WATER RESOURCES RESEARCH, VOL. 49, 3912–3926, doi:10.1002/wrcr.20287, 2013

Assessing the value of cooperation and information exchange in large water resources systems by agent-based optimization

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Received 12 November 2012; revised 13 March 2013; accepted 29 April 2013; published 3 July 2013.

[1] Many large-scale water resources systems, especially in transboundary contexts, are characterized by the presence of several and conflicting interests and managed by multiple, institutionally independent decision makers. These systems are often studied adopting a centralized approach based on the assumption of full cooperation and information exchange among the involved parties. Such a perspective is conceptually interesting to quantify the best achievable performance but might have little practical impact given the real political and institutional setting. In this work, we propose a novel decision-analytic framework based on multiagent systems to model and analyze different levels of cooperation and information exchange among multiple decision makers. The Zambezi River basin is used as a case study. According to the proposed agent-based optimization approach, each agent represents a decision maker, whose decisions are defined by an explicit optimization problem considering only the agent's local interests. The economic value of information exchange is estimated comparing a noncooperative setting, where agents act independently, with the first basic level of cooperation, i.e., coordination, characterized by full information exchange. The economic value of cooperation is also estimated by comparison with the ideal, fully cooperative management of the system. Results show that coordination, obtained with complete information exchange, allows the downstream agents to better adapt to the upstream behaviors. The impact of information exchange depends on the objective considered, and we show coordination to be particularly beneficial to environmental interests.

Citation: Giuliani, M., and A. Castelletti (2013), Assessing the value of cooperation and information exchange in large water resources systems by agent-based optimization, *Water Resour. Res.*, *49*, 3912–3926, doi:10.1002/wrcr.20287.

1. Introduction

[2] The presence of multiple, institutionally independent but physically interconnected decision makers is a distinctive feature of many water resources systems, especially in transboundary river basins: water flows and by moving, creates a hydrological interdependency between basin users [*Alam et al*., 2009]. More than 250 rivers in the world belong to transnational basins, accounting for about 60% of freshwater worldwide [*United Nations Environment Programme*, 2002]. Yet, disputes arise over contested use of water at different spatial and institutional scales. While control over water resources might not be achieved through water wars [*Zeitoun and Warner*, 2006], subnational disputes often occur [*Wolf*, 1998; *Julien*, 2012], and whether violent or not, they increase the pressure on water resources along with climate-change induced water scarcity, increasing water demand, and decreasing quality.

[3] Water resources management in complex, multiparty contexts has been predominantly studied assuming a centralized decision-making framework, where water allocation in time and space is optimized assuming full control over release and distribution decisions, and full knowledge of the current system conditions. Most of the world's largest and disputed transnational river basins has been studied from this perspective, exploring the potential for a more efficient water management at a systemwide scale: the Nile [e.g., *Guariso and Whittington*, 1987; *Wu and Whittington*, 2006; *Block and Strzepek*, 2010], the Zambezi [e.g., *Gandolfi et al*., 1997; *Tilmant et al*., 2010, 2012], and the Euphrates-Tigris [e.g., *Kibaroglu and Unver*, 2000; *Altinbilek*, 2004].

[4] A growing number of authors argue that the adoption of a centralized point of view might be conceptually interesting to quantify the best performance ideally achievable by a water system [*Yang et al*., 2009] and to get insights on strategies to foster cooperation [*Anghileri et al*., 2012], but of little operational impact given the real political and institutional context [*Leitmann et al*., 1987; *Waterbury*, 1987; *Whittington et al*., 2005; *Madani*, 2010; *Sheikhmohammady et al*., 2011; *Tilmant and Kinzelbach*, 2012]. Indeed,

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0043-1397/13/10.1002/wrcr.20287

centralized management assumes a cooperative attitude and full information exchange by the involved parties, and these rarely correspond to the actual sociopolitical setting in a river basin. When decision makers belong to different countries or institutions, or even sectors, it is very likely that they act considering only their local objectives, producing global externalities that negatively impact on other objectives [*Bernauer*, 2002].

[5] Similarly, although data and information sharing at the basin level is considered to be a precondition to achieve cooperation [*Gerlak et al*., 2011], a full information exchange practice is far from being applied in most of transboundary basins. Especially upstream countries have a tendency to restrict information exchange as it is not in their local interest to give full access to the available information, thus ensuring a favorable position with respect to the countries with no access to information [*Timmerman and Langaas*, 2005].

[6] In this paper, we try to move beyond the centralized and full information exchange assumption and propose a decision-analytic framework for large-scale water resources systems characterized by multiple and originally noncooperative decision makers. The approach is based on multiagent systems (MASs) [see *Wooldridge*, 2009], a modeling framework that naturally allows to represent a set of self-interested agents acting in a distributed decision-making process at the agent level. According to this MAS paradigm, an agent is defined as a computer system situated in some environment and capable of autonomous actions to meet its design objectives but also able to exchange information with the neighbor agents and change its behavior accordingly.

[7] MAS approaches have been largely adopted to study environmental systems for a multiplicity of purposes (for a review, see *Bousquet and Le Page* [2004] and *Athanasiadis* [2005, and references therein]). In most of these works, MAS are used to mimic the interaction among agents acting on the basis of a limited number of preassigned behavioral rules, whereas their potential to autonomously and adaptively decide by optimizing their local objectives [*Shoham and Leyton-Brown*, 2008] is not fully exploited. In the water resources literature, only few studies have considered truly optimizing agents: an agent-based application for a static optimization problem was introduced by *Yang et al*. [2009] and further developed by *Giuliani et al*. [2012a]. A similar approach was developed to optimize preseason farmers decisions [*Ng et al*., 2011] and to simulate an optimization-driven water market [*Huskova and Harou*, 2012] as well as emission trading [*Nguyen et al*., 2013]. According to this agent-based optimization approach, in our MAS framework each decision maker is represented by an agent, whose decisions are defined by an explicit optimization problem considering only the agent's local interests. Starting from this noncooperative configuration, we then explore different degrees of cooperation and information exchange among the agents.

[8] According to *Watkins* [2006], three levels of cooperation can be identified in a water resources system: *coordination* by information sharing, *collaboration* by developing adaptable national plans, and *full cooperation* by developing joint ownership of infrastructure assets. We focus on the case of completely independent and noncooperative agents and assess the role of information exchange by introducing coordination as a first level of cooperation. The advantage of this basic level of cooperation is its intrinsic feasibility, as the independent, local optimal strategy of each agent is guaranteed. Indeed the practicability of cooperative solutions requires that the benefits to any participant are at least equal to what that participant would obtain by acting unilaterally [*Wu and Whittington*, 2006], and the glue for any stable cooperation among multiple decision makers has to be the self-interest of each participating actor [*Waterbury*, 1997]. Therefore, more sophisticated cooperation strategies require to design compensation measures (e.g., international incentives), which modify the benefits of the agents to satisfy this condition of individual rationality [*Madani and Lund*, 2012]. Noncooperation and coordination are then comparatively analyzed with respect to a reference scenario of full cooperation and complete information exchange among the agents, which is equivalent to the ideal centralized solution of the problem. The differences in the system-level benefits achievable under the different scenarios allow to estimate both the economic value of full cooperation (VFC), i.e., the benefits obtained by full cooperation with respect to the one with coordination only, and the economic value of information exchange (VIE), i.e., the benefits obtained with coordination with respect to the one with no cooperation.

[9] The Zambezi River basin is used to illustrate the methodology. It represents one of the largest river basins in Africa and is shared by eight countries: Angola, Botswana, Malawi, Mozambique, Namibia, Tanzania, Zambia, and Zimbabwe. The four largest reservoirs in the basin (Ithezhithezhi, Kafue Gorge, Kariba, and Cahora Bassa) are mainly operated for maximizing the economic revenue from hydropower energy production, with considerable negative effects on the aquatic ecosystem in the Zambezi delta due to the alteration of the natural flow regime [*Beilfuss and dos Santos*, 2001; *Tilmant et al*., 2010]. Currently, the four reservoirs are managed by independent and noncooperative decision makers. We comparatively analyze this situation with respect to a first level of cooperation, i.e., the coordination, by introducing information sharing among the agents. Moreover, we also consider the ideal, fully cooperative centralized solution with complete information exchange among the agents. Previous works on the Zambezi River have approached the problem by a single-objective perspective: *Gandolfi et al*. [1997] maximize the total hydropower energy production and add different operational constraints to account for secondary objectives; *Tilmant et al*. [2010] develop a water-economic model of the system where environmental indicators are monetized and aggregated to the hydropower objective into a basin-wide net benefit function. In this work, we preserve the multiobjective nature of the problem by formulating a multiobjective optimization problem, whose resolution yields to a set of Pareto-optimal solutions, meaning that they cannot be improved in a given objective without degrading their performance in another objective. Then, analyzing the Pareto-efficient solutions, it is possible to evaluate a posteriori the trade-offs between the conflicting objectives [*Wu et al*., 2010] and the corresponding shadow prices, i.e., the marginal worsening in one objective corresponding to the improvement in the other one. The multiobjective approach

allows to obtain problem-specific estimate of the economic valuation of originally nonmonetary objectives, like the protection of the ecosystem in the Zambezi delta, for which the values proposed in the literature are highly uncertain.

[10] The optimization of the agents' decisions is done according to a model predictive control (MPC) scheme [see *Bertsekas*, 2005], which is particularly suitable for large-scale systems as well as for decentralized control strategies, overcoming the curse of dimensionality that limits the applicability of classical control techniques such as stochastic dynamic programming and approximated approaches [e.g., *Castelletti et al*., 2010]. Though being largely adopted in process-engineering problems [*Scattolini*, 2009], MPC is nearly unexplored in the water resources management [*Niewiadomska-Szynkiewicz et al*., 1996; *Negenborn et al*., 2009; *Anand et al*., 2011] and especially in noncooperative settings. In particular, given the increasing ability in forecasting techniques which allow to obtain accurate forecast of the inflow processes in the Zambezi River basin, MPC seems particularly promising for this specific problem.

[11] In summary, this paper contains three main contributions: (i) we propose a novel decision-analytic framework for studying water resources management in noncooperative, multiple decision makers' problems defining agents' behaviors based on the autonomous resolution of optimization problems, instead of a priori behavioral rules; (ii) we analyze the role of information exchange and the benefits that can be achieved with this simple coordination mechanism: it does not affect the benefits of the upstream agents and consequently, is feasible by nature as each agent cannot improve his benefit acting unilaterally; and (iii) we propose to estimate the value of cooperation and information exchange in a multiobjective problem by working on the Pareto front to a posteriori estimate the economic value of the ecological objectives, whose monetization is usually affected by high uncertainty.

[12] This paper is organized as follows: the next section describes the methodology; section 3 presents a description of the Zambezi River case study. Results are reported in section 4, and final remarks, along with a discussion on the limitations of the proposed approach as well as issues for further research, are presented in the last section.

2. Methods and Tools

2.1. Multiagent Systems

[13] To explore different degrees of cooperation and information exchange among multiple decision makers competing for the same water resource, we use a MAS framework [*Wooldridge*, 2009]. A MAS consists of multiple interacting autonomous agents and their environment. Agents are intelligent in the sense that they can solve tasks (e.g., act according to a set of predefined rules or optimize an objective function) and exchange information with each other. In this paper, we consider self-optimizing agents, who are able to self-determine their behavior based on some optimality criteria [*Shoham and Leyton-Brown*, 2008]. Each agent can therefore decide to optimize its local objective function only, without considering the effects of his decision on the objectives of the other agents. Moreover, the MAS framework allows also to model agents which join in groups (coalitions) sharing common interests (e.g., national objectives). For example, the four agents in Figure 1a are modeled as organized in two coalitions and thus solve two optimization problems with two objectives each. The explicit formulation and solution of an optimization problem by each agent further develop the agent-based optimization approach introduced by *Yang et al*. [2009] and replace the a priori defined rules adopted in most of agent-based water resources applications [e.g., *van Oel et al*., 2010; *Zechman*, 2011; *Le et al*., 2012, and references therein].

[14] In an MAS framework, it is possible to associate each agent with a portion of the environment that the agent observes and controls (Figure 1a). This makes MAS particularly suitable for modeling large-scale river basins, where each agent may represent one decision maker (*active-controller agent*) and/or one stakeholder (*reactive agent*) associated with a portion of the system. For example, in Figure 1b a typical transnational water system composed by an upstream and a downstream country and two federated stakeholders per country is represented as a MAS, where each coalition of two agents controls only one of the two reservoirs in series. *Russell and Norvig* [1995] identifies five major distinguishing properties for characterizing the environment wherein agents act and interact. Interestingly, these can be easily mapped into typical features of water systems: (i) *nondeterministic*, due to the presence of stochastic external drivers (e.g., rainfall and temperature); (ii)

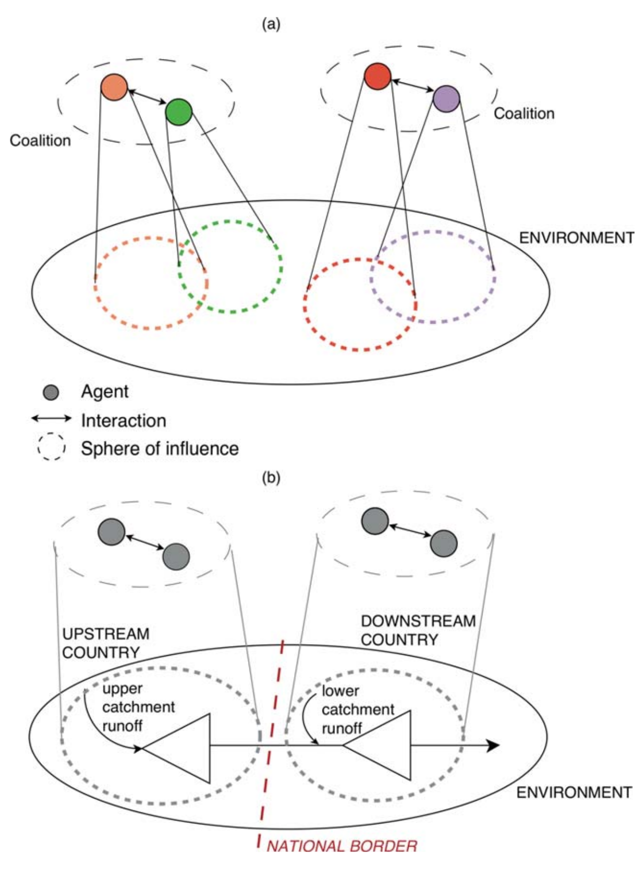

Figure 1. Representation of (a) a generic MAS and (b) a typical transboundary national water system as a MAS.

dynamic, as they evolve in time; (iii) *continuous* and spatially distributed; and (iv) *accessible* or *inaccessible* depending on the degree of information sharing among the agents. In an accessible environment, each agent can obtain complete, accurate, and up-to-date information about the environment state (e.g., current water level in the reservoirs), which means full information exchange among decision makers and/or stakeholders. Most frequently, real-world environments are not accessible because noncooperative agents may also not agree on sharing information on their respective subsystems. Realistically, there exists a third intermediate situation where the agents partially exchange information: typically, they may share hydrological data but do not reveal their management objectives [*Giuliani et al*., 2012b].

2.2. Cooperation and Information Exchange

[15] As anticipated, in this work we consider three different scenarios of cooperation/information exchange: (i) *fully cooperative and informative* agents, who agree to establish a joint action strategy and exchange all the information; (ii) *coordinated* agents, corresponding to an accessible environment, where agents exchange full information on their subsystems but do not cooperate to find a globally optimal solution; and (iii) *noncooperative and noninformative* agents, representing an inaccessible environment, where agents are completely individualistic and do not share any information.

[16] In the typically conflicting upstream/downstream relationship within transboundary river basins in Figure 1b, the first scenario corresponds to the classical centralized management approach, where a central authority is assumed to be in charge of designing the management on a basinwide scale and all the agents act in order to maximize the global benefit. In the second scenario, which is the first level of cooperation, upstream agents look at their objectives only, with no consideration of the externalities produced to the downstream agents. Yet, according to the accessible environment hypothesis, in this case there is complete information sharing between the agents (i.e., hydrological data and management objectives). Based on this information, the downstream agents can model the optimal behavior of the upstream agents (i.e., their release decisions) and decide their best strategy coordinately with the upstream management. Finally, in the third scenarios, the downstream agents, who are clearly affected by the upstream management but have no information about it, can only model the total inflow to their subsystem as a stochastic input and subsequently solve their optimal operation problem accordingly.

[17] Depending on the scenario adopted, the formulations of the optimization problems solved by the agents to design their optimal decisions are different as described next.

2.2.1. Fully Cooperative and Informative Scenario

[18] Under this scenario, the agents, beyond sharing information, agree on sharing also the operating objectives in order to establish a joint management strategy for the entire system. This is equivalent to the centralized approach commonly adopted in most of the water resources literature, in which the management problem is formulated as a q-objective, stochastic, periodic, nonlinear, closed-loop optimal control problem [e.g., see *Castelletti et al*., 2008a, and references therein], i.e.,

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

where $\mathbf{J}(p) = [J^1, \ldots, J^q]$ is the vector objective function, and the operating policy p is defined as a sequence of operating rules $p = \{m_t(\cdot), t = 0, \ldots T\}$, being T the period, mapping the current state $\mathbf{x}_t \in \mathbb{R}^m$ of the system into the feasible release decision $\mathbf{u}_t \in \mathcal{U}_t(\mathbf{x}_t) \subseteq \mathbb{R}^n$, i.e., $\mathbf{u}_t = m_t(\mathbf{x}_t)$. The state evolves accordingly to a state transition function $\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \boldsymbol{\varepsilon}_{t+1})$ affected by a stochastic external driver vector $\boldsymbol{\varepsilon}_{t+1} \in \mathbb{R}^l$.

[19] The resolution of problem (1) does not yield a unique optimal solution but a set of Pareto-optimal solutions. By adopting the weighting method, problem (1) can be reformulated as

$$p^* = \arg\min_p \boldsymbol{\lambda} \cdot \mathbf{J}(p), \tag{2}$$

where $\boldsymbol{\lambda}$ is the vector of weights, with $\sum_{k=1}^{q} \boldsymbol{\lambda}^k = 1$ and $\boldsymbol{\lambda}^k \geq 0\ \forall k$. By solving the problem for different values of the weights $\boldsymbol{\lambda}$, a finite subset of the generally infinite Pareto-optimal policy set is obtained.

[20] Stochastic dynamic programming [*Bellman*, 1957] is the most flexible and accurate method for solving problem (1) but suffers from the so-called "curse of dimensionality," which limits its applicability to very small-scale systems. To overcome the burden of dimensionality, in this paper, we use MPC [see *Bertsekas*, 2005; *Scattolini*, 2009, and references therein], a real-time control approach based on the sequential resolution of multiple open-loop control problems defined over a finite, receding time horizon [*Mayne et al*., 2000]. At each time t, a forecast of the external drivers (e.g., the inflow), called nominal value, is provided over the finite horizon $[t, t+h]$ by a predictor that uses all the information available at time t (e.g., precipitation and inflow at previous time). The corresponding sequence of optimal decisions $\mathbf{u}_t^*, \ldots, \mathbf{u}_{t+h-1}^*$ is then obtained by solving a mathematical programming problem assuming that the realization of the disturbances will be equal to the predicted nominal value. However, only the control $\mathbf{u}_t^*$ is actually applied. At time $t+1$, a new problem is formulated over the horizon $[t+1, t+1+h]$ on the basis of the updated information available, i.e., the state of the system at time $t+1$ as well as updated forecasts of the external drivers [*Castelletti et al*., 2008b]. This feedback can partially compensate the effects of the disturbances, as it is very unlikely that the actual realization of the disturbances is equal to the predicted nominal values, with the system actually not evolving as expected. The availability of good forecast reduces the distance between expected and actual conditions, thus allowing to obtain decisions close to optimality.

[21] Adopting an MPC approach, also referred to as naive feedback control [*Bertsekas*, 1976], problem (2) can be reformulated as

$$\mathbf{u}^* = \arg\min{}_{\mathbf{u}_t, \ldots, \mathbf{u}_{t+h-1}} \boldsymbol{\lambda} \cdot \mathbf{J}(\cdot) \tag{3a}$$

subject to

$$\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \boldsymbol{\varepsilon}_{t+1}) \tag{3b}$$

$$\mathbf{u}_t \in \mathcal{U}_t. \tag{3c}$$

2.2.2. Noncooperative Scenario

[22] Under this scenario, the agents look at their local objectives and do not share information on the respective subsystems. Thus, the *i*th agent's problem (or the problem of the *i*th coalition of agents) becomes

$$\mathbf{u}^{*i} = \arg\min_{\mathbf{u}_t^i, \ldots, \mathbf{u}_{t+h-1}^i} \boldsymbol{\lambda}^i \cdot \mathbf{J}^i(\cdot) \tag{4a}$$

subject to

$$\mathbf{x}_{t+1}^i = f_t\left(\mathbf{x}_t^i, \mathbf{u}_t^i, \boldsymbol{\varepsilon}_{t+1}^i\right) \tag{4b}$$

$$\mathbf{u}_t^i \in \mathcal{U}_t^i \subset \mathcal{U}_t, \tag{4c}$$

where the *i*th agent considers his local objective functions $\mathbf{J}^i$ only, and his decisions are limited to a subset $\mathcal{U}_t^i$ of the entire feasible decision set $\mathcal{U}_t$. Moreover, the *i*th agent is able to observe only the state variables $\mathbf{x}_t^i$ belonging to his portion of the system. In this scenario the upstream agents are in a favorable condition as they can independently decide what is the best for themselves, while the downstream agents will be affected by and have to adapt to these decisions. This two-step approach is the most common in real-world problems, as in *Goor et al*. [2007] and *Anghileri et al*. [2012]. Without information exchange, the information available to the *i*th agent comprises only the variables directly observed and controlled by the agent himself. Everything else is a stochastic driver for his subsystem (e.g., the downstream agents in Figure 1b, having no information on the decisions made by the upstream agents, can only model the total inflow to their subsystem as a stochastic input). Conversely, the introduction of information exchange enlarges the information system on which the decisions of the downstream agents are made as described in the next section.

2.2.3. Coordinated Scenario

[23] Under this scenario, the agents look at their local objectives but now also share information on the respective subsystems. On the basis of this information, which comprises hydrological data and the other agents' operating objectives, the downstream agents can develop a model of the upstream subsystem $\psi(\cdot)$ equivalent to the one used by the upstream agents to optimize their decisions. According to this model, the downstream agents can simulate off-line the upstream optimal behavior and exploit an enlarged information system to make more informed decisions. For example, let us assume that the downstream reservoir in Figure 1b is regulated for hydropower energy production. In a dry season the downstream agents may decide to release less than the turbine capacity in order not to drawdown the reservoir level. However, knowing that the best strategy for the upstream agents is to release a large amount of water, the downstream agents can increase the releases, and consequently the production, because the reservoir is expected to be recharged by the upstream releases.

[24] According to this scenario, the *i*th agent's problem (or the problem of the *i*th coalition of agents) becomes

$$\mathbf{u}^{*i} = \arg\min_{\mathbf{u}_t^i, \ldots, \mathbf{u}_{t+h-1}^i} \boldsymbol{\lambda}^i \cdot \mathbf{J}^i(\cdot) \tag{5a}$$

subject to

$$\mathbf{x}_{t+1}^i = f_t\left(\mathbf{x}_t^i, \mathbf{u}_t^i, \mathbf{w}_t^i, \boldsymbol{\varepsilon}_{t+1}^i\right) \tag{5b}$$

$$\mathbf{u}_t^i \in \mathcal{U}^{\mathbf{i}}{}_t \subset \mathcal{U}_t \tag{5c}$$

$$\mathbf{w}_t^i = \psi\left(\mathbf{I}_t^{-i}\right), \tag{5d}$$

where the variables have the same meaning introduced earlier, $\mathbf{w}_t^i$ are the variables affecting the *i*th agent subsystem dependent on the decisions of the other agents, which can be described by the model ψ based on the exchanged information $\mathbf{I}_t^{-i}$ related to the subsystem observed by the other agents.

3. Zambezi River Basin Case Study

[25] The Zambezi River basin is one of the largest river basins in Africa. It is shared by eight countries, and it is mainly regulated for hydropower energy production in four main reservoirs (i.e., Itezhitezhi, Kafue Gorge, Kariba, and Cahora Bassa), and recently, ecological preservation in the Zambezi delta was introduced as the operation of the dams significantly altered the natural flow pattern in the delta. The proposed decision-analytic framework based on MASs allows to explore different degrees of cooperation and information exchange among the agents also considering the multiobjective nature of the problem.

3.1. System Description

[26] The Zambezi River basin (Figure 2) is located in southeast Africa and drains a catchment area of 1.39 million km^2. The river flows eastward for 2750 km, from the headwaters, in the Kalene hills in northwest Zambia, to the Indian Ocean in Mozambique. The river consists of three sections: *upper*, from the sources to Victoria Falls; *middle*, from the Falls to Cahora Bassa, including the junction with Kafue River tributary; and *lower*, from Cahora Bassa to the Indian Ocean, including the Shire River tributary flowing from Lake Malawi. The northern part of the basin belongs to the tropical summer rainfall zone, while moving south the climate becomes more arid.

[27] Because of the high runoff generated in the upper parts of the basin, combined with a fall of more than 1000 m during its course to the ocean, the river provides a good opportunity for hydropower energy production. Two dams are located on the tributary Kafue River, which belongs entirely to Zambia and has a catchment area of 155,000 km^2. The Government of Zambia built the Kafue Gorge dam in 1972 and then coupled it with the Itezhitezhi dam in 1977, which integrates the insufficient storage at Kafue Gorge due to the high losses for evaporation caused by the presence of the Kafue Flats, an extensive floodplain area where the river flows slowly for 250 km (it takes about 2 months from Itezhitezhi dam to reach the Kafue Gorge one) with an average gradient of 2.7 cm/km. The operation

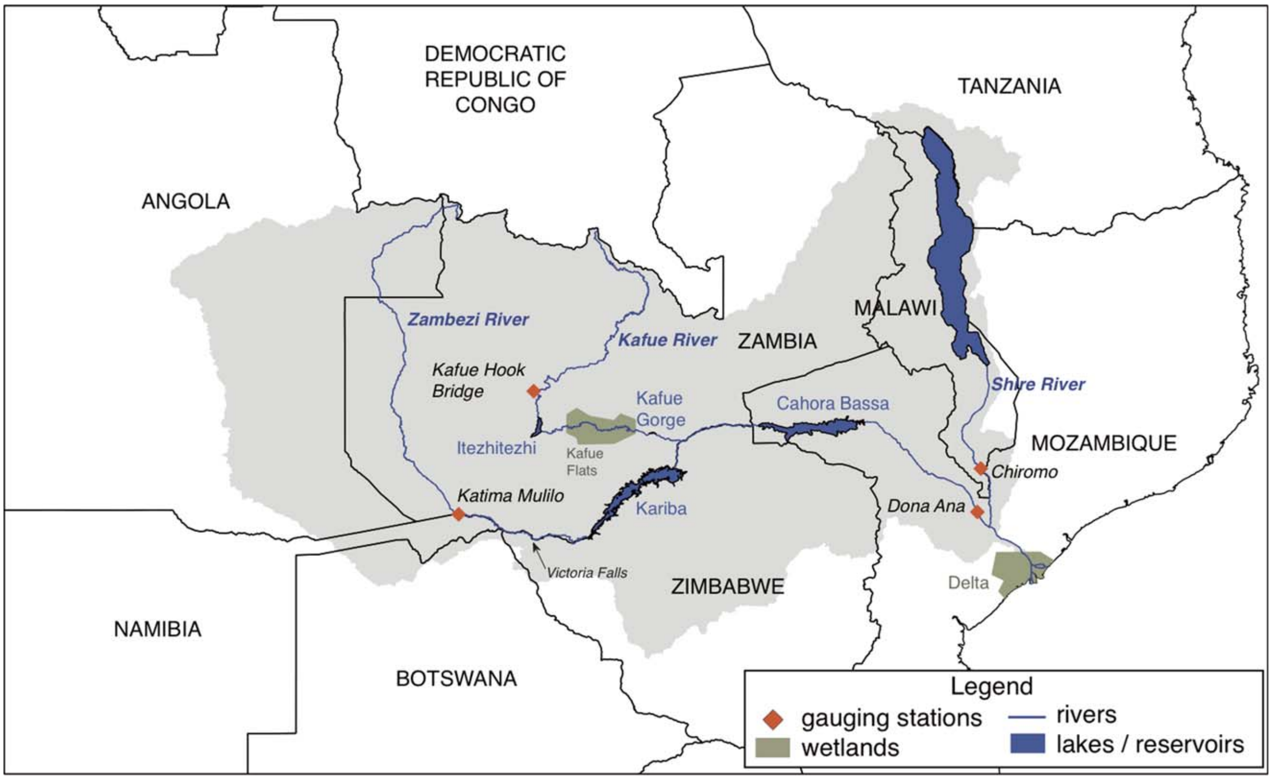

Figure 2. The Zambezi River basin.

of Itezhitezhi dam is governed by hydropower generation needs at Kafue Gorge Dam, except for an ecological constraint in March imposing a minimum flow of 300 m^3/s to preserve the Kafue Flats ecosystem [*Beilfuss and dos Santos*, 2001]. In the lower Kafue catchment there are several agricultural users with an associated water demand of nearly 15 m^3/s; however, more than half of this flow returns to the system [*Beilfuss and dos Santos*, 2001], and therefore, it is assumed as negligible in this work.

[28] Kariba and Cahora Bassa are the two largest reservoirs on the mainstream. Kariba dam, divided in North and South Banks, belonging respectively to Zambia and Zimbabwe, was completed in 1959; the two countries jointly manage the reservoir through the Zambezi River Authority comprising ministries from both Zambia and Zimbabwe. Cahora Bassa dam was filled in 1974 in Mozambique and controls a large portion of the flow in the lower section. The main characteristics of the four dams are listed in Table 1.

[29] Kariba and Itezhitezhi-Kafue Gorge reservoirs regulate almost 90% of the flow in the middle Zambezi, while Cahora Bassa controls a large portion of the flow in the Zambezi delta. According to *Beilfuss and dos Santos* [2001], the flows to the delta observed after the completion of Cahora Bassa (i.e., 1974–1999) have been reduced during the entire flooding season with respect to the condition before the construction of the dam (i.e., 1930–1974), including a 64% reduction in the mean monthly flow during February-April. The Zambezi runoff measured at Muturara (Dona Ana gauging station) decreased from 3200 m^3/s between 1930 and 1958 to 2200 m^3/s over the past 25 years. Many works have recently studied the ecology of the Zambezi River basin and the effect on these large storage operation on the ecosystem [*Timberlake*, 2000; *Beilfuss*,

Table 1. Main Existing Dams in the Zambezi River Basin[a]

	Itezhitezhi	Kafue Gorge	Kariba	Cahora Bassa
Live storage (km^3)	5[b]	0.7[b]	69[c]	52[d]
Dead storage (km^3)	–[b]	–[b]	116[c]	13[d]
Maximum release capacity[b] (m^3/s)	4200	4250	9500	13,950
Number of turbines[b]		6	4 (NB)−6 (SB)	5
Maximum power per turbine[b] (MW)		150	150 (NB)−111 (SB)	415
Maximum discharge per turbine[b] (m^3/s)		42	200 (NB)−140 (SB)	452
Head[b] (m)		397	108 (NB)−110 (SB)	128

[a]Kariba data are detailed for NB = North Bank; SB = South Bank.
[b]*Gandolfi et al*. [1997].
[c]Zambezi River Authority.
[d]Hidroelectrica de Cahora Bassa.

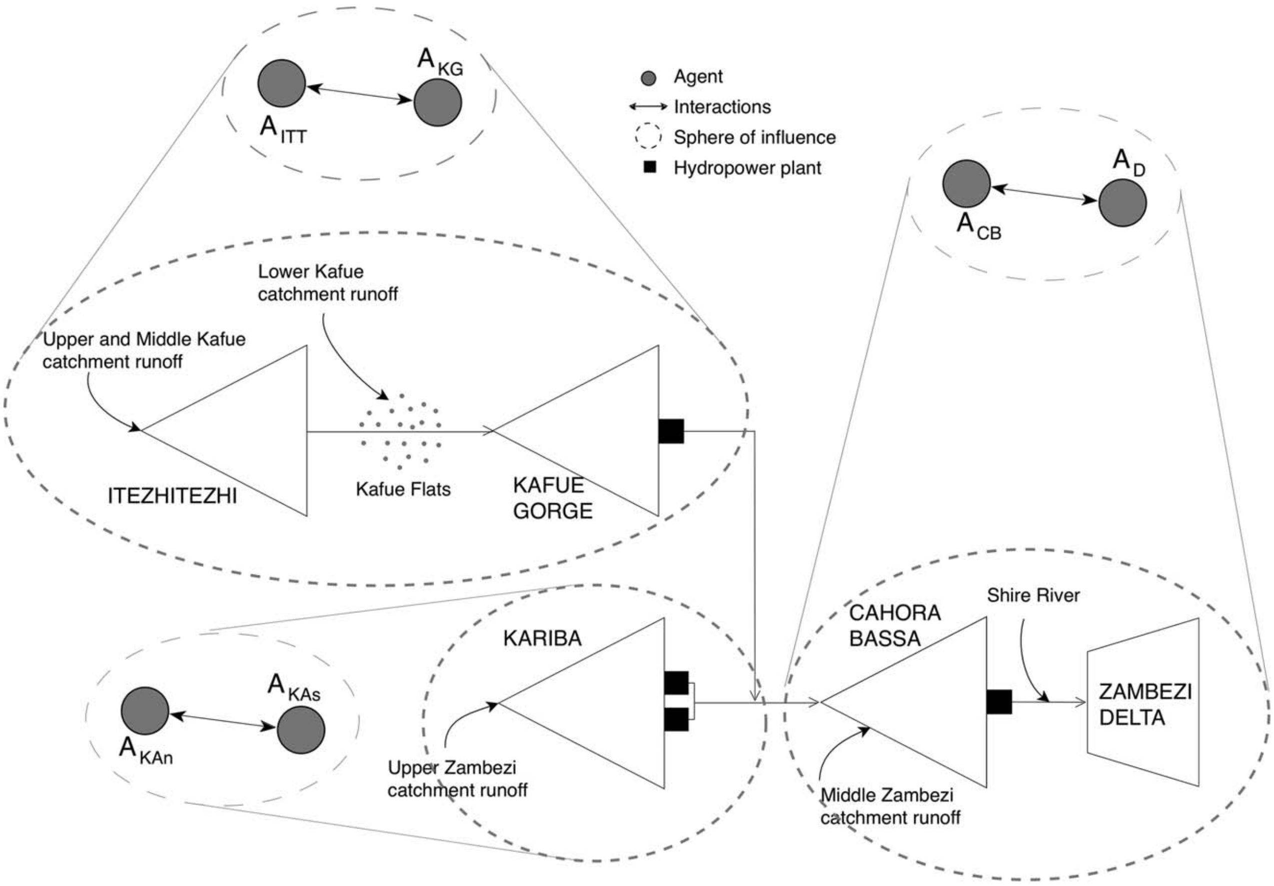

Figure 3. Agent-based model of the Zambezi system.

2001; *Beilfuss and Brown*, 2010; *Tilmant et al*., 2010]. As in *Tilmant et al*. [2010]; this paper focuses on the delta region where a target pulse of 7000 m^3/s during the peak flow season in February and March was established to restore part of the natural seasonal flow regime.

[30] The river discharge in the delta can be actually disaggregated into the releases from Cahora Bassa reservoir and the contribution from the lower Zambezi catchment tributaries, among which the Shire River is the largest one. The Shire River is the outflow of Lake Malawi, the only natural lake in the Zambezi basin, and his average annual runoff at Chiromo station is 483 m^3/s. Since 1960, Lake Malawi outflow has been partially regulated by the Liwonde Barrage aiming to maintain dry season flows in the Shire River for run-of-river hydropower generation. This paper does not consider the regulation of Liwonde Barrage, and the Shire River is considered as an inflow.

3.2. Zambezi River Agent-Based Model

[31] The agent-based model of the Zambezi River system (Figure 3) comprises six agents representing the six water-related interests in the system, i.e., the five hydropower plants and the environment in the delta. The five agents associated to the power plants (Itezhitezhi (A_{ITT}), Kafue Gorge (A_{KG}), Kariba North Bank (A_{KAn}), Kariba South Bank (A_{KAs}), and Cahora Bassa (A_{CB})) are *active-controller agents*, who operate on a dynamic portion of the system having an internal state (the reservoir storage) and therefore decide according to a closed-loop control scheme. The agent in the delta (A_E) is, instead, a *reactive agent*, who does not make any decision but represents the ecological interest in the delta region. According to the real political and institutional setting in the basin, we grouped the agents in three coalitions of two agents sharing a common strategy: Itezhitezhi and Kafue Gorge dams require to be jointly operated by agents A_{ITT} and A_{KG} for hydropower production at Kafue Gorge; the regulation of Kariba North and South Banks for hydropower production is established by the Zambezi River Authority, represented by agents A_{KAn} and A_{KAs}; the regulation of Cahora Bassa is designed by the last coalition including agents A_{CB} and A_E and has to consider both hydropower production and ecological preservation of the delta. Only the last coalition is interested in the protection of the environment in the delta as, according to the agent-based model of the system, this coalition represents the interests of Mozambique country.

[32] The water system dynamics is described by the mass balance equations of the reservoirs storages with a monthly time step, i.e.,

$$\begin{aligned}
s_{t+1}^{\mathrm{ITT}} &= s_t^{\mathrm{ITT}} + \left(\varepsilon_{t+1}^{\mathrm{ITT}} - r_{t+1}^{\mathrm{ITT}}\right)\cdot\Delta - e_t^{\mathrm{ITT}}\\
s_{t+1}^{\mathrm{KG}} &= s_t^{\mathrm{KG}} + \left(\varepsilon_{t+1}^{\mathrm{KG}} + r_{t+3}^{\mathrm{ITT}} - r_{t+1}^{\mathrm{KG}}\right)\cdot\Delta - e_t^{\mathrm{KG}}\\
s_{t+1}^{\mathrm{KA}} &= s_t^{\mathrm{KA}} + \left(\varepsilon_{t+1}^{\mathrm{KA}} - r_{t+1}^{\mathrm{KA}}\right)\cdot\Delta - e_t^{\mathrm{KA}}\\
s_{t+1}^{\mathrm{CB}} &= s_t^{\mathrm{CB}} + \left(\varepsilon_{t+1}^{\mathrm{CB}} + r_{t+1}^{\mathrm{KA}} + r_{t+1}^{\mathrm{KG}} - r_{t+1}^{\mathrm{CB}}\right)\cdot\Delta - e_t^{\mathrm{CB}},
\end{aligned} \tag{6}$$

where ε_{t+1}^i (m^3/month) (i = ITT, KG, KA, CB) is the inflow to the ith reservoir in the interval $[t, t+1)$; Δ is the

Table 2. Model Prediction Performance Measured With the Nash-Sutcliffe Efficiency Index Over the Validation Period 1974–1980[a]

Inflow	R^2
Itezhitezhi	0.772
Kafue Gorge	0.772
Kariba	0.770
Cahora Bassa	0.992
Shire River	0.768

[a]Cahora Bassa inflows are synthetically generated.

integration time-step; the release r^i_{t+1} (m^3/month) is given by the release function $r^i_{t+1} = f\left(s^i_t, u^i_t, \varepsilon^i_{t+1}\right)$, where u^i_t (m^3/month) is the decision (control), and $r^i_{t+1}(\cdot)$ is a nonlinear function describing the stochastic relation between the decision u_t and the actual release r_{t+1} [*Piccardi and Soncini-Sessa*, 1991]; finally, e^i_t (m^3/month) is the mean monthly losses for evaporation. In particular, the evaporation at Kafue Gorge is calibrated [*Gandolfi et al.*, 1997] to take care also of the significant evaporation losses in the Kafue Flats. According to the monthly time step adopted, river branches are modeled as plug-flow canals with negligible travel time, except for the Itezhitezhi-Kafue Gorge connection which requires 2 months.

[33] At the basinwide level, reservoir operation aims at satisfying four different objectives: to maximize the hydropower production (TWh/yr) at Kafue Gorge ($J^{H,\mathrm{KG}}$, associated to the agents A_{ITT}-A_{KG}), at Kariba North and South Banks ($J^{H,\mathrm{KA}}$, related to agents A_{KAn}-A_{KAs}), and at Cahora Bassa ($J^{H,\mathrm{CB}}$) and to protect the ecosystem in the Zambezi delta (J^E), both associated to agents A_{CB}-A_{E}. Previous studies considered the environmental requirements in the delta region as an additional constraint [*Gandolfi et al.*, 1997], or as an economic objective by monetizing river flows through a marginal-benefit function [*Tilmant et al.*, 2010]. In this paper, the environmental objective is instead represented by a specific objective function J^E (associated to agent A_{E}) defined as the average water deficit in the delta with respect to the target peak flow of 7000 m^3/s in February and March. The cooperative solution to problem (3) yields a set of Pareto-optimal or trade-off solutions between the two main objectives, i.e., total hydropower energy production $J^{H,\mathrm{tot}}$ and ecological preservation J^E, and enables a trade-off analysis. On the other side, in both the coordinated and noncooperative scenarios the multiobjective problem is defined at the agent (actually coalition of agents) level. The first coalition (agents A_{ITT} and A_{KG}) operates Itezhitezhi and Kafue Gorge and solves a single-objective problem with respect to $J^{H,\mathrm{KG}}$ (i.e., maximization of hydropower production at Kafue Gorge). The second one (agents A_{KAn} and A_{KAs}) operates the two power plants at Kariba solving again a single-objective problem with respect to $J^{H,\mathrm{KA}}$ (i.e., maximization of hydropower production at Kariba). The third coalition, representing the Mozambique interests (agents A_{CB} and A_{E}), operates Cahora Bassa dam and solves a two-objective problem related to the maximization of hydropower production at Cahora Bassa $J^{H,\mathrm{CB}}$ as well as the protection of the Zambezi delta J^E. In sum, we define two single-objective optimization problems for the upstream agents and a two-objective optimization problem for the downstream agents, yielding to a Pareto front in the downstream objective space $J^{H,\mathrm{CB}}$ and J^E.

[34] To solve the problem with an MPC scheme, we developed a h step ahead inflow prediction ($h = 3$ months). Among the set of alternative modeling approaches (autoregressive models, neural networks, extremely randomize trees, etc.), linear periodic PAR(1) models [*Salas et al.*, 1980] were identified because they are able to provide good forecasts of the inflow processes according to the adopted monthly time step, see the explained variance in Table 2. In particular, the interannual variability characterizing the inflows in the Zambezi system [*Rocha and Simmonds*, 1997; *Mazvimavi and Wolski*, 2006] has limited impacts on the considered objectives and it can be captured by autoregressive models.

[35] The available data for the Itezhitezhi inflow are measured at Kafue Hook Bridge station and cover the period (1974–2003). The predictive model was calibrated on the period (1981–2003) and validated on the simulation horizon (1974–1980). The quantification of the lateral contribution from the Kafue Flats to Kafue Gorge is highly uncertain, with several values proposed in the literature varying between a conservative hypothesis of neglecting this contribution to estimates based on the Ithezithezi inflow. According to *Gandolfi et al*. [1997] and *Tilmant et al*. [2010], we defined the lateral contribution as the 30% of the Ithezithezi inflow, and therefore, the calibration and validation periods are the same as for the former model. The data about Kariba inflow, measured at Katima Mulilo station, cover the period (1943–2003); the predictive model was calibrated on the two periods (1943–1973)–(1981–2003) and validated on the simulation horizon. The paucity of data from the Middle Zambezi Catchment (only monthly average inflows from *Beilfuss and dos Santos* [2001] are available) required a process of synthetic time series generation to extend the available data. Finally the Shire flows, measured at Chiromo station, cover the period (1953–1980), and the predictive model was calibrated on the first part of the series (1953–1973) and validated on the simulation horizon. Apart from the Middle Zambezi Catchment, the data used in this work, represented in Figure 4, were provided by the Global Runoff Data Centre (http://www.bafg.de/).

4. Results

[36] Real-time control in the form of MPC with a 3 month ahead inflow forecast is implemented in this work to

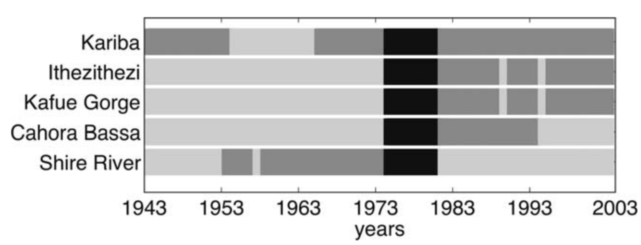

Figure 4. Available inflows data (Source: Global Runoff Data Centre): the validation-simulation period is in black, the data used in calibration are in dark gray, and missing data are in light gray.

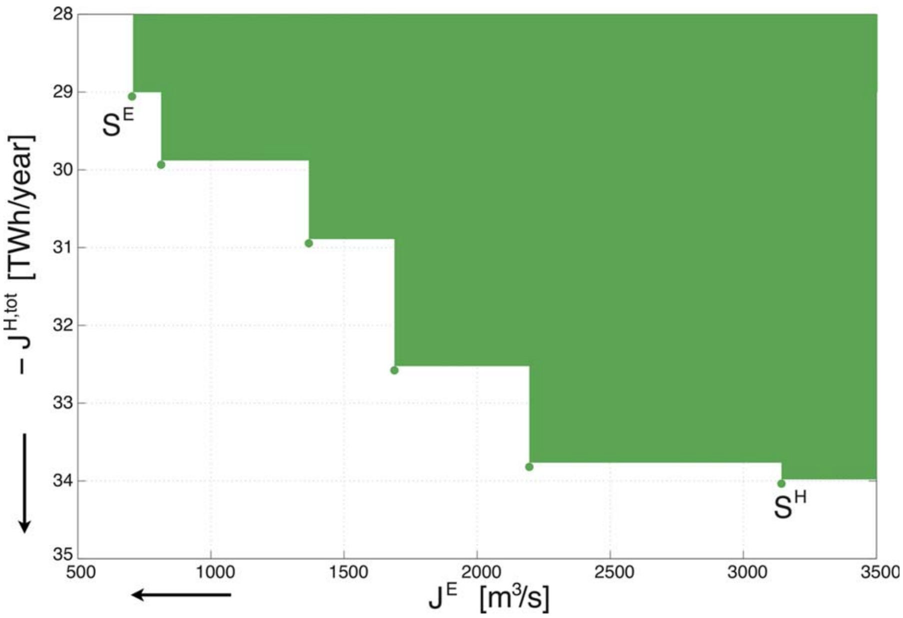

Figure 5. Fully cooperative (centralized) Pareto front in the objective space $J^{H,\mathrm{tot}}$ and J^E.

optimize the management of the Zambezi River system for the fully cooperative, coordinated and noncooperative scenarios. The results are obtained simulating the system with a monthly time step on the historical time series of inflows on the period 1974–1980.

4.1. Fully Cooperative Solutions

[37] In order to evaluate the trade-off relationships between hydropower production and ecological preservation of the Zambezi delta, the Pareto front in the objective space $J^{H,\mathrm{tot}}$ and J^E was approximated by solving problem (3) for different combinations of weights $\boldsymbol{\lambda}$. Figure 5 shows the obtained Pareto-efficient solutions: with solution S^H, which considers only the hydropower objective, the energy production is equal to 34.03 TWh/yr, and the corresponding average flow deficit in February and March is equal to 3143 m^3/s. This result is comparable with the value obtained by *Gandolfi et al*. [1997] on the basis of which we calibrated our model. The resulting energy production seems instead overestimated, in particular at Kafue Gorge and Kariba, with respect to the one obtained by *Tilmant et al*. [2010] using models calibrated on historical productions. Adopting the same correction, we obtain an energy production equal to 30.3 TWh/yr, which is consistent with the historical productions. However, the real decision makers acting in the system do not look at hydropower production only but implicitly consider and weight also other minor objectives (e.g., irrigation supply in the Kafue catchment). Moreover, the decision makers can also store water when the power plants are unavailable deciding to turbine later with a higher head. Hence, it seems reasonable that the historical production is lower than the value we obtain. The introduction of the environmental objective alters the decision makers' objective balance. For this reason, although the values used by *Gandolfi et al*. [1997] probably overestimate the hydropower production, they provide a solid ground to project the decision makers' behavior in a multiobjective context. Moreover, the primary aim of this work is not to improve the efficiency of hydropower energy production system in the Zambezi River basin but rather to assess the differences in the objective values due to different scenarios of cooperation and information exchange as explained next.

[38] The hydropower production for solution S^E, which considers only the ecological objective, is lower than that for S^H and equals 29.05 TWh/yr, with the flow deficit decreased to 703 m^3/s. The comparison of the average monthly flows in the Zambezi delta for these two solutions (Figure 6a) shows a distinctive difference in the flows in February and March due to the ecological objective. Although solution S^E, aiming at minimizing the difference with respect to the target peak flow of 7000 m^3/s in February and March, does not obtain a null deficit, it is able to restore a peak flow close to the natural condition. However, this release strategy reduces water availability in the rest of the year, while the hydropower-based regulation of Cahora Bassa dam produces almost constant flows in the delta. It is also worth noting that the water released for environmental purposes is actually wasted with respect to hydropower production, as shown in Figures 6b and 6c, where the different contributions to the flows in the delta are separated: S^E spills a significant volume of water in February and March trying to guarantee the target flow, while spillway outflows are obviously more limited for S^H.

[39] The trade-off between the two objectives can be estimated by pair comparison of the solutions in the objective space: the improvement in one objective is compensated by the worsening of the other. As an example, the difference in hydropower production between S^H and S^E ($34.03 - 29.05 = 4.98$ TWh/yr) is balanced by the decrease of average water deficit in the delta in February and March (from 3143 to 703 m^3/s). Note that the curvature of the trade-off curve is almost constant and does not significantly change near the extremes. This unexpected result can be

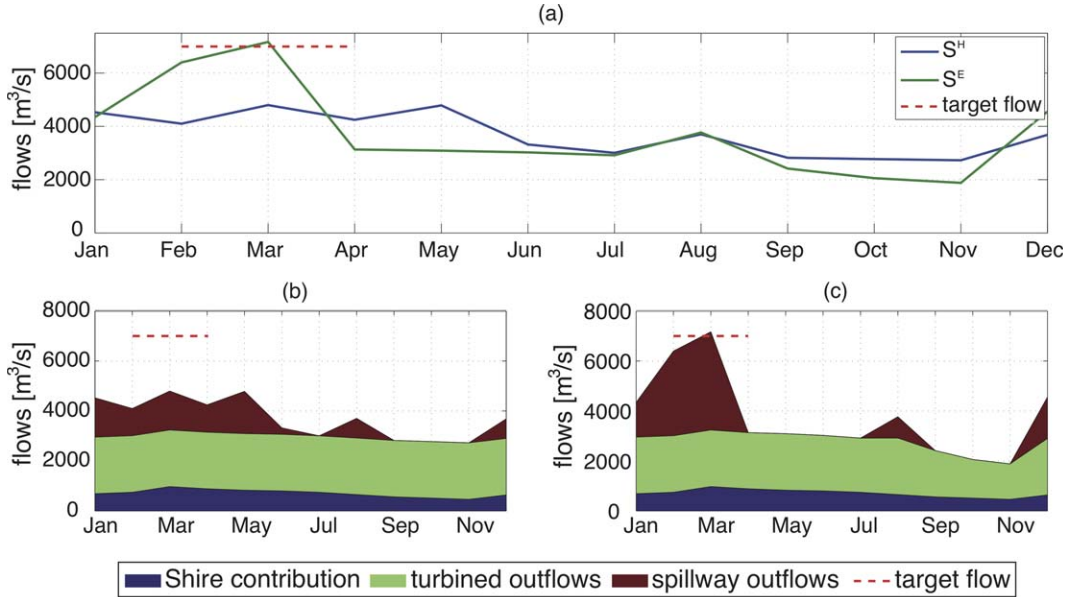

Figure 6. (a) Comparison of average monthly flows in the delta along with their different contributions for the two extreme solutions of the fully cooperative Pareto front (b) S^H and (c) S^E.

explained by the limited length of the peak flow season when the environmental flow target has to be satisfied: the aggregation of the hydropower production along the entire year mitigates the negative impacts of the "unproductive water" released in the peak flow season. The curvature of the Pareto front obtained by computing the two objectives only in February and March changes moving along the front.

[40] The economic cost of the water deficit in the delta can be estimated by considering the hydropower revenue instead of the energy production. According to *Tilmant et al*. [2010] and *Whittington et al*. [2005], we assume a constant price of electricity equal to 80 US$/MWh, which is independent from the actual power production as a detailed model of the entire South African Power Pool (SAPP) would be too complex, and moreover, the energy produced in the Zambezi system is low compared to that of South Africa. By the analysis of the last prices available on the SAPP website, it seems that the proposed value is slightly overestimated. However, we adopted the price found in the literature to enable comparison with previous works. The Pareto-optimality concept guarantees that the decrease in the hydropower revenue associated to a given solution with respect to solution S^H is compensated by the corresponding reduction of the environmental costs in the delta. Therefore, the cost of the water deficit ν^{λ} of the solution S^{λ} associated to the vector of weights $\boldsymbol{\lambda}$ in the objective space can be estimated as the slope of the line connecting that solution to solution S^H [*Wu et al*., 2010], i.e.,

$$\nu^{\lambda} = \frac{|J^{H,\mathrm{tot}}(S^H) - J^{H,\mathrm{tot}}(S^{\lambda})| \times 10^6 \times 80}{|J^E(S^H) - J^E(S^{\lambda})|} \qquad US\$/m^3/s. \quad (7)$$

[41] Comparing solution S^H with the other extreme of the Pareto front S^E (obtained with $\boldsymbol{\lambda} = [0.0001, 0.9999]$ in order not to consider multiple optima), the yearly economic cost of the water deficit in the delta is $\nu^E = 4.98 \times 10^6 \times 80/2440 = 1.6319 \times 10^5$ US$/(m^3/s). The value of ν^{λ} is actually different for each point of the Pareto front, as each solution corresponds to a different balance of the two objectives and its range of variability is between 0.1805×10^5 and 1.6319×10^5 US$/(m^3/s), while the mean value is $\overline{\nu} = 1.0825 \times 10^5$ US$/(m^3/s).

[42] It is interesting to observe that both the average value $\overline{\nu}$ and the whole range of variability of ν^{λ} are very close to the upper bound of the marginal-benefit functions proposed in the literature to monetize the benefits associated with the flows in the delta, i.e., 1.7143×10^5 US$/(m^3/s), corresponding to 1000 US$/ha [*Woodward and Wui*, 2001; *Brander et al*., 2006; *Tilmant et al*., 2010]. This result suggests that the explicit consideration of an environmental objective is equivalent to assigning a high economic value to the ecological preservation of the aquatic ecosystems. From a practical point of view, this result also confirms the findings of *Whittington et al*. [2005]: water resources management does not sufficiently consider the environmental requirements which assume secondary importance. Indeed, the range of wetland economic valuation spans from this upper bound to a lower bound of only 100 US$/ha, corresponding to 1.7143×10^4 US$/(m^3/s) that is much lower than the obtained ν^{λ}.

4.2. Coordinated and Noncooperative Solutions

[43] In order to assess the role of information exchange, the system was then simulated under different levels of cooperation, in particular assuming the noncooperative scenario and the coordinated one, which basically differ in the degree of information sharing. The agents' objectives are then evaluated one by one. Figure 7 shows a graphical representation of the objectives, comparing the agent-based solutions in these two scenarios with a fully cooperative compromise solution. This latter is shown for demonstration purposes and was selected among the set of Pareto-optimal solutions obtained in the cooperative scenario by

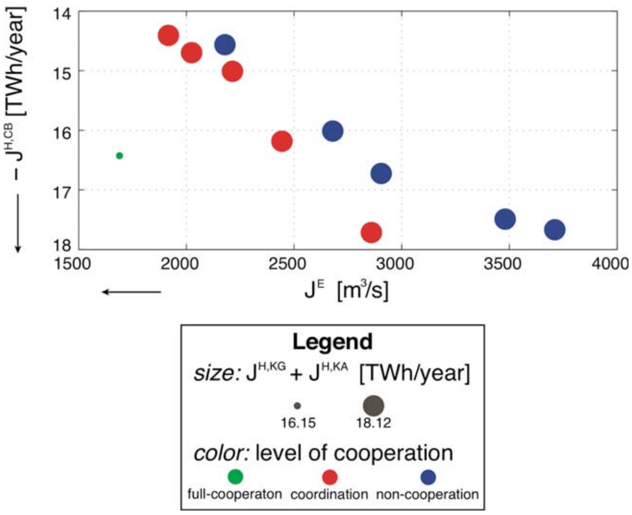

Figure 7. Projection of the 4-D Pareto front in the objective plan $J^{H,\mathrm{CB}}$ and J^E; circle size represents the upstream agents' objectives $J^{H,\mathrm{KG}} + J^{H,\mathrm{KA}}$ (the bigger the circle, the better is the solution); the agent-based solutions in the noncooperative (blue circles) and in the coordinated (red circles) scenarios are compared with a fully cooperative compromise solution (the green circle).

adopting the criterion of the minimum distance with respect to the Utopia point [*Eschenauer et al*., 1990], which identifies the absolute optima of all the objectives and is usually an unfeasible solution.

[44] Not surprisingly, all the agent-based solutions produce the same performances on the upstream objectives $J^{H,\mathrm{KG}}$ and $J^{H,\mathrm{KA}}$ in every scenario (the blue and red circles in Figure 7 have the same size) because the upstream agents act independently. Moreover, these solutions outperform the centralized ones for the upstream objectives (blue and red circles are bigger than the green one). On the other side, looking at the downstream objectives $J^{H,\mathrm{CB}}$ and J^E, the fully cooperative solution outperforms the others (the green point is placed in the bottom left part of Figure 7): the joint management is clearly able to better exploit the upstream-downstream relationships in order to guarantee a good compromise among all the agents' objectives.

[45] For both the coordinated and noncooperative scenarios, a set of Pareto-optimal solutions (Figure 8) between the downstream objectives $J^{H,\mathrm{CB}}$ and J^E are obtained by changing the vector of weights $\boldsymbol{\lambda}^i$ in the optimization problem of agents A_{CB} and A_{E}. The interesting evidence is that increasing the degree of information exchange improves the performance of the downstream agents in both the objectives: the noncooperative Pareto front obtained with noninformation sharing (blue points) is dominated by the coordinated one, which assumes complete information sharing (red points). To quantify the role of information on the whole Pareto front, it is possible to look at the values of the *hypervolume indicator* [*Zitzler et al*., 2003] in the two scenarios. The hypervolume indicator measures the volume of objective space dominated by a given Pareto front, thus allowing the comparison of Pareto fronts obtained with different methods respecting the dominance relationships [*Knowles and Corne*, 2002], i.e., high values of this indicator are obtained for Pareto fronts that are both converged and diverse. The hypervolume indicator is equal to 0.426 in the case of noncooperation, while it is equal to 0.495 for coordinated agents. These values confirm, from a quantitative point of view, the general superiority of the solutions obtained by simple cooperation through full information exchange: the noninformation sharing solutions are indeed Pareto-dominated by the coordinated ones, and information exchange allows to improve both the considered objectives. Moreover, these advantages for the downstream agents are obtained without affecting the upstream decisions and thus

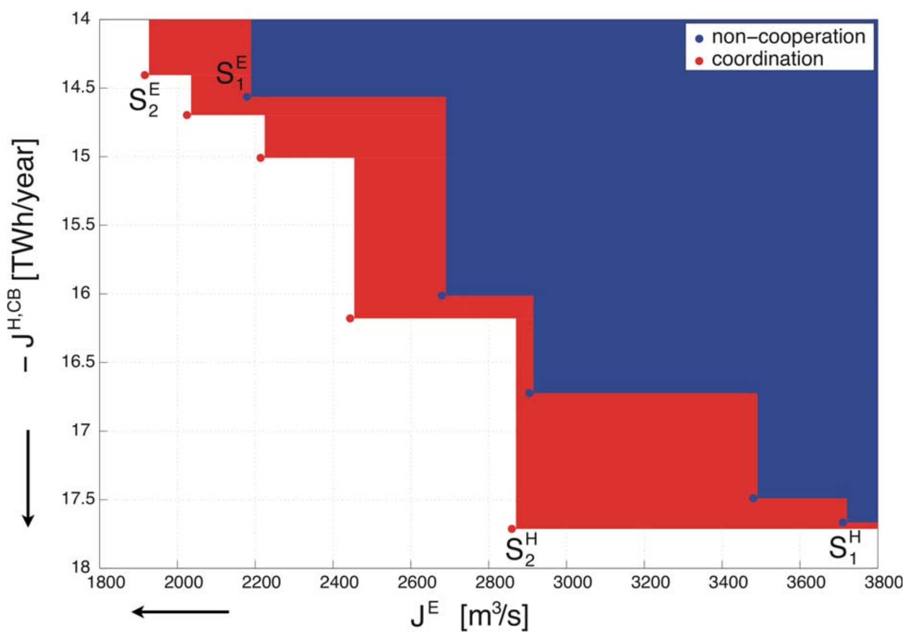

Figure 8. Pareto front in the downstream agents' objective space $J^{H,\mathrm{CB}}$ and J^E for different scenarios of information sharing (i.e., noncooperation and coordination).

Table 3. Solutions Selected in the Pareto Space According to the Minimum Distance From Utopia Point Criterion

Scenario	$J^{H,\mathrm{KG}}$ (TWh/yr)	$J^{H,\mathrm{KA}}$ (TWh/yr)	$J^{H,\mathrm{CB}}$ (TWh/yr)	JE (m3/s)
Noncooperation	7.67	10.45	14.56	2178
Coordination	7.67	10.45	14.40	1916
Full cooperation	7.63	8.51	16.42	1689

the corresponding benefit. Finally, observe that the improvement by information exchange varies along the Pareto front, meaning that the role of information sharing might depend upon the objective considered. Specifically, the improvements in the two extreme solutions are equal to 0.27% (hydropower only) and 12.04% (environment only), thus suggesting that the information exchange, and consequently the cooperation, has a higher marginal value for the environmental objective.

4.3. VFC and VIE

[46] The earlier analysis demonstrates that even a basic level of cooperation, only based on the exchange of information among the agents, might increase both the benefits for the downstream agents and the overall utility at the basinwide level with respect to a noncooperative setting. An economic evaluation of the improvements potentially achievable by cooperation, and information exchange might represent an effective basis to identify the most suitable policy mechanisms (e.g., economic incentives) to be implemented in order to favor a more cooperative attitude [*Whittington et al*., 2005]. From the comparative analysis of the solutions obtained respectively with the fully cooperative and the coordination scenarios against the noncooperative one it is possible to infer the economic VFC and VIE associated to the differences in the performances at the basinwide level.

[47] To this end, the physical objectives (energy production and flow rate deficit) must be converted into monetary values. In the case of the hydropower energy production, the conversion is made by assuming again the African energy price equal to 80 US$/MWh [*Tilmant et al*., 2010; *Whittington et al*., 2005]. For the water deficit in the delta, the cost can be computed using the values ν^{λ} previously estimated on the fully cooperative Pareto front. Since the marginal value of the information varies along the Pareto front and depends upon the objective considered, we first considered the two extreme solutions of the Pareto front, and subsequently, we analyzed a compromise solution.

[48] For the hydropower extreme of the Pareto front (points S_1^H and S_2^H in Figure 8), the annual energy production by the coordination strategy is 0.0471 TWh/yr more than the noncooperative case. This difference corresponds to 3.76×10^6 US$/yr, which is the economic VIE for hydropower energy production. Dually, considering the other extreme, which only minimizes objective J^E (points S_1^E and S_2^E in Figure 8), the reduction of the flow deficit is equal to 262.428 m^3/s. Hence, the VIE for an ecological management of Cahora Bassa is estimated adopting the value of ν^E previously identified for solution S^E (1.6319×10^5 US$/($m^3$/s)) and equals 42.82×10^6 US$/yr.

[49] Finally, it is interesting to estimate the role and the economic value of cooperation by comparing one solution for each of the three considered scenarios. Since the fully cooperative solutions were obtained by solving problem (3) in a centralized way, while the agent-based solutions are derived assuming different levels of cooperation in the resolution of problems (4) and (5), the selection of which solutions to compare is not straightforward. Therefore, for each scenario, the "most interesting" solution is again identified according to the criterion of the minimum distance from the Utopia point [*Eschenauer et al*., 1990]. The three selected solutions are reported in Table 3. It is evident that the fully cooperative solution is worse for the upstream agents, especially for the Kariba hydropower production, but enables improved performance for the downstream agents' objectives that are more damaged in the other scenarios by the individualistic strategies adopted upstream, as already shown in Figure 7. The economic values of full cooperation and information exchange were then estimated by looking at the monetary gain corresponding to the four objectives in the three considered solutions (assuming the average cost of the water deficit $\overline{\nu}$): the fully cooperative solution guarantees a monetary gain equal to 2.42×10^9 US$/yr, which is significantly higher than 2.39×10^9 and 2.37×10^9 US$/yr given by the coordinated and noncooperative solutions, respectively. These results allow to estimate a VIE and a VFC equal to 15.7×10^6 and 28.2×10^6 US$/yr, respectively. On the basis of this information, the agents (and hence the real decision makers) might reconsider their behaviors and introduce a complete information exchange which produces advantages to the downstream agents without affecting the benefits for the upstream ones. Moreover, given the reference of the fully cooperative solutions along with the VFC, the knowledge of the best performance ideally achievable can be used to get insights on strategies to foster more sophisticated cooperation and negotiation strategies.

5. Discussion and Conclusions

[50] In this paper we proposed a novel agent-based decision-analytic framework for studying different degrees of cooperation and information exchange among multiple decision makers and/or stakeholders in large-scale water resources systems and providing insight on management and negotiation strategies. The approach also allows to economically quantify the VFC and the VIE, which might be a fundamental information to set up a negotiation process. The transnational Zambezi River basin is used as a case study.

[51] The agent-based model of the Zambezi River comprises five active-controller agent, representing the managers of the five main hydropower plants in the system, and a reactive agent modeling the ecosystem of the river delta. Three different scenarios of cooperation and information exchange among the agents have been evaluated: (i) fully cooperative and informative agents, who agree to act coordinately and exchange all the information, which is equivalent to assuming an overall central decision maker who manages simultaneously the entire system; (ii) coordinated agents who exchange information, without, however, actively cooperate to find a globally optimal solution; and (iii) noncooperative and noninformative agents, who are completely individualistic and do not share any information.

[52] Results show that it is possible to improve the conditions of the downstream agents representing the Mozambique interests (i.e., hydropower production at Cahora Bassa and protection of the ecosystem in the Zambezi delta) with respect to the actual noncooperative setting by introducing coordination among the agents. This simple mechanism allows the downstream agents to more effectively adapt to the upstream strategies only because they know these strategies. Pareto front solutions obtained in the coordinated scenario outperform the corresponding solutions with no cooperation at all. According to the concept of Pareto dominance, coordination is therefore worthwhile in large water resources systems as it allows to obtain solutions that are better (at least for one objective) with respect to the noncooperative one.

[53] The multiobjective nature of the analysis allowed to estimate the trade-offs between hydropower energy production and the protection of the Zambezi delta. The explicit consideration of an environmental objective corresponds to assigning a high economic value to the ecological preservation of the aquatic ecosystems in the delta, close to the upper limit of the range of wetland valuation proposed in the literature. Moreover, it is interesting to observe that the role as well as the economic VIE changes according to the considered Pareto-efficient solution, and in particular, the marginal value is higher for the environmental objective.

[54] More in general, information exchange might have a primary role in rebalancing the upstream/downstream asymmetry in the Zambezi River basin, as it allows the downstream agents to better adapt to the upstream management strategies, with no consequence for these latter. Compared to the ideal centralized solution (full cooperation and information exchange), the feasibility of this coordinated solution is guaranteed as each agent cannot improve his benefit acting unilaterally.

[55] Finally, the economic VFC and VIE are estimated by comparing one solution for each scenario: the economic gain achievable at system level by moving from coordination to the ideal full cooperation is 28.2×10^6 US$/yr, while the introduction of the information exchange as a first level of cooperation, i.e., coordination, with respect to the noncooperative scenario produces an economic gain equal to 15.7×10^6 US$/yr. In case we adopted the historical production based calibration of the models as in *Tilmant et al*. [2010], we obtain a reduction of the energy production resulting in different VIE and VFC. In particular, the fully cooperative, coordinated and noncooperative solutions guarantee monetary gains equal to 2.14×10^9, 2.087×10^9, and 2.073×10^9 US$/yr, respectively. The corresponding VIE is equal to 14.7×10^6 US$/yr, while the VFC is 58.4×10^6 US$/yr as the fully cooperative solution is better than the coordinated one in the downstream objectives, which do not vary, and is worse in the upstream objectives, which are reduced. Consequently, the gap between the coordinated and the fully cooperative solutions increases.

[56] Note that, in reality, the VIE depends on two factors: first, the agents (institutions) have a constrained capacity, which limits their ability in the exploitation of the shared information, depending on the accuracy of the models they use. In this work, we assume that the costs to develop these models are negligible with respect to the benefits produced by the use of the models to optimize the operation in the system. Furthermore, the VIE tends to decrease in time, because by acquiring experience over time, the agents have more data available for the identification of more and more effective forecast models. The availability of better forecasts allows the agents in the noncooperative scenario to obtain performances closer to the ones in the coordinated scenario, with the gap decreasing in time, meaning that the VIE decreases as well. The accuracy of the forecast models is however limited, and the VIE does not tend to zero.

[57] In conclusion, it is worth summarizing the limitations of the proposed framework, in particular with respect to the computational costs and the scalability for larger systems. The computational costs are related to the adopted optimization algorithm and not to the underlying agent-based framework. The centralized solution is by far the more expensive, while the noncooperative one is the more flexible. As the problem scales up, a number of algorithms can be adopted to mitigate the computational burden, ranging from approximate dynamic programming [*Powell*, 2007] for relatively small systems to simulation-based optimization methods (e.g., Parametric-Simulation-Optimization) [see *Koutsoyiannis and Economou*, 2003]. For each algorithm using the weighting method, the associated computational costs grow exponentially with the number of objectives considered. The number of weight combinations required to accurately approximate the real continuous Pareto front might change from problem to problem. Clearly, the higher the accuracy the higher the computational costs. The interaction with the decision maker usually helps in refining the approximation (adopting a more dense sampling of the weight space) in the region of interest for the decision maker. Since we were not able to interact with the real decision makers involved in the problem, the weights were selected to ensure that the shape of the front was reasonably represented. Alternative methods exist for effectively dealing with many objective problems, including the Borg multiobjective evolutionary algorithm [*Hadka and Reed*, 2012; *Reed et al*., 2013].

[58] Future research will concentrate on assessing the possibility of finding solutions at other levels of cooperation, mainly between coordination and full cooperation. In particular, the MAS framework provides also effective algorithms for solving static distributed optimization problems, like distributed constraint satisfaction problems [*Yokoo and Hirayama*, 2000] and distributed constraint optimization problems [*Modi et al*., 2005], which are mainly unexplored in the water resources literature [*Giuliani et al*., 2012a]. Finally, the mechanisms to obtain these solutions, e.g. constraints, taxes, and subsides, have to be studied in depth according to game theory and policy-making concepts [*Maskin*, 2008; *Pannell*, 2008; *Madani*, 2010].

[59] **Acknowledgments.** The authors would like to thank the Global Runoff Data Center which provided the data used in this work, Amaury Tilmant for the useful discussion, and information provided about the Zambezi system and Rodolfo Soncini-Sessa for the useful advices and interesting discussion throughout the development of the work. Matteo Giuliani was partially supported by *Fondazione Fratelli Confalonieri*.

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