The impact of assuming perfect foresight for investment analysis in water resources systems

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November 22, 2022

Abstract

Perfect foresight hydroeconomic optimization models are tools to evaluate impacts of water infrastructure investments and policies considering complex system interlinkages. However, when assuming perfect foresight, management decisions are found assuming perfect knowledge of climate and runoff, which might bias the economic evaluation of investments and policies. We investigate the impacts of assuming perfect foresight by using Model Predictive Control (MPC) as an alternative. We apply MPC in WHAT-IF, a hydroeconomic optimization model, for two study cases: a synthetic setup inspired by the Nile River, and a large-scale investment problem on the Zambezi River Basin considering the water-energy-food nexus. We validate the MPC framework against Stochastic Dynamic Programming and observe more realistic modelled reservoir operation compared to perfect foresight, especially regarding anticipation of spills and droughts. We find that the impact of perfect foresight on total system benefits remains small (<2%). However, when evaluating investments and policies using with-without analysis, perfect foresight is found to overestimate or underestimate values of investments by more than 20% in some scenarios. As the importance of different effects varies between scenarios, it is difficult to find general, case-independent guidelines predicting whether perfect foresight is a reasonable assumption. However, we find that the uncertainty linked to climate change generally has more significant impacts than the assumption of perfect foresight. Hence, we recommend MPC to perform the economic evaluation of investments and policies, however, under high uncertainty of future climate, increased computational costs of MPC must be traded off against computational costs of exhaustive scenario exploration.

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Key Points:

- We apply Model Predictive Control (MPC) to overcome the perfect foresight assumption in a large-scale hydroeconomic optimization model.
- We compare perfect foresight, stochastic dynamic programming, Model Predictive Control and rule-based decisions for investment analysis.
- The assumption of perfect foresight can impact decisions, however climate or socio-economic uncertainty is expected to be more important.

Abstract

Perfect foresight hydroeconomic optimization models are tools to evaluate impacts of water infrastructure investments and policies considering complex system interlinkages. However, when assuming perfect foresight, management decisions are found assuming perfect knowledge of climate and runoff, which might bias the economic evaluation of investments and policies. We investigate the impacts of assuming perfect foresight by using Model Predictive Control (MPC) as an alternative. We apply MPC in WHAT-IF, a hydroeconomic optimization model, for two study cases: a synthetic setup inspired by the Nile River, and a large-scale investment problem on the Zambezi River Basin considering the water-energy-food nexus. We validate the MPC framework against Stochastic Dynamic Programming and observe more realistic modelled reservoir operation compared to perfect foresight, especially regarding anticipation of spills and droughts. We find that the impact of perfect foresight on total system benefits remains small (<2%). However, when evaluating investments and policies using with-without analysis, perfect foresight is found to overestimate or underestimate values of investments by more than 20% in some scenarios. As the importance of different effects varies between scenarios, it is difficult to find general, case-independent guidelines predicting whether perfect foresight is a reasonable assumption. However, we find that the uncertainty linked to climate change generally has more significant impacts than the assumption of perfect foresight. Hence, we recommend MPC to perform the economic evaluation of investments and policies, however, under high uncertainty of future climate, increased computational costs of MPC must be traded off against computational costs of exhaustive scenario exploration.

1 Introduction

Developing hydropower and irrigation while preserving ecosystems will contribute to reach the Sustainable Development Goals (UN General Assembly, 2015), but might also increase competition for the scarce water resource. Therefore, decision-makers need tools that consider the interdependencies within the water-energy-food nexus (Albrecht et al., 2018; Baldassarre et al., 2019; Bhave et al., 2016; Miralles-Wilhelm, 2016; Rising, 2020). Hydroeconomic optimization models, which associate an economic impact to each management decision and thus transform a complex multi-objective management problem into a simpler single-objective problem (Bauer-Gottwein et al., 2017; Harou et al., 2009) are attractive candidates. In this category, models representing numerous nexus interactions and multiple reservoirs (Block & Strzepek, 2010; Draper et al., 2003; Kahil et al., 2018; Khan et al., 2018; Payet-Burin et al., 2019; Vinca et al., 2020) often assume perfect foresight. Perfect foresight is a common approach used in sectorial planning models (Expósito et al., 2020; Keppo & Strubegger, 2010), where the system is optimized over the whole planning period with assumed perfect knowledge of the future. This means that optimization models with perfect foresight anticipate future conditions, such as droughts, and adjust, for instance, by selecting crops with lower water requirements or storing additional water. In actual operation, water planners and managers do not have perfect foresight, and are limited by the availability and skill of existing forecasting systems. A more realistic way of modelling reservoir operation and agriculture decisions could improve the reliability of the results of investment evaluation and cost benefit analysis (Anghileri et al., 2016; Jahani et al., 2016; Khadem et al., 2018; Sahu, 2016).

Stochastic Dynamic Programming (SDP) (Scarcelli et al., 2017; Soleimani et al., 2016) and Stochastic Dual Dynamic Programming (SDDP) (Pereira-Cardenal et al., 2016; Tilmant et al., 2012) have been used to represent water management problems and infrastructure evaluation in a nexus context while considering the stochastic nature of the water inflow. However, SDP suffers the *curse of dimensionality* as problem complexity increases exponentially with problem size, hence it is restricted to applications with a limited number of reservoirs and interactions; while SDDP can be applied to larger systems, it is still limited to convex future benefits.

Simulation frameworks (Cervigni et al., 2015; Howells et al., 2013; Yates et al., 2005), do not assume perfect foresight, as the system management is determined for each time step using allocation rules. However, allocation rules are usually based on current or past socio-economic conditions and might not be economically optimal in another context (Pereira-Cardenal et al., 2016). This might lead to biased performances when exploring a range of possible scenarios, which is a key process when exploring robust decisions considering the large uncertainties of the future climate and socio-economic development (Bhave et al., 2016; Giuliani & Castelletti, 2016; Herman et al., 2015, 2020).

Model predictive control (MPC) is a framework that enables to use a perfect foresight optimization model while considering limited knowledge of the future. In this approach, which replicates potential actual operation, optimal management decisions are iteratively solved in each time step, using forecasted information available at the time of decision. Model predictive control was originally developed for power plants and refineries in 1970 and is now used in a large variety of fields from food processing to aerospace applications (Qin & Badgwell, 2003). MPC has many advantages: (1) it makes use of an existing perfect foresight framework, (2) it does not suffer the *curse of dimensionality*, as computation costs do not increase exponentially with problem size (3) it can be applied to non-linear frameworks, (4) it is not limited to hydrologic uncertainty. Yet, the application of MPC to water resource systems is seldom: Khadem et al. (2018) apply a specific form of MPC, by solving the CALVIN perfect foresight model (Draper et al., 2003) year by year, still assuming a perfect foresight of a year; Anghileri et al. (2016) apply MPC to a simple water resource system model to evaluate the value of forecasts. The purpose of this work is to demonstrate that MPC is a powerful framework to overcome the perfect foresight assumption in large-scale multi-sector hydroeconomic models and to investigate the impacts of assuming perfect foresight when evaluating the economic value of infrastructure. We use the open-source hydroeconomic optimization model WHAT-IF (Payet-Burin et al., 2019), which links in a holistic framework, representations of the water, energy, and agriculture systems.

The study is organized as follow:

In section 2 we present the WHAT-IF model and the Model Predictive Control Framework. Section 3 describes the study cases: a synthetic setup inspired by the Nile River and a large scale problem in the Zambezi River Basin from Payet-Burin et al. (2019), where water infrastructure and policies are planned to satisfy growing food and energy demands. In section 4 we discuss the parametrization of the MPC framework. In section 5 we investigate the impacts of assuming perfect foresight when performing the economic evaluation of investments through with-without analysis. In the Nile case, we validate the MPC framework against Stochastic Dynamic Programming and highlight some of effects of the perfect foresight assumption. We also compare it to a rule-based simulation framework. Using a large range of scenarios, we investigate in which cases the perfect foresight assumption affects the economic evaluation of two hypothetical projects. Finally, we perform the same analysis for the economic evaluation of hydropower, irrigation development, and an environmental flow policy on the Zambezi River Basin.

2 Methods

2.1 The hydroeconomic optimization model: WHAT-IF

WHAT-IF is an open-source hydroeconomic optimization model, linking representations of the water, energy, and agriculture systems in a holistic framework (Payet-Burin et al., 2019). In WHAT-IF decision variables for water management (e.g. water storage and supply), energy management (e.g. power capacity construction, production, transmission, and supply) and agriculture management (e.g. crop choice, irrigation, transport, and supply) are solved to maximize the welfare economic objective function which is the sum of all consumer and producer surpluses. The model operates at a monthly time step for long hydrologic time series. It is a perfect foresight framework as optimal decisions are found with full knowledge of the future over the planning horizon. In addition to the description of WHAT-IF in Payet-Burin et al. (2019), in the current version of the model hydropower production is the product of releases and a volume-dependent head, which leads to a non-linear optimization model and more realistic reservoir release decisions.

The model is coded in the python programming language: the problem is formulated with Pyomo (Hart et al., 2017) and solved with the non-linear solver IPOPT (Wächter & Biegler, 2005) using the HSL mathematical software library (Research Councils UK, 2020).

2.2 Model Predictive Control Framework

The basic concept of Model Predictive Control (MPC) is to iteratively optimize decision variables (also called "control actions") of a system over a forward moving time window at a given sampling interval. The MPC framework suits real-time water management, repetitively answering the question "given the current available information about the future what is the best decision to take now?". For example, every month, for the Colorado Reservoir System, the Bureau of Reclamation updates the "24-Month study" (Bureau of Reclamation, 2019) describing the expected behavior of the system for the next two years, based on which the operation rules for the current month are set. In this study, the MPC framework is implemented to simulate a more realistic operation of the water infrastructure than the one resulting from perfect foresight optimization runs, and thus, evaluate more accurately the potential economic impacts of water infrastructure investments and policies.

Figure 1 summarizes the framework: Every time step, a forecast of the hydrologic parameters is generated for the prediction horizon. The forecast might be an ensemble forecast, or a single forecast as in **Figure 1**. The prediction horizon is the time window for which the system is optimized (e.g. 2 years). The choice of the prediction horizon depends on the quality of the forecast, the time scales and memory effects inherent in the problem and the available computational resources. Over the prediction horizon all the decision variables are solved (e.g. water storage, and supply) using the perfect foresight model with the forecast information, but only the decision variables for the current time step are implemented. The process is repeated over the planning horizon (e.g. 30 years), at each time step the prediction horizon is moved forward, a new forecast is generated considering the new information available, and the optimal decision variables for the current time step are implemented. If the model contains a mix of monthly and yearly decision variables, the prediction horizon is adjusted to cover a complete year. Yearly decision variables of the model (e.g. crop choice and power capacity investments) are only determined for time steps that start a new year.

Regarding reservoir operation, the decisions taken in a given month might impact reservoir levels several years later. Because for large models it would be computationally too expensive to consider a very long prediction horizon (e.g. several decades), a storage target or hedging rule (You & Cai, 2008) at the end of the prediction horizon is implemented in order to account for the value of water in the reservoir beyond the prediction horizon. Khadem et al., (2018) suggest a complex but general method to evaluate the storage value; the MPC framework presented here is not as sensitive to the assumed end storage value, because only the first decisions are implemented, hence we choose a simple method based on the shadow value (or dual value) of water from a perfect foresight run.

To find the optimal decision variables from the forecast, different methods can be used. For a single forecast F^s the model M is run once $DV^s = M(F^s)$ and resulting optimal decision variables for the current time step t_0 are implemented $DV_{t0} = DV_{t0}^s$. For an ensemble forecast of n members $\{F^k, k \epsilon 1..n\}$, a simple approach is to run the model separately for each ensemble member $\{DV^k = M(F^k), k \epsilon 1..n\}$ and assume that the optimal decision variables are the average of the ensemble optimal decision variables $DV_{t0} = average(DV_{t0}^k, k \in 1..n)$. The probabilistic method is to merge the individual problems from the different ensemble members into a single optimization problem $DV^e = M(F^k, k \epsilon 1..n)$, in which the decision variables for the first time step are shared $DV_0^{e,1} = DV_0^{e,2} ... = DV_0^{e,n}$ and the objective function obj_e is an average of the individual objective functions weighted by their respective likelihood K: $obj_e = \sum obj_k \cdot K_k, k \epsilon 1..n$.

Here we assume that only the hydrology is uncertain and that other parameters, such as energy demand and renewable energy production can be predicted. If intermittent renewable power sources play an important role, the same approach can be implemented with wind and sun forecasts in addition to hydrologic forecasts.

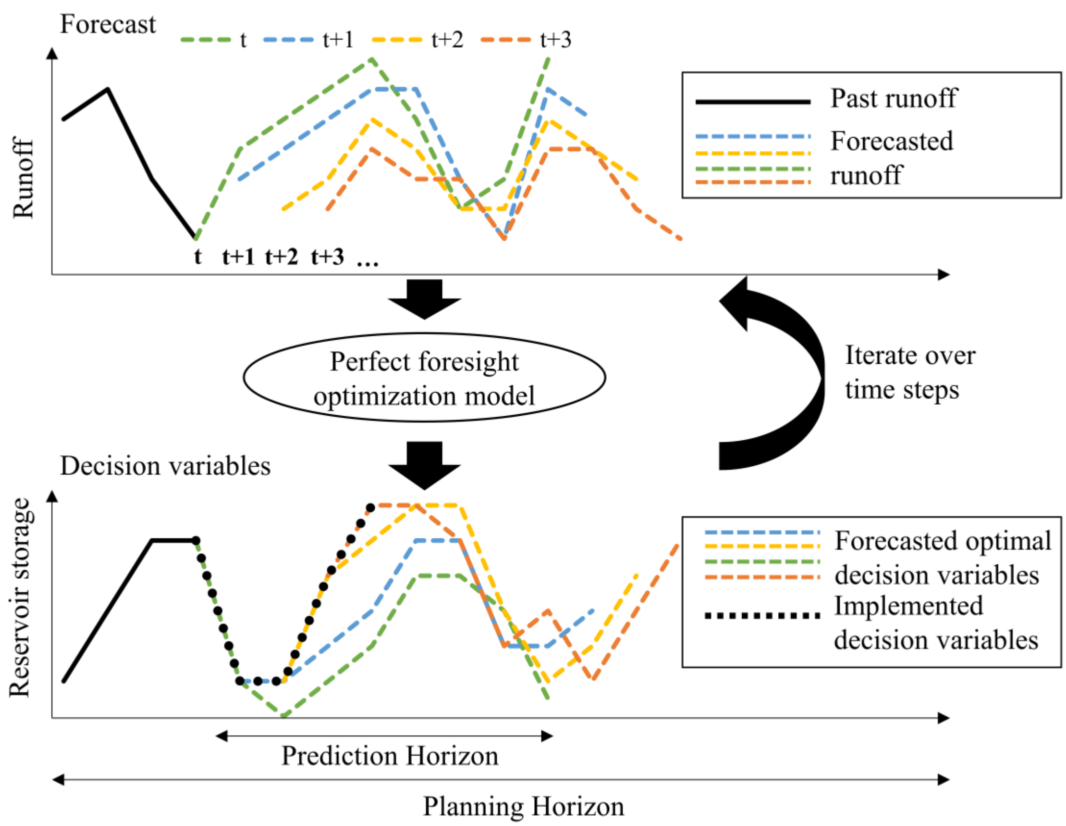

Figure 1. Model Predictive Control (MPC) framework. The methodology is illustrated with runoff as forecasted parameter with a single forecast, and reservoir storage as a decision variable; in the model all forecasted parameters and decision variables are solved simultaneously.

3 Overview of two study cases

The Nile synthetic study case is used to demonstrate the MPC framework and evaluate the effects for a large range of scenarios. The Zambezi River Basin study case is used to demonstrate the applicability of the MPC framework to large-scale water-energy-food nexus models.

3.1 Nile synthetic study case

To illustrate the methodology, we use a synthetic study case inspired by the High Aswan Dam (HAD) in Egypt (***Figure 2***). The dam receives inflow from Soudan and has an active capacity of 90 BCM (Billion Cubic Meters). We represent Egypt as a single water demand node of 53 BCM /year, with a seasonal profile and a demand curve. The demand curve is inspired from El-Gafy and El-Ganzori (2012), the average economic value of irrigation water is around 2 L.E/m^3 (0.130\$/m^3), and there is about a factor 10 between high value crops such as vegetables and low value crops such as rice. The hydropower plant linked to the dam has a capacity of 2100 MW, producing around 10 GWh per year. The head in the reservoir varies from 36 to 64 meters and the hydropower turbine capacity from 1200 to 2500 m^3/s; for simplicity, we assume a linear head-volume dependence. Hydropower production is valued using a fixed output price of 50\$/MWh. We use a monthly runoff time series at Dongola from 1970 to 2000. To simplify, the water share of Soudan (18.5 BCM/year) and the average evaporation from the dam (10 BCM/year) is subtracted from the inflow, leaving an average water availability of 58 BCM/year.

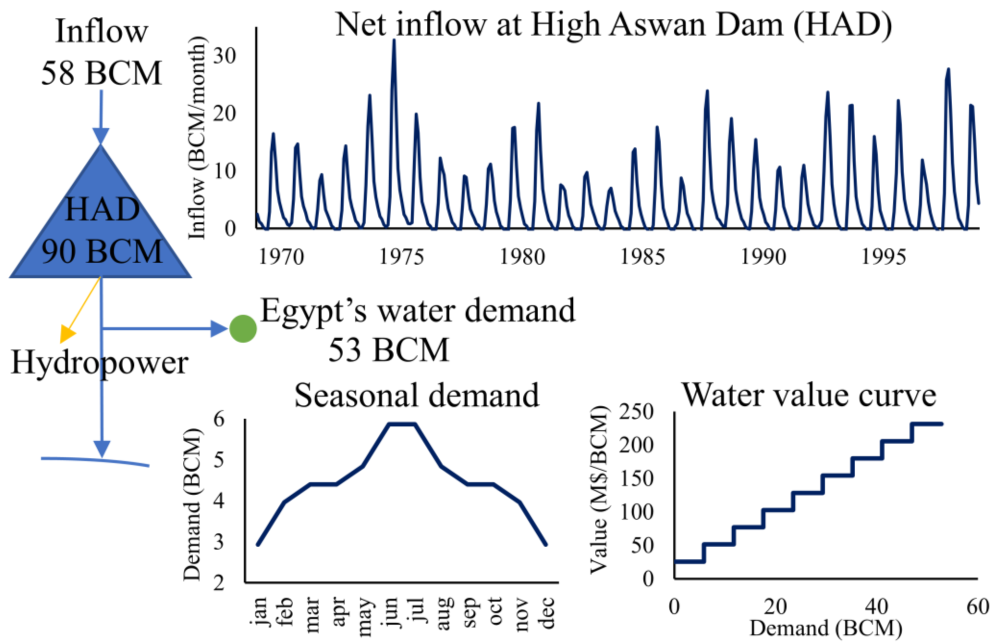

Figure 2. Conceptual scheme of the Nile synthetic study case. Water units are in Billion Cubic Meters (BCM).

The operation rule used in the simulation (SIM) framework is from Mobasher (2010), and works as follows: If the reservoir level in July is above 60 BCM, the water releases for the rest of the year are proportional to the July reservoir level (from 1800 m³/s for 60 BCM to 2850 m³/s for 90 BCM) or higher to fully satisfy the agricultural demand. If the reservoir level in July is lower than 60 BCM, the agriculture demand is curtailed by: 5% from 55 to 60 BCM, 10% from 50 to 55 BCM and 15% under 50 BCM. The releases are then proportional to the agricultural demand and no extra water for hydropower is released.
As a benchmark, we also implemented the stochastic dynamic programming (SDP) framework for this study case (see Loucks and Van Beek (2005) for the development of the SDP method). the main limitation of SDP is that it cannot be applied to larger systems, however, for this simple study case SDP is straightforward and can be used to validate the MPC method. We divide the inflow in three classes for each month: low, average, and high inflow which correspond respectively to the 0 to 30th, 31 to 60th, and 61 to 100th percentiles of the inflows. We consider the 15th, 45th and 80th inflow percentiles to be representative inflows for the 3 classes. We find that the definition of classes has little impact on results. We then obtain storage water values in the High Aswan Dam for the different classes of inflow (see supporting information).

3.2 Zambezi River Basin study case

We use the modelling framework and dataset of the Zambezi River Basin from Payet-Burin et al. (2019). The river basin is divided in 26 catchments with runoff and precipitation time series covering 40 years; the average yearly runoff is 114 10^9m³. In each catchment domestic, agricultural, and industrial water demands are represented, as well as environmental flow constraints at the level of the main wetlands (Kafue flats, Baroste plain, and Mana pools) and the Zambezi delta (**Figure *3***). The main reservoirs of the river basin (Itezhi-Tezhi, Kariba, and Cahora Bassa dams) have an active storage capacity of 127 10^9m³ and are the main consumptive water user of the river basin through evaporation losses. The agricultural water demand is calculated based on FAO 56, crop yields are based on FAO 33, and the crop choice is part of the optimization framework. Unlike in Payet-Burin et al. (2019), rainfed production and crop markets are not represented, only irrigated agriculture is represented and valued at the farm level using FAO data (FAO, 2018). Thermal power is represented as aggregated production units per country. A power market per country is represented, including South Africa, with corresponding power demands. The power transmission network is represented with a transport model considering aggregated transmission lines between countries. A capacity expansion model represents additional investments in thermal and solar power.

We use the reference "2030" scenario from Payet-Burin et al. (2019), considering the forecasted water, crop and energy demands in the river basin in 2030 and the natural flooding environmental policy of 7000 m³/s in february. The evaluated water infrastructure development plan (Payet-Burin et al. (2019), World Bank (2010)) considers 15 hydropower projects with 7.2 GW of new operating capacity and 336 000 ha of new areas equipped for irrigation, almost doubling the current irrigated area. To evaluate the MPC framework in different water scarcity levels, we consider three different climate change scenarios from Cervigni et al. (2015) as in Payet-Burin et al. (2019).

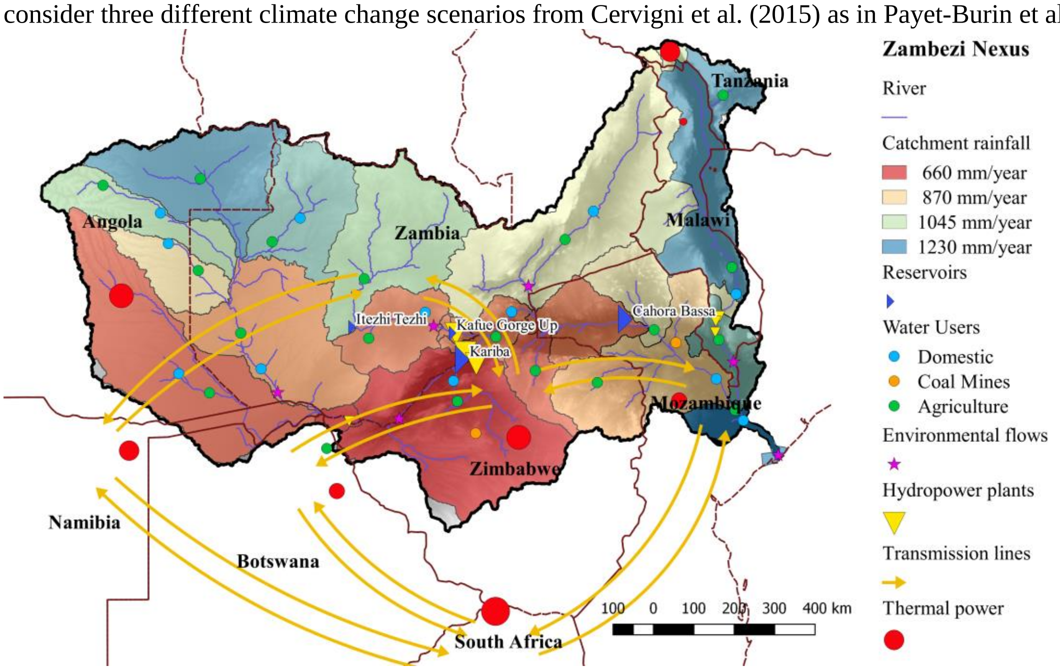

Figure 3. Zambezi River Basin water-energy-food nexus framework.

4 Parametrization of the Model Predictive Control framework

We test how different parameters of the MPC framework affect performance on the Nile and Zambezi River Basin study cases. To do so, we compare the objective function (Nile: benefits from water allocation and energy production; Zambezi: total producer and consumer surplus for water, energy and crops) of the MPC framework with different parameters against the perfect foresight framework. The difference is then called "Gap to perfect foresight" and represents the distance to the optimal solution, in this section we don't explore yet the drivers of the difference. When comparing the different frameworks, the last 3 years out of the 30 years planning period are solved under perfect foresight. This ensures that results are not significantly impacted by boundary effects (e.g. different runs not finishing with the same reservoir level). In the Nile study case, we evaluate the parameters for a range of scenarios considering different runoff levels by multiplying all values with a constant change factor. In the Zambezi study case, we consider three climate change scenarios.

4.1 Bootstrapping forecast performance

We use nearest neighbors bootstrapping (Lall & Sharma, 1996; Yates et al., 2003) to generate single and ensemble forecasts for the MPC framework (see supporting information). We assess the performance of the average forecast using bootstrapping by comparing it to monthly runoff climatology and the Thomas-Fiering method (Harms & Campbell, 1967). We observe that the bootstrapping method performs better than climatology and the Thomas-Fiering method for lead times under 3 to 5 months (Figure 4). The advantage of nearest neighbors bootstrapping against the Thomas-Fiering method is that it can be used to simultaneously predict runoff, rainfall, and evapotranspiration. The purpose is not to demonstrate the bootstrapping's performance as a forecasting tool, but to show that it performs adequately to be used within the MPC framework for investment evaluation.

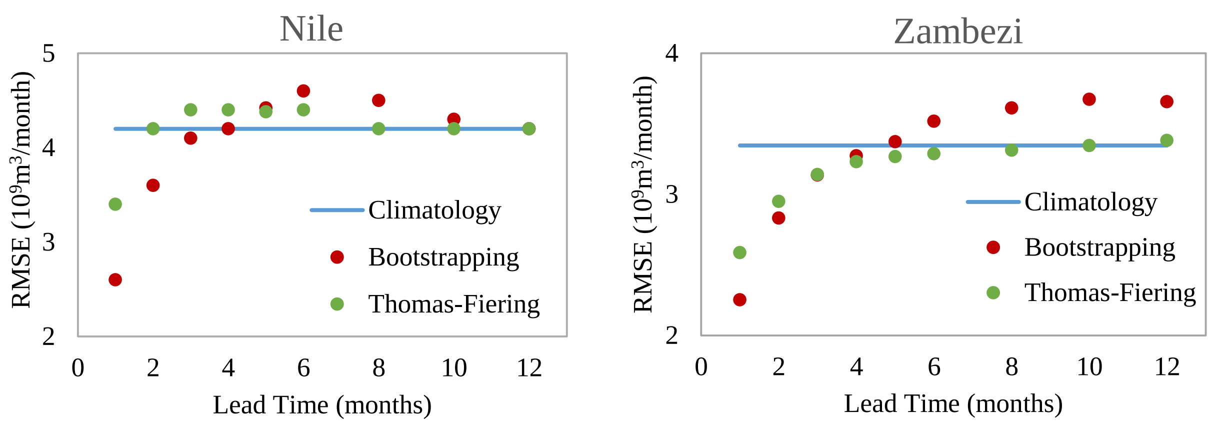

Figure 4. Bootstrapping forecast performance. Root mean square error (RMSE) of the total forecasted runoff in the river basin for different lead times; the bootstrapping forecast is benchmarked against the Thomas-Fiering method and monthly runoff climatology.

Subsequently, we investigate how the forecast quality affects the performance of MPC. To simulate different forecast qualities, we add a perfect forecast length varying from 0 to 36 months to the bootstrapping forecasts. When generating a forecast, a perfect forecast length of 3 months means that the true time series is used for the next 3 months (hence a "perfect" forecast), and only the following months are forecasted with the nearest neighbor bootstrapping method. We observe that for water-rich scenarios, a 1-year perfect forecast is almost equivalent to perfect foresight, while for water-scarce scenarios, several years of perfect forecast are beneficial, showing that long-term interannual storage plays an important role (**Figure 5**). However in all cases a perfect forecast of a year improves considerably (artificially) the performances; even if not exactly comparable, this illustrates some limitations of using a year by year perfect foresight optimization framework as in Khadem et al. (2018). The purpose of using the MPC framework here, is to represent a realistic infrastructure operation; if in actual operation more complex or simpler forecasts are used to operate infrastructure, those can be implemented in the MPC framework.

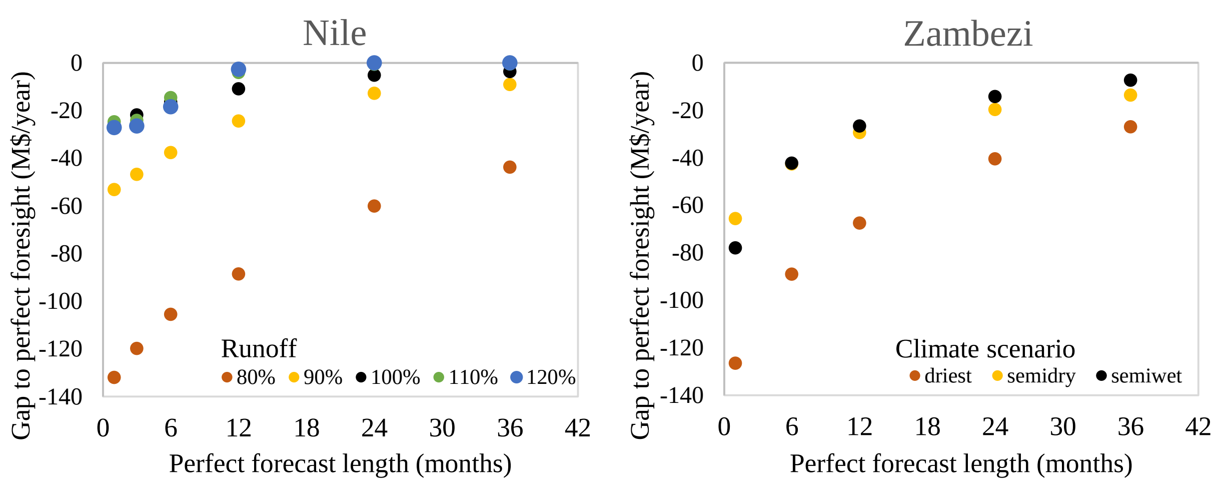

Figure 5. Impact of forecast quality on Model Predictive Control framework performance. The gap to perfect foresight is the difference between the values of objective function of the MPC and Perfect Foresight framework.

4.2 Choice of optimal decision variables for the current time step

As described in section 2.2, different methods can be used to find the optimal decisions in the current month, based on a single forecast or an ensemble of forecasts. We compare the methods summarized in Table 1.

Table 1. Summary of methods to derive present decision variables from forecast.

Method name	Description
A	Single weighted forecast (or "tracer" forecast) based on a 20-ensemble forecast. The model is run for the single forecast giving a single set of optimal decisions.
B	Ensemble forecast of **n** members. The optimization problem is solved separately for the ensemble members and the optimal decisions are the average of the ensemble optimal decisions.
C	Ensemble forecast of **n** members. Single probabilistic optimization problem merging the individual problems using equality constraints between decision variables in the current time step. Average objective function weighted by respective likelihoods.
D	Same as C, except that a 20 members ensemble forecast is converted to a 2 members ensemble forecast divided into high and low flow forecasts.

For the Nile study case, methods **B** and **C** are used with both 5 and 20 ensemble members, while for the Zambezi study case, only 5 ensemble members are used to reduce computational costs. We observe that methods **A**, **C**, and **D** perform similarly, while method **B** performs worse. If the problem was fully linear and had no binding constraints, averaging the forecasts (method **A**) or averaging the solutions generated by these forecasts (method **B**) should give the same result. However, we find that averaging the individual decisions derived from an ensemble forecast is not an appropriate method. Method **C** performs best as it has the finest resolution in terms of representing the probability of the hydrologic parameters. Method **D** is the same as **C** with 20 members, except that a 20-member ensemble forecast is merged into a 2-member ensemble forecast (low and high runoff forecast). As methods **C** and **D** perform very close, considering that a higher number of ensemble forecasts is computationally expensive, we find method **D** to be a good trade-off. Method **A** is found to perform almost as good and is even simpler as it uses a single forecast, however it can lead to irrational management. Indeed, if high runoff leading to spills is forecasted, in the optimization problem it may be equally profitable to spill water now or in the future as the problem assumes future is certain. This can lead to spills that could have been delayed or avoided, as the forecast might be wrong, and no spill would be necessary in the future. In actual operation, decision of spilling would be delayed until it is certain that there is too much water in the system or that flood control criteria become binding. When considering an ensemble forecast premature spills do not happen, as one of the forecasts would likely represent a scenario with low-flows. This could also be addressed by including artificial "penalties" in the optimization problem, that are small enough to not influence the other trade-offs. To avoid those artificial penalties, we prefer to opt for method **D** for the rest of the study, considering a low and high flow forecast with their respective likelihoods in a probabilistic optimization problem.

Table 2: Performance of the different methods to identify current decisions based on forecast. The gap to perfect foresight is the difference between the objective function of the MPC framework against the Perfect Foresight framework. Green, orange, and red colors indicate respectively high, medium and low performance.

Gap to perfect foresight (M$/month)	Scenario (runoff)							
	Nile					Zambezi		
Method	80%	90%	100%	110%	120%	semi-wet	semi-dry	driest
A	-94	-72	-52	-29	-23	-78	-69	-131
B_5	-134	-93	-67	-36	-26	-108	-87	-113
B_20	-138	-102	-73	-38	-28			
C_5	-103	-83	-42	-26	-26	-82	-63	-120
C_20	-90	-76	-28	-28	-26			
D	-111	-81	-45	-30	-23	-77	-59	-132

4.3 Prediction Horizon

The prediction horizon determines the timeframe for which the optimization problem is solved in every time step. Regardless of the prediction horizon length, it is only the first time step (one month) decision that is implemented in the system model. For the Zambezi study case, the prediction horizon needs to cover entire years as the model contains yearly decision variables, hence the shortest prediction horizon is one year. We vary the length of the prediction horizon to evaluate the impact of this parameter (Figure 6). We observe that considering a prediction horizon under one year leads to lower performances, horizons above one to two years lead to the best performance. As the forecast has short-term skills, increasing the prediction horizon above two years does not clearly improve performances, we even observe performance decrease in the Zambezi case. Based on this we consider a prediction horizon of 2 years for the rest of the study. Note that with a (theoretical) perfect forecast (section 4.1) we still find improved performance when increasing the prediction horizon above 2 years for all cases and scenarios.

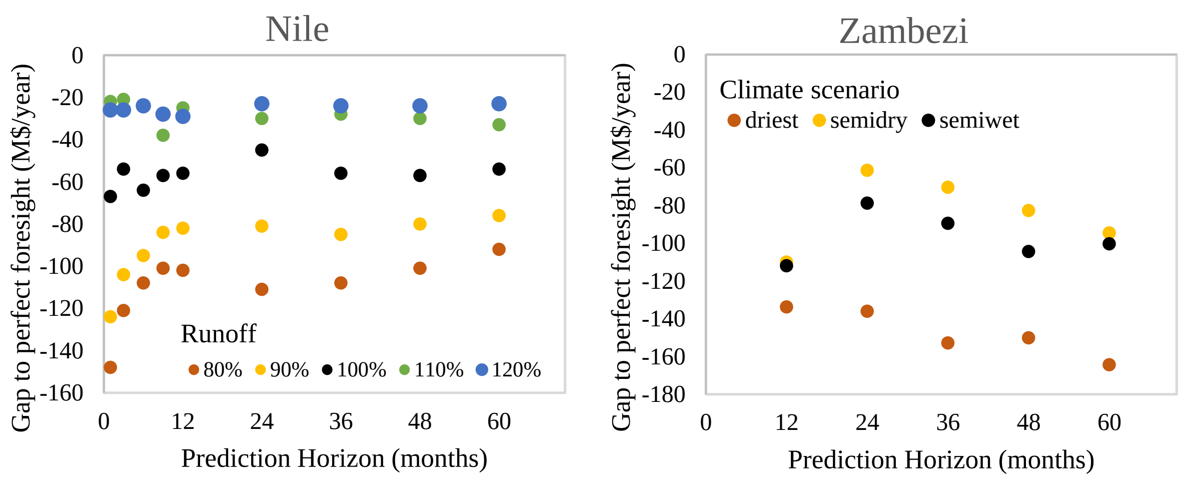

Figure 6: Impact of the prediction horizon on the performance of the MPC framework. The gap to perfect foresight is the difference between the values of objective function of the MPC and Perfect Foresight framework.

5 Impact of perfect foresight on the economic evaluation of investments and policies

5.1 Nile study case

In this section we compare the Perfect Foresight (PF), Model Predictive Control (MPC), Stochastic Dynamic Programing (SDP), and Simulation (SIM) frameworks on the Nile synthetic case and for a range of scenarios. The objective function of the PF, MPC, and SDP frameworks is to maximize total economic benefits from water demand satisfaction and hydropower production. The SIM framework follows the operation rule presented previously (section 3.1).

We observe that the global economic output in the four frameworks is very similar (Table 3); the main difference is that the PF framework leads to higher hydropower production and lower demand curtailments. The operation rule of the SIM framework might not be as optimal for this synthetic case as it was designed for the real conditions, but we observe that it performs closely to the other frameworks in terms of total system benefits.

Table 3. Key indicators for the different frameworks on the Nile study case.

Framework	PF	MPC	SDP	SIM
Total benefits (M$/year)	7 229	7 204	7 189	7 087
Difference to MPC (%)	**+0.3%**	**-**	**-0.2%**	**-1.6%**
Hydropower production (GWh/year)	9.6	9.2	9.2	9.2

Hydropower spill ($10^9 m^3$/year)	3.2	4.5	5.3	5.0
Hydropower value (M$/year)	479	463	458	462
Demand curtailment ($10^9 m^3$/year)	1.3	1.4	1.7	4.8
Demand Value (M$/year)	6 750	6 741	6 732	6 626

Regarding reservoir management, we observe two effects of perfect foresight: (1) high flows are anticipated by releasing additional water before, thus avoiding spills (release higher than turbine capacity), (2) low flows are anticipated by storing additional water before, achieving a better head management and leading to less water demand curtailment (Figure 7). Both effects together explain the higher hydropower production observed for the PF framework. We also observe that MPC and SDP lead to almost identical reservoir operations. MPC and SDP frameworks can be implemented in actual operation. Hence, we can assume that they represent a potential reality and that differences observed for PF and SIM are biases linked to the intrinsic assumptions linked to these frameworks.

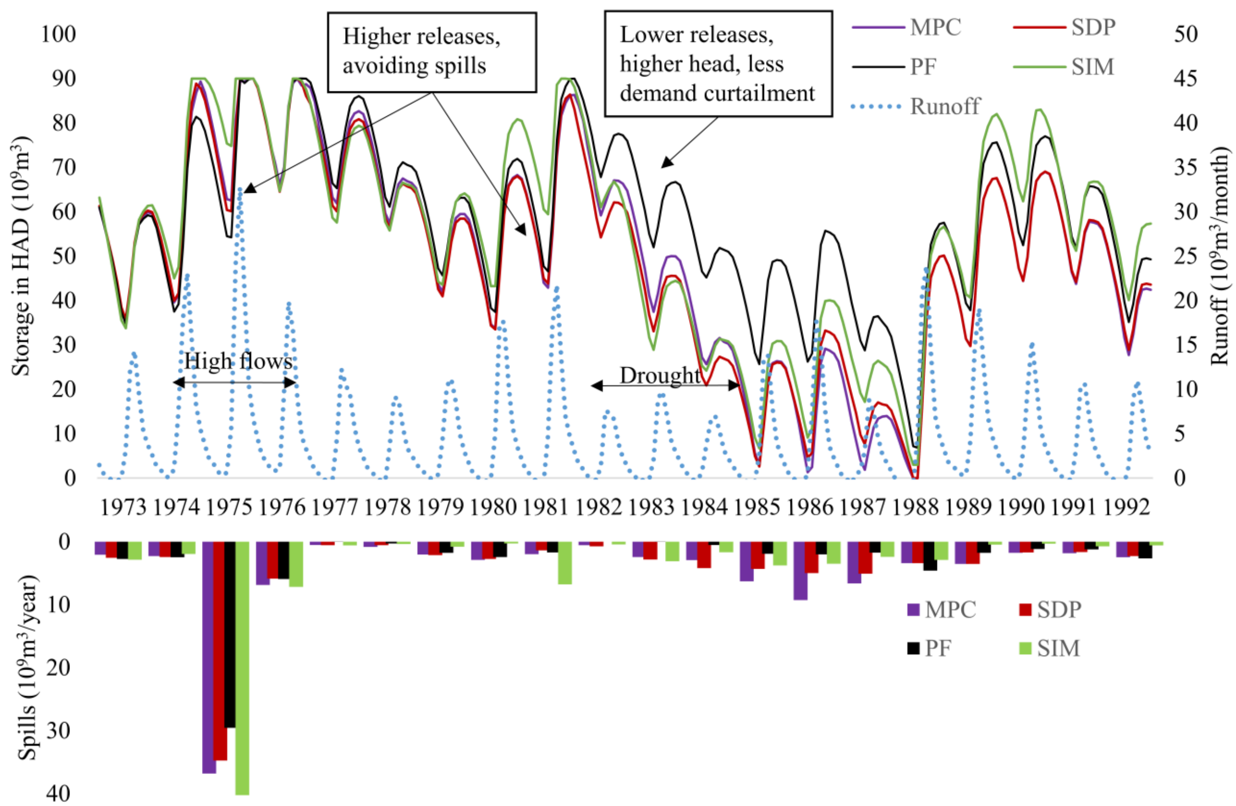

Figure 7. Modelled reservoir management of the High Aswan Dam (HAD) for the different frameworks. MPC, PF, SIM, and SDP indicate respectively Model Predictive Control, Perfect foresight, Simulation, and Stochastic Dynamic Programming.

To investigate how these effects vary depending on the context, we perform the comparison between the frameworks for different scenarios by varying runoff and water demand. Change in runoff and water demand is implemented by multiplying all values by a constant factor. Change in water demand keeps the proportions of the temporal distribution and demand curve of current water demand. We see the effects highlighted in Figure 7 take different proportions depending on the scenario (Figure 8).

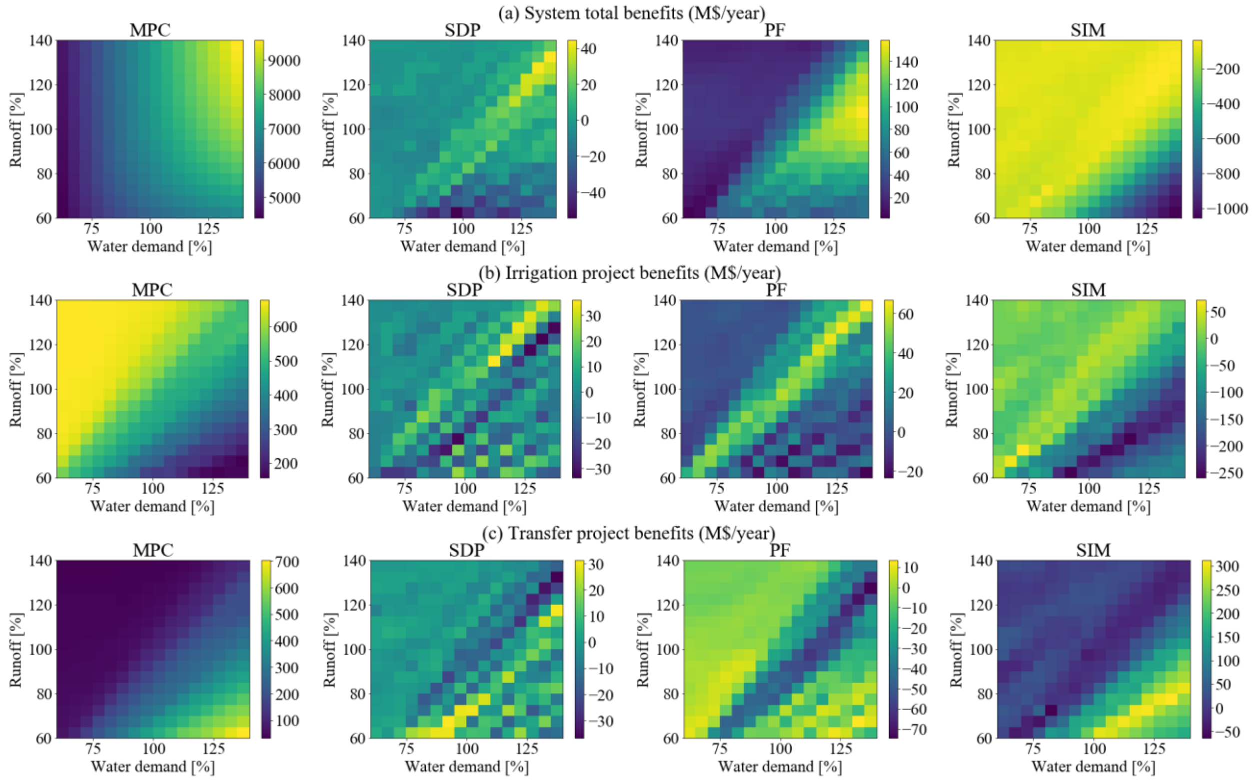

Figure 8. Economic evaluation of baseline (a) and project development (b & c) with the different frameworks. For Model Predictive Control (MPC) the absolute value is shown, for Stochastic Dynamic Programming (SDP), Perfect Foresight (PF), and Simulation (SIM) the incremental value compared to MPC is shown. Irrigation and Transfer benefits are calculated through with-without analysis.

The analysis of scenarios of total system benefits (Figure 8.a) confirms that MPC and SDP behave similarly, even if trends of differences are visible, they are considerably smaller compared to other frameworks. That said, all frameworks are close in terms of total system benefits: PF overestimates benefits by +0.2% to +1.7%, while SIM is underestimating benefits by -1 to -12%. The results by indicators are available in the supporting information. The SIM framework assumes the same reservoir operation rule applies in all scenarios; as expected, it underperforms in scenarios different from the reference scenario, particularly when increasing water scarcity. However, for total system benefits, the uncertainty linked to the framework is small compared to other sources of uncertainties (e.g. data, temporal and spatial aggregation, other model assumptions) for this kind of analysis.

In a second step, we investigate how the choice of framework affects the economic valuation of projects in a with-without analysis. We consider two (hypothetical) projects: (1) an irrigation extension project, corresponding to an increase in the water demand by 10% (homogeneously distributed in the temporal-demand and value-demand profiles); and (2) a water transfer project adding 10% of water upstream of the dam, represented by a constant additional inflow of 0.45 $10^9 m^3$ per month. We evaluate the economic impact of these projects (computed as total benefits with the projects minus total benefits without the project) for the different scenarios of runoff and initial water demand (Figure 8.b and Figure 8.c). The impact of the irrigation project (Figure 8.b) corresponds to two horizontal moves right in Figure 8.a, and the impact of the water transfer project (Figure 8.c) is similar to two vertical moves up.

We observe that:

(1) SDP and MPC behave similarly as for total system benefits, even if trends of differences are visible, they are smaller compared to other frameworks (Figure 8.b and Figure 8.c).

(2) PF overestimates irrigation project benefits by 5% to 12% in the diagonal where water demand is close to water availability (Figure 8.b). The reason is that the irrigation project's increase in water demand moves the system from a state where foresight has low value towards a state where foresight has high value (Figure 8.a). PF

underestimates transfer project benefits by -20 to -35% in the diagonal where water demand is slightly above water availability (Figure 8.c). The value of additional water is underestimated with perfect foresight, because it moves the system from a state where foresight has high value towards a state where foresight has low value (Figure 8.a). Outside the diagonal, PF is close to both MPC and SDP. With water abundance or stress, the value of foresight is respectively either low or stable, hence it does not affect the with-without analysis significantly.

(3) SIM underestimates irrigation projects benefits by -40% to -80% (Figure 8.b) in water-scarce scenarios (high demand and low availability). In water-abundant scenarios (high availability and low demand), SIM performs similarly to other frameworks, as the release rules are not stressed by water shortages. SIM overestimates transfer project benefits by +30% to +60% in water-scarce scenarios (Figure 8.c), because the transfer project eases the water stress that SIM does not cope well with.

In contrast to global system benefits, the differences found in the with-without analysis can impact decision-making on project development. When performing the with-without analysis, the impact of assuming perfect foresight is more important in scenarios where the importance of perfect foresight varies between the with and the without run. This does not necessarily correspond to scenarios for which the impact of perfect foresight on total benefits is strongest. However, the value of investments varies importantly depending on the water demand and available runoff (with a factor 3 to 7), hence uncertainty in these parameters is likely to have more impact than the bias introduced by perfect foresight. In general, to use a non-adaptative simulation rule is clearly inappropriate to explore scenarios with a different system state: as observed here, even small changes (e.g. +10% demand combined to -10% runoff) can lead to considerably different results (respectively -34% and +23% for the irrigation and water transfer project benefits).

5.2 Zambezi River Basin study case

We now apply the Model Predictive Control (MPC) framework to a large-scale problem on the Zambezi River Basin considering multiple interactions between the water, energy and food systems. We evaluate the economic impact of different projects and policies from World Bank (2010) by performing with-without analyses for three different climate change scenarios from Cervigni et al. (2015). We compare the Perfect Foresight (PF) to the MPC framework in order to evaluate the bias introduced by the perfect foresight assumption (Table 4). The individual results of the largest hydropower and irrigation projects are highlighted, while "all projects" also include other investments.

The climate change scenarios correspond to different water-scarcity levels, in the semi-wet, semi-dry and driest scenarios the water consumption represents respectively 17%, 23%, and 34% of the available runoff. We observe that for the semi-wet and semi-dry scenarios the differences between the PF and MPC frameworks are mostly under 5% (Table 4), which is small compared to other possible sources of uncertainty (e.g. climate, socio-economic development). However, for the driest scenario important differences appear for some investments.

The economic value of all irrigation investments is only overestimated by 4% with perfect foresight (Table 4), but up to 90% for the Shire Irrigation investment, while the value is almost the same for the Delta irrigation investment. In Payet-Burin et al. (2019) the Shire River is found to be the most water-scarce zone with high inflow variability and low storage capacity, which explains why with perfect foresight the project is found more profitable as water scarcity can be anticipated. The Delta irrigation project is in the Zambezi Delta, where there is the most flexibility due to all upstream reservoirs and where the water has the lowest value as there are no downstream uses, which might explain the small difference between the MPC and PF frameworks. When implementing all irrigation projects (Table 5), perfect foresight leads to higher agricultural production (+45 M$/year), which is partially due to higher irrigation water allocation (+241 Mm³/year) as less water is spilled downstream (-127 Mm³/year).

Environmental flow (e-flow) opportunity costs, which are the direct forgone benefits by ensuring a minimum flow to ecosystems (excluding the direct and indirect benefits of protecting ecosystems), are underestimated by 23% with the perfect foresight assumption. The difference is explained by lower trade-offs with agricultural production (-61 M$/year), energy production (-11 M$/year), and domestic and industrial water users (-6 M$/year) (Table 5). With perfect foresight low flows can be anticipated, hence extra water can be stored to accommodate ecosystems and other water users, while in actual operation, when low flows are not anticipated, high value water users might be curtailed in order to satisfy the environmental constraint (as we assume environmental flows have the highest priority).

The economic values of all hydropower projects are overestimated by 9% with perfect foresight (Table 4), and similar trend is observed at the individual scale (+8% for Batoka Gorge, +12% for Mphanda Nkuwa). However, we see two opposite effects compensating each other: the value of the additional reservoir capacity in Mphanda Nkuwa is considerably underestimated with perfect foresight (-25 M$/year, -53%), while the value of the hydropower turbines is considerably overestimated (+47 M$/year, +71%). Hence, we find that the value of reservoirs tends to be underestimated with perfect foresight, while the value of hydropower plants is overestimated. When implementing all hydropower projects (Table 5), perfect foresight leads to an underestimation of trade-offs with the industrial and domestic water users (-8 M$/year) and agricultural production (-31 M$/year). While the additional hydropower production is almost the same for both frameworks, perfect foresight avoids more energy production costs by alternative sources (-31 M$/year). Similar effects are found for the impact of the e-flow policy and the irrigation development (Table 5): with perfect foresight the projects/policies lead to more hydropower curtailment, but to a lower economic impact on the energy system (lower energy production costs). The reason is that with perfect foresight hydropower curtailments are timed to minimize the need of extra power capacity development, while in actual operation, this is not feasible.

These numbers can be compared to the uncertainty linked to climate change; from the driest to the semi-wet scenario, the value of all irrigation projects varies from 723 to 883 M$/year (+22%), the value of all hydropower projects from 736 to 1163 M$/year (+58%), and the opportunity costs of the environmental policy from 284 to 55 M$/year (-80%). Furthermore, in Payet-Burin et al. (2019), other factors such as yield growth, international crop prices, carbon taxes, and cost of renewable technologies are found to be as important regarding the uncertainty of the future value of investments.

In conclusion, when evaluating the economic impact of investments in the Zambezi River Basin, we find that the perfect foresight assumption has negligible impacts for the semiwet and semidry climate scenarios. In the driest climate scenario, some investment values are over or under-estimated by more than 20%, but overall the uncertainty linked to the climate is more important than the bias linked to the perfect foresight framework. However, the perfect foresight assumption could impact the decision-making process when testing the robustness of investments regarding climate uncertainty.

Table 4. Impact of the perfect foresight assumption on the economic evaluation of infrastructure development and policies. diff. indicates the relative difference as (PF-MPC)/MPC. All projects includes also other projects as in World Bank (2010). The infrastructure investments costs (CAPEX) are provided as an indicative value.

	Climate scenario	CAPEX	Investment benefits (M$/year) semi-wet			semi-dry			driest		
	Investment	M$	MPC	PF	**diff.**	MPC	PF	**diff.**	MPC	PF	**diff.**
Irrigation	Shire	280	109	109	**0%**	110	109	**-1%**	32	61	**90%**
	Delta	573	138	138	**0%**	138	138	**0%**	144	137	**-5%**
	Kariba	787	346	344	**-1%**	319	322	**1%**	285	308	**8%**
	All projects	2 501	883	884	**0%**	836	843	**1%**	723	754	**4%**
e-flow	Opportunity *costs*	-	55	52	**-5%**	123	116	**-5%**	284	218	**-23%**
Hydropower	Batoka Gorge	3 603	407	406	**0%**	392	392	**0%**	328	355	**8%**
	Reservoir		5	2		5	1		-8	1	
	Hydropower		402	404	**0%**	387	390	**1%**	336	354	**5%**
	Mphanda Nkuwa	2 142	326	333	**2%**	272	279	**3%**	101	113	**12%**
	Reservoir		14	16	**13%**	25	21	**-17%**	48	23	**-53%**
	Hydropower		311	317	**2%**	247	258	**5%**	53	90	**71%**
	All projects	10 972	1163	1196	**3%**	1033	1039	**1%**	736	804	**9%**
	Reservoir		26	27	**5%**	33	33	**-1%**	86	82	**-5%**
	Hydropower		1137	1169	**3%**	1000	1006	**1%**	650	721	**11%**

Table 5. Key indicators for the with-without analysis of selected investments and policies. diff. indicates the relative difference as (PF-MPC).

Investment	**All irrigation projects**			**E-flow policy**			**All hydropower projects**		
Key indicators [M$/year]	MPC	PF	diff.	MPC	PF	diff.	MPC	PF	diff.

Total economic impact	723	754	**31**	-284	-218	**66**	736	804	**68**
Water User Benefits	7	0	**-7**	-6	0	**6**	-6	2	**8**
Energy Supply Benefits	0	0	**0**	0	0	**0**	0	0	**0**
Energy Production Costs	96	98	**2**	222	211	**-11**	-742	-773	**-31**
Crop Supply Benefits	1065	1110	**45**	-70	-9	**61**	-5	38	**43**
Crop Production Costs	253	257	**4**	-13	-1	**12**	-5	9	**14**
Downstream flow (10^6m^3/year)	-4761	-4888	**-127**	954	560	**-394**	1038	714	**-324**
e-flow fail (10^6m^3/year)	-45	0	**45**	21	0	**-21**	20	0	**-20**
Hydropower production (GWh/year)	-1975	-2142	**-167**	-3571	-3990	**-418**	17476	17501	**25**
Irrigation consumption (10^6m^3/year)	4619	4859	**241**	-597	-153	**443**	-705	-457	**249**
Irrigated area (1000ha)	292	292	**0**	-12	-2	**11**	-7	4	**11**

5 Discussion and Conclusion

In this paper, we show how the Model Predictive Control framework can overcome assuming perfect knowledge of the future in hydroeconomic optimization models. The method is attractive as it does not necessarily require additional data and can be applied to complex large-scale models. We validate the method by comparing it to Stochastic Dynamic Programming on a simple study case. We highlight impacts of assuming perfect foresight: high flows are anticipated in the model by earlier water releases avoiding spills; low flows are anticipated by storing additional water avoiding curtailments. On a more complex system in the Zambezi River Basin, we show that perfect foresight also results in better timing of hydropower production leading to less power capacity construction. By using a wide range of scenarios, we show that the importance of these effects is highly dependent on the system state. We find that perfect foresight overestimates total system benefits by less than 2% for all scenarios (compared to Model Predictive Control), while a pure simulation framework shows differences up to 12% for the water-scarcest scenarios. The specific focus of the paper is to analyze the impact of assuming perfect foresight in cost-benefit analysis of investments and policies through with-without analysis. On the Nile synthetic case, for some scenarios the perfect foresight assumption is found to have no impact. But for other scenarios, the value of an irrigation project is overestimated by 5 to 12% while the value of a transfer project is underestimated by 20 to 35%. We also show that using a non-adaptative simulation rule is clearly inappropriate when exploring scenarios with a different system state as economic impacts are over and underestimated by more than 30% for a large range of scenarios. Hence, while perfect foresight can introduce bias in the economic analysis, the assumption seems more reasonable than using a simulation framework with static rules.

The impact of assuming perfect foresight is confirmed when applying the methodology to a large-scale problem on the Zambezi River Basin involving interactions between the water, energy and agriculture systems. Perfect foresight does not affect the economic evaluation of potential investments in two out of three climate change scenarios. However, in the driest climate change scenario, the value of one irrigation projects is overestimated by 90% while other projects show little bias, the opportunity costs of an environmental flow policy are underestimated by 23%, the value of reservoir capacity development is underestimated by 5 to 53%, and the value of hydropower turbines are overestimated by 5 to 71%. In general, we find the impact to be less important on larger investments.

Contrary to total system benefits, the differences found in the with-without analysis can impact decision-making on project development. While perfect foresight provides an upper bound to total economic benefits of a system, this is does not hold for economic evaluation of investments through with-without analysis. In with-without analysis, the impact of the perfect foresight assumption depends on the current system state and towards which state the project moves the system. As different effects are impacting the results, it is difficult to predict in which cases the perfect foresight assumption will lead to biased cost-benefit results as it might vary from case to case. We can however formulate these general insights:

In water scarce situations (where demand is large relative to supply and/or variability is high relative to storage), perfect foresight will tend to overestimate benefits of infrastructure, because close to perfect water management is more valuable. In abundant situations, perfect management is less valuable so perfect foresight will be closer to reality. With regards to infrastructure, perfect foresight will tend to overestimate the benefits from infrastructure using water (e.g. irrigation and turbines), while benefits from infrastructure for managing flows (e.g. reservoirs) tend to be underestimated.

Hence when using perfect foresight models, we recommend the use of a framework like Model Predictive Control to perform the economic evaluation of investments and policies, or to control the validity of the perfect foresight assumption. However, we find that the uncertainty linked to exogenous parameters like climate change (or socio-economic development not explored in this paper) is likely to have more impact than the bias introduced by perfect foresight. While the framework is not limited by the curse of dimensionality, it does increase computation costs. If those become a burden when evaluating a large range of scenarios for robust decision-making, a trade-off must be found between uncertainty introduced by the perfect foresight assumption and uncertainty introduced by exploring less scenarios. When researchers for computational reasons opt for perfect foresight, these insights can be useful for conducting sensitivity analyses or stating qualifications.

Acknowledgments, Samples, and Data

Innovation Fund Denmark, COWIfonden, and COWI A/S funded the industrial PhD project in which this research was carried out. The authors also thank Alyssa McCluskey and Charles Fant for providing the runoff time-series for the Nile and Zambezi study case respectively. The WHAT-IF model with the MPC framework is available on Github (https://github.com/RaphaelPB/WHAT-IF); different branches exist for the Nile and Zambezi study case. The dataset on the Zambezi study case is available in the Github repository as well as in https://zenodo.org/record/2646476#.X0UgejVS-uU.

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Water Resources Research

Supporting Information for

The impact of assuming perfect foresight for investment analysis in water resources systems

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Introduction

This supporting information provides (1) details on how nearest neighbors bootstrapping is implemented in the model, (2) the reservoir storage values in the Nile case from Stochastic Dynamic Programming, and (3) additional results to the Nile study case. The model and data for the different study cases is available at https://github.com/RaphaelPB/WHAT-IF

Text S1. Forecasting using Nearest Neighbors bootstrapping

Nearest neighbors bootstrapping (Lall & Sharma, 1996) is a method to generate synthetic time series or forecasts using observed time series while preserving important correlations and autocorrelations (Yates et al., 2003). The concept is to find a system state in the historical archive, which is similar to the current state of the system and then assume that future evolution will be similar to the evolution observed in the past. The approach can be divided in three steps: (1) Define the feature vector characterizing the current state of the system, (2) Find the nearest neighbors (closest past system states) in the observed time series, (3) Sample from the nearest neighbors to generate a forecast or a synthetic time series.

At a given time step (i), we consider here as feature vector (Di), the ensemble of: total runoff (Q_i), average precipitation (P_i), and average reference evapotranspiration (E_i) in the system.

$$D_i = [Q_i, P_i, E_i]$$

The ensemble of feature vectors of past occurrences (D) is defined for the ensemble of time steps corresponding to the same month as the current time step ($T_{month(i)}$).

$$D = ([Q_t, P_t, E_t] \mid t \in T_{month(i)})$$

$$D = ([Q_t, P_t, E_t] \; \forall \, t \in T \mid month(t) = month(i))$$

$$D = ([Q_t, P_t, E_t] \; \forall \, t \in T_{month(i)})$$

The distance (r_t) of a past state (D_t) to the current system state (D_i) is calculated using the Euclidian norm between feature vectors:

$$r_t = \sqrt{\sum_j w_j \cdot \left(D_i^j - D_t^j\right)^2}$$

where w_j are the weights of the elements of the feature vector (runoff, precipitation, and evapotranspiration here). We define the weights as the inverse of the standard deviation of the elements of the feature vector. For example, the runoff weight takes the form:

$$w_Q = {}^{1}\!/_{std(Q_t \mid t \in T_{month(i)})}$$

The k nearest neighbors are the k past system states with the lowest distance to the current state. The choice of k can be optimized, Lall and Sharma (1996) suggest the square root of the total amount of samples. Because we use 40 years or 360 months length time series, we choose k=20. The nearest neighbors are ranked from lowest to highest Euclidian distance. To sample among the nearest neighbors, we define the sampling Kernel based on the rank of the neighbors, as in Yates et al. (2003).

$$K_l = {}^{1/l}\!/_{\sum_{n=1..k} 1/n}$$

where l is the rank of the neighbors. This approach assumes that only the rank affects the probability; Akbari et al. (2011) describe alternative sampling Kernels.

To generate an ensemble forecast, the desired number of neighbors are sampled with probability K. To generate an average forecast, the nearest neighbors are weighted according to their probability to generate a single weighted forecast ($\widehat{D}_{i+m}$):

$$\widehat{D}_{i+m} = \sum_{l=1..k} K_l \cdot D_{t(l)+m}$$

Where m is the forecast lead time (in time steps) and $t(l)$ is the time step corresponding to the l-th ranked neighbor. We also generate weighted ensemble forecasts, by classifying the k-nearest neighbors in different categories based on the total predicted runoff (e.g. 50% lowest and highest predictions) and then computing the weighted average forecast within the categories. The likelihood of the categories is then the sum of the neighbor's likelihoods belonging to this category. This last method enables to generate an ensemble forecast with less members that still contains information from the k-nearest neighbors.

Text S2 Nile study case: storage value with Stochastic Dynamic Programing (SDP)

Loucks and Van Beek (2005) describe the development of the SDP method. The code implementing the SDP framework is https://github.com/RaphaelPB/WHAT-IF under the "Nile synthetic case" branch in the file "Nile_SDP_water_value.py". The SDP framework is not part of the WHAT-IF tool and was only implemented on this specific study case to compare results with the Model Predictive Control framework. **Figure S1** shows example of the reservoir storage value for three scenarios obtained from backwards runs in the SDP framework. When comparing the full range of scenarios exploring total runoff and water demand, the reservoir storage value is calculated individually for each scenario.

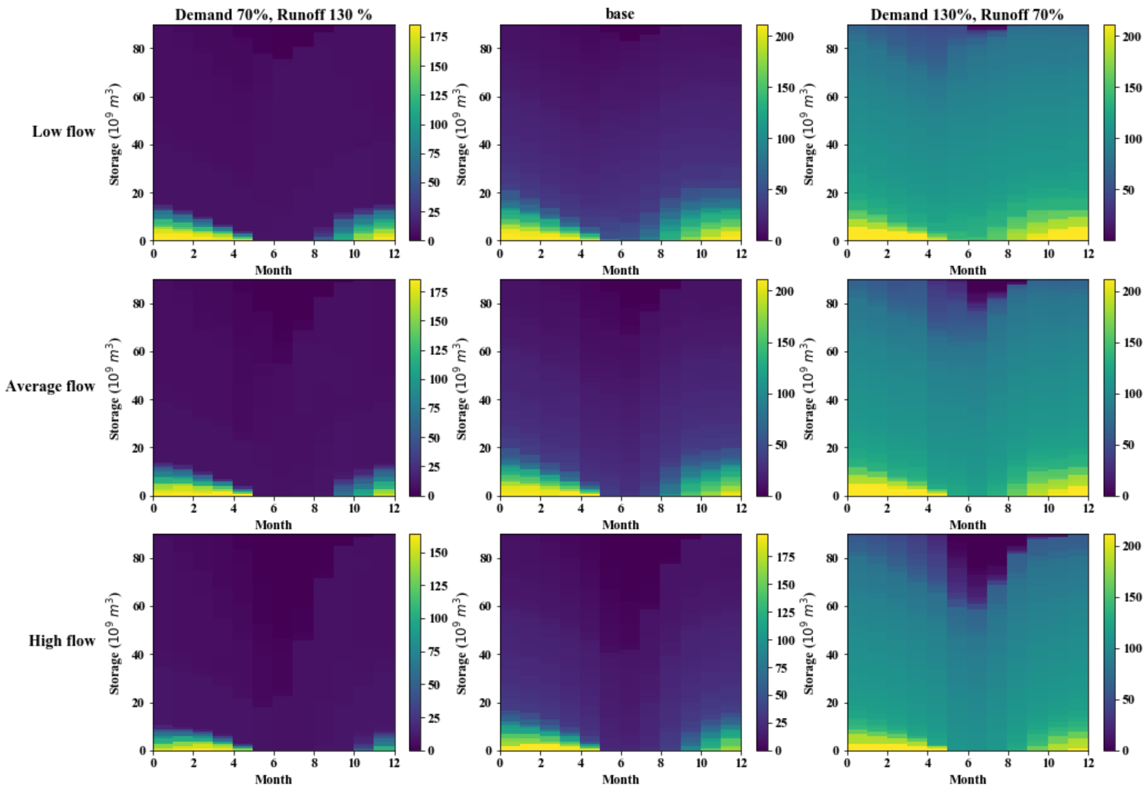

Figure S1. Reservoir storage value evaluated through the SDP backward runs. The value of reservoir storage depends on the current inflow and is different for each scenario.

Text S3 Nile study case: additional results to the projects and scenario evaluation

This section provides two additional figures to the paper: **Figure S2** shows the differences between the frameworks on key indicators not restricted to total system benefits (Allocation value, Hydropower value, Spills and Storage), **Figure S3** shows the impact on total system benefits and cost-benefit analysis when evaluating the project development as in the Paper, but displays the results in terms of relative value (percentage).

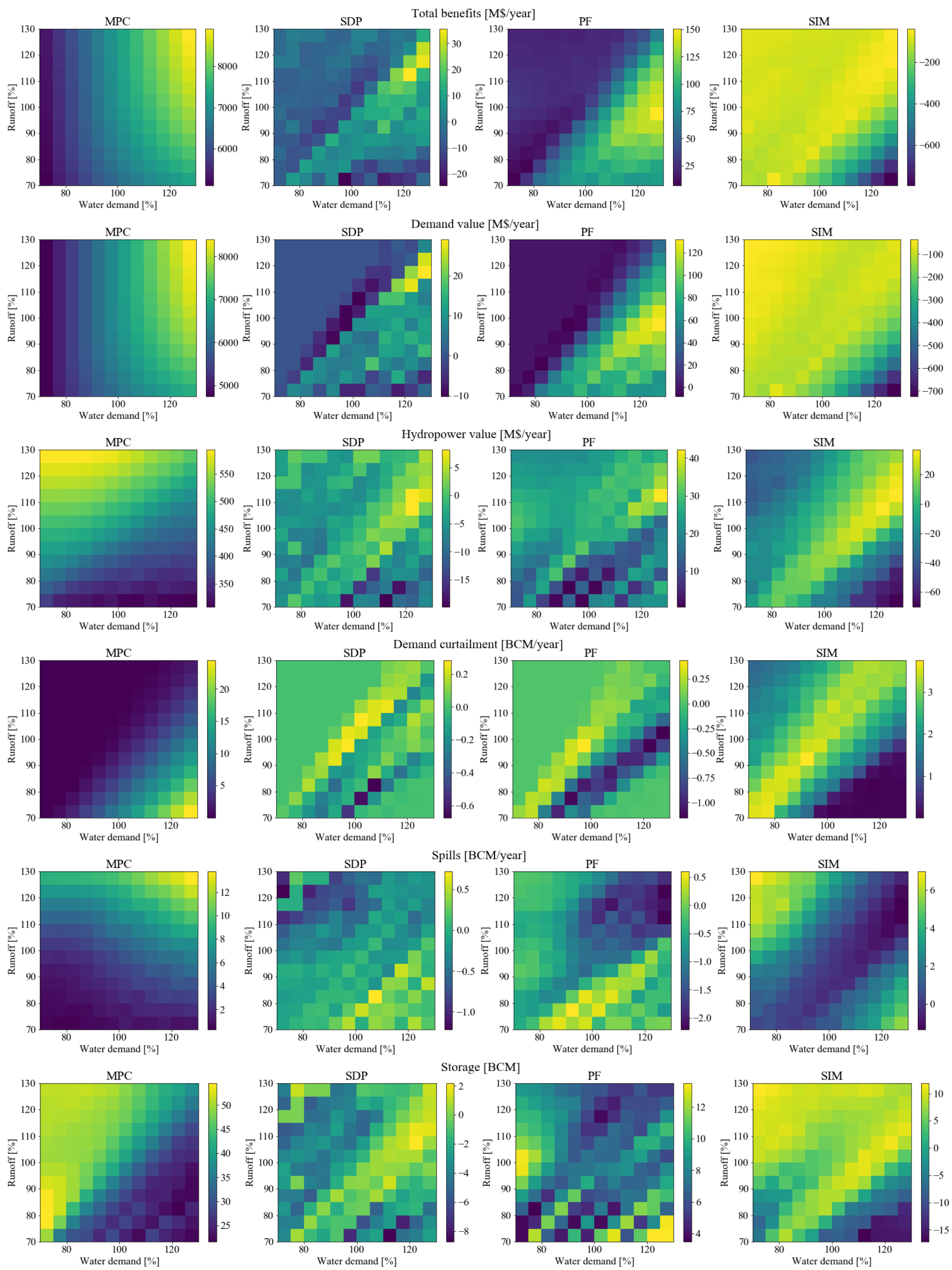

Figure S2. Key indicators on the Nile study case. MPC in absolute values, other frameworks are relative to MPC

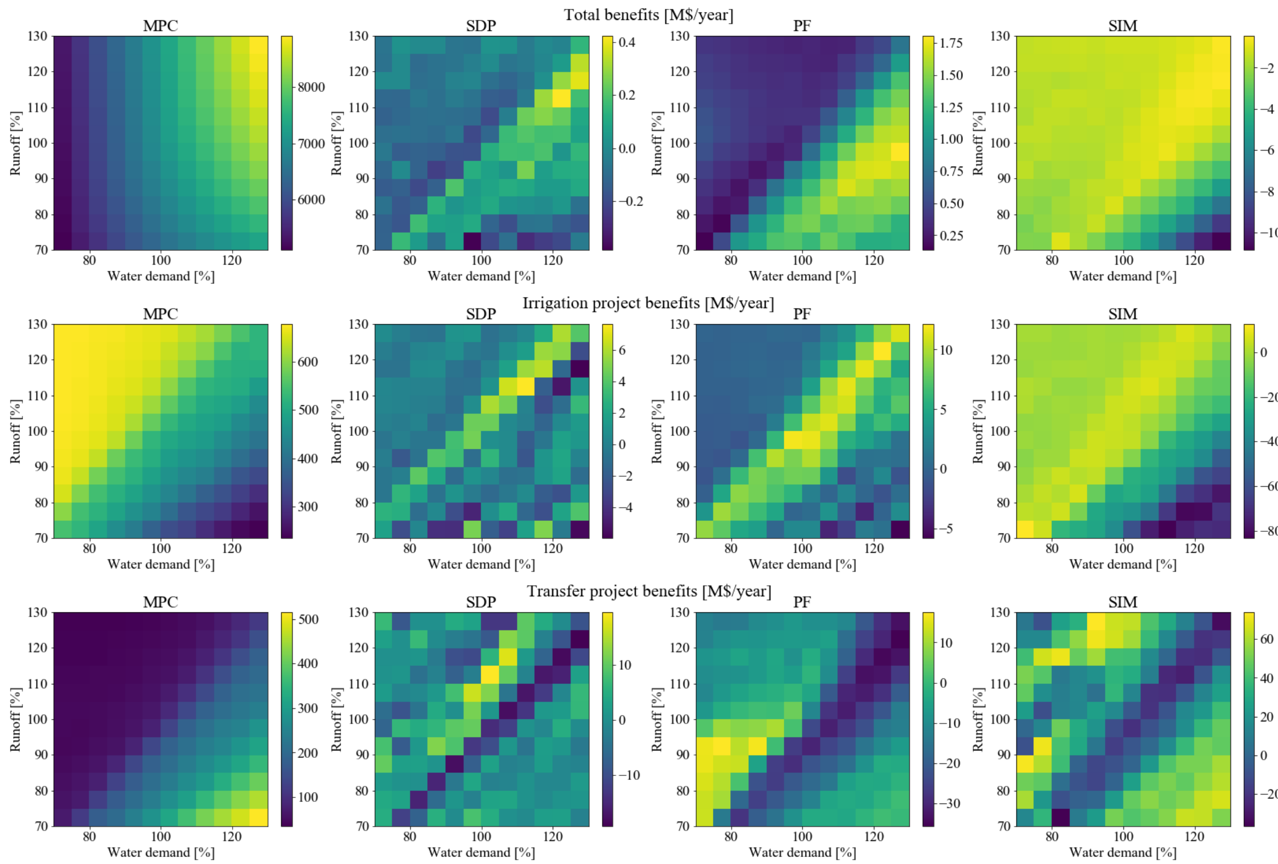

Figure S3. Economic evaluation of project development with the different frameworks. MPC in absolute values, other frameworks are in relative changes (%): (framework-MPC)/MPC

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