A framework for joint management of regional water-energy systems

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PhD Thesis
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Preface

The work presented in this PhD thesis was conducted at the Department of Environmental Engineering of the Technical University of Denmark (DTU), from 1 September 2009 to 31 July 2013. Associate Professor Peter Bauer-Gottwein was the main supervisor. Professor Karsten Arnbjerg-Nielsen (DTU) and Adjunct Professor Henrik Madsen (DHI) were co-supervisors.

A stay at the Department of Electric Power Engineering of the Norwegian University of Science and Technology was hosted by Professor Ivar Wangesteen.

The project was funded by the FIVA International School of Water Resources, DHI, and the Technical University of Denmark.

The PhD thesis is based on three papers that have been submitted for international peer-reviewed journal publication.

I. Pereira-Cardenal, S.J., Madsen, H., Riegels, N.D., Jensen, R., Mo, B., Wangensteen, I., Arnbjerg-Nielsen, K., Bauer-Gottwein, P.: Assessing climate change impacts on the Iberian power system using a coupled water-power model. Under revision.

II. Pereira-Cardenal, S.J., Mo, B., Riegels, N.D., Arnbjerg-Nielsen, K., Bauer-Gottwein, P.: Using power market models in the optimization of multi-purpose reservoir systems. Submitted.

III. Pereira-Cardenal, S.J., Mo, B., Gjelsvik, A., Riegels, N.D., Arnbjerg-Nielsen, K., Bauer-Gottwein, P.: Joint optimization of regional water-power systems. Submitted.

The papers are referred to by their Roman numerals throughout the thesis (e.g. Pereira-Cardenal et al. **I**).

In this online version of the thesis, the papers are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request
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Long hours at the University were livened up by all the great people passing through here: my officemates Claire, Claus and Niels; our neighbors Julie, Ida and Sanne; and all the others who left or are about to leave: Ana, Masu, Nanna, Julie, Flavio, Valerie, Laure, Aaron, et al. And thank you to my friends in Denmark; life is wonderful when you have real friends.

Thank you to Blanca for her love and support; and to my brothers, Alfredo and Lenin, for always being there for me. Thank you to my parents Gloria and Ricardo, for their infinite love and inspiration.

Abstract

Water and energy systems are closely linked. Energy is needed in most stages of water usage, while water is needed to extract and process energy resources and generate electric power. However, policy goals associated with providing adequate water and energy supplies are often in opposition, causing conflicts over these two resources. This problem will be aggravated by population growth, rising living standards and climate change, highlighting the importance of developing integrated assessment and solutions.

In this context, this study focused on the interaction between water and electric energy (or power) systems, with the goal of identifying a method that could be used to assess the broader spatio-temporal interactions between water and energy systems.

The proposed method is to include water users and power producers into a joint optimization problem that minimizes the cost of power production and maximizes the benefits of water allocation. This approach turns the multi-objective problem of water and power system management into a single objective one: net costs minimization. The economic value of water is calculated as a function of the state of the system, and this value is used to determine optimal allocations for each time step of the planning horizon. The physical linkages between the two systems are described as constraints in the optimization problem, and the problem is solved using stochastic dynamic programming or stochastic dual dynamic programming.

The method was implemented on the Iberian Peninsula to assess some of the interactions between the water and power system. The impact of climate change on the current Iberian power system was assessed. It was found that expected precipitation reductions will reduce runoff, decrease hydropower production, and increase irrigation water demand; whereas expected temperature increases will modify seasonal power demand patterns.

The proposed approach was also used to determine hydropower benefits in a coupled water-power system, and the results compared with traditional methods that represent hydropower benefits through exogenous prices. It was found that representing hydropower benefits through a constant price can be inadequate because it does not reflect the seasonality in power demand and water inflows, which affect the availability, and therefore value, of hydropower. Monthly prices were able to represent seasonality but resulted in unrealistic operation rules, such as emptying the reservoir during the month

with the highest price, which can only be avoided through the inclusion of additional constraints. In contrast, including a simple representation of the power market into a hydro-economic model resulted in more realistic reservoir operation policies that adapted to changing inflow conditions.

The effects of spatial aggregation on the analysis of water-power systems were evaluated by comparing results from an aggregated and a partially disaggregated model. The aggregated model, where all reservoirs were represented as a single equivalent energy reservoir, provided valuable insights into the management of water and power systems, but only at the Peninsula scale. The disaggregated model revealed that optimal allocations were achieved by managing water resources differently in each river basin according to local inflow, storage capacity, hydropower productivity, and irrigation demand and productivity. This highlights the importance of considering spatial differences in this type of analysis.

The method was successfully used to assess linkages between the water and the power systems of the Iberian Peninsula. The framework is flexible and can potentially be used to model more aspects of the water-energy nexus, for instance: the energy requirements of the transport sector and the impact of biofuels on agriculture; the impact of reduced river discharge on cooling of thermal power plants; or the impact of carbon capture and storage on water resources. The increasing pressure of population growth, rising living standards, and climate change on water, energy, land, and climate systems will increase the need for integrated methods and models to assess the linkages between these systems. The methodological framework proposed here is a step forward in the development of these integrated tools.

Dansk sammenfatning

Vand- og energisystemer er tæt forbundne. Der er behov for energi i de fleste trin i vandforsyning, mens vand er nødvendig for at udnytte og bearbejde energiressourcer og generere elektrisk strøm. Politiske målsætninger om at sikre tilstrækkelig vand og energi er dog ofte modstridende og forårsager konflikter om disse to ressourcer. Dette problem vil blive forværret yderligere af befolkningsvækst, stigende levestandard og klimaændringer, hvilket understreger vigtigheden af at udvikle integrerede vurderinger og løsninger.

Dette studie bygger videre på denne problemstilling, og fokuserer på samspillet mellem vand- og elkraftsystemer, med det mål at identificere en metode, til at vurdere den bredere spatiotemporale interaktion mellem vand- og energisystemer.

Den foreslåede metode kombinerer vandforbrugere og energiproducenter i et fælles optimeringsproblem, hvor omkostningerne til elproduktion minimeres og værdien af vandfordeling maksimeres. Denne metode ændrer managementproblemet af vand- og energisystemet fra at have flere målsætninger til kun at have et enkelt: minimering af nettoomkostningerne. Den økonomiske værdi af vand er beregnet som en funktion af systemets tilstand, og denne værdi anvendes til at bestemme optimale tildelinger for hvert tidskridt i planlægningshorisonten. De fysiske forbindelser mellem de to systemer er beskrevet som begrænsninger af optimeringsproblemet, og problemet er løst ved hjælp af stokastisk dynamisk programmering eller stokastisk dual dynamisk programmering.

Metoden blev implementeret på Den Iberiske Halvø for at vurdere nogle af samspillene mellem vand- og elsystemet. Effekten af klimaændringer på det nuværende Iberiske elsystem blev vurderet. Det blev fundet, at den forventede reduktion af nedbøren vil mindske afstrømningen og produktionen af vandkraft samt øge efterspørgselen på vand til kunstvanding, mens de forventede temperaturstigninger vil ændre den sæsonbestemte efterspørgsel på strøm.

Den foreslåede metode blev brugt til at bestemme værdien af vandkraft i et koblet vand-elsystem, og resultaterne var sammenlignelige med traditionelle metoder, hvor værdien af vandkraft repræsenteres gennem eksterne priser. Sættes værdien af vandkraft til en konstant pris, blev det fundet at sæsonudsvingene i efterspørgslen og afstrømningen repræsenteres dårligt, hvilket kan gøre denne antagelse uegnet. Dette skyldes, at tilgængeligheden

og dermed værdien af vandkraft påvirkes. Månedlige priser kunne repræsentere sæsonudsving bedre, men resulterede i urealistisk management, såsom tømning af reservoiret i løbet af den måned med højest pris, som kun kan undgås gennem inddragelse af yderligere begrænsninger. Tilføjelse af en simpel repræsentation af elmarkedet i en hydro-økonomisk model resulterede derimod i en mere realistisk reservoirmanagement som tilpasses ændringer i afstrømning.

Effekten af en spatial aggregering på en analyse af vand-elsystemer blev evalueret ved at sammenligne resultater fra en aggregeret og disaggregeret model. Den aggregerede model, hvor alle reservoirer var repræsenteret som et enkelt ækvivalent energireservoir, forudsatte værdifuld indsigt i forvaltningen af vand og elsystemer på et generelt plan for hele Den Iberiske Halvø. Den disaggregerede model viste, at optimale allokeringer blev opnået ved at styre vandressourcerne forskelligt i hvert afstrømningsområde i henhold til lokal indstrømning, lagerkapacitet, vandkraftsproduktivitet og kunstvandings-efterspørgsel og -produktivitet. Dette understreger betydningen af at inkludere spatiale forskelle i denne type analyser.

Metoden blev med succes anvendt til at vurdere samspillet mellem vand- og elsystemerne på Den Iberiske Halvø. Metoden er fleksibel og kan potentielt anvendes til at modellere flere aspekter af vand-energi-neksus. Eksempelvis kan nævnes energikrav i transportsektoren og effekten af bioenergi på landbrug, konsekvenser for køling af termiske elværker ved mindre afstrømning i floderne samt effekten på vandressourcerne ved at opsamle og lagre kulstof. Det stigende pres fra befolkningstilvæksten, stigende levestandard, og klimaændringer på vand, energi, jord, og klima, øger behovet for integrerede metoder og modeller til vurdering af forbindelsen mellem disse systemer. Den her foreslåede metodologiske ramme, er et skridt fremad i udviklingen af disse integrerede værktøjer.

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List of abbreviations

CF	Change factor
DP	Dynamic programming
FCF	Future cost function
IP	Iberian Peninsula
LP	Linear programming
MIBEL	Iberian Power Market
RCM	Regional climate model
SDDP	Stochastic dual dynamic programming
SDP	Stochastic dynamic programming
WVT	Water Value Table

1 Introduction

Water and energy systems are closely linked. Energy is needed to extract, treat and distribute water, and to collect and treat wastewater; whereas water is needed to extract primary energy, refine fuel, and generate electric power (Olsson, 2012). However, policy goals associated with providing adequate water and energy supplies are often in opposition (Hoffman, 2010), causing serious conflicts in many regions of the world (Gleick, 1993a; Olsson, 2012).

This problem will be exacerbated by growing population, rising living standards (that increase demand for more and better water and energy supply), and climate change (King et al., 2008; Hoffman, 2010).

Even though many aspects of this interdependency were described two decades ago by Gleick (1993b; 1994), the realization of the importance of assessing this issue and the need to find integrated solutions is recent (e.g. Hoffman, 2004; DOE, 2006; King et al., 2008; IEEE, 2010; Olsson, 2012).

One way of assessing linkages between water and energy systems is through spatio-temporal models. Models provide an efficient way of analyzing spatial and temporal data to estimate the interaction and impacts of components under different design and operating policies and can be used to evaluate alternative ways of meeting management objectives (Loucks and van Beek, 2005).

However, modeling water and energy systems jointly is a difficult task because of the complex connections and feedbacks between these two systems and with other systems. For instance, in 2004 the energy supply and transportation sectors accounted for 25.9% and 13.1% of global anthropogenic green house gas emissions respectively (IPCC, 2007), thereby contributing to climate change which may in turn modify energy demand (Isaac and van Vuuren, 2009) and reduce hydropower generation potential (Lehner et al., 2005; Schaefli et al., 2007; Vicuna et al., 2008). At the same time, biofuel production —aimed at reducing emissions from the transport sector— has a negative impact on water resources and food production (de Fraiture et al., 2008; IEEE, 2010), and the future deployment of carbon capture and storage facilities to reduce emissions from the energy sector will increase pressure on water resources (IEEE, 2010). This example illustrates the complex interconnection between water and energy systems that is known as the *water-energy nexus*.

Recognizing the problem's complexity, the focus of this study is on the interaction between water and electric energy (or power) systems, in an attempt to find methods that can be used in dealing with the water-energy nexus.

Joint modeling of water and power systems is difficult because of differences in their spatio-temporal scales and their current management. First, power systems typically span an entire country or region and power supply must meet demand on a second-by-second basis. In contrast, water systems are spatially defined by a catchment area and hydraulic connections; and the water storage in rivers, lakes, groundwater, reservoirs and other water infrastructure allows some flexibility in balancing supply and demand. Second, the current management of these systems is markedly different: electricity is commonly traded in a wholesale market, while water is allocated using a wide variety of water rights regimes (Bruns et al., 2005).

In this context, the PhD study was focused on applying optimization techniques to model the water and power systems of the Iberian Peninsula (IP) jointly, with the goal of developing a method that can be used to assess the water-energy nexus.

The main objectives of this research were to:

- Develop a method to model the spatial and temporal interactions between water and power systems.
- Improve the representation of hydropower benefits in hydro-economic models.
- Evaluate the influence of spatial aggregation on water-power analysis.
- Assess some of the potential impacts of climate change on the water-power system of the IP.

This thesis provides a summary of the three papers submitted for publication as part of the PhD study, as well as an overview of the methods and the main findings of the investigation. It is structured as follows. Chapter 2 reviews relevant literature. Chapter 3 presents the case study area where the proposed methods are applied. Chapters 4 and 5 provide an overview of the methods and the main results, respectively. Chapter 6 summarizes the conclusions of this study and Chapter 7 lists the future research directions identified throughout this project. Chapter 8 includes the list of references, and Chapter 9 the three scientific papers.

2 Context

2.1 Economic resource allocation

Economics is generally regarded as the study of allocation of scarce resources. While energy and water resources are abundant in nature, their availability varies widely in time and space, resulting in local scarcity. The allocation of these resources should therefore be efficient in order to maximize the net benefits that society as a whole can derive from their usage. In the following, concepts relevant to the application of economic criteria in the allocation of water and power resources are introduced.

2.1.1 Power markets

There are important differences between electrical energy and other commodities (Kirschen and Strbac, 2004):

- The physical system is faster than any market.
- Supply and demand must be balanced on a second-by-second basis.
- Power produced by different generators is undistinguishable and is pooled on its way to the consumers.
- The demand is cyclical and predictable.
- Because production facilities must follow large changes in demand, base-load energy is produced by different generating units than peak-load energy, and at different prices.

Electricity sectors evolved with state- or privately-owned vertically integrated geographic monopolies that were subject to price and entry regulation, where an individual electric utility provided the primary components of electricity supply: generation, transmission, distribution, and retail supply (Joskow, 2006). Since the mid-1980s, several countries introduced market reforms including liberalization, privatization and/or restructuring of the electricity supply sector in order to make the industry more efficient, prices more transparent, and transfer the risks from consumers to suppliers (Sioshansi, 2008). The extent of restructuring and its outcome varies from case to case, and has been subject to comprehensive reviews in the electricity market literature (see Sioshansi and Pfaffenberger, 2006; Al-Sunaidy and Green, 2006; Williams and Ghanadan, 2006; Sioshansi, 2008).

Deregulated power markets are typically organized around two instances depending on the time horizon: short-term trading is done in a pool market,

whereas medium- and long-term trading is done in a futures market (Conejo et al., 2010).

The pool is composed of day-ahead, adjustment, and balancing markets. In the day-ahead and adjustment markets, generators submit offers to produce (a certain amount of power at a certain price for a given time period) while retailers and large consumers submit bids to buy (an amount of power at a given price and period); the data are used to construct the supply and demand functions, and their intersection represents the market equilibrium and provides the market clearing price and the traded quantity (Conejo et al., 2010). The balancing market is cleared through an auction on hourly (or smaller) basis and covers for generation deficit and excess (Conejo et al., 2010).

The futures market is an auction market where participants trade physical or financial products for future delivery and it is used to hedge against the uncertainties in future pool price (Conejo et al., 2010). There may also be bilateral trading between producers and consumers, reserve markets (to cover for technical failures or unanticipated fluctuations in demand and supply) and regulation markets (to follow the demand in real-time), but these are outside the scope of this study.

2.1.2 Economic water allocation

Water is essential for life. This was acknowledged by the United Nations General Assembly in Resolution A/64/292, in which it "recognizes the right to safe and clean drinking water and sanitation as a human right that is essential for the full enjoyment of life and all human rights" and calls upon states to help "scale up efforts to provide safe, clean, accessible and affordable drinking water and sanitation for all".

Besides covering basic human and ecosystem needs, water is used as input to production processes, as a diluting agent, and as an aesthetic/recreational good; therefore, its economic value should also be acknowledged. The fourth Dublin Principle states that "water has an economic value in all its competing uses and should be recognized as an economic good", and that "past failure to recognize the economic value of water has led to wasteful and environmentally damaging uses of the resource" (UN, 1992). This has been also recognized in the European Union through the Water Framework Directive, which requires member states to use economic principles and instruments in water management and policy making in order to provide adequate water for sustainable, balanced and equitable water use; to reduce

groundwater pollution; and to protect territorial and marine waters (EU Comission, 2000).

The *First theorem of welfare economics* states that an equilibrium allocation achieved by a set of competitive markets will be a Pareto-efficient allocation (Varian, 2006), so under ideal market conditions the individual pursue of profit or utility maximization by market agents (consumers and producers) will result in society's economic efficiency.

However, market failures are common when dealing with water resources because (Griffin, 2006): a) some water uses constitute a *public good*, b) certain uses generate *externalities*, c) water supply is often a *natural monopoly* and d) privately motivated agents tend to *overdiscount* the future value of water, leading to low conservation of depletable resources and low investment in long-term projects. Other concerns include issues of equity, imperfect information, and high transaction costs.

Despite these difficulties, several methods have been designed for economic valuation of water use for different sectors, including irrigation agriculture (Johansson, 2000), ecosystems (Perman and Perman, 2003), industry and municipal use (Young, 2005).

Hydro-economic models have been used to incorporate economic criteria in the identification of allocation options that improve efficiency and transparency in water use (Harou et al., 2009). Hydrologic, agronomic and economic relationships are integrated into modeling frameworks that maximize (minimize) the benefits (costs) of water uses, including irrigation, urban water uses and ecological uses (e.g. Cai et al., 2003; Draper et al., 2003; Jenkins et al., 2004; Pulido-Velazquez et al., 2008; Tilmant et al., 2008). Harou et al. (2009) present a recent overview of hydro-economic models and examples of their application for different purposes.

There are ways of considering equity in hydro-economic models. For instance, Tilmant et al. (2009) propose redistributing the benefits gained by optimal allocation in a two step approach. First, an optimization model is used to determine economically efficient allocation policies that maximize basin-wide net benefits. Second, financial compensations are calculated such that: a) users whose water allocation is curtailed receive compensations at least equal to their foregone benefits, and b) users experience higher

allocations contribute to the compensations in proportion to their productivity.

2.2 Reservoir optimization

Hydropower reservoirs play a central role in the interaction between water and power systems because the water can be readily used to generate electricity or to satisfy water demands, and because they provide the most effective means of storage. Optimal operation of reservoir systems consists in determining a sequence of reservoir releases (and resulting volumes) that maximize or minimize a performance criterion, while complying with physical and management constraints.

Dynamic programming (DP) is among the most popular reservoir optimization techniques, because it decomposes the multi-stage reservoir problem into a series of simpler sub-problems which can be non-linear and stochastic (Rani and Moreira, 2010). DP and stochastic DP (SDP) have been extensively used in water resources management (Yakowitz, 1982). Other optimization methods, including non-linear programming, optimal control theory, and heuristics are reviewed by Labadie (2004) and Rani and Moreira (2010).

SDP can be used to obtain optimal release or storage policies, the latter being of special interest to reservoir operators (Labadie, 2004). Rational reservoir operation rules can also be obtained through the *water value method* (Stage and Larsson, 1961). The method consists of calculating the cost-to-go function for each stage (time period) through the traditional Bellman formulation, and then taking the derivative of such costs with respect to the reservoir level. The result is a *water value table* that shows the expected value of a marginal amount of water (as a function of the storage, the inflow state, and the stage) if it is stored for later use. These values are then used as marginal costs of hydropower in a hydro-thermal system simulation (e.g. Wolfgang et al., 2009).

Optimization techniques based on DP have a major limitation: the need to discretize the state variables results in exponential growth of memory and computational requirements as the number of state variables increases. This limitation, known as the *curse of dimensionality*, limits the applicability of DP methods to systems of three or four reservoirs (Labadie, 2004). The issue becomes more severe in the stochastic case, because the stochastic variable

(typically the inflow) is added to the state vector and must also be discretized.

Extensions to DP have been proposed to overcome the issue of dimensionality, as discussed by Labadie (2004) and Rani and Moreira (2010). Various aggregation techniques have also been used (Turgeon, 1980; Saad et al., 1996; e.g. Archibald et al., 1997), but they inevitably result in loss of information during the aggregation process (Labadie, 2004).

Stochastic Dual Dynamic Programming (SDDP), a method developed within the electric power community by Pereira and Pinto (1991), has been used to optimize large systems without facing the dimensionality limitations. SDDP combines DP (which can handle a large number of stages but only a few states) with Benders decomposition (which can handle a large number of states but only a few stages) to optimize systems of many reservoirs. The method iterates between stochastic simulation and optimization phases until a sufficiently good solution is found. SDDP has recently received increased attention in the water resources community and was successfully applied to optimize the operation of multi-purpose reservoir systems (e.g. Tilmant and Kelman, 2007; Goor et al., 2011).

SDDP relies on linear programming to approximate the cost-to-go function through hyperplanes. The issue of dimensionality is overcome, but this requires the problem to be linear (or at least convex), thereby removing some of the advantages of DP-based methods.

3 Case study: The Iberian Peninsula

The IP is a good study case to assess some of the components of the water-energy nexus, because:

- There are strong interdependencies between water and energy systems.
- Some of these interdependencies may be affected by climate change.
- The hydrological and the power systems are shared between the two countries, with small exchanges with other countries.

Figure 1 shows the major components of the hydrological system and the power system of the IP. It is clear that most power generation plants are located next to water bodies: hydropower in mountains and river valleys that provide sufficient head, and thermal power next to rivers, lakes and the sea that secure a steady source of cooling water. Transmission lines tend to follow the rivers, possibly because power generation and human settlements — the major centers of power consumption— are located next to water bodies.

In order to quantify some of the linkages between water and energy systems, the proposed method is to couple a model of the water system with a model

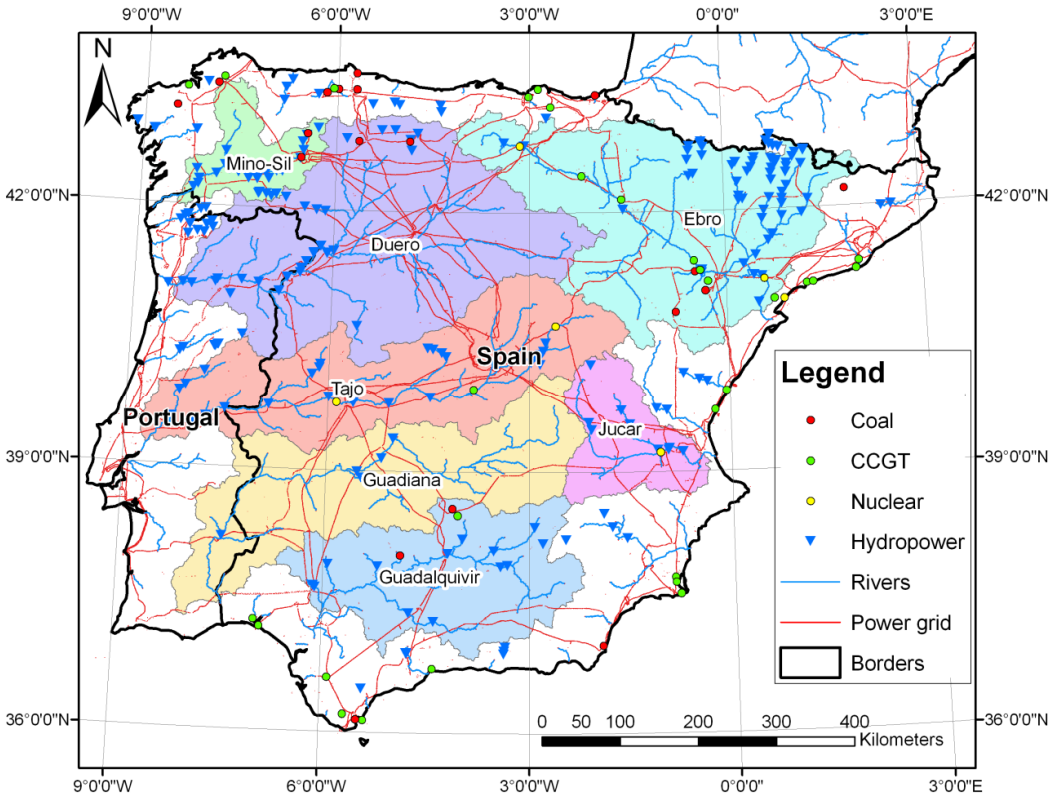

Figure 1. Hydrological and power system of the IP. Only 400 kV lines are shown. (MARM, 2012; SNIRH, 2012b; REE, 2013).

of the power system. The coupled problem becomes a resource allocation problem which is solved by reservoir optimization methods using economic principles.

The Iberian hydrological system was represented through a rainfall-runoff model and an aggregated model of the hydropower reservoirs. The power system was modeled through an inelastic power demand and a simple power supply function. Power demand was always satisfied, whereas water demands (from different users) were satisfied only if the allocations minimized total expected costs.

For simplicity, only irrigation and hydropower were included as water users in this implementation. In Spain, agricultural demand represents 75% of total consumption, while residential and industrial demands represent 17% and 6%, respectively (MMA, 2007). In the Spanish river basins included in the model, irrigation exceeds 75% of total consumption except for Tajo and Miño-Sil, with 52% and 17%, respectively (MMA, 2007). The situation is expected to be similar in the Portuguese portion of these catchments. Nevertheless, residential, industrial, and ecological uses can be easily included in the model as constraints (i.e. the total or a fraction of the demand must be satisfied) or as decision variables (through a demand function).

In this chapter, a few aspects of the water and energy nexus in the IP are introduced. The representation of the Iberian hydrological and power systems is described. The expected impacts of climate change on hydrology and the power system are estimated.

3.1 The water-energy nexus

Water and energy systems are tightly coupled in the IP. The water needs of the energy sector and the energy needs of the water sector in Spain have been assessed by Carrillo and Frei (2009) and Hardy et al. (2012), respectively. In Spain, the water sector accounts for 5.8% of total energy demand, and the energy sector accounts for 3.2% of total water consumption and 25% of withdrawals (Hardy et al., 2012). Hardy and Garrido (2010) describe additional linkages between the water and energy systems in Spain, including the following:

- Power is the main variable cost factor in all stages of water usage.
- Efficiency of irrigation systems has increased at the expense of much higher electricity consumption.

- Production of biofuels, which is encouraged by European climate change mitigation policy, requires a considerable amount of water for irrigation and processing, and competes for land and water resources with traditional crops.
- Some renewable energy sources with high potential in dry areas may become problematic if their water demands cannot be guaranteed.

In most cases, climate change may exacerbate the problem. According to MMA (2005), changes in the hydrological system may affect Spanish energy policy by: a) reducing hydropower generation, b) increasing power demand from new desalination plants, and c) increasing power consumption for groundwater pumping and conveyance in order to cover new water deficits. Furthermore, new release policies aimed at satisfying agricultural demands (over hydropower) may reduce power generation (MMA, 2005). Climate change may also affect the Spanish power system by (MMA, 2005): a) reducing the efficiency of the Rankine cycle (used in thermal generation), b) increasing the environmental impact of cooling towers, and c) reducing transmission capacity. No such assessments were found for Portugal, but the situation is expected to be similar.

3.2 Hydrological system

The IP covers an area of 583 000 km^2. Its location and topography, combined with the effects of atmospheric circulation patterns create a precipitation gradient with high precipitation in the northwest and low precipitation in the southeast (Lorenzo-Lacruz et al., 2013). This causes strong variations in the distribution of water resources among the basins: the Miño-Sil, Duero, Tajo and Ebro (in the northern half of the country) have high annual discharge; Guadiana and Guadalquivir have modest discharge; and Jucar and Segura, in the southeast of the Peninsula have low annual discharge.

These differences in the spatial distribution of water resources, and the differences in the temporal distribution of precipitation have been compensated by the construction of a large number of dams that allows for the regulation of 40% of the natural annual flows in Spain alone (Berga-Casafont, 2003).

3.2.1 Rainfall-runoff model

The seven major basins of the Peninsula were divided into three subcatchments each and a rainfall-runoff model was setup for the 21 resulting subcatchments. The rainfall-runoff model was implemented in NAM (Nielsen and Hansen, 1973), a lumped conceptual modeling system with water balance

Table 1. Source and spatio-temporal resolution of the datasets

Data	Source	Spatial resolution	Temporal resolution
Precipitation (ES)	Spain02 (Herrera et al., 2012)	0.20°	daily
Precipitation (PT)	PT02 (Belo-Pereira et al., 2011)	0.20°	daily
Temperature	E-Obs (Haylock et al., 2008)	0.22°	mean daily
Reference evapotranspiration	Function of temperature (Oudin et al., 2005)	0.22°	mean daily
Discharge (ES)	CEDEX (2012)	38 stations	mean daily
Discharge (PT)	SNIRH (2012b)	5 stations	mean daily
Irrigation water demand	Wriedt et al. (2009)	10 × 10 km	mean annual

equations in four storages that represent the land phase of the hydrological cycle: snow storage, surface storage, lower soil zone storage and groundwater storage. The model requires daily precipitation, reference evapotranspiration and air temperature inputs, as well as river discharge for calibration. The source and resolution of the data used in the model are shown in Table 1.

Details on the calibration and validation procedure are available in Pereira-Cardenal et al. **I**. The calculated runoff was used to generate energy inflow time series using an aggregation methodology also described in Pereira-Cardenal et al. **I**.

3.2.2 Hydropower reservoirs

There are 116 hydropower reservoirs with installed capacity above 10MW in the IP, representing approximately 85% of total hydropower capacity. Because of the *curse of dimensionality* mentioned above, the reservoirs were converted to one or several equivalent energy reservoirs, using the method detailed in Pereira-Cardenal et al. **I**. The data needed for this aggregation procedure (reservoir head, installed capacity, minimum and maximum volume, and mean annual inflow) were obtained from (2012) for Spain, and from SNIRH (2012a) and EDP (2012) for Portugal.

3.2.3 Irrigation demand

Mean annual irrigation requirements were extracted from the distributed irrigation dataset in Wriedt et al. (2009). Figure 2 shows these data and the river basins used in this study. Annual precipitation estimates available from the dataset were added to the annual irrigation requirements to obtain total water demand. This was done to later subtract precipitation estimates (for the control and the climate change scenarios) from the total water demand in order to obtain irrigation water requirements under control and climate change scenarios. The annual values were distributed over the months of the year in proportion to observed monthly requirements in the Ebro Basin (J. Galvan, personal communication, 10 August 2012), i.e. it was assumed that all catchments had the same temporal irrigation pattern. Irrigation data were also converted to

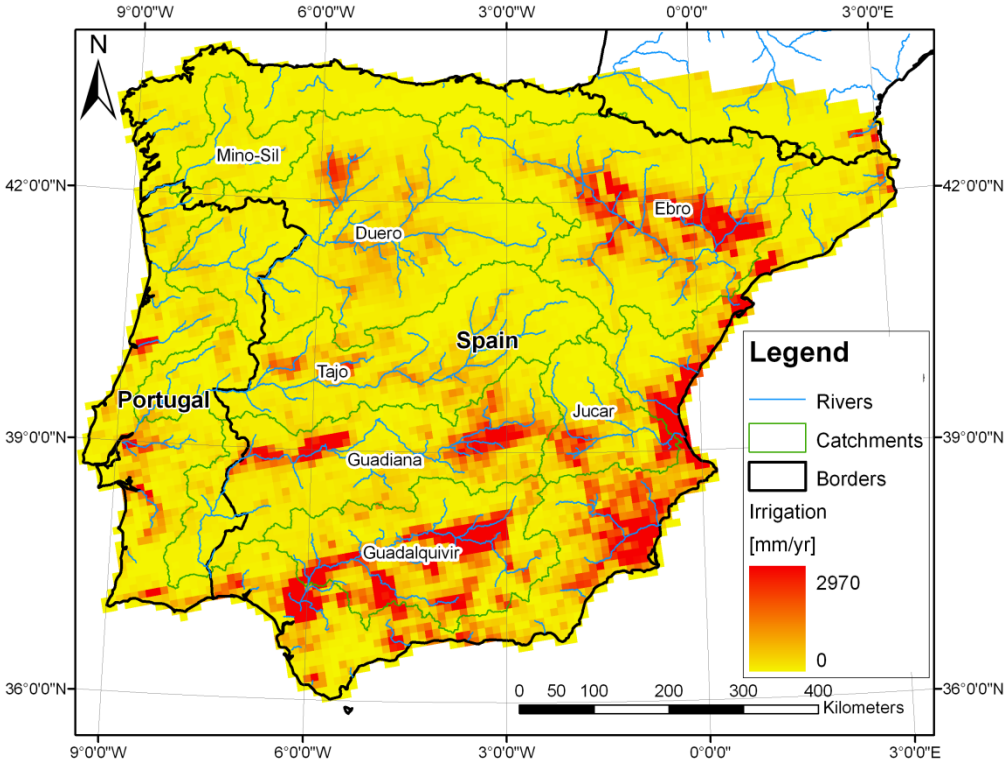

Figure 2. Mean annual irrigation requirements (source: Wriedt et al., 2009).

energy units, using an aggregation methodology briefly described in Section 4.1 and detailed in Pereira-Cardenal et al. **I**.

In the optimization methods used to couple the water and energy systems, irrigation allocation was considered as a constraint that must be satisfied (Pereira-Cardenal et al. **I**), or as a decision variable that is adjusted to achieve maximum benefits (Pereira Cardenal et al. **II**, **III**). In the second case, an irrigation demand function must be used in order to determine optimal water allocation.

Two demand functions were used based on the spatial scale of the problem and data availability. In Pereira-Cardenal et al. **II**, which considers irrigation aggregated at the peninsula level, net benefits and allocation distribution among crops in Spain (MMA, 2007) were used to construct the demand function shown in Table 2. In Pereira-Cardenal et al. **III**, which considers irrigation aggregated at the river basin level, data on annual water allocations for ranges of net benefits in each river basin in Spain (MMA, 2007) were used to define irrigation users as follows (Table 3). A constant willingness to pay for water was assumed for all water allocations, and the net benefits were used as a proxy for marginal benefits. The annual values were also distributed in proportion to monthly observations in the Ebro Basin, and converted to energy units.

Table 2. Irrigation allocations and marginal benefits per crop

Crop	Marginal benefits [€/m^3]	Irrigation allocations [10^6m^3/yr]
Cereals	0.03	4060.08
Rice and Corn	0.07	5924.34
Other crops	0.23	6180.83
Citrus	0.35	2613.40
Olives	0.44	1471.70
Fruits (non-citrus)	0.47	1382.55
Vines	0.53	636.54
Vegetables	1.16	891.47
Protected*	3.57	331.56
Total	**0.28**	**23489.35**

*: high-value vegetables grown in greenhouses

Table 3. Irrigation allocations and marginal benefits per basin

River basin	Total allocation	Allocation distribution [%] (at given marginal benefit [€/m^3])									Coefficients** [GWh/hm^3]	
	[10^6 m^3/yr]	0.003*	0.010*	0.017*	0.11	0.30	0.50	0.80	2.0	4.0	u	g
Tajo	1840.94	10.5	10.5	10.5	48.6	1.7	4.9	2.5	10.9	0.0	0.22	0.17
Ebro	5827.83	3.9	3.9	3.9	43.9	22.5	19.8	1.3	0.7	0.0	0.05	0.16
Duero	2515.44	7.7	7.7	7.7	55.8	15.5	5.2	0.5	0.0	0.0	0.35	0.47
Guadalquivir	6824.33	6.9	6.9	6.9	32.6	28.7	12.5	4.4	0.6	0.5	0.01	0.02
Guadiana	4726.59	16.3	16.3	16.3	24.2	3.8	12.5	3.0	7.7	0.0	0.20	0.04
Jucar	1630.56	2.1	2.1	2.1	30.6	20.6	30.7	10.8	0.6	0.4	0.07	0.13
Miño-Sil	123.66	3.0	3.0	3.0	18.2	0.0	72.7	0.0	0.0	0.0	0.08	0.51
Total	**23489.35**	**6.9**	**6.9**	**6.9**	**37.0**	**18.2**	**15.6**	**4.9**	**2.7**	**0.9**	**0.115**	**0.128**

*: In the original data these three demand brackets were part of one bracket with a net benefit range of 0 – 0.02 €/m^3.
In this implementation, the bracket was divided in order to make a more gradual representation of the marginal benefits.
**: *u* and *g* are energy conversion coefficients explained in Section 4.1.

Because of lack of data, it was assumed that all demands have the same temporal distribution, and that the data for Spain (irrigation distribution among crops and net benefit ranges) are representative for Portugal. Despite significant groundwater abstractions in many river basins, irrigation was modeled as a surface water user; it was assumed that groundwater abstractions will eventually result in river discharge reductions. This assumption ignores abstractions from aquifers that are not connected to surface water, and over-abstraction (abstractions that exceed recharge).

Due to the coarse spatial scale of the model, only the consumptive use of irrigation was considered. The portion of the abstractions for leaching of salts and to compensate for application efficiency will return to the system, so *return flows* were ignored.

3.3 Power system

The Iberian Electricity Market (MIBEL) was created in 2007 by the combination of the Spanish and the Portuguese electricity markets. The functioning of the MIBEL follows the description of deregulated power markets in Section 2.1.1.

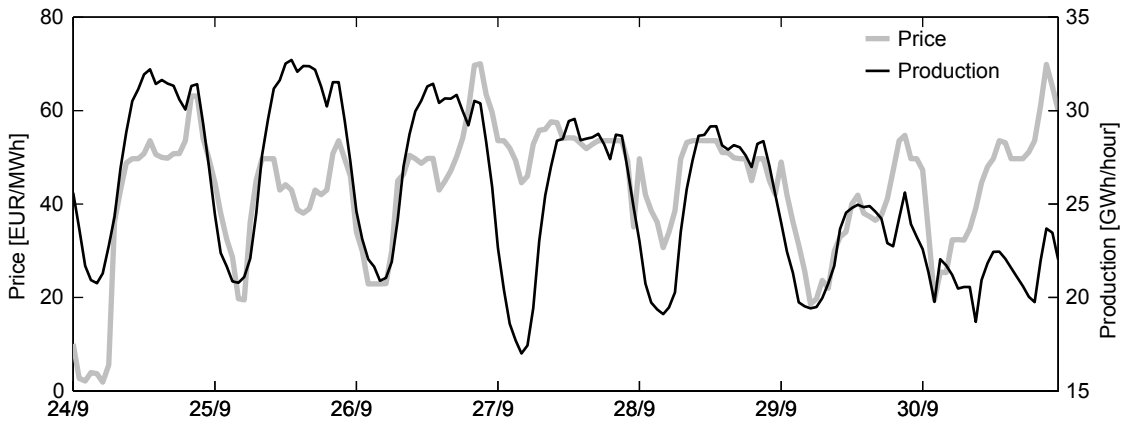

Figure 3. Hourly production and price in the MIBEL, September 2012 (OMIE, 2012).

Production in the MIBEL follows the typical yearly, weekly and daily patterns, as shown in the figures below. Figure 3 shows the hourly power production and prices in the MIBEL during the last week of September, 2012. As mentioned above, the hourly price varies considerably as a function of the demand. When demand is lowest, typically from 02:00 to 05:00, only the cheapest power plants remain in production, so the price is low. During peak hours, more production plants have to go on line in order to satisfy demand, raising the price. The very low prices during the early hours of September 24 are due to high wind speeds that resulted in a record production of wind power (REE, 2012).

The daily power production and prices are shown in Figure 4. The weekly production pattern is clear: production decreases considerably during weekends, and increases again with the resumption of economical activities on Monday. The price patterns are less clear, possibly because of climatic factors and data aggregation.

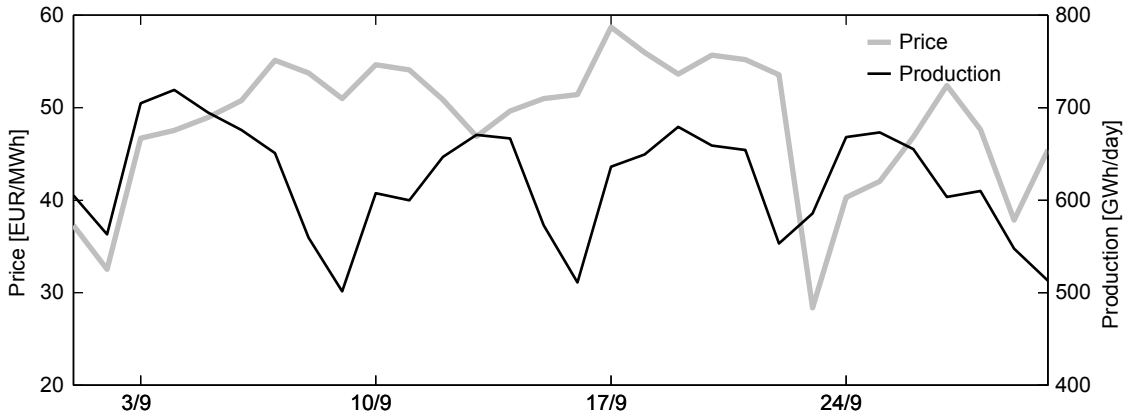

Figure 4. Daily production and price in the MIBEL, September 2012 (OMIE, 2012).

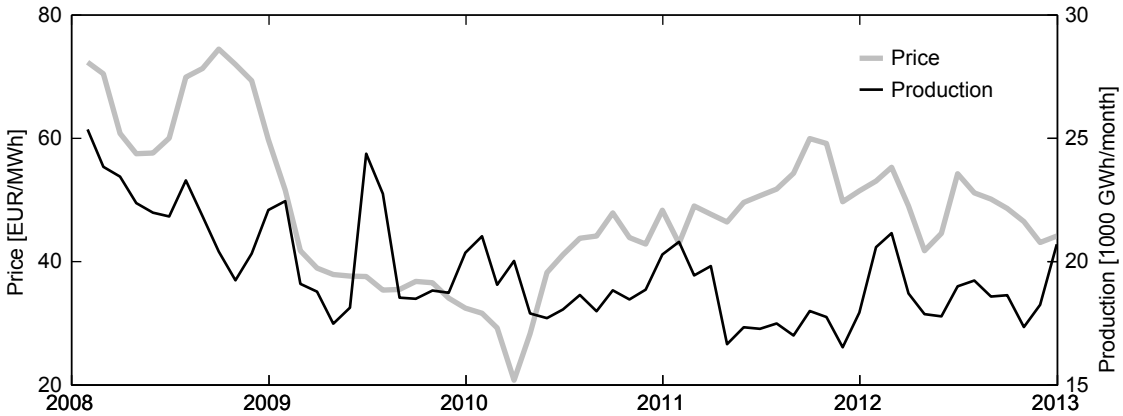

Figure 5. Monthly production and price in the MIBEL, 2008 – 2012 (OMIE, 2012).

Finally, Figure 5 shows power production and prices from January 2008 – December 2012. Some patterns are visible, for instance, generation always increases during the winter in order to cover winter demands. However, the patterns are less clear because of the economic crisis in Spain and Portugal, which lowered power demand considerably, and the low oil prices during 2009, which lowered electricity prices.

The following sub-sections describe how the power demand and supply were simulated in the model.

3.3.1 Power demand

The power demand was assumed inelastic and was calculated through the heating and cooling degree-day approach presented by Valor et al. (2001). The method uses linear regressions to estimate daily power demand based on population and daily temperature data. Population data were obtained from LandScan (Bright et al., 2008), mean daily temperature from E-Obs' gridded product (Haylock et al., 2008), and electricity demand from OMIE (2012). More details can be found in Pereira-Cardenal et al. **I**.

3.3.2 Power supply

Two different representations of the power supply function were used according to the research objectives. In Pereira-Cardenal et al. **I**, which assesses the impact of potential climate change on the power system, power generation was simulated as four different technologies with a constant marginal cost obtained from CNE (2008). In Pereira-Cardenal et al. **II** and **III**, which consider economic resource allocation, a more detailed power supply function was empirically constructed from the hourly market results (clearing price and production), as explained in Pereira-Cardenal et al. **II**. The power supply

Table 4. Characteristics of generation technologies

	Installed capacity [MW]	Marginal costs [€/MWh]	Observed production [GWh/yr]	Emission factor [ton CO_2/MWh]
Nuclear	6 392	18	57 864 (17.8%)	0
Coal + CCGT	40 242	57	129 443 (40.4%)	0.584
Hydropower	19 490	-	37 880 (11.6%)	0
Special regime*	28 519	-	98 393 (30.2%)	0.107

*: Special regime is a group of technologies (60% renewable) in the MIBEL that are always cleared regardless of the price.

functions are shown in Table 4 and Table 5. Further details can be found in the corresponding papers.

Table 5. Supply function excluding hydropower and special regime

Generation segment	Marginal costs [€/MWh]	Gen. capacity [MWh/week]
1	0.00	500 000
2	17.61	500 000
3	39.39	500 000
4	46.15	500 000
5	50.50	500 000
6	59.36	500 000
7	63.99	500 000
8	67.76	500 000
9	70.50	500 000
10	75.49	500 000

3.4 Climate change

A climate change scenario was developed to assess the impact of possible climate change on the Iberian power system. The scenario included a description of future inflows, irrigation demand, and power demand; and was created by recomputing these datasets using climate change estimates of precipitation, temperature and reference evapotraspiration.

Precipitation and temperature time series under the climate change scenario were generated through the *delta-change* method, in which the average monthly change (or change factor, CF) in climate model output between control and future simulation periods is used to scale observed daily precipitation and temperature data (Fowler et al., 2007). The reservoir optimization algorithm is run in weekly time steps (Section 0); therefore, more sophisticated methods that better represent extreme values were not used because these values would be averaged out.

CFs were calculated for three regional climate models (RCM) from the ENSEMBLES Project (van der Linden and Mitchell, 2012). The RCMs from this project use the A1B emissions scenario, which assumes a world of very rapid economic growth, a population that peaks by 2050, quick spread of new and efficient technologies, and a balanced emphasis on energy sources (Nakiâcenoviâc et al., 2000). The three RCMs that perform best over the IP (Herrera et al., 2010) were used (Table 6).

Table 6. Regional climate models used to derive change factors

Model	Institution	Reference
CLM	Swiss Institute of Technology (ETHZ)	Jaeger et al. (2008)
M-REMO	Max Planck Institute for Meteorology (MPI)	Jacob et al. (2001)
RACMO	Koninklijk Nederlands Meteorologisch Instituut (KNMI)	van Meijgaard et al. (2008)

The three sets of monthly CFs were averaged to obtain a single set of monthly precipitation and temperature CFs for each catchment, which were then applied to observed data (1961–1990) in order to generate climate change (2036–2065) precipitation and temperature series. The monthly temperature and precipitation CFs over the IP are shown in Figure 7 and Figure 8, respectively. The temperature series was used to generate reference evapotranspiration estimates for the climate change scenario.

Irrigation water demand in the IP will be higher because of increased evapotranspiration and reduced precipitation. Monthly changes in calculated evapotranspiration were applied to total water demand, and the climate change precipitation series were subtracted to obtain future irrigation water demands.

Changes in seasonal temperature patterns will also affect power demand patterns. Power demand time series for the climate change scenario were estimated from the corresponding temperature series as described in Section 3.3.1. A comparison of the estimated annual energy inflows, energy demand, and irrigation demand for the control and climate change scenarios is shown in Figure 6.

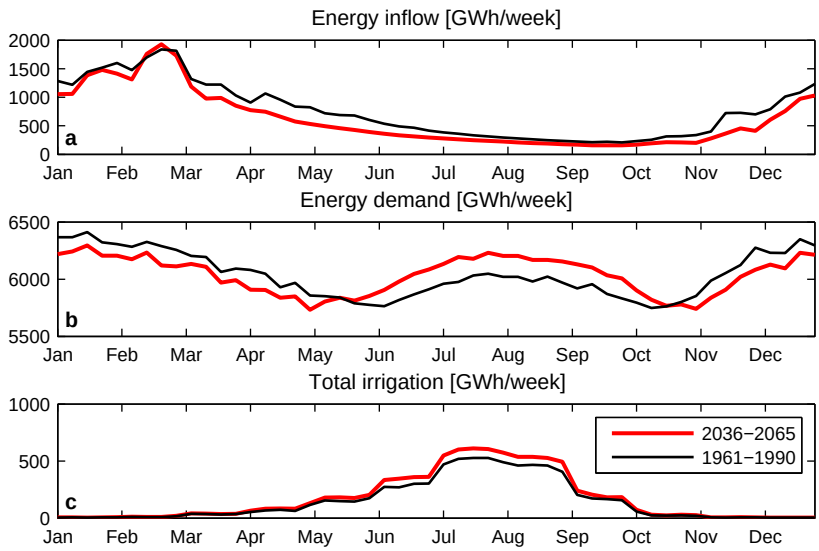

Figure 6. Changes in energy inflows, energy demand and irrigation demand.

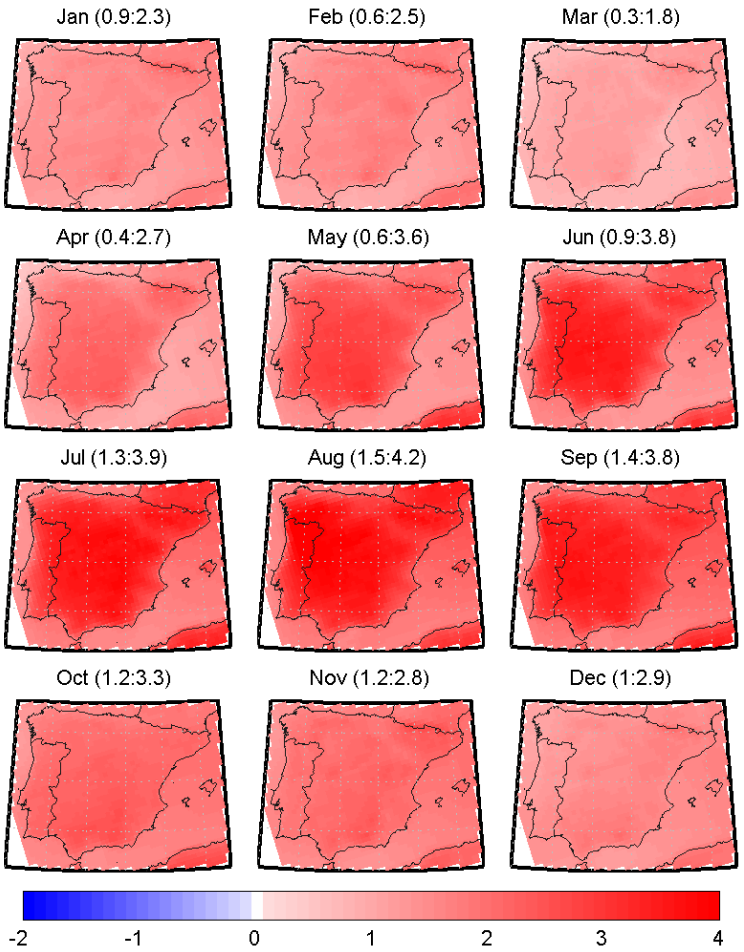

Figure 7. Temperature change factors 2036–2065 v. 1961–1990 [°C]. Numbers in parenthesis show the min and max change factor found.

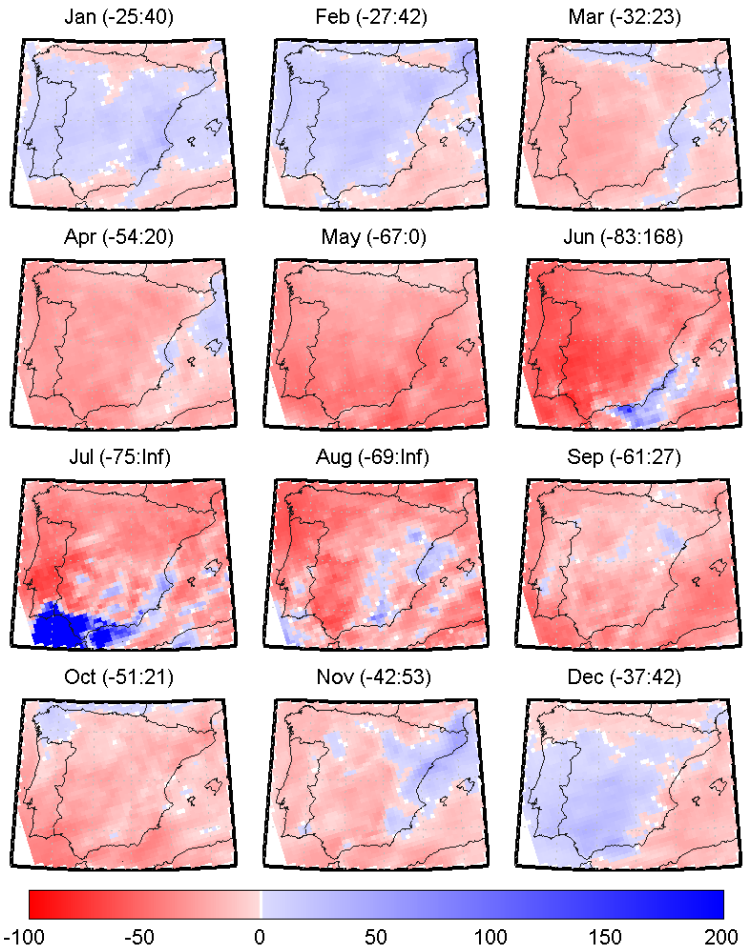

Figure 8. Precipitation change factors 2036–2065 v. 1961–1990 [%]. Numbers in parenthesis show the min and max change factor found.

4 Methods

In the previous section, some of the aspects of the water-energy nexus in the IP were introduced; the representation of the hydrological and power system model was described; and the procedure to estimate the impacts of climate change on the hydrological and power system was outlined. Following from the presentation of economic resource allocation in Section 2.1, a framework to manage water and power systems jointly is proposed.

The framework consists in combining the water and power system in a joint economic optimization problem, as shown in Figure 9. Water availability is estimated through a rainfall-runoff model, and the main water users are described through either demand functions or constraints. Power availability and needs are represented through supply and demand functions, respectively. Because hydropower production has a low direct variable cost but a high opportunity cost, the economic value of hydropower is determined by the optimization algorithm depending on the cost of alternative power generation technologies.

All these components enter the optimization problem as part of the objective function or the constraints. The objective function is the measure of model performance (e.g. cost minimization) and is composed of decision variables and cost parameters. The decision variables are the choices available to the decision maker, like irrigation allocations, hydropower releases, and alternative power generation; and its values are to be determined by the model. The cost parameters are the coefficients in the objective function, and determine the gains or losses of the values assigned to the decision variables. These include irrigation marginal benefits and generation marginal costs.

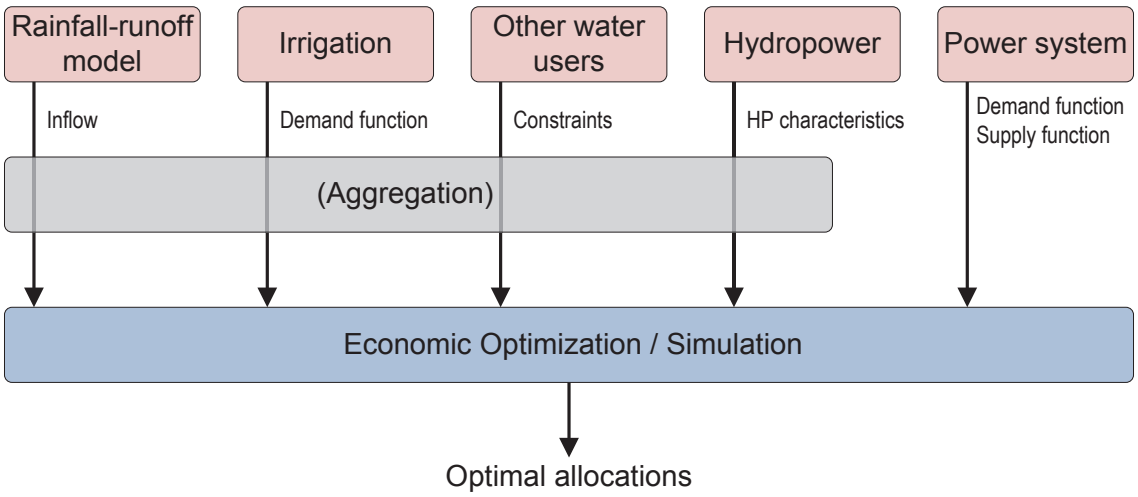

Figure 9. Water-power modeling framework.

The constraints are mathematical expressions of the limitations that restrict the alternatives of the decision makers, such as minimum irrigation allocations, maximum power generation (installed capacity), minimum ecological flows or maximum hydropower releases. The power and the water balance are also described as constraints, using the estimated power demands and water inflows.

When solved, the optimization problem provides optimal values for each decision variable over the planning horizon. These values are optimal with respect to the chosen performance criterion, which in this case is net costs minimization.

Hydropower reservoirs make the problem more computationally demanding because their storage couples successive time steps. It may be necessary to reduce the number of reservoirs sent to the optimization algorithm by using aggregation techniques. However, this is optional and depends on the number of reservoirs in the system and the ability of the algorithm to handle multiple reservoirs.

The reservoir aggregation technique and the optimization algorithms used in this study are described in the following sections.

4.1 Reservoir aggregation

Because of *curse of dimensionality* mentioned above, it is not possible to use discrete DP methods to optimize more than three or four reservoirs simultaneously. Therefore, the volumes and flows representing the hydrological system were converted to power and energy units, respectively, and aggregated into *equivalent energy reservoirs*.

Two aggregation levels were applied depending on the optimization method. When using SDP, the seven major river basins of the IP were aggregated into one equivalent reservoir; when using SDDP, each river basin was aggregated into one equivalent reservoir, resulting in a system of seven reservoirs in parallel.

Three conversion factors are used in the aggregation methodology (Table 7). The *energy equivalent of catchment runoff* is a conversion factor based on the hydropower equation that expresses the full hydropower potential of the runoff generated in the catchment. The other two factors deal with irrigation: the *energy equivalent of catchment outflow* indicates the amount of energy that is lost when water is allocated to upstream irrigation, and the *average energy*

Table 7. Water to energy conversion factors [kWh/m^3]

Conversion factor	Symbol	Definition
Energy equivalent of catchment runoff	*e*	Amount of hydropower that a volume of runoff entering a catchment can potentially generate on its path to the sea.
Energy equivalent of catchment outflow	*u*	Amount of hydropower per cubic meter that water leaving the catchment could produce on its path to the sea.
Average energy production	*g*	Average upstream energy production per unit of observed discharge

production indicates the amount of hydropower releases that are needed to satisfy downstream irrigation demand.

Factor *e* is multiplied by the estimated catchment runoff (Section 3.2.1) to generate the energy inflow series that are used in Sections 4.2.1 and 4.3.1. The irrigation conversion factors *u* and *g* are used in the constraints of the SDP and SDDP optimization algorithms (Section 4.2.2 below), and their values in the catchments of the IP are shown in Table 3. Pereira-Cardenal et al. **I** provides details on the aggregation methodology and a sample implementation.

4.2 Stochastic dynamic programming

The SDP algorithm decomposes the original problem into sub-problems that are solved sequentially, allowing for the explicit representation of on inflow uncertainty. SDP was used in the first two papers to a) assess the impact of potential climate change on the current power system, using irrigation as a constraint; and b) to improve the representation of hydropower benefits in hydro-economic models, using irrigation as a decision variable.

4.2.1 Inflow: discrete Markov chain

The state variables used to describe the hydrological system at the beginning of each stage t were the equivalent energy storage E_t and the equivalent energy inflow Q_t. The SDP algorithm requires the discretization of the state variables, so the energy inflows were simulated as a Markov chain. Five inflow classes were defined for each week of the year:

Table 8. Energy inflow classes

Inflow class	Inflow percentile
Very dry	0 – 10
Dry	10 – 30
Average	30 – 70
Wet	70 – 90
Very wet	90 – 100

The weekly transition probability matrices were calculated from the 30-year series of aggregated equivalent energy inflows.

4.2.2 SDP representing irrigation as a constraint

The objective was to determine production levels of thermal and hydropower units such as to minimize expected production cost, subject to meeting the power demand d_t and the irrigation demand w_t for every time step t until the end of the planning horizon T.

Let $\mathbf{c}$ be the $1 \times I$ vector of constant marginal costs for every non-hydro producer i, and $\mathbf{p}_t$ a $1 \times I$ vector of power production for every producer i during time step t. The recursive SDP equation of the optimal value function $F^*(E_t, Q_{t-1})$ can be written as:

$$F_t^*\left(E_t, Q_{t-1}^k\right) = \min_{\mathbf{p}} \left[\mathbf{c}^T\mathbf{p} + \sum_{l=1}^{L} a_{kl} \times F_{t+1}^*\left(E_{t+1}, \overline{Q}_t^l\right)\right] \tag{1}$$

where $a_{k,l}$ is the transition probability from inflow Q^k in stage $t-1$, to inflow Q^l in stage t. Q_t was defined as the mean weekly energy inflow within each of the classes defined in Section 4.1, and was calculated by multiplying the runoff to each catchment with its respective runoff energy equivalent.

The problem in (1) is subject to constraints on equivalent energy balance (2), minimum and maximum hydropower generation (3), minimum and maximum equivalent energy storage (4), power demand fulfilment (5), and minimum and maximum thermal power generation (6):

$$E_t = E_{t-1} + Q_t - \mathbf{u}^T\mathbf{w}_t - H_t \tag{2}$$

$$0 \le H_t \le \overline{H} \tag{3}$$

$$\underline{E} \le E_t \le \overline{E} \tag{4}$$

$$\sum_{i=1}^{I} p_{i,t} = d_t - H_t \tag{5}$$

$$0 \le p_{i,t} \le \overline{p}_i \tag{6}$$

where H_t is hydropower production. Upstream irrigation abstractions are considered as sinks in the balance equation of the equivalent energy reservoir $\left(\mathbf{u}^{\mathrm{T}}\mathbf{w}\right)$, and downstream irrigation allocations are represented as a time-dependant lower bound on hydropower releases:

$$H_t \geq g\sum_{s=1}^{U} w_{s,t} \tag{7}$$

Other constraints on releases and storage normally apply, e.g. environmental flows or flood control levels, but these were not considered because the lack of such data for the 116 reservoirs that were aggregated.

Using mean weekly power and irrigation demands, the optimization scheme was solved backwards for several years until a steady-state solution was reached. When the inflow and storage were not able to meet total irrigation demand, the water value (see below) was set to 180 €/MWh, which is the maximum price of electricity allowed in the MIBEL.

4.2.3 SDP representing irrigation as a decision variable

The objective here was to determine power production levels and irrigation allocations such as to minimize expected power production cost and maximize expected irrigation benefits, subject to meeting the power demand d_t for every time step of the planning horizon. The recursive equation was modified by adding irrigation allocations and their marginal benefits to the objective function:

$$F_t^*\left(E_t, Q_{t-1}^k\right) = \min_{\mathbf{w},\mathbf{p}} \left[\mathbf{c}^T\mathbf{p}_t - \mathbf{f}^T\mathbf{w}_t + \sum_{l=1}^{L} a_{kl} \times F_{t+1}^*\left(E_{t+1}, \overline{Q}_t^l\right)\right] \tag{8}$$

where $\mathbf{w}_t$ is a vector of irrigation allocations and $\mathbf{f}$ is a vector of marginal irrigation benefits for each crop, as explained in Section 3.2.3. This new problem is subject to the same constraints as the previous case: (2) – (7). Irrigation allocations are now a decision variable, so an additional constraint is used to keep allocations within bounds:

$$0 \leq w_{s,t} \leq \overline{w}_{s,t} \tag{9}$$

The optimization scheme was also solved backwards until a steady solution was reached, using mean weekly power and irrigation demands.

4.2.4 Water value method

The SDP method described above provides the minimum expected cost of system operation from any stage (and state) until the end of the planning horizon. The water value method was used to develop rational reservoir operating rules, given uncertain future inflows.

The method consists in calculating the total cost of operating the system for each state and stage using SDP. Once steady state has been reached, the water

values θ (€/MWh) for each inflow scenario and week of the year are calculated by taking the derivative of the total costs with respect to the reservoir level:

$$\theta = \frac{\partial F}{\partial E} \approx \frac{\Delta F}{\Delta E} \tag{10}$$

where the optimal value function F has units of € and the energy storage E has units of MWh.

The water values represent the expected value of a marginal amount of water (energy) if it is stored for later use. They are used as the marginal costs of the releases, and added to the objective function of a linear problem used to simulate the system:

$$F_t^* = \min_{\mathbf{w},\mathbf{p},\Delta E} \left[\mathbf{c}^T\mathbf{p} - \mathbf{f}^T\mathbf{w} + \theta_{t,k}^T \Delta E_t \right] \tag{11}$$

The term $\mathbf{f}^T\mathbf{w}$ is not included in (11) if irrigation is considered as a constraint. This problem is subject to the same constraints as (1) or (8), depending on whether irrigation is included as a constraint or a decision variable, and an additional constraint on reservoir releases ΔE_t:

$$0 \leq \sum \Delta E_t \leq \overline{H} \tag{12}$$

The linear problem (11) was solved forwards on weekly time steps using simulated control (1961–1990) or climate change (2036–2065) data of energy inflows, irrigation demand and power demand. The results of this simulation include time series of irrigation allocation, power production levels, equivalent energy storage and reservoir releases.

4.3 Stochastic dual dynamic programming

The SDDP algorithm consists of two phases: a *backward optimization* phase that generates cuts to approximate the future cost function (FCF) from the last time step to the first; and a *forward simulation* phase that uses the representation of the FCF to simulate the system. The backward and forward phases provide lower and upper bounds to the true function, respectively; and the algorithm iterates until the convergence criterion is met.

4.3.1 Inflow: continuous Markov process

In SDDP, instead of representing inflow uncertainty through a discrete Markov chain as it was done in the SDP method (Section 4.2.1), the inflow uncer-

tainty is handled through a Markov process with discrete time steps and continuous state. Given inflows with weekly mean μ, weekly variance σ^2, and lag-one weekly autocorrelation coefficient ρ, the current inflow to the reservoirs Q_t can be calculated from a periodic autoregressive model PAR(1):

$$Q_t = \mu_t + \rho_{t-1,t} \frac{\sigma_t}{\sigma_{t-1}} \left(Q_{t-1} - \mu_{t-1} \right) + \xi_t \sigma_t \sqrt{1 - \rho_{t-1,t}^2} \tag{13}$$

where Q_t is the $N \times 1$ vector of lateral energy inflows to each reservoir n at stage t. The random perturbation ξ_t can be obtained from the Cholesky factorization of the lag-zero cross-correlation matrix between the N inflow series at stage t (Tilmant and Kelman, 2007).

Given the inflows Q_{t-1} that were estimated from the rainfall-runoff model (Section 3.2.1) and converted to energy units (Section 4.1), we forecasted Q_t using (13) without the noise term (last term of the RHS). The forecast over the 30-year inflow series provided a set of 30 residuals for each week of the year, which contained the distribution of the noise term. After removing outliers, the residuals were sampled to obtain five (K) weekly inflow noise vectors, which were then used to generate the inflow scenario tree. Figure 10 shows an example of a scenario tree with two branches (K = 2) from each node.

In order to ensure consistency between the inflows in the forward and backward runs and improve convergence, the same noise vectors were used to

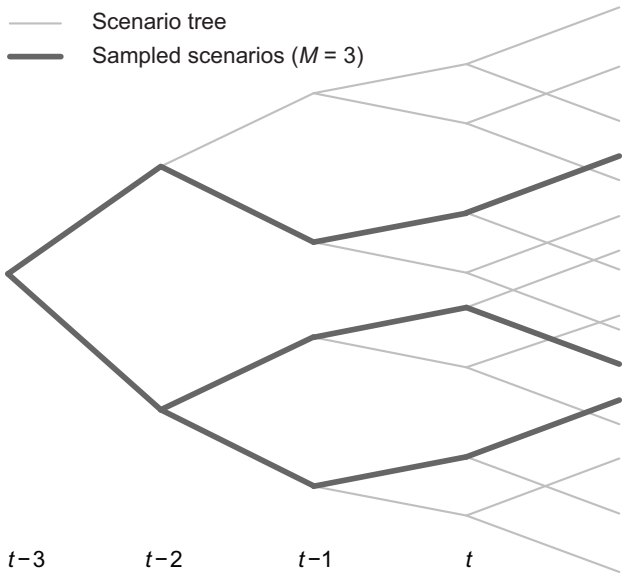

Figure 10. Example scenario tree with two branches at each stage

generate the *backward openings* (see below).

4.3.2 Forward simulation

The forward simulation is used to: a) check the feasibility of the FCF approximation found during the previous backward run; b) provide feasible starting volumes for the next backward recursion; and c) calculate the upper bound of the total operation cost.

The five discrete vectors that were determined to represent the inflow distribution at each stage can be regarded as a scenario tree with five branches from each node. Such a tree grows very fast with the number of stages. To handle it, the forward run samples M scenarios from the complete scenario tree (Figure 10) and optimizes each m scenario sequentially from the first to the last stage.

The objective of this optimization is the same as in the SDP with irrigation allocations as decision variables: to determine power production levels and irrigation allocations such as to minimize expected power production cost and maximize expected irrigation benefits, subject to meeting the power demand d_t for every time step of the planning horizon. The recursive equation can be written as:

$$F^*_{t,m}\left(E_{t,m}, Q_{t-1,m}\right) = \min_{\mathbf{w},\mathbf{p}} \left[\mathbf{c}^{\mathrm{T}}\mathbf{p}_t - \mathbf{f}^{\mathrm{T}}\mathbf{w}_t + F^*_{t+1}\left(E_{t+1,m}, Q_{t,m}\right)\right] \tag{14}$$

where m is one of the M inflow scenarios sampled at the beginning of the current iteration. The FCF is here presented by a set of L constraints, also known as Benders' cuts, that are a linear approximation to the true cost function:

$$F^*_{t+1} + {\varphi^l_{t+1}}^{\mathrm{T}} E_{t+1,m} \geq {\gamma^l_{t+1}}^{\mathrm{T}}\left(Q_{t,m} - Q^*_{t,m}\right) + \delta^l_{t+1} \tag{15}$$

where δ^l_{t+1} is a constant term and φ^l_{t+1} and γ^l_{t+1} are vectors of slopes with respect to storage and inflow, respectively, that belong to the lth cut and have been calculated at stage $t + 1$ during previous backward recursions (see Section 4.3.3).

The linear problem in (14) is also subject to constraints on equivalent energy balance (2), minimum and maximum hydropower generation (3), minimum and maximum equivalent energy storage (4), power demand fulfillment (5), minimum and maximum thermal power generation (6), and minimum and maximum irrigation demand (9). Irrigation abstractions are handled as before —upstream allocations as sinks in (2) and downstream allocations as a lower bound on hydropower releases (7)—, but the marginal benefits **f** and the irri-

gation demands $\mathbf{w}_t$ are different for every catchment, as explained in Section 3.2.3.

4.3.3 Backward recursion

The backward recursion is used to: a) construct the cuts that approximate the FCF; and b) provide a lower bound to the true cost function. In the backward run of each iteration, the algorithm starts at the last stage T and passes information on the future cost to the previous stage, until the first stage is reached.

Starting with the last stage of the planning period, K vectors of inflow Q_t^k ($k \in [1,\ldots,K]$), known as backward openings, are generated for every m inflow scenario using $Q_{t-1,m}^*$ and the noise inflow vector described in Section 4.3.1. For every inflow scenario m and backward opening k, the one-stage problem in the backward recursion takes the form:

$$F_{t,m}^{*,k}\left(E_{t,m}^*, Q_{t-1,m}^*\right) = \min_{\mathbf{w},\mathbf{p}} \left[\mathbf{c}^{\mathrm{T}}\mathbf{p}_t - \mathbf{f}^{\mathrm{T}}\mathbf{w}_t + F_{t+1}^{*,k}\left(E_{t+1,m}^k, Q_{t,m}^k\right)\right] \tag{16}$$

where $E_{t,m}^*$ is the trial value obtained in stage $t-1$ during the previous forward recursion. The constraints are the same as in the forward simulation, and the FCF takes the form:

$$F_{t+1}^{*,k} + \varphi_{t+1}^{l\,\mathrm{T}} E_{t+1,m}^k \geq \gamma_{t+1}^{l\,\mathrm{T}}\left(Q_{t,m}^k - Q_{t,m}^*\right) + \delta_{t+1}^l \tag{17}$$

The dual of this inequality constraint is $\lambda_{t,m}^k$. The equivalent energy balance equation becomes:

$$E_{t+1}^k = E_{t,m}^* + Q_{t,m}^k - u^{\mathrm{T}}\mathbf{w}_t - H_t^k \tag{18}$$

The dual of this equality constraint is the $N \times 1$ vector $\pi_{t,m}^k$, which represents the change in the objective function value with respect to a small relaxation of the water balance constraint:

$$\frac{\partial F_t^{*,k}}{\partial E_{t,m}^*} = \pi_{t,m}^k \tag{19}$$

The slope with respect to storage in each reservoir n is obtained by averaging the duals obtained from solving (16) K times:

$$\varphi_{t,m}(n) = \frac{1}{K}\sum_{k=1}^{K}\pi_{t,m}^k(n) \tag{20}$$

The change in the objective function value at stage t with respect to a change in inflow during stage $t-1$ is obtained from:

$$\begin{aligned}\frac{\partial F_t^{*,k}}{\partial Q_{t-1,m}} &= \frac{\partial F_t^{*,k}}{\partial Q_{t,m}^k} \cdot \frac{\partial Q_{t,m}^k}{\partial Q_{t-1,m}} \\ &= \left(\pi_{t,m}^k(n) + \sum_{l=1}^{L} \lambda_{t,m}^{l,k} \gamma_{t+1}^l(n)\right) \cdot \left(\frac{\sigma_t(n)}{\sigma_{t-1}(n)} \rho_{t-1,t}(n)\right) \\ &= \gamma_{t,m}^k(n)\end{aligned} \tag{21}$$

Note that the partial derivative of $F_t^{*,k}$ with respect to $Q_{t,m}^k$ is obtained by adding the impact of inflow changes on the current and the future operation of the system. The partial derivative of current inflow with respect to previous inflow is obtained from the inflow model in (13). The vector of expected slopes with respect to inflows is given by:

$$\gamma_{t,m}(n) = \frac{1}{K} \sum_{k=1}^{K} \gamma_{t,m}^k(n) \tag{22}$$

The constant scalar $\delta_{t,m}$ is calculated as:

$$\delta_{t,m} = \frac{1}{K} \sum_{k=1}^{K} F_t^{*,k} + \varphi_{t,m}{}^{\mathrm{T}} E_{t,m}^* \tag{23}$$

A set of M cut parameters $\delta_{t,m}$, $\varphi_{t,m}$, and $\gamma_{t,m}$ are generated at every stage t of each backward iteration, and added to the set of L parameters (calculated in previous iterations) that approximate the FCF at stage $t-1$. The number of cuts L grows by M in each iteration, gradually improving the approximation until convergence.

The creation of the backward openings and the cuts is illustrated in Figure 11. The openings are created by adding the inflow noise vector $Q_{t,m}^k$ to the corresponding storage $E_{t,m}^*$ obtained from the mth forward simulation (Figure 11a). The K cuts created for each m forward scenario (Figure 11b) are averaged to construct M cuts (Figure 11c). The maximum over the M cuts is the linear approximation to the FCF (Figure 11d).

Note that the M resulting cuts will be added as constraints in all M scenarios at stage $t-1$. In order to "share" the cuts among scenarios, the inflow scenario tree used in the forward simulation must have common samples, i.e. the distribution of the inflow noise vector must be the same for all scenarios within a given stage t and independent of the inflow history. In this case, the

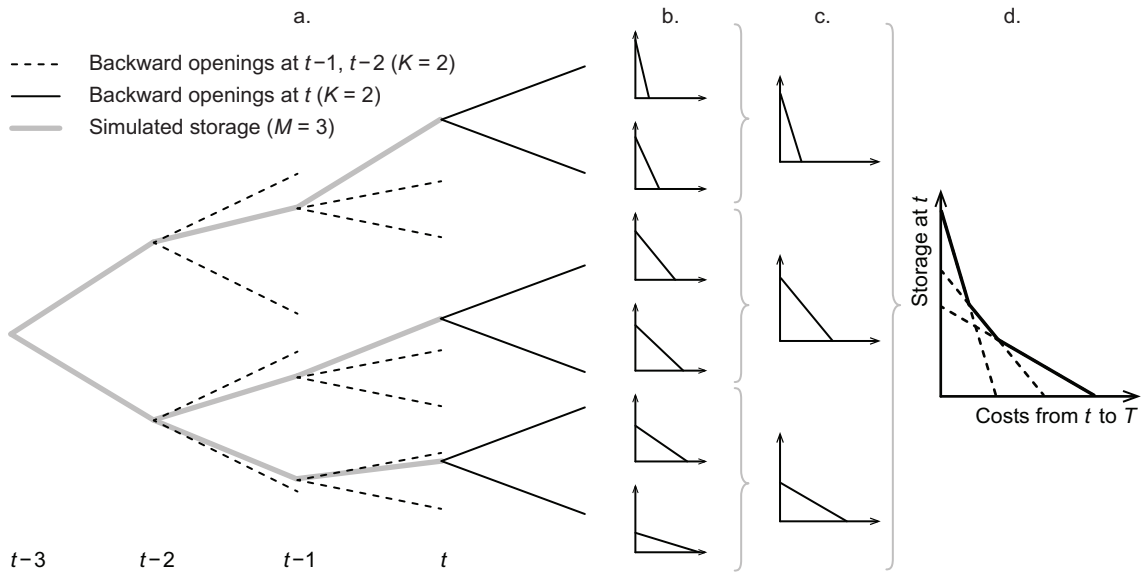

Figure 11. Construction of backward openings and cuts.

same inflow noise vector was used in the forward and backward phases (compare the branches of Figure 10 with the openings in Figure 11a).

4.3.4 Convergence

The set of cuts provides a lower bound to the total cost. The backward recursion accumulates the future costs from the end of the planning period to the beginning, so at stage one the function $F^*_{1,m}\left(E^*_{1,m}, Q^*_{0,m}\right)$ underestimates the total cost of system operation. The lower bound $\underline{Z}$ is then obtained from:

$$\underline{Z} = \frac{1}{M}\sum_{m=1}^{M} \frac{1}{K}\sum_{k=1}^{K} F^{*,k}_{1,m}\left(E^*_{1,m}, Q^*_{0,m}\right) \tag{24}$$

Forward simulation of the system —using Benders' cuts which tend to underestimate the total cost— results in an overestimation of the total cost of system operation, providing an upper bound. The expected upper bound $\mu_{\overline{Z}}$ is obtained from the sum of immediate costs (and benefits) throughout the planning period:

$$\mu_{\overline{Z}} = \frac{1}{M}\sum_{m=1}^{M}\sum_{t=1}^{T}\left(\mathbf{c}^{\mathrm{T}}\mathbf{p}_{t,m} - \mathbf{f}^{\mathrm{T}}\mathbf{w}_{t,m}\right) \tag{25}$$

and the 95% confidence interval (C.I.) is given by:

$$\overline{Z} \in \left[\mu_{\overline{Z}} - 1.96\frac{\sigma_{\overline{Z}}}{\sqrt{M}}, \mu_{\overline{Z}} + 1.96\frac{\sigma_{\overline{Z}}}{\sqrt{M}}\right] \tag{26}$$

where $\sigma_{\overline{Z}}$ represents the standard deviation of the upper bound. The algorithm iterates until the lower bound is inside the confidence interval of the upper bound. The approximation is then considered statistically acceptable, the algorithm stops, and the problem is solved.

4.3.5 Comparing SDP and SDDP

Now that both methods have been presented, a brief comparison is provided following Pereira et al. (1999). Assume that the objective is to minimize the operation costs of a hydro-thermal system from time step t to the end of the planning horizon T, and that the storage state is discretized into 11 steps (0, 10, 20, …, 100%), here represented by the grid of black circles. In both methods, the sum of immediate and future costs (as a function of storage) is calculated at stage t, and then used at stage $t - 1$ as the future cost function.

In the version of SDP implemented here, the FCF is built by interpolating the future costs that are calculated at every state discretization. Figure 12 shows the calculation of the FCF from the first three reservoir levels at stage. On the left panel, the thin gray lines represent optimal reservoir volumes considering three inflow classes, and the red circles in the grid represent the reservoir states that will be evaluated from stage t to the beginning of the planning period at state $t - 3$. On the right panel, the three red circles start building the approximation of future costs as a function of storage.

In SDDP, the FCF is built by linear extrapolation. Figure 13 shows how the costs are only evaluated at a few reservoir levels that were identified in the previous forward simulation (left panel). The dual of the reservoir balance

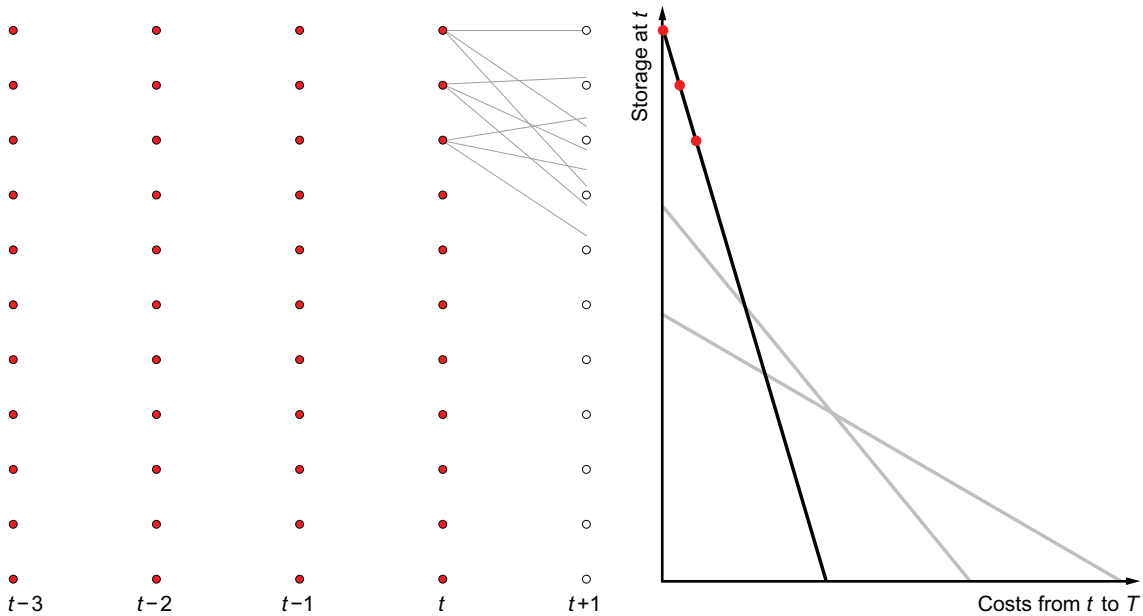

Figure 12. Approximation of the future cost function in SDP.

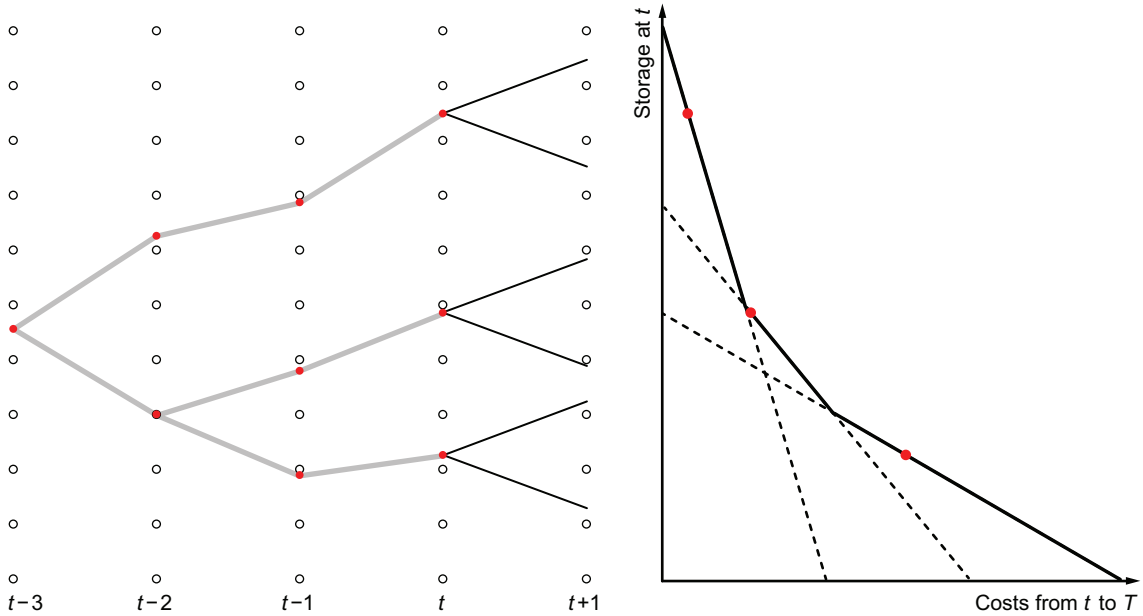

Figure 13. Approximation of the future cost function in SDDP.

equation at the optimal solution represents the change in costs with respect to a small change in storage, which corresponds to the slope of the cuts that approximate the FCF (right panel). The advantage of SDDP is that a small number of evaluations can provide a good approximation of the FCF. If the approximation is not good enough (as defined by the convergence criterion), then a new iteration is done and the approximation improved by adding more cuts to the FCF.

5 Results and Discussion

The main findings of the study are summarized and discussed in this section. The first three sub-sections correspond to the work presented in the three scientific papers. Potential impacts of climate change on the Iberian power system are presented in Section 5.1; a method to improve the representation of hydropower benefits is presented in Section 5.2; the influence of spatial aggregation on water-power analysis is shown in Section 5.3. The main limitations of the study are discussed in Section 5.4.

5.1 Climate change impact on power system of the IP

The goal was to assess some of the potential impacts of climate change on the Iberian power system under its current state. This was achieved by solving the optimization problem using a climate change scenario that contained data on potential future inflows, irrigation demands, and power demands. The expected change on these input series is shown in Figure 6.

Solving the SDP in (1) and calculating the derivative of the costs with respect to the reservoir level (10) provides a water value table (WVT) that indicates the expected value of a marginal amount of storage in the reservoir. Figure 14 shows the WVT for the control (a) and climate change (b) scenarios as a function of the week of the year, the reservoir level, and the inflow state.

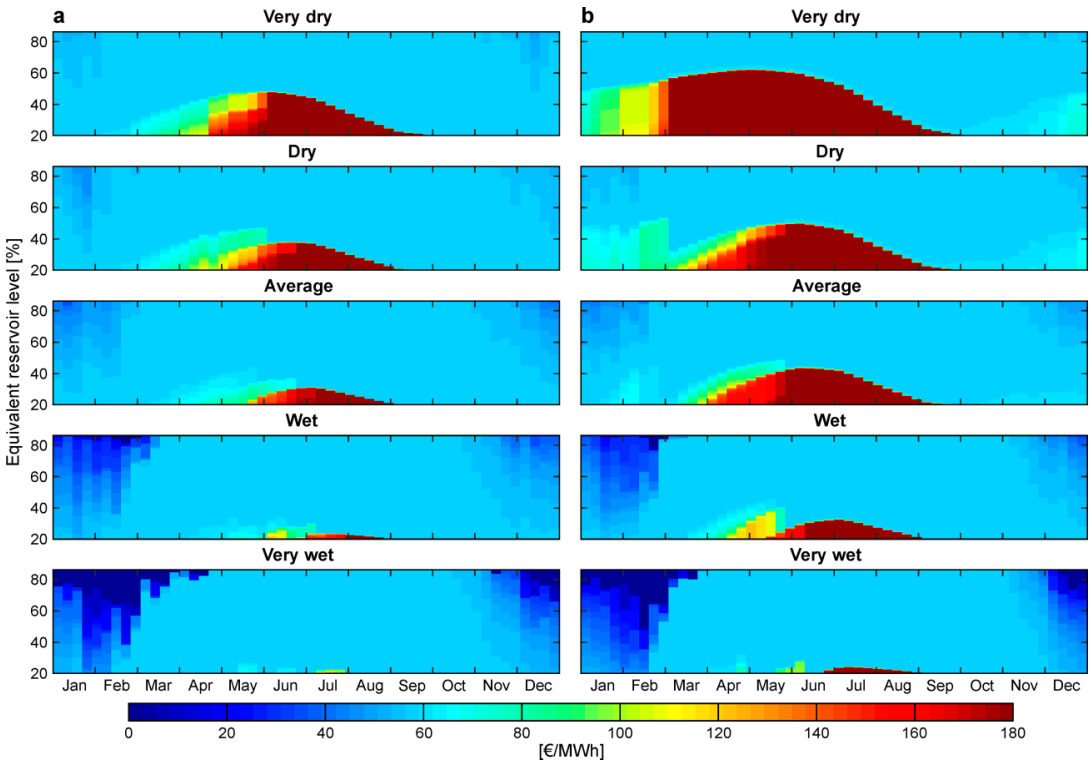

Figure 14. Water value tables for a) control and b) climate change scenarios [€/MWh].

The impact of climate change on the optimal reservoir management is reflected on the WVTs: lower inflows and higher irrigation demand increased water values (Figure 14b), which increased the price of hydropower and reduced production. The dark-red area, which represents the volume that must be stored to satisfy expected future irrigation demand, became larger and resulted in a more conservative operation policy.

Under the climate change scenario, lower precipitations and higher temperature reduced inflows and increased irrigation demand, causing a reduction in hydropower production by 24% (from 11.5% to 8.7% of mean annual generation), and an increase in thermal power generation by 6.7% (from 40.5% to 43.3%). These changes in the energy mix increased annual CO_2 emissions of the Iberian power generation sector from 71.9 to 76.9 million tons. Higher expected temperatures modified seasonal power demand, reducing winter demand and increasing summer demand.

Observed and simulated weekly energy storages are compared in Figure 15. The observed storage series (a) is smoother than simulated one (b), possibly because the former results from the aggregation of 100+ observed manage-

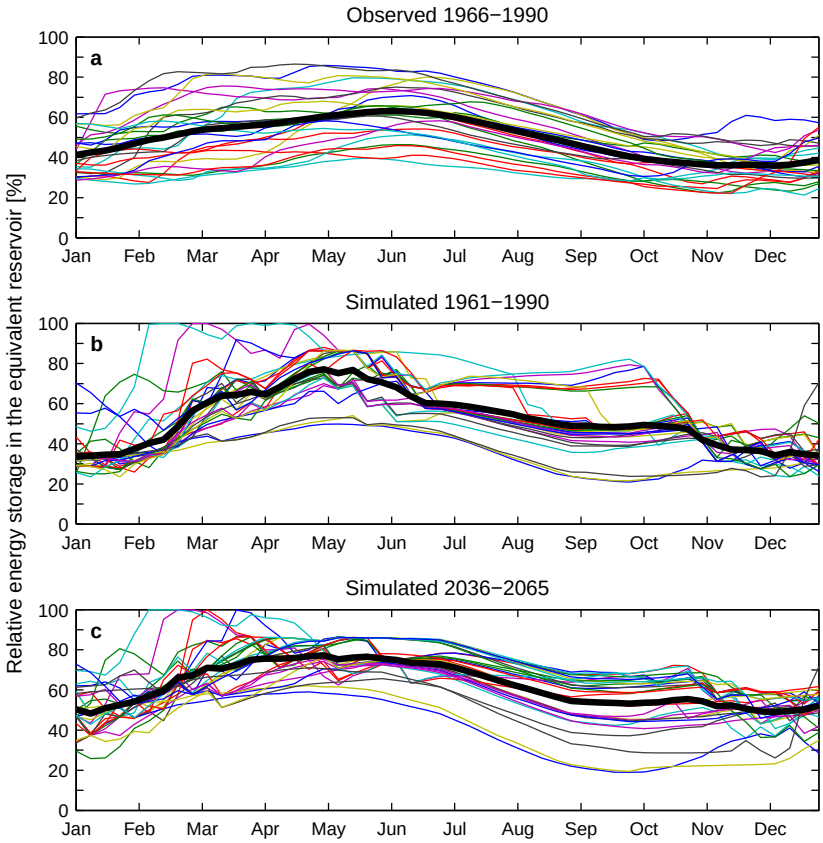

Figure 15. Annual effective relative energy storage: observed, control and future scenarios.Thin, color lines represent individual years; thick black lines represent the average year

ment decision (and their constraints), while the latter corresponds to only one management problem. Lower energy inflows and higher irrigation demands in the climate change scenario increased the risk of irrigation curtailment, so storage levels were higher in the climate change (c) than in the control (b) scenario.

Lehner et al. (2005) found similar reductions in hydropower potential for Spain and Portugal by the 2020s; while SINTEF (2011) and Seljom et al. (2011) found future increases in hydropower production in the Nordpool area and Norway, respectively. This highlights the importance of performing such assessments at a regional level.

SDP was an appropriate tool to assess interactions between water and energy systems under climate change conditions; however, it is difficult to disaggregate the results to the catchment or reservoir level (Labadie, 2004). Hence, conclusions about energy mix and reservoir management under climate change scenarios can only be drawn at the peninsula level. This could be improved by either using disaggregation techniques or solving the problem with optimization algorithms capable of handling a larger number of reservoirs.

5.2 Hydro-economic modeling and power markets

The goal was to develop a methodology that would improve the assessments of economic trade-offs between hydropower and other water users, by incorporating power markets into hydro-economic models. The water value method was used to compare three approaches of representing hydropower benefits in hydro-economic models: a) a power market; b) monthly hydropower prices; and c) a constant hydropower price.

Figure 16 shows the contour plots of the resulting water value table. In a *very dry* year, the water values for a low reservoir during the summer were very high in all approaches, because of the high costs of not supplying irrigation demand. In contrast, during *average* to *very wet* years energy inflows were sufficient to supply irrigation demand, so the water values (even with an empty reservoir) were low.

Again, the water values were used to drive simulations of the system with different representations of hydropower benefits. Using monthly hydropower prices caused excessively high storage before and during the irrigation season (Figure 18b). Furthermore, most of the storage was released in September, when the price of hydropower was highest (Figure 17b). Using a constant price resulted in very low storage levels (Figure 18c). Most of the releases

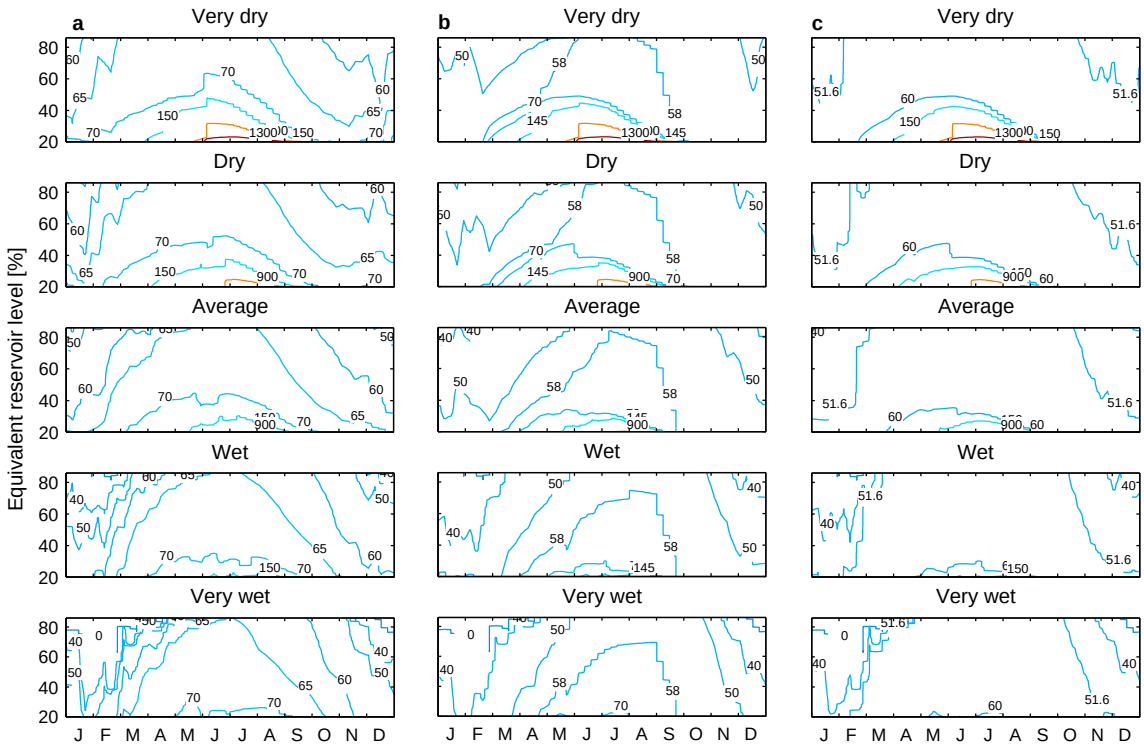

Figure 16. Water values [€/MWh] from optimization a) considering the power market, b) assuming a monthly-varying hydropower price, and c) assuming a constant price.

occurred during the irrigation season, when the total benefits (constant hydropower plus irrigation) were highest (Figure 17c).

Representing hydropower benefits through a power market provided more realistic results. The reservoir was not completely emptied during the autumn —as it occurs in the other two approaches— because of high water values at low reservoir levels (Figure 18c). Furthermore, reservoir operation changed depending on inflow conditions, resulting in low storage during dry years and high storage during wet years.

These results indicate that using constant power prices (e.g. Cai et al., 2003) does not reflect the inflow and power demand seasonality, which affects the availability (and therefore the value) of hydropower. Monthly-varying power prices (e.g. Tilmant and Kelman, 2007) capture seasonal effects, but can cause unrealistic operation rules that can only be avoided through additional constraints. Using a simple power market to represent hydropower benefits provides reservoir operation policies that are more realistic, and that adapt better to changing inflow conditions.

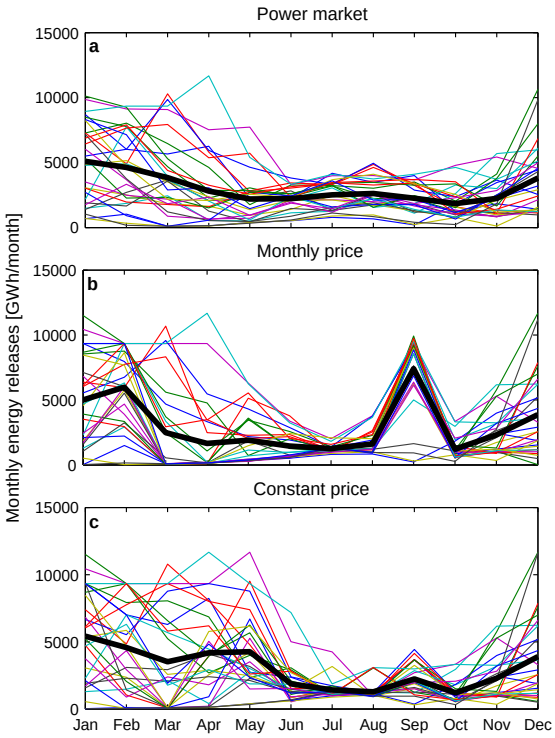

Figure 17. Monthly energy releases [GWh/month] from simulations using water values a) considering a power market, b) assuming a monthly-varying hydropower price, and c) assuming a constant price. Thin color lines represent individual years; black lines represent the average year.

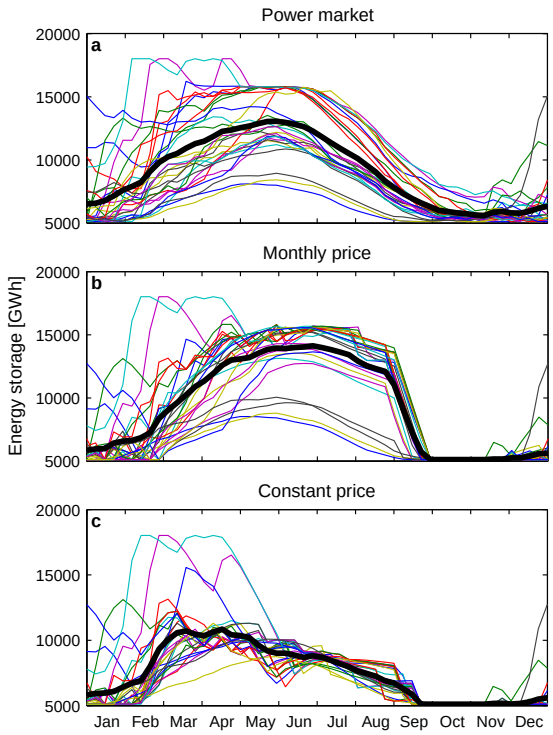

Figure 18. Energy storages [GWh] from simulations using water values a) considering a power market, b) assuming a monthly-varying hydropower price, and c) assuming a constant price. Thin color lines represent individual years; black lines represent the average year.

5.3 Optimization of regional water-energy systems

Combining SDP with the water value method proved to be a useful approach to assess some of the linkages between water and energy systems. However, because of the computational limitations faced by SDP, those linkages could only be studied at an aggregated level. To overcome this issue, SDDP was used to optimize a coupled model of the power system and the seven major river basins of the IP. An aggregated model (at the peninsula level) was used to evaluate the impact of aggregation.

Figure 19 shows the convergence of the SDDP algorithm for the aggregated and the disaggregated models. The aggregated model, which has one reservoir, converged faster than the disaggregated one, which has seven.

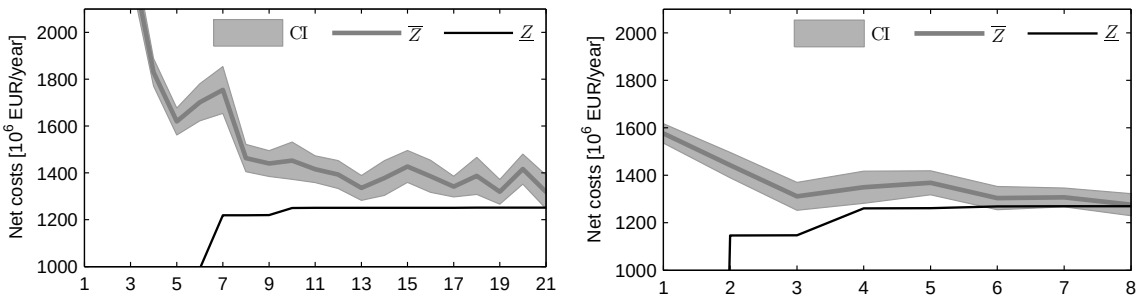

Figure 19. Convergence of a) disaggregated and b) aggregated model. (CI is the confidence interval)

The mean storage was very similar in the aggregated and disaggregated models (Figure 20a), and resulted from a policy of producing hydropower during the winter and summer demand peaks. Although the releases also followed a similar trend (Figure 20b), those from the aggregated model were higher from May to July, because irrigation was prioritized. In contrast, releases from the disaggregated model were higher during January–February and September–October, at the expense of higher irrigation curtailments.

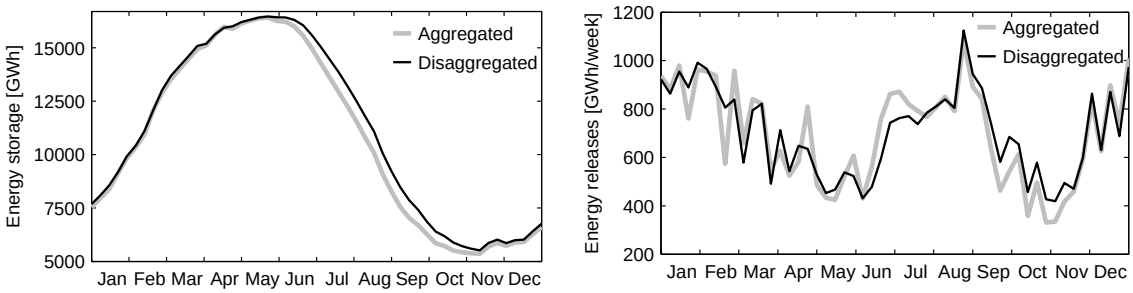

Figure 20. Total energy storage (a) and energy releases (b) in aggregated and disaggregated models

Despite storage similarities between the models, the river basins from the disaggregated model showed distinct storage strategies (Figure 21): storage in Tajo, Ebro, Duero and Miño-Sil was released before the beginning of the inflow season in October; whereas the storage in Guadalquivir, Guadiana and Jucar was never depleted.

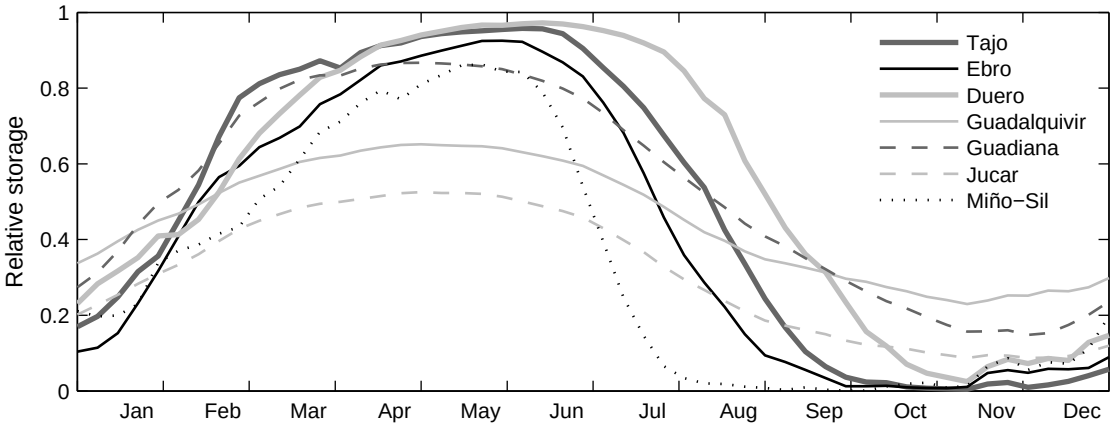

Figure 21. Mean weekly relative energy storage defined as $(\boldsymbol{E_t} - \underline{\boldsymbol{E}})/(\overline{\boldsymbol{E}} - \underline{\boldsymbol{E}})$.

As shown in Table 9, Irrigation allocations were also different between the aggregated and disaggregated models. Because the disaggregated model contained information about the energy equivalent of irrigation water demand in each catchment, inefficient allocations were curtailed. This information was averaged out in the aggregated model, so most allocations were not curtailed. More specifically, allocations were curtailed for crops with irrigation marginal benefits lower than the sum of replacement cost of power lost to irrigation sinks and the opportunity costs of generating hydropower at the current (instead of at a later) stage: $\mathbf{f} + \mathbf{c}_t^T\mathbf{g} < \mathbf{c}_t^T\mathbf{u} + \mathbf{c}_{t'}^T\mathbf{g}$. Here $\mathbf{c}$ corresponds to the price of the marginal power producer at a given stage; *t* and *t'* represent the current and any other time step.

Table 9. Irrigation demand fulfillment, aggregated and disaggregated models

River basin	Mean demand fulfillment [%]	Mean demand fulfillment [%] (at given marginal benefit [10^6€/Hm^3])								
		0.003	0.010	0.017	0.11	0.30	0.50	0.80	2.0	4.0
Tajo	79.08	0.8	0.8	99.5	99.8	99.8	99.8	99.8	99.8	N/A
Ebro	92.64	53.9	66.3	70.5	93.6	99.3	99.6	99.6	99.7	N/A
Duero	77.02	<0.1	<0.1	<0.1	100.0	100.0	100.0	100.0	100.0	N/A
Guadalquivir	99.40	97.8	97.9	98.1	99.5	100.0	100.0	100.0	100.0	99.99
Guadiana	66.75	0.2	0.2	96.6	99.3	99.9	99.9	99.9	99.9	N/A
Jucar	95.52	<0.1	85.6	87.1	94.6	99.5	99.9	99.9	100.0	99.96
Miño-Sil	96.69	<0.1	99.7	99.7	99.7	N/A	99.7	N/A	N/A	N/A
Total	**86.88**	**31.0**	**34.3**	**84.1**	**97.6**	**99.7**	**99.8**	**99.9**	**99.9**	**100.0**
Aggregated	91.94	0.0	99.9	99.9	99.9	100.0	100.0	100.0	100.0	100.0

There are clear management differences between the aggregated and the disaggregated model, which highlights the importance of the spatial representation in this type of analysis.

5.4 Limitations of the study

Several assumptions and simplifications were made because of the limited time frame of the PhD program. Many uncertain inputs were assumed to be known and therefore treated deterministically, for instance: the power supply function, the irrigation demand function, and the total power demand. In the optimization problems, the inflows were treated stochastically to consider inflow variability within the estimated time series, but these time series resulted from a deterministic rainfall-runoff model with uncertain inputs. The average change factors derived from the regional climate models and used to construct the climate change scenario are another source of uncertainty that was not considered. Power demand uncertainty could be handled within SDDP by the addition of a state variable (if a suitable power demand model were available); and a sensitivity analysis could have been carried out to assess the uncertainty of the rainfall-runoff model —*before* its results were converted to energy and used as input to the optimization model. However, the other sources of uncertainty would have to be handled by running the optimization and simulation phases a large number of times, which would be very computationally expensive.

Another source of uncertainty is the model structure: the parameters and structure of the rainfall-runoff model; the usage of fixed heads in the conversion of inflows and irrigation demands from water to equivalent energy units; and the representation of irrigation abstractions only from surface water. Again, uncertainty in the rainfall-runoff model could have been handled by sensitivity analysis *before* the optimization model, while the conversion from water to energy units can only be evaluated *after* the optimization model, making it computationally infeasible. Groundwater abstractions could be included by adding reservoirs to represent groundwater storage; however, this would introduce nonlinearities that would have to be handled in order to keep convexity.

Possibly, the most significant sources of uncertainty are the spatial aggregation of the hydrological system and the temporal aggregation of the power system. In Pereira-Cardenal et al. **I** and **II** the hydrological system was aggregated in space so the problem could be solved using SDP without facing the curse of dimensionality, but the results were only valid at the Peninsula scale. This was overcome in Pereira-Cardenal et al. **III** by using SDDP, which allowed the representation of the hydrological system at the river basin scale. This optimization method can be used to optimize a larger number of

reservoirs, although some level of aggregation will always be necessary for systems as large as the IP.

The other limitation is the temporal aggregation of the power system. It was shown in Figure 3 that hourly power production and prices vary considerably within the week. Using hourly time steps would allow a more realistic representation of the power system, including a better representation of the power supply and demand functions, and the inclusion of pumped-storage hydropower. However, hourly time steps would have made the problem computationally intractable. Some alternatives to include production and price variability within a week would be to divide the week into a few *load segments* with a certain demand profile (e.g. Wolfgang et al., 2009) or to derive *hydropower revenue functions* for each week (e.g. Madani and Lund, 2009).

These sources of uncertainty were not considered because the focuse of the study was to propose a methodological framework to assess the interactions between water and energy systems. However, such issues must be considered if the framework is to be used for detailed studies or for decision support.

6 Conclusions

The goal of this study was to develop a method to assess spatio-temporal interactions between water and power systems, which could potentially be used to evaluate the water-energy nexus. The proposed method is to include water users and power producers into a joint optimization problem that minimizes the cost of power production and maximizes the benefits of water allocation. This approach turns the multi-objective problem (water and power system management) into a single objective one: net costs minimization. The economic value of water is calculated depending on the state of the system, and used to determine optimal allocations for each time step of the planning horizon. The physical linkages between the two systems and the management restrictions are described as constraints in the optimization problem.

The method was successfully implemented to assess some of the interactions between the water and power systems in the Iberian Peninsula. In a first modeling effort, the impact of potential climate change on the current Iberian power system was assessed. It was found that climate change may reduce hydropower generation by 24%, increasing thermal generation and its associated CO_2 emissions.

In a second modeling effort, common methods for representing hydropower benefits within hydro-economic models were evaluated. Using constant benefits did not represent seasonal water availability, while using monthly benefits to represent seasonal variability resulted in unrealistic management policies. The proposed method resulted in reservoir operation policies that were more realistic and could adapt better to inflow variability.

In the first two implementations, aggregation techniques were used to reduce the dimensionality of the optimization problem. The last modeling effort consisted in comparing results from an aggregated and a partially disaggregated model, in order to evaluate the effects of spatial aggregation on the analysis of water-power systems. It was found that the aggregated model provided valuable insights into the management of water and energy systems, but only at the aggregated scale. In contrast, the disaggregated model revealed that optimal allocations were achieved by managing water resources differently in each river basin, according to local inflow, storage capacity, hydropower productivity, and irrigation demand and productivity. This highlights the importance of considering spatial differences in such integrated assessments.

The suggested method relies on mathematical optimization algorithms to determine the optimal use of water and power resources. Therefore, the size of the systems that the method can handle depends on the chosen optimization algorithm. Stochastic dynamic programming was found to be adequate only for the aggregated representation of the hydrological system. Stochastic dual dynamic programming, in contrast, was capable of solving models with higher spatial resolution, and has the potential for solving large scale problems with many reservoirs.

Despite the simplifications and assumptions made, the suggested method proved to be adequate for assessing the spatio-temporal interactions of water and power systems. Furthermore, the method is flexible and can potentially be used to model other aspects of the water-energy nexus, for instance: the energy requirements of the transport sector and the impact of biofuels on agriculture; the impact of reduced river discharge on cooling of thermal power plants; or the impact of carbon capture and storage on water resources.

7 Further research

Further research should be conducted in order to address the limitations of this study, and to move forward in the development of tools for integrated assessment of the water-energy nexus.

Further spatial disaggregation of the hydrological system would allow for a more realistic representation of hydropower reservoirs and a better spatial differentiation of irrigation agriculture that would improve the identification of upstream-downstream trade-offs.

A more realistic representation of the power market could be achieved by considering temporal variability at scales shorter than the weekly time steps used here. This would result in a better representation of power supply and demand functions and allow for the inclusion of pumped-storage hydropower.

These improvements would already allow the inclusion of other components of the water-energy nexus into the modeling framework. For instance, desalination and pumping could be used to shift the timing of power demands. Furthermore, spatial disaggregation of thermal power producers would make it possible to assess the impact of reduced river discharge on cooling of thermal power plants, or the impact of carbon capture and storage projects on river discharge.

The proposed methodological framework should also be expanded to include more aspects of the water-energy nexus. For example, the impact of biofuels on agriculture and water resources, and its efficiency as a climate change mitigation option could be assessed by adding a market for transport energy, a simple representation of the agricultural system, and an accounting mechanism for the green house gas emissions of all the components in the integrated system. This type of assessments is very ambitious, but such studies must be carried out if we are to manage our resources sustainably.

8 References

Al-Sunaidy A, Green R (2006) Electricity deregulation in OECD (Organization for Economic Cooperation and Development) countries. Energy 31:769-787

Archibald TW, McKinnon KIM, Thomas LC (1997) An aggregate stochastic dynamic programming model of multireservoir systems. Water Resour Res 33:333-340

Belo-Pereira M, Dutra E, Viterbo P (2011) Evaluation of global precipitation data sets over the Iberian Peninsula. J Geophys Res 116. doi: 10.1029/2010JD015481

Berga-Casafont L (2003) Presas y Embalses en la España del siglo XX. Revista de Obras Públicas37-40

Bright EA, Coleman PR, King AL, Rose AN (2008) LandScan 2007. Oak Ridge National Laboratory.Oak Ridge, TN

Bruns BR, Ringler C, Meinzen-Dick RS, International Food Policy Research Institute (2005) Water rights reform: lessons for institutional design. International Food Policy Research Institute, Washington, D.C

Cai XM, McKinney DC, Lasdon LS (2003) Integrated hydrologic-agronomic-economic model for river basin management. Journal of Water Resources Planning and Management-Asce 129:4-17

Carrillo AMR, Frei C (2009) Water: A key resource in energy production. Energy Policy 37:4303-4312

CEDEX (2012) Anuario de Aforos. Centro de Estudios y Experimentacion de Obras Publicas. http://hercules.cedex.es/general/default.htm. Accessed 1 November 2012

CNE (2008) Propuesta de Revision de la Tarifa Electrica a partir del 1 de julio de 2008. Comisión Nacional de Energia. Madrid

Conejo AJ, Carriâon M, Morales JM (2010) Decision making under uncertainty in electricity markets. Springer, New York

de Fraiture C, Giordano M, Liao YS (2008) Biofuels and implications for agricultural water use: blue impacts of green energy. Water Policy 10:67-81

DOE (2006) Energy demands on water resources - Report to Congress on the Interdependency of Energy and Water. US Department of Energy.

Draper AJ, Jenkins MW, Kirby KW, Lund JR, Howitt RE (2003) Economic-engineering optimization for California water management. Journal of Water Resources Planning and Management-Asce 129:155-164

EDP (2012) Mapa das Centrais Hidroeléctricas. http://www.a-nossa-energia.edp.pt/centros_produtores/producao.php?cp_type=he&map_type=he#mapContainer. Accessed 1 February 2012

EU Comission, 2000. Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 Establishing a Framework for Community Action in the Field of Water Policy. Official Journal L 327, 0001-0073. 22-12-2000.

Fowler HJ, Blenkinsop S, Tebaldi C (2007) Linking climate change modelling to impact studies: recent advances in downscaling techniques for hydrological modelling. Int J Climatol 27:1547-1578

Gleick PH (1993a) Water and Conflict - Fresh-Water Resources and International Security. International Security 18:79-112

Gleick PH (1994) Water and Energy. Annual Review of Energy and the Environment 19:267-299

Gleick PH (1993b) Water and Energy. In: Gleick,P.H., Pacific Institute for Studies in Development,E.a.S., and Stockholm Environment Institute (eds) Water in crisis
a guide to the world's fresh water resources, edn. Oxford Univ Press, New York, pp. 67-79

Goor Q, Kelman R, Tilmant A (2011) Optimal Multipurpose-Multireservoir Operation Model with Variable Productivity of Hydropower Plants. Journal of Water Resources Planning and Management-Asce 137:258-267

Griffin RC (2006) Water resource economics
the analysis of scarcity, policies, and projects. MIT Press, Cambridge, Mass

Hardy L, Garrido A (2010) Análisis y evaluación de las relaciones entre el agua y la energía en España. Observatorio del Agua. Madrid

Hardy L, Garrido A, Juana L (2012) Evaluation of Spain's Water-Energy Nexus. International Journal of Water Resources Development 28:151-170

Harou JJ, Pulido-Velazquez M, Rosenberg DE, Medellin-Azuara J, Lund JR, Howitt RE (2009) Hydro-economic models: Concepts, design, applications, and future prospects. J Hydrol 375:627-643

Haylock MR, Hofstra N, Tank AMGK, Klok EJ, Jones PD, New M (2008) A European daily high-resolution gridded data set of surface temperature and precipitation for 1950-2006. J Geophys Res 113. doi: 10.1029/2008JD010201

Herrera S, Fita L, Fernandez J, Gutierrez JM (2010) Evaluation of the mean and extreme precipitation regimes from the ENSEMBLES regional climate multimodel simulations over Spain. J Geophys Res 115. doi: 10.1029/2010JD013936

Herrera S, Gutierrez JM, Ancell R, Pons MR, Frias MD, Fernandez J (2012) Development and analysis of a 50-year high-resolution daily gridded precipitation dataset over Spain (Spain02). Int J Climatol 32:74-85

Hoffman AR (2004) The Connection: Water and Energy Security. Institute for the Analysis of Global Security. www.iags.org/n0813043.htm. Accessed 1 November 2012

Hoffman AR (2010) The Water-Energy Conundrum: Can We Satisfy the Need for Both? Journal of Energy Security. http://www.ensec.org/index.php?option=com_content&view=article&id=266:the-water-energy-conundrum-can-we-satisfy-the-need-for-both&catid=110:energysecuritycontent&Itemid=366. Accessed 1 June 2013

IEEE (2010) Special Report: Water vs. energy. Ieee Spectrum 47:26-27

IPCC (2007) Climate change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge

Isaac M, van Vuuren DP (2009) Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. Energy Policy 37:507-521

Jacob D, Van den Hurk BJJM, Andrae U, Elgered G, Fortelius C, Graham LP, Jackson SD, Karstens U, Kopken C, Lindau R, Podzun R, Rockel B, Rubel F, Sass BH, Smith RNB, Yang X (2001) A comprehensive model inter-comparison study investigating the water budget during the BALTEX-PIDCAP period. Meteorol Atmos Phys 77:19-43

Jaeger EB, Anders I, Luthi D, Rockel B, Schar C, Seneviratne SI (2008) Analysis of ERA40-driven CLM simulations for Europe. Meteorol Z 17:349-367

Jenkins MW, Lund JR, Howitt RE, Draper AJ, Msangi SM, Tanaka SK, Ritzema RS, Marques GF (2004) Optimization of California's water supply system: Results and insights. Journal of Water Resources Planning and Management-Asce 130:271-280

Johansson RC (2000) Pricing irrigation water. World Bank, Rural Development Department, Washington, DC

Joskow PL (2006) Introduction to Electricity Sector Liberalization: Lessons Learned from Cross-Country Studies. In: Sioshansi,F.P. and Pfaffenberger,W. (eds) edn. Elsevier, Amsterdam,

King CW, Holman AS, Webber ME (2008) Thirst for energy. Nature Geoscience 1:283-286

Kirschen DS, Strbac G (2004) Fundamentals of power system economics. John Wiley & Sons, Chichester, West Sussex, England

Labadie JW (2004) Optimal operation of multireservoir systems: State-of-the-art review. Journal of Water Resources Planning and Management-Asce 130:93-111

Lehner B, Czisch G, Vassolo S (2005) The impact of global change on the hydropower potential of Europe: a model-based analysis. Energy Policy 33:839-855

Lorenzo-Lacruz J, Moran-Tejeda E, Vicente-Serrano SM, Lopez-Moreno JI (2013) Streamflow droughts in the Iberian Peninsula between 1945 and 2005: spatial and temporal patterns. Hydrol Earth Syst Sc 17:119-134

Loucks DP, van Beek E (2005) Water Resources Systems Planning and Management. UNESCO,

MARM (2012) Sistema Integrado de Información del Agua. http://servicios2.marm.es/sia/visualizacion/descargas/capas.jsp. Accessed 1 February 2012

MMA (2005) Evaluación Preliminar de los Impactos en España por Efecto del Cambio Climático. Ministerio de Medio Ambiente. Madrid

MMA (2007) El Agua en la Economia Española: Situación y Perspectivas. Ministerio del Medio Ambiente. Madrid

Nakiâcenoviâc N, Intergovernmental Panel on Climate Change, Working Group (2000) Special report on emissions scenarios
a special report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge

Nielsen SA, Hansen E (1973) Numerical simulation of the rainfall-runoff process on a daily basis. Nord Hydrol 4:171-190

Olsson G (2012) Water and Energy. IWA Publishing, London

OMIE (2012) Resultados del Mercado. Operador del Mercado Iberico de Electricidad - Polo Espanol. http://www.omie.es/files/flash/ResultadosMercado.swf. Accessed 1 November 2012

Oudin L, Hervieu F, Michel C, Perrin C, Andreassian V, Anctil F, Loumagne C (2005) Which potential evapotranspiration input for a lumped rainfall-runoff model? Part 2 - Towards a simple and efficient potential evapotranspiration model for rainfall-runoff modelling. J Hydrol 303:290-306

Pereira MVF, Pinto LMVG (1991) Multistage Stochastic Optimization Applied to Energy Planning. Math Program 52:359-375

Perman R, Perman R (2003) Natural resource and environmental economics. Pearson Addison Wesley, Harlow, Essex

Pulido-Velazquez M, Andreu J, Sahuquillo A, Pulido-Velazquez D (2008) Hydro-economic river basin modelling: The application of a holistic surface-groundwater model to assess opportunity costs of water use in Spain. Ecol Econ 66:51-65

Rani D, Moreira MM (2010) Simulation-Optimization Modeling: A Survey and Potential Application in Reservoir Systems Operation. Water Resources Management 24:1107-1138

REE (2012) Boletín Mensual, Septiembre 2012.

REE, 2013. Mapa del Sistema Eléctrico Ibérico. REE.

Saad M, Bigras P, Turgeon A, Duquette R (1996) Fuzzy learning decomposition for the scheduling of hydroelectric power systems. Water Resour Res 32:179-186

Schaefli B, Hingray B, Musy A (2007) Climate change and hydropower production in the Swiss Alps: quantification of potential impacts and related modelling uncertainties. Hydrol Earth Syst Sc 11:1191-1205

Sioshansi FP (2008) Introduction: Electricity Market Reform – Progress and Remaining Challenges. In: Sioshansi,F.P. (ed) Competitive Electricity Markets: Design, Implementation, Performance, edn. Elsevier, Amsterdam,

Sioshansi FP, Pfaffenberger W (2006) Electricity market reform
an international perspective. Elsevier, Amsterdam

SNIRH (2012a) Caracteristicas das Albufeiras.
http://snirh.pt/index.php?idMain=1&idItem=7&albufcode=. Accessed 1 February 2012a

SNIRH (2012b) Redes de Monitorizacao. Sistema Nacional de Informacao de Recursos Hidricos. www.snirh.pt/index.php. Accessed 1 November 2012b

Stage S, Larsson Y (1961) Incremental Cost of Water Power. T Am Inst Electr Eng 80:361-364

Tilmant A, Goor Q, Pinte D (2009) Agricultural-to-hydropower water transfers: sharing water and benefits in hydropower-irrigation systems. Hydrol Earth Syst Sc 13:1091-1101

Tilmant A, Kelman R (2007) A stochastic approach to analyze trade-offs and risks associated with large-scale water resources systems. Water Resour Res 43:

Tilmant A, Pinte D, Goor Q (2008) Assessing marginal water values in multipurpose multireservoir systems via stochastic programming. Water Resour Res 44:

Turgeon A (1980) Optimal Operation of Multi-Reservoir Power-Systems with Stochastic Inflows. Water Resour Res 16:275-283

UN (1992) The Dublin Statement on Water and Sustainable Development. Dublin

Valor E, Meneu V, Caselles V (2001) Daily air temperature and electricity load in Spain. J Appl Meteorol 40:1413-1421

van der Linden P, Mitchell JFB (2012) Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project. Met Office Hadley Centre. Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK

van Meijgaard E, van Ulft L, van de Berg W, Bosveld F, van den Hurk B, Lenderink G, Siebesma A (2008) The KNMI regional atmospheric climate model RACMO, version 2.1, Tech. Rep. 302. R. Neth. Meteorol. Inst., De Bilt . Netherlands

Varian HR (2006) Intermediate microeconomics
a modern approach. W.W. Norton & Co, New York

Vicuna S, Leonardson R, Hanemann MW, Dale LL, Dracup JA (2008) Climate change impacts on high elevation hydropower generation in California's Sierra Nevada: a case study in the Upper American River. Clim Change 87:S123-S137

Williams JH, Ghanadan R (2006) Electricity reform in developing and transition countries: A reappraisal. Energy 31:815-844

Wolfgang O, Haugstad A, Mo B, Gjelsvik A, Wangensteen I, Doorman G (2009) Hydro reservoir handling in Norway before and after deregulation. Energy 34:1642-1651

Wriedt G, Van der Velde M, Aloe A, Bouraoui F (2009) Estimating irrigation water requirements in Europe. J Hydrol 373:527-544

Yakowitz S (1982) Dynamic-Programming Applications in Water-Resources. Water Resour Res 18:673-696

Young RA (2005) Determining the economic value of water
concepts and methods. Resources for the Future, Washington, DC

9 Papers

I. Pereira-Cardenal, S.J., Madsen, H., Riegels, N.D., Jensen, R., Mo, B., Wangensteen, I., Arnbjerg-Nielsen, K., Bauer-Gottwein, P.: Assessing climate change impacts on the Iberian power system using a coupled water-power model. Under revision.

II. Pereira-Cardenal, S.J., Mo, B., Riegels, N.D., Arnbjerg-Nielsen, K., Bauer-Gottwein, P.: Using power market models in the optimization of multi-purpose reservoir systems. Submitted.

III. Pereira-Cardenal, S.J., Mo, B., Gjelsvik, A., Riegels, N.D., Arnbjerg-Nielsen, K., Bauer-Gottwein, P.: Joint optimization of regional water-power systems. Submitted.

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