automata

Reservoirs play a critical role in water resources management among diverse climatic regions—including hydropower generation in humid environments as well as water supply and drought mitigation in arid and semi-arid zones. Moreover, regarding water resources management, climate change can significantly alter the spatio-temporal distribution of rainfall and evaporation patterns, causing water shortages and degrading water quality in reservoirs<sup>1,2</sup>. These climatic shifts are expected to further strain reservoirs, which serve as vital sources of water supply<sup>3,4</sup>. In addition to the impacts of climate change on the hydrological cycle, reservoir operation and management practices also influence water quantity and quality. Additionally, inadequate reservoir operation policies and ineffective management practices can result in inefficient reservoir management, suboptimal downstream water releases, and significant water quality challenges. Poor management often fails to adapt to changing climatic conditions, further complicating efforts to balance water supply, ecosystem sustainability, and downstream demands. The management of reservoir operations, including systems like SWSs, plays a crucial role in influencing water quality, thermal stratification, and eutrophication<sup>5,6</sup>. Effective reservoir management

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strategies are therefore essential for mitigating the impacts of climate change, ensuring a sustainable water supply in terms of both quantity and quality, and enhancing biological conditions.

Previous studies have highlighted the effectiveness of SWSs as an optimization framework in reservoir management, demonstrating their ability to enhance both the quantity and quality of released water<sup>7–12</sup>. To build on these findings, this research proposes the development of an optimization framework, supported by reservoir simulation, to identify and refine SWSs that achieve the best quantity and quality of water demand as well as the best eutrophic conditions for reservoir. Also, maintaining downstream ecosystems, along with the quantity and quality of released water, is essential for effective reservoir management. While it is imperative to enhance the conditions for downstream and reservoir ecology, there is a lack of research that has examined these subjects across extensive domains<sup>11,13</sup>. Climate variability and change significantly impact the spatio-temporal distribution of precipitation and evaporation, which in turn leads to variations in the availability of water resources<sup>14</sup>. This has profound implications, particularly for reservoir systems, where the interactions between climate patterns and watershed characteristics can influence inflow dynamics. Changing precipitation and evaporation patterns can cause shifts in the inflows of reservoirs, resulting in reduced inflows during dry spells or excess water during wet periods<sup>15</sup>. In addition to water quantity, these changes can impact water quality—affecting parameters like temperature, turbidity, nutrients, and oxygen levels. For example, higher temperatures may promote algae blooms, and reduced inflow during droughts can lead to less dilution of pollutants<sup>15</sup>. According to Azadi, et al.<sup>16</sup> semi-arid regions could see inflow reductions of up to 30% under certain climate change scenarios, further straining water supply systems. Lower inflows often result in higher pollutant concentrations, reduced oxygen levels, and increased problems such as thermal stratification. Rheinheimer, et al.<sup>17</sup> found that climate-driven changes in inflow dynamics negatively affect dissolved oxygen (DO) levels and nutrient cycling, worsening eutrophication and damaging aquatic life and ecosystems. The growing interactions between climate change and human activities pose a threat to water security. While most studies have focused on water quantity, water quantity and quality are important for sustaining ecosystems and human well-being<sup>15,18</sup>.

SWS strategies have become crucial tools for managing fluctuations in integrated water resource management. Originally designed to mitigate thermal stratification, their role has expanded to improving reservoir conditions in terms of climate change<sup>11</sup>. Duka, et al.<sup>13</sup> demonstrated that selective withdrawal can improve thermal stratification management and help maintain downstream water quality within acceptable levels, even amid changing climate conditions. However, eutrophic conditions in reservoirs have been less explored, with most studies focusing primarily on water availability and the quality of released water. Apart from these aims, the sustainability and improvement of overall reservoir conditions have not been adequately examined.

Climate change and variability are major sources of uncertainty in water resources management, with the potential to significantly impact a system's ability to maintain stable quantity and quality conditions, especially in reservoirs<sup>19,20</sup>. To address these uncertainties and associated challenges, the RDM framework offers a valuable tool for enhancing water resource management and reservoir operations under various uncertain future scenarios. Specifically designed to provide robust strategies, the RDM framework helps manage water systems effectively<sup>21–23</sup>.

The SWS method can significantly enhance the RDM framework by enabling reservoir operators to adjust water withdrawal strategies in response to changing conditions. A recent study by Nikoo et al. (2024) highlighted the effectiveness of integrating SWS with the RDM framework to improve water quality within a reservoir system, even under challenging climatic conditions. Additionally, various management scenarios can evaluate the long-term performance of reservoirs by combining indices of sustainability, reliability, vulnerability, and resilience<sup>24–26</sup>. Reservoir management involves maintaining its operational capacity and ensuring it can adapt to future changes without significant water quality degradation. Okkan, et al.<sup>3</sup> evaluated the reliability and resilience of reservoir management scenarios under climate change uncertainty. However, despite growing recognition of RDM and sustainability indicators, research combining these to enhance SWS techniques remains limited. The dominant goal of our study is to develop a novel framework integrated with RDM principles to optimize SWSs in reservoir management, while addressing the challenges posed by climate change and uncertainties in water inflows and meteorological parameters. This study integrates the CE-QUAL-W2 reservoir simulation model with the MOPSO optimization algorithm to enhance operational performance. Indeed, the optimization aims to ensure water supply, maintain downstream water quality, and mitigate the eutrophic state of the reservoir. Subsequently, we incorporate uncertainty factors—such as temperature, dew point, wind speed, and inflow—into the RDM framework. A major innovation of this research is the integration of CA into the RDM framework, where CA is used to model the dynamic and temporal changes of reservoir operations. The efficacy of CA in water quality and quantity management under varying climatic conditions has been demonstrated by Kazemnadi, et al.<sup>8</sup>. We utilize the concept of CA to systematically improve SWS strategies by simulating reactions to various climatic and operational factors. This allows for identifying the most robust strategies by evaluating reliability, vulnerability, and resilience based on the sustainability index. Overall, we aim to address the following questions:

1. To evaluate the performance of a machine-learning rainfall-runoff model developed to predict reservoir inflows using historical rainfall and inflow data and generate future inflow data through precipitation data via statistical downscaling for use in the RDM framework under climate change.
2. To develop a coupled simulation-optimization framework that combines simulation and optimization algorithms to optimize water quantity (ensuring downstream water demand) and water quality (improving water quality in the reservoir and the released water) in reservoir management.
3. To develop a RDM framework that incorporates CA models and SIs to evaluate the effectiveness of SWSs under climatic uncertainties in integrated reservoir management, where key uncertainty factors include future climate projections (SSPs), which influence the variability of climatic parameters (precipitation, temperature, wind speed, and dew point) and inflow projections obtained through the rainfall-runoff model.

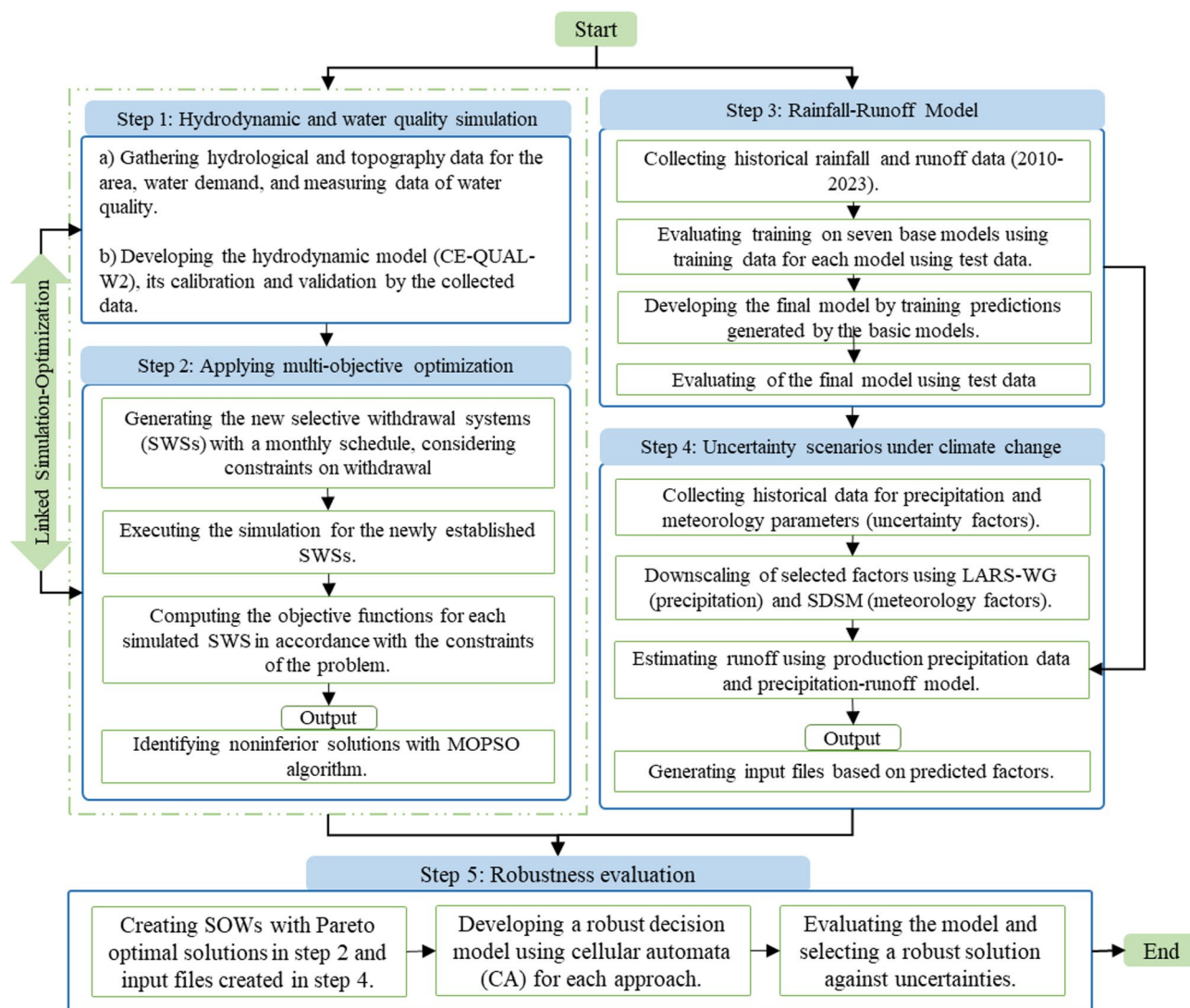
The subsequent sections of the article are organized as follows: Sect. 2 outlines the model framework and provides a detailed description of the case study. Section 3 presents the results of reservoir optimization, water quality simulation, and robustness evaluation using the developed models. Section 4 discusses the optimal and resilient designs of SWSs, and Sect. 5 concludes the study.

## Methodology

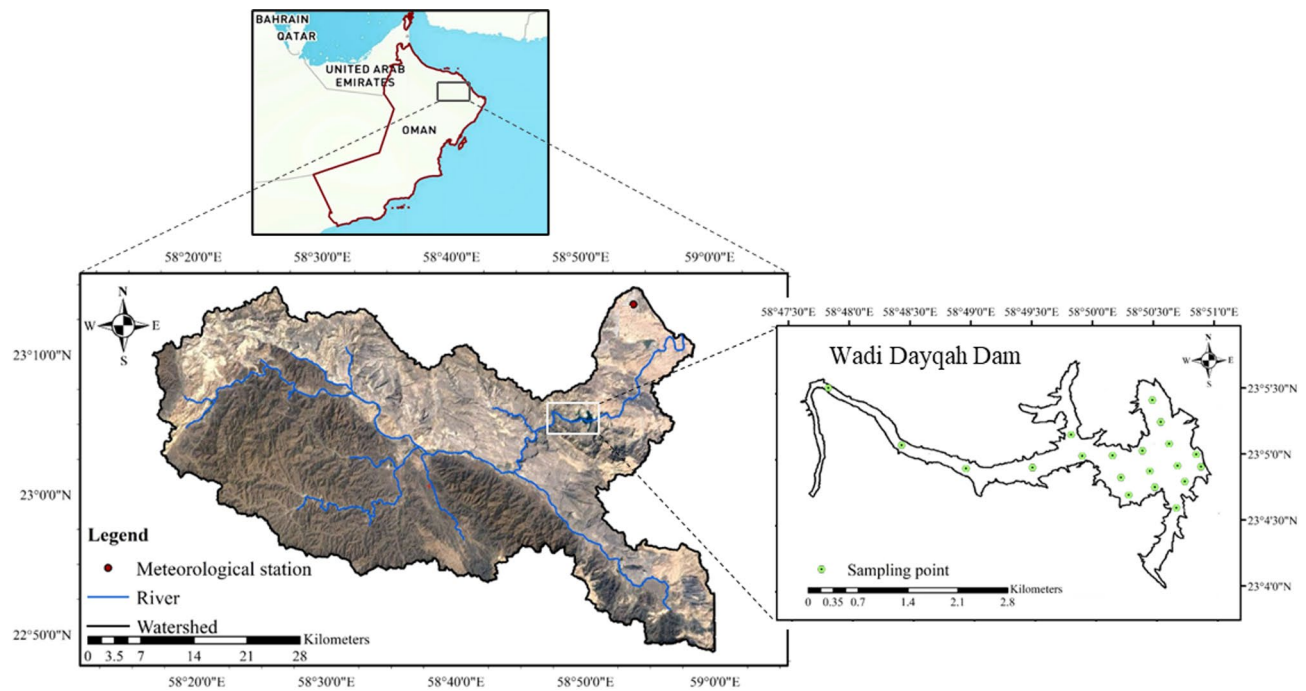
In this study, a detailed framework that integrates RDM with a simulation-optimization approach is assessed for its effectiveness in analyzing the optimal and robustness of SWSs. The methodology is illustrated in Fig. 1, and the following sections outline the key steps of the proposed modeling framework.

### Study area and data

The Wadi Dayqah Dam, which is the largest dam in Oman, is located at the geographical coordinates of 23°5'36" N, 23°3'58" E and 58°50'58" E, 58°47'38" E as shown in Fig. 2. The primary purpose of constructing the dam is to provide potable water to the cities of Muscat and Quriyat, and to reduce the risk of floods. The main dam comprises 572,000 cubic meters of compacted concrete, with a height of 75 m and a length of 435 m. Furthermore, a saddle dam exists with a capacity of 960,000 cubic meters, standing 48 m tall and extending 360 m in length. The main and saddle dams are constructed to save and retain the water of the Wadi Dayqah River for the purpose of agricultural, residential consumption, and ecological demands. These constructions have the capacity to supply around 100 MCM of water to the users of Muscat and Quriyat. The intake tower is strategically positioned within the dam's spillway zone, featuring a total of six water withdrawal levels. This includes a primary gate situated at the lowest extraction point. It is noteworthy that the water discharged from the reservoir on a daily basis serves to supply three downstream aqueducts. A monthly release of 1 MCM is allocated to meet the drinking water



**Fig. 1.** Flowchart of the proposed methodology for robust decision-making for optimized SWSs under climate change.



**Fig. 2.** Location of study area (the Wadi Dayqah water basin and the dam, Oman), river, Meteorological station, and Sampling stations, using ArcGIS 10.2.0.3348.

demands. Furthermore, biannual withdrawals—which are totally 20 MCM—are released from the reservoir to supply the agricultural rights of the farmers in the Quriyat region—located downstream of the dam—and the environmental rights—which are mainly aimed at controlling seawater intrusion that has caused the salinization of the downstream aquifer in the coastal zone.

To investigate SWSs, this study employed six outlets, labeled Gate 1—the main gate—through Gate 6. These outlets are located at elevations of 124 m (main gate, or Gate 1), 128 m, 137 m, 146 m, 155 m, and 164 m above sea level (A.S.L.)<sup>27</sup>.

In this study, the CTD (AAQ-RINKO) was used to gather the water quality data from the Wadi Dayqah dam at twenty sampling points (Fig. 2) from the reservoir's surface to a depth of 35 m. From January 1, 2023, to December 11, 2023, turbidity, Chl-a, pH, DO, temperature, electrical conductivity (EC), and salinity were monitored at various depths. The data was collected in a time sequence of once to three times each month, depending on reservoir and meteorological conditions, for 19-time sets. With a speed of 0.5 m/s, the device descends into the water column at the designated speed, reporting the vertical profile of the qualitative variables with an accuracy of 0.1 to 1 m. Additionally, diverse samplings were made to collect samples from eight separate points at the reservoir, each at five different depths, once a month, in order to quantify iron (Fe) and total phosphate (TP). The values of these water quality variables are also established after the use of a specific procedure on the collected samples in the laboratory.

### Water quality simulation

This study employed the two-dimensional (longitudinal and vertical) hydrodynamic and water quality model, CE-QUAL-W2, to simulate the Wadi Dayqah Dam. The data required to run the model include meteorological data, input contamination loads, bathymetric data, inflow and outflow rates, wind sheltering, and shading for each segment. By using CE-QUAL-W2 to simulate the reservoir, a range of water quality variables can be obtained<sup>28</sup>. The simulation model outputs include the water quality at each outlet and the water quality conditions in the reservoir. The model results are then utilized to evaluate optimization objective functions and assess reservoir sustainability indicators in the RDM framework. The time steps used for simulation in the optimization and the RDM framework are monthly, with a one-year planning horizon.

### Reservoir simulation-optimization model

This study aims to develop a novel framework incorporating RDM principles to optimize SWSs in reservoir management, addressing climate change and uncertainties. This method combines multi-objective optimization by using the MOPSO algorithm with reservoir hydrodynamic and water quality simulations by using the CE-QUAL-W2 model. Simulating the reservoir's hydrodynamics and water quality enables the evaluation of variations in water levels, flow rates, and the dispersal of pollutants over time<sup>29</sup>. Combining the simulation with the MOPSO algorithm enhances reservoir efficiency and enables effective water resource management. The MOPSO was selected for its strong performance in balancing convergence and diversity. It offers a reasonable balance between solution diversity and convergence, which trades off between the objectives of this study. The



MOPSO algorithm uses particle social behavior to optimize multiple objectives. The optimization objectives of this study are to meet various consumption demands, improve the quality of released water, and minimize the trophic condition in the reservoir. The MOPSO algorithm uses reservoir simulation results to generate a set of optimal solutions that effectively balance these objectives.

The simulation spans from January 1, 2023, to December 31, 2023. As part of the optimization process, the decision variables are the opening rates for the six gates of the Wadi Dayqah dam over the 12 months of the year 2023, resulting in a total of 72 decision variables. By accounting for downstream water demand, water quality standards, and the reservoir's eutrophication index, the dam operation plan and discharge quantities from each reservoir outlet can be determined. Additionally, due to being the strictest among water quality standards, drinking water standards are applied to ensure the quality of water in terms of drinking, agricultural, and environmental uses.

The equations of the eutrophication index are provided in Section S.1 of the Supplementary Information. This study shows the objective functions from Eqs. (1)–(3), respectively, related to the quantity water demand, minimizing the squared relative difference between water demand and actual releases; the quality of water demand, minimizing the normalized violation of drinking water quality standards for multiple parameters; and eutrophication level of the reservoir, minimizing the average normalized eutrophication index over selected depths. Additionally, the optimization constraints from Eqs. (4)–(8) include: mass balance constraint between inflow, release, and storage; upper and lower bounds on reservoir storage; limits on release volumes; a minimum demand; and a constraint to prevent the eutrophic state of the reservoir.

$$\text{Minimize } F_1 = \sum_{t=1}^{NT} \left( \frac{D_t - R_t}{D_t} \right)^2 \quad (1)$$

$$\text{Minimize } F_2 = \begin{cases} \sum_{t=1}^{NT} \sum_{p=1}^{NP} \left( \frac{WQ_{t,p} - WQ_{standard,p}}{WQ_{standard,p}} \right)^2, & WQ_{standard,p} < WQ_{t,p} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$\text{Minimize } F_3 = \sum_{t=1}^{NT} \sum_{d=1}^{ND} \frac{EI_{t,d}}{EI_{Eutrophic}} \quad (3)$$

Subject to:

$$S_{t+1} = S_t + I_t - R_t \quad (4)$$

$$S_{min} \leq S_t \leq S_{max} \quad (5)$$

$$R_{min} \leq R_t \leq R_{max} \quad (6)$$

$$D_{min} = R_{min} \quad (7)$$

$$EI_{t,d} < EI_{Eutrophic} \quad (8)$$

Where NT, NP, and ND represents the number of time steps, the number of water quality variables, and the number of selected depths, respectively;  $D_t$ ,  $R_t$  and  $S_t$  denote the water demand, released water and water storage of the reservoir at time step  $t$ , respectively;  $WQ_{t,p}$  is the amount or concentration of water quality variable  $p$  at time step  $t$ ;  $EI_{t,d}$  is eutrophication index at the depth  $d$  at time step  $t$ ;  $I_t$  represents the inflow at time step  $t$ ;  $S_{min}$  and  $S_{max}$  are the minimum and maximum values of water storage in the reservoir, respectively;  $R_{min}$  and  $R_{max}$  are the minimum and maximum values of released water across all time steps, respectively; and  $EI_{Eutrophic}$  is the eutrophication nutrient index, which corresponds to the threshold of the eutrophic reservoir.

### Climate change projection

General Circulation Models (GCMs) are sophisticated tools used to project future climate scenarios<sup>30</sup>. These models simulate climate processes through mathematical representations grounded in thermodynamics and fluid dynamics<sup>31,32</sup>. In this study, we follow the guidelines of the international Coupled Model Intercomparison Project Phase 6 (CMIP6), which combines socioeconomic development pathways with greenhouse gas concentration pathways. We project key climatic variables—precipitation, air temperature, dew point temperature, and wind speed—for the historical period from 1990 to 2020, as well as for future periods of 2030–2060, 2050–2080, and 2070–2100, by using these scenarios. Therefore, we choose three commonly used scenarios—SSP1-2.6, SSP2-4.5, and SSP5-8.5—as they represent the various future uncertainties regarding societal development and radiative forcing levels by the end of the 21st century. SSP126, with 2.6 W/m<sup>2</sup> by the year 2100, is a remake of the optimistic scenario and is designed a sustainable and “green” pathway. SSP245 with an additional radiative forcing of 4.5 W/m<sup>2</sup> reflects “Middle of the road” or medium pathway. Additionally, SSP585 represents a fossil-fueled development path with high emissions and radiative forcing of 8.5 W/m<sup>2</sup>. These pathways are used to simulate a range of plausible future climates in 2050, 2080, and 2100, allowing us to assess the robustness of each SWS under different levels of climate change.

Two software models—that is, Long Ashton Research Station Weather Generator (LARS-WG) and Statistical DownScaling Model (SDSM)—are used for statistical downscaling. The SDSM model is used to generate temperature, wind speed, and dew point temperature for future periods, and the LARS-WG model is used to predict precipitation<sup>33,34</sup>. The LARS-WG system functions by calibrating and verifying historical data from 1990 to 2020 in order to provide monthly climate data for certain future scenarios. SDSM is the process of

transforming local synoptic station data and GCM variables into an appropriate format, and then this is calibrated and validated using historical data. As a result, both models generate daily climatic data for the designated future timeframes and chosen scenarios.

### Rainfall-runoff model

We developed a comprehensive rainfall-runoff model using advanced machine learning techniques<sup>35</sup>. Instead of relying on a single model, we integrated multiple base models through a stacking strategy, which enhanced forecast accuracy. This model reduces the limitations of individual models while maximizing their strengths<sup>36,37</sup>. In this section, we trained machine learning models such as Decision Tree, AdaBoost, Gradient Boosting, XGBoost, LightGBM, Multi-Layer Perceptron (MLP) neural network, and K-Nearest Neighbors (KNN) to generate input data for a final linear regression model. The final linear regression model then synthesized the results of the concurrently trained models to provide the final predictions, and the time steps used are monthly.

### Uncertainty analysis using the RDM framework

Evaluating the performance of SWSs under uncertain climate change scenarios is essential for ensuring the robustness of reservoir systems in terms of water quantity and quality assessments. In Sect. 2.3 of the multi-objective simulation-optimization process, the most optimal SWSs for the specified climatic and operational conditions, along with the objective functions, are represented by non-inferior solutions. To address scenario uncertainties, we will implement the RDM framework, which includes three main methods for analyzing uncertainty: (1) identifying uncertainty factors and developing future SOWs, (2) assessing robustness using multiple sustainability criteria, and (3) scenario discovery. A brief description of these methods is provided below.

#### *Identifying uncertainty factors and creating future sows*

It is essential to identify the uncertainty factors affecting reservoir operations to accurately predict future, particularly those related to climate variables<sup>11</sup>. This method involves examining key factors, including inflow rates, water quality variables, and climatic conditions. The hydrological, water quality, and biological dynamics of the reservoir are closely linked to inflow rates. As a result, fluctuations in inflow levels can significantly impact hydrodynamic conditions, such as flow patterns and thermal stratification. These shifts, in turn, may increase the likelihood of events like algal blooms and other water quality concerns<sup>38,39</sup>. Furthermore, the thermal stratification and mixing processes inside the reservoir are significantly influenced by climatic factors, including air temperature and wind speed<sup>40</sup>.

In this study, the generation of SOWs is used to evaluate the robustness of optimal reservoir operation policies (SWSs) under climate change uncertainties. Initially, a set of non-inferior solutions (SWSs) is obtained through the optimization, which provides a balanced trade-off among multiple objectives. Indeed, to assess the robustness of these optimal SWSs under climate change, each non-inferior solution is combined with a range of future climate scenarios. These scenarios are developed to show plausible variations in climatic and hydrological parameters, air temperature, dew point temperature, wind speed, and reservoir inflow (derived from the rainfall-runoff model). By integrating these climatic uncertainties with each SWS, a comprehensive set of SOWs is generated. This approach provides the evaluation of the performance of optimized reservoir operation strategies under projected future scenarios—ensuring greater sustainability and robustness of SWSs.

Deep uncertainty arises when future outcomes are impossible to forecast with exact certainty because the probability of future occurrences and the connections among significant factors are either unknown or very uncertain<sup>21,41</sup>. In response to these conditions, the RDM framework stands out as a key method, systematically analyzing a broad range of potential future scenarios<sup>42,43</sup>. The RDM framework requires the integration of uncertainty into the decision-making process, typically through the development of multiple SOWs, which serve as the basis for assessing and choosing resilient solutions<sup>44</sup>. The proposed methodology ensures that the RDM framework identifies not only the most robust solutions for the current conditions but also those that are sustainable in future uncertainties<sup>23</sup>.

#### *Evaluation of robustness*

Sustainability indicators, such as reliability, vulnerability, and resilience, are commonly used to evaluate the robustness of SOWs in reservoir management<sup>24,45</sup>. The sustainability index evaluates the system's adaptability, the likelihood of future failures, and its stability over time. It is also important to consider the system's sensitivity to issues like water quantity and water quality<sup>3</sup>. Sustainability indicators for discovering the robustness of various SOWs contribute to decision-makers assessing strategies that remain effective across a range of future scenarios for three approaches. These approaches include: Approach 1, water deficit approach, which evaluates system performance based on the quantity and frequency of water shortages relative to demand; Approach 2, undesirable water quality approach, which focuses on quantifying the extent and duration of water quality variables exceeding thresholds; and Approach 3, reservoir's nutrient condition approach, which assesses the reservoir's eutrophic state through nutrient indicators. The following describes how to calculate the sustainability indicators for each approach.

**Sustainability index** The sustainability index is a comprehensive metric that assesses the robustness of a system by combining reliability, resilience, and inverse vulnerability<sup>3,26</sup> through three approaches (j). In this study, a failure at each time step is defined as a condition where any of the following criteria are not met. This index is calculated using Eq. (9):

$$SI_j = (Rel_j \times Res_j \times (1 - Vul_j))^{1/3} \quad (9)$$

**Vulnerability index** The following explains how to calculate the vulnerability index for these three approaches (j) using Eqs. (10)–(12)<sup>46</sup>:

$$Vul_1 = \frac{[\sum_{i=1}^T Def(t)] / \text{No. of times } Def > 0 \text{ occurred}}{\text{mean of demands } Def} \quad (10)$$

$$Vul_2 = \frac{[\sum_{p=1}^P \sum_{i=1}^T WQ_{t,p}] / \text{No. of times undesirable} > WQ_{standard,p} \text{ occurred}}{WQ_{standard,p}} \quad (11)$$

$$Vul_3 = \frac{[\sum_{i=1}^T EI(t)] / \text{No. of times } Troph > EI_{Eutrophic} \text{ occurred}}{EI_{Eutrophic}} \quad (12)$$

where,  $Def(t)$  represents the water deficit at time step  $t$ ; "No. of times  $Def > 0$  occurred" indicates the number of time steps during which a water deficit was encountered; the term  $WQ_{t,p}$  refers to the water quality value for time step  $t$  and variable  $p$ ; "No. of times undesirable" indicates the number of time steps when the released water quality was outside the standards drinking water quality range;  $EI(t)$  is the eutrophication index of the reservoir at time step  $t$ ; and "No. of times  $Troph$ " refers to the number of time steps during which the reservoir experienced a trophic state.

**Reliability index** The following Eqs. (13)–(15) outline how to calculate the reliability index using three approaches (j)<sup>3,25</sup>:

$$Rel_1 = \frac{\sum_{i=1}^T R_t}{\sum_{i=1}^T D_t} \quad (13)$$

$$Rel_2 = \frac{\sum_{p=1}^P \sum_{i=1}^T (WQ_{standard,p} - WQ_{t,p})}{\sum_{p=1}^P \sum_{i=1}^T WQ_{standard,p}} \quad (14)$$

$$Rel_3 = \frac{\sum_{i=1}^T (EI_{Eutrophic} - EI_t)}{\sum_{i=1}^T EI_{Eutrophic}} \quad (15)$$

**Resiliency index** The resilience index is an important metric that evaluates a system's ability to resist failures and maintain operations<sup>47</sup>. Equation (16) can be used to calculate the resilience index for each of the three approaches (j).

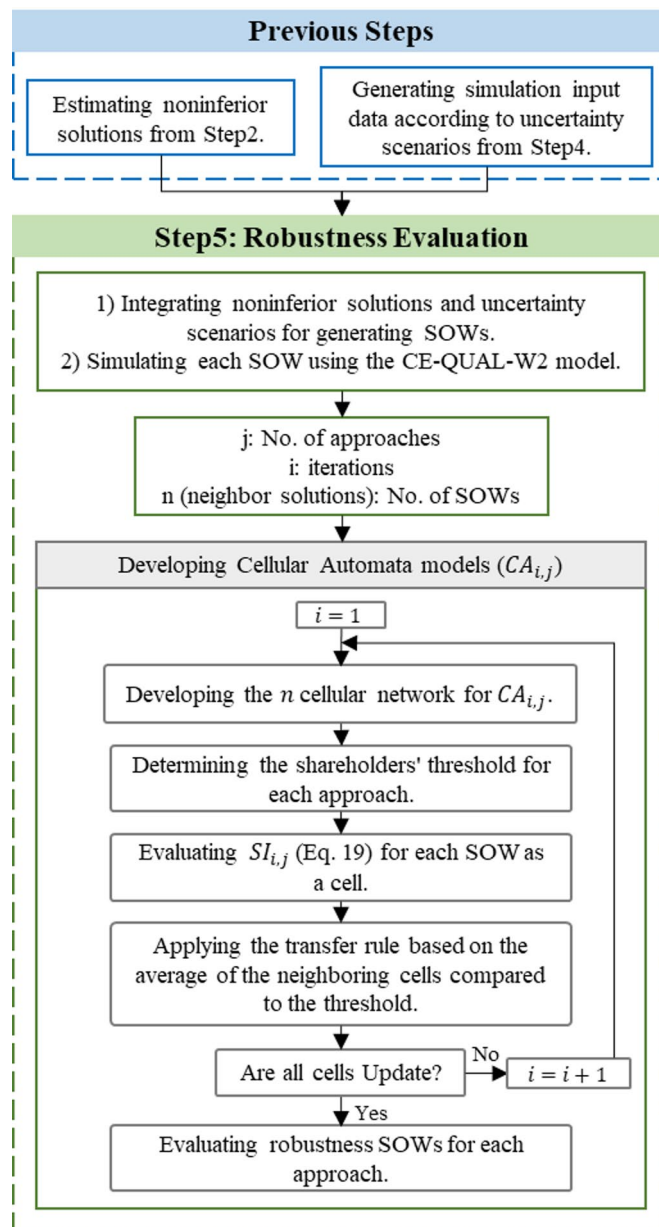
$$Res_j = 1 - \frac{\text{No. of times failure}}{N} \quad (16)$$

In this study, the threshold value computed for the water deficit approach (Approach 1) is derived from the SI value obtained based on the determined amount of water released from the reservoir. The water deficit threshold represents the minimum amount of water that must be released from the reservoir to meet the water needs of downstream and prevent problems such as environmental demand and water shortage. Second, in the undesirable water quality approach (Approach 2), the threshold value is computed from the SI value obtained based on drinking water quality standards. The undesirable water quality threshold typically includes criteria such as maximum permissible concentrations of water quality variables that must be met for safe water consumption. Third, the threshold for the reservoir nutrient condition approach (Approach 3) is based on the eutrophication index at the eutrophic threshold.

#### Scenario discovery and cellular automata for RDM

After estimating sustainability indicators, CA models are used to explore robust solutions within the RDM framework, assessing how different approaches perform under uncertain future conditions<sup>48</sup>. In this step, we use distinct SOWs that combine different uncertainty factors and non-inferior solutions from the optimization framework for system analysis<sup>49</sup>. According to Sect. 2.6.1, these SOWs are developed by modifying key input files and operational strategies to effectively represent a range of potential future events<sup>50</sup>. For each SOW, hydrodynamic simulations are also performed and then the SI indicators, which evaluate system performance against various thresholds, are computed<sup>51–53</sup> (shown in Fig. 3).

In CA models, transition rules determine each state of a cell (SOW), which is updated in each iteration based on its current state and the states of its neighboring cells. Neighborhood refers to the set of cells that influence the update of a cell by considering its adjacent cells with the same SWS, according to the transition rules. The models use transfer criteria that are based on the Sustainability Index obtained from the different SOWs. These rules use thresholds that align with stakeholder objectives for each approach, according to Sect. 2.6.2.4. In this model, the cell neighborhoods are described as the SOWs that are next to a specific cell inside the same set of SWS, therefore reflecting the impact of neighboring situations. The transfer rule in CA models requires that if the average state



**Fig. 3.** Flowchart of step 5 (RDM framework) with details, after simulating SOWs,  $CA_j$  models were developed for three approaches.

of neighboring cells surpasses the thresholds established for stakeholder objectives, the state of the current cell is modified<sup>8,54</sup>. As shown in Fig. 3, this methodology systematically evaluates the strength and durability of SOWs for each approach, ensuring the sustainability of the RDM process against failure.

Using CA in the RDM framework brings significant value by enabling exploration based on meteorological and precipitation uncertainties in the sustainability of solutions across diverse future scenarios. Unlike traditional scenario assessments that evaluate each solution independently, the CA model considers the impact of neighboring scenarios (SOW) through transition rules. This approach identifies sustainable solutions that are not only optimal under specific conditions but also robust to wide-ranging uncertainties.

## Results

### Water quality simulation

The water quality variables of the reservoir—namely, temperature, DO, turbidity, chlorophyll-a, pH, EC, salinity, TP, and iron—and hydrodynamics of Wadi Dayqah reservoir were simulated using the CE-QUAL-W2 model. The simulation is calibrated and validated by using data obtained from the reservoir. As mentioned in Sect. 2.1, measured water quality data are collected from 19 time-sets, of which 14 are used for calibration and 5 for validation. An assessment of the model's performance is conducted using statistical measures, such as the coefficient of determination ( $R^2$ ), Nash-Sutcliffe efficiency (NSE), and root mean square error (RMSE). Table 1



demonstrates  $R^2$  values ranging from 0.631 to 0.961 during calibration and 0.618 to 0.961 during validation. Likewise, the NSE values vary between 0.481 and 0.905 for calibration as well as between 0.416 and 0.887 for validation, indicating a reliable level of performance. The calibrated simulation forms the basis for multi-objective optimization and the RDM framework.

Among the simulated variables, EC, Fe, and TP show relatively lower NSE values during validation. This is likely due to the limited number of measurement points for these variables in each time series, compared to other parameters such as temperature and DO, which had more complete spatial coverage. As a result, the model's ability to accurately calibrate and validate these parameters is limited. Nevertheless, their impact on the optimization and the RDM framework results is minor. This is because, aside from EC and Fe, the other key water quality parameters demonstrate satisfactory predictive performance with acceptable errors during calibration and validation.

Reservoir simulation-optimization model

The optimization of the Wadi Dayqah Dam's SWS is designed to balance the competing objectives of water quantity (Eq. 1), water quality (Eq. 2), and eutrophication (Eq. 3) control with respect to constraints (Eqs. 4–8) for the year 2023. The MOPSO produces twenty non-inferior solutions, detailed in Fig. 4. These solutions illustrate the trade-offs among the three primary objectives, offering a range of reservoir management strategies. In addition, key Optimization metrics—including number of particles and iteration as well as run-time—are listed revealed in Table 2.

A key outcome of the optimization is the implementation of a biannual release plan, ensuring the minimum release of 20 MCM of water to meet downstream agricultural and environmental needs. The monthly patterns of water withdrawal (Fig. S1 and Fig. S2 in the Supplementary Information) identify February and May as the most suitable months for these releases. These strategies directly result in the optimization process, as these months align with the specified target functions, ensuring compliance with the objectives.

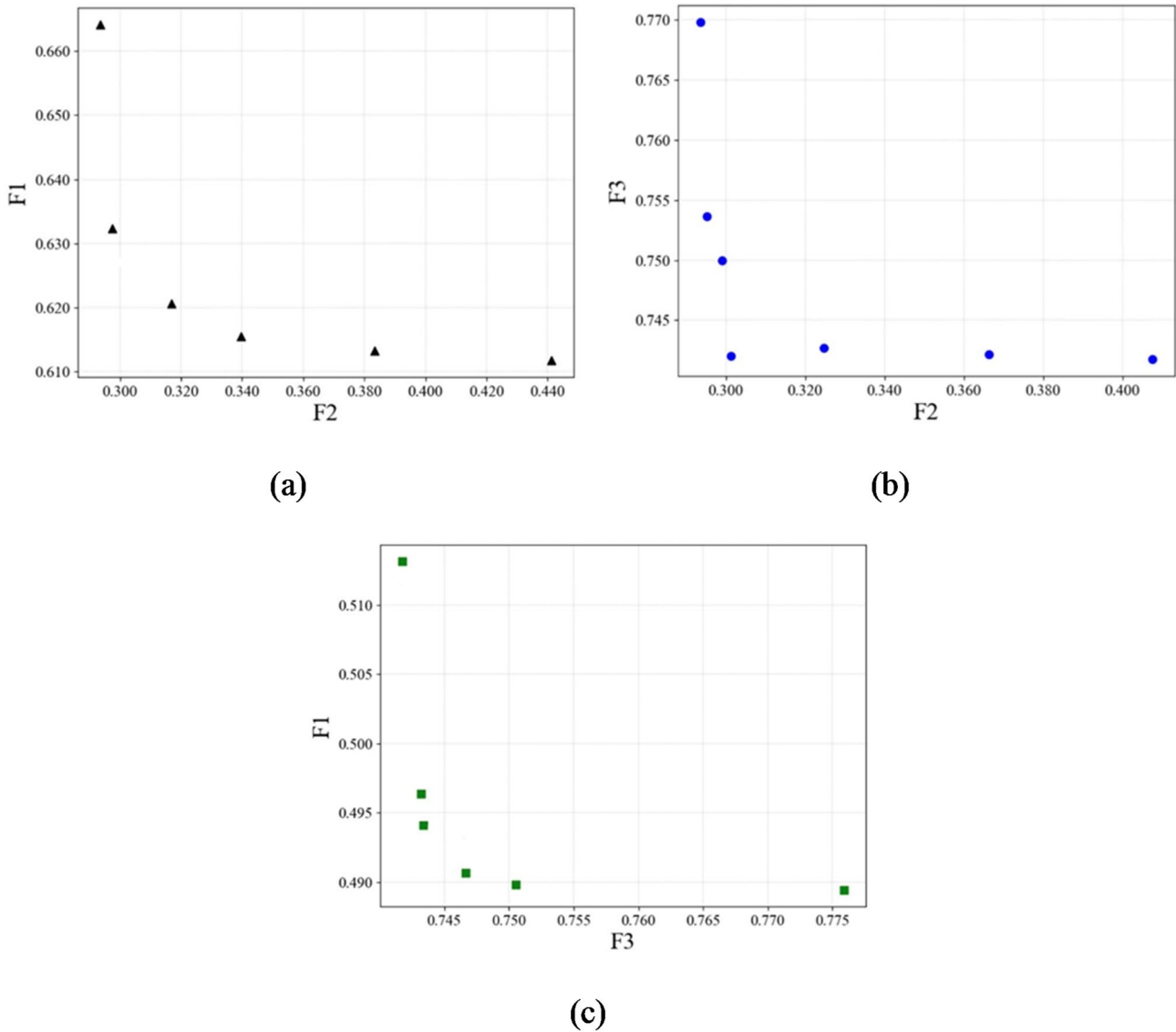
The main gate, Gate 1, plays a vital role in the SWS's operation due to its larger diameter and higher discharge capacity. It is primarily utilized to manage significant water outflows during the critical release periods in February and May. This strategy ensures the necessary water quantities to maintain the reservoir's water quality and trophic conditions. While other gates contribute to total withdrawals, the majority of water is released through Gate 1, which has been identified in this study as the most efficient gate for handling large volumes during high-demand periods. According to Nikoo, et al.<sup>11</sup> the Gate 1's water extraction is particularly sensitive in January and April. Our optimization method, however, demonstrates that using Gate 1 for biannual releases in February and May is effective. Notably, this study also improves the reservoir's eutrophication index, a factor not considered in the analysis by Nikoo, et al.<sup>11</sup>.

Rainfall-runoff model

The model is trained and evaluated using rainfall and runoff data collected from the Quriyat synoptic station over an 11-year period, spanning from 2010 to 2021. The dataset is split into 7 years for training, 2 years for testing, and 2 years for validation. It successfully identifies complex trends and peaks within the dataset. Additionally, the model's performance was assessed using various statistical indicators.

Data for	No. of time sets	Water quality variables	Performance Indices		
			R <sup>2</sup>	NSE	RMSE
Calibration	14	Temperature	0.961	0.905	0.532
		DO	0.86	0.792	0.878
		Chl-a	0.758	0.641	0.427
		TP	0.722	0.576	<0.01
		Turbidity	0.764	0.558	0.161
		Salinity	0.647	0.488	<0.005
		EC	0.631	0.481	<0.005
		pH	0.745	0.507	0.633
		Fe	0.639	0.493	<0.02
Validation	5	Temperature	0.961	0.887	0.584
		DO	0.817	0.682	0.982
		Chl-a	0.745	0.686	0.573
		TP	0.686	0.534	<0.01
		Turbidity	0.748	0.501	0.248
		Salinity	0.618	0.463	<0.005
		EC	0.622	0.485	<0.005
		pH	0.674	0.511	0.812
		Fe	0.643	0.416	<0.02

Table 1. Performance indices of the CE-QUAL-W2 model.



**Fig. 4.** Non-inferior solutions estimated from MOPSO multi-objective simulation-optimization for objective functions presented in Eqs. (1)–(3).

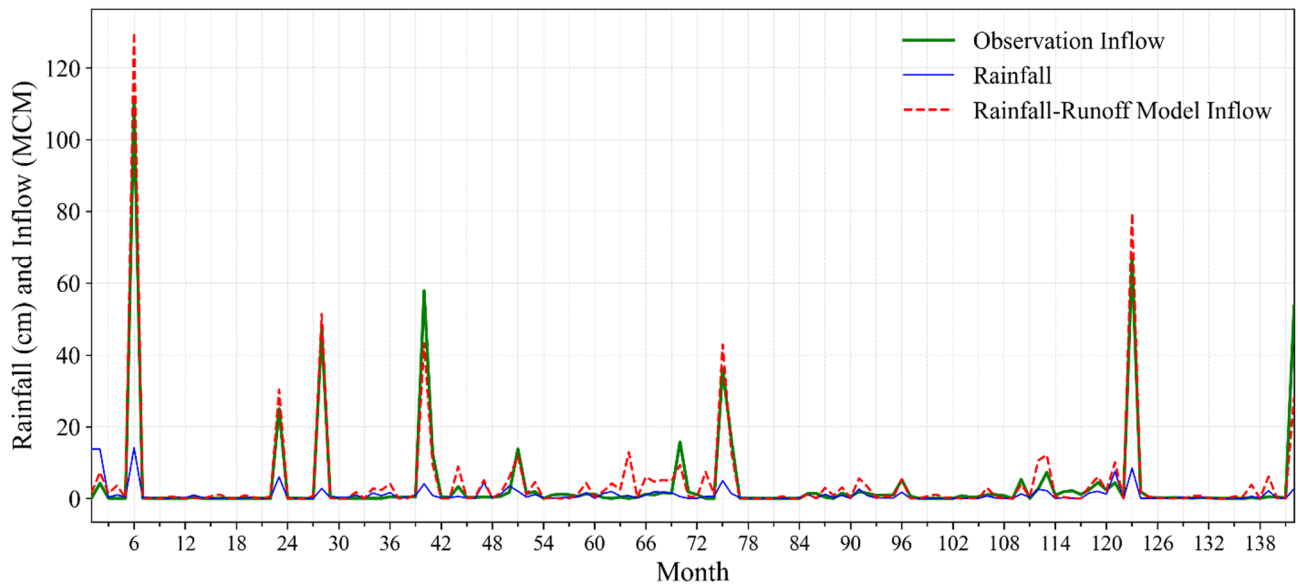
The MOPSO algorithm's implementation	
No. of particles	75
No. of iteration	100
each iteration run-time	1875s
total run-time	187500s

**Table 2.** Computational efficiency of MOPSO: particles, iterations, and execution run-time.

The results presented in Table 3 indicate that the final model performs well for the training, testing, and validation sets. These findings also highlight the model's ability to accurately predict runoff from rainfall, even during the peak weather events. The model's prediction is reflected in the RMSE values, which were 2.26 for the training set and 5.72 for the testing set. These results are consistent given the underlying unpredictability of the data and the complex rainfall-runoff association<sup>55,56</sup> as seen in the peaks of 2010, 2013, and 2020 (Fig. 5). It should also be noted that machine learning models can generalize patterns from the training data, and in cases of low rainfall or noise, may produce minor positive outputs due to overfitting or regularization effects, especially when using ensemble methods like stacking<sup>36,57</sup>. Additionally, these models, like XGBoost and MLP, inherently

Performance indices	$R^2$	NSE	RMSE	Data period (year)
Train set	0.95	0.82	2.26	7
Test set	0.8	0.63	5.72	2
Validation set	0.76	0.44	5.87	2

**Table 3.** The values of performance indices for the training, validation, and testing sets of the Rainfall-Runoff model.



**Fig. 5.** Comparison of observed and Rainfall-Runoff model inflow to the reservoir with rainfall over 11 years (2010–2021).

GCM	Climatic factors	$R^2$	NSE	MSE	RMSE
CanESM5	Temperature	0.794	0.684	7.06	2.657
CanESM5	Dew point temperature	0.752	0.569	7.721	2.779
CanESM5	Wind speed	0.777	0.6494	2.661	1.631
HadGEM3-GC31-LL	Rainfall	0.871	0.779	11.742	3.427

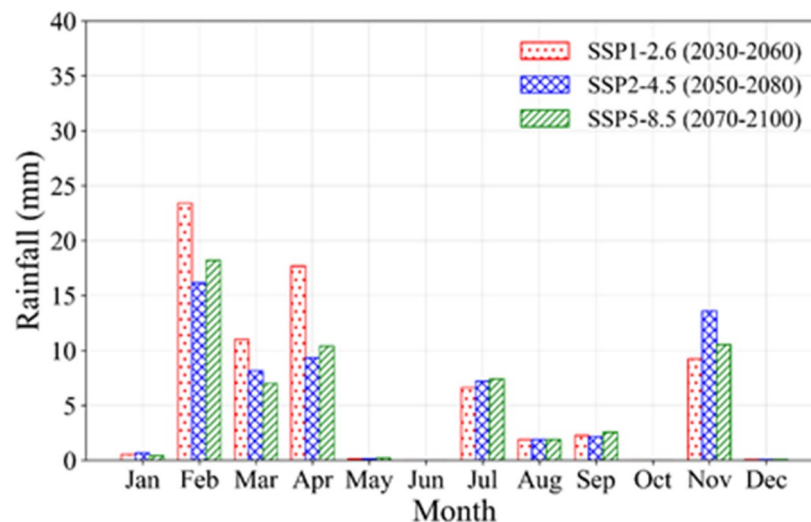
**Table 4.** The values of performance indices for GCM models.

avoid predicting exact zeros due to their functions, especially after combining outputs in a linear regression model<sup>58</sup>.

**Identifying Climatic factors in the context of climate change**

Precipitation data from 1990 to 2020 are analyzed to evaluate the LARS-WG model. The data are downscaled for a 30-year baseline period using the HadGEM3-GC31-LL model. As shown in Table 4, the correlation between the model’s simulations and the rainfall data is acceptable, based on the performance indicators, highlighting the model’s accuracy and effectiveness. Additionally, the SDSM model is assessed and downscaled using historical data (including temperature, dew point temperature, and wind speed) from the same period, along with the CanESM5 model. These two GCMs, CanESM5 and HadGEM3-GC31-LL, are selected based on their spatial resolution, proven performance in regional climate studies—particularly in hyper-arid and arid zones<sup>59,60</sup>—and the availability of required climatic variables—precipitation, temperature, wind speed, and dew point temperature—making them well-suited for the present study.

The LARS-WG model is used to generate projected scenarios for rainfall changes, with the objective of understanding the possible fluctuations and variability of rainfall patterns under various scenarios for future time periods. The projected scenarios are developed based on three climatic scenarios—SSP126, SSP245, and SSP585—covering three specific time periods: 2030–2060, 2050–2080, and 2070–2100. The years 2045, 2065, and 2085 are selected as exemplary examples to demonstrate the projected changes for each period. Figure 6 illustrates the rainfall magnitudes produced for selected scenarios, emphasizing the differences in rainfall



**Fig. 6.** Generated annual precipitation values for the three selected climate scenarios using the LARS-WG model.

amounts under various climatic scenarios and demonstrating the possible impacts of climate change in the study region. The selected scenarios are SSP126 for the period 2030–2060, SSP245 for 2050–2080, and SSP585 for 2070–2100.

Similarly, the SDSM model is used to generate projected scenarios for future changes in temperature, dew point temperature, and wind speed. These scenarios are developed for the same periods and climate scenarios as those in the LARS-WG model. An example of the generated climatic data is shown in Fig. 7, which presents values for the selected scenarios alongside historical data over a 5-year period. The charts illustrate the projected fluctuations in climatic factors, emphasizing the potential impacts of different climate scenarios on future weather patterns.

The inflow data for the reservoir is generated by applying the rainfall-runoff model to projected scenarios. The current model uses rainfall data to predict runoff entering the reservoir. By applying this model, inflow data are calculated for each projected period based on various rainfall scenarios. Figure 8 shows the computed inflow values for three selected scenarios, alongside the simulated inflow data.

### Quantifying the robustness of the sows

This section evaluates the robustness of SOWs in the presence of uncertainty. These models evaluate the effects of climatic and management uncertainty on the operations of the water resources system and the long-term sustainability of SWSs. Approach 1, Approach 2, and Approach 3 are employed to assess the resilience of management alternatives in the presence of uncertainty, wherein sustainability indicators such as reliability, vulnerability, and resiliency are computed and examined. Figure 9 demonstrates the evaluation of SOWs using these different approaches, highlighting the varying levels of sustainability.

Figure 9 examines the reliability, vulnerability, resilience, and sustainability indices for different SOWs in all three approaches. Each glyph and line represents a SOW and is color-coded according to its sustainability index. Blue symbols denote robust situations, but red glyphs signify poor performance in the presence of profound uncertainty. Approach 3 has a much lower sustainability index than the first and second approaches. In Approach 1, the vulnerability index is lower than in the other approaches. Additionally, as shown in Fig. 12, three SOWs under Approach 3 exhibit significantly low reliability indices, which correspond to SSP585 scenarios.

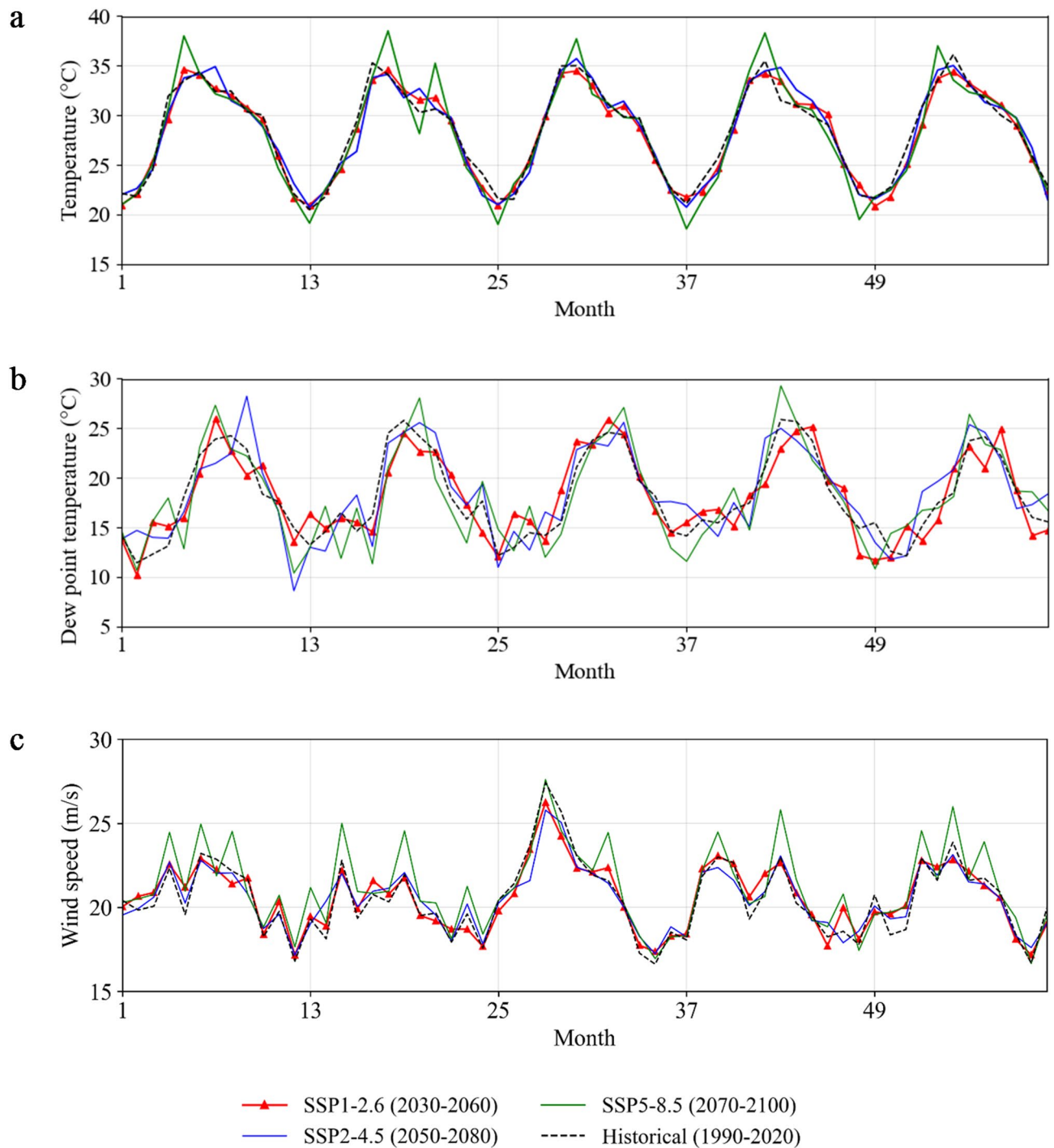
### Robustness of SWSs in three approaches using CA model

As demonstrated in Sect. 3.5, Approach 1 shows the highest level of robustness, followed by Approach 2, with Approach 3 showing the least. The final stage of the RDM process involved increasing the number of iterations in the CA model to 100 to obtain more robust non-inferior solutions using the CA model and the SI. As shown in Fig. 10, the non-inferior solutions for each method are presented using the adjusted SI after 100 iterations. In Approach 1, the solution SWS17 achieves the highest adjusted SI of 0.898, indicating it is the most optimal and resilient option. In Approach 2, SWS14 is identified as the most robust solution with an adjusted SI of 0.709. Similarly, in Approach 3, SWS17 emerges as the most robust option, with an adjusted SI of 0.533.

## Discussion

### Optimization of SWSs

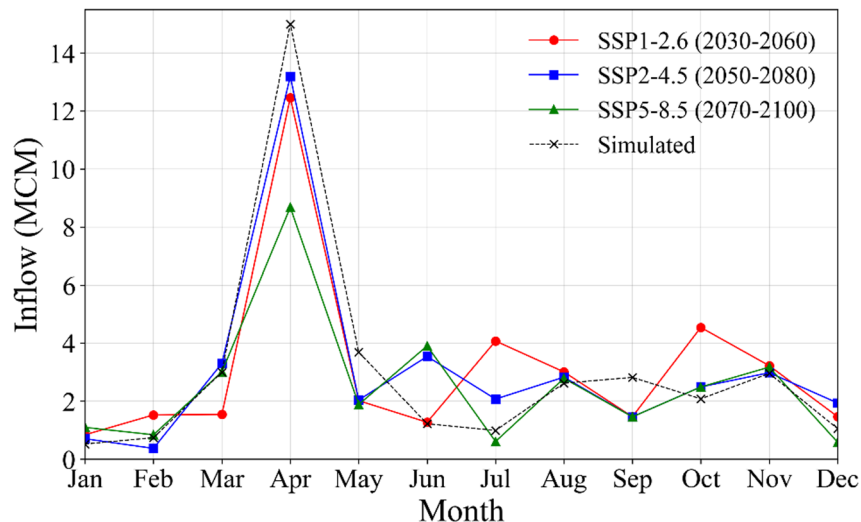
Although environmental flow constraints are not explicitly addressed in the optimization model, they are indirectly considered by releasing biannual withdrawals of 20 MCM to prevent seawater intrusion in the downstream and to maintain groundwater quality in Quriyat. Furthermore, recent studies regarding ecological-hydrological management suggest that integrated models that combine water quality, environmental flow,



**Fig. 7.** Average monthly values of climate variables, such as: (a) temperature; (b) dew point temperature; and (c) wind speed, for the selected climate scenarios and observed data over a 5-year period.

and drought resilience can provide a more comprehensive framework for decision-making<sup>61–63</sup>. These studies highlight that incorporating hydrological drought states into reservoir operation rules can simultaneously improve system reliability and sustain environmental flows to wetlands<sup>61</sup>. They also emphasize that advanced simulation–optimization frameworks are effective in balancing reservoir releases with downstream habitat requirements<sup>62</sup>. Moreover, integrating ecological indicators into reservoir operation strategies has been shown to substantially reduce hydrological alteration while maintaining acceptable levels of hydropower production<sup>63</sup>. Therefore, integrating such approaches into the current framework could further enhance the sustainability and resilience of reservoir operations. Therefore, integrating such points into the current framework could further enhance the sustainability and resilience of reservoir operations. Additionally, by using drinking water quality standards, which are the strictest water quality standards, the optimization and the RDM framework ensure





**Fig. 8.** Calculated inflow values to the reservoir for three selected climatic scenarios, along with simulated inflow data.

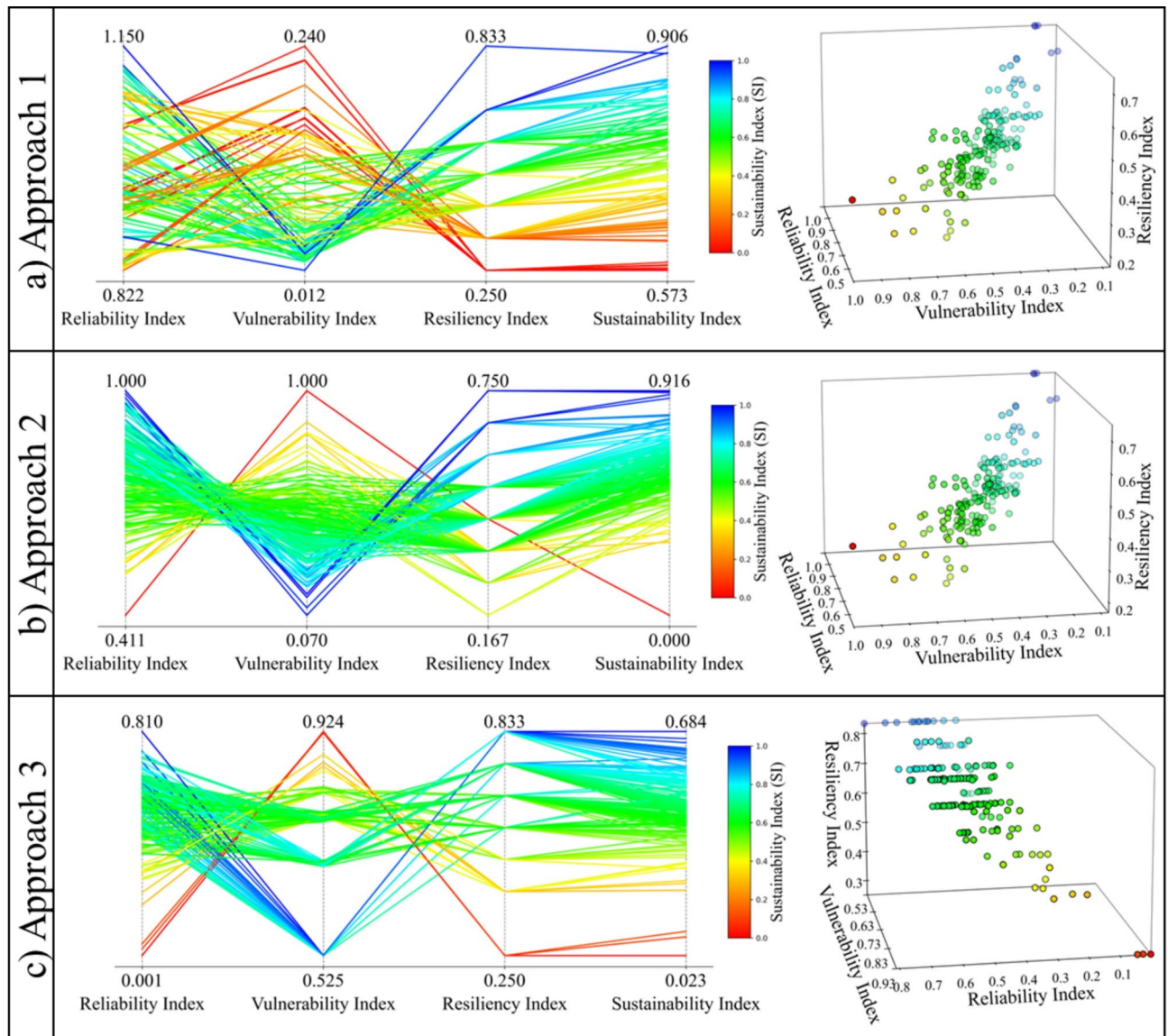
that the allocated water for environmental, agricultural, and domestic purposes meets the required quality thresholds<sup>64</sup>.

This section aims to evaluate how effectively the three selected SWSs (SWS1, SWS2, and SWS3) enhance the quality of water released. Each SWS is assessed against a simulated model, considering TSI and the five critical variables that influence water quality—including turbidity, salinity, EC, TP, and DO. The study demonstrates how these systems could improve water quality outcomes by showing the number of days each SWS outperforms the simulated model. The analysis and results are based on the data presented in Fig. 11, which offers a detailed graphical representation of the performance of the SWSs relative to the simulated model. As depicted in Fig. 11a, the DO levels in the simulated model exhibit a greater decline compared to SWSs. This improvement in DO can be attributed to the diverse water withdrawals and reservoir management practices, particularly through the reservoir gates. Between days 220 and 320, the DO levels in the SWSs show improvement, with a less pronounced downward trend than in the simulated model. This suggests that optimized management strategies have been effective in mitigating the decrease in DO levels over time<sup>9,65</sup>. Regarding turbidity (Fig. 11b), both SWS1 and SWS3 exhibited significant improvements compared to the calibrated model, particularly in the second half of the year, with over 70% of the days showing lower turbidity levels in the SWSs than in the calibrated baseline model<sup>65</sup>. In Fig. 11c, d, the EC and salinity levels in the SWS options are lower than those in the simulated scenario, reflecting the success of the optimization process. The optimized solutions show a reduction in EC, a key indicator of salinity, compared to the baseline. Compared to the simulated model, EC and salinity in the SWS methods decrease between days 100 and 150. Furthermore, Fig. 11e shows that the water discharged from the reservoir had higher phosphorus levels between days 150 and 200. This might be explained by pollution inputs that had an impact on the water quality of the reservoir<sup>66</sup>.

Figure 11f illustrates the variations in the TSI for the reservoir in 2023 by comparing three specific SWS alternatives with the simulated model. TSI is a quantitative measure used to evaluate the nutrient concentrations and the proliferation of algae and aquatic plants in a reservoir<sup>67,68</sup>. The TSI in the simulated model exhibits more significant variations compared to the SWS alternatives, particularly during the middle months of the year. The rise in TSI can be attributed to the abrupt surge of nutrients into the reservoir. Conversely, the SWSs demonstrate superior sustainability in TSI levels, indicating that implementing optimized withdrawal systems has successfully controlled nutrient levels and hindered the growth of excessive algae and aquatic plants. Figure 8 illustrates the water flow into the Wadi Dayqah dam in the simulated model as well as in three different projections of the climate. The simulated model indicates a substantial increase in inflows during April, which is strongly correlated with a quick spike in TSI as seen in Fig. 11f. The sudden increase in water flow is expected to raise the nutrient content in the reservoir, thereby disrupting the trophic balance<sup>68,69</sup>. The optimized SWS strategies, however, are shown to help mitigate these nutrient states.

### Robustness of SWSs

Figure 12 examines the adjusted SI after 10 iterations for SOWs within three distinct approaches employing the CA model. The projected scenarios are categorized into three groups: SSP126 (defined as projected scenarios 1, 2, 3), SSP245 (defined as projected scenarios 4, 5, 6), and SSP585 (defined as projected scenarios 7, 8, 9) for the periods 2030–2060, 2050–2080, and 2070–2100, respectively. The findings illustrate the distinct responses of SWSs to various uncertainties in each approach. For example, in Approach 1, which specifically addresses a water deficit, SWS17 has greater robustness, especially under SSP126, suggesting its capacity to provide water supply requirements. Nevertheless, SWS17 has a modest level of performance in Approach 2, which specifically targets undesirable water quality, indicating that it is a less reliable choice for water quality management. Under Approaches 2 and 3, SWS14 and SWS17 are chosen as the most optimal options for scenario SSP126, respectively.

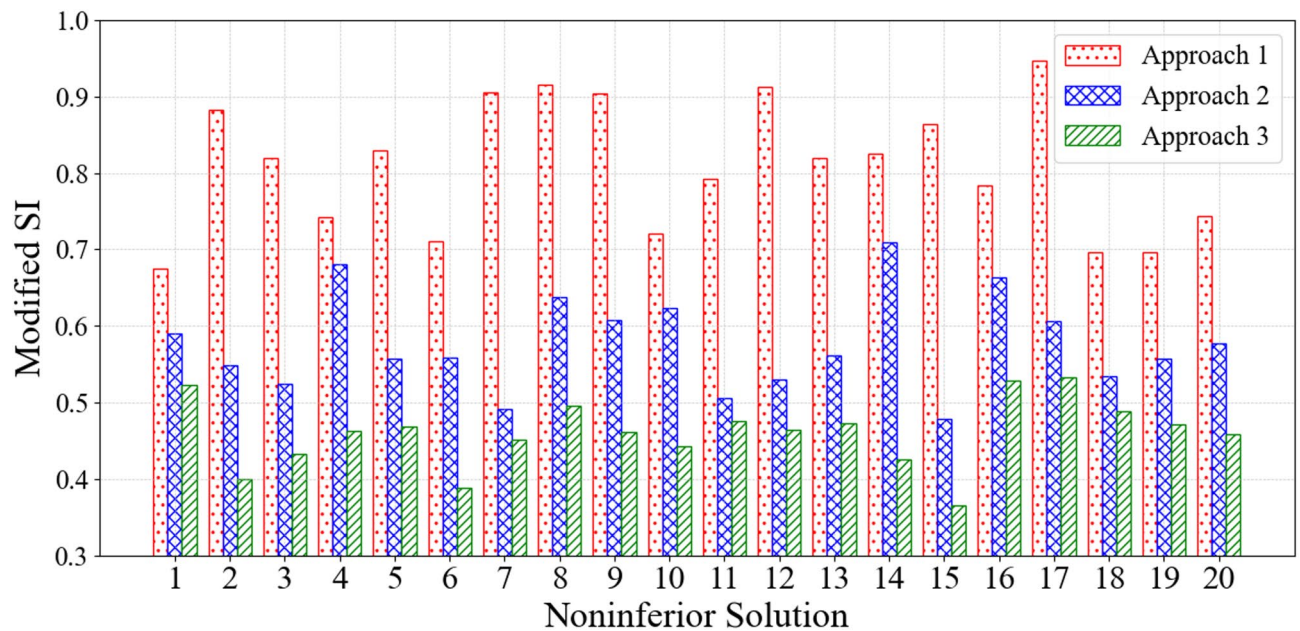


**Fig. 9.** A schematic representation of the reliability, vulnerability, resilience, and sustainability indices for each SOW under different approaches. Each glyph and line correspond to an SOW. Based on the sustainability index values, SOWs with stricter management plans for both quantitative and qualitative reservoir control better align with stakeholder preferences and are more resilient to deep uncertainty.

To explain, in Approach 2, Fig. 12b shows that SWS14 is the most sustainable solution obtained, and moreover, according to Fig. S1, if the part of the water withdrawal allocated to agriculture and environment is carried out in February (in addition to January and May), this SWS can operate more robustly in the RDM framework. Additionally, in Approach 3, SWS16, SWS17, SWS1, and SWS8 have shown more sustainability than the other SWSs according to Fig. 12c. Furthermore, in Fig. S2 and Fig. S3, the major portion of the biannual water withdrawals in these SWSs is less allocated to Gate 1 than that in other SWSs, and this part of water withdrawal is allocated to Gate 2, which plays an important role in improving the reservoir eutrophic states at the projected scenarios. Unlike the other SWSs, SWS 6 is not sustainable under SSP585, especially by 2080 and 2100. As shown in Fig. S3, due to limited water withdrawal from Gate 2, this strategy is not a robust option under future climate conditions. In other words, allocating a greater share of the biannual withdrawals to Gate 2 helps mitigate eutrophication and contributes to a more sustainable trophic state of the reservoir under future climate scenarios.

### Analysis of optimal and robust SWSs

Our analysis revealed that SWS17 was the most optimal and robust solution for both Approach 1 and Approach 3. In contrast, SWS14 was identified as the best choice for Approach 2. As outlined in Sect. 3.2, May and February were selected for biannual withdrawals based on the optimization strategy. Figure 13 illustrates the water withdrawal pattern across multiple gates during these months for both SWS14 and SWS17. The graph's



**Fig. 10.** The adjusted SI of the SWSs obtained from the CA model after 100 iterations for each approach and non-inferior solutions.

radial axis is represented using a logarithmic scale (base 10), where the water volumes are shown in cubic meters. Importantly, the lowest value on the axis (-1) is used to indicate zero withdrawals in order to preserve clarity in the visual depiction. In Fig. 13a, which represents the optimized and robust SWS14 for Approach 2, Gate 1 (elevation 124 m A.S.L.) accounts for the largest share of withdrawals during February. Gate 5 (elevation 155 m A.S.L.) also contributes significantly to the water release, indicating that Approach 2 focused on improving the quality of the released water, leverages water from lower layers of the reservoir. Giving priority to Gate 5 is in accordance with the objective of releasing water of higher quality, therefore ensuring compliance with downstream water quality standards. Conversely, in Fig. 13b, which illustrates the most robust strategy for Approach 1 and Approach 3, Gate 1 continues to be the principal point of entry throughout February. After Gate 1, Gate 2 (elevation 128 m A.S.L.) represents a greater number of withdrawals. Thus, these approaches, which prioritize improving the reservoir's ecological equilibrium and trophic state, seek to discharge water from a lower level (Gate 2) to sustain ideal environmental conditions. Therefore, these patterns of selective withdrawal not only enhance water quantity and quality outcomes but also increase the system's resilience under varying future conditions.

Although the proposed framework was demonstrated by the Wadi Dayqah Dam, the methodology can be generalized and applied to other reservoir systems with similar available data and operational constraints.

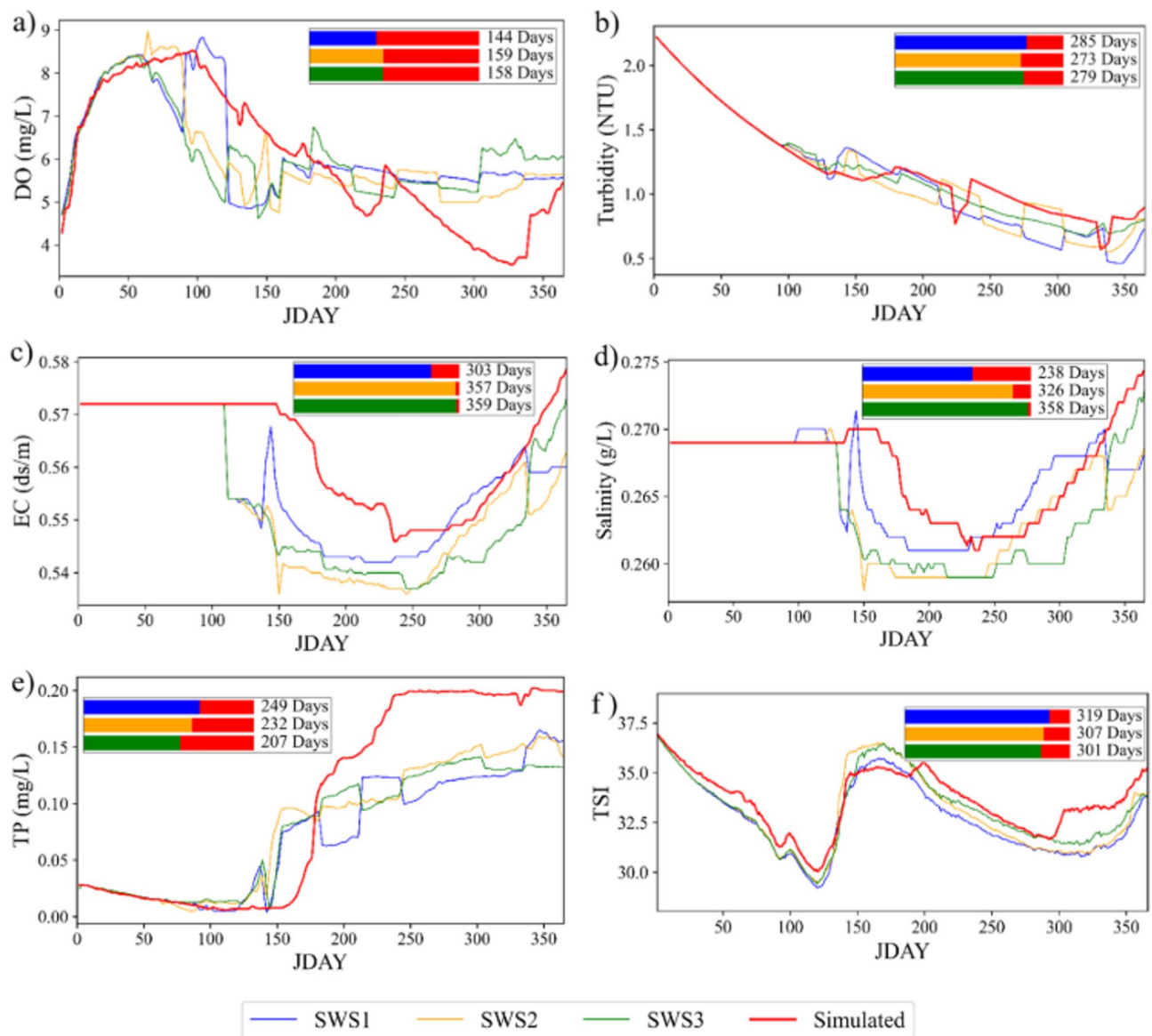
## Conclusion

Managing both water quantity and quality in reservoir systems is crucial for improving regional water management in an efficient way. In this study, we developed and presented a comprehensive framework aimed at improving the efficiency of SWSs to meet downstream requirements, enhance the quality of discharged water, and manage eutrophic conditions in reservoirs. The proposed framework is specifically applied to the Wadi Dayqah Reservoir in Oman. For 2023, simulation and optimization were conducted using a monthly time step. We incorporated uncertainty factors driven by climate change across three scenarios—SSP126, SSP245, and SSP585—covering three future periods. By integrating optimal SWS solutions with climate uncertainties, the resulting SOWs were evaluated using sustainability indicators across three approaches: water deficit, undesirable water quality, and eutrophic conditions. The robustness of each SWS for these approaches was evaluated using the CA model within the reservoir.

The results revealed that for biannual withdrawals, a key operational strategy for this reservoir, May and February were identified as the optimal months. Within the RDM framework, SWS14 demonstrated the highest robustness for the second approach, while SWS17 was the most robust for both the first and third approaches. In the case of SWS14 for the second approach, after Gate 1 (which had the lowest withdrawal), Gate 5 (elevation 155 m A.S.L.) showed the second-largest withdrawal, indicating that the strategy aimed to improve the quality of released water by releasing water from a higher gate. Conversely, for SWS17 under the first and third approaches, Gate 2 (elevation 128 m A.S.L.) exhibited the second-largest withdrawal after Gate 1, suggesting that this strategy sought to maintain reservoir water quality by releasing water from lower layers.

The results of our study are aimed at enhancing regional water security through the efficient management of the Wadi Dayqah Dam. By optimizing water resource management and improving withdrawal robustness, our findings will help ensure a sustainable supply of water to Muscat and Quriyat, meeting agricultural, environmental,

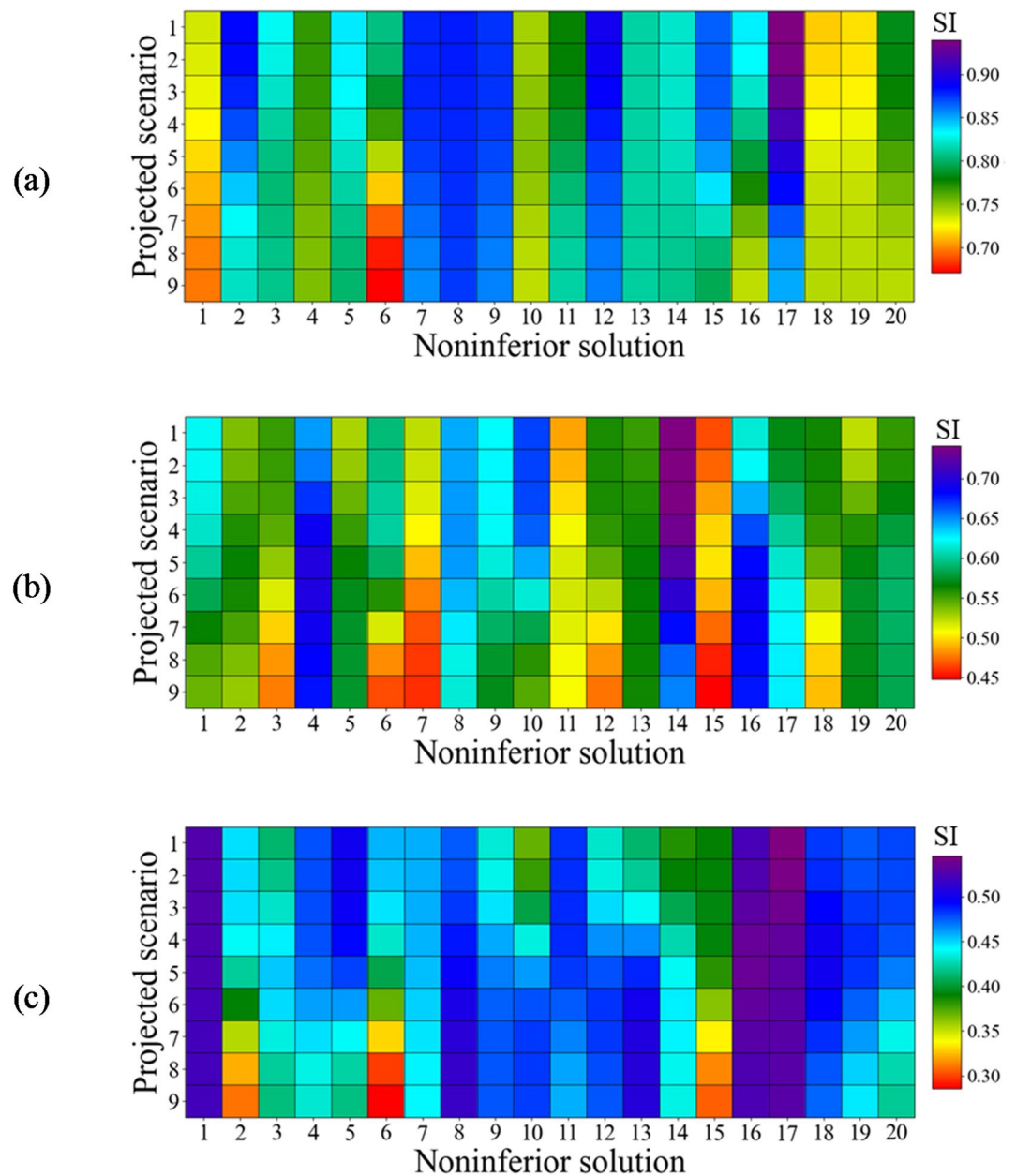




**Fig. 11.** Comparative analysis of water quality variables, such as (a) DO; (b) Turbidity; (c) EC; (d) Salinity; and (e) TP; and (f) TSI for three SWSs (SWS1, SWS2, SWS3) versus the Simulated model. The number of days each SWS performs better than the Simulated model is indicated by the color-coded bars, highlighting the effectiveness of each system in optimizing water quality and reservoir conditions throughout the year.

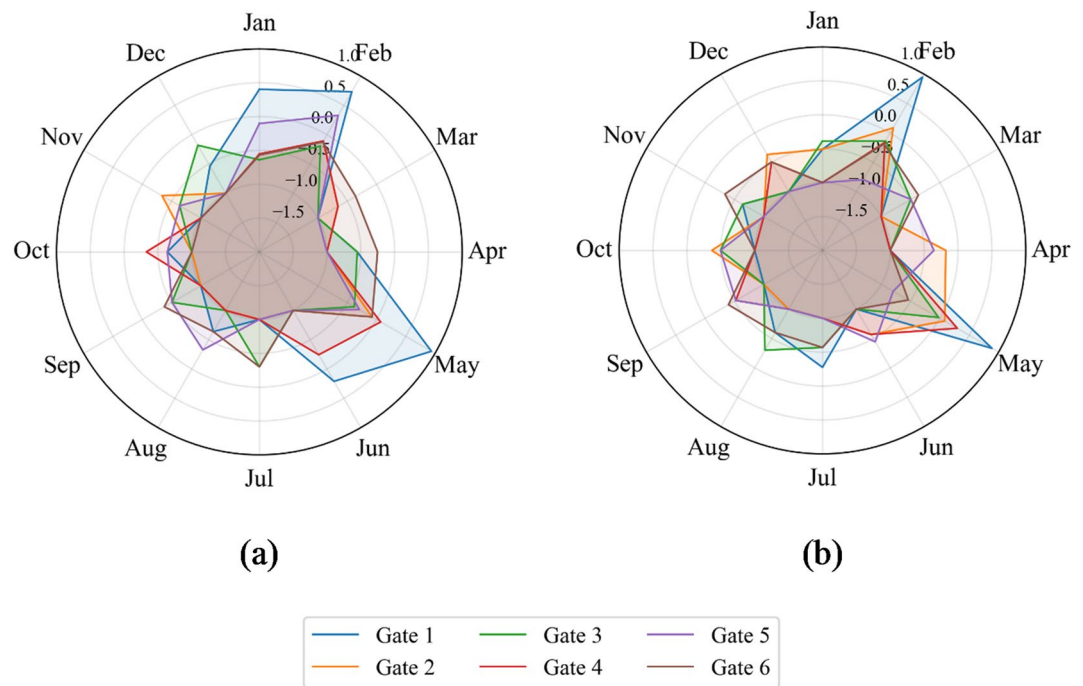
and domestic needs. These insights will also strengthen the long-term resilience of water management systems, addressing the growing demands of a rapidly expanding population. Furthermore, the findings can be applied to other reservoir systems and geographical regions, contributing to broader water security efforts.

Future studies are recommended to investigate the sensitivity of the results to the stakeholder-defined thresholds used in sustainability assessment, since this can further enhance adaptability of the optimization and the RDM framework. Additionally, to achieve a more comprehensive model for decision-making, integrating environmental flow requirements and drought resilience into the presented framework can also enhance the sustainability and robustness of reservoir operations.



**Fig. 12.** Schematic of the adjusted SI values after 10 iterations for each state obtained through the CA model across the (a) Approach 1; (b) Approach 2; and (c) Approach 3.





**Fig. 13.** Logarithmic representation of water withdrawal rates (MCM) from different gates in (a) SWS14; and (b) SWS17.

### Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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F.A.: Conceptualization, Software, Validation, Investigation, Writing - Original Draft, Visualization; M.H.N.: Supervision, Methodology, Software, Conceptualization, Methodology, Investigation, Writing - Review & Editing; M.R.N.: Supervision, Methodology, Software, Conceptualization, Writing - Review & Editing; A.M.: Validation, Review & Editing; M.A-W.: Data Curation, Resource, Review & Editing; G.A-R.: Data Curation, Resource, Review & Editing.

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## Declarations

## Competing interests

The authors declare no competing interests.

## Additional information

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