# Identifying and modelling dynamic preference evolution in multipurpose water resources systems

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**Key Points:**

- We explore how variability in hydro-climatic forcing may produce a change in the preferences of multipurpose water systems' operators
- We map the identification of the preference among multiple objectives onto a multi-lateral negotiation process
- We model preference dynamics via periodic negotiations implementing the availability bias concept from cognitive psychology

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## Abstract

Multipurpose water systems are usually operated on a tradeoff of conflicting operating objectives. Under steady-state climatic and socio-economic conditions, such tradeoff is supposed to represent a fair and/or efficient preference. Extreme variability in external forcing might affect water operators' risk aversion and force a change in her/his preference. Properly accounting for these shifts is key to any rigorous retrospective assessment of the operator's behaviors, and to build descriptive models for projecting the future system evolution. In this study, we explore how the selection of different preferences is linked to variations in the external forcing. We argue that preference selection evolves according to recent, extreme variations in system performance: underperforming in one of the objectives pushes the preference toward the harmed objective. To test this assumption, we developed a rational procedure to simulate the operator's preference selection. We map this selection onto a multilateral negotiation, where multiple virtual agents independently optimize different objectives. The agents periodically negotiate a compromise policy for the operation of the system. Agents' attitudes in each negotiation step are determined by the recent system performance measured by the specific objective they maximize. We then propose a numerical model of preference dynamics that implements a concept from cognitive psychology, the availability bias. We test our modeling framework on a synthetic lake operated for flood control and water supply. Results show that our model successfully captures the operator's preference selection and dynamic evolution driven by extreme wet and dry situations.


## 1 Introduction

Recent estimates suggest that existing dams control around 46% of the world largest rivers, i.e., rivers having an average flows above 1000 $m^3$/s [*Lehner et al.*, 2011]. This figure is expected to grow rapidly following the renewed interest in dams as a primary mean to secure water and energy in fast developing African and Asian countries [*World Bank*, 2009; *Zarfl et al.*, 2014]. Massive infrastructure expansion will further enlarge the number of river systems whose dynamics is not only determined by their natural streamflow regime according to naturally varying rainfall, climate, and hydrologic conditions [*Botter et al.*, 2010], but is mediated by human decisions driven by one or multiple operating purposes [*Caldas et al.*, 2015]. Understanding and representing such human component is therefore crucial for characterizing the observed complex dynamics of these systems [e.g., *Van Emmerik et al.*, 2014; *Elshafei et al.*, 2015], for retrospectively assessing the behavior of the water operators and the associated system performance [e.g., *Hejazi and Cai*, 2011], and for constructing more reliable and credible projections of the future evolutions [e.g., *Wagener et al.*, 2010].

This evidence has been the inspiring principle for the development of a number of modeling frameworks explicitly representing both the natural and the human components, along with their reciprocal interactions, feedbacks, and coevolution in time [e.g., *Sivapalan and Blöschl*, 2015]. These frameworks include Coupled Human-Natural Systems [*Liu et al.*, 2007], Coupled Environmental-Human Systems [*Horan et al.*, 2011], Socio-Hydrology [*Sivapalan et al.*, 2012], and Socio-Environmental Systems [*Filatova et al.*, 2016]. Within these approaches, human behaviors are generally represented according to two distinct perspectives [*Smith*, 1991]: descriptive models, which describe the internal decision mechanisms, and normative models, which focus on motivation-based actions that maximize idealized objective functions. Specifically, descriptive models implement behavioral rules describing human actions in response to changing forcing (e.g., hydro-meteorological). Rules are inferred either from observational data [e.g., *Hejazi et al.*, 2008] or general theories [e.g., *Giacomoni and Berglund*, 2015; *Sanderson et al.*, 2017]. The resulting models often include a large number of assumptions and parameters, which limit the possibility of generalizing these behaviors to study future decisions under altered boundary conditions. Besides, a rigorous validation of behavioral rules against observational data not used in the model calibration is often impossible or missing, and thus detrimental to the reliability of the models' outputs [*Ligtenberg et al.*, 2010]. Normative models, instead, assume that rational agents maximize a certain utility function [*Becker*, 1978; *Kagel and Roth*, 1995] and human decisions are the argument of an optimization problem. This hypothesis has been often contradicted by observations of individual behaviors [*Simon*, 1957, 1982; *Kahneman et al.*, 1991], but it can be considered acceptable in case of institutional decisions or average behaviors of groups of individuals (e.g., group of farmers) having a clear, single operating target [*Giuliani et al.*, 2016a]. Assuming this objective captures the real interest driving the observed behaviors and such objective is time-invariant, then future behaviors can be correctly reproduced by solving the same optimization problem under different boundary conditions. For example, hydropower operators make decisions by maximizing the resulting revenue for the energy company or by minimizing the deficit with respect to an energy demand. Energy price and demand and the hydrology will change in the future, while the overall objectives of the companies will very likely remain the same, i.e., the hydropower operators will continue maximizing the revenue or satisfying the demand [e.g., *Turner et al.*, 2017].

Most water systems, however, are operated to meet multiple competing purposes, and this makes it impossible to determine a single optimal solution to the formulated optimization problem and, correspondingly, to extract a single behavior of human operators. Rather, in a multi-objective context the single optimal solution is replaced by a set of Pareto optimal solutions, where each alternative represents a different tradeoff between the considered objectives. Here, the operator's behavior is not univocally defined but strongly depends on the relative importance assigned to the different operating objectives, namely his/her set of preferences. This tradeoff generally represents the outcome of a negotiation process with the involved stakeholders [e.g., *Swartz*, 2006] and is expected to ensure a fair water allocation among the competing demands under long-term average hydroclimatic and socio-economic forcing. The identification of the operator's preferences in terms of tradeoff among competing objectives represents the first challenge for accurately modelling observed human behaviors in multipurpose water systems.

Then, assuming we can identify such tradeoff from observed behaviors, the identified preferences are not static behavioral attributes [*Guiso et al.*, 2013]. Rather, they may evolve in time when exposed to changing external forcing (e.g., extreme drought or flood events), which can make the system temporarily underperforming in one or more operating objectives. By reacting to this imbalance, the preferences shift towards a new equilibrium in order to reduce the frequency of unsatisfactory system states, bringing the short-term performance closer to the one expected on the long-term [*Simpson et al.*, 2016]. For example, an extreme flood event may raise concerns about flood risk [e.g., *Haasnoot and Middelkoop*, 2012; *Di Baldassarre et al.*, 2013; *Viglione et al.*, 2014] and suggests to increase dike heights or to enlarge the flood pool for augmenting the reservoir buffering capacity. On the contrary, prolonged and intense drought events may amplify human sensibility towards water scarcity [e.g., *Aghakouchak et al.*, 2014], promoting an increase in the efficiency of the water supply system by modernization of the infrastructure and by more effective hedging strategy. Reproducing the dynamics of human preferences driven by the changing external forcing is the second main challenge for building projections of coupled natural and human processes' co-evolution.

This paper contributes a new data-driven modeling approach to describe observed tradeoff (preference) evolution in time as a dynamic process combining the selection of different optimal tradeoffs among the operating objectives with the variation of external forcing (e.g., extreme flood or drought events) altering the expected system performance. Our approach fits together with emerging works in socio-hydrology exploring the mutual shaping of hydrological extremes and societies [e.g., *Di Baldassarre et al.*, 2015; *Kuil et al.*, 2016; *Di Baldassarre et al.*, 2017]. Specifically, we first map the system operator selection of a tradeoff onto a multilateral negotiation process, formalized according to a newly developed protocol called Set-based Egocentric Concession (SEC) protocol. The tradeoff evolution is then modeled by means of SEC negotiations periodically repeated in time implementing the concept of availability bias [*Tversky and Kahneman*, 1973], where the outcomes of the future negotiation (i.e., the selection of the new tradeoff) are influenced by the recent system performance in each operating objective.

In the computer science literature, negotiation frameworks are traditionally designed to model autonomous agents that competitively bargain to identify the solution of a cooperative problem [e.g., *Rubinstein*, 1982], with several applications also developed in environmental problems [e.g., *Frisvold and Caswell*, 2000; *Thoyer et al.*, 2001; *Šauer et al.*, 2003; *Madani*, 2011, 2013]. In this work, the modeled agents represent the different objectives that the water operator is called to balance in the management of the system [*Franssen*, 2005; *Kasprzyk et al.*, 2016]. The negotiation starts with each agent proposing its favorite solution maximizing the specific objective it represents. The mediator checks if the negotiation reached an agreement (i.e., if a shared solution exists among the proposals). Otherwise, each agent updates its own proposal by including new solutions that are less satisfactory for the proposing agent than the ones previously proposed. The negotiation continues until a solution performing acceptably on all the objective is found. The agreement is therefore a good representation of the tradeoff selected by the operator. The agents' attitudes during the negotiation determine a specific balance between the different objectives in the final agreement. Rigid agents only accept solutions with limited degradation of performance with respect to their individual optimum, while more cooperative agents are willing to accept larger reductions in their individual satisfaction. The observed tradeoff can be therefore identified by properly calibrating the attitude of each agent in the simulated negotiations. This looks similar to the identification of a vector of preference weights used to balance different objectives in a traditional multi-objective decision making approach [*Cohon and Marks*, 1975]. Yet, the proposed SEC protocol fits a decentralized approach addressing each objective in a distinct way, allowing attitudes to be private features of the agents, as opposed to weights that are public and also interrelated because they sum to one. SEC negotiations are then repeated in time on a regular basis, with the attitudes of the agents reflecting the operator's preferences that are conditioned on the recent system performance. This link between recent system performance, which depends on the experienced hydro-meteorological conditions, and agents' attitudes allows simulating the evolution of the selected tradeoff as driven by extreme wet and dry situations.

The approach is demonstrated on a synthetic case study, where a lake is operated to balance shoreline floods and irrigation deficit downstream. The system is exposed to highly variable inflow patterns, which alternate periods of high, normal, and low flow conditions that strongly impact on the two competing objectives. The calibration of the agents' attitudes for simulating their negotiations according to the proposed SEC protocol allows identifying the tradeoff adopted in the lake operations. The time evolution of the operator's tradeoff after extreme wet or dry periods is then reproduced by periodically repeating the SEC negotiations and updating the agents' attitudes on the basis of the recently experienced system performance. For example, if the flooding agent has experienced large damages produced by an extreme flood event, its attitude during the negotiation becomes more rigid to obtain an agreement that corresponds to a tradeoff more in favor of flood protection. Conversely, if the agent has experienced very low (or no) flood damages, its attitude will be more cooperative.

The rest of the paper is organized as follows: the next section introduces our modeling framework and the numerical case study; section 3 presents the numerical results; final remarks, along with directions for further research, are presented in the last section.

## 2 Material and methods

The proposed approach for modeling the dynamic evolution of water operators' preferences is composed of two components: a first step aiming at the identification of the selected tradeoff among a vector of $N$ competing objectives $\mathbf{J} = |J^1, \ldots, J^N|$ (to be maximized) under average hydroclimatic conditions by means of the Set-based Egocentric Concession negotiation (Figure 1a), and a second step reproducing the dynamic evolution of this tradeoff when exposed to changing external forcing (e.g., extreme wet or dry periods).

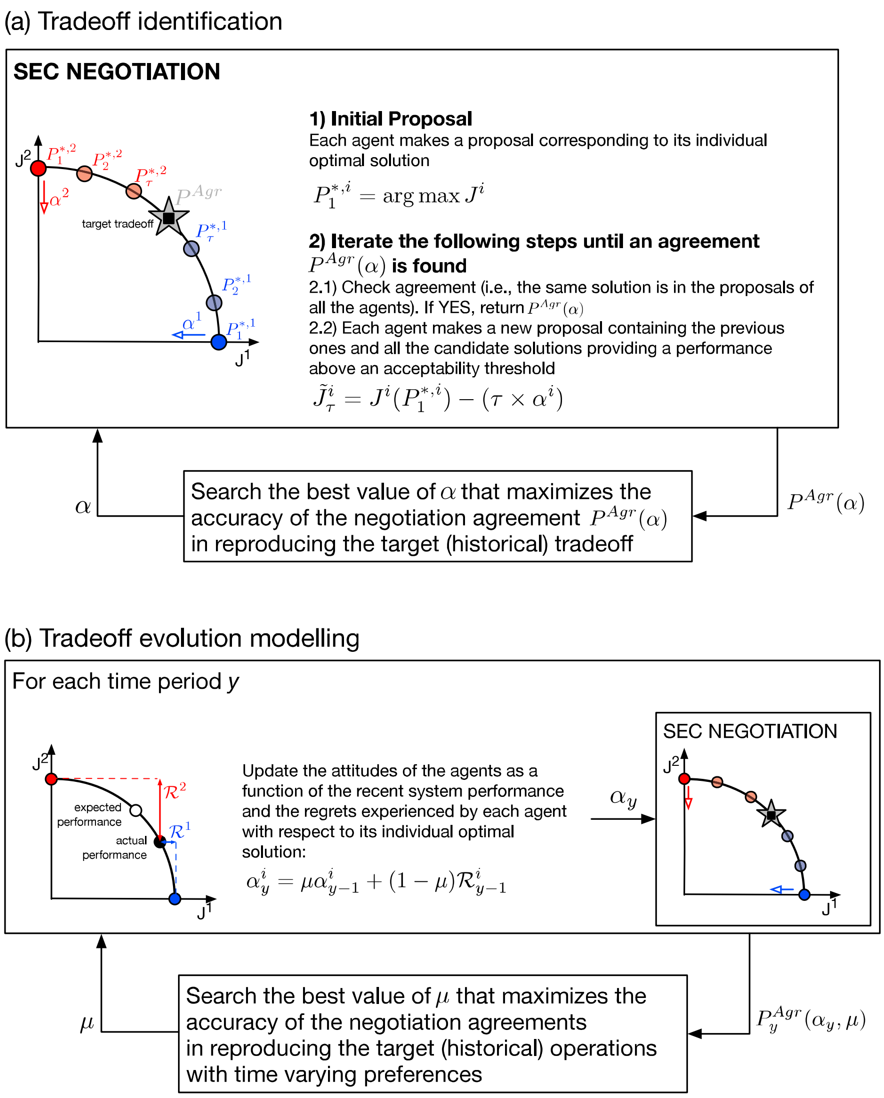


**Figure 1.** Schematization of the tradeoff identification (panel a) and tradeoff evolution modeling (panel b).

This tradeoff evolution modelling relies on repeated SEC negotiations where the agents' attitudes are updated according to the recent system performance (Figure 1b). In the next two sections we provide a detailed description of these two components, while section 2.3 illustrates the synthetic case study used for testing our modeling framework. It is worth mentioning that the proposed method applies to systems where preference dynamics impact on operational decisions or on a sequence of infrastructural decisions (e.g., the expansion of a water supply system), while it does not fit with static planning decisions made once (e.g dam design).

### 2.1 Tradeoff identification

For the problem of tradeoff identification (Figure 1a), we developed the Set-based Egocentric Concession protocol. Similarly to other negotiations protocols [e.g., *Rosenschein and Zlotkin*, 1994; *Faratin et al.*, 2002; *Saha and Sen*, 2007; *Lopez-Carmona et al.*, 2011], SEC is based on a negotiation mechanism where, at each step $\tau$, each agent $i$ simultaneously makes a proposal $P^i_\tau$, defined as a set of candidate solutions attaining an acceptable performance in the objective $J^i$ represented by agent $i$. Specifically, agents never remove any previously proposed candidate solution, while adding one or more solutions to their proposal set. The proposals are collected by a mediator, which verifies if the negotiation has reached an agreement. The presence of the mediator allows reducing the number of messages exchanged by the agents and improving agents' privacy. The negotiation then proceeds toward an agreement thanks to the egocentric nature of the protocol as each agent is not allowed to make proposals less preferred by other agents than what has been already proposed. This feature ensures that the protocol is monotonic [*Endriss*, 2006], where each new proposal must contain a concession to another agent. Given the conflicting nature of the agents' interests, a decrease in the utility of one agent is equivalent to an increase in the utility of another one. The negotiation continues with the agents making new proposals, corresponding to concessions made to the other agents, until the mediator notifies them that an agreement $P^{Agr}$ has been reached. This occurs when the $i$-th agent proposal $P^i_\tau$ contains (at least) a specific candidate solution that is also included in all other agents' proposals $P^{-i}_\tau$.

At the beginning of the negotiation $\tau = 1$, the $i$-th agent makes a proposal that corresponds to the optimal solution $P^{*,i}_1$ with respect to his/her single objective $J^i$. Since the objectives are conflicting, $P^{*,i}_1$ will correspond to a solution characterized by a poor performance according to the point of view of the other agents. Then, at each negotiation step, the agents use a constant concession strategy [*Bădică and Bădică*, 2012] to select the next set of candidate solutions $P^i_{\tau+1}$, which contains their previous candidate solutions along with all the solutions that provide a performance above an acceptability threshold defined as $\tilde{J}^i_\tau = J^i(P^{*,i}_1) - \delta^i_\tau$. This threshold is lowered at each negotiation step $\tau$ with a constant rate $\alpha^i$, i.e., $\delta^i_\tau = \tau \times \alpha^i$. Therefore, the proposal set of each agent grows with the number of negotiation steps, including more and more alternatives which are less favorable with respect to the single agent objective. The value of $\alpha^i$ characterizes the attitude of the $i$-th agent: small values of $\alpha^i$ characterize an agent which is rigid in conceding, and the resulting operating policy will be polarized toward its objective; conversely, large values of $\alpha^i$ correspond to a more cooperative attitude, with the agent willing to accept agreements which might be far from its individual optimum. The identification of the tradeoff can be hence performed via calibration of the agents' attitudes by setting proper values of the concession rates $\boldsymbol{\alpha}$ in order to drive the final agreement of the SEC negotiation as close as possible to the target tradeoff.

Additional details about the algorithm used by each agent during the SEC negotiation, along with a discussion of some properties of the protocol (e.g., termination condition, privacy, Pareto optimality, possibility of discovering solutions in concave regions of the Pareto front [*Endriss*, 2006; *Amigoni et al.*, 2016]) are reported in the Supporting Information.

### 2.2 Tradeoff evolution modelling

The SEC negotiations described in the previous section allow identifying a static tradeoff. Here, we expand the protocol to capture the temporal dynamics of tradeoff evolution as a consequence of changing external forcing (Figure 1b). The key idea is to numerically model the agents' attitudes, i.e., the concession rates $\alpha^i$, as a function of the recent system performance which, in turn, varies when exposed to changing external forcing. Similarly to the approach proposed in *Di Baldassarre et al.* [2017], we implement an autoregressive dynamic model implementing the availability bias expressed in *Tversky and Kahneman* [1973], which is formulated as follows

$$\alpha_y^i = \mu\alpha_{y-1}^i + (1-\mu)\mathcal{R}_{y-1}^i \tag{1}$$

where $\alpha_y^i$ is the attitude (concession rate) of agent $i$ during the negotiation at the beginning of the time period $y$; $\mu$ is a behavioral parameter reflecting the agent's memory; $\mathcal{R}_{y-1}^i$ is the regret of agent $i$, defined as the difference between the utility of agent $i$ over the time period $[y-1, y)$ under the agreement reached during the last negotiation and the maximum possible utility of agent $i$. The first addendum quantifies the inertia of the agent's attitude, with the new value $\alpha_y^i$ that depends on the one adopted in the previous negotiation $\alpha_{y-1}^i$. The second addendum, instead, represents the level of satisfaction of the agent about the outcome of the previous negotiation. The effect of this outcome is halved after $\log 0.5/\log\mu$ periods.

A distinct feature of our modeling approach is the calibration of the behavioral parameter $\mu$ with respect to the observed decisions of the water operator. This calibration is crucial for capturing the observed evolution of the agents' attitudes: if $\mu = 0$, there is no memory and the new concession rate only depends on the most recent system performance; conversely, $\mu = 1$ yields a constant concession rate which is no longer dependent on the system performance. Intermediate values of $\mu$ produces a dynamic evolution of the agents' attitudes: agent $i$ becomes more rigid (i.e., lower values of $\alpha_y^i$) after having experienced high values of regret, while its attitude remains almost constant in case the outcome of the previous negotiation is satisfactory (i.e., the recent performance is close to the maximum utility agent $i$ could have obtained independently).

### 2.3 Test case study

We demonstrate the proposed framework on a numerical case study inspired by the Lake Como system in northern Italy [*Pianosi et al.*, 2013; *Giuliani et al.*, 2016b]. The daily dynamics of the system is described by the mass-balance equation of the lake storage ($x_t$), which is regulated to provide a reliable irrigation supply to downstream farmers and to control floods along the lake shores. These two competing interests are modeled using the following two objective functions (both to be maximized):

- Flooding ($J^1$): the average daily lake level exceedance with respect to the flooding threshold (multiplied by -1 to ensure the correct direction of optimization).
- Irrigation ($J^2$): the daily water deficit with respect to the irrigation demand (multiplied by -1 to ensure the correct direction of optimization).

The daily operation of the lake is formalized as a Standard Operating Policy [*Draper and Lund*, 2004], defined as a parameterized piecewise linear function mapping the lake storage into release decision $u_t = \pi_\theta(x_t)$, where $\theta \in \Theta$ is the vector of the policy parameters. The value of the parameters, and thus the shape of the policy, is determined by the tradeoff between the agents' objectives: the best solution in terms of $J^1$ is to maintain very low storage values by releasing the maximum volume of water in each time step to minimize the flood risk; conversely, the best solution in terms of $J^2$ is to release the water demand and store any excess of water to face future dry periods. The full set of Pareto

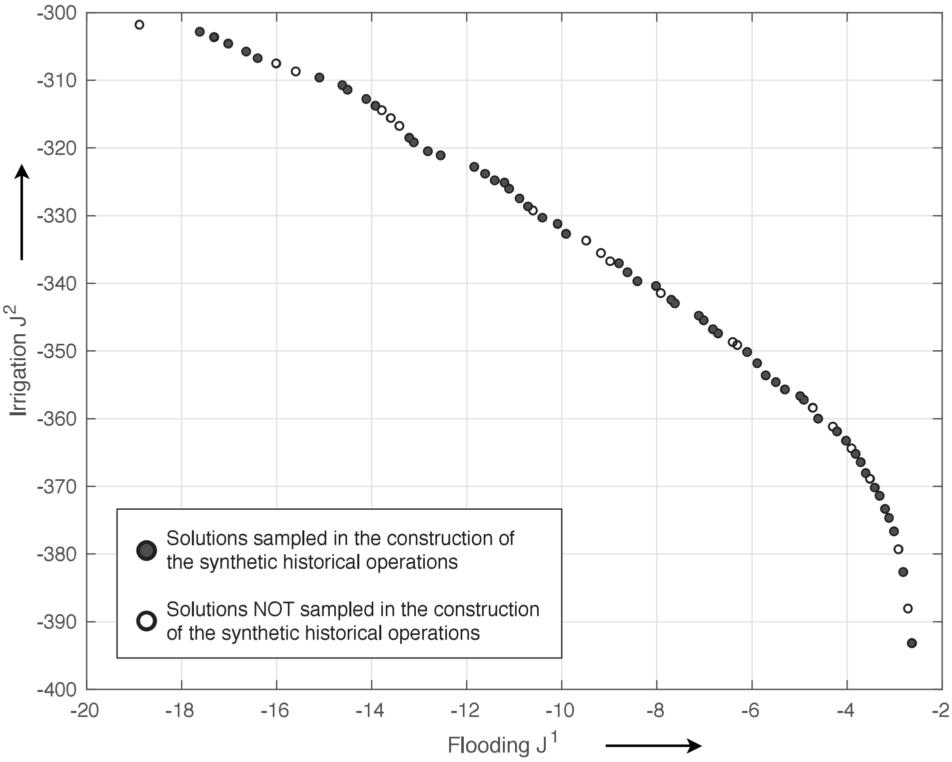


**Figure 2.** Pareto optimal operating policies' performance in terms of Flooding (x-axis) and Irrigation (y-axis) objectives. Black circles represent solutions sampled in the construction of the synthetic historical operations with time-varying operator's preferences, whereas white circles are solutions which were not used.

optimal operating policies can be obtained by solving the following problem

$$\theta^* = \arg\max_{\theta} \mathbf{J} \tag{2}$$

where $\mathbf{J} = [J^1, J^2]$. Determining $\theta^*$ is equivalent to finding the corresponding parameterized operating policies $\pi_\theta(x_t)$ [*Giuliani et al.*, 2016c]. Sampling a sequence of tradeoff solutions from the Pareto optimal set (see Figure 2) allowed the construction of a synthetic historical operations of the system with time-varying preferences according to the variability of the inflow scenario. In the next section, we will demonstrate the potential of our modeling approach (Figure 1) for identifying the tradeoff of this synthetic historical operations, obtained by a single sampled policy over a time period with steady-state inflow, and for reproducing the dynamic evolutions of the tradeoff over the whole sequence of sampled policies. The full formulation of Problem (2) is reported in the Supporting Information, while the source code and data are available on Github (https://github.com/Lordmzn/evolving-tradeoffs).

| Climate state | $F(\cdot)$ | $m\ [m^3/s]$ | $s\ [m^3/s]$ | $b$ |
|---|---|---|---|---|
| Dry | 0.15 | log(15) | 0.3 | 0.9 |
| Normal | 0.75 | log(40) | 0.65 | 0.7 |
| Wet | 0.1 | log(75) | 0.75 | 0.5 |

**Table 1.** Parameters used in the inflow scenario generation: $F(\cdot)$ is the probability of occurrence of the climate state; $m$ and $s$ are the mean and standard deviation defining the log-normal distribution; $b$ is the autocorrelation coefficient; the autocovariance is equal to 0.75 in each scenario.

During the negotiation, each agent solves a single-objective variant of Problem (2) optimizing the operating policy with respect to its individual objective. In addition, each agent has to explore its fitness landscape (i.e., a multidimensional landscape defined by the possible solutions of the optimization problem mapped into the corresponding objective function value [*Maier et al.*, 2014]) in order to implement the constant concession strategy of the SEC protocol (see section 2.1). We perform this step before the beginning of the negotiation through a uniform sampling in the operating policy parameter space $\Theta$, from which the objective functions $\mathbf{J}$ are evaluated via simulation of the system dynamics over a given inflows trajectory sufficiently long to represent wet, normal, and dry conditions.

The synthetic inflow trajectory is constructed with a two-level procedure: a Thomas-Fiering model, where daily inflows are generated by an autoregressive model (AR) with log-normal distribution [*Harms and Campbell*, 1967], combined with an hidden Markov model which determines its parameters according to three different climate states corresponding to dry, normal, and wet conditions. The parameters used for the inflow generation are reported in Table 1. The resulting empirical cumulative distribution function for the different climate states and the associated relevant statistics for the two objectives are illustrated in Figure 3.

## 3 Numerical results

We numerically tested our modeling approach on the synthetic case study introduced in the previous section by performing the following experiments: *i*) we demonstrate the ability of SEC negotiations (section 2.1) in identifying alternative tradeoffs in repeated negotiations over a sequence of 100 periods, which includes dry, normal, and wet condi-

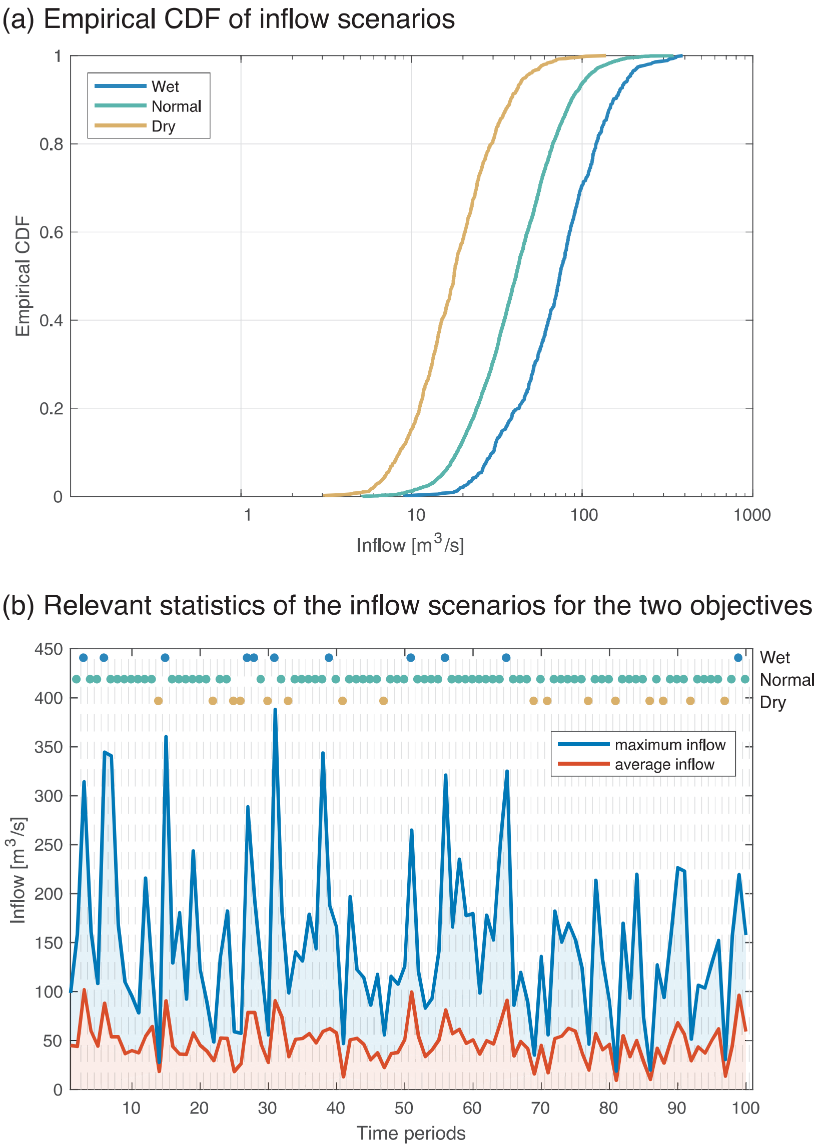


**Figure 3.** Cumulative distribution functions for the synthetic inflows (panel a), where the color indicates the underlining Dry, Normal or Wet parameter set (see Table 1). Relevant statistics for the two considered objectives (i.e., maximum and average inflow over the time period for flooding and irrigation, respectively) of the generated inflow scenario over 100 time periods (panel b).

tions, with the goal of reproducing the synthetic historical operations of the system with time-varying tradeoffs; *ii*) we calibrate our dynamic attitudes model (section 2.2) over a sequence of 1000 periods trying to explicitly condition the evolution of the tradeoffs upon the recent system performance. In each experiment, the domain of the attitude parameters is $\alpha^1 = [0.005; 0.5]$ and $\alpha^2 = [0.005; 2.5]$. In the tradeoff identification, we calibrate the agents' attitude in order to reproduce the synthetic historical tradeoff by searching the best value of $\boldsymbol{\alpha}$ over a regular grid of 36 possible values for each parameter. In the tradeoff evolution modelling, the values of $\boldsymbol{\alpha}$ are dynamically updated using eq. 1, with the simulation initialized with $\alpha^1 = \alpha^2 = 0.1$. To demonstrate the scalability of the approach to more than two objectives, in the Supporting Information we report another tradeoff evolution modelling experiments run for a three objectives/agents problem.

### 3.1 Tradeoff identification

In this section, we run a retrospective analysis where the proposed SEC negotiation protocol is used to identify the selected tradeoffs from observations of the synthetic historical operations of the system over a scenario composed of 100 time periods characterized by dry, normal, or wet conditions according to the probabilities reported in Table 1. In each time period, the two agents, representing the flooding and the irrigation objectives respectively, negotiate the value of the Standard Operating Policy parameters $\theta \in \Theta$ for different combinations of concession rates $\boldsymbol{\alpha}$, defined over a uniform grid obtained as the Cartesian product of the respective discretized domains. Each combination of $\alpha^i$ (with $i = 1, 2$) produces a different negotiation outcome (i.e., standard operating policy), corresponding to a different balance of the conflicting objectives based on the attitudes of the two agents. The simulation of the negotiated policies produces a set of release trajectories. The tradeoff of the synthetic historical operations can be hence identified by looking at the accuracy in reproducing the synthetic historical release trajectory, measured in terms of coefficient of determination $R^2$. The negotiated policy attaining the maximum value of $R^2$ is the one having the closest tradeoff to the synthetic historical one.

Figure 4 illustrates the SEC negotiation process in a single time period: at the beginning of the negotiation ($\tau = 0$), each agent explores its fitness landscape by mapping each parameter vector $\theta \in \Theta$, which defines a different Standard Operating Policy, into its corresponding objective function $J^1$ or $J^2$ computed over the entire inflow scenario to represent the long-term average hydrologic conditions. The colormap is proportional

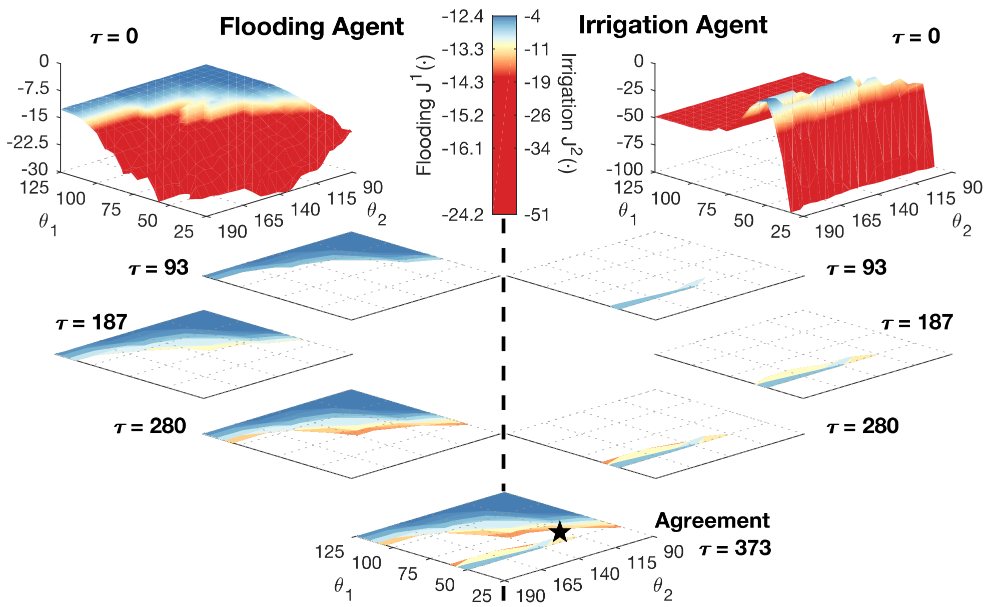


**Figure 4.** Excerpt of the SEC negotiation in a single time period. At the beginning of the negotiation, each agent explores its fitness landscape. The colormap is proportional to the performance of each solution, moving from blue (good performance) to red (poor performance). The negotiation starts with both agents proposing their individual optimal solutions in the first step and proceeds with the agents enlarging their proposal set at each step with less preferred solutions. Eventually, an agreement is found when a specific solution is included in the proposals of all the agents.

to the performance of each solution, moving from blue (good performance) to red (poor performance). Then the negotiation starts with both agents proposing their individual optimal solutions in the first negotiation step and proceeds with the agents enlarging their proposals at each step (e.g., $\tau$ = 30, 110, 177 representing 25%, 50%, 75% of the negotiation) including less preferred solutions according to the monotonic concession strategy. The concession of each agent is modulated by its attitude $\alpha^i$. Eventually, an agreement is found when a specific solution is included in the proposals of all the agents.

The best combination of concession rates for this specific time period is $\boldsymbol{\alpha} = [0.01, 0.05]$. The resulting operating policy accurately reproduces the synthetic historical one ($R^2$ = 0.95) and attains almost equivalent performance in terms of flood control and irrigation supply, i.e. $\mathbf{J}$ = (-10.82, -389.6) against a target performance $\mathbf{J}^T$ = (-11.14, -365.5).

In this tradeoff identification experiment, we repeated the SEC negotiations in each time period, independently searching the values of $\boldsymbol{\alpha}$ that produce a trajectory of releases

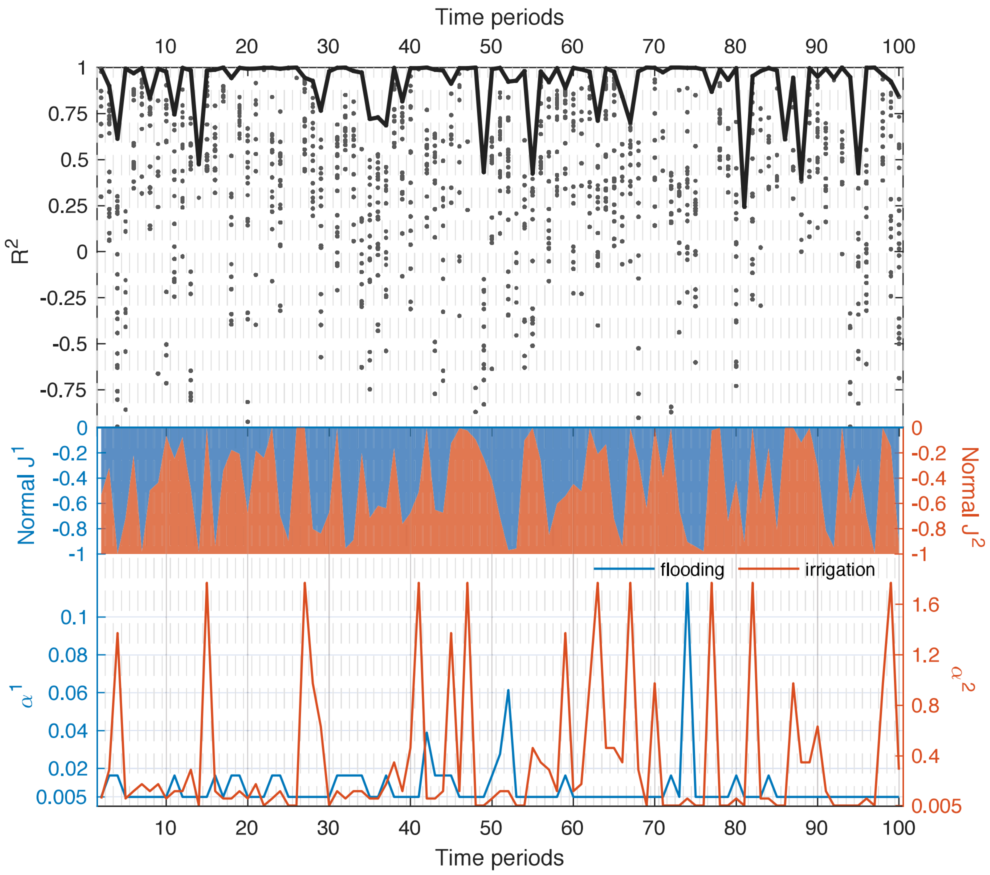


**Figure 5.** Model accuracy over a 100 time periods scenario obtained through repeated SEC negotiations (top), corresponding tradeoff (middle), and associated best values of $\alpha$. In the top panel, the black solid line represents the best solution found in each time period, while the single dots are solutions obtained with other values of $\alpha$.

reproducing the synthetic historical one. Numerical results are illustrated in Figure 5, which shows the values of $R^2$ obtained over the 100 time periods. The black solid line represents the best solution found in each time period (the single dots are instead solutions obtained with other values of $\alpha$), which attains an average $R^2$ equal to 0.91 over the entire evaluation scenario. The low $R^2$ values in the figure can be explained by the discretized domains of $\alpha$ and of the policy parameters adopted during the agents' negotiations, while the synthetic hystorical operations was designed without such constraint. These results demonstrate the flexibility of SEC negotiations in modeling the diverse tradeoffs (middle panel of Figure 5) adopted in the synthetic historical operations by modifying the agents' attitudes over the different time periods (bottom panel).

### 3.2 Tradeoff evolution modelling

The results of the repeated negotiations illustrated in Figure 5 require the selection of proper concession rate values $\alpha$ in each time period by maximizing the accuracy in reproducing the synthetic historical sequence of releases. Conversely, these values can be determined by means of the dynamic attitudes model described in section 2.2 for projecting possible evolutions of the operator's tradeoff in the future, when we have no historical operations to reproduce. The core of the model is eq. (1), which implements the availability bias and defines the attitude of each agent as a function of the recent system performance. This function requires the calibration of the behavioral parameter $\mu$ over a sufficiently large dataset of observed tradeoff changes. To this purpose, in this second experiment we considered a scenario composed of 1000 time periods, which is assumed to represent the long-term average hydrologic conditions used to estimate the maximum expected utility of each agent for the computation of the regret $\mathcal{R}^i_{y-1}$ in eq. (1). We repeated the SEC negotiations over each time period $y = 1, \ldots, 1000$, where, rather than searching the best values of $\alpha$ for each time period as in the Figure 5, we updated the vector $\boldsymbol{\alpha}$ via eq. (1). The procedure is repeated for different values of $\mu$ sampled from a uniform grid in the range [0.01, 1], where $\mu = 1$ yields constant values of $\alpha$ over time, thus representing a stationary preference set.

The accuracy of the attitude's dynamic model as a function of the behavioral parameter $\mu$ is illustrated in Figure 6 (top panel). Numerical results show that the proposed model is sensitive to the adopted values of $\mu$, with variable accuracy levels ranging from $R^2 = 0.58$ (for $\mu = 1$) to $R^2 = 0.63$ (for $\mu = 0.736$). This limited sensitivity of the model performance with respect to $\mu$ is probably due to the linear, low-order autoregressive model formulation used in the analysis and to the nature of the specific problem (e.g., in the three objective problem reported in the Supplementary Information the values of $R^2$ vary between 0.65 and 0.85). The underlying relationship between the experienced inflow scenario and the dynamics of the agents' attitudes is represented in Figure 6 (bottom panel). Depending on the value of $\mu$ reported on the $y$-axis, the attitudes of the two agents have different correlations with the inflow scenarios, characterized in terms of the maximum and the average inflow in the time period to represent relevant statistics for flood protection and irrigation supply. The attitude of the agent representing the flooding objective (left panel) is positively correlated with the maximum inflow in the time period, with the highest correlations observed for low values of $\mu$ and short lag-times. Conversely, the attitude of the agent representing the irrigation objective (right panel) is negatively correlated with the average inflow in the time period, with the maximum negative correlation observed again for low values of $\mu$ and short lag-times. This situation corresponds to extremely sensitive attitudes, with the agents becoming highly conservative every time a flood/drought event occurs. When $\mu = 0.736$, the value producing the highest model accuracy, we can observe positive and negative correlations over longer lag-times. This result demonstrates that the proposed attitude's dynamic model, which defines the values of $\alpha$ on the basis of the recent system performance, is indirectly reproducing the evolution of the tradeoff as driven by the changing inflow scenarios.

To better understand the relationships among agents' attitudes, utilities, and underlying hydrologic conditions, Figure 7 illustrates an excerpt of the results in terms of system performance obtained by the synthetic historical operations in each time period (top panel), agents' attitudes values for two different values of $\mu$ (middle panels), and the maximum and the average inflow in the time period (bottom panel). The figure shows how after large inflow peaks (e.g., the peak of the blue line at time period 217 in the bottom panel), the values of $\alpha^1$ tend to increase, and this effect lasts for longer when the agents' have a longer memory (i.e., $\mu = 0.736$). Similarly, periods of low inflow (e.g., the low values of the red line at time period 210 in the bottom panel) produce increasing values of $\alpha^2$. In both cases, these modifications of the agents' attitudes successfully capture the change of tradeoff in the synthetic historical operations (top panels), which, after observing a low performance in one of the two objectives, tend to favor the underperforming one in the next time periods (e.g., see the increasing values of $J^2$ after the dry periods 209-210, which resulted in a very low performance in terms of water supply).

Finally, it is worth noting that the values of $\mathrm{R}^2$ reported in Figure 6 are significantly lower than the ones discussed in the previous section, where the repeated calibration of $\alpha$ in each time period allowed attaining an average $\mathrm{R}^2$ equal to 0.911. This degradation of performance is probably due to the structural limitations associated to the linearity and low autoregressive order of the implemented attitudes' dynamic model. However, this value of accuracy per se, obtained over a very long time series of interdependent natural and human processes, represents a promising starting point for modeling evolving water operator's preferences and projecting the coevolution of the system under changing climate and socio-economic drivers.

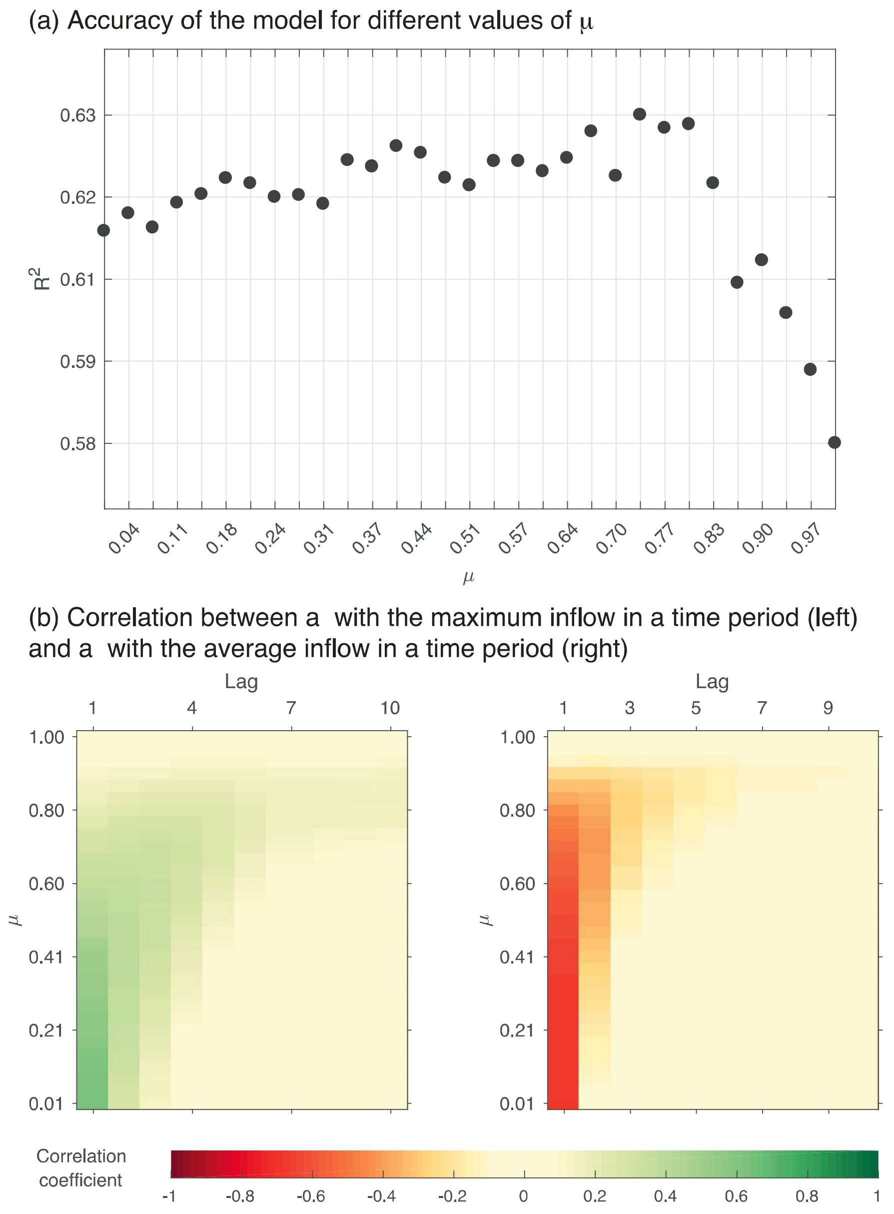


**Figure 6.** Accuracy of the attitudes' dynamic model in reproducing the synthetic historical releases over a 1000 time periods scenario (panel a). Correlation analysis between the trajectories of the parameters $(\alpha^1, \alpha^2)$ and some features of the inflow scenario (maximum inflow and average inflow, respectively) for different values of $\mu$ and increasing lag-times (panel b).

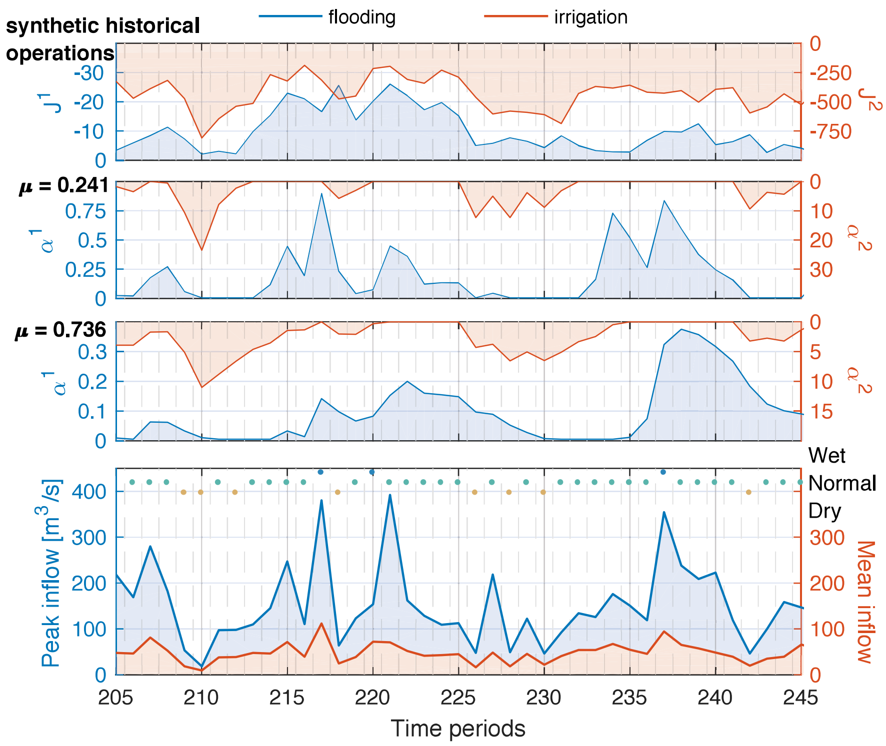


**Figure 7.** Dynamic preference response in terms of synthetic historical operations and agents' attitudes for different values of $\mu$ to the experienced inflow conditions.

## 4 Conclusions

This paper contributes a new modeling approach for the identification of the tradeoff selected by a water operator in the management of a multipurpose water resource systems, and the model-based simulation of the dynamic evolution of such tradeoff when exposed to extremely wet and dry events. The tradeoff identification is reproduced via multilateral negotiations according to a new Set-based Egocentric Concession protocol. The evolution of the tradeoff is then modeled through the repetitions of the SEC negotiations, with the attitudes of the agents determined by the recent system performance. A synthetic case study representing a lake operated for flood control and irrigation supply exposed to dry, normal, and wet conditions is used to demonstrate the proposed approach.

Numerical results show that SEC negotiations allow identifying the operator's tradeoff via calibration of the attitudes of the agents involved in the negotiation. The identified tradeoffs reproduce the synthetic historical operations of the lake over a sequence of 100 time periods with variable external forcing and water operator's preferences. The resulting model accuracy (average $R^2$ higher than 0.9) demonstrates the potential of SEC in supporting retrospective analysis of observed human behaviors in multipurpose contexts. SEC negotiations are then successfully coupled with the autoregressive dynamic attitude model, which, according to the availability bias, links the evolution of the selected tradeoff with the recently experienced system performance. Our results show that the best model parameterization attains acceptable accuracy levels (i.e., $R^2$ = 0.63) over a 1000 time periods simulation horizon, thus representing a promising solution for describing the coevolution of the natural processes and human behaviors under changing climate conditions.

Future research efforts will focus on testing the proposed approach in a real world system to retrospectively identify the historical tradeoff and to make a projection of the system evolution under changing climatic and socio-economic forcing. This will require long behavioral time series exposed to a sufficiently high number of shocks, which would also allow a better exploration of the sensitivity of our results to some key parameters (e.g., agents' attitudes and memory) and model settings (e.g., increasing the order of the autoregressive attitude model). In addition, looking at long-term projections and non stationary alterations of the hydrologic conditions will also require exploring the dynamics of the Pareto front. In fact, while under stationary conditions we can focus on modelling the tradeoff dynamics along a given Pareto front computed over average conditions, under non-stationary conditions this reference front is very likely evolving as well. However, although the results of this paper were generated for a synthetic case study, they demonstrate the potential of the proposed approach. A key outcome of this study is the formalization of a modeling procedure able to reproduce potentially evolving water operators' preferences as driven by extreme wet and dry events. This result has significant implications for the construction of reliable projections of the future evolutions of Coupled Human-Natural Systems.

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