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Research article

Solving the robustness puzzle: The joint impact of optimization approach, robustness metrics, and scenarios on water resources management under deep uncertainty

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ABSTRACT

The concept of robustness has been widely used in water resources management to identify solutions that perform satisfactorily across a range of plausible future conditions to increase confidence in decision-making in a deeply uncertain future. However, the selection of an appropriate metric to quantify robustness remains challenging due to the existence of multiple choices reflecting different risk preferences. In addition, different scenarios can be used to represent plausible future conditions, which adds another layer of complexity to solution identification. While previous studies have explored the impact of different robustness metrics and scenarios on the robustness of the solutions obtained, these two aspects have usually been investigated in isolation. In addition, the majority of past studies utilize post-optimization robustness analysis, where solutions are optimized under each future scenario before the robustness of these solutions is quantified across all scenarios. In contrast, how these impacts may vary when the robustness of potential solutions is explicitly optimized, is unknown. Therefore, in this study, the joint impact of the choice of robustness metric, scenarios, and optimization approach on system robustness and performance is investigated. Results from two real-world case studies show that the optimization approach can have a significant impact on system robustness and performance when scenarios represent a wide range of plausible future conditions, but this impact also depends on which robustness metrics are used. The results of this study provide insight into identifying robust solutions using different robustness metrics through different optimization approaches, leading to the fit-for-purpose selection of both robustness metric and optimization approach.

1. Introduction

The identification of robust solutions is crucial when making water resources systems planning and management decisions. Most decisions made in the present will have long-lasting consequences as the future unfolds in response to long-term climatic and socioeconomic changes. Therefore, the traditional approach to managing water resources systems that relies on historical climate and inflow records has become inadequate (Şen, 2021; Wu et al., 2023). Long-term unknowns, known as deep uncertainty, make it difficult to predict how water resource systems will perform in the future, and thus also make it difficult to plan and manage these systems in the present (Maier et al., 2016). Therefore, robust planning and management strategies (referred to as robust solutions hereafter) that perform consistently well under a wide range of plausible future conditions, irrespective of which of these conditions will eventually occur, are preferred (Kasprzyk et al., 2013; Lempert, 2019; Lempert et al., 2006).

The identification of robust solutions can be achieved via the utilization of formal optimization approaches, such as evolutionary algorithms, as these algorithms can deal with large search spaces and competing objectives (Maier et al., 2014, 2019). However, embedding robustness objectives into the optimization processes is generally

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computationally challenging: the calculation of a single robustness value requires the system to be simulated many times – one for each of the plausible future conditions (i.e., scenarios) considered, resulting in a significant number of model evaluations. As a result, past studies on robust water resources management have generally optimized the desired performance indicators (e.g., water supply reliability) under each plausible future condition separately before evaluating the robustness of these solutions via simulation to identify the solutions that are most robust (e.g., Beh et al., 2015; Bonham et al., 2022, 2024; Herman et al., 2014; Kasprzyk et al., 2013; Meysami and Niksokhan, 2020; Mortazavi-Naeini et al., 2014; Mousavi Janbehsarayi et al., 2024; Pei et al., 2024; Ren et al., 2019). This approach is referred to as post-optimization robustness analysis (PORA) in this study. However, PORA does not guarantee that the most robust solutions are identified, as it optimizes for performance indicator values that use different scenario information, rather than robustness. To address this issue, Beh et al. (2017) directly incorporated the evaluation of robustness as an objective function in the optimization process, where a metamodel is used to speed up the optimization process to make the explicit optimization of robustness computationally feasible. This approach is referred to as robust optimization (RO) in this study. The RO approach has also been applied to a number of water system-related management problems (e.g., Giuliani and Castelletti, 2016; Huang et al., 2024; Kwakkel et al., 2016b).

Regardless of which optimization approach (i.e., PORA or RO) is used, a robustness metric needs to be selected to quantify the robustness of potential solutions. This adds another layer of uncertainty to the solution development process, as there are many different metrics that can be selected, each of which reflects different risk preferences of decision makers (Giuliani and Castelletti, 2016). In addition, the calculation of robustness metrics requires a number of subjective choices to be made in the calculation process, including (i) which variables to use to calculate the robustness metric - absolute performance values, relative performance values, or regret-based values; (ii) which and how many scenarios to include; and (iii) which statistical moments (e.g., mean or standard deviation) to use to aggregate performance values across scenarios (McPhail et al., 2018). As a result, for a given potential solution, the value of robustness is often different when a different robustness metric is used; and different robust solutions are often obtained as a result of the selection of different robustness metrics, leading to a substantial difference in future system performance (Giuliani and Castelletti, 2016; Herman et al., 2015; Kwakkel et al., 2016a; McPhail et al., 2018).

Consequently, in recent years, many studies have been dedicated to investigating the impact of the selection of robustness metrics on both the robustness values and relative rankings of different solutions obtained (Giuliani and Castelletti, 2016; Herman et al., 2015; Kwakkel et al., 2016b; Lempert and Collins, 2007; McPhail et al., 2018). For example, Herman et al. (2015) compared the rankings of solutions selected based on four robustness metrics and highlighted the differences in decision-related recommendations and performances from each of these metrics. Similarly, McPhail et al. (2018) compared the relative ranking of various solutions when different robustness metrics are used and found that the rankings of alternative solutions are likely to be similar between different metrics. Based on this study, McPhail et al. (2021) provided guidelines for the selection of the most suitable robustness metric(s) based on factors such as the suitability of using absolute or relative performance and the risk attitudes of decision makers. However, most of these studies are based on PORA only, and the impact of robustness metrics on water resources management using the RO approach remains unclear.

In addition, how robust a robust solution is can be strongly dependent on the scenarios considered in the optimization process (Cohen and Herman, 2021; Giudici et al., 2020; McPhail et al., 2020; Watson and Kasprzyk, 2017). As found by McPhail et al. (2020), the robustness values of solutions are significantly affected by the scenarios included in the robustness evaluation, although the corresponding rankings of the solutions are relatively stable. Similarly, Cohen et al. (2021) found that the inclusion of a few extreme scenarios in the optimization process may influence the robust solutions identified and lead to costly or risky decisions, highlighting the importance of considering the characteristics of scenarios in the identification of robust solutions, especially when using the RO approach, where the optimization process can be disproportionately influenced by these extreme scenarios. However, the impact of scenarios on water resources management using the RO approach remains unclear.

Although both robustness metric and scenario selection have a significant impact on the solutions identified, their impact has been investigated in isolation in past studies. Consequently, their joint impact on which solutions are considered most robust is not fully understood. In addition, in the majority of previous studies, only the PORA approach has been used, while the RO approach has not been considered.

In order to address the shortcomings of previous studies outlined above, the primary objective of this study is to provide insight into the joint impact of the three most important aspects affecting the identification of robust solutions for water resources systems planning and management under deep uncertainty, including (i) the optimization approach used, (ii) the robustness metric(s) selected, and (iii) which scenarios are used. This aim is achieved via a series of computational experiments designed to maximize the diversity of the three impacts considered, thereby enhancing the generality of the findings. In addition, the computational experiments are repeated for two water resources management case studies with distinct characteristics to cover a broad spectrum of management issues commonly encountered in real-world water resources management. These new insights into how optimization approaches, scenarios, and robustness metrics affect system robustness and performance contribute to a broad body of knowledge that is expected to assist decision makers in selecting the most appropriate methods for their specific needs and making more informed and robust decisions in the face of deep uncertainty.

The remainder of this paper is structured as follows. In Section 2, the methods used to investigate the joint impact of optimization approach, robustness metric, and scenarios on the identification of the most robust solutions are introduced. This includes a comparison between the solutions identified using different combinations of (i) PORA and RO (ii) performance indicators, as represented by the two case studies, (iii) robustness metrics, and (iv) future scenario sets. Results, along with a discussion, are presented in Section 3. Conclusions are presented in Section 4.

2. Methods

Following the unifying framework of McPhail et al. (2018) for the calculation of robustness (Fig. 1), the identification of robust solutions requires the specification of (i) the alternative solutions (for which the robustness is to be evaluated), which can be identified using either the PORA or RO approach, (ii) the performance indicators, which quantify the outcome of interest for the system under consideration such as water supply reliability (iii) the plausible future conditions (i.e., scenarios), over which the performance indicators of the alternative solutions are to be calculated, and (iv) the metrics used to calculate robustness values using different statistics.

There are three factors in the identification of robust solutions that can potentially have a significant impact on the robust solutions identified. These factors are optimization approaches (i.e., PORA and RO), robustness metrics, and scenarios. To understand the joint impact of these factors on which solutions are considered most robust, as well as their associated system performance, results under different combinations of these factors are obtained and compared. To investigate the impact of the choice of optimization approach on which solutions are most robust, decision alternatives are obtained using either PORA or RO. To investigate the impact of scenarios, different sets of plausible future

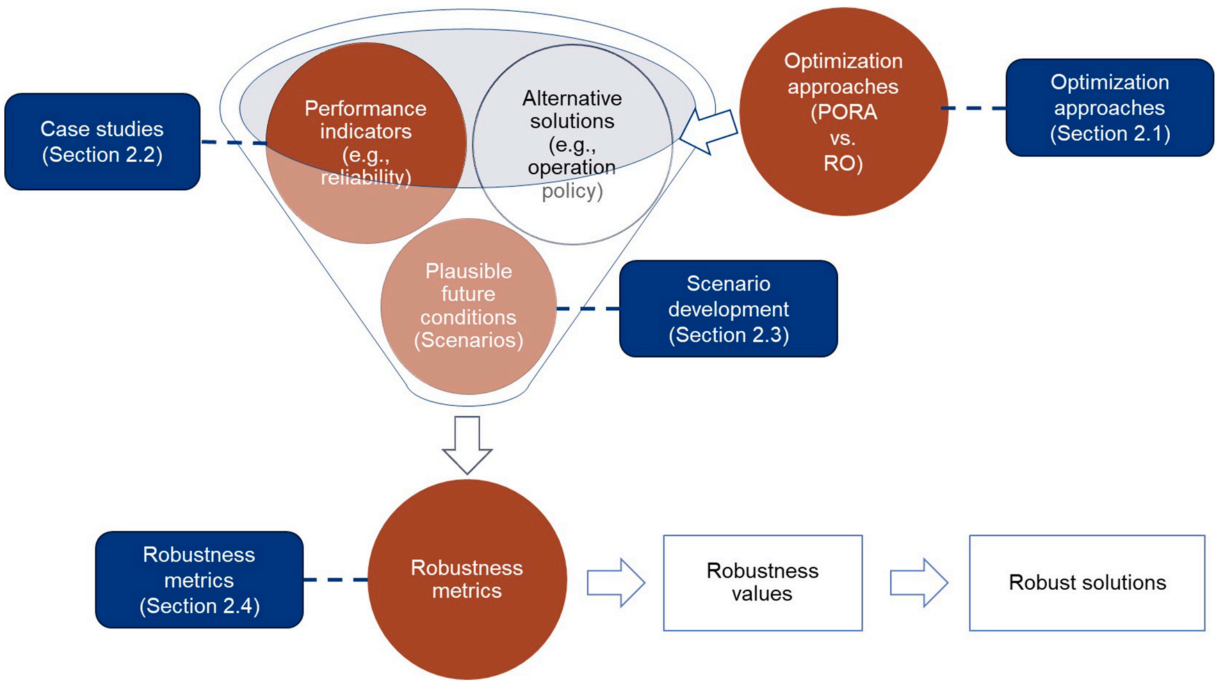

Fig. 1. Components involved in the identification of robust solutions (Adapted from McPhail et al. (2018)).

conditions (scenarios) are considered, including one set of scenarios where the variation of plausible future conditions is relatively small and one where this variation is relatively large. To investigate the impact of robustness metrics, commonly used metrics that span the full spectrum of risk appetites are considered, including Best-case, Hurwicz optimism-pessimism rule, Laplace's principle of insufficient reason, Mean-variance, and Undesirable deviations, Worst-case. Consequently, results are compared from experiments using different combinations of RO and PORA, robustness metrics, and scenario sets. To increase the generalizability of the findings, two different water resources management case studies in different areas of the world (i.e., Australia and Italy) are used, each with multiple performance indicators addressing different management aspects of water resources systems, including water supply reliability and security, and flood control. A summary of the different combinations of case study, optimization approach, robustness metric, and scenario set is provided in Table S1 and Table S2 in the Supplementary material, highlighting the different key aspects affecting the identification of robust solutions investigated.

In all computational experiments, both overall system robustness and actual system performance are evaluated. The robustness values of solutions are calculated across scenarios using the same metric, which provides an understanding of how robust the solutions identified are (i.e., how the solutions generally perform across scenarios). The system performance values of solutions are evaluated using each of the

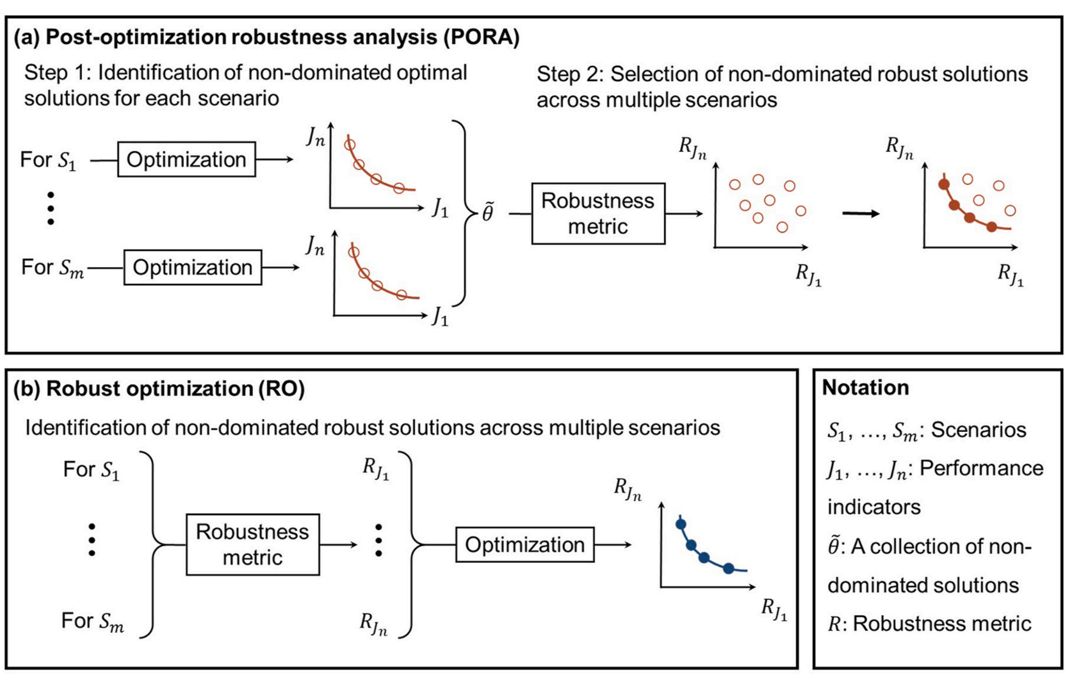

Fig. 2. Optimization approaches: (a) Post-optimization robustness analysis (PORA) and (b) Robust optimization (RO).

performance indicators for all scenarios considered, which provides an estimation of actual system performance.

In the remainder of this section, details of the two optimization approaches considered (i.e., RO and PORA) are provided in Section 2.1. Details of the two case studies, including the performance indicators used, are given in Section 2.2, followed by details of the scenario sets in Section 2.3 and the robustness metrics in Section 2.4. The evaluation framework developed is described in Section 2.5.

2.1. Optimization approaches

To investigate the impact of different optimization approaches on robust solutions, both PORA and RO are used, as summarized in Fig. 2.

PORA consists of two main steps, as shown in Fig. 2a: Step 1 consists of identifying scenario-dependent, non-dominated optimal solutions (in terms of their performance values) and Step 2 consists of selecting the non-dominated robust solutions (in terms of their robustness values evaluated across multiple scenarios) from the scenario-dependent non-dominated solutions identified in Step 1. For example, for a problem with n performance indicators $\{J_1, \ldots, J_n\}$ and m scenarios $\{S_1, \ldots, S_m\}$ to represent future uncertainty, a robustness metric that is applied to each performance indicator is denoted as R. In Step 1, solutions are optimized under each scenario through the evaluation of objective functions using an optimization algorithm. The n optimization objective functions are formulated using performance indicators $\{J_1, \ldots, J_n\}$ (e.g., reliability, vulnerability). A set of non-dominated optimal solutions (i.e., Pareto optimal solutions or the Pareto front) is derived under each scenario, marked as unfilled dots in Fig. 2a. This optimization process is repeated for all scenarios $\{S_1, \ldots, S_m\}$ to obtain m sets of non-dominated optimal solutions, and then these solutions are combined as $\widetilde{\theta}$. In Step 2, the combined non-dominated optimal solutions $\widetilde{\theta}$ are re-evaluated under each scenario to calculate the robustness values $\{R_{J_1} \ldots, R_{J_n}\}$ using the selected robustness metric R. A single set of non-dominated robust solutions under all scenarios (marked as red solid dots) is identified using non-dominated sorting algorithms.

With the alternative approach of RO (as shown in Fig. 2b), non-dominated robust solutions are obtained directly by using robustness values as the objective functions in optimization. For the same problem introduced above, the optimization objective functions $\{R_{J_1} \ldots, R_{J_n}\}$ are formulated by using the selected robustness metric R as the functions of the performance indicators $\{J_1, \ldots, J_n\}$ across multiple scenarios $\{S_1, \ldots, S_m\}$, so that the non-dominated optimal solutions are robust solutions. Therefore, a single set of non-dominated robust solutions (marked as blue solid dots) can be directly derived through the optimization process without the need for any post-optimization analysis.

Regardless of whether the PORA or RO approach is used for multi-objective optimization, a set of non-dominated robust solutions is obtained, with each representing the trade-offs among robustness values of different performance indicators. Robust solutions positioned at different locations on the Pareto front may favor the robustness of certain performance indicators over others; thus different solutions from the Pareto front (in terms of the robustness values of system performance indicators) may have different tradeoffs in terms of performance indicators (Bonham et al., 2022). For example, solutions closer to one end of the front (e.g., R_{J_1}) may prioritize the robustness of performance indicator J_1. Given the distinctly different characteristics of robust solutions on the Pareto front, decision makers who might value one performance indicator over others can select the solution best aligned with their prioritizations (Smith et al., 2019a, 2019b).

2.2. Case studies

As mentioned above, in order to maximize the generalizability of the findings, two distinctly different water resources management case studies are selected to reflect the variability and complexity that are commonly encountered in real-world water resources management practices. The first case study, the upper Adelaide River dam in Northern Australia (Fig. 3a), is selected to represent robust reservoir management considering water supply under deep uncertainty. The second case study, Lake Como in Northern Italy (Fig. 3b), is selected to represent a lake planning and management problem considering both water supply and flood prevention under deep uncertainty. Consequently, these case studies provide a representation of the diverse regulatory and contextual backgrounds found in practice. Details of the two case studies, including the performance indicators used in each, are provided in the following sections. A summary of the characteristics of the two case studies is provided in Table S2 in the Supplementary material.

2.2.1. Case study 1 - Upper Adelaide River dam

The Upper Adelaide River dam is a hypothetical reservoir system in Northern Australia (Fig. 3a). This system was investigated by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) as part of the Northern Australia Water Resource Assessment due to its topographic suitability in Darwin catchments (Petheram et al., 2018). As a result of the seasonality of the rainfall in Northern Australia, this reservoir can potentially support agricultural development and provide urban water for this region. The reservoir has a dam height of 23 m with a maximum capacity of 298 Mm^3 and is supported by a catchment with an area of 525 km^2.

Two performance indicators are considered for this case study, including water supply deficit (SD) and water storage violation (SV), as the main purpose of the potential Upper Adelaide River dam is to provide a reliable water supply. The performance indicators are defined as follows.

- Water supply deficit, which can be evaluated using

$$J^{SD} = \frac{1}{H}\sum_{t=1}^{H} \Gamma(w_t > r_t) \tag{1}$$

where H is the length of the simulation horizon, $\Gamma(w_t > r_t)$ is the number of days when the water release r_t on day t cannot meet the water demand w_t. Water supply deficit is the percentage of time when a deficit occurs. Its value ranges from 0 to 1, with a value of 0 indicating that water release can always meet the demand (best) and a value of 1 indicating that water release can never meet the demand (worst). This performance indicator mainly considers providing reliable water supply to fulfill the demand.

- Water storage violation, which can be evaluated using

$$J^{SV} = \frac{1}{H}\sum_{t=1}^{H} \Gamma(h_t < h^c) \tag{2}$$

where $\Gamma(h_t < h^c)$ is the number of days when the reservoir water level h_t goes below a critical threshold h^c of 18m. Water storage violation is the percentage of time when storage violation occurs. Its value ranges from 0 to 1, with a value of 0 indicating that the water level in the reservoir is always above the threshold (best) and a value of 1 indicating that the water level in the reservoir is always below the threshold (worst). This performance indicator mainly considers storing a certain amount of water in the storage to maintain water supply security for future demand.

Due to climate change and population growth, the development of future management policies for this potential reservoir system remains challenging. For this case study, a three-layer feed-forward multilayer perceptron (MLP) Artificial neural network (ANN) model is parameterized as the reservoir operation policy model to guide the daily water release decisions based on environmental variables such as net inflow (Giuliani et al., 2016; Huang et al., 2024). To identify robust solutions (i.e., robust operation policies), the parameters of the reservoir operation

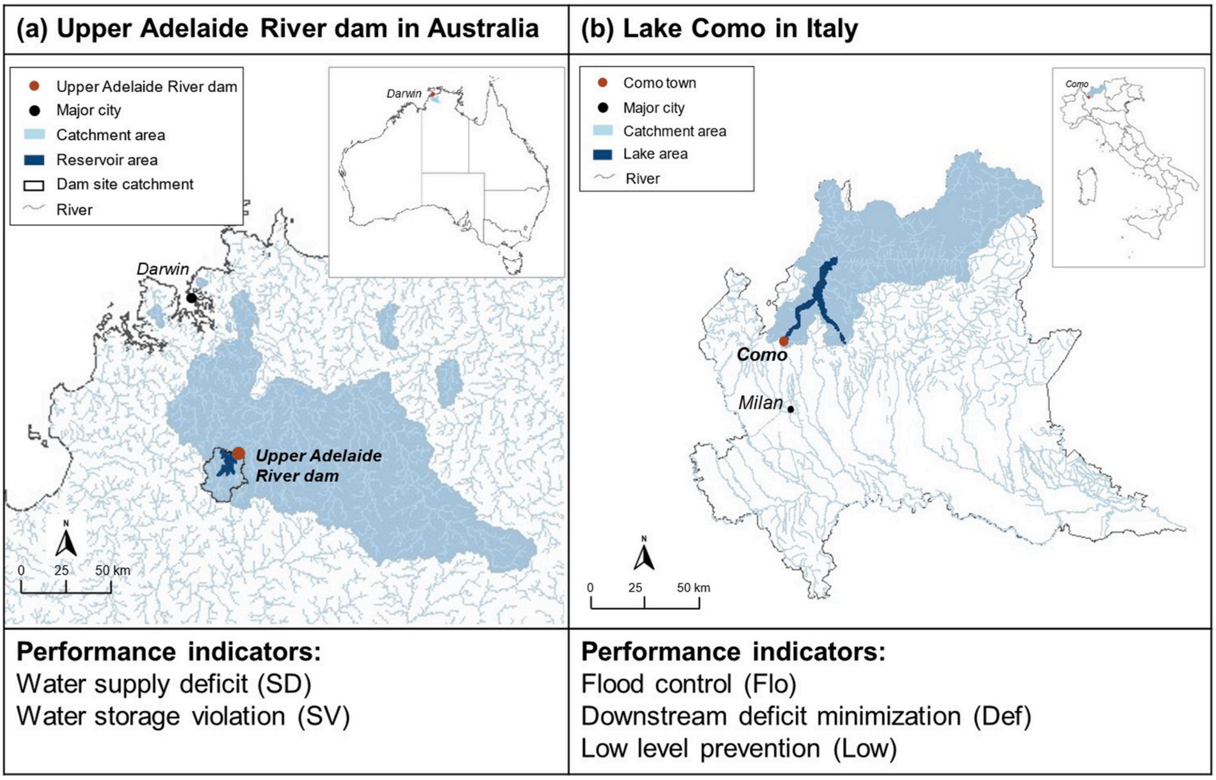

Fig. 3. Maps and performance indicators of the two case studies: (a) Upper Adelaide River dam in Australia; (b) Lake Como in Italy.

policy model (i.e., decision variables) are optimized to minimize water supply deficit and water storage violation. The optimization process is performed using a multiobjective evolutionary algorithm – Non-dominated sorting genetic algorithm II (NSGA-II, see Deb et al. (2002)). Details of the model and multi-objective optimization setup can be found in Text S1 in the Supplementary material.

2.2.2. Case study 2 - Lake Como

Lake Como is the third-largest lake in Italy (Fig. 3b), with a total volume of 23,400 Mm^3 and an active storage of 246.5 Mm^3. The 5039 km^2 catchment has a hydrological regime consisting of dry winters and summers, and wet springs and autumns due to the influence of snowmelt and rainfall. The purpose of Lake Como for this region is multifaceted, such as flood protection, water supply for agricultural districts and hydropower plants, navigation, tourism, and aquatic ecosystem protection.

Three performance indicators are considered, including flood control (Flo), downstream deficit minimization (Def), and low-level prevention (Low). The performance indicators are defined as follows.

- Flood control, which can be evaluated using

$$J^{flo} = \frac{1}{N_y} \sum_{t=1}^{H} \Gamma\left(h_t > h^f\right) \tag{3}$$

where N_y is the number of years of the simulation horizon, $\Gamma\left(h_t > h^f\right)$ is the number of days when the water level h_t in the lake is above the flooding threshold h^f of 1.73 m. The flood control performance indicator is the mean annual number of days with an exceedance of the flooding threshold in Lake Como. Its value ranges from 0 to 365, with a value of 0 indicating that the lake water level never exceeds the flooding threshold (best) and a value of 365 indicating that the lake water level always exceeds the flooding threshold (worst). This performance indicator considers the protection of the lake shores, in particular of the city of Como, from lake floods.

- Downstream deficit, which can be evaluated using

$$J^{def} = \frac{1}{H} \sum_{t=1}^{H} ((w_t - r_t), 0)^n \tag{4}$$

where r_t is water released from the lake on day t subtracted by the minimum environmental flow, w_t is the downstream water demand for both downstream agricultural districts and of the hydropower plants on day t. The exponent n is equal to 2 during the irrigation season (from 1st April to 10th October) and equal to 1 for the rest of the year to allow the water supply deficit to have a greater impact during the irrigation season. This performance indicator considers water supply to satisfy water demand for downstream users.

- Low-level prevention, which can be evaluated using

$$J^{low} = \frac{1}{N_y} \sum_{t=1}^{H} \Gamma\left(h_t < h^l\right) \tag{5}$$

where $\Gamma\left(h_t > h^l\right)$ is the number of days when the water level h_t in the lake is below the low-level threshold h^l of −0.2 m. The low-level prevention performance indicator is the mean annual number of days with the lake level below the low-level threshold. Its value ranges from 0 to 365, with a value of 0 indicating that the lake water level is never below the low-level threshold (best) and a value of 365 indicating that the lake water level is always below the low-level threshold (worst). This performance indicator considers avoiding the extremely low lake water levels that negatively affect navigation, tourism, and the aquatic ecosystem.

Due to the development of new flood barriers in the city of Como, planning and management strategies are needed for Lake Como, considering future climate change. This includes the re-definition of the upper and lower bounds of the operational space (i.e., the volume within which the operator can decide the daily amount of water to be released) and corresponding operation policies. In this case study, a radial basis function (RBF) network is used as the reservoir operation policy model to represent the relationship between relevant environmental variables (e.g., lake level) and water releases (Giuliani et al., 2018, 2021). To identify robust solutions, including both operational space and operation policies, the upper and lower bounds of the operational space and parameters of the reservoir operation policy model (i.e., decision variables) are optimized to minimize the three performance indicators. The optimization process is performed by using a multi-objective evolutionary algorithm – The Borg Multiobjective Evolutionary Algorithm (Borg MOEA, see Hadka and Reed (2013)). Details of the model and multi-objective optimization setup can be found in Text S2 in the Supplementary material.

2.3. Scenario development

To understand the impact of different types of scenarios on identified robust solutions and associated system robustness and performance, two distinct sets of scenarios are used for optimization and performance evaluation. The members of the first set of scenarios have similar properties (e.g., hydroclimatic properties) with each other, covering relatively small ranges of uncertain variables, and are therefore referred to as Similar scenarios in this study. The members of the second set of scenarios have very different properties, covering very different ranges of uncertain variables, and are therefore referred to as Diverse scenarios. In this study, we consider near-future conditions as Similar scenarios and far-future conditions as Diverse scenarios, given the relatively broad range of plausible future conditions in the latter (as shown in Fig. 4).

For case study 1 (Upper Adelaide River dam), 15 scenarios are developed within each scenario set to represent a range of plausible future conditions considering uncertainty in both water availability and demand due to climate change and agricultural development. Specifically, scenarios are synthetically generated based on different combinations of the key variables by perturbing historical time series (e.g., rainfall, evaporation, and water demand) based on current best knowledge of the plausible changes. The climate change factors used for perturbation are available on the Climate Change in Australia website (CSIRO and Bureau of Meteorology). These factors are generated based on various Coupled Model Intercomparison Project Phase 5 (CMIP5) global climate models corresponding to different Representative Concentration Pathways (RCPs). Water demand change factors for perturbation are developed based on the Northern Australia Water Resource Assessment for Darwin catchments (Vanderzalm et al., 2018). Details of scenario development can be found in Text S3 in the Supplementary material. The Similar scenario set represents future water availability and demand conditions over the time period of 2030–2039, and the Diverse scenario set represents future water availability and demand conditions over the time period of 2080–2089.

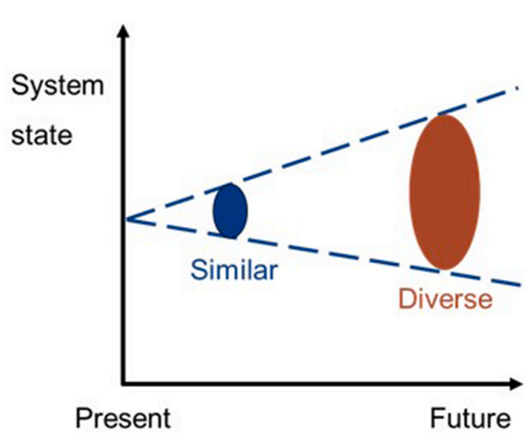

Fig. 4. Schematic representation of two scenario sets (i.e., Similar and Diverse) in this study (Adapted from Maier et al. (2016)).

For case study 2 (Lake Como), nine scenarios are developed to represent a range of plausible future conditions considering uncertainty in precipitation, evaporation, and streamflow due to climate change. Specifically, scenarios are generated considering the combination of three RCPs (RCP 2.6, RCP 4.5, and RCP 8.5) and three pairs of global and regional circulation models (ICHEC + RACM, ICHEC + RCA4, and MPI + RCA4) based on the CMIP5 (Taylor et al., 2012). The resulting temperature and precipitation trajectories are statistically downscaled and used as inputs to a hydrological model to generate inflows to Lake Como. Details of scenario development can be found in Text S4 in the Supplementary material. The Similar scenario set represents future climate conditions over the time period of 2030–2039, and the Diverse scenario set represents future climate conditions over the time period of 2080–2089.

2.4. Robustness metrics

As mentioned previously, six different robustness metrics are used, as shown in Table 1. As can be seen, the Best-case (also known as Maximax) metric focuses on the best possible performance across all scenarios, while the Worst-case (also known as Maximin) metric focuses on the worst possible performance across all scenarios (Wald, 1950). The Hurwicz optimism-pessimism rule metric combines the two above-mentioned approaches by calculating the weighted mean of the best and worst possible performance (Hurwicz, 1951). The Principle of insufficient reason metric provides information on the average performance across all scenarios given that the probabilities associated with different future conditions cannot be assigned under deep uncertainty (De Laplace, 1995). The Mean-variance metric provides information on both the average performance and the variability of performance across all scenarios (Hamarat et al., 2014). The Undesirable deviations metric utilizes the concept of regret, which is primarily concerned with negative deviations from the median performance (Kwakkel et al., 2016a). Specifically, the Undesirable deviations metric calculates the difference from the median performance across the worst-performing scenarios, where performance values are worse than the median performance.

The selected robustness metrics also represent a wide spectrum of risk attitudes of decision makers. The relative level of risk attitudes that robustness metrics reflect are shown in Fig. 5. Calculation of the Best-case metric is only based on the scenario where the best possible performance occurs, thus this metric reflects an optimistic attitude. Calculation of the Worst-case metric is only based on the scenario where the worst possible performance occurs, and this metric therefore reflects a pessimistic attitude. The Laplace's principle of insufficient reason and the Mean-variance metrics reflect a neutral risk attitude, as the calculations of these metrics are based on all scenarios, thus these two metrics both reflect a balanced perspective of system performance across all plausible future conditions. The risk attitude represented by the Hurwicz's optimism-pessimism rule metric depends on the selected weighting used for its calculation. Consequently, this metric could reflect varied levels of risk attitudes. In this study, we assume the weightings for Best-case performance and Worst-case performance are

Table 1
Summary of robustness metrics used in this study.

Notation	Metric	Description
R1	Best-case	Best possible performance
R2	Hurwicz optimism-pessimism rule	The weighted mean of the best and worst possible performance
R3	Laplace's principle of insufficient reason	The expected level of performance
R4	Mean-variance	A function of the mean and variance in performance
R5	Undesirable deviations	Difference between performance worse than the median and the median performance
R6	Worst-case	Worst possible performance

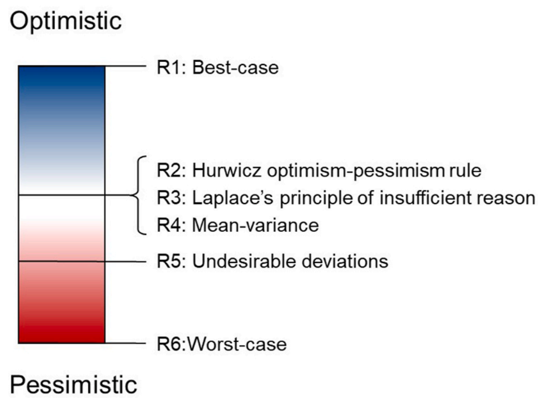

Fig. 5. Classification of robustness metrics selected in this study in terms of relative level of risk attitudes from optimistic (blue) to pessimistic (red) (Adapted from McPhail et al. (2018)).

equal, and thus the risk attitude this metric reflected is neutral. The Undesirable deviations metric provides information on the regret from the median for scenarios where the system performs worse than the median and is therefore associated with a more pessimistic risk attitude (i.e., more conservative) compared with the Laplace's principle of insufficient reason and Mean-variance metrics.

2.5. Evaluation framework

To understand the joint impact of the optimization approach, robustness metric, and scenarios used on the solutions identified and their system robustness and performance, an evaluation framework is developed, as shown in Fig. 6. Within this framework, both the robustness values and system performance values are analyzed via simulation for the non-dominated solutions obtained from both the PORA and RO approaches illustrated in Fig. 2.

To assess the impact of changes in optimization approach, robustness metric, and scenarios on overall system robustness, robustness values are calculated for all combinations of the above factors considered. This can be done by calculating the value of each of the $\{R_{J_1}, \ldots, R_{J_n}\}$ across each of the scenario sets used for optimization. As shown in the parallel axes plot in Fig. 6a, one robust solution is represented using one line that intersects different vertical axes. The intersection of one line with one vertical axis represents the value the robustness value of that solution achieves for the performance indicator this axis represents. Robust solutions obtained from both PORA and RO are evaluated and marked in red and blue colors in Fig. 6a, respectively. Since the management objectives are minimized for both case studies, lines close to the bottom of the plot indicate solutions with better system robustness. This parallel coordinate plot allows us to observe the relative magnitude of robustness values of each performance indicator for each non-dominated solution, as well as the tradeoffs between the two adjacent robustness values of the performance indicators (Fleming et al., 2005; Inselberg, 1985).

To assess the impact of changes in optimization approach, robustness metric, and scenarios on system performance, system performance values are calculated for the different performance metrics for all combinations of the above factors considered. The system performance values for each of the indicators considered are calculated under each scenario for the most robust solutions (e.g., the solution marked by a green solid dot in Fig. 6) identified from each combination of optimization approach, robustness metric, and scenario set (in Table S1 in the Supplementary material). This can be done by calculating the performance values of robust solutions using the system simulation model. For each scenario considered, the performance values are obtained using each performance indicator (e.g., water supply deficit) calculated for all robust solutions from each of the robustness metrics considered. Similar to system robustness evaluation, robust solutions obtained from both PORA and RO are evaluated and marked in red and blue colors in Fig. 6b, respectively. Consequently, better system performance is represented by smaller values, as the management objectives are minimized for both case studies. In addition, a smaller range of performance values across all scenarios (i.e., a smaller range in the boxplots) indicates that the solution shows better system performance consistency under uncertainty.

3. Results and discussion

3.1. Impact on system robustness

To illustrate the joint impact of optimization approach, robustness metric, and scenarios on system robustness, system robustness values of robust solutions identified using different optimization approaches (i.e., PORA and RO) are shown using parallel axes plots in Fig. 7. In the figure, the robustness values under the Similar scenario set and the Diverse scenario set are presented in the left and right panels, respectively, for case study 1 (in the top row) and case study 2 (in the bottom row). In each plot, each polyline corresponds to one robust solution identified using PORA (red) or RO (blue). Each vertical axis represents the relative magnitude of robustness values of one performance indicator (e.g., water supply deficit labeled as SD for case study 1), and the preferred direction for each vertical axis is downward. The intersection point between one polyline and one vertical axis represents the value the solution (represented by the polyline) achieves for the robustness value calculated based on the performance indicator represented by the axis.

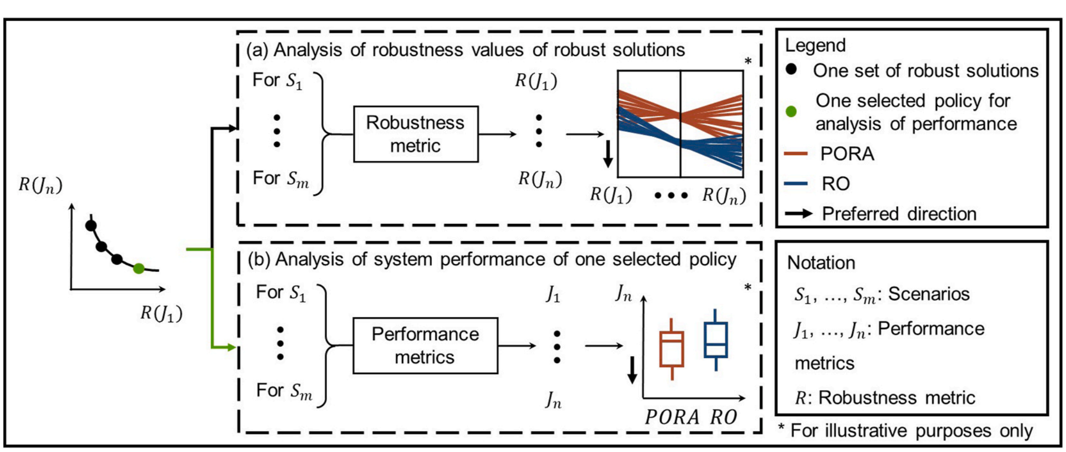

Fig. 6. Framework to evaluate the joint impact of robustness metrics, scenarios, and optimization approaches on system robustness and performance.

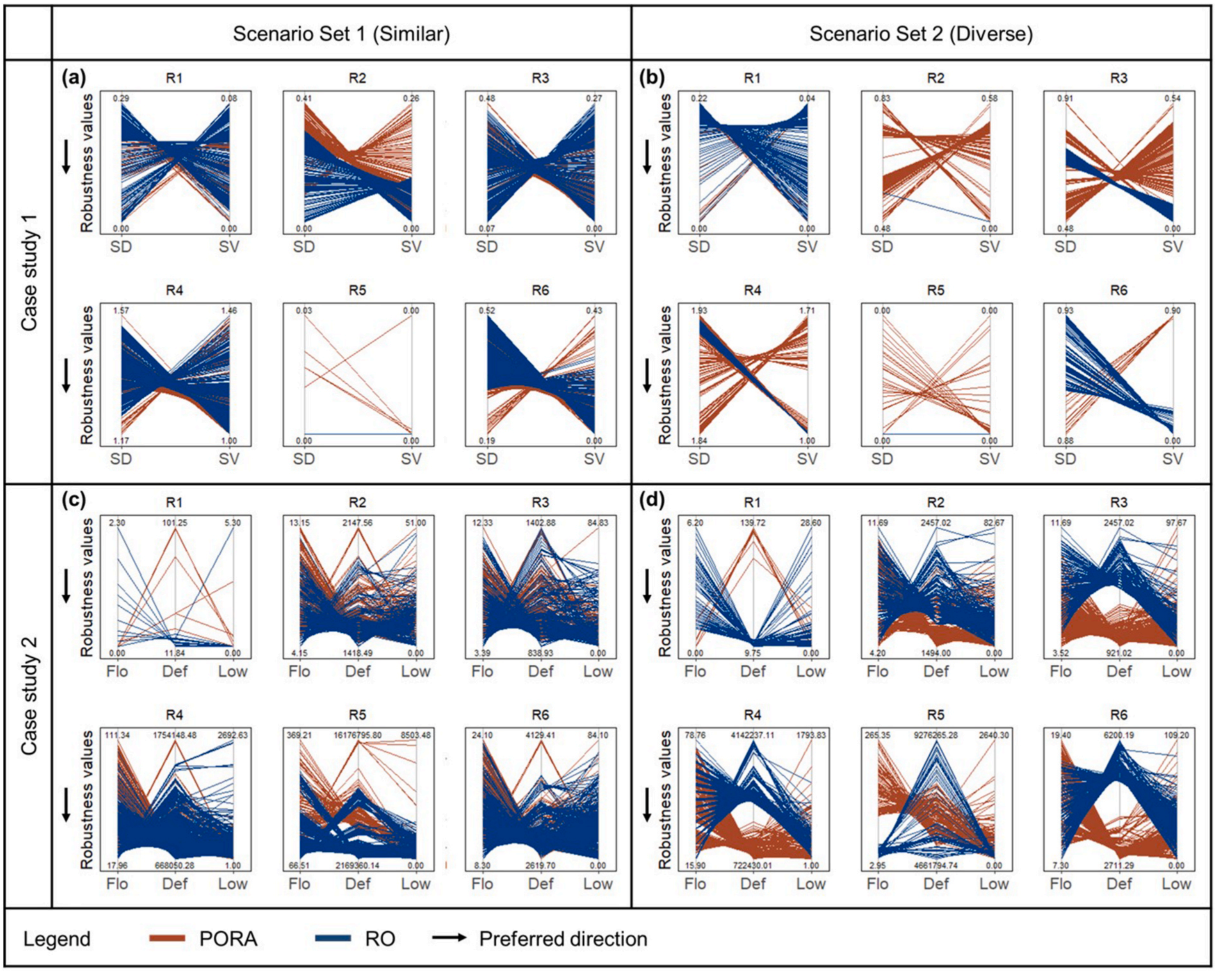

Fig. 7. System robustness values of robust solutions identified using PORA (red) or RO (blue) for different scenario sets (in different columns) and case studies (in different rows). Plot (a): robustness values under the Similar scenario set for case study 1; Plot (b): robustness values under the Diverse scenario set for case study 1; Plot (c): robustness values under the Similar scenario set for case study 2; Plot (d): robustness values under the Diverse scenario set for case study 2. Each subplot (R1 to R6) represents one robustness metric used in the optimization process, within which each vertical axis represents one performance indicator considered and each line represents a solution in the non-dominated set of robust solutions. Performance indicators considered include water supply deficit (SD) and water storage violation (SV) for case study 1; flood control (Flo), downstream deficit minimization (Def), and low-level prevention (Low) for case study 2.

Crossing lines represent the tradeoffs between two adjacent robustness values of the performance indicators, where the tradeoffs are indicated by the degree to which the lines cross. In contrast, horizontal lines indicate that the two adjacent robustness values of the performance indicators are highly correlated. This is shown for all six robustness metrics (from R1 to R6) evaluated, with each plot showing results from one metric. The preferred direction for all axes is downward due to the minimization problem considered.

The results show that the RO approach can generally lead to comparable or, in some cases, improved system robustness values compared to the PORA approach. This is demonstrated by the blue lines being positioned below or overlapping the red lines in Fig. 7. This improvement occurs because robustness is optimized directly during the optimization process when the RO approach is used. The improvement in robustness value is most evident for case study 1 when the Undesirable deviations metric (i.e., R5) is selected, as the magnitude of the average improvement in system robustness is the largest among all six robustness metrics considered. This is mainly because the Undesirable deviations metric emphasizes differences between performance values over absolute performance values themselves, which means that the robustness values of robust solutions identified under the combination of this metric and the RO optimization approach can be very close to zero (i.e., the ideal point of the optimization).

The magnitude of improvement in robustness using the RO approach depends on the scenario set used in optimization. For example, for case study 1, when scenarios used in optimization are similar, the differences in system robustness obtained using different optimization approaches are trivial. This is evident in Fig. 7a, where the red and blue lines mostly overlap with each other for most robustness metrics and performance indicators, indicating the robustness values obtained from different optimization approaches are very close to each other. However, when scenarios are diverse (Fig. 7b), the improvement in overall system robustness when using RO is more pronounced, especially in terms of water storage violation. The robustness values of water storage violation from solutions identified using RO can be much better than those identified using PORA, regardless of which robustness metric is used.

The improvement in robustness value as a result of using the RO approach under Diverse scenarios can be explained based on the characteristics of the robust solutions identified using this approach. For case study 1, the decision variables optimized are the parameters of the ANN-based reservoir operation policies, which directly affect water release decisions as a result of these policies. Water release decisions derived from robust solutions identified using the RO approach are generally less variable, compared to water release decisions derived from robust solutions identified using the PORA approach for the diverse scenarios (in Fig. S1 and Table S4 in the Supplementary material). This is mainly due to the emphasis of the RO approach on performance consistency across all scenarios. Similar characteristics of robust solutions can be observed for case study 2. For this case study, decision variables that define robust solutions include both planning (i.e., the upper and lower bounds of the operational space) and management (i.e., parameters of operation policies) decisions. The planning decision is particularly critical, as it determines the fundamental limits within which management decisions operate across all scenarios. The upper and lower bounds of the operational space derived from robust solutions identified using the RO approach are generally more consistent compared with those derived from robust solutions identified using the PORA approach (in Table S4 in the Supplementary material).

However, the RO approach does not always outperform PORA. This is potentially due to the characteristics of the performance indicators considered and their inherent tradeoffs in multi-objective optimization. The tradeoffs can be seen in the parallel axis plots with the intersecting lines between vertical axes, and better performance in one performance indicator (i.e., one vertical axis) often comes at the expense of inferior performance in another. For example, as shown in Fig. 7b, although the improvement in the robustness values of water storage violation is evident, the improvement in terms of the robustness values of water supply deficit is not evident. This can be explained by the multi-objective tradeoffs between the original performance indicators, where the improvement of water storage violation could lead to the degradation of water supply deficit.

The impact of multiobjective tradeoffs on overall system robustness is more pronounced when there are more than two management objectives, due to the significantly increased complexity of the resulting optimization process. This can be observed from the results of case study 2, where three performance indicators are considered, and there is no clear advantage in using RO over PORA. As can be seen in Fig. 7d, while the improvement in overall system robustness can still be observed in two of the three performance indicators (i.e., flood control and low-level prevention) when scenarios are diverse, a noticeable deterioration of system robustness can be seen in terms of downstream deficit minimization. This is because when simultaneously optimizing for many conflicting objectives (i.e., performance indicators, or robustness of performance indicators in this case), non-dominated solutions can be identified with a large deterioration in one (or some) objective(s) and only a small improvement in others (Ishibuchi et al., 2008). Consequently, the PORA and RO approaches may explore different regions of the objective space, or the solutions derived from the RO approach may only represent a subset of solutions identified using the PORA approach.

The deterioration in system robustness in terms of downstream deficit minimization can also be attributed to the use of the RO approach in combination with diverse scenarios. The inclusion of diverse scenarios can complicate the process of identifying solutions with consistent performance across different scenarios considered. This is because diverse scenarios often involve a wide range of future conditions, some of which may be highly atypical or extreme. The presence of these extreme scenarios can disproportionately affect the robust solutions identified, as discussed in Cohen et al. (2021). Therefore, it becomes challenging to develop a single metric that can accurately reflect the robustness of the system across all possible scenarios. This impact is particularly pronounced when the RO approach is used, where solutions that are overly focused on extreme scenarios may be prioritized during the optimization process, potentially skewing overall system robustness.

It is evident from the results above that while RO enhances overall system robustness, its effectiveness is influenced by the scenarios considered and the multi-objective trade-offs inherent in the optimization problems. This complexity underscores the need for careful consideration of the scenarios used and the tradeoffs involved in the multi-objective optimization process.

3.2. Impact on system performance

To assess the joint impact of optimization approaches, robustness metrics, and scenarios on system performance, performance values are evaluated for each of the performance indicators considered, as discussed in Section 2.5. System performance of robust solutions identified using different optimization approaches (i.e., PORA and RO) are presented in Fig. 8. In the figure, the system performance of solutions obtained under the Similar scenario set and the Diverse scenario set are presented in the left and right panels, respectively; and for case study 1 in the top row and case study 2 in the bottom row. In each plot, the performance values of robust solutions identified using PORA (red) or RO (blue) across all scenarios within each scenario set are presented for each performance indicator considered and for each robustness metric (from R1 to R6) selected. The preferred direction for all performance indicators is downward.

Generally, RO can achieve similar or improved system performance compared with PORA. Across most combinations of optimization approach, robustness metric, and scenario set considered, similar or better values of performance indicators can be achieved using RO. This is indicated by the similar or relatively smaller median values of performance indicators observed in the blue boxplots compared to the red ones in Fig. 8. Additionally, RO tends to provide similar or more consistent performance under uncertain future conditions in some cases, as indicated by the narrower range of performance values represented by the blue boxes compared to the red ones. This is particularly the case for the Diverse scenario set. The insensitivity of system performance to uncertain future conditions makes RO more advantageous for decision-making under uncertainty where consistency is required, such as estimating reservoir service life (Huang et al., 2024).

However, there are exceptions where solutions obtained using PORA outperform those obtained using RO due to the choice of robustness metrics. For example, when using the Undesirable deviations metric (R5) in conjunction with the RO approach, significantly worse performance in terms of the water supply deficit values can be seen in case study 1. As shown in Fig. 8a and b, water supply deficit values are close to a value of 1, indicating that water release constantly fails to meet demand. This is because the calculation of the Undesirable deviations metric only considers the differences in performance from the median under scenarios where performance values are worse than the median, introducing intrinsic risk aversion. This calculation indicates that using this metric prioritizes achieving consistent outcomes, but can inadvertently lead to undesirable actual system performance, especially when Diverse scenarios that encompass a broad range of future conditions are considered. Similarly, when the Mean-variance metric is used, the RO approach can lead to worse system performance in terms of water supply deficit compared to PORA, particularly under the Diverse scenario set. As shown in Fig. 8a and b, the water supply deficit performance values of robust solutions obtained using the Mean-variance metric (R4) with the RO approach are much higher compared to those obtained using the PORA approach with the same robustness metric. This is because the consideration of variance across scenarios in the calculation of the Mean-variance metric leads to suboptimal results. A similar pattern is observed for case study 2, where using the Undesirable deviation metric (R5) also results in poorer performance using the RO approach compared to using the PORA approach (Fig. 8c and d). This result highlights that some robustness metrics may not be suitable to be explicitly integrated as an objective into the optimization process, such as when using the RO optimization approach. Therefore, it is recommended that these metrics be used for robustness evaluation in the PORA approach. In the RO approach, the Hurwicz optimism-pessimism rule metric (R2) or Laplace's principle of insufficient reason metric (R3) can be used to represent a risk-neutral attitude and the Worst-case metric (R6) can be used to represent a risk-averse attitude from stakeholders. In addition, it is important to mention that the Mean-variance metric (R4) and the Undesirable deviation metric (R5) could lead to

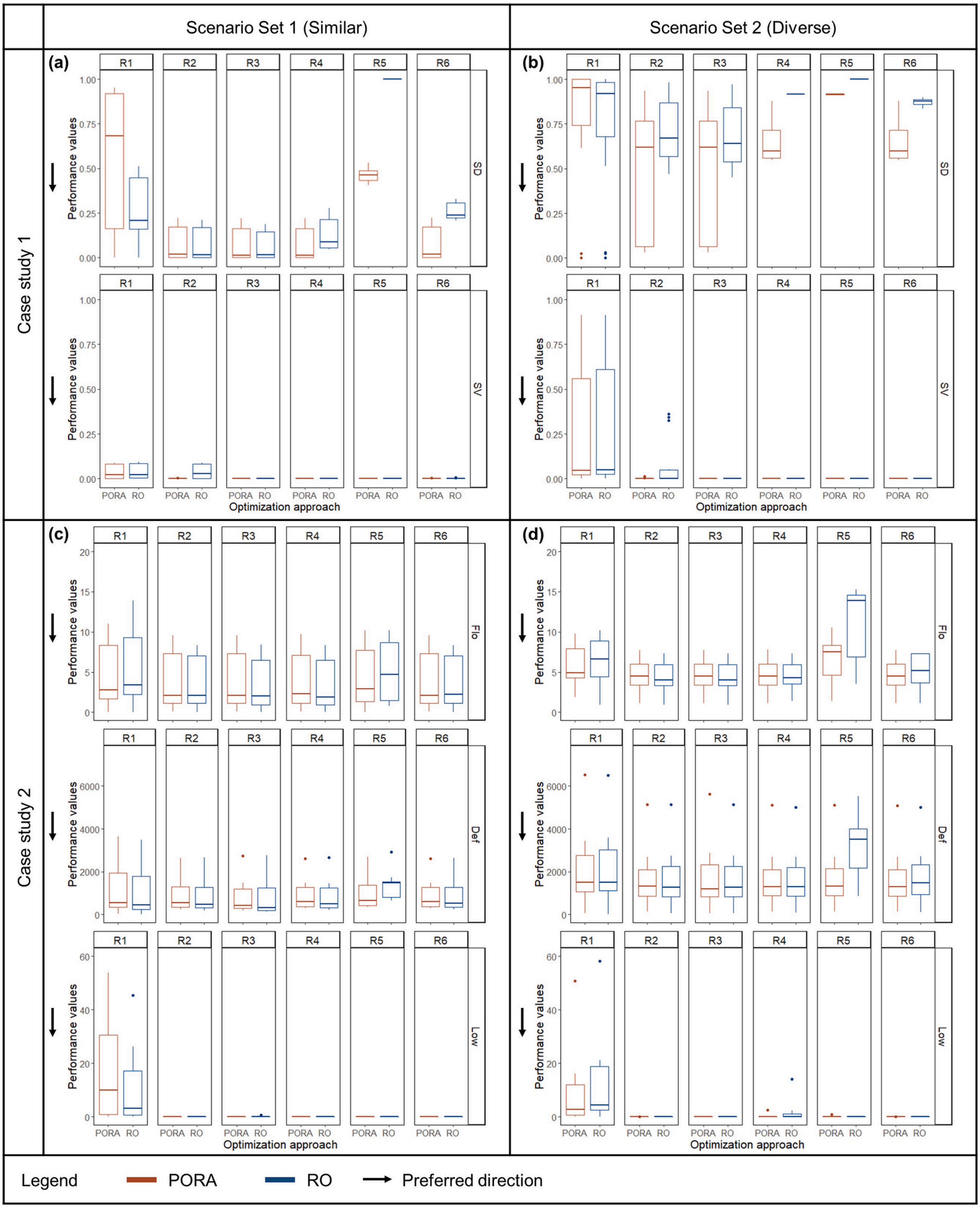

Fig. 8. System performance values of robust solutions identified using PORA (red) or RO (blue) for different scenario sets (indifferent columns) and case studies (in different rows). Plot (a): system values under the Similar scenario set for case study 1; Plot (b): system values under the Diverse scenario set for case study 1; Plot (c): system values under the Similar scenario set for case study 2; Plot (d): system values under the Diverse scenario set for case study 2. Each subplot (R1 to R6) represents one robustness metric used in the optimization process, within which the performance values are plotted for each performance indicator considered (labeled on the y-axis). The box represents the performance of the selected solution across all scenarios within the scenario set. Performance indicators considered include water supply deficit (SD) and water storage violation (SV) for case study 1; flood control (Flo), downstream deficit minimization (Def), and low-level prevention (Low) for case study 2.

different units of measurement for the performance indicators, making it more difficult to interpret the physical implications. In contrast, since the PORA approach selects robust solutions from those that have already demonstrated good performance in each scenario, it provides a more stable foundation for the interpretation of the solutions identified and their associated performance to ensure a starting point for negotiation among decision makers. These solutions are grounded in observable physical performance, making it easier to interpret their implications in real-world applications.

In addition, the joint impact of the optimization approach, robustness metric, and scenarios on system performance may also be affected by the characteristics of performance indicators considered. For example, limited impact of the optimization approach and robustness metric can be observed for the water storage violation performance indicator for case study 1. As shown in Fig. 8a, the values of water storage violation consistently range between 0 and 0.1, with most of the values at 0. This indicates that the water level in the storage can satisfy the predefined water level threshold for case study 1. Similar results have been observed for case study 2 for the low-level prevention performance indicator h, where values of the indicator show a high level of similarity across the different optimization approaches and robustness metrics considered, as shown in Fig. 8c and d. This indicates that the water storage violation and low-level prevention indicator may not be sensitive to optimization or robustness approaches, suggesting that decision makers might prioritize selecting the suitable optimization approach and robustness metric for other performance indicators for which these factors have a greater impact.

Furthermore, robust solutions that are non-dominated in terms of the robustness of system performance across all scenarios considered can behave differently in terms of performance indicators, regardless of the optimization approach, robustness metric and types of scenarios used. The reasons for this are two-fold, as mentioned in Section 2.1. First, different solutions from the Pareto front (in terms of robustness values) may have different tradeoffs in terms of performance indicators. Second, differences in the prioritization of performance indicators by different decision makers can lead to the selection of different solutions from the Pareto front. For example, a solution that is located in the region favoring the robustness of low-level prevention would result in a low (favorable) performance value based on this particular indicator. This is because this solution leads to operation policies consisting of withholding water releases and maintaining stable water levels in the lake. However, this could result in higher (less favorable) values for other performance indicators, such as the flood control performance indicator, because water held in the lake could increase the risk of overflow. In contrast, a solution located in the region prioritizing the flood control performance indicator would lead to decisions that proactively release water from the lake to manage the risks of flooding during heavy rainfall or snowmelt, which can compromise performance related to the objective of preventing low water levels. These competing priorities highlight the complex trade-offs inherent in multi-objective optimization, which are exacerbated when decision makers prioritize different performance indicators (Bonham et al., 2022, 2024). These conflicting priorities make it challenging to find one universally robust solution, as each decision maker's unique preferences influence the robustness and performance of the solutions selected.

Although RO can generally achieve similar or improved system performance in most cases, the effectiveness of RO in enhancing actual system performance also depends on the robustness metric used. Some robustness metrics, such as the Mean-variance and Undesirable deviations metrics, may not be suitable to be used with the RO optimization approach, as the calculation of these metrics places too much emphasis on the differences across scenarios, so that actual system performance in terms of performance indicators related to management objectives may be reduced in order to improve system robustness.

4. Conclusions

Robustness has long been considered in water resources systems-related decision-making under uncertainty to obtain robust solutions that perform consistently well across various plausible future conditions. However, the identification of robust solutions is a complicated task, as different robustness metrics reflect different risk preferences from decision makers, and different scenarios can be used to represent plausible future conditions. While the impact of robustness metrics and scenarios on which robust solutions are obtained has been considered in recent studies, they are often considered in isolation. In addition, these studies are typically based on post-optimization robustness analysis (PORA), while the impact of robust optimization (RO) has been largely overlooked. This is despite the fact that RO has sometimes been shown to lead to promising results due to the explicit incorporation of robustness metrics in the optimization process.

In this study, the joint impact of the optimization approach, robustness metric, and scenarios used on overall system robustness and system performance have been investigated. Two distinctly different water resources management case studies have been selected to reflect the varying complexities that are commonly encountered in real-world water resources management practice and to increase the generalizability of the results obtained, including the Upper Adelaide River dam in Australia and Lake Como in Italy.

Results show that the RO optimization approach effectively identifies more robust solutions, although its practicality depends on the robustness metric used. Some robustness metrics, such as the Undesirable deviations, may not be suited to be explicitly used as an optimization objective. In addition, the impact of scenarios on the solutions identified cannot be neglected. Specifically, if the future is less uncertain (i.e., scenarios are similar), robust solutions identified from both RO and PORA can lead to similar system robustness and performance, with robust solutions identified from RO having slightly better performance. If the future is more uncertain (i.e., scenarios are diverse), the differences between RO and PORA become more pronounced. While the RO approach generally leads to consistent performance across the wide range of future scenarios considered, the robustness of some performance indicators may be worse due to multi-objective tradeoffs, wherein certain objectives may predominate the selection process.

In summary, our findings highlight that the optimization approach, robustness metric, and scenarios used all significantly impact system robustness and performance. The impact of optimization approaches is most pronounced when scenarios have very different properties, with RO showing greater performance consistency. The selection of robustness metric(s) influences the practicality of robust solutions, as it has been found that metrics that emphasize variability across scenarios are not suitable for direct integration into the optimization process. In addition, the impact of scenarios cannot be ignored, as the inclusion of extreme scenarios may disproportionally affect the optimization process and lead to skewed tradeoffs. These findings enable future studies to develop targeted and context-specific robust solutions for water resources management problems under deep uncertainty. To further enhance the generalizability of findings, future research could consider extending the scope of analysis to cover a broader range of case studies with more management objectives (i.e., many-objective management problems). In addition, integrating human factors (e.g., different prioritization of performance indicators) into a systematic assessment of the impact on robust solutions identified could also lead to the development of more practical and actionable decision support systems, thus addressing the challenges posed by deep uncertainty in decision-making processes.

CRediT authorship contribution statement

Jiajia Huang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization.

Matteo Sangiorgio: Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Wenyan Wu:** Writing – review & editing, Methodology, Conceptualization. **Holger R. Maier:** Writing – review & editing, Methodology, Conceptualization. **Quan J. Wang:** Writing – review & editing, Conceptualization. **Justin Hughes:** Writing – review & editing, Data curation, Conceptualization. **Andrea Castelletti:** Writing – review & editing, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Wenyan Wu reports a relationship with Australian Research Council that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.123540.

Data availability

Data will be made available on request.

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