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MANAGEMENT OF MULTI-PURPOSE RESERVOIRS UNDER CLIMATE CHANGE: IMPACT ASSESSMENT AND ADAPTATION STRATEGIES

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Summary

Climate change is considered as one of the major forces that will affect water availability in the future. Identifying possible response strategies is a complex task because future projections are deeply uncertain and hydro-climatic conditions are expected to evolve gradually in the next decades. Current water management practices may not be robust enough to cope with the climate change impacts on water supply, flood control, agriculture, energy and ecosystems. Methods and tools to assist water resource planners and decision makers are thus required. In this thesis we assess how current and novel, adaptive approaches to water resource management can be used to cope with uncertain and nonstationary hydro-climatic conditions. We discuss the two mainstream approaches to assess climate change impact and to design adaptation strategies, i.e., the scenario-based approach and the vulnerability-based approach. We explore more in depth the vulnerability-based approach, which, in our opinion, is the most promising way to tackle the problems related to the sustainability of the water uses. To this end, we use modelling and optimization tools to explore vulnerabilities and adaptive capacities of water systems and to produce knowledge that is relevant in the decision making context. In particular, we integrate the simulation models usually employed to estimate the impacts of climate change on water resources by considering water-value models, decision models, and multi-objective optimization techniques which allow to describe the complex interactions between social, economic, and environmental aspects. The main contributions of the thesis can be summarized in the following points: *i)* we exploit simulation and optimization techniques to re-frame the institutional

setting where reservoirs are operated, demonstrating that a shift toward a more cooperative and flexible setting can increase the overall efficiency of water resource management and can improve the resilience to unforeseen events, *ii)* we propose an impact assessment procedure to assess the ability of water resource management practices to compensate future water stresses as projected by climate models, *iii)* we present tools to assess the inherent adaptation capacity of water system to hydro-climatic changes which, on the one hand, allow to gain a deeper knowledge of the water system characteristics, and, on the other hand, can drive the identification of the most promising adaptation measures to further enhance the adaptation potential of water systems; *iv)* we address the topic of trend detection in environmental time series combining novel and traditional tools in order to simultaneously tackle the issue of seasonality and interannual variability, which usually characterize natural processes; *v)* we use stochastic recursive control and model predictive control to test if adaptive management is a viable adaptation measure to climate change. Models and optimization techniques are tested on real-world case studies to discuss their potential and limitations.

Sommario

Il cambiamento climatico è considerato una delle maggiori forzanti che influenzeranno la disponibilità idrica nel futuro. Individuare possibili strategie di risposta è un compito complesso, da un lato, perché gli scenari futuri sono profondamente incerti e, dall'altro, perché le condizioni idroclimatiche evolveranno gradualmente nei prossimi decenni. Si ritiene che le attuali pratiche di gestione delle risorse idriche non siano in grado di far fronte ai possibili impatti dei cambiamenti climatici in termini di fornitura irrigua ed energetica, controllo delle esondazioni e protezione degli ecosistemi. Sono quindi necessari metodi e strumenti per supportare i decisori politici nella pianificazione e gestione delle risorse idriche. L'obiettivo di questa tesi è valutare se e come le pratiche attuali e nuovi approcci adattivi alla gestione delle risorse idriche siano in grado di far fronte a condizioni idro-climatiche incerte e non stazionarie. Durante la trattazione, presentiamo i due principali approcci utilizzati in letteratura per valutare l'impatto dei cambiamenti climatici e per definire strategie di adattamento: l'approccio scenario-based e vulnerability-based. Approfondiamo in particolare il secondo che, a nostro parere, rappresenta il modo più promettente per affrontare il tema della sostenibilità dell'uso delle risorse idriche. A tal fine, presentiamo strumenti di modellistica e ottimizzazione per identificare le vulnerabilità e le potenzialità delle diverse pratiche di gestione, in modo da produrre informazioni utili al processo decisionale nell'ottica dei sistemi di supporto alle decisioni. In particolare, integriamo i modelli di simulazione solitamente utilizzati per stimare gli impatti dei cambiamenti climatici aggiungendo indicatori quantitativi legati all'utilizzo delle risorse idriche,

modelli decisionali e tecniche di ottimizzazione multi-obiettivo che, combinati insieme, permettono di descrivere il complesso sistema di interazioni socio-economiche e ambientali tipico dei problemi decisionali in campo ambientale. I principali contributi della tesi possono essere riassunti nei punti seguenti: *i)* sfruttiamo tecniche di simulazione e ottimizzazione per ridefinire il contesto istituzionale in cui serbatoi idrici sono gestiti, dimostrando come uno spostamento verso contesti più collaborativi e flessibili sia in grado di aumentare l'efficienza complessiva di gestione delle risorse idriche e possa migliorare la capacità di reagire efficacemente a eventi imprevisti, *ii)* proponiamo una procedura di valutazione d'impatto dei cambiamenti climatici per stabilire la capacità delle diverse pratiche di gestione delle risorse idriche di compensare a eventuali stress idrici futuri, *iii)* presentiamo strumenti per valutare la capacità intrinseca dei sistemi idrici di adattarsi ai cambiamenti idro-climatici in modo da guidare, in un secondo momento, la scelta delle misure di adattamento più efficaci nell'aumentare tale potenziale; *iv)* affrontiamo il tema della identificazione di trend nelle serie temporali di variabili ambientali, quali portata, temperatura e precipitazione, combinando strumenti tradizionali e innovativi che siano in grado di affrontare contemporaneamente il problema della stagionalità e della variabilità interannuale, che di solito caratterizzano i fenomeni naturali; *v)* usiamo tecniche di controllo ricorsivo stocastico e di controllo predittivo per verificare se la gestione adattativa delle risorse idriche possa essere considerata una misura di adattamento efficace per far fronte al cambiamento climatico. Tutti gli strumenti modellistici e di ottimizzazione sono testati su casi di studio reali in modo da poterne discutere le potenzialità e i limiti.

Contents

CHAPTER 1

Introduction

Climate change has been recognized as one of the major threats to future water availability, at least in developed countries (e.g., Bates et al., 2008). Current water management and planning practices have been argued as not able to tackle future water supply, flood protection, agriculture, energy and ecosystems (Milly et al., 2008; Walker, Marchau, and Swanson, 2010). Although the scientific community agrees on the fact that adapting to climate change involve changing the way we look at water resources planning and management, there is less agreement on the best practices to cope with climate change and to adapt to the new future water availability. Depending on the perspective adopted in addressing these topics, impact assessment studies belong to two mainstream approaches: the *scenario-based* and *vulnerability-based* approach.

Scenario-based approach

The first generation of impact and adaptation assessment studies is called *scenario-based* or *top-down*. It relies on a modeling chain that usually includes: *i)* the choice of one or more future emission scenarios, *ii)* the simulation of Global Circulation Model (GCM) to build global climate scenarios, *iii)* the use of Regional Circulation Model (RCM) and/or statistical downscaling to estimate climate scenarios at the local scale, *iv)* the projection of these climatic scenarios into streamflow scenarios via simulation of hydrological models, and *v)* the simulation of the impacts on water resources. Adaptation measures are finally designed in order to reduce the estimated negative impacts.

The main criticality of the scenario-based approach is that it usually results in very uncertain estimates of future impacts which makes almost impossible the definition of clear and useful adaptation measures. This is a consequence of the so called "cascade of uncertainty": every step of the study adds and enhances uncertainty which is finally reflected in a broad range of impacts. This condition of deep uncertainty (Walker, Marchau, and Swanson, 2010) has discouraged serious interest in the definition of adaptation actions by the policy makers, the so called "policy inertia", because of the perception that the actions should be taken in the future, whithout knowing precisely when, or because uncertainty is perceived as lack of knowledge (Burton et al., 2002). As a consequence, the implementation of the adaptation strategies, which were eventually identified as the most effective ones, has been delayed.

The other main criticality is related to the fact that the time and magnitude of adaptation is totally driven by the future climate scenario and by how reliable it is. Even if GCMs have become more and more sophisticated in time, they were not developed to provide the level of accuracy required for adaptation studies (Kundzewicz and Stakhiv, 2010). GCMs are built to evaluate how climate reacts to different Green House Gas (GHG) concentrations in the atmosphere. They are thus considered a valid tool to define mitigation strategies, i.e., actions for limiting global climate change by reducing the emissions of GHGs or enhancing their sinks, rather than to define adaptation strategies, i.e., actions for reducing the vulnerability of water systems to the changes occured in the climate (Füssel, 2007). In fact, adaptation measures are usually site specific, whereas climate scenarios can provide reliable information only at the global scale. Actually, some authors claim that GCMs are not even able to accurately reproduce the climate on regional spatial scales and large temporal scales (e.g., Koutsoyiannis et al., 2008; Curt et al., 2003), and the fact that different GCMs agree on future climate scenarios does not imply that those scenarios are reliable, because all the models may be comparable but biased (Blöschl and Montanari, 2010).

In the field of water resources, climate models are usually considered inadequate for direct use in planning and management problems (Kundzewicz and Stakhiv, 2010; Dessai et al., 2009). Although some authors claimed for the improvements of GCMs, current decision making problems are characterized by a level of uncertainty that cannot be simply reduced by more sophisticated models (Walker, Marchau, and Swanson, 2010). For instance, no modelling tool or improved knowledge can help in delineate a reliable projection of the economy and society for the next centuries, as required to define the emission scenarios. Uncertainty in future projections can not be totally eliminated and researchers must find ways to deal with it (Blöschl and Montanari, 2010; Dessai et al., 2009). The acknowledgment of this "limit to predictability" has undermined the classical predict-and-control paradigm used in water resources planning and management (Pahl-Wostl, 2007), bringing the water management and hydrology community to look for different approaches.

Vulnerability-based approach

The second generation of impact and adaptation assessment studies totally reverses the perspective by grounding adaptation in the present (Burton et al., 2002). It is called *vulnerability-based* or *bottom-up* approach, since it does not primarily rely on the analysis of future climate scenarios, but on the observation of the current functioning of water systems. It generally requires to *i)* identify the water system vulnerabilities to current climate variability and non-climate factors (e.g., society, land use, economy, ...) and *ii)* define better (e.g., more effective and efficient) ways to deal with these factors. The rationale behind this approach is that water managers have always reacted and adapted to anomalies in the hydro-climatic conditions (for example after a big drought or flood). Their strategy is usually to reduce water system vulnerability and enhance flexibility to respond to unforeseen events (Lempert and Schlesinger, 2000). Briefly, the vulnerability-based approach try to address the question: what can we do now to be prepared in the future to possible changes in the climate and hydrology?

Since adaptation measures should be based on the analysis of the weaknesses and the strenghts of the water systems, they are usually case specific and there is no single approach for assessing, planning, and implementing them. Nonetheless, they should exhibit the following characteristics: robustness and flexibility (to cope with uncertainty), efficiency (to yields benefits even in absence of climate change), and reversibility (to reduce the consequences of being the wrong option in the future). The two main frameworks proposed in the literature to guarantee such features are robust decision making (e.g., Lempert and Schlesinger, 2000; Wilby and Dessai,

2010) and adaptive decision making (e.g., Georgakakos et al., 2012; Steinschneider and Brown, 2012). In robust decision making, adaptation measures are required to perform reasonably well under a large set of alternative future scenarios. The approach still relies on the hypothesis that we can reliably predict future drivers and water system responses, at least to some extent. In adaptive decision making, adaptation measures are revised periodically to promptly react to changes in the decision making context. It thus relies on the insight that deep uncertainty of future projections can not be reduced and the design of adaptation measures should be a continuous process of improvement (Pahl-Wostl, 2007). Adaptive management has been described as “a real paradigm shift in water management from what can be described as a prediction and control to a management as learning approach” (Swanson et al., 2010). Although different, the two approaches are not exclusive, but can overlap in practical applications.

In the framework of deep uncertainty of future projections, historical records represent the ground to test water system skills of adaptation. Actually, the use of historical records is criticized by some researchers (e.g., Milly et al., 2008) because of the hypothesis of stationarity which it underpins, i.e., the fact that it is sufficient to look into past records to know and decide about the future. In a stationarity context, extreme events (heat waves, floods, ...) experienced in the past are acceptable because they are considered as extraordinary and unusual events (i.e., with a large return period). In a non-stationarity context, those extraordinary events are less acceptable because they may become increasingly "normal" or ordinary (Füssel, 2007). There is still a large discussion about this topic between those who claims that the past is the only lesson we can learn from, and those who claim that the past is less relevant because climate change will force us to face with events that are outside the range of what we have experienced so far.

Thesis objectives and organization

The present Ph.D. thesis offers several contributions to define the role of water resource management in facing the challenges posed by climate change, i.e., deep uncertain and rapidly changing environmental conditions. Focusing on multi-purpose reservoirs, we assess the potential of current and novel management practices, in particular adaptive management, in coping with increased water stresses induced by climate change.

We show how System Analysis, i.e., the combination of simulation and optimization models (Philbrick and Kitanidis, 1997), is a powerful tool to describe the complex interactions between social, economic, and environmental aspects of water systems under uncertain hydro-climatic conditions. In particular our analysis is characterised by the combined use of *water-value models*, *decision models*, and *multi-objective optimization techniques*. *Water-value models* allow to determine the social, economic, and environmental value of water availability by adopting a set of performance indicators which, if defined with a stakeholders-oriented perspective, allows to explicitly take into account the water-users preferences. *Decision models* allow to describe the behaviour of the water resource managers thus specifying how water resources are distributed in space and time and among competing uses. Finally, *multi-objective optimization techniques* allow to derive optimal or efficient management strategies thus contributing to the definition of effective adaptation measures.

Our purpose is to provide examples of applications of these tools to real-world case studies, to discuss their potential and limitations, and ultimately contribute to invalidate policy inertia. We rely on the vulnerability-based approach to demonstrate that tools exist to handle the complexity of water systems, to increase management efficiency, and to handle uncertainty. Although, by definition, the design of vulnerability-based adaptation measures is strongly case-study dependent, we adopt a wider perspective, so to highlight more general research problems framing them into the current research literature.

Summarizing, the specific aim of the research is to develop methods and tools to: *i)* model current water systems to gain knowledge about their strenghts and vulnerabilities, *ii)* increase management efficiency and assess its potential under climate change scenarios, *iii)* quantify the impacts of hydrological changes into water resources, and *iv)* test adaptation management as tool to tackle hydrological uncertainty in rapidly changing environments. The main innovative contributions of the thesis are: *i)* to demonstrate the value of System Analysis in dealing with climate change issues, *ii)* to analyse the relationship between climate change and inherent hydro-climatic variability, *iii)* to consider the multi-objective nature of water resource management to describe the trade-offs between competing uses, *iv)* to test the methodologies on real-world case studies and discuss their actual applicability.

The thesis is organized as follows. In Chapter 2 we discuss how to increase water system flexibility and efficiency by a change in the institutional framework in which reservoirs are operated. We focus on the case study of Lake Como (Italy) by considering the three main reservoirs located in the water system which are operated for satisfying two competing interest, i.e., irrigation supply and hydropower production. We show how the introduction of a coordination mechanism among the operation of the three reservoirs allows to succesfully react to drought events, thus coping with natural climate variability and, possibly, climate change.

In Chapter 3 we assess if the coordination mechanism defined in the previous chapter is able to compensate for future water stresses as projected by several Regional Climate Models. We propose a procedure for the quantitative assessment of climate change impacts on water resources in the frame of the scenario-based approach and we discuss the limits of the classical predict-and-control paradigm in case of deep uncertainty. We show that the quantification of climate change impacts on water resources is not fully reliable, but that still the analysis can produce useful knowledge about the water system, e.g., to understand why and to which kind of hydrological changes a water system is vulnerable depending on the system characteristics.

In Chapter 4 we investigate the relationship between hydrological changes and their impacts on water resources. We discuss the topic of trend detection referring in particular to the seasonality and the interannual variability characterizing natural processes. We analyse the case study of Lake Maggiore, a multi-purpose regulated lake in Northen Italy, focusing on two competing water resources: flood protection and irrigation supply. The aim is, on the one hand, to identify possible nonstationary behaviour in the historical records, and, on the other hand, to assess the inherent buffering capacity of the water system to hydrological changes.

Focusing on the same case study, Chapter 5 test an adaptive management approach to design the lake operation. We define a recursive optimization procedure in which the hydrological statistical model is updated on a yearly basis, discarding progressively old records in favour of new ones. The purpose is to make water management more flexible and reactive to hydrological changes.

Finally, in Chapter 6, we test a different adaptive management approach in which mid- (seasonal) and long-term forecasts are used to increase the efficiency of water system management. We focus on the case study of the Oroville reservoir (California), a mixed rain-snow dominated catchment in which the prediction of timing and quantity of snowmelt can increase the ability of the reservoir operation in facing drought events.

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CHAPTER 2

Multi-reservoir coordinated control for efficient management

Adaptation involves a wide range of measures, not only technical, but also institutional, legal, and behavioural (Füssel, 2007). Water storing facilities in a watershed are very often operated independently one to another to meet specific operating objectives, with no information sharing among the operators. This uncoordinated approach might result in disputes and conflicts among different water users, or inefficiencies in the watershed management, when looked at from the viewpoint of an ideal central decision-maker. In this chapter we present an example where the reframe of the institutional setting can improve the overall water system efficiency. As a case study, we analyse the reservoir network of Lake Como catchment (Italy), where a long lasting conflict exists between upstream hydropower production and downstream irrigation water users. We show how a coordination mechanisms, designed with the ultimate goal of enlarging the space for negotiated agreements between competing uses, can improve the overall system efficiency. The proposed coordination mechanism can be implemented to successfully react to particularly dry conditions, thus improving the resilience to drought events due to natural climate variability and, possibly, climate change. We show how modelling and optimization tools can be used to explore vulnerabilities and adaptive capacities of water systems and to produce knowledge that is relevant in the decision making context.

This chapter is based on D. Anghileri, A. Castelletti, F. Pianosi, R. Soncini-Sessa, and E. Weber, "Optimizing watershed management by coordinated operation of storing facilities", *Journal of Water Resources Planning and Management*, 139(5):492–500, 2013.

2.1 Introduction

Regulated lakes and reservoirs enhance the economic, social and environmental value of watersheds by enabling water reallocation in space and time. Watersheds are often composed of multiple distributed storage units, which are generally operated independently to meet different targets. The lack of coordination in the operation of the storing facilities generates inefficiency, economic loss, and can induce conflicts, especially in dry periods. Similar water conflicts are only expected to increase in upcoming years due to the combined effect of increasing pressures on natural resources, diverse stakeholder perspectives, and climate change.

Many studies demonstrate that it is possible to augment water availability without the need for large-scale infrastructural actions, but by acting on how water facilities are managed. In fact, operating rules and institutional settings, which are conservative and resistant to changes by their nature (Walker, Marchau, and Swanson, 2010), may prove inadequate to manage water in contexts different from the ones in which they were planned to act (e.g., Georgakakos et al., 2012; Willis et al., 2011). This can be a relevant limit in uncertain and rapidly changing environments. The critical analysis of the current institutional frameworks and the proposal of more flexible ones can improve the efficiency of water resources management and can promove the adaptive capacity of water system to climate change and natural variability.

In this work we use simulation and optimization tools referring to Systems Analysis (Philbrick and Kitanidis, 1997) to analyze different management settings. The goal is to assess which are the most promising ones in terms of efficiency, reliability, vulnerability, and resilience in meeting water management targets. In particular, we propose a two-step approach to design a coordination mechanisms of reservoir operation at the watershed scale. First, we compute the multi-objective centralized solution to assess the associated maximum potential benefits and to understand whether the limits to the current system performance arise from physical constraints (e.g., limited system storing capacity) or from the institutional, legal and operational framework. Second, we analyze the system behavior under different Pareto-optimal operating policies to define a possible empirical coordination mechanism that can move the current uncoordinated management towards the ideal centralized operation.

With respect to other studies adopting a system analytic framework for similar purposes (e.g. Whittington, Wu, and Sadoff, 2005; Goor et al., 2007), in our study: *i*) we generate feed-back operating policies (see, e.g., Castelletti, Pianosi, and Soncini-Sessa, 2008) to filter the uncertain nature of the inflow process; *ii*) we adopt a multi-objective approach to analyze the centralized solutions in the Pareto space; and *iii*) we develop an empirical coordination mechanism design to move the current uncoordinated management towards the ideal centralized operation.

The proposed approach is demonstrated on the Lake Como water system in the Italian Southern Alps, which includes one large regulated lake, 16 hydropower reservoirs, and a large socio-economic system where multiple, conflicting water-dependent activities coexist (Giacomelli, Rossetti, and Brambilla, 2008). This water system is a paradigmatic example of many Alpine watersheds: large storage capacity distributed in small reservoirs, mainly operated for hydropower production and located in the upper watershed region; regulated lakes in the middle region; and multiple water consumption users, mainly wide agricultural areas, in the lower region. For the Lake Como water system, we comparatively analyze two management extremes: the current situation (uncoordinated management), where each operator takes the daily release decision independently from each other, with no information sharing, and maximizing (or minimizing) his operating objective only; and the ideal centralized management, in which we assume that a hypothetical super decision-maker coordinates the operation of the whole system, exploiting all the information available and balancing all the operating objectives. Correspondingly, in the uncoordinated management case the operating policies are computed by solving multiple single-objective optimization problems, one for each operator; while in the centralized case, they are designed by solving one single multi-objective problem. Subsequently, the obtained policies are evaluated via simulation over a historical inflow scenario to get insight into their behaviour. The analysis suggests a possible coordination mechanism consisting of constraining the upstream reservoir minimum release in response to particularly critical, and thus conflicting, conditions.

2.2 Case study: Lake Como

Lake Como water system (Figure 2.1) develops along the River Adda, Northern Italy, with a topology common to many Alpine watersheds: a large storage capacity distributed in many small-to-medium reservoirs constructed to exploit the huge hydropower potential of the upper watershed region; a large regulated lake in the middle region; and multiple water consumption users, mostly farmers, in the lower region. With an overall storing capacity of 545 million m^3, about twice the active storage of Lake Como (247 million m^3), the 16 hydropower Alpine reservoirs operated by four different power companies generates 12% of the national hydroelectric energy. Downstream from Lake Como, the Adda river feeds a cultivated area of about 1320 km^2, where maize is the most widely grown and productive crop (52 % of the area and 1.5 Mton/year), and a system of small run-of-river power plants (installed capacity 92 Mw). The annual average water supply from the lake is about 4400 million m^3.

Snowmelt from May to July is the most important contribution to the creation of the seasonal storage, which is reallocated over time with two different strategies according to the two primary objectives of watershed management. Hydropower reservoirs exploit the accumulated volume in the following fall and winter (Figure 2.2a), when the demand for energy peaks and the production is more valuable. The lake goes through the first draw-down cycle in the summer to provide adequate supply (Figure 2.2b) for the peak demand period. This results in the potential for conflict between farmers and hydropower companies, which is highest in particularly dry summers, when farmers associations claim that critical water shortages could be mitigated if the water retained by the hydropower companies were available. The dispute reached a crescendo on the unprecedented summer droughts of 2003 and 2005, when several power companies were forced by the Regional Authority to release extra water volumes to provide agriculture with some relief. This caused significant economic losses to the companies and little benefit to the farmers. Lately, the hydropower companies started a lawsuit that was settled with the Regional Authority having to pay back them in compensation, because the injunction was not compliant with the companies' abstraction licenses. Similar situations are expected to increase in the next years due to climate change which is expected to impact significantly the variability of precipitation and temperatures in the Alpine environment, with potentially intensive fallout upon stream flow regime (Barontini et al., 2009) and seasonal snow cover availability (Barnett, Adam, and Lettenmaier, 2005; Bavay et al., 2009).

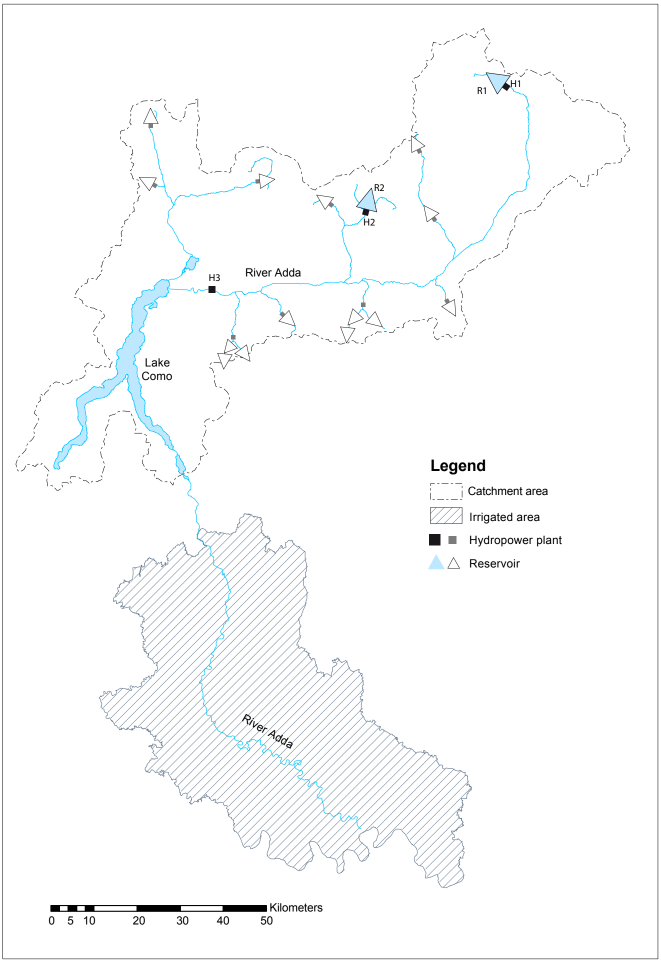

Figure 2.1: *The Lake Como watershed. Letters indicate the Alpine reservoirs and hydropower plants considered in this study.*

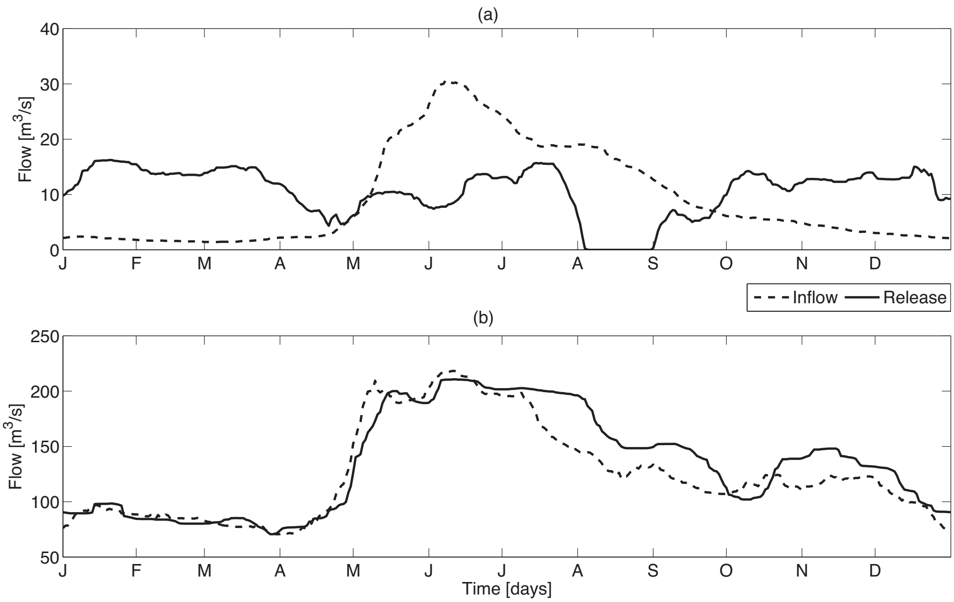

Figure 2.2: *Historical inflow (dashed) and release (solid) of the hydropower reservoir R1 (a) and lake Como (b) (14-days moving median over the period 1996-2005).*

While hydropower reservoirs are owned and operated by private companies, the lake regulation is under the responsibility of a governmental board, which, besides water supply for irrigation, also accounts for several secondary economical, environmental, and recreational issues, including flood protection of the lake shores, fish conservation, and navigation. As the natural and socio-economic system evolves, the nature and relevance of these secondary objectives change: for example, whereas flood control around the lake has been for long time one of the most important concerns of lake regulation (Castelletti et al., 2010), it will be resolved by the undergoing construction of flood protection dykes in the major city of Como. The safeguard of the downstream river and riparian ecosystem is expected to be guaranteed by the introduction of a minimum environmental flow constraint on the reservoir release (also included in the reservoir model).

The conflict between energy and food production is, instead, a long lasting issue, which is expected to increase in the upcoming years under pressure of undergoing global change (Anghileri, Pianosi, and Soncini-Sessa, 2011). This study focuses on this primary dispute, even if, in principle, no methodological limitation exists on the number and type of interests that can be considered.

Lake Como regulation has been extensively studied, and is well recognized as a prominent example of multi-objective optimization problem (e.g Guariso, Rinaldi, and Soncini-Sessa, 1986). The potential of the centralized operation of the lake and the upstream reservoirs to enlarge the space for negotiated agreements is, instead, still unexplored.

2.3 Centralized, uncoordinated, and coordinated management

In this study, we use Systems Analysis to *i*) assess and quantify the room for mitigating the long lasting conflict between farmers and hydropower companies by centralized operation of the storing facilities in the watershed; *ii*) explore and define coordination mechanisms that could be implemented in order to drive the performances toward that of this ideal centralized policy, while maintaining the current, uncoordinated structure of the system. The analysis focuses on the two largest (nearly 50% of the total hydropower storing capacity) reservoirs in the watershed ($R1$ and $R2$ in Figure 2.1). The others were not included for the lack of data and thus the result described below has to be considered as a lower bound of the ideal potential improvement under the centralized operation.

We consider and compare the management schemes depicted in Figure 2.3 and 2.4. The left scheme reflects the current *uncoordinated management* approach, where each storing facility is operated independently by different operators, with different operating objectives, and considering different, unshared information systems: each operator makes his release decision u_t^i (the water volume to be released in the next 24 hours) given the storage s_t^i and maximizing (or minimizing) his own objective only. The three operating rules $u_t^i = m^i(s_t^i, t)$ of each storing unit are derived independently by solving three different single-objective optimization problems. The scheme on the right characterizes the hypothetical condition where a single super-operator has full access to the system data conditions and makes all the decisions simultaneously, balancing upstream (hydropower) and downstream (irrigation) interests (*centralized management* hereon). The associated operating rule $\mathbf{u}_t = \mathbf{m}(\mathbf{s}_t, t)$ provides the decision vector $\mathbf{u}_t = |\ u_t^1\ u_t^2\ u_t^3\ |$ as a function of the state vector $\mathbf{s}_t = |\ s_t^1\ s_t^2\ s_t^3\ |$ and is computed by solving one bi-objective (hydropower and irrigation) optimization problem. Given the multi-objective nature of the problem, the solution is a set of Pareto-optimal operating policies that can be used to assess the room for improvement of the system performance in the objective space. In between these two extreme schemes is the *coordinated approach* (Figure 2.4), where each facility is operated independently, like in the uncoordinated case, but a coordination mechanism exists among the reservoirs.

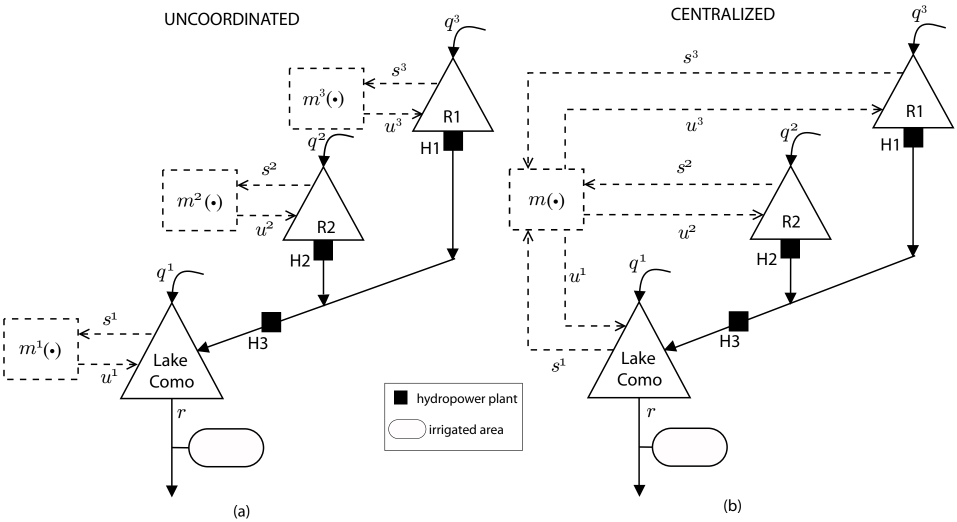

Figure 2.3: *The model scheme under uncoordinated (left) and centralized (right) management.*

This mechanism is formulated as a constraint on the upstream releases. The idea here is that, in stress conditions (i.e., high water demand for irrigation and low downstream storage), the Regional Authority may impose a minimum flow to the upstream hydropower companies. From the mathematical standpoint, the problem formulation and approach is just the same as in the uncoordinated case, but for the definition of the minimum flow constraint, which is case-dependent and thus will be discussed in the next section.

In all schemes, the model of the system includes a mass balance equation for each reservoir and for Lake Como and a conceptual model of the three power plants (see, for more details, Castelletti and Soncini-Sessa, 2007). Although simple, the model proves adequate at the considered space and time scale, as detailed in Anghileri, Soncini-Sessa, and Weber, 2011. The irrigation objective (to be minimized) is the squared daily deficit in the water supply [$(m^3/s)^2$/day]

$$J_{irr} = \frac{1}{h}\sum_{t=0}^{h-1}[\max(w_t - r_{t+1}, 0)]^2 \tag{2.1}$$

where r_{t+1} [m^3/s] is the average daily release from Lake Como from t to $t+1$, w_t [m^3/s] is the water demand for irrigation, and h [day] is the length of the simulation horizon. The water demand is a periodic parameter, whose annual pattern (Figure 2.5a) is estimated combining the water requirements,

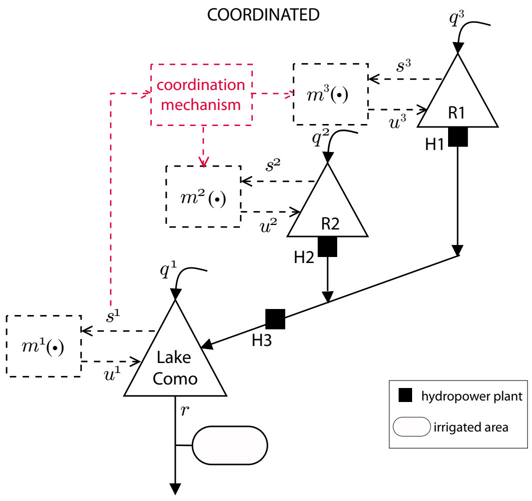

Figure 2.4: *The model scheme under coordinated management.*

as declared in the farmers abstraction licenses, and the historical time series of diverted flows. The exponent of two is introduced 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, Stedinger, and Loucks, 1982).

The hydropower production objective (to be maximised) is the daily average total revenue [euro/day] from power generation in the three power plants:

$$J_{hyd} = \frac{1}{h} \sum_{t=0}^{h-1} \sum_{i=1}^{3} R_t^i \tag{2.2a}$$

where R_t^i is the daily revenue from the i-th plant, i.e.

$$R_t^i = \sum_{j=0}^{n_t^i} \theta_{t,j} G_i \quad i = 1, 2, 3 \tag{2.2b}$$

and n_t^i is the number of the i-th plant working hours in day t (obtained as the ratio between the daily reservoir release volume and the maximum power plant capacity); G_i is the energy production per hour [MWh] at full capacity in plant i; and $\theta_{t,j}$ is the energy price [euro/MWh] in the j-th most profitable hour of day t. Energy price is modeled as a time-varying, periodic parameter (Figure 2.5b), whose annual pattern is estimated from time

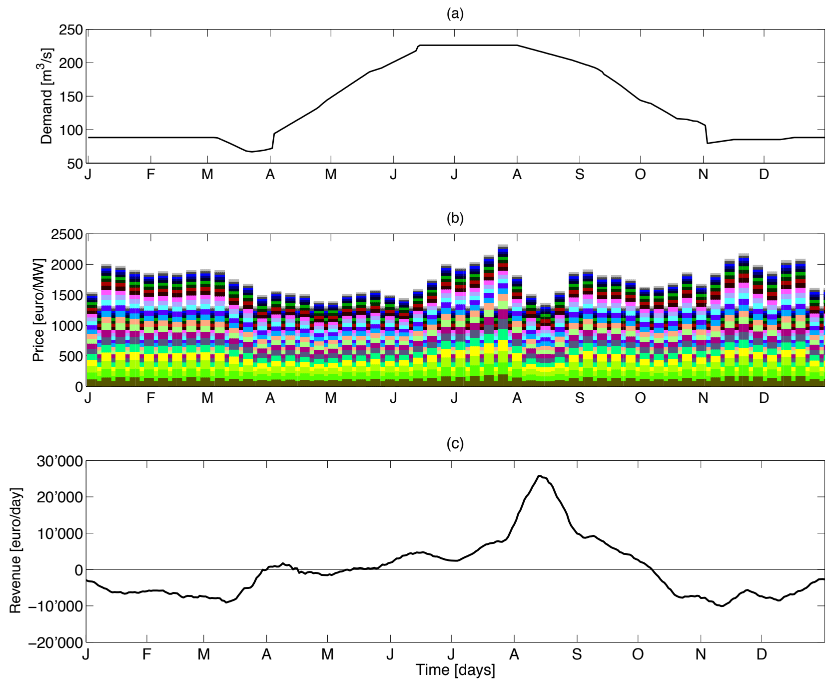

Figure 2.5: *(a): Yearly pattern of water demand. (b): Yearly pattern of the energy price (each band represents the energy price in the j-th most profitable hour). (c): Difference in daily hydropower revenue (14-days moving average over years 1996-2005) between centralized policy C6 and uncoordinated UC.*

series of energy prices over the period 2005-2006 (the first two years since the introduction of the energy market). In other words, we are assuming that both the local energy production is not influencing the price formation and that the year-to-year variations in the price for a given day are negligible. Moreover, the objective formulation assumes that the reservoir operator has a perfect price forecast and is able to prioritize the daily production in the more profitable hours (Castelletti and Soncini-Sessa, 2007). Consequently, simulation results represent the maximum revenue that could be achieved by hydropower companies and, as such, they constitute a reference value, i.e., the so called performance upper bound (Alemu et al., 2011). The implications of this assumption are limited in this study since the focus is on the difference between centralized and uncoordinated policies rather than the absolute objective values.

All the optimization problems are solved by traditional Stochastic Dynamic Programming (Labadie, 2004). In the SDP model, the natural inflows q^i_{t+1} to the reservoirs are modelled as cyclostationary, lognormal, stochastic processes with probability distribution estimated over historical data of the period 1996-2005. The objective functions are the expected values of Equations (6.1) and (2.2) with respect to all the possible inflow trajectories, as given by their probability distribution functions, over an infinite horizon (Bertsekas, 1976). When solving the centralized bi-objective optimization problem, the weighted sum method is used to aggregate the objective functions and, by sampling the weight values, a set of Pareto-optimal solutions (operating policies) is derived.

SDP has been implemented using the successive-approximations algorithm (White, 1963). Given the relatively simple system topology with two reservoirs in parallel, we adopted an aggregation/decomposition method (e.g. Turgeon, 1981), lumping the two storing units into a single equivalent reservoir, in order to reduce the computing time. The discretization grids for the inflow, the release decision and the storage has respectively 5, 24 and 29 points for the equivalent hydropower reservoir, and 9, 216 and 54 for Lake Como. Subsequently, the Pareto-optimal policies have been simulated using the original water system model, including the two hydropower reservoirs separately. The decomposition scheme assumes that the optimal release from the equivalent reservoir is split among the two hydropower reservoirs according to a constant coefficient, proportional to the ratio of the mean annual inflow volume to one reservoir and the mean annual total inflow volume to both the reservoirs. The assumption of a constant decomposition coefficient could be somehow limiting to the full exploration of the solution space. However, it guarantees that the designed centralized operating policies, which provides an equal increase in the hydropower revenue for both companies, would be more acceptable for the stakeholders in a real negotiation context. A more detailed discussion of the aggregation/decomposition procedure is reported in Anghileri, Soncini-Sessa, and Weber (2011).

After optimization, the Pareto-optimal operating policies are evaluated by simulation under time series of observed natural inflow over a historical horizon, and their quality measured in terms of the objective values (Equations 6.1 and 2.2) over the same horizon. Deterministic simulation is preferred over stochastic (e.g., Monte Carlo) simulation because, although not fully consistent with the optimization, where a stochastic model of the inflow is used, it provides two advantages. First, the estimated impacts are not affected by any error in the inflow models; second, they are more informative for stakeholders and decision-makers who can compare them against the historical situations they directly experienced. The limitation of this approach is that the statistical significance of the results can be affected

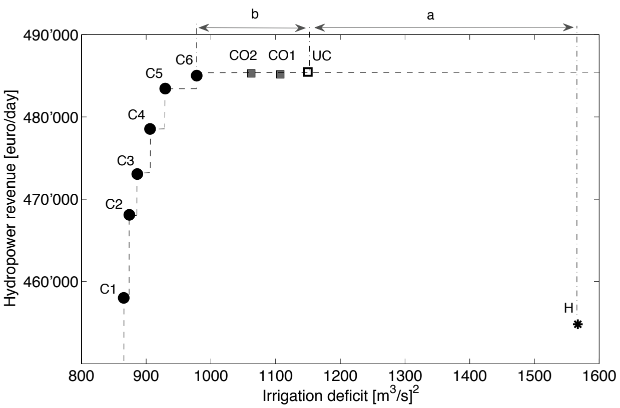

Figure 2.6: *Irrigation against hydropower objective under centralized (circles), non-centralized (rectangle) policies, and the historical operation performance (star) over the horizon 1996-2005.*

by the length of the available time series.

2.4 Results and discussion

Figure 2.6 plots the value of the irrigation objective (Equation 6.1) against the hydropower objective (Equation 2.2) under different operating policies, computed over the horizon 1996-2005. Point H is the historical (uncoordinated) performance, computed using the time series of historical reservoir releases over the same horizon. The other points are obtained by simulated releases produced by different policies under centralized (circles), uncoordinated, and coordinated (rectangles) management scheme.

2.4.1 Step 1: the ideal centralized solution

Six centralized policies (points C1 to C6) are shown, representing different tradeoffs among the two objectives. Not surprisingly, all the centralized policies dominate, in the Pareto sense, the historical policy (point H). However, the comparison is not completely fair. In fact, the historical lake regulation was not uniquely aimed at supplying water to irrigation but also accounted for several secondary interests (mainly flood control) that were neglected in optimizing the centralized policies (see previous Section). This partially explains the large improvement in the irrigation objective between point H and points C1 to C6. The vertical distance between H and C6, the best centralized policy for hydropower, is instead due to the discrepancy between the energy market prices (2005-2006) used in the model and the dominantly non-market price pattern of the evaluation horizon (1996-2005).

To fully assess the potential improvement of the ideal centralized operation over uncoordinated, points C1 to C6 should be rather compared with point UC, which represents the system performances under the uncoordinated policies that consider the novel energy price pattern for the hydropower reservoirs, and the irrigation objective only for lake regulation. The horizontal distance between H and UC (*a* in Figure 2.6) is the loss farmers face for considering other interests rather than irrigation supply only; while the distance between UC and C6 (*b* in Figure 2.6) is the (minimum) loss to be ascribed to the lack of coordination between hydropower reservoirs and the lake. The latter can be interpreted as the game theory concept of the "Price of Anarchy" for the downstream water users.

What is mostly remarkable in the comparison between UC and C6 is the almost negligible difference on the vertical axis, which means that the improvement in the irrigation objective comes at no cost to the hydropower companies. To understand the reason, we compared the system trajectories under the two policies. Figure 2.5c shows the difference in the daily hydropower revenue among the centralized C6 and uncoordinated UC policy (averaged over the years in the simulation horizon). The loss in the winter period (from October to March) is compensated by the gain in the summer period (June to September), and especially in August. The result is obtained by largely increasing the hydropower reservoirs release in the summer period which positively affects also the downstream system, as more water is made available in the period when the irrigation demand is highest (see Figure 2.5a).

Further analysis of the Pareto-optimal policies is given in Table 2.1, which shows the average hydropower revenue of the three plants H1, H2 and H3, and several performance measures of reliability, resilience, and vulnerability (Hashimoto, Stedinger, and Loucks, 1982) of the irrigation water supply (percentage of deficit days over the year; mean length of deficit periods; and mean of the maximum annual deficit over the evaluation horizon). The table shows that, coherently with Figure 2.6, hydropower revenue under the uncoordinated policy UC is approximately the same as in the centralized policy C6 for all plants, while decreasing in the other centralized policies (from C5 to C1) that progressively increase the weight of the irrigation objective. Conversely, the irrigation objective worsens (increases) from C1 to C6 and it is definitely worse under the UC policy. The same holds for the vulnerability indicator, while the reliability indicator produces just the opposite ranking (performances improves from C1 to C6

Table 2.1: *Evaluation indicators for the uncoordinated (UC) and centralized (C1-C6) policies over the horizon 1996-2005.*

Indicator type	Description	C1	C2	C3	C4	C5	C6	UC
Hydropower								
Objective	Mean revenue (10^3 euro/day)	458	468	473	478	483	485	485
	Mean revenue of plant H1 (10^3 euro/day)	301	308	311	315	319	319	319
	Mean revenue of plant H2 and H3 (10^3 euro/day)	157	160	162	163	165	166	166
Irrigation								
Objective	Mean squared deficit $(m^3/s)^2$	865	874	886	906	929	978	1154
Vulnerability	Mean of maximum deficit per year (m^3/s)	68	70	72	73	76	76	88
Reliability	Mean number of deficit days (%)	63	61	60	59	59	58	57
Resilience	Mean length of a deficit period (days)	26	26	27	25	26	25	26

and UC), which confirms that there exists a conflict between vulnerability and reliability. As previously anticipated, power 2 in the definition (Equation 6.1) of the irrigation objective highly penalizes large failure events while allowing many smaller failure events to occur (i.e., low vulnerability but also low reliability). Observe, however, that the reduction in reliability from UC to C1 is rather limited (about 10% against a variation in vulnerability of about 27%), and that the importance of vulnerability over reliability clearly emerged from interviews with the farmers' associations. Finally, resilience does not show significant variations from one policy to another.

2.4.2 Step 2: the coordination mechanism

The win-win centralized policy C6 cannot be actually implemented since it presupposes an unrealistic institutional framework with one decision–maker responsible for all the storing facilities in the watershed. The next step in our study is thus to explore whether we can find any coordination mechanism that can be applied in the current institutional framework in order to drive the actual decision-makers, namely the hydropower companies, closer to point C6.

To this end, we can exploit the findings from the previous analysis. In fact, the comparison between the uncoordinated solution UC and the centralized policy C6 has revealed that in the summer season, when the irrigation demand is higher, C6 produces higher releases from the hydropower reservoirs than UC. A deeper analysis shows that the extent of the increase also depends on the storage of downstream Lake Como. For instance, Figure 2.7 plots the simulated release decisions from the hydropower reservoir

R1 against the simulated storage of Lake Como in the period from May to September, under the uncoordinated (black points) and centralized (grey circles) policy. It can be seen that at very low storage values, all release values (even zero) can occur under the uncoordinated policy while only high values are taken under the centralized policy. In general, under the centralized policy there is a clear relation between the minimum release taken at given storage and the storage value itself. As a cooperation mechanism, we thus define a minimum flow constraint that the upstream hydropower reservoirs must comply within the irrigation season (May to September) and that is a function of the storage in Lake Como, as given by the black line in Figure 2.7.

The possible reaction of the hydropower companies to the introduction of such constraint is estimated by re-optimizing their (single-objective) policy including the constraint, according to the coordination scheme depicted in Figure 2.4. The simulation of this coordinated policy over the horizon 1996-2005 produces point CO1 in the objective space (Figure 2.6). As expected, the new point lies in between the ideal centralizes solution C6 and the uncoordinated solution UC, having about the same hydropower revenue while reducing the irrigation deficit with respect to UC.

More sophisticated definitions of the constraint can be considered; for instance, the analysis presented in Figure 2.7 can be replicated over shorter sub-periods within the irrigation season in order to define a time-varying constraint. For instance, point CO2 in Figure 2.6 is obtained by optimization and simulation of a coordinated policy with four different minimum flow constraint definitions within the season: the irrigation objective is further improved at no cost for hydropower producers.

2.5 Conclusions

In this chapter, we used Systems Analysis to first assess the space for improvement made possible by the ideal, fully coordinated (centralized) management of water resources at the watershed scale and, subsequently, to design coordination mechanisms to drive the current uncoordinated structure and inefficient operation towards the ideal centralized solution performance.

The study was conducted on Lake Como water system, Italy, analysing the long-lasting conflict between hydropower producers in the lake catchment area and farmers downstream from the lake. Stochastic Dynamic Programming was used to design the operating policy of the hydropower reservoirs and the regulated lake under the current uncoordinated situa-

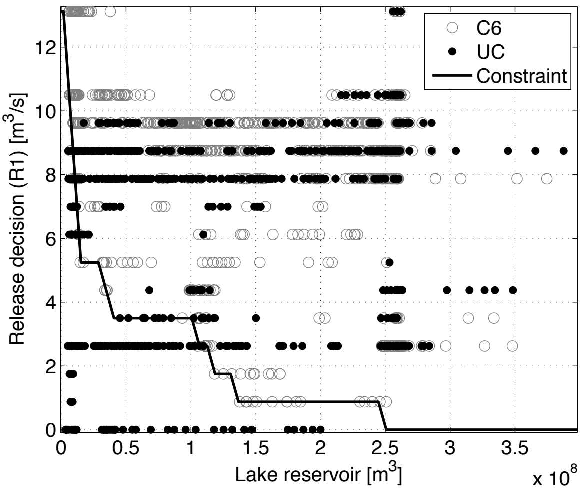

Figure 2.7: *Hydropower release decision of reservoir R1 as a function of lake storage under centralized policy C6 (grey circles) and uncoordinated policy UC (black points). The minimum release constraint on R1 is represented by the black line.*

tion and assuming an ideal centralized perspective. As expected, computational results show that the centralized management is globally more efficient than the uncoordinated one. More interestingly, they demonstrate that in the centralized approach there exists a win-win solution in which the irrigation deficit can be significantly reduced without economic loss in the hydropower production with respect to the uncoordinated management. The analysis of this solution suggests a coordination mechanism based on constraining the minimum release of hydropower reservoirs in particularly critical situations, i.e., drought events, which can significantly improve the current uncoordinated operation.

These results were obtained under a number of simplifying assumptions (e.g., data availability allowed for considering only 50% of the overall hydropower storage capacity and over a rather short simulation horizon; a number of secondary objectives, like recreational concerns, were neglected in the Lake Como optimization) that were discussed in the chapter and may be the subject of future improvement. Finally, the results are strongly dependent from the structure of the energy prices which can greatly vary among the years. The efficacy of the proposed coordination mechanism should thus be checked in an adaptive context, where the effects of the proposed action are revised periodically.

Besides the relevance on the case study, this work demonstrates the general value of the proposed methodology for water resources management. The design of centralized policies, although not of direct operational value, enhances our understanding of the sources (e.g., physical or institutional) of water conflicts and provides useful insights for defining flexible management mechanisms. Design of coordinated policies opens up the space for proposing win-win solutions that could significantly mitigate water disputes and increase water resource management.

The existence of such solutions does not imply that they can be successfully implemented. As for the case study presented, there is no reason for the hydropower producers to spontaneusly accept to coordinate the operation of their reservoirs with the operation of the lake. This may be imposed by the Regional Authority with the aim of increasing the society welfare, but it is likely to suscitate the hydropower producer opposition. In fact, although the coordinated management proved not to decrease their revenue, it may be perceived as a limitation to the exercise of their water rights.

In the literature, there has been little or no consideration of the social acceptability of adaptation measures as obstacle in the adaptation process (Burton et al., 2002), but it might be relevant, expecially in the case of soft adaptation measure rather than of infrastructural adaptation measures, which are usually constrained by large economic costs. Financial instruments, as insurances and option-based contracts, proved to be effective means to facilitate the trade of water volumes between conflicting water uses (Steinschneider and Brown, 2012 and references therein). They can not be directly exported to the Italian context, which does not have a water market, but further analysis could explore the identification of suitable mechanism to facilitate the practical implementation of the coordinated management.

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CHAPTER 3

Sustainability of efficient management under climate change projections

We want to assess if the coordination mechanism designed in the previous chapter is an effective adaptation measure to face future hydrological changes as projected by different Regional Climate Models. We present a procedure which, starting from future climate scenarios, allows to extend the traditional estimate of impacts on hydrology to water resources at the basin scale. The specific features of our approach are that: *i)* the quantification of impact on water resources is based on a set of performance indicators defined together with the stakeholders, thus explicitly taking into account the water user preferences; *ii)* we explicitly include decision-making into the assessment procedure by simulating management policies obtained using optimal control techniques; *iii)* the multi-objective nature of the management problem is fully preserved by simulating a set of Pareto-optimal management policies, which allows for evaluating not only variations in the indicator values but also tradeoffs among conflicting objectives. This analysis give us the opportunity to discuss the main limitations of the scenario-based approach to climate change impact assessment studies. In particular, we show why it can hardly be used to define effective adaptation measures. Nonetheless, we show how the procedure can be exploited to understand why a water system is vulnerable and to which kind of hydrological changes it is vulnerable and how optimization techniques can be used to fully characterize the sources and propagation of uncertainty in the assessment procedure.

The chapter is based on D. Anghileri, F. Pianosi, and R. Soncini-Sessa, "A framework for the quantitative assessment of climate change impacts on the water-related activities at the basin scale", *Hydrology and Earth System Sciences*, 15(6):2025–2038, 2011.

3.1 Introduction

Climate change emerged as one of the major forces that will affect water availability in the future (Bates et al., 2008). In the last 20 years, a great research effort has been devoted to increasing our knowledge about atmospheric and ocean circulation and estimating future climatic scenarios. Unfortunately, the complexity and computational burden of circulation model do not allow for simulation at the local spatial scale where the impacts on water resources must be estimated. To fill the gap between global and local scale, many methods were developed to downscale General Circulation Model (GCM) and Regional Circulation Model (RCM) projections.

So far, most impact studies have focused on the hydrological response at the basin scale (e.g., Jasper et al. (2004); Bronstert et al. (2007); Groves, Yates, and Tebaldi (2008); Abbaspour et al. (2009)). Further evaluations on the ecosystem and human activities are qualitative and expert-based. Only recently new research efforts have been initiated to extend quantitative assessment from hydrological variables to the natural, economical and social sphere, e.g., hydropower production (Schaefli, Hingray, and Musy, 2007; Christensen and Lettenmaier, 2007), floods, ecosystem and agriculture (Hingray et al., 2007). The purpose is to provide a transparent and reproducible evaluation of the potential impact of climate change and thus the essential knowledge base to support the planning of effective adaptation measures. It is of fundamental importance to increase public awareness, support water resource planners and promote stakeholders' participation in decision-making process (Wood, Lettenmaier, and Palmer, 1997). The need for increasing stakeholder participation in this type of analysis is well-recognized, for instance by the European Environmental Agency which claims that, "until now no reports on the impacts of climate change on the water resources of the European Alps have included specific stakeholder-oriented information on strategies to adapt to these impacts" (EEA, 2009,

p. 18, sec. 1.2).

Quantitative assessment of climate change impacts on water resources, both in the biological and human sphere, is very complex, for several reasons. First, if the analysis must account for the true expectations and needs of the water users, defining quantitative indicators requires a long and complex process of knowledge elicitation from experts and stakeholders' representatives (Soncini-Sessa, Castelletti, and Weber, 2007). This is not always straightforward, especially when not strictly economic issues are concerned. Second, the system management must be modelled. Some authors (Schaefli, Hingray, and Musy, 2007) try to reproduce the historical management by inferring it from historical time series; others (Ajami, Hornberger, and Sunding, 2008) propose and test different management strategies. The former approach is questionable because the system management is likely to change following changed meteo-hydrological conditions; the latter does not guarantee that the best adaptation policy has been considered, confounding the effect of climate change with that of using a sub-optimal policy. Finally, uncertainty deeply affect the impacts quantification. The evolution of socio-economic drivers, e.g., population growth and economic and technological development, cannot be exactly predicted. For a given driver scenario, the response of the climate and water system is estimated by simulation models that inevitably exhibit structural and parameter errors. All these uncertainties are propagated and possibly amplified in the modelling chain from the global climate to the impact assessment (Schaefli, Hingray, and Musy, 2007). Uncertainty analysis must therefore be an integral part of any impact study.

Since taking into account all the uncertainty sources simultaneously requires a huge computational effort, impact studies usually analyse only the most relevant sources at the temporal and spatial scale of interest. For instance, Arnell (2004) assesses the hydrological implications of climate change using several consistent climate and socio-economic scenarios. Brekke et al. (2009) analyse projections from 17 different GCMs, while Lopez et al. (2009) use an ensemble of projections of the same GCM under different parameterizations or *perturbed physics ensembles*. Dèquè et al. (2007) compare the projection of many different RCMs on the European domain, while Bronstert et al. (2007) compare three different downscaling methods to estimate the long-term water availability, drought conditions and floods. Ajami, Hornberger, and Sunding (2008) analyse uncertainty rising from different hydrological model structures and parameterizations. Less attention is usually devoted to assessing the uncertainty due to the intrinsic variability of climate or *multi-decadal variability* (Arnell, 2003), which limits the statistical significance of any impact quantification based on finite time series of climatic variables, either observed or obtained by model simulation. Even if relevant, this aspect is disregarded by many authors, possibly bringing to misleading impact assessments.

The purpose of this chapter is to present a framework for the quantitative assessment of the climate change impacts on water resources and the associated uncertainty analysis. The approach is demonstrated by application to Lake Como basin, Italy, a complex water system in the Southern Alpine region. Briefly, it is composed of an irrigation-fed agricultural district downstream of the lake, which is one of the largest irrigated area in Europe, and of a hydropower reservoir network located in the lake catchment, which provides nearly 25% of the national hydropower production. Other interests in play are preventing floods on the lake shores and preserving ecosystems both in the lake and along the river.

The novelties of our approach are the following: (i) the quantification of the impacts is based on a set of performance indicators defined together with the stakeholders representatives, thus explicitly taking into account the water users preferences; (ii) the multi-objective nature of the management problem is fully preserved by simulating a set of Pareto-optimal management policies under different climatic scenarios, which allows for evaluating not only variations in the indicator values but also tradeoffs among conflicting objectives; (iii) uncertainty analysis results in deriving confidence bounds around the simulated Pareto frontiers.

3.2 Impact assessment procedure

Traditional approaches to climate change impact assessment at the basin scale rely on a modelling chain that usually includes the generation of future emission scenarios, the simulation of GCM to build global climate scenarios, the use of RCM and statistical downscaling to estimate climate scenarios at the basin scale, and the projection of climatic scenarios into discharge scenarios via simulation of hydrological models. The modelling chain often stops here, while further evaluation of hydrological scenarios is committed to experts.

In this work we extend quantitative assessment also to impacts on water resources like agriculture and hydropower generation. To this end, the modelling chain must be extended to include the simulation of the water system management and the evaluation of the impacts by means of performance indicators (Figure 3.1). Both tasks are not trivial since they require a deep knowledge of the system functioning in all its aspects, from engineering to social and economic issues.

The definition of performance indicators is a challenging task, especially when not strictly economic issues are concerned, e.g., impact of changed hydrological regime on the riparian ecosystems, or when the relation between water availability and economic outcome is complicated. For instance in the irrigation district downstream from Lake Como a reduction in the water supply from the canals can be partially compensated by pumping from groundwater, which saves the crop but is costly. Definition and validation of the indicators used in this study was performed by interacting with stakeholder representatives and deriving a set of criteria that reflects their judgments and expectations (Castelletti et al., 2007).

Simulating the system management is an issue because it requires modelling the behaviour of the managers of the reservoirs and distribution network. In this study, we formulate the decision-making problem faced by the human regulators as an optimal control problem, and use multi-objective optimization techniques to derive Pareto-optimal management policies (see right side of Figure 3.1), thus obtaining an upper bound of system performances that may be achieved by a fully rational decision-maker (Soncini-Sessa, Castelletti, and Weber, 2007). To link stakeholder expectations and decision-making process, we use the performance indicators defined by the stakeholder representatives as the objectives of the optimal control problem. Since the problem is a multi-objective one, the solution is not a unique optimal management policy but a set of Pareto-optimal policies, each providing a different tradeoff between the conflicting objectives. Choosing one policy within this set is not a technical task but a political one, requiring subjective weighting of the objectives, and as such it must be left to stakeholders and decision-makers. Therefore our analysis will be conducted by considering the entire collection of Pareto-optimal policies.

3.3 Case study: Lake Como

The water system of Lake Como is described in the previous chapter (Section 2.2). Although the management of Lake Como has been intensively studied since from the first study by Guariso, Rinaldi, and Soncini-Sessa, 1986, we reframed the problem to test if a change in the water system institutional setting can increase the overall system efficiency. In this chapter we would like to test if the new proposed framework is resilient to climate change. In particular, we refer to the centralized management scheme (right picture in Figure 2.3) since it represents the upper bound performances.

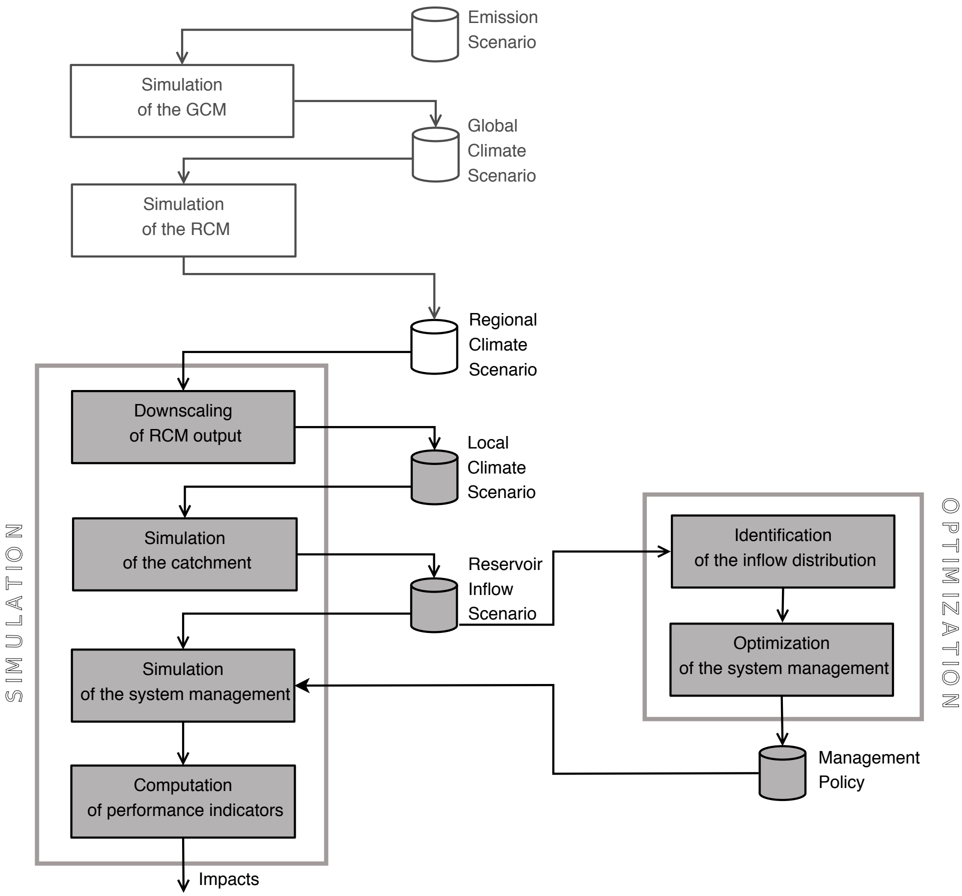

Figure 3.1: *The procedure for quantitative assessment of climate change impacts on water resources: simulation tools on the left side, optimization tools on the right side.*

3.4 Application of the impact assessment procedure

In the next paragraphs we describe the modelling units developed for assessing the impacts of climate change. For the reader convenience, we define some of the terms that will be used in the following:

- *historical climate*: the time series of precipitation and temperature observed in the catchment (gauge records from 1967 to 1980)
- *historical inflow*: the time series of observed discharge from the catchment, flowing into the reservoirs (gauge records from 1967 to 1984)
- *historical inflow scenario*: the time series of simulated discharge ob-

tained by feeding the catchment model with historical climate

- *backcast (forecast) climate scenario*: the time series of simulated precipitation and temperature provided by a circulation model over the backcast (forecast) period 1961-1990 (2071-2100)

- *backcast (forecast) inflow scenario*: the time series of simulated discharge obtained by feeding the catchment model with the backcast (forecast) climate scenario

3.4.1 Downscaling procedure

The climate of the Alps is strongly influenced by local phenomena (orographic forcing, rain-shadowing, etc.). In such cases, RCMs provide more realistic climatic forecast at the regional scale with respect to GCMs, since the mismatch of scale between the resolution of the climate models and the scale of interest for regional impacts is lower (Mearns et al., 2003; Fowler, Blenkinsop, and Tebaldi, 2007; Frei et al., 2006). The climatic time series considered in this study were derived as part of a larger multimodel ensemble in the framework of the European project PRUDENCE (see `http://prudence.dmi.dk/` and Christensen and Christensen (2007)). As backcast and forecast climate scenarios we considered the daily precipitation and mean temperature time series over the backcast period 1961-1990 and the forecast one 2071-2100 respectively. Each scenario was simulated using the emission scenario A2 (IPCC, 2000) and the GCM HadAM3H (Pope et al., 2000) as driving data.

Even if RCMs provide good estimate of the climate at the regional scale, some biases from the local climate of interest may still exist. In this study, RCMs' output were corrected via the statistical downscaling method known as Quantile Mapping. For a given variable, the cumulative density function (cdf) of the backcast is first matched with the cdf of the observations, thus generating a correction function depending on the quantile. The correction function is then used to unbias the variable from the forecast quantile by quantile. This method has been used in many hydrological impact studies, using a correction function at either annual or seasonal level (Dèquè, 2007; Boè et al., 2007).

One major limitation of statistical downscaling is that the goodness of the correction strongly depends on the quality of the available observations. To mitigate such effect, the backcast period was split into two sub-periods that were used for calibration and validation respectively. Both an annual and seasonal correction function were derived over the calibration period for both temperature and precipitation, and the one producing the smaller mismatch between downscaled and observed data over the validation sub-period was adopted. This is an annual correction function for the precipitation time series, and a seasonal correction function for the temperature time series.

Figure 3.2 compares some statistics of the downscaled output of the RACMO RCM (Lenderink et al., 2003) over the backcast and forecast period. The forecast climate scenario shows an increase in monthly mean temperature (of about 4 degree Celsius) and a shift in the precipitation pattern (decrease in spring and summer and increase in autumn and winter) while the annual precipitation volume is only slightly lower than in the backcast scenario.

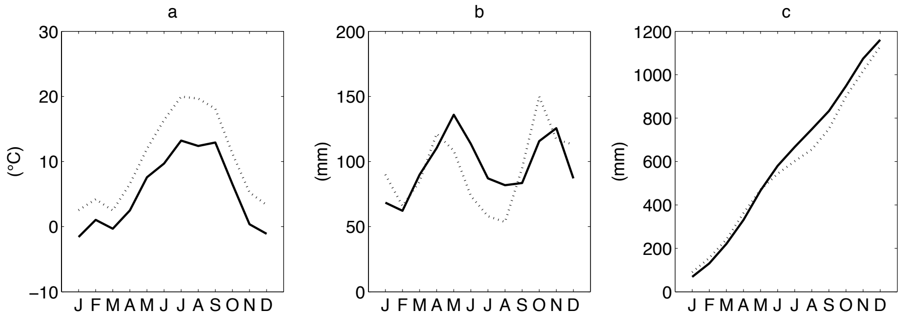

Figure 3.2: *Mean monthly temperature in the backcast (solid) and forecast (dotted) scenario (a); total monthly precipitation (b); and cumulate precipitation over the year (c) with downscaled RACMO RCM.*

3.4.2 Catchment model

The catchment response to climatic input is simulated through a lumped, conceptual model, partially based on the HBV model (Bergstrom, 1976). The lumped modelling approach guarantees efficient parameterization even with limited historical time series. However spatial processes are neglected. In our case study spatial heterogeneity is not significant, but for elevation. Nonetheless comparison of our proposed model and an elevation-based model (Consorzio dell'Adda, 1986) shows that lumping does not induce significant loss of information.

Our model is composed of three modelling units. First, the precipitation input is splitted into snowfall and rainfall: average daily temperature in a reference station is used to determine the freezing level and snowfall is computed as a fraction of the total precipitation, through a proportionality

Table 3.1: *Parameterers of the optimally calibrated* HBV *model for the lake Como (LC) catchment and the hydropower reservoir (HR) catchment, and relevant performance indicators over the validation dataset (1977-84).*

	model parameters	LC	HR
FC	maximum soil moisture content (mm)	251.9	238.5
LP	limit for potential evapotranspiration	1	0.9
ALFA	response box parameter	0.04	0.02
BETA	exponential parameter in soil routine	0.14	1.06
K	recession coefficient for upper tank (day^{-1})	0.29	0.11
K4	recession coefficient for lower tank (day^{-1})	0.04	0.04
PERC	maximum flow from upper to lower tank (mm/day)	6.98	0
CFLUX	maximum value of capillarity flow (mm/day)	0	0
MAXBAS	transfer function parameter (day)	1.01	1.21
	performance indicators		
R^2	coefficient of determination (-)	0.654	0.799
MAE	mean absolute error (m^3/s)	57.5	3.22
RVE	relative volume error (-)	0.23	0.09

coefficient that accounts for the catchment's area located above the freezing level. Then, the snowpack dynamics is described by a mass balance equation, while a degree-day approach is used to determine the snowmelt. Finally, the HBV model is used to simulate the soil water balance and subsequent runoff, as a consequence of melt-water, rainfall, and evapotranspiration. The latter is computed throught the Blaney-Criddle method (Brouwer and Heibloem, 1986).

Two different parameterizations were used for the two catchment, the one feeding the equivalent hydropower reservoir (catchment surface area of about 350 km^2) and the other feeding Lake Como (4200 km^2). They were derived using the Genetic Algorithm implemented in the Matlab Global Optimization Toolbox and time series of daily precipitation, temperature and flow. Precipitation is the spatial average from several meteorological stations; temperature data come from two reference stations, one for each of the two catchments; flow data are derived by inversion of the reservoir mass balance equations. The objective function of the automatic calibration procedure is the coefficient of determination (one minus the ratio between error variance and measured flow variance). Table 3.1 shows the optimal parameter values of the HBV soil-moisture routine for the two catchments.

The calibrated model was evaluated by means of several performance indicators computed over the validation period 1977-1984 (last lines in Table 3.1) and graphical tools like scatter plot, duration curves and hydrographs of observed and simulated flow (Figure 3.3). They show that the model error is quite significant especially for high flow. Nonetheless the model accuracy is acceptable for the scope of this study, as we will show in Section 3.6.2.

Note that in this study we did not include a model of the glacier dynamics. At present, the contribution of glacier melting is usually negligible but for extremely hot and dry summer periods, as for instance the 2003 drought. However, under future climate scenario of increased temperature, glacier melting may become relevant. Also, there exist multiple evidences of a constant glacier reduction since from the beginning of the 20th century (Smiraglia and Diolaiuti, 2006), which means that glacier melting may give a positive contribution to flow in the middle-term while disappearing in the long run. However, such an evolution cannot be reproduced in our study.

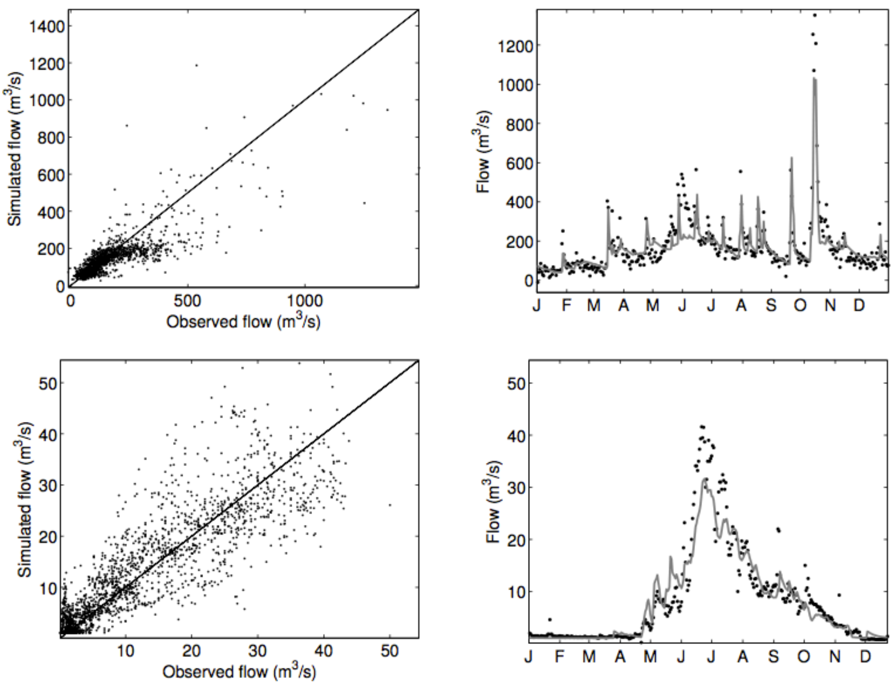

Figure 3.3: *Left: observed vs simulated flow from lake Como catchment (top) and hydropower reservoir catchment (bottom) in the validation period (1977-1980). Right: observed flow (dots) and simulated flow (grey line) in 1980.*

3.4.3 Reservoir and management model

The water system reservoir network is modelled as described in Section 2.3 of the previous chapter when referring to the centralized management approach. In this work, we will use the set of management policies reported therein as the reference to evaluate how reservoir management performances may change under climate change. It consists of eight different policies, each corresponding to a different tradeoff, including the two extreme policies that consider either irrigation or hydropower only.

3.4.4 Performance indicators

The definition of indicators was developed together with the stakeholder representatives in a former research project (Castelletti et al., 2007). In that project, a representative person for each stakeholder group was identified. These were: the managers of the hydropower companies; the leaders of the irrigation consortia (representative for the farmers); officials from Como city and other towns along the lake shores (representative for the flooding, navigation, fishing and tourism issues); the manager of the Nature Park located along the lake effluent river. The indicators were identified by structured interviews and validated during a final meeting, where each stakeholder representative was asked to rank different situations and it was checked that the ranking was consistent with the one determined by the indicator. In this study, we focus only on the hydropower and irrigation indicators: the hydropower indicator is the average daily revenue from hydropower production, the irrigation indicator is the squared daily deficit in the water supply. Both were described in detail in Section 2.3 of the previous chapter.

3.5 Water resource impacts

The performance indicators were used when designing the optimal management policies. In fact, the objective functions of the stochastic optimal control problem are the expected values of the performance indicators with respect to all the possible trajectories of the inflows (i.e., the inflow probability distribution) over an infinite horizon ($h \to \infty$). Note that, since the inflow probability distribution is estimated over historical time series, the result is optimal as long as the hydrological behaviour of the system remains stationary. For each Pareto-optimal policy reported in the previous chapter, the expected values of the indicators can be assessed by Markov or Monte Carlo simulation. Alternatively, it is possible to use deterministic simulation and compute the indicator values over a single finite horizon. The latter approach is computationally less demanding and can provide a more informative output to stakeholders: for instance, using a historical horizon they can compare the simulated behaviour of the system with the historical one, which they directly experimented. The performance indicators under the historical inflow over the period 1967-1984 are shown in Figure 3.4 (black dots). Note that even if produced by Pareto-optimal policies, they do not necessarily belong to the Pareto Frontier of the two-objective control problem, as they are obtained under historical inflow and not under the inflow probability distribution used in optimization. For this reason they will be called the Image of the Pareto Frontier (IPF). It can be noticed that the historical IPF (black dots in Figure 3.4) can greatly improve the satisfaction of both the water users with respect to the historical management (cross in Figure 3.4) and represent an effective tool to mitigate the conflict between upstream and downstream water users.

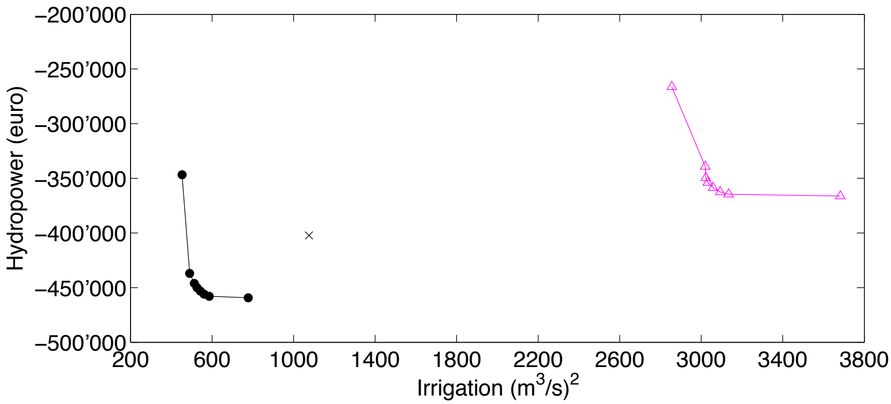

Figure 3.4: *Image of the Pareto Frontier (IPF) under historical inflow 1967-1980 (black dots) and forecast inflow scenario 2071-2100 by RACMO RCM (magenta triangles). The cross is the historical management. Hydropower revenue (on the vertical axis) is changed in sign.*

The historical IPF also constitutes a reference for comparison with system performances under climate change: Figure 3.4 shows also the IPF under the forecast inflow scenario (2071-2100), as given by RACMO RCM and projected through our simulation procedure (magenta triangles). For all the policies, the system performances worsen with respect to both objectives, and particularly irrigation. In fact, the forecast climate scenario predicts a significant reduction of water availability just in late spring and summer, when the water demand for irrigation is higher. The results is that failures in the water supply become more frequent.

3.6 Uncertainty analysis

The trustability of the results presented in the previous section depends on the robustness of the adopted simulation procedure, which is affected by two major sources of uncertainty. First, the comparison is based on indicator values computed over finite system trajectories. Would results be significantly different under a different choice of the simulation horizon? We will discuss how the natural variability of the climate affect the robustness of the estimated impacts. Second, as in any impact assessment analysis we shall consider what is the contribution of modelling errors. We will distinguish three types of uncertainties: those introduced in modelling the physical system, those introduced in modelling the socio-economic system, and those introduced in modelling the behaviour of the water system manager.

3.6.1 Inherent climate variability

To assess the uncertainty in the indicator values due to the choice of the simulation horizon, we computed seven different IPFs with a sliding window of $h = 10$ years over the period 1967-1984 (grey dots in Figure 3.5.a). It can be seen that differences are generally small, exception made for two IPFs, which present a strongly lower irrigation cost: they correspond to simulation horizon that do not include the year 1973, characterized by one of the most severe droughts of the 20th century. The estimated indicator values are indeed sensitive to single extreme events occurring or not occurring in the selected horizon. The length of the horizon also affects the results. The historical IPF (black dots), although including the dry year 1973, shows lower irrigation costs because the same events are averaged over a longer simulation horizon (14 years instead of 10).

The same problem arises when using climate scenarios. Indeed, the problem is accrued because, due to the chaotic nature of the climate models, time series of simulated precipitation and temperature, then projected into flows, can only be interpreted as equiprobable to observations (Royer, 2000). It follows that, even assuming that the RCM perfectly reproduced the climate dynamics (i.e., even neglecting the modelling error issue), we could not expect its output time series to perfectly overlap historical observations. Indeed, the observed climate over 1967-1980 is simply equiprobable to any 14-years long time series in the backcast period. To assess the uncertainty in the indicator values due to such statistical equiprobability, we computed

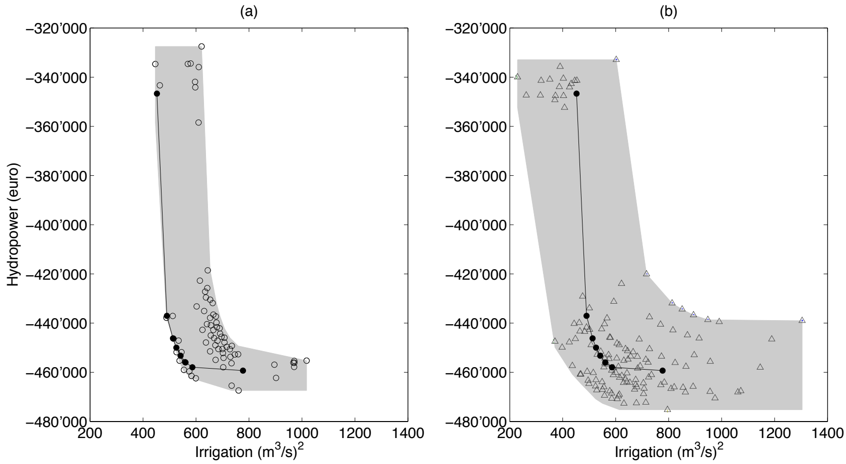

Figure 3.5: *Left panel: IPFs under historical inflow over a sliding window of 10 years between 1967 and 1984. Black dots are the IPF under historical inflow over the entire horizon 1967-1980. Rigth panel: IPFs under backcast inflow scenario over a sliding window of 14 years between 1961 and 1990. Black dots are the IPF under historical inflow scenario over the entire horizon 1967-1980.*

several IPFs under the backcast scenario with a sliding window of $h = 14$ years. They are shown in Figure 3.5.b: as expected, none of these IPFs is superimposed to the historical one, but they are scattered around it. Finally, the IPF under the entire backcast scenario of 30 years from 1961 to 1990 can be computed: it is represented by the triangles in Figure 3.6. This IPF may be used as a fair reference for comparison with the IPF under forecast scenario, in place of the historical IPF (1967-1984), since it is based on the same simulation model and horizon length h as the forecast IPF.

Although the use of a finite horizon and the statistical interpretation of the RCM output do not allow for a univocal quantification of the system performances over the past, this intrinsic variability is negligible with respect to the variation that is expected to be induced by climate change, as shown in Figure 3.6. This is consistent with other research: for instance, Arnell (2003) demonstrates that changes in mean seasonal discharge in many basins in Britain are outside the range of natural climate variability by 2050s, but that climate change signal and natural variability could be difficult to distinguish when considering nearer horizons.

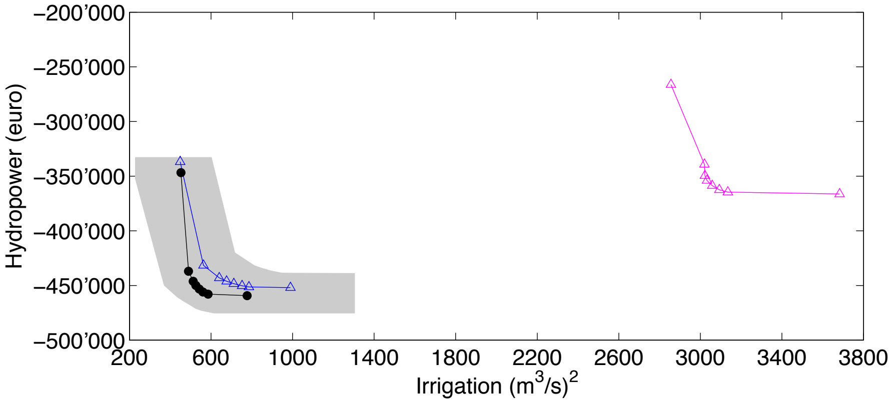

Figure 3.6: *IPF under historical inflow 1967-1980 (black dots), backcast inflow scenario 1961-1990 by RACMO RCM (blue triangles) and forecast inflow scenario 2071-2100 by RACMO RCM (magenta triangles). The grey region represents the natural variability of backcast climate scenario obtained as the envelope of the IPFs over a sliding window of 14 years reported in Figure 3.5.b.*

3.6.2 Modelling the physical system

The description of the physical system includes modelling the climate dynamics through the GCM, RCM and statistical downscaling; modelling the catchment response; and modelling the reservoirs.

Structural uncertainty is particularly high in the climate and hydrological modelling. For GCMs and RCMs, uncertainty rises from limited understanding of the processes occurring in the atmosphere, ocean, criosphere, etc...; from the mismatch in scale between the grid resolution of the RCM and the catchment boundaries; and from error induced by using a coarse spatial resolution. Downscaling is not sufficient to restore all the characteristics of the climate time series observed at the basin scale: for instance, the Quantile Method used in this study cannot correct the temporal properties of the precipitation series (e.g., length of dry spells). For the catchment model, structural error is also significant because of the oversimplified description of the actual processes occurring in the basin and the lumping of all space processes into one average process. Structural error is much smaller in the reservoir models, which indeed are very accurate and can be considered as exact at the spatial and temporal scale of interest. The only source of structural error is that in the reservoir mass balances because the contribution of evaporation is not considered: this can be considered negligible in the present condition, however it may be not in the future under increased temperature.

Besides structural uncertainty, the simulation output is also affected by parameter uncertainty. In particular for downscaling and the catchment model, the problem is that parameterizations were selected by minimization of the simulation error over historical time series. This approach is questionable when the model is used for projecting future climate scenarios that may violate the stationary assumption underlying calibration over historical time series. Unfortunately there is no solution to this paradox: the past is the only testing ground we have to assess the validity of our models.

Regardless of the distinction between structural and parameter uncertainty, the impact of the model error can be assessed, at least for the catchment model, by a simple experiment: to simulate the system under the historical inflow scenario, i.e., the discharge time series produced by the catchment model when fed by the historical climate. The corresponding IPF is shown in Figure 3.7 (white dots). It can be seen that it does not perfectly overlap the historical IPF (black dots), as expected if there were no error in the catchment model. However the modelling error is rather limited compared to variability induced by the use of equiprobable climate scenarios and the full range of indicator values is reproduced.

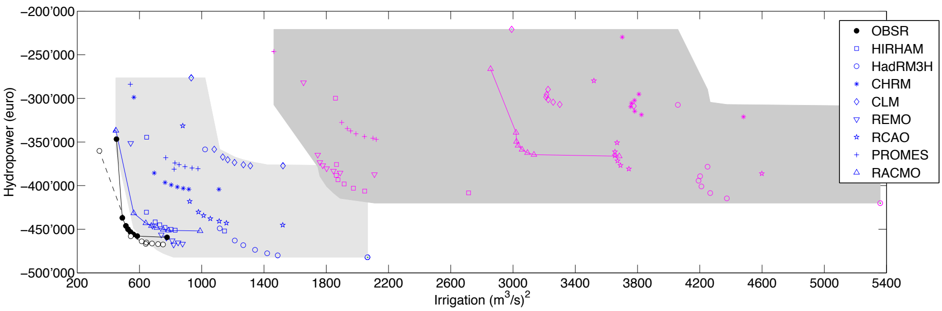

Figure 3.7: *IPF under historical inflow 1967-1980 (black dots), IPF under historical inflow scenario 1967-1980 (white dots), IPFs under backcast inflow scenarios (1961-1990) using eight different RCM models (blue symbols), IPFs under forecast inflow scenarios (2071-2100) with the same eight different RCMs (magenta symbols).*

As for the climate model, the impact of structural uncertainty may be assessed by simulating and comparing different circulation models. Generally, since the winter climate is mainly driven by global circulation while the summer climate is largely influenced by local phenomena, the choice of the GCM is the main source of uncertainty in winter time, while the RCM is more important in the summer (Jacob et al., 2007). Besides this distinction, some studies (Dèquè et al., 2007; Schaefli, Hingray, and Musy, 2007) seem to indicate that the choice of the GCM is the most critical. However, as for the RCM scenarios generated in the PRUDENCE project and used in this analysis, Hingray et al. (2007) show that variability among RCMs is comparable to the variability induced by the GCM choice. Following these considerations and for brevity's sake, in this work we will focus only on the RCM variability. Starting from the climate scenario from seven different RCMs (beyond the RACMO model) provided by the PRUDENCE project, we applied the downscaling method to each of them and then projected climate input into inflow scenarios. Figure 3.7 shows the IPFs under these eight backcast (blue) and forecast (magenta) inflow scenarios. It can be seen that the spread of the IPFs is rather high even over the backcast scenario: the RACMO RCM, that we used so far as the reference model, produces an IPF quite close to the historical one, together with the REMO and HIRHAM, while other RCMs seem to be less accurate in reproducing the historical system performances. The spread of the IPFs strongly increases in the forecast scenario - although all future scenarios are derived from the same emission scenario, A2, and GCM boundary condition, HadAM3H.

To conclude, our study provides one more confirmation that circulation models, and specifically RCMs, are a major source of uncertainty in impact assessment studies (e.g., Hingray et al. (2007)), much more relevant than other sources like uncertainty from using finite simulation horizon or inner climate variability, as it can be seen by comparing the extent of the uncertainty regions (grey area) in Figures 3.5.a, 3.5.b and 3.7. Notwithstanding this high uncertainty, comparison of the uncertainty regions over backcast and forecast scenarios (Figure 3.7) suggests that a significant worsening of the system performances can be expected: there is basically no overlapping between the backcast and forecast uncertainty region.

3.6.3 Modelling the socio-economic system

The description of the socio-economic system includes the definition of the emission scenario, the policies used to manage the reservoirs, and the definition of the performance indicators. Uncertainty associated to these choices is rather different from uncertainty in modelling the physical system. In the latter case, uncertainty stems from our limited capacity of reproducing reality through models and, to some extent, it can be objectively quantified by comparison of model output with observations from the real system. Uncertainty in modelling the socio-economic system, instead, can rarely rely on observations or reference values. For instance, there is no exact choice of the emission scenario, and the only way to assess the impact of such choice is to repeat the entire simulation procedure under a different scenario.

The same holds for the choice of the performance indicators. Since they are aimed at reflecting the stakeholder preferences, stating whether they actually capture the stakeholder opinions is very difficult. For the hydropower producers, the choice of the revenue is rather straightforward, while for the farmers the definition of the indicator is more difficult. The proper choice would be the revenue from the crop production, however this indicator would need a model of the crop growth that is expensive to develop and often does not guarantee reliable results. The average squared deficit that we used in our analysis is a proxy indicator easy to compute and that received the approval of the farmers' representatives, and as such it is hardly questionable.

What can be argued is the value of the parameters inside the indicator formulation. So far, we implicitly assumed a business-as-usual scenario for the energy price and water demand. However, the pattern of energy price may change in the future following changed conditions in the energy market, while the water demand may be reduced thanks to improvement in the irrigation technique (e.g., from submersion to more efficient systems) or changes in the crops. Climate change itself will probably drive such changes. Therefore, the analysis so far must not be interpreted as a prediction of the future conditions, which would be unrealistic because the socio-economic system would certainly evolve and adapt to the possibly reduced water availability, but rather as the demonstration that the current socio-economic conditions cannot be maintained in the future.

3.6.4 Modelling the behaviour of the water system manager

The business-as-usual assumption involves also the system management. In fact, variations in the hydrological conditions, as well as potential variations in the energy price or water demand, will lead the reservoir managers to change their behaviour. In our analysis we simulated the management policies that proved Pareto-optimal over historical inflow statistics, energy price, etc. but they would not be Pareto-optimal any more if these conditions changed. Even if we set aside the issue of energy prices or water demand, still the results shown so far may be overly pessimistic because based on sub-optimal policies, and there may be room for improvement by re-optimizing the management policies under the new inflow scenarios.

To explore this room for improvement, we ran the following experiment. We used the forecast inflow scenarios produced by the downscaled output of the RACMO RCM to re-estimate the probability distribution of the reservoir inflows and, based on this new distribution, re-run Stochastic Dynamic Programming, thus obtaining eight Pareto-optimal policies for the new climate scenario. Then, we simulated the new policies under the entire forecasting horizon and derived the IPF represented by the black triangles in Figure 3.8. It can be seen that the system performances improve with respect to the original, sub-optimal IPF (magenta triangles), especially for the irrigation objective. Nonetheless, the improvement is not sufficient to compensate for changed hydro-climatic conditions, as it can be seen by comparison with the IPF under backcast inflow scenario (blue triangles). Notice that, this time, the comparison between these two IPFs is not affected by uncertainty in modelling the manager behaviour, since in both cases we assume the best possible behaviour, in Pareto-sense, that a rational decision-maker could follow for the corresponding inflow scenario and the selected performance indicators.

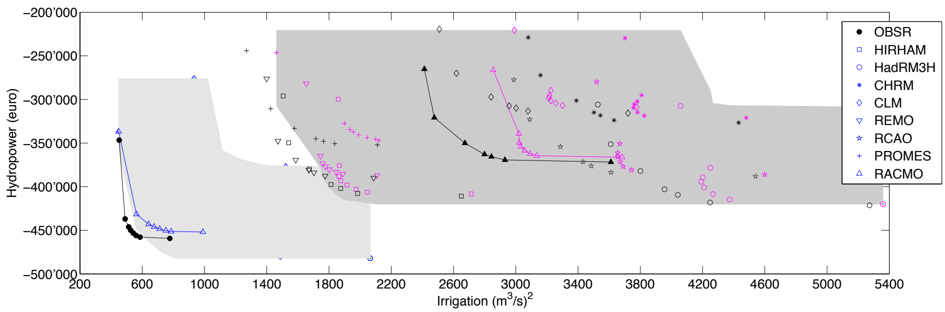

Figure 3.8: *IPFs under: historical inflow 1967-1980 (black dots), backcast inflow scenario 1961-1990 by RACMO RCM (blue triangles), forecast inflow scenarios (2071-2100) of eight different RCMs (magenta symbols), forecast RACMO inflow scenarios (2071-2100) using optimal management policies for future climate (black symbols).*

One interesting feature is that, while re-optimization allows for a significant improvement in the irrigation objective, the enhancement for hydropower production is almost negligible. The reason relies in the ratio of reservoir storage to mean annual inflow, which is about 0.6 for the hydropower reservoirs and only 0.06 for Lake Como. This means that hydropower reservoirs can easily face the shift in the seasonal inflow distribution projected by future scenario, but not the reduction of the annual volume, which causes their losses. Lake Como instead, whose capacity is too small to suffer from the reduction of the annual inflow volume, can effectively modify its operation to partially mitigate the lowering of summer flows.

It is interesting to assess if the new optimal management policies are more resilient to the RCM uncertainty than the business-as-usual policies. We thus computed the two performance indicators by simulating the impact assessment procedure, using as input the forecast climate scenario from the other seven RCMs (beyond the RACMO model) and the new management policies, optimal for the RACMO forecast inflow scenario. As Figure 3.8 shows, when considering the new management policies (black symbols) we obtain better performances with respect to the business-as-usual policies (pink symbols) under all the RCMs. However, the overall uncertainty is just slightly reduced: the impacts are as widespread as in the business-as-usual experiment (dark grey region in the figure). Qualitatively similar results (not shown) are obtained if using other RCMs, i.e., HIRHAM and CLM, to derive the inflow statistics for the management re-optimization. This seems to reinforce the conclusion that, notwithstanding the large uncertainty in RCM projections, the historical operating policies will not be able to cope with future hydrological conditions.

The IPFs plotted so far represent the average impacts over 30 years, i.e., the length of the time series provided by the climate models. Figure 3.9 shows the impacts when simulating the management policies, optimal under the RACMO forecast inflow scenario, computed over the three decades 2071-2180, 2081-2190, and 2091-2100 (black dashed lines). It is easy to indentify a strong trend: the estimated impacts become more and more negative as time passes by. This seems to suggest that the future inflow statistics change during the 30 year period 2071-2100 and better performances may be obtained by considering this trend into the optimization procedure.

3.7 Conclusions

This chapter presents a framework for the quantitative assessment of the climate change impacts on the water resources at the basin scale. The proposed simulation procedure starts from the downscaling of Regional Circulation Model output, and, through the projection into the hydrological scenario and simulation of the system management, ends up with the computation of performance indicators. One major feature of our approach is that the multi-objective perspective is preserved throughout the entire simulation procedure. In fact, instead of simply reproducing the current system

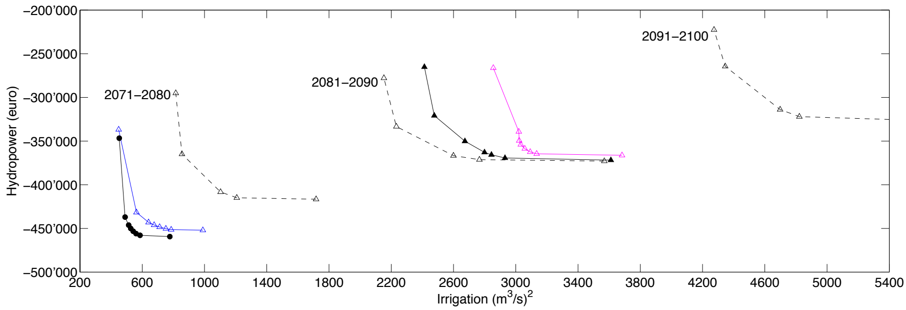

Figure 3.9: *IPF under historical inflow 1967-1980 (black dots), backcast inflow scenario 1961-1990 by RACMO RCM (blue triangles), and forecast inflow scenario 2071-2100 by RACMO RCM (magenta triangles). IPF under forecast RACMO inflow scenarios using optimal management policies for future climate: average over 2071-2100 (black symbols) and over the three decades 2071-2180, 2081-2190, and 2091-2100 (black dashed lines).*

management, we first derive a set of Pareto-optimal policies and then simulate all of them over the historical, backcast, and forecast scenario. The advantage is that tradeoffs between different objectives can be explored under present and future climate conditions, and further that the comparison of past and future performances is not affected by subjective choice of the management policy.

The approach is demonstrated by application to the complex and intensively exploited system of Lake Como, Italy. It shows that all the climate change projections considered in the study dramatically impact the water resources in the basin and that the coordination mechanism designed in the previous chapter to adapt to climate variability can not effectively face climate change in the long run. The results presented were obtained using current energy price and water demand pattern, and thus they must not be interpreted as a prediction of the actual future conditions but rather as the demonstration of the unsustainability of the current ones.

The results are highly affected by uncertainty. We analyzed both the uncertainty stemming from the inherent climate variability and the modelling uncertainty. Among the latter, we analysed the uncertainty induced by modelling the behaviour of the water system manager by re-optimizing the management policies under future hydrological conditions. The analysis proved that, although the uncertainty due to the inherent climate variability is quite significant, it is negligible with respect to other sources of modelling uncertainty. More precisely, climate modelling, in our case RCMs, seems to contribute the most to the overall uncertainty. Despite this deep uncertainty prevents from the exact quantification of the impacts in terms of performance indicators, some information can still be derived by the application of this scenario-based assessment procedure. For instance, the comparison of the uncertainty regions where current and future performances are expected to fall clearly indicates that a significant loss will be induced by climate change, especially for the irrigation sector.

Deep uncertainty prevents also from the definition of an actual implementable adaptation measure. For example, the impacts of the future optimal management policies strongly depends on the projected hydrological conditions. Moreover, the analysis does not clearly indicate when re-optimization of the management policies should be done. In fact, we demonstrated that the performances of the future optimal management policies degradate as time pass by. The adaptation may, then, be more effective if done on a shorter time scale. These topics will be discussed more deeply in the next two chapters. Nonetheless, re-optimization of the management policies helped in understanding to which kind of hydrological changes the reservoirs are vulnerable. As for the case study, for example, the hydropower reservoirs proved to be vulnerable to a reduction of the annual inflow volume, while Lake Como to a seasonal shift of the inflow. This is related to the reservoir features, in particular to the ratio of reservoir active storage to mean annual inflow volume.

While increasing complexity and accuracy of the simulation model will increase the trustability of the results, we question this will be sufficient to compensate for the large uncertainty that affects the assessment analysis, because of the inner variability of climate, our limited capacity in reproducing the complex circulation dynamics, and the errors induced by mismatches in scale. Therefore we think that the research effort to improve the model accuracy should be coupled with an equal effort towards developing effective methods to handle uncertainty in the decision-making context. This is especially true when dealing with multi-objective problems, where modelling and optimization is aimed at providing the knowledge base for political discussion and decision-making, not at replacing it. The role of uncertainty analysis in this process is very delicate. From the modeler standpoint, uncertainty analysis enhances the robustness of the assessment results, while for political decision-makers it may be perceived as undermining their trustability. Communicating the information contained in the IPF graphs shown in this paper is difficult and time consuming: it requires the decision-makers to make an effort towards understanding at least the general principles of the underlying assessment methodology; and the willingness to assimilate a sophisticated message rather than simple answers. Effective communication of modelling results and their associated uncertainty should become integral part of the research in this area.

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CHAPTER 4

Time series analysis and trend detection

Water systems have an inherent adaptation capacity (Pahl-Wostl, 2007). In fact, changes in the hydrological regime can be naturally compensated by water systems, at least to some extent. It is important to recognize this inherent buffering capacity because, on the one hand, it allows to gain a deeper knowledge of the water system characteristics, and, on the other hand, it can drive the identification of the most promising adaptation measures to further enhance the adaptation potential of water systems. In this chapter we investigate the relationship between hydro-climatic changes and their impacts on water resources at the basin scale, proposing some tools that can be used to assess the inherent adaptation capacity of water systems. More precisely, we address the topic of trend detection in environmental time series combining novel and traditional tools in order to simultaneously tackle the issue of seasonality and interannual variability, which usually characterise natural processes. The chapter's contribution is twofold. First, we propose a novel tool to be applied in Exploratory Data Analysis, named MASH (Moving Average over Shifting Horizon). It allows to simultaneously investigate the seasonality in the data and filter out the effects of interannual variability, thus facilitating trend detection. We describe how to combine the MASH with statistical trend detection tests, like the Mann-

Kendall test, the Seasonal Kendall test, and the Linear Regression test, and Sen's method, to quantify the trends occurring in different seasons. Second, we estimate the impacts of hydrological changes in terms of water resources and we discuss their relevance from the water resources management perspective. We define and simulate a set of indicators of performances, resilience, reliability, and vulnerability, so to assess the ability of the water resources systems to absorb changes in the hydrological patterns.

This chapter is based on D. Anghileri, F. Pianosi, and R. Soncini-Sessa, "Trend detection in seasonal data: from hydrology to water resources", *Journal of Hydrology*, Accepted for publication in 2014.

4.1 Introduction

Trend detection techniques have gained renewed interest in the last decades in climate change studies, where they are used to detect changes in the magnitude of temporal and spatial distribution of hydro-climatic variables like temperature and precipitation (see among others, Brunetti et al., 2001; Oguntunde, Abiodun, and Lischeid, 2011), and water availability, e.g. river streamflow (Déry et al., 2011; Rougé, Ge, and Cai, 2013) or groundwater depletion (Aeschbach-Hertig and Gleeson, 2012). Conversely, the impacts of hydrological changes in terms of economic costs and benefits, utility, or risk for the human society, are still difficult to anticipate and quantify. In fact, the very definition of indicators to measure the impacts on water resources may be not univocal, historical records (e.g. losses due to floods or droughts) are rarely available, and the drivers of change, besides meteo-hydrological conditions, may be manifold (e.g. economic development, urbanization in flood-prone areas, etc.).

A comprehensive trend detection study usually includes Exploratory Data Analysis (EDA, see Tukey, 1977) and the application of formal mathematical methods. EDA stands for any technique of data analysis besides formal statistical methods. It usually employs graphical tools, e.g., time series plots and scatter plots, and it is aimed at better understanding the available data and the underlying processes. Mathematical methods include statistical tests for detecting the presence of a trend, e.g., the Mann-Kendall test or the Spearman's rho test and regression techniques to quantify the magnitude of the trend, e.g., linear regression or Sen's slope. EDA and statistical tests complete each other: EDA can support the selection of appropriate statistical tools and techniques, while statistical tests can confirm the significance of the trends detected by visual inspection. A comprehensive review of the state-of-the-art in the field can be found in Kundzewicz and Robson, 2004 and, more recently, in Sonali and Kumar, 2013.

When dealing with time series of environmental variables, trend detection is often complicated by the seasonality and the interannual variability characterizing natural systems. Seasonality stands for the cyclical, usually yearly, behaviour exhibited by natural processes, which makes trend detection results largely depending on the selected time scale of analysis (e.g. weekly, monthly, yearly). For example, in the case study discussed in this chapter, a catchment in the Italian-Swiss Alps, the runoff is mainly affected by snow accumulation in Winter, snowmelt in Spring, and rainfall in Autumn, and such processes have changed differently in time, giving raise to different trends depending on the season. Interannual variability stands for the fact that the hydro-climatic system naturally exhibits wide fluctuations from one year to another. This can generate apparent trends, especially when the recorded time series are short.

The issues posed by seasonality are usually solved by repeating the analysis for eachmonth or group of months (season). Results can be then combined into a global index of trend direction and significance, as done for instance by the Seasonal Kendall test (Hirsch and Slack, 1984). This approach has some limitations. First, its application requires defining a priori the number and length of the seasons. Second, the use of a summary statistic may cancel out trends occurring in different seasons when they have different directions. Alternatively, data can be deseasonalized by subtracting seasonal means, medians, or other periodic functions so that conventional trend detection tests can be applied to the time series of residuals. This approach, however, cannot detect specific trends occurring in different seasons and has generally lower power to detect trends than other methods (Helsel and Hirsch, 2002). As for interannual variability, moving average smoothing as LOcally WEighted Scatterplot Smoothing (Cleveland and Devlin, 1988) can be used used to highlight trends or patterns that would be otherwise difficult to detect. However, to the authors' knowledge none of these methods also address the seasonality issue.

In this chapter we investigate the relationship between hydro-climatic trends and their impacts on water resources at the basin scale. We propose a novel approach to EDA, named Moving Average over Shifting Horizon (MASH), which allows to cope at the same time with both seasonality and interannual variability in detecting trends. We quantify the trends that can be visually detect using the MASH with some trend detection methods like the Mann-Kendall test, Sen's method, the Seasonal Kendall test, and least squares Linear Regression. Those techniques are applied not only to time series of hydro-meteorological variables, but also to investigate trends in indicators of performances, resilience, reliability, and vulnerability, so to assess the ability of the water resources systems to absorb changes in the hydrological patterns. As a case study we use the regulated Alpine lake Maggiore, at the border between Switzerland and Italy. This case study is particularly interesting for our purpose because of the relevance of the socio-economic component in the system, especially the stakes of flood control and downstream irrigation supply, and the high seasonality and interannual variability of the climatic and hydrological system.

4.2 Trend detection techniques

4.2.1 Mann-Kendall test and Sen's method

In order to identify hydrological trends, we first applied the widely used Mann-Kendall test (Mann, 1945; Kendall, 1975) to the time series of annual inflow volume. The test statistic is

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \text{sign}(x_j - x_i)$$

where x_i and x_j are the observations (inflow in our case) at time (year) i and j, and N is the number of observations (number of years). A positive value of S indicates an increasing trend, a negative value indicates a decreasing trend, while $S = 0$ means that no trend is detected.
The statistical significance of the trend is assessed by computing the standard normal statistic Z

$$Z = \begin{cases} \frac{S-1}{\sigma} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sigma} & \text{if } S < 0 \end{cases}$$

and the associated p-value. In the above equations, σ is the standard deviation of S, which can be estimated as

$$\sigma = \sqrt{\frac{N(N-1)(2N+5)}{18}}$$

The null hypothesis of trend absence is rejected at significance level α if the p-value is less than or equal to α. In this work we will consider $\alpha = 0.1$ as a reference significance level, however this will not be viewed as a strict threshold but rather, we will consider the continuous range of p-values as a measure of statistical confidence: the lower the p-value, the higher the

confidence in rejecting the null hypothesis and viceversa.
The magnitude of the trend can be assessed by Sen's method (Sen, 1968). It assumes that the trend is linear and estimates the trend slope b as the median slope between all possible pairs x_i and x_j, i.e.,

$$b = \text{median}\left(\frac{x_j - x_i}{j - i}\right) \forall j > i; \quad i = 1, 2, \cdots, N-1; \quad j = 2, \cdots, N$$

4.2.2 Moving Average over Shifting Horizon (MASH)

To further investigate trends while simultaneously tackling the issue of seasonality and interannual variability, we propose and apply one more tool, named Moving Average over Shifting Horizon (MASH). The goal is to assess variations in the seasonal pattern of the flow. The seasonal pattern is represented by the 365 values of average daily flow over the year. When averaging, we consider data over consecutive days in the same year, and over the same days in consecutive years. However, the horizon of consecutive years is progressively shifted ahead to allow for any trend to emerge. The MASH is thus a matrix

$$MASH = \left[\begin{array}{c|c|c|c} \mu_{1,1} & \mu_{1,2} & \cdots & \mu_{1,N_h} \\ \mu_{2,1} & \mu_{2,2} & \cdots & \mu_{2,N_h} \\ \cdots & \cdots & \cdots & \cdots \\ \mu_{365,1} & \mu_{365,2} & \cdots & \mu_{365,N_h} \end{array}\right] \tag{4.1}$$

where the columns are the mean flow seasonal pattern computed over N_h different horizons. More precisely $\mu_{t,h}$ is the average daily flow on the t-th day of the year in the h-th horizon, computed as

$$\mu_{t,h} = \underset{y\in[h,h+Y-1]}{\text{mean}} \left[\underset{d\in[t-w,t+w]}{\text{mean}} x_{d,y}\right] \tag{4.2}$$

where $x_{d,y}$ is the inflow on the d-th day of the y-th year of the time series, $2w + 1$ is the number of days and Y is the length (years) of the shifting horizon (see Figure 4.1). The number N_h of horizons is univocally related to Y by the equation $N_h = N_y - Y + 1$, where N_y is the number of years in the original time series.

4.3 Case study: Lake Maggiore

Lake Maggiore is an Alpine regulated lake at the border between Italy and Switzerland (Figure 4.2). The lake is fed by a catchment of about 6600

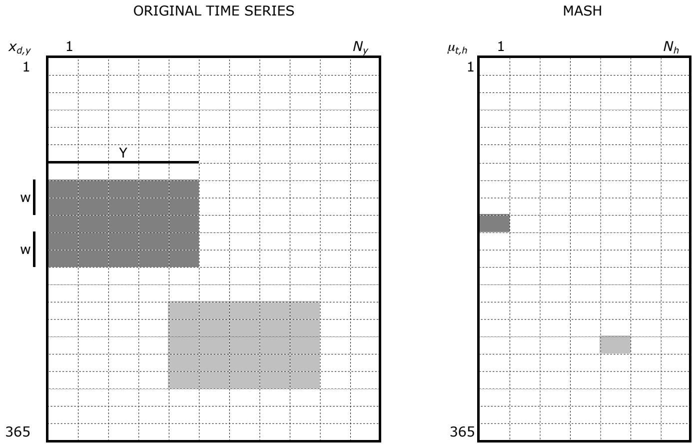


Figure 4.1: *From the original time series to the Moving Average over Shifting Horizon (MASH). Daily original time series $x_{d,y}$ (where d is the day of the year and y the year of the time series) are averaged considering data over $2w + 1$ consecutive days and Y consecutive years (grey regions in the figure) thus obtaining the MASH $\mu_{t,h}$ (where t is the day of the year and the h is the horizon).*

km^2 and its hydrological regime follows a strong seasonal pattern. The low flow seasons are summer, when rainfall is at a minimum, and winter, when precipitation is mainly accumulated as snow in the upper part of the catchment. The high flow seasons are spring, due to the contribution of both snowmelt and rainfall events, and autumn, when severe floods due rainfall may occur. The hydrology of the lake catchment is also influenced by the operation of several hydropower reservoirs that were constructed from the beginning of the 20th century to 1973. Although distributed in many and often small storage facilities, their overall capacity is larger than the capacity of the lake (Ciampittiello, 1999).

The lake was dammed in 1943 in order to supply the large downstream irrigated area which is fed by the lake release through a wide distribution network of canals. The lake has an active storage of about 420 million m^3. Currently, the lake regulation must also consider other interests besides irrigated agriculture. For example, the lake storage is used to reduce flooding events on the lake shores and in recent years increasing attention has been given to environmental protection in the lake and the effluent river. A Minimum Environmental Flow constraint has been progressively increased in time from an original value of 3 m^3/s up to 13 m^3/s, and a further increase is currently under discussion.

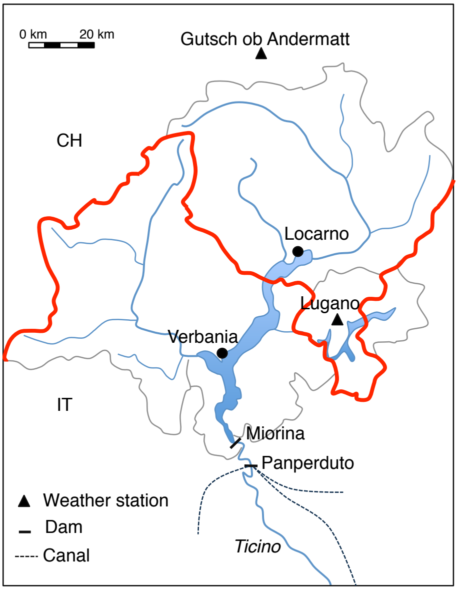


Figure 4.2: *The lake Maggiore water system. The bold red line is the border between Switzerland (CH) and Italy (IT).*

4.4 Trends in the hydrological time series

We analysed time series of net inflow to the lake over the period 1974-2010. They are estimated by inversion of the mass balance equation starting from daily measurement of the reservoir water level and of the total daily release. From these daily data, time series of monthly and annual inflows are also derived.

4.4.1 Application of trend detection tests

In our case study, the application of the Mann-Kendall test to the time series of annual inflow volume detects a decreasing trend which, however, has a relatively high p-value (see first row in Table 4.1). As discussed in the introduction, this is not sufficient to conclude that there are no statistically significant trends because, given the seasonality of the hydrological pattern, trends may be not detectable at the annual scale. So, we applied the Seasonal Kendall test on a monthly basis (Hirsch and Slack, 1984). The result shows a decreasing trend which is, in this case, statistically significant at significance level $\alpha = 0.1$ (see second row in Table 4.1). However, the Seasonal Kendall test produces a summary statistic for the whole year and does not give information about the single months/seasons. Therefore,

Table 4.1: *Results of the statistical trend detection tests applied to the streamflow time series on an annual, seasonal, and monthly basis: Mann-Kendall test (test statistics S and Z, test significance p-value, and Sen's slope b), Linear Regression test (test statistics T, test significance p-value, and slope of the estimated linear relationship m).*

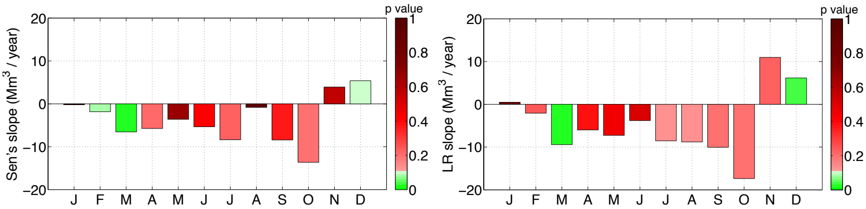
	Mann-Kendall test				Linear regression test		
	S	Z	p-value	b Mm^3/year	T	p-value	m Mm^3/year
Year	-86	-1.111	0.266	-36.50	-1.6761	0.103	-55.73
Seasonal	-608	-2.291	0.022				
Jan	-4	-0.039	0.969	-0.21	0.2142	0.832	0.47
Feb	-130	-1.687	0.092	-1.83	-1.2009	0.238	-2.07
Mar	-180	-2.341	0.019	-6.54	-2.4710	0.019	-9.43
Apr	-96	-1.242	0.214	-5.74	-0.8917	0.379	-5.99
May	-34	-0.431	0.666	-3.60	-0.7635	0.450	-7.26
Jun	-64	-0.824	0.410	-5.34	-0.6697	0.508	-3.81
Jul	-94	-1.216	0.224	-8.36	-1.5609	0.128	-8.55
Aug	-8	-0.091	0.927	-0.82	-1.5669	0.126	-8.80
Sep	-70	-0.902	0.367	-8.41	-1.3056	0.200	-10.06
Oct	-100	-1.294	0.195	-13.62	-1.3077	0.199	-17.37
Nov	44	0.562	0.574	3.92	1.2129	0.233	10.98
Dec	128	1.661	0.097	5.39	2.1742	0.037	6.16

we repeated the Mann-Kendall test and Sen's method using the twelve time series of monthly inflow volume. Results are reported in Table 4.1 and displayed in Figure 4.3a. The height of the bar is the trend intensity b for each month while the bar color indicates the p-value of the Mann-Kendall test. Figure 4.3a shows that trends differ in direction and size from month to month: inflows largely reduce in March, April, June, July, September and October, while they increase in November and December. The significance of the trend is also very variable: the p-value is lower than 0.1 only in February, March and December, while it is much higher in other months, even above 0.5 in May, August and November.

These differences in statistical significance may be partially explained by the interannual variability of the monthly inflows. In fact, trends are more difficult to detect when observations are widely spread and the length of the time series are relatively short (Yue, Pilon, and Cavadias, 2002), as in our case. Figure 4.4 shows, for each month, the p-value against the standard deviation of the linear trend residuals (RS), computed as

$$RS = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - b)^2}$$

This variable can be regarded as a measure of the interannual variability of



(a) (b)

Figure 4.3: *(a) Sen's slope and p-value of the Mann-Kendall and (b) Linear Regression slope and associated p-value applied to the time series of monthly inflows over the horizon 1974-2010.*

the monthly inflow time series. Figure 4.4 shows that the p-value generally increases (i.e., the confidence level decreases) with RS, with the exception of January, where the p-value is high even if interannual variability is small, which can be taken as a strong indication that no significant trend exists; and March, where the p-value is low even for intermediate RS, which on the contrary means that the detected trend is really statistically significant. On the other hand, the high p-value associated to the trends detected in August, May and November should not be immediately taken as an evidence of low statistical confidence because it may also be the effect of the high interannual variability of those months.

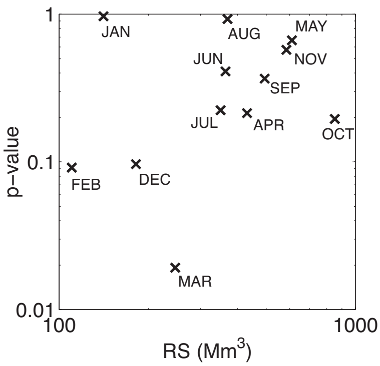


Figure 4.4: *p-value of the Mann-Kendall as a function of interannual variability, measured by the standard deviation of the residuals (RS) with respect to Sen's slope.*

Kundzewicz and Robson, 2004 suggest to consider more than one statistical test to provide a stronger evidence for the detected changes. Among the most widely used statistical test for trend detection, we decided to apply the Linear Regression test. It is a parametric test that can identify linear trends in time series of independent, normally distributed variables. The test statistic is the slope of the least-squares linear regression line divided by its standard error (for more details see Sonali and Kumar, 2013). Both the annual and monthly inflow time series fullfill the normality distribution and independency assumptions. The results of the Linear Regression tests are reported in Table 4.1 and displayed in Figure 4.3b in a fashion similar to the one used for the Mann-Kendall test: the height of the bar represents the intensity of the linear trend, i.e., the slope of the linear regression, while the color of the bar represents the associated p-value. The comparison between Figures 4.3a and 4.3b shows that the trends are detected coherently by the two test in the majority of the months, even though there are differences in some cases. In January the Mann-Kendall test detects a decreasing trend, while the linear regression detects an increasing trend, but in both cases the associated p-values are very high, meaning that the confidence in the results is low. The other main differences can be seen in August and November. In these cases the sign of the trends are coherently detected but the intensity is quite different. In both cases the differences are due to few very high inflow values at the beginning or at the end of the time series. It is widely known, in fact, that linear least squares regression is very sensitive to outliers (see for instance the forth and fifth data points in the time series in Figure 4.5, which significantly increase the slope of the least-squares regression line with respect to Sens's slope).

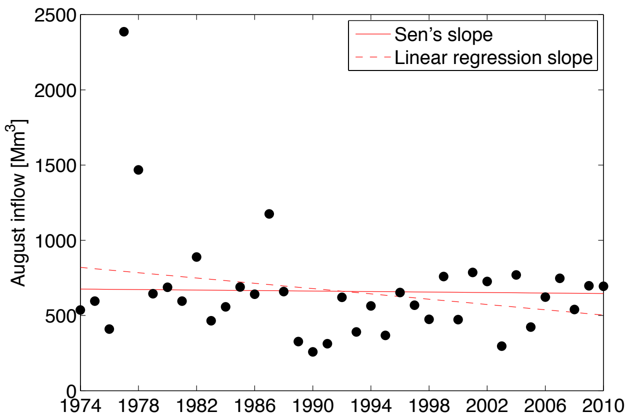


Figure 4.5: *August total inflow: regression computed with Sen's slope method and least squares Linear Regression.*

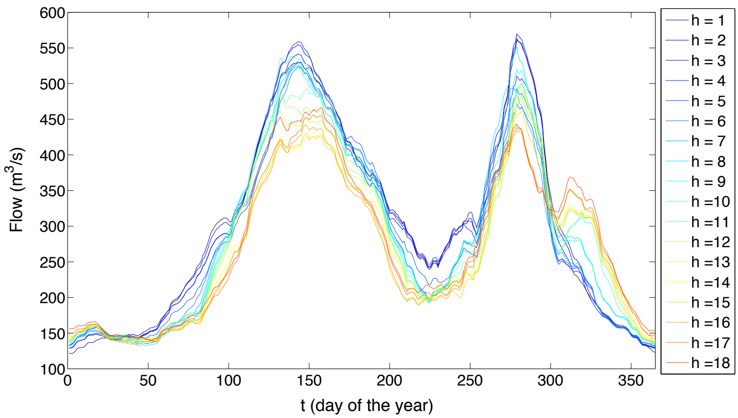


Figure 4.6: *MASH of daily inflows ($w = 10$ days, $Y = 20$ years, time horizon 1974-2010). The line labeled as $h = 1$ is the moving average computed over the horizon 1974-1993, the line labeled as $h = 2$ is the moving average computed over 1975-1994, etc.)*

4.4.2 Application of the MASH

As an example of the application of the Moving Average over Shifting Horizon (MASH), Figure 4.6 provides a visual representation of the MASH of historical inflows with $w = 10$ days and $Y = 20$ years. Since the original time series covers a period of $N_y = 37$ years, from 1974 to 2010, the MASH is composed of $N_h = 18$ flow seasonal patterns. The line labeled as $h = 1$ is the moving average inflow computed over the horizon 1974-1993, the line labeled as $h = 2$ is the moving average inflow over 1975-1994, etc. Older horizons are plotted with blue lines and more recent horizons with red lines. The results in Figure 4.6 are consistent with the trends reported in Figure 4.3a: an inflow reduction in Spring, Summer and early Autumn, and the emergence of a new peak in late Autumn, which reflects into the inflow increase in November and December detected by the Mann-Kendall test. The plotted MASH allows however to have a concise and informative representation of how the hydrological seasonal pattern has changed in time.

Figure 4.7 shows another way of visualizing the MASH that highlights the variations in the duration of the different hydrological seasons, rather than the variations in flow magnitude. Once again Figure 4.7 shows that the Autumn flooding season has enlarged when moving from older to more recent time horizons (i.e., from the left to the right in this figure) and that the snowmelt season has reduced.

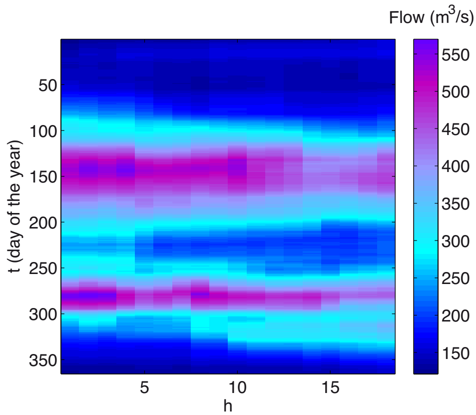


Figure 4.7: *MASH of daily inflows ($w = 10$ days, $Y = 20$ years, time horizon 1974-2010). The variations in the duration of the different hydrological seasons are highlighted.*

These results were obtained using $w = 10$ and $Y = 20$. The choice of these values comes from the following considerations. Parameter w filters out the day-to-day variability: small values may be insufficient to smooth out such variations and let the seasonal pattern emerge, on the other hand very large values of w may smooth out also seasonal variations. In our case study, manual tuning proved that $w = 10$ (i.e. averaging over 10·2+1=21 days) is a reasonable compromise, although slightly smaller or larger values provide qualitatively similar results (not shown). Parameter Y filters out the year-to-year variability. According to the WMO guidelines (*Guide to Climatological Practices - WMO No. 100* 2011), comparison between 30-years-long periods should be sufficiently independent on the inherent variability when dealing with hydrological time series, while larger periods should be considered for precipitation time series. On the other hand, when the length of the time series is not significantly larger than 30, $Y = 30$ produces time horizons that largely overlap to each other. In this case the MASH lines tend to converge to the same seasonal pattern, thus making trend detection almost impossible. For instance, $Y = 30$ will produce in our case only 8 time horizons, the first and the last being different only for 7 years. Figure 4.8 shows the sensitivity of the MASH results when Y ranges from 1 to 30 years. No trend is distinguishable for $Y = 1$ because interannual variability prevails. However, filtering the flow pattern even over few consecutive years, e.g., $Y = 5$, is sufficient to make the trend emerge. The trend is qualitatively similar as Y increases, exception made for the Autumn flood period: with $Y = 15$ the flood period seems to shift in time when moving from older horizons (blue lines) to more recent ones (red lines), while with $Y = 20$ it seems that the flood period is extending rather than shifting forward, with a second peak flood emerging in late Autumn. The reduction in Spring and Summer flows, instead, is consistently reproduced across different values of Y. Finally, with $Y = 30$ trends are hardly detectable as we already discussed. Unfortunately, as for the other smoothing techniques present in the literature, there is no general rule to choose the smoothing parameters w and Y. Therefore, when applying the MASH, we recommend to perform a sensitivity analysis, similar to the one here reported, to assess the robustness of any detected trends.

To assess the statistical significance of the trends visually detected by the MASH, we propose to apply a statistical trend detection test to the MASH results. Precisely, we first derive a ”smoothed” time series of daily flows by stacking the columns of the matrix in Eq. (4.1), we then derive the twelve associated time series of monthly flows, and we finally apply the statistical test to each of them. Since these twelve time series are autocorrelated as a consequence of the across-years averaging, we used the modified Mann-Kendall test proposed by Hamed and Rao, 1998 that can handle autocorrelated time series. Results are reported in Figure 4.8b. It shows that: *(i)* for $Y = 1$ trends are not statistically significant, probably because there is no filtering of interannual variability as already discussed when describing Figure 4.3a, which coincides with this panel; *(ii)* for $Y = 30$ the statistical significance is also weak because the number of shifting horizons is too small; *(iii)* for intermediate values of Y, trends are consistent in direction and generally statistically significant (i.e., low p-values).

4.5 Origin of the hydrological trends

In the previous section, we showed that the flow patterns seem to have changed in the last thirty years in the case study area. These changes may have been induced by different drivers, for instance climate or land use changes. A comprehensive analysis of the relative contribution of such drivers goes beyond the scope of our analysis. However we can at least assess whether changes in the streamflow are consistent with changes in the local climate. We thus analysed precipitation and temperature data from several stations located in the study area catchment. We show the results of two representative stations: Gütsch ob Andermatt and Lugano.

Being located at 2287 m a.s.l., the Gütsch ob Andermatt station is representative for the snow fall, accumulation and melt processes in the catchment. The Seasonal Kendall test detects a statistically significant, increasing trend in temperature (S=1233, Z=4.65, p-value$<$0.001) and a decreas-

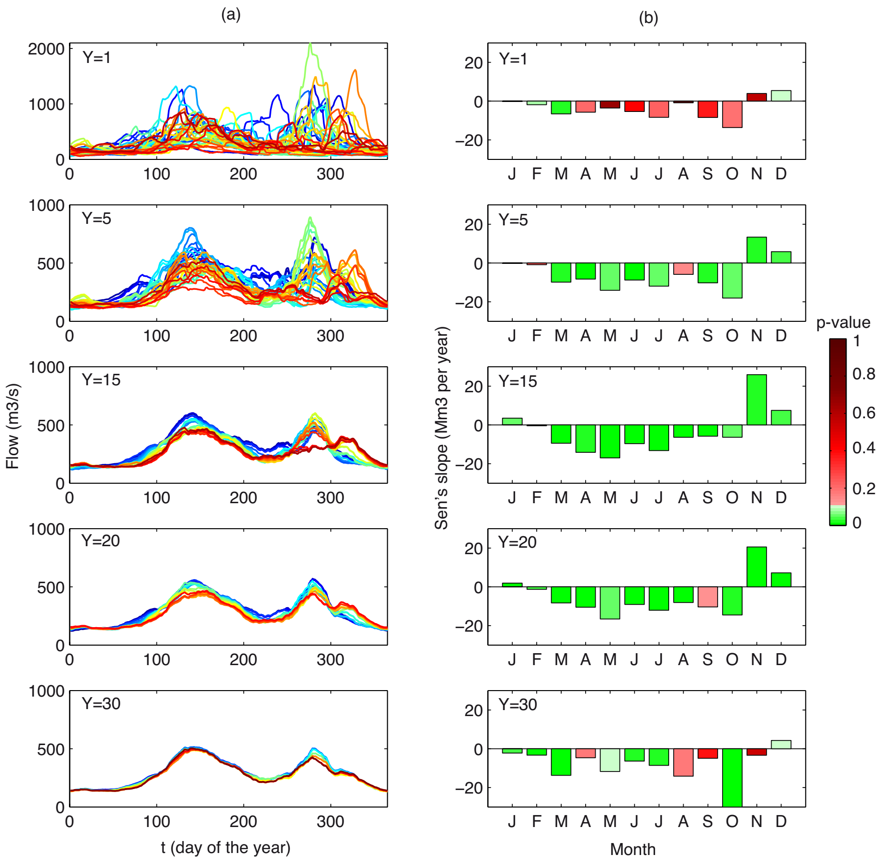


Figure 4.8: *(a) MASH of daily inflows with different Y values ($w = 10$ days, time horizon 1974-2010): older horizons are plotted with blue lines and more recent horizons with red lines. (b) Sen's slope and p-value of the Mann-Kendall applied to the corresponding MASH.*

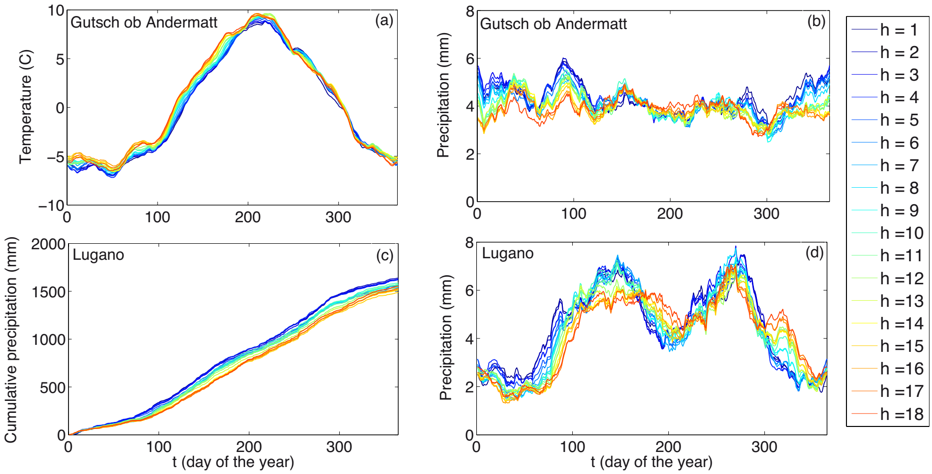


Figure 4.9: *MASH of (a) temperature and (b) precipitation in Gütsch ob Andermatt station; (c) cumulative precipitation and (d) precipitation in Lugano station (w = 10 days, Y = 20 years, time horizon 1974-2010).*

ing trend in precipitation (S=-527, Z=-2.07, p-value=0.039). We used the MASH to investigate the seasonal patterns of the two variables (top panels in Figure 4.9). The increase in the temperature is recognizable all over the year, especially from January to July (Figure 4.9a), while the decrease in the precipitation seems to be concentrated in Winter and early Spring (Figure 4.9b). The combination of the two suggests a decrease in snowfall which may be the reason for the reduction of the lake inflows in the Spring period, when snowmelt gives the main contribution to runoff.

Being located at very high elevation, the Gütsch ob Andermatt station is not affected by heavy rainfall events that produce the Autumn inflow peaks. We thus analysed precipitation data from the Lugano station, more representative of the pluviometric regime in the lower part of the lake catchment. The Seasonal Kendall test applied to the time series of total monthly precipitation volume detects a decreasing trend (S=-200 and Z=-0.75) which is however not statistically significant (p-value = 0.453). The MASH results are reported in the lower panels of Figure 4.9. Figure 4.9c shows that cumulative precipitation along the year is decreasing, while Figure 4.9d shows a decrease in magnitude and a temporal shift of the Spring peak, while an increase in late Autumn. These opposite behaviours may partially explain the high p-value of the Seasonal Kendall test.

Overall the analysis seems to suggest that climate may be the main driver of the variations detected in the inflow pattern. However, our analysis is limited in scope and details. For instance, we did not consider that temperature increases may induce hydrological trend also by increasing evapotranspiration. Herrnegger, Nachtnebel, and Haiden, 2012 show that evaporation is a significant term in the water budget even in Alpine catchments. However, the same authors show that evaporation can be largely underestimated when using simplified relationships like the Hargreaves and Thornthwaite equations, and recommend using the Penman-Monteith equation which requires a larger amount of meteorological data besides temperature. More importantly, other possible drivers should be considered, for instance changes in land use or in the operation of upstream barriers, which may influence the hydrological cycle even more than climate change (see, for instance, Grafton et al., 2012). Therefore, a more comprehensive analysis should be conducted to reinforce the preliminary conclusions here reported.

4.6 Impacts of the hydrological trends on water resources

The final step in our analysis is aimed at assessing whether the trends in hydrological seasonal patterns also have had impacts on water resources. We focus on the two main issues concerning the lake regulation, namely flood protection around the lake and water supply to the wide downstream irrigated areas. To assess the satisfaction of these two interests, we used two performance indicators that should reflect the stakeholder's preference system. The indicators were identified through interviews to the stakeholder representatives in a previous project on participatory and integrated water resources management in the basin (see Soncini-Sessa et al., 2007). The performance indicator for flood protection is the average flooded area in Locarno and Verbania, the two main cities on the lake shores, which is computed as a superlinear function of the lake level. The performance indicator for irrigation supply is the squared supply deficit with respect to the water demand at the Panperduto diversion dam on the downstream River Ticino (see Figure 4.2). Squaring is used to account for the farmers' risk aversion: the same total deficit volume is less dangerous if distributed over time, since the potential damage of a sequence of small deficits is lower than for a single large deficit. A detailed description of these indicators and their identification process is given in Soncini-Sessa et al., 2007.

4.6.1 Trends in performances

The value of the performance indicators are computed on a daily basis using the historical time series of lake level and release. Results are then averaged across days and years using the MASH. Since flooding and deficit are usually concentrated in few events, typically in Autumn (flooding) and Summer (deficit), seasonal patterns are not significant. Therefore, we use a slightly modified version of Eq. (4.2), where the inner average over a moving window is replaced by the annual average

$$\tilde{\mu}_h = \underset{y\in[h,h+Y-1]}{\text{mean}} \left[\underset{d\in[1,365]}{\text{mean}} \; x_{d,y} \right] \tag{4.3}$$

We tested two options: $Y = 1$, corresponding to take each year separately, and $Y = 20$, which means averaging across 20 consecutive years, thus obtaining the usual 18 shifting horizons in the period 1974-2010. Results are reported in Figure 4.10. It can be seen that, when considering each year separately ($Y = 1$, upper panels), no clear trend can be identified by visual inspection. The Mann-Kendall test detects a decreasing trend for the flooded area and an increasing trend for irrigation deficit but at low statistical confidence (the associated p-values are 0.15 and 0.3). Again, this can be ascribed to interannual variability. Performance indicators are, indeed, particularly sensitive to extreme events: the average flooded area is very high in 1977 and 1993 because of two big Autumn floods, while irrigation deficit was particularly large in 1976, 2003 and 2005, when prolonged dry spells occurred. When indicators are averaged across years ($Y = 20$, lower panels in Figure 4.10), the influence of extreme events is partially filtered out and a decreasing trend for flooding and an increasing trend for deficit emerge. In this case we used the modified Mann-Kendall test to account for autocorrelation. Trends are detected with a higher confidence, in fact the p-values are 0.0015 and 0.026. These trends can be linked to the hydrological trends in Figure 4.6. The increase in irrigation deficits can be abscribed to the detected reduction in Spring and Summer inflows, while the decreasing trend of the average flooded area may be explained by the reduction in the early Autumn inflows. Notice that, on the other hand, the inflow increase in late Autumn has no negative impacts on flooding, probably because these late floods are sufficiently small to be tackled by the lake regulation or the associated lake levels are lower than the flooding treshold.

The robustness of these results was tested by a sensitivity analysis (not shown) similar to the one presented in Figure 4.8 for the hydrological trends. Briefly, the direction of the trend remains the same as parameter Y varies, but its intensity (measured by Sen's slope b) and statistical significance (p-value) can vary considerably. In general, the sensitivity seems to be higher in this analysis than in the one about hydrological conditions, possibly because the highly non-linear definition of the performance indicators increases the sensitivity with respect to extreme events.

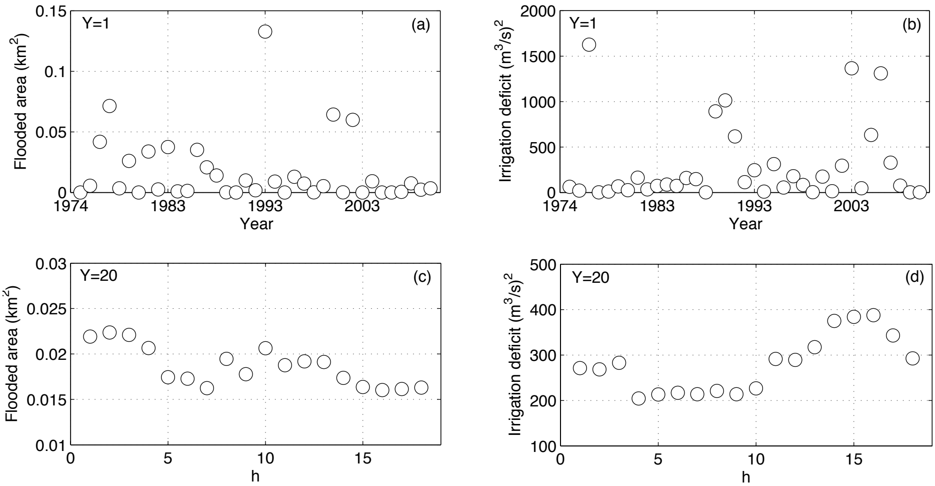


Figure 4.10: *Top panels: time series of (a) average daily flooded area and (b) irrigation squared deficit over each year of the horizon 1974-2010. Bottom panels: MASH (with* $w = 182$ *and* $Y = 20$*, time horizon 1974-2010) of the same time series.*

In order to complete the analysis, we also evaluated the resilience, reliability, and vulnerability of the water resource systems (Hashimoto, Stedinger, and Loucks, 1982) through the following indicators: mean length of a deficit period (flooding event) per year, number of days in which a deficit (flood) occur per year, and maximum deficit (flooded area) per year. These indicators were then averaged across years (again using different values for Y) and trends were detected. Table 4.2 shows the result when using $Y = 20$: flood protection is positively affected from all the points of view: vulnerability decreases (i.e., peak floods follow a decreasing trend) while resilience and reliability increase (i.e., flood duration and frequency exhibit a decreasing trend). Irrigation instead is negatively affected with all respects, even if the statistical significance of the trends is lower, especially for the resilience indicator.

4.6.2 Discussion of the results

The relevance of the variations in the indicator values reported in Figure 4.10 and Table 4.2 is not easy to interpret. For instance, from line 3 of Table 4.2 it follows that the average length of a flood event has reduced by more than 6 days in 37 years (following a rate of -0.17 days/year) and, similarly, the number of flooding days has reduced by almost 10 days (line 4), the average length of deficit periods has increased by 5.5 days (line 7)

Table 4.2: *Mann-Kendall test significance (p-value) and Sen's slope (b) applied to the MASH of the flood protection and irrigation supply indicators ($Y = 20$, u.o.m = unit of measurement).*

Indicator	u.o.m.	b (u.o.m./year)	p-value
Flood protection			
Performance (mean flooded area)	km^2/day	-3.2×10^{-4}	0.002
Vulnerability (maximum flooded area)	km^2/day	-1.2×10^{-2}	<0.001
Resilience (length of a flood event)	days/year	-0.17	<0.001
Reliability (number of flooding days)	days/year	-0.27	0.025
Irrigation supply			
Performance (mean squared deficit)	$(m^3/s)^2$	7.7	0.026
Vulnerability (maximum deficit)	m^3/s	0.4	0.018
Resilience (length of a deficit period)	days/year	0.15	0.510
Reliability (number of deficit days)	days/year	1.2	0.008

and the number of deficit days by 44.4 (line 8). How critical are such figures from the standpoint of the stakeholders? This question is not easy to address without their direct involvement, however we can give some benchmark numbers. The results in Table 4.2 were obtained by simulation of the irrigation withdrawal at Panperduto dam (see Figure 4.2) with a Minimum Environmental Flow (MEF) constraint of 13 m^3/s. However, in reality this constraint has been progressively increased from an original value of 3 to the current value of 13 m^3/s, and a further increase is under discussion. Now, the average number of deficit days over the 1974-2010 horizon with a MEF of 13 m^3/s is 87 days/year, while it would be 20 days/year lower using a constant MEF of 3 m^3/s, and higher of 16 days/year with the value of 20 m^3/s now under discussion. So, the reduction in reliability induced by the hydrological trend (+44 days/year in 37 years) is the same order of magnitude as variations induced by changes in the normative framework, which are the result of negotiations among Stakeholders and are considered acceptable by all of them.

Our opinion is thus that the effect of the hydrological trends on water resources should be considered rather limited. This may have two explanations. On the one hand, the water system is able to partially mitigate the impact of hydrological changes because of threshold effects, as happens, for instance, in the case of flooding, where increases in average inflows as those detected in November (see Figure 4.3a), do not reflect into increased flooding as long as flooding thresholds are not exceeded. On the other hand, such "natural" ability of absorbing the variations of external forcing is probably further enhanced by the system operation. This may be the case of irrigation supply, where the inflow reduction in the snowmelt season may have been contrasted by a more efficient regulation of the lake.

4.7 Conclusions

In this chapter we used traditional and novel tools to detect trends in hydro-climatic time series of the lake Maggiore water system (Italy-Switzerland) and to quantify their effects on water resources. The analysis reveals several statistically significant trends in the considered time horizon from 1974 to 2010: an inflow reduction in the snowmelt season, a drier Summer, and a shift of the Autumn flood season with, on average, lower flood peaks. The application of the same trend analysis tools to meteorological records (temperature and precipitation) shows that coherent trends can be detected in the climate regime, suggesting that local climate might be the main origin of the hydrological changes. Further research is needed to reinforce the analysis of meteorological trends and investigate other potential drivers of change, like land use or the operation of barriers in upstream regulated river reaches. Furthermore, it would be interesting to assess whether the detected trend would be confirmed over a longer time of horizon by expanding the length of the time series back in time (not available in this study). On the other hand, the effects of the detected hydrological trends on water resources are a reduction of flooding along the lake shores and a reduction in irrigation supply to downstream areas. Such trends are statistically significant although rather limited.

The chapter also offers a methodological contribution by proposing a novel tool for time series analysis and trend detection, named Moving Average over Shifting Horizon (MASH). Its main advantage is that it can simultaneously handle seasonality and interannual variability. The goal of the MASH is, in fact, to assess temporal variations in the seasonal pattern of a variable. It essentially works by taking a statistic of data over consecutive days in the same year and over the same days in consecutive years. The statistic here considered is the mean, but others, e.g., the median, could be used as well. The results of the MASH can be effectively visualized in different fashions, making it easier to analyse seasonal processes and detect trends by visual inspection. The MASH can be used during Exploratory Data Analysis and it can be combined with statistical tests like the Mann-Kendall test, the Linear Regression test, or the Seasonal Kendall test. The MASH results can suggest the more appropriate statistical method and/or the definition of the hydrological seasons to be tested.

The MASH has two tuning parameters, the number of days and years used for averaging. As when using other smoothing techniques, it is difficult to establish general rules for fixing these parameters. This may represent a limitation of this type of techniques since it introduces a certain degree of subjectivity in the analysis, even though the MASH only requires defining two parameters, which is a rather limited number with respect to other smoothing techniques. Therefore, we strongly recommend that sensitivity analysis with respect to the smoothing parameters be always performed when applying the MASH. Generally speaking, our experience shows that the MASH results are reasonably robust when analysing smooth processes, i.e., with a relatively low dynamics, while they are more sensitive to parameter settings when time series exhibit abrupt changes. For hydrologic variables, the MASH is thus suitable to detect trends in medium/large catchments, like the one here considered, but it might prove less adequate for smaller catchment with shorter travel time. Regarding climatic variables, MASH results might be less robust when analysing precipitation time series.

One interesting result of this analysis is that significant changes in hydrological conditions of the Lake Maggiore catchment have a rather limited impact in terms of water uses. This may be due to multiple reasons. Some trends, for instance the reduction in intensity of the early Autumn floods, are actually positively reflected in terms of water resources. Second, the water system can naturally absorb disturbances within a certain range: the emerging floods in late Autumn, for instance, are sufficiently small and they do not produce floodings. Lastly, the resilience of the water system may have been enhanced by the system management that has possibly adapted to the changing hydrological conditions. This may explain why the reduction of Spring and Summer inflows has had a relatively limited impact on the water supply for irrigation. This is still a hypothesis at this stage and should be further investigated. Further research will also explore if and how the hypothesized adaptation strategy may be formalized and improved by mathematical methods like adaptive optimization. We address this issue in the next chapter.

The analysis presented in this chapter does not consider the possibility that the hydro-climatic time series may exhibit long term persistence, also known as "Hurst Effect" (e.g., Koutsoyiannis, 2011), i.e., the fact that the process which generated the data may present fluctuations on long timescales. If this was the case, the records could be only a small portion of a long term cycles, whose characteristics may be difficult to infer and which may mislead trend estimation. In particular, the presence of long term persistence could lead to a potential lack of reliability of statistical tests considered in this study, since they assume the data to be independently and identically distributed (see among others Koutsoyiannis and Montanari, 2007). Further research will be aimed at exploring the presence of long term persistence in the available records and its effect on the detected trends.

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CHAPTER 5

Stochastic recursive control for adaptive management

Adaptive management is a continuous decision making process in which decisions are periodically revised and eventually adjusted as a consequence of feedbacks and changed boundary conditions. The adaptive management seems a promising approach to respond to the challenges posed by climate change. It has been proposed as a new approach to replace the predict-and-control paradigm and effectively face future uncertainty. In this chapter we present a possible adaptive optimization procedure where the reservoir operating policy is periodically reviewed to adjust to a changing hydrology. In particular, we compare two opposite management paradigms: the one, i.e., static approach, where the stationarity principle is assumed to hold true throughout the entire life time of the water system, and the one, i.e., adaptive approach, where the stationary principle is abandoned, old data are progressively discarded, and there is a learning process that spans over the entire life time of the system. We test the procedure on the Lake Maggiore case study introduced in the previous chapter. Starting from the results of the trend analysis presented in the previous chapter, historical hydrological records are used as the ground to test water system skills of adaptation.

This chapter is partially based on D. Anghileri, F. Pianosi, and R. Soncini-Sessa, "Assessing the sensitivity of an alpine reservoir to hydrological change and improving its operation by adaptive optimization", in *Proceedings of IAHS-IAPSO-IASPEI Assembly 2013*.

5.1 Introduction

In the context of climate change, research has been mainly devoted to develop future climatic and hydrological scenarios (e.g., Abbaspour et al., 2009; Groves, Yates, and Tebaldi, 2008) and to assess the related water system vulnerabilities (e.g., Schaefli, Hingray, and Musy, 2007; Christensen et al., 2007; Anghileri, Pianosi, and Soncini-Sessa, 2011). Only in recent years, increasing attention has been paid to test new water management practices (e.g., Lempert and Schlesinger, 2000; Georgakakos et al., 2012; Steinschneider and Brown, 2012), since the current ones may prove inadequate to face future deep uncertainty (Pahl-Wostl, 2007; Walker, Marchau, and Swanson, 2010).

Adaptive management is one of the approaches that have been proposed to deal with rapid climate and socio-economic changes. It is a sequential decision process in which: *i)* an action is taken, *ii)* new information is obtained via system monitoring, and *iii)* a new action is taken in response to the new information available. It is, thus, a continuous learning process where decisions are taken knowing that they will be revised and, eventually, adjusted as a consequence of feedbacks or changed boundary conditions (i.e., economy, society, hydrology, climate, ...). Adaptive management has been described as “a real paradigm shift in water management from what can be described as a prediction and control to a management as learning approach” (Swanson et al., 2010).

Although the basic idea of the adaptive approach is quite straightforward, existing management rules are rarely updated in light of changed conditions or new available knowledge (McCray, Oye, and Petersen, 2010; Willis et al., 2011). Also in the academic context, studies related to adaptive management are still relatively few (see Walker, Marchau, and Swanson (2010) and references therein, Georgakakos et al., 2012; Lempert and Schlesinger, 2000). In fact, although the approach is theoretically promising to respond to the challenges posed by climate change, it may present some criticalities in real-world decision-making applications. For example, in complex water systems, it may be difficult recognize which drivers should induce the revision process, to which extent they should change before actually affecting the decision-making process, and how to validate the effectiveness of the reviewed decisions. Finally it may be even more difficult to implement them in the management context especially if they are rigid and, thus, resistant to innovations. Such issues are addressed only by few authors in the literature (e.g., Lempert and Schlesinger, 2000; Swanson et al., 2010).

In this chapter we discuss how the operation of a reservoir can effectively face a changing hydrology. In this context, one big issue is how to properly model the nonstationary hydrological process. This point is also raised in the famous paper of Milly et al. (2008). Claiming the death of stationariety, the authors suggest that "we need to find ways to identify nonstationary probabilistic models of relevant environmental variables and to use those models to optimize water systems". If we base the analysis on historical time series, the detection of temporal dependencies can be complicated by the inherent variability of hydrological processes. Especially when dealing with short or low quality time series, we may not recognize the underlying long-term dynamic (Blöschl and Montanari, 2010).

Starting from the results of the trend analysis done in the previous chapter, we compare two alternative strategies to design Lake Maggiore operation using the historical inflow time series as testing ground. More precisely, we compare a static approach, in which we design the lake operating policies assuming that the hydrology is stationary, and an adaptive approach, in which the lake management policies are re-optimized every year in order to adapt to the possibly ongoing hydrological trends. The impacts of these different strategies are evaluated in terms of water supply to the downstream irrigated area and control of flooding events around the lake shores.

5.2 Static and adaptive approach to reservoir management

We compare two different approaches for designing the operating policy of a reservoir: a static approach and an adaptive approach. The static approach mimics the currently most common management practice: the reservoir operating policy is defined once and used for the entire lifetime of the water system. The adaptive approach, instead, represents a flexible management practice where the reservoir operating policy is periodically reviewed to adjust to a changing environment. In this study, we assume that all the boundary conditions to the reservoir operation, e.g., the water use needs, hold steady, except for hydrological processes which may change in time.

To design the reservoir operating policy, we define an optimal control problem which represents the decision-making problem faced by the human regulator, and we use optimal control techniques to solve it. More precisely, we use Stochastic Dynamic Programming (SDP) (Labadie, 2004), an explicity stochastic optimization approach in which the reservoir inflow is modelled by defining its probability distribution function (pdf).

In the static approach (top panel of Figure 5.1), we suppose that the hydrological process is stationary, i.e., that the parameters defining the inflow pdf are time-invariant. According to the WMO guidelines (*Guide to Climatological Practices - WMO No. 100* 2011), a period of 30 years should be sufficient to represent the inherent variability of the hydrological process. We, thus, calibrate the inflow pdf using the first 30 years of the available historical inflow time series and we solve the relative optimal control problem. The remaining inflow time series is used to validate the optimal operating policies via deterministic simulation.

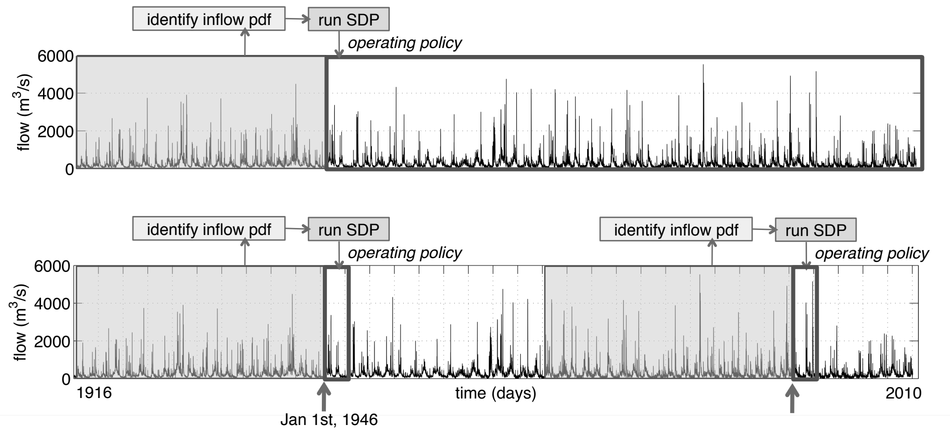

Figure 5.1: *In the static management approach (top panel) historical inflows over the first 30 years (grey box) are used to design the reservoir operating policy, and the remaining time series is used for simulation. In the adaptive management approach (bottom panel), the operating policy is designed every year considering the last 30-years inflows, and then simulated for one year ahead (as an example, this iterative procedure is reported only twice, at the time instants indicated by the arrows).*

In the adaptive approach (bottom panel of Figure 5.1), we suppose that the hydrological process is nonstationary, i.e., that the parameters defining the inflow pdf vary in time. The first challenge is to properly represent both the interannual variability and the long-term time evolution of the hydrological process. The second challenge is to understand when the hydrological process has changed so that the inflow pdf and the reservoir operation should be revised accordingly. In this study, we estimate the pdf with the highest possible frequency, i.e., one year. In so doing, we are applying a so called time-triggered policy review (Swanson et al., 2010), i.e., review based on a pre-defined time interval. As in the previous case, we assume that 30 years are enough to characterize the interannual variability of the hydrological process. Summarizing, in the adaptive approach we calibrate a new inflow pdf every year, January 1st, using the previous 30 years and we solve the relative optimal control problem. The resulting operating policies are, then, simulated against historical inflow of the following year. The adaptive approach consists, thus, in a sequence of optimization and 1-year deterministic simulation runs.

5.3 Case study: Lake Maggiore

We compare the static and adaptive approaches through application to the real-world case study of Lake Maggiore. The case study was already introduced in the previous chapter. The readers are thus referred to Section 4.3 for the description of the water system. When designing the reservoir operating policies, we focus on the two interests that historically have driven the lake regulation: flood control along the lake shores and irrigation supply. They are described in Section 5.5.

5.4 Inflow time series analysis

In the previous chapter we analysed the time series of inflow to Lake Maggiore from 1974 to 2010 showing that there have been an increase in average temperature, a reduction of snowfall and a shift in rainfall distribution along the year which affected the hydrological regime of the catchment. We intentionally did not consider older records because they were influenced by the construction of the hydropower reservoir located upstream from the lake, thus potentially confounding the effect of climate change. In this chapter, we are interested in nonstationary hydrological process, despite its drivers, so we extend the analysis to the time series of reservoir inflow from 1916 to 2010. It is thus interesting to repeat the trend analysis on this larger period to test if the previous results are confirmed or not.

Figure 5.2a shows the results of the Mann Kendall test for trend detection (Kendall, 1975) and the Sen's Slope (Sen, 1968) for the 12 time series of total monthly inflows. The length of the bar represents the trend intensity computed as the Sens's Slope for each month, while the colour indicates the p-value of the Mann-Kendall test. The analysis shows that there is an increase of winter flow from January to March (although only in February the trend is statistically significant below a significance level of 0.05). All the other months show a decreasing trend with different intensity (June, July, and August being statistically significant).

Figure 5.2b shows the results of the Mann Kendall test and the Sen's Slope when applied to the time series of percentiles of the inflow duration curve over one year. Most of the percentiles shows a decreasing trend with intensity growing with the percentile value and statistically significant at generally low significance level (below 0.1 for the 35th-85th percentiles). This seems to suggest that the entire distribution of inflows has changed, especially with respect to high flows, and that the stationarity principle has not hold true over the last century.

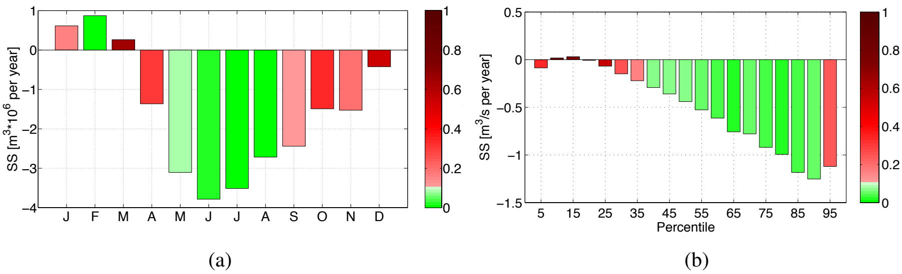

Figure 5.2: *Results of the Mann-Kendall test and the Sen's Slope (SS) of the time series (1916-2010) of (a) monthly inflows to Lake Maggiore, (b) percentiles of the flow duration curve. The length of the bar represents the SS while the colour represents the p-value of the statistical test.*

The results obtained when looking at the period 1916-2010 (Figure 5.2a) are quite different from those obtained when looking at the period 1974-2010 (first panel of Figure **??**b). The negative trends in the late spring and summer are confirmed, although the magnitude (SS) and the significance (p-value) are different. Trends in autumn are partially confirmed, although they are not statistically significant, i.e., they have a high p-value, in both cases. This may be an effect of the large variability of the inflow in the flood season, as already discussed in the previous chapter. Finally, trends in the winter season are totally reversed. For instance, February shows a negative trend on the period 1974-2010 and a positive trend on the period 1916-2010, and both are significant from the statistical point of view. This may be a consequence of the inclusion of the period in which the upstream hydropower reservoir were built. If we now compare the seasonal pattern of the inflow, for example considering the Moving Average over Shifting Horizon results (not shown) we can observe that the intensity and timing of the snowmelt peak seems to reduce and shift forward on the period 1974-2010, while it seems rather to follow a cycle on the period 1916-2010.

This comparison confirms that trend detection is strongly affected by the length of the time series under analysis and the hydrological inherent variability.

5.5 The optimal-control problems

In this study, we define 66 optimal control problem: 1 to implement the static approach and 65 (= 2010-(1916+30)+1) to implement the adaptive approach. They are all formulated in the same manner, except for the pdf of the reservoir inflows.

We formulate two objectives control problems, because we focus on the two interests that historically have driven the lake regulation: flood control along the lake shores and irrigation supply. The flood control objective is the daily average flooded area (km^2) in Locarno and Verbania, the two cities on the lake shores which are mainly affected in case of floods. It is computed as a superlinear function of the lake level h_t

$$J_{flo} = \frac{1}{h}\sum_{t=0}^{h-1} f(h_t) \tag{5.1}$$

where h [day] is the length of the simulation horizon.

The irrigation objective is the sum of the squared supply deficits of the three irrigation districts feeded by the lake releases

$$J_{irr} = \frac{1}{h}\sum_{t=0}^{h-1}\sum_{i=1}^{3} D_t^i \tag{5.2a}$$

where D_t^i is the squared deficit of the i-th irrigation district, i.e.

$$D_t^i = \Big[\max(w_t^i - r_{t+1}, 0)\Big]^2 \quad i = 1, 2, 3 \tag{5.2b}$$

where r_{t+1} [m^3/s] is the average daily release from the lake, w_t^i [m^3/s] is the water demand for the i-th irrigation district, which is computed from the irrigation abstraction licences and the historical diverted flow. Squaring in the deficit definition is used to account for the farmers' risk aversion, i.e., the fact that, for reducing crop stress, they prefer to distribute a given total deficit volume over time since the damage of a sequence of small deficits is lower than the damage of a single large deficit. A more comprehensive description of the objectives and their identification process is given in Soncini-Sessa et al. (2007).

Since SDP is a single objective method, J_{flo} and J_{irr} were aggregated by weighted sum. When solving the control problem associated to the static approach, we tested different combinations of the weights and the one corresponding to the solution along the Pareto frontier which is closest to the utopia point was selected. The same combination is also used at each optimization run of the adaptive approach.

The constraints of the optimal control problems are composed of the model of the water system and the reservoir inflow model. The the water system model is a mass balance equation describing the lake dynamic at daily time step and a model of the downstream network of canals that distributes the daily lake release among the different irrigation districts. The inflow pdfs are described by lognormal distributions. In the static approach, we use the time series from 1916 to 1945 to derive the cyclostationary statistics of the lake inflows, i.e., daily mean μ_t and standard deviation σ_t in each day of the year $t = 0, 1, \cdots, 364$. Note that, since there are no records before 1916, this estimate represents a good approximation of the knowledge the lake regulator should have had at the beginning of the dam operation in 1943. In the adaptive approach, we estimate the 65 pdfs using the Moving Average over Shifting Horizon (MASH) presented in the previous chapter, considering 30 consecutive years and 21 consecutive days. More precisely, the pdf in the first control problem is estimated using the inflow records over the period 1916-1945 (being equal to the one used in the static approach) the pdf in the second control problem is estimated over the period 1917-1946, and so on. In the adaptive approach, the pdf used in the static approach is thus updated every year progressively discarding old records in favour of the new ones. Figure 5.3 shows how the parameters of the pdfs change and, as an example, Figure 5.4 shows how the pdfs change in time in four days of the year, one for each season: January 1st, April 1st, July 1st, and October 1st.

5.6 Results and discussion

We compare the control policies obtained in the static and adaptive approach through a deterministic simulation of observed inflow over the horizon 1947-2010. The analysis of lake levels and releases allows us to estimate the distance in system performances between the two management paradigms. By construction, the first year of simulation produces the same

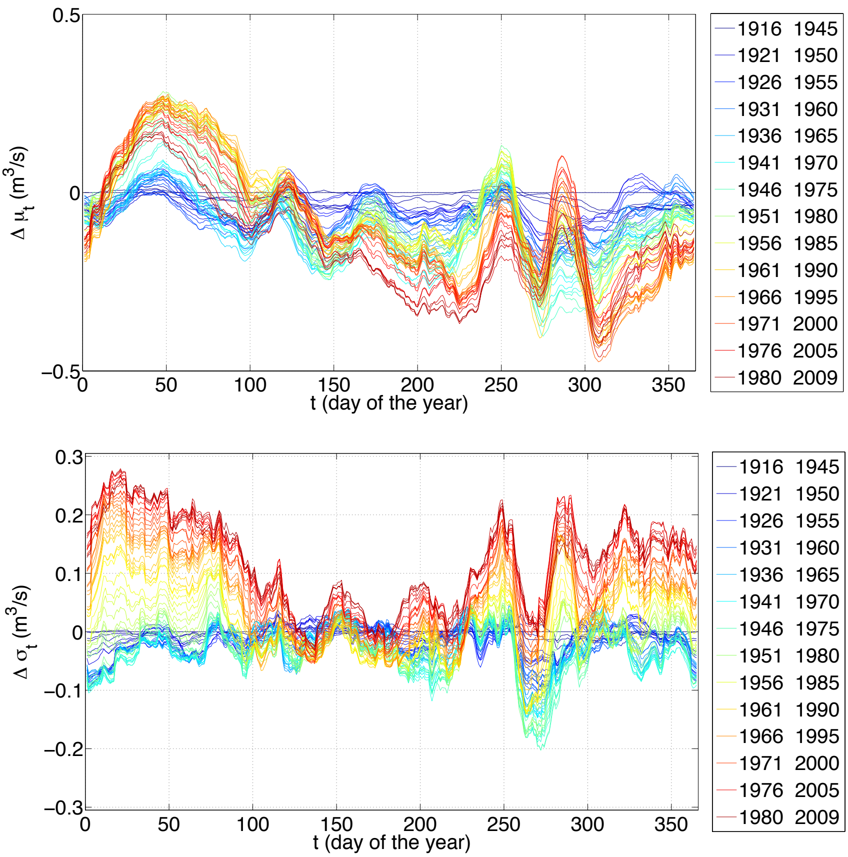

Figure 5.3: *Variation of the parameters of the lognormal pdfs in time: μ_t and σ_t on the top and bottom panels respectively. Values represent the difference between the parameter of the pdfs estimated in the adaptive approach minus the one estimated in the static approach.*

results in both approaches, since the pdfs and the relative control problems coincide. The system trajectories should tend to diverge as time passes by, if: *i)* the hydrology is indeed well represented by the sequence of inflow pdfs of the adaptive approach, *ii)* the inflow pdfs of the adaptive approach differ from the pdf of the static approach enough to affect the operation of the reservoir.

Figure 5.5 shows the mean daily value of flooded area and deficit in irrigation supply, for every year in the evaluation horizon 1946-2010 and over the entire horizon. The static approach produces better performances when looking at the flooded area in every flooding event. A deeper analysis of the simulated system trajectories (not shown) seems to suggest that the

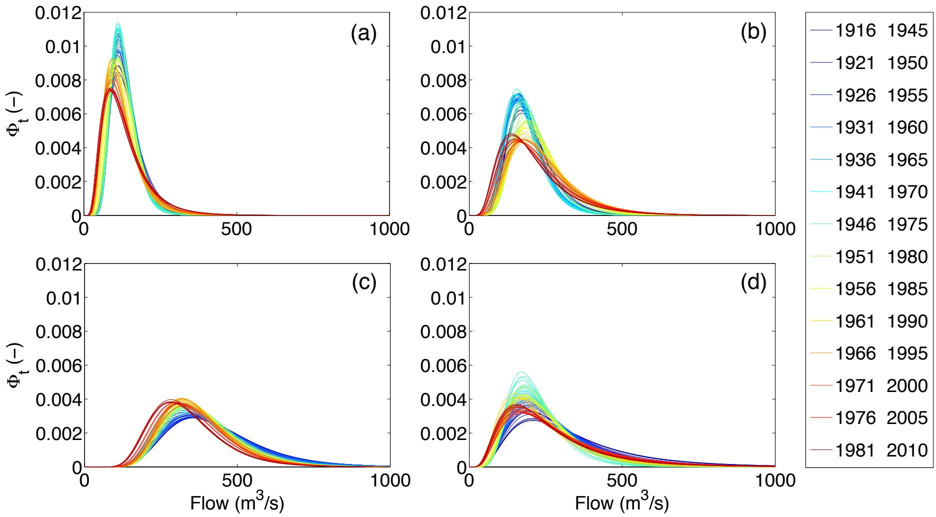

Figure 5.4: *Time evolution of the lake inflow pdfs used in the adaptive approach on: (a) January 1st, (b) April 1st, (c) July 1st, and (d) October 1st.*

static policy is more risk adverse than the adaptive one. The reason may be that the inflow pdf in the flooding season computed over the first 30 years is wider with respect to the updated distributions used in the adaptive paradigm. However, we question if this result is robust. Indeed a sensitivity analysis with respect to the length of the horizon revealed that trends in the inflow statistics of the autumn flood period are qualitatively different as the number of years varies (a similar effect was already observed and commented in the previous chapter, see Section 4.4.2). As a consequence, the results of the optimization could be particularly sensitive to this choice too.

On the other hand, Figure 5.5 shows that the adaptive approach produces better performances in terms of irrigation supply, as it is able to reduce the irrigation deficit in almost every drought event. Figure 5.6 shows the relative enhancement of the irrigation performances from the static to the adaptive management. It is computed as the difference between the objective values in the adaptive and static approach, normalized by the objective value in the static approach. The figures show that the enhancement increases in time, meaning that, following the adaptive approach, the lake operation is able to adapt to summer seasons which become increasingly dry, while the static management policy becomes increasingly unsuitable to supply the irrigation demand.

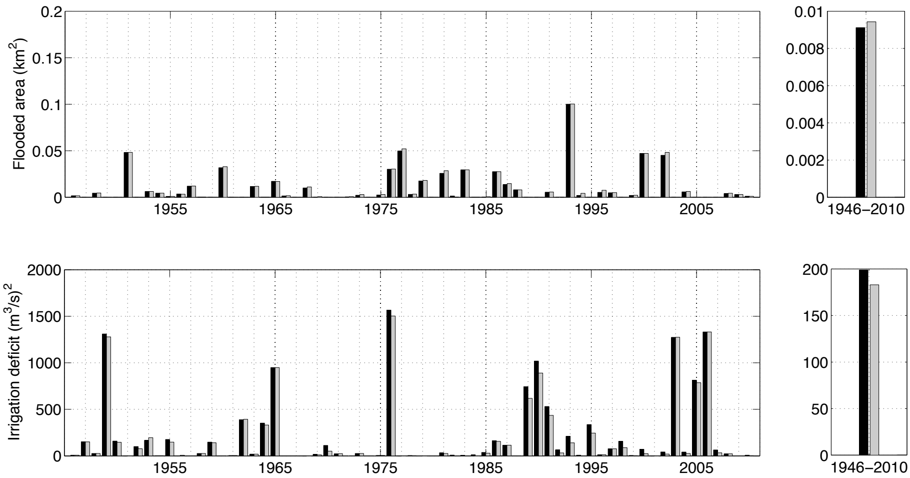

Figure 5.5: *Mean daily value of flooded area and deficit in irrigation supply for each year in the evaluation horizon 1946-2010 and overall average produced by the static management approach (black) and the adaptive management approach (grey).*

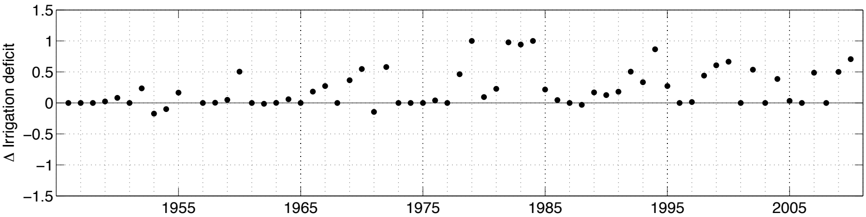

Figure 5.6: *Relative variation of the mean daily value of the irrigation objective over the evaluation horizon 1946-2010. The figures are computed as the difference between the objectives value in the adaptive and static approach, normalized by the objective value in the static approach.*

Overall, the results do not show the preeminence of the adaptive management approach on the static one or viceversa. The reasons may be different and will deeply commented in the following section. For the moment, notice that the comparison among the static and adaptive approach may be biased because we used the same combination of weights for aggregating the two objectives at each optimization run, but the constraints, more specifically the inflow pdfs, changed. In such conditions, we are not guaranteed to obtain the same trade-off solution. In other words, the change in the performances may be driven by a change in the relative importance of the two objective when designing the reservoir operating policy.

5.7 Conclusions

In this chapter, we investigated hydrological changes in the catchment of the multipurpose regulated Lake Maggiore and compared two different management paradigms for the regulation of the lake: the traditional static approach, where we suppose that the operating policy is designed once for all, and a novel adaptive approach, where we suppose that the operating policy is re-designed every year using updated statistics of the lake inflow. We estimated stochastic models of the inflow using moving windows of 30 years over the historical records (1916-2010) and we derived the corresponding optimal lake operating policies when balancing flood control and irrigation supply, the two main water system interests. Results seem to suggest that the adaptive approach produces better performances in terms of irrigation supply, while the static approach is slightly better for flood control. Overall, none of the two approaches seems to outperform the other.

Further research is needed to improve and complete the analysis. Nonetheless current results give some insights on the methodology. First, the comparison between the two approaches should be performed by looking at the entire Pareto Front. Focusing on one fixed combination of the two objectives, like we did, does not guarantee a fair comparison among the trade-off solutions, because we may change the relative importance of the two in designing the reservoir policy. The Pareto front should rather be computed either re-running the optimization for different combinations of the weights, although it will be computationally expensive, or using a non-parametric multi-objective approach, e.g. Multi Objective Genetic Algorithms, that provide the approximation of the entire Pareto front in one optimization run. Moreover, the analysis of the Pareto Front allows to assess how the conflict between competing water uses evolves in time. Preliminary results on Lake Maggiore show that the performances of the two extreme mono-objective solutions, where the lake is managed for flood control or irrigation supply only, do not vary in time, while the performances of the trade-off bi-objective solutions do. If confirmed by further analysis, this would suggest that the main stressor for lake operation is the presence of multiple and competing water uses and not hydrological changes.

Second, we fear that the hydrological model we used can not properly represent the hydrological process and its eventual evolution in time. In our opinion, the differences in the reservoir operation performances are confounded by the hydrological modelling errors, including both errors in the model structure and the parameter estimates. In particular we think that 30 years of records are not enough to properly represent extreme hydrological events. This point, also acknowledged by WMO (*Guide to Climatological Practices - WMO No. 100* 2011) referring to precipitation, is remarkable when considering flood control as operating objectives. More appropriate statistical techniques, rather than moving average, may help in better estimating the statistical properties of the hydrological process and especially the tail of its pdf. However, we question if improving the hydrological model would be sufficient to effectively tackle flood control. In this case, in fact, the problem may rely in the update the hydrological model parameters. Water managers are, in fact, interested in being able to deal with flood events with a large return period. Since time series of records are usually short and floods are very rare events, discarding old records in favour of new ones does not increase the pieces of information available to reservoir operation optimization. Indeed, this updating procedure impoverish the set on which the operating policies learn how to deal with floods.

Third, as approached so far, the dichotomy between the static and the adaptive approach underpins a dichotomy between the use of a stationary and a nonstationary model to describe the inflows. Technically, in the current implementation of the adaptive approach, we are still assuming that hydrology is stationary for 30+1 years. A nonstationary model would rather describe how the parameters of the inflow pdf vary in time. We preferred not to use such a model because it might result in overconfidence about our ability to predict the future, since that relationship would allow for forecasts of inflow pdf at any time into the future. This could be misused, resulting in a totally biased representation of the future, since, as discussed in the last two chapters, trend detection is easily influenced by the period of analysis and other assumptions, e.g., the method chosen to detect trends. Anyway, the adaptive approach does not necessarily require to describe the hydrological process with a nonstationary model. For example we can update the inflow pdfs by including into the calibration set all the new records that become available year by year. This setting could be used to test the influence of the calibration set length in properly representing the hydrological process and could partially mitigate the problem discussed in the previous point related to the richness of information for flood control.

Concluding, we think that further research is needed to test the potentiality of the adaptive management approach to deal with changes in decision making problems and more successful real-world case studies should be provided. Beside research on methods, we think that attention should be paid also to aspects related to the practical implementation of the adaptive approach. For instance, when designing the reservoir operating policies we can easily derive the entire Pareto front, but we must choose only one solution to be implemented in the real water system management. The choice of this solution is not trivial, especially when more than one decision-makers and stakeholders are involved. In participated decision process, this choice would require a huge effort in involving the stakeholders into the decision-making process which may require several months or even years to come to an end (e.g., Soncini-Sessa et al. (2007)). This means that the process of selecting one efficient policy may be longer than the time that policy is suppose to be used, thus becoming completely useless. We think that the implementation of the adaptive approach requires a change in how the decision-making process is perceived by both the stakeholders and decision-makers and the researches working on the decision making support systems. We agree with Walker, Marchau, and Swanson (2010) who claim that all the actors of the decision making process should agree on the objectives to be achieved and on the methods used to pursue those objectives. They all should be aware that their participation is not an una tantum effort, rather a continuous involvement into the decision making process.

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CHAPTER 6

Model predictive control for adaptive management

A way to cope with the deep uncertainty related to climate change is to search for adaptation strategies that do not rely on climate projections, but on mid (seasonal) and long term forecasts (Steinschneider and Brown, 2012). In this chapter we present another possible adaptive optimization procedure where the recursive application of a forecasting model and an optimization procedure can make management strategies more flexible and efficient. More precisely, the procedure is composed of: a streamflow forecasting model, an optimization model of the water resource management, and a simulation model of the water system response. We demonstrate it through the application to the Oroville-Thermalito complex (California). It is a mixed rain-snow dominated catchment, where the prediction of the volume and timing of melting flow can greatly enhance the reservoir management performances. We assess the value of two realistic forecasting models based on Extended Streamflow Prediction with and without Snow Water Equivalent assimilation when the reservoir is operated for drought control. The research was developed in collaboration with the Pacific Northwest National Laboratory and the University of Washington.

6.1 Introduction

Reservoir operating rules inform release decisions based on competing demands, priorities, available storage, and reservoir characteristics. The information base on which release decisions are made includes at minimum the reservoir storage, however, reservoir management can greatly benefit by consideration of other pieces of information, as for instance streamflow forecasts (e.g., Pianosi and Soncini-Sessa, 2009; Georgakakos and Graham, 2008). "Forecast accuracy" indicates how precisely the forecasting model can predict future hydrological events. It is usually assessed by comparing retrospective forecasts with observed streamflow time series. However, when forecasts are used to improve reservoir operation, it is more interesting to assess the "forecast value", i.e., how useful forecasts are from the point of view of the decision making process.

Streamflow forecasts are provided over a wide range of lead times, from days or less to seasons or longer. In the literature, a large attention has been devoted to explore the value of short term streamflow forecasting models when reservoirs are operated for flood control. Studies concerning the relationship between long term forecasting models and reservoir management for seasonal purposes are relatively few. The majority of them deals with hydropower production (Koskela, 2009; Yeh, Becker, and Zettlemoyer, 1982; Hamlet, Huppert, and Lettenmaier, 2002; Maurer and Lettenmaier, 2004), while only few focuses on other purposes, e.g., irrigation or municipal supply (Yao and Georgakakos, 2001; Georgakakos et al., 2005). Their general approach is to compare reservoir operation in the case of "no forecast", i.e., when a conservative forecast, such as average historical streamflow, is taking into account, and in the case of "perfect forecasts", i.e., when the forecasting model is supposed to foresee exactly future streamflow. Further analysis usually involve artificial forecasts, obtained by increasingly degrading the perfect forecast, to assess the relationship between forecast value and accuracy. Few studies assess, instead, the value of more realistic forecasting models (e.g., Yao and Georgakakos, 2001).

Forecast value is directly related to forecast quality, but it is influenced by many other factors, e.g., reservoir capacity, operation objectives, and flexibility of the operating rules. Generally speaking, short term forecasts are useful when the reservoir is operated for flood protection, while long term forecasts when it is operated for hydropower generation and/or water supply. Short term forecasts are more informative for small reservoirs, i.e., reservoir which have a capacity smaller than their annual inflow volume, while long term forecasts are more useful in case of large reservoirs. Finally, the response of the water system operation to forecast is strongly dependent on the flexibility of the management system (Yao and Georgakakos, 2001; Hamlet, Huppert, and Lettenmaier, 2002; Rosenberg, Wood, and Steinemann, 2011; Andersen, Hiskey, and Lackawathana, 1971). A rigid decision making system may not be able to exploit the information provided by forecasts. A shift toward dynamic decision schemes which are designed to incorporate forecast information is encouraged to enhance the value of forecasting models (Yao and Georgakakos, 2001).

In this work we analyse the case study of the Oroville-Thermalito reservoir complex in the Feather River Basin, California, to explore the effect of different realistic forecasting models on optimal release strategy. Streamflow in the Upper Feather Basin is strongly seasonal signal, with most of the flow occurring during the winter, from rainfall at lower elevations, and the spring, from melt of the previous winter's snow accumulation. Accurate prediction of the volume and timing of snowmelt, which is possible via various means, including monitoring of accumulated winter precipitation, and measurements of high elevation snowpack, has the potential to improve reservoir operation. California and its complex water system has been extensively studied. Recently, Yao and Georgakakos (2001) and Georgakakos et al. (2005) proposed integrated forecast-decision systems to improve water-use efficiency in Northern California. Previously, Yeh, Becker, and Zettlemoyer (1982) studied the operation of the Oroville-Thermalito reservoir complex to assess the value of long term streamflow forecasts in terms of hydropower production, flood protection, and water conservation for irrigation and environmental uses. Considering artificial streamflow forecasts, they simulated the current reservoir operation on a monthly time step to derive the benefits of the inclusion of forecasts as function of lead time and accuracy.

In this study, we extend the analysis by Yeh, Becker, and Zettlemoyer (1982) by re-optimizing the Oroville reservoir operation so to integrate in the decision making process the pieces of information provided by different realistic forecasting models. In particular, we use Deterministic Dynamic Programming (Bellman, 1957) to optimize seasonal reservoir operation based on different forecasts of reservoir inflows. We first determine the maximum reservoir performance by forcing the optimization with observed inflows, which is equivalent to a perfect forecast. We then generate forecast inflow sequences using the Variable Infiltration Capacity (Liang et al., 1994) hydrological model. Forecast initial conditions are created using observed meteorology, including snow data assimilation, while inflow forecasts are based on Extended Streamflow Prediction (ESP) approach (Day, 1985). ESP is a widely used approach and, in particular, it is used by the National Weather Service to produce forecasts for the water supply activities in the western U.S.A. (Rosenberg, Wood, and Steinemann, 2011). Although the results inform on the forecast skill level for the specific Feather River basin, the methodology should be transferable to other systems, especially elsewhere in the western U.S.A., and in other locations with strongly seasonal runoff regimes.

6.2 Adaptive decision scheme

To assess the value of long term streamflow forecasts, we use an adaptive decision scheme composed of three steps: *i)* a forecasting model to produce an estimate of the reservoir inflows, *ii)* an optimal control problem to derive the optimal reservoir releases, and *iii)* a deterministic simulation to quantify the reservoir operation performances.

In the first step, we use the Extended Streamflow Prediction (ESP) approach (Day, 1985). An hydrological model is run, first, in nowcast mode using observed meteorological forcings of the 3 months prior to the forecast day ($t = 0$ in Figure 6.1) to obtain an estimate of the hydrological initial conditions on that day. These initial conditions are, then, used to run the hydrological model in forecast mode with 1-year-long observed meteorological forcings resampled from the historical period, thus obtaining the final hydrological forecast ensemble. Although using ensemble forecasts is recognized to lead to better reservoir operation performances (e.g., Yao and Georgakakos, 2001), we reduce the ensemble to a single trace by averaging all the original ensemble members. Considering the uncertainty characterization embedded into the forecast ensemble will be the object of future work. Since ESP is based on resampling from the past, the skills of the forecasting model depend strongly on the knowledge of initial conditions of the hydrological model. The approximation of the initial conditions can be improved by data assimilation (Figure 6.1). Since the focus of this research is on snow-dominated water systems, we use Snow Water Equivalent (SWE) observation on the forecast day.

In the second step of the adaptive decision scheme, we define a deterministic control problem to derive the optimal sequence of release decision from the reservoir given the inflow sequence obtained in the previous step. The decision time step is one day and the length of the optimization horizon is one year, since this is the length of the streamflow forecasts provided by the forecasting model. We solve the optimal control problem by using

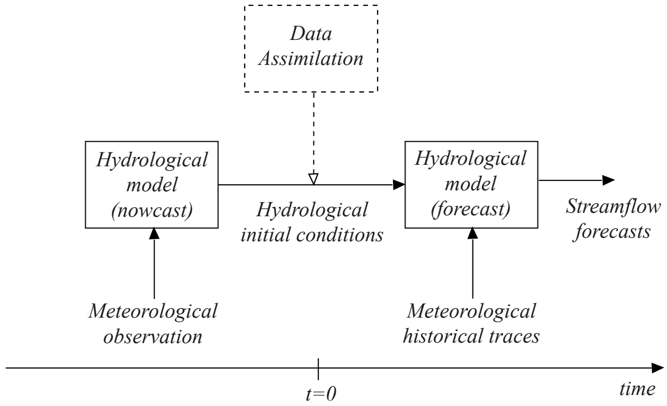

Figure 6.1: *Streamflow forecasting model (adapted from Wood and Lettenmaier, 2006).*

Deterministic Dynamic Programming (DDP) (Bellman, 1957).

In the final step, we estimate the response of the water system via deterministic simulation over an historical horizon. The simulation allows to mimic the dynamic of reservoir storage and actual release under the sequence of optimal release decisions and the inflow time series observed in the simulation horizon. The aim of this step is to reproduce what would have happened in the water system if the reservoir was operated following the proposed adaptive decision scheme.

The three steps procedure is iterated every 7 days, i.e., the number of days intercurrent between one streamflow forecast and the next, to cover the evaluation horizon, a decade in our case. The value of the streamflow forecasts is then computed by calculating the average value of some performance indicators over the evaluation horizon.

In this work, we assess the value of two realistic streamflow forecasting models, i.e., ESP with and without SWE assimilation (Figure 6.2a). We consider also three benchmarks to assess the minimum and maximum achievable reservoir operation performances. The lower-bound performance is assessed through the "no forecast" benchmark (Figure 6.2b), in which the reservoir operation is based only on past observation of the inflow. The sequence of inflow used in the optimal control problem is the climatology, i.e., the cyclostationary mean computed over the historical time series. The upper-bound performance is assessed through the "perfect forecasts" benchmark (Figure 6.2c), which assumes perfect skill of the streamflow forecasting model. The experiment is performed by solving the optimal control problem using the sequence of observed reservoir inflow. We consider another upper-bound performance, the "perfect meteorological forecast" benchmark (Figure 6.2d), which assumes that the forecasting model is able to foresee exactly future weather (not streamflow) and to simulate the hydrological model to obtain the resulting streamflow, which is used in the optimal control problem.

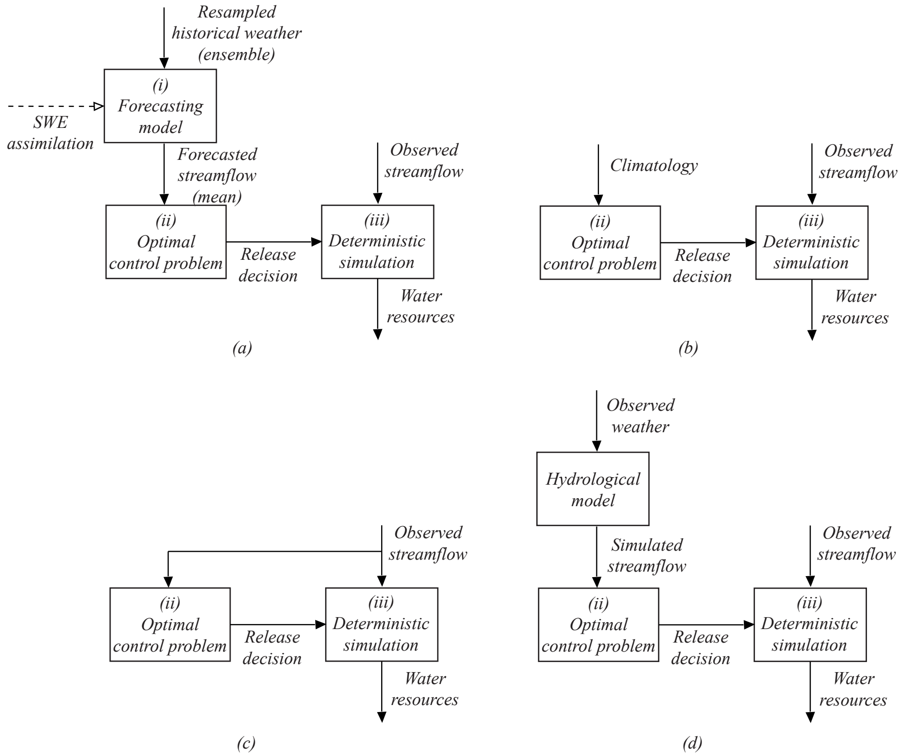

Figure 6.2: *Experiment settings when considering (a) two realistic streamflow forecasting models, Extended Streamflow Prediction with and without Snow Water Equivalent assimilation, (b) "no forecast" benchmark, (c) "perfect forecast" benchmark, and (d) "perfect meteorological forecast" benchmark.*

6.3 Case study: Oroville-Thermalito reservoir complex

The Oroville-Thermalito reservoir complex is a water storage and delivery system of reservoirs, canals, power and pumping plants. The Oroville, with a storage capacity of 3,538,000 acre feet (af), is the main reservoir of the complex. The other two, i.e. Thermalito Forebay and Afterbay, have considerably smaller capacity and are used mainly as pool for pumping back water into the Oroville reservoir during off-peak hours and to divert water into the canals feeding local agricultural districts. Along with many other reservoirs situated in California, the Oroville-Thermalito reservoir complex is part of the State Water Project, whose main purpose is to store and distribute water to satisfy the needs of urban and agricultural water users and environment in northern California, and the San Francisco Bay area (Figure 6.3). In addition, the Oroville is operated for hydropower generation and flood control on the downstream Feather River and the Sacramento River.

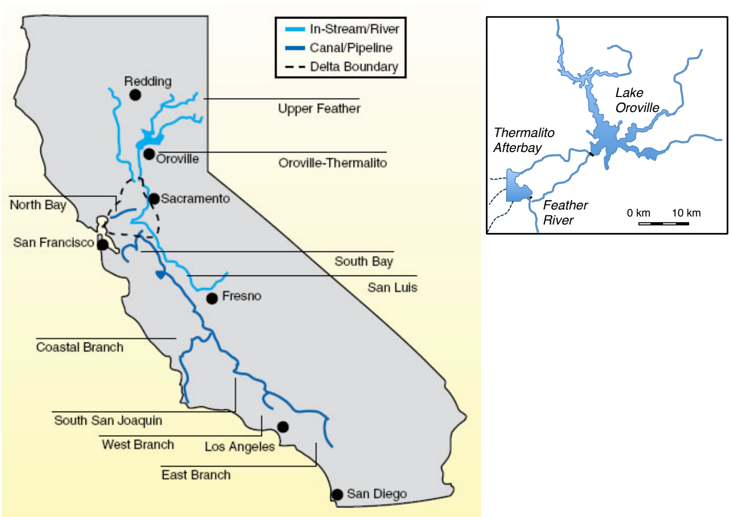

Figure 6.3: *State Water Project facilities and Oroville-Thermalito complex (adapted from www.lao.ca.gov)*

The Oroville is fed by the Feather River which collects water from a 3,950 squared miles (mi^2) catchment. The mean annual inflow volume is about 4,000,000 af. The climate of the area is Mediterranean, i.e., wet winters and warm, dry summers, with most of the precipitation occurring during the cold season, from November to March. As most of the catchments of the western U.S.A., it is a mixed snow-rain dominated catchment with the most of the water flowing into the reservoir in winter and spring (Figure 6.4). Snowmelt is the primary source, contributing about 40% of the total streamflow (Wigmosta et al., 2011), but there is a high variability in precipitation and temperature leading to interannual differences in streamflow and in the timing and quantity of snowmelt (Kalra, Ahmad, and Nayak, 2012).

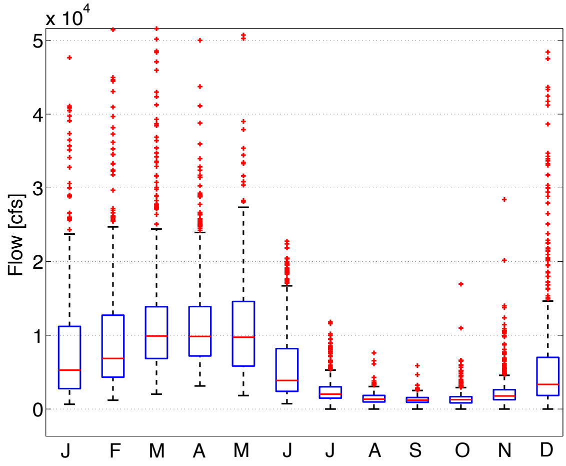

Figure 6.4: *Monthly boxplot of the Oroville inflow time series over the period 2000-2010.*

The Oroville reservoir is currently operated on the basis of the flood-control rule curves showed in Figure 6.5. They define the maximum reservoir storage for each day of the year as a function of the weighted accumulated precipitation on the catchment (the higher the precipitation, the lower the storage). The curves divide the reservoir capacity in two pools: the flood control pool, i.e., the space above the curves, which is reserved for flood control, and the conservation pool, i.e., the volume that can be filled for all other purposes. During the flood season, between mid October and the end of March, the maximum storage is low because the frequent storm events could potentially cause flooding; during the conservation season, between May and mid September, the reference reservoir storage is high to meet the other operation objectives. In between there are two transition periods in which the storage is progressively decreased or incremented in order to prepare to the following wet and dry season respectively. The curves were developed by the U.S. Army Corps of Engineers in 1971 based on the historical inflow hydrology, physical constraint (e.g., downstream channel capacity), and historical operation objectives (mainly flood protection and water supply). They represent the historical balance between flood control and water supply objectives.

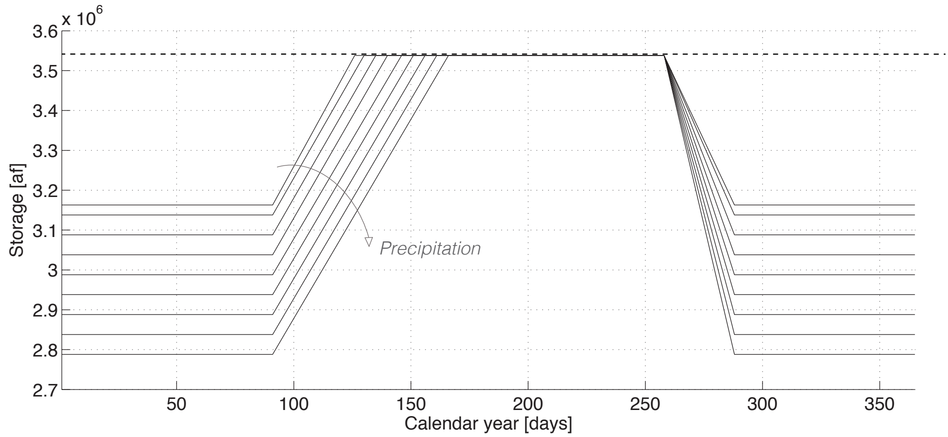

Figure 6.5: *Flood rule curves (solid lines) used in the current operation of the Oroville reservoir as function of time and precipitation. The capacity of the reservoir is represented with the dashed line.*

6.4 Application of the adaptive decision scheme

6.4.1 Forecasting model

The long term retrospective hydrologic forecast dataset is developed by the Pacific Northwest National Laboratory in collaboration with the University of Washington. They use the Variable Infiltration Capacity (VIC) model (Liang et al., 1994) which is a grid-based distributed model with a daily time resolution and $1/8^{th}$ degree spatial resolution (approximately 126-172 km^2, depending on latitude with smaller values in the northern latitudes of the U.S.A., and larger value in southern latitudes). To produce the forecast ensemble, VIC is forced with 1-year-long observed meteorological forcings resampled from the historical period (49 ensemble members from the period 1990-2005) using a leave-one-year-out approach and starting on the forecast day. The forecasts are issued every week. A detailed description of the forecasting models and a discussion of their accuracy is given in Wigmosta et al. (2011).

6.4.2 Optimal control problem

We formulate an optimal control problem to design the operation of the Oroville reservoir to meet flood control and downstream water requirements for irrigation, municipal supply, and environmental conservation both in the downstream Feather River and in the San Francisco Bay area. Hydropower production is the only actual interest which is not considered, because the hourly dynamic of the hydropower plants may not be properly described at the daily time step used in the control problem formulation.

Flood control is included in the constraint set. More precisely, the reservoir storage is upper bounded by the most conservative flood rule curves (the lowest curve in Figure 6.5): in so doing we ensure flood risk to be at minimum with respect to the current operation rules. The downstream water supply is, instead, included in the objective function, which is formulated as the squared deficit volume with respect to the downstream demand

$$J_{irr} = \frac{1}{h}\sum_{t=0}^{h-1}[\max(w_t - r_{t+1}, 0)]^2 \tag{6.1}$$

where r_{t+1} is the average daily release from Oroville reservoir, w_t is the downstream water demand, and h [day] is the length of the simulation horizon. The squaring is used to induce the reservoir operation to eventually distribute deficits in time.

A realistic description of the downstream water demand w_t is difficult to obtain. In fact, actual water demands are decided yearly depending on the hydrological conditions of the different catchments of California. For example crop selection is initially decided in November, mainly looking at current reservoir storages using climatology as future streamflow projection. The decision is then updated in May, when more realistic streamflow forecast, based on snowpack measurements, are available (Rosenberg, Wood, and Steinemann, 2011). Moreover, the operation of the Oroville is strictly interconnected with the operations of the other reservoirs of the State Water Project. It is thus almost impossible to define which part of the total demand should be ascribed to the Oroville operation only. Since the most of the elements which define the water demand are not included on the problem formulation, we represent the downstream demand with an a priori trajectory which is the sum of two components: the volume derived by the Thermalito Afterbay canals feeding the local irrigation districts, and the volume released in the downstream Feather River to supply all the other interests. As for the first, Figure 6.6a shows the observed flow diverted from Thermalito Afterbay in the period 2000-2010 and the moving average over 7 days, which we take as reference. As for the second, we asked the California Water resources Department to compute the volumes released by the Oroville on the period 2000-2010 through the use of the CalSim model, which they developed to simulate the water resource management (http://modeling.water.ca.gov/hydro/model/). The flow simulated in summer, i.e., during the irrigation seasons, shows high variance (Figure 6.6b) which can not be reduced in the current formulation of the control problem. In this work, we, thus, consider the 50-th quantile shown in the boxplot as reference demand pattern.

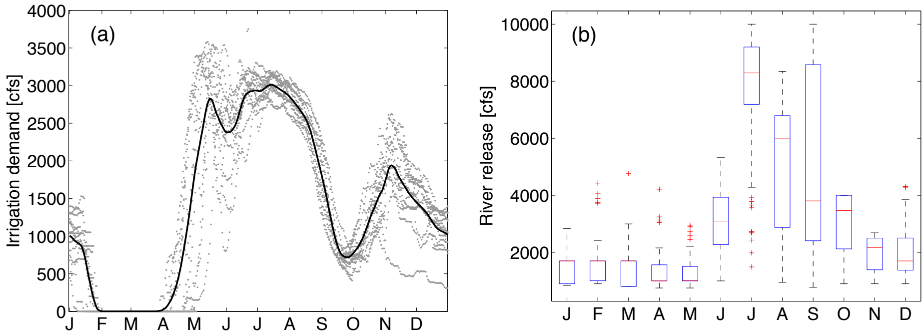

Figure 6.6: *The two components of the downstream demand: (a) daily flow derived by Thermalito Afterbay (grey dots) and moving average over 7 days (solid line); (b) monthly boxplot of the flow released in the Feather River simulated by the CalSim model (the $50-th$ quantile is taken as reference).*

6.4.3 Deterministic simulation

The reservoir operation is simulated over the evaluation horizon 2000-2010, using the observed time series of full natural flow available on the California Data Exchange Centre web site (http://cdec.water.ca.gov/).

Given the value of the reservoir storage in the first day of the evaluation horizon, the simulation allows to compute the sequence of daily storages and actual releases from the reservoir. The release time series is then used to compute the time series of downstream supply deficit. The comparison among the different forecasting models is assessed by analysing the mean annual value of the supply deficit for each year of the evaluation horizon 2000-2010.

Figure 6.7 shows the annual inflow volume to the Oroville reservoir. Since its operation is designed to minimize the downstream supply deficit, the periods 2001-2002 and 2007-2009 are particularly interesting, since they represent two dry spells, i.e., years when inflow volume is lower than average, computed over the entire evaluation horizon.

6.4.4 Validation

To validate the water system model, we optimize the operation of the water system using the historical time series of inflow to the reservoir. The aim is

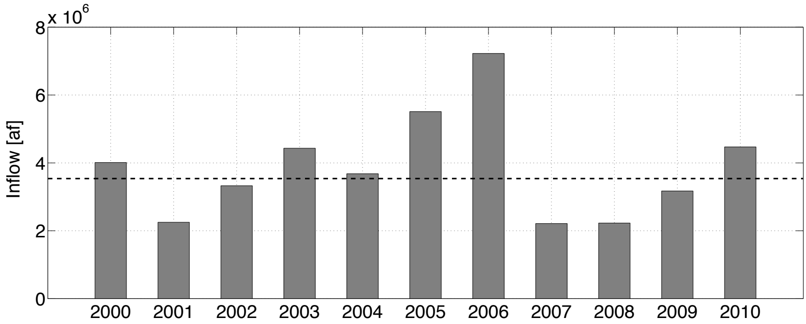

Figure 6.7: *Annual inflow volume to the Oroville reservoir. The capacity of the reservoir is represented with the dashed line.*

to assess the capacity of the simulation and optimization model to resemble the historical management in a realistic manner, although the simplifying assumption described in the previous paragraphs. Figure 6.8 shows the simulated and observed reservoir storage trajectories in three years of the evaluation horizon (2002-2004). As consequence of the constraint impose in the optimal control problem formulation, the simulated storage does not exceed the rule curve, while the observed storage does. Note, in fact, that the actual rule curve is computed on a daily basis, taking into account the catchment hydrological conditions, and may differ from the one we chose. Nonetheless, the comparison among the two reveals that the model provides a realistic representation of the actual operation of the reservoir. Also the downstream demand pattern is credible since the drawdown of the reservoir in the simulation is comparable to the actual one.

6.5 Value of the forecasting models

We assess how much the decision making process can theoretically benefit from the use of streamflow forecasts. We thus compare the upper bound performances of the "perfect forecast" benchmark with the lower bound performances of the "no forecast" benchmark. As already explained, the first assumes forecast be exactly equal to the observed streamflow, while the second assumes flow be equal to climatology (Figure 6.2b-c). Figure 6.9 shows that there is a large room for improvement, especially when prolonged dry spells occur, e.g. during 2001-2002 and 2007-2009. In these cases, the "perfect forecast" operation produces a small deficit during the first year (2000 and 2007 respectively), although this could be totally avoided as the "no forecast" operation proves, thus saving water to reduce

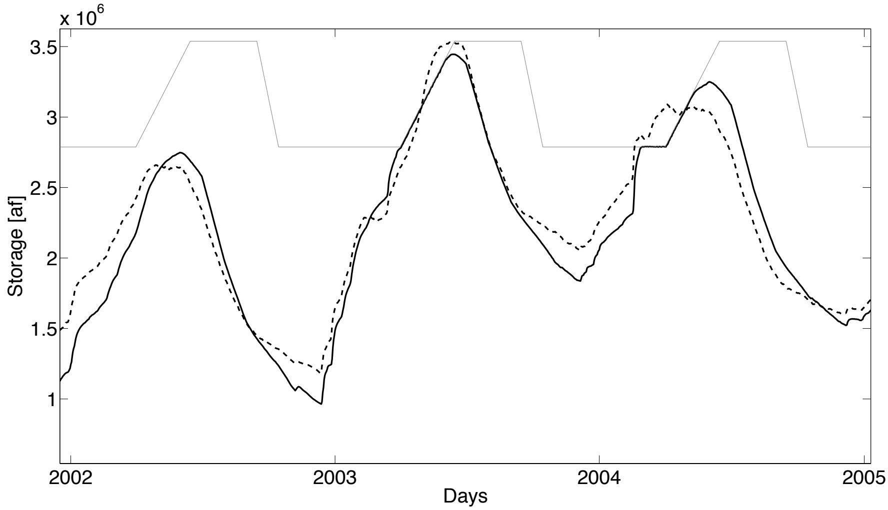

Figure 6.8: *Observed storage trajectory (dashed line), simulated one (black solid lines) and flood rule curve (grey solid line) used in the optimal control problem formulation.*

deficits in the following years. The reason is that in dry years "perfect forecast" predicts that future inflow is lower than average (see Figure 6.10), while "no forecast" assumes that future inflows will be sufficient to satisfy the water demand during both the current and the next year.

We considered a different upper bound, the "prefect weather forecast", in which we assume that the forecasting model can perfectly foresee weather and simulate reservoir inflow using the hydrological VIC model (Figure 6.2d). The distance with respect to "perfect forecast" performances represents the loss in performances induced by the inaccuracy of the hydrological model. Since the performances are comparable (Figure 6.9), the VIC model can be considered sufficiently accurate for the purposes of reservoir operation. In fact, looking at the streamflow time series (Figure 6.10), the model can properly represent the seasonal pattern, while it is less accurate in reproducing flood peaks, which are not very relevant in this work since we did not consider flood control as operation objective. The "perfect weather forecast" operation can even perform better than the "perfect forecast" one (e.g., 2001 and 2002 in Figure 6.9). This happens when the inflow volume is slightly underestimated. In this cases, the reservoir operation is more conservative causing the storage to be higher and available for supply in the following year.

Considering the realistic forecasting models of Figure 6.2a, Figure 6.9 shows that the performances of the ESP approach are almost equivalent to

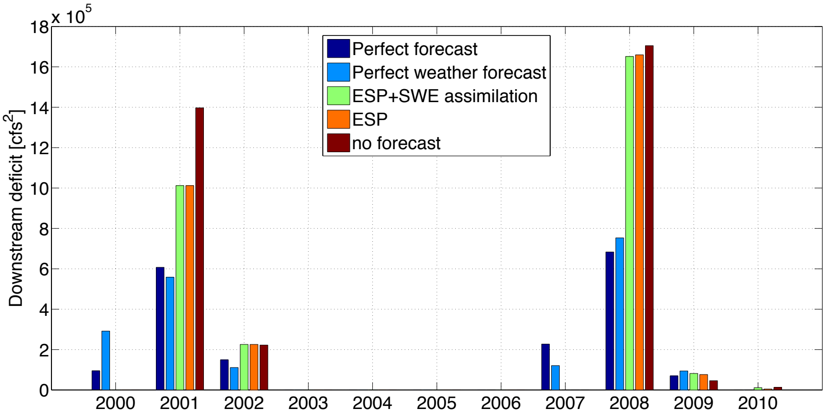

Figure 6.9: *Reservoir operation performances when using different forecasting models.*

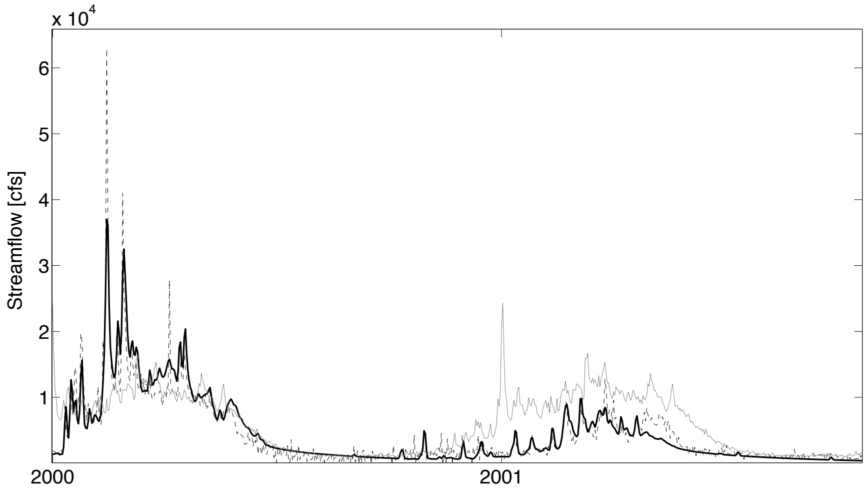

Figure 6.10: *Streamflow forecasts in 2000-2001: "perfect forecast" (dashed line), "perfect weather forecast" (black solid lines), and "no forecast", i.e., climatology (grey solid line)*

the ones of the "no forecast" benchmark. In fact, the skill of the forecasts is essentially that of climatology, especially in the long run. Referring to the Oroville catchment, also Wigmosta et al., 2011 state: "the forecasts are long lead (12 months) but their skill is seasonal and limited to spring forecasts in this mixed rain-snowmelt dominated basin". Figure 6.11 shows the pattern of the forecasts issued the first day of each month in 2001 in the case of perfect forecasts, ESP approach and climatology. The forecasts obtained with the ESP approach differ from climatology only in winter and spring when the hydrological initial condition significantly affect the streamflow patterns. The differences with respect to climatology last for weeks or months, depending on the time of the year when the forecasts are issued, but they totally vanish after the summer. The differences are too small to allows the reservoir for hedging the future dry conditions, but they are still informative for the reservoir operation in short term (see Figure 6.11 forecasts issued from January to June).

Since the accuracy of initial conditions are critical for improving streamflow forecasts, data assimilation may assume an important role. However, the forecasts accounting for SWE assimilation do not allow to further improve reservoir operation. One possible explanation is that the differences, with respect to ESP without data assimilation, last only for few weeks after the forecast day and do not affect the long term trajectory.

6.6 Conclusions

In this chapter we assessed the potential of long-term streamflow forecasts in enhancing reservoir operation efficiency. To this end, we designed the optimal reservoir operation using an adaptive approach, in which the streamflow forecasts are used to derive the optimal sequence of reservoir release decision in meeting its operation objectives. More precisely, we analysed the case study of the Oroville-Thermalito reservoir complex (California) operated for flood control, municipal and irrigation supply, and environmental conservation. We assessed the theoretical improvement that can be achieved by the inclusion of future streamflow information in the decision making process. We demonstrated how the use of an accurate forecasting model can significantly improve the operation performances, especially in case of prolonged dry spells. The improvement seems to be driven by the accuracy of the forecasting model in representing streamflow patterns in the medium-long term. We assessed also the value of realistic forecasting models based on the Extended Streamflow Prediction approach, with and without Snow Water Equivalent assimilation. Since the forecast

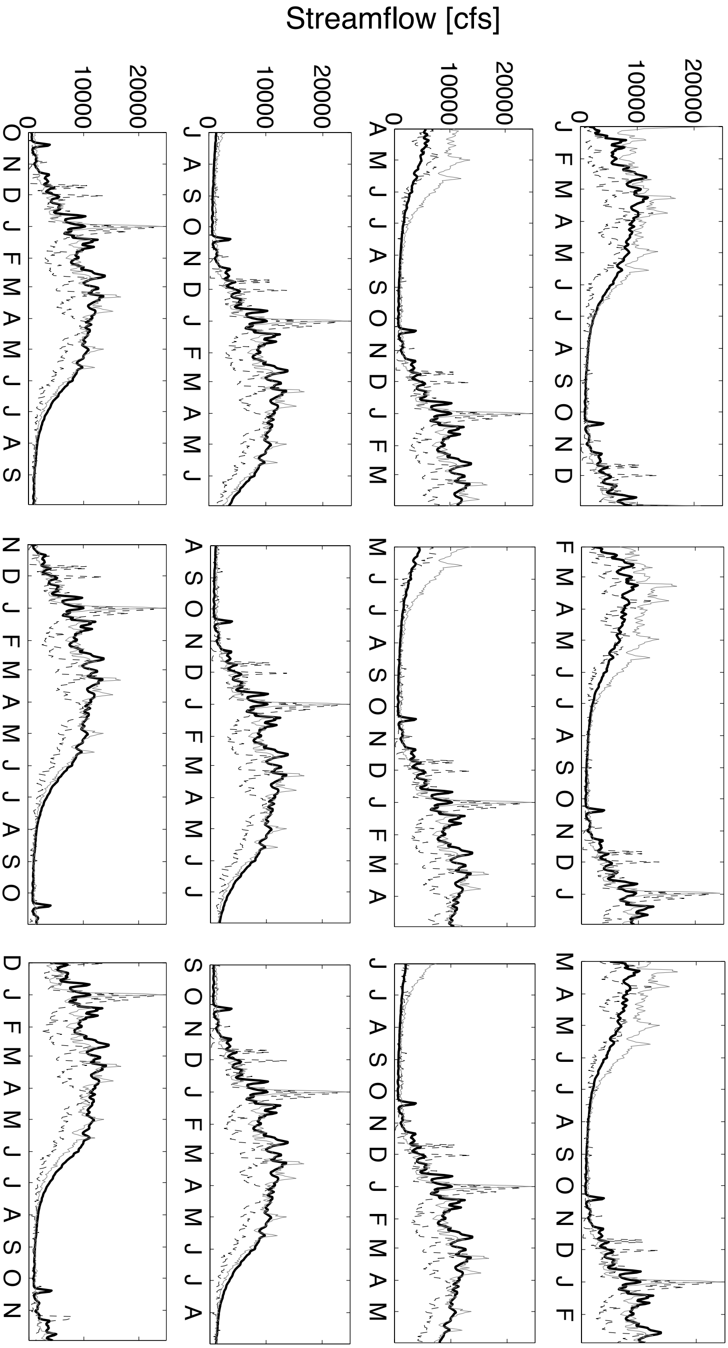

Figure 6.11: *Streamflow forecasts issued the first day on each month of 2001: "perfect forecast" (dashed line), ESP approach (black solid lines), and "no forecast", i.e., climatology (grey solid line)*

skills in rain-snow dominated catchment, like the one feeding the Oroville reservoir, are seasonal and limited to spring, the forecasting models are not able to provide useful information. Their skills are, in fact, comparable to those of climatology. However, accurate short-term forecasts can contribute to slightly reduce seasonal supply deficit. Assimilation of SWE does not increase the value of streamflow forecasts, probably because its effect on the streamflow trajectories lasts only for few weeks after the forecast day. Further research will be aimed at understanding more deeply this issue.

The research results suggest that mid-long term forecast have the potential to improve reservoir operation. This potential seems to be more theoretical than actual. In fact, realistic forecasting models allow for accurate prediction only on lead time from weeks to few months depending on the time of the year when the forecasts are issued. However, the results presented in this chapter were obtained considering a single streamflow trajectory, i.e., the average of the original forecast ensemble. Considering the uncertainty characterization embedded into the ensemble when designing the optimal reservoir operation may lead to better performances (e.g., Yao and Georgakakos, 2001).

The results obtained are strongly dependent on the reservoir operation objectives, the hydrological features and other characteristic of the water system. Further research will explore the relationship between these characteristics and the forecast value. In particular, we will assess the transferability of the case study results to other water systems using alternative reservoir characteristics of the Oroville-Thermalito reservoir complex as a surrogate for alternate reservoir configurations. For instance, we will explore the sensitivity of reservoir operation performance to the ratio of reservoir mean inflow volume to reservoir capacity and downstream demand requirements.

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CHAPTER 7

Conclusions

In this thesis we discussed how traditional and novel, adaptive approaches to water resource management can be used to deal with deep uncertain and changing hydro-climatic conditions. We presented a set of simulation and optimization models, referring to System Analysis, that can be used to describe the vulnerabilities and strengths of the water systems and to identify the room for improving the efficiency of water resource management. In particular, we integrated simulation models that are usually employed to estimate the impact of climate change and to define adaptation measures with water-value models, decision models, and optimization techniques which allow to describe stakeholder expectations on water uses and the behaviour of the water system managers. We demonstrated those modelling and optimization tools through the application to three real-world case studies. Applications in realistic decision making contexts can, on the one hand, provide the ground to thoroughly test them and, on the other hand, can increase their acceptability to stakeholders and decision makers, thus contributing to force climate change policy inertia.

In Chapter 2 we used the case study of Lake Como (Italy) to analyse the current water system institutional framework, and we demonstrated that reframing the institutional setting toward a more cooperative and flexible one can reduce water system vulnerability to dry spells.

In Chapter 3 we extended the analysis of the previous chapter to assess the potential of the management strategies, which proved to be the most efficient ones in the present hydro-climatic conditions, to deal with future water availability as projected by climate models. As a result of multiple uncertainties in the impact assessment procedure, the exact quantification of climate change impacts on water resources was not fully possible. Nonetheless, the analysis proved to be useful in understanding the threats to future reservoir operations. For example, it demonstrated that re-optimization of the reservoir management policies can only partially compensate for the losses induced by climate change in the case of the lake management, but that it can not reduce the losses for the hydropower reservoirs located in the water systems. This difference is the result of the combination of the future streamflow features and the physical characteristics of the reservoirs. The analysis thus produced knowledge that is not only relevant for the specific case study, but it can be exported also to other contexts.

In Chapter 4 we used the case study of Lake Maggiore (Italy) to analyse how hydrological processes has changed in the last century and if these changes have affected water resources. We demonstrated that the water system has an inherent buffering capacity which allows to naturally compensate hydrological variability.

In Chapter 5, we explored the possibility of further enhancing the resilience of the water system to hydrological changes by acting on the reservoir management strategy. Specifically in this and the following chapter we tested adaptive management approaches as viable adaptation measures to climate change. Adaptive management requires decisions to be continuously revised to react to changes in the decision making context. It is based on the insight that uncertainty can be reduced via system monitoring by gaining information useful from the management point of view. We proposed two formulations of the adaptive management approach which differ because of the pieces of information gained by the system monitoring, one looking into past hydrological records, the second foreseeing future streamflow.

In Chapter 5, we developed a stochastic recursive optimization approach for the case study of Lake Maggiore. We modeled the statistical properties of the inflows to the lake by using probability distribution functions estimated from historical records. These stochastic hydrological models were updated every year to account for new available records and progressively discarding the old ones. These models were then used to recursively design the reservoir operation so to possibly adapt to hydrological nonstationary conditions. The performances of the reservoir operation did not allow to validate the usefulness of the adaptive approach. Our hypothesis is that, on the one hand, the modelling tools we used to represent the hydrological dynamics are overly simplified and probably inadequate for the purpose of the analysis, on the other hand, the methodology should be improved to better describe the relationship between conflicting objectives and to consider different hydrological models updating schemes.

In Chapter 6, we tested the second type of adaptation management using prediction of future streamflow to improve water resource management. We compared the value of two different realistic long term streamflow forecasting models in improving reservoir operation for water supply. We focused on the case study of Oroville-Thermalito complex (California), a mixed rain-snow dominated water system. We showed that, although reliable streamflow forecasts can theoretically improve reservoir operation, the realistic forecasting models currently available are not able to provide the pieces of information needed for mitigating droughts, i.e., reliable estimates of water volume in the long term. Further research should be devoted to the development of more sophisticated forecasting models able to foresee drought events in advance, for example exploiting the long term information contained in climatic indices.

The analysis revealed that application of methods and tools to real-world case studies may pose additional difficulties. The complexity of the water systems, the multi-objective nature of water resources, and the use of historical observed records are all elements that contribute to complicate the analysis. One example relies in our efforts in distinguishing natural variability and climate change signal in streamflow time series. The differences between the two are clear when dealing with climate model projections. More precisely, when, in Chapter 3, we simulated the management of Lake Como water system into the future, we could recognize a clear tendency in time towards more and more negative water resources impacts. On the contrary, the two components are less distinguishable when analysing observed time series. In particular, when we analysed the historical inflows to Lake Maggiore over the last century (Chapters 4 and 5), a clear distinction between climate change signal and natural variability was not possible. Although this difference may have other explanations, e.g., the temporal slices used in the two analysis, we believe that the main reason relies in the complexity characterizing real processes with respect to models.

Overall, our research showed that the proposed modelling and optimization tools can be effectively exploited in the context of water resource management and climate change, although further research on adaptive management is necessary to totally validate the approach. We used them more as a means to produce knowledge on the analysed water systems, rather then to design adaptation measures that could actually be implemented. For example, in the case studies of Lake Como and Lake Maggiore they were used to understand the water system vulnerabilities, to identify the room for making water resource management more efficient, and to identify the drivers which represent threats to water resources. In the case study of the Oroville-Thermalito complex they indicated which is the weakest link in the forecasting and optimization modelling chain, pointing the direction in which research efforts should be focused. We think that simulation and optimization models can not be used as tools to define what should be implemented in the future, as in the classical predict-and-control paradigm, and uncertainty can not be analysed a posteriori analysis to test the robustness of the decisions. They should rather be used as tools to describe uncertainty as an inborn feature of decision making process and to provide the knowledge base for political discussion and decision-making. We don't think that increasing complexity and accuracy of the modelling tools will be sufficient to compensate for the large uncertainty that affects our knowledge about the future. We rather think that efforts in enhancing modelling tools should be coupled with an equal effort towards developing effective methods to handle uncertainty in the decision-making context and to communicate uncertainty to decision makers and stakeholders.

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