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Is robustness really robust? How different definitions of robustness impact decision-making under climate change

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Abstract Robust decision-making is being increasingly used to support environmental resources decisions and policy analysis under changing climate and society. In this context, a robust decision is a decision that is as much as possible insensitive to a large degree of uncertainty and ensures certain performance across multiple plausible futures. Yet, the concept of robustness is neither unique nor static. Multiple robustness metrics, such as maximin, optimism-pessimism, max regret, have been proposed in the literature, reflecting diverse optimistic/pessimistic attitudes by the decision maker. Further, these attitudes can evolve in time as a response to sequences of favorable (or adverse) events, inducing possible dynamic changes in the robustness metrics. In this paper, we explore the impact of alternative definitions of robustness and their evolution in time for a case of water resources system management under changing climate. We study the decisions of the Lake Como operator, who is called to regulate the lake by balancing irrigation supply and flood control, under an ensemble of climate change scenarios. Results show a considerable variability in the system performance across multiple robustness metrics. In fact, the mis-definition of the actual decision maker's attitude biases the simulation of its future decisions and produces a general underestimation of the system performance. The analysis of the dynamic evolution of the decision maker's preferences further confirms the potentially strong impact of changing robustness definition on the decision-making outcomes. Climate change impact assessment studies should therefore include the definition of robustness among the uncertain parameters of the problem in order to analyze future human decisions under uncertainty.

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1 Introduction

In a rapidly changing context, climate change and growing populations are challenging the long-term planning and management of environmental resources systems due to increasingly uncertain hydrometeorologic regimes and co-varying water, energy, and food demands (Arnell and Lloyd-Hughes 2014; Harrison et al. 2015). Growing awareness of potential climate change impacts (e.g., Anderson et al, 2008, Nelson et al. 2010), along with their recognized uncertainty (Lempert et al. 2004; Paton et al. 2013; Gober 2014), motivates a better understanding of human decisions under uncertainty. In traditional decision theory (French 1988), a decision-making problem under uncertainty is formulated when the consequence of a decision depends on a number of external, uncertain factors defining different states of the world, which cannot be described via any stochastic model, but rather in a deterministic and set-membership based fashion (see Ben-Tal et al. 2009; Bertsimas et al. 2011, and references therein). On the contrary, if the available information allows formulating a probabilistic description of the uncertain states of the world, the problem is defined as decision-making under risk.

Over the last years, a number of methods have been proposed for describing decisions under set-membership uncertainty (for a review see Herman et al. 2015, and references therein), also referred to as deep uncertainty (Lempert and Schlesinger 2000; Lempert 2002), particularly to support long-term planning under future climatic and socio-economic scenarios, whose probabilities are not known or widely agreed on (e.g., Haasnoot et al. 2012; Kasprzyk et al. 2012; Herman et al. 2014; Beh et al. 2015; Jager et al. 2015). The main objective in most of these works is the identification of robust solutions, namely decisions that are insensitive against variations of the problem's parameters (Matalas and Fiering 1977; Herman et al. 2015), which generally refer to an ensemble of future climate and socio-economic scenarios. Yet, the formal definition of robustness is not unique, as multiple robustness metrics do exist to capture diverse degrees of pessimism/optimism by the decision maker (DM). Solving the meta-problem of deciding how to decide (Schneller and Sphicas 1983) requires selecting the robustness metric that better captures the DM's attitude and allows simulating its response to future uncertain scenarios. This choice introduces another uncertain independent parameter in the problem formulation, and raises the following key question: *is robustness really robust?*

In addition, the DM's preferences are not static behavioral attributes. Rather, they can evolve in time based on new experience and insights (Guiso et al. 2013), which potentially reduce the uncertainty of the future state of the world (Walker et al. 2013). The DM's behaviors can indeed be dynamically altered by learning from the outcomes of the implemented decisions or in response to dynamic changes in asset thresholds (e.g., Lybbert and Barrett 2007; Brunnermeier and Nagel 2008). For example, a pessimistic DM, originally making decisions on the basis of the worst-case scenario, might become less pessimistic after experiencing a number of positive returns associated to realizations of uncertain factors less severe than in the worst-case scenario. On the contrary, an optimistic DM, used to assume risks by making decisions on the basis of the best scenario, might become more and more cautious after experiencing a sequence of failures. Ignoring such behavioral dynamics and their dependency on the underlying evolution of the state of the world introduces an attribution bias in the modeled DM's behavior (Lybbert et al. 2013), which further complicates the simulation of its future decisions.

In this paper, we explore how alternative definitions of robustness, capturing distinct and potentially dynamic DM's attitudes, impact on decisions under deep uncertainty. To answer this question, we focus on water resources systems and study the future behavior of a water reservoir operator. We consider Lake Como, a regulated lake located in Northern Italy, which is operated trading off irrigation supply and flood control. To account for the changing climatic conditions, we analyze the system under an ensemble of climate change scenarios, comprising different Radiative Concentration Pathways, Global, and Regional Circulation Models (IPCC 2014). The uncertainty associated to climate scenarios allows showing how misdefining the robustness metric adopted by the DM biases the simulation of its future decisions and produces an underestimation of the projected system performance. Moreover, we explore the impacts of alternative definitions of robustness by analyzing the variability in the DM's decisions obtained assuming different robustness metrics. Finally, insights on the time evolution of the DM's preferences, which support a better understanding of its future behaviors, are obtained by combining the analysis of the tradeoffs in the objective space (i.e., flooding against irrigation) with the exploration of the tradeoffs existing between alternative robustness metrics.

2 Robustness metrics

In this section, we report five classical different definitions of robustness metrics formulated for a generic maximization problem under uncertainty (French 1988), where the performance $f(a, w)$ of an alternative a depends on the state of the world $w \in \Xi$ that will realize in the future. It is worth noting that these metrics can lead to different and mutually contradicting decisions. In fact, they violate at least one of the principles for consistent choice discussed in French (1988). The direct interaction with the DM to characterize its attitude and select the metric closest to its preferences is hence fundamental in the absence of normative approaches to describe decisions under uncertainty. The metrics we consider in this work are the following:

- The *maximin* metric (Wald 1950) focuses on the worst possible performance of each alternative, also known as security level, and selects the alternative a^* such that

$$a^* = \arg\max_a \left(\min_{\Xi} f(a, w) \right) \tag{1}$$

  This metric is generally associated with a pessimistic point of view as it assumes that the worst will happen. However, it is worth noting that the alternative selected ensures certain performance levels.
- The *maximax* metric focuses on the best possible performance of each alternative and selects the alternative a^* such that

$$a^* = \arg\max_a \left(\max_{\Xi} f(a, w) \right) \tag{2}$$

  This metric is generally associated with an optimistic point of view as it assumes that the best state of the world will realize.
- The *optimism-pessimism* rule (Hurwicz 1951) tries to combine the maximin and maximax approaches by means of a weighted average of the pessimistic and optimistic performance. This metric selects the alternative a^* such that

$$a^* = \arg\max_a \left(\alpha \min_{\Xi} f(a, w) + (1 - \alpha) \max_{\Xi} f(a, w) \right) \tag{3}$$

where $0 \leq \alpha \leq 1$ is a specific index describing the relative importance of the best-case and worst-case state of the world. This coefficient depends on the personal attitude of the DM and should be calibrated by direct interaction.

– The *minimax regret* metric (Savage 1951) bases decisions on the regret, defined as the difference between the performance resulting from the best alternative given that w_j is the true state of the world and the performance of a under w_j, i.e.

$$r_j(a) = \max_a \left(f(a, w_j) \right) - f(a, w_j) \tag{4}$$

Then, this metric selects the best alternative a^* adopting a pessimistic approach, namely by minimizing the maximum regret across the states of the world, i.e.

$$a^* = \arg\min_a \left(\max_\Xi r(a) \right) \tag{5}$$

– The *principle of insufficient reason* (Laplace 1951) suggests that in the absence of knowledge on the probabilities associated to the different states of the world, the decision could be taken by assigning equal probability to all the states (i.e., $P = 1/n$). Then, the initial problem under uncertainty is transformed into a decision-making problem under risk, where the best alternative a^* is selected as the one associated to the maximum expected performance, i.e.

$$a^* = \arg\max_a \left(\frac{1}{n} \sum_{j=1}^{n} f(a, w_j) \right) \tag{6}$$

The choice of these metrics allows creating a spectrum of attitudes, from full optimism to extreme pessimism, to capture the variability in the DM's behaviors. In addition, they are more suitable for the considered water system operations problem than satisficing metrics (e.g., Lempert and Collins 2007), because these latter refer to the tendency of decision makers to seek outcomes that meet one or more requirements, but may not achieve optimal performance (Simon 1959). However, in our study site the adaptation of the lake regulation has no cost and, consequently, the lake operator will naturally adapt looking for optimal performance.

3 Study site

3.1 The Lake Como system

Lake Como is a regulated lake in Northern Italy (Fig. 1) with an active storage capacity of 254 Mm^3 and fed by a 3,500 km^2 catchment. The hydro-meteorological regime is the typical Alpine one, with scarce discharge in winter and summer, and peaks in late spring and autumn due to snowmelt and rainfall, respectively. The lake inflow and effluent is the Adda River, feeding eight run-of-river hydroelectric power plants and serving a dense network of irrigation canals, which supports five agricultural districts with a total surface of 1,400 km^2. Major crops are cereals, especially maize, along with temporary grasslands for livestocks. Irrigation is practiced with the border method or free-surface flooding. The regulation of the lake aims also to prevent flooding along the lake shores, particularly in Como city, which is the lowest point of the shoreline.

Snowmelt from May to July is the most important contribution to seasonal lake storage (green area in Fig. 2a). This volume of water can be used in different ways according to the

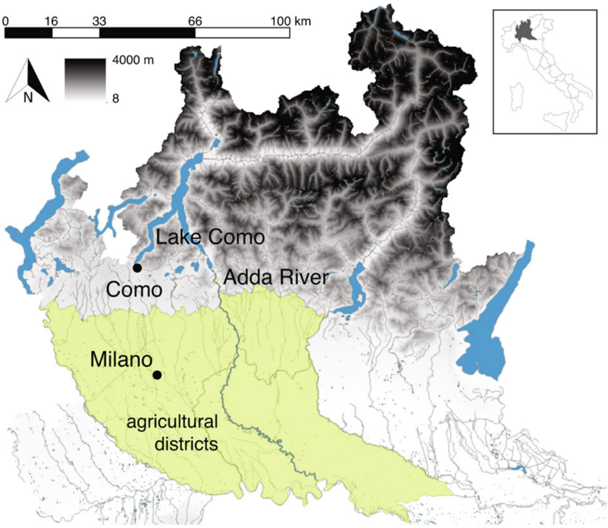


Fig. 1 Map of the Lake Como system

two competing objectives that drive the lake regulation. The farmers would prefer to store most of the spring inflows and release this water later for satisfying the summer demand peak. Yet, storing this water increases the lake levels and, consequently, the flood risks. The optimal flood protection would be instead obtained by drawing down the lake level as much as possible. These opposite operating strategies generate a clear conflict between flooding and irrigation, which, according to previous works (e.g., Castelletti et al. 2010), are modeled using the following two objectives:

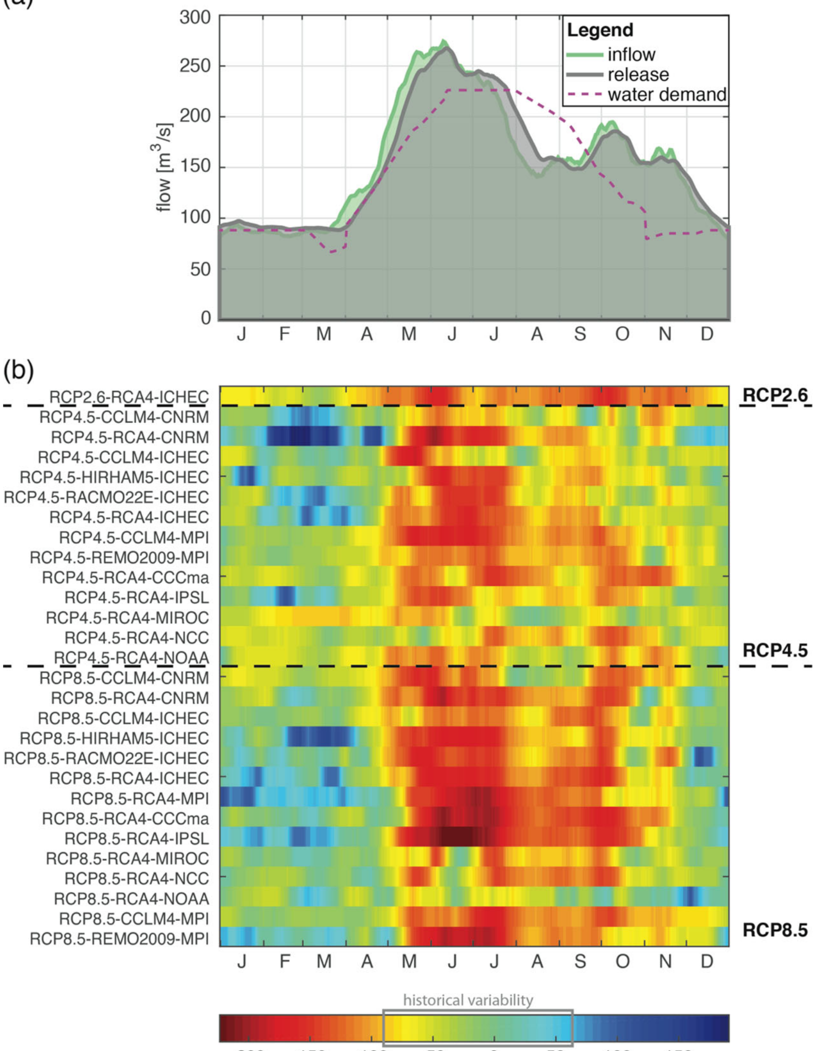
- *Flooding*: the storage reliability (to be maximized), defined as $f_{stor.rel.} = 1 - n_F(a)/H$, where $n_F(a)$ is the policy dependent number of days during which the lake level is higher that the flooding threshold of 1.24 m and H is the evaluation horizon. This formulation does not consider the magnitude of extreme damages because lake floods mostly produces indirect damages related to commercial activity and transport interruptions.
- *Irrigation*: the daily average volumetric reliability (to be maximized), defined as $f_{vol.rel.} = 1/H \cdot \sum_{t=1}^{H}(Y_t(a)/D_t)$, where $Y_t(a)$ (m^3) is the daily water supply by policy a and D_t (m^3) the corresponding demand.

The set of Pareto optimal operating policies π_θ^*, which describes alternative regulation of the lake over the historical climate conditions w^H, is obtained via Evolutionary Multi-Objective Direct Policy Search, a simulation-based optimization approach which combines direct policy search, nonlinear approximating networks, and multi-objective evolutionary algorithms (Giuliani et al. 2015a). The Pareto optimal set π_θ^*, which determines the release decision as a function of the day of the year, the current lake storage, and the previous day inflow, is obtained by solving the following problem:

$$\pi_\theta^* = \arg\max_{\pi_\theta} \mathbf{f}(\pi_\theta, w^H) = |f_{stor.rel.}(\pi_\theta, w^H), f_{vol.rel.}(\pi_\theta, w^H)| \tag{7}$$

where the policies π_θ are parameterized as Gaussian radial basis functions, which have been demonstrated to be effective in solving this class of problems

(a)



(c)

	CCLM4	HIRHAM5	RACMO22E	RCA4	REMO2009
CNRM	4.5; 8.5			4.5; 8.5	
ICHEC	4.5; 8.5	4.5; 8.5	4.5; 8.5	2.6 4.5; 8.5	
MPI	4.5; 8.5			8.5	4.5; 8.5
CCCma				4.5; 8.5	
IPSL				4.5; 8.5	
MIROC				4.5; 8.5	
NCC				4.5; 8.5	
NOAA				4.5; 8.5	

Fig. 2 Historical cyclostationary daily mean of Lake Como inflow over the period 1946-2011 (panel (a)); inflow daily anomalies with respect to historical mean under the different climate scenarios over the period 2096-2100, with the historical variability, evaluated by the 10th and 90th percentile, represented by the gray box (panel (b)); summary of the climate scenarios considered, where rows and columns represent combinations of RCMs and GCMs, respectively, and each cell specifies the available RCPs (panel (c))

(e.g., Giuliani et al. 2014, 2015b). To perform the optimization, we use the self-adaptive Borg MOEA (Hadka and Reed 2013), which has been shown to be highly robust across a diverse suite of challenging multi-objective problems, where it met or exceeded the performance of other state-of-the-art MOEAs (Hadka and Reed 2012).

3.2 Scenarios

Climate change is expected to impact on the Alpine systems in multiple ways (e.g., Faggian and Giorgi 2009; Anghileri et al. 2011; Beniston et al. 2011). Water availability is indeed projected to decrease, potentially leading to severe water stress for the agricultural districts (Iglesias and Garotte 2015). In addition, the increasing temperature will alter the hydrologic regime and, particularly, the snowpack dynamics (McDowell et al. 2014). Under a warmer climate, snow melt will starts early, thus shifting the spring peak in the lake inflows, with direct impacts in terms of flood control as well as indirect negative effects for the farmers due to the increased length of the dry summer. The regulation of Lake Como is expected to quickly and easily adapt to this change after experiencing some favorable or adverse events, particularly because changing the operating policy of the lake is a flexible adaptation options, which does not require any infrastructural intervention.

In this work, we consider a climate change ensemble which comprises 28 alternative scenarios (see Fig. 2b-c), defined as combinations of different Radiative Concentration Pathways, Global, and Regional Circulation Models. The projected time series of temperature and precipitation are obtained from the application of a cascade of models: the RCPs' scenario provided by the Intergovernmental Panel on Climate Change (IPCC 2014) is used as input to a general circulation model (GCM), which provides the boundary conditions for a regional circulation model (RCM). Since the spatial resolution of the RCMs is too rough to provide representative climatic scenarios at the basin scale, a statistical downscaling method based on quantile mapping (Boé et al. 2007) is applied to correct RCM outputs at the catchment scale. A site-specific, quantile-quantile correction function is estimated by comparing observations of precipitation and temperature with the outputs obtained from the RCMs' simulations over the historical control period (1965-1980). The data used for the downscaling were obtained from the EURO-CORDEX project (see www.euro-cordex.net).

The downscaled trajectories of precipitation and temperature are then used as inputs to generate the projected Lake Como inflow for the time period 2096-2100. A HBV hydrology model is used to simulate the soil water balance and subsequent runoff produced by rainfall, snowmelt, and evapotranspiration. The resulting ensemble of inflow's trajectories is represented in Fig. 2b as the daily inflow anomalies under the different scenarios with respect to the historical cyclostationary daily mean of the lake inflow over the period 1946-2011 (panel (a)). All the scenarios suggest a general reduction of the water available in spring and summer. In addition, the figure shows that a variety of possible future hydroclimatic conditions is considered, including very dry or wet springs (e.g., RCP4.5-RCA4-MIROC and RCP4.5-RCA4-CNRM, respectively), variable time shifts of the spring peak (e.g., RCP4.5-CCLM4-CNRM, RCP4.5-RCA4-CNRM, RCP4.5-RACMO22E-ICHEC, and RCP4.5-RCA4-ICHEC), and very dry summers, especially under the RCP8.5 (e.g., RCP8.5-REMO2009-MPI, RCP8.5-RCA4-CCCma, RCP8.5-RCA4-IPSL).

This high variability in the projected hydroclimatic scenarios introduces significant uncertainty in the analysis of climate change impacts on the Lake Como system. Since at present the distribution of these future scenarios remains uncertain or contested (Lempert 2002), the simulation of the future decisions of the Lake Como operator can be performed by solving a decision-making problem under uncertainty and requires the characterization of the DM's attitude in terms of robust decisions. The projection of its future behavior can be obtained by reformulating Problem (7), where the same objectives introduced in the previous section are now evaluated over the ensemble of climate change scenarios $w \in \Xi$ just described, i.e.

$$\pi_\theta^* = \arg\max_{\pi_\theta} \Psi_\Xi \left[\mathbf{f}(\pi_\theta, w)\right] \quad (8)$$

where $\Psi_\Xi[\cdot]$ is one of the robustness metrics described in Section 2, which capture the optimistic/pessimistic attitude of the DM and aims to filter the performance uncertainty associated to the climate change scenarios. The comparison of the Pareto optimal sets obtained by adopting different robustness metrics in solving Problem (8) allows quantifying the uncertainty associated to the DM's attitudes and the impacts of misdefining them. In addition, Problem (8) can be extended by optimizing the Lake Como operations with respect to 10 different objectives, representing couples $(f_{stor.rel.}, f_{vol.rel.})$ evaluated according to the five robustness metrics considered, in order to explore possible dynamic evolution of the DM's preferences both in terms of tradeoff between flooding and irrigation, and in terms of pessimistic/optimistic attitude.

4 Results and discussion

4.1 Policy performance uncertainty

The variety of hydroclimatic conditions shown in Fig. 2b introduces relevant uncertainties to the long-term performance of alternative Lake Como operating policies. Figure 3 illustrates the performance, evaluated in terms of flooding (i.e., storage reliability) and irrigation (i.e., volumetric reliability), of 19 Pareto optimal operating policies (black circles) designed over the historical control period (1976-1980). This performance is contrasted with the re-evaluation of the same policies over the period 2096-2100 under the 28 climate change scenarios considered (gray circles). Results show that the uncertainty in the hydroclimatic scenarios is transferred to the operating policies performance. Depending on the scenario considered, the projected climate change impacts might produce co-benefits for the history-based policies or degrade their performance. A significant number of solutions, namely 46 % over 532 alternatives (i.e., 19 policies times 28 scenarios), show improved performance on both the operating objectives (see the green area of the objective space). Under other scenarios, the performance either improves in one objective while worsening in the other (i.e., the yellow area) or degrade in both the objectives (i.e., white area of the objective space, accounting for 40 % of the simulated alternatives).

Figure 3 also suggests that irrigation is more sensitive to the negative effects of climate change, with the worst solutions attaining a performance in terms of volumetric reliability equal to 0.5 (i.e., an average reduction of 37 % with respect to the performance under historical conditions). On the contrary, the worst case performance in terms of flooding is 0.71, with 98 % of the solutions successfully attaining a storage reliability greater than 0.85. This asymmetry in the climate change impacts is maintained in the quantification of the policy performance uncertainty. The average range of variability for the 19 history-based policies across the 28 scenarios is equal to 0.06 for flooding and 0.39 for irrigation, ultimately challenging the projection of the Lake Como system under these future climate scenarios.

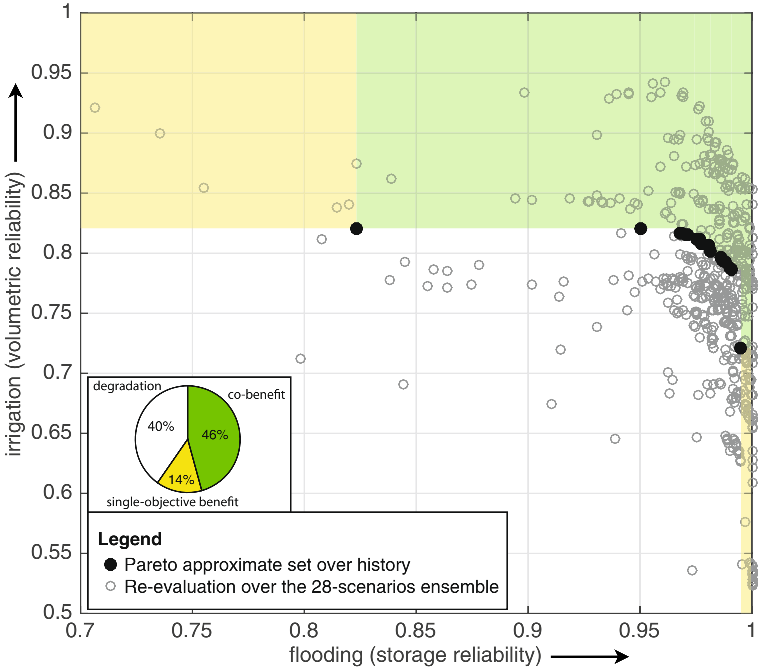


Fig. 3 Performance of the Pareto optimal policies over history *(black circles)* and their re-evaluation over the 28 scenarios *(gray circles)*, which produce co-benefit *(green area)*, single-objective benefit *(yellow area)*, or performance degradation *(white area)*

4.2 Analysis of different robust policies

The results discussed in the previous section show that the performance of the history-based policies evaluated over the ensemble of climate change scenarios is largely uncertain. Most of the approaches proposed in the literature would thus analyze the future DM's behavior by assuming the DM will adapt to the changing climate and will be "robust" with respect to the uncertainty of the different scenarios. To explore the variety of alternative robust behaviors, we solved Problem (8) with the five robustness metrics described in Section 2. Figure 4a compares the different Pareto optimal sets, obtained with alternative metrics, by representing their performance with distinct shapes. Not surprisingly, the performance of the solutions degrades for increasing levels of pessimism. The performance of the policies designed with the maximax metric (black upward triangles) are indeed the closest to the absolute optimal solution, located on the top-right corner of the figure, while the ones obtained with the principle of insufficient reason (black circles), the optimism-pessimism rule (black plus), and the maximin metric (black downward triangle) are more and more distant from that point. The figure also shows that the definition of the robustness metric is impacting on the shape of the tradeoff curve between flooding and irrigation. The conflict is almost cancelled under the maximax metric, with the corresponding Pareto optimal set that comprises 4 solutions and covers a performance range equal to 0.004 in the two objectives, while the conflict becomes more evident adopting the maximin or the minimax regret metrics, with the corresponding Pareto optimal set comprising 36 and 63 solutions, respectively, and exploring a range of performance equal to 0.5 in terms of flooding and 0.12 in terms of irrigation.

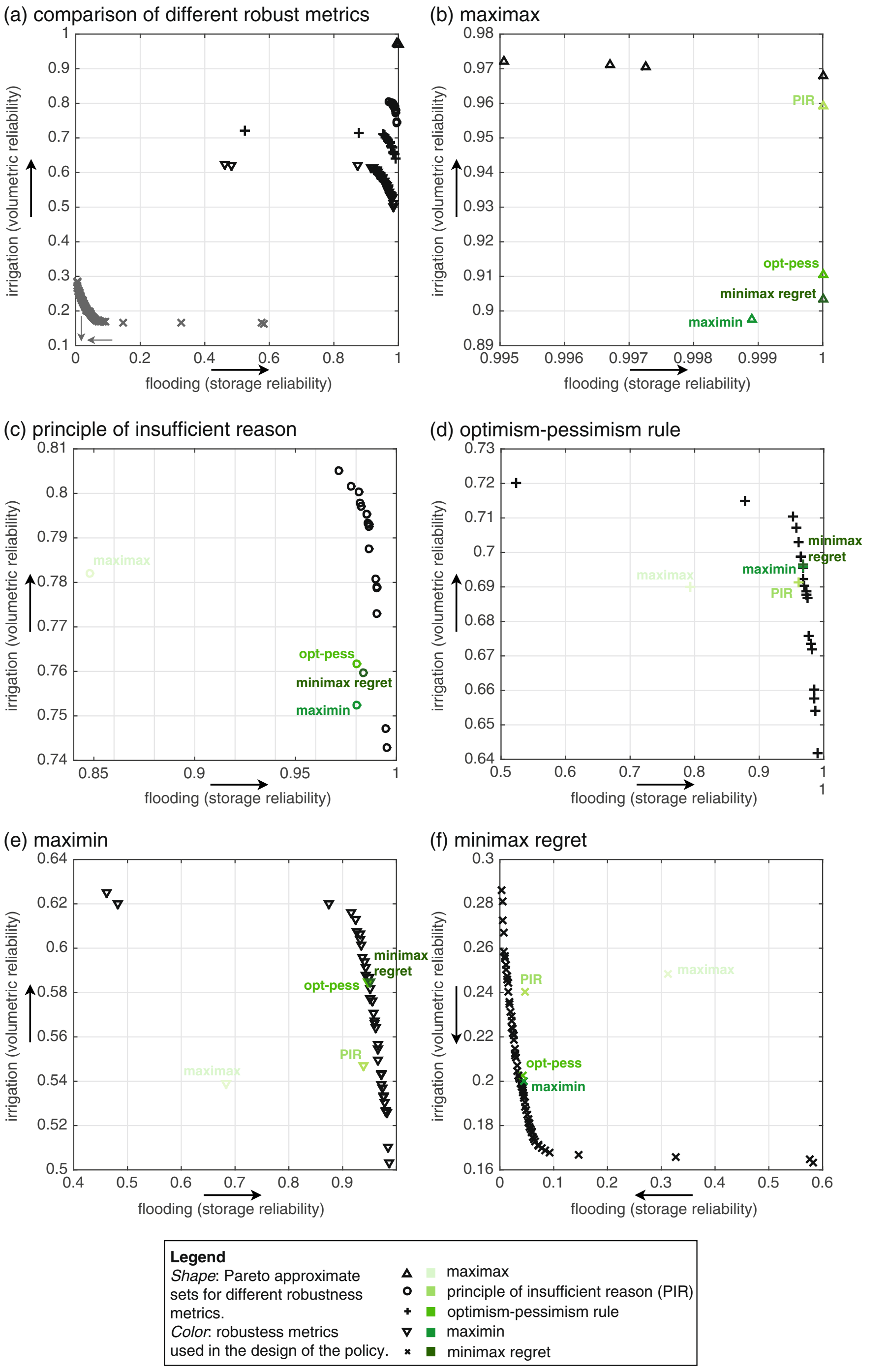


Fig. 4 Performance of the Pareto optimal sets obtained with different robustness metrics (panel (a)) and comparison of these latter *(black shapes)* with solutions designed according to discordant robustness metrics *(green shapes in panels b-f)*

The difference in the Pareto optimal sets obtained adopting different robustness metrics suggests to explore the impacts of misdefining the DM's robustness on the analysis of the system performance under climate change, namely assuming the future DM's behavior is projected according to a metric that is not capturing its preferences. Note that the same effects are obtained also in the case of a correct initial definition of robustness, which, however, can evolve in time, for example after experiencing frequent system's failures. Results are shown in Fig. 4b-f, where black solutions represent the Pareto optimal set obtained with a given metric and are contrasted with some solutions designed according to discordant definitions of robustness (green shapes). These are selected from their respective Pareto optimal sets (Fig. 4a) according to the criterion of the minimum distance with respect to the Utopia point (Eschenauer et al. 1990), which identifies the absolute optima of all the objectives. Results clearly show that misdefined robustness metrics produce solutions that are dominated by the ones obtained with the proper characterization of the DM's attitude. For example, Fig. 4c suggests that if the DM attitude was captured by the principle of insufficient reason, all the solutions designed with a misdefined metric (green circles) would be dominated by the Pareto optimal set designed assuming the principle of insufficient reason (black circles). The same is observed in all the five panels, with degradation of performance becoming larger in the more pessimistic metrics, such as the solutions obtained with the maximax metric that have poor performance when evaluated via the maximin or minimax regret metrics (Fig. 4e-f).

4.3 Analysis of tradeoffs across robustness metrics

To further analyze the differences between the alternative definitions of robustness, we run a multi-objective/multi-robustness optimization, namely we solved Problem (8) by optimizing the operating policies with respect to 10 different objectives, representing couples of flooding and irrigation evaluated according to the five robustness metrics considered. The aim of this experiment is to complement the analysis of the tradeoff between flooding and irrigation with the exploration of the tradeoffs between alternative robustness metrics. Results are reported in Fig. 5 by means of a parallel axes plot (Inselberg 1997), which shows each Pareto optimal solution as a line crossing the vertical axes at the values of their corresponding performance. The objective values are normalized between their minimum and maximum values and the axes are oriented so that the direction of preference is always upward. The ideal solution would be a horizontal line running along the top of all of the axes and the conflicts are designated as diagonal lines between two adjacent axes. Despite the asymmetry in the climate change impacts generates limited conflicts in terms of flooding (Fig. 5a), clear tradeoffs between the different robustness metrics emerge when looking at the irrigation objective (Fig. 5b). In this case, the ranking of the solutions strongly depends on the metric considered. Attaining a high volumetric reliability adopting the maximin metric (i.e., dark red lines on the top of the second vertical axis) corresponds to intermediate or low performance on the same objectives evaluated according to the principle of insufficient reason or the maximax metric. A weak conflict exists also in the ranking provided by the maximin metric and the optimism-pessimism rule, while the best solutions in terms of maximin metric have the best performance also in terms of minimax regret. These results confirm that the adoption of alternative definitions of robustness is relevant for the projections of the future decisions under climate change.

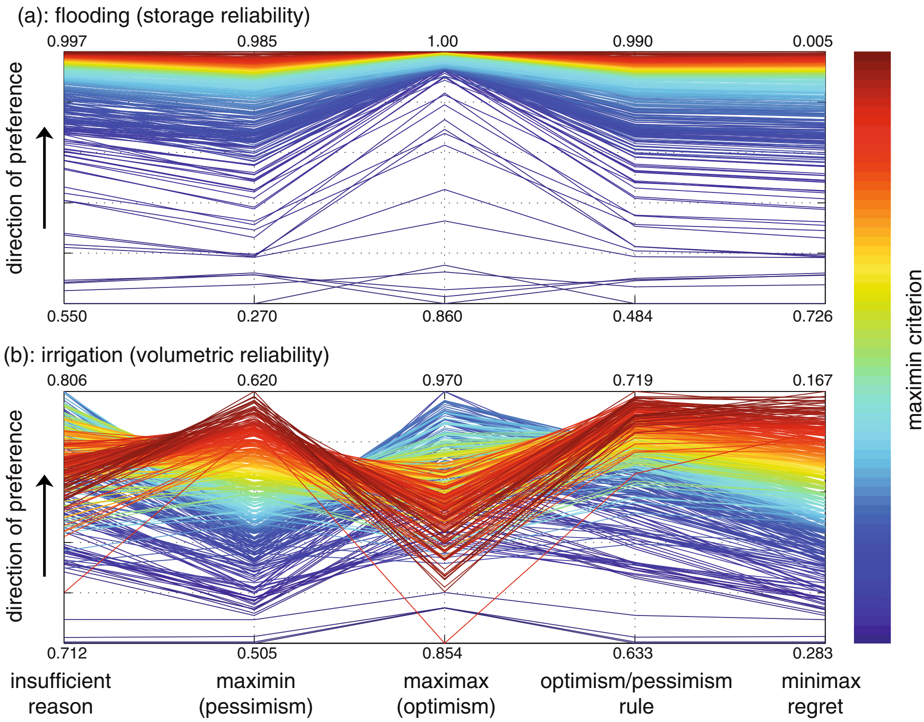


Fig. 5 Parallel-axes representation of the Pareto optimal solutions of the 10-objectives policy design problem (i.e., combinations of 2 objectives and 5 robustness metrics), where the objective values are normalized between the minimum and maximum of each objective and the axes are oriented so that the direction of preference is always upward

Further insights on the possible time evolution of DM's preferences can be obtained by analyzing the tradeoffs across robustness metrics. An example is illustrated in Fig. 6 assuming that the DM is originally neutral and evaluates the operating policy performance according to the principle of insufficient reason. Then, its preferences change in time while experiencing the negative impacts of climate change on irrigation, moving towards a more and more pessimistic attitude. This evolution can be analyzed by exploring the tradeoff between the performance in terms of irrigation evaluated with the principle of insufficient reason and the same objective evaluated according to the maximin metric (Fig. 6a). The effects of this evolution from policy P1 to policy P5 on the associated regulation are represented in Fig. 6b–f, which show the Lake Como release as a function of the day of the year (x-axis) and the lake level (y-axis). To support the analysis of the policies, the figures illustrate the downstream water demand (dashed magenta line) that the DM has to satisfy. Results show that policy P1 suggests high release (blue area) in summer following the water demand pattern. The evolution from policy P1 to policy P5 implies a decrease of the lake releases in the late spring (i.e., the blue area is shrinking) with the aim of storing a sufficient volume of water in the lake during the spring peak of the inflow to face the severe summer droughts. This modification of the DM's attitude and of the associated robustness metrics is therefore strongly impacting the future lake regulation and, consequently, has to be included in the set of uncertain factors, along with the climate scenarios, for analyzing candidate solutions for managing the Lake Como system under climate change.

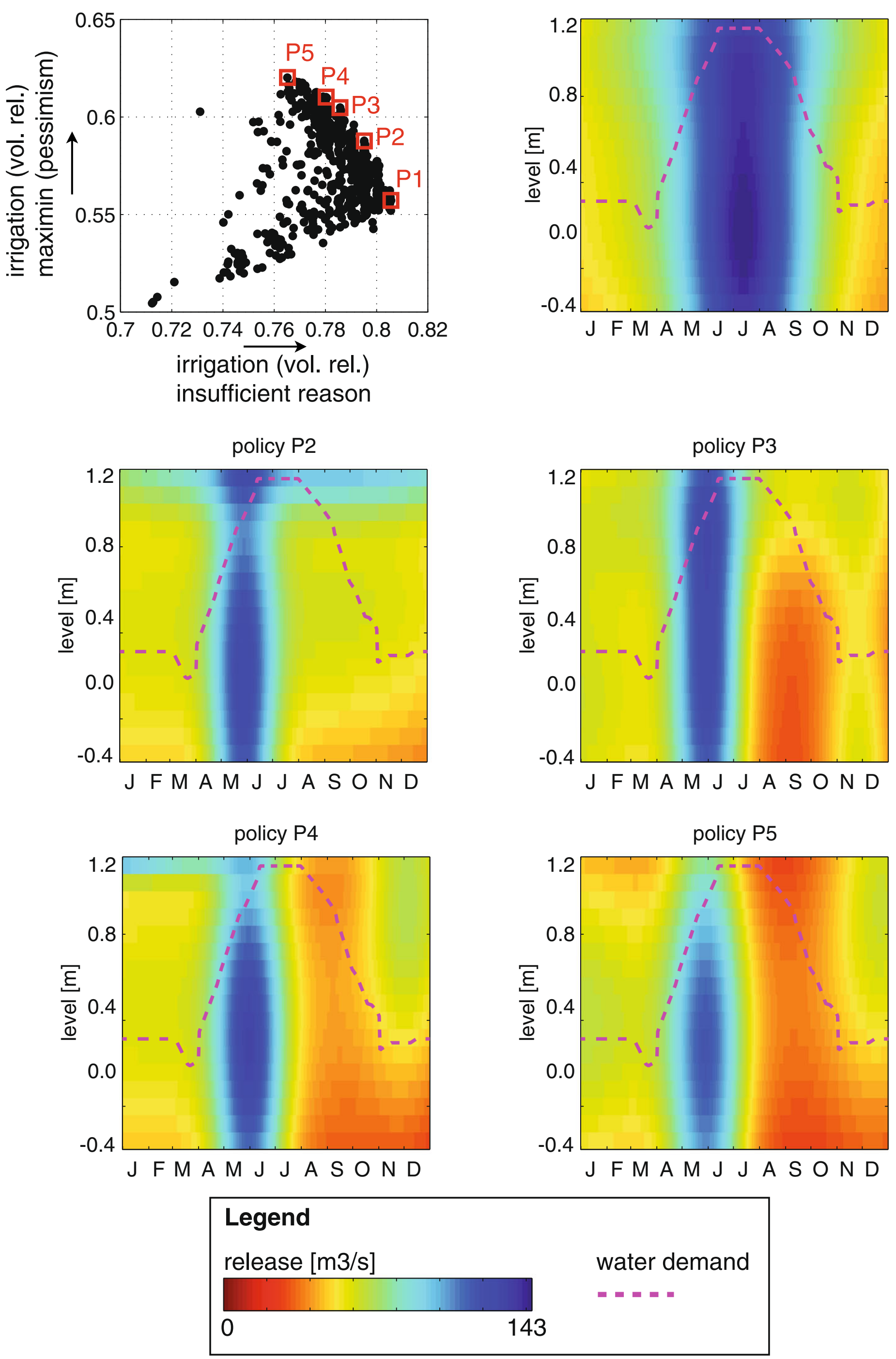


Fig. 6 Time evolution of DM's preferences illustrated by comparing 5 different operating policies selected on the tradeoff between the irrigation objective evaluated with the principle of insufficient reason and the same objective evaluated with the maximin metric

5 Conclusions

The large uncertainty associated to the projections of future hydroclimatic and socio-economic conditions is more and more challenging the long-term planning and management of environmental resources systems. Over the last years, robust approaches have been widely adopted to identify solutions whose quality is insensitive against variations of the problem's parameters. However, multiple robustness definitions do exist to capture diverse optimistic/pessimistic attitudes by the Decision Maker. This paper explores the impacts on human decisions under uncertainty of alternative definitions of robustness, which capture distinct and potentially dynamic DM's preferences.

Our analysis on the Lake Como system, where the DM is called to cope with the uncertainty associated to the projected climate scenarios, demonstrates that misdefining the robustness metric capturing the DM's attitude biases the simulation of its future decisions (Lybbert and Barrett 2007). Numerical results show that solutions obtained with misdefined robustness metrics generally underestimate the system performance with respect to the one achievable with a correctly defined metric, with the degradation of performance that is larger in the case of the more pessimistic metrics. The analysis of the tradeoffs between alternative robustness metrics, which produce conflicting solutions' rankings, confirms the strong impact of the definitions of robustness on the decision-making process and also provides insights on the dynamic evolution of the DM's preferences. The exploration of the tradeoff between the principle of insufficient reason and the maximin metric allows simulating the response of the DM's behavior to the underlying changes in the climate, which produce negative impacts on the irrigation supply. Results show that this dynamic evolution from neutral to pessimistic decisions is strongly impacting the lake regulation, thus demonstrating the potential inaccuracy of analysis relying on static estimates of DM's attitudes (Lybbert et al. 2013).

The conclusion from this work is that the definition of robustness adopted in climate change impact assessment studies to project future human decisions under uncertainty should be included among the uncertain parameters of the problem, along with the uncertain scenarios used for describing changing climate and society. The large impacts of the alternative definitions of robustness on the future decisions under uncertainty emphasizes the importance of setting an appropriate robustness metric for the specific problem under study (e.g., Dohmen et al. 2011; Drouet et al. 2015) and suggests using multiple metrics, particularly when the characterization of the DM's behavior is not accurate and robustness is therefore not really robust. Further research will focus on relating time-evolving tradeoffs and DM's attitude to changing external drivers (e.g., persisting extreme drought condition) and on extending the present analysis from a management problem, where the simulated decisions involve only changing the lake operation without structural modifications of the system, to a planning problem (e.g., water supply capacity expansion), where the biases introduced by misdefining robustness may increase the financial risk associated to economic investments required for the development of the project.

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