PLANNING THE OPTIMAL OPERATION OF A MULTI-OUTLET WATER RESERVOIR WITH WATER QUALITY AND QUANTITY TARGETS

Andrea Castelletti[1], M. ASCE; Hiroshi Yajima[2]; Matteo Giuliani[3]; Rodolfo Soncini-Sessa[4]; and Enrico Weber[5]

ABSTRACT

The integration of quality and quantity issues in the management of water resources systems is key to meet society's long-term needs for freshwater while maintaining essential ecological services and economic benefits. Current water management practices are mostly targeted towards quantitative uses and quality is usually addressed separately as an independent problem. One of the reasons for the lack of integration lies in the inadequacy of optimization techniques nowadays available to cope with the large, distributed, simulation models adopted to characterize the coupled ecological and biochemical processes in water bodies. In this paper we propose a novel approach based on the conjunctive use of a batch-mode Reinforcement Learning algorithm and a 1D coupled hydrodynamic-ecological model to design the optimal operation of a multipurpose water reservoir accounting for both quantity and quality targets. We consider up to five operating objectives, including both in-reservoir and downstream water quality parameters, and design efficient operating policies conditioned upon not only the current storage but also water characteristics, such as

[1]Assistant Professor, Dept. Electronics and Information, Politecnico di Milano, P.za Leonardo da Vinci, 32, 20133 Milano, Italy. E-mail: castelle@elet.polimi.it.
[2]Associate Professor, Dept. Management of Social Systems and Civil Engineering, Tottori University, Koyama, Tottori 680-8552, Japan. E-mail: yajima@cv.tottori-u.ac.jp.
[3]PhD student, Dept. Electronics and Information, Politecnico di Milano, P.za Leonardo da Vinci, 32, 20133 Milano, Italy. E-mail: giuliani@elet.polimi.it.
[4]Professor, Dept. Electronics and Information, Politecnico di Milano, P.za Leonardo da Vinci, 32, 20133 Milano, Italy. E-mail: soncini@elet.polimi.it.
[5]Research Associate, Dept. Electronics and Information, Politecnico di Milano, P.za Leonardo da Vinci, 32, 20133 Milano, Italy. E-mail: weber@elet.polimi.it.

temperature and total suspended solids at different depths. The approach is applied to a real world case study in Japan consisting of a water reservoir, Tono Dam, equipped with a selective withdrawal structure and used for flood protection, power generation, irrigation and recreational purposes. Results show that a potential control over in-reservoir and downstream water quality can be gained without impairing the hydraulic capacity of the reservoir by effectively exploiting - through the operating policy - the operational flexibility provided by the selective withdrawal structures.

Keywords: selective withdrawal systems; reservoir operation; water quality; reinforcement learning; optimization

INTRODUCTION

Dealing with a scarce resource, traditional reservoirs operating strategies are generally designed to meet only the quantitative demand in river basins, e.g., agricultural supply, hydropower production, and flood control. Water quality rarely competes with these water uses and is usually addressed separately as an independent problem assuming the primary quantity target forms constraints on the management options. As a consequence, most of the lakes in the world suffer water quality deterioration and sedimentation to the point where the primary storage functions are being impaired (ILEC 2005). Poor understandings of aquatic and riparian ecosystems and the lack of quantification of social and environmental objectives are some of the possible reasons for the inadequate development of water-quality based management strategies, taking advantage of the close relationships and synergies between quality and quantity (Dhar and Datta 2008). Another, more technical reason is the lack of mathematical tools capable of effectively combining the complexity of the distributed parameter, physically-based models usually adopted to describe hydrodynamics and biochemical conditions of water bodies (for a review, see Ostfeld and Salomons (2005)) and the computational burden of rational, optimization based, decision-making (Castelletti et al. 2011).

As reported in Dortch (1997), three are the options available to affect in-reservoir and downstream water quality in water systems: *i*) pre-treatment or control of reservoir inflows (e.g., upstream settling basins, some type of watershed control or land management activity); *ii*) in-reservoir management or treatment techniques (e.g., destratification, aeration, diluition, etc.); *iii*) management of reservoir outflows (e.g., controlling the outflow rate, outflow location and timing or releases treatments). In this paper, we focus on the third option and consider the case in which the control on the outflow is performed by equipping the reservoir with a multilevel intake, or selective withdrawal system (SWS), that allows releasing water at different depths with different physico-chemical properties (Bohan and Grace 1973; Davis et al. 1987; Smith et al. 1987). The obtained flexibility in the selection of the outlet offers advantages for more continuously meeting water quality goals, especially in reservoirs affected by seasonal stratification, or for responding to short term events (Gelda and Effler 2007). SWSs were originally designed starting from the 1950s and 1960s to control the water temperature in the receiving river using data collected from the reservoir of interest (Nece 1970). Then, numerical models have been developed to assist the design and evaluation of these infrastructures in order to predict the effects on water quality and design water quality targeted operation in new and existing reservoirs (Vermeyen et al. 2003).

Water quality objectives can be broadly divided into in-reservoir and downstream objectives. Most of the works proposed in the literature consider only downstream objectives and one single water quality parameter at a time. The effects of different release strategies for single-outlet dams have been widely studied for the control of the outflow salinity (Orlob and Simonovic 1982; Dandy and Crawley 1992; Nandalal and Bogardi 1995), turbidity (Ikebuchi and Kojiri 1992), and specific ecological parameters as BOD, DO, or TOC (Dhar and Datta 2008; Westphal et al. 2003). Multi-outlet reservoirs studies concentrated on the problem of maintaining a desired discharge temperature (Fontane et al. 1981; Hanna et al. 1999; Sherman 2000; Hanna and Saito 2001; Gelda and Effler 2007; Baltar and Fontane 2008), which is key to preserve fish habitat (Vermeyen 1999) but is also an important factor affecting irrigation and pollution control (Fontane et al. 1981). The control of downstream temperature is not the only controllable variable and SWSs can be also exploited in order to influence sedimentation and ecological discharge parameters (Hayes et al. 1998; Kerachian and Karamouz 2006).

So far, relatively few studies have considered in-reservoir quality targets and, to the authors' knowledge, optimization-based approaches are nearly unexplored. Ferris and Lehman (2007) identified the causal factors affecting algal bloom and modeled this phenomenon to test the possibility of influencing algal growth with few ad-hoc alternatives. A similar approach was developed by Lee and Guy (2012) to assess the room for reducing in-reservoir sedimentation through outflow management. Simplifications such as the steady-state assumption were introduced to control eutrophication (Kuo et al. 2008; Huang et al. 2012). Alternative approaches are based on heuristic optimization algorithms, like Genetic Algorithms (GAs): Khan et al. (2012) developed a Reservoir Optimization-Simulation with Sediment Evacuation model based on GAs to design management strategies considering sediment evacuation in addition to classical quantity objectives as irrigation supply and hydropower generation. Chaves and Kojiri (2007) adopted a Stochastic Fuzzy Neural Network approach to obtain a quasi-optimal solution considering both quantity and quality objectives.

A general methodology for designing the optimal operation of SWSs considering multiple water quantity and quality objectives, both in-reservoir and downstream, is still needed. In this work, a novel approach is proposed for designing Pareto-optimal operating policies for SWS reservoirs. The approach exploits the feedback between the selection of outlet locations for water quantity demand and the water quality patterns within the reservoir (Gelda and Effler 2007), making it possible to satisfy downstream objectives and, simultaneously, affect in-reservoir water quality. In particular, we adopt a Reinforcement Learning (RL) approach combined with a 1D coupled hydrodynamic-ecological model of the lake (DYRESM-CAEDYM) to design Pareto-optimal operating policies conditioned upon some key information on the current conditions of the lake as captured by the model. Unlike simulation-based optimization methods (e.g., Implicit Stochastic Optimization (Labadie 2004) or Parametrization Simulation and Optimization (Koutsoyiannis and Economou 2003)) that do not offer any performance guarantee and proof of convergence, the proposed approach is an approximation of traditional Dynamic Programming (DP) and as such ensures some anticipated favorable properties of the policy obtained (Powell 2007). More precisely, we use a batch-mode algorithm, called fitted Q-iteration (Ernst et al. 2005; Castelletti et al. 2010), that allows learning the operating policy offline on a sample data-set constituted of observational data and/or the outputs of simulated experiments. The approach offers two important features that make it particularly suitable for the high dimensional problem here considered: first, the use of simulation to estimate quantities of interest, thus avoiding model-based computations that would make the approach inapplicable in combination with a high fidelity model of the water quality processes (i.e. the so called curse of modeling (Tsitsiklis and Van Roy 1996)); second, it adopts a non-parametric function approximation (Ernst et al. 2005) of the value function and thus considerably mitigates the curse of dimensionality associated with DP based or derived approaches.

The approach is demonstrated on Tono Dam (Japan), an artificial reservoir constructed for flood protection, power generation, supplying agricultural water downstream and recreational purposes. Due to the region's climate, the lake is characterized by prolonged periods of stratification that negatively impact the water quality both in-reservoir and in the lake's outflow. With the purpose of conjunctively controlling water quality and quantity, the dam was equipped with a SWS. In this study, the SWS operation is optimized with respect to five objectives and the Pareto frontier of the problem is computed. The operating policies corresponding to the extremes of the front are first analyzed in order to gain insight on the strategy adopted by the algorithm for each single objective separately. Then a compromise policy that simultaneously considers all the objectives is analized.

The paper is organized as follows: the Tono Dam case study is firstly described, followed by the presentation of the methodology. Results and discussion are then reported, while final remarks along with issues for further research are presented in the last section.

SYSTEM DESCRIPTION

Tono Dam

Tono Dam is located at the confluence of Kango and Fukuro rivers (Figure 1a), in the western part of Japan. The construction works were completed in 2011. With a height of 75 m (Figure 1b), the dam forms an impounded reservoir of 12.4 x 10^6 m^3 (gross capacity), with a surface area of 0.64 km^2 and fed by a 38.1 km^2 catchment.

The reservoir was primarily constructed to support irrigated agriculture, for flood control and recreational purposes, and is also connected to a small hydropower plant (1.1 MW installed capacity). Due to the region's climate, the lake is characterized by prolonged periods of stratification that produce negative effects on water quality both in-reservoir and in the lake's outflow. With the purpose of conjunctively controlling water quality and quantity, the dam was equipped with a selective withdrawal system (SWS) constituted by a rack of 15 vertically stacked siphons (Figure 1c) allowing to release water from the active storage at different depths. Siphons are operated by inflating or deflating air, and blending is allowed: the total amount of water released through the SWS is equally divided among the active siphons. Floods are only controlled using a flood orifice gate at elevation 182.8 m a.s.l. that operates on the flood control volume. Selective release is not available in the sediment storage, however two more siphon gates are equipped below 156 m to release water in winter period (from December to March) or to release the minimum environmental flow in particularly dry periods, when the water level drops below the lower bound of the active storage. In normal conditions between April and October, the minimum environmental flow is guaranteed through the top 15 siphons, when the level drops below the SWS lower limit, the sediment outlet is activated.

Social, economic and environmental issues

While one of the main purposes of Tono dam operation is to provide water for irrigation, the SWS might have an impact on several other water uses. We distinguish between *in-reservoir* and *downstream* issues, the former being affected by level variations, the latter by the release.

In-reservoir

Too low reservoir *levels*, which can be generated in the attempt to release water to satisfy agricultural water demand, can potentially reduce the recreational value of the lake. In order to emphasize this recreational interest, the SWS management has to consider to keep the lake level as close as possible to a reference level of 182.8 m a.s.l. as the normal high water level. This, however, implies stocking a significant volume of water in the reservoir with potentially negative effects both in-reservoir, e.g., boosting algal blooms, and downstream, e.g., water shortages.

Odors and unattractive appearance of *algal blooms* can detract from the recreational value of the lake affecting the quality of the water stored in the reservoir. The physical processes driving the bloom of algae are particularly complex. However, thermal stratification has a dominant role. Controlling the temperature profile is a mechanical way of controlling the depth of nutrient load intrusion and therefore the algae bloom, which is basically sensitive to the available light, is stimulated by an intrusion in the layer of shallow stratificaton (Yajima et al. 2006). Moreover the temperature profile might vary as a consequences of withdrawing at different levels (Gelda and Effler 2007). Generally, the deeper the withdrawal the more the deepening of the thermocline. Yet, this implies releasing colder water with potentially negative effects downstream and might affect sedimentation in the way explained below.

High levels of in-reservoir *sedimentation* can remarkably reduce the reservoir life by inducing the rapid silting of the impoundment. Sedimentation is basically driven by the inflow and re-suspension can be assumed as negligible considering the reservoir depth (Evans 1994). In particular, inflow intrusion is governed by the in-reservoir temperature profile and the inflow temperature because floods are more likely to intrude just above the thermocline (Yajima et al. 2006). Therefore, to maximize sediment evacuation, the release should be set at the depth at which the turbid inflow is intruding and then, if necessary, dynamically moved to the deeper siphons to intercept the maximum concentration of suspended solids not yet evacuated. Moreover, some recent studies (Yajima et al. 2006) have shown that using the top siphon combined with the spillways leads the inflow to the shallower depth and facilitate sediment flushing from the spillway. These ways of operating the SWS might have negative effects on the other sectors, like, for instance, the ecosystem downstream, which might be damaged by too warm water. Also recreation could be affected, since by keeping the thermocline in the shallow layer, algal blooms are more likely to occur as explained above.

Downstream

Farmers are interested in reducing the water supply deficit, which has a direct effect on the seasonal harvest and, therefore, on the annual income, which is the criterion through which the farmers judge the level of attractiveness of an operating policy (Hashimoto et al. 1982).

The riverine ecosystem downstream from the dam is potentially threatened by large deviations of the water *temperature* from the seasonal natural patterns that might negatively affect faunal richness in both fishes and invertebrates (Hanna and Saito (2001) and references therein). According to Fontane et al. (1981) and Baltar and Fontane (2008), a simple and physically rooted criterion to reduce the effect of artificially induced temperature variations is to force the outflow temperature to be as closest as possible to the (natural) inflow temperature.

MATERIALS AND TOOLS

Planning efficient operating rules for the SWS based solely on the indications reported beforehand might turn out particularly difficult in this absence of quantitative references from the historical operation (the dam has been just constructed). Moreover, while potentially effective strategies can be anticipated for most of the involved issues separately considered, their interaction and the associated conflicts make it hard to empirically formulating adequately balanced rules. In this study, we adopt a batch-mode Reinforcement Learning approach to design Pareto-optimal feedback operating policies for the SWS. The operating policy is computed by repeatedly solving a regression problem on a data-set of one-step transitions of the reservoir system generated by multiple simulations of a physically-based coupled hydrodynamic-ecological model of Tono Dam under different external driver and release decision scenarios. The procedure adopted is described in the flowchart of Figure 2 and its building blocks are described next.

Problem formulation

Given the current system conditions as described by the state vector $\mathbf{x}_t \in \mathbb{R}^m$ (e.g., storage, temperature, suspended solid), a daily feedback operating policy p for the SWS returns the volume $u_t^i = m_t(\mathbf{x}_t)$, $i = 1, \ldots, n$, to be released over the time interval $[t, t+1)$, i.e. the next 24 hours, from each of the n SWS outlets and for each day t. The problem of designing the set of Pareto-optimal policies can be formulated as an optimal control problem of a dynamic system evolving according to a model $\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \boldsymbol{\varepsilon}_{t+1})$, controlled by a vector $\mathbf{u}_t \in \mathcal{U}_t(\mathbf{x}_t) \subseteq \mathbb{R}^n$ of n feasible decisions, and affected by l stochastic external drivers $\boldsymbol{\varepsilon}_{t+1} \in \mathbb{R}^l$ (e.g., inflow, wind, solar radiation, nutrient load), i.e.

$$p^* = \arg\min_p \boldsymbol{\lambda} \cdot \mathbf{J}(p) \tag{1}$$

in which $\mathbf{J}(p) = [J^1, \ldots, J^q]$ is the vector objective function and $\boldsymbol{\lambda}$ is the vector of weights with $\sum_{k=1}^q \lambda^k = 1$ and $\lambda^k \geq 0\ \forall k$. The k-th objective is formulated as the expected total discounted cost over an infinite horizon (see, for more details, Castelletti et al. (2008))

$$J^k = \lim_{h\to\infty} \mathop{\mathrm{E}}_{\boldsymbol{\varepsilon}_1,\ldots,\boldsymbol{\varepsilon}_h} \left[\sum_{t=0}^{h-1} \gamma^t g_{t+1}^k(\mathbf{x}_t, \mathbf{u}_t, \boldsymbol{\varepsilon}_{t+1}) \right] \tag{2}$$

where $g_{t+1}^k(\cdot)$ is the k-th immediate cost function associated to each system transition and γ is a discount factor ($0 < \gamma \leq 1$).

By reformulating and solving the problem for different values of the weights $\boldsymbol{\lambda}$, a finite subset of the generally infinite Pareto-optimal policy set is obtained (Weighting Method).

The DYRESM-CAEDYM model

The characterization of the system dynamics $f_t(\cdot)$ involves the description of the main hydrodynamic and ecological processes arising in the reservoir. In principle, a 3D spatially-distributed model (e.g., ELCOM-CAEDYM (Yajima et al. 2006)) would be the best choice in terms of accuracy and physically meaningful description of the involved processes. However, the reservoir is being created by damming two rivers in a quite narrow and steep section of their course and vertical phenomena are dominating. Therefore, a simpler 1D model might be an acceptable surrogate. By working with a 1D model, a full characterization of the spatial dynamics between the inlet and the outlet of the reservoir is lost, however the run-to-real time ratio drops off to nearly 1/12300 from the 1/30 of an equivalent 3D model. Yet, compared with the simple lumped models traditionally used for reservoir policy design, 1D models still have a very high number of state variables, which constitutes the main limitation for their inclusion within a classical optimization framework.

In this study we adopted the 1D DYRESM-CAEDYM model developed by the Centre for Water Research at the University of Western Australia (Hipsey et al. 2006; Imerito 2007). The model consists of two main components: a 1D hydrodynamic model (DYRESM-Dynamic Reservoir Simulation Model), including a vertical distribution of temperature, salinity and density in a reservoir, and an aquatic ecosystem model (CAEDYM-Computational Aquatic Ecosystem Dynamics Model), which simulates a range of biological, chemical and physical processes, expressing the variables that are commonly associated with water quality (such as total phosphorus, total nitrogen, chlorophyll-a, etc.). The model is based on a Lagrangian architecture that models the reservoir as horizontal layers of uniform properties (i.e. temperature and water qualities). The thickness of the layers varies in time depending on the water density profile. In our model, the minimum and the maximum thickness of a layer is set to 1 m and 2 m, respectively, which correspond to allow the definition of more than 30 layers in the Tono Dam reservoir. Twenty-one state variables are defined for each layer, for a total of nearly 600 state variables (including the level). Details on the model calibration can be found in Yajima et al. (2006)

Operating objectives

According to the multi-objective nature of the problem, an immediate cost function $g_t^k(\cdot)$ is defined for each sector of interest affected by the SWS operation:

- *Level*: the squared positive difference of lake level with respect to the reference level $\bar{h} =$ 182.8 m:

$$g_{t+1}^{lev} = \left(\max\left(\bar{h} - h_{t+1}, 0\right)\right)^2 \tag{3}$$

- *Algal bloom*: the daily average hourly maximum concentration of chlorophyll-a (Chl-a) in the see-through layer:

$$g_{t+1}^{algae} = \frac{1}{24}\sum_{\tau=1}^{24} \max_{z_\tau \in z_E}(chla_\tau(z_\tau)) \tag{4}$$

  where $chla_\tau$ is the Chl-a concentration [μg/L] at the τ-th hour of day t, z_τ is the depth with respect to the lake surface, z_E is the see-through layer depth set at 7 m below water surface, where the thermocline is generally formed in summer.

- *Sedimentation*: the daily volume of sediment expelled with the release, which has to be maximized in order to reduce the silting of the reservoir and increase its expected life:

$$g_{t+1}^{sed} = TSS_{t+1}^{out} \tag{5}$$

  where $TSS_{t+1}^{out} = \sum_{i=1}^{N} tss_{t+1}^{i} r_{t+1}^{i} + tss_{t+1}^{spill} r_{t+1}^{spill}$ with r_{t+1}^{i} [m^3/day] being the volume of water released from the i-th siphon of the SWS, tss_{t+1}^{i} the average total suspend solid concentration [g/m^3] in the corresponding layer, tss_{t+1}^{spill} the average total suspend solid in the layer of the spillway, and r_{t+1}^{spill} the actual release from the corresponding layer.

- *Irrigation*: the squared water daily deficit with respect to the agricultural water demand w_t:

$$g_{t+1}^{irr} = \beta_t \left(\max\left(w_t - (r_{t+1} - q_{t+1}^{MEF}), 0\right)\right)^2 \tag{6}$$

where r_{t+1} is the total release from the dam (including SWS and spillway), q_{t+1}^{MEF} is the minimum environmental flow, and β_t is a time-varying coefficient taking into consideration the different relevance of the water deficit in different periods of the years. In particular, the immediate cost is elevated to the square to favour operating policies that reduce severe deficits in a single time step, while allowing for more frequent, small shortages, which cause less damage to the crop. This ensures that vulnerability is a minimum (Hashimoto et al. 1982).

- *Temperature*: the squared difference between the inflow and outflow temperature (as in Fontane et al. (1981) and Baltar and Fontane (2008)):

$$g_{t+1}^{temp} = (T_{t+1}^{out} - T_{t+1}^{in})^2 \tag{7}$$

where T_{t+1}^{out} is the average temperature in a section just downstream of dam outlet and $T_{t+1}^{in} = \frac{T_{t+1}^K a_{t+1}^K + T_{t+1}^F a_{t+1}^F}{a_{t+1}^K + a_{t+1}^F}$ with T^K and T^F being the average temperature [°C] of the inflow respectively in the Kango and Fukuro rivers, and a_{t+1}^K and a_{t+1}^F the corresponding flows.

Batch-mode Reinforcement Learning

To solve Problem (1) in this work we adopt a batch-mode Reinforcement Learning (RL) algorithm called fitted Q-iteration (Ernst et al. 2005; Castelletti et al. 2010). The fitted Q-iteration (FQI) combines RL concepts of off-line learning and functional approximation of the value function, from which the policy is derived, using tree-based regression. The optimal operating policy is determined on the basis of experience samples previously collected from the system or simulations thereof, i.e. a variety of system conditions experienced by the system under different combinations of release decisions and external driver realizations with the associated resulting immediate costs. Strictly, such experience is represented as a finite data-set $\mathcal{F}$ of tuples of the form $< t, \mathbf{x}_t, \mathbf{u}_t, t+1, \mathbf{x}_{t+1}, g_{t+1} >$, where

$$g_{t+1} = \sum_{k=1}^{q} \lambda^k g_{t+1}^k \tag{8}$$

The underlying idea of FQI is to replace the recursive solution of the Bellman equation by DP with a sequence of non-linear regressions over the data-set $\mathcal{F}$ (see, for further details, Castelletti et al. (2010)) with the purpose of obtaining an approximation of the optimal, but uncomputable, DP solution.

State reduction

Although FQI alleviates the curse of dimensionality, it can handle no more than few dozens of state variables, while the 1D DYRESM-CAEDYM model embeds several hundreds (about 600). To combine the 1D model and FQI, a reduction of the state vector dimension is unavoidable. The original state vector $\mathbf{x}_t$ is transformed into a smaller vector $\tilde{\mathbf{x}}_t \in \mathbb{R}^{\tilde{m}}$, with $\tilde{m} << m$, such that $\tilde{\mathbf{x}}_t$ is still significant in conditioning the release decision, but makes the control problem computationally tractable. The FQI will then work on a new data-set $\tilde{\mathcal{F}}$, containing the reduced state vector $\tilde{\mathbf{x}}_t$ instead of $\mathbf{x}_t$. Both formal (see the review by (Castelletti et al. 2012)) and empirical (expert based) approaches can be adopted to perform such reduction: the former are mainly based on Dynamic Emulation Modeling (DEMo) (ibidem), the latter exploit domain knowledge to identify the most interesting variables to be considered.

Setting the Experiments

In this section we describe the main assumptions made and the modeling solutions adopted to apply the above methodology to the Tono Dam case study.

Decision Variables

The SWS was planned to allow releasing at different depths and, possibly, blending water volumes with different physicochemical characteristics. This is reflected in our model by two decision variables: u^{-3} is the volume to be releases at 3 meters below the water surface, u^{-13}

at 13 meters. In both cases, the decision is defined with respect to the water body surface (see Figure 1b). These water depths should correspond, respectively, to the epilimnium and the hypolimnium of the stratified reservoir (Yajima et al. 2006). The vector of the decision variables $\mathbf{u}_t = [u_t^{-3}, u_t^{-13}]$ is defined over a feasibility set $\mathcal{U}_t(\mathbf{x}_t)$ that takes into account which outlets are available given the current storage, the physical constraints imposed by the siphons, and the SWS characteristics (Figure 1c). Precisely, each siphon cannot convey more than 7.353 m^3/s, while the maximum flow rate allowed through the SWS outlet is 13.780 m^3/s. The water volume released through each siphon cannot be freely decided, but depends on the total amount released from the SWS, which is hydraulically equally divided among the open siphons. When more than one siphon is opened, each siphon cannot be operated at the maximum capacity.

State Variables

Reasonably, not all the state variables in the 1D DYRESM-CAEDYM model are equally relevant in the causal network linking the release decisions, and thus the operating policy, and the objectives. Some of them have little or no effect in conditioning the policy and can be removed. In this study, we used an expert-based approach to reduce the original, large dimensional state vector to a lower order vector $\tilde{\mathbf{x}}_t$ including only 5 state variables, all having a direct effect on the value of the objectives. These are the reservoir's level h_t, the temperature T_t^i and the total suspended solid TSS_t^i in the 1D model layer corresponding to the controlled outlet (with i=-3; -13). Observe that, since the controlled siphons depends on the position of the lake surface (Figure 1b), also the corresponding state variables are defined according to the same moving reference.

Learning data-set

The learning data-set $\tilde{\mathcal{F}}$ was constructed by running simulations of the 1D DYRESM-CAEDYM model over the period 1995-2006 (calibration period) under 100 different release scenarios generated pseudo-randomly with the aim of exploring the reduced state-decison space as more homogeneously as possible. The resulting data-set $\tilde{\mathcal{F}}$ is composed by 437,800 tuples, a dimension which can be hardly managed by the FQI algorithm as its computational complexity grows more than linearly with the number of tuples $\#\tilde{\mathcal{F}}$ (i.e. $\#\tilde{\mathcal{F}} \cdot log(\#\tilde{\mathcal{F}})$). A resampling was then performed by trial-and-error to reduce the number of tuples thus obtaining a reduced data-set of 4378 tuples which represents a good compromise between the computational requirements and space-decision space exploration. The resampling procedure preserves the decision frequencies of the large data-set and, therefore, also the homogeneus exploration of the state-decision space.

Benchmark

Since Tono Dam was under construction at the time this paper was being prepared, there was not historical reference for the resulting Pareto-optimal operating policies. However, a release scenario is available for the period between 1990 and 1999. In a former study, the dam construction authority (Japanese Ministry of Land, Infrastructure and Tourism) concluded that 7 m depth withdrawal between April and October and 28 m depth withdrawal (the lower of the two siphon gates in the sedimentation zone) between November and next year March is the desirable SWS operation for Tono Dam. Therefore this operational scenario is assumed as a benchmark to evaluate the Pareto-optimal operating policies computed in this paper. Since it is partially overlapping the calibration period (1995-2006), only the first 5 years from 1990 to 1994 (validation period) have been considered in the comparison. The performances of the benchmark with respect to the five considered objectives are reported in Table 1. Actually, two objectives are reported for the *irrigation* sector: the first one, which is considered in the optimization, is the daily quadratic water deficit defined in eq. (6); since the physical meaning of this immediate cost is hardly interpretable, a second objective defined as the daily water deficit along the year is reported to support policy evaluation, but it is not considered in the optimization. It is worth noting that the benchmark operation assumes the *irrigation* as the main objective and, indeed, the daily water deficit is nearly insignificant (0.028 m^3/s). Consequently the room for further improvements of this objective is limited.

RESULTS

In this section the operating policies obtained by solving Problem 1 for 50 different combinations of the weights are evaluated through simulation (dashed path in Figure 2) over the period 1990-1994 (validation period). Results are evaluated in three steps: first, the approximate 5D Pareto-front is analyzed to explore trade-offs, conflicts, and correlations among the objectives; second, the extremes points of the front, i.e. the policies obtained by setting to zero all the weights in eq. (8) but one, are considered to assess the individual SWS operation strategies; third, the Pareto front is explored in order to find out possible interesting compromise solutions between the five conflicting objectives.

5-D Pareto front

The 5-D Pareto front is represented through projections in the space of the *algae* and *sedimentation* objectives in Figure 3 and Figure 4. In particular, Figure 3 shows that the best performing alternatives with respect to *algae* and *sedimentation* (in the bottom-left part of the figure) negatively impact on the *level* objective (very small circles): the optimal operation for the first two criteria tends to release large amount of water to flush out both nutrients and sediments producing a drawdown of lake level. As anticipated, *algae* and *sedimentation* objectives are only partially conflicting (bottom-left part of the figure): sediment evacuation is maximized by keeping the thermocline in the shallow layer, which is a favorable condition for algal blooms too. The best alternatives for *algae* performs fairly well also with respect to the *temperature* objective (blue circles) and, therefore, these two objectives seem to be not in conflict. Also observe that all the Pareto-optimal alternatives significantly outperform the performance of the benchmark with respect to the *algae* objective. Moreover, the benchmark is poorly performing with respect to *sedimentation* and *level* objective. Finally, the benchmark performance on the *temperature* objective is intermediate with respect to the range of variability obtained with the Pareto optimal alternatives.

The performances of the *irrigation* objective are reported in Figure 4 against *sedimentation* and *algae* (this latter can be considered as representative also of the *temperature*, as explained above). The best performing alternatives on *algae* (*temperature*) and *sedimentation* correspond to high values of irrigation deficit (yellow circles), meaning that the first three objectives are also conflicting with *irrigation*. Some interrelations exist between *irrigation* and *level* in the top-right part of the figure corresponding to negative performances on *algae* (*temperature*) and *sedimentation*. So, two groups of conflicting alternatives can be identified: on one side, possible compromises between *level* and *irrigation*, on the other side, compromises between *algae*, *temperature*, and *sedimentation*. A slight improvement in the objectives of the first group produces a significant worsening in the performances of the second group and vice-versa.

Pareto front extremes

In Table 1 we compare the optimal single-objective policies mapping into the extreme points of the Pareto front, obtained by setting to zero all the components of the weights vector ($\boldsymbol{\lambda} = |\lambda^{lev}\lambda^{algae}\lambda^{sed}\lambda^{irr}\lambda^{temp}|$), but the one corresponding to the objective considered. The associated policies are named accordingly (e.g., the extreme policy for level p^{lev} is obtained by setting $\boldsymbol{\lambda} = |1\ 0\ 0\ 0\ 0|$). The performance is evaluated as the improvement with respect to the benchmark, which is the current best available solution. Results show that the SWS operation has a considerable impact on all the water-related issues considered and all the optimal policies significantly outperform the benchmark. Not surprisingly, the room for improvement on the irrigation sector is quite limited since this objective was the primary target considered in designing the benchmark policy. The analysis of the release strategy adopted by the individual policies is useful to validate the behaviours we prefigured in the description of the main issues involved in the problem (see above). In what follows, we therefore evaluate the different policies by analyzing the temporal pattern of the main variables (Figures 5-9). We do not analyze p^{irr} in detail as it is almost equivalent to the benchmark.

Level

The improvement obtainable with policy p^{lev} with respect to the benchmark is significant: a high and constant lake level is highly conflicting with the release of water for other uses, particularly for irrigation in dry years, which is the target of benchmark operation. The system controlled with this policy behaves in a quite easily interpretable way (Figure 5b): the optimal policy p^{lev} tries to keep the lake at the constant level of 182.8 m a.s.l. (37.8 m from the bottom) by keeping the release at a minimum.

Algal bloom

The improvement obtained by policy p^{algae} over the benchmark is remarkable (a daily average of nearly 4.7 μg/L of Chl-a), meaning that the SWS operation might positively impact algal blooms. Without constraints on the reservoir level, blooms are controlled by increasing the release in spring/summer (Figure 6b), when algal blooms are more likely to occur, thus flushing away water volumes with high Chl-a concentration. The resulting reservoir levels are generally lower than those produced by the benchmark (Figure 6a) and follow the natural inflow pattern. In other words, the reservoir capacity is not exploited and the reservoir follows a river-like behaviour.

Sedimentation

The improvement of policy p^{sed} on the benchmark is less significant than with policy p^{algae} and p^{lev}. Yet, the SWS operation seems to affect also the silting of the reservoir. Again, the behaviour of the system controlled by policy p^{sed} follows the inflow dynamics: without any constraint on lake level or penalty on wasting water, the optimal policy suggests to release the inflow in order to flush out the maximum amount of sediments. This is evident when comparing the inflow and total release patterns (Figure 7b). Furthermore, releasing the inflow produces two favourable conditions: first, low lake levels reduce the retention time of the reservoir and, therefore, prevent in-reservoir sedimentation, as also observed by Lee and Guy (2012). Second, since the sediments tend to intrude along the thermocline (Yajima et al. 2006), which means that the highest TSS concentration is found around the thermocline, the optimal policy moves the temperature profile so as to have the thermocline in correspondence of one of the two depths where the release can be performed. As shown in Figure 7c, the optimal policy maintains, on average, the thermocline around 13 m depth, while with the benchmark policy the thermocline is constantly deeper, generally deeper than 13 m from the surface, and so is not able to release the same amount of sediments as p^{sed} because sediments are trapped in the uncontrollable region of the reservoir. The TSS concentration profiles for the benchmark and policy p^{sed} for a small flood event are shown in Figure 8a-b: after the flood event of January 9-10, policy p^{sed} is able to release more sediment and to reduce the TSS concentration in the lake by adopting a more effective release strategy than the benchmark. The benchmark in January releases only from the outlet at 28 m depth according to the rule defined by the dam construction authority. On the contrary, the strategy adopted by policy p^{sed} (Figure 8c) first releases at -3 m in order to keep the thermocline shallower (Gelda and Effler 2007) and, then, opens the -13 m siphon in order to actually release the sediments.

Temperature

Lake level dynamics under policy p^{temp} follow a nearly periodic pattern (Figure 9b), with values constantly lower than the benchmark (Figure 9a) generated by higher releases. With this strategy, the optimal policy is able to stabilize the thermocline between 5 and 10 m depth (Figure 9c) and to exploit blending between the two controlled siphons to generate the same temperature as the inflow. The benchmark follows a different and less effective strategy by maintaining the lake at higher levels. As a consequence, in summer the thermocline decreases at 13 m depth or deeper and blending can not be exploited to meet the target temperature of the outflows since the water has the same temperature at the two controlled depths. Probably, a further release decision variable at 7 m depth (which is the average depth at which the thermocline is located during the stratification) could make it easier to intercept the intruding inflow and, therefore, to further reduce the difference between the inflow-outflow temperature. This will be the subject of subsequent research.

Pareto front compromises

In this section, we analyze one policy (policy p^5 in Table 2 and Figures 3-4) particularly interesting in terms of balance of the different objectives, which thus constitutes a strong candidate to be the final compromise solution in a real policy making context. Obviously, this is a subjective evaluation by the authors and the real Decision Maker (DM) might prefer different alternatives. However, the aim of this analysis is to show that there is room to design compromise policies outperforming the benchmark and of practical interest. As an example, in Table 2 we also report the performance of other two alternatives showing slightly different trade-offs among the objectives but still good candidates as best compromise.

As shown in Figure 10, policy p^5 really represents a possible interesting compromise solution among the five conflicting objectives: although there exist some better alternatives for each objective, which however are dominated on the other objectives, policy p^5 balances all the considered objectives. Indeed, the presence of multiple objectives allow to obtain very good performances (bottom part of the figure) only on few, non-conflicting objectives which are identified by horizontal lines. However, these solutions negatively impact on the remaining objectives, graphically represented by oblique lines. It is worth noting that the conflicts previously identified between the two groups of objectives (*algae*, *sediment* and *temperature* on one side and *level* and *irrigation* on the other one) are particularly evident in Figure 10 looking at the high number of crossing lines between *temperature* and *level*. Among the set of alternatives, policy p^5 represents instead a possible compromise as it is almost an horizontal line, meaning that the satisfaction of the five objectives is almost equivalent.

The SWS operating strategy of policy p^5 (Figure 11) is a mix of the different Pareto extreme policies which tries to consider all the objectives and, depending on the period of the year, it focuses on different objectives as shown in Figure 12. This copromise strategy is also evident looking at Figure 13: following p^{algae}, p^{sed} and p^{temp}, policy p^5 activates a drawdown cycle in summer by increasing the release, while it stores water in the winter and early spring period to satisfy the *level* and *irrigation* objectives.

CONCLUSIONS

Despite the recent progress in the design of optimal planning and management strategies for water resources systems, most of the studies reported in the domain literature deals with quantitative objectives only, e.g., agricultural supply, hydropower energy production, and flood control. However, a really sustainable operation should also consider water quality targets. This paper illustrates a novel approach to design optimal operating policies for water reservoirs equipped with multiple outlet release schemes which optimize quantity and quality objectives both in-reservoir and downstream.

We combined a 1D physically-based description of the hydrodynamic and ecological processes taking place in the lake with a batch-mode Reinforcement Learning algorithm to design quasi optimal release strategies conditioned upon an augmented state including not only the current storage but also water characteristics, such as temperature and total suspended solid at different depths. The use of a batch-mode approach makes it possible to combine simulation experiments conducted with a high fidelity physically-based model and the guarantees on the policy optimality property offered by Dynamic Programming family methods, which is particularly useful in a complex, many-objective context with no historical reference for the operation.

The application to Tono Dam case study shows that the operation designed with the proposed approach outperforms the current best available solution on all the objectives independently considered but also produces compromise policies that considerably improve the water quality objectives in-reservoir and downstream at the cost of a very small, practically negligible, reduction of the irrigation supply. For example, with the examined compromise policy the improvements in the algae, sedimentation and temperature objectives with respect to the benchmark are equal to 42%, 14% and 5% respectively, while the worsening of the irrigation objective is equal to 15%. However, given the strong conflict between the level objective and the water quality interests, favoring these latter produces a significant decrease in the level objective performance, i.e. from 35.9 m^2 to 120.9 m^2.

Future research will concentrate on increasing the number of controlled siphons to improve operation flexibility: allowing the release at more different depths should make it possible to open the siphons at the point with the maximum sediment concentration, as well as to do blending depending to the thermocline position. Further improvements on the methodological ground can be achieved by: *i*) substituting the original high fidelity model for a lower order dynamic emulator (Castelletti et al. 2012); *ii*) adopting Active Learning approaches (Rachelson et al. 2011) to improve the simulation-based exploration of the system behavior and generate an equally informative data-sample with lower dimensionality and so lower associated computational cost, but also potentially improved performance; *iii*) using projections method (e.g., principal component analysis (Galelli et al. 2011)) to aggregate interrelated objectives thus allowing a more dense Pareto front approximation and the use of visualization technique to jointly explore the decision and the objective space (Kollat and Reed 2007).

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List of Tables

TABLE 1. Performances of the Pareto front extreme policies. The gray shaded objective was not directly considered in the optimization.

Sector	Description	Unit of Measure	Benchmark	Policy	Improvement
Level	daily quadratic positive difference w.r.t. the reference level of 182.8 m a.s.l.	$(m)^2$	35.9338	0.0195	35.9143
Algae	daily average maximum concentration of Chl-a in the see-through layer	$\mu g/L$	6.8133	2.1293	4.684
Sedimentation	daily volume of sediment expelled with the release	g/day	$2.8102 \cdot 10^6$	$2.8699 \cdot 10^6$	$5.97 \cdot 10^4$
Irrigation	daily quadratic water deficit modulated by β	$(m^3/day)^2$	$6.9408 \cdot 10^7$	$6.5449 \cdot 10^7$	$3.959 \cdot 10^6$
Irrigation (2)	daily water deficit along the year	m^3/s	0.0280	0.0270	0.001
Temperature	daily average quadratic difference of temperature between inflow and outflow	$(°C)^2$	4.3818	2.5143	1.8675

TABLE 2. Performances of three interesting compromise alternatives. The gray shaded objective was not directly considered in the optimization.

Policy [weights]	**Level** $(m)^2$	**Algae** μg/L	**Sedimentation** g/day	**Irrigation** $(m^3/day)^2$	**Irrigation (2)** m^3/s	**Temperature** $(°C)^2$
p^5 [.33 .13 .0001 .2099 .33]	120.9102	3.9351	$3.2093 \cdot 10^6$	$7.9648 \cdot 10^7$	0.0374	4.1692
p^{5a} [.35 .10 .0001 .1999 .35]	151.2584	3.3330	$2.7721 \cdot 10^6$	$7.7229 \cdot 10^7$	0.0348	3.6647
p^{5b} [.31 .15 .0001 .2299 .31]	111.6356	4.1838	$3.0261 \cdot 10^6$	$7.5715 \cdot 10^7$	0.0346	4.2691
Best case	0.0195	2.1293	$3.8376 \cdot 10^6$	$4.0183 \cdot 10^7$	0.0177	2.2275
Worst case	322.6452	6.8133	$2.4509 \cdot 10^6$	$14.2593 \cdot 10^7$	0.0504	12.4755

List of Figures

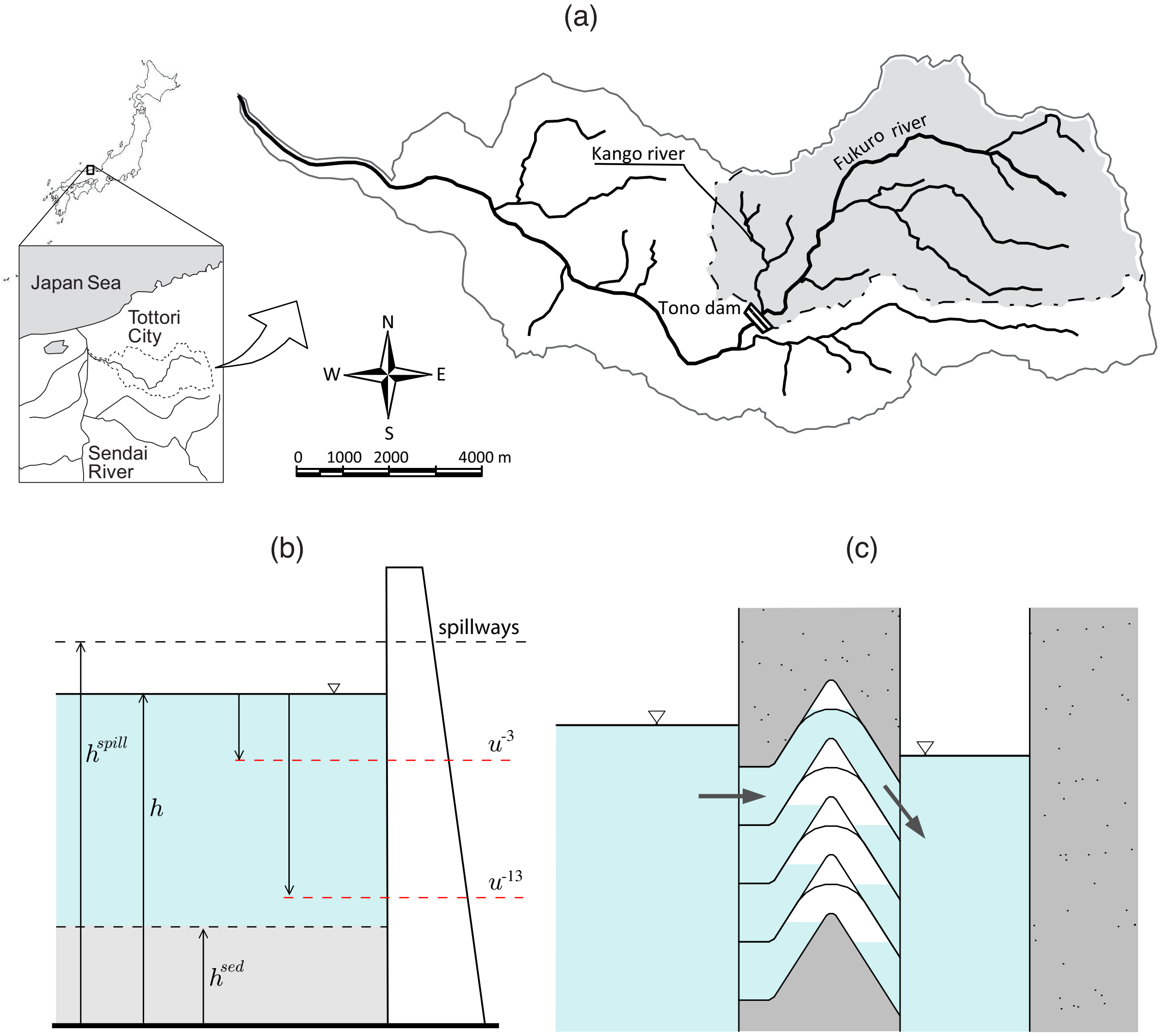

FIG. 1. Tono Dam location in Western Japan (panel a), the main characteristics of the reservoir with the decision variables adopted in this study (panel b), and the schematization of the SWS structure (panel c).

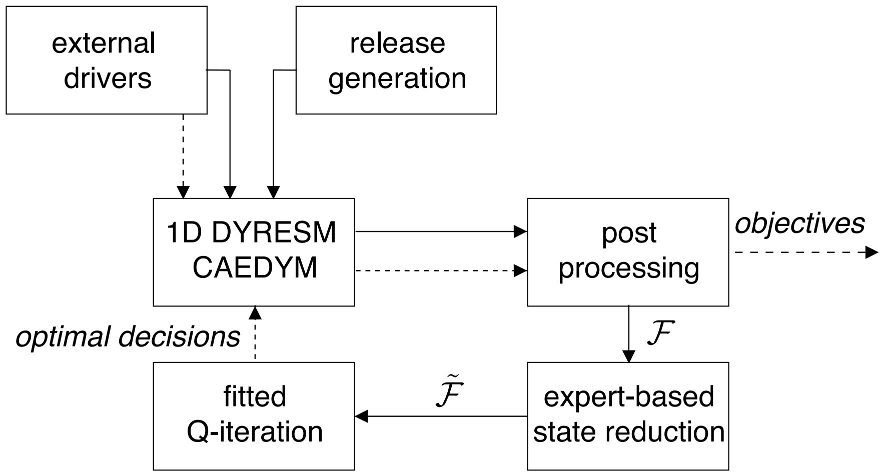

FIG. 2. Schematization of the procedure adopted. The black line is the optimization workflow, the dashed line is evaluation via simulation of the optimal operating policy.

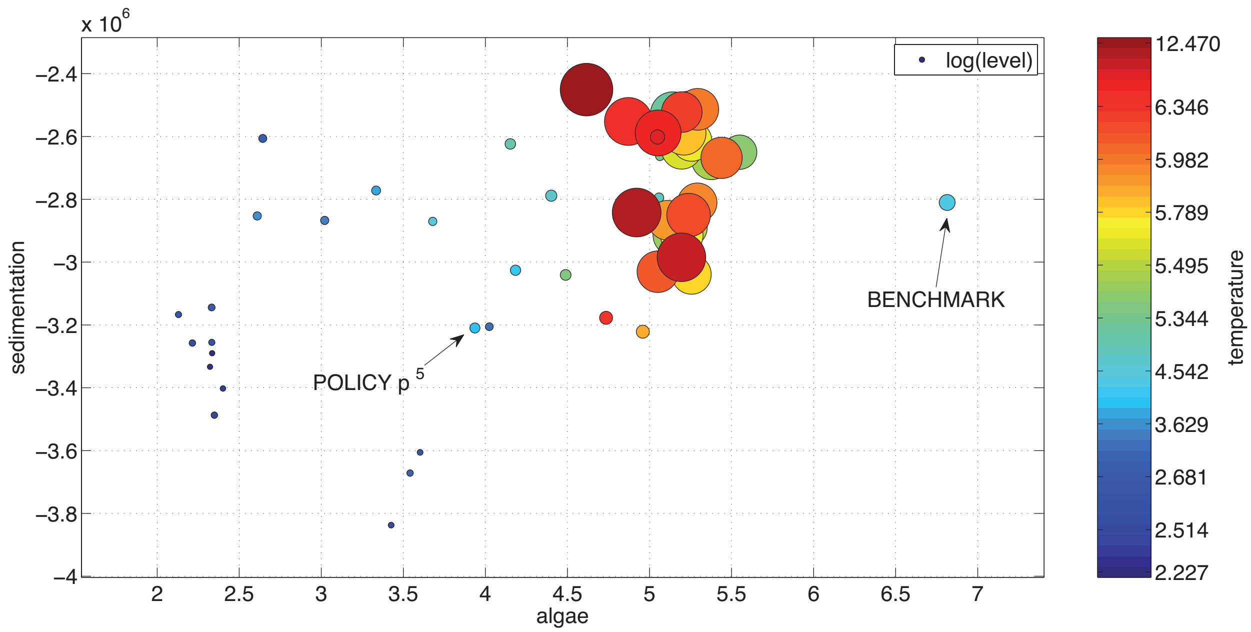

FIG. 3. Projection of the 5D Pareto front in the objectives space algae-sedimentation; circles size is proportional to the logarithm of the level objective (the bigger the circle, the better is the alternative); colors provide the temperature objective. The irrigation objective is not represented. Policy p^5 represents a possible compromise alternative.

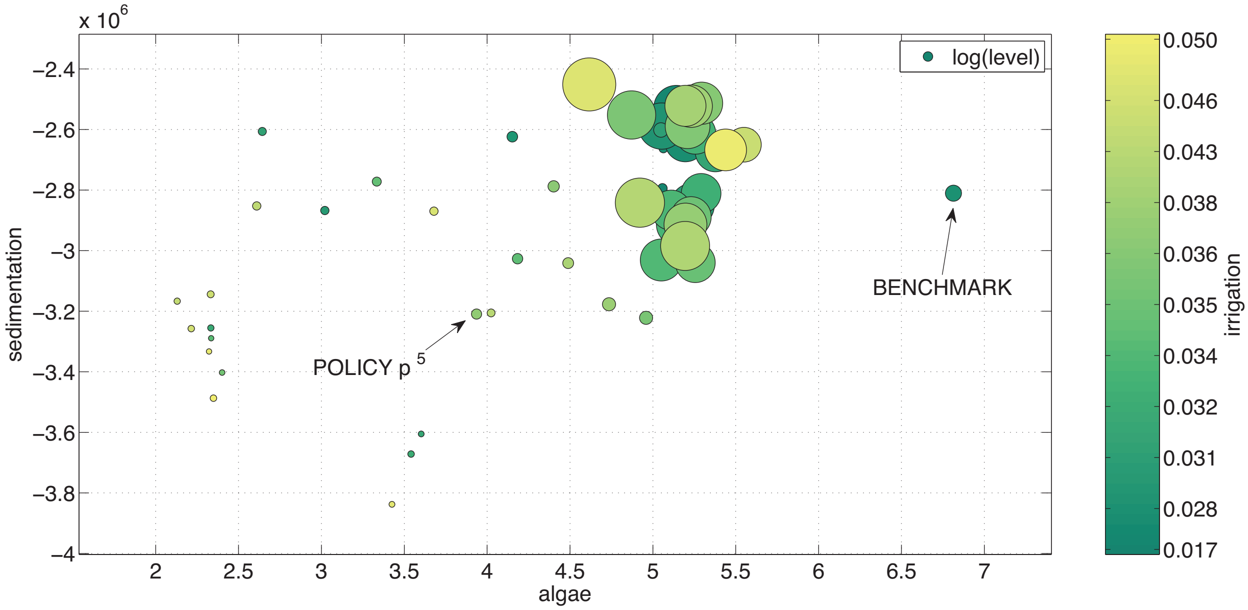

FIG. 4. Projection of the 5D Pareto front in the objectives spacealgae-sedimentation; circles size is proportional to the logarithm of the level objective (the bigger the circle, the better is the alternative); colors provide the temperature objective. The temperature objective is not represented. Policy p^5 represents a possible compromise alternative.

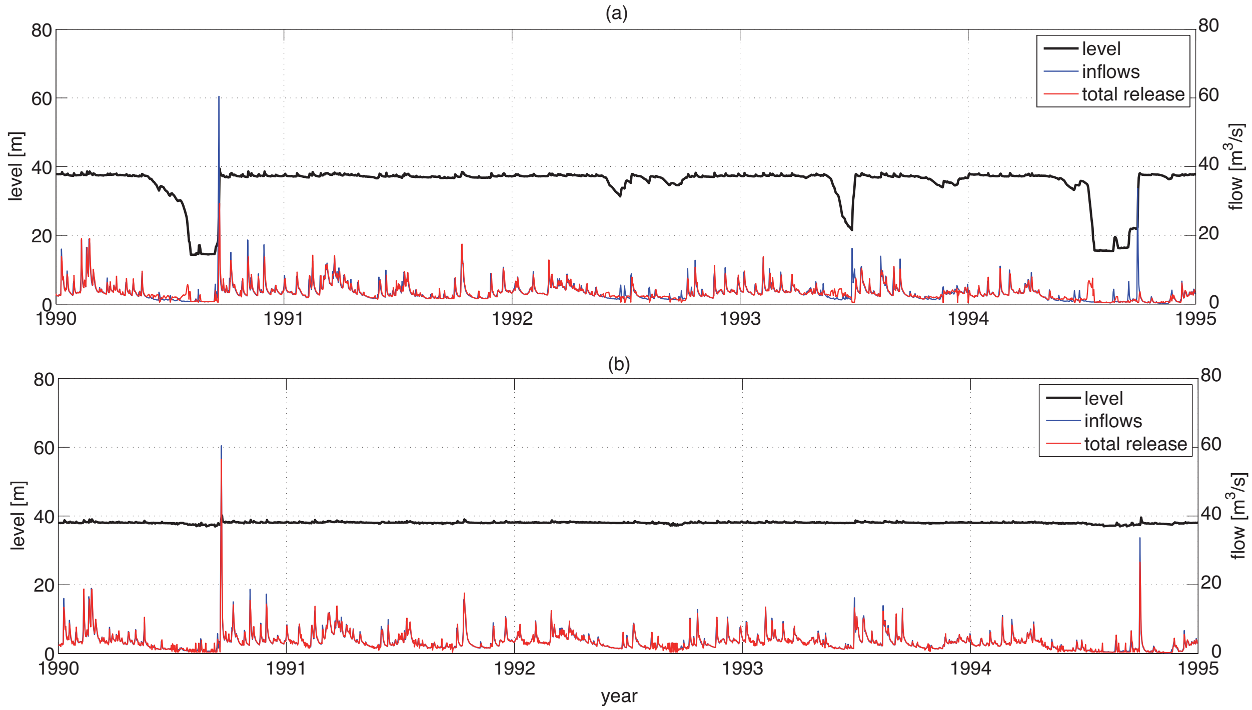

FIG. 5. Water surface level (black line), inflow (blue line), and the total actual release (red line) produced by the benchmark in panel (a) and policy p^{lev} in panel (b) over the validation period.

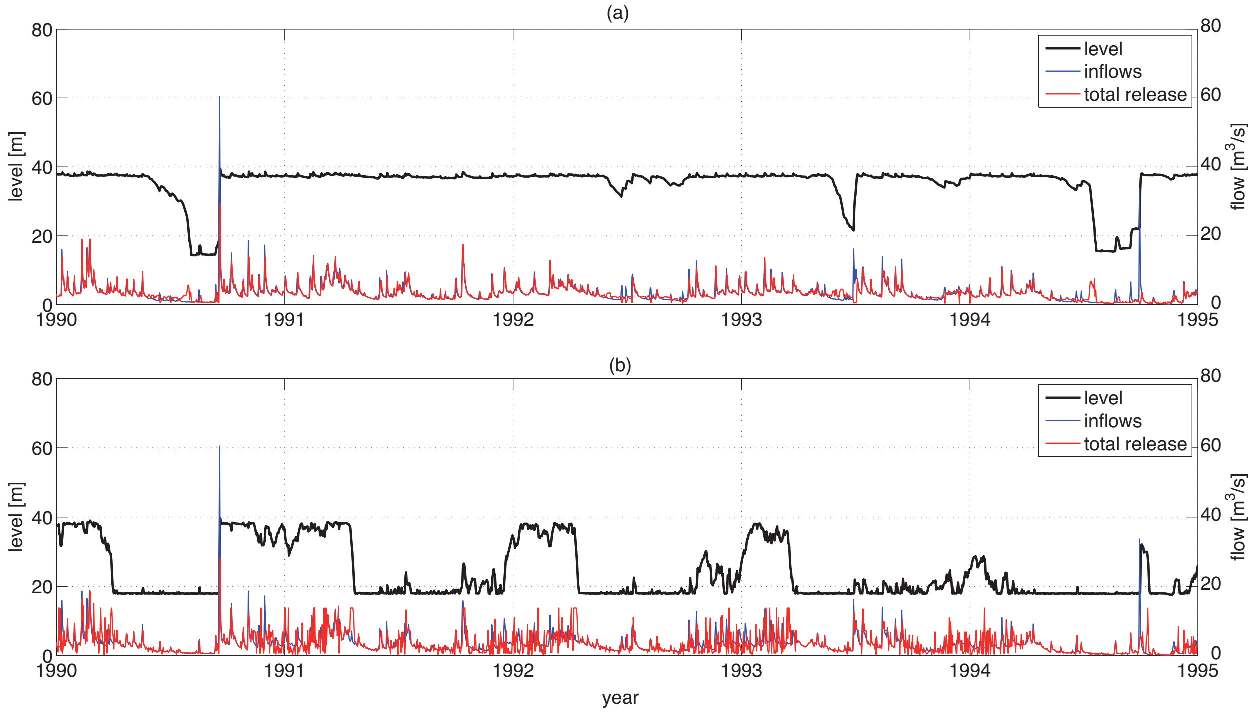

FIG. 6. Water surface level (black line), inflow (blue line), and the total actual release (red line) produced by the benchmark in panel (a) and policy p^{algae} in panel (b) over the validation period.

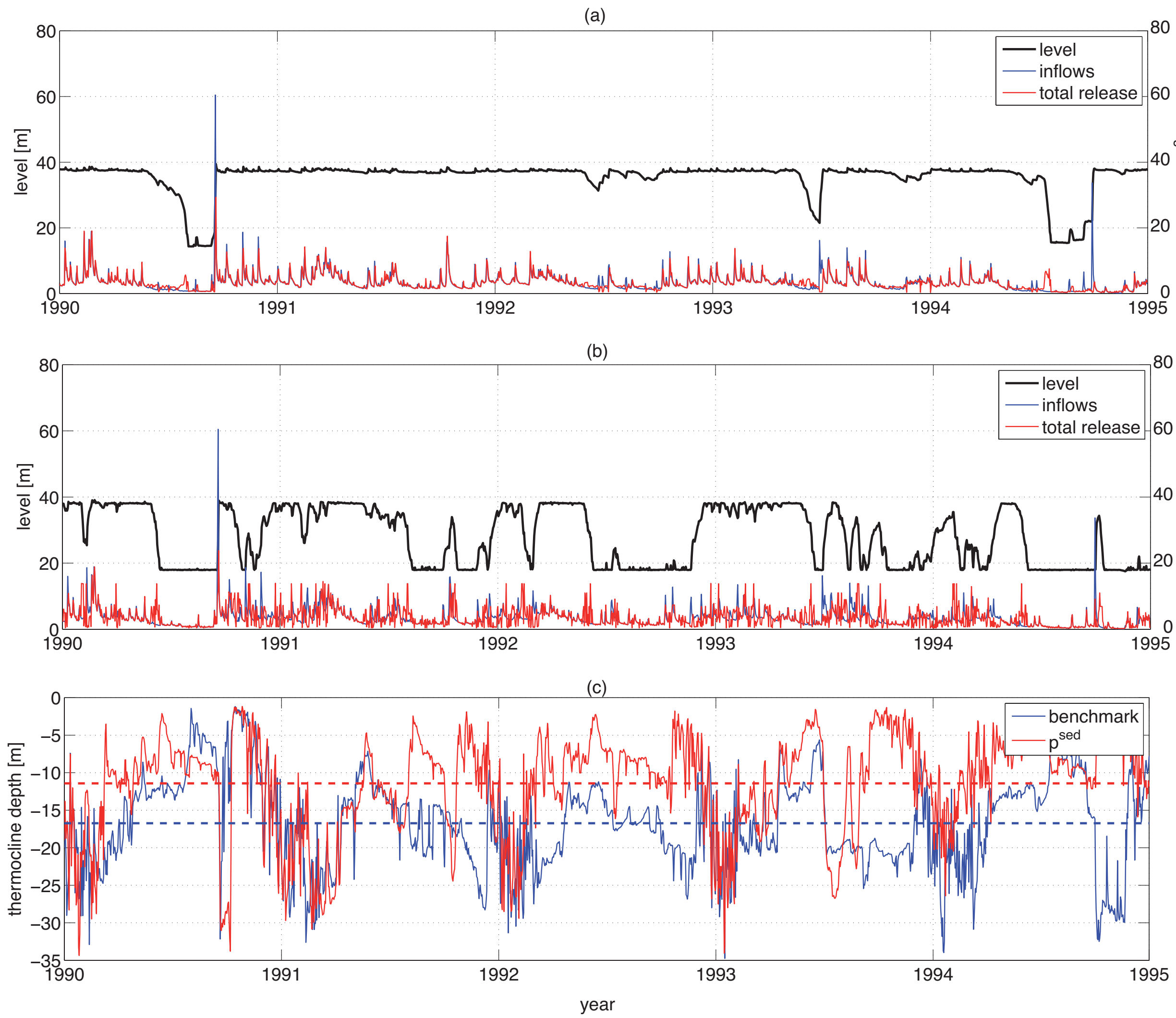

FIG. 7. Water surface level (black line), inflow (blue line), and the total actual release (red line) produced by the benchmark in panel (a) and policy p^{sed} in panel (b) over the validation period. Panel (c) reports the thermocline depth for the same alternatives over the validation period (the dotted lines represent the average depth).

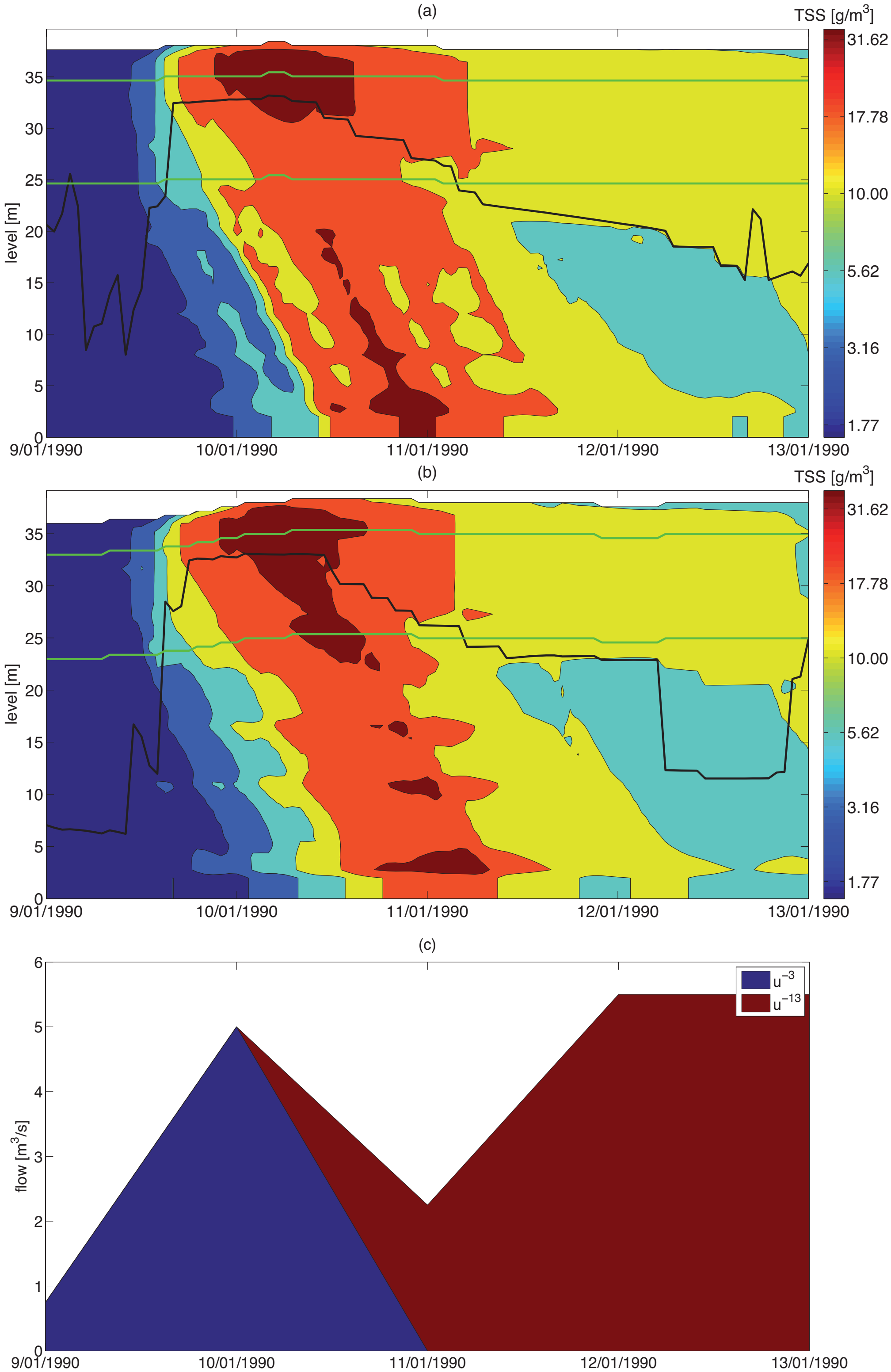

FIG. 8. TSS concentration profiles for a small flood event in January 1990 for the benchmark in panel (a) and policy p^{sed} in panel (b). The black line represents the thermocline and the green lines represent the positions of the controlled outlets (3 and 13 m depth). Panel (c) shows the outlets operating strategy for policy p^{sed} in the same period.

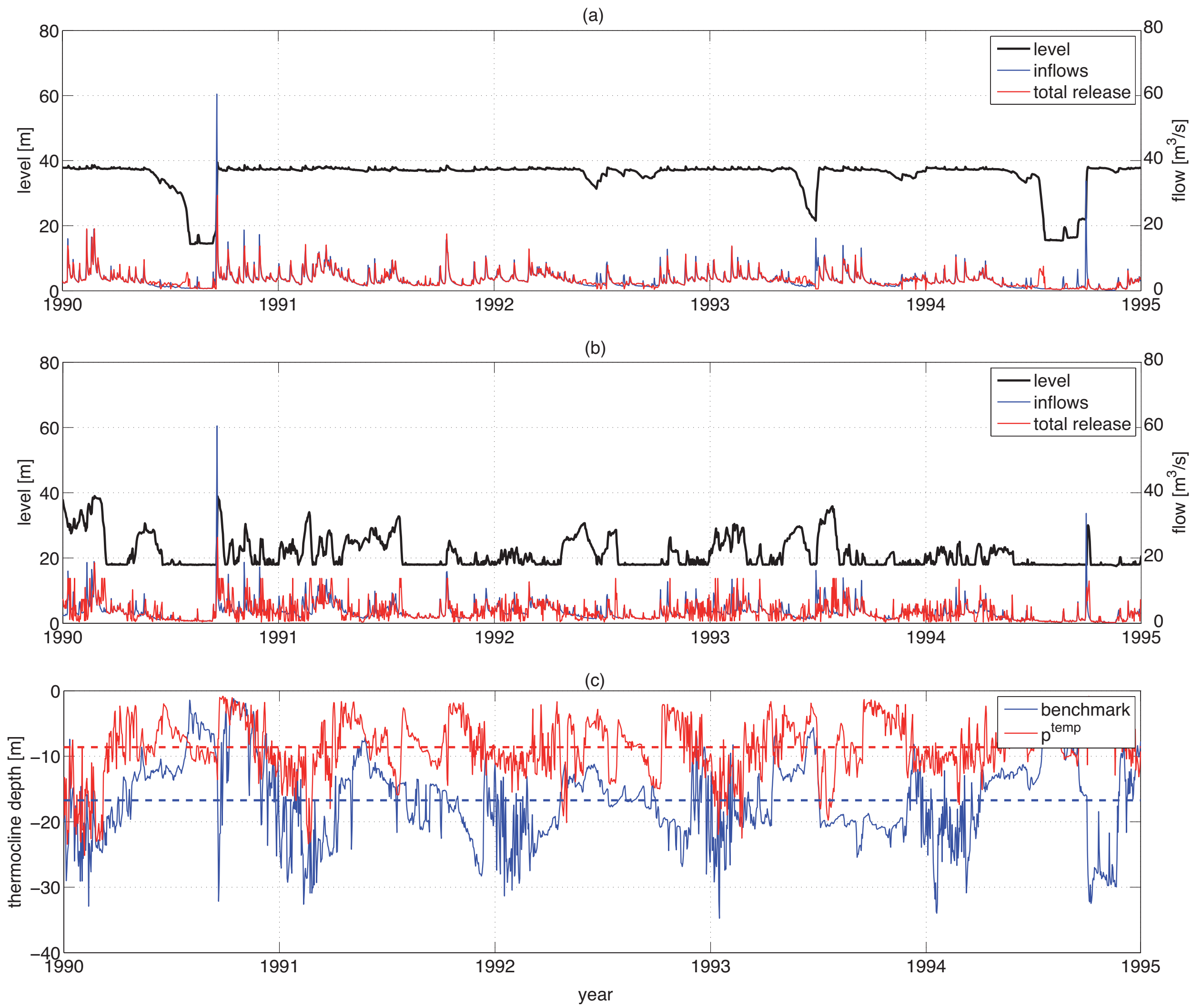

FIG. 9. Water surface level (black line), inflow (blue line), and the total actual release (red line) produced by the benchmark in panel (a) and policy p^{temp} in panel (b) over the validation period. Panel (c) reports the thermocline depth for the same alternatives over the validation period (the dotted lines represent the average depth).

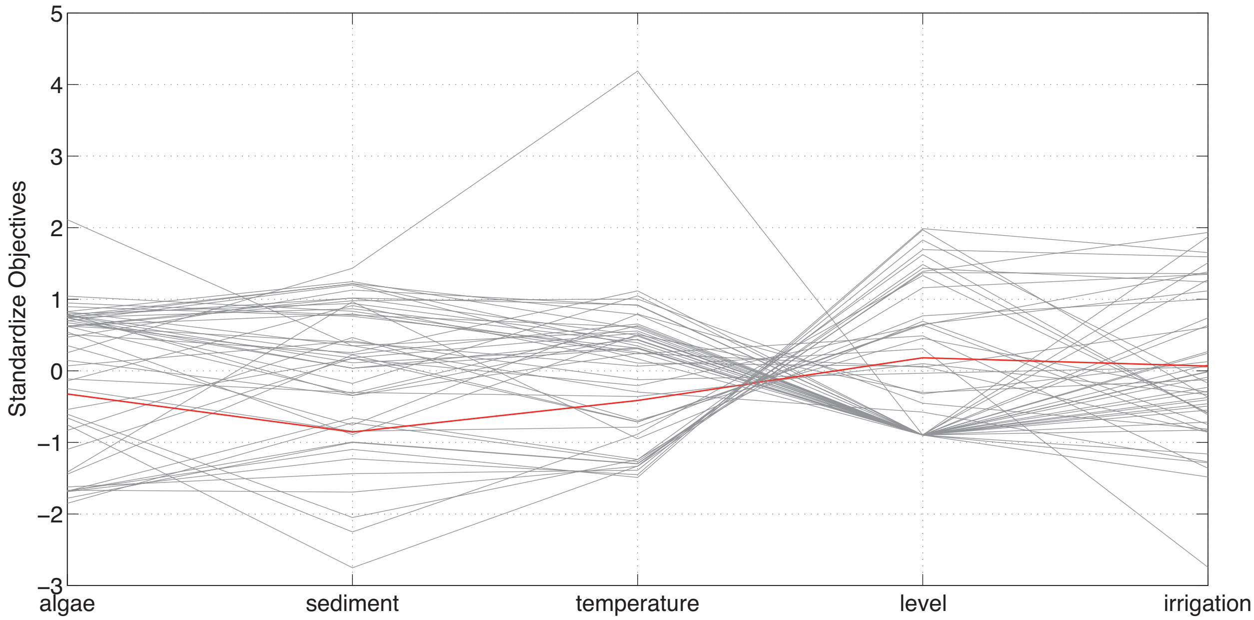

FIG. 10. Representation of the performances of policy p^5 (red line) with respect to all the other alternatives. For illustration purposes the objectives are standardized (zero mean and unit standard deviation).

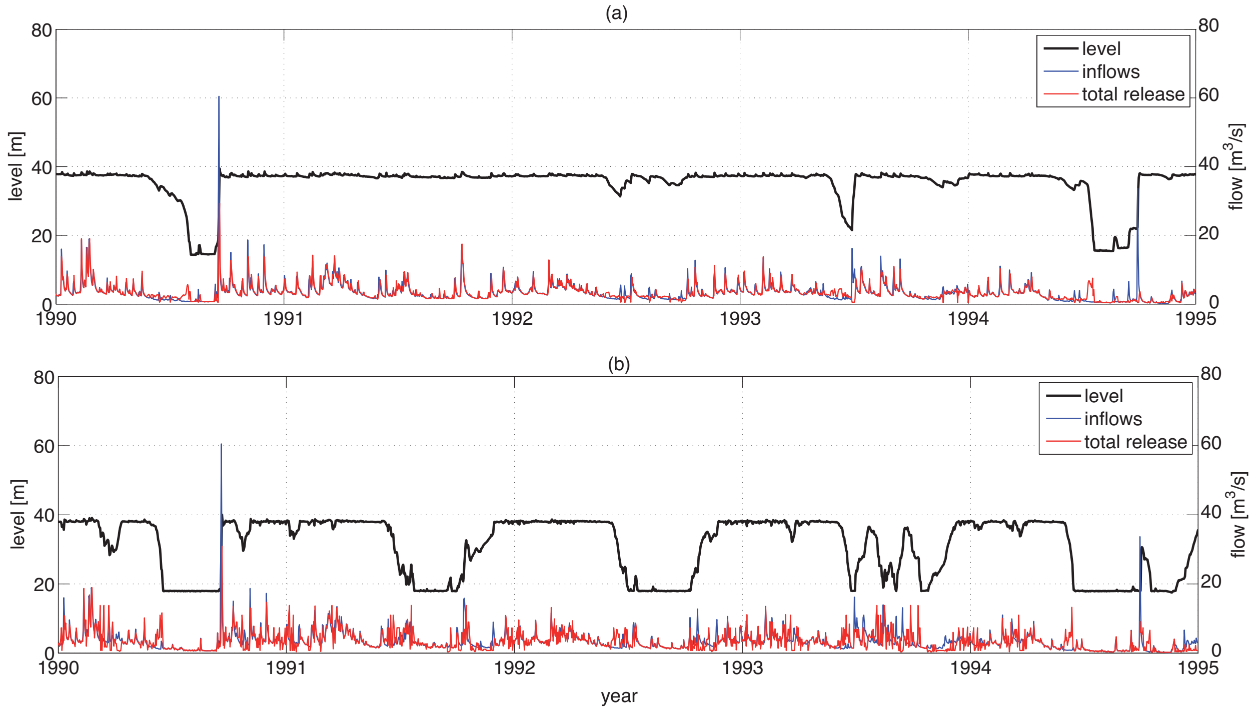

FIG. 11. Water surface level (black line), inflow (blue line), and the total actual release (red line) produced by the benchmark in panel (a) and policy p^5 in panel (b) over the validation period.

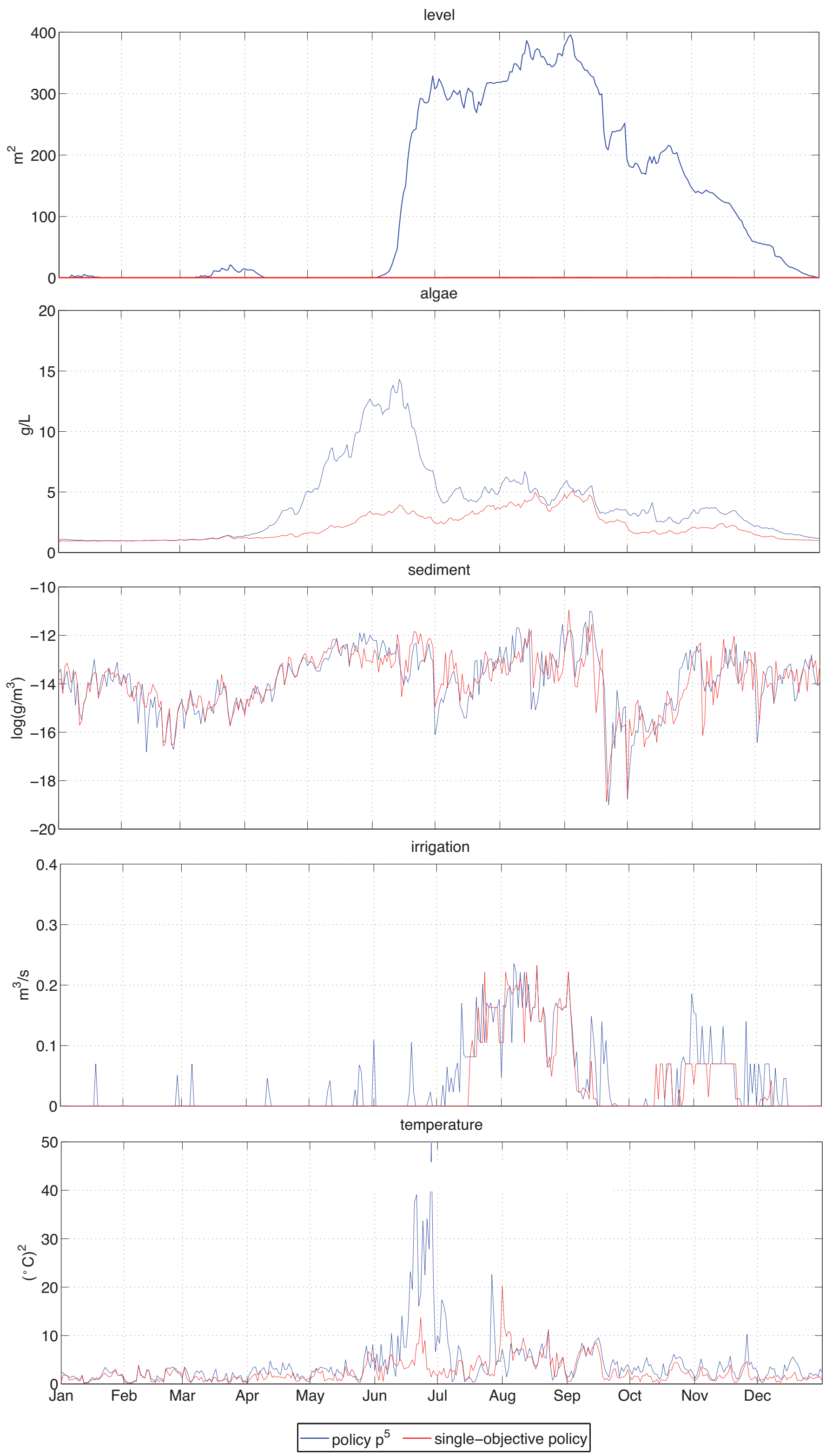

FIG. 12. Comparison of the cyclostationary means (over the validation period) of the immediate costs $g_t^k(\cdot)$ between policy p^5 and the single-objective policies.

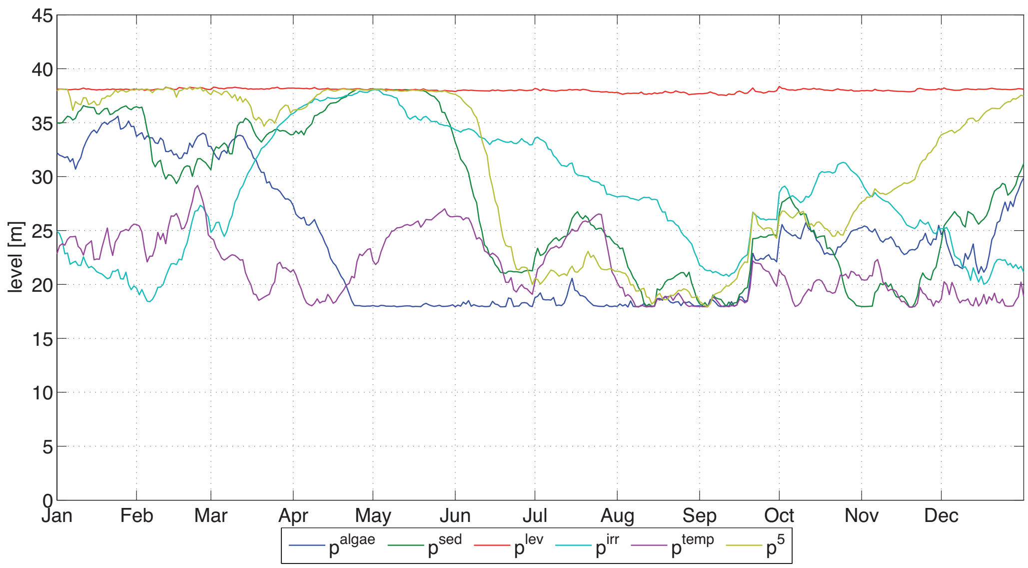

FIG. 13. Cyclostationary mean (over the validation period) of the lake levels for different policies.